



**HAL**  
open science

# From a Synthetic Auto-Biographical Memory toward the Emergence of Different Levels of Self: a Case Study with the iCub Humanoid Robot

Grégoire Pointeau

► **To cite this version:**

Grégoire Pointeau. From a Synthetic Auto-Biographical Memory toward the Emergence of Different Levels of Self: a Case Study with the iCub Humanoid Robot. Neuroscience. Université Claude Bernard - Lyon I, 2015. English. NNT : 2015LYO10175 . tel-01269702

**HAL Id: tel-01269702**

**<https://theses.hal.science/tel-01269702>**

Submitted on 5 Feb 2016

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



A THESIS SUBMITTED IN FULFILLMENT OF THE REQUIREMENT FOR THE  
DEGREE OF DOCTOR OF PHILOSOPHY OF THE UNIVERSITÉ LYON 1 :  
NEUROSCIENCES ET SCIENCES COGNITIVES.

---

**From a Synthetic Auto-Biographical Memory  
toward the Emergence of Different Levels of Self.  
A Case Study with the iCub Humanoid Robot.**



---

*Author :*  
Grégoire POINTEAU

*Supervisor :*  
Dr. Peter Ford DOMINEY

*Jury :*  
Rémi GERVAIS, CRNL - INSERM, Université Lyon 1  
Rachid ALAMI, LAAS - CNRS, Universités de Toulouse  
Frédéric ALEXANDRE, INRIA, Universités de Bordeaux  
Jose SANTOS-VICTOR, Instituto Superior Técnico, Lisboa

Tuesday 6th October 2015

*Laboratory :*  
Institut National de la Santé et de la Recherche Médicale.  
Stem-cell and Brain Research Institute  
Cortical Networks for Cognition Interaction



## Remerciements

Je suis d'un naturel bavard, et réaliser ce travail en solitaire m'aurait été tout simplement impossible. C'est pourquoi je vais essayer de remercier toutes les personnes qui m'ont aidé à amener cette thèse à son terme.

En tout premier lieu, je souhaiterai remercier le président du jury Mr. Rémi Gervais ainsi que Mr Rachid Alami, Mr Jose Victor-Santos et Mr. Frédéric Alexandre, d'avoir accepté de composer mon jury de thèse, ainsi que d'avoir accepté le rôle de rapporteur de mon manuscrit.

Je tiens à remercier tout particulièrement Peter Dominey mon directeur de thèse pour m'avoir donné l'opportunité de faire ce doctorat ainsi que pour tout ce qu'il m'a transmis sur le métier de chercheur. Il s'agit en tout premier lieu du goût de la recherche et la curiosité qui se mue parfois en excitation presque enfantine sur le monde en général. Au delà des neurosciences, ce sont tous les sujets et toutes les questions qui se posent qui méritent une réponse. C'est cet aspect de découverte et de curiosité que je garderai le plus de ma thèse, cette envie de répondre aux interrogations quotidiennes et cette fascination pour le monde qui nous entoure.

Aussi, je voudrai remercier Peter pour sa disponibilité et son écoute durant ces trois ans. Et puis surtout je souhaiterai le remercier pour son implication personnelle, pour les moments sérieux, les moments de détente, les moments d'encouragements, les barbecues, l'explication du football américain, la NASA...

Je souhaite également remercier mes collègues et collaborateurs proches des projets EFAA puis WYSIWYD et tout particulièrement Stéphane Lallée, avec qui nous avons des débats parfois sur-réalistes que ce soit scientifiques ou bien sur la société. Nous étions soit franchement d'accord, soit franchement en désaccord mais il y avait rarement de demie mesure. Mais avant tout Stéphane m'a appris énormément sur l'iCub et sur les sciences cognitives en général, et son esprit curieux était très contagieux.

Je voudrai remercier aussi Maxime Petit pour m'avoir supporté dans le travail en binôme, et puis pour savoir faire preuve de rigueur ou d'intuition suivant les besoins du moment.

Mais surtout je voudrai remercier Stéphane et Maxime pour les moments passés dans ces projets, que ce soit à Lyon, à Londres, à Barcelone ou à Gênes! Quand on voit le soleil que 4 fois par an, il faut en profiter, et puis sortir 3 geeks sur la plage ça fait toujours son petit effet!

Egalement dans les projets EFAA et WYSIWYD, je voudrai remercier Vicky Volousty avec qui j'ai peut être partagé plus de tapas que de robotique, mais la voir baby-sitter Stéphane Lallée est un régal pour les yeux! Merci également à Ugo Pataccini d'avoir réussi à nous supporter et à réparer toutes nos bêtises (surtout quand Maxime et moi avons cassé le robot en le faisant jouer à Street Fighter...).

Un immense merci à mon équipe du laboratoire avec qui j'ai travaillé : Anne-Laure Méalier pour la fraîcheur Stéphanoise et Guillaume Gibert pour les bougonneries Lozériennes. Merci à vous pour toutes les fois où vous m'avez sorti du pétrin dans la gestion de l'iCub et de son système.

Aussi un merci à Jocelyne Ventre-Dominey, Carol Madden et Nicolas Cazin pour la vie scientifique de l'équipe et l'émulation constante dans laquelle j'ai baigné.

Bien que nous n'ayons jamais travaillé directement ensemble, je souhaiterai remercier Florian

Lance pour les 2 ans et demi passés avec moi. Avoir quelqu'un d'aussi compétent au laboratoire, c'est précieux.

Merci également à Marwin Sorce qui aurait du être mon premier stagiaire et puis qui s'est débrouillé tout seul au bout d'une demie heure, s'en est presque vexant...

Mais au delà du travail je souhaite remercier particulièrement Florian et Marwin auquel je souhaite rajouter Cédric Manesse, pour les moments passés pendant ma thèse avec eux. Ils sont dotés d'une réactivité assez impressionnante pour aller boire un verre! Ma thèse aurait été bien différente, scientifiquement et humainement sans vous!

Je voudrai également remercier les membres du laboratoire pour la vie de tous les jours et pour créer cette ambiance scientifique dans laquelle nous baignons tous les jours. Merci donc à Loïc, le gang des filles : Julie, Julie et Angèle, Pierre, Rita, Charlie, Mailys, Frédéric, Camille, Clément, Tanguy, Yann, Anne-Lise, Sullivan ainsi que tous les membres passés et présents du laboratoire, qu'ils soient scientifiques, techniques, administratifs ou logistiques, merci à tous pour ces échanges et cette vie quotidienne!

Je tiens également remercier particulièrement Chandara Nay pour m'avoir aidé dans tous les dédales administratifs et toujours avec ce sourire rassurant.

Un grand merci à ceux qui ont compté pour moi pendant ma formation à l'INSA. En premier les musiques études (et assimilés) : Mélanie, Maxime, Marianne, Axel, Julie, Nathalie, Yannick, Fabien, Antoine et Magdalena. J'ai beaucoup de souvenirs avec vous tous, et je vous dois ma première, puis ma deuxième année, mais surtout je vous dois des moments formidables, pas toujours sous le signe de la logique et de l'intelligence mais qu'importe.

Ensuite les BIM : Sacha, Hugo, Elsa et Elsa, Audrey, Julien, Léa, Romain, Raphaëlle et Bérénice. Je vous dois à vous, ma troisième puis quatrième année (la cinquième j'y suis arrivé presque tout seul).

Samuel, je savais pas dans quelle catégorie te mettre, choisis ce que tu préfères, tu es un grand garçon!

Je souhaite également remercier les gens avec qui j'ai partagé ma vie ces dernières années que ce soit à travers la musique ou autre. Adrien Litas tout d'abord pour tout ce qu'il a fait pour moi, pour tous ces moments partagés sans que je puisse pourtant les définir clairement... Bref, juste pour être la quand il le faut!

Merci également à Ricardo Andrade pour l'accueil à Sao Paolo et pour tout ce que tu as fait pour nous à Lyon.

Ensuite les petits Saumons, Christophe, Allan, Valérian, Victor, Robin et Damien. Enfin les Velcros et Polochons, Corentin, Victor, Colin, Thomas, Joseph et Hugo pour me permettre de refaire de la musique, avec un remerciement spécial pour Aude Miaglia pour m'avoir supporté pendant toutes ces années.

Merci également à Didier Mollon pour m'avoir permis d'utiliser son tableau : *"La Femme"* comme image de couverture.

Je voudrai maintenant remercier spécialement Alice Julien-Lafferrière. Il me faudrait bien plus que ces 160 pages pour te dire tout ce pourquoi je tiens à toi. Je te dois cette thèse pour tous les matins où tu es à mes côtés depuis ces années. Dans ces pages, il y a ton sourire, ton intelligence, ta gentillesse, ta folie et ta rigueur, ton énergie, ta sensibilité, il y a une partie de toi.

J'en oublie certainement encore, et je m'en excuse. Je souhaite encore une fois remercier tous ceux qui de près ou de loin, directement ou indirectement, ont participé à ce travail (merci Zazie!).

Et enfin comment faire une thèse qui est censée expliquer en quoi la mémoire et l'expérience, et en particulier l'enfance, forgent une personnalité et une notion de soi, sans remercier ma famille. Je voudrai remercier mon père, ma mère, mon frère et mes sœurs (ho ho). Tout au long de ma thèse, je n'ai cessé de lire que l'environnement riche et stimulant était bénéfique pour le développement, et si il y a bien une chose dont je n'ai pas manqué, c'est d'un environnement riche et stimulant avec des parents curieux et aimants et un grand frère et deux grandes sœurs brillantes et exemplaires à tous niveaux! Merci également à ceux qui vont accompagner, Charlotte, François, Adrien et Otto. Pour toutes ces années de découvertes, de curiosité, d'exemplarité, de jeux, je souhaite vous dédier cette thèse.

## Abstract

The objective of the following study is to define the influence of an Autobiographical Memory and its two main components : the Episodic Memory and the Semantic Memory in the emergence of the notion of “*self*”. I will focus on the functional part of the autobiographical memory rather than on its technical and neuronal aspect. Then I will describe the implementation of an synthetic autobiographical memory in an Humanoid Robot : the iCub. I will show how this synthetic autobiographical memory can participate with the help of several reasoning modules, in the emergence of the self. Concerning the aspect of self, we decided to work about Ulric Neisser’s four components of the self described in 1995 : the Ecological Self, the Interpersonal Self, the Conceptual Self and the Temporally Extended Self.

I will present the technical platform we use. This system is composed at its center by the humanoid robot iCub, interacting through a reactive table (the ReacTable) with a Human Agent. The interaction is mainly through speech. The world as it is perceived by the robot is constantly updated in its internal “*working memory*” (the Objects Properties Collector : OPC).

I will then describe our Synthetic Autobiographical Memory, composed of two part, an Episodic-Like Memory and a Synthetic Semantic Memory that model respectively the Episodic and Semantic human memories. The Episodic-Like Memory will store snapshots of the working memory, while the Synthetic Semantic Memory stores information related to knowledge extracted by the reasoning modules through a mental working memory.

Next I will for each level of self that we examined, explained how a Synthetic Autobiographical Memory could contribute to its emergence, starting by the Ecological Self which concerns someone’s impact and direct influence on the world. Concerning the Ecological Self, I will show a system of forward model through mental imagery. This forward model allows the robot to simulate through its mental working memory the consequences of his physical action on the world, such as it is defined by Neisser.

After that I will focus on the Interpersonal Self which is related to the social interaction. I will first show how the system of mental working memory developed previously could help to understand a social interaction and the role effect of each agent. Secondly, I will explain the “*I and You Experiment*” which consists in understanding and using correctly a personal pronoun given its context. Our specificity is that we extended the work from Gold and Scassellati not only to personal pronouns but to proper nouns too. At last for the Interpersonal Self, I will describe a system of Shared Plans as part of social ritual.

I will then developed the Conceptual Self. The first part of it is an “high level reasoning” : using the mental working memory to simulate and predict complex plans. I will give two examples of

it : the ABCD game, and the Table of Hanoi. Then, as second part of the Conceptual Self, I will develop the use of the mental working memory in the *Theory of Mind*. It consists in using the mental working memory to predict the mental state of another agent and the experiment we used for it was the Sally-Anne task modified for the iCub.

The last level of self that I will develop in this thesis is the Temporally Extended Self. There will be no proper demonstration of its functioning because I will show that the Temporally Extended Self emerges as the three other level are active. However, I will show two manifestations of it : one is the Synthetic Autobiographical Memory running on the long term, and the second is an interaction with the robot about his own personal history.

At the end of my thesis, I will discuss several points : the limitation of our model, the Private Self which is a component also defined by Neisser but that we decided voluntarily to put aside, the differentiation between the robot self and the human self, some aspect of plasticity of the Human memory. I will then conclude with an opening on the futures possibilities of our system.

## Résumé

L'objectif de l'étude suivante est de déterminer l'influence de la mémoire autobiographique et de ses deux principaux composants : la mémoire épisodique et la mémoire sémantique dans l'émergence de la notion de soi. Je vais me concentrer sur la composante fonctionnelle de la mémoire autobiographique davantage que sur ses aspects anatomiques et neuronaux. Je vais ensuite décrire l'implémentation d'une mémoire autobiographique synthétique chez un robot humanoïde : iCub. Puis, je vais montrer comment cette mémoire synthétique peut participer avec l'aide de procédés de raisonnement, à l'émergence d'un "soi". Concernant cet aspect du soi, nous avons décidé de concentrer notre travail sur la définition d'Ulric Neisser de 1995 de quatre composants du soi : le "Soi Ecologique", le "Soi Interpersonnel", le "Soi Conceptuel" et le "Soi Etendu dans le Temps".

Je vais dans un premier temps décrire la plateforme technique mise en place. Notre système est composé à son centre du robot Humanoïde iCub, interagissant à travers une table réactive (la ReacTable) avec un agent Humain. L'interaction est majoritairement vocale. Le monde perçu par le robot est constamment mis à jour dans sa "mémoire de travail" interne (appelée OPC pour Objects Properties Collector).

Je vais ensuite décrire la Mémoire Autobiographique Synthétique (SABM), composée d'une Episodic-Like Memory (ELM) et d'une Synthetic Semantic Memory (SSM) qui vont modéliser respectivement les mémoires épisodique et sémantique de l'Homme. La ELM va stocker des "instantanés" de l'état de la mémoire de travail, alors que la SSM va stocker les informations relatives au savoir, extraites par les modules de raisonnement au travers d'une mémoire de travail mentale.

Ensuite, je vais pour chaque niveau de soi expliquer en quoi, notre SABM pourrait contribuer à l'émergence en commençant par le "Soi Ecologique", qui concerne l'impact personnel physique et l'influence direct d'une personne sur le monde. Concernant ce "Soi Ecologique", je vais présenter un système de "forward model" à travers une imagerie mentale. Ce "forward model" va permettre au robot de simuler à travers son imagerie mentale, les conséquences de ses actions physiques sur le monde, tel que défini par Neisser.

Après cela, je vais présenter le "Soi Interpersonnel" qui est relié aux interactions sociales. Je vais donc dans premier temps montrer comment notre système de mémoire de travail mentale précédemment introduite, pourrait aider à comprendre une interaction social et le rôle de chaque agent. Dans un second temps, je vais expliquer l'expérience "I and You" qui consiste à comprendre et utiliser correctement un pronom personnel en fonction du contexte de l'interaction. La spécificité de ce travail qui est une extension du travail de Gold et Scassellati est qu'il est dirigé envers non seulement les pronoms personnels mais également les noms propres. Enfin dans un troisième temps je vais présenter un système de "Plans Partagés" comme partie prenante d'un rituel social.

Je vais ensuite développer le “Soi Conceptuel”. Ce développement se fera d’abord par la présentation d’un système de “Raisonnement de Haut Niveau” qui utilise notre système de mémoire de travail mentale pour simuler et prédire des plans complexes. Je donnerai deux exemples de son utilisation : le “Jeu ABCD” et les “Tables de Hanoi”. Ensuite dans une seconde partie, je présenterai l’utilisation de cette mémoire de travail mentale dans le contexte de la Théorie de l’Esprit. Cela consiste en l’utilisation d’une imagerie mentale pour prédire l’état d’esprit d’un agent. Nous avons pour cela repris l’expérience de la “Poupée de Sally” adaptée pour le robot.

Enfin, le dernier niveau que je vais développer dans cette thèse et le “Soi Etendu dans le Temps”. Il n’y aura pas de démonstration à proprement parlé de son fonctionnement car je vais montrer que ce niveau semble émerger par l’activité des niveaux précédents. Toutefois je vais présenter deux de ses manifestations : l’une étant la SABM sur le long terme, et la seconde étant une interaction avec le robot au sujet de son histoire personnelle.

A l’issue de ma thèse, je vais discuter plusieurs points : les limitations de notre modèle, le “Soi Privé” qui est défini comme un composant du “Soi” par Neisser et que nous avons délibérément laissé de côté, la distinction qu’il peut être faite entre le “soi” du robot et le “Soi” de l’Homme, et enfin certains aspects de plasticité de la mémoire Humaine. Je vais finalement conclure avec une ouverture sur les possibilités futures de notre système.

# Table of Content

<b>Table of Content</b>	<b>9</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Memory	5
1.2 Self	11
1.2.1 The life of Phineas Gage	11
1.2.2 Neisser's levels of self	15
1.3 Context and objectives of the thesis	18
1.3.1 Context of the Thesis : the EFAA and WYSIWYD European projects.	18
1.3.2 Objectives	22
1.3.3 Publications	23
<b>2 A Synthetic Autobiographical Memory for Reasoning</b>	<b>25</b>
2.1 Concepts of Memory	25
2.1.1 Declarative versus non-declarative Memory	26
2.1.2 Episodic Memory versus Semantic Memory	30
2.1.3 Autobiographical Memory	33
2.1.4 Development of the ABM and cultural differences	34
2.2 A Synthetic Autobiographical Memory	37
2.2.1 System Overview	37
2.2.2 Episodic-like Memory	47
2.2.3 Synthetic Semantic Memory	49
2.3 Creation of Knowledge	50
2.3.1 First level : Extraction of Knowledge from the ABM	52
2.3.2 Retro Reasoning	62
2.3.2.1 Second level of Reasoning	62
2.3.2.2 Third level of Reasoning	63
<b>3 Ecological Self</b>	<b>65</b>
3.1 Ecological Self	65
3.2 Forward Model Through Mental Imagery	65
3.2.1 System Description	66
3.2.2 Mental Imagery : Experiment	67
3.2.3 Discussion	71
<b>4 Interpersonal Self</b>	<b>73</b>
4.1 Mental Imagery Extended to Interaction	76
4.2 Language and social references : the "I and You Experiment"	79
4.2.1 System Specificities	81
4.2.2 Method	82
4.2.3 Learning Mechanism	85
4.2.4 Experiment and results	87
4.2.5 Discussion of the results	95
4.3 Shared Plan	99
4.3.1 Learning Phase	102
4.3.2 Execution and Generalization	103
4.3.3 Conclusion about Shared Plans	103
4.4 Contribution of these systems to the Interpersonal Self : Conclusion and Discussion	104
<b>5 Conceptual Self</b>	<b>108</b>

5.1	High Level Reasoning and Prediction Based on Experience . . . . .	110
5.1.1	Planning and Goal Directed Reasoning . . . . .	111
5.1.2	Proof of Concept : the ABCD game . . . . .	112
5.1.3	The Table of Hanoi . . . . .	118
5.1.3.1	System and Learning Phase . . . . .	118
5.1.3.2	Results . . . . .	121
5.2	Theory of Mind . . . . .	123
5.2.1	The ability to “Mentalize” : developmental Aspect . . . . .	123
5.2.2	The the iCub performing the Sally-Anne experiment . . . . .	128
5.3	Discussions about the Conceptual Self . . . . .	130
<b>6</b>	<b>Temporally Extended Self</b> . . . . .	<b>132</b>
6.1	SABM . . . . .	135
6.2	The TES as integration of all the other levels of self. . . . .	136
6.3	Conclusion on the TES . . . . .	139
<b>7</b>	<b>Discussion</b> . . . . .	<b>141</b>
7.1	Summary of the study . . . . .	141
7.2	The private self . . . . .	143
7.3	Robot Self vs Human Self . . . . .	145
7.4	Other aspect of the memory system as builder of the self . . . . .	146
7.4.1	Tuning of the robot . . . . .	146
7.4.2	Plasticity of the memory . . . . .	147
7.5	Importance of the embodiment . . . . .	150
7.5.1	A Human-Like Concept . . . . .	151
7.5.2	The limit of the embodiment . . . . .	153
<b>8</b>	<b>Conclusion</b> . . . . .	<b>155</b>
	<b>Bibliography</b> . . . . .	<b>159</b>
<b>9</b>	<b>Appendices</b> . . . . .	<b>169</b>
9.1	Lifespan . . . . .	170
9.2	Video SABM . . . . .	172
9.3	Published articles . . . . .	177
9.3.1	TADM : Successive Developmental Levels of Autobiographical Memory for Learning Through Social Interaction . . . . .	177
9.3.2	TAMD : The Coordinating Role of Language in Real-Time Multimodal Learning of Cooperative Task . . . . .	191
9.3.3	Interaction Studies : Reasoning Based on Integrated Real World Experience Acquired by a Humanoid Robot . . . . .	207
9.3.4	Living Machine : Embodied Simulation Based on an Autobiographical Memory . . . . .	249
9.3.5	EPIROB : Emergence of the Use of Pronouns and Names in Triadic Human-Robot Spoken Interaction . . . . .	261
9.3.6	Frontiers : Exploring the Acquisition and Production of Grammatical Construction Through Human-Robot Interaction . . . . .	269
9.4	EFAA WYSIWYD Description of Work . . . . .	304
9.4.1	EFAA DOW . . . . .	304
9.4.2	WYSIWYD DOW . . . . .	308

## **Abbreviations**

**ABM** Autobiographical Memory  
**ABMR** Autobiographical Memory Reasoning  
**Ad** Addressee  
**Ag** Agent  
**CS** Conceptual Self  
**CKF** Consolidation of Knowledge Function  
**ES** Ecological Self  
**EFAA** Experimental Functional Android Assistant  
**ESK** Event Specific Knowledge  
**ELM** Episodic-Like Memory  
**IS** Interpersonal Self  
**MOPC** Mental Objects Properties Collector  
**OPC** Objects Properties Collector  
**PAOR** Predicate Agent Object Recipient  
**PDDL** Planning Domain Definition Language  
**PS** Private Self  
**SABM** Synthetic Autobiographical Memory  
**SOM** Self Organized Maps  
**SP** Shared Plan  
**Sp** Speaker  
**SSM** Synthetic Semantic Memory  
**Su** Subject  
**SWoOz** Super Wizard of Oz  
**TaOH** Table Of Hanoi  
**ToM** Theory of Mind  
**ToOH** Tower Of Hanoi  
**TES** Temporally Extended Self  
**WM** Working Memory  
**WYSIWYD** What You Say Is What You Did  
**HRI** Human-Robot Interaction

## Introduction

In a world where the digital systems are more and more present, a new challenge has risen over the last decades : artificial intelligence, and more than this, artificial beings. The world is looking for artificial beings, or at least artificial like-beings. The automates of tomorrow need not only to answer correctly to a task that have been assigned to them, but also to behave with humans.

In this context, the scientists face a huge challenge. Our society is expecting machines that could not only understand classical problems as it is nowadays (like building a car) but to understand humans, their will, their needs, their feelings. But how could a man or a woman trust a robot, or a program, about its decisions if it is not able to show the same capabilities? If we want the robot to understand someone's will, the robot needs to differentiate each of us as we do every day. Each of us, the humans, are different. This is one of the most basic human skills, to recognize each other easily, and our society is based on this fact : I am someone different from my neighbor and I deserve acknowledgment for who I am. My story is different from my neighbor's story, and we expect, as for the human, that the robot to be able to make this distinction.

Here again, to be fully integrated in our every day life, the robots should be able to react differently with each of us, to react like one of us, to anticipate our needs, as much as we anticipate theirs. This problem is not just for the robot with a body, but also all the computer program that we use every day : phone, computer, car. We want the robot to recognize us as someone, and behave also like one of us, to be themselves!

But why am I myself? What do I call myself? Why are people so unique? Of course the genetic code can explain certain physical differences. But what will push someone to react differently from his neighbor? Even twins don't have the same behavior where they share almost the same genetic heritage. Why can one say that he can predict the action of another? Because they have known each other for a long time, and have a shared experience. After a trauma, we can hear one say : "He will never be the same". This sentence is symptomatic of the importance of experience for someone's self. The experience that one can have is what will define who he is.

This experience can be observed at different scales. We can decide to look at it from the scale of a population as did Tomasello [Tomasello, 2009]. Tomasello claims that the memory can be observed at the scale of a population, and that the Humans are able to transmit knowledge from one generation to another, and to create some kind of shared memory, that anyone in the society can access. This is what can give a society a "self" (culture).

The memory can be also studied from a smaller scale : the individual scale. Even if this topic has been studied extensively in the past decades (even centuries), many processes are still blurred. However, great scientists and psychologists as Tulving [Tulving, 1985], Cohen [Cohen and Conway, 2007], Conway [Conway and Pleydell-Pearce, 2000], and many others, have permitted the new scientist to have a clear view of what are the main functions of memory. The goal now of the new generation, is to continue the research on the memory itself on one hand. And on the other hand, we have to be able to recreate a memory, to model the more precisely as possible each aspect of it.

But memory is not just a "big bag" of events or concept or even knowledge. The history of a man, is anchored in his body, and in his interaction with the world and more of it, in the interaction with other agents. Wilson claims that cognition, and memory as part of it, is embodied [Wilson, 2002]. We thus need a support to embody this memory if we want to be able to reach the first sight of "self". It allows us to perform some prediction in time or

space, to know what and why to learn [Vernon et al., 2007].

In this context, Asada claims that certain types of behaviors are better learned than pre-programmed [Asada et al., 2009]. This is particularly true in the case of social behavior of social convention. The robot iCub, is a humanoid robot of the size of a 3 years old child, with 53 degrees of freedom and is a state of the art (even more) robot [Metta et al., 2008]. The iCub is thus a perfect candidate for our studies about the memory, the self and their modeling. He allows us to have an embodied system, and also, thanks to his humanoid form, a good candidate for Human-Robot interaction about sociability.

During this thesis I will develop the concept of memory, and more particularly the concept of Autobiographical Memory (**ABM**) as an embodied faculty. I will also explain the reasoning tools that we developed for the robot in order to be able to manipulate his autobiographical memory, create new knowledge, and re-organize his memory. In order to provide a coherent structure to the presentation of this work, I will organize the progressive development accordingly to the levels of self as proposed by Neisser. I'll thus develop the concept of self, or the *4 concepts of selves*, as defined by Neisser in his book of 1995 : "*Criteria for an Ecological Self*" [Neisser, 1995] or in [Neisser, 1988] : *ecological self, interpersonal self, conceptual self, and temporally extended self*. We will put aside the *private self* (the fifth level of self for Neisser) that appears later in the development of the child. Finally, I will explain the reasoning functioning that we developed, how and why we can say that we reach the first sight of notion of self with the robot. I must stress that I do not claim to have implemented the self in a robot. Rather developed and implemented algorithms that make specific contributions to the capabilities corresponding to Neisser levels of self.

As the introduction of robots into our daily life becomes a reality, the social compatibility of such robots gains importance. In order to meaningfully interact with humans, robots must develop an advanced real-world social intelligence that includes novel perceptual,

behavioural, emotional, motivational and cognitive capabilities. The *Experimental Functional Android Assistant* (EFAA) and the *What You Say Is What You Did* (WYSIWYD) projects both contribute to the development of socially intelligent humanoids by advancing the state of the art in both single human-like social capabilities and in their integration in a consistent architecture.

In the context of these two projects, we propose a biomimetic, brain-inspired approach. The central assumption is that social robots must develop a sense of self as to overcome the fundamental problem of social inference. It is only in possessing the core aspects of a human-like self, that inferences about others can be made through analogy. The EFAA/WYSIWYD Architecture, is based on our growing understanding of the neuronal mechanisms and psychological processes underlying social perception, cognition and action and will exploit the availability, among the members of the consortium, of a number of complementary prototype robot-based perceptual, cognitive and motor architectures. These projects are integrating across these existing architectures, by directing focused effort on specific core problems, and by exploiting the availability of unique advanced real-time neuronal simulation and hardware.

This thesis project is more specifically situated in the context of work on Reasoning and Planning, and the impact of Memory (more particularly an Autobiographical Memory).

Our objective was to provide the system with the capability to exploit its previous experience in order to prepare for future experiences within the local peripersonal space. Thus we shall maintain a spatially coherent representation of its relation to the task environment using a combination of cues derived from path integration and distal sensing based on our understanding of the neuronal mechanisms underlying spatial cognition. Within this context we shall be able to learn and use action plans that represent the iCub and its interaction with object and with other agents. These plans will refer to the iCub in the context of an internal representation the self, and other agents and objects within

peripersonal space. The flow of interactions, guided in part by these plans will be under the control of a limited spoken language interaction capability, extending the state of the art in this domain . By maintaining an explicit autobiographical memory, the system will begin to develop an integrated model of itself. This will include representation of actions, their required initial conditions and resulting conditions. These capabilities will provide the basis for goal directed reasoning based on the sequencing of state-action-state links from the current state to the goal state. As the basis of these capabilities is memory.

## 1.1 Memory

Every person's lifestory is different one from another. Even the way two people will recall a same story will be different, given their emotional states or internal feelings such as pain. The way we will reconstruct a past event will also vary given our knowledge at the time we rebuild it. Before describing the technical details of my work, I will make first a rapid overview of the human side of memory.

The pathologies linked to memory cover also a very wild scale. It can impact our capacity to recall old event, or our ability to fix new memory, or just with time, fade one's ability for example to play piano... The field of the memory is very large, and can be apprehended from many directions : psychology, cognition, social, developmental, clinical, and neuropsychology at least.

The field of memory has been extensively explored since the beginning of human history. For the ancient Greeks, the titanide Mnemosyne (see Fig 1.1), the daughter of Gaïa and Ouranos, the goddess of Memory. She gave birth to the nine Muses for whom Zeus was the father and invented words and language. She is the one that gave a name to all the things. Mnemosyne is also the holder of all the legends.

This vision is the more accurate and poetic definition of the memory. Indeed by naming



Figure 1.1: Mnemosyne the personification of memory by Dante Gabriel Rossetti.

all things and creating language, Mnemosyne gave the humans a way to communicate and to talk about them and the world, about their past, their present and their future. But also by giving birth to the nine Muses, she gave to the men the arts. It can not be any story, any art, any social discussion and any taste without memory. It can not be any self without memory.

In Edda, the Nordic mythology, Mimir is the god of memory and knowledge. Mimir is the keeper of a fountain of knowledge under the tree Yggdrasill. This fountain contained the knowledge of all things but to have access to it, Odin had to pay the price of one eye to taste the memory of the world (see Fig 1.2). Here also, the memory and the knowledge are very close.

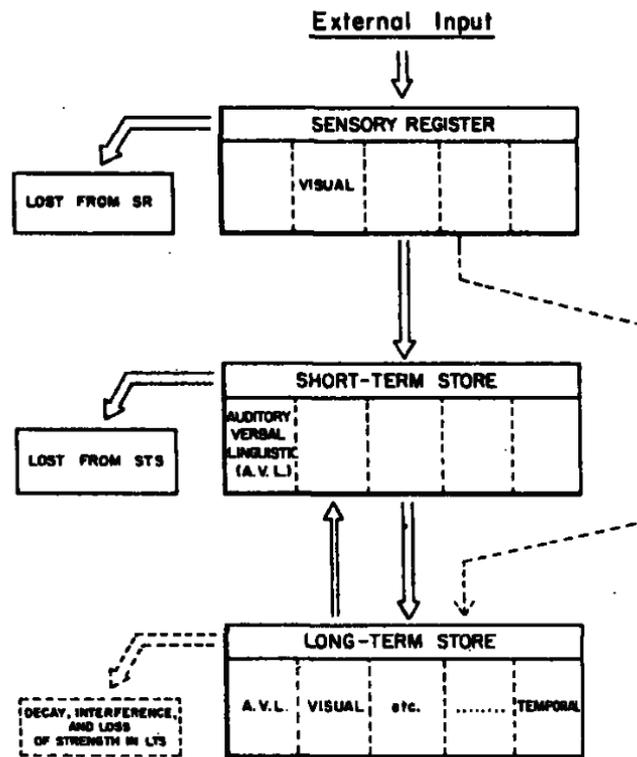
First under the view of philosophy and theology, then through psychology and nowadays mainly through biology, memory has always been a huge question for the men.



Figure 1.2: Representation of the myth of Mimir and Odin.

In 1891, Théodule Ribot, the future founder of the journal “*Revue*”, develops his “*Law of Retrograde Amnesia*”. He conjectures that the aging memory deteriorates orderly and not anarchically. This order is from the most recent to the oldest memory, and from the most complex to the simplest [Ribot, 1891]. One explication of it is that the storage in the brain of old memories might be different than the recent ones. This would imply that in case of mental decline of disease young memories are more likely to be disturbed than old memories. This can be seen in the case of Alzheimer’s patient : they can recall of memories such as childhood event, but express more difficulty to recall recent events.

In 1885, the first experiment study of human memory and of forgetting is published by Hermann Ebbinghaus in his book “*Über das Gedächtnis : untersuchungen zur experimentellen psychologie*” (Memory : A Contribution to Experimental Psychology) (citeebbinghaus1885gedachtnis (reedited in English in 1913). His contribution was huge in term of methodology : he wanted to study memory without any cognitive or semantic priors on the stimulus. He thus created a system of non-sens syllable : consonant-vowel-consonant. After removing the syllable that could have a prior meaning (DOT, BUT, HIM...) the list of non-sens syllable has vocation to be used to study memory process.



**FIG. 1. Structure of the memory system.**

Figure 1.3: Human memory system from [Atkinson and Shiffrin, 1968].

Later, in 1938, the neurosurgeon Wilder Penfield during his studies about epilepsy, makes the first hypothesis of a link between the temporal lobe and memory [Penfield, 1938]. Indeed, the recall of memories can be induced by an electric stimulation of the temporal lobes.

The first general model of the human memory system was made by Atkinson and Shiffrin in 1968 [Atkinson and Shiffrin, 1968]. They claim that the memory is divided in 3 component : a sensory register, a short-term store (working memory or short term memory) and a long term store. These three component are linked as described in Fig 1.3. They use as evidence for their theory some lesions in the hippocampus that induce a separation of the two memory system (short term and long term).



Figure 1.4: According to Tulving, animals such as the cat do not have episodic memory, and although they can learn many things they do not remember past experiences as we do. They just “know”. Drawing from his wife, Ruth Tulving.

One of the biggest impact on the study of memory was made by perhaps the most famous researcher about memory : the Estonian-Canadian Endel Tulving, in 1972 [Tulving and Donaldson, 1972]. Indeed, Tulving is the first to make a distinction between Episodic and Semantic memory. Episodic memory would be the conscious recollection of previous experiences (event with context) while semantic memory is the recollection of facts and general knowledge (see Fig 1.4).

Two years later, in 1974 Alan Baddeley divide the short term memory in several sub-systems of “working memory”, including a phonological loop that treats the speech, and a visuo-spatial sketch pad that manipulates the visual inputs (see Fig 1.5 [Baddeley and Hitch, 1974]). It has to be noted, that these systems should be independent and with a limited capacity.

In 1980 with the help of the new techniques of neuro-imaging, Neal Cohen and Larry

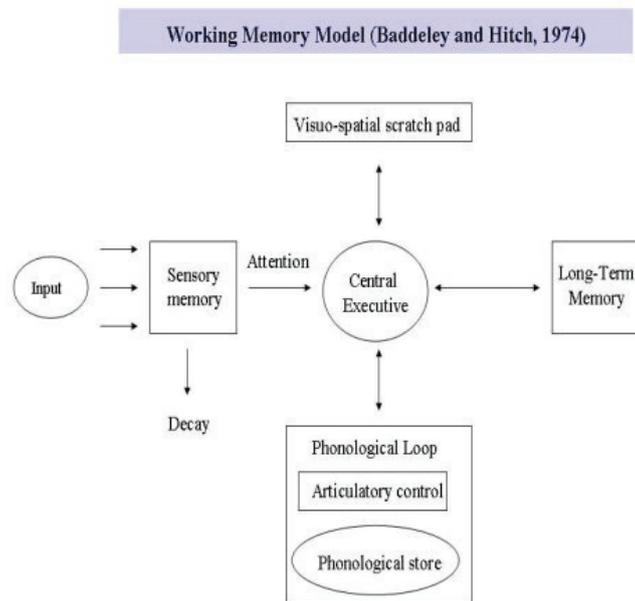


Figure 1.5: Components of the working memory, from [Baddeley and Hitch, 1974].

Squire introduce the concepts of a procedural memory (implicit for the skills and habits) and a declarative memory which is an explicit memory [Cohen and Squire, 1980].

Today, a continuous and ongoing research effort tries to understand the functioning of memory and diverse aspects of the system of Human memory remain unknown. The study of memory continues to maintain a prominent place in modern neurosciences [Binder and Desai, 2011].

It is interesting to see the embodied aspect of the concept of memory that is, the physical substrate in which the memory is implemented Whatever may be the field, the term of memory is more or less never put into question : we can talk about “collective memory” as well as the “memory of the computer” or even the “cellular memory”. Whatever may be the context, the term of memory is always understandable. But it is also clear that all these memories are different in everything but the goal. This simple fact highlight the impact of the body, from a material point of view (such as computer memory) or immaterial

(collective memory, or tradition). The functioning of a memory depends mostly of its body. But even if I said that all the memory systems have a same goal, they don't all reach it, or maybe not of the same way. We will study the impact of the body on memory, and of memory on the body. For this reason, we decided to focus our work on the functioning of a memory system, inspired by the human memory system, that can allow the humanoid iCub to learn from its interaction with people, to begin to take steps towards constructing a self.

## 1.2 Self

We have seen that the field of memory has fascinated humanity since always. In every mythology, in every culture, memory has been a subject of myth and of study. But the topic of the self and beyond it, of Humanity, is something even bigger. A quick comparison using google scholar gives us the following results : *“autobiographical memory”* : 178 000 results, *“stem cell”* (a field growing exponentially since a few decades) : 2 700 000 results, *“sense of self”* (which is a precise request, *“self”* cannot be searched alone it would have no sense) : 3 870 000 results. This illustrates the vast ocean on which we are sailing when we try to deal with the *“self”*.

Many religions have argued that the self was something divine, that it cannot be observed or studied from a scientific and experimental point of view. It is true that the topic of the self is something very controversial, but also very complex to study. What is the part of the self that can be explained by the neurology, but before this, the self can it be explained or at least studied from a scientific and pragmatic point of view? To this question, the life of Phineas Gage begins to provide us some light.

### 1.2.1 The life of Phineas Gage

The story of Phineas Gage is well known in the scientific world (and even in popular culture). It is the story of a man that lived in the 19th century. Phineas Gage was a humble

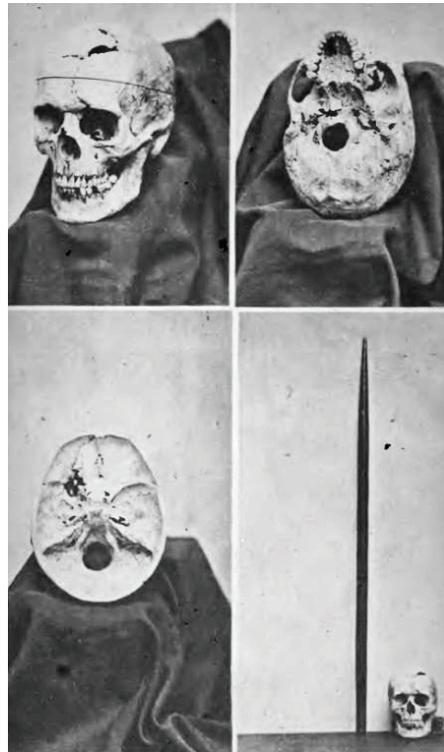


Figure 1.6: Frontispiece, showing multiple views of the exhumed skull, and tamping iron, of brain injury survivor Phineas Gage, from [Jackson, 1870].

American railroad construction foreman. He was liked by his family, his friends, and the people who worked for him talked about a nice man. Phineas Gage was working on the railroad and was manipulating explosives daily.

On day, while he was manipulating a small charge, there was an accident and the charge blew, projecting an iron rod through his head. The rod was 1.1m long, and 3.2cm of diameter and sharpened at its extremity. The iron crossbar of 6kg was found 25m away from Gage (see Fig 1.6 and 1.7). Gage miraculously survive and moreover, he didn't even faint, and even if he was in shock, he managed to speak in only a few minutes. However Gage shown some convulsive motions after the impact.

After a recovery period of less than two months, Phineas Gage retrieved his physical



Figure 1.7: Photograph of cased-daguerreotype studio portrait of brain-injury survivor Phineas P. Gage (1823–1860) shown holding the tamping iron which injured him. Includes view of original embossed brass mat. Color, unretouched. From the collection of Jack and Beverly Wilgus. Because a daguerreotype is almost always laterally (left-right) reversed, a second, compensating reversal has been applied to produce this image, so as to show Gage as he appeared in life; that this shows Gage correctly is confirmed by contemporaneous medical reports describing his injuries, as well as from the injuries visible in Gage’s skull, still preserved. Photograph by Jack and Beverly Wilgus of daguerreotype from their collection.

abilities, and sensory perceptions. He was able to speak, to maintain a conversation, to understand complex situation, to recognize his family or friends, to understand other people behavior, but Gage wasn’t Gage anymore. For the Doctor Harlow [Harlow, 1869] that was in charge of him at this time :

*“The equilibrium or balance, so to speak, between his intellectual faculties and animal propensities, seems to have been destroyed. [...] In this regard his mind was radically changed, so decidedly that his friends and acquaintances said he was no longer Gage.”*

Gage became rude with the people around him. He was now an egocentric man unable to carry a project to its term. The respectful man had disappeared and now was a man that didn’t care about his relative and couldn’t stand the critics especially directed against his desires.

Gage lived a few times as a horse breeder or stagecoach driver, but it was not very successful, and he finished at the Barnum Museum of New-York as an attraction. Gage died at the age of 37 of an epilepsy attack stronger than the others. During 12 years after his accident, Gage hasn't been able to have a social behavior appropriate.

The case of Phineas Gage is quite interesting for us and several points need to be highlighted. First of all, this case put in light the part of the social behavior in Human evolution. Phineas Gage died alone and even his family had given up on him in the end. He had lost his ability to bond with people. He was unable to keep any friend or girlfriend, and thus wasn't able to reproduce. For Damasio [[Damasio, 2008](#)], this ability to make friend and to be social is a plus for the survival of Human, and may be an inherited characteristic. This is a step forward in the view of Aristotle about men :

*“Man is by nature a social animal ; an individual who is unsocial naturally and not accidentally is either beneath our notice or more than human. Society is something that precedes the individual. Anyone who either cannot lead the common life or is so self-sufficient as not to need to, and therefore does not partake of society, is either a beast or a god.”*

It has to be noted that Aristotle to define a man that is not in the society (such as Phineas Gage) is defined as either a “beast”, which is the term used by Phineas Gage contemporaries to describe him after his accident, or a god but I have serious doubts about it...

Another fact, linked to the social aspect of men, is that this social abilities seem to be situated in a precise place in the brain. Indeed, the area of the brain damaged by the cross bar has been precisely defined : the temporal lobes (mainly the left one, but also a bit the right one) [[Damasio et al., 1994](#)]. Antonio and Hanna Damasio don't claim that the frontal lobe might be the “brain area for the self” in any case, but it seems to be involved in the process of social understanding which modify the self. Other cases similar to Gage's case have been reported with the same consequences : when the frontal lobe is injured, the patient expresses

difficulties to understand others and his behavior is radically different from before the injury.

Thirdly but not least, we can see with the case of Phineas Gage that the brain is clearly responsible for our behavior (and thus our self) and a modification of it implies a modification of the self. We can thus study the self from an anatomical and neurological point of view. Neurological and anatomical of course, but not alone, it has to be done with also the psychology and even anthropology if the Men are such a social animal. We will see later on, that the understanding of other is a major component of what we will define as levels of self.

### 1.2.2 Neisser's levels of self

It is easy to get lost while attempting to characterize a clear definition of the self. For this reason, we decided to direct our research upon the works of one of the most influential psychologist of the last century : Ulric Neisser.

Ulric Neisser was born in 1928 in a Jewish family of Kiel in Germany. In 1933, with the rise of the third Reich, his family decided to move to the United States where he will discover both baseball (he refers to it very often in his writings) and psychology. He graduated from Harvard in the department of Social Relations in 1956. The social and cultural aspect of Men will follow him all along his career. He then moved to the University of Pennsylvania where he wrote is famous book : “*Cognitive Psychology*” [Neisser, 1967]. In 1967, while the field of the same name was trying to expand, it took a huge boost with the publication of this book that gives the bases of the cognitive psychology.

In his following book in 1976 : “*Cognition and Reality*” [Neisser, 1976], Neisser both attacked the contemporary field of cognitive psychology, and argued his theory of an ecological self. Indeed, Neisser rejected the experimental method of his peers which was for him, too much directed toward laboratory experiments. He thus started to develop his idea of the importance of the ecological factor as part of the cognition. Ecological

should here be interpreted coherent in a “natural way”, which implies the environment, the body state and the cultural state. In particular Neisser defends the idea of a perception not only as external (such as vision or hearing), but also as internal (the metabolic network).

Neisser died in 2012 but he left a definition of the self as a decomposition of five different levels.

From [Neisser, 1995] :

- **The Ecological Self** *is the individual situated in and acting upon the immediate physical environment. That situation and that activity are continuously specified by visual/acoustic/kinesthetic/vestibular information. As we shall see, infants perceive themselves to be ecological selves from a very early age.*
  
- **The Interpersonal self** *is the individual engaged in social interaction with another person. Such interactions are specified (and reciprocally controlled) by typically human signals of communication and emotional rapport : voice, eye, contact, body contact, etc. This mode of self-knowledge, too, is available from earliest infancy.*
  
- **The conceptual self** *or self-concept, is a person’s mental representation of his/her own (more or less permanent) characteristics. That representation, which varies from one culture to another as well as from one person to the next, is largely based on verbally acquired information. Hence, we can think of it as beginning in the second year of life.*
  
- **The temporally extended self** *is the individual’s own lifestory as he/she knows it, remembers it, tells it, projects it into the future. It cannot appear until the child already has a conceptual self, a narratively organized episodic memory, and an explicit understanding of the continuity of persons over*

*time - say, until the fourth year.*

- **The private self** appears when the child comes to understand and value the privacy of conscious experience; when it becomes important that no one else has access to his/her thoughts, dreams, and interpretations of experience. I do not know whether this insight appears regularly enough to be counted as a developmental milestone, but it surely requires a temporally extended self which to reflect.

We can already see here the hierarchy put in place by these levels. We will thus follow this order in our work. As Neisser claimed it in “*Cognition and Reality*”, the first and most elementary level of self, is the Ecological Self (**ES**), that will be in our case, for the robot, the ability to understand the direct world, and the direct consequences of his action. Then, the the robot need to have a sense of Interpersonal Self (**IS**) and to understand his social interactions mainly through language. Building on this, the Conceptual Self (**CS**) can arise. It will be manifested as some insights of Theory of Mind, and mental representation of other people’s belief, and by high level reasoning implying understanding the complex implications of an action. Finally, we will show the manifestation of the sense of the Temporally Extended Self (**TES**) that can manifest as a way to recall the past, to bend it from imagination, and to consciously access to the robot life story.

As we stated earlier, we decided to put aside the Private Self. Indeed, the private self is not as well defined by Neisser, and appears later in the child development. We want to focus her on our work about the development of the child until  $4\frac{1}{2}$  years old. Also, the Private Self can be seen as an “super extension” of the **TES**, and thus we decided to focus on the four other levels of self.

The implication of an **ABM** in the emergence of the senses of self can be, like in the case of the **TES**, evident. Indeed we intuitively see how the **ABM** will feed the **TES** and how

the memories will be bricks of the life story. But in some cases, the use of the **ABM** is more uncertain. We will thus explain how, directly or indirectly the memories of the **ABM** will be use to understand the world, for each person in his own way, to develop these notions of self.

Accordingly to these four levels of self and the prominent role of the **ABM**, I will divide this thesis in five chapters. The first chapter will be dedicated to the Synthetic Autobiographical-Memory (**SABM**) : what is the functioning of the Human **ABM**, and how to model it on an Humanoid robot? The four next chapter will then describe the progressive emergence of the 4 level of self we decided to focus about : **ES**, **IS**, **CS** and **TES**. I will then conclude about the model we proposed and how these four levels can be related one with another. Finally I will discuss our results, our limitations, and our perspectives.

Again, I want to stress the this thesis does not attempt to address the question of creating a self in a robot. Rather, it provides a set of concrete new development in the state of the art of robot cognitive systems and link these to the levels of self defined by Neisser.

### 1.3 Context and objectives of the thesis

#### 1.3.1 Context of the Thesis : the **EFAA** and **WYSIWYD** European projects.

As I said, this thesis has been realized as part of two European Projects : **EFAA** for the period 2011-2013, and **WYSIWYD** for the period 2014-2016. The objective of these two projects are the following (extracted from the *description of work*, included in the appendices 9.4) :

**EFAA** : *“The Experimental Functional Android Assistant (EFAA) project will contribute to the development of socially intelligent humanoids by advancing the state of the art in both single human-like social capabilities and in their integration in a consistent architecture.”*

**WYSIWYD** : “[the WYSIWYD Project] *will create a new transparency in human robot interaction (HRI) by allowing robots to both understand their own actions and those of humans, and to interpret and communicate these in human compatible intentional terms expressed as a language-like communication channel we call WYSIWYD Robotese*”

These projects regroup 5 European laboratories for EFAA, and 6 for WYSIWYD. The partners of the projects are the following :

- **Istituto Italiano de Tecnologia** - Genoa - Italy. PI : Giorgio Metta. The IIT is the laboratory that developed the robot iCub that is the core of the project. Their part in the projects is a technological support, and the link between the hardware, and the “low level software”. They are involved in the motor command, vision, and global informatic architecture of the robot and of the project (technical tools such as Git for versioning, Travis or AppVeyor for the automatic verification of code). They are present in both EFAA and WYSIWYD. My interaction with them was mainly about technical support, help for the development, and hardware-related problems.
- **University of Sheffield** - United Kingdom. PI : Tony Prescott. USFD was dedicated to the tactile interface of the robot in the EFAA project while in the WYSIWYD project, they are more focused in the autobiographical memory, at the scale of streamed data (more a machine learning work). My interaction with them was mostly about the complementarity between our and their SABM : the SABM from INSERM is more action-based and “high level”, while the USFD SABM will be directed about movement and continuous stream of data.
- **IMPERIAL College** - London - United Kingdom. PI : Yiannis Demeris. Imperial is focus about machine learning, and perception through kinect or through the cameras of the robot. My interaction with them was to create a common format from what they detect, to what could fit in our SABM. They are part of both EFAA and WYSIWYD

- **Universitat Pompeu Fabra** - Barcelona - Spain. PI : Paul Verschure. The team SPECS (Synthetic Perceptive, Emotive and Cognitive Systems) is involved in the cognitive architecture, and in the Human-Robot Interaction : development of a reactive layer, of a social perception and of action-intention grammar. They are present of both EFAA and WYSIWYD and are also the coordinators of the projects. My interaction with UPF was important and in particular for the development of the cognitive architecture of the robot (to define the place of the SABM and the reasoning modules in the global architecture).
- **University of LUND** - Department of Philosophy - Sweden. PI : Peter Gärdenfors. The university of Lund arrived in 2014 for the WYSIWYD project. Their work is in the robot understanding of the Human. This work is directed both on the language understanding, and also in the visual analysis of a scene. My collaboration with them started later, and is mainly focused about the language understanding.

All the partners are developing on a common open source c++ project. Some c++ libraries have been developed and are used by all the partners to command the robot, to make some speech recognition, to record a memory in the SABM or to get a memory (this will be detailed later). Each laboratory has a team of two or three PhD Student or post-doc, dedicated to the project, and we meet around five times per year to integrate the specific work of each laboratory.

The role of the INSERM in Lyon in theses two projects is displayed in the Fig 1.8, 1.9, 1.11 and 1.10. The objectives of the two projects are focused as we can see, about the development of an autobiographical memory, that will set the basis of the technical architecture of the SABM we will develop and that will be articulated around language. The WYSIWYD project will be more related to the “self”, and particularly to the narrative self, that can be seen as the Temporally Extended Self.

Description of deliverables
D3.1) Peri-personal spatial reasoning and spoken language interaction: Peri-personal spatial reasoning and spoken language interaction: Demonstration of robot capability to understand and produce spatial language in the context of manipulation of objects in the peripersonal space: Report comprising a manuscript submitted for publication, and video. [month 12]
D3.2) Autobiographical memory and goal-directed reasoning: Autobiographical memory and goal-directed reasoning: Demonstration of the ability to use autobiographical memory for reasoning about novel situations: Report comprising a manuscript submitted for publication, and video. [month 24]
D3.3) Integrated capabilities and demonstration: Integrated capabilities and demonstration: Report comprising demonstration of integrated capabilities [month 36]

Figure 1.8: List of the deliverables of the work package dedicated to INSERM in the EFAA project

<p><b>Task 3.3 Autobiographical memory and integrated cognitive model of self</b> (Task Leader: INSERM; Other Partners involved: UPF, Imperial)</p> <p>Autobiographical memory will be implemented in the form of a continuous interaction history that encodes the temporal sequence of events that the robot has experienced throughout its existence. This includes perceived objects and events, actions generated by the robot, and observed as performed by other agents. In coordination with WP1, this autobiographical memory will provide part of the basis for the definition of self. In coordination with WP2, the interaction history will also provide the basis for recognition and extraction of repeating behavioural sequences that can form the basis of action plans.</p> <p><b>Task 3.4 Goal directed reasoning, executive control and attention:</b> (Task Leader: INSERM ; Other Partners involved: UPF, IIT, Imperial)</p> <p>In WPs 1 and 2, actions will be linked with their initial and final states. As part of T3.3 the interaction history will encode behavioural sequences that link a succession of actions to a final goal. Within the contextual layer of the DAC architecture, these sequences encoded in the autobiographical memory will be operated upon by a probabilistic matching process so that the system can detect that it is in a potentially repeating subsequence, in order to anticipate future events. The same matching process will allow the system to detect behavioural sequences that have previously led to the current goal. In this context, mental simulation of action, and associated reasoning will be developed as an extension of related work by IIT in the EU GNOSYS project, and related work by UPF in rule learning within the DAC architecture.</p>
--

Figure 1.9: List of the main tasks of the work package dedicated to INSERM in the EFAA project

Objectives
O3.1: To use existing state of the art spoken language technology to implement a platform for speech recognition and synthesis that provides a robust spoken language-based interface and is fully integrated with the WYSIWYD architecture.
O3.2: To design and implement efficient learning algorithms for cross situational binding of words and grammatical constructions to representations within the conceptual system, including the representation of self, driven by an intrinsic motivation to share mental states, and to validate these algorithms in the human-iCub-Reactable experimental setup where the human interacts with the robot via the learned vocabulary and grammatical constructions.
O3.3: To design and implement algorithms that allows the interface between grammatical constructions and the autobiographical memory in order to develop the narrative/conceptual self.

Figure 1.10: Objectives of the work package dedicated to INSERM in the WYSIWYD project

Task 3.3 Narrative Self (Leader: INSERM, Participants: USFD, IMPERIAL, UPF) [M12-M36]  
 Language allows the individual to construct narrative of its own experience, which when assembled over extended time allows the construction of narrative or conceptual self (Neisser 1995; Gallagher 2000). In this task we will implement an interface between the language capabilities in Tasks 3.1 and 3.2, and the autobiographical memory (WP2), such that language based representations of the activities of the embodied self will be included in the autobiographical memory, allowing the development of the narrative self. The embodied self will be instantiated in the domain of the body schema development in interaction with WP1, where the conceptual space will have a direct correspondence to the sensorimotor space. This will then be extended to self in the context of interactions with others (Rochat 2009; Rochat 2011), the autobiographical self in WP2 and intentionality in WP4. Structuring of this narrative self is provided by the linking to the WR-DAC contextual sequential memory systems (WP5).

Figure 1.11: Description of the task 3.3 of the work package dedicated to INSERM in the WYSIWYD project

Being part of these two European projects gives a significant help in many aspects. They indeed provide a technical support for the state of the art robot that is the iCub. It allows also to share point of view and ideas with scientists from all Europe. It gives also a technical context well defined while being free to develop whatever could be useful for the projects. These European projects allow to start such an ambitious and complex work not from the beginning. In Lyon, we were just one team of the project but the context was such as every pieces could work one with another. For instance, the detection of a human agent is not one of our competence but is one of the Imperial College of London. I could thus rely on their work to focus only on my part of the work.

### 1.3.2 Objectives

All the work that will be presented in this thesis (the modules developed and experiment) have been developed in Lyon at the INSERM by me. In the context of these two European Project, my thesis work will be directed in three main directions and under some constraints. Firstly, the development of an synthetic autobiographical memory, based on the knowledge of the functioning of the Human memory in term of architecture and of goals. Technically, this development should follow the EFAA and WYSIWYD software architecture (especially the YARP framework that will be detailed in 2.2.1, and the EFAA-WYSIWYD architecture). This corresponds to the EFAA deliverable 3.2, and task 3.3.

The second objective is the development of a set of reasoning modules, based on the

SABM. These modules should be able to create some knowledge related to a Human-Robot Interaction in the human world. This knowledge can be the understanding of an action such as : “putting an object to the left”, that the robot should be able to understand, and to recognize. This knowledge can also be related to the HRI itself and the result would be for the robot to understand the role of each person during a shared interaction, and be part of it. This corresponds to the EFAA deliverable 3.1 and 3.2, task 3.1, and WYSIWYD objective 3.2.

The third objective is the elaboration and realization of experiments that would show the ability of the robot to develop a behavior characteristic to each of the levels of self defined by Neisser in the context of a Human-Robot Interaction. These experiment should show the ability of the robot to understand in the case of the **ES** the consequence of its own action ( “*What would happen if I move this object to the left*”), for the **IS** the role of each person during an interaction ( “*Who is the agent of each action ?*”, the robot should understand the statement of a plan with several agents and the role of each person), for the **CS** the robot should be able to predict someone else’s state of mind( “*I think that he thinks that...*”) and for the **TES** the robot should be able to refer to his own past and to analyze it using the three other levels. This work corresponds to the WYSIWYD objective 3.2 and task 3.3.

### 1.3.3 Publications

The work presented in the following chapters has been published in the following articles (they can be found entirety in the appendices) :

- **Pointeau, G., Petit, M., and Dominey, P. F. (2014a).** “*Successive Developmental Levels of Autobiographical Memory for Learning Through Social Interaction.*” IEEE Transactions on Autonomous Mental Development, 6(3) :200-212.

- **Pointeau, G., Petit, M., and Dominey, P. F. (2013).** “*Embodied simulation based on autobiographical memory.*” In *Biomimetic and Biohybrid Systems*, pages 240-250. Springer.
- **Pointeau, G., Petit, M., Gibert, G., and Dominey, P. F. (2014b).** “*Emergence of the use of pronouns and names in triadic human-robot spoken interaction.*” In *Development and Learning, 2014. ICDL 2014. IEEE 13th International Conference on.*
- **Petit, M., Lallée, S., Boucher, J.-D., Pointeau, G., Cheminade, P., Ognibene, D., Chinellato, E., Pattacini, U., Gori, I., Martinez-Hernandez, U., et al. (2013).** “*The coordinating role of language in real-time multimodal learning of cooperative tasks.*” *Autonomous Mental Development, IEEE Transactions on*, 5(1) :3-17.
- **Petit, M., Pointeau, G., and Dominey, P. F. (“accepted”).** “*Reasoning based on consolidated real world experience acquired by a humanoid robot.*” *Interaction Studies*.
- **Hinaut, X., Petit, M., Pointeau, G., and Dominey, P.F. (2014).** “*Exploring the acquisition and production of grammatical constructions through human-robot interaction with echo state networks.*” *Frontiers in neurorobotics*, 8.

## A Synthetic Autobiographical Memory for Reasoning

As stated in [Pointeau et al., 2014a], one of the principal arguments for developmental robotics is that certain types of behavior are perhaps better learned (adapted, acquired, developed) than pre-programmed. This applies particularly to situations in which the robot is expected to acquire knowledge about the world and how to perform in the world via interacting with humans. In human developmental studies, significant attention has been allocated to the mechanisms that underlie the ability to acquire and build knowledge and encode the individuals accumulated experience, and to use this accumulated experience to adapt to novel situations ([Wells, 1981] [Kolb, 2014] [Nelson, 2009] [Siegler, 1976] [Piaget and et Niestlé, 1948]). In particular we consider research on ABM and mechanisms by which ABM can be used to generate new knowledge.

In this chapter, I will define the model of Synthetic Autobiographical Memory (**SABM**) that we developed, and the reasoning tools that operate on it. I'll first address the concept of memory, that we will divide in two parts, the Episodic-Like Memory (**ELM**) and the Synthetic Semantic Memory (**SSM**). Then, I'll explain the creation of knowledge and the reasoning tools that allows passage from the **ELM** to the **SSM**.

### 2.1 Concepts of Memory

When one ears memory, a diversity of aspects can come to the mind. Tulving in 1985 has defined the memory as the six following functions [Tulving, 1985] :

1. neurocognitive capacity to encode, store, and retrieve information

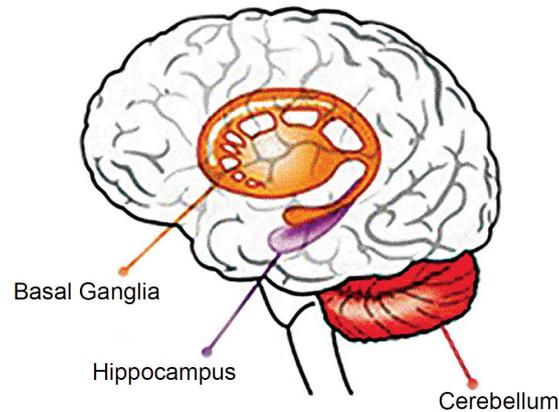


Figure 2.1: Representation of the Striatum (labeled here as Basal Ganglia), Hippocampus and Cerebellum in the Human Cortex. From a internal UCLA review from Allison K. Krupa.

2. hypothetical storage in which information is held
3. information in that store
4. some property of the information
5. componential process of retrieval of that information
6. individual's phenomenal awareness of remembering something

In this definition we can see two opposing concepts. We have on one side, something about action or behavior, and on the other hand we have something about cognition and thought. This is the first level of division of the memory : declarative (thought, cognition) and nondeclarative (action, behavior).

### 2.1.1 Declarative versus non-declarative Memory

The memory is not unique. One cannot talk about ONE MEMORY but should talk about MEMORIES. Indeed, experimental animal studies and human neuro-imaging studies have shown that the brain contains multiple memory system. All this memory system are different functionally, but also are located at different places in the brain ([Poldrack et al., 2001], and Fig 2.1). The main distinction made is between declarative and nondeclarative memory.

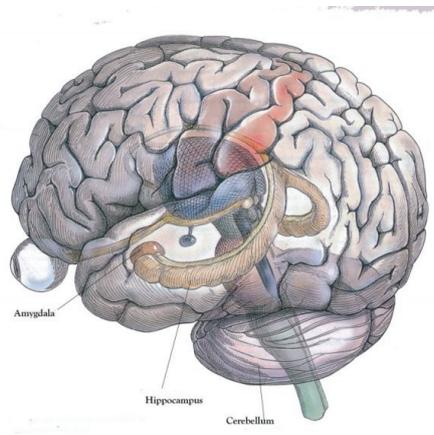


Figure 2.2: Representation of the Amygdala, Hippocampus and Cerebellum in the Human Cortex.

These two kind of memory have different capacity to recall stored information.

First of all, in term of location in the brain. We know from neuro-biological, neuro-imaging, or pathological studies [Squire, 1992], that these two components are implemented in distinct brain systems. While simplifying for the sake of clarity, we can say that declarative memory involves the hippocampus of the medial temporal lobe (Fig 2.2), and the nondeclarative memory involves the Striatum of the Basal Ganglia (Fig 2.4).

Again, simplifying, neuro-scientists have studied patients with amnesia (hippocampal damage) and with Parkinson disease (striatal damage) to have more information about the relation between these areas. Parkinson 's disease patients shown impaired procedural learning (nondeclarative memory) however, they still have declarative memory [Knowlton et al., 1996]. One the other hand, Amnesic patient shown a normal learning of tasks (nondeclarative memory) but have shown problem concerning the declarative knowledge [Tranel et al., 1994].

As I stated earlier and as we can instinctively remark, the declarative memory function will be related to cognition and though where the nondeclarative memory will be dedicated to actions and behaviors. Squire defines the declarative memory as : [Squire, 2004].

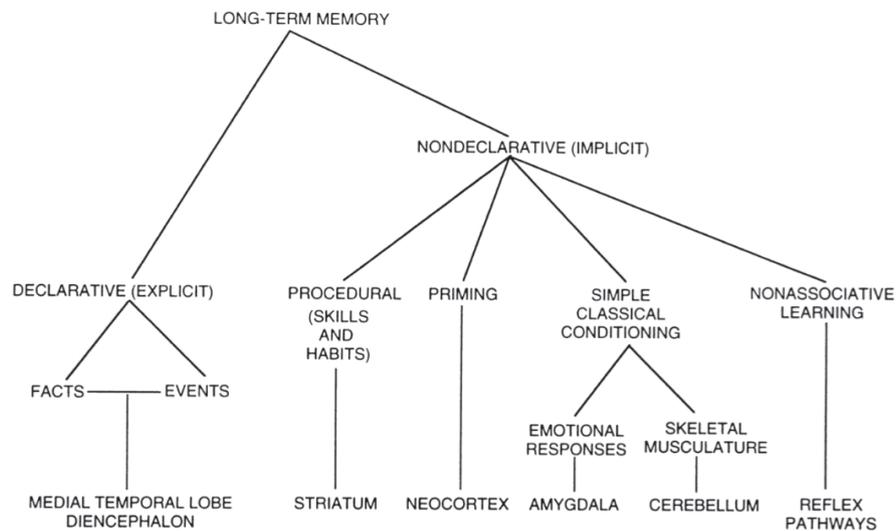


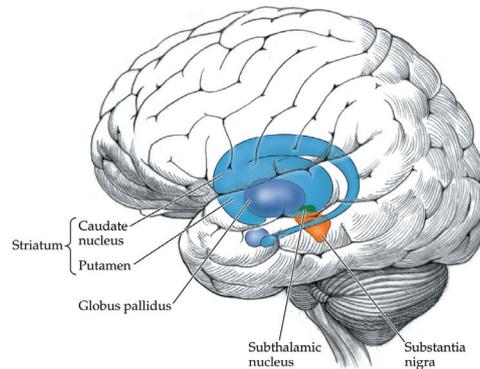
Figure 2.3: Taxonomy of the division of mammalian long-term memory system, from [Squire, 2004].

*“the kind of memory that is meant when the term « memory » is used in everyday language. It refers to the capacity for conscious recollection about facts and events [...]. declarative memory allows remembered material to be compared and contrasted. It supports the encoding of memories in terms of relationships among multiple items and events. Declarative memory is representational”*

Squire here gives us an enlightened version of declarative memory concept. He justifies his use of the term “representational” by the fact that declarative memory is a model of the world and thus can be right or wrong as any model. The nondeclarative on the other hand cannot be wrong or false, it “is” and the recall of information is done “by rote”.

According to Cohen and Squire [Cohen and Squire, 1980] the declarative memory is described as “a flexible memory for past events and facts”, and the nondeclarative memory is “characterized by relatively inflexible knowledge”.

The time required to “fix” a memory also varies. In the case of the nondeclarative memory, Poldrack claims that the nondeclarative memory is a gradual learning system



*Biological Psychology 6e, Figure 11.18*

© 2010 Sinauer Associates, Inc.

Figure 2.4: Representation in the Human Cortex, of the Striatum (in the Basal Ganglia).

among many trials, whereas the declarative memory seems to be involved in the rapid learning even about individual trials [Poldrack et al., 2001].

This can be seen with the following example : Basketball. To learn the rules of basketball, or even the concept of “to put the ball in the basket”, I don’t need thousand or trials, after only 2 trials, one failed, one successful, I can understand what I have to do to win : put the ball in the basket. This is declarative memory. To have the exact good movement to put the ball in the basket, I’ll need thousand of trials (in my case, many more than a thousand I think...) to reach the perfect hand and body movement. This is the work of the nondeclarative memory.

The nondeclarative memory will thus “store” the procedural memory that will be skills and habits : the “how to” (ex : basketball shooting, riding a bike). The procedural memory will also contain the very basic “every day” knowledge as walking or using a key. The second part of the nondeclarative memory is the priming (related to perceptual representation system). The Human as many animal is “primed”. The term priming here is for the capacity to access quickly to a conscious memory with a primer. For example, if we ask the name of a tool to a child, most of the answer will be “a hammer”, and if we ask for a color, we might have a big proportion of “red”. But this is variable. If a child is submitted to another stimuli very often (as living in a snowy landscape) the

answer can vary. Another component is the system of non associative learning. This is a permanent system of habituation that will change the weight of response to any external stimulus. The non associative learning is mainly the management of reflexes and can be found a different time scale : minutes, hours, days or even weeks.. The last part of the nondeclarative memory is the simple classical conditioning. For more details, see Fig 2.3.

The declarative and nondeclarative memory have different purposes and Sherry and Schacter have shown that these systems would have evolved in parallel to serve these different goals ([Sherry and Schacter, 1987]). However, one can replace another in case of failure as in the case of a pathology. Many neuro-imaging ([Dagher et al., 2001] [Owen et al., 1998] [Moody et al., 2004] [Poldrack and Packard, 2003]) and animal neuro-physiology ([Squire and Zola, 1996] [Packard and McGaugh, 1996]) experiments have shown that these two system are : independent (anatomically and functionally distinct), work together and interfere (communicate between each other). This implies that in particular in the case of Parkinson's disease patients, the Hippocampus can take partially the relay of the Striatum in the case of a cognitive task such as the Tower of London, but of course this replacement (on one side or the other) has a cost for the organism.

### 2.1.2 Episodic Memory versus Semantic Memory

We will now focus about the declarative memory and its components. Schacter et al. have listed five memory systems [Schacter et al., 2000] from neural imaging studies :

- working memory
- semantic memory
- episodic memory
- perceptual representation system
- procedural memory

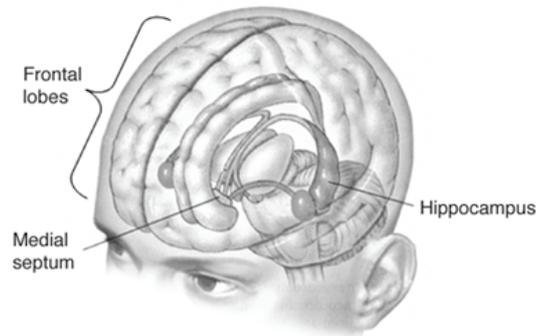


Figure 2.5: Representation of the Human frontal lobe.

The working memory, semantic memory and episodic memory, are considered as part of the declarative memory whereas the perceptual and procedural memory are nondeclarative. The episodic memory and the semantic memory will be the two main part of the **SABM** that I implemented as we will see later on. But what are the differences between these two conscious memory systems ?

In 1972, Tulving brought to light the differences between an episodic memory and a semantic memory [Tulving, 1972]. These distinctions are in term of information processed and in the general functioning. The semantic memory will “store” the general knowledge base, while the episodic memory will “store” events being given a time and a space. The difference for Tulving, is as the difference between declarative and nondeclarative, also anatomic. Indeed, in 2002, he showed [Tulving, 2002] that the pathways used for the semantic memory may be localized in the frontal lobes of the left hemisphere of the brain and the inferior parietal lobe, while the pathways used for the episodic memory involve additional process in the right hemisphere (see Fig 2.5). Since, more recently (2011), Binder has shown that the semantic systems seems widely distributed [Binder and Desai, 2011].

But the differentiation between these two memory system are also (from Tulving) to be put under the light of evolution. The semantic memory under its form and function may be common to other animal, and phylogenetically ancient. The episodic memory on

the other hand is “recently evolved, late developing, and early deteriorating past oriented memory system, more vulnerable than other memory system to neuronal dysfunction, and probably unique to Humans” (from [Tulving, 2002]).

To come back to the example that I gave for the difference between declarative and nondeclarative memory with the rules of basketball (see 2.1.1), lets get back to the day we learned basketball. To remember the gymnasium, the people present, the color or the jersey, the odour of the ball, will involve the episodic memory. To remember the rules of basketball will be semantic memory.

But Brewer makes a very important point on the impact of the self between semantic and episodic memory [Brewer, 1986]. He reminds us that many of self-related fact are not totally autobiographical memory or episodic memory per say, but are more semantic memories. For example our date and place of birth, or the name of school we attended are semantic knowledge even if they are self related.

It has to be noted also that there is a difference of development of these anatomical structure. Indeed after the first year of life, the medial temporal lobe is mature and functional while the frontal lobe will continue its development until the 5 of 6 years of life [Nelson and Fivush, 2004].

Concerning what Tulving says about the fragility of episodic memory, Damasio made some observations going in this direction in 1999 [Damasio and Dolan, 1999]. Damasio has studied a patient with retrograde amnesia. The patient met a new doctor. The doctor introduced a new game to the patient. The doctor left, and after a few minutes, came back. The patient couldn’t recognize the doctor, but knew the rules of the game.

At this point, one can say that we didn’t gave an exact distinction between episodic and autobiographical memory. Episodic memory is a part of the ABM, actually it is the

more evident part of it. But the difference lies in the fact that episodic memory is a well defined neurological structure and function, while ABM is more a functional system that will encompass the episodic memory. I need to make clear also at this point that we want to keep for our system the functionality (the goal) and the architecture of the system of memory : the ELM and the SSM are two separated systems, that communicate but work independently.

### 2.1.3 Autobiographical Memory

What is an autobiographical-memory ? Conway and Rubin define the **ABM** as follow [Conway et al., 1993] :

*“Autobiographical memory is memory for the event of one’s life... It constitutes a major crossroads in human cognition where considerations relating to the self, emotions, goals, and personal meanings all intersect”.*

Nelson proceeds in this way [Nelson and Fivush, 2004] :

*“... we assume that autobiographical memory depends partly on neurological developments necessary for the development of memory and, specifically, episodic memory, but that autobiographical memory emerges from interactive development across social, cognitive, and communicative domains to serve functional goals”.*

But she insists in adding the a social component to the ABM :

*“We define autobiographical memory as declarative, explicit memory for specific points in the past, recalled from the unique perspective of the self in relation to others.”.*

This social component is essential in our following definition of the ABM. We cannot remove the relation to others in this definition. Indeed the emergence of the ABM is done during pre-school years and is induced by social interaction. Nelson uses the

term emergence in reason of the ABM as a dynamic developmental system. This point is further developed by several scientist ([Oyama, 2000], [Gottlieb, 1997]) that claims that anatomically, the system of the memory grows in size and in complexity at the same time.

Many authors highlight the impact of goals and self in the mechanism of memory. When we talk about self, in this case, we talk about a sense of self that experiences, at special time and space, the event : auto-noesis. Indeed, ABM is not only a reference to the self, but can have event that have a personal meaning that can be driven by goals, motivation or emotions [Conway et al., 1993], constructed by social interaction, and by interaction with the world.

For Nelson and Fivush, the ABM *“is a type of declarative memory, and its most distinctive form is episodic in Tulving’s sense”* and it is explicit. However, where episodic memory has a specific neurological structure, the neurological roots of the ABM are still unclear. Also, as precised earlier, some event of our life such as dates of birth, are semantic memory, but are part of the ABM which makes the ABM more complex and more complete than just an episodic memory.

#### 2.1.4 Development of the ABM and cultural differences

Even before birth, there is some evidence of sign of type of memory. In particular a child is able a few hours after birth to recognize his or her mother’s voice ([DeCasper and Fifer, 1980], [DeCasper and Spence, 1986]). Also, after a few months (around 6) it is possible to show that a child is able to recall short events and routines [Nelson and Fivush, 2004].

The ABM is not something fixed. It is important to keep in mind that it varies over time, social and cultural origin : (from [Nelson and Fivush, 2004])

*“(a) There is a gradual emergence of autobiographical memory across the preschool years rather than a point before which there are no autobiographical*

*memories and after which there are. (b) language is a fundamental social cultural tool in the development of an autobiographical memory system; and (c) there are cultural, gender and individual differences in autobiographical memory across the life span that need to be explained.”*

Concerning the time of development of the ABM, the Figure 2.6 present a baseline of the timescale of its emergence. This representation and all the data that will follow must be taken carefully and in any case represent the truth. These markers are general insight to understand the chronology of the ABM but vary, as I said, between individuals.

During the first year the medial temporal brain structures grows until reaching its full size and functional maturity. The child reach very quick two main notions : the intentionality of others and self [Tomasello, 2009], and what Damasio called a “core self” [Damasio, 2000]. These notions are both related to goal-directed actions (intentionality). Damasio claims that the emergence of the faculty of differentiation of the child own action and action of others is the basis of his core self. This implies also a physical self-awareness.

This “comprehension” of the goal of the action of others and self, comes from the social and cultural context and interaction experienced by the baby during his or her first year. This goal-directed action will be develop later, in the part 4.3 with the introduction of the notion of “shared plan”. It has been shown also that during this first year, the child start to “record” some event for short periods of time.

In the continuation of this, rises during the second year more interactions and in particular spoken interaction between mainly the parents and the child. During this period, the child will develop his/her first representation of self in the way that he/she starts to understand himself or herself as “me”. During this period of time also emerges the language. Now, the child has a tool to communicate with the others. He or she starts to understand sentences, syntax and a bit of semantic. This understanding leads the child to the

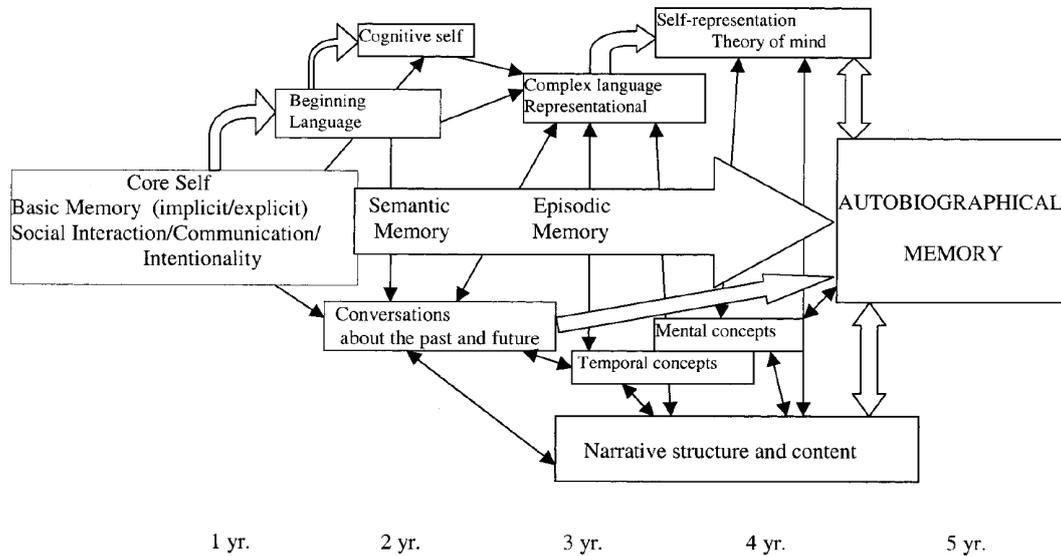


Figure 2.6: Hypothetical relations in developments from 1 to 5 years of age leading to the emergence of the autobiographical memory. Larger arrows indicate more direct influences ; double-headed arrows indicate reciprocal influences. Years (yr.) in the bottom scale indicate approximate ages when influences come into play on average in normal development. Areas above the center are presumed to be more endogenous and those below more exogenous as sources of development. From [Nelson and Fivush, 2004].

understanding of dialogue and stories. This will build the foundation for what we will call the “narrative self” or “temporally extended self”. We will developed this topic in the part 6.

Nelson has shown that it is after the beginning of the second year that the child starts to develop a sense of the “conceptual self” (that will be discussed in the part 5). Around three years marks the beginning of the self-recognition among others, in particular the false belief understanding and the emergence of theory of mind (the ability to understand other people’s intention [Nelson, 2003a], [Nelson, 2003b]).

All of this different blocks that will constitute the ABM are, if not directly or anatomically related, very inter-dependent. The development of each level is dependent of the previous one, and the emergence of the ABM is continue and influenced by numerous factor.

I need to make a clarification at this point, the work that is presented here is biologically motivated rather than bio-mimetic. For this reason, the system described is not accurate from a neurological or physiological point of view. Many studies have been made about the faithful modeling of the mnemonic system, most of them about the working memory ([Fix et al., 2007a] [Fix et al., 2007b] [O’Reilly et al., 1999]). We here do not claim to have a biologically plausible system in terms of interaction between the different parts of our ABM, or by the type of data flowing from one part to another. However, we try to fit as much as possible on the architecture of the memory as described by Tulving, with an episodic memory distinct from the semantic memory.

## 2.2 A Synthetic Autobiographical Memory

### 2.2.1 System Overview

Now that we defined the ABM, we will detail the Synthetic Autobiographical Memory (SABM) that we developed for our robot.

**The iCub** First of all, we have to give the reader an overview of the conditions in which the system is supposed to work. In terms of physical interaction, the iCub, and the Human (also referred to as “Agent”) are physically engaged in an interaction around a reactive table : the ReacTable. The iCub (see Fig 2.7) is an open source robotic platform with morphology similar to a  $3\frac{1}{2}$  years old child (about 104 cm tall) and is carried by an autonomous kart (iKart) that will allow the iCub to interact face to face with a human agent at a relatively good height.

Working with the iCub means having to deal with different levels of actions or functions. We use level, not in the sense of complexity, but in the sense of “cognitive complexity”. For example, the vision, is a very complex aspect of robotics, but in our global architecture, it is an input and thus at the base. Reasoning capacity will be what we will call “high level”. Once again, I want to be very clear on the fact that these levels don’t imply complexity

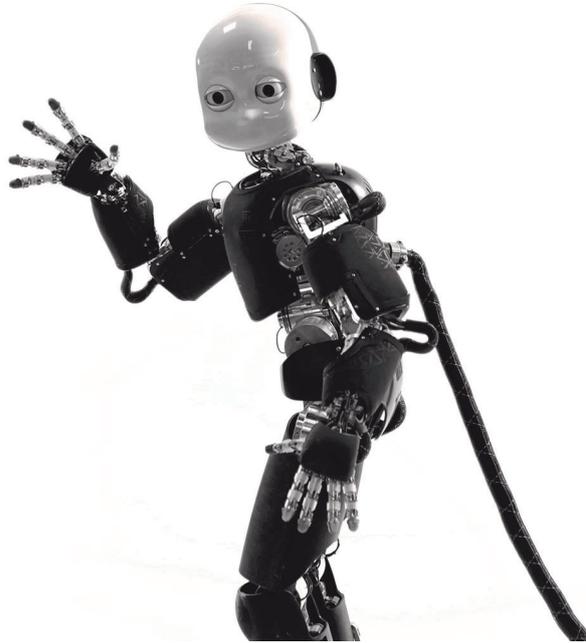


Figure 2.7: The humanoid robot iCub.

but a place in the chain of reasoning. Vision, or motor command are fields that can reach an absolutely massive level of complexity.

The iCub is thus driven by a set of c++ libraries of primitives actions ( $\text{grasp}(x, y, z)$ ,  $\text{release}(x, y, z)$ ,  $\text{look}(x, y, z)$ ). these libraries are represented in purple as “*iCub Motor Cmd*” in the Fig 2.8. Working with primitive actions allow us to free from the “low level” problems of motor control. Our problem will be : when to send a command and which command to send? The execution of the command itself isn’t our main goal. I am not saying that the body is not important for the use of the self or memory (see 7.5 for the impact of the embodiment) but the effect of the body will be more visible and more important for a learning phase. We will discuss this later, I just need to make clear that the details of execution of the action is not the primary goal.

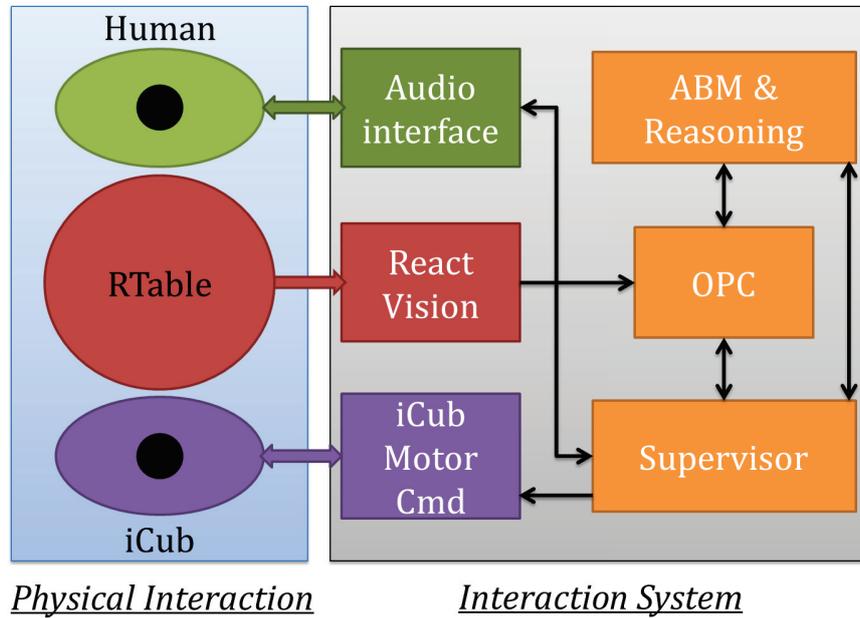


Figure 2.8: System architecture overview. Human and iCub interact face-to-face across the ReactTable, which communicates object locations via ReactVision to the object property collector (OPC). The Supervisor coordinates spoken language and physical interaction with the iCub via spoken language technology in the Audio interface. The ABM system encodes world states and their transitions due to human and robot action as encoded in the OPC. Adapted from [Pointeau et al., 2014a].

**The ReactTable** In the current research we extend the perceptual capabilities of the iCub with the ReactTable [Geiger et al., 2010]. The ReactTable has a translucent surface, with an infra-red (IR) illumination beneath the table, and an IR camera that perceives tagged objects on the table surface with an accuracy of mm. Thus, tagged objects can be placed on the table, and their location accurately captured by the IR camera (see Fig 2.9 and Fig 2.10).

Interaction with the external world requires that the robot is capable of identifying its spatial reference frame with the objects that it interacts with. In the human being, aspects of this functionality is carried out by the dorsal stream, involving areas in the posterior parietal cortex which subserve complex aspects of spatial perception [Shmuelof and Zohary, 2005]. In our system, the 2-D surface of the table is calibrated into the joint space of the iCub by a linear transformation calculated based on a sampling of calibration points on the

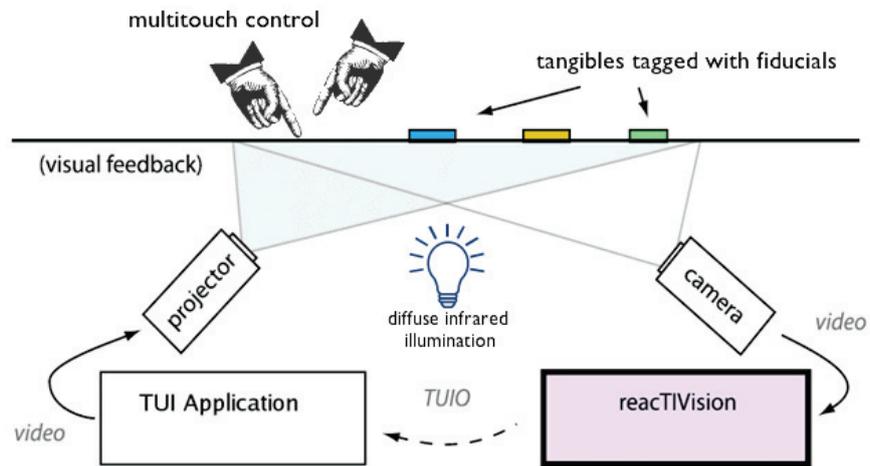


Figure 2.9: Representation of the functioning of the ReactTable.

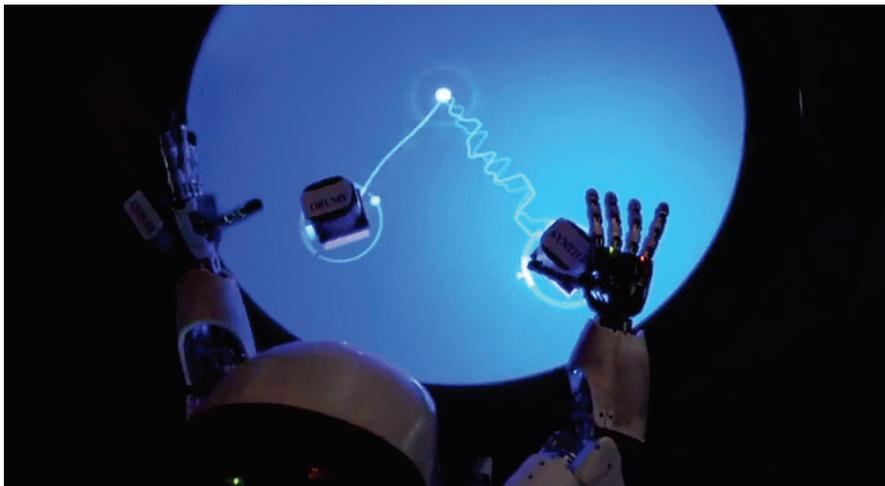


Figure 2.10: View of the functioning of the ReactTable from the iCub point of view.

table surface that are pointed to by the iCub. These points are physically identified in the Cartesian space of the iCub, and on the surface of the ReacTable, thus providing the basis for calculation of a transformation matrix which allows the projection of object coordinates in the space of the table into the Cartesian space of the iCub. These coordinates can then be used as spatial arguments by any action system of the iCub, which provides basic physical actions including point-to  $(x,y,z)$ , put(source X, Y, Z; target x, y, z),grasp  $(x,y,z)$ , and release  $(x, y, z)$ .

**The Objects Properties Collector** As we've seen previously, the robot needs an Episodic Memory, a Semantic Memory, a Working Memory (WM), and some functions to access any of this components. The WM is not a part of the ABM, and it will be treated externally.

The WM in our case will be represented by the *Objects Properties Collector* (OPC). The OPC is a real time repository for all state information related to objects in the environment. Object position data from the ReacTable is formatted and stored in the OPC in a name referenced manner. The motor control level allows processing of commands like “put guitar left” by querying the OPC to determine the location of the guitar in iCub coordinates in order to perform the grasp action using the motor command. Likewise, spatial location names like “left” are stored as entities in the OPC with their coordinates generated and stored in the OPC bases.

The OPC is constituted of *Entities* with for each Entity, an proper ID (OPCid) and a name. We then have three classes inherit from the Entities : *Action Object* and *Adjective*. All of them have the properties of the entities (see Fig 2.11).

The action and adjective have also an argument that will characterize the action or adjective. We have then the *Objects* that define an object physical (like the ReacTable itself) or not (like a location on the table). Each object has different properties : the *presence* which is a boolean (*true* if present, *false* if absent), the *position* which is a triplet

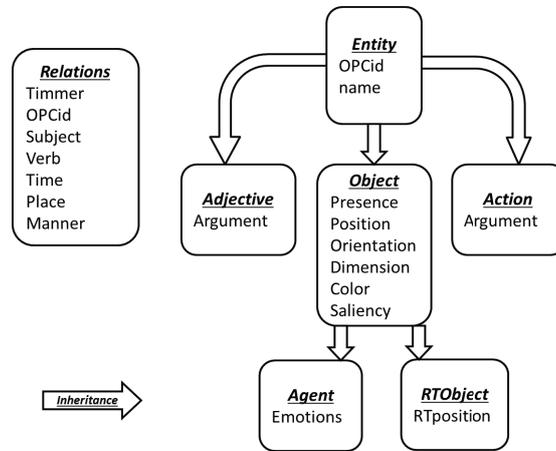


Figure 2.11: Organization of the objects properties collector.

( $x, y, z$ ) in the coordinate frame of the iCub (ego-position), the *orientation* which is also a triplet ( $x, y, z$ ) in the coordinate of the iCub, the *dimension* which is a triplet ( $x, y, z$ ), the color which is a triplet (R, G, B) and the *saliency*.

The saliency is something specific : it defines the attractiveness of the object. This value is a number that can change dynamically according to the environment. An object moving fast with high acceleration will have a strong saliency. When the robot hears about a known object, this will also increase the saliency of the object .

The saliency is handled by a small module called *PASAR*, that will just calculate the acceleration of the objects present and take into account the burst of appearance and disappearance in the computation of the saliency.

On one hand, the saliency will enable the robot to know which are the objects of focus during an interaction. If there is an interaction without vocal clues, the robot will focus his attention on the object with the biggest saliency. He will also direct his gaze toward the object with the biggest focus.

On the other hand there is an “*inhibition of return*”. This system will lower the saliency

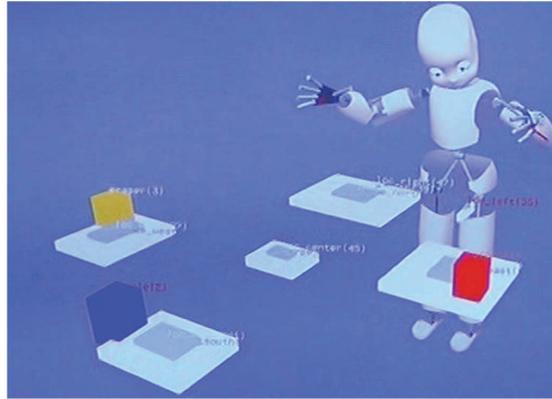


Figure 2.12: Example of representation of the content of the OPC for the robot. We can see the robot with three concrete *RObject* (cross in red, circle in blue and eraser in yellow) and abstract object which are locations : north, south, east, west and center.

of the object that is looked at by the robot. This models the disinterest of the robot for an object after a few time.

”Beneath” the objects, we have to classes of entities : *Agent* and *RObject*. The agents are of course the different humans or robots present (the iCub itself, has his own agency, but we will come back to this later). An agent is an object because he has every properties of the objects : a spatial position, a size, a color, an orientation in space and a presence. But the agents also have emotions. An emotion consist of a name (of the emotion : i.e. *anger*), and a value of this emotion. The emotions are in our system not yet totally functional. The *RObjects* (for *ReacTable Object*) are every object that is detected by the *ReacTable*. The *RObjects* have, in addition to the properties of the objects, the *rtposition* which is a triplet  $(x, y, z)$ . This triplet indicate the location in the frame of the *ReacTable*. One can claim that a *RObject* is by fact, always at the height of the *ReacTable* and thus the  $z$  coordinate is useless. That is true, but we keep the *rtposition*  $z$  for practical reasons (offset of the iKart, of for some offset for grasping function).

A finger on the *ReacTable* can be detected and will be set as a *RObject*. An agent can thus show a position of the *ReacTable* just by pointing at it.

The last possible entries of the OPC are the *Relations*. A relation is composed by an *OPCid*, a *Subject*, a *Verb* that are mandatory. Then we can add to the relation some complement of *Time*, *Place*, or *Manner*. All these relations have a life time : *Timmer*, that will allow to a dynamic relations. these relations will help mainly for the action of the agents for example : “*Agent - Wave - Slowly*”.

The representation of this OPC can be display on a GUI (Graphical User Interface), and we can thus see the world as it is perceived by the robot (see Fig 2.12). The robot has the perception of his sensors, but also can add some abstract objects (as a location).

From a technical point of view, the WYSIWYD and EFAA project are made in collaboration with different European laboratories. We agreed to use the language *c++* for the implementation.

**Audio Interface** To interact with an agent in a human way, we use an audio interface to make the bridge between the robot and any vocal command of the agent. The audio interface and `speechRecognizer` used are based on Microsoft speech recognizer SAPI5.1. The system, given a grammar, can detect the semantic role of each word in a sentence. For example, we used sentences like : “*Peter put the cross to the left*” or “*You point the circle*”. In these sentences, the first word will be extracted as the subject (or pronoun), the second as a verb, and the last one as the object of the sentence.

Once again this system allows us to detach from the problems posed by low-level speech recognition. One can say that we recognize only what we want to recognize, which is partially true, but we can argue that the problem of speech recognition is a full part problem and we have to choose where to put the threshold between vocal recognition and sentence recognition. We decided to put it on sentence recognition.

**Supervisor** To make the link between the different component of our system, we need a module that can handle the information of the different other module and triggers the corresponding behavior. This module has been the object of many changes during the last few years. It has been first developed using the programming language RAD [Sutton et al., 1998]. Then this system has been replace by a module called *MainLoop*, that was handling a majority of all module of the EFAA project. Now, we use a module called *qRM* for Quick Robot Manager. The term *Supervisor* will refer to any of this three system.

The Supervisor provides the general management function for the human-robot interaction, via a state-based dialog management system. This allows the user to enter different interaction states. The Supervisor is state based, with specific responses and commands from the user. It analyzes the input from the Audio Interface, and for example, queries the SABM, or use the Reasoning tools, and creates an answer that can be a vocal command synthesized by a state-of-the-art speech synthesis, or a motor command.

The connectivity between these different functional modules is implemented in an inter-process communication protocol, YARP for *Yet Another Robot Platform* [Metta et al., 2006]. Each module has ports, that can send or receive *Bottle*, which will content a message of any kind of data (numbers, images, sentences...). Yarp is a system platform independent. Thus one of the big advantage of our system is that we can put it on (almost) any robot. The only thing to modify to pass from, for example, the iCub to a Nao Aldebaran, is to change the Motor Command module. Everything else can remain the same.

**Synthetic Autobiographical Memory** We will now detail the architecture of our SABM. Technically the SABM is set as a Functionally, the SABM is composed of two memory sub-systems as described by above, an episodic-like memory, and a synthetic semantic memory. In terms of implementation the ABM content storage is managed by a PostgreSQL data base manager [Momjian, 2001], and access requests are handled by a c++ SABM module.

The ELM and the SSM are thus PostgreSQL database, that will contain the memory of the robot. As for every component of the declarative memory, we want to be able to access

the ELM or SSM on purpose. For this we have a module called SABM which is a c++ program with a wrapper for PostgreSQL. The figure 2.13 represent the functioning of the SABM with the rest of the system. We can see that the *Supervisor* can act in two different ways. At first, it can send command to the SABM directly (arrow 3) to trigger a snapshot for example at the beginning or the end of an action, or to get precise information about the content of the ELM. Once this request is send to the SABM c++ module, the SABM will in the case where it has to create a new memory, take a snapshot of the OPC (arrows 7 and 8). As we explained the OPC is already pre-processed data, and this content will be store in the (arrow 1.a) ELM, with the information related to the objects (position, presence ...) but also with the “meta information” given by the supervisor about the action. The request from the Supervisor can also be a “question” (and not a snapshot). In this case the SABM module in c++ will ask the ELM for a precise (or several) event in (arrow 1.b) and will get an answer under the form of an OPC content (arrow 2). This system will allow the iCub to manipulate always the same format of data (under the form of an OPC). The second possibility of the Supervisor is to query the Reasoning module (arrow 4). This query can be for example to ask the reasoning module to create some knowledge. This creation will be explain in more details in the part 2.2.3. In term of communication, the reasoning will ask to the SABM c++ module information (arrow 5) related to the actions. The reasoning module will thus get information under the form of OPC content (arrow 6) and will be able to manipulate it easily. Once the robot will have created knowledge, it will send it back to the SLM or directly to the Supervisor to be used (arrow 9). This knowledge will be mainly under the form of point cloud, or vector of data and will not be interpretable at first glance.

My personal work during this thesis was thus the development of the component of this Fig 2.13 at the exception of the OPC.

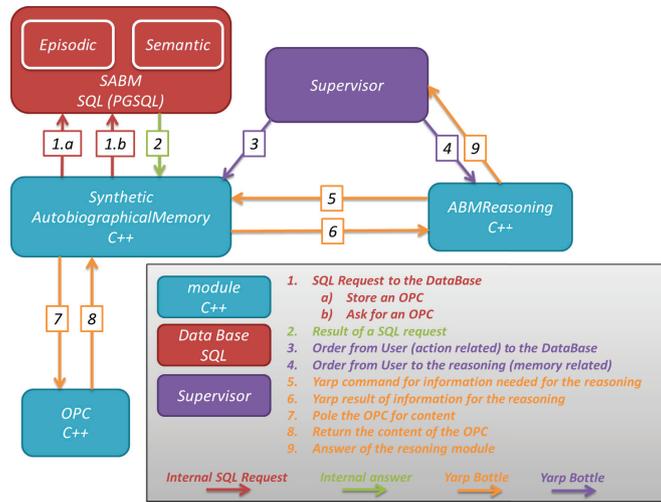


Figure 2.13: Overview of the memory functioning including the SABM PostgreSQL Database, the Supervisor, the Reasoning Module, and the OPC. Arrows 1-2 : SQL queries, and replies to SABM are managed by a Autobiographical Memory interface module. Arrow 3 : User interacts with SABM related to action status, and 4 : Memory content. Arrows 5-6 : SABM reasoning requests and receives state data from OPC. Arrow 7-8 : ABMmanager requests and receives state data from OPC. Arrow 9 : Final response of SABM Reasoning to the supervisor. From [Pointeau et al., 2014a]

### 2.2.2 Episodic-like Memory

When the Human performs an action, a message is sent to the ABM which saves the current state of the world for the robot (the current OPC) in the episodic memory in SQL. In the context of the interactions with the human the robot is informed at the beginning and at the end of each action. With the state of the OPC before and after an action, the robot can extract the preconditions and effects for that action, as inspired from [Mirza et al., 2008]. The SQL structure of the ABM is illustrated in Fig 2.14 and corresponds mainly to the structure of the OPC but with a few additions.

The ELM is divided in 12 tables that can be divided in 3 parts : the “self related”, the “action related” and the “world related”. The table *main* is above the other and contain the “contextual information” of the event : the time where the event occurred, the name and type of the action, the number of instance that we will use a primary key to link each table, and a tag *begin* to precise if the event is the beginning or the end of the action.

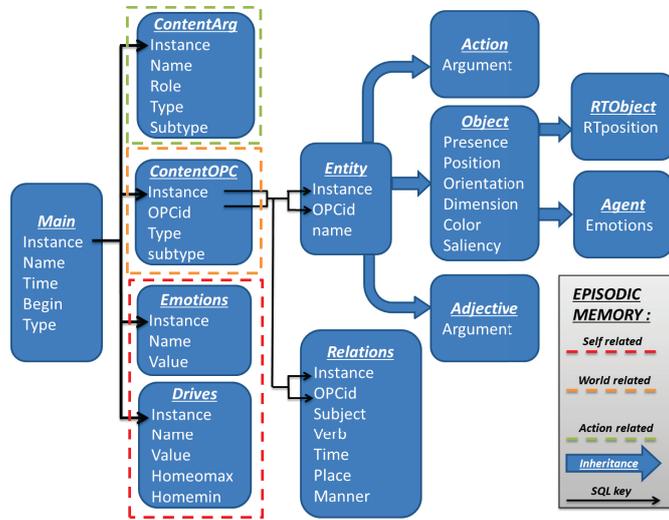


Figure 2.14: Architecture of the episodic like memory storage in PostgreSQL. The main data type is specified as ContentArg, ContentOPC. Each interaction has the content of the OPC at a given time (state of the world), but also, information concerning the context of the action (who, what, when. . .). The content of a memory can be divided in 3 sections : self-related, world-related, and action-related. From [Pointeau et al., 2014a]

**World Related** : In this part, we found the tables that will save the state of the world at a given time. This state of the world is given by the WM, in our case the OPC. We thus have the tables : *Relation*, *Entity*, *Action*, *Object*, *Adjective*, *RTOBJECT*, and *Agent* with the proper inheritance. Each entity has thus a doublet *instance-OPCid* which is unique and that allow us to retrieve the state of any entity at any time given these parameters.

Above the seven table of the OPC, we have the table *ContentOPC* which will for each instance store the doublet *instance-OPCid*, and will add a *type* and *subtype* (mainly use for research purpose in the ELM). The *type* will distinguish between relation and entity, while *subtype* will define the precise type of entity (*RTOBJECT*, *Object*, *Agent*, *Action* or *Adjective*). We could access these information with the table, but the research a facilitated a lot with this system.

name	type	subtype	role
Grégoire	entity	agent	agent1
put	external	default	verb
croco	entity	rtobject	object1
south	external	default	adjective
quickly	external	default	adjective

Tableau 2.1: Content of the table `contentArg` for one instance. The corresponding action is : “Grégoire put the croco quickly to the south.”

**Action Related** : this part is composed only of the table *ContentArg*. In this table we will put the information concerning the event. We store the arguments of the action. Each argument has a *name*, a *role*, a *type* and a *subtype*. these information are given by the supervisor, or by any module calling the remembering function. For example for the action : “Grégoire put the croco quickly to the south”, we will have three argument. See table 2.1

**Self Related** : In this part, we have to tables : *Emotions* and *Drives*. In the table emotion, we put the different emotions of the robot given by a name and a scalar value. In the table drives, we put the different drives with their value and for each drive the homoeostasis maximum and minimum. To satisfy a drive, the value should be between the maximum and the minimum. these two tables have not been totally used yet.

Each time we want to “save a memory”, we will make a “snapshot” of the OPC into the ELM, with the appropriate contextual information about the action to fill the `ContentArg` table and the `Main` table. The time of saving a memory is around 100 to 200ms which doesn’t allow us to make a “steaming recorder”. This is why we decided to focus on the contextual information more that the frequency.

### 2.2.3 Synthetic Semantic Memory

The second part of the declarative memory that we want to model here is the semantic memory. We thus has created an Synthetic Semantic Memory (SSM). The SSM is created on the same concept as the ELM. It is a set of PostgreSQL data base tables. The structure

of the SSM is illustrated in the Fig 2.15.

The semantic memory is built from the contents of the ELM that have been processed by the reasoning tools that we will explain later. The role of our SSM is to store easily knowledge for the robot. We will explain later how the knowledge is created, for now we will explain the form of the data we store. We use mainly 2 tables for each knowledge : one to store the name and/or argument of the knowledge (example north for a spatial knowledge, before for a temporal knowledge), and a second one with the data, for example some time stamps for the temporal data or some spatial data for the spatial knowledge.

This knowledge is under different form :

**Spatial Knowledge** : it consists of two table : *SpatialKnowledge* and *SpatialData*. Each spatial knowledge correspond at an action and an argument (for example : “put north”). *SpatialKnowledge* will store the name and argument and associate an ID (instance). In *SpatialData*, we will store the data relative to each time this doublet action-argument has been seen. We dissociate the  $vX$ ,  $vY$  data that are the final (x, y) location of the object involved in the action, and the  $vDX$ ,  $vDY$  which is the (x, y) displacement of the object of focus of the action (relative displacement).

**Temporal Knowledge** : We will store here the time stamp of different action with a common temporal argument.

### 2.3 Creation of Knowledge

What is the knowledge? This only question would be a full topic of research and might be to long to explore here. I will thus summarize this question to the following : what is the knowledge inside the semantic memory? Binder gives us a first definition :

*“Semantic memory includes all acquired knowledge about the world and is the basis for nearly all human activity. [...] semantic memory is one of*

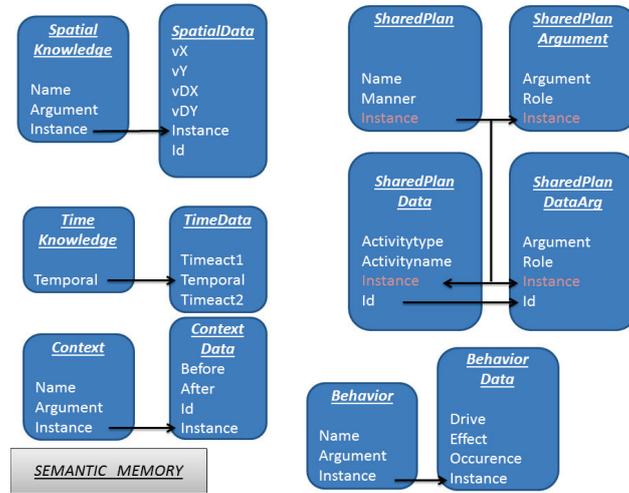


Figure 2.15: Architecture of the synthetic semantic memory storage in PostgreSQL. For each type of knowledge, a first table stores the general information concerning the knowledge (name, argument...) while a second table stores the “technical information” : the positions of each move in the case of a spatial knowledge, or the time-stamp in the case of a temporal knowledge. Each Spatial Knowledge contains 2 vectors : the coordinates of the shift of the object of focus of the action, and the final state of the object of focus. Each Time Knowledge entry contains 2 vectors : the timestamps of the beginning of the action, and the timestamps of the end of the action. From [Pointeau et al., 2014a].

*our most defining human traits, encompassing all the declarative knowledge we acquire about the world. A short list of examples includes the names and physical attributes of all objects, the origin and history of objects, the names and attributes of actions, all abstract concepts and their names, knowledge of how people behave and why, opinions and beliefs, knowledge of historical events, knowledge of causes and effects, associations between concepts, categories and their bases, and on and on.” [Binder and Desai, 2011].*

Here Binder gives a list (not exhaustive) of what can be store in the semantic memory, and we will build on this our SSM. In our case this will be for the robot to store his own definition of an action (simple or complex) and of an adjective. This will be put under the view of a HRI.

Jouen has shown that the modality of learning and of restitution of the knowledge were independent from the capacity to have access to it [Jouen et al., 2015]. She shown

with a study by FIRN that the comprehension of an image or a sentence involve the same areas of the brain. This goes in the same direction that the study of Markov about the organization of the brain in “bottleneck” [Markov et al., 2013], that correlates the study from Martin [Martin et al., 2008] about a continuity of the treatment of knowledge in the brain regardless of the modality of the information. In our case, the OPC will play the role of this centralization of information before its integration in the SSM.

**Different level of reasoning** : We have developed in our system different levels of reasoning. The levels refer to the data which will be used for the reasoning. The first level of reasoning will be the work on the raw data of the ELM to create a first level of knowledge. The other levels of reasoning will work on the knowledge created at the level just bellow. Each time, will will use the knowledge of level  $i-1$  to create the knowledge of level  $i$ .

### 2.3.1 First level : Extraction of Knowledge from the ABM

In order to adapt to novel situations a system must have memory of its experience, but this is not sufficient. The system must be able to extract regularities from specific cases, that can then be applied to the general case. We have developed some reasoning tools that we will describe here. They are contained in a c++ program called *abmReasoning* (ABMR). The ELM provides a record of experience, ABMR will operate on the content of the ELM to structure this information and create the SSM. The ABMR module will extracts spatial, temporal and contextual structure, by looking at preconditions and effects of the actions that have been performed by the human and/or the robot. A simplification of the functioning of the CKF can be found in the Fig 2.16.

***First level reasoning (Consolidation of Knowledge):  
(spatial and temporal)***

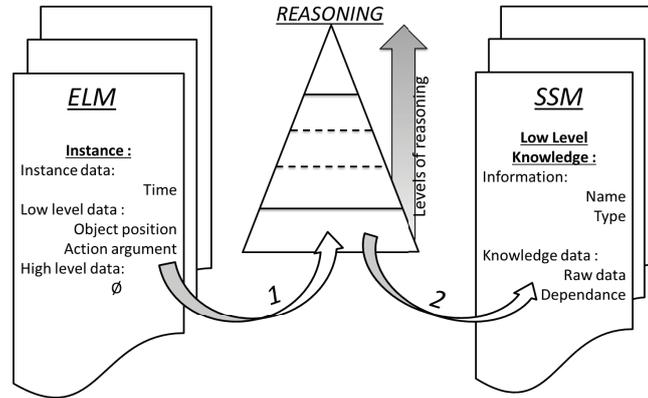


Figure 2.16: First level of reasoning (CKF). The iCub gets the events in the ELM, and create the simple meanings associated. This first level use mainly clustering-like tools.

**Getting the data :** The first part of the learning will be the gathering of the data for a simple action. As we explained in the part 2.2.1, we have the iCub and the Agent interacting around the Reactable. The vocal input is taken by a microphone and a speech recognizer. The sentence we will say to the robot are of the following kind : “*I put the croco slowly to the left*” or “*Carol push quickly the cube left*”. The iCub makes then a “snapshot” of the world and save his memory (get the dynamical content of the OPC in the ELM). The Agent indicates to the robot the end of the action, and the iCub will make a second snapshot of the OPC with the final state of the world after the action in the ELM. The robot have thus the raw data of the objects in the OPC, but also some contextual information about the action given by the speech recognizer or any module of treatment of language.

We will have a set of action that the robot has witnessed. We will then run a function that we call Consolidation of Knowledge Function (CKF). The functioning of the first level of reasoning is summarized in the Fig 2.16. This CKF is based on the mammalian sleep-based memory consolidation ([Payne and Nadel, 2004] [Frank and Benington, 2006]). At the shutdown of the system, the robot will enter in a form of “dream” mode which is in

reality a function of consolidation of his knowledge. During this mode, the robot will go through all his actions performed in the current session, and will generalize over this data, and consolidate the resulting semantic knowledge in the database. At the initialization of the system, the ABM Reasoning module will load the semantic knowledge that has been previously stored in the autobiographical memory through consolidation.

We get a set of 53 sentences for the first draft of the experiment. The subjects used were : “Carol”, “I”, or “Grégoire”. The verb used were : “put” or “push”. The objects used were : “croco”, “mouse”, “cube”. And finally, the adjectives used were : “slowly”, “north”, “center”, “south”, “east”, “quickly” and “west”. The list of the argument and combination used can be seen in the table 9.1.

**Getting the temporal adjective :** This consolidation will focus on the adjectives and verbs of the actions in a first time. The concept is to gather all action related to an adjective, and to find the common denominator between all this action. We only have access to information about the spatial position of the objects and the timing of the action. We thus consider that the adjective the robot ears are related to time or space in the case of a simple action. One could argue that the adjective could be about many other thing (as manner) but we decided to focus on adjective that the robot can perceive the action. However this limitation will be addressed in the discussion.

But what define the influence of an adjective on the related actions? There is an influence is on a particular property, the actions related to an adjectives are different of the action in general. To do so, we will for each adjective heard plot the histogram of the timing of the actions, and compare it to the distribution of the timing of all the other actions. The robot will thus calculate an ANOVA or a Wilcoxon test to compare the distribution, and we fix a threshold as internal parameter (in general 0.05) and if the p-value of the test is significant according to our threshold, we can thus conclude that the adjective concerned as an effect about the timing of the action related.

However, the effect of an adjective can stay unnoticed in the case where the range of timing of the action is bigger than the difference itself. For example in the case of an action fast like “pointing” which will last 2s if done quickly of 4s if done slowly, an action as put (which include a grasp and a release) can last for the robot between 20s to 30s. In this case, it will be complicated to detect a general effect of the timing, we have to compare the timing for a couple : adjective + action. We can thus see the effect on each verb of an adjective.

The expected results are that for an temporal adjective we will have a significant differences between the distribution related to the adjective and the general distribution, while for another type of adjective (“left”, “near” ...) we won’t have any differences.

The different distribution and p-values of the Wilcoxon test can be found in the Fig 2.17.

In the case of a significant p-value, the robot will store the knowledge related to the coherent label as the timing distribution for this label.

**Getting the spatial adjective :** The second step of this first level of reasoning will be focus on the spatial redundancies. The concept will be the same that for the temporal properties. For each entry in the ELM, the iCub will get the vector of displacement (relative move) of the object of focus during the action (i.e. the difference between the final position and the initial position) and the final vector of the location of the object (absolute move). For each adjective ( “*quickly*”, “*left*”) in an action that involve an object of focus( “*put*”, “*push*”... but not “*waving*” for example), the iCub calculate the distribution ellipse for the relative, and absolute move. The robot will next compare the dispersion of each ellipse and according to a threshold, the iCub will determinate the relation between an action and a spatial property. The dispersion score is given by the determinant of the covariance matrix of the scatter.

But in most cases, the adjective alone, is not related to spatiality directly. We have

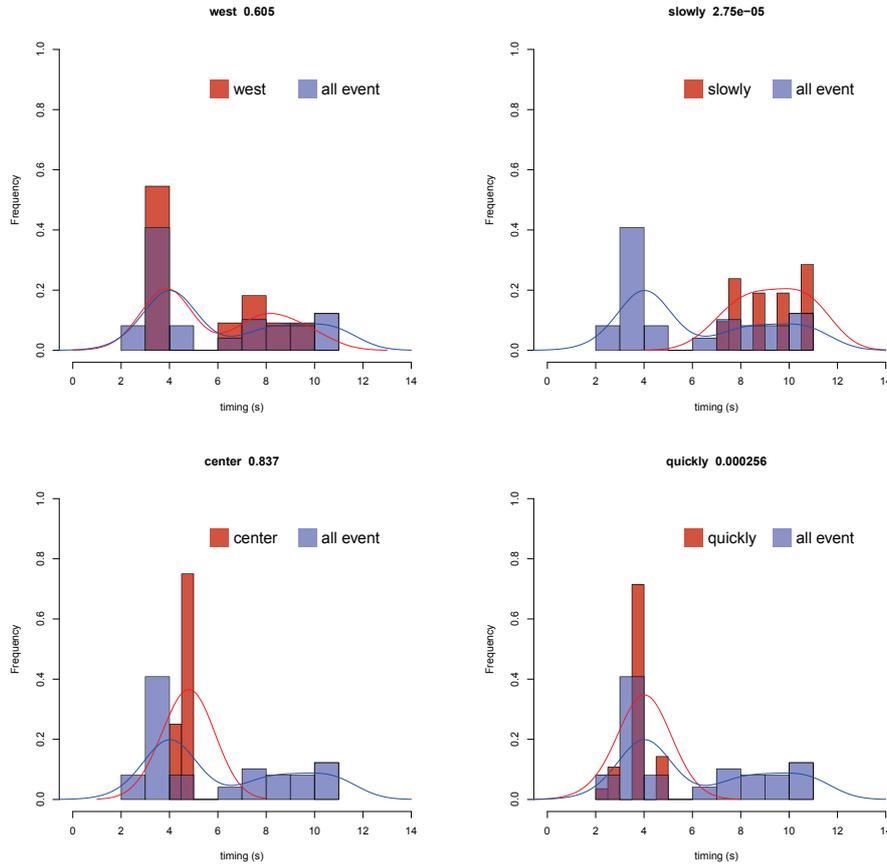


Figure 2.17: Compared distribution of the timing of **every actions in blue**, and a **precise event in red**. The score is the p-value of the Wilcoxon test. The hypothesis  $H_0$  is : “the two populations are similar”. Top left : case of the word “*West*”. The distribution of the time of action associated to the word “west” is the same that any other action : timing is not related to the word “*west*”. Top right : case of the word “*Slowly*”. The distribution of the time of action associated to the word “slowly” is different from the distribution of timing of all the other action (p-value of Wilcoxon test is  $2.75 \cdot 10^{-5}$  : timing is related to the word “*Slowly*”. Bottom left : case of the word “*Center*”. The distribution of the time of action associated to the word “center” is the same that any other action : timing is not related to the word “*Center*”. Bottom right : case of the word “*Quickly*”. The distribution of the time of action associated to the word “quickly” is different from the distribution of timing of all the other action (p-value of Wilcoxon test is  $2.56 \cdot 10^{-4}$  : timing is related to the word “*Quickly*”).

to give a couple “action” + “label”. And we apply the same concept to each couple. The plots of the dispersion ellipses can be found in the Fig 2.18.

On the Fig 2.18, we can clearly see on the 4 labels that the first one, the dispersions for the label “quickly” is unexploitable. All the properties that we can take into account have the same redundancy. We can thus conclude that “quickly” is not an adjective related to spatiality. The adjective “north” or “west” for example show some very low dispersion for 2 properties : put-XY and push-DELTA. Indeed the ellipses related to these properties have some very low dispersion. We can thus conclude that the label “north” is related to the final location of an object on the reactable if it is used with the verb “put”, while, it is related to the relative displacement if it is use with the verb “push”.

Based on this spatial knowledge, the robot can now discriminate between spatially oriented actions such as “push” and “put”. For actions in which the property of interest which is the final state, the system will learn the corresponding absolute location. The ABMR will then insert this location in the OPC. The ellipse of the property of interest will become the “mental representation” of the robot for that location. This is illustrated in Fig 2.19.

The learning of a spatial knowledge is summarized in the Table 2.2

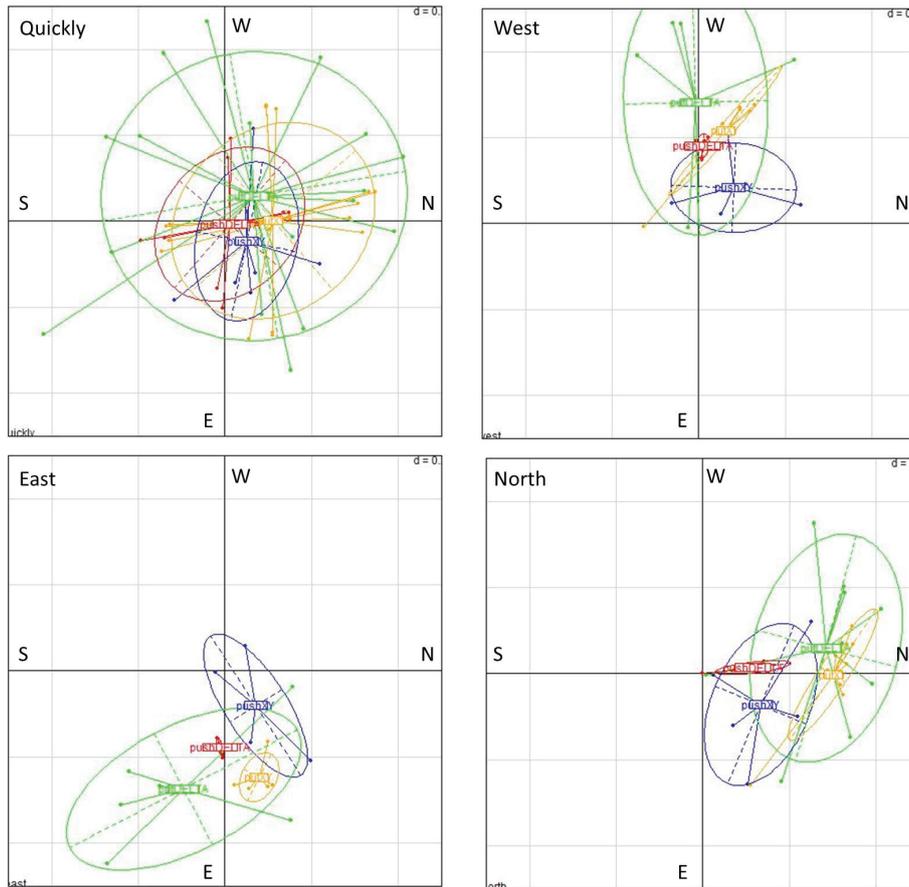


Figure 2.18: Compared dispersion of the the space data for 4 labels : “quickly” (top left), “west” (top right), “east” (bottom left) and “north” (bottom right). We remind that the Reactable is oriented along the  $x$  axis in front of the robot (“north” in the  $x$  axis). In green are the ellipses of the relative move (delta) related to the action **put** (put-delta). In red are the ellipses of the relative move (delta) related to the action **push** (push-delta). In orange are the ellipses of the absolute move related to the action **put** (put-XY). In blue are the ellipses of the absolute move related to the action **push** (push-XY).

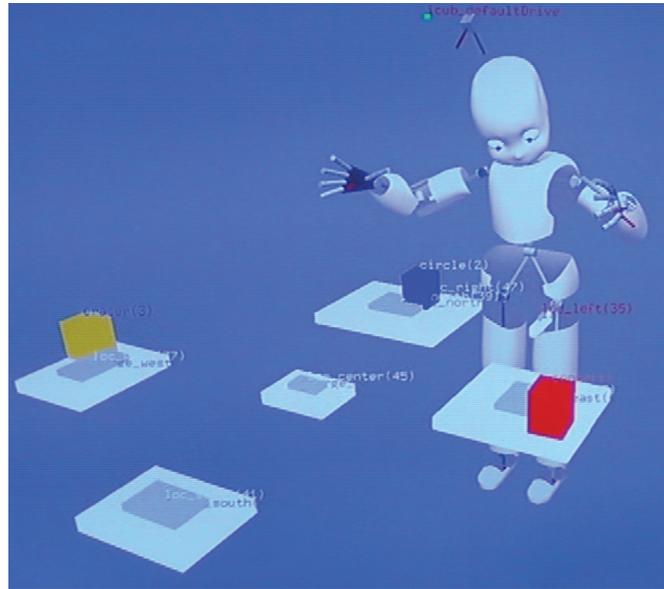


Figure 2.19: Illustration of the internal representations of the learned positions for “north”, “west”, “east”, “south” and “center” as white rectangles in the robot’s peripersonal space. The colored objects are representations of the RTOBJECTS on the reactable that have been placed à West (yellow), South (blue) and East (red) respectively. From [Pointeau et al., 2014a]

---

#### Pseudo-code for Learning Spatial Actions and Locations

---

```

extract_spatial_regularities(ELM, SSM) {
  for each SPATIAL ACTION IN THE ELM
  {
    extract (X,Y) COORDS of object before and after each case of this action
    calculate RELATIVE DISPLACEMENT of the object
    update absolute and relative coords in SSM
    calculate the DISPERSION of the absolute FINAL POSITION and RELATIVE DISPLACEMENTS
    IF dispersionfinal position < THRESHOLD
      then { ACTION is ABSOLUTE
        update location definition in OPC
      }
    IF dispersion displacement < THRESHOLD
      then ACTION is RELATIVE
        update ACTION DEFINITION in SSM
  }
}

```

---

Tableau 2.2: Pseudo code of the learning of spatial knowledge during the CKF.

**Spatial Discrimination :** Now that the robot has this spatial knowledge, he can use it, of course, to act, but also to recognize an action of an agent. Indeed, we want the robot to be able to understand the action of an agent in order to later, understand his goals. To determine this, for each move that the robot has to discriminate, the ABMR extracts the position of the object of focus before and after the action. The ABMR then for each candidate spatial-knowledge calculates the Mahalanobis distance to the scatter of interest. The Mahalanobis distance permits one to check the distance of a point to the center of an ellipse according its dispersion. The Mahalanobis distance ( $D$ ) is given by the equation 2.1 where  $x$  is the position of the point (either the final state or the relative displacement) of the move which we want to discriminate.  $\Sigma$  is the covariance matrix of the scatter of the spatial knowledge we want to compare to, and  $\mu$  is its mean.

$$D_M(x) = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)} \quad (2.1)$$

ABMR thus obtains  $N$  different Mahalanobis distances where  $N$  is the number of spatial-knowledge elements that the robot knows (the couple “verb”+”label” that have a property with a low dispersion). ABMR will then rank all the possible actions according to their Mahalanobis distance, and finally calculate a score of confidence given by the ratio of the second smaller distance by the smaller distance. If this ratio is low (close to 1) this means that the robot cannot discriminate with precision between at least 2 different actions. If the score is high (superior to a confidence threshold i.e. : 5), the robot can discriminate with confidence the move it just observed.

The pseudo-code of the discrimination process is given in the Table 2.3

---

Pseudo-code for Spatial Actions Discrimination

---

```

Discriminate_ action (FOCUS_ OBJECT) {
    for each SPATIAL-KNOWLEDGE IN THE SSM
    {
        calculate the MAHALANOBIS DISTANCE (MD) between the
        focus object (final or shift) and the corresponding SPATIAL-KNOWLEDGE
        IF MD < MINMD
            {
                CONFIDENCE = MINMD/MD
                MINMD = MD
                RECOGNIZED_ SPATIAL_ ACTION = SPATIAL-KNOWLEDGE
            }
    }
    return (RECOGNIZED_ SPATIAL_ ACTION, CONFIDENCE)
}

```

---

Tableau 2.3: Pseudo code of the discrimination of an agent's move.

**Link with the SSM** We have seen how the robot can create his first level of knowledge in term of spatial and temporal knowledge. But now, we want to write it in our SSM to rapidly have access to it. Indeed, the time needed to parse the ELM to create the temporal and spatial knowledge is not compatible with a real time execution and a normal HRI. The robot will thus write in the SSM the distribution corresponding to each label. The iCub will have in his SSM the usable data. Indeed, with directly the scatter of interest for each label, the robot can easily extract the information of interest and use it for a discrimination or an action.

But why do we write this data (the temporal distribution, or the spatial distribution) in the SSM? As I said we want the robot to act in a laps of time compatible with a HRI. To parse his memory (ELM) to create a clean the raw data, the robot need around 0.5s per action. In the case of the 52 actions. The robot can create his knowledge “on the fly”

while he witness actions. But if we shut down the robot and restart the next day, the robot would need around 25s just to recreate these knowledge. To “load” the knowledge itself takes around 0.5s per knowledge. On a big set of action (several hundred in the case of the ELM after more than one year) we cannot afford to loose 5 minutes at each restart, while 10s maximum would load all the knowledge ready to use, for the robot.

### 2.3.2 Retro Reasoning

Who has never experienced to replay a event of his life in his head, with light of new knowledge? That could be just to watch “*The Planet of the Ape*” and to realize it was Earth all along, and to replay all the movie in his head, but not happening on a far far planet, but on Heart. But it can also be calling a friend, having no response, meeting this friend that explain that he changed his number. Our memory of this event will be changed.

This is a concept that we wanted to use for the robot. Now that he has some first level of knowledge, the iCub can use it to replay his ELM and modifying it with new contextual information given by his SSM. The main concept of this retro reasoning can be found in the Fig 2.20.

#### 2.3.2.1 Second level of Reasoning

The second level of reasoning will thus be just parsing the ELM and adding some contextual information mainly as relation. For example in the case of an action “Carol put the croco to the west”, at first the croco was on the location “center”. We thus add the relation related to this snapshot : “croco is center”. At the end of the action, the state of the world is such as the croco is on the location “west”. Also the robot can analyze the timing of an action and can had a temporal label to an action after it.

This second level of reasoning is not the more important, and is sometime useless after a long time of learning. Indeed, if the robot has already the knowledge of a location, and that

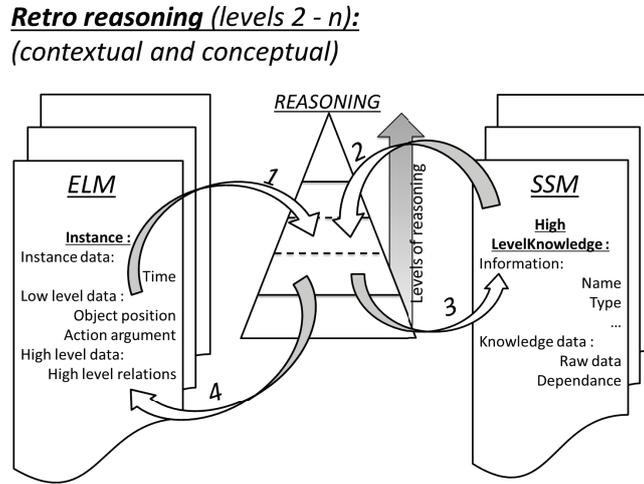


Figure 2.20: Retro reasoning for levels 2 to n. Once the first level of knowledge has been created by the CKF, the next levels are a recursive loop that will use the  $(i - 1)$  level of knowledge created, as new data, to create the level  $i$  of knowledge

an object is on this location, a relation will be added to the OPC automatically. The second level of reasoning is useful when the robot learn a new knowledge (spatial or temporal).

To do this second level of reasoning, the iCub need to replay the events of the ELM “in his head”. We thus plugged a second OPC to the robot, that we call “mentalOPC” (MOPC). This MOPC is not plugged to any sensor and can be accessed only by the ABMR module. The iCub will get the state of the world of the real world at a certain time through the ELM, load it in the MOPC and will reanalyze it with his new knowledge in the SSM, and will add information concerning this event in the ELM. This level of knowledge correpond to adding the context to the memories. We will come back more in detail about this MOPC in the part 3.2.2, all we need to now at this step, his that it is a kind of sand box for the robot to reanalyze the past or simulate according to his will.

### 2.3.2.2 Third level of Reasoning

Once we have “updated” the memory of the robot with some new knowledge, we have “updated” the event and the data present in the ELM. The third level of reasoning will be based on the same principle that the first level. The robot will try to extract some

contextual regularities.

This level of reasoning will be based only (at this stage of work) on the locations. For each action, we will get the contextual information given by the second level of reasoning (such as : “croco is left”). The iCub will then gather for each type of action or couple acion+label (as for the first level of reasoning) this contextual information and will just get the percentage of each relation before and after each action.

For example, in the case of the action “Carol put the croco to the west”, the couple “put+west” will be analyze. A high percent (almost all, except for some noise) of this actions will have a post condition : “croco is west”. Concerning the pre condition, we will have low but a non null percent for any other relation that “croco is west”. The pre condition of “put croco west” will however give a pre condition which is : “croco is **not** west”. This third level of reasoning we allow the robot to learn that : “put an object to the west” is not to grasp an object and to release it in some particular (x,y,z) condition, but on a clearly define location : “west”.

Autobiographical Memory is the basis of higher cognitive function in man, including aspects of language and the emergence of self [Nelson and Fivush, 2004]. We will now see how this emergence can be achieve on the first level of self : the Ecological Self.

## Ecological Self

### 3.1 Ecological Self

*“The ecological self is the individual situated in and acting upon the immediate physical environment. That situation and that activity are continuously specified by visual/acoustic/kinesthetic/vestibular information. [...] infants perceive themselves to be ecological selves from a very early age.”*

This definition of the Ecological Self (ES) is given by Neisser in his article : *“Criteria for an ecological self”* of 1995 ([Neisser, 1995]). Neisser seems to put this level of self as the first self developed by the child, and somehow, the more prominent in the development. Indeed, this level refers to the relation between the person as a physical body, and his direct environment. Before going further in the understanding of the world, the other agents, their action, and trying to predict some high level knowledge, one has to develop a sense of self related to his direct physical body.

The goal of the following experiment will be for the robot, to be able to predict correctly (according to his experience) the impact of his action on the world. Concretely, it will be for the robot to predict for example was is to “put an object to the left”, and to be able to correlate his prediction with his action.

### 3.2 Forward Model Through Mental Imagery

The robot of tomorrow needs to behave freely in their environment and their first level of it is through their actions and body. Neisser refers much on vision and body

to define the ES. In our case and due to hardware limitation (the skin of the iCub was delivered only on January 2015 and after much of these experiments), we decided to focus the ES on the iCub's action because this will be his first contact to its environment.

From a very young age the child is able to understand the consequences of simple movements on the world. In a frame of evolution, it is crucial for survival to be able to generate and exploit internal models of the body, the environment, and of their interaction. As it has been shown by Friston and others ([Bubic et al., 2010] [Friston, 2005]), one of the central function of the brain is to allow prediction. These prediction in the early age concern mostly our ES and the interaction of the body with the world.

### 3.2.1 System Description

As we has seen in 2.2.1, our iCub is doted of an OPC, as a working memory. But [Bubic et al., 2010] has shown the interest of a “mental world” to allow mental simulation. We then decided to give to the iCub, a second OPC (the MOPC described briefly in 2.3.2.2) that it could manipulate at will. This MOPC will be available as a “sandbox” for the iCub to reanalyze the past and extract redundancy as for the retro-reasoning. In our case, we will use it not to go back in past, but to travel in the future and to make some prediction.

The iCub can load in this MOPC a previous memory stored in the ELM, and manipulate it as a human would anticipate an action of “think about something”. We thus developed a small program called “OPCManager” that will be able to manipulate this mental OPC, to synchronize it with the real one, or to compare them if needed. To avoid any confusion, for this part only we will use the terms ROPC for the real OPC and MOPC for the mental OPC.

The OPC manager ensures the proper functioning of the ROPC and the MOPC. The ROPC should maintain an accurate reflection of the physical state of the world. This state will be modified after the execution of actions. Thus, when the robot or the human

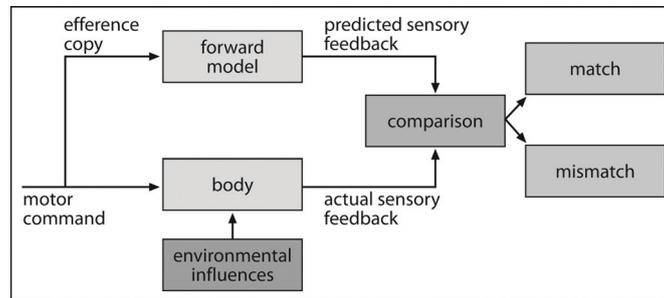


Figure 3.1: Illustration of the forward model in the context of motor control. The motor command is sent to the motor command system and to the internal model. Subsequent comparison allows the system to determine if the grasp was correctly executed. Figure from From [Bubic et al., 2010].

perform an action of the type “put the triangle on the left”, the physical state changes that result from this will be that the triangle is at the north location. For the ROPC, these changes will occur as part of the normal functioning as it is updated by perceptual inputs from the ReacTable. This corresponds to the update of an internal model (the ROPC) via perception (ReactVision inputs to ROPC).

Except this addition of MOPC and OPCManager, the system is similar to the one described previously : iCub and Human interacting around the reactable, the ABM, ABMR and a supervisor.

### 3.2.2 Mental Imagery : Experiment

We decided to give to our iCub a MOPC, but how to use it in the context of the ES? We have seen that the robot is able to create some “high level knowledge” using this MOPC by resimulating the past to analyze it to the light of “middle level knowledge”. Now we want to use this high level knowledge. To do so we will use the MOPC in the context of a classical forward model (see Fig 3.1).

Before executing an action, the iCub will try to predict the consequence of its action. To do so, he will a first synchronize the MOPC on the ROPC to have the same initial situation.

Then, the robot will use the knowledge create by the third level of reasoning corresponding to the action required. For example, the iCub has an object in front of him, and want to put it on his left. The second level of reasoning gave him the location “left” that is now an abstract object of the ROPC, and the third level gave that the consequence of the action “put-object-left”, is that the object intersect the location “left”. I insist that all this information are extracted through experience in the ELM and then, stocked in the SSM.

The robot will thus in his MOPC simulate this consequence by moving the object onto the location “left” in his MOPC. Then, the iCub will execute the action, and he can compare the result of his action. The Fig 3.2 and 3.3 respec. gives us an overview of the awareness of the robot for this same action successful and respec. failed. This figure are the content of both ROPC (bottom) and MOPC (top) before (left) and after (right) the action.

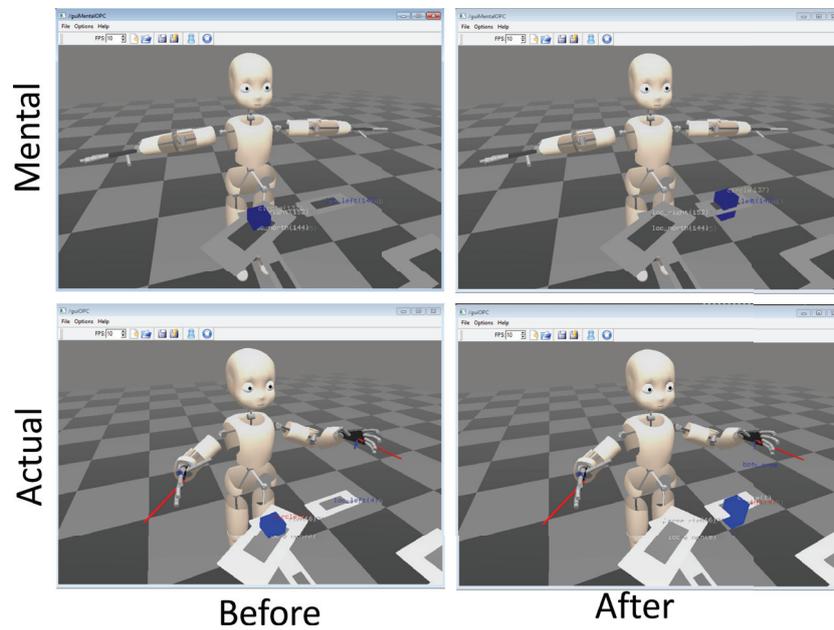


Figure 3.2: Simulation of the action “Put the circle to the left”. The circle is the blue object. This is the mental image (above) and the actual physical state of the world (bellow). Before the action is the left column, and after the action is the right column. In this case the action was successful : the final state (after) of the mental and actual world are the same. We have no semantic difference. From [Pointeau et al., 2013a]

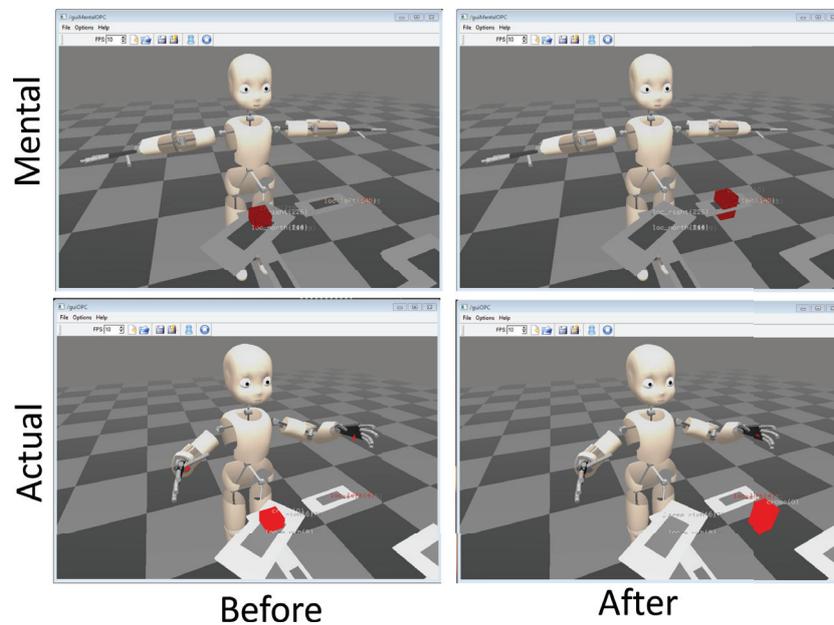


Figure 3.3: Simulation of the action “Put the cross to the left”. The cross is the red object. This is the mental image (above) and the actual physical state of the world (bellow). Before the action is the left column, and after the action is the right column. In this case the action was a failure : the final state (after) of the mental and actual world are not the same. In the mental world, the cross intersect the location “left” while in the real world it is not the case. We have thus a semantic difference. From [Pointeau et al., 2013a]

```

Entity : circle
robot_position_x -0.025075
robot_position_y 0.016605
robot_orientation_z -0.048426
rt_position_x 0.112762
rt_position_y 0.180602

No semantical differences

```

Figure 3.4: Computed differences between the MOPC and the ROPC after the successful action “put-circle-left”. *robot\_position* is the position of the object in the referential of the robot, while *rt\_position* is the position of the object in the referential of the reactable. The semantic information are high level information such as intersections.

In the case of the successful action (Fig 3.2), if we ask the OPCManager for the differences between the two OPCs we will have the following results (Fig 3.4) :

We have a few differences due to the fact that in the simulation, the robot puts the object in the middle of the location left, while in reality, even if the iCub tries to reach it, there is always a small deviation due to motor control. We thus have some insignificant differences but no high level differences (such as intersection of an object with a location or near another object, presence or absence, no new relation in the OPC). The robot can conclude that his action was successful and that he reached his goal (put the circle on the location “left”). He successfully predicted the impact of his body on his direct environment.

In the case of a failed action Fig 3.3, if we ask the OPCManager for the differences between the two OPCs we will have the following results (Fig 3.5) :

As before, we have a few low level differences in the location of the object cross, but if we update the beliefs of the iCub in both case (high level knowledge) and we compare it, we have a difference : the relation “cross is left” has been removed in the ROPC. This is a high level differences and on this information, the robot can conclude that his action failed, and he can adapt his behavior in consequence.

```

Entity : cross
robot_position_x -0.091195
robot_position_y -0.035511
robot_orientation_z 0.179689
rt_position_x 0.194235
rt_position_y 0.183612

Semantical differences :

Entity : icub
Beliefs removed :cross is left (mental - actual)

```

Figure 3.5: Computed differences between the MOPC and the ROPC after the failed action “put-cross-left”. *robot\_position* is the position of the object in the referential of the robot, while *rt\_position* is the position of the object in the referential of the reactable. The semantic information are high level information such as intersections.

### 3.2.3 Discussion

With the help of a forward model mechanism, we can provide the iCub of a way to interpret the consequences of his action upon the world. This is the case for simple action, has we have seen, but it can also be used in the case of more complex plan of action (the shared plan : see 4.3).

Our system require several component to run :

- a full system of ABM to collect the experience in the ELM, and to store the knowledge in the SSM.
- a Reasoning module (ABMR) to parse it the experience in the ELM to create this high level knowledge.
- a mental world to be able to manipulate the concept learned and to predict the next state of the world.

However in this study, we don’t rely on the vision as mentioned Neisser, but we can ask if the vision is preponderant for humans in its development is not the fact that it is the

more developed sensor we have? For the robot the most accurate sensor that we have in our system is the ReacTable and taking our data from here is almost equivalent to taking data from another visual sensor.

Another notion that could be discussed is about the fact that we don't rely on the body per say in our study. Indeed, the body is not very involved. However we are talking here about action that are in the set of primitives action doable by the robot. From this fact, most of the information in the ELM then in the SSM are based about movement done either by the Human or by the robot itself. Thus for achieving an action with the process of forward model, we don't rely much on the body of the iCub, but for setting this forward model, and to gather the data that we will use, we need this embodied actions.

## Interpersonal Self

What are the tools that allow one to react in a direct social interaction? From the very young age, humans are able to detect if someone's acts or movements are directed toward him or not. This is the part that Neisser qualifies of Interpersonal Self (IS). In his article : “*Five kinds of self-knowledge*”, Neisser defines the IS as :

*“The interpersonal self is the self as engaged in immediate unreflective social interaction with another person”* (from [Neisser, 1988]).

We can find an analog definition in his book of 1995 :

*The interpersonal self is the individual engaged in social interaction with another person. Such interactions are specified (and reciprocally controlled) by typically human signals of communication and emotional rapport : voice, eye contact, body contact, etc. This mode of self-knowledge, too is available from earliest infancy* (from [Neisser, 1995]).

The IS will be included in what is called *inter-subjectivity*. The inter-subjectivity is a big word to consider that we have at least 2 subjects interacting. But this interaction need to be based on **joint** and **mutual** “*nature/direction/timing/intensity*” from the two agents. Joint : because of the “synchronization” needed to interpret the actions of other as related to mine. Mutual because both of the agents have to be aware and perceive the other in term of action and “*interactive responses*”. But this inter-subjectivity is not exclusive in term of agent involved and this joint interaction should also be perceived from an external

agent.

Murray and Trevarthen have shown that infants of a very young age (between 6 to 12 weeks old), can detect this kind of reciprocal interaction. Indeed in their experiment of 1986 [Murray and Trevarthen, 1986] they brought to light this phenomena in light. The set-up was the following : a mother and her 6 to 12 weeks child were in two separated rooms. The baby and the mother were interacting through a live-size closed-circuit televisions. The real-size television coupled to a set of microphone allow a live interaction. The first minute of interaction is live. The interaction between the mother and the child proceeds naturally. Indeed the babies : *“looked intently at their mothers with open and relaxed mouth, slightly raised eyebrows, and other sign of interest”*. The first minute of the mother side is recorded, and replayed to the child. This is exactly the same moves, the same words and the same behavior of the mother, however : *“the babies that have been happy a minute ago now exhibited signs of distress : they turned away from the mother’s image, frowned, grimaced, and fingered their clothing”*. Neisser explains it as :

*“so the interpersonal self is specified by the orientation and flow of the other individual’s expressive gestures [...] the interpersonal self is developed and confirmed by the effects of our own expressive gestures on our partner”... These examples [...] show again that inter-subjectivity is an emotional business : the two partners are obviously sharing an affect”*.

This inter-subjectivity cannot be faked : a subject with whom I’m engaged in an interaction **is** or **isn’t** part of this interaction. This is a reason of why children develop this ability to interact so early.

Neisser also brings to light the “organized” nature of this level of self : *“... most of the relevant information is essentially kinetic, i.e. consists of **structures** over time”*. This structural component will be at the core of our studies on the IS. In our case, we decided not to focus on the emotional part of the IS, but mainly on the structural part of the IS,

which means, to focus on the “high level” relation of the robot with his social environment. Indeed, Neisser draws a link between autism and a “failure” of the IS :

*“The mechanism can fail, and it has often been suggested that the dramatic condition called infantile autism, characterized from the outset by a lack of interest in relationships with people, results from just such a failure”.*

The IS implies that the agent (child or robot), in contact with other agents, *“looks for - and finds - the social consequences of its own social behavior”*. Neisser thus refuses as evidence the ability of very young infants to recognize their mother’s voice or even the innate imitation because there is no part of this “social consequences”.

In terms of child development, Neisser fixes that : *“The interpersonal self begins just as early as the ecological self; both are based on perceptually available information”*. This is why, we will first see how the mental imagery developed in the previous chapter can also be used to understand other people’s behavior. In the second part, we will discuss this vision from Neisser of the ability to understand “social consequences” in the *“I and You experiment”*. And finally, later in his development, the IS gets another form, and the child starts to learn that *“people are not just participants in our interactions but have beliefs, intentions, and feeling of their own”*. This topic will be addressed in the third part of this chapter about the “Shared Plans”.

The objective of the following experiments will be for the robot to understand through language the statement of a plan. This plan can involve one agent (as for the part 4.1) where the robot will need to understand the consequence of the actions of this agent and if according to his experience, his prediction of the plan fits with its execution. But the plan can involve several agents (including the robot) and the robot will thus need to first understand, the role of each agent in the interaction (as for 4.2), and finally to integrate both of these aspects to be able to create and be part of a Shared Plan (as for 4.3).

## 4.1 Mental Imagery Extended to Interaction

Now that the robot is able to understand through language the deidic information of an interaction (“*who is supposed to do what?*”), we need a way to verify this information. And to do so, we can use the mental imagery developed for the ES in 3.2.2.

The concept will be the same that for the ES : a forward model, but this time not applied to the robot itself, but in the perspective of his interaction. After hearing a sentence such as : “I put the cross to the west”, the robot can analyze the situation. He will quickly understand that the Human in front of him, who is the speaker will be the agent of the action. The robot doesn’t need to move. Now with his forward model, the robot can predict the result of the action of the Human in his mental world (MOPC), and reuse the OPCManager to differentiate both OPCs to check the action (see Fig 4.1).

The result of the difference between the 2 OPCs will be of the same form as for the actions of the robot (see Fig 4.2) :

```
Entity : cross
robot_position_x 0.162014
robot_position_y -0.706807
robot_orientation_z 0.324926
rt_position_x -0.151903
rt_position_y 0.490982

Semantical differences:

Entity : icub
Beliefs removed : cross is west (mental - actual)
```

Figure 4.2: Computed differences between the MOPC and the ROPC after the human action “put-cross-west”. The human actually put the cross onto the location “east” instead of “west” as announced.

In our case, the robot can detect a mismatch between the declaration of the action of the agent, and its realization. Now the robot can act in consequence and different reactions are possibles :

- **The prediction is wrong or incomplete** : The knowledge of the iCub is too

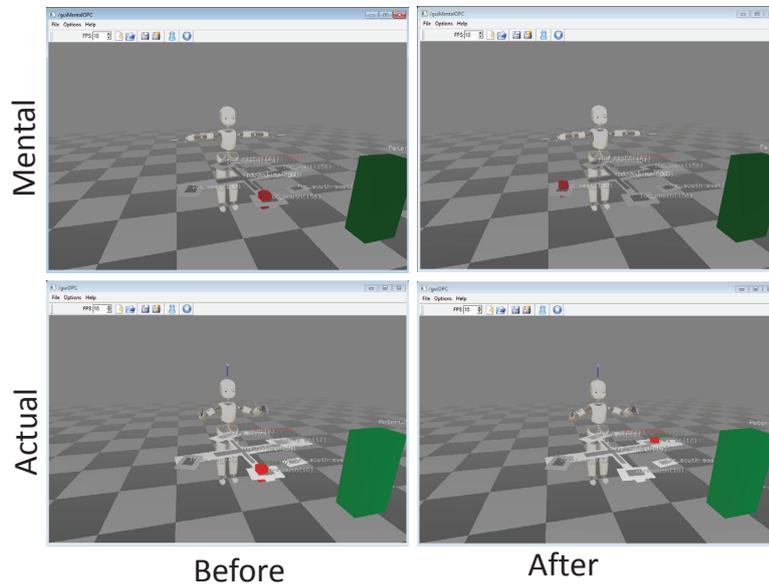


Figure 4.1: Simulation of the action of an external agent : “I put the cross to the west”. The cross is the red object. The green parallelepiped is the agent detected by the kinect. On top is the mental simulation of the action : before (left) the cross is at the location south, and after (right) the cross is indeed at the location “west”. On bottom is the actual world : before the action, the object is “south” (left) and after (right) the object is “east”.

- limited to fully understand the action, the action is correct but the robot cannot understand it yet. The iCub could ask for some complementary information concerning the action. This can also be a mismatch between the concept of the Human and of the iCub. For example for some people “fast” will not be “as fast” as for other people.
- **The Human motor action failed** : The Human failed in his action : the robot can ask if he wants help to perform his action, of just notify him that his action failed.
  - **Both the prediction and the motor action are successful** : The Human was lying on purpose.

This “feature” will allows the robot to analyze now the connection between language and action for the human. We have seen that we already have a tool to discriminate simple action (see 2.3.1) but this mental imagery extended to Human action allows to analyze higher level action. The robot is able, to immediately analyze and reinforce the social

interaction he is in.

## 4.2 Language and social references : the “I and You Experiment”

This level of self is mainly based on the understanding of direct interaction of the other. Neisser places it on several plans including many “body languages clues”. As we already explain, we decided not to work on sensory exploration of the Human body. Yet we don’t have access to face detection or recognition, neither that emotion. The main input that we have concerning Human behavior is language and we decided to focus on it. It has to be noted that also for Imbens-Bailey, a tool to understand social references as pronoun is mandatory in the expression of the self ([Imbens-Bailey and Pan, 1998]).

The interpersonal self is related to deixis in its more social part (see Fig 4.3). Indeed the future of social robotic lies in social interaction. This means not in one-to-one, but with a robot as part of a social group, and able to interact with several persons. Most of the common researches in social robotic or in HRI in general are in the understanding of one-to-one interaction ([Roy and Pentland, 2002] [Steels and Kaplan, 2002] [Hinaut et al., 2014] [Dominey and Boucher, 2005]). Yet, Gold and Scassellati have shown that this kind of interaction are insufficient to learn a correct use of personal pronouns [Gold and Scassellati, 2006a].

Oshima-Takane claims that the use of pronoun as “I” or “You” are learned by observation of a student in a (at least) triadic interaction ([Oshima-Takane et al., 1999] [Shultz et al., 1994]). It has been in this way some model already created to understand the use of this two pronoun by Gold and Scasselatti using fast mapping ([Gold and Scassellati, 2006c] [Gold et al., 2007] [Gold and Scassellati, 2006b]). We decided to start from this system and to extend it to the learning of both personal and impersonal pronoun, but also to use it in a reversible way : to understand it, and to use it correctly. Once again here, our objective is not only to create knowledge, but to be able to use it for discrimination of for acting.

As for our other problem, we have to set a limit of what are the capacities that the robot

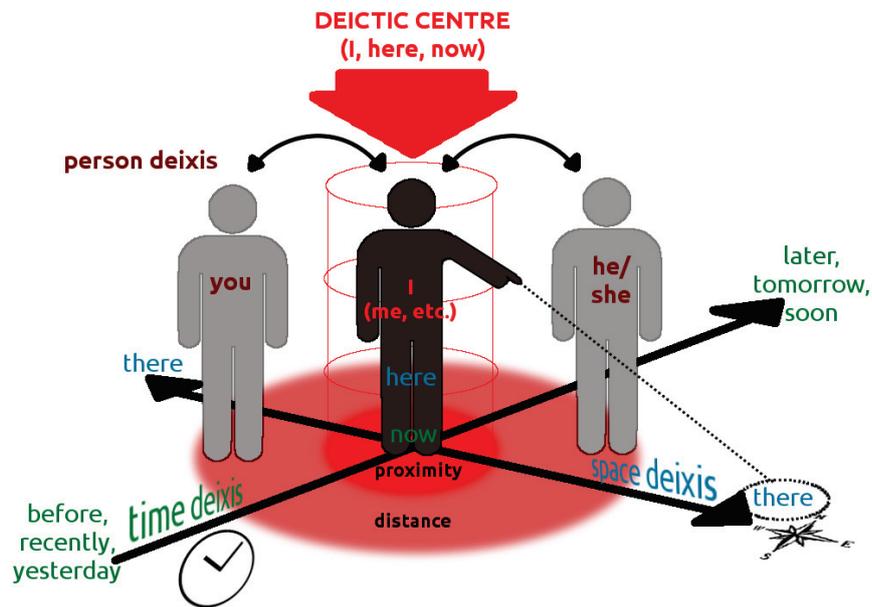


Figure 4.3: Description of the deixis. It consists of the relations that an agent has with the world and with others.

has, and what he should be able to develop. Corkum and Moore ([Corkum and Moore, 1998]) have shown that at about 9 months, children can detect the direction of an adult’s gaze. This age has been put in evidence by Tomasello [Tomasello, 2009] as the “*Nine month revolution*” and is the starting point of a full understanding of a complex interaction, including triadic interaction. Thus, this will be the starting point of our system. We will give the robot the possibility to detect these interaction properties.

Our experiment will be the following : The iCub will witness one or two agents, engaged in a dyadic or triadic interaction. The data we will for each action the collection of the following properties : Who speaks to whom ? Who makes the action ? What is the pronoun used ? Concretely, the robot will be with one or two agent, that will say a sentence such as : “You put the block to the west” to the another agent that will perform the action.

This work has been the subject of a paper published in 2014 at the : 4<sup>th</sup> *International*

*Conference on Development and Learning and on Epigenetic Robotics (ICDL EPIROB)* [Pointeau et al., 2014b]. The following part will retake most of this work plus some that has been done since.

#### 4.2.1 System Specificities

The technical system for this experiment is a bit more complex than the classical system we use. Indeed, as we explain earlier, we need to have access to certain body-language clues. To do so, we decided to use not only one Kinect placed above the iCub as usual, but two Kinects (see Fig 4.4). The Kinect 1, fixed above the iCub will detect the agent and will allow the iCub to follow their movement. The iCub will detect who is acting, by looking at the acceleration of each agent. This implies that if an agent is not acting, we have to ask him to stay still.

The Kinect 2 will be placed at around 90cm in front of the robot, directed toward the human agent(s). It will detect the rigid head motion of several human partners by using the Random Forest algorithm developed by Fanelli [Fanelli et al., 2011]. We will thus have access to the orientation of each agent, and with it to the interlocutor of the speaker.

In summary : Kinect 1 gives us the agent (who act), while the Kinect 2 gives us the receiver of the speech information (to who an agent speaks).

Another change to the usual system, is the addition of two binaural microphones placed in the robot's ears. The acoustic signals were retrieved in real-time thanks to the Jack library. The Interaural Intensity Difference (IID) was computed. In fact, sound coming from the right has a higher intensity in the right ear microphone than on the left ear one. This difference allowed us to determine if the sound was coming either from left or right. In the triadic setup, the robot was able to determine who the speaker was (see Fig 4.5). With our usual system (ReacTable + speechRecognizer) and this few additions, we are able to detect the four element of interaction that will be important for our study :

- **Speaker** : (**Sp**) detected with the binaural microphone
- **Addressee** : (**Ad**) the person to whom the speaker talks, detected with the Kinect

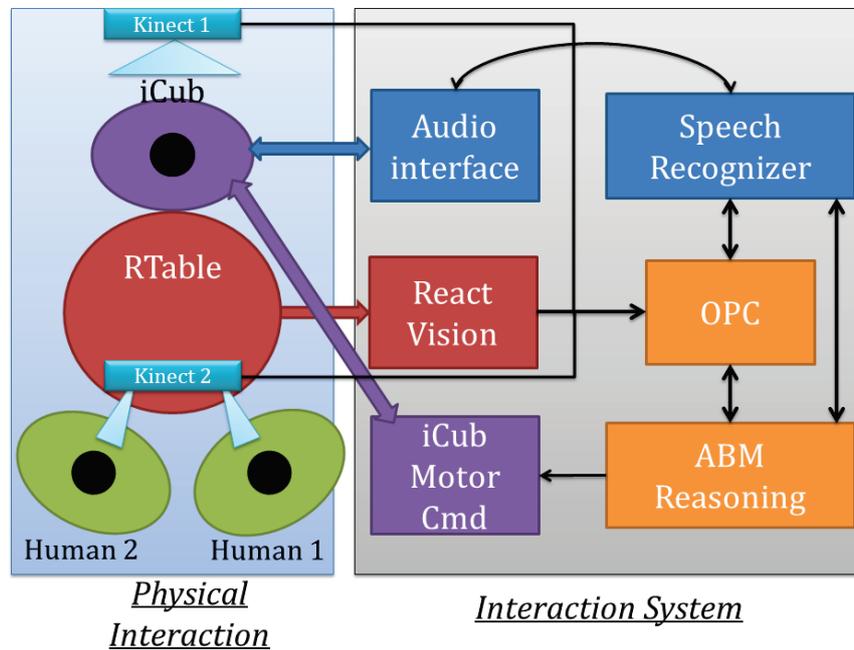


Figure 4.4: Physical and software architecture of the system used for the “I and You Experiment”. From [Pointeau et al., 2014b]

- 2 (orientation of the head)
- **Subject : (Su)** grammatical subject of the sentence, detected through the speech recognizer (grammar parser)
- **Agent : (Ag)** detected with the Kinect 1, by calculating the acceleration of each agent in the OPC.

#### 4.2.2 Method

In our study, the robot will have a set of training data. For each set of learning data, we will use the pronouns : “I” and “You”, and the proper names : “Peter”, “Maxime” and “Grégoire” (will be referred as “known names”). The robot will witness and mark in his ELM the events with the four properties filled. This learning phase can be simulated by directly inject some artificial data in the ELM (see 4.2.4).



Figure 4.5: System running when the robot is interacting with 2 agents around the Reactable for the “I and You Experiment”. From [Pointeau et al., 2014b]

After a learning phase, to test the system, we will for each of the four possible modalities (Sp, Ad, Ag, Su) give a random but doable (ie : Sp different of Ad) set of the three other modalities, and ask for the fourth one. For example, we want the robot to analyze the following situation : Peter looks at the iCub and says to the iCub “I put the croco to the west” and we want that the robot understand who is putting the croco to the west. We will give the system : Su = “I” ; Sp = “Peter” ; Ad = “iCub” and the system should return : Ag = “Peter”. Another example would that the robot sees Maxime moving (Ag = “Maxime”) and he wants to describe it (Sp = “iCub”) to Peter (Ad = “Peter”). The system should return : Su = “Maxime”. With any 3 of the 4 properties (Sp, Ag, Ad, Su), the iCub should be able to return the fourth property when possible.

During all the learning phase, the robot will remain silent. We consider that the robot doesn’t have the knowledge yet to speak. This is why during this learning phase, the robot will be only observer which means in term of condition : Sp  $\neq$  iCub.

To test the system, we decided”John” and “Mark” will never appear during the learning phase, but only the testing phase and will be referred as “unknown names”. We want the

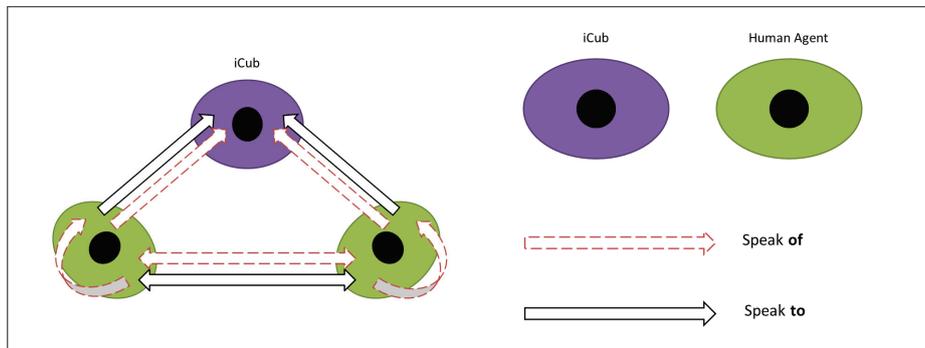


Figure 4.6: Example of all available interaction for one of the learning conditions (left). Right : black arrows mean that the origin agent SPEAK TO the target agent (origin = Sp, target = Ad). Red arrows mean that the origin agent SPEAK OF the target agent’s action (target = Ag). From [Pointeau et al., 2014b]

robot to be able to understand the meaning of these two words as a third person pronoun, that refer to a precise agent.

This system allows us to test different condition of learning easily, just by simulating the learning data by adding “fake memories” in the ELM. This will allow us to determine how the system learn with constrained conditions such as autism or blindness. But it will also help us to determine which kind of interaction are needed the child to learn the use and understanding of personal and impersonal pronoun.

As we said earlier, Tomasello has shown that the child is not able before the “nine month revolution” to fully understand a spoken interaction where he/she is not involved (neither speaker nor addressee). This is what Oshima-Takane calls the “Addressee Condition” [Oshima-Takane et al., 1999], and will be summarized by : Ad = iCub. Another kind of condition that we tested is the case of “blind” children. The particularity of “blind” children is that they can only detect the actions related to them : Ag = iCub [Gold and Scassellati, 2009]. We will have two conditions with respectively two or three agents, where the Ag of the action is always the iCub. The Fig 4.6 is an example of a tested condition with the corresponding legend.

### 4.2.3 Learning Mechanism

**Data formalization :** Before starting to exploit the data, we need to parse them correctly. As we said, for each interaction, we have 4 properties : Sp, Su, Ag and Ad. We take the Su as the property of higher level. For each Su, we build a cubic  $N^3$  matrix (three dimensions : one for Sp, one for Ad and one for Ag), where N is the number of label encountered. A label can be any Ag, Ad or Sp encountered (i.e. : “Maxime”, “Greg”...). A label corresponds to a way to refer to a person for the robot. In most cases, the label will correspond to the proper name of the person (e.g. Peter), but it can be something generic (e.g. Agent\_ 5). However, Su include personal pronouns (“I”, “You”) and proper names that have been used in a sentence. The matrix is then filled with the number of events encountered. The notation  $M_{Su}(Sp, Ad, Ag)$  gives us the number of events encountered with a particular set of Su, Sp, Ad and Ag.

For example, in the case of the sentence : “You point the toy”, where : Su=“You”, Sp=“Greg”, Ad=“Maxime”, Ag=“Maxime”, we will add 1 in the matrix :  $M_{You}(Greg, Maxime, Maxime)$ , and for “John pushes the cross”, where : Su=“John”, Sp=“Peter”, Ad=“Greg”, Ag=“John”, we will add 1 in the matrix :  $M_{John}(Peter, Greg, John)$ . We can expect to have only zero in the case of Sp = Ad, because we consider the case where one doesn’t talk to himself.

In the case of the apparition of a new label, the matrix will grow and fill the new case according to the number of utterances. After the learning phase, we will have as many matrices as we have of different Su, and each matrix will be of size  $N^3$  with N the number of label encountered.

We said that Su is the property of higher level because the data are made of the way to have easily access to the data relative to the Su. However if we want to have access to the data concerning another property, we need to consider all of our data as a matrix of 4 dimension  $MxN^3$  with N the number of label and M the number of known subject.

For the present study, we used 7 different conditions. One of them is made with the system described above, while the other are simulated. In the case of the simulated data, we just fill the ELM with the kind of interaction we want. Each different situation is repeated

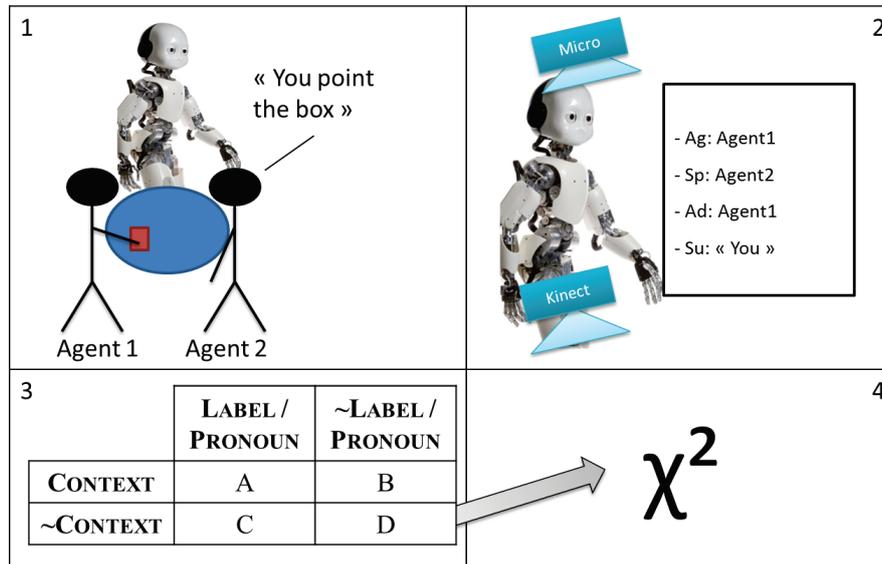


Figure 4.7: Setup of the whole interaction : 1) The robot witness a scene and memorizes it in his ELM. 2) The external sensors get the information relative to the interaction. 3) The robot builds his maps of contingencies. 4) The robot calculates the likelihood for each association of a pronoun or label (name) with a context.

5 times. For example we want to test a dyadic spectator condition. We will create the event of an interaction where two agent are interacting in front of the iCub. Agent 1 will be for example Ag, and Sp, he will use Su="I" and Ad is the Agent 2. This interaction will be repeated 5 times in the ELM in order to have enough data to be able to analyze it.

**Fast mapping :** The learning system per say, is based on the system developed by Gold and Scassellati as briefly explain Fig 4.8. The idea will be to calculate the likelihood of using a certain property (result) given a certain context (the 3 given properties). To find a missing label (Sp, Ad, Ag) or a respectively a pronoun (Su), we list all the labels (resp. pronouns) known, and for each, we calculate a Chi Square associated to the corresponding situation (see Fig 4.8 and Table 4.1). With the p-value associated to this Chi Square we have access the presence or not of a link between the property and the context. If the p-value is lower than a threshold (fixed at 5%) we take into account the distribution of the event. The pseudo code of a decision is shown in the Table 4.2 and the setup of the system

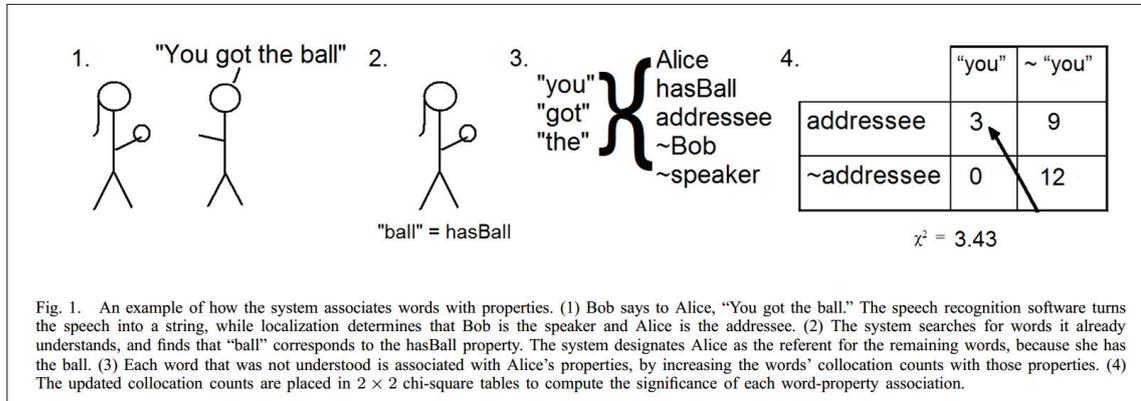


Figure 4.8: Fast mapping of the system of Gold and Scassellati. From [Gold and Scassellati, 2006a])

	LABEL/PRONOUN	~LABEL/PRONOUN
Context	A	B
~Context	C	D

Tableau 4.1: Table of fast mapping for a specific label/pronoun and a specific context. A correspond to the number of event witnessed with the use of a specific label in a specific context. B is the number of event with another label for this context. C is the number of use of the label in another context, and D is the use of another label for another context.

can be found in the Fig 4.7.

#### 4.2.4 Experiment and results

As we said earlier, for this experiment, we tested 7 different conditions. For one, the data where collected through real interactions. The 6 other conditions were simulated : we injected directly in the system the memory of the events with the condition we wanted to test. For each of these condition we will test 6 functionality of the system :

- **Understanding "I"** : The pronoun "I" is used as context and we want the robot to find the corresponding Ad, Ag or Sp. We want the robot to understand correctly a sentence with "I" as Su.
- **Correct use of "I"** : We give a situation as "I" is the lacking property for Su

---

Pseudo-code For the decision in the fast mapping

---

```

for each KNOWN LAB./PRO.
{
If : P-VALUE( $\chi^2$ ) < THRESHOLD
    - Don't change the LAB./PRON. SCORE
Else :
    - Add to the SCORE OF THE LAB./PRON. the DISTRIBUTION OF THE PROPERTY : (A/C - B/D) }
If : ONE OR MORE LAB./PRON HAS A SCORE > 0
    - Return the LAB./PRON. with the higher SCORE
Else :
    - Remove LAB./PRON with SCORE < 0

```

---

Tableau 4.2: Pseudo code corresponding to the searching part of the fast mapping. The result will be either the more likely label (resp. pronoun), or it will be the list of the label (resp pronoun) known without the impossible ones (I don't know what to use, but I know what I cannot use).

- and we want the robot to be able to use “*I*” correctly in a sentence.
- **Understanding “*You*”** : The pronoun “*I*” is used as context and we want the robot to find the corresponding Ad, Ag or Sp. We want the robot to understand correctly a sentence with “*You*” as Su.
  - **Correct use of “*You*”** : We give a situation as “*I*” is the lacking property for Su and we want the robot to be able to use “*You*” correctly in a sentence.
  - **Understanding a known or unknown name** : We use a name as Su of a sentence, and we want the robot to be able to find the corresponding situation. If the name is unknown, the robot should understand that this name doesn't have the same meaning as “*I*” or “*You*”.
  - **Correct use of a known or unknown name** : We give a situation as the Su to use is a known or unknown name, and we want the robot to be able to formulate a sentence with this name as Su.

### A) Triadic Spectator

This first condition Correspond to a complete triadic condition where every one talk to every one about every one (see Fig 4.9. This is the condition with the “real collected data”. Indeed this condition was made with 3 subjects in front of the robot with the full system.

Interaction	Sp	Ad	Ag	Su
1	Greg	Maxime	Greg	"I "
2	Greg	Maxime	Maxime	"You"
3	Greg	Maxime	Peter	"Peter"
4	Greg	Peter	Greg	"I "
5	Greg	Peter	Maxime	"Maxime"
6	Greg	Peter	Peter	"You"
7	Maxime	Peter	Greg	"Greg"
8	Maxime	Peter	Maxime	"I "
9	Maxime	Peter	Peter	"You"
10	Maxime	Greg	Greg	"You"
11	Maxime	Greg	Maxime	"I "
12	Maxime	Greg	Peter	"Peter"
13	Peter	Maxime	Greg	"Greg"
14	Peter	Maxime	Maxime	"You"
15	Peter	Maxime	Peter	"I "
16	Peter	Greg	Greg	"You"
17	Peter	Greg	Maxime	"Maxime"
18	Peter	Greg	Peter	"I "

Tableau 4.3: Set of interaction witnessed by the robot in the case of the condition "triadic spectator". The three agents were interacting in front of the Reactable.

We used a set of 18 sentences that are described in the Table 4.3 that are not repeated. This set of data is "perfect" in the sense where all the possible interactions (except iCub acting, but we will see it is not important) are witnessed.

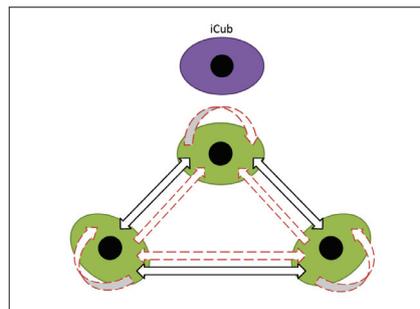


Figure 4.9: Condition : triadic spectator. Three agents that are not the iCub, talk to each other, about each other.

As expected with this "perfect" set of data, the robot learns perfectly all he was supposed to :

UNDERSTANDING OF “I”	✓
CORRECT USE OF “I”	✓
UNDERSTANDING OF “YOU”	✓
CORRECT USE OF “YOU”	✓
UNDERSTANDING OF A KNOWN NAME	✓
CORRECT USE OF A KNOWN NAME	✓

The robot indeed clearly learn to use or understand “*I*” and “*You*” or even a known name ( “*Peter*”...). However of course, the robot is unable to understand an unknown name or to use it correctly. Indeed for us, the understanding of a unknown name needs a bit of knowledge (“I don’t know the agent, but I know that this word is a name, therefor it refers to an agent”) but we will talk more about it later.

### B) Dyadic Spectator

This condition refers to the iCub watching to agent talking to each other about each other (see Fig 4.10). This is a spectator condition. That means that the iCub will never be involved in any interaction. He will neither act ( $Ag \neq \text{“}iCub\text{”}$ ), talk ( $Sp \neq \text{“}iCub\text{”}$ ), be the direct interlocutor ( $Ad \neq \text{“}iCub\text{”}$ ) or be involved in a sentence ( $Su \neq \text{“}iCub\text{”}$ ).

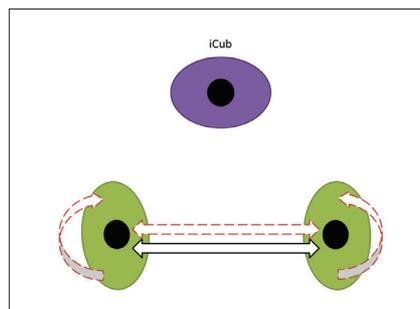


Figure 4.10: Condition : dyadic spectator. The iCub watches two agents, talking to each other, about each other.

The agents only use “*I*” and “*You*”. They never use any name. We have thus a total of 4 possible sentences, repeated 5 times each, for a total of 20 training sentences.

UNDERSTANDING OF “I”	✓
CORRECT USE OF “I”	✓
UNDERSTANDING OF “YOU”	✓
CORRECT USE OF “YOU”	✓
UNDERSTANDING OF A KNOWN NAME	✗
CORRECT USE OF A KNOWN NAME	✗

The robot understands and uses correctly the pronouns “I” and “You” but as expected, doesn’t understand the names (all unknown for this trial).

### C) Triadic Agent

In this condition, the iCub will be interacting with two human agents (see Fig 4.11). The three of them can act, the three of them can be addressee, but the iCub doesn’t speak ( $Sp \neq \text{“iCub”}$ ). Concerning the Su possible, “I” and “You” will be use, and also the names of the two agent present. We have a set of 12 different combination, repeated 5 times each, for a total of 60 training sentences.

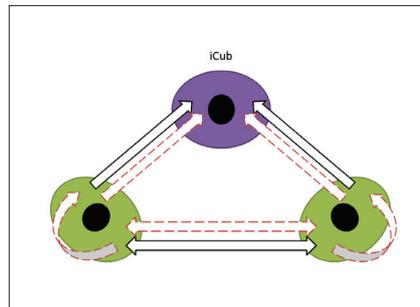


Figure 4.11: Condition : triadic agent. Two agents talk to each other and to the iCub about the three of them.

The results are similar to those for the triadic spectator, except that this time the robot is unable to use correctly the pronoun “I”. When the robot is talking about him doing an action, he will prefer using “iCub” rather than “I” while for the other agent, he can use it correctly. But an interesting fact is that if we ask the robot who would be the agent in the case of a sentence said by the iCub using “I”, the robot correctly understands that “I” refers to him.

UNDERSTANDING OF “I”	✓
CORRECT USE OF “I”	✗
UNDERSTANDING OF “YOU”	✓
CORRECT USE OF “YOU”	✓
UNDERSTANDING OF A KNOWN NAME	✓
CORRECT USE OF A KNOWN NAME	✓

#### D) Triadic Blind

This condition is a bit special. It refers to a system with agents with the iCub. A blind iCub (see Fig 4.12). Therefore, the iCub can only detect action where he is the agent (Ag= “*iCub*”). However we consider that the iCub can detect whether the agent is talking to him, or to someone else by the intensity of the auditory signal. Thus, in this condition one agent can talk to the other or to the iCub, about the iCub (third person). We have a set of 4 different sentences, repeated 5 times each, for a total of 20 training sentences.

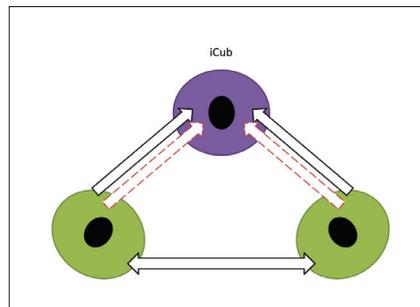


Figure 4.12: Condition : triadic blind. Two agents talk to each other and to the iCub, about the iCub’s actions.

The results for this conditions are a bit odd. The robot understands and uses correctly “You” but not “I” (because he has never heard it). Also, the robot is confused with understanding and using the name “iCub”. It could be the same as “he” or could just refer to “someone else”. We will discuss the result more in details later.

UNDERSTANDING OF “I”	✗
CORRECT USE OF “I”	✗
UNDERSTANDING OF “YOU”	✓
CORRECT USE OF “YOU”	✓
UNDERSTANDING OF A KNOWN NAME	✗
CORRECT USE OF A KNOWN NAME	✗

### E) Blind dyadic

The iCub is alone with another agent (see Fig 4.13). This is a “blind” condition. The robot is the only one to act (Ag= “iCub”). The agent talk (Sp= “Agent”) to the iCub (Ad= “iCub”) about the iCub’s action (Su= “You”). We have only one sentence possible ( “You ... “) repeated 5 times.

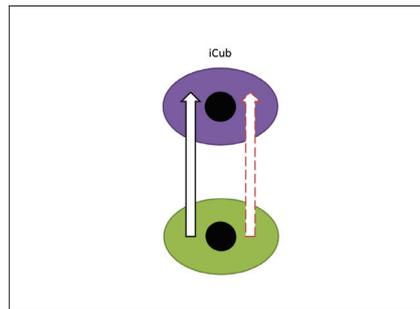


Figure 4.13: Condition : dyadic blind. An agent talks to the iCub about the iCub’s actions.

As expected for this learning phase, the robot is unable to learn anything. Neither the use or the understanding of any name or pronoun. This is evident because he doesn’t have access to many different interaction due to the learning condition.

UNDERSTANDING OF “I”	✗
CORRECT USE OF “I”	✗
UNDERSTANDING OF “YOU”	✗
CORRECT USE OF “YOU”	✗
UNDERSTANDING OF A KNOWN NAME	✗
CORRECT USE OF A KNOWN NAME	✗

### F) Addressee triadic agent

The addressee condition corresponds to what we defined in the method (4.2.2) as a condition

that is anterior to the “nine months revolution” where the child is only able to detect an interaction directed toward him (Ad= “*iCub*”, see Fig 4.14). We will thus have two human agents with the iCub, talking only to the iCub, about the action of the three of them. We have a set of 6 different sentences (2 Sp talking to 1 Ad about 3 Ag), repeated 5 times, for a total of 30 training sentences.

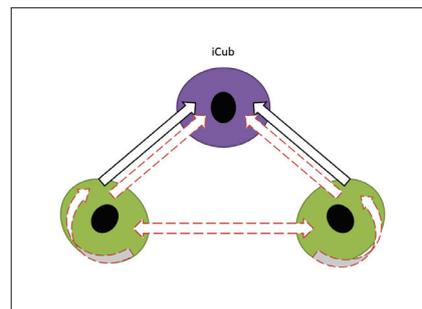


Figure 4.14: Condition : addressee triadic. Two agents talks to the iCub about the actions of everyone.

The results are that the robot correctly understands and uses “I” and “You” and understand a known name as pronoun (ie : “Peter does ...”) but not an unknown name. In this condition, the robot never hears his own name. We will discuss later of a strange fact, that is that the robot understand and use correctly the pronoun “*You*” while he shouldn’t have enough information to discriminate between his name of a pronoun.

UNDERSTANDING OF “I”	✓
CORRECT USE OF “I”	✓
UNDERSTANDING OF “YOU”	✓
CORRECT USE OF “YOU”	✓
UNDERSTANDING OF A KNOWN NAME	✓
CORRECT USE OF A KNOWN NAME	✓

### G) Addressee dyadic

In this condition, an agent will be with the iCub and talk to him about the actions of the two of them (voir Fg 4.15). We have 1 Sp, talking to 1 Ad, about 2 Ag, thus 2 different

sentences repeated 5 times for a total of 10 training sentences.

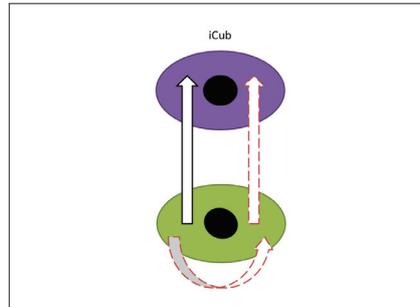


Figure 4.15: Condition : addressee dyadic. An agent talks to the iCub about the actions of the both the human and the robot.

The results once again are a bit odd. Indeed, one notable thing in this condition is that the robot fully understands and uses correctly “I” and “You”, even if he did not hear them in at least two different situations, where we could expect the robot to understand that, as a child does sometimes, his name is “You” and the name of the human is “I”. We will discuss it in the following section.

UNDERSTANDING OF “I”	✓
CORRECT USE OF “I”	✓
UNDERSTANDING OF “YOU”	✓
CORRECT USE OF “YOU”	✓
UNDERSTANDING OF A KNOWN NAME	✗
CORRECT USE OF A KNOWN NAME	✗

#### 4.2.5 Discussion of the results

From a global point of view, the result obtained by our system of cross validation are the ones we expected based on the child development studies. The main positive result is the case of a full interaction learning with 3 different agents. This condition provides the more information to the robot, and with a few number of sentences (18) but all different, we have a perfect mastery of the knowledge by the robot. This comfort us in the idea that a rich environment, not in term of number of instance, but in term of diversity, is better for the development of the child. This system is mainly done to put the robot in the middle of

many person, with a full sensitivity (neither blind or “addressee”). All the system work in real time : either the filling of the matrices (learning phase) or the computation (working phase) are in real time. Also the system is not greedy in term of computation capacity, and a simple “every day” laptop can run the system in real time. However we have a list of limitations that should be discussed.

#### **A) Problem of the non-generalization of plural**

For now the system is limited to singular form, and we consider that for each property (Ag, Su, Sp or Ad) we can only have one person. The reality is different. We can have the robot in an interaction with several person, and we can have 1 to  $n$  agent for each property. In the case of Ag, it is easy to get. For Su, it begins to become more complicated, but we can access the information with our speech recognizer (i.e. : “You, John, Mary and July are playing outside”), but we will have to ask ourselves how to segment this information : as one group, or as three sentences of one Su different each times ? I think the answer should be in the between to extract each Su independently then to perform a treatment on each to get the meaning of each known Su, and then start filling the matrices. For the Ad, it start to become more complex. How the robot can detect who are the addressee of a sentences from a sensory point of view ? This is not my precise field, but I would say that the best idea would be to integrate a Human feedback, at least in the learning phase. The idea of a Human feedback will be discussed more in details later. And finally concerning the multiple Sp, this part is a bit more tricky. Indeed the use of the pronoun “we” is complicated. Only one person is the speaker per say, but then who should we consider as Sp.

We have to improve the system to allows it to pass from a one-to-one mapping to a  $n$ -to- $m$  mapping. This will be quiet interesting in the treatment of “You” that should rely only on the way to formalize the matrices.

#### **B) Generalization to unknown names**

We have seen that the robot cannot generalize a sentences where the Su is an unknown name. But as human, we are able to understand, even in the case of a name we never heard, that it is a name. There is multiple fact that lead us to such a capacity. The first is that we are, as the iCub able to parse a sentence in order to extract the Su easily. For example if I say the sentence : “Bixente plays with the ball”, the grammatical subject of the sentence is Bixente. It is neither “*I*” or “*You*”, which means that neither the Sp or the Ad are the agent. It is therefor a third external person. There is a limited set of pronoun, and during school and life, we learned all the existing one, and Bixente is not one of them. Thus, we assume that Bixente is a name, and is also the Ag of the sentence.

### **C) Gender or social relationship**

During a real Human-Human interaction, we use not only deictic information such as Sp, Ad, Ag... But we also use a lot of more social or contextual information. For example we take into account the sex of the agent present to determine the target of “she” or “he”. We also have some more complex social relationship such as parent/child, professor/student. A improvement of the system in this way would be the same as the preview point, and could be solve by changing the format of the labels in the matrices. We need to find a way to pass from simple textual label, to maybe a relation of the OPC. However, before being able to understand complicated subject such as “professor” or “dad”, we need to be able to understand the relationship that it implies which is not the case in the robot for now.

### **D) Properties focus and weight**

The result found in the condition “Adresse dyadic” are however a bit strange. The iCub has only witnessed the Human saying “*I*” for himslef, and “*You*” for the iCub. We where expecting the robot to understand that “*You*” refers to him and was not relative. But the iCub is able to understand a sentence with “*You*” that is not directed toward him. We thus expected the robot to be confused between the use of “*I*” for Sp=Ag and when it refers to the Human, and vice versa for “*You*” and the robot. Why the robot does not think he is “*You*” and the Human is “*I*” ? The answer, is because we put the same weight to each property. The simple properties like : “Ag=Human” have as much weight as a property “double” like “Sp=Ag”,

or a property “triple” like “Sp fixed, Ad fixed, Su fixed”. A “triple” property corresponds to an exact known situation, and a “simple” property to a simple fact. A “double” property is less intuitive : the robot searches a more complex correspondence between different contextual information. In our case, when the robot has to use “I”, he checks for example the case where he has to talk about his own actions : “Sp=Ag” ; “Ad!=Ag” ; “Ag=iCub”. These three properties are true. The first two will be in favor of using “I” and the third one is in favor of “You”. Because each property has the same weight, the robot will choose to use “I”.

With a bigger weight to the simplest properties, and for the exact known situation, we could solve this kind of situation and recreate the ambiguity seen in children as shown by Gold and Scassellati [Gold and Scassellati, 2009]. We tried thus to put some different weight to the different properties. With a triplet 5-2-5 corresponding to the simple-double-triple contextual property, we finally retrieve the developmental observation of Oshima-Takane in the case of the “blind” or “addressee” condition. However for now, this solution is not totally satisfying and a bit too much artificial.

### 4.3 Shared Plan

The ability to cooperate through shared action is one of the main distinction between Human and the other non-human primates ([Tomasello et al., 2005]). A shared plan (SP) is a structured sequence of actions each of which is allocated to one of the multiple partners who are using this shared plan to achieve a shared goal that would not be achievable by a single person. All the agents respect and understand a turn-taking, even very young children (see Fig 4.16).

Tomasello and his colleagues have shown the ability of young children that don't master language yet, to understand the role of each agent in some simple plan of cooperation, without any instruction ([Warneken and Tomasello, 2007] [Sisbot et al., 2007]). However, if the plan becomes too complicated, most of the time the use of language is required, in particular if the plan need to be negotiated in real-time ([Warneken et al., 2006] [Warneken and Tomasello, 2007]). Tomasello goes further by suggesting that language's main function relies in this capacity to elaborate, negotiate and execute shared plan ([Tomasello et al., 2005]). However, language is not the only tool used to communicate while performing a cooperation. Gaze is one of the most reliant communication tool used in this kind of interaction ([Bampatzia et al., 2014] [Lallée et al., 2013] [Boucher et al., 2012]).

A SP (also called cooperative plan) can be defined as a : *“goal directed action plan, consisting of interlaced turn-taking actions by two cooperating agents, in order to achieve a common goal that could not be achieved individually”* (see Fig 4.17). As we can see, the basic element of our system is an action. We have see earlier how we segment the actions and store them in the ELM; we will based our SP on the actions defined in the ELM. The turn taking can be discussed because, an agent can perform several actions before that the other agent has to act, and this criteria varies in function of the segmentation of the actions. The core notions of this definition are the need of a cooperation, and a common goal.

In our case, we will use mainly the language and the action discrimination descri-

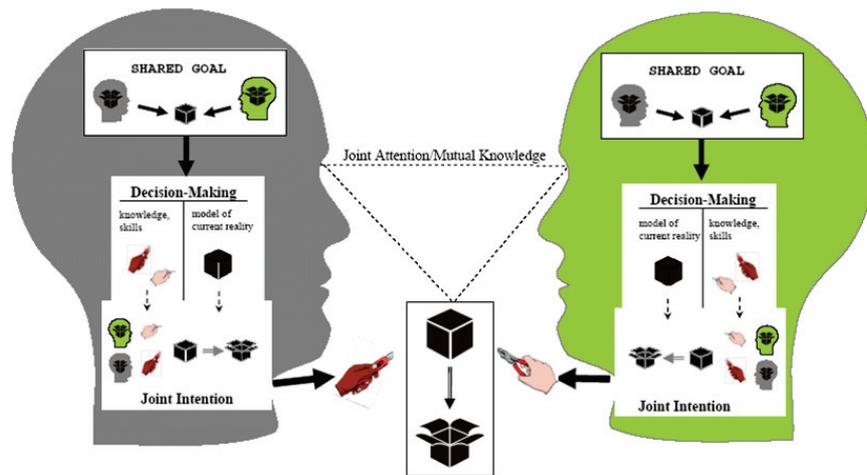


Figure 4.16: Representation of two agent involved in a common shared plan. From [Tomasello et al., 2005]

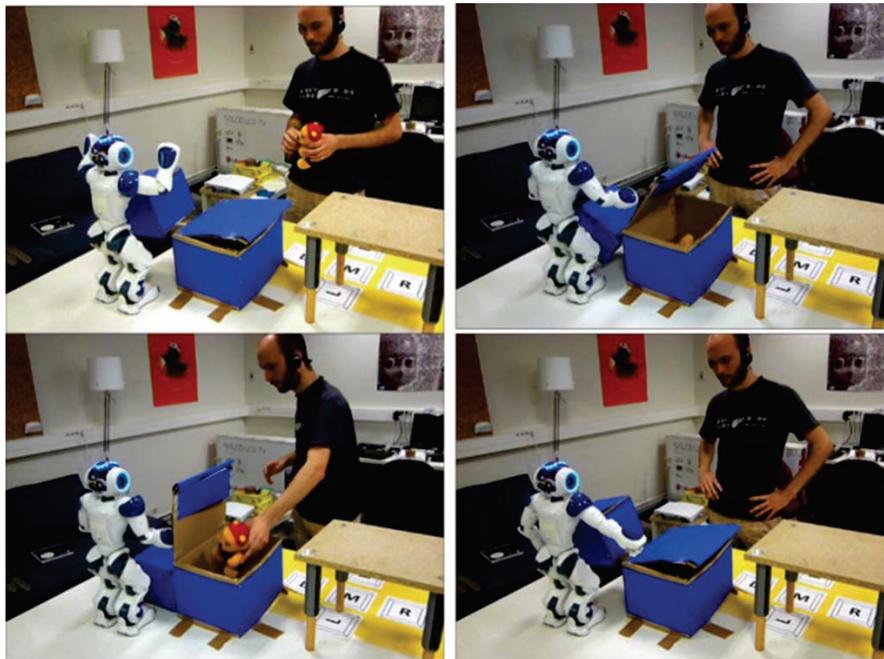


Figure 4.17: A Shared plan execution with a Nao and an agent. Up left : Human takes the toy, Up right, Nao opens the box, Bottom left : Human places the toy in the box. Bottom right : Nao closes the box. From [Petit et al., 2013]

bed above (see part 2.3). Indeed, the study of the gaze of even any body movement, and all the behavioral clues given by an silent agent could be very useful (for example : [Lallée et al., 2010] or [Lallée et al., 2012]). But this need to work at a lower level and to integrate tools that are not part of our direct field of research. This tools can be plugged to our system through the OPC as relation (i.e. : “*Agent is looking at object*”) but this is a very vast an very complex field that we only want the results.

Our interest in shared plans is motivated by extensive developmental studies which indicate that such shared plans are at the heart of the human ability to cooperate ([Hamann et al., 2011] [Tomasello et al., 2005]). The core unit of these SP are *actions* [Petit et al., 2013]. Carey claims that the ability to segment a SP into action is innate for Human [Carey, 2000]. Tomasello indicates also the core goal of language for Humans is to be able to share intentions and will to cooperate.

However, to work, this system needs a notion of intentional agency. As we have seen previously, the notion of agents are already define in the OPC and accessible at any time by the iCub. The segmentation of the SP into actions is done by the “supervisor”.

For example, let’s say that we want to teach the robot what is it to “swap” to objects on the table. The agent present will the specify to to the robot the name and arguments of the plan : “*You and I will swap the ball and the toy*”. The grammar parser will give use the following information :

agent1	”I”
agent2	”You”
plan	”swap”
object1	”ball”
object2	”toy”

Lets take the example of an agent that would like to swap to objects on the table with

the iCub. The initial situation is the following : the ball is on the left, while the toy is on the right. To teach a shared plan “swap”, the human initially specifies “You and I will swap the ball and the toy”. This specifies the name of the plan, “swap”, and the arguments (which are recognized as known objects and agents). The human will enumerate the corresponding actions : “I put the ball center. You put the toy left. I put the ball right”. The system automatically matches the arguments of the initial specification with the arguments of the component actions. This way, the system can generalize over these arguments. Thus, the shared plan “swap” for 2 objects can be generalized at several levels. A generalization can be made at the level of the agents (any agent can be involved in a swap), and the objects (swapping an eraser and a box, in the same way as for a ball and a toy).

#### 4.3.1 Learning Phase

The learning phase of a SP is done naturally just by using language. The Human will first explain the plan and the arguments used for the plan (agents, objects, arguments), then he will according to the plan, ask the robot to perform an action, or perform it himself, until the end of the plan. Then the Human will announce the end of the shared plan. The iCub will then generalize each action according to the role of each argument, and store in the ABM the list of actions to perform with which argument. For example the plan “swap – iCub Human – ball toy” will be saved by name as :

---

Swap / Ball - Toy / iCub - Human

---

Swap(Agent1, Agent2, Object1, Object2)

DEFAULT :

**Object1** = *Ball*

**Object2** = *Toy*

**Agent1** = *iCub*

**Agent2** = *Human*

**PUT**(Agent2, Object1, Center)

**PUT**(Agent1, Object2, Left)

**PUT**(Agent2, Object1, Right)

---

### 4.3.2 Execution and Generalization

Now that our robot has witnessed a SP, we want him to be able to be part of it with another agent. When the Human asks the robot to execute a SP, he can give the robot specific arguments or not. In the case where the Human gives arguments to the iCub in the command to execute a SP, the robot will execute the actions of the shared plan, mapping the arguments onto the parameters of the plan. In the case where the Human doesn't provide arguments, the iCub will use by default the arguments used the first time it learned the shared plan. The robot can integrate any agent to a shared plan, and also switch the roles.

If the Human now says : “*You and Maxime swap the eraser and the guitar*”, the speech recognizer in the supervisor will extract the role of each word of the sentence, and map them respectively :  $\$Shared\_Plan = swap$ ,  $\$Agent1 = You$  (iCub),  $\$Agent2 = Maxime$ ,  $\$Agent3 = eraser$ ,  $\$Agent4 = guitar$ . It will then invoke the SP “swap” with these arguments.

The shared plan is thus a function with multiple arguments, constructed of multiple actions that take different combinations of these arguments. Because of this function based definition, the shared plan can be used to execute behaviors beyond those that were previously learned, by applying the function with new arguments.

### 4.3.3 Conclusion about Shared Plans

We have seen in this study a simple way for a robot to recall SP, and to analyze them easily. Our system presents multiple advantages in term of functioning, but also a set of limitation that we will develop now. We will also try to analyze how this system help in the development of an interpersonal self.

One of the obvious positive point of our system relies in its simplicity. Once the ELM has been set, the system runs autonomously, and for a very low set of instructions (state the plans through the speech recognizer), the system is able to recall and generalize plans

using a very low memory space or computation capabilities. This system has to be thought of as part of a bigger system. It relies on the “I and You” module developed earlier, that will get the good references at the statement of the plan, but also on the forward model (see part 3.2.2) to be able to renegotiate the plan according to the success or not of each action.

This system can be seen as a platform for applying many tools. One of them is the reasoning system developed in part 2.3. The robot can analyze a plan according to the goal of it. Swapping to object is no more, *put obj1 center - put obj2 left - put obj 1 right*, but with the help of the retro reasoning, the robot can understand the goal of it : the location of begging and end have been switched for the two object, and the robot can be able to extend the meaning of “swap” not only for objects or agent as it is in its first version, but also in term of goal.

Another tool that can be plugged is anticipation (as in [Dominey et al., 2005] and [Dominey et al., 2008]). The robot can use its reasoning and forward model, to discriminate the action of the agent with who he is interacting, and try to find the matching SP to anticipate the next action and thus limit the verbal interaction and the need for verification, giving a smoother dialogue.

On another hand, a point that would need to be improve is the fact that for now,

#### 4.4 Contribution of these systems to the Interpersonal Self :

##### Conclusion and Discussion

We have seen in this chapter three systems, that are somehow interconnected, where one can help the other and *vice versa*. We claim that these systems bring to the robot a sense of interpersonal self. We will see how these contributions are made and what are their limitations. But first, for all of these systems a few questions and remarks can arise for an external eye :

**A) Protocol of Interaction :**

One can say that the protocols of interactions are handcrafted, e.g., consisting of speech-based instructions where the meanings of each sentence are known to the programmer. That is the case for the segmentation of actions, meaning of the word and of the sentence, but also at a larger scale, to trig either the learning or execution phase. All of these points are not unknown to us and are of course legit. Indeed, the segmentation by sentence of our system, and also, the system of speech recognition itself is a bias in the interaction in the sense where we have to define the incoming sentence (see 2.2.1). First, concerning sending the corresponding grammar to each “node” of the interaction, where the system can recognize only the precise sentence that could be heard at this given time, this has been done only to avoid the problems of misrecognition that are not in our field of interest. The day where we will find a perfect speech recognizer able to hear all of our words in the good order, and taking into account the punctuation, we won’t need our system of independent grammar anymore, especially with a poor English accent that you can find in the french laboratories. We only send a set of construction of sentences with a list of vocabulary.

Concerning the fact that the speech recognizer return not only the word recognized, but also its role in the sentence (example : “Peter agent” / “Ball object” ...), we developed in the team a method for learning grammars in a usage-based manner : [Dominey and Boucher, 2005] [Hinaut and Dominey, 2013] [Hinaut et al., 2014] [Lallée et al., 2010]. This system is a recurrent neuronal network model, used with our robotic platform to match a grammatical sentence construction to a meaning form : predicate-argument-object-recipient. During the learning phase, the network gets as input the sentence stated by the agent with all the words in the corresponding order : “To the left, Peter put the ball” and the meaning associated under the form **PAOR** : (put-Peter-ball- $\emptyset$ ). The sentence is parsed sentence using closed class word (grammatical clues such as : “to, the, as, was, -ed, ., ...”) and open class word (any other word, mainly vocabulary : “Peter, ball, put, left, cat...”). The input of the reservoir will be the list of closed class word in the corresponding order, and a signal of open class word when one is encountered. The robot will learn the mapping

between the order of the word of the sentence and the PAOR structure. Once a sentence is heard we can send it to the reservoir, and get the PAOR meaning of it. This system can also be used in reverse (from a PAOR to a sentence). The reservoir can also be fed with the sentences and meaning that are already in the ELM. From a very pragmatical point of view, the ABM is still evolving in its development, and we don't have access to all the sentence ever heard by the robot and their meaning. However, this system is now functional. Even with this system of mapping of word/role, we recall that our goal here is to extract social and global meaning to be able to perform an interaction. The meaning of the word matters here more than how to extract his role.

### **B) Link to the Interpersonal Self**

The notion of IS is embedded in the social interaction with other, and getting the ability to understand the social clues given by other. These two studies have shown a way for the robot to understand and to be both conscious spectator and actor of his social environment. This complex understanding allows us to free ourselves from the classical HRI with one robot, one human, to go to more realistic interaction, and a better understanding of the robot of the world and agents in front of him. Even if for some technical issues (we are limited to language clues for our social interaction) the robot is able to understand the premises of the typically human signals of communication : relative role of the subject of a sentence, role of an agent during a complex task of cooperation.

All this language tools help the robot to coordinate joint action with one or several agent with the appropriates Human and this relationship between an individual, robot or human, and his social environment is a part of what Neisser define as the Interpersonal Self.

However, we admit that this 3 studies are just some proof of concept. Our fast mapping system, that relies on a recurrent neural network (that are both based on the data contained in the ELM) help the SP analyzer. But this 3 systems are still at an experimental aspect,

and the next step is the fully integration of all these systems.

We gave earlier a definition from Neisser of the involvement of the IS : *“That attribution is justified only if the infant looks for - and finds - the social consequences of its own social behavior”*. In our case, we can say that we solve (at least at our level of perception and action) this condition.

Now that our system has been given an ES and IS, we will see how these two levels coupled to the SABM can help in the emergence of the Conceptual Self.

## Conceptual Self

The next step in the emergence of Neisser's sense of self will explore the Conceptual Self (CS). We often refer to the CS in every days life, when we talk about the "self". Indeed, Neisser claims that the other levels are also represented in the CS :

*“The conceptual self, or self-concept, is a person’s mental representation of his/her own (more or less permanent) characteristics. That representation which varies from one culture to another as well as from one person to the next, is largely based on verbally acquired information. Hence, we can think of it as beginning in the second year of life.”*

The CS corresponds to the notion of “having a concept of himself as a particular person”. We are distinct agents of the same environment. We have a set of intrinsic “properties” that define us, and that differ from the neighbor. And Neisser goes further by putting into light the contribution of experience in the development of CS :

*“Where do cognitive models come from? Like all other theories, they are based on a mixture of instruction and observation. We acquire concepts from our parents and our peers and our culture, and in some cases from reading and schooling as well.”* [Neisser, 1988]

This definition of Neisser goes in the way we have been developing our system : from experience to sense of self. Neisser also divide the CS in many distinct parts. We will focus

on the two main of it :

### A) Role Theories

The “Role Theories” correspond to our place in the society. This part is in link with the Interpersonal Self and the relation to others. But this time it is not as much about understanding the other, but more about : “How do I fit with the social interaction”. We want to understand other and to adapt our behavior in consequence.

### B) Internal models

This part concerns “our bodies and our minds”. It refers to the way to represent more “low level” information and can be refereed as the input from the Ecological Self in the CS, but this time it is at a more “high level” understanding. In include among others the **Theories of the Mind** that represent our ability to put ourselves into someone else’s cognitive shoes.

Neisser makes also references to the *Trait attributions* that are situated at the boundary between the two other parts (social role and internal model). This aspect is in cause in the case of false beliefs (the internal model doesn’t transmit the corresponding information to the social role).

Our work concerning the CS will be based on this two part<sup>1</sup>. The first will focus on the understanding of how to build model of representation and “high level” reasoning. The robot through interaction and learning is asked to solve the Tower of Hanoi problem [Petit et al., ming]. The second one will an experimentation of Theories of the Mind and will be based on the Sally-Anne experiment [Pointeau et al., 2013a].

---

1. At this step of the manuscript, I would like to make a quick digression for a personal opinion. During my PhD, I have been working with the robot, on the robot to fix it, with simulation, with real data, on psychological effects of memory, even with naive subjects... And even if I loved all the work I’ve done in general, from all the studies we have made, the part that excited me the most was this Conceptual Self. We were finally putting the finger where we wanted : to the “most common” definition of the “self”. Maybe not the definition of the scientist, but certainly the one known from the public. The scientist in my have been happy all along in this PhD, but the non scientist in me, has been fascinated and excited about this.

This first experiment is not per se a manifestation of the CS and is situated at its border. Indeed this High Level Reasoning as we will see will use part of the previous levels of self to emerge. It is not by itself a manifestation of the CS but it will be a part of the link between the previous levels and the CS. The objective is to provide the system with the appropriate tools to reason using some concepts that are more advanced than just the immediate impact of someone on the world (as it is the case for the ES). For this reason I decided to put this experiment in this chapter about the CS because even if it isn't exactly a manifestation of it, the CS will be built on it.

The goal of the second experiment will be to test the ability of the robot to take someone else's point of view (the Theory of Mind). Our criteria of success will thus be the famous Sally-Anne task that will be detailed in 5.2.

## 5.1 High Level Reasoning and Prediction Based on Experience

The ability to reason can be considered to rely on two complementary components. First, a system must have access to some form of knowledge or expertise from which it can reason, e.g. the autobiographical memory of artificial system ([Dore et al., 2010] [Ho et al., 2009]). Second, the system must have some form of reasoning capability that allows that knowledge to be used in a systematic way ([Hayes-Roth, 1997] [Alami et al., 1998]). We already developed this aspect in the part 2.3. In this experiment, we wanted to go further in the learning, and we wanted to give the robot an ability to reason that would be based on high level of abstraction to be able to adapt his behavior and his reasoning to the state of the world. To express his part of ES, the robot needs to re-adapt, and to free himself from an explicit, innate knowledge, given by the programmer. The reasoning and the behavior of the robot should come from his own experience.

At the light of child development, Carey has shown that the infant begins to extract regularities from his environment, and in a recursive manner to further extract structure based on this growing repertoire ([Carey and Xu, 2001] [Carey, 2009]). In this context and

to learn through social interaction, there are three main components that have to be taken into account : the action, the goal state and the situational constraints [Gergely et al., 1995]. Once learned, the child can reason and select actions in order to achieve a goal, in particular when the other is explicitly stating his intentions [Gergely and Csibra, 2003].

The goal of this research is to provide a real-time goal-directed reasoning capability to the iCub, loosely based on a developmental trajectory where knowledge, from successively refined levels, contributes to the ability to reason, based on this teleological stance. When we reach the highest level of this representational hierarchy, the information will be appropriate for reasoning, not only at the spatial level as previously investigated ([Kalkan et al., 2013] [Takács and Demiris, 2008] [Welke et al., 2013]) but also on the contextual level (e.g. effect of an object on another one).

We will first test these reasoning abilities on a simple game where the robot should rotate an object on the table always in the same direction. Then, we will go on a more complex interaction where the robot has to solve the “Tower of Hanoi” without ever having see the solution.

### 5.1.1 Planning and Goal Directed Reasoning

We already briefly explained in 2.3.2.2 how the system could be able to make some “retro reasoning”. We will now show a concrete example of its use. Indeed the retro reasoning is an internal tool using mental imagery, to create high level knowledge in the SSM. But this knowledge can be used not only in the same case than for the ES as a forward model, but also to create some building blocks for some higher level reasoning. This will give to the iCub at each moment, what actions are available, and what will be the consequences of them, and to predict the state of the world at several action steps. We will thus plug a planner of action : a standardized planning language **PDDL** (Planning Domain Definition Language).

PDDL is a framework in which the domain of a task can be described (including specification of the “rules” in terms of pre- and post-conditions for actions), and in which a given problem or goal can be specified ([Helmert, 2009] [Ghallab et al., 1998]). This can then be provided as input to a planner, which will attempt to find a sequence of action executions that takes the system from the current state to the specified goal state. Thus, in order to be used, a PDDL planner needs this information, as specified in two different files : a domain and a problem definition. The domain file contains the set of known actions, including their respective preconditions and effects, whereas in the problem file, we have the current situation description (i.e. the list of all initial conditions) and the desired goal.

Traditionally, these files are hand-coded, with fixed set of actions given to a robot in order to solve a precise kind of problem with variable initial conditions. In our system, these data will be automatically generated in real-time by the iCub, allowing a developmental inspired approach based on experience that accumulates and becomes successively refined via the level 1 to 3 of reasoning. This is possible by extracting knowledge from the Semantic Memory to produce well-formed PDDL domain definition. The problem definition will be made by a direct request to the SABM about the current situation and the goal is defined from interaction with the human.

The global architecture of our system is now thus extended as display on the Fig 5.1. As we can see, we added in the loop the PDDL that will get information from the ABMR (and by extension to the SABM).

### 5.1.2 Proof of Concept : the ABCD game

In order to provide a concrete domain in which to pursue this work, we elaborated a simple board-game interaction scenario, illustrated in Fig 5.2. In this game, four spatial locations will be learned by the iCub, via observation of the human actions. In addition,

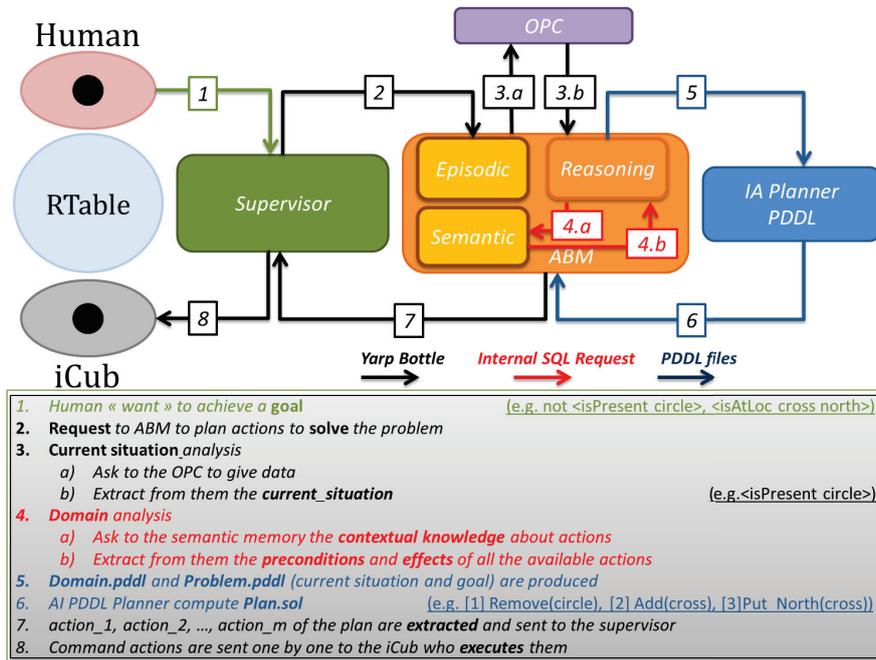


Figure 5.1: Extended architecture with rule extraction and rule based planning and reasoning. At first, is the Human “order”. The Human will announce a sentence such as : “I want the circle on B and I do not want the cross on C” (1). The information is then transmitted to the SABM which has to solve that problem (2). The system will then establish the state of the current world state by querying the OPC (3.a, 3.b), and writing it into the problem PDDL file, along with the human’s stated goal. Then, the system will interrogate the SSM to retrieve the contextual knowledge corresponding to the pre- and post-conditions of all the known actions, and use this to build the PDDL domain file (5). The AI Planner is then executed, to produce a plan (6), made up of the sequence of action which needs to be performed in order to achieve the goal from the current situation. This file is parsed and the action sequence is sent to the Supervisor (7), which then controls the iCub to execute the moves (8), and thus to achieve the human’s goal without any explicit information from him about “how to” do it.

the iCub learns regularities concerning how objects can be moved between these locations. The demonstrated moves form a circular game path, meaning pieces can only move from A to B, from B to C, from C to D and from D to A. For instance, if the object is on A, a player must make 3 successive moves to put it at D. This provides a simple scenario for testing the ability to learn from experience and reason on the acquired knowledge.

The learning of this action is the same that for any other action, with the supervisor that will trigger a first snapshot, the agent executes the action, then a second snapshot.

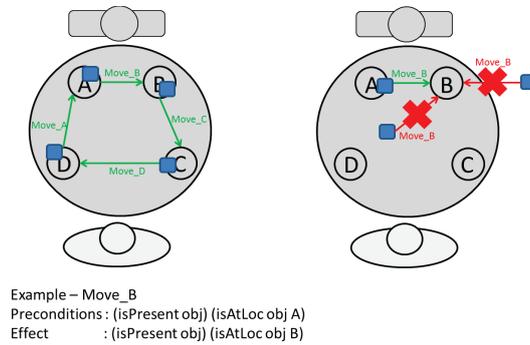


Figure 5.2: Example of definition of different moves in the ABCD experiment. To be able to perform the action “Move\_B - Object”, the object needs to be at location A. There is a pre- and post-condition for each action.

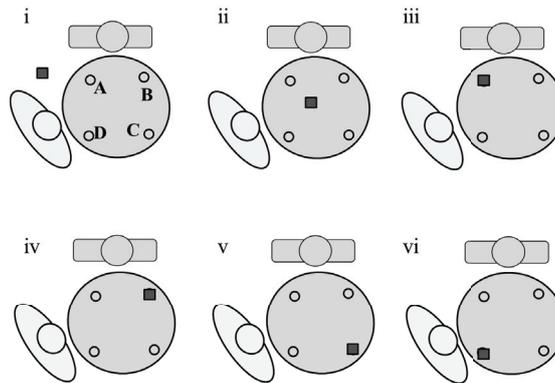


Figure 5.3: Interaction scenario schema. Four learned locations on the ReacTable with a human agent (oval body), the iCub (rectangular body), and an object (dark square). The learned locations are labeled A to D. i) Object is off the table. ii) Human has placed the object on the table, in an undefined location. iii) Human or the iCub has placed the object on the location A. iv) Human or the iCub has placed the object at B. v-vi) Human has placed the object at C, then D, respectively.

The characteristic regularity is that actions can be performed with any objects, but there is a “from-to” structure that to go to B you must be at A, to C you must be at B, etc. as illustrated in Fig 5.2. The ABMR module collects the statistics on the pre- and post-conditions of these movements, and generates a set of entries in the SSM “Context” entry, for each type of move, according to its initial and final location. The Fig 5.3 show a full cycle of actions in the ABCD Game.

Now that the robot as extracted the pre- and post-conditions of the actions, and expli-

citly put them in the SSM, he can start to create the PDDL files that he needs. These two files are : the “domain file” and the “problem file”.

### A) The Domain File

The domain file will be for the robot, the “field of possible”, with the list of all the known actions, with their pre- and post-condition and arguments. For example in the case of the action “Move\_B - obj” the pre- condition is : “*isAtLoc obj A*” whereas the post-condition is : “*isAtLoc obj B*”.

Each action can have arguments (like the object in the case of “move” or “push”). This field of possible will be modified according to the parameters (for example, in the case of “add object” : we will have as pre-condition : object is absent, and as post-condition : object is present, no matter what the object is).

All this knowledge about pre- and post-conditions is extracted from the ContextualKnowledge classe of the SSM. Indeed the robot will parse for each action, the properties (relations of the OPC such as : “obj isAtLoc North”) that are above (or below) an empirically determined threshold for positive (or negative) conditions. The domain file for the ABCD game can be found in the Fig 5.4

### B) The Problem File

Once we set this field of possible of the robot, we will create a Problem File that will be both the current state and the final goal. The current state of the world include the objects present in the OPC with their type (“objects” for “circle” or “croco”, and location for “A” or “north”). We will also get the relation from the OPC at the initial situation : “cross isAtLoc A” “cross isPresent”.

The goal of the problem will be specified by speech by the Human, and announced as a set of conditions. The goal will also be represented as relations for the OPC. In the case : “I want the circle on D”, the final goal will be “circle isAtLoc D”. An example of problem file

```

;; STRIPS domain automatically generated by ABMReasoning, part of EFAA
(define (domain efaa)
  (:requirements :strips :typing :equality)
  (:predicates
    (isPresent ?obj)
    (isAtLoc ?obj ?loc)
    (Object ?obj)
    (Locations ?loc)
  )
  (:action add
    :parameters (?obj1)
    :precondition (and (not (isPresent ?obj1) ) )
    :effect (and (isPresent ?obj1) )
  )
  (:action remove
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) )
    :effect (and (not (isPresent ?obj1) ) )
  )
  (:action move-B
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) (isAtLoc ?obj1 A) )
    :effect (and (isPresent ?obj1) (not (isAtLoc ?obj1 A)) (isAtLoc ?obj1 B) )
  )
  (:action move-C
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) (isAtLoc ?obj1 B) )
    :effect (and (isPresent ?obj1) (not (isAtLoc ?obj1 B)) (isAtLoc ?obj1 C) )
  )
  (:action move-D
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) (isAtLoc ?obj1 C) )
    :effect (and (isPresent ?obj1) (not (isAtLoc ?obj1 C)) (isAtLoc ?obj1 D) )
  )
  (:action move-A
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) (isAtLoc ?obj1 D) )
    :effect (and (isPresent ?obj1) (not (isAtLoc ?obj1 D)) (isAtLoc ?obj1 A) )
  )
)

```

Extracted from ABM (based on reasoning from previous interaction with the human)

Figure 5.4: Domain file from the ABCD game.

can be found in the Fig 5.5.

### C) PDDL Run

Once we have the problem and domain files created, the iCub can start to reason on it. To do so, he will run the PDDL planner to get a sequence of actions from the domain, to go from the initial to final state of the problem. We decided to use the LPG-td planner from [Fern et al., 2002]. In our case, we have the cross in position A, and we ask the iCub : “I want the cross in D”. We set the planner to 2 second maximum of search, and to keep the 30 best solution from lower to better quality. The quality of a plan depends of the cost of each plan We can put a different cost (energy, or time...) per action, and we will search for

```

;; STRIPS problem automatically generated by ABMReasoning, part of EFAA
(define (problem efaa-prob)
  (:domain efaa)
  (:objects
    Ball circle cross eraser Square Toy
    A B C D
  ) ;; end :objects
  (:init
    ;;types
    (Object Ball) (Object circle) (Object cross) (Object eraser) (Object Square) (Object Toy)
    (Locations A) (Locations B) (Locations C) (Locations D)
    ;;init-conditions
    (isPresent cross) (isAtLoc cross A)
  ) ;; end :init
  (:goal
    (and (isAtLoc cross D)
    ) ;; end and
  ) ;; end goal
) ;; end define

```

Extracted from ABM (current situation)

Extracted from Speech Processing (Human expressing desires)

Figure 5.5: Problem file from the ABCD game.

```

; Version LPG-td-1.0
; Seed 52616643
; Command line: lpg-td-1.0 -n 30 -cputime 2 -o domainEFAA.pddl -f problemEFAA.pddl -out solutionEFAA
; Problem problemEFAA.pddl
; Actions having STRIPS duration
; Time 0.05
; Search time 0.00
; Parsing time 0.03
; Mutex time 0.00
; Quality 3

Time 0.05
0: (MOVE-B CROSS) [1]
1: (MOVE-C CROSS) [1]
2: (MOVE-D CROSS) [1]

```

Automatically generated by PDDL planner

Figure 5.6: Solution in the case of the ABCD game.

the plan that cost the less. In our case, all the actions have the same cost, so the best plan will be the one with less action. Either after the 2s, or when all possibilities have been tries, the planner return a file with the at more the 30 best plan (see Fig 5.6). The robot will then extract the list of action of the best plan, and execute them. In our example of the ABCD game, we have shown that the robot was able to understand the rules of the game, and to play it. Indeed, if the cross is on A and we want it on D, the robot will first move it to B, then to C and finally to D.

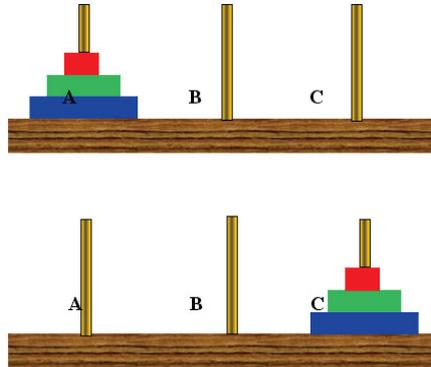


Figure 5.7: Principle of the “Tower of Hanoi” problem. We have a set of disks of different sizes. A disk cannot be above a smaller disk. The objective is to move a ordered pile of disks from one stick to another, with the less moves possible.

### 5.1.3 The Table of Hanoi

#### 5.1.3.1 System and Learning Phase

We have been able to show that our system was working for a problem with a small set of possibilities. We want now to test it on a more complex problem. We decided to use the Tower of Hanoi (**ToOH**) to test our model. The ToOH is a game invented by a french mathematician Edouard Lucas in 1892, that consist in moving several disks of different diameters from a starting tower to final another using a intermediate tower, and this, with a minimum of steps (see Fig 5.7). There is only two requirements, we can move one disk at the time, and we cannot put a disk above a disk with a smaller diameter. The minimum number of step for each game with  $n$  disks is  $2^n - 1$ . Indeed, for each disk that we add, we have to move once the  $n - 1$  stack, move the  $n^{th}$  disk, then move the  $n - 1$  stack again on it. For example, for 3 disks, the minimum of step required is thus  $2^3 - 1 = 7$ . This will be our objective.

Due to the motor capabilities of the iCub, we decided to modify a bit the Tower of Hanoi to the Table of Hanoi (**TaOH**). The principle will be the same but horizontal instead of vertical. The robot will have to learn 3 locations : “left”, “middle” and “right”, then the different moves allowed. Instead of disks, the robot will use `rtObjects` : block that can

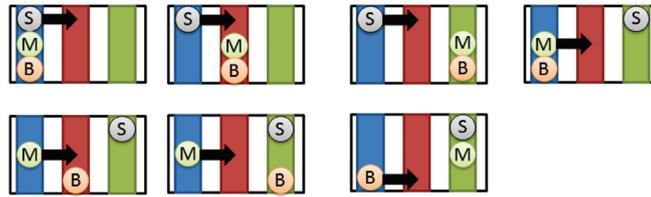


Figure 5.8: Set of the seven moves used to teach the robot the rules of the TaOH.

be easily manipulate on the ReacTable, that will be labeled as “small”, “medium” and “big”.

After a small phase of teaching the robot the different locations (as seen in the part 2.3.1), we started to show the robot the moves in the context of the TaOH.

The human demonstration of these moves (HANOI-BIG ?FROM ?TO, HANOI-MEDIUM ?FROM ?TO, HANOI-SMALL ?FROM ?TO) is done in the same way as for Experiment 1. It should be noted that, because of the generalization of learning, we need only to perform the moves from “Left” to “Middle”, and the iCub will be able to generalize to other move locations. In particular, it has never seen an actual Hanoi game, from the beginning to the end, only a set of illustrative moves : we used a minimal and predefined set of actions to show that the iCub can learn to solve TaOH without any need for seeing the actual solution, but the same results can be achieved by observing a real attempt of TaOH realized by a naive subject. These locations can then be used to demonstrate the moves that allow the system to learn the rules governing how object positions influence legal moves. The set of moves witness by the robot is shown in the Fig 5.8.

A summary of the learning flow concerning the learning of the rules and the stream of information from extraction of knowledge to the planner can be found in the Fig 5.9 and 5.10.

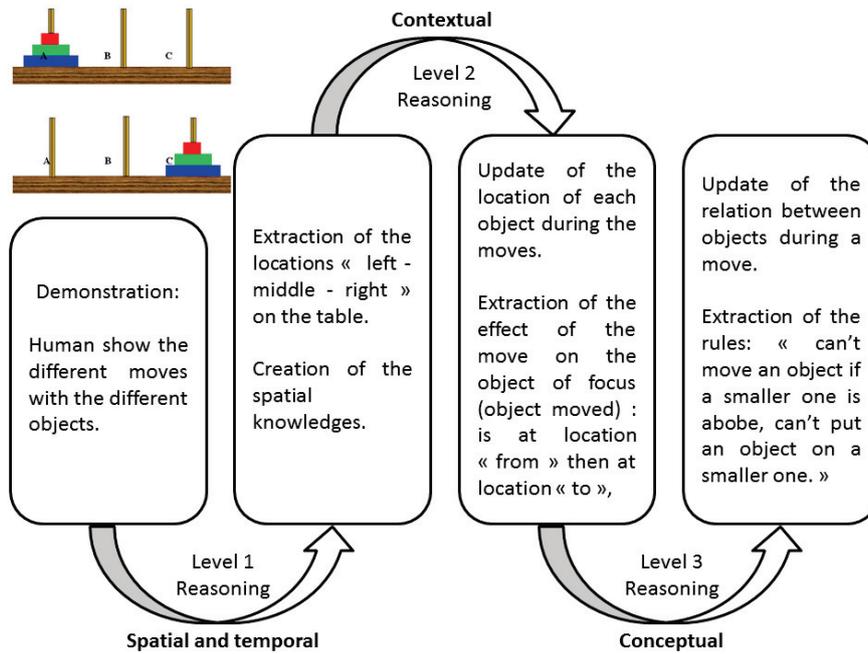


Figure 5.9: Effect of the different levels of reasoning to solve the problem of the “Table of Hanoi” using CKF and Retro-Reasoning.

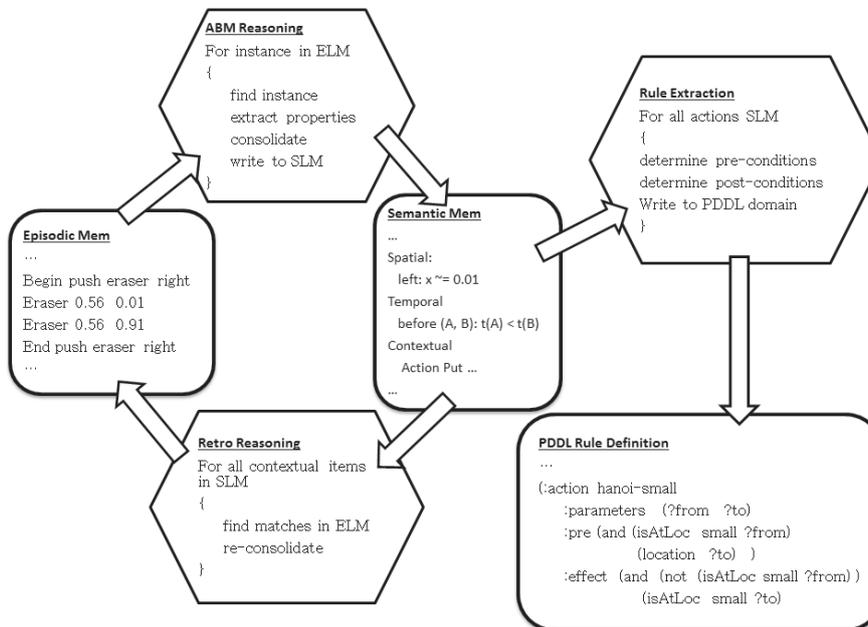


Figure 5.10: Overview of the flow of information in refinement of knowledge

```

;; STRIPS domain automatically generated by ABMReasoning, part of EFAA
(define (domain efaa)
  (requirements :strips :typing :equality)
  (:types location object)
  (:predicates
    (object ?obj)
    (location ?loc)
    (isAtLoc ?obj ?loc)
    (isAtLoc ?obj ?loc)
  )
  (function hanoi-small
    (parameters (ifrom ?to)
      :precondition (and (isAtLoc small ?from) (location ?to) )
      :effect (and (not (isAtLoc small ?from)) (isAtLoc small ?to) )
    )
    (function hanoi-medium
      (parameters (ifrom ?to)
        :precondition (and (isAtLoc medium ?from) (not (isAtLoc small ?from)) (not (isAtLoc small ?to)) (location ?to) )
        :effect (and (not (isAtLoc medium ?from)) (isAtLoc medium ?to) )
      )
    (function hanoi-big
      (parameters (ifrom ?to)
        :precondition (and (isAtLoc big ?from) (not (isAtLoc small ?from)) (not (isAtLoc medium ?from)) (not (isAtLoc medium ?to)) (location ?to) )
        :effect (and (not (isAtLoc big ?from)) (isAtLoc big ?to) )
      )
    )
  )

```

Extracted from ABM  
(Based on previous interactions with the human)

Figure 5.11: Domain file generated for the TaOH

```

;; STRIPS problem automatically generated by ABMReasoning, part of EFAA
(define (problem efaa-prob)
  (:domain efaa)
  (:objects
    small medium big
    left middle right
  )
  ;; end :objects
  (:init
    ;;types
    (object small) (object medium) (object big)
    (location left) (location right) (location middle)
  )
  ;;init-conditions
  (isAtLoc small middle) (isAtLoc medium middle) (isAtLoc big middle)
  )
  ;; end :init
  (:goal
    (and (isAtLoc big left) (isAtLoc small left) (isAtLoc medium left)
    )
    ;; end and
  )
  ;; end goal
)
;; end define

```

Extracted from ABM (current situation)

Extracted from Speech Processing  
(Human expressing desires)

Figure 5.12: Problem file generated for the TaOH

### 5.1.3.2 Results

The Domain File for the problem of the TaOH is produced exactly as for the ABCD game. The file can be seen in the Fig 5.11. As we can see, the rules are objects-related and no more locations-related.

We then set the initial situation : the three objects were set on the location “middle”, and ask for the final goal. The goal is stated by speech : “I want the big on the left, and, I want the medium on the left, and I want the small on the left”. The robot will automatically with these information create the Problem file (see Fig 5.12).

The planner will then find the best solution to solve the problem knowing the domain. This solution is shown in the Fig 5.13. The robot will then execute the best solution and solve the TaOH with 3 objects in indeed 7 steps as expected. The execution is displayed in the Fig 5.14 and conclude the loop from Human interaction for the learning of low level

```

; Version LPG-td-1.0
; Seed 114675836
; Command line: lpg-td-1.0 -o domainEFAA_hanoi.pddl -f problemEFAA_hanoi.pddl -n 30 -cputime 2 -out solutionEFAA_hanoi
; Problem problemEFAA_hanoi.pddl
; Actions having STRIPS duration
; Time 0.03
; Search time 0.01
; Parsing time 0.02
; Mutex time 0.00
; Quality 7

Time 0.03
0: (HANOI-SMALL MIDDLE LEFT) [1]
1: (HANOI-MEDIUM MIDDLE RIGHT) [1]
2: (HANOI-SMALL LEFT RIGHT) [1]
3: (HANOI-BIG MIDDLE LEFT) [1]
4: (HANOI-SMALL RIGHT MIDDLE) [1]
5: (HANOI-MEDIUM RIGHT LEFT) [1]
6: (HANOI-SMALL MIDDLE LEFT) [1]

```

Automatically generated by PDDL planner

Figure 5.13: Solution file generated for the TaOH

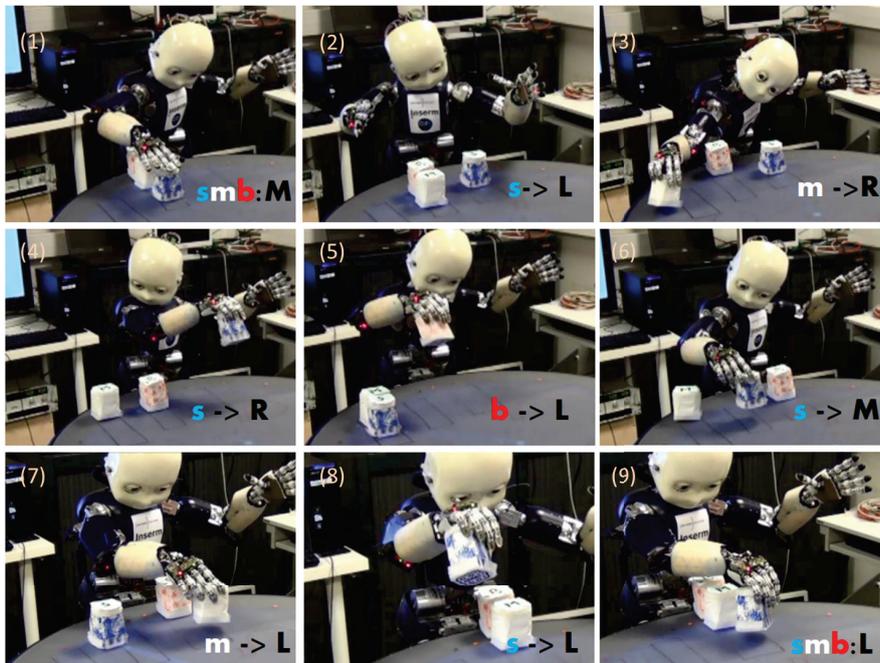


Figure 5.14: Different step of the execution of the solution for the TaOH. (1) objects are middle. (2) moving small to the left. (3) moving medium to the right. (4) moving small to the right. (5) moving big to the left. (6) moving small to the middle. (7) moving medium to the left. (8) moving small to the left. (9) all the objects are left.

knowledge (location) to high level knowledge (TaOH rules), solving complex problem asked by a Human, and acting to execute the corresponding task.

## 5.2 Theory of Mind

We have seen in the part 3.2.2 that a forward model could allow one to simulate the result of his own actions, or actions of others. But we discovered that this mental world that we use for the simulations of action, can also be use in the context of Theory of Mind ToM. The robot will use his “mental sand box” to represent the mental state of others.

### 5.2.1 The ability to “Mentalize” : developmental Aspect

Frith explain the success of human social interactions as “*depending of the development of a social intelligence*”. He gives it several components : “*recognize conspecifics, to know one’s place in the society, to learn from the others and to teach novel skills to others, the capability to understand and manipulate the mental states of other people and thereby to alter their behavior*” [Frith and Frith, 1999]. We will focus particularly one this last point.

Frith give to the aspect of ToM the following definition : “*The awareness that other people have beliefs and desires different from our own and that their behavior can be explained by these beliefs and desires has been referred to as theory of mind or intentional stance*”.

One of the main distinction between Human and other animals is this ability to represent the mental state of other at a high level. It however has been shown that monkeys can use the direction of the gaze to adapt their behavior [Emery et al., 1997]. Indeed the great apes are social animals like the Human and behave accordingly but for Byrne and Whiten [Byrne and Whiten, 1990] the events where apes use deception to manipulate the behavior of others, can be attributed to some kind of rapid learning about coincident events rather than the ability to mentalize. For Heyes [Heyes, 1993], there is not enough evidence (particularly in laboratories) to show that the great apes are able to mentalize or use intentional deception.

We use every day our beliefs rather than reality to act (for example Descartes said :



Figure 5.15: Representation of pretense : “*Calvin and Hobbes*” from Bill Watterson

“when a put a stick in the water, my reason unbend it.”). But false beliefs can be also implanted by deception, or removed by education.

From a developmental point of view some first insights of the ToM can be witnessed from 18 months. Around this age, Leslie has shown that infant are able to represent an agent’s informational relation to an event, that will lead him to the understanding pretense [Leslie, 1987]. This is also around this age that if an infant witnesses an adult attempt to complete an action, but fail to finish, the child is able to imitate and complete this action ([Meltzoff, 1995] [Tomasello et al., 2005]). This mark the age of “pretense”. As Calvin and Hobbes walk by his snowmen in his garden, and imagine himself as a dinosaur eating people (see Fig 5.15), pretense is defined by Leslie as : “Pretend is a special case of acting as if where the pretender correctly perceives the actual situation”. Fein insists on the role of the memory into this pretense as a catalog where the child will compare different object and decide to apply some transformations [Fein, 1975]. These transformations will select some of the feature of a situation or an object and will ignore the others.

Leslie claims that this pretense is the first step toward the ToM :

*“The emergence of pretense is not seen as a development in the understanding of objects and events as such but rather as the beginning of a capacity to understand cognition itself. It is an early symptom of the human mind’s ability to characterize and manipulate its own attitudes to information. Pretending oneself in thus a special case of the ability to understand pretense in others [...]. In short, pretense is an early manifestation of what has been called theory of mind”.*

The ToM can be defined as the ability of a person to “impute mental states to self and to others and to predict behavior on the basis of such states” [Premack and Woodruff, 1978]. We will see later one of his most classical way of representation under the form of the “Sally-Anne” experiment.

For Leslie, the pretense, and then the ToM needs several components. At first, the child needs primary representations defined as : *“transparent, [...] they directly represent objects, states of affairs, and situations in the world.”*. These primary representations are somehow linked to the ES, as being the relation between and individual and its direct and immediate physical environment. It is the sum of all the senses and analysis of the world at a given time. These primary representations will lead to direct action on the world and *vice-versa*, the child’s actions on the world will impact his primary representations.

The child needs also the pretend representations that will be : *“opaque [...]. They are in effect not representations of the world but representations of representations”*. These pretend representations described by Leslie are what Pylyshyn call : *metarepresentation* [Pylyshyn, 1978]. The child will also be able to act upon these metarepresentations. This full architecture can be found described in the Fig 5.16.

This system is the first step toward the pretense and thus the ToM. While going further in his development, the child reaches at the age of three years old, the proper

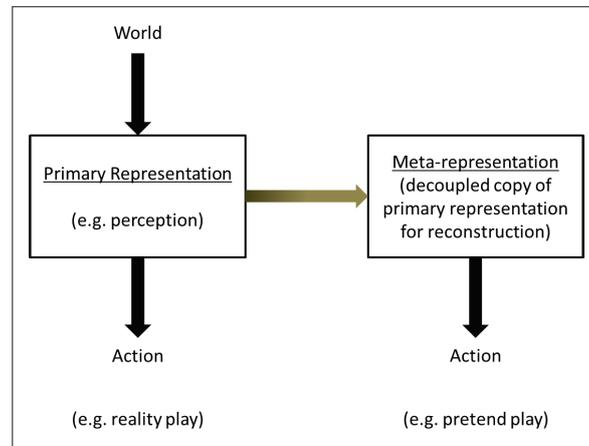


Figure 5.16: A general model for pretend play (adapted from [Leslie, 1987])

vocabulary to express mental states during a conversation ([Bretherton and Beeghly, 1982] [Shatz et al., 1983]). These verbs are such as : “*think, know, remember, pretend, dream, wonder, believe*” and are used correctly during spontaneous speech between  $2\frac{1}{2}$  and 3 years old.

The age of four marks another important step in the capacity to mentalize. Indeed, at the age of four, the ability to mentalize is almost fully operational [Sodian, 1991] and as Leslie notices it, this ability to mentalize and pretend will stop developing any further once it have emerge to this point. Several studies have shown that from (around) the age of four, most of the children are able to solve a tasks as described in the Fig 5.17 that we will call the “*Sally-Anne task*” ([Baron-Cohen et al., 1985] [Wimmer and Perner, 1983]). An experimenter and a child (to test) are across a table. On the table are two dolls, Sally and Anne, a basket and a box. At first Sally puts a toy in the basket and close it. Then Sally leaves and Anne moves the toy from the basket to the box. Both the basket and the box are closed. Sally comes back and shouldn’t remark the change. Then the test is to ask to the child where Sally would look for her toy. The expected answer from a child able to manipulate mental states of other people is : in the box. We will focus our following study on this particular point : the understanding of a false belief.

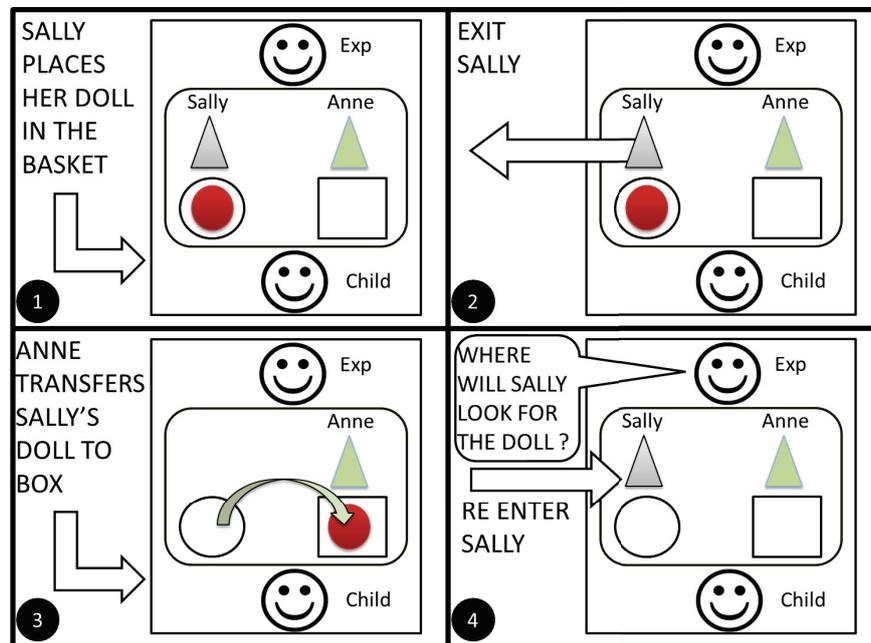


Figure 5.17: Definition of the *Sally-Anne* experiment. 1 : An experimenter is in a room with a child and two “human” dolls : Sally and Anne. In front of Sally is a basket and in front of Anne is a closed box. The child sees a “toy” doll in the basket then the experimenter closes it. 2 : Sally leaves the room. 3 : Anne transfers the “toy” doll to the box and closes it. The child witnesses the transfer. 4 : Sally comes back in the room, the basket and the box are closed and no one can see inside. The experimenter asks the child where Sally will look for her doll.

However it may appear that the development of mentalizing doesn't occur as we described here and the children diagnosed with autism are part of it [Fombonne, 1999]. Indeed, Frith explain as following [Frith and Frith, 1999] :

*“In certain cases the development of mentalizing is severely compromised. This is the case for children diagnosed with autism. In infancy, these children are remarkable by not appearing to orient toward other people's focus of attention, by not showing or pointing out things, and by not engaging in pretend play. Many individuals with the diagnosis of autism remain unable to understand the concept of a false belief.”*

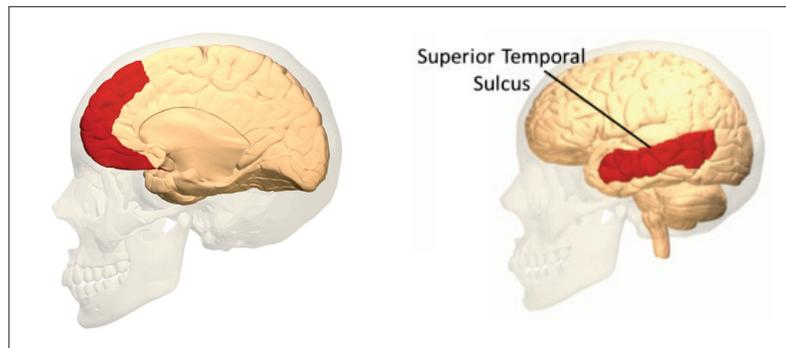


Figure 5.18: Right : Representation of the prefrontal cortex, including the medial and ventromedial prefrontal. Left : Superior Temporal Sulcus

This inability to understand and/or manipulate other people’s mental state is however not related to other mental abilities such as “intelligence”. Studies have been made with autistic, normal and retarded children implying manipulation of mental state, and it shows that the only group that failed the test were the autistic children that had an higher IQ than the retarded children group [Sodian and Frith, 1992].

From an anatomical point of view, the brain region related to the ToM is not yet totally defined. However several regions have been identified as implied in process of mentalizing or using mental state. These regions are mainly situated in the prefrontal cortex (concerning thoughts : [Nancy Kanwisher, 1997], pain and action : [Rainville et al., 1997]) and in the superior temporal sulcus [Leslie, 1994] (see Fig 5.18).

### 5.2.2 The the iCub performing the Sally-Anne experiment

Now that we have seen the required component to allow one to mentalize, we want to use it for the robot in order to solve the Sally-Anne experiment, or at least an “robot version” of this test. To do so, we have seen that we required some primary representations that will be the OPC plugged on the classical sensors that we have (ReacTable, Kinect, sensory motors, audition), and our metarepresentations will be the MOPC as presented earlier.

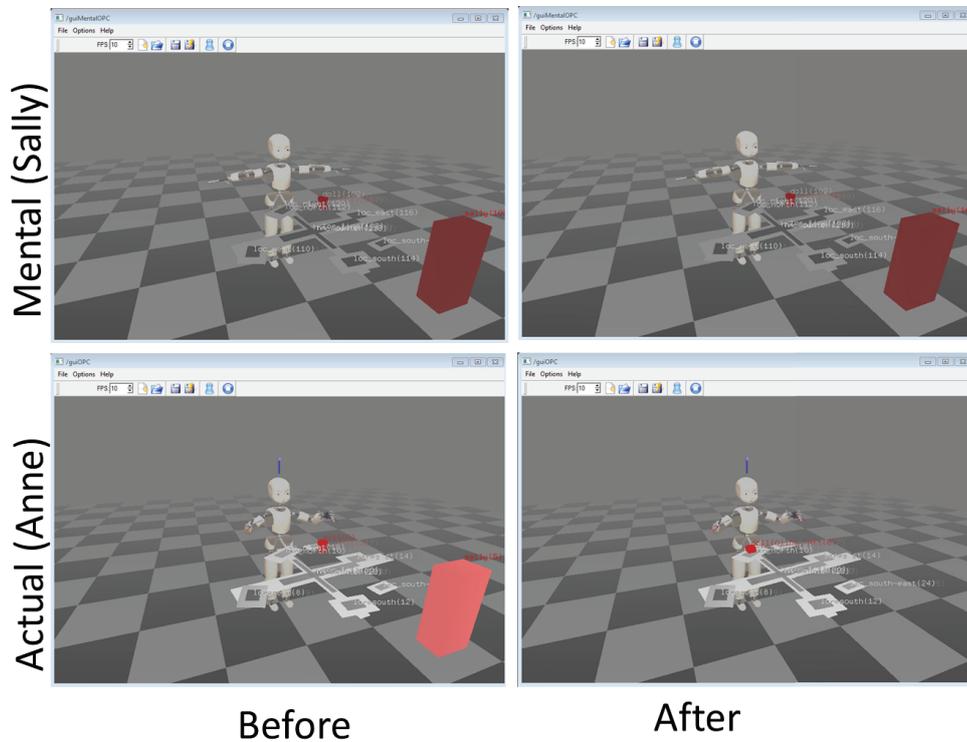


Figure 5.19: Contents of the MOPC and the real OPC in the Sally-Anne task. In the “Before” column is represented the contents of both OPC when the toys has been placed at the first location. The MOPC is the metarepresentations of the iCub and therefor of what Sally has seen. In the “After” column is the actual situation represented the world as perceived by the robot (real OPC) where the toy is on the location North, while in the Mental situation is still the situation as seen by Sally before leaving.

The experiment itself was the following : the iCub and a Human agent (labeled as *Sally*) are interacting across the ReacTable. The agent puts an object on the location “left”. the iCub will synchronize the MOPC on the OPC, and block the MOPC to the state of the world as it appears while the agent is still present. The agent leaves and another agent moves the object to the location “north”. This situation can be seen on the Fig 5.19.

If we ask the iCub the differences between both OPCs at the end of the experiment, we obtain the following results (see Fig 5.20) :

- **iCub’s beliefs** : the Toy is now at the location “column” and “north”, Sally is no

```

3 entities changed :
Entity : doll
    robot_position_x -0.034557
    robot_position_y 0.276599
    robot_orientation_z -0.042716
    rt_position_x -0.118581
    rt_position_y -0.252269

Entity : icub
    Beliefs added :    doll is column  doll is north (after)
    Beliefs removed : doll is left  Sally is isPresent (before)
Entity : Sally

The beliefs of Sally didn't change, because she wasn't here.
Sally's beliefs are : doll is left.

```

Figure 5.20: Results returned by comparing the real OPC and MOPC. The comparison indicates a significant difference, corresponding to difference between the “false belief” attributed to Sally in the MOPC and the “true beliefs” attributed to Anne in the OPC.

- more present.
- **Sally’s belief** : They are still the same as when she was here : the Toy is at the location “left”.

These differences show that the use of our MOPC as a tool for handling the metarepresentations allows our system to mentalize the believed state of another agent. This experiment has potential impact on the ongoing debate of what is required for passing false belief tasks will be discussed in the next section. The differences of the OPCs are also more detailed in the Fig 5.20.

As we can see the robot is thus able to pass a simplified version of the Sally-Anne task, and is able to project someone else’s beliefs in its own internal representation.

### 5.3 Discussions about the Conceptual Self

These two experiments (the high level reasoning and the Sally-Anne task) both give us a direction to research, but also a first step to continue toward a conceptual self. We have seen how we could answer to the two problematic of Neisser : the Role Theories and the Internal Models.

Our system is however not yet fully functional and would need a set of improvements.

Part of this improvements could be a more a more complete perceptual system to allow the reasoning system to work not only on space but also on other modalities. Also, for now, this reasoning is triggered by a Human command and should be integrated as automatic for the robot : to go from an event to a routine for the reasoning. This remark could be extend to the part about the ToM, where for now, the robot needs a special command to create someone else's list of beliefs.

Being given this technical details and the potential lack of scale of the system, we clearly show a significant breakthrough in the field of robot understanding a human agent based on his experience.

But this reasoning about agents and the implication of actions can be seen at a larger time scale, from a backward perspective : the Temporally Extended Self.

## Temporally Extended Self

This fourth level of self can be seen as the “highest level of self” in our autobiographical hierarchy. Neisser gives two first short definitions as follow :

*“The temporally extended self is the individual’s own lifestory as he/she knows it, remembers it, tells it, projects it into the future. It cannot appear until the child already has a conceptual self, a narratively organized episodic memory, and an explicit understanding of the continuity of persons over time - say, until the fourth year.” [Neisser, 1995]*

*“The extended self is the self as it was in the past and as we expect it to be in the future, known primarily on the basis of memory.” [Neisser, 1988]*

This notion of continuity applies at the individual level as the notion of psychological continuity. This notion of TES can be related to the notion of the narrative self of Bruner or Gergen ([Bruner and Bruner, 2009] [Gergen and Gergen, 1988]). A central aspect of this narrative self construction concerns how the narrative includes the interaction between self and others over time. It is apparently this relational aspect that is crucial in defining the self.

For Neisser, the TES includes the ability to “remember”, and maybe the definition of amnesia as “*the pathology of the extended self*”, is the best definition of the TES [Neisser, 1988].

However, the TES needs to be separated from the others uses of the past, particularly the ones that don't involved past self. For example the case of learning from experience is a manifestation of the memory, but not a proper manifestation of the TES, and Neisser distinguishes the "*knowing how*" from the "*knowing that*". The first be part of the nondeclarative memory, while the second will be a manifestation of the TES.

As we already talked about in the part about semantic and episodic memory (2.1.2), I can remember that my birthday is the 5th of December of 1988, but this is not properly speaking due to my episodic memory, but more to my semantic memory, this manifestation of knowledge about my lifestory is a part of this lifestory, but not a first plan level of manifestation of my TES. Neisser focuses more about what he calls "scripts" or "routines" which are regular events of one's life.

The way of remembering events should thus be a mix of process : on one hand, the "remembering" per say of something I did, and on the other hand, the remembering *that* I did something. If I want to remember the time I went to the restaurant for my father 50th birthday, I will have an episodic memory. But the development of the lunch will be a familiar routine as follow : *we went to the restaurant, we get seated, we ordered an apéritif, we ordered the food, we waited for the food, we ate the food, we ordered a dessert, we ate the dessert, paid the restaurant and we left*. This more general representation is what Neisser calls "script". Both process are part of the TES, and Neisser insists on the fact that TES can be though "*as a kind of accumulated total of such memories : the things I remember having done, and the things I think of myself as doing regularly*".

We see here clearly the implication of the ABM in the TES, directly, and indirectly. The direct part is evident, it is the calls to the episodic memory or semantic memory for "recalling" events. But indirectly also for the creation of these scripts.

From a developmental point of view, there are several steps that lead to the TES. We have already seen that the episodic and semantic memories arise during early childhood (before around  $2\frac{1}{2}$ ). This “script knowledge” of regular, sequenced events of the life (such as going to the restaurant) arises during the third year of life first with a basic form, then around  $4\frac{1}{2}$  with a more complete form [Gruendel and Nelson, 1986]. A child of 3 years old, knows many scripts such as getting up, getting dressed, having breakfast.

However for Neisser the important part of the TES, is not only being able to remember an event under the form of a script or routine, but it is to be able “*to remember [this routine] when it is not being executed*”. This includes the ability of being aware of “*oneself as existing outside the present moment, and hence of the extended self*”. We clearly see here the implication of both the conceptual and interpersonal selves in this understanding.

As the opposite of the other levels of self and especially the conceptual self and the ability of pretense, Neisser explains that the TES grows together with one individual life and on can recall more easily emotional events of life. Indeed I remember very clearly the time I’ve read the book *1984* from Georges Orwell and the sentence “*To die hating them, that was freedom*”. I remember having be shaken by this sentence and today, I can’t really remember the exact condition I was before reading, or even the previous or the next sentence, but I know that this sentence changed me as part of my self.

We can consider that the cooperative joint plans that the robot learns (SP) through its interaction with the human, correspond in some way to his TES, as well as the IS, but the aim of the experiment about the SP, was to prove the ability of the robot to analyze each agent’s role in such scripts and to understand how each person could influence the SP.

## 6.1 SABM

The first manifestation of the TES can be at the very first level of our SABM. In november 2012 the SABM system became sufficiently reliable (technically) that it was enabled and since than, has been continuously encoding the experience of the iCubLyon01. That encoded experience provides a record of the different kinds of interactions that has had, with different people, over time. As illustration in the Fig 6.1, we can see that at different periods, different type of experience has been acquired. Learning about object and the results of actions provides the basis for further learning about how to combine these actions into SP, or high level reasoning, of every level of knowledge that we have seen previously.

These records are a clear manifestation of the TES of the robot. And by looking the lifespan of the robot in the Fig 6.1, one can ask a few questions. What is this big empty gap between months 9 and 10 and between the months 13 and 23? The answer is that the SABM is plugged on the real robot in our laboratory of Lyon. The months 9 and 10 correspond to mid-July to mid-September 2013. For many European Projects such as EFAA or WYSIWYD, we have what we call some “integrations” where all the partners meet for a few weeks, and integrate the work of each laboratory. In our case, we went to Genoa, in the laboratory of IIT for a summer School called Veni VEDI Vici the two last weeks of July 2013, and for the two first weeks of September 2013, we where in Barcelona in UPF for the summer School BCBT. The month of August is the main month for vacation in France. This explain the gap for the months 9 and 10.

But what about the gap for the months 13 to 23? The iCub as we said is an experimental robot, and we had a big hardware problem with the boards (embarked controllers) of the iCub, and on several cables of both arms. Then we moved from one room to another in our Laboratory of Lyon. During this time, most of the experiments with the SABM were done but without using the iCub itself (for example the elaboration of the “*I-You experiment*”).

These explications are neither an excuse or a justification, but more a illustration of

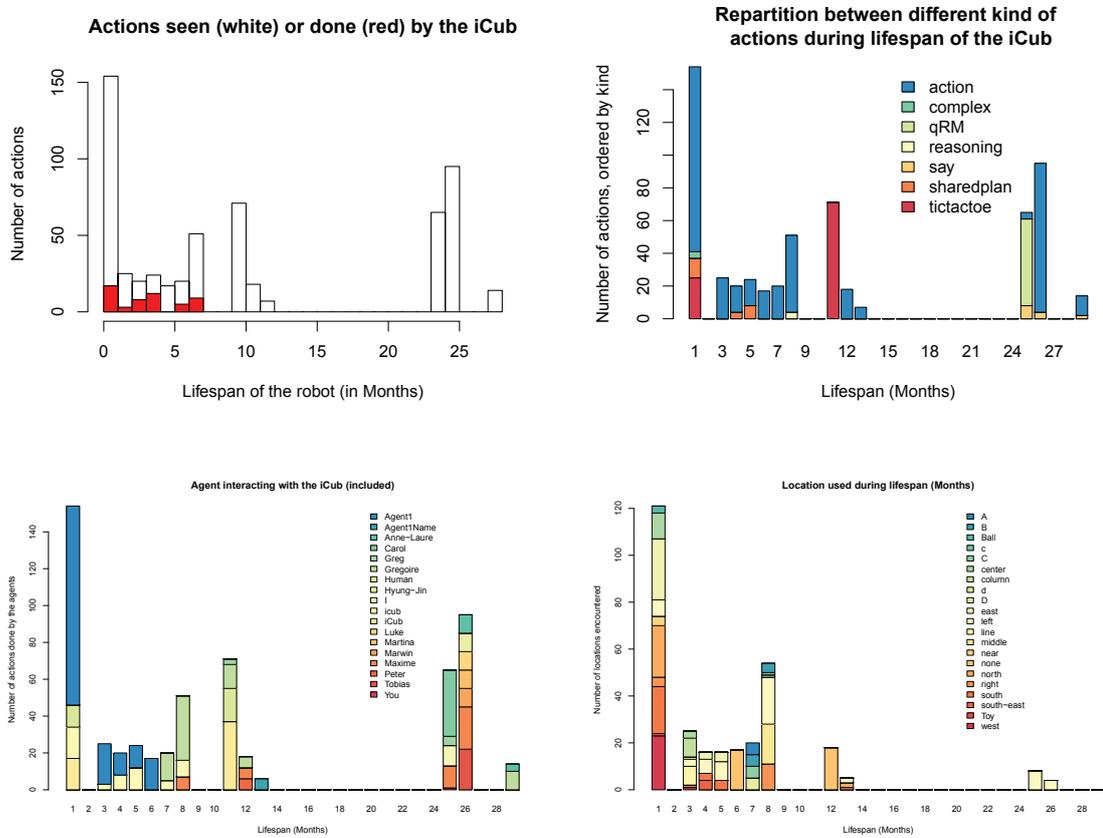


Figure 6.1: Illustration of the lifespan of the iCubLyon01 from the 13th November 2012 to the 20th March 2013. Top left : number of action witnessed (white) or executed (red) by the iCub. Top right : type of the actions recorded in the ELM (in majority they are simple actions in blue). Bottom left : agent interaction with the iCub. During the first weeks, the agents were always : “Agent1”, then we can see the elaboration of the functionality of naming the agents. Bottom right : argument used as spatial during the lifetime of the robot. Full size images can be found in appendix (9.1).

the aspect of narrative self that emerge from the ELM. Indeed what the robot recall, is what he really witnessed.

## 6.2 The TES as integration of all the other levels of self.

The TES can be seen also as the integration of the three other levels of self. Actually, every result we shown earlier, are a manifestation of the TES. When the robot is able to understand the meaning of an action, and the consequences of his own movements through

his ES, it is indirectly a part of the TES because it is the expansion of his long term memory (ELM) into an understanding of his body and his interaction to the world. When the robot is able to understand the different social interactions, and the different roles that an agent can have in for example a SP, as part of his IS, it is also a manifestation of his TES. And finally, when the robot is able to create some high level knowledge, and to simulate someone else's internal mental state, it is once again an indirect manifestation of the TES as in the sense of Neisser : *“The extended self is the self as it was in the past and as we expect it to be in the future”*.

An experiment to put in light the role of the TES has been done in the laboratory (but is not yet the subject of a publication). It consists of a dialogue with the robot concerning his memories. The final dialogue is transcript in the Table 6.1 and in the Fig 6.2.

If we decide to decompose this interaction, we can see several levels of implication of the TES. One of them is the use of the ELM to recall a precise event such as : *“When was the last time you saw Peter ?”*, where the robot reloads the correspondent memory in his MOPC. He recreates the situation, and now can act on it. The robot can simulate an action given this context : *“The last time Peter was here, the cross was on the location east. If I had pushed it to the west, the cross would not be at the location east anymore”*. This kind of situation (which is not fully described in the video) could allow the robot to re-experiment a situation, and to try to find the possible consequences of another action given a initial situation. The robot could experiment a kind of high level “babbling” based on a situation and his experience.

Another manifestation of the TES in this video, is the ability of the robot to simulate in his MOPC a SP. When asked to explain a SP, the robot is not only able to enunciate the corresponding “script”, but also to simulate it in his MOPC. An important fact to be noted is that the simulation in the MOPC is not in this case the memories in the ELM that compose the SP, but a full execution of the SP in the MOPC. The robot doesn't simulate

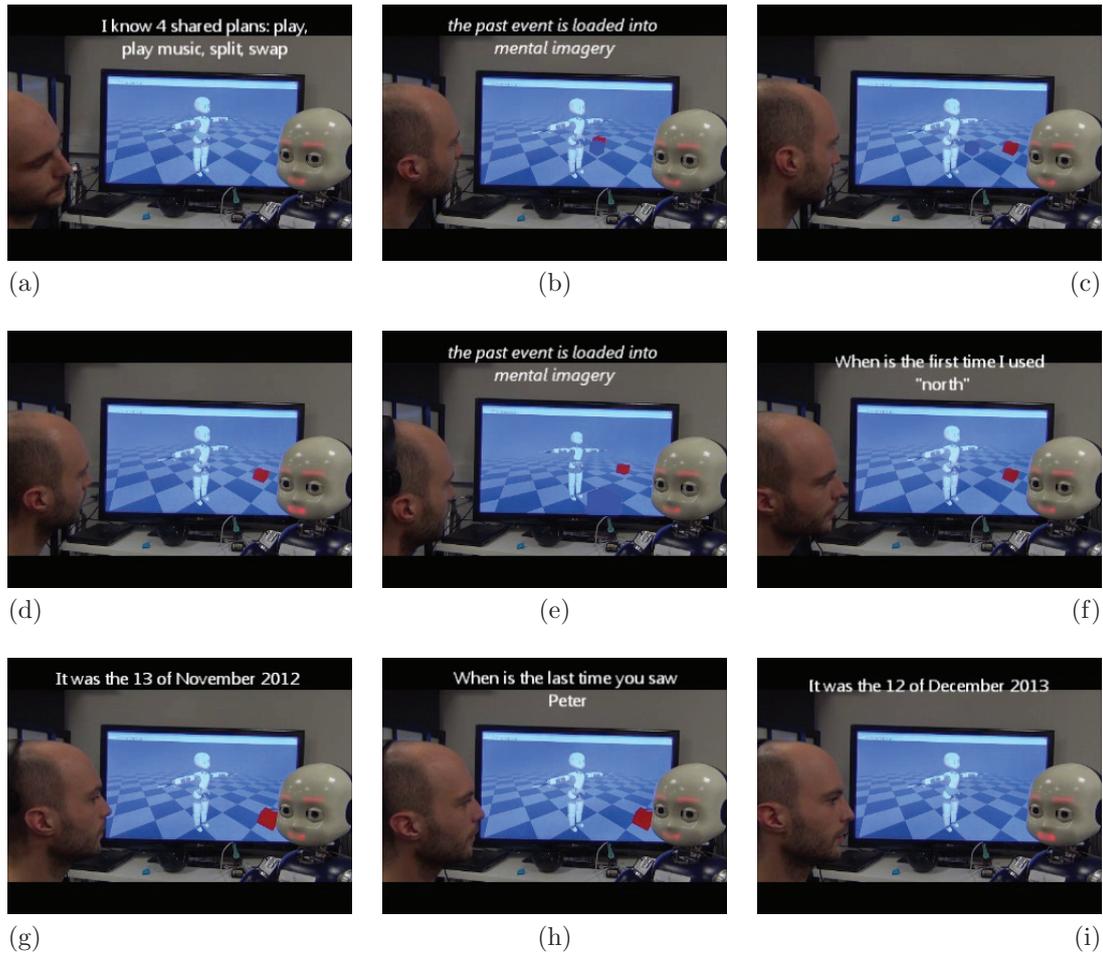


Figure 6.2: Dialogue with the iCub about his memory. (a) The iCub enunciates the SP he knows. (b) the iCub explains the SP “play-music” and loads the steps in his MOPC. (c) and (d) the iCub keeps enunciating “play-music” and simulates it in his MOPC.(e) the iCub explains “swap”. (f) the Agent asks a precise event in the ELM. (g) the iCub answers the question and re-simulate the past situation in his MOPC. (h) the Agent asks for another precise event. (i) the iCub simulates the past event in his MOPC. The images can be found in the appendix (9.2).

Timing	Agent	Sentence
0 :08	G	“Do you know any shared plan ?”
0 :11	R	“I know four shared-plan : play ; play-music ; split ; swap”
0 :19	G	“Can you explain me play-music ?”
0 :23	OPC	loading in the mental OPC
0 :28	R	“iCub put the cross to the left then Agent1 put the cross to the east then iCub put the circle to the left then Agent1 put the circle to the south
0 :52	G	“Who was present ?”
0 :54	R	“You were present”
1 :02	G	“Let’s talk about something else. Can you explain me swap ?”
1 :06	OPC	loading in the mental OPC
1 :10	R	“Agent1 put the circle to the center iCub put the cross to the west Agent1 put the circle to the east
1 :35	G	“Let’s talk about something else. When was the first time I used north ?”
1 :37	OPC	loading in the mental OPC
1 :39	R	“It was the 13th of November of 2012.”
1 :49	G	“How many times this happened ?”
1 :53	R	“It happened 22 times.”
1 :58	G	“When was the last time you saw Peter ?”
2 :01	R	“It was the 12th of December of 2013”

Tableau 6.1: Retranscription of a dialogue with an human agent (G) and the iCub (R).

the corresponding situation, but the action themselves.

### 6.3 Conclusion on the TES

It is difficult to design a experiment that shows a clear manifestation of the TES because. By definition, the TES is built on the three other levels of self seen previously. But a manifestation of the TES couldn’t be simply these three other levels working jointly with the SABM? Neisser uses the term of “emergence” to characterize the different level of self, and this term is especially strong in the case of the TES : we see here clearly that its manifestation appears through the interactions or the changes of these lower levels and makes arise a level of complexity that is difficult to predict or describe by the analysis of

these systems in isolation.

These two simple situations correspond exactly to the definition of Neisser of the TES : the robot sees himself in the past, and from this past simulate the future. He can analyze his everyday life scripts not from a episodic perspective but from a semantic perspective, and as Neisser declared, he can remember them and simulate them while he is not living them.

## Discussion

Now that we have seen how technically our robot could with the help of a SABM, express at his own way different levels of self, we can take a step back and discuss several point that can be important in our case.

### 7.1 Summary of the study

In this thesis I have first defined an **ABM** and its two main components the Episodic Memory and the Semantic Memory. We have seen how the architecture of the SABM could help to create different notion of *self*. I have then defined these notions of *self* with the work of Endel Tulving and categorized its manifestation in 4 plus 1 parts, the Ecological Self (**ES**), the Interpersonal Self (**IS**), the Conceptual Self (**CS**), the Temporally Extended Self (**TES**) and the Private Self. I will explain why we had put aside the Private Self and focus on the four other levels in this study.

I have presented the technical platform we use. This system is composed at its center by the humanoid robot iCub, interacting through a ReacTable with a Human Agent. The interaction is mainly through speech. The world as it is perceived by the robot is constantly updated in its Objects Properties Collector (**OPC**).

I have then described our **SABM**, composed of two part, an **ELM** and a **SSM** that model respectively the Episodic and Semantic human memories. The ELM stores snapshots of the OPC, while the SSM stores information related to knowledge extracted by the Autobiographical Memory Reasoning (**ABMR**) through a Mental Objects Properties

Collector (MOPC) and various techniques of reasoning.

Next I have for each level of self that we examined, explained how a SABM could contribute to its emergence, starting by the ES which concerns the impact and direct influence of someone on the world. Concerning the ES, I have shown a system of forward model through mental imagery. This forward model allows the robot to simulate through its MOPC the consequences of his physical action on the world, such as it is defined by Neisser.

After that I focused on the IS which is related to the social interactions. I have firstly shown how the system of MOPC developed previously could help to understand a social interaction and the role/effect of each agent. Secondly, I explained the “*I and You Experiment*” which consists in understanding and using correctly a personal pronoun given its context. Our specificity is that we extended the work from Gold and Scassellati not only to personal pronouns but to proper nouns too. At last for the IS, I showed a system of Shared Plan (SP) as part of social ritual.

I then developed the CS. The first part of it it a “high level reasoning” : using the MOPC to simulate and predict complex plans. I gave two examples of it : the ABCD game, and the Table of Hanoi. Then, as second part of the CS, I developed the use of the MOPC in Theory of Mind (ToM). It consists in using the MOPC to predict the mental state of another agent and the experiment we used for it was the Sally-Anne task modified for the iCub.

The last level of self that I developed in this thesis was the TES. There is no proper demonstration of its functioning because I showed that the TES emerge as the three other levels are active. However, I showed two manifestations of it : one was the SABM running on the long term, and the second was an interaction with the robot about his own personal history.

There are still some discussion possible about our model, and some improvement could be find.

## 7.2 The private self

The first point I would like to address in the case of the “*Private Self*”. I recall the definition given by Neisser of the Private Self :

**The private self** *“appears when the child comes to understand and value the privacy of conscious experience; when it becomes important that no one else has access to his/her thoughts, dreams, and interpretations of experience. I do not know whether this insight appears regularly enough to be counted as a developmental milestone, but it surely requires a temporally extended self which to reflect.”* [Neisser, 1995]

All along our work, we claim to work on the levels of self defined by Neisser but we put aside this level. Now is the time I would like to come back on it. The PS seems to develop around  $4\frac{1}{2}$  years old and correspond to a notion of “free will” and to the fact that a person is the own keeper of his memories, thoughts and dream.

In the case of the iCub, we, researchers, have access all time to any data of the robot, and the notion of privacy (in the frame of Neisser’s PS) is difficult to reach in a robot.

However, going in the direction of the PS, or at least addressing the topic of conscious experience, several experiments have been run in our laboratory under the Super Wizard of Oz (SWoOz) Project. The aim of the project (as described in the Fig 7.1) is to teleoperate the iCub, while interacting with a human partner ([Gibert et al., 2013] [Gibert et al., ] [Gibert et al., 2014]). The aim of the project is focused about Human-Human, Human-Robot and Human-Avatar interaction.

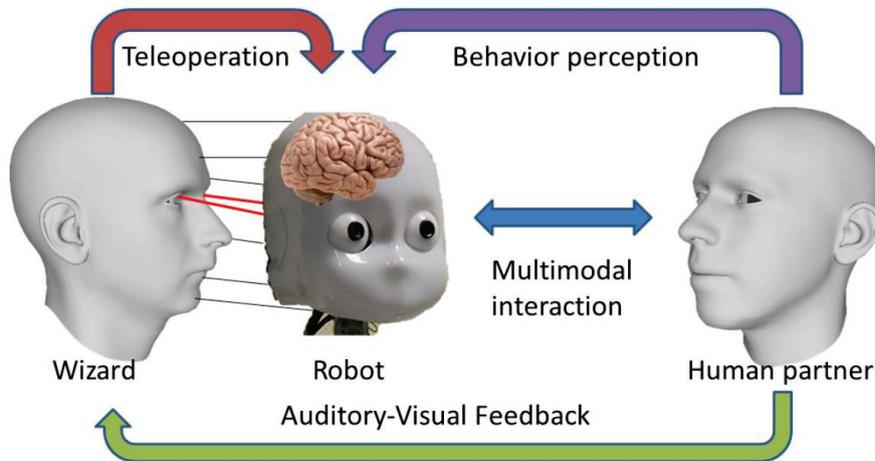


Figure 7.1: Concept of the SWoOz Project. Human partner will interact with a robot : the iCub. The iCub is teleoperated by an agent (the Wizard). This platform can thus be used to analyze Human-Human interaction as well as Human-Robot interaction.

Yet, we could see here a way to teach the robot to act, by acting for him. By taking the control of the robot, we could increase significantly the experience of the robot. The would result in a “mix” interaction where the robot would be witnessing his experience instead of being actor of it.

What could be the difference between being actor or spectator of his experience ? The robot would learn the “way of thinking” and solving problem of one person. Maybe in a precise situation it might have several possibilities and maybe several solution. If the robot doesn’t have this capability of exploring his range of possible, might result a learning much slower. The differentiation between being spectator or actor of his learning have been shown many times ([Prince, 2004] [Grabinger and Dunlap, 1995] [Pointeau et al., 2013b]).

Without any initiative, will the robot be able to develop a PS, or more generally, will this self be the self of the robot, or the self of the human ?

### 7.3 Robot Self vs Human Self

This question is in my opinion the most difficult questions we had about the self of the robot, and I am not sure I have an answer. We thus can try to have a reflection about this point.

We have shown that the robot was extracting his self from his experience. His experience comes mainly from human actions, but also from his own. But what is the root of his own action? Does our robot have a free will? I would answer no to this question without hesitation. The range of possible for a robot is at some point (even very low) given by the Human. The iCub's action happen in a Human world. The robot is depending a lot on Human actions that can be from the teaching to the robot to the programming itself or even the conception. This would turn the scale in favor of a human self for the robot. Yes but...

Yes but, in the end the robot has his own hardware conception, his own sensor, he “understands” the world in our case mainly through an interactive table and has a dissociation of his body (hardware and sensors) and his “mind” (computers). The actions made by the iCub, happen in a Human world, but made by a robot and interpreted by a robot. This would turn the scale in favor of a robot self.

But if we come back to this idea of a “free will” of the robot, we could ask the question, does a Human have a free will? Or does the biology and the neural system “chooses” for us? A answer to this question would be that, the complexity of the neural system gives us (right or wrong) the sensation of free will. Maybe this is an answer to the question of a robot self and free will. We have shown that the robot could express behavior characteristic of the human self, but concerning the free will, we could argue. And maybe this human neural complexity could also be an answer for the free will of the robot.

I would like to share at this point a personal opinion concerning the role of the human

in autonomous robotic. For the same reason that the complexity of the nature itself, and the complexity of the neural system gives us a impression (once again right or wrong, the problem is not here) of free will, I would say that, the iCub, and autonomous robot in general are like a solid in space : it will move forever is there is at first even a very insignificant force to push it. The role of the Human in the development of autonomous robot, is to give to the robot this ability to travel endlessly, but also to give this first impulsion, as tiny as it is.

## 7.4 Other aspect of the memory system as builder of the self

I would like now to address several points that are linked to the memory system, and that can have an impact on the way the levels of self are expressed.

### 7.4.1 Tuning of the robot

One important part of the programming that we showed, is that it needs the declaration of many internal parameters and thresholds for many reason. Most of them are used for the differentiation of actions : for example a threshold to determine that the adjectives “quickly” and “slowly” are related to time and not “south” or “east”. The statistical test will return a p-value, but the robot need to make the decision to consider this p-value as significant or not.

It cannot be denied that this thresholds and parameters will have an impact on the behavior of the robot in his decision making. For example, by manipulating these threshold, we can easily change a slow learner, into a fast learner robot.

We can however put so “dynamic” threshold that could evolve given the experience of the robot (this is one of the axis of work with the Europeans partner of the project **WYSIWYD**).

### 7.4.2 Plasticity of the memory

We have in this thesis established a model a memory absolute and infallible : what is perceived is recorded, and can be found at any time. But the human memory seems not to be so perfect.

We can cite many diseases linked to memory such as amnesia (anterograde or retrograde) that can be caused by brain damage, psychological trauma or disease [Nadel and Moscovitch, 1997]. Roughly, amnesia is a loss of memory that can be manifested in both ways : backward (impossibility to recall old memories) or forward (impossibility to fix new memory).

Agnosia is another of this memory's disease. It manifests itself by an incapacity to recognize some normally known stimulus and it is a disease of the nondeclarative memory, but it seems also to manifest itself through speech [Heilman et al., 1975]. Here again the origins of agnosia can be multiple but most of them seem involve the ventral stream of the brain [Cavina-Pratesi et al., 2009].

Alzheimer disease one of the most known memory disease [Querfurth and LaFerla, 2010]. Even if main causes of the diseases are still unknown, it seems that its origin might be genetic although many factor seem to come from lifestyle. We could add other example of memory disease, but what is important to see in these disease, is the fact that they seem to be caused by either external factor such as accident, or by a genetic dysfunction. Theses disease don't seem to be caused by the natural functioning of the memory.

This bring us to another important property of the memory : the construction of false memories. The creation of fake memory from the brain has been studied a lot and Bernstein states the following :

*“In essence, all memory is false to some degree. Memory is inherently a reconstructive process, whereby we piece together the past to form a coherent*

*narrative that becomes our autobiography. In the process of reconstructing the past, we color and shape our life's experiences based on what we know about the world. Our job as memory researchers and as human beings is to determine the portion of memory that reflects reality and the portion that reflects inference and bias.*" [Bernstein and Loftus, 2009]

Bernstein here puts in light an important fact : the part of reconstruction of a memory. Once again, our SABM is "absolute" in the sense that it will reconstruct the exact same memory if asked. It can of course extrapolate and simulate from it, but it will recall a memory perfectly (at least as good as it was recorded).

The Human brain doesn't seem to have this functioning and it may lead to the creation of false or at least re-arranged memories. Several studies have treated this topic of creation of false memories, and the impact it can have in society ([Porter et al., 1999] [Loftus et al., 1997] [Gudjonsson and Pearse, 2011]). I would like to report in more details one of these studies, an article published recently by Julia Shawn (early 2015) : [Shaw and Porter, 2015]. In this study, Shaw and her colleagues have taken 60 students on average 20 years old that have never been involved in any crime. The student met the experimenters three times for 40 minutes in the laboratory at weekly interval.

The caregivers were asked to fill out a questionnaire to give the experimenters some details about specific events the students might have experienced between 11 to 14 years old. These details were about a specific event of the student life, but also about their lifestyle.

During the first interview, the experimenters told the students 2 stories : one true (given by the caregiver) and a second false but enriched by details from the caregivers. The false stories were divided in two categories : the first was a set of events that involved the Police (theft, assault or assault with a weapon) while the second set had a strong emotional valence (loss of a huge amount of money, serious personal injury or an attack by

a dog). When asked to explain the false event, the student had some difficulties but were encouraged by the experimenters and reassured by the experimenters. At the end of the session, the experimenters asked the student to work on it for the next interview.

The second and third interview were based on the same principle. At the end of the third session, the students were informed that the memory was false and were asked *how often they had visualized the memory at home*, and they had to rate on a scale from 1 to 7 how surprised they were that the memory was false, and how suspicious the interviewer was. They were of course also asked if they thought the memory was real, and paid \$50.

The results of the experiments are startling. Indeed over the 30 subjects that were faced with a false assault involving the Police, 71% (21) declared that they believed the event occurred and they forgot it. Concerning the 20 that were confronted to the false assault (assault without weapon and assault with a weapon), 11 of them gave precise details of the encounter with the Police (such as physical description of the officers). Concerning the students confronted to the events with high emotional valence, this proportion rises to 76,76% (23).

The student were also asked to compare the vividness of the sensory component of the memories (the visual, auditory, olfactory and tactile part of the memory) between the true and the false event and the results are very similar (see Fig 7.2).

Shaw concludes her article by the following statement :

*“A number of current theories, such as fuzzy-trace theory (Brainerd & Reyna, 2002), propose that a memory may be retrieved not by accessing a fixed representation of a past event, but rather by reactivating incomplete fragments that can be either distorted or accurate, and that may have arisen from other real events (Stark et al., 2010). This implies that false memories may actually be recalled in a way that is surprisingly similar to how memories for real events*

**Table 2.** Sensory Components of the True and False Memories

Condition and memory type	Visual		Auditory		Olfactory		Tactile	
	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI
Criminal condition ( $n = 21$ )								
False memory	0.86	[0.74, 0.99]	0.39	[0.21, 0.56]	0.14	[0.01, 0.26]	0.30	[0.13, 0.46]
True memory	0.95	[0.88, 1.03]	0.48	[0.30, 0.66]	0.23	[0.08, 0.38]	0.48	[0.30, 0.66]
Noncriminal condition ( $n = 23$ )								
False memory	0.85	[0.72, 0.97]	0.41	[0.23, 0.58]	0.15	[0.02, 0.27]	0.29	[0.13, 0.45]
True memory	0.94	[0.85, 1.02]	0.50	[0.32, 0.68]	0.24	[0.09, 0.39]	0.48	[0.30, 0.65]

Note: This table reports data only for those participants who were classified as having false memories. For a given memory, participants indicated whether each sensory component was present (1) or absent (0). CI = confidence interval. Gustatory details are omitted from this table because of very low prevalence rates.

Figure 7.2: Table of results concerning the experiment from [Shaw and Porter, 2015].

*are retrieved*”.

In contrary to the other deficiencies of memory that I talked before, the creation of false memory doesn’t seem to have an external origin such as a cerebral or physical accident, or any disease, but seems to be a natural process.

In our objective to create a memory the closer that we can in the functioning (from a macro scale I remind), our system should be able to be “fooled” and to create false memory. On direction of work could be in the reconstruction of memories in the the MOPC, that could be more “relation-based” that “stated-based” : to rely more on the SSM that on the ELM.

## 7.5 Importance of the embodiment

This work claims to be done on a humanoid robot, the iCub. But one could argue that the embodied part of the study is not needed for most of the reasoning part, or even for the simulation. This is right concerning the computation itself, and also the sensors. We have seen here that most of our sensors are external to the robot (the Kinect or the ReacTable for example). Since the month of March of 2015 (while I finish writing this document), we started to rely on the vision of the robot to detect both agents and object. This is a good argument against the use of a body for the robot. Indeed we get the same results because the information located in the OPC are the same, just coming from different sensor. The

computation also is delocalized and the POSTGRESQL server or any c++ module can be run externally. Why do we thus talk of an embodied system? We will now discuss the importance of the body in our study.

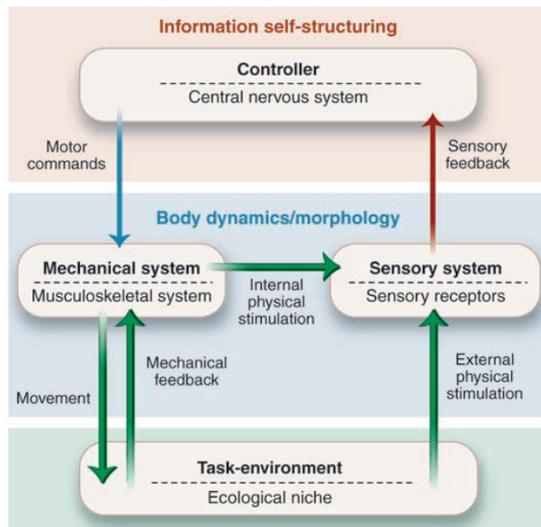
### 7.5.1 A Human-Like Concept

As Asada claimed, some behavior are better learn than pre-programmed [Asada et al., 2009]. In our case the robot will learn his behavior through Human-Robot Interactions and through World-Robot Interactions. These interactions happen of course in the Human world and as we have seen are often part of shared plan where the robot can and should take the different roles possible. The robot needs to experiment both Human-Robot and World-Robot Interactions, in order to adapt to the human world and to the object world. As so, he will be able to actively participate to many plans, including the “shared plans”. But the interaction the robot has to witness, needs to be real and formatted toward a Human perspective if we want to be able to make emerge some “human-like” senses of self as I shown in the different chapters of this thesis. This “human-like sense of self”, built on the SABM, needs some “human-like” interactions to emerge. This was our very own goal, and the nature of the different experiment justify the use of the term “embodied”.

To go further in this way, Pfeifer says [Pfeifer et al., 2007] :

*“Biological organisms have evolved to perform and survive in a world characterized by rapid changes, high uncertainty, indefinite richness, and limited availability of information. Industrial robots, in contrast, operate in highly controlled environments with no or very little uncertainty.”*

Pfeifer here clearly shows the impact of the embodiment in robotics, and as we want to have a robot with a sense of self the closer of the human as possible, the humanoid embodiment is necessary. He shows it more clearly on the Fig 7.3. We can clearly see that the robot need to be at the border of the ecological niche, that in our case is



**Fig. 1.** Implications of embodiment (the interplay of information and physical processes). Driven by motor commands, the musculoskeletal system (mechanical system) of the agent acts on the external environment (task environment or ecological niche). The action leads to rapid mechanical feedback characterized by pressure on the bones, torques in the joints, and passive deformation of skin tissue. In parallel, external stimuli (pressure, temperature, and electromagnetic fields) and internal physical stimuli (forces and torques developed in the muscles and joint-supporting ligaments, as well as accelerations) impinge on the sensory receptors (sensory system). The patterns induced thus depend on the physical characteristics and morphology of the sensory systems and on the motor commands. Especially if the interaction is sensory-motor coordinated, as in foveation, reaching, or grasping movements, information structure is generated. The effect of the motor command strongly depends on the tunable morphological and material properties of the musculoskeletal system, where by tunable we mean that properties such as shape and compliance can be changed dynamically: During the forward swing of the leg in walking, the muscles should be largely passive, whereas when hitting the ground, high stiffness is required, so that the materials can take over some of the adaptive functionality on impact, such as the damped oscillation of the knee joint.

Figure 7.3: From [Pfeifer et al., 2007]

the physical world (need for an embodied system). But we go further in the sense that we need not only for the robot to be part of it, but to be part of it in a certain way : a human way, and this leads us to embodied and humanoid. Especially, we have seen for example that the iCub learns spatial location, action or rules (as in the case of the TaOH) by observing the human and then after learning, performs the same action. Thus the iCub must be physically embodied in this ecological niche to interact and learn from humans.

However we can talk about an embodied system not only as the scale of the robot itself and its humanoid aspect, but also concerning the way our whole system is running. Of course the term embodied is voluntarily too strong, but I would like to put in light the importance to have a system based on a human model, as much physically that more deeply in the concept. As I said in the introduction, the goal of this thesis was to create a system of autobiographical memory, based on the human autobiographical memory, that could contribute to the emergence of human levels of self. We thus needed to create a SABM formatted to human event and to human world. That means having a system able to understand the perception not only under an computational format, but also under

a more “human-understanding” format. Many choices have been made in this direction, to create a SABM directed toward a human understanding of the world. We decided on purpose, not to create a most efficient system of learning, that could be totally wrong in cases, but that would be coherent with the human experience of the robot.

### 7.5.2 The limit of the embodiment

Even very complex, the iCub has some limitations for this kind of study. One of them is of course the absence of human-like physiology. Indeed, the state of the metabolic system impact a lot on the performances of the memory system. When I talk about metabolism here, it can be induced by hormones [McGaugh, 1989], drugs [McGaugh and Petrinovich, 1965], sleep [Walker and Stickgold, 2014] or any event that could lead to a change in the metabolic system. In 2003, Sommerfield has shown the negative impact of hypoglycemia on working-memory, inducing problem in the long term memory [Sommerfield et al., 2003]. The whole metabolism has an impact on our memory system and we are not able to model it. Steffen Klamt has shown that the study of metabolic networks is confronted to a combinatorial explosion in term of complexity [Klamt and Stelling, 2002].

But there is also higher process (that will impact of the metabolism) that can induce also impairment or improvement in the memory system. It can be the effect of the age [Park et al., 1997], of stress [Lupien et al., 2005], of emotions [LeDoux, 1994] an particularly of fear [Fanselow and Gale, 2003].

We can however try to model some of this aspect with for example the use of the salience and of return of inhibition as explained in 2.2.1. We can also use the part of novelty in an action to regulate its strength in the memory system (we recall more easily our first kiss, that the second). It exists solution to model (or at least to start to model) the impact of the body or at least of the “state of mind” on the memory.

I have explained earlier the importance to have an embodied system and moreover, a

humanoid one, but the complexity of the human metabolic network is another giant step required for the understanding and the modeling of the human self.

## Conclusion

The topic of the self in man is an ongoing topic for philosophers, psychologists, neurologists, anthropologists, even jurists and many others. Claiming to have created a self in a robot would be very pretentious and I hope I have made clear all along this manuscript that in any case we contend having created a self in a robot.

The objective stated at the beginning of this thesis was to provide the system with the capability to exploit its previous experience in order to prepare for future experiences within the local peripersonal space.

All along this document I showed how a SABM working together with a reasoning system, could result in the emergence of Neisser's level of self. I tried to make clear that we do not claim that we achieved to give our robot any sense of self. We gave our robot several essential components in its emergence.

I have shown also a set of limitations of our system. Concerning the content itself, we have seen that the recording of events of the ELM could be modified in order to map to the Human memory system as explained by Tulving or Squire, meaning a more abstract recording of events. Concerning the form of the system, we have seen that many of its limitations lie in the robot perception. But this shouldn't be an excuse for us not to develop more sophisticated reasoning or encoding systems. The interactions also are for now still a bit scripted and would gain a lot by being more natural. But these two last remarks are more related to the form than to the content of the system.

Put aside these limitations, the different experiments that I showed, and that have been published and thus accepted by the scientific community, are undoubtedly a step forward the emergence of sense of self for the robots of tomorrow. This sense may be slightly different from a Human self as we discussed in the part 7.3.

I believe that one of the biggest difference that can rise between the Human self and our robot self lies in the emotional valence of each memory. Indeed an memory with a high emotional valence can be either strongly anchored in the memory, or at contrary put aside from conscious memory [Cahill and McGaugh, 1995]. In our system, all memories have the same emotional valence and the robot has never “lived a huge joy” or a trauma. This emotional event can lead to a distinct manifestation of someone’s self (for example as a phobia) [Squire, 2004].

What we have shown in this research is the importance of an organized system of memory, based on the human system of memory, for the analyze and the understanding of the world through experience, in order to be able to develop the firstfruit of the manifestation of the different senses of self. Likewise, once our system will be more reliable from a technical aspect, it could be used for several applications that I will develop now.

A third field is the study of the Human. This may seem very pretentious, but as Richard Feynman said in 1988 :

*“What I cannot create, I do not understand.”*

A first application of our model is of course commercial, in every day Human-Robot Interaction. Indeed a robot able to remember a precise customer, that knows how to behave with each of them differently has a significant added value. This applies in a classical commercial use (such as in a mall) but also in the medical field. Lets imagine a wing of an hospital that need sterile room. Having an autonomous, intelligent robot that behave (almost) as a Human could be a huge help for the hospital staff, as much as for the patients.



**Fig. 2** Three interactional conditions: adult (*top*), robot (*middle*) and touchscreen computer game (*bottom*). The confederate sits to the participant's right

Figure 8.1: The three possible interactions developed by Kim and colleagues in [Kim et al., 2013].

A second application is in the field of study of the Human-Robot Interaction. This field has been studied a in the last decades : [Robins et al., 2004] [Robins et al., 2005]. An interesting part of this possible Human-Robot Interaction are with autistic children. Indeed, the autistic children may have difficulties to interact with people partially because of the unpredictable Human behavior [Feil-Seifer and Matarić, 2009]. A robot could have a specific and adapted response to the autistic child while remaining into borders. Here the goal of the robot is not so much to interact with the child, but to be a catalyst of the interaction, then a vector of it to redirect it with another Human agent present (for example the parent, see Fig 8.1). This field seems very promising as the study of Kim attests [Kim et al., 2013].

Our model could be a first step in a more elaborate and a even more realistic system to study the memory system, and the ability to develop a sense of self. We are maybe

yet far from this objective but other projects such as the *Human Brain Project* go in this direction.

The complexity of the human brain is far beyond us at every level. But each day, we go a bit further in its direction. Robotics is one of the step we have to make to reach it. The human brain is fascinating at all levels and the more I work on the human brain the more I realize its superb complexity, and the more I work with robot, the more I love Humans.

## Bibliography

- [Alami et al., 1998] Alami, R., Chatila, R., Fleury, S., Ghallab, M., and Ingrand, F. (1998). An architecture for autonomy. *The International Journal of Robotics Research*, 17(4) :315–337.
- [Asada et al., 2009] Asada, M., Hosoda, K., Kuniyoshi, Y., Ishiguro, H., Inui, T., Yoshikawa, Y., Ogino, M., and Yoshida, C. (2009). Cognitive developmental robotics : a survey. *Autonomous Mental Development, IEEE Transactions on*, 1(1) :12–34.
- [Atkinson and Shiffrin, 1968] Atkinson, R. C. and Shiffrin, R. M. (1968). Human memory : A proposed system and its control processes. *Psychology of learning and motivation*, 2 :89–195.
- [Baddeley and Hitch, 1974] Baddeley, A. D. and Hitch, G. (1974). Working memory. *Psychology of learning and motivation*, 8 :47–89.
- [Bampatzia et al., 2014] Bampatzia, S., Vouloutsi, V., Grechuta, K., Lallée, S., and Verschure, P. F. (2014). Effects of gaze synchronization in human-robot interaction. In *Biomimetic and Biohybrid Systems*, pages 370–373. Springer.
- [Baron-Cohen et al., 1985] Baron-Cohen, S., Leslie, A. M., and Frith, U. (1985). Does the autistic child have a “theory of mind” ? *Cognition*, 21(1) :37–46.
- [Bernstein and Loftus, 2009] Bernstein, D. M. and Loftus, E. F. (2009). How to tell if a particular memory is true or false. *Perspectives on Psychological Science*, 4(4) :370–374.
- [Binder and Desai, 2011] Binder, J. R. and Desai, R. H. (2011). The neurobiology of semantic memory. *Trends in cognitive sciences*, 15(11) :527–536.
- [Boucher et al., 2012] Boucher, J.-D., Pattacini, U., Lelong, A., Bailly, G., Elisei, F., Fagel, S., Dominey, P. F., and Ventre-Dominey, J. (2012). I reach faster when i see you look : gaze effects in human–human and human–robot face-to-face cooperation. *Frontiers in neurorobotics*, 6.
- [Bretherton and Beeghly, 1982] Bretherton, I. and Beeghly, M. (1982). Talking about internal states : The acquisition of an explicit theory of mind. *Developmental psychology*, 18(6) :906.
- [Brewer, 1986] Brewer, W. F. (1986). What is autobiographical memory ?
- [Bruner and Bruner, 2009] Bruner, J. S. and Bruner, J. S. (2009). *Actual minds, possible worlds*. Harvard University Press.
- [Bubic et al., 2010] Bubic, A., Von Cramon, D. Y., and Schubotz, R. I. (2010). Prediction, cognition and the brain. *Frontiers in human neuroscience*, 4.
- [Byrne and Whiten, 1990] Byrne, R. W. and Whiten, A. (1990). *Tactical deception in primates : the 1990 database*. German Primate Center.
- [Cahill and McGaugh, 1995] Cahill, L. and McGaugh, J. L. (1995). A novel demonstration of enhanced memory associated with emotional arousal. *Consciousness and cognition*, 4(4) :410–421.
- [Carey, 2000] Carey, S. (2000). The origin of concepts. *Journal of Cognition and Development*, 1(1) :37–41.
- [Carey, 2009] Carey, S. (2009). *The origin of concepts*. Oxford University Press.
- [Carey and Xu, 2001] Carey, S. and Xu, F. (2001). Infants’ knowledge of objects : Beyond object files and object tracking. *Cognition*, 80(1) :179–213.
- [Cavina-Pratesi et al., 2009] Cavina-Pratesi, C., Kentridge, R., Heywood, C., and Milner, A. (2009). Separate processing of texture and form in the ventral stream : evidence from fmri and visual agnosia. *Cerebral Cortex*, page bhp111.
- [Cohen and Conway, 2007] Cohen, G. and Conway, M. A. (2007). *Memory in the real world*. Psychology Press.

- [Cohen and Squire, 1980] Cohen, N. J. and Squire, L. R. (1980). Preserved learning and retention of pattern-analyzing skill in amnesia : Dissociation of knowing how and knowing that. *Science*, 210(4466) :207–210.
- [Conway and Pleydell-Pearce, 2000] Conway, M. A. and Pleydell-Pearce, C. W. (2000). The construction of autobiographical memories in the self-memory system. *Psychological review*, 107(2) :261.
- [Conway et al., 1993] Conway, M. A., Rubin, D. C., Collins, A., Gathercole, S., Conway, M., and Morris, P. (1993). The structure of autobiographical memory. *Theories of memory*, pages 103–137.
- [Corkum and Moore, 1998] Corkum, V. and Moore, C. (1998). The origins of joint visual attention in infants. *Developmental psychology*, 34(1) :28.
- [Dagher et al., 2001] Dagher, A., Owen, A. M., Boecker, H., and Brooks, D. J. (2001). The role of the striatum and hippocampus in planning a pet activation study in parkinson’s disease. *Brain*, 124(5) :1020–1032.
- [Damasio, 2008] Damasio, A. (2008). *Descartes’ error : Emotion, reason and the human brain*. Random House.
- [Damasio and Dolan, 1999] Damasio, A. and Dolan, R. J. (1999). The feeling of what happens. *Nature*, 401(6756) :847–847.
- [Damasio, 2000] Damasio, A. R. (2000). *The feeling of what happens : Body, emotion and the making of consciousness*. Random House.
- [Damasio et al., 1994] Damasio, H., Grabowski, T., Frank, R., Galaburda, A. M., Damasio, A. R., et al. (1994). The return of phineas gage : clues about the brain from the skull of a famous patient. *Science*, 264(5162) :1102–1105.
- [DeCasper and Fifer, 1980] DeCasper, A. J. and Fifer, W. P. (1980). Of human bonding : Newborns prefer their mothers’ voices. *Science*, 208(4448) :1174–1176.
- [DeCasper and Spence, 1986] DeCasper, A. J. and Spence, M. J. (1986). Prenatal maternal speech influences newborns’ perception of speech sounds. *Infant behavior and Development*, 9(2) :133–150.
- [Dominey et al., 2005] Dominey, P. F., Alvarez, M., Gao, B., Jeambrun, M., Cheylus, A., Weitzenfeld, A., Martinez, A., and Medrano, A. (2005). Robot command, interrogation and teaching via social interaction. In *Humanoid Robots, 2005 5th IEEE-RAS International Conference on*, pages 475–480. IEEE.
- [Dominey and Boucher, 2005] Dominey, P. F. and Boucher, J.-D. (2005). Learning to talk about events from narrated video in a construction grammar framework. *Artificial Intelligence*, 167(1) :31–61.
- [Dominey et al., 2008] Dominey, P. F., Metta, G., Nori, F., and Natale, L. (2008). Anticipation and initiative in human-humanoid interaction. In *Humanoid Robots, 2008. Humanoids 2008. 8th IEEE-RAS International Conference on*, pages 693–699. IEEE.
- [Dore et al., 2010] Dore, A., Cattoni, A. F., and Regazzoni, C. S. (2010). Interaction modeling and prediction in smart spaces : a bio-inspired approach based on autobiographical memory. *Systems, Man and Cybernetics, Part A : Systems and Humans, IEEE Transactions on*, 40(6) :1191–1205.
- [Emery et al., 1997] Emery, N. J., Lorincz, E. N., Perrett, D. I., Oram, M. W., and Baker, C. I. (1997). Gaze following and joint attention in rhesus monkeys (*macaca mulatta*). *Journal of comparative psychology*, 111(3) :286.

- [Fanelli et al., 2011] Fanelli, G., Weise, T., Gall, J., and Van Gool, L. (2011). Real time head pose estimation from consumer depth cameras. In *Pattern Recognition*, pages 101–110. Springer.
- [Fanselow and Gale, 2003] Fanselow, M. S. and Gale, G. D. (2003). The amygdala, fear, and memory. *Annals of the New York Academy of Sciences*, 985(1) :125–134.
- [Feil-Seifer and Matarić, 2009] Feil-Seifer, D. and Matarić, M. J. (2009). Toward socially assistive robotics for augmenting interventions for children with autism spectrum disorders. In *Experimental robotics*, pages 201–210. Springer.
- [Fein, 1975] Fein, G. G. (1975). A transformational analysis of pretending. *Developmental Psychology*, 11(3) :291.
- [Fern et al., 2002] Fern, A., Givan, R., and Siskind, J. M. (2002). Specific-to-general learning for temporal events with application to learning event definitions from video. *Journal of Artificial Intelligence Research*, pages 379–449.
- [Fix et al., 2007a] Fix, J., Rougier, N., and Alexandre, F. (2007a). From physiological principles to computational models of the cortex. *Journal of Physiology-Paris*, 101(1) :32–39.
- [Fix et al., 2007b] Fix, J., Vitay, J., and Rougier, N. P. (2007b). A distributed computational model of spatial memory anticipation during a visual search task. In *Anticipatory Behavior in Adaptive Learning Systems*, pages 170–188. Springer.
- [Fombonne, 1999] Fombonne, E. (1999). The epidemiology of autism : a review. *Psychological medicine*, 29(04) :769–786.
- [Frank and Benington, 2006] Frank, M. G. and Benington, J. H. (2006). The role of sleep in memory consolidation and brain plasticity : dream or reality? *The Neuroscientist*, 12(6) :477–488.
- [Friston, 2005] Friston, K. (2005). A theory of cortical responses. *Philosophical transactions of the Royal Society B : Biological sciences*, 360(1456) :815–836.
- [Frith and Frith, 1999] Frith, C. D. and Frith, U. (1999). Interacting minds—a biological basis. *Science*, 286(5445) :1692–1695.
- [Geiger et al., 2010] Geiger, G., Alber, N., Jordà, S., and Alonso, M. (2010). The reactable : A collaborative musical instrument for playing and understanding music. *Her&Mus. Heritage & Museography (4)*, pages 36–43.
- [Gergely and Csibra, 2003] Gergely, G. and Csibra, G. (2003). Teleological reasoning in infancy : The naive theory of rational action. *Trends in cognitive sciences*, 7(7) :287–292.
- [Gergely et al., 1995] Gergely, G., Nádasdy, Z., Csibra, G., and Biro, S. (1995). Taking the intentional stance at 12 months of age. *Cognition*, 56(2) :165–193.
- [Gergen and Gergen, 1988] Gergen, K. J. and Gergen, M. M. (1988). Narrative and the self as relationship. *Advances in experimental social psychology*, 21(1) :17–56.
- [Ghallab et al., 1998] Ghallab, M., Knoblock, C., Wilkins, D., Barrett, A., Christianson, D., Friedman, M., Kwok, C., Golden, K., Penberthy, S., Smith, D. E., et al. (1998). Pddl-the planning domain definition language.
- [Gibert et al., 2014] Gibert, G., Lance, F., Petit, M., Pointeau, G., and Dominey, P. F. (2014). Damping robot’s head movements affects human-robot interaction. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction*, pages 162–163. ACM.
- [Gibert et al., 2013] Gibert, G., Petit, M., Lance, F., Pointeau, G., and Dominey, P. F. (2013). What makes human so different? analysis of human-humanoid robot interaction with a super wizard of oz platform. In *International Conference on Intelligent Robots and Systems*.

- [Gibert et al., ] Gibert, G., Petit, M., Pointeau, G., and Dominey, P. Super wizard of oz technique to study human-robot interaction.
- [Gold et al., 2007] Gold, K., Doniec, M., and Scassellati, B. (2007). Learning grounded semantics with word trees : Prepositions and pronouns. In *Development and Learning, 2007. ICDL 2007. IEEE 6th International Conference on*, pages 25–30. IEEE.
- [Gold and Scassellati, 2006a] Gold, K. and Scassellati, B. (2006a). Grounded pronoun learning and pronoun reversal. In *Proceedings of the 5th International Conference on Development and Learning*.
- [Gold and Scassellati, 2006b] Gold, K. and Scassellati, B. (2006b). Learning acceptable windows of contingency. *Connection Science*, 18(2) :217–228.
- [Gold and Scassellati, 2006c] Gold, K. and Scassellati, B. (2006c). Using context and sensory data to learn first and second person pronouns. In *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction*, pages 110–117. ACM.
- [Gold and Scassellati, 2009] Gold, K. and Scassellati, B. (2009). Using probabilistic reasoning over time to self-recognize. *Robotics and autonomous systems*, 57(4) :384–392.
- [Gottlieb, 1997] Gottlieb, G. (1997). *Synthesizing nature–nurture : Prenatal roots of instinctive behavior*. Lawrence Erlbaum Associates Publishers.
- [Grabinger and Dunlap, 1995] Grabinger, R. S. and Dunlap, J. C. (1995). Rich environments for active learning : A definition. *Research in Learning Technology*, 3(2).
- [Gruendel and Nelson, 1986] Gruendel, J. and Nelson, K. (1986). *Event knowledge : Structure and function in development*. Lawrence Erlbaum Associates.
- [Gudjonsson and Pearse, 2011] Gudjonsson, G. H. and Pearse, J. (2011). Suspect interviews and false confessions. *Current Directions in Psychological Science*, 20(1) :33–37.
- [Hamann et al., 2011] Hamann, K., Warneken, F., Greenberg, J. R., and Tomasello, M. (2011). Collaboration encourages equal sharing in children but not in chimpanzees. *Nature*, 476(7360) :328–331.
- [Harlow, 1869] Harlow, J. M. (1869). *Recovery from the passage of an iron bar through the head*. Clapp.
- [Hayes-Roth, 1997] Hayes-Roth, F. (1997). Artificial intelligence : What works and what doesn't ? *AI Magazine*, 18(2) :99.
- [Heilman et al., 1975] Heilman, K., Scholes, R., and Watson, R. (1975). Auditory affective agnosia. disturbed comprehension of affective speech. *Journal of Neurology, Neurosurgery & Psychiatry*, 38(1) :69–72.
- [Helmert, 2009] Helmert, M. (2009). Concise finite-domain representations for pddl planning tasks. *Artificial Intelligence*, 173(5) :503–535.
- [Heyes, 1993] Heyes, C. M. (1993). Anecdotes, training, trapping and triangulating : do animals attribute mental states ? *Animal Behaviour*, 46(1) :177–188.
- [Hinault and Dominey, 2013] Hinault, X. and Dominey, P. F. (2013). Real-time parallel processing of grammatical structure in the fronto-striatal system : a recurrent network simulation study using reservoir computing. *PloS one*, 8(2) :e52946.
- [Hinault et al., 2014] Hinault, X., Petit, M., Pointeau, G., and Dominey, P. F. (2014). Exploring the acquisition and production of grammatical constructions through human-robot interaction with echo state networks. *Frontiers in neurorobotics*, 8.

- [Ho et al., 2009] Ho, W. C., Dautenhahn, K., Lim, M. Y., Vargas, P. A., Aylett, R., and Enz, S. (2009). An initial memory model for virtual and robot companions supporting migration and long-term interaction. In *Robot and Human Interactive Communication, 2009. RO-MAN 2009. The 18th IEEE International Symposium on*, pages 277–284. IEEE.
- [Imbens-Bailey and Pan, 1998] Imbens-Bailey, A. and Pan, B. A. (1998). Pragmatics of self-and other-reference in young children. *Social Development*, 7(2) :219–233.
- [Jackson, 1870] Jackson, J. B. S. (1870). *A descriptive catalogue of the Warren Anatomical Museum*. A. Williams.
- [Jouen et al., 2015] Jouen, A., Ellmore, T., Madden, C., Pallier, C., Dominey, P., and Ventre-Dominey, J. (2015). Beyond the word and image : characteristics of a common meaning system for language and vision revealed by functional and structural imaging. *NeuroImage*, 106 :72–85.
- [Kalkan et al., 2013] Kalkan, S., Dag, N., Yürüten, O., Borghi, A. M., and Sahin, E. (2013). Verb concepts from affordances. *Interaction Studies Journal*.
- [Kim et al., 2013] Kim, E. S., Berkovits, L. D., Bernier, E. P., Leyzberg, D., Shic, F., Paul, R., and Scassellati, B. (2013). Social robots as embedded reinforcers of social behavior in children with autism. *Journal of autism and developmental disorders*, 43(5) :1038–1049.
- [Klamt and Stelling, 2002] Klamt, S. and Stelling, J. (2002). Combinatorial complexity of pathway analysis in metabolic networks. *Molecular biology reports*, 29(1-2) :233–236.
- [Knowlton et al., 1996] Knowlton, B. J., Mangels, J. A., and Squire, L. R. (1996). A neostriatal habit learning system in humans. *Science*, 273(5280) :1399–1402.
- [Kolb, 2014] Kolb, D. A. (2014). *Experiential learning : Experience as the source of learning and development*. FT Press.
- [Lallée et al., 2010] Lallée, S., Madden, C., Hoen, M., and Dominey, P. F. (2010). Linking language with embodied and teleological representations of action for humanoid cognition. *Frontiers in neurorobotics*, 4.
- [Lallée et al., 2013] Lallée, S., Hamann, K., Steinwender, J., Warneken, F., Martienz, U., Barron-Gonzales, H., Pattacini, U., Gori, I., Petit, M., Metta, G., et al. (2013). Cooperative human robot interaction systems : Iv. communication of shared plans with naïve humans using gaze and speech. In *Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on*, pages 129–136. IEEE.
- [Lallée et al., 2010] Lallée, S., Lemaignan, S., Lenz, A., Melhuish, C., Natale, L., Skachek, S., van Der Zant, T., Warneken, F., and Dominey, P. F. (2010). Towards a platform-independent cooperative human-robot interaction system : I. perception. In *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on*, pages 4444–4451. IEEE.
- [Lallée et al., 2012] Lallée, S., Pattacini, U., Lemaignan, S., Lenz, A., Melhuish, C., Natale, L., Skachek, S., Hamann, K., Steinwender, J., Sisbot, E. A., et al. (2012). Towards a platform-independent cooperative human robot interaction system : Iii an architecture for learning and executing actions and shared plans. *Autonomous Mental Development, IEEE Transactions on*, 4(3) :239–253.
- [LeDoux, 1994] LeDoux, J. E. (1994). Emotion, memory and the brain. *Scientific American*, 270(6) :50–57.
- [Leslie, 1987] Leslie, A. M. (1987). Pretense and representation : The origins of” theory of mind.”. *Psychological review*, 94(4) :412.

- [Leslie, 1994] Leslie, A. M. (1994). Tomm, toby, and agency : Core architecture and domain specificity. *Mapping the mind : Domain specificity in cognition and culture*, pages 119–148.
- [Loftus et al., 1997] Loftus, E. F. et al. (1997). Creating false memories. *Scientific American*, 277(3) :70–75.
- [Lupien et al., 2005] Lupien, S. J., Fiocco, A., Wan, N., Maheu, F., Lord, C., Schramek, T., and Tu, M. T. (2005). Stress hormones and human memory function across the lifespan. *Psychoneuroendocrinology*, 30(3) :225–242.
- [Markov et al., 2013] Markov, N. T., Ercsey-Ravasz, M., Van Essen, D. C., Knoblauch, K., Toroczkai, Z., and Kennedy, H. (2013). Cortical high-density counterstream architectures. *Science*, 342(6158) :1238406.
- [Martin et al., 2008] Martin, R., Houssemand, C., Schiltz, C., Burnod, Y., and Alexandre, F. (2008). Is there continuity between categorical and coordinate spatial relations coding? : Evidence from a grid/no-grid working memory paradigm. *Neuropsychologia*, 46(2) :576–594.
- [McGaugh, 1989] McGaugh, J. L. (1989). Involvement of hormonal and neuromodulatory systems in the regulation of memory storage. *Annual review of neuroscience*, 12(1) :255–287.
- [McGaugh and Petrinovich, 1965] McGaugh, J. L. and Petrinovich, L. F. (1965). Effects of drugs on learning and memory. *International review of neurobiology*, 8 :139–196.
- [Meltzoff, 1995] Meltzoff, A. N. (1995). Understanding the intentions of others : re-enactment of intended acts by 18-month-old children. *Developmental psychology*, 31(5) :838.
- [Metta et al., 2006] Metta, G., Fitzpatrick, P., and Natale, L. (2006). Yarp : yet another robot platform. *International Journal on Advanced Robotics Systems*, 3(1) :43–48.
- [Metta et al., 2008] Metta, G., Sandini, G., Vernon, D., Natale, L., and Nori, F. (2008). The icub humanoid robot : an open platform for research in embodied cognition. In *Proceedings of the 8th workshop on performance metrics for intelligent systems*, pages 50–56. ACM.
- [Mirza et al., 2008] Mirza, N. A., Nehaniv, C. L., Dautenhahn, K., and te Boekhorst, R. (2008). Developing social action capabilities in a humanoid robot using an interaction history architecture. In *Humanoid Robots, 2008. Humanoids 2008. 8th IEEE-RAS International Conference on*, pages 609–616. IEEE.
- [Momjian, 2001] Momjian, B. (2001). *PostgreSQL : introduction and concepts*, volume 192. Addison-Wesley New York.
- [Moody et al., 2004] Moody, T. D., Bookheimer, S. Y., Vanek, Z., and Knowlton, B. J. (2004). An implicit learning task activates medial temporal lobe in patients with parkinson’s disease. *Behavioral neuroscience*, 118(2) :438.
- [Murray and Trevarthen, 1986] Murray, L. and Trevarthen, C. (1986). The infant’s role in mother–infant communications. *Journal of child language*, 13(01) :15–29.
- [Nadel and Moscovitch, 1997] Nadel, L. and Moscovitch, M. (1997). Memory consolidation, retrograde amnesia and the hippocampal complex. *Current opinion in neurobiology*, 7(2) :217–227.
- [Nancy Kanwisher, 1997] Nancy Kanwisher, Josh McDermott, M. M. C. (1997). The fusiform face area : a module in human extrastriate cortex specialized for face perception. *The Journal of Neuroscience*, 17(11) :4302–4311.
- [Neisser, 1967] Neisser, U. (1967). *Cognitive Psychology*. American Psychologist.

- [Neisser, 1976] Neisser, U. (1976). *Cognition and reality : Principles and implications of cognitive psychology*. WH Freeman/Times Books/Henry Holt & Co.
- [Neisser, 1988] Neisser, U. (1988). Five kinds of self-knowledge. *Philosophical psychology*, 1(1) :35–59.
- [Neisser, 1995] Neisser, U. (1995). Criteria for an ecological self.
- [Nelson, 2003a] Nelson, K. (2003a). Narrative and self, myth and memory : Emergence of the cultural self.
- [Nelson, 2003b] Nelson, K. (2003b). Self and social functions : Individual autobiographical memory and collective narrative. *Memory*, 11(2) :125–136.
- [Nelson, 2009] Nelson, K. (2009). *Young minds in social worlds : Experience, meaning, and memory*. Harvard University Press.
- [Nelson and Fivush, 2004] Nelson, K. and Fivush, R. (2004). The emergence of autobiographical memory : a social cultural developmental theory. *Psychological review*, 111(2) :486.
- [O’Reilly et al., 1999] O’Reilly, R. C., Braver, T. S., and Cohen, J. D. (1999). A biologically based computational model of working memory. *Models of working memory : Mechanisms of active maintenance and executive control*, page 375.
- [Oshima-Takane et al., 1999] Oshima-Takane, Y., Takane, Y., and Shultz, T. R. (1999). The learning of first and second person pronouns in english : network models and analysis. *Journal of Child Language*, 26(03) :545–575.
- [Owen et al., 1998] Owen, A. M., Doyon, J., Dagher, A., Sadikot, A., and Evans, A. C. (1998). Abnormal basal ganglia outflow in parkinson’s disease identified with pet. implications for higher cortical functions. *Brain*, 121(5) :949–965.
- [Oyama, 2000] Oyama, S. (2000). *Evolution’s eye : A systems view of the biology-culture divide*. Duke University Press.
- [Packard and McGaugh, 1996] Packard, M. G. and McGaugh, J. L. (1996). Inactivation of hippocampus or caudate nucleus with lidocaine differentially affects expression of place and response learning. *Neurobiology of learning and memory*, 65(1) :65–72.
- [Park et al., 1997] Park, D. C., Hertzog, C., Kidder, D. P., Morrell, R. W., and Mayhorn, C. B. (1997). Effect of age on event-based and time-based prospective memory. *Psychology and aging*, 12(2) :314.
- [Payne and Nadel, 2004] Payne, J. D. and Nadel, L. (2004). Sleep, dreams, and memory consolidation : the role of the stress hormone cortisol. *Learning & Memory*, 11(6) :671–678.
- [Penfield, 1938] Penfield, W. (1938). The cerebral cortex and consciousness.
- [Petit et al., 2013] Petit, M., Lallée, S., Boucher, J.-D., Pointeau, G., Cheminade, P., Ognibene, D., Chinellato, E., Pattacini, U., Gori, I., Martinez-Hernandez, U., et al. (2013). The coordinating role of language in real-time multimodal learning of cooperative tasks. *Autonomous Mental Development, IEEE Transactions on*, 5(1) :3–17.
- [Petit et al., ming] Petit, M., Pointeau, G., and Dominey, P. F. (“forthcoming”). Reasoning based on consolidated real world experience acquired by a humanoid robot. *Interaction Studies*.
- [Pfeifer et al., 2007] Pfeifer, R., Lungarella, M., and Iida, F. (2007). Self-organization, embodiment, and biologically inspired robotics. *science*, 318(5853) :1088–1093.

- [Piaget and et Niestlé, 1948] Piaget, J. and et Niestlé, D. (1948). La naissance de l'intelligence chez l'enfant.
- [Pointeau et al., 2013a] Pointeau, G., Petit, M., and Dominey, P. F. (2013a). Embodied simulation based on autobiographical memory. In *Biomimetic and Biohybrid Systems*, pages 240–250. Springer.
- [Pointeau et al., 2013b] Pointeau, G., Petit, M., and Dominey, P. F. (2013b). Robot learning rules of games by extraction of intrinsic properties. In *ACHI 2013, The Sixth International Conference on Advances in Computer-Human Interactions*, pages 109–116.
- [Pointeau et al., 2014a] Pointeau, G., Petit, M., and Dominey, P. F. (2014a). Successive Developmental Levels of Autobiographical Memory for Learning Through Social Interaction. *IEEE Transactions on Autonomous Mental Development*, 6(3) :200–212.
- [Pointeau et al., 2014b] Pointeau, G., Petit, M., Gibert, G., and Dominey, P. F. (2014b). Emergence of the use of pronouns and names in triadic human-robot spoken interaction. In *Development and Learning, 2014. ICDL 2014. IEEE 13th International Conference on*.
- [Poldrack et al., 2001] Poldrack, R. A., Clark, J., Pare-Blagoev, E., Shohamy, D., Moyano, J. C., Myers, C., and Gluck, M. (2001). Interactive memory systems in the human brain. *Nature*, 414(6863) :546–550.
- [Poldrack and Packard, 2003] Poldrack, R. A. and Packard, M. G. (2003). Competition among multiple memory systems : converging evidence from animal and human brain studies. *Neuropsychologia*, 41(3) :245–251.
- [Porter et al., 1999] Porter, S., Yuille, J. C., and Lehman, D. R. (1999). The nature of real, implanted, and fabricated memories for emotional childhood events : implications for the recovered memory debate. *Law and human behavior*, 23(5) :517.
- [Premack and Woodruff, 1978] Premack, D. and Woodruff, G. (1978). Does the chimpanzee have a theory of mind? *Behavioral and brain sciences*, 1(04) :515–526.
- [Prince, 2004] Prince, M. (2004). Does active learning work? a review of the research. *Journal of engineering education*, 93(3) :223–231.
- [Pylyshyn, 1978] Pylyshyn, Z. W. (1978). When is attribution of beliefs justified?[p&w]. *Behavioral and brain sciences*, 1(04) :592–593.
- [Querfurth and LaFerla, 2010] Querfurth, H. W. and LaFerla, F. M. (2010). Alzheimer's disease. *New England Journal of Medicine*, 362(4) :329–344. PMID : 20107219.
- [Rainville et al., 1997] Rainville, P., Duncan, G. H., Price, D. D., Carrier, B., and Bushnell, M. C. (1997). Pain affect encoded in human anterior cingulate but not somatosensory cortex. *Science*, 277(5328) :968–971.
- [Ribot, 1891] Ribot, T. (1891). *Les maladies de la mémoire*. G. Bailliere.
- [Robins et al., 2005] Robins, B., Dautenhahn, K., Te Boekhorst, R., and Billard, A. (2005). Robotic assistants in therapy and education of children with autism : can a small humanoid robot help encourage social interaction skills? *Universal Access in the Information Society*, 4(2) :105–120.
- [Robins et al., 2004] Robins, B., Dickerson, P., Stribling, P., and Dautenhahn, K. (2004). Robot-mediated joint attention in children with autism : A case study in robot-human interaction. *Interaction studies*, 5(2) :161–198.
- [Roy and Pentland, 2002] Roy, D. K. and Pentland, A. P. (2002). Learning words from sights and sounds : A computational model. *Cognitive science*, 26(1) :113–146.

- [Schacter et al., 2000] Schacter, D. L., Wagner, A. D., and Buckner, R. L. (2000). *Memory systems*. E. Tulving : The Oxford handbook of memory. Oxford University Press.
- [Shatz et al., 1983] Shatz, M., Wellman, H. M., and Silber, S. (1983). The acquisition of mental verbs : A systematic investigation of the first reference to mental state. *Cognition*, 14(3) :301–321.
- [Shaw and Porter, 2015] Shaw, J. and Porter, S. (2015). Constructing rich false memories of committing crime. *Psychological science*, page 0956797614562862.
- [Sherry and Schacter, 1987] Sherry, D. F. and Schacter, D. L. (1987). The evolution of multiple memory systems. *Psychological review*, 94(4) :439.
- [Shmuelof and Zohary, 2005] Shmuelof, L. and Zohary, E. (2005). Dissociation between ventral and dorsal fmri activation during object and action recognition. *Neuron*, 47(3) :457–470.
- [Shultz et al., 1994] Shultz, T. R., Buckingham, D., and Oshima-Takane, Y. (1994). 20 a connectionist model of the learning of personal pronouns in english.
- [Siegler, 1976] Siegler, R. S. (1976). Three aspects of cognitive development. *Cognitive psychology*, 8(4) :481–520.
- [Sisbot et al., 2007] Sisbot, E. A., Marin-Urias, L. F., Alami, R., and Simeon, T. (2007). A human aware mobile robot motion planner. *Robotics, IEEE Transactions on*, 23(5) :874–883.
- [Sodian, 1991] Sodian, B. (1991). The development of deception in young children. *British Journal of Developmental Psychology*, 9(1) :173–188.
- [Sodian and Frith, 1992] Sodian, B. and Frith, U. (1992). Deception and sabotage in autistic, retarded and normal children. *Journal of Child Psychology and Psychiatry*, 33(3) :591–605.
- [Sommerfield et al., 2003] Sommerfield, A. J., Deary, I. J., McAulay, V., and Frier, B. M. (2003). Moderate hypoglycemia impairs multiple memory functions in healthy adults. *Neuropsychology*, 17(1) :125.
- [Squire, 1992] Squire, L. (1992). Declarative and nondeclarative memory : Multiple brain systems supporting learning and memory. *Cognitive Neuroscience, Journal of*, 4(3) :232–243.
- [Squire, 2004] Squire, L. R. (2004). Memory systems of the brain : a brief history and current perspective. *Neurobiology of learning and memory*, 82(3) :171–177.
- [Squire and Zola, 1996] Squire, L. R. and Zola, S. M. (1996). Structure and function of declarative and nondeclarative memory systems. *Proceedings of the National Academy of Sciences*, 93(24) :13515–13522.
- [Steels and Kaplan, 2002] Steels, L. and Kaplan, F. (2002). Aibo’s first words : The social learning of language and meaning. *Evolution of communication*, 4(1) :3–32.
- [Sutton et al., 1998] Sutton, S., Cole, R. A., De Villiers, J., Schalkwyk, J., Vermeulen, P. J., Macon, M. W., Yan, Y., Kaiser, E. C., Rundle, B., Shobaki, K., et al. (1998). Universal speech tools : the csu toolkit. In *ICSLP*, volume 98, pages 3221–3224.
- [Takács and Demiris, 2008] Takács, B. and Demiris, Y. (2008). Balancing spectral clustering for segmenting spatio-temporal observations of multi-agent systems. In *Data Mining, 2008. ICDM’08. Eighth IEEE International Conference on*, pages 580–587. IEEE.
- [Tomasello, 2009] Tomasello, M. (2009). *The cultural origins of human cognition*. Harvard University Press.

- [Tomasello et al., 2005] Tomasello, M., Carpenter, M., Call, J., Behne, T., and Moll, H. (2005). Understanding and sharing intentions : The origins of cultural cognition. *Behavioral and brain sciences*, 28(05) :675–691.
- [Tranel et al., 1994] Tranel, D., Damasio, A. R., Damasio, H., and Brandt, J. P. (1994). Sensorimotor skill learning in amnesia : additional evidence for the neural basis of nondeclarative memory. *Learning & Memory*, 1(3) :165–179.
- [Tulving, 1972] Tulving, E. (1972). Episodic and semantic memory 1. *Organization of Memory*. London : Academic, 381 :e402.
- [Tulving, 1985] Tulving, E. (1985). Elements of episodic memory.
- [Tulving, 2002] Tulving, E. (2002). Episodic memory : from mind to brain. *Annual review of psychology*, 53(1) :1–25.
- [Tulving and Donaldson, 1972] Tulving, E. and Donaldson, W. (1972). Organization of memory.
- [Vernon et al., 2007] Vernon, D., Metta, G., and Sandini, G. (2007). A survey of artificial cognitive systems : Implications for the autonomous development of mental capabilities in computational agents. *Evolutionary Computation, IEEE Transactions on*, 11(2) :151–180.
- [Walker and Stickgold, 2014] Walker, M. P. and Stickgold, R. (2014). Sleep, memory and plasticity. *Neuroscience and Psychoanalysis*, 1 :93.
- [Warneken et al., 2006] Warneken, F., Chen, F., and Tomasello, M. (2006). Cooperative activities in young children and chimpanzees. *Child development*, 77(3) :640–663.
- [Warneken and Tomasello, 2007] Warneken, F. and Tomasello, M. (2007). Helping and cooperation at 14 months of age. *Infancy*, 11(3) :271–294.
- [Welke et al., 2013] Welke, K., Kaiser, P., Kozlov, A., Adermann, N., Asfour, T., Lewis, M., and Steedman, M. (2013). Grounded spatial symbols for task planning based on experience. In *13th International Conference on Humanoid Robots (Humanoids)*. IEEE/RAS.
- [Wells, 1981] Wells, G. (1981). *Learning Through Interaction : Volume 1 : The Study of Language Development*, volume 1. Cambridge University Press.
- [Wilson, 2002] Wilson, M. (2002). Six views of embodied cognition. *Psychonomic bulletin & review*, 9(4) :625–636.
- [Wimmer and Perner, 1983] Wimmer, H. and Perner, J. (1983). Beliefs about beliefs : Representation and constraining function of wrong beliefs in young children’s understanding of deception. *Cognition*, 13(1) :103–128.

## Appendices

Tableau 9.1: List of the arguments used in the sentences collected by the ABM.

Agent	Verb	Object	Adjective 1	Adjective 2
Carol	put	croco	south	slowly
Carol	put	mouse	east	slowly
You	put	croco	west	quickly
I	push	croco	north	quickly
I	put	croco	south	slowly
I	push	mouse	west	slowly
I	put	croco	north	quickly
I	put	croco	east	quickly
I	push	mouse	west	slowly
Carol	push	croco	north	slowly
Carol	put	croco	north	quickly
Carol	push	mouse	north	slowly
Carol	put	mouse	north	quickly
Carol	push	croco	north	quickly
Carol	push	croco	north	quickly
Carol	push	croco	south	quickly
Carol	push	croco	south	quickly
Carol	push	croco	west	quickly
Carol	push	croco	west	quickly
Carol	push	croco	east	quickly
Carol	push	croco	east	quickly
Carol	push	croco	west	slowly
Carol	push	croco	west	slowly
Carol	push	mouse	east	slowly
I	push	mouse	east	slowly
I	put	croco	west	slowly
I	put	croco	west	slowly
Carol	put	mouse	west	slowly
Carol	put	croco	north	slowly
Greg	put	croco	north	slowly
Greg	put	mouse	north	slowly
I	put	croco	east	slowly
Carol	put	mouse	east	slowly
Carol	put	croco	east	slowly
Carol	put	cube	south	slowly
Carol	put	croco	south	slowly
Carol	put	mouse	south	slowly
I	put	mouse	west	quickly
Carol	put	cube	west	quickly
Carol	put	croco	west	quickly

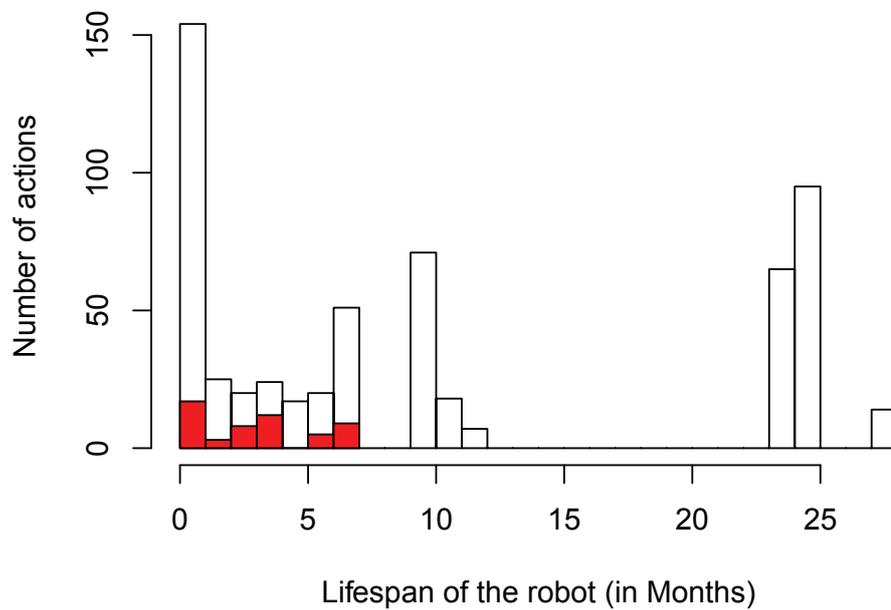
Continued on next page

Tableau 9.1 – continued from previous page

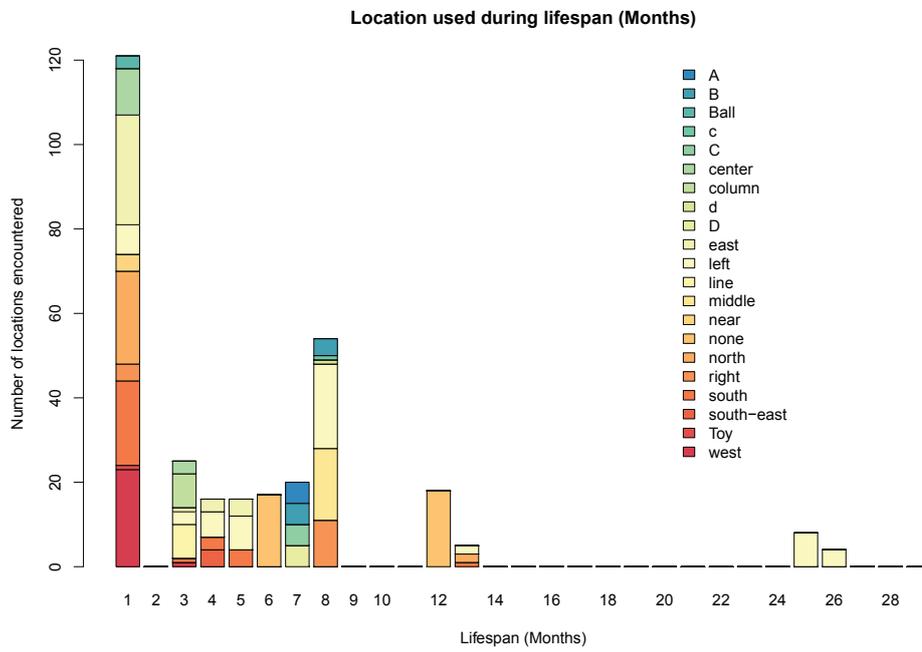
Agent	Verb	Object	Adjective 1	Adjective 2
Carol	put	mouse	north	quickly
Carol	put	cube	north	quickly
Carol	put	croco	north	quickly
Carol	put	cube	east	quickly
Carol	put	mouse	east	quickly
Greg	put	croco	east	quickly
Greg	put	croco	south	quickly
Carol	put	cube	south	quickly
Carol	put	mouse	south	quickly
Carol	put	cube	center	quickly
Greg	put	croco	center	quickly
Carol	put	mouse	center	quickly
Carol	put	mouse	center	quickly

### 9.1 Lifespan

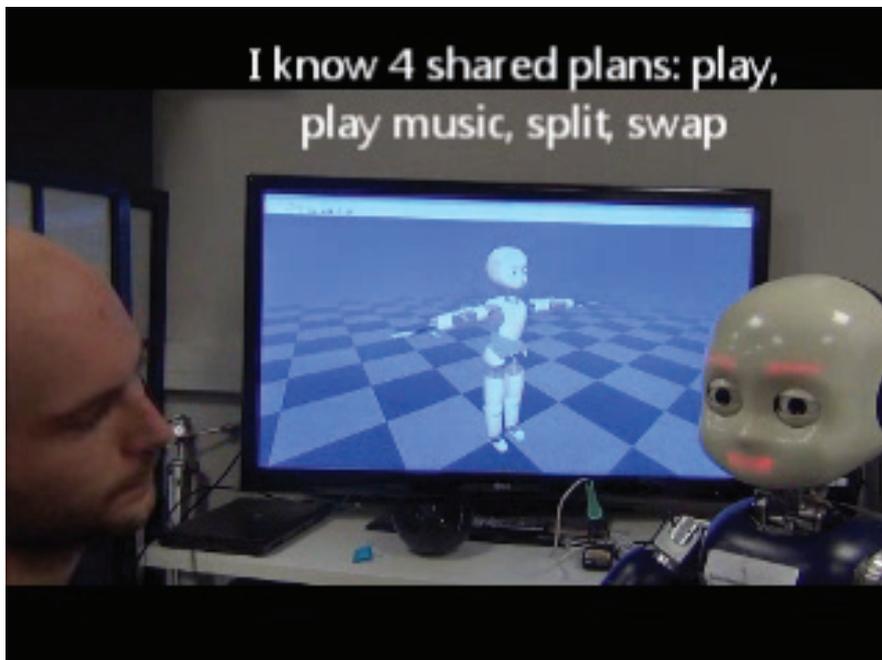
**Actions seen (white) or done (red) by the iCub**

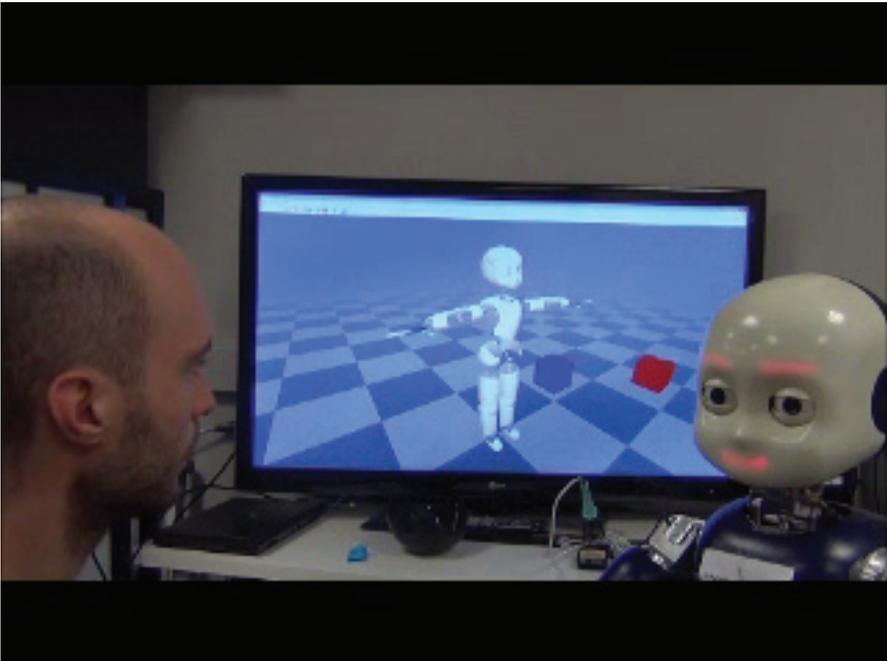
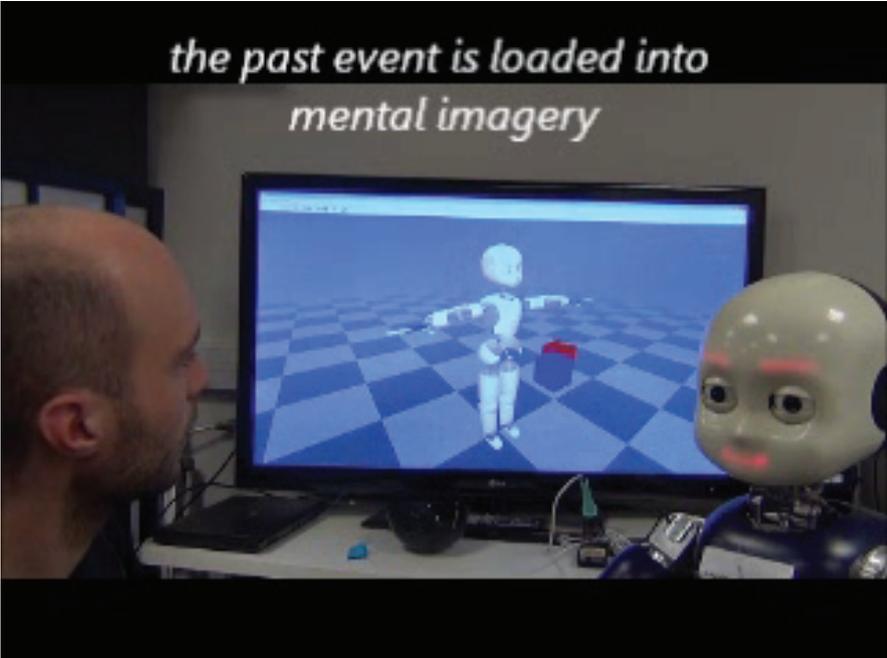


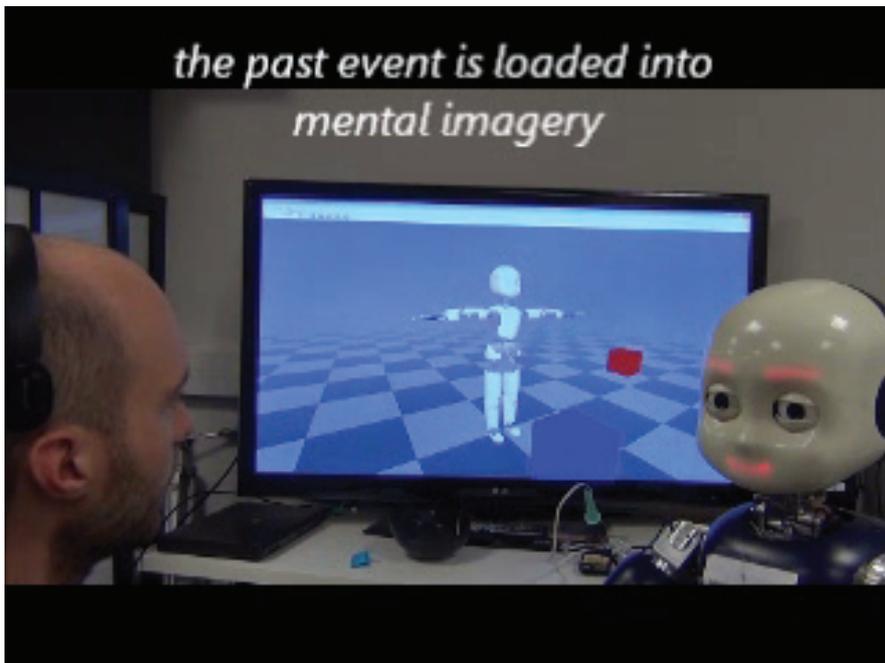
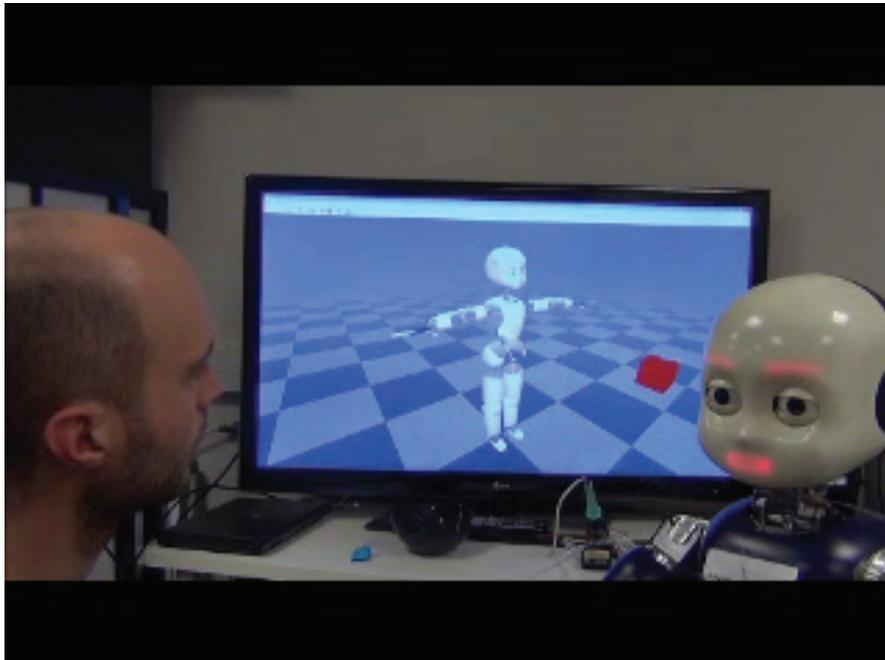


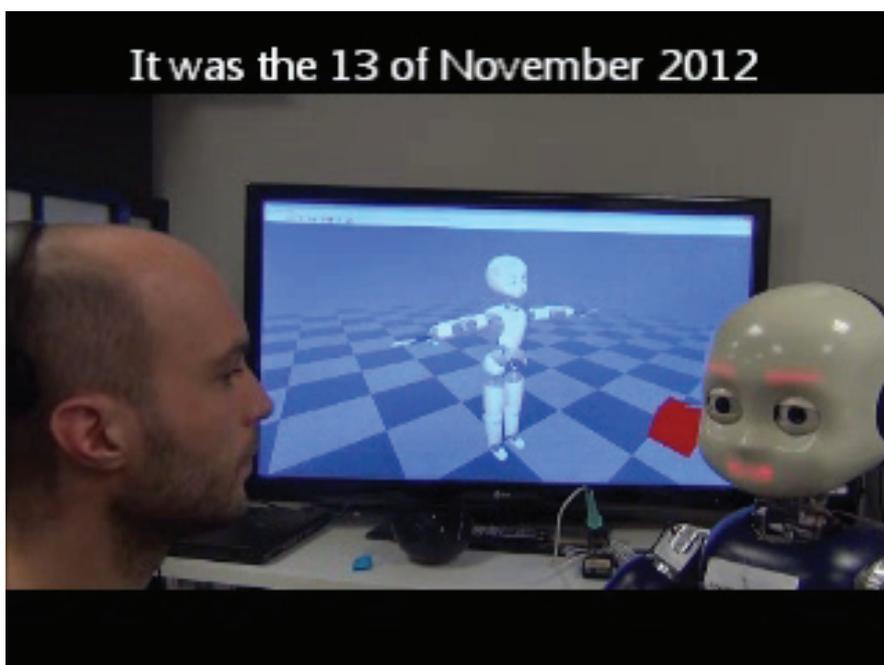
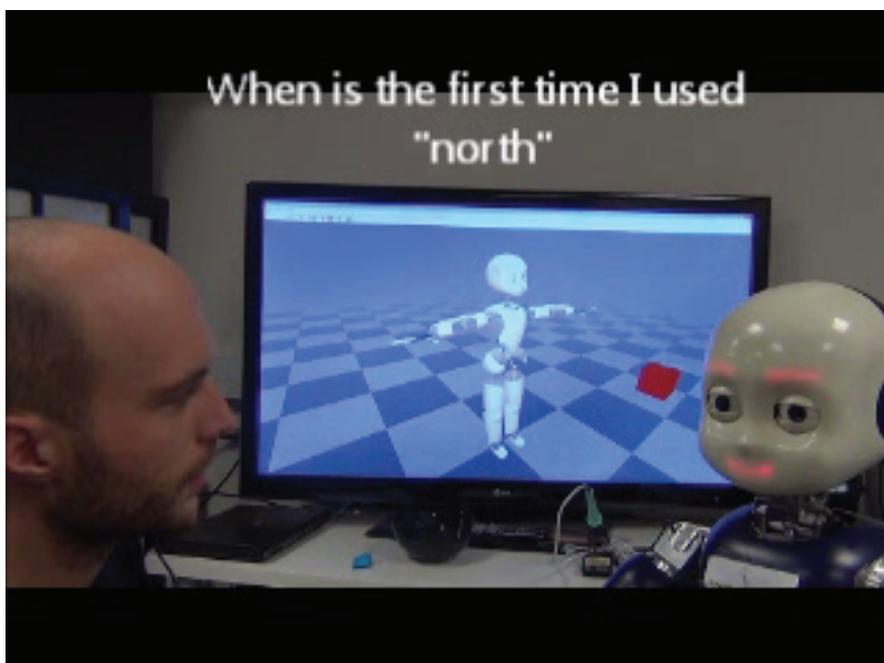


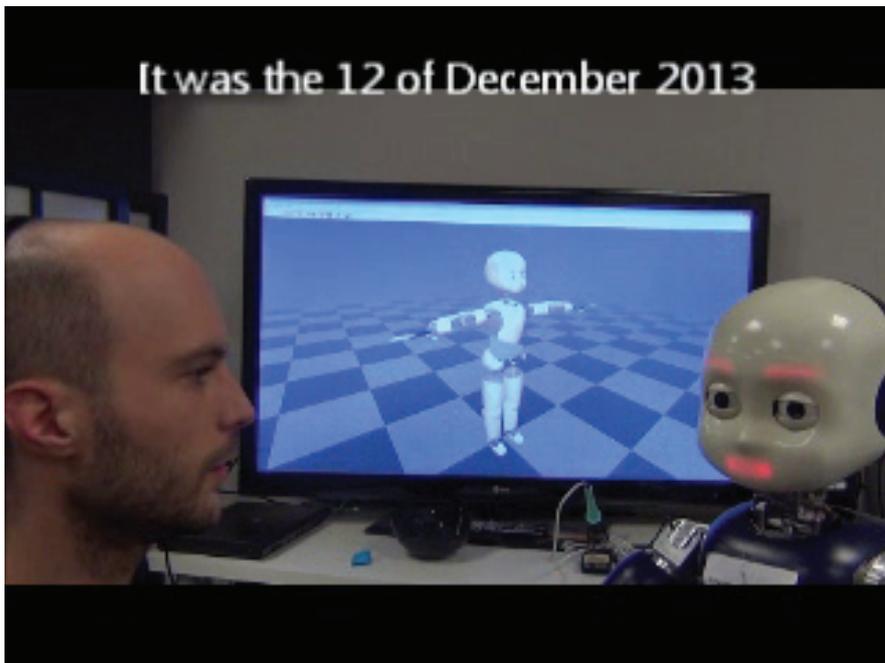
## 9.2 Video SABM











### 9.3 Published articles

#### 9.3.1 TADM : Successive Developmental Levels of Autobiographical Memory for Learning Through Social Interaction

Authors : **Pointeau, G.**, Petit, M., and Dominey, P. F.

Title : "Successive Developmental Levels of Autobiographical Memory for Learning Through Social Interaction."

Journal : IEEE Transactions on Autonomous Mental Development, 6(3) :200-212.

Year : 2014

# Successive Developmental Levels of Autobiographical Memory for Learning Through Social Interaction

Grégoire Pointeau, Maxime Petit, and Peter Ford Dominey

**Abstract**—A developing cognitive system will ideally acquire knowledge of its interaction in the world, and will be able to use that knowledge to construct a scaffolding for progressively structured levels of behavior. The current research implements and tests an autobiographical memory system by which a humanoid robot, the iCub, can accumulate its experience in interacting with humans, and extract regularities that characterize this experience. This knowledge is then used in order to form composite representations of common experiences. We first apply this to the development of knowledge of spatial locations, and relations between objects in space. We then demonstrate how this can be extended to temporal relations between events, including “before” and “after,” which structure the occurrence of events in time. In the system, after extended sessions of interaction with a human, the resulting accumulated experience is processed in an offline manner, in a form of consolidation, during which common elements of different experiences are generalized in order to generate new meanings. These learned meanings then form the basis for simple behaviors that, when encoded in the autobiographical memory, can form the basis for memories of shared experiences with the human, and which can then be reused as a form of game playing or shared plan execution.

**Index Terms**—Autobiographical memory, cooperation, development, interaction, learning, shared plans.

## I. INTRODUCTION

ONE of the principal arguments for developmental robotics is that certain types of behavior are perhaps better learned (adapted, acquired, and developed) than preprogrammed [1]. This applies particularly to situations in which the robot is expected to acquire knowledge about the world and how to perform in the world via interacting with humans. In robotic systems based on human-inspired robot task learning [2], significant attention has been allocated to the mechanisms that underlie the ability to acquire knowledge from and encode the individual’s accumulated experience [3], and to use this accumulated experience to adapt to novel situations [4]. In this context we consider research on autobiographical memory

(ABM) and mechanisms by which ABM can be used to generate new knowledge [5].

The objective of the current research is to demonstrate how an autobiographical memory system, coupled with mechanisms for detecting and extracting regularities, can be used to construct a progressive hierarchy of spatial, and temporal relations that provide the basis for learning and executing shared plans. A shared plan is a structured sequence of actions each of which is allocated to one of the multiple partners who are using this shared plan to achieve a shared goal. Our interest in shared plans is motivated by extensive developmental studies which indicate that such shared plans are at the heart of the human ability to cooperate [6], [7].

In order to most clearly describe the system and its operation, the rest of the paper is structured as follows: Section II describes the architecture. Section III describes the learning methods for extracting knowledge about space, time, actions and shared plans, and explains how this semantic knowledge is consolidated from experience encoded in the episodic memory. Section IV describes detailed demonstration examples with the data in the episodic and semantic memory. At the end of section IV we provide links to several video demonstrations. The paper concludes with the discussion in Section V.

## II. SYSTEM ARCHITECTURE

Here we present the architecture for a system that implements an autobiographical memory (ABM) and processes that operate on the contents of that memory in order to extract and render useful its inherent structure. The system is designed to allow face-to-face physical interaction between the iCub and the human, using the instrumented ReacTable for joint object manipulation. These interactions form the source for the contents of the ABM. The view of objects on the ReacTable, and the iCub, as seen from the perspective of the human user is illustrated in Fig. 1. An overview of the interaction between component elements of the system is provided in Fig. 2. Connectivity between the different functional modules is implemented in an interprocess communication protocol, YARP [8].

### A. Physical Robot Platform

The current work was performed on the iCubLyon01 at the INSERM Robot Cognition Laboratory in Lyon, France. The iCub is a 53 DOF humanoid platform developed within the EU consortium RobotCub. The iCub [9] is an open-source robotic platform with morphology approximating that of a 3 1/2 year-old child (about 104 cm tall), with 53 degrees of freedom distributed on the head, arms, hands and legs. The head has 6 degrees of

Manuscript received March 24, 2013; revised July 23, 2013; accepted February 18, 2014. Date of publication April 08, 2014; date of current version September 09, 2014. This work was supported by the European Commission under Grant EFAA (ICT-270490).

The authors are with the Robot Cognition Laboratory of the INSERM U846 Stem Cell and Brain Research Institute, Bron 69675, France (e-mail: Gregoire.pointeau@inserm.fr; maxime.petit@inserm.fr; peter.dominey@inserm.fr).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TAMD.2014.2307342

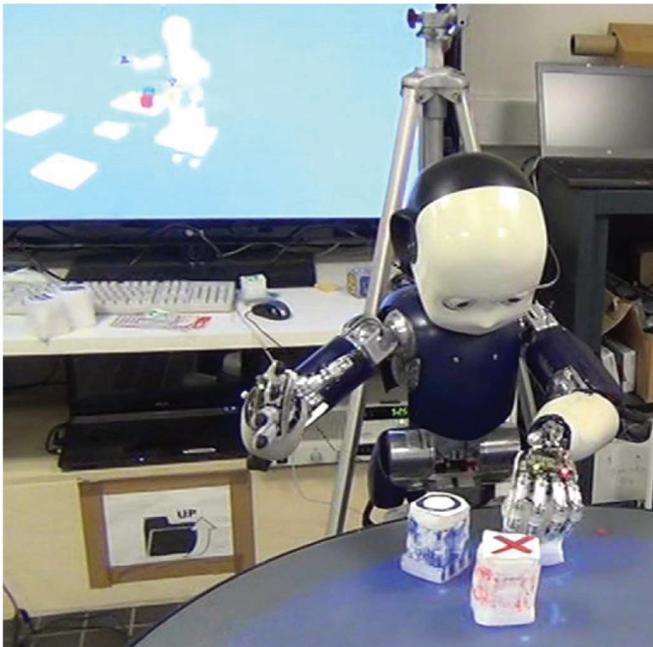


Fig. 1. iCub robot manipulating an object on the ReacTable, from the perspective of the human who is engaging in a face-to-face interaction with the robot. The screen behind displays the inner perception of the world of the robot.

freedom (roll, pan and tilt in the neck, tilt and independent pan in the eyes). Three degrees of freedom are allocated to the waist, and 6 to each leg (three, one, and two, respectively, for the hip, knee, and ankle). The arms have 7 degrees of freedom, three in the shoulder, one in the elbow and three in the wrist. The iCub has been specifically designed to study manipulation, for this reason the number of degrees of freedom of the hands has been maximized with respect to the constraint of the small size. The hands of the iCub have five fingers and 19 joints. Motor control is provided by a dynamic force field controller (DForC) [10] which performs inverse kinematics and spatially oriented actions including point-to, put, grasp, and release.

### B. Perceptual, Motor, and Interaction Capabilities

1) *ReacTable*: In the current research we extend the perceptual capabilities of the iCub with the ReacTable. The ReacTable has a translucent surface, with an infrared (IR) illumination beneath the table, and an IR camera that perceives tagged objects on the table surface with an accuracy of  $\sim 5$  mm. Thus, tagged objects can be placed on the table, and their location accurately captured by the IR camera.

Interaction with the external world requires that the robot is capable of identifying its spatial reference frame with the objects that it interacts with. In the human being, aspects of this functionality is carried out by the dorsal stream, involving areas in the posterior parietal cortex which subserve complex aspects of spatial perception [11]. In our system, the 2-D surface of the table is calibrated into the joint space of the iCub by a linear transformation calculated based on a sampling of four calibration points on the table surface that are pointed to by the iCub. Thus, four points are physically identified in the Cartesian space of the iCub, and on the surface of the ReacTable, thus providing the basis for calculation of a transformation matrix which allows

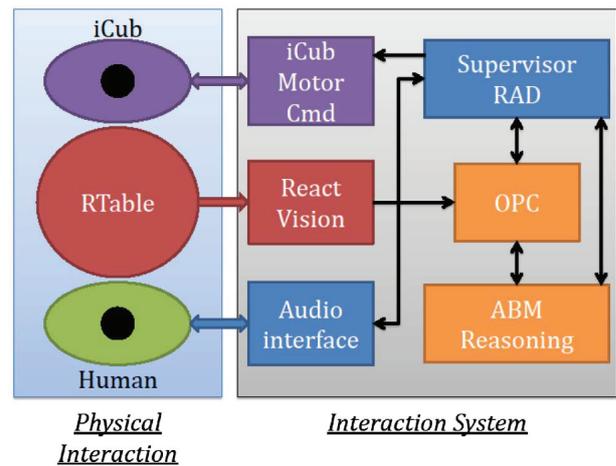


Fig. 2. System architecture overview. Human and iCub interact face-to-face across the ReacTable, which communicates object locations via ReactVision to the object property collector (OPC). The Supervisor coordinates spoken language and physical interaction with the iCub via spoken language technology in the Audio interface. The autobiographical memory system encodes world states and their transitions due to human and robot action as encoded in the OPC.

the projection of object coordinates in the space of the table into the Cartesian space of the iCub. These coordinates can then be used as spatial arguments to the DForC action system of the iCub, which provides basic physical actions including point-to ( $x, y, z$ ), put (source  $X, Y, Z$ ; target  $x, y, z$ ), grasp ( $x, y, z$ ), and release ( $x, y, z$ ).

2) *Supervisor*: The Supervisor provides the general management function for the human-robot interaction, via a state-based dialog management system. This allows the user to enter different interaction states related to teaching spatial, temporal primitives and shared plans. The Supervisor is implemented with the CSLU rapid application development (RAD) Toolkit [12], a state-based dialog system which combines state-of-the-art speech synthesis (*Festival*) and recognition (Sphinx-II) in a GUI programming environment. RAD allows scripting in the TCL language and permits easy and direct binding to the YARP domain, so that all access from the Supervisor with other modules in the architecture is via YARP.

The Supervisor is state based, such that by specific responses and commands from the user, the system can enter states for teaching new spatial and temporal primitives, specifying the shared plan, and finally, executing the shared plan during the cooperative task execution.

In the mixed-initiative interaction, the Supervisor asks the human what they will do together. This leads to the possible entry into different dialog states. Each state contains a grammar that allows the human to pronounce new sentences that have not previously been used (e.g., “I put the eraser on the left” during spatial interaction, “Before I put the toy north I put the trumpet west” during interaction related to temporal processing). The grammars process well-formed English sentences, and extract the appropriate arguments. Importantly, these grammars allow the human teacher the ability to specify completely new and unanticipated (by the programmer) definitions for locations, actions, temporal relations, and then use all these to specify unanticipated (by the programmer) shared plans built from these novel learned components.

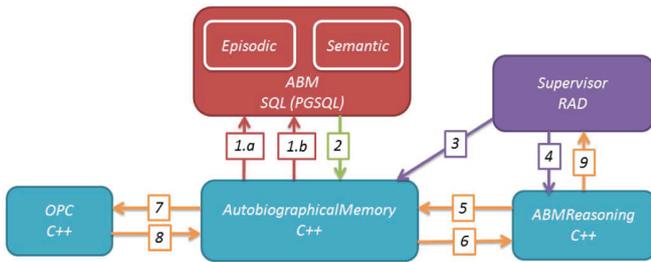


Fig. 3. Overview of the memory functioning including the ABM SQL Database, the Supervisor, the Reasoning module, and the OPC. This provides a partial zoom in on Fig. 2. 1-2. SQL queries, and replies to ABM are managed by a C++ Autobiographical Memory interface module. 3. User interacts with ABM related to action status, and 4. Memory content. 5-6. ABM reasoning requests and receives content via YARP connections. 7-8. ABM manager requests and receives state data from OPC. 9 Final response of ABM Reasoning to the supervisor.

3) *Object Properties Collector (OPC)*: The OPC is a real-time repository for all state information related to objects in the environment. Object position data from the ReacTable is formatted and stored in the OPC in a name referenced manner. The motor control level allows processing of commands like “put guitar left” by querying the OPC to determine the location of the guitar in iCub coordinates in order to perform the grasp action using DForC.

Likewise, spatial location names like “left” are stored as entities in the OPC with their coordinates generated and stored in the OPC based on statistical learning (described below).

C. *Autobiographical Memory (ABM) and Reasoning*

The organization of the ABM within the system is illustrated in Fig. 3. The purpose of the ABM is to encode the robot’s experience, including input from the human, actions performed by the human, actions performed by the robot itself, and the state of the world before and after such actions [13]. Reasoning mechanisms can then operate on this content, in order to extract regularities such as spatial location names, action plans etc. Functionally, the ABM [14] is composed of two memory subsystems as described by Tulving [15], an episodic-like memory, and a semantic memory. In terms of implementation the ABM content storage is managed by a PostgreSQL data base manager, and access requests are handled by the Autobiographical Memory C++ module.

1) *Episodic-Like Memory (ELM)*: When the Human performs an action, a message is sent to the ABM which saves the current state of the world for the robot (the current OPC) in the episodic memory in SQL. In the context of the interactions with the human the robot is informed at the beginning and at the end of each action. With the state of the OPC before and after an action, the robot can extract the preconditions and effects for that action [16]. The SQL structure of the ABM is illustrated in Fig. 4.

2) *Semantic Memory (SM) and Reasoning*: The SQL structure of the SM is illustrated in Fig. 5. The semantic memory is built from the contents of the ELM that have been processed by *ABM Reasoning*. *ABMReasoning* is coded in C++, and its

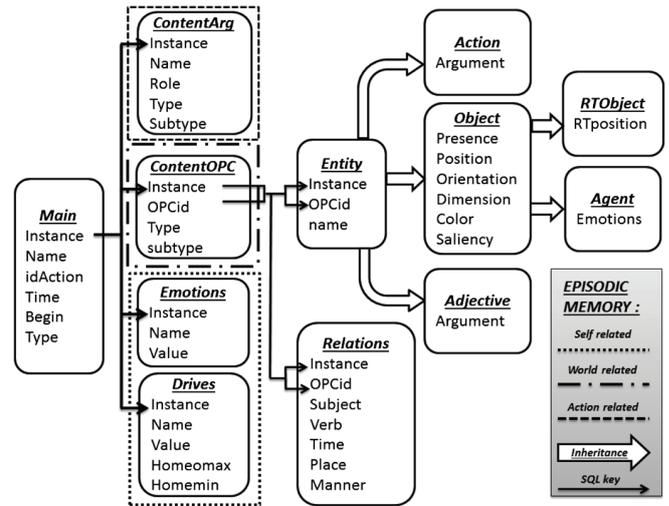


Fig. 4. Architecture of the episodic memory storage in PostgreSQL. The main data type is specified as ContentArg, ContentOPC. Each interaction has the content of the OPC at a given time (state of the world), but also, information concerning the context of the action (who, what, when...). The content of a memory can be divided in 3 sections: self-related, world-related, and action-related.

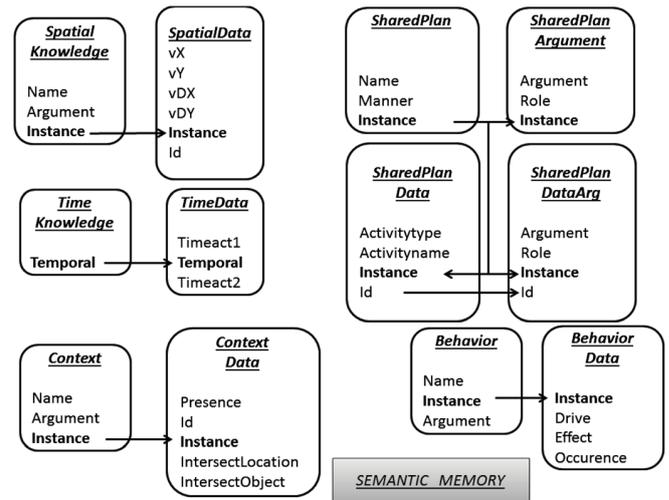


Fig. 5. Architecture of the semantic memory storage in PostgreSQL. For each type of knowledge, a first table stores the general information concerning the knowledge (name, argument...) while a second table stores the “technical information”: the positions of each move in the case of a spatial knowledge, or the time-stamp in the case of a temporal knowledge. Each Spatial Knowledge contains 2 vectors: the coordinates of the shift of the object of focus of the action, and the final state of the object of focus. Each Time Knowledge entry contains 2 vectors: the timestamps of the beginning of the action, and the timestamps of the end of the action.

role is to retrieve the information stored in the ELM and to generalize over this information, in order to extract the pertinent information of each action. The *ABMReasoning* Module thus constructs a Semantic Memory with the pertinent information related to context/spatial/temporal information, but also, related to the different shared plans known by the robot.

3) *Consolidation of Semantic Memory*: The robot will thus store individual memory elements in his episodic memory. However, each time the cognitive system is initialized, it must

recompute over the entire episodic memory to build the semantic memory, as outlined above. To avoid this reprocessing, we build and save the semantic memory in a manner similar to the way that the human does, based on consolidation. At the shutdown of the system, the robot will enter in a form of “dream” mode which is in reality a function of consolidation of his knowledge [17], [18]. During this mode, the robot will go through all his actions performed in the current session, and will generalize over this data, and consolidate the resulting semantic knowledge in the database. At the initialization of the system, the *ABM Reasoning* module will load the semantic knowledge that has been previously stored in the autobiographical memory through consolidation. Consolidation employs the learning capabilities described in section III.

### III. LEARNING CAPABILITIES

In order to adapt to novel situations a system must have memory of its experience, but this is not sufficient. The system must be able to extract regularities from specific cases, that can then be applied to the general case. The ELM thus provides a record of experience, and *ABM Reasoning* operates on the contents of the ELM to structure this information and create the SM. The *ABM Reasoning* module extracts spatial and temporal structure, and preconditions and effects of the actions that have been performed by the human and the robot. To do so actions are discriminated according to their “type.” We have thus:

- 1- action: a simple action involving one object, one agent and one argument (i.e.: “iCub put the toy north”). These actions will refer to spatial knowledge, and to contextual knowledge;
- 2- complex: a complex will be the addition of 2 actions with a temporal argument. (i.e.: before “action A,” “action B”), the temporal argument will be extracted and the robot will build his temporal knowledge;
- 3- shared Plan: a sequence of several actions or complex, with arguments including: agents and objects.

#### A. Learning Spatial Actions and Location Meanings

The understanding of spatial knowledge is based on spatial coordinate information coming from the ReacTable and stored in the OPC. With the ReacTable, the robot can have access to the exact position of an object before and after an action. We can thus extract final position and the relative move (i.e., the difference between the final position and the initial position).

1) *Learning*: A spatially oriented action will be determined with parameters including a *name* (i.e.: “put” or “push”) and a *spatial argument* (i.e.: “north” “east” “near”...). For each named action, *ABM Reasoning* will create a spatial knowledge entry (see Fig. 5). Each spatial knowledge entry will include the set of coordinates of the manipulated object before and after the action. From at least 3 occurrences of an action, the robot will calculate the distribution ellipse for the final location, and the relative movement. The robot will next compare the dispersion of each ellipse and will determine the property of interest (i.e.,

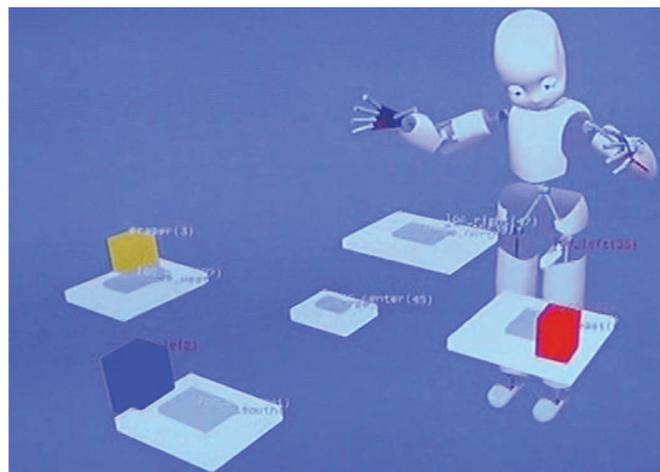


Fig. 6. Figure illustrating the internal representations of the learned positions for North, West, South, East, and Center as white rectangles in the robot’s peripersonal space. The colored objects are representations of objects on the ReacTable that have been placed at West (yellow), South (blue), and East (red), respectively.

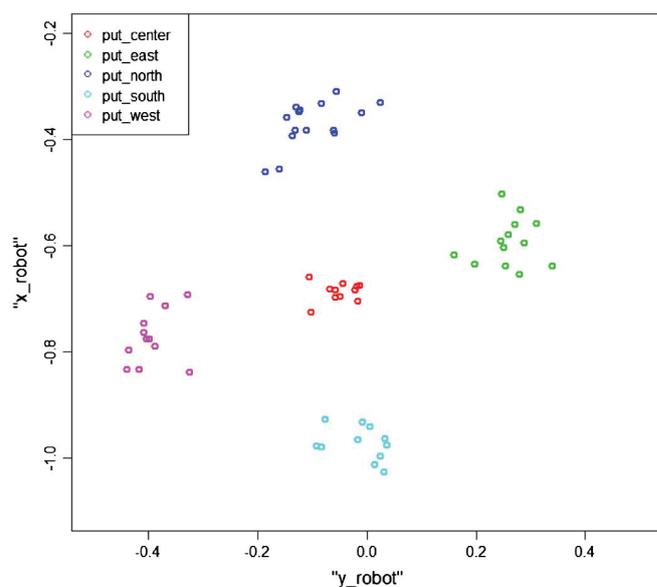


Fig. 7. Absolute spatial knowledge of the robot, after learning North, West, South, East, and Center in the context of the action “put.” The robot is centered in (0, 0) and looking to the south. We can see that the axes are not totally perpendicular, due to a bias in the orientation of the robot and the inherent coordinate axis of the table.

the property with minimal dispersion or variability) for the action. This dispersion score is given by the determinant of the covariance matrix of the scatter. For example in the case of a “put”, the important property that is discovered by this analysis is the final position of the object while in the case of a “push” the important property is the relative movement. Thus, the system automatically can determine whether a spatial property is an absolute final location, or a relative displacement vector. This distinction is illustrated in Figs. 6, 7, and 8.

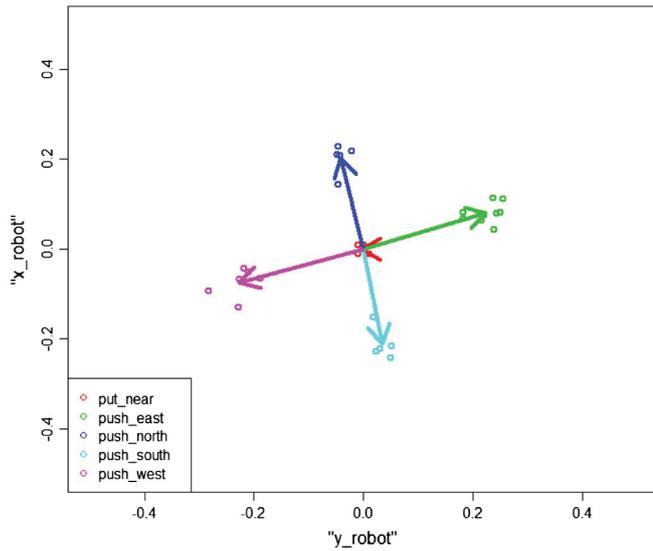


Fig. 8. Relative spatial knowledge of the robot after learning North, West, South, East, and Near, in the context of the action “push.” The vectors displayed are the relative movement needed to perform the corresponding action. In the case of the “put near,” the vector is null because the relative placement of the two objects has to be null.

#### Pseudo-code for Learning Spatial Actions and Locations

```

extract_spatial_regularities(ELM, SM){
  for each spatial action in the ELM
  {
    extract (x,y) coords of object before and after each
    case of this action
    calculate relative displacement of the object
    update absolute and relative coords in SM
    calculate the dispersion of the absolute final position
    and relative displacements
    if dispersion final position  $\approx 0$ 
      then {action is absolute
            update location definition in OPC
          }
    elseif dispersion displacement  $\approx 0$ 
      then action is relative
      update action definition in SM
  }
}

```

*ABM Reasoning* will iterate through all its spatial Knowledge as indicated in the pseudocode above. For actions in which the property of interest which is the final state, the system will learn the corresponding absolute location. The *ABM Reasoning* will then insert this location in the OPC. The ellipse of the property of interest will become the “mental representation” of the robot for that location. This is illustrated in Fig. 6.

In the case where there is more than one spatial argument, especially when the second spatial argument is another object (for example: “put the toy near the cross”) the *ABM Reasoning* will take the distance between the 2 objects before and after the action. We can thus extract relative locations such as: “near” “above” “under.”

This method thus allows the system to learn spatial actions with final position or relative movements. Once such an action is learned, the robot can execute the action: either with the final location of the object in case of an absolute move, or with the vector shift in the case of a relative action.

Once the *ABM Reasoning* has determined if the pertinent property of a move is its final absolute position or its relative movement, it can use this information to extract locations and actions.

2) *Action Discrimination*: Once the *ABM Reasoning* has built the spatial knowledge in the SM from the data stored in the ELM, the system can use this knowledge to discriminate new actions performed by the Human. For example, did the human make an action directed towards a fixed location, or was it a relative movement? To determine this, for each move that the robot has to discriminate, the *ABM Reasoning* extracts the position of the object of focus before and after the action. The *ABM Reasoning* then for each candidate spatial-knowledge calculates the Mahalanobis distance to the scatter of interest. The Mahalanobis distance permits one to check the distance of a point to an ellipse according to the dispersion of the ellipse. The Mahalanobis distance ( $D$ ) is given by the following formula:

$$D_M(x) = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)} \quad (1)$$

where  $x$  is the position of the point (either the final state, or the relative movement) of the move which we want to discriminate.  $\Sigma$  is the covariance matrix of the scatter of the spatial knowledge we want to compare to, and  $\mu$  is its mean.

*ABM Reasoning* thus obtains  $N$  different Mahalanobis distances, where  $N$  is the number of spatialKnowledge elements that the robot knows, as indicated in the pseudocode above. *ABM Reasoning* ranks all the possible actions according to their Mahalanobis distance, and finally calculates a score of confidence given by the ratio of the two smaller distances. If this score is low (close to 1), this means that the robot cannot discriminate with precision between at least 2 different actions. If the score is high (superior to a confidence threshold i.e.: 5), the robot can discriminate with confidence the move it just observed.

#### Simplified Pseudo-code for Spatial Action Discrimination

```

Discriminate_action(focus_object){
  for each spatialKnowledge in SM
  {
    Calc Mahalanobis distance (MD) between the focus
    object (final or shift) and spatialKnowledge (final or
    shift)
    if MD < minMD
      {
        confidence = minMD/MD
        minMD = MD
        recognized_spatial_action = spatialKnowledge
      }
  }
  return(recognized_spatial_action, confidence)
}

```

Based on learned spatial knowledge, the robot can now discriminate between spatially oriented actions such as push and put. In action recognition mode, the human will indicate the object of focus, e.g., “Watch the circle” and will then perform the move. As described, the system will iterate through the different spatial actions to determine that which has the lowest Mahalanobis with the target action, and return that as the recognized action.

### B. Learning Temporal Relation Meanings

The learning of temporal knowledge is similar to the learning of spatial knowledge, with one important distinction. We implemented an a-priori consideration related to the distinction between space and time. If the human produces a description that refers to a single event, then we assume that the domain of interest is space. If multiple events are concerned then we assume that the domain of interest is the temporal relation between those events. This is intuitive, as a single action cannot have an effect of time, but only on the context and the spatial position of the objects. The Human will announce the complex action he wants to teach in the following form:

(Temporal Argument, Action A, Action B)

For example: “*Before I put the circle to the left, I push the cross to the north*”. The human will then perform the two actions in the correct order he wants to teach. The robot will first discriminate the two actions it observes (as just described), and then compare the difference of time of execution  $\Delta T$  which corresponds to the time of the execution of the Action B minus the time of the execution of the Action A. For the case of a temporal relation such as “after,” the *ABM Reasoning* will have  $\Delta T < 0$ , and in the case of “before,” the *ABM Reasoning* will have  $\Delta T > 0$ . The *ABM Reasoning* calculates for each temporal argument encountered the mean  $\Delta T$ . Generally the sign is enough, but the robot can determine if there was a pause between the 2 actions. In this manner the system can acquire knowledge of temporal terms including “before” and “after”.

This processing is summarized in the pseudo-code below.

#### Pseudo-code for Learning Temporal Relation

```
extract_temporal_regularities(ELM, SM){
  for each temporal relation in the ELM
  {
    extract timestamps for each of the two actions
    populate Timeact1 and Timeact2 vectors in SM
    calculate  $\Delta T$  between Timeact1 and Timeact2
    update temporal definition in SM
  }
}
```

Once several examples of the same form (e.g., “*Before I put the toy north, I put the trumpet West*”) the system will encode that the second action in the statement actually occurs first in time, that is, the  $\Delta T$  is negative. This knowledge can then be used in execution, and in recognition.

### C. Learning Shared Plans

As stated above, a shared plan is a plan that includes actions that will be performed by the robot and the human as part of

a structured cooperative activity [19], [20]. To teach a shared plan “swap,” the human initially specifies “*You and I will swap the ball and the toy.*” This specifies the name of the plan, swap, and the arguments (which are recognized as known objects and agents.) The human will enumerate the corresponding actions: “*I put the ball center. You put the toy left. I put the ball right.*” The system automatically matches the arguments of the initial specification with the arguments of the component actions. This way, the system can generalize over these arguments. Thus, the shared plan “swap” for 2 objects can be generalized at several levels. A generalization can be made at the level of the agents (any agent can be involved in a swap), and the objects (swapping an eraser and a box, in the same way as for a ball and a toy).

1) *Learning*: During the learning, the Human will first explain the plan and the arguments used for the plan (agents, objects, arguments), then he will according to the plan ask the robot to perform an action, or perform it himself, until the end of the plan. Then the Human will announce the end of the shared plan. The iCub will then generalize each action according to the role of each argument, and store in the ABM the list of actions to perform with which argument. For example the plan “swap–ball – toy–iCub – Human” will be saved by name as:

```
Swap(Agent1, Agent2, Object1, Object2) {
  Default: Object1 = Ball,
  Object2 = Toy, Agent1 = iCub,
  Agent2 = Human
  PUT (Agent2, Object1, Center)
  PUT (Agent1, Object2, Left)
  PUT (Agent2, Object1, Right) }
```

2) *Execution and Generalization*: When the Human asks the robot to execute a shared plan, he can give the robot specific arguments or not. In the case where the Human gives arguments to the iCub in the command to execute a shared plan, the robot will execute the actions of the shared plan, mapping the arguments onto the parameters of the plan. In the case where the Human doesn’t provide arguments, the iCub will use by default the arguments used the first time it learned the shared plan.

If the human now says “*You and Maxime swap the eraser and the guitar,*” the speech recognition in the Supervisor will extract the following mappings:  $\$shared_{plan} = \text{swap}$ ,  $\$Agent1 = \text{robot}$ ,  $\$Agent2 = \text{Maxime}$ ,  $\$Object1 = \text{eraser}$ ,  $\$Object2 = \text{guitar}$ . It will then invoke the Swap plan with these arguments.

The shared plan is thus a function with multiple arguments, constructed of multiple actions that take different combinations of these arguments. Because of this function based definition, the shared plan can be used to execute behaviors beyond those that were previously learned, by applying the function with new arguments.

### D. Contextual Knowledge

Contextual knowledge refers to the context or state of the world before, and after an action has taken place (e.g.: “The toy is present”, “The ball is on the west”). The same kind of training examples that are used for learning spatial concepts are also used here, but instead of storing the position, the iCub will store the contextual information: e.g., “*Is the object present before?*” (pre-condition) “*Is the object present after?*” (effect).

The system will extract properties of each action. For the action “put,” the object has to be present before the action, and will be present after the action. For the action “remove” the object has to be present initially, and will not be present after the action. For the action “add” the object has to initially not be present, and will then be present after the action. This information can be used in goal based reasoning, and in allowing the system to determine if a requested action can be performed.

#### E. Knowledge Consolidation Function (KCF)

In consolidation, the robot will iterate through the new contents of its episodic memory and update the semantic memory in the autobiographical memory using the learning capabilities described above that generate spatial, temporal, and conceptual knowledge. The robot will replay all of the episodic memory in its internal representation. In order to allow generalization, the KCF will systematically replace the objects of focus by neutral objects. For example for the learning of the spatial primitives, the object of focus will always be a neutral object. The KCF can then extract the regular properties for named spatial and temporal primitives using the methods described in the pseudo-code above. The robot will also build and display during this time the learned locations (e.g., *East*, *West*, etc. as illustrated in Fig. 6.) and we can see the evolution of these locations (size, confidence, orientation) during the chronological restitution of the memories. During the KCF the robot will also consolidate knowledge that can’t be displayed, including temporal knowledge, contextual knowledge, and shared plans.

The interest of this consolidation function is to extract regularities from specific examples in the ABM so that they are available for generalization to new examples, thus taking the form of a semantic memory [17], and to do this in a way that saves this information for future use. For example, for the spatial-knowledge, the robot will directly have the coordinates of all the points of the ellipses needed for each learned spatial location. When we start the system, the iCub will have access to all the semantic knowledge previously consolidated from its experience. If during the current session the robot acquires new knowledge, it will be able to use this knowledge, but only while the system is running. In order to retain this knowledge for the future, the acquired knowledge must be consolidated and saved to the semantic memory.

The system functions in real-time. The only process that has any noticeable delay is the consolidation, which is performed incrementally, at the end of each interaction session. The construction of the semantic memory is thus a cumulative and iterative process that lasts between 1 and 2 second per action (or roughly 5 minutes for a ELM of 300 interactions), depending of the capabilities of the computer.

## IV. DEMONSTRATION EXAMPLES

Here we provide details on the functioning of the different algorithms with specific examples. These examples are taken from interactions that have occurred over the lifespan of the robot encoded in the ABM system. The first entry in the ELM was November 13, 2012. At the time of submission, the ELM contained 470 main entries; with 235 interactions, and over 15 000 entries in the SQL contentOPC table. The SM contained

TABLE I  
ELM CONTENTS (SEE FIG. 4) FOR A “PUT CROSS NORTH” ACTION, BEFORE THE ACTION

<b>instance</b>	423
<b>time</b>	2013-02-11 16:19:07
<b>activityname</b>	put
<b>activitytype</b>	action
<b>begin</b>	true
<b>agent1</b>	Greg
<b>object1</b>	cross
<b>spatial1</b>	north
<b>cross_position</b>	{-0.937498,0.21317 }

TABLE II  
ELM CONTENTS FOR A “PUT CROSS NORTH” ACTION, AFTER THE ACTION

<b>instance</b>	424
<b>Time</b>	2013-02-11 16:19:14
<b>activityname</b>	put
<b>activitytype</b>	action
<b>begin</b>	false
<b>agent1</b>	Greg
<b>object1</b>	cross
<b>spatial1</b>	north
<b>cross_position</b>	{-0.383123,0.110094 }

27 actions (contextual knowledge), 6 shared plans, 25 spatial knowledge and 2 temporal knowledge entries.

#### A. Spatial Knowledge: “put north” and “push east”

1) *Learning*: We will now observe how the system will learn two separate actions: “put north” and “push east”. The Human announces the action that he will demonstrate to the robot, e.g., “I put the cross to the north” or “I push the circle to the east.” The *ABM Reasoning* first extracts the position of the object of focus before and after the demonstrated action. The data contained in the ELM SQL tables for a “put\_north” are illustrated in Table I.

*ABM Reasoning* then computes the changes between before and after the move, yielding the coordinates of the final state and the shift in position:

- final position (x,y): -0.383123, 0.110094;
- shift (x,y): 0.554375, -0.103076.

*ABM Reasoning* then inserts this data into the shift and final state vectors in the spatial knowledge table of the SM for put\_north. For these two example cases, we respectively performed 8 “put north” and 8 “push east” actions. The contents of the SM representation for the 8 repetitions of “put north” is represented in Table III. A demonstration of spatial learning is provided in a video in section IV.E.

2) *Action Discrimination*: With the 8 values of each move, the *ABM Reasoning* is now able to calculate the covariance of each set of data. Based on the determinant of each matrix, the *ABM Reasoning* can determine the dispersion of each ellipse. We can see in Fig. 9 that the dispersion of the relative move in the case of a “put\_north” is bigger than the dispersion of the final state. The important property of a “put\_north” is thus

TABLE III

: SM CONTENTS (SEE FIG. 5). COORDINATES OF THE FINAL STATES AND THE SHIFTS OF OBJECT DURING THE ACTION "PUT\_NORTH". THE DETERMINANT CORRESPONDS TO THE DETERMINANT OF THE ASSOCIATED MATRIX COVARIANCE. THE BOLD TEXT (-0.38 ... ETC) CORRESPONDS TO THE VALUES EXTRACTED FROM ELM, ILLUSTRATED IN TABLE II

PUT NORTH			
Final state		Shift	
X	Y	$\Delta X$	$\Delta Y$
-0.461489	0.185575	0.267147	0.224226
-0.349934	0.010019	0.637937	-0.281065
-0.34734	0.123795	0.352484	0.407423
<b>-0.383123</b>	<b>0.110094</b>	<b>0.554375</b>	<b>-0.103076</b>
-0.38296	0.060517	0.023641	-0.089278
-0.339428	0.129931	0.505289	0.051755
-0.38695	0.059239	0.229395	0.218771
-0.343506	0.123458	0.583222	0.260215
Covariance Matrix		Covariance Matrix	
0.00162852	-0.00092534	0.04507017	-0.01121819
-0.00092534	0.00296477	-0.0112189	0.0532542
Determinant		Determinant	
3.971919e-06		0.002274329	

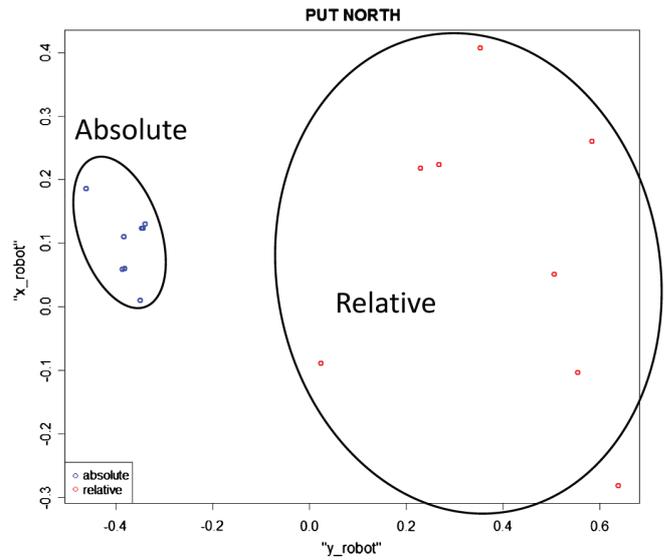


Fig. 9. Distribution of the relative and absolute characterization of a set of "put\_north" actions. In blue is the final position in the referential of the iCub of the object in the case of a "put\_north". The red dots correspond to the displacement of the object in the case of a "put\_north".

TABLE 4

: SM CONTENTS. COORDINATES OF THE FINAL STATES AND THE SHIFTS OF OBJECT DURING THE ACTION "PUSH\_EAST". THE DETERMINANT CORRESPONDS TO THE DETERMINANT OF THE COVARIANCE MATRIX ASSOCIATE

PUSH EAST			
Final state		Shift	
X	Y	$\Delta X$	$\Delta Y$
-0.387384	0.028732	0.081009	-0.243392
-0.749191	0.137393	0.112633	-0.254916
-0.860451	-0.146369	0.081287	-0.249699
-0.466151	-0.178792	0.043383	-0.238239
-0.899213	-0.171303	0.064635	-0.215064
-0.580631	-0.187402	0.114414	-0.236762
-0.604645	-0.152004	0.076452	-0.219622
-0.605602	-0.156417	0.069063	-0.182481
Covariance Matrix		Covariance Matrix	
0.032510078	0.001789776	0.000565710	-0.00022413
0.001789776	0.014258656	-0.00022413	0.000555806
Determinant		Determinant	
0.0004603467		2.641897e-07	

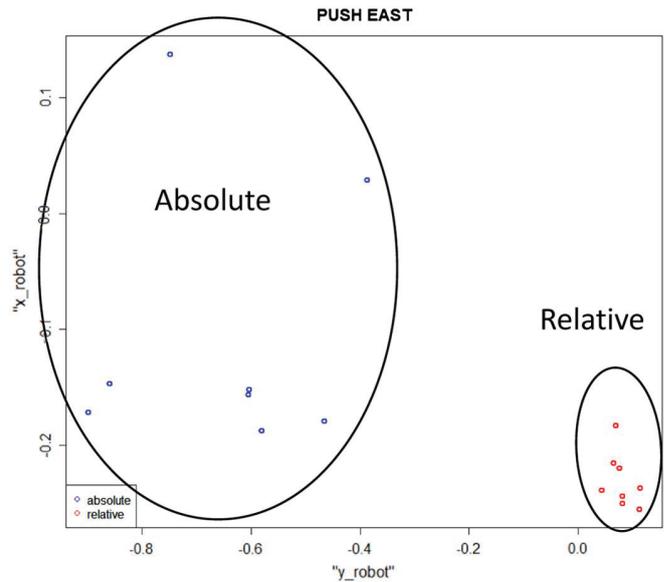


Fig. 10. Distribution of the relative and absolute move of a "push\_east". In blue is the final position in the referential of the iCub of the object in the case of a "push\_east". The red dots correspond to the displacement of the object in the case of a "push\_east".

the final state, and not the relative move. In the case of the "push\_east", the opposite effect is observed in Fig. 10.

Now, we want the robot to determine the type of two unknown actions. We thus present a "put\_north" and a "push\_east" and test whether the system can make the correct discrimination.

The (x,y) coordinates for the two moves are:

Move 1:

- Origin: (-0.485323; 0.336908);
- End: (-0.332629; 0.082922);
- Relative Shift: (0.152694; -0.253986).

Move2:

- Origin: (-0.6746665, 0.026064);
- End: (-0.605602, -0.156417);
- Relative Shift: (0.0690645, -0.1824810).

The *ABM Reasoning* will now calculate the Mahalanobis distance of each new move to the respective clusters. To recognize "put\_north" the *ABM Reasoning* will calculate the Mahalanobis distance from the End position of the movement (X,Y) to the ellipse of the Final states (X,Y), while for "push\_east" the *ABM Reasoning* will calculate the Mahalanobis distance from the Relative Shift of the movement ( $\Delta X, \Delta Y$  and  $\Delta X, \Delta Y$ ).

We obtain the following Mahalanobis distances:

- 185. • Move1 to "put\_north": 1.084648;
- Move1 to "push\_east": 9.296242;
- Move2 to "put\_north": 94.61302;
- Move2 to "push\_east": 4.196914.

According to these results, and looking for the interpretations with minimal Mahalanobis distances, we can clearly determine that Move1 is a “put\_north” and Move2 is a “push\_east.” This demonstrates how movements can be identified based on the spatial characteristics of their displacement and final position.

### B. Temporal Knowledge: “before”

1) *Learning*: Here we demonstrate how we can teach the robot the notion of “before”. In order to do this, we first explain to the robot the two actions that the Human will perform, using the term to be learned “before”. In our case: “*Before I put the circle to the north, I push the cross to the east*”. Then for each action the Human will announce the object of focus, and then perform the action. For this example will we obtain: “*Watch the cross*”–Human pushes the cross east–“*Watch the circle*”–Human puts the circle north. The *ABM Reasoning* will discriminate the two actions and retrieve the absolute time of each action. The time stamps are the following:

- “Action1: put–circle–north: 15:48:50”;
- “Action2: push–cross–east: 15:48:32.”

After subtraction of the two timers, the *ABM Reasoning* can determine that the difference of timer value of Action2–Action1 is negative. This is the important property of the temporal “before”.

2) *Execution*: Once the robot has learned the concept of “before” or “after.” we can ask it to execute a complex action using these terms. We will ask the robot the following sentence: “*Before you push the cross to the south, I put the circle to the west*”. The *ABM Reasoning* will extract the 2 actions with the corresponding arguments and the temporal argument:

- Action1: “iCub–push–cross–south”;
- Action2: “Human–put–circle–west”;
- Temporal: before.

Once the *ABM Reasoning* has obtained this information it can return the answer which will be the list of action to execute in the proper order:

- human put circle west: absolute (-0.77072; 0.393074);
- iCub push cross south: relative (-0.21070; -0.034001).

This information can now be used by DForC to perform the action. The robot will wait for the human to perform the put action. When this is detected, the robot will then perform its push action.

### C. Shared Plan: “swap”

1) *Learning*: We now want the robot to learn a shared plan and to generalize it. To illustrate, we will teach the plan “swap”. The concept is the following: there are two objects in opposite location on the table (west and east) and we want to swap them. The Human announces the full shared plan: “*You and I swap the cross and the circle*”. Then, the human has two choices:

- explain the full plan;
- explain action by action.

In the first case, the Human will announce: “*I put the cross center; then you put the circle west, then I push the cross east*”. In the second case the human will simply announce the object of focus and execute an action, or ask only one action to the robot, and repeat this until the plan has been specified. In this second case, the human has to specify the end of the shared plan, as a teacher would do for a student.

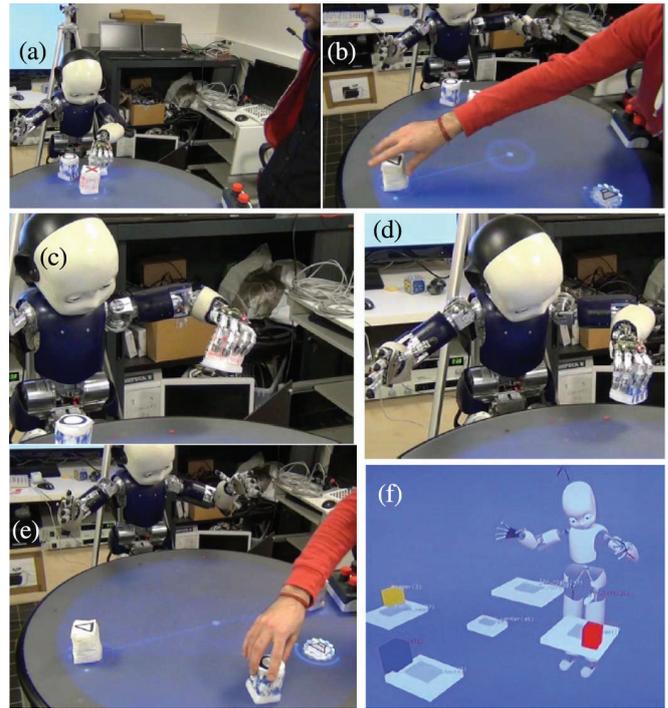


Fig. 11. Different steps of the iCub during the execution of a shared plan for the music game. A. Initial configuration of 3 elements. Robot places object 1 north. B. Human takes this object and places it west. C. Robot places object 2 North, for the human, who then puts it East (not shown). D. Robot places final object north. E. Human takes object and places it South. F. Final internal representation of objects on ReacTable to produce the song as the joint goal of the shared plan.

The *ABM Reasoning* will extract the role of each argument (for example: Human = Agent1; iCub = Agent2; cross = object1; circle = object2 ...) and build a shared plan according to these roles:

1. Agent1–put–Object1–center;
2. Agent2–put–Object2–west;
3. Agent1–push–Object1–east.

2) *Execution and generalization*: Consider that now we want to execute a swap, but with the iCub acting first, and with two other objects: “toy” and “drum”, and also we want to change the agents. We will announce the following plan: “*Peter and you swap the toy and the crocodile*”. The iCub will extract the role of each argument and build the following plan:

1. iCub–put–toy–center;
2. Peter–put–crocodile–west;
3. iCub–push–toy–east.

The iCub will then build the corresponding actions with the coordinates of the moves for DForC and the acting module.

### D. Shared Plan: “Cooperative musical plan”

It is important to note that the shared plan learning capability allows for the learning of an arbitrary number and variety of shared plans.

1) *Learning*: In this example we will focus on a more complex and cooperative goal. We said earlier that the *ReacTable* is a tool developed initially for musical entertainment. Each object corresponds to a different sound or auditory function, and a particular configuration of objects on the table will correspond to a particular music form. In this example we create an interactive

plan with the iCub passing the objects to the Human, one after the other, to the north of the table, where the Human can reach them. The Human will then place them at the appropriate locations on the *ReacTable* in order to generate the desired musical configuration.

The plan is taught by the human announcing the sequence of actions to the robot. As described above, the system generates a shared plan in the same way as for the shared plan “*swap*”. The resulting shared plan is presented below. A demonstration of learning such a plan is provided in the video in section IV.E.2.

```
music(Agent1, Agent2, Object1, Object2, Object3) {
  Default: Object1 = Drum,
  Object2 = Guitar, Object3 = Keyboard,
  Agent1 = Human, Agent2 = iCub
  put (Agent1, Object1, North)
  put (Agent2, Object1, South)
  put (Agent1, Object2, North)
  put (Agent2, Object2, West)
  put (Agent1, Object3, North)
  put (Agent2, Object1, East)
}
```

2) *Execution and Generalization*: Fig. 9 illustrates successive steps in the execution of this shared plan, after the human announces “*you and I play music game.*” As stated, the robot can generalize this shared plan in two distinct ways: First, the agents can be changed—the plan could be executed with any pair of known agents. Second, the objects that are used in the shared plan can be changed, so the human could say “*You and I play music with the keyboard, the eraser and the triangle.*” The system will map keyboard, eraser and triangle onto Object1, Object2 and Object3 arguments in the shared plan definition. Demonstration of the execution of such a shared plan is provided in the video in Section IV-E.3.

#### E. Video Demonstrations

In order to illustrate the functioning of the system, we include here links to demonstrations of: 1) learning a spatial location; 2) learning a shared plan; and 3) executing the shared plan.

1) *Learning Spatial Location “south-west”*.: In this demonstration, we observe the human interacting with the robot, and we see the contents of the OPC in real-time on the GUI. As the human demonstrates actions directed to this location, we see the formation of the representation of this location, based on the learning mechanisms described in Section III-A.

<http://youtu.be/AYjciXmIAxY>

2) *Learning a Shared Plan with Two Agents and Two Objects*: In this demonstration, we observe the human demonstrating a new shared plan to the robot, based on the learning mechanisms described in Section III-C.

<http://youtu.be/GhlKHPZZn30>

3) *Executing a Shared Plan with Two Agents and Two Objects*: In this demonstration, we observe the human requesting the robot to perform the new shared plan using different arguments than those used in teaching. This demonstrates the capability to generalize a shared plan to new objects.

<http://youtu.be/eFeD-2S-V7M>

## V. DISCUSSION

Robots that will interact with humans in novel environments must be prepared to adapt to new contexts. This will require the structured use of memory acquired over the lifespan [21]. In this research, we have demonstrated the construction of a system for the acquisition and synthesis of memory of experience, partially inspired by aspects of the architecture of human memory. The path of the storage of information follows that for human memory as described by Tulving [22]. First in an episodic-like memory described as a “autobiographical stream” by Battaglia *et al.*[23], and then a semantic memory that is built or consolidated from the episodic-like memory.

Episodic memory is about specific events in time, whereas semantic memory includes the memory necessary for the use of language including the meaning of words [15]. Interestingly, in building a system that can make use of its memory, we have “rediscovered” or “reinvented” aspects of this distinction in human memory systems first proposed by Tulving. That is, the system must have a veridical record of its experience (the episodic memory) then a “digested” version of this information that has been refined and formatted so that it can be used for perception and action in new situations, and can be communicated about with language (the semantic memory).

The current research is novel for two reasons. First, it demonstrates how an autobiographical memory can be used to store specific perceptual episodes, and how these can be used in order to generate categorical representations of space, time and action. This is the first robotic implementation of a combined episodic and semantic memory system. This is significant because it allows robots to learn from their experience, and it also can help to provide insight into the processes necessary for infants to make the transition from perceptual to conceptual representations [24], as we make the transition from episodic to semantic memory. The second significant contribution is that we then demonstrate how these learned action concepts can be further structured into more temporally extended interaction scenarios, in the form of shared plans. Together, this means that the system is entirely open ended—it allows the robot to learn new spatio-temporal primitives, and then allows it to structure these interaction primitives into cooperative plans, so that through this learning, the robot can acquire arbitrary new tasks (within its physical capabilities).

Indeed, it is impossible for the system to store every possible internal representation and to associate it with an action output. Therefore, the system must be capable of generalization. We have demonstrated this generalization at multiple levels. First, in terms of spatial locations, the system learns both absolute positions, as well as relative displacements. These spatial notions can generalize over all manipulable objects. The system can thus recognize a previously unseen object–location pair, and perform previously unlearned object location actions (e.g. “*put the triangle north*”). Likewise, the system can learn temporal relations between actions, and use this temporal relational knowledge to recognize these relations between actions, and also to perform new actions based on these temporal relations. This generalization capability extends up to the shared plans that are learned.

Once the human has taught the robot the “swap” plan, the robot can then apply this plan to objects that were not used in the teaching. Thus, via generalization, the system can accommodate an open set of possible states that had not been experienced in training.

In terms of performance evaluation, we have demonstrated that the system is capable of learning a diverse set of spatial locations, and relative displacements. In parallel, the system has learned that the action “*put*” is associated with absolute locations, whereas the action “*push*” is associated with relative displacement vectors. The system has also learned temporal relations including before and after. Once these spatio-temporal primitives have been acquired, the system is then able to combine them into novel cooperative action sequences including a swapping procedure, and a “music game”. This evaluation allows us to confirm the open ended learning capabilities of the system, and its ability to transform the perceptual experience of the robot into exploitable knowledge. Future studies will evaluate the robustness of the system in more extended user studies.

One of the perceived limitations of the current work is the relatively reduced environment and the apparent simplicity of the concepts that are being learned. However, while the spatial relations that we examine (absolute positions and relative displacements) are fairly simple, they allow for increasing complexity in two distinct manners. From a developmental perspective, children learn spatial relations in a perceptually anchored manner, so that at 6–7 months, spatial relations are specific to the objects they are learned with. Later, by 9–10 months, children begin to generalize over objects [24]. In our system, the consolidation of experience from multiple examples allows the system to develop representations that generalize over objects. Thus, while these relations may be simple, they generalize, and they allow the system to develop a rich vocabulary of spatial knowledge. The second way in which these simple relations allow for increasing complexity, is that they provide the basis for representing actions that can be combined into more elaborate ways, by using learned temporal relations like before and after, and in shared action plans, which allow for the coordination of action between the human and the robot. Thus, the learned primitives may be relatively simple, but they can be used to build up rich and complex behavior.

One might argue that because our environment is relatively simple, the system may fail to scale to more complex environments. This raises general issues about learnability. In our system, as for the child, the role of the teacher in structuring information for the robot is crucial. Previous research has demonstrated how indeed, the way that actions are demonstrated to children tends to emphasize the initial and final states [25]. More generally, based on the organization of joint experience around the objects of shared interest, we argue that even in a richer environment, these mechanisms of joint attention will eliminate the construction of irrelevant associations [26].

In the context of assessing our work in the framework of autonomous mental development (AMD), we can consider a set of possible gaps or challenges between this work and true AMD. Here we pose these challenges, and our position.

- (a) Challenge: The protocols of interactions are handcrafted, e.g., consisting of speech-based instructions where the meanings of each sentence are known to the programmer. Response: No—the language interactions employ a grammar that allows the user to create new sentences that are not handcrafted. These new sentences cannot be known to the programmer of the system, and they contribute to the open flexibility of the system. The grammar is prespecified. We have developed methods for learning grammars in a usage-based manner [27], [28], and such systems should be integrated into an AMD approach.
- (b) Challenge: Each of the displacements is marked by speech instructions whose meanings are known to the programmer. Response: No—none of the meanings of the spatial action terms are known to the programmer. It is the user who will determine the meaning of locations, displacements and actions. However, the instructions that allow the user to initiate and terminate the demonstration are built into the interaction grammar. Again, ideally even these would be learned from experience.
- (c) Challenge: Each task consists of a sequence of displacement segments. Response: In the current “world” of interaction, the tasks are performed on the ReacTable, and involve the movement of objects by the human and the robot. We are currently extending this to include a more extended environment through the use of vision and 3D perception.
- (d) Challenge: The start and end of task sequence are marked by speech instructions whose meanings are known to the programmer. Response: Yes, as stated above, language is used to provide segmentation information to the system. Future work will incorporate more autonomous methods including temporal and spatial grouping [29].
- (e) Challenge: It is assumed that there is no error in the recognition of all the speech commands. Otherwise, consolidation is mixed up. Response: No—there can be errors in the demonstrations. The consolidation is based on a statistical processing in which the errors will be dominated by correct demonstrations.
- (f) Challenge: The role of human and robot in each displacement of the plan sequence is specified by speech commands whose meanings are known to the programmer. Response. No - The individual commands, like “put” or “push” that will make up the plan sequence must first be learned. They are known to the human teacher—who teaches them to the robot, but they are not known (they cannot be known) by the programmer. However, understanding of language related to the specification of who does what, using “I” and “you”, is built-in by the programmer. Future work will address the robot learning of the perspectival use of “I” and “you” [30].
- (g) Challenge: The training phase and the performance phase need to be switched by instructions to enter different program modes.

Response: Yes. Future research should address how training and performance become intermingled, as the robot gracefully determines when it has sufficient ability to make the transition to performance without specific instruction. We have made progress in this automatic learning in [31]

- (h) Challenge: The consolidation is offline in a separate operation phase.

Response: No—consolidation also occurs online, but for the consolidation results to be written permanently into the semantic memory requires the offline processing.

- (i) Challenge: The semantic memory corresponds to the classification of displacements and/or sequences where each class is specified by the human teacher.

Response: No - The semantic memory contains information about spatial locations and displacements, actions (including pre and postconditions), and temporal relation that are *demonstrated* by the human teacher. So what is specified by the teacher is the physical demonstration of the action, location etc., accompanied by a name for the demonstrated element. The semantic content of the demonstrated location, action, etc. is extracted by the system from the *perceptual information*. Interestingly, the use of word labels to invite the child to form new categories has been demonstrated in children [32], [33]. We will further investigate this symbiosis between development of language and development of the conceptual system.

- (j) Challenge: The learned sensory input consists of a pair of 2-D coordinates plus a known object label, so the system does not do or learn object recognition in terms of type, shape, size, orientation, etc.

Response: Yes—in this research, the system does not learn about the physical properties of objects. This is a limitation of the use of the ReacTable where gain in spatial accuracy versus perceptual richness. Future research will employ a richer perceptual domain.

Overall, the current research represents part of a series of developments that gradually steps towards true AMD. Several lines of research will take us in this direction. Importantly, we must address how language and the conceptual system codevelop, including how the structure of language can influence the structure of the conceptual system. A first step in this direction has been characterized by Waxman [32], [33], who sees that words are an invitation to the infant to form categories [related to points (a) and (f)]. This has recently been exploited in the context of AMD [34]. We must improve the richness of the perceptual system, including vision, so that the system has access to the rich structure in the surrounding world [see points (c) and (j)], and we must consider how the inherent structure of spatio-temporal action can be used for the segmentation of distinct actions (d).

When situating this work in the context of AMD, two distinctions must be made. The first concerns how humans - the programmer and the teacher - are involved in the system. The programmer has created an interaction infrastructure (coordinated

by the Supervisor program), and an autobiographical memory system. The human teacher (who is referred to simply as the human) uses the interaction infrastructure to communicate new knowledge to the system. This results in the population of the episodic memory. The second distinction has to do with segmentation and consolidation. The segmentation of interactions is partially constrained by the interaction system, and so we can consider that it is not fully autonomous. This must be addressed, related to point (g). Where we have concentrated on autonomy is in the consolidation of knowledge to create the semantic memory, and the hierarchical use of knowledge at one level to be integrated at the next, which allows the system to acquire new meanings, new behaviors and new cooperative interactions with the human, none of which were known to the programmer.

#### ACKNOWLEDGMENT

The authors would like to thank U. Pattacini and I. Gori from the IIT for the development of the DForC reach and grasp controllers and IIT for extensive help and support with the iCub. They would also like to thank S. Hidot for his advice in the statistical analysis.

#### REFERENCES

- [1] M. Asada *et al.*, "Cognitive developmental robotics: A Survey," *IEEE Trans. Auton. Mental Develop.*, vol. 1, no. 1, p. 22, May 2009.
- [2] X. Wu and J. Kofman, "Human-inspired robot task learning from human teaching," presented at the IEEE Int. Conf. Robot. Autom. (ICRA 2008), 2008, IEEE.
- [3] F. Broz *et al.*, "Learning behavior for a social interaction game with a childlike humanoid robot," presented at the Social Learn. Interactive Scenarios Workshop, 2009, Humanoids.
- [4] G. Pointeau, M. Petit, and P. F. Dominey, "Robot learning rules of games by extraction of intrinsic properties," presented at the ACHI 2013 6th Int. Conf. Adv. Computer-Human Interact., 2013.
- [5] M. A. Conway and C. W. Pleydell-Pearce, "The construction of autobiographical memories in the self-memory system," *Psychol. Rev.*, vol. 107, no. 2, pp. 261–88, 2000.
- [6] K. Hamann *et al.*, "Collaboration encourages equal sharing in children but not in chimpanzees," *Nature*, vol. 476, no. 7360, pp. 328–31, 2011.
- [7] M. Tomasello *et al.*, "Understanding and sharing intentions: The origins of cultural cognition," *Behav. Brain Sci.*, vol. 28, no. 05, pp. 675–691, 2005.
- [8] G. Metta, P. Fitzpatrick, and L. Natale, "YARP: Yet another robot platform," *Int. J. Adv. Robot. Syst.*, vol. 3, no. 1, pp. 43–48, 2006.
- [9] G. Metta *et al.*, "The iCub humanoid robot: An open platform for research in embodied cognition," presented at the PerMIS: Perform. Metrics for Intell. Syst. Workshop, Washington, DC, USA, 2008.
- [10] I. Gori *et al.*, "DForC: a Real-Time Method for Reaching, Tracking and Obstacle Avoidance in Humanoid Robots".
- [11] L. Shmuelof and E. Zohary, "Dissociation between ventral and dorsal fMRI activation during object and action recognition," *Neuron*, vol. 47, no. 3, pp. 457–470, 2005.
- [12] S. Sutton *et al.*, "Universal speech tools: The CSLU toolkit," presented at the 5th Int. Conf. Spoken Language Process., 1998.
- [13] D. Stachowicz and G. Kruijff, "Episodic-like memory for cognitive robots," *IEEE Trans. Auton. Mental Develop.*, vol. 4, no. 1, pp. 1–16, Mar. 2012.
- [14] F. Ruini *et al.*, "Towards a bio-inspired cognitive architecture for short-term memory in humanoid robots," *Adv. Auton. Robot.*, pp. 453–454, 2012.
- [15] E. Tulving, "Episodic and semantic memory," in *Organization of Memory*, E. Tulving and W. Donaldson, Eds. New York, NY, USA: Academic Press, 1972, pp. 381–402.
- [16] N. A. Mirza, "Developing social action capabilities in a humanoid robot using an interaction history architecture," presented at the 8th IEEE-RAS Int. Conf. Humanoid Robots, 2008.

- [17] M. G. Frank and J. H. Benington, "The role of sleep in memory consolidation and brain plasticity: Dream or reality?," *The Neuroscientist*, vol. 12, no. 6, pp. 477–488, 2006.
- [18] J. D. Payne and L. Nadel, "Sleep, dreams, and memory consolidation: The role of the stress hormone cortisol," *Learn. Memory*, vol. 11, no. 6, pp. 671–678, 2004.
- [19] M. Petit *et al.*, "The coordinating role of language in real-time multimodal learning of cooperative tasks," *IEEE Trans. Autonom. Mental Develop.*, vol. 5, no. 1, pp. 3–17, Mar. 2013.
- [20] S. Lallée *et al.*, "Towards a platform-independent cooperative human-robot interaction system: III. An architecture for learning and executing actions and shared plans," *IEEE Trans. Autonom. Mental Develop.*, vol. 4, no. 3, pp. 239–253, Sep. 2012.
- [21] R. Wood, P. Baxter, and T. Belpaeme, "A review of long-term memory in natural and synthetic systems," *Adapt. Behav.*, vol. 20, no. 2, pp. 81–103, 2012.
- [22] E. Tulving, "Concepts of memory," *The Oxford Handbook of Memory*, pp. 33–43, 2000.
- [23] F. P. Battaglia and C. M. Pennartz, "The construction of semantic memory: Grammar-based representations learned from relational episodic information," *Frontiers Comput. Neurosci.*, vol. 5, 2011.
- [24] P. C. Quinn, "Concepts are not just for objects: Categorization of spatial relation information by infants," in *Early Category and Concept Development: Making Sense of the Blooming, Buzzing Confusion*, D. H. Rakison and L. M. Oakes, Eds. London, U.K.: Oxford Univ. Press, 2003, pp. 50–76.
- [25] Y. Nagai and K. J. Rohlfing, "Computational analysis of motionese toward scaffolding robot action learning," *IEEE Trans. Autonom. Mental Develop.*, vol. 1, no. 1, pp. 44–54, May 2009.
- [26] P. F. Dominey and C. Dodane, "Indeterminacy in language acquisition: The role of child directed speech and joint attention," *J. Neuroling.*, vol. 17, no. 2–3, pp. 121–145, 2004.
- [27] P. Dominey and J. Boucher, "Learning to talk about events from narrated video in a construction grammar framework," *Artif. Intell.*, vol. 167, no. 1–2, pp. 31–61, 2005.
- [28] X. Hinaut and P. F. Dominey, "Real-time parallel processing of grammatical structure in the fronto-striatal system: A recurrent network simulation study using reservoir computing," *PLoS One*, vol. 8, no. 2, pp. 1–18, 2013.
- [29] S. Lallée *et al.*, *Linking language with embodied teleological representations of action for humanoid cognition*. Lausanne, Switzerland: Frontiers in Neurobotics, 2010.
- [30] K. Gold and B. Scassellati, "Using probabilistic reasoning over time to self-recognize," *Robot. Autonom. Syst.*, vol. 57, no. 4, pp. 384–392, 2009.
- [31] P. F. Dominey *et al.*, "Anticipation, and initiative in human-humanoid interaction," presented at the Humanoids, IEEE-RAS Int. Conf. Humanoid Robots, 2008.
- [32] S. R. Waxman and B. Markow Dana, "Words as invitations to form categories: Evidence from 12-to 13-month-old infants," *Cogn. Psychol.*, vol. 29, no. 3, pp. 257–302, 1995.
- [33] S. R. Waxman and I. Braun, "Consistent (but not variable) names as invitations to form object categories: New evidence from 12-month-old infants," *Cognition*, vol. 95, no. 3, pp. B59–B68, 2005.
- [34] N. Althaus and D. Mareschal, "Modeling cross-modal interactions in early word learning," *IEEE Trans. Autonom. Mental Develop.*, vol. 5, no. 4, pp. 288–297, Dec. 2013.



action.



He is focusing about the reasoning and planning in robotics, especially with the iCub platform, and more precisely, within a context of spoken language interaction with a human.



He is currently a CNRS Research Director at the INSERM Stem Cell and Brain Research Institute in Lyon France, where he directs the Robot Cognition Laboratory. From 1984 to 1986, he was a Software Engineer at the Data General Corporation, and from 1986 to 1993, he was a Systems Engineer at NASA/JPL/CalTech. In 1997, he became a Tenured Researcher, and in 2005, a Research Director with the CNRS in Lyon France. His research interests include the development of a "cognitive systems engineering" approach to understanding and simulating the neurophysiology of cognitive sequence processing, action and language, and their application to robot cognition and language processing, and human–robot cooperation. He is currently participating in several French and European projects in this context.

**Grégoire Pointeau** received the M.Sc. degree in biosciences (bioinformatics and modeling specialty) from the National Institute of Applied Sciences (INSA), Lyon, France, in 2011, and the master's degree in cognitive science at the University of Lyon, Lyon, France. He is currently working toward the Ph.D. degree at the Robot Cognition Laboratory in Lyon as part of the FP7 EFAA Project.

He is interested in the accumulation of experience and autobiographical memory in the elaboration of the self, in the context of human–robot social inter-

**Maxime Petit** received the M.Sc. degree in computer sciences (cognitive sciences specialty) from the University of Paris-Sud, Orsay, France, and the engineering degree in biosciences (bioinformatics and modeling specialty) from the National Institute of Applied Sciences (INSA), Lyon, France, in 2010. He is currently working toward the Ph.D. degree at the Stem-Cell and Brain Research Institute, from the unit 846 of the National Institute of Science And Medical Research (INSERM) in Bron, France, working in the Robotic Cognition Laboratory team.

**Peter Ford Dominey** received the B.A. degree from Cornell University, Ithaca, NY, USA, in 1984, in cognitive psychology and artificial intelligence. He received the M.Sc. and Ph.D. degrees in computer science from the University of Southern California, Los Angeles, CA, USA, in 1989 and 1993, respectively, developing neural network models of sensorimotor sequence learning, including the first simulations of the role of dopamine in sensorimotor associative learning, and pioneering work in reservoir computing.

### 9.3.2 TAMD : The Coordinating Role of Language in Real-Time Multimodal Learning of Cooperative Task

Authors : **Petit, M.**, Lallée, S., Boucher, J.-D., Pointeau, G., Cheminade, P., Ognibene, D., Chinnellato, E., Pattacini, U., Gori, I., Martinez-Hernandez, U., et al.

Title : "The coordinating role of language in real-time multimodal learning of cooperative tasks."

Journal : IEEE Transactions on Autonomous Mental Development, 5(1) :3-17.

Year : 2013

# The Coordinating Role of Language in Real-Time Multimodal Learning of Cooperative Tasks

Maxime Petit, Stéphane Lallée, Jean-David Boucher, Grégoire Pointeau, Pierrick Cheminade, Dimitri Ognibene, Eris Chinellato, Ugo Pattacini, Ilaria Gori, Uriel Martinez-Hernandez, Hector Barron-Gonzalez, Martin Inderbitzin, Andre Luvizotto, Vicky Vouloutsi, Yannis Demiris, Giorgio Metta, and Peter Ford Dominey

**Abstract**—One of the defining characteristics of human cognition is our outstanding capacity to cooperate. A central requirement for cooperation is the ability to establish a “shared plan”—which defines the interlaced actions of the two cooperating agents—in real time, and even to negotiate this shared plan during its execution. In the current research we identify the requirements for cooperation, extending our earlier work in this area. These requirements include the ability to negotiate a shared plan using spoken language, to learn new component actions within that plan, based on visual observation and kinesthetic demonstration, and finally to coordinate all of these functions in real time. We present a cognitive system that implements these requirements, and demonstrate the system’s ability to allow a Nao humanoid robot to learn a nontrivial cooperative task in real-time. We further provide a concrete demonstration of how the real-time learning capability can be easily deployed on a different platform, in this case the iCub humanoid. The results are considered in the context of how the development of language in the human infant provides a powerful lever in the development of cooperative plans from lower-level sensorimotor capabilities.

**Index Terms**—Cooperation, humanoid robot, shared plans, situated and social learning, spoken language interaction.

## I. INTRODUCTION

THE ability to cooperate, creatively establish, and use shared action plans is, like language and the underlying social cognitive and motivational infrastructure of commu-

nication, one of the major cognitive capacities that separates humans from nonhuman primates [1]. In this context, language itself is an inherently cooperative activity in which the listener and speaker cooperate, in order to arrive at the shared goal of communication. Tomasello *et al.* make the foundational statement that language is built on the uniquely human ability to read and share intentions, which is also the foundation for the uniquely human ability and motivation to cooperate. Indeed, Tomasello goes one step further, suggesting that the principal function of language is to establish and negotiate cooperative plans [1].

The building blocks of cooperative plans are actions. In this context, it has been suggested that we are born with certain systems of “core cognition,” which are “identified by modular innate perceptual-input devices” [2]. One of the proposed elements of core cognition is agency. This includes an innate system for representing others in terms of their goal directed actions, and perceptual mechanisms such as gaze following that allow the developing child to monitor the goal directed actions of others. Thus we consider that these notions of agency are given in the system, though the degree to which they may actually be developed versus innate remains an open question [2].

A cooperative plan (or shared plan) is defined as a goal directed action plan, consisting of interlaced turn-taking actions by two cooperating agents, in order to achieve a common goal that could otherwise not have been achieved individually [1]. Interestingly, infants can establish shared plans without the use of language, if the shared goal and corresponding plan are sufficiently simple. However, once the plans reach a certain level of complexity, and particularly if the plan must be renegotiated in real-time, then language is often invoked to establish and negotiate who does what [3], [4]. Thus, cooperation requires communication, and when things get complex, language is the preferred communication method. Indeed, much of early language maps onto physical parameters of goal directed action [5], [6].

In the construction grammar framework, Goldberg identifies how the structure of language is mapped onto the structure of meaning such that “constructions involving basic argument structure are shown to be associated with dynamic scenes . . . such as that of someone volitionally transferring something to someone else, someone causing something to move or change state” [5]. Thus, grammatical constructions implement the mapping from linguistic utterances to meaning, in the form of action and perceptual scene specifications. The nature of the link between language and action, and how that link is established, is an open topic of research in child development and developmental robotics [7].

Manuscript received January 04, 2012; revised May 03, 2012 and June 15, 2012; accepted June 25, 2012. Date of publication July 26, 2012; date of current version March 11, 2013. This work was supported by the European Commission under Grants EFAA (ICT-270490) and CHRIS (ICT-215805).

M. Petit, S. Lallée, J.-D. Boucher, G. Pointeau, P. Cheminade, and P. F. Dominey are with SBRI, Institut National de la Santé et de la Recherche Médicale (INSERM), Bron 69675, France (e-mail: maxime.petit@inserm.fr; stephane.lallee@inserm.fr; jean-david.boucher@inserm.fr; greg.pointeau@gmail.com; kaosumog@gmail.com; peter.dominey@inserm.fr).

D. Ognibene, E. Chinellato, and Y. Demiris are with the Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2BT, U.K. (e-mail: d.ognibene@imperial.ac.uk; e.chinellato@imperial.ac.uk; y.demiris@imperial.ac.uk).

U. Pattacini, I. Gori, and G. Metta are with the Cognitive Robotics Department, Italian Institute of Technology, Genoa 16163, Italy (e-mail: ugo.pattacini@iit.it; ilaria.gori@iit.it; giorgio.metta@iit.it).

U. Martinez-Hernandez and H. Barron-Gonzalez are with the Department of Psychology, University of Sheffield, Sheffield, U.K. (e-mail: uriel.martinez@sheffield.ac.uk; hector.barron@sheffield.ac.uk).

M. Inderbitzin, A. Luvizotto, and V. Vouloutsi are with SPECS, Universitat Pompeu Fabra, Barcelona, Spain (e-mail: martin.inderbitzin@upf.edu; luvizotto@gmail.com; vidago@gmail.com).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TAMD.2012.2209880

In the context of this debate, following a usage-based approach [6], we have demonstrated how such constructions can be learned in a usage-based approach, as the mapping between the argument structure of sentences and argument structure of robotic representations of action meanings [8]. This “usage-based” development of grammatical constructions (versus a more nativist approach) is also a topic of debate, similar to the case for agency cited above.

Independent of the nativist vs. usage-based debate, we can take the position that via such constructions, language is uniquely situated in its capability to allow agents to construct and negotiate shared cooperative plans. Our approach is to implement a scaffolded system based on this capability. In this scaffolding, we build in simple grammatical constructions that map onto the argument structure of actions that can be performed by the robot. This allows a scaffolding for the creation of action plans. We have previously used spoken language to construct diverse action plans for a robot cooperating with a human [9], [10], but the plans were not shared, in that they only specified the robot’s actions. We then introduced a shared planning capability where a robot could observe a sequence of actions, with an agent attributed to each by the user via language. This generated a true shared plan, that could pass the test of role reversal [11]. Role reversal occurs when the two participants in a cooperative task can exchange roles, thus indicating that they both have a “bird’s eye view” of the shared plan, which is a central part of the requirements for true cooperation [12].

In a series of studies we then more carefully reexamined the bases of shared planning. In the first study [13], we implemented a capability for learning to perceive and recognize novel human actions based on the structure of perceptual primitive constituting those actions. We next implemented the corresponding ability to learn to execute complex actions based on the composition of motor primitives, and to make the link between perception and action via imitation [14]. Finally, we extended this capability to multiple actions in shared plans, where the human could use spoken language to specify a shared plan that could then be executed by the robot, again displaying role reversal [15].

While this work represented significant progress, it left several issues unanswered. First, when a shared plan “goes wrong” there is no mechanism to fix it. Language can fulfill this role—indeed much of human language is about coordinating and correcting shared plans [16]. Second, in our previous work, teaching the shared plan was in a fixed modality, typically with the human speaking the shared plan, action by action. Here we extend this so that language becomes the central coordinator, a scaffold, which allows the user to then specify individual actions by: 1) kinesthetically demonstrating the action; 2) performing the action himself so the robot can perceive and imitate; or 3) for known actions—to specify the action verbally. Learning by visual and kinesthetic demonstration are highly developed and well documented means for transmission of skill from human to robot, e.g., [17]–[19]. We will demonstrate how this provides a novel interaction framework that where language coordinates these three potential modalities for learning shared plans.

The transmission of knowledge from humans to robots can take multiple forms. We consider three specific forms. “Imitation” will refer to learning in which the human performs the action to be learned, and the robot observes this and performs a mapping from observation space onto its execution space, as defined in [20]. Likewise, based on [20] we will refer to “kinesthetic teaching” as a form of “demonstration” where the passive robot is moved through the desired trajectory by the human teacher. Finally we will refer to “spoken language programming” [21] as the method described above where well-formed sentences are used to specific robot actions and arguments, either in isolation or in structured sequences. Language has been used to explain new tasks to robots [22], and is especially useful for scaffolding tasks, when the teacher uses previously acquired skills to resolve a new and more complex tasks [23].

Imitation has been successfully used on diverse platforms [24]–[29]. It is an easy way for the teacher to give the robot the capacity to perform novel actions, and is efficient in high dimensional spaces, and as a mechanism for communication [30]. It also speeds up the learning time by reducing the repetitions required for trial-and-error learning [31], and it can lead to open-ended learning without previous knowledge of the tasks or the environment [32].

Demonstration (also called self-imitation) [33], [34] avoids the problem of mapping from teacher to observer space. While this problem exists during imitation, it is eliminated in demonstration, as the human directly move the limbs of the robot [20] thus avoiding the “Correspondance Problem” [28]. It also does not require expert-knowledge of the domain dynamics, allowing the teacher to be a nonexpert [20].

Some authors have also studied multimodal learning, combining these techniques; including imitation and instructions [35]–[37] or demonstration and instruction [38]. In this research we build upon and extend these multimodal approaches. We implement a multimodal learning architecture which allow a user to teach action to robots (iCub and Nao) using one or a combination of language instructions, demonstration or imitation. More precisely, demonstration is a form of “tele-operation” by “kinesthetic teaching” and imitation is mediated by “external sensor” as defined in [20]: demonstration by kinesthetic teaching because the teacher operates directly on the robot learner platform, and imitation by external sensor because we are using kinect as perceptual device to encode the executing body’s moves.

Thus the novelty of the current research is threefold—first it demonstrates a rich language capability for establishing and negotiating shared plans in real time. Second, it does this by allowing a multimodal combination of spoken language programming, imitation and demonstration based learning. Finally, it demonstrates that, with an appropriate robotic platform, language can be used as the glue that binds together learning from these different modalities. These capabilities are demonstrated on two robots, the Nao and the iCub, which allow us to take advantage of the specific motor capabilities of each, including the more dexterous manipulation capabilities of the iCub.

193

## II. SYSTEM REQUIREMENTS AND DESIGN

The goal of the current research is to demonstrate that a learning system that is based on the human developmental

capability to map language onto action can provide the basis for a multimodal shared plan learning capability. In order to proceed with this analysis, we consider a scenario that involves multimodal learning. This will allow us in particular to determine the requirements involved in a human–robot cooperation to achieve an unknown task with real-time learning.

Consider a scenario where a humanoid robot and a human are in a face-to-face interaction, with a box and a toy put on a table. The human wants to clean the table, by putting the toy in the box. In order to do that, he must first grasp the toy, then open the box, then put the toy in the box, and finally close the box. Let us further consider that the human cannot grasp the toy and open the box at the same time, and that he thus needs help in performing this task. The human will ask the robot to “clean the table.” The robot doesn’t yet know the plan so it will ask the human to explain. The user will describe each step of the plan, which is composed by several sequential actions:

- “I grasp the toy, then;
- you open the box, then;
- I put the toy in the box, then;
- you close the box.”

After checking whether the stated shared plan has been understood correctly, the robot will check each action that it should perform. The robot recognizes that there are some problems because it does not know how to open or close the box. It will ask for the help of the human, who has to teach it however he wants.

For opening the box, the human will decompose the teaching in two parts: at first, going to a safe initial position and next imitating him. After the opening action is learned, the user will teach the closing behavior, by directly demonstrating the motion by moving the arm of the robot. Finally, the robot has learned the whole shared plan and each action it should perform, and so the two agents can proceed and clean the table together. This scenario allows us to identify the functional requirements for the system. The system should:

- 1) understand human language, including mapping grammatical structure onto internal representation of action;
- 2) appropriately distinguish the definition of self and the other for relative pronouns (e.g., “I,” “You”);
- 3) manage a memory of known shared plan and actions;
- 4) become active in the discussion by asking human when a problem occurred;
- 5) perform Inverse kinematics mapping to learn from human action by imitation;
- 6) encode proprioception induced when the human is moving the robot to teach;
- 7) perceive the state of objects in the world.

In the following sections, we will define an overall system architecture that accommodates requirements 1)–4) in a platform independent manner, suggesting that these are the core learning functions. We will further demonstrate how this system can be used for real-time multimodal shared plan learning on the Nao with requirements 5) and 6), and on the iCub with point 7).

### III. SYSTEM DESIGN OVERVIEW

Here, we present the system architecture for the learning and execution of cooperative shared plans. We begin with the com-

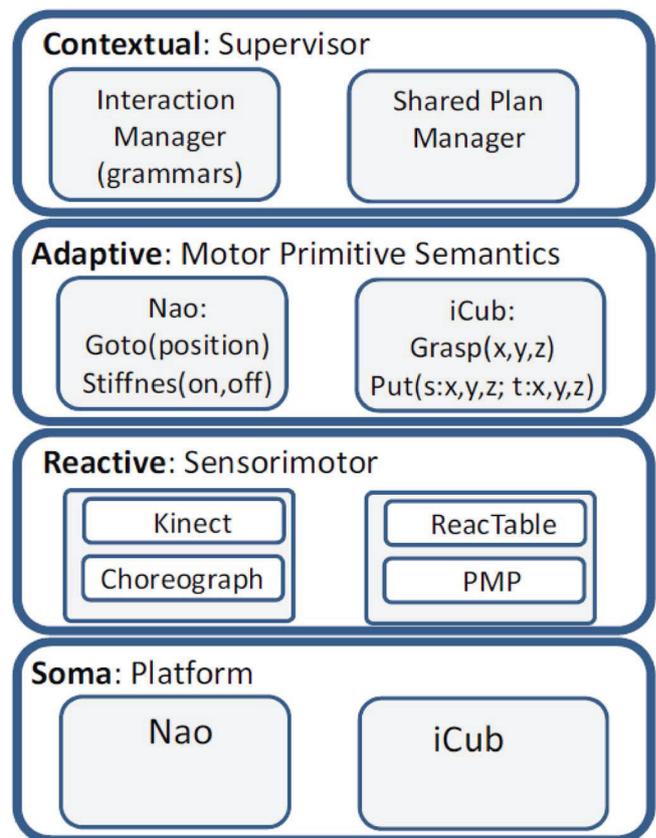


Fig. 1. Biomimetic Architecture for Situated Social Intelligence Systems (BASSIS).

ponents that are independent of the physical platform, and then introduce the platform specific components.

The BASSIS architecture (see Fig. 1) is a multiscale architecture organized at three different levels of control—reactive, adaptive, and contextual, where the different levels of self are all based on the physical instantiation of the agent through its body (soma). It is based on the distributed adaptive control architecture [39]–[41]. Soma corresponds to the physical platform, instantiated as the Nao or iCub in our experiments. The Reactive or sensorimotor layer employs Kinect for perception and Choreograph™ (Aldebaran) for motor control on the Nao, and the ReacTable sensitive table, and the passive motion planner (PMP) and iKin inverse kinematic solver for iCub. The Adaptive layer defines adaptive motor capabilities for each robot. In the current context, this adaptation can take place through learning within the human–robot interaction. The Contextual layer is platform independent, and implements a Supervisor function, with a grammar-based Interaction Manager, and a Shared Plan Manager. Within the BASSIS framework, the Contextual layer implements a form of long term memory that we exploit here in the context of learning shared action plans.

#### 194 Supervisor

The Supervisor function consists in two related capabilities. The first is general management of the human–robot interaction via a state-based dialog management capability. The second is

capability to learn and execute shared plans. Both of these functions are platform independent.

1) *Interaction Management*: Interaction management is provided by the CSLU Toolkit [42] rapid application development (RAD) state-based dialog system which combines state-of-the-art speech synthesis (*Festival*) and recognition (Sphinx-II recognizer) in a GUI programming environment. RAD allows scripting in the TCL language and permits easy and direct binding to the YARP domain, so that all access from the Interaction Management function with other modules in the architecture is via YARP.

The system is state-based with states for specifying the shared plan, modifying the shared plan, if there are errors, teaching specific actions within the shared plan, and finally, executing the shared plan during the cooperative task execution. Interaction management also allows the system to indicate error states to the user, and to allow him to explore alternate possibilities to rectify such errors, as illustrated in Section IV-A.2.

2) *Shared Plan Learning*: The core aspect of the learning capability is the capability to learn and execute shared plans, and to learn constituent actions that can make up those plans. As defined above, a shared plan is a sequence of actions with each action attributed to one of two agents in a turn-taking context. Shared plans can be learned via two complimentary learning mechanisms. The first method involves a form of spoken language programming, in which the user verbally describes the succession of action-agent components that make up the shared plan. Recognition is based on a grammar that we have developed for this purpose:

- 1) \$SharedPlan = pedro%%\*sil%% \$agent \$command  
[({linkWord \$agent \$command})];
- 2) \$agent = you | I;
- 3) \$command =
  - a. \$action1 [\*sil%%]
  - b. \$action2 [\*sil%%];
- 4) \$pause = [\*sil%%][\*any%%][\*sil%%];
- 5) \$object = winnie | toy | chest;
- 6) \$posture = initial-position;
- 7) \$action1 =
  - a. grasp \$pause \$object
  - b. reach \$pause \$object
  - c. open \$pause \$object
  - d. close \$pause \$object
  - e. move-to \$pause \$posture;
- 8) \$action2 =
  - put \$pause \$object \$pause [in%%] \$pause \$object;
- 9) \$linkWord = then | after-that | next | and;

Line (1) specifies that a shared plan begins with the “imperative” “Pedro” (the robot’s name) followed by an optional silence (\*sil%%), then an agent and command, followed by [0-n] groups made of a link word, an agent and a command. Agent terminals are identified in (2). Commands can take 1 or two arguments, as specified, respectively, in (7) and (8). Interestingly, in this grammar, the set of terminal nodes (actual words to be recognized) is only 16 distinct words. Thus, the speaker independent recognition system is in a well-defined recognition niche, and the system works with few to no errors.

In the case that errors are made, either in recognition, or by the user forgetting a command, saying a wrong command etc.

we have a “spoken language programming” editing capability. Editing can involve the following edits: replace one command with another. In this case the user repeats the faulty command, and then the correct one (in cooperation with the dialog system of the robot). Delete a command, in which case the user states the command to be deleted. Insert a command, in which case the user says before or after a given command, and then the new command.

The second learning mechanism is evoked at the level of individual actions, and allows the user to teach new component actions to the robot. This involves a combination of spoken language programming and perceptual action recognition. Perceptual action recognition can occur via action recognition with the Kinect, and via kinesthetic demonstration, which will be detailed below. The robot can then use the resulting shared plan to take the role of either agent, thus demonstrating the crucial role-reversal capability that is the signature of shared planning [1], [12].

As illustrated in the example dialog with the Nao below, this provides a rich capability to negotiate a complex cooperative task using spoken language. The resulting system can learn how to perform novel component actions (e.g., open, close), and most importantly, it can learn arbitrary novel turn-taking sequences—shared plans—that allow the user to teach in any novel cooperative behavior to the robot in real-time. The only constraint is on the set of composite actions from which the novel behavior can be constructed.

## B. YARP

Software modules in the architecture are interconnected using YARP [43], an open source library written to support software development in robotics. In brief YARP provides an intercommunication layer that allows processes running on different machines to exchange data. Data travels through named connection points called ports. Communication is platform and transport independent: processes are not aware of the details of the underlying operating system or protocol and can be relocated at will across the available machines on the network. More importantly, since connections are established at runtime it is easy to dynamically modify how data travels across processes, add new modules or remove existing ones. Interface between modules is specified in terms of YARP ports (i.e., port names) and the type of data these ports receive or send (respectively for input or output ports). This *modular* approach allows minimizing the dependency between algorithm and the underlying hardware/robot; different hardware devices become interchangeable as long as they export the same interface.

## C. Humanoid Robot Nao and Kinect

The Nao (Fig. 3) is a 25 degrees of freedom humanoid robot built by the French company Aldebaran. It is a medium size (57 cm) entertainment robot that includes an onboard computer and networking capabilities at its core. Its open, programmable and evolving platform can handle multiple applications. The onboard processor can run the YARP server (described below) and can be accessed via telnet connection over the internet via WiFi.

More specifically, the Nao is equipped with the following: CPU x86 AMD Geode with 500 MHz, 256 MB SDRAM

and 1 Gb Flash memories, WiFi (802.11g) and Ethernet,  $2 \times 640 \times 480$  camera with up to 30 frames per second, inertial measurement unit (2 gyro meters and 3 accelerometers), 2 bumper sensors and 2 ultrasonic distance sensors.

In this research, we extend the perceptual system of the Nao to include a 3D motion capture capability implemented with the Kinect™ system. The Kinect recognizes a human body image in a configuration posture (see Fig. 3), and then continuously tracks the human body. Joint angles for three degrees of freedom in the shoulder and one in the elbow are extracted from the skeleton model, and mapped into the Nao joint space to allow real-time telecommand of the two arms.

#### D. iCub Humanoid and Reactable Perceptual System

The iCub is a 53 DOF humanoid platform developed within the EU consortium RobotCub. The iCub [44] is an open-source robotic platform with morphology approximating that of a 3(1/2) year-old child (about 104 cm tall), with 53 degrees of freedom distributed on the head, arms, hands and legs. The current work was performed on the iCubLyon01 at the INSERM laboratory in Lyon, France. The head has 6 degrees of freedom (roll, pan and tilt in the neck, tilt and independent pan in the eyes). Three degrees of freedom are allocated to the waist, and 6 to each leg (three, one and two respectively for the hip, knee and ankle). The arms have 7 degrees of freedom, three in the shoulder, one in the elbow and three in the wrist. The iCub has been specifically designed to study manipulation, for this reason the number of degrees of freedom of the hands has been maximized with respect to the constraint of the small size. The hands of the iCub have five fingers and 19 joints.

1) *Motor Control*: Motor control is provided by PMP. The passive motion paradigm (PMP) [45] is based on the idea of employing virtual force fields in order to perform reaching tasks while avoiding obstacles, taking inspiration from theories conceived by Khatib during 80s [46]. Within the PMP framework it is possible to describe objects of the perceived world either as obstacles or as targets, and to consequently generate proper repulsive or attractive force fields, respectively. A meaningful example of attractive force field that can be produced is the so called spring-mass-damper field; in this case the relevant parameters are the stiffness constant and the damping factor, which regulate the force exerted by a target placed in a given spatial location. An effective model that represents repulsive force fields is the multivariate Gaussian function, which accounts for a field centred at an obstacle and is characterized by the typical bell-shaped decay. According to the composition of all active fields, the manipulator's end-effector is eventually driven towards the selected target while bypassing the identified obstacles; evidently, its behavior and performances strictly depend on the mutual relationship among the tuneable field's parameters.

However, in order to tackle the inverse kinematics problem and compute the final trajectory of the end-effector, the original PMP makes use of the Transposed Jacobian algorithm; this method is well known to suffer from a number of weaknesses [47] such as the difficulty to treat constraints of complex kinematic structures as the iCub arm turns to be [48], [49]. Therefore, we have decided to replace the Transposed Jacobian approach with a tool that relies on a powerful and fast nonlinear

optimizer, namely Ipopt [50]; the latter manages to solve the inverse problem while dealing with constraints that can be effectively expressed both in the robot's configuration space (e.g., joints limits) and in its task-space. This new tool [49] represents the backbone of the Cartesian Interface, the software component that allows controlling the iCub directly in the operational space, preventing the robot from getting stuck in kinematic singularities and providing trajectories that are much smoother than the profiles yielded by the first implementation of PMP.

In this changed context, the Cartesian Interface lies at the lowest level of the revised PMP architecture, whose simplified diagram is shown in Fig. 3. At higher level the pmpServer element is responsible of composing the final force field according to the objects currently stored in an internal database. Users can add, remove or modify this database in the easiest way by forwarding requests to the server through a dedicated software interface, made available by the pmpClient component. It is important to point out that the properties of objects stored in the database can be retrieved for modification in real-time in order to mirror the environment as it evolves over time. All the software components of the revised PMP architecture can be openly accessed from the iCub repository.

2) *Perception*: In the current research we extend the perceptual capabilities of the iCub with the Reactable™. The Reactable is licensed by Reactable Systems. The Reactable has a translucent surface, with an infrared illumination beneath the table, and detection system that perceives tagged objects on the table surface with an accuracy of  $\sim 5$  mm. Thus, tagged objects can be placed on the table, and their location accurately captured by the infrared camera.

Interaction with the external world requires that the robot is capable of identifying its spatial reference frame with the objects that it interacts with. In the human being, aspects of this functionality is carried out by the dorsal stream, involving areas in the posterior parietal cortex which subserve complex aspects of spatial perception [51]. In our system, the 2D surface of the table is calibrated into the joint space of the iCub by a linear transformation calculated based on a sampling of three calibration points on the table surface that are pointed to by the iCub. Thus, three points are physically identified in the Cartesian space of the iCub, and on the surface of the Reactable, thus providing the basis for calculation of a transformation matrix which allows the projection of object coordinates in the space of the table into the Cartesian space of the iCub. These coordinates can then be used as spatial arguments to the PMP action system of the iCub, described above, which provides basic physical actions including point-to( $x, y, z$ ), put(source  $X, Y, Z$ ; target  $x, y, z$ ), grasp( $x, y, z$ ), release( $x, y, z$ ).

#### IV. MULTIMODAL LEARNING I: NAO & KINECT

Here we demonstrate the system functionality for real-time learning, in which language, spatial perception (via Kinect), and proprioception are combined to allow the Nao to learn a shared plan which is then executed in real-time with the human teacher. The idea is to solve a common problem encountered during daily life which is cleaning a table with some objects on it. As defined in the requirements analysis in Section II, the goal is to place the object from the table to a chest. However, the chest

needs to be opened before doing that, and we need to close it afterward to complete the task.

#### A. Learning the Shared Plan and Component Actions

Here we present the time-tagged unfolding of the cooperative dialog where the shared plan is established, and indicate how the system components are engaged to permit the corresponding interaction, and learning and execution of the shared plan.

1) *Establishing the Shared Plan*: The user begins by giving the name of the cooperative shared plan:

00:25 Nao: Tell me what I have to do.

00:26 Human: "Pedro, help me to clean the table."

The Nao recognizes the spoken order and checks in the shared plan manager if it knows this plan, and determines that there is no definition for such a plan. . .

00:30 Nao: "The shared plan is clean.

00:36 Nao: "Please explain me."

The shared plan manager creates an empty shared plan called "*clean the table*" and it is ready to be filled with the human description.

The user verbally explains all the steps of the shared plan, including both moves of the robot and himself. It is worth noting that the shared plan is initially specified in ~10 s.

00:37 Human: "I reach the toy, then I reach the trash box then you open the trash box then I put the toy in the trash box then you close the trash box."

The Nao will segment the global shared plan in a sequential set of 3 actions using the grammar built in the spoken language interface, and then repeats it to be sure it has perfectly understood the whole interaction:

00:50: Nao: "I reach the toy, you reach the trash box, then I open the trash box, you put the toy in the trash box, I close the trash box. Do you agree with this plan?"

Two remarks should be made. First, note that in order to be intuitive and understandable, for relative pronouns "You" or "I" rather than repeating these literally, the Nao has created the plan by replacing the relative agent by the absolute ones: the human for "I" and the Nao for "You" because the human was speaking.

2) *Correcting the Shared Plan*: The second remark here is that there is in fact an error in the plan. Nao states that it should reach for the toy, rather than the human doing so. When the Nao is repeating the plan, it is not only to check if it has understood the orders but it also provides the human a way to verify his plan.

The user has here the possibility to edit the shared plan (Section II.A.2), and will do it by answering that he does not agree with this, for instance:

Human: "No I do not".

Thus the robot will ask where the problem is:

01:05 Nao: "So, What did I misunderstand?"

Here, the human has several ways to edit the plan:

— he could specify that there is a problem with a specific action by repeating it and could, after that, remove it or replace it by another one;

— he could erase everything and describe the plan again from scratch;

— he could insert a missing action.

In this dialogue example described below, the problem is with the agent of the first action. The Nao said "I reach the toy", but the intended action was "You reach the toy," with "you" referring to the human, so in response to the robot's question "what did I misunderstand?" the human names the erroneous action:

01:08 Human: "I reach the toy."

Thus, this dialog is motivated by the user's recognition that an error has occurred, followed by his specification of the erroneous component. This will trigger an editing of the plan, with the Nao asking

01:10 Nao: "What do you want me to do instead?"

A new command can now be inserted to replace the erroneous one.

01:13 Human: "I reach the toy."

This illustrates the detailed manipulation of relative pronouns, as the human is now speaking from his own perspective, and thus refers to himself as "I". To confirm the edit, the Nao then places a "virtual cursor" after the element to be replaced, and before the next action, and verifies that the new command should be inserted there:

01:15 Nao: "So where—I reached the toy, instead, you will reach the toy.

Do you agree with this plan?"

01:24 Human: "Yes, I do."

The robot now has a complete shared plan including tasks for the user and for itself. The next step is to verify that all of the tasks assigned to the robot are known.

3) *Learning Component Actions*: The Nao iterates through the shared plan until it encounters an action assigned to it, determines if it knows the action, and informs the user if not. A query is made to the Motor Primitive Library where the list of current known behaviors of the Nao is stored into. There may be several unknown behaviors in a new plan, thus to keep the interaction more animated the system selects one of the three interrogatory sentences at random.

Here, the Nao recognizes that it has to perform the "open" action, which is unknown for now and will call the human for help:

01:26 Nao: "Behavior 'open' is unknown. I am going to learn 'open' "

This will put the supervisor in the learning state. The human could create the behavior in the Motor Sequence Learning with one or a combination of these methods (see Fig. 2):

— calling a known behavior by language;

— asking the robot to imitate him;

197 — physically demonstrating the action by moving the robot's arms.

As illustrated in Fig. 4 (left column), the chest can be opened by pushing a lever, and the human will choose to teach "open"

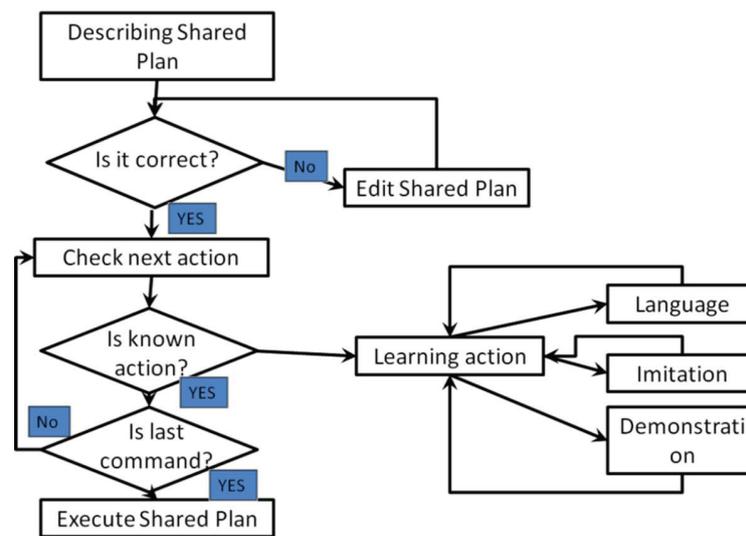


Fig. 2. Shared Plan Manager. In the initial state, the user describes the entire shared plan. The robot repeats the understood plan, allowing editing. Then, for each action, if it is unknown, the system enters specific states for learning by language, imitation or demonstration. When all actions are learned, the shared plan is executed.

by decomposing the action in two steps: First, the robot needs to move its arms up in the air, before, second, going down to push the lever. The “put-the-hands-up” is a known action, so the human will command this action.

01:34 Nao: “Tell me what to do.”  
 01:36 Human: “Move to Kinect init.”

This is recognized to be a known behavior in Motor Primitive Library, so the robot asks for a confirmation before performing the action:

01:38 Nao: “I am going to move to Kinect init. Are you sure?”  
 01:42 Human: “Yes I am.”

After the user’s acknowledgment, Nao executes the behavior and the resulting joint angle trajectory will be stored in the new “open” behavior of motor sequence learning to begin the construction of this action.

The robot informs the user that the action is finished and it is waiting for the following command:

01:51 Nao: “Tell me what to do.”

The human proceeds to the second step of the teaching by calling the imitation method:

01:53 Human: “Imitate me.”  
 01:56 Nao: “Imitation activated. Tell me when it is finished.”

The system then enters the state (see Fig. 2) where joint angles are read from the Kinect device based on the observed human demonstrator (which is calibrated in the hands up position). The user then demonstrates the motion required to open the box, using visual feedback from the Nao in real-time. The corresponding joint angle trajectory is concatenated to those from the previous method. The user then terminates the imitation:

02:17 Human: “It is finished.”

The “open” behavior has thus been learned by the Nao in real-time as a complex joint trajectory, and is transferred from Motor Sequence Learning to Motor Primitive Library so that it is now available as a command.

Following the flow outlined in Fig. 2, the Nao proceeds to the next behavior it should perform in the shared plan, and again there is an unknown action: “close”:

02:20 Nao: “The behavior ‘close’ is unknown. I am going to learn ‘close.’”  
 02:27 Nao: “Tell me what to do.”

An empty “close” behavior is created in motor sequence learning. This time, the human chooses to teach the action using the demonstration method:

02:29 Human: “Let me move your arms.”

This places the supervisor in a state where it commands the Nao to set the stiffness of the arms to zero so that they can be manipulated by the human:

02:33 Nao: “Stiffness changed. Tell me when it is finished.”

As illustrated in Fig. 4 (right column) the human then physically demonstrates the action, pushing the Nao’s hand and arm through a trajectory that closes the box. Once the demonstration is finished, the human terminates the learning, and asks the robot to proceed with the shared plan execution:

02:46 Human : “It is finished.”

Thus, this dialog fragment, and Fig. 4, illustrate two complementary learning methods: imitation of an action trajectory performed by the human, and physical demonstration where the human physically guides the learned trajectory of the robot. Depending on the nature of what is to be learned, the user can choose the more appropriate method.

### B. Executing the Shared Plan

The shared plan is now fully specified, and the Nao begins execution, illustrated in Fig. 5.

02:56 Nao: “The current step is you reach toy. You are supposed to reach. Tell me when it is done.”  
 03:01 Human: “It is done.”  
 03:03 Nao: “The current step is I open trash box.”

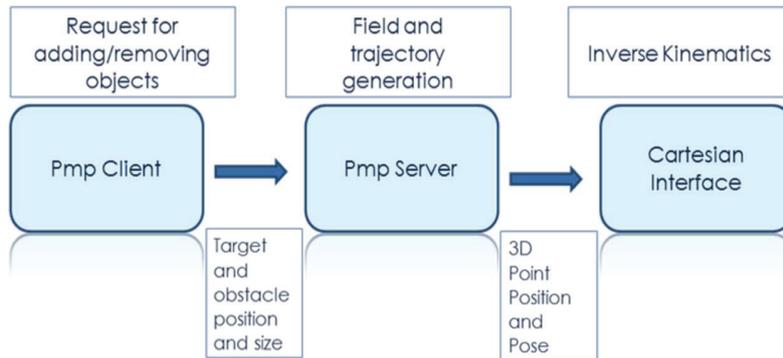


Fig. 3. PMP software architecture.

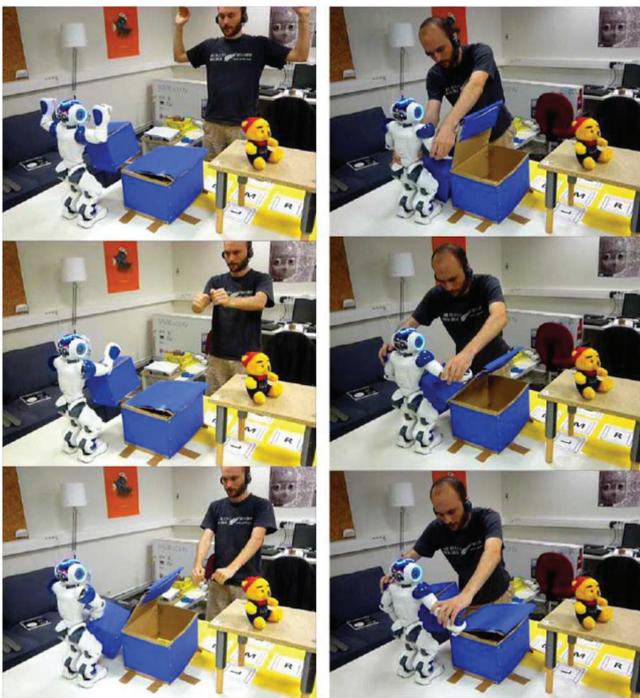


Fig. 4. Multimodal learning. (Left column) Using perceptual based imitation, the human demonstrates to the Nao how to open the box, and the Nao performs the action in real-time, mirroring the action of the human. (Right column) Using kinesthetic demonstration the human teaches the Nao how to close the box.

Here the robot uses the learned action trajectory to reproduce the “open” movement:

03:27 Nao: “The current step is you put the toy trash box. You are supposed to put. Tell me when it is done.”

03:34 Human: “It is done.”

03:37 Nao: “The current step is I close trash box.”

The Nao then uses the joint trajectory that was taught by kinesthetic demonstration, to close the box. At this point the toy has successfully been closed in the box, and the shared plan is finished”

03:52 Nao: “This was the last command.”

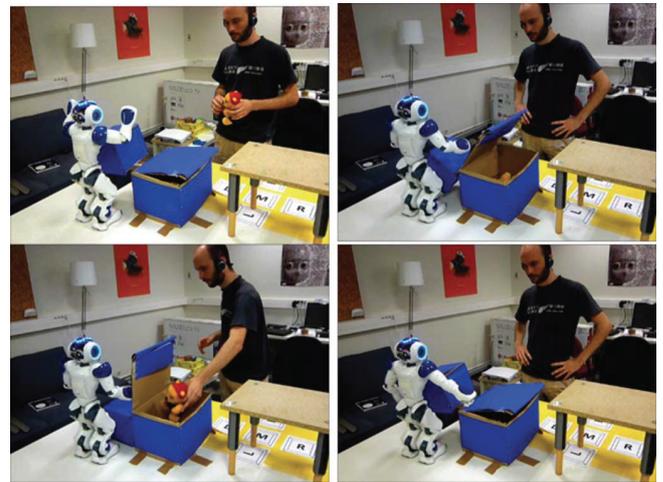


Fig. 5. Shared plan execution. Left column: Human takes toy, Nao opens box, human places toy in box. Right column: Nao closes box.

### C. Performance Analysis

We analyze performance from three separate executions of the learning task described above. Two were performed in the laboratory, and the third was performed during the Robocup @home Open Challenge 2011 in Istanbul, July 2011. In this case, we were required to install and set up the system in 3 minutes, and then had five minutes to perform the task, with no possibility to shift to a different time, or to have another 5 minutes in case of failure. The task was successfully completed, and our “Radical Dudes” team placed 4th/19 in the Open Challenge. This demonstrates the robustness of the system.

For each of the three sessions where the shared plan was learned and then executed, we measured the time to complete the open-the-box and close-the-box actions during the learning phase, and then during execution of the learned shared plan. Execution time is measured from the onset of the human command, to the execution of the action and onset of next request by the Nao. Thus, during learning, the execution time includes the teaching component. In order to compare the effect of learning on the time to complete individual actions, we performed nonparametric Wilcoxon signed-rank test comparing each action when it was being learned vs. when it had been learned, collapsing across sessions. There were two actions per session (open and close), each performed once in learning and once in execution after learning. With the three sessions,

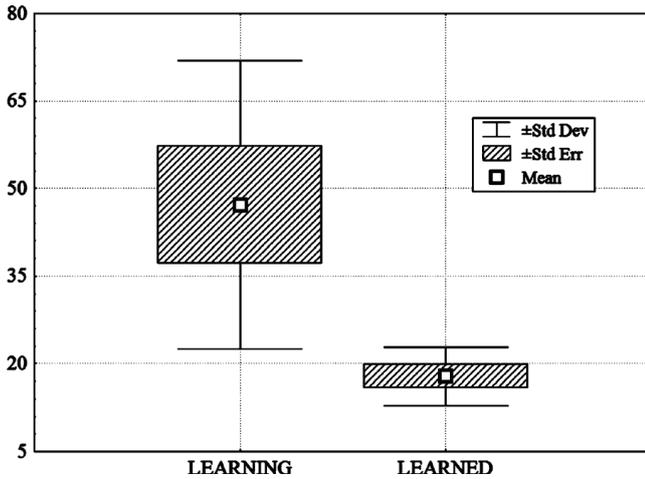


Fig. 6. Effects of shared plan learning on overall action execution time in seconds.

this provided a total of 6 learning-learned comparisons. As illustrated in Fig. 6, there is a significant reduction in execution time during the shared plan execution. This was confirmed in a significant learning effect in the Wilcoxon signed-rank test,  $N = 6$ ,  $Z = 2.20$ ,  $p = 0.027$ . We thus demonstrated that the system can learn to produce arbitrary sequences of actions with a turn-taking structure. The principle limiting factor is simply the set of basic level actions from which the shared plans can be constructed. Three repetitions of the “clean-up” shared plan, including one during the Robocup@Home Open Challenge, demonstrate the reliability of the system. Over these three trials, we also demonstrated a significant effect of this learning (as opposed to simply commanding the robot) in terms of behavior execution time after learning.

#### D. Nao Experiment Discussion

We have previously demonstrated how the user can employ language to teach new actions [13], [14], and then combined the previously learned actions into a new shared plan [11], [15]. The current research extends this shared plan learning. For the first time, we demonstrate how spoken language can be used to coordinate online multimodal learning for a shared cooperative plan. The multiple modalities include imitation of actions performed by the human (using the Kinect), human demonstration of a desired trajectory by physically manipulating the robot arm, and finally, spoken language based invocation of known actions, with all of these modalities contributing to a coherent and integrated plan. We should stress that learning by imitation, demonstration and spoken language programming all have been extensively studied in the past. What is new here is the combination of these multiple modalities in a coherent and seamless manner, under the control of language. It is worth noting that while we emphasize the learning of the “clean the table” shared plan, the grammar-based learning capability allows for the construction of arbitrary turn-taking action sequences.

## V. MULTIMODAL LEARNING II: ICUB & REACTABLE

While the learning that we observed in the previous section has certain components that are platform specific (e.g., the mor-

phology of the Nao, and the mapping of the Kinect to that morphology), the principal learning component which is based on spoken language is platform independent. Indeed, it provides a method for the linking together of action primitives into shared plans that can subsequently be used to achieve cooperative activity.

#### A. Learning the Shared Plan and Component Actions

In the first experiment with the iCub, the human explains a shared cooperative task similar to that used with the Nao, where the goal is to “hide” a toy under a box. The grammar is of the same structure as that used for the Nao. The principal difference is that it is constructed so that the plan is successively constructed from single actions that are concatenated with the previous actions (4):

- 1) \$subjects = I | Me | You | Stephane | Maxime | Peter | iCub;
- 2) \$objects = box | toy | trumpet | drums | left | middle | right;
- 3) \$action = :
  - a) \$subjects [\*sil%% | \*any%%] grasp [\*sil%% | \*any%%]\$objects|;
  - b) \$subjects [\*sil%% | \*any%%] point [\*sil%% | \*any%%]\$objects|;
  - c) \$subjects [\*sil%% | \*any%%] put [\*sil%% | \*any%%] \$objects
  - d) \$subjects [\*sil%% | \*any%%] uncover [\*sil%% | \*any%%] \$obj.
- 4) \$sharedPlan = concatenate(\$sharedPlan, \$action).

Here we illustrate how by exploiting this grammar, the shared plan manager can construct the shared plan from the sequence of actions described by the subject:

```
00:00 ICub: "What can I help you with?"
00:02 Human: "Shared Plan."
00:05 ICub: "Shared Plan menu."
00:07 Human: "You and I hide the toy with the box."
```

The Supervisor consults the Shared Plan Manager, and determines that there is no definition for this plan:

```
00:11 ICub: "Tell me how you and I can hide toy box?"
00:13 ICub: "What is next?"
00:17 Human: "You put box left."
00:20 ICub: "Did you say 'you put box left'?"
00:23 Human: "Yes I did."
00:25 ICub: "What is next?"
00:27 Human: "I put toy middle."
00:30 ICub: "Did you say 'I put toy middle'?"
00:32 Human: "Yes I did."
00:35 ICub: "What is next?"
00:38 Human: "You put box toy."
00:40 ICub: "Did you say 'You put box toy'?"
00:43 Human: "Yes I did."
00:46 ICub: "What is next?"
00:48 Human: "Finished."
```

The successive actions of the shared plan have now been extracted, and the plan is stored as

```
Hide(you, I, toy, box)
  {(You put (box left))
   (I put (toy middle))
   (You put (box toy)).}
```

In the definition, the four arguments to hide are instantiated with the “you, I, toy, box.” When the shared plan is used in the future, it can be called with different arguments, e.g., hide (John, you, trumpet, carton) for “John and you hide the trumpet with the carton,” and these new arguments will be systematically substituted into the component actions of the shared plan. This provides the ability generalize to new objects and agents, including providing a capability for role reversal as specified in Section C.

### B. Executing the Shared Plan

01:00 Human: “You and I hide the trumpet with the box.”

Note here that the system allows arguments to be used in the “hide” shared plan. Here trumpet will be hidden.

01:04 ICub: “I will put the box on the left. You will put the trumpet on the middle. I will put the box on the trumpet. Should we proceed?”

01:24 Human: “Yes we should.”

01:26 ICub: “I will put the box on the left.”

The robot performs its action, illustrated in Fig. 7(A)–(B).

02:02 ICub: “You will put the trumpet on the middle.”

The human makes the move, and the robot detects the change of position of the trumpet to the middle [see Fig. 7(C)].

02:12 ICub: “I will put the box on the trumpet.”

The iCub performs the final move, covering the trumpet with the box (Fig. 7(D)–(E)), completing the shared plan.

02:48 ICub: “Shared Plan menu.”

### C. Role Reversal

In the cooperative task, the user can decide who takes which role. This implies the principal of role reversal. As stated in the introduction, role reversal is taken as evidence that the agent has a global representation of the actions that both agents will perform. This representation allows the agent to take on the role of either of the two participants in the shared plan [12].

In order to reverse roles, the human can use the same shared plan, and indicate role reversal by specifying the arguments in the reversed order. He can say “you and I hide the toy in the box” or “I and you hide the toy in the box.” As specified in Section V-A above, depending on how the pronouns I and you are ordered in the specification, the roles of the human and robot will be reversed.

00:08 Human: “I and You will hide the toy in the box.”

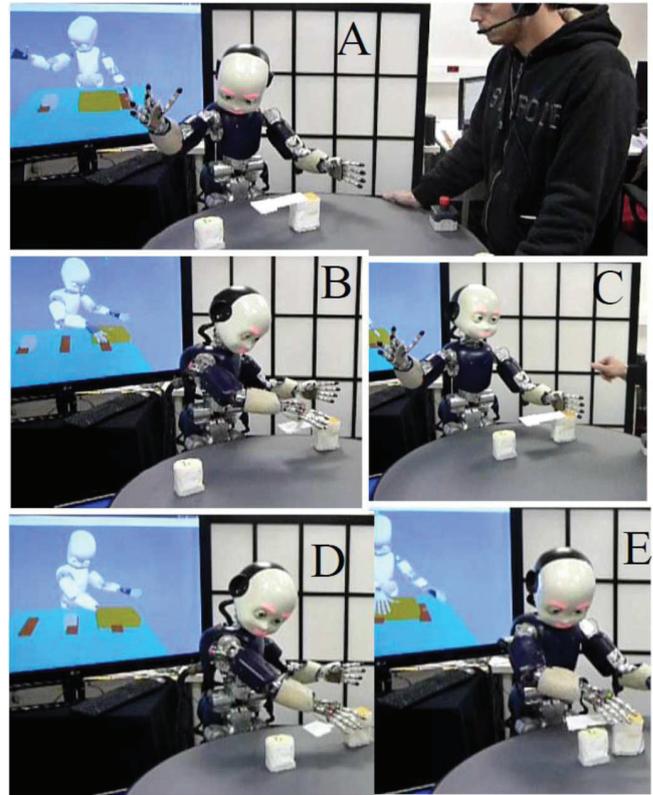


Fig. 7. Learning and performing the “hide the toy” cooperative plan. Setup with the “toy” on the left of the table, and “box” on the right. Spatial representation on iCub GUI left rear. B. iCub puts the box on its left. C. human put the toy in the middle. D. iCub reaches for the box, and F. puts the box on the toy. Note the grasping precision.

00:13 ICub: “You will put the box on the left. I will put the toy on the middle. You will put the box on the toy. Should we proceed?”

00:29 Human: “Yes we should.”

00:31 ICub: “You will put the box on the left.”

Here the robot detects the change of position of the box to the left.

00:37 ICub: “I will put the toy on the middle.”

01:13 ICub: “You will put the box on the toy.”

01:19 ICub: “Shared Plan menu.”

Role reversal is a specific instance of a more general capability that is provided by the system. That is, once a shared plan has been learned with a given set of agent arguments, the arguments for the two agents can be instantiated with different instances, e.g., I and you vs. you and I.

### D. Performance Analysis

<sup>201</sup> We repeated the shared plan learning, execution and role reversal twice each. The timing of the principal events is illustrated in Fig. 8. It is noteworthy that the system allows the multiple-action shared plan to be specified in well-under one

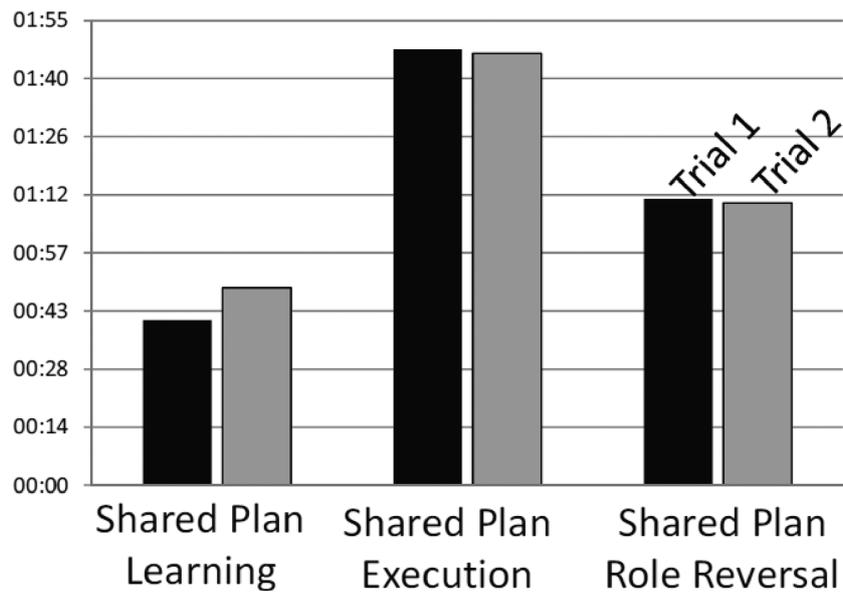


Fig. 8. Event durations (in seconds:minutes) for two trials (Trial 1 in black, trial 2 in grey) of the learning, execution and role reversal for the “hide the toy” shared plan.

minute, and then executed in this same time scale, both in the standard format, and the role reversal.

Note that in Fig. 8, the role reversal condition is executed more rapidly than the standard condition. This is due to the relative slowness of the robot actions, with respect to those of the human. In the standard sequence, the robot performs two actions (moving the box away from the center, and then over the toy) while the human performs only one action (placing the toy in the middle to be covered). This is reversed in the role, reversal, and thus the effect of the slowness of the robot is reduced.

### E. iCub Discussion

These experiments extend the results with the Nao, which is in part achieved because of the more dexterous grasping capabilities of the iCub. In the current experiments we demonstrated how an arbitrary shared plan could be established in less than one minute, and then immediately be used to execute the cooperative task. In addition, we demonstrate how this shared plan can be used to allow role reversal, in which the two agents swap roles. Again, for Carpenter *et al.* [12] this is a hallmark of shared plan use, as it clearly demonstrates that the agents have a “bird’s eye view” or global view, of the shared activity. Technically this requires that all of the actions that can take place in the shared plan can be executed physically by both the human and the robot. Because of the high spatial precision of the ReacTable, and the precision grasping capabilities of the iCub, this is a technical reality.

## VI. DISCUSSION AND FUTURE WORK

The current research can be situated within the larger context of cognitive developmental robotics [52], with physical embodiment playing a central role in structuring representations within the system, through interaction with the environment,

including humans. In development, the early grammatical constructions that are acquired and used by infants define structural mappings between the underlying structure of everyday actions, and the expression of this structure in language [6], [53]. We have exploited this mapping, in building systems that can learn grammatical constructions from experience with the environment [8], [54]. Here we exploit this type of grammatical construction, by building such constructions into the grammars that are used for speech recognition. These constructions that map onto the basic structure of action (e.g., *agent action object*) correspond to the basic argument constructions that are the workhorses of initial language [6], [53]. The “ditransitive” construction is a good example that has been extensively studied [5]. In a canonical form of this construction “Subject Verb Recipient Object” (e.g., John gave Sally a flower), Subject maps onto the agent of the transitive action specified by Verb, and Recipient receives the Object via that transitive action. The current research demonstrates how language, based on these constructions, can be used to coordinate real-time learning of cooperative actions, providing the coordination of multiple demonstration modalities including vision-like perception, kinesthetic demonstration [13], [29], [55]–[58], and command execution via spoken language. In this sense, language serves a dual purpose: First and most important, it provides the mechanism by which a cooperative plan can be constructed and modified. Second, during the construction of the shared plan, one of the modalities by which actions can be inserted into the plan is via the spoken issue of a command. We demonstrate that in this framework, the constructive features of language can be mapped onto different robot platforms. This requires the mapping of the argument structure of grammatical constructions onto the predicate-argument structure of the command and perceptual operators of the given platform [13], [55]. Doing so, we subsequently achieve performance, where the systems can learn and perform new cooperative behaviors in the time frame of

2–3 minutes. The introduction of structured language provides a powerful means to leverage sensory-motor skills into cooperative plans, reflecting how the development of language in human children is coincident with an explosion in their social development in the context of triadic relations between themselves, another person and a shared goal [1]. We should note that the “ecological validity” of the kind of language that the user can employ is somewhat restricted to simple grammatical constructions. That is, people cannot use fully unconstrained natural language, such as relative clauses, and pronouns. Still, this allows sufficient expressive ability for the user to construct elaborated shared plans.

The approach to learning that we have taken thus consists in the implementation of a highly structured scaffolding that allows the user to teach the robot new action components, and then to teach the robot how to organize these actions into more elaborate turn-taking sequences that constitute shared plans. The advantage of this approach is that it is powerful and scales well. It is powerful because it allows the user to specify arbitrary turn-taking sequences (which can even include solo sequences that are performed only by one of the agents), and the set of elementary actions can also be augmented through learning. All of this learning can be done with a single trial. The advantage of this is that learning is rapid. Indeed, related studies have demonstrated that for complex tasks such as those used here, human and neural network simulations fare better with high level instruction (imitation or verbal instruction) than with lower level instruction (reinforcement learning) [59]. The disadvantage is that the teaching must be perfect. Thus, in demonstrating a trajectory, the system cannot benefit from a successive refinement over multiple trials [60].

One of the limitations of this work is that there is not a systematic mechanism for the long-term accumulation and synthesis of such learning. In the future it will be important for these developmental acquisitions to be integrated into the system over a life-time scale [61]. Another limitation is that in the current research the behavior is determined by the shared plan, and there is no choice. To cope with changing task contingencies, the system will require more adaptive behavior including the ability to choose between competing options [62]. Perhaps one of the most fundamental limitations of the current research, which lays a foundation for future research, has to do with the deeper nature of the shared plan. This is the notion of the shared intention. Our robots can learn a plan that allows them to perform a cooperative task, and even to demonstrate role reversal. Yet the true notion of the actual final goal, the shared intention, to get that toy into the box, is currently not present. We have started to address this issue by linking actions to their resulting states, within the action representation [56]. We must go further, in order to now expand the language capability to address the expression and modification of internal representations of the intentional states of others.

The current research proposes an interaction architecture, for on-line multimodal learning, and demonstrates its functionality. It is not an extended user study that allows for the collection of data whose variability can be statistically analyzed in a population of subjects. Within the interactions that we test, the most pertinent parameter that reflects the change in the real-time flow

and fluidity of the interactions is related to the time required for different component actions, and their changes as a function of learning. We thus demonstrate the feasibility of using spoken language to coordinate the creation of arbitrary novel turn-taking action sequences (which we refer to as shared plans). This includes the ability to create new actions (through demonstration and imitation), and to embed these actions in new turn-taking shared plans. Clearly a more robust demonstration of the performance of the architecture (and effective time gains before/after learning) should use naïve users and include metrics related to interaction quality, success etc. This is a topic of our ongoing research.

## REFERENCES

- [1] M. Tomasello, M. Carpenter, J. Call, T. Behne, and H. Moll, “Understanding and sharing intentions: The origins of cultural cognition,” *Behav. Brain Sci.*, vol. 28, pp. 675–691, 2005.
- [2] S. Carey, *The Origin of Concepts*. Boston, MA, USA: MIT, 2009.
- [3] F. Warneken, F. Chen, and M. Tomasello, “Cooperative activities in young children and chimpanzees,” *Child Develop.*, vol. 77, pp. 640–663, 2006.
- [4] F. Warneken and M. Tomasello, “Helping and cooperation at 14 months of age,” *Infancy*, vol. 11, pp. 271–294, 2007.
- [5] A. Goldberg, *Constructions: A Construction Grammar Approach to Argument Structure*. Chicago, IL, USA: Univ. Chicago Press, 1995.
- [6] M. Tomasello, *Constructing a Language: A Usage Based Approach to Language Acquisition*. Boston, MA, USA: MIT Press, 2003.
- [7] K. Rohlfing and J. Tani, “Grounding language in action,” *IEEE Trans. Autom. Mental Develop.*, vol. 3, p. 4, Dec. 2011.
- [8] P. Dominey and J. Boucher, “Learning to talk about events from narrated video in a construction grammar framework,” *Artif. Intell.*, vol. 167, pp. 31–61, 2005.
- [9] P. Dominey, A. Mallet, and E. Yoshida, “Progress in programming the hrp-2 humanoid using spoken language,” in *Proc. IEEE Int. Conf. Robot. Autom.*, 2007, pp. 2169–2174.
- [10] P. Dominey, A. Mallet, and E. Yoshida, “Real-time cooperative behavior acquisition by a humanoid apprentice,” presented at the Int. Conf. Human. Robot., Pittsburg, PA, USA, 2007.
- [11] P. Dominey and F. Warneken, “The basis of shared intentions in human and robot cognition,” *New Ideas Psychol.*, vol. 29, p. 14, 2011.
- [12] M. Carpenter, M. Tomasello, and T. Striano, “Role reversal imitation and language in typically developing infants and children with autism,” *Infancy*, vol. 8, pp. 253–278, 2005.
- [13] S. Lallée, S. Lemaignan, A. Lenz, C. Melhuish, L. Natale, S. Skachek, T. van Der Tanz, F. Warneken, and P. Dominey, “Towards a platform-independent cooperative human-robot interaction system: I. Perception,” presented at the IROS, Taipei, Taiwan, 2010.
- [14] S. Lallée, U. Pattacini, J. Boucher, S. Lemaignan, A. Lenz, C. Melhuish, L. Natale, S. Skachek, K. Hamann, J. Steinwender, E. A. Sisbot, G. Metta, R. Alami, M. Warnier, J. Guitton, F. Warneken, and P. F. Dominey, “Towards a platform-independent cooperative human-robot interaction system: II. Perception, execution and imitation of goal directed actions,” in *Proc. IROS*, San Francisco, CA, USA, 2011, pp. 2895–2902.
- [15] S. Lallée, U. Pattacini, S. Lemaignan, A. Lenz, C. Melhuish, L. Natale, S. Skachek, K. Hamann, J. Steinwender, E. A. Sisbot, G. Metta, J. Guitton, R. Alami, M. Warnier, T. Pipe, F. Warneken, and P. Dominey, “Towards a platform-independent cooperative human-robot interaction system: III. An architecture for learning and executing actions and shared plans,” *IEEE Trans. Autom. Mental Develop.*, vol. 4, no. 3, pp. 239–253, Sep. 2012.
- [16] H. H. Clark, “Coordinating with each other in a material world,” *Discourse Studies*, vol. 7, pp. 507–525, Oct. 1, 2005, 2005.
- [17] B. Argall, S. Chernova, M. Veloso, and B. Browning, “A survey of robot learning from demonstration,” *Robot. Autom. Syst.*, vol. 57, pp. 469–483, 2009.
- [18] M. Kaiser and R. Dillmann, “Building elementary robot skills from human demonstration,” in *Proc. Int. Conf. Robot. Autom.*, 1996, pp. 2700–2705.
- [19] M. Nicolescu and M. Mataric, “Natural methods for robot task learning: Instructive demonstrations, generalization and practice,” in *Proc. 2nd Int. Joint Conf. Autom. Agents Multiagent Syst.*, Melbourne, 2003, pp. 241–248.

- [20] B. D. Argall, S. Chernova, M. Veloso, and B. Browning, "A survey of robot learning from demonstration," *Robot. Autom. Syst.*, vol. 57, pp. 469–483, 2009.
- [21] P. Dominey, A. Mallet, and E. Yoshida, "Real-time spoken-language programming for cooperative interaction with a humanoid apprentice," *Int. J. Humanoids Robot.*, vol. 6, pp. 147–171, 2009.
- [22] V. Tikhonoff, A. Cangelosi, and G. Metta, "Integration of speech and action in humanoid robots: iCub simulation experiments," *IEEE Trans. Autom. Mental Develop.*, vol. 3, no. 1, pp. 17–29, Mar. 2011.
- [23] Y. Zhang and J. Weng, "Task transfer by a developmental robot," *IEEE Trans. Evol. Comput.*, vol. 11, no. 2, pp. 226–248, Apr. 2007.
- [24] P. Andry, P. Gaussier, S. Moga, J. P. Banquet, and J. Nadel, "Learning and communication via imitation: An autonomous robot perspective," *IEEE Trans. Syst., Man, Cybernetics, Part A: Syst. Humans*, vol. 31, no. 5, pp. 431–442, Sep. 2001.
- [25] P. Andry, P. Gaussier, and J. Nadel, "From Visuo-Motor Development to Low-Level Imitation 2002."
- [26] C. A. Calderon and H. Hu, "Robot imitation from human body movements," presented at the AISB05 3rd Int. Symp. Imitation Animals Artifacts, 2005.
- [27] S. Calinon, F. D'Halluin, E. L. Sauser, D. G. Caldwell, and A. G. Billard, "Learning and reproduction of gestures by imitation," *IEEE Robot. Autom. Mag.*, vol. 17, no. 2, pp. 44–54, Jun. 2010.
- [28] K. Dautenhahn and C. L. Nehaniv, *The Correspondence Problem*. Cambridge, MA, USA: MIT Press, 2002.
- [29] Y. Demiris and B. Khadhouri, "Hierarchical attentive multiple models for execution and recognition of actions," *Robot. Autom. Syst.*, vol. 54, pp. 361–369, 2006.
- [30] C. Breazeal and B. Scassellati, "Robots that imitate humans," *Trends Cogn. Sci.*, vol. 6, pp. 481–487, 2002.
- [31] S. Schaal, "Is imitation learning the route to humanoid robots?," *Trends Cogn. Sci.*, vol. 3, pp. 233–242, 1999.
- [32] M. Lungarella, G. Metta, R. Pfeifer, and G. Sandini, "Developmental robotics: A survey," *Connect. Sci.*, vol. 15, pp. 151–190, Dec. 01, 2003, 2003.
- [33] J. Saunders, C. L. Nehaniv, and K. Dautenhahn, "Using self-imitation to direct learning," in *Proc. 15th IEEE Int. Symp. Robot Human Interact. Commun. (ROMAN)*, 2006, pp. 244–250.
- [34] J. Saunders, C. L. Nehaniv, K. Dautenhahn, and A. Alissandrakis, "Self-imitation and environmental scaffolding for robot teaching," *Int. J. Adv. Robot. Syst.*, vol. 4, 2008.
- [35] A. Cangelosi and T. Riga, "An embodied model for sensorimotor grounding and grounding transfer: Experiments with epigenetic robots," *Cogn. Sci.*, vol. 30, pp. 673–689, 2006.
- [36] K. Coventry, A. Cangelosi, R. Rajapakse, A. Bacon, S. Newstead, D. Joyce, and L. Richards, , C. Freksa, M. Knauff, B. Krieg-Brückner, B. Nebel, and T. Barkowsky, Eds., *Spatial Prepositions and Vague Quantifiers: Implementing the Functional Geometric Framework Spatial Cognition IV. Reasoning, Action, Interaction*. Berlin, Germany: Springer-Verlag, 2005, vol. 3343, pp. 98–110.
- [37] J. J. Steil, F. Röthling, R. Haschke, and H. Ritter, "Situated robot learning for multi-modal instruction and imitation of grasping," *Robot. Autom. Syst.*, vol. 47, pp. 129–141, 2004.
- [38] J. Weng, "Developmental robotics: Theory and experiments," *Int. J. Humanoid Robot. (IJHR)*, vol. 1, pp. 199–236, 2004.
- [39] P. F. Verschure, T. Voegtlin, and R. J. Douglas, "Environmentally mediated synergy between perception and behaviour in mobile robots," *Nature*, vol. 425, pp. 620–624, Oct. 9, 2003.
- [40] A. Duff, M. S. Fibla, and P. F. Verschure, "A biologically based model for the integration of sensory-motor contingencies in rules and plans: A prefrontal cortex based extension of the distributed adaptive control architecture," *Brain Res. Bull.*, vol. 85, pp. 289–304, June 30, 2011.
- [41] P. F. Verschure and T. Voegtlin, "A bottom up approach towards the acquisition and expression of sequential representations applied to a behaving real-world device: Distributed adaptive control III," *Neural Netw.*, vol. 11, pp. 1531–1549, Oct. 1998.
- [42] S. Sutton, R. Cole, J. Villiers, J. Schalkwyk, P. Vermeulen, M. Macon, Y. Yan, E. Kaiser, B. Rundle, and K. Shobaki, "Universal speech tools: The CSLU toolkit," presented at the 5th Int. Conf. Spoken Language Process., 1998.
- [43] P. Fitzpatrick, G. Metta, and L. Natale, "Towards long-lived robot genes," *Robot. Autom. Syst.*, vol. 56, pp. 29–45, 2007.
- [44] G. Metta, G. Sandini, D. Vernon, L. Natale, and F. Nori, "The iCub humanoid robot: An open platform for research in embodied cognition," in *PerMIS: Performance Metrics for Intelligent Systems Workshop*, Washington, DC, USA, 2008, pp. 19–21.
- [45] V. Mohan, P. Morasso, G. Metta, and G. Sandini, "A biomimetic, force-field based computational model for motion planning and bi-manual coordination in humanoid robots," *Autonom. Robots*, vol. 27, pp. 291–307, 2009.
- [46] O. Khatib, "Real-time obstacle avoidance for manipulators and mobile robots," *Int. J. Rob. Res.*, pp. 90–98, 1986.
- [47] L. Sciavicco and B. Siciliano, *Modelling and Control of Robot Manipulators 2005*.
- [48] A. Parmiggiani, M. Randazzo, L. Natale, G. Metta, and G. Sandini, "Joint torque sensing for the upper-body of the iCub humanoid robots," presented at the IEEE Int. Conf. Humanoid Robots, Paris, France, 2009.
- [49] U. Pattacini, F. Nori, L. Natale, G. Metta, and G. Sandini, "An experimental evaluation of a novel minimum-jerk cartesian controller for humanoid robots," presented at the IROS, Taipei, Taiwan, 2010.
- [50] A. Wächter and L. T. Biegler, "On the implementation of a primal-dual interior point filter line search algorithm for large-scale nonlinear programming," *Math. Program.*, vol. 106, pp. 25–57, 2006.
- [51] L. Shmuelof and E. Zohary, "Dissociation between ventral and dorsal fMRI activation during object and action recognition," *Neuron*, vol. 47, pp. 457–470, 2005.
- [52] M. Asada, K. Hosoda, Y. Kuniyoshi, H. Ishiguro, T. Inui, Y. Yoshikawa, M. Ogino, and C. Yoshida, "Cognitive developmental robotics: A survey," *IEEE Trans. Autom. Mental Develop.*, vol. 1, no. 1, pp. 12–34, May 2009.
- [53] A. Goldberg, *Constructions: A Construction Grammar Approach to Argument Structure*. Chicago, IL, USA: Univ. Chicago Press, 1995.
- [54] P. Dominey and J. Boucher, "Developmental stages of perception and language acquisition in a perceptually grounded robot," *Cogn. Syst. Res.*, vol. 6, pp. 243–259, 2005.
- [55] S. Lallée, S. Lemaignan, A. Lenz, C. Melhuish, L. Natale, S. Skachek, T. van Der Tanz, F. Warneken, and P. Dominey, "Towards a platform-independent cooperative human-robot interaction system: II. Perception, execution and imitation of goal directed actions," presented at the IROS, 2011, presented at the.
- [56] S. Lallée, C. Madden, M. Hoen, and P. Dominey, "Linking language with embodied teleological representations of action for humanoid cognition," *Frontiers Neurobot.*, 2010.
- [57] S. Lallée, F. Warneken, and P. Dominey, "Learning to collaborate by observation," presented at the Epirob, Venice, Italy, 2009.
- [58] G. Metta, G. Sandini, L. Natale, L. Craighero, and L. Fadiga, "Understanding mirror neurons: A bio-robotic approach," *Interact. Stud.*, vol. 7, pp. 197–232, 2006.
- [59] F. Dandurand and T. R. Shultz, "Connectionist models of reinforcement, imitation, and instruction in learning to solve complex problems," *IEEE Trans. Autom. Mental Develop.*, vol. 1, no. 2, pp. 110–121, Aug. 2009.
- [60] S. Calinon, F. Guenter, and A. Billard, "On learning, representing, and generalizing a task in a humanoid robot," *IEEE Trans. Syst. Man. Cybern. B Cybern.*, vol. 37, pp. 286–298, Apr. 2007.
- [61] Y. Demiris and A. Meltzoff, "The robot in the crib: A developmental analysis of imitation skills in infants and robots," *Infant Child Develop.*, vol. 17, pp. 43–53, Jan. 2008.
- [62] T. J. Prescott, F. M. Montes Gonzalez, K. Gurney, M. D. Humphries, and P. Redgrave, "A robot model of the basal ganglia: Behavior and intrinsic processing," *Neural Netw.*, vol. 19, pp. 31–61, Jan. 2006.



**Maxime Petit** received the M.Sc. degree in computer sciences (cognitive sciences specialty) from the University of Paris-Sud, Orsay, France, in 2010, and an engineering degree in biosciences (bioinformatics and modeling specialty) from the National Institute of Applied Sciences (INSA), Lyon, France, the same year. He is currently working towards the Ph.D. degree at the Stem-Cell and Brain Research Institute, from the unit 846 of the National Institute of Science And Medical Research (INSERM) in Bron, France, working in the Robotic Cognition Laboratory team.

He is focusing about the reasoning and planning in robotics, especially with the iCub platform, and more precisely, within a context of spoken language interaction with a human.



**Stéphane Lallée** received the Master's degree in cognitive science and human-machine interface engineering from the University of Grenoble, Grenoble, France, in 2008. He received the Ph.D. degree in cognitive neuroscience from Lyon University, Lyon, France, in 2012, developing a distributed architecture for human-robot cooperation.

He joined the Robot Cognition Laboratory in 2008, and has played a leading role in the iCub project in Lyon since the arrival of the iCub in 2009.



**Jean-David Boucher** received the Ph.D. degree in cognitive science and robotics from the the Robot Cognition Laboratory, University of Lyon, Lyon, France, in 2010.

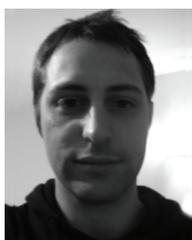
He continued there as a Postdoctoral Fellow on the CHRIS project. He currently teaches programming at Monash University, Melbourne, Australia, and pursues research on human-robot interaction.



**Grégoire Pointeau** received the M.Sc. degree in biosciences (bioinformatics and modeling specialty) from the National Institute of Applied Sciences (INSA), Lyon, France, in 2011, and the Master's degree in cognitive science at the University of Lyon, Lyon, France. He is currently working toward the Ph.D. degree at the Robot Cognition Laboratory in Lyon as part of the FP7 EFAA project.

He is interested in the accumulation of experience and autobiographical memory in the elaboration of the self, in the context of human-robot social inter-

action.



**Pierrick Cheminade** received the Technical Dipl. in computer sciences from the University Institute of Technology, Puy-en-Velay, France, in 2008.

Before working in the game industry he was an independent web developer. He began his career in 2008 at DreamonStudio Lyon, France, and then worked for two years at Little World Studio (2008-2011 Lyon France) before working at the Robot Cognition Laboratory, on the Nao, at the Inserm-U846 (2011). In 2012 he released several games as an independent on the Ios platform. He is

currently working as a game programmer for Codemaster (Southam United Kingdom).



**Dimitri Ognibene** received the B.Sc. degree computer engineering from the University of Palermo, Palermo, Italy, in 2004, and the Ph.D. degree in robotics from the University of Genoa, Genoa, Italy, in 2009.

He was Research Assistant the CNR ISTC in Rome from 2005 until 2011. In 2010, he was visiting scholar at the University of Massachusetts Amherst, Amherst, MA, USA. He is currently a Research Associate at Imperial College London, London, U.K.

His research interests include the computational principles of visual attention, resource allocation, and learning and development in natural and artificial systems. He is now working on probabilistic social attention systems for humanoid robots.

20



**Eris Chinellato** (M'03) received the B.Sc. degree in industrial engineering from the Università degli Studi di Padova, Padova, Italy, in 1999, the M.Sc. degree in artificial intelligence from the University of Edinburgh, Edinburgh, U.K., in 2002, and the Ph.D. degree in intelligent robotics from Jaume I University, Spain, in 2008.

He is now working at Imperial College London on neural models of social interaction to be applied to the iCub humanoid robot. He has published in influential journals and proceedings in both robotics and neuro-

science, and has served as reviewer and program committee member for several IEEE journals and conferences. His interdisciplinary research, integrating robotics with experimental and theoretical neuroscience, focuses on sensorimotor integration in both natural and artificial systems.



**Ugo Pattacini** received the M.S. degree (with Hons.) in electronic engineering from University of Pisa, Pisa, Italy, in 2001, and the Ph.D. degree in robotics, neurosciences, and nanotechnologies from Istituto Italiano di Tecnologia (ITT), Genova, Italy, in 2011.

He is currently a Postdoctoral Fellow in the Robotics, Brain, and Cognitive Sciences Department (RBCS) at IIT. From 2001 to 2006, he worked as an Embedded Software Developer for Formula 1 applications first at Racing Department of Magneti Marelli in Milan and then joining Toyota F1

team in Cologne, dealing with the design and the implementation of proprietary hard-constrained real-time operating systems, vehicle dynamics and torque-based traction control strategies. From 2006 to 2007, he moved to Earth Observation Business Unit of Thales Alenia Space in Rome where he was concerned with the specifications design and trade-off analyses of the satellite data acquisition system for COSMO-SkyMed (ASI) and GMES (ESA) scientific program. From 2008, he is involved in the development of the humanoid iCub at IIT focusing his interests mainly on the advancement of robot motor capabilities and pursuing a methodology that aims to combine traditional model-based approaches with the most recent machine learning techniques.



**Ilaria Gori** was born in Rome, Italy, on November, 6th 1986. She received the Bachelor's degree in management engineering with the score of 110/110 at Sapienza, University of Rome, Rome, Italy, in July 2008. In 2010, she graduated (*cum laude*) in computer engineering at Sapienza, University of Rome, with a specialization in artificial intelligence.

She wrote her Master's thesis at Imperial College, in London, where she lived for six months in 2010. Then she worked for two months in a software development company in 2010. In January 2011, she

started a Ph.D. in robotics, cognition and interaction technologies at Istituto Italiano di Tecnologia, Genova, Italy, that she is currently carrying out. She is mainly interested in computer vision and machine learning, but she also worked in robotics.

Ms. Gori published a paper at ISVC 20 summarizing her Master's thesis, and she won a Best Paper Award.



**Uriel Martínez-Hernandez** is currently working towards the Ph.D. degree in automatic control and systems engineering at the University of Sheffield, Sheffield, U.K.

His current research is about exploration and object recognition based on active touch sensing using the fingers of the ICUB robot. Also in this project, he is working together with the Psychology department.

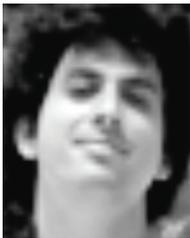


**Hector Barron** is an Engineer with a first degree in computer science. He worked several years in applying computer vision and machine learning upon real-time systems. Attracted by cognitive science, he is proposing increasing the capacities of spatial reasoning for navigation tasks. Upon the Bayesian framework, this work explores interesting insights from neuroscience and psychology.



**Martin Inderbitzin** received the Ph.D. degree in computer science and robotics in the Synthetic, Perceptive, Emotive, and Cognitive Systems (SPECS) Group, in Barcelona.

He studied Embodied Models of Emotions—Verification of Psychological and Neurobiological Theories of Emotions Using Virtual and Situated Agents. He is currently R&D Director Projekt Pot Shot Experience Design, Zürich, Switzerland, where he will investigate video mapping and interactivity developing embodied experiences.



**Andre Luvizotto** received the B.Sc. degree in music, 2005, and the M.Sc. degree in electrical engineering, in 2008, both in UNICAMP, with the cooperation of NICS—“Núcleo Interdisciplinar de Comunicação Sonora.” In his Master’s thesis, he worked with sonological models, based on wavelet transform. He is currently working towards the Ph.D. degree at the SPECS group at the Universitat Pompeu Fabra, Barcelona, Spain.

He joined SPECS in February, 2008. He is currently working on the EFAA project, with a computational model for visual and auditory invariant representations, based on temporal population code.



**Vicky Vouloutsis** received the B.A. degree in computer science from the Technological Educational Institute of Athens, Athens, Greece, 2008. In 2009, she came to Barcelona where she received the M.Sc. degree in cognitive systems and interactive media from the Universitat Pompeu Fabra, in 2011. She completed her Master’s thesis on biologically inspired computation for chemical sensing in SPECS where she is currently working as a continuation of her Master’s thesis.



**Yiannis Demiris** (M’01–SM’08) received the B.Sc. and Ph.D. degrees in intelligent robotics from the University of Edinburgh, Edinburgh, U.K., in 1994 and 1999, respectively.

He joined the faculty of the Department of Electrical and Electronic Engineering at Imperial College London in 2001 where he is currently a Reader in human-centred robotics and heads the Personal Robotics Laboratory. His research interests include biologically inspired robotics, human-robot interaction, developmental robotics, and robotic as-

sistive devices for adults and children with disabilities. He was the Chair of the IEEE International Conference on Development and Learning in 2007 and the Program Chair of the ACM/IEEE International Conference on Human-Robot Interaction in 2008. He has organized several international workshops on robot learning, bioinspired machine learning, and epigenetic robotics.

Dr. Demiris has received fellowships from the AIST-MITI in Japan, and the European Science Foundation, and currently participates in several EU FP7 research projects in Human–Robot Interaction. In 2012, he received the Rector’s Award and the Faculty of Engineering Award for Excellence in Engineering Education.



**Giorgio Metta** received the M.Sc. (with Hons) and Ph.D. degrees in electronic engineering from the University of Genoa, Genoa, Italy, in 1994 and 2000, respectively.

He is currently a Senior Scientist at IIT and Assistant Professor at the University of Genoa where he teaches courses on anthropomorphic robotics and intelligent systems for the bioengineering curricula. From 2001 to 2002, he was Postdoctoral Associate at the MIT AI-Lab where he worked on various humanoid robotic platforms. He has been an Assistant

Professor at the University of Genoa since 2005 and with IIT since 2006. His research activities are in the fields of biologically motivated and humanoid robotics and in particular in developing life-long developing artificial systems that show some of the abilities of natural systems. His research developed in collaboration with leading European and international scientists from different disciplines including neuroscience, psychology, and robotics. Giorgio Metta is author or coauthor of approximately 100 publications. He has been working as research scientist and co-PI in several international and national funded projects. He has been reviewer for international journals, and national and international funding agencies.



**Peter Ford Dominey** received the B.A. degree in cognitive psychology and artificial intelligence from Cornell University, Ithaca, NY, USA, in 1984. He received the M.Sc. and Ph.D. degrees in computer science from the University of Southern California, Los Angeles, CA, USA, in 1989 and 1993, respectively, developing neural network models of sensorimotor sequence learning, including the first simulations of the role of dopamine in sensorimotor associative learning, and pioneering work in reservoir computing.

He is currently a CNRS Research Director at the INSERM Stem Cell and Brain Research Institute in Lyon, France, where he directs the Robot Cognition Laboratory. From 1984 to 1986, he was a Software Engineer at the Data General Corporation, and from 1986 to 1993 he was a Systems Engineer at NASA/JPL/CalTech. In 1997 he became a tenured researcher, and in 2005 a Research Director with the CNRS in Lyon France. His research interests include the development of a “cognitive systems engineering” approach to understanding and simulating the neurophysiology of cognitive sequence processing, action and language, and their application to robot cognition and language processing, and human–robot cooperation. He is currently participating in several French and European projects in this context.

**9.3.3 Interaction Studies : Reasoning Based on Integrated Real World Experience Acquired by a Humanoid Robot**

Authors : **Petit, M.**, Pointeau, G., and Dominey, P. F.

Title : "Reasoning based on consolidated real world experience acquired by a humanoid robot."

Journal : Interaction Studies

Year : accepted with minor revisions - 2015

1           **Reasoning Based on Consolidated Real World Experience**

2                           **Acquired by a Humanoid Robot**

3                           Maxime Petit, Grégoire Pointeau, Peter Ford Dominey\*

4                           Robot Cognition Laboratory, INSERM U846, Bron France

5                           Personal Robotics Lab, Imperial College, London UK

6                           m.petit@imperial.ac.uk, gregoire.pointeau@inserm.fr, peter.dominey@inserm.fr

Inserm U846  Stem Cell and Brain Research Institute  18, avenue du doyen Jean Lépine  69675 Bron cedex  France  Tel : +33-4 72 91 34 84  Fax : +33-4 72 91 34 61	Electrical & Electronic Engineering Department  Imperial College  London SW7 2AZ  United Kingdom  Tel : +44-207 594 6323  Fax : +44-207 594 6274
--	--

7    Keywords: humanoid robot; embodied; physical interaction; experience;  
8    reasoning; planning; autobiographical memory; learning; human-robot interaction.

9    Manuscript statistics:

10   Words: 7,890 (excluding references)

11   Figures: 17

12   Pages: 41

13   Authors Biographical Notes : 100, 83, 98 (<100)

15 **Maxime Petit** received a M.Sc. degree in computer science from the University of Paris-Sud, France, and an engineering degree in biosciences (bio-informatics and modelling) from the National Institute of Applied Sciences (INSA) Lyon, France, both in 2010. In 2014, he received a Ph.D. from the National Institute of Science and Medical Research (INSERM), in the Stem-Cell and Brain Research Institute (SBRI) in Lyon, within the Robot Cognition Laboratory (RCL).

21 He is a Research Associate at the Personal Robotics Lab of Imperial College (London). His research interests include reasoning and planning in robotics, linked to spoken language interactions with a human.

24

25

26 **Grégoire Pointeau** received the M.Sc. degree in biosciences (bio-informatics and modelling specialty) from the National Institute of Applied Sciences (INSA) of Lyon, France, in 2011, and then pursued Master's studies in Cognitive Science at the University of Lyon. He is currently a Ph.D. student at the Robot Cognition Laboratory (RCL) in Lyon as part of the FP7 EFAA and WYSIWYD projects.

31 He is interested in the accumulation of experience and autobiographical memory in the elaboration of the self, in the context of human-robot social interaction.

33

34 **Peter Ford Dominey** is a CNRS Research director at the INSERM SBRI, directing the RCL.

35

36 He completed the BA at Cornell University (1984) and obtained the M.Sc. (1989) and Ph.D. (1993) in computer science from the University of Southern California. He was a Software Engineer (Data General Corporation, 1984-1986), and a Systems Engineer (NASA/JPL/CalTech, 1986-1993). In 1997 he became a tenured researcher, and in 2005 a CNRS Research Director.

41 His research interests: a "cognitive systems engineering" approach to understand and simulate the neurophysiology of cognitive sequence processing and their application to robot cognition, language interactions and human-robot cooperation.

43

44

45       **Abstract.**

46       The development of reasoning systems that can exploit expert knowledge  
47 from interaction with humans is a non-trivial problem, particularly investigating  
48 how the information can be coded in the knowledge representation. For example,  
49 as in human development, the acquisition of knowledge at one level requires the  
50 consolidation of knowledge from a lower level. How is the accumulated experi-  
51 ence structured to allow the individual to apply knowledge to new situations, thus  
52 reasoning and adapting?

53       We investigate how this can be done automatically by a robotic system iCub  
54 that interacts with humans to acquire knowledge via demonstration. Once consol-  
55 idated, this knowledge can be used in further acquisition of experience concerning  
56 the preconditions and consequences of actions. Finally, this knowledge is translat-  
57 ed into rules that are used for reasoning and planning in novel problem solving  
58 situations, including a Tower of Hanoi scenario. We thus demonstrate proof of  
59 concept for an interaction system that uses knowledge acquired from human inter-  
60 action to reason about new situations.

## 61   **1   Introduction**

62       The ability to reason can be considered to rely on two complimentary components.  
63 First, a system must have access to some form of knowledge or expertise from which it  
64 can reason, e.g. the autobiographical memory of artificial system (Dore, Cattoni, &  
65 Regazzoni, 2010; Ho et al., 2009). Second, the system must then have some form of  
66 reasoning capability that allows that knowledge to be used in a systematic way (Hayes-  
67 Roth, 1997). Within this context, the current research attempts to determine how experi-

68   ence that a robot can acquire through interaction with a human can be used as the basis  
69   for knowledge-based reasoning. Allowing robots to learn from experience has been a  
70   long-term goal in cognitive robotics (Cangelosi et al., 2010; Crangle & Colleen, 1994;  
71   Wood, Baxter, & Belpaeme, 2011). Spoken language has been used to “program” ro-  
72   bots, that is, to specify procedures for how to achieve tasks, including navigation  
73   (Lauria, Bugmann, Kyriacou, & Klein, 2002), interaction (Dominey, Mallet, &  
74   Yoshida, 2007a, 2007b; Dominey & Mallet, 2009; Doshi & Roy, 2008; McGuire et al.,  
75   2002) and more elaborate shared plans for joint cooperative action with the human  
76   (Lallee et al., 2011, 2012; Lallee et al., 2010; Lallee, Warneken, & Dominey, 2009;  
77   Petit et al., 2013). In this framework, knowledge is transferred from the human to the  
78   robot in a direct manner. Ideally, the robot should be able to extract information from its  
79   experience rather than having the knowledge explicitly specified. This knowledge could  
80   then be used order in to allow the robot to reason about new situations. Indeed, in tradi-  
81   tional AI (Hayes-Roth, 1997), knowledge engineers would elicit expert knowledge from  
82   experienced people, and codify it so that this expert knowledge would allow the system  
83   to reason. In the modern context of adaptive cognitive systems for robots, the goal is to  
84   allow the robot itself to become an expert by accumulating knowledge, especially se-  
85   mantic knowledge, from its own experience ( Roy, 2002a, 2002b, Gorniak & Roy,  
86   2004).

87

88       We focus on knowledge generation and representation, and in particular, how  
89   knowledge about the domain can be acquired in an autonomous manner. Based on ob-  
90   servations of events and their variations or co-variations, human adults can use the

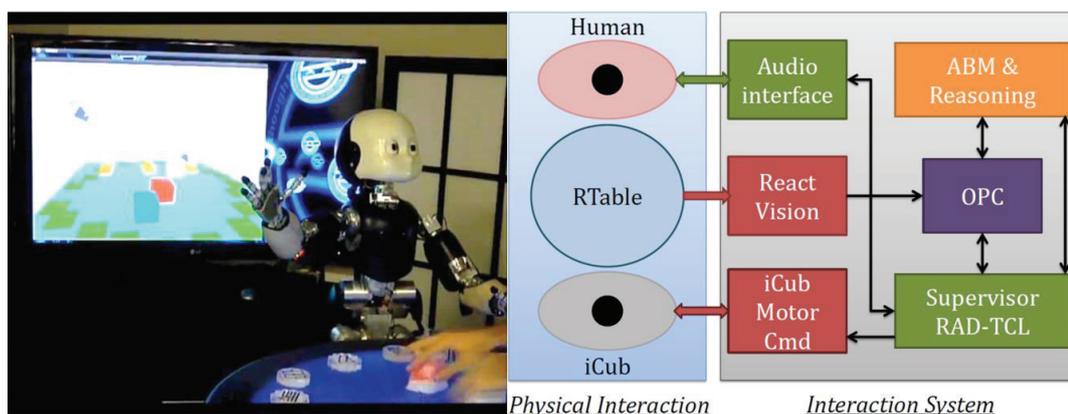
91 powerful reasoning tool of inference about the causes or consequences of events  
92 (Cheng, 1996).

93 From the outset of development, the infant begins to extract regularities from the en-  
94 vironment, and in a recursive manner to further extract structure based on this growing  
95 repertoire (Carey & Xu, 2001; Carey, 2009). We consider that the child takes a teleolog-  
96 ical stance (Gergely, Nádasdy, Csibra, & Bíró, 1995) by taking into account three com-  
97 ponents : the action, the goal state and the situational constraints, learning them through  
98 social learning by observing other’s actions and inferring their goal. Once learned, the  
99 child can then reason and select actions in order to achieve a goal, in particular when the  
100 other is explicitly stating his intentions (Gergely & Csibra, 2003).

101 The goal of this research is to provide a real-time goal-directed reasoning capability  
102 to robots, loosely based on a developmental trajectory where knowledge from succes-  
103 sively refined levels contributes to the ability to reason, based on this teleological  
104 stance. When we reach the highest level of this representational hierarchy, the infor-  
105 mation will be appropriate for reasoning, not only at the spatial level as previously in-  
106 vestigated (Kalkan, Dag, Yürüten, Borghi, & Sahin, 2013; Takács & Demiris, 2008;  
107 Welke et al., 2013) but also on the contextual level (e.g. effect of an object on another  
108 one).

109 Actions encountered by the robot are stored in its AutoBiographical-like Memory  
110 (ABM) and then statistically processed in order to extract contextual knowledge about  
111 them (Pointeau, Petit, & Dominey, 2013a, 2013b, 2014). This knowledge is formatted  
112 into rules (based on the Planning Domain Definition Language (PDDL) format  
113 (Helmert, 2009; McDermott et al., 1998)) allowing an AI planner to produce the se-  
114 quence of actions allowing the robot to fulfill a goal. We will demonstrate the system

115 capabilities with two concrete example tasks, where the robot learns the physical struc-  
 116 ture of the environment, the rules of the tasks, and then demonstrates its ability to use  
 117 this knowledge to reason in novel situations. The first task, or game, involves rules  
 118 about how objects can be displaced from one location to another in terms of pre- and  
 119 post-conditions for actions. The second game is more involved, based on the Tower of  
 120 Hanoi, adapted to our environment and here called the “Table of Hanoi”. In this context  
 121 the system must learn about the particular properties of objects in terms of when and  
 122 where they can move, based on the presence of other objects at the source and target  
 123 destinations.

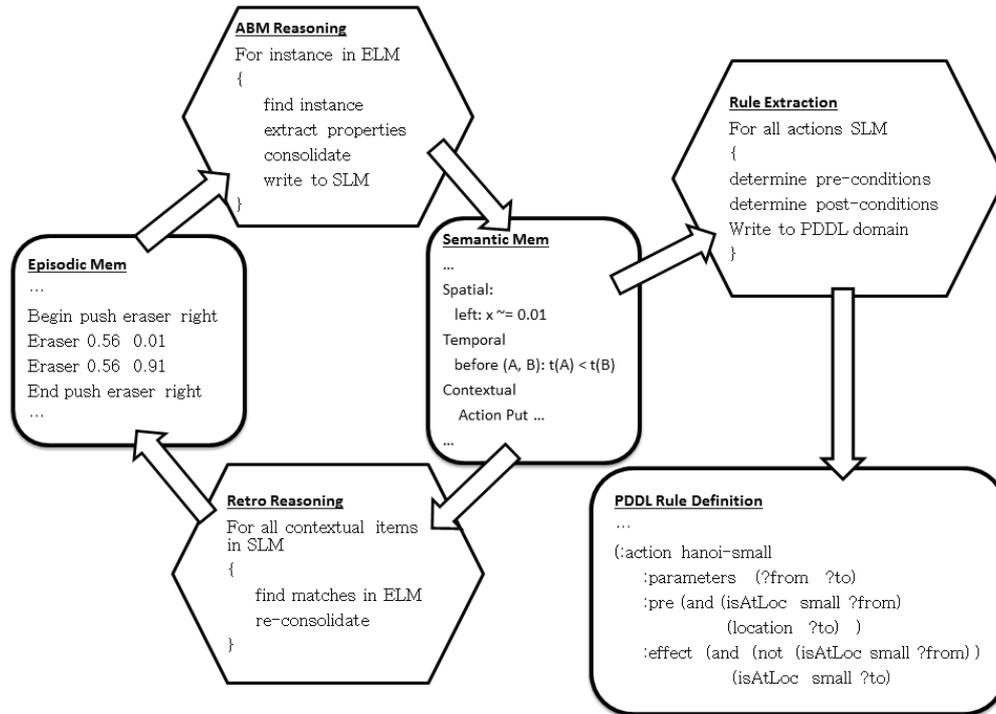


125 **Figure 1: LEFT. Human-robot physical interaction platform, with the iCub and ReacTable. RIGHT:**  
 126 **Physical interaction architecture. Human and robot interact by co-manipulating objects. ReactVision detects**  
 127 **objects on the table surface and populates the OPC. Supervisor manages spoken language interaction. ABM**  
 128 **Reasoning manages the autobiographical memory.**

## 129 2 Robot System Description

130 We first describe the global architecture of the robot and control system, and then  
 131 provide a more detailed description of the memory and reasoning systems. The human-  
 132 robot interaction set-up is illustrated in Figure 1. ICub interacts with humans, using an  
 133 interactive table allowing precise object localization. As seen in the figure, a Graphical  
 134 User Interface displays the robot and the positions of recognized objects on the table.

135 An overview of the system architecture is illustrated in Figure 1. Part of the core basis  
 136 of our research is the implementation of a multi-level memory system, shown in Figure  
 137 2.



138  
 139 **Figure 2 : Overview of the flow of information in refinement of knowledge.**

140 Following Figure 2, direct perceptual experience is represented in the episode-like  
 141 memory (ELM), and through the detection and extraction of recurring regularities (e.g.  
 142 the word “left” and spatial coordinates within a certain dispersion ellipse), a higher level  
 143 semantic memory is generated through a process referred to as consolidation (inspired  
 144 by the same term in animal physiology). This accumulated knowledge (e.g. meaning of  
 145 the term “left”) can lead to a reinterpretation of past experiences in the ELM, in a pro-  
 146 cess that we refer to as “retro-reasoning”. Using this knowledge about spatial locations,  
 147 the system can begin to extract regularities about pre-and post-conditions that hold be-  
 148 fore and after acting, respectively. This information can be transformed into a format

149 compatible for AI planners, thus allowing iCub to use its accumulated experience to  
150 reason about new situations. Given this overview, we now describe the system in more  
151 detail.

## 152 **2.1 iCub**

153 The current work was performed on the iCubLyon01 at the INSERM Robot Cogni-  
154 tion Laboratory in Lyon, France. ICub (Metta, Sandini, Vernon, Natale, & Nori, 2008)  
155 is an open-source robotic platform, developed in the EU consortium Robotcub, with  
156 morphology approximating that of a 3½ year-old child (104cm tall), and 53 degrees of  
157 freedom distributed on the head, arms, hands and legs. Motor control for iCub requires  
158 identification of object locations in space, and computation of the required joint trajec-  
159 tories (Gori, Pattacini, Nori, Metta, & Sandini, 2012). As part of the iCub software ar-  
160 chitecture the YARP communication protocol is used throughout the system, in order to  
161 allow well defined port-based client-server connections between the different compo-  
162 nents described below.

## 163 **2.2 ReacTable**

164 In order to allow high precision perception of objects, both for understanding scenes  
165 and events, we have adopted the ReacTable™ interactive table. ReacTable has a trans-  
166 lucid surface, with infrared (IR) illumination and IR camera detection systems beneath  
167 the table that perceives tagged objects on the table surface with an accuracy of ~5mm.  
168 Thus, tagged objects can be placed on the table, and their location accurately captured  
169 by the IR camera.

170 Interaction with the external world requires that iCub is capable of identifying its spa-  
171 tial reference frame with the objects that it interacts with. This is similar to the human,  
172 where aspects of this functionality is carried out by the dorsal visual stream, involving  
173 areas in the posterior parietal cortex which subserve complex aspects of spatial percep-  
174 tion (Shmuelof & Zohary, 2005). In our system, the 2D surface of the table is calibrated  
175 into the joint space of iCub by a transformation calculated based on a sampling of cali-  
176 bration points on the table surface that are pointed to by iCub. These coordinates can  
177 then be used as spatial arguments to the action system of iCub, described below, which  
178 provides basic physical actions including point-to(vector), put(vectorSource, vectorTar-  
179 get), grasp(vector), release(vector). In the current experiments, all objects can be  
180 grasped with the same grasp parameters, so these are not independently specified.

### 181 **2.3 Object Properties Collector**

182 The common space in which the human and robot interact with objects is on the sur-  
183 face of the ReacTable. The current state of the world, in terms of those objects, the hu-  
184 man and iCub, is stored in the Object Properties Collector (OPC) which thus contains  
185 all the information about objects, agents, entities or relations. The OPC can be consid-  
186 ered as the mental representation for iCub: all the information gathered by the Reac-  
187 Table, or any other sensor will be stored in the OPC in real time.

188 The ReacTable2OPC client receives the data about the position of objects from the  
189 ReacTable software and stores this in the OPC. The data acquired from each object once  
190 on the table includes: unique ID, position, angle, speed, rotation and whether the object  
191 is still present on the table or not.

## 192 **2.4 Interaction Supervisor**

193 The Supervisor (Figure 1 and Figure 3) provides the general management function  
194 for the human-robot interaction, implemented using a state-based dialog management  
195 capability. This allows the user to enter different interaction states related to teaching  
196 spatial location, action and temporal primitives and shared plans. The Supervisor func-  
197 tion is implemented with the CSLU Rapid Application Development Toolkit (Sutton et  
198 al., 1998), a state-based dialog system which combines speech synthesis (Festival) and  
199 recognition (Sphinx-II) in a GUI programming environment.

200 We have previously explored how the argument structure of sentences (e.g. “Put the  
201 circle on the left”) allows for a structured mapping onto the argument structure of per-  
202 ceptual and motor commands for robots, and we use such mappings here (Dominey,  
203 2003; Dominey et al., 2007a, 2009; Lallee, Madden, Hoen, & Dominey, 2010; Petit et  
204 al., 2013).

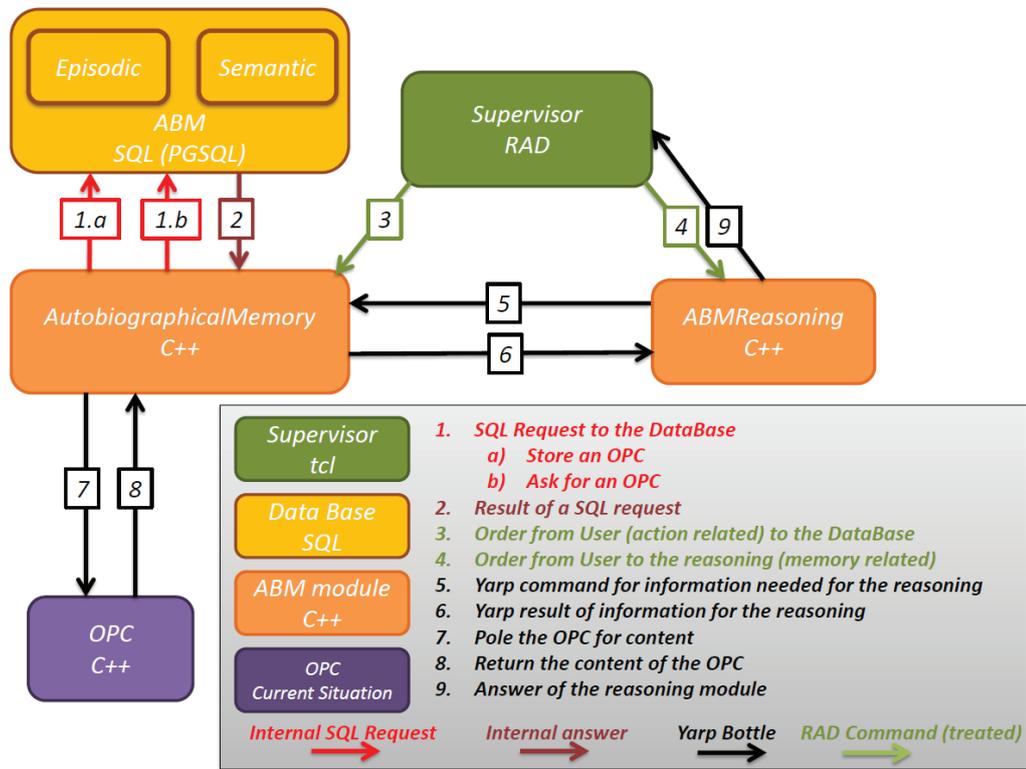


Figure 3: Overview of the memory architecture including the SQL Database, Supervisor, ABM Reasoning, and OPC. 1-2. SQL queries, and replies to ABM are managed by a C++ Autobiographical Memory module. 3. User interacts with ABM related to action status, and 4. Memory content. 5-6. ABM reasoning requests and receives content via YARP connections. 7-8. ABM manager requests and receives state data from OPC. 9 Final answer of ABM Reasoning to the supervisor

### 211 3 Autobiographical Memory and Reasoning

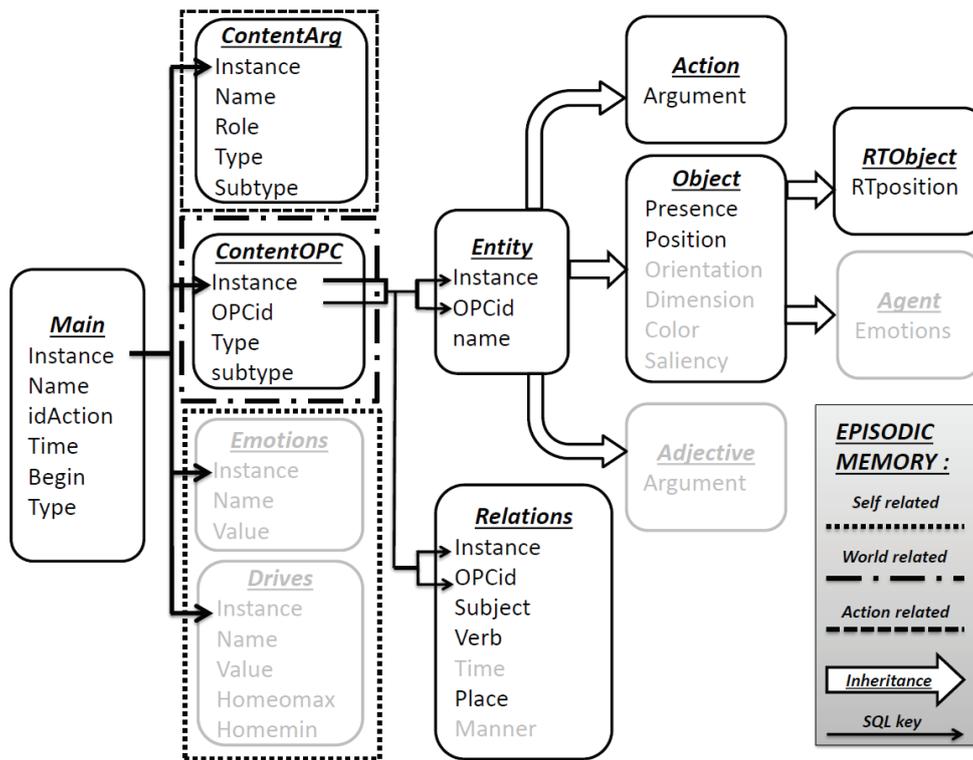
212 A central aspect of this research is that the experience of the robot shall be captured in  
 213 a structured, time ordered record, and that this record can be used to generate appropri-  
 214 ate behavior in the future. We previously implemented an autobiographical memory  
 215 (ABM) that consists of an episodic-like memory (ELM) and a semantic memory (SM)  
 216 based on successive developmental levels through social interactions (Poiteau et al.,  
 217 2014) schematized in Figure 3, which has been extended to add a level 3 reasoning loop  
 218 to the existing consolidation and retro-reasoning (explained in 3.2 and 3.3).

219 The ABM is a PostgreSQL database storing data from the OPC each time an action  
 220 occurs (episodic memory). It also encodes the knowledge extracted after reasoning

221 about this data (semantic memory). Thus, the Episodic-Like Memory is a component of  
222 the ABM containing data from the OPC (i.e. current state of the world) before and after  
223 each action performed either by iCub or the human. The Semantic Memory is a compo-  
224 nent of the ABM built after reasoning about past experience, based on statistical analy-  
225 sis of data from ELM. Both are implemented in PostgreSQL. The Autobiographical  
226 memory (ABM) is a set of functions that operate on these SQL tables, and interact with  
227 the ABM Reasoning module which performs reasoning over past experience and  
228 memory consolidation in order to generate the SM and update the ELM. The Supervisor  
229 provides the spoken language interface with the human, and manages high level interac-  
230 tion.

### 231 **3.1 Episodic-Like Memory**

232 The ELM is organized around actions and the state of the world before and after ac-  
233 tions. The SQL data structure of the ELM is illustrated in Figure 4. This action-centered  
234 approach is useful in that it helps to solve the problem of how to segment the perceptual  
235 stream of events (Zacks, Speer, Swallow, Braver, & Reynolds, 2007). When the human  
236 announces that he will perform an action, a message is sent to the ABM Reasoning, and  
237 the current state of the world (snapshot of the current state of OPC) is stored in the epi-  
238 sodic memory in the ELM SQL tables, before the action occurs. Likewise, the system is  
239 informed at the end of each action, and takes an OPC snapshot. With the state of the  
240 OPC before and after an action, the system can extract the pre-conditions and effects for  
241 actions (Mirza, Nehaniv, Dautenhahn, & Boekhorst, 2008; Payne & Nadel, 2004).



242

243 **Figure 4 : SQL format of the Episodic memory, with in light gray unused data from the current research.**  
 244 **The main data type is specified as ContentArg which defines arguments for actions, and ContentOPC defines**  
 245 **entities that are in the OPC. Each interaction has the content of the OPC at a given time (state of the world)**  
 246 **but also, information concerning the arguments of the action (who, what, when...).**

### 247 3.2 Semantic Memory

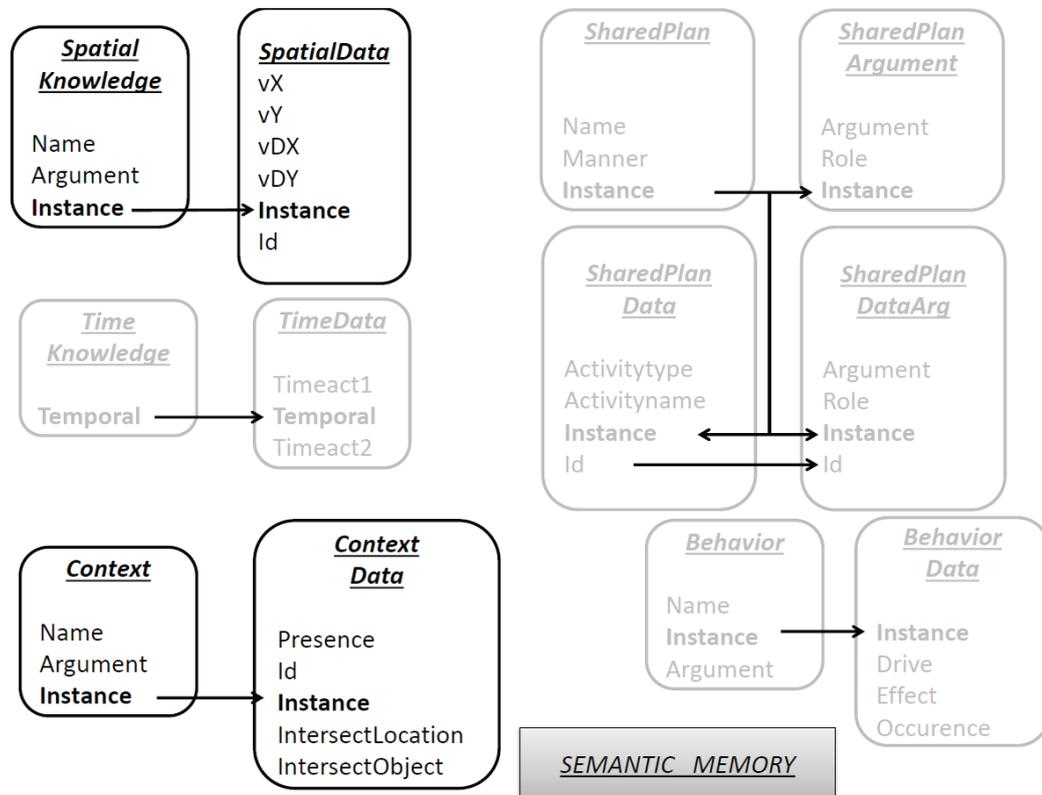
248 The semantic memory is derived by ABM Reasoning, from experience encoded in the  
 249 ELM. ABM Reasoning is coded in C++, and its role is to retrieve the information stored  
 250 in the ELM and to generalize over this information, in order to extract the pertinent in-  
 251 formation of each action. The ABM Reasoning thus constructs a Semantic Memory  
 252 with the pertinent information related to context/spatial/temporal information. The sys-  
 253 tem will then store its semantic knowledge into the appropriate part of the ABM, i.e. the  
 254 SM.

255 We refer to this generation of semantic memory as “consolidation”, derived from  
 256 mammalian sleep-based memory consolidation (Payne & Nadel, 2004). During consoli-

257 dation, the system will iterate through all actions performed in the current session, and  
258 will generalize over this data, and consolidate the resulting semantic knowledge in the  
259 database (See (Poiteau et al., 2014) for details). This consolidation is the first level of a  
260 system of Retro Reasoning (described in the section 3.3) and is displayed in Figure 6.

```
261 CONSOLIDATION (level 1 reasoning) pseudocode:  
262 For each ACTION in the ELM  
263     {  
264         Retrieve the COORDINATES of the object of focus before and after the move.  
265         Calculate the DISPLACEMENT of the object  
266         Populate the corresponding SPATIAL KNOWLEDGE entry and ACTION DEFINITION  
267     in the SM.  
268         Calculate the DISPERSION of the displacement to determine if the action is abso-  
269     lute or relative.  
270         If the ACTION is absolute (is location):  
271             Update the LOCATION DEFINITION in the OPC.  
272     }  
273
```

274 This pseudo code describes how the encoding of in the ELM of multiple repetitions  
275 of actions with spatial parameters like “put to north” can be processed to determine us-  
276 ing Mahalanobis distance that north here refers to an ellipse fixed location (as opposed  
277 to “push toward north”, producing a relative displacement), which can be learned, and  
278 stored in the OPC as a new, learned, named location. This information is also coded in  
279 the semantic memory (illustrated in Figure 5) in the spatial data component.



280

281 **Figure 5 : SQL format of the Semantic Memory, with in light gray unused data from the current research.**  
 282 For each type of knowledge, a first table stores the general information concerning the knowledge (name, ar-  
 283 gument...) while a second table stores the “technical information”: the positions of each move in the case of a  
 284 spatial knowledge, or the time-stamp in the case of a temporal knowledge. For each memory is created an  
 285 instance (corresponding to a given time).

### 286 3.3 Retro Reasoning

287 Once the system has extracted these initial concepts, including spatial properties re-  
 288 lated to locations, displacements and actions, it can use this knowledge to construct  
 289 higher level knowledge representations. ABM reasoning will once again iterate through  
 290 the contents of the ELM, and for actions, will be able to extract knowledge about the  
 291 pre- and post- conditions. For example, in the case where a move has a precondition  
 292 (e.g. for a board game in which the only legal move to location B is from location A),  
 293 iCub will observe the moves made by the human, and then learn the locations A and B  
 294 (as outlined in the pseudocode above and detailed in (Pointeau et al., 2014)). Once iCub

295 knows locations A and B, it can then perform retro reasoning, and observe that each  
296 time the action: “move-B object” was performed, the object was always first at A. This  
297 leads to the extraction of the pre-condition: “Object is at A”, and similarly for the post  
298 condition “Object is at B”. Based on this retro reasoning, the system will know that to  
299 perform the action “move-B”, the condition “Object is in A” is mandatory. Also, iCub  
300 will know that the action to perform in order to have “Object is in B” is “move-B ob-  
301 ject”. This information is coded in the context data (before and after fields) of the SM  
302 (see Figure 5).

### 303 **3.4 Level 3 Reasoning**

304 The knowledge that has been acquired through retro reasoning now makes it possible  
305 to perform more pertinent reasoning about the conditions that hold before and after ac-  
306 tions. The ABM Reasoning will again iterate through the ELM and match this with the  
307 knowledge stored in the SM and will extract new regularities at a higher level. The dif-  
308 ference with the first level reasoning is that the ABM Reasoning will now write high  
309 level relations in the ELM such as: “Object is at Location A” that iCub could not have  
310 known at the time of the initial observations, because the location A had not yet been  
311 learned. The system can also create higher level knowledge in the SM. For example, in  
312 the case of the move of the medium object of the Hanoi Tower, the knowledge will be:  
313 “Big object can be at location *From* or location *To*, but the small object can’t be at loca-  
314 tion *From* nor location *To*.” The function of this level of reasoning is described in the  
315 pseudo code.

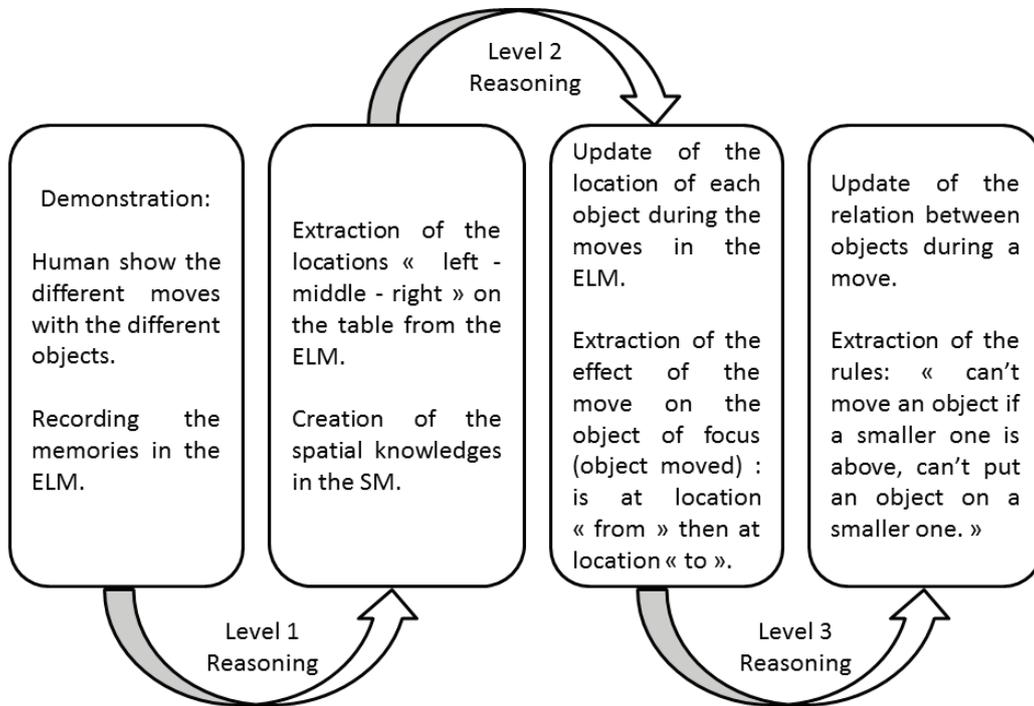
316

<u>LEVEL 3 REASONING (pseudo code)</u>
--

```
For each ACTION
{
  for STATE      and      the action
  {
    determine ALL RELATIONS between the object of focus and all objects that hold before
    and after
    calculate PROBABILITY/PERCENTAGE for each relation over all instances in ELM
    store appropriately in      and      FIELDS OF CONTEXT in SM
  }
}
```

317 **3.5 From interaction to successive level of representation**

318 We show in Figure 6 the link between these reasoning layers from interaction experi-  
319 ence to levels of representations. Human demonstrations lead to changes in the states of  
320 objects as represented in the OPC. Level-one reasoning detects spatial regularities in  
321 terms of the elliptical forms of point cloud distributions of objects in the demonstrated  
322 actions and creates this new spatial knowledge. The second level allows to detect the  
323 starting location and final location of each move independently. The third level will get  
324 these starting and final locations (and no more the coordinates) and extract regularities  
325 with them. These states are recorded in the ELM, associated in time with the named  
326 actions, and locations.



328

329 **Figure 6 : Example of the effect of the different levels of the retro reasoning (case of the Tower of Hanoi)**330 **4 Planning and Goal Directed Reasoning**

331 The previously explained Retro-Reasoning, based on the ELM and SM allows iCub  
 332 to obtain information about its known actions, in particular pre-conditions, which have  
 333 to be true if iCub wants to execute the actions, and effects, which will be the changes in  
 334 the world because of these actions.

335 This gives iCub the capacity to know, for a given current state of affairs, what actions  
 336 are available, and to predict the successive states of the world after several actions. By  
 337 using these two features, and checking pre-conditions of the next actions against the  
 338 state of the world attained with the effect of the previous action, the system will be able  
 339 to reason about a goal and plan successive actions in order to achieve the goal. This re-

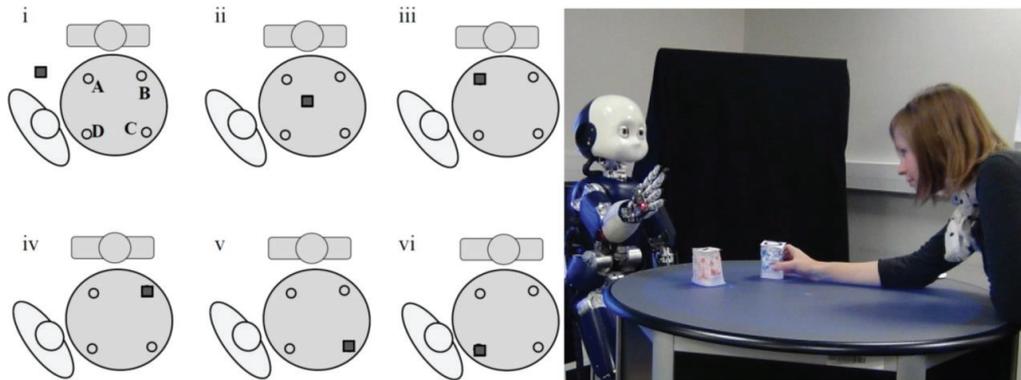
340 quires the representation of the acquired knowledge of pre- and post-conditions in a  
341 format that can be used for reasoning. This is implemented on the robot by extracting  
342 and formatting pre- and post-conditions as rules compatible with the standardized plan-  
343 ning language PDDL (Planning Domain Definition Language).

#### 344 **4.1 Planning Domain Definition Language (PDDL) Framework**

345 PDDL is a framework in which the domain of a task can be described (including  
346 specification of the “rules” in terms of pre- and post-conditions for actions), and in  
347 which a given problem or goal can be specified (Helmert, 2009; McDermott et al.,  
348 1998). This can then be provided as input to a planner, which will attempt to find a se-  
349 quence of action executions that takes the system from the current state to the specified  
350 goal state. Thus, in order to be used, a PDDL planner needs this information, as speci-  
351 fied in two different files: a domain and a problem definition. The domain file contains  
352 the set of known actions, including their respective preconditions and effects, whereas  
353 in the problem file, we have the current situation description (i.e. the list of all initial  
354 conditions) and the desired goal.

355 Traditionally, these files are hand-coded, with fixed set of actions given to a robot in  
356 order to solve a precise kind of problem with variable initial conditions. In our system,  
357 these data will be automatically generated in real-time by iCub, allowing a developmen-  
358 tal inspired approach based on experience that accumulates and becomes successively  
359 refined via the level 1-3 reasoning. This is possible by extracting knowledge from the  
360 Semantic Memory to produce well-formed PDDL domain definition. The problem defi-  
361 nition will be made by a direct request to the ABM about the current situation and the  
362 goal is defined from interaction with the human. In order to provide a concrete domain

363 in which to pursue this work, we elaborated a simple board-game interaction scenario,  
 364 illustrated in Figure 7. In this game, four spatial locations will be learned by iCub, via  
 365 observation of the human actions. In addition, iCub learns regularities concerning how  
 366 objects can be moved between these locations. The demonstrated moves form a circular  
 367 game path, meaning pieces can only move from A to B, from B to C, from C to D and  
 368 from D to A. For instance, if the object is on A, a player must make 3 successive moves  
 369 to put it at D. This provides a simple scenario for testing the ability to learn from expe-  
 370 rience and reason on the acquired knowledge.

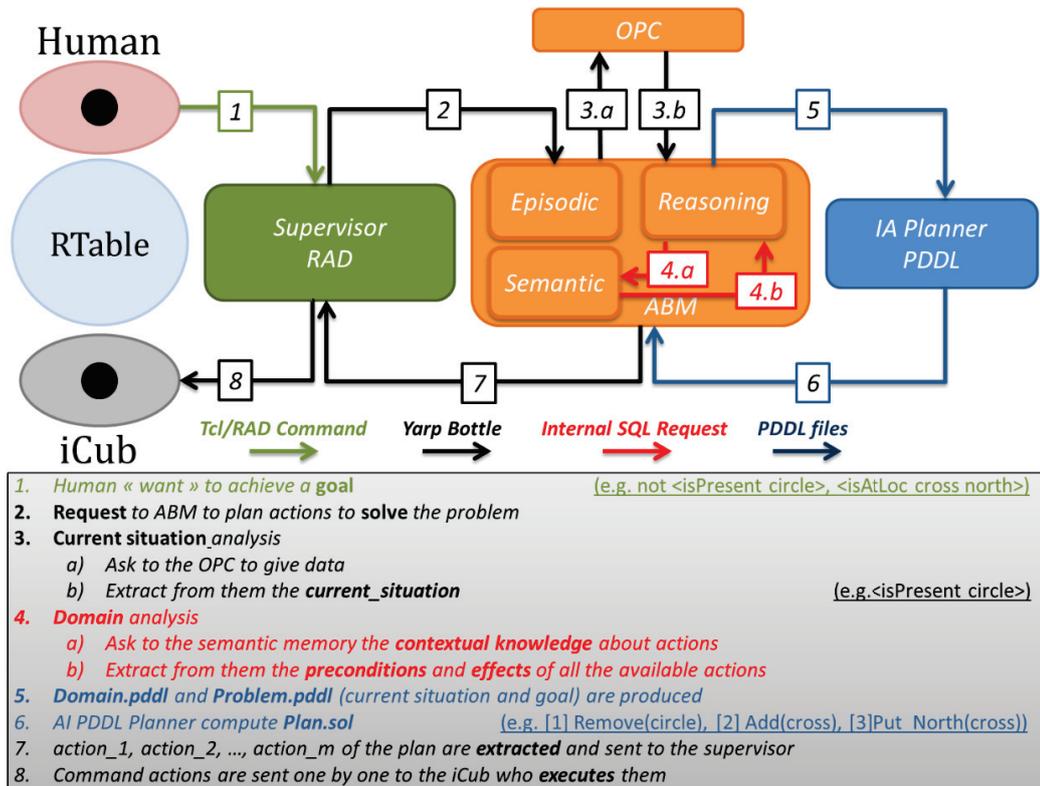


371

372 **Figure 7 : Interaction scenario schema. Four learned locations on ReacTable with human (oval body), iCub**  
 373 **(rectangular body) and object (dark square). The learned locations are labeled A-D. i. Object is off the table.**  
 374 **ii. Human has placed the object on the table, in an undefined location. iii. Human or iCub has placed the ob-**  
 375 **ject location A. iv. Human or iCub has placed the object at B. v-vi. Human has placed the object at C, then D,**  
 376 **respectively.**

377 We have extended the architecture from Figure 3, as now illustrated in Figure 8, to al-  
 378 low for the PDDL rule extraction and planning for on-line problem solving. Figure 8  
 379 illustrates in more detail the flow of information from the human interaction to the plan  
 380 execution, with the different representations of knowledge, starting in the lowest level  
 381 “perceptual” representations in the ELM, to the pre-condition, post-condition represen-  
 382 tations of actions in the PDDL format, appropriate for use with available state of the art  
 383 reasoning engines. The process begins by the expression of the human's desired goal,  
 384 using speech, indicated by the keyword "want", followed by the goal to reach (1). The

385 Supervisor handles this request and sends it to the ABM module of iCub (2) which has  
386 to solve that problem. The system will then establish the state of the current world state  
387 by querying the OPC (3.a, 3.b), and writing it into the problem PDDL file, along with  
388 the human's stated goal. Then, the system will interrogate the semantic memory to re-  
389 trieve the contextual knowledge corresponding to the pre- and post-conditions of all the  
390 known actions, and use this to build the PDDL domain file (5). The AI Planner is then  
391 executed, to produce a plan (6), made up of the sequence of action which needs to be  
392 performed in order to achieve the goal from the current situation. This file is parsed and  
393 the action sequence is sent to the Supervisor (7), which then controls iCub to execute  
394 these moves (8), and thus to achieve the human's goal without any explicit information  
395 from him about "how to" do it.  
396



397

398 **Figure 8 : Extended architecture with rule extraction and rule based planning and reasoning.**

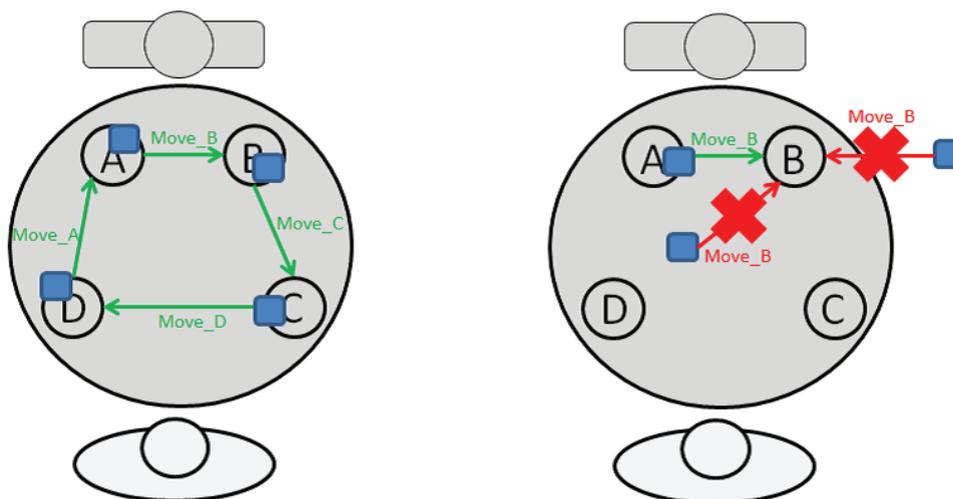
## 399 5 Experiments

400 We now demonstrate the operation of the system with two experiments that exercise  
 401 the ability of the system to extract the structure of knowledge derived from experience,  
 402 and to reason based on that experience. Both experiments involve interaction tasks that  
 403 can be organized according to rules or actions that have pre- and post-conditions.

### 404 5.1 Experiment 1: Learning Rules About Spatial Movement – Proof of Concept

405 The goal of the first experiment is to demonstrate that the system is capable of ex-  
 406 tracting pre-conditions and post-conditions for learned actions, and is then able to use  
 407 these in the PDDL environment for goal based reasoning in real-time. iCub will learn

408 two types of actions. The first action is to add an object into the interaction space, by  
 409 putting it on the table. By definition, in terms of our physical constraints, this action can  
 410 only be performed by the human. The second action is to move an object from one loca-  
 411 tion to another. The two actions will be learned independently. The link between them  
 412 will be that the precondition of one is the effect of the other. In the first experiment, the  
 413 initial state will be with the object off the table, as illustrated in Figure 7i, and goal state  
 414 will be announced to iCub to put the object at location D as illustrated in Figure 7vi.  
 415 iCub should be able to reason from experience that to put the object at “D”, it must be  
 416 moved from “C”, and so on, chaining from the initial state to the final goal state.



**Example – Move\_B**

**Preconditions:** (isPresent obj) (isAtLoc obj A)

417 **Effect** : (isPresent obj) (isAtLoc obj B)

418 **Figure 9 :** Example of definition of different moves in the ABCD experiment. As illustrated, the Move\_B ac-  
 419 tion has the precondition that the object must be at location A before Move\_B can be executed.

420 Figure 9 illustrates how the action of moving an object to location B is learned. First,  
 421 the human has to show iCub how the new actions work by example. He will say to iCub  
 422 what he will do (e.g. “I move the circle to B”). The sentence is parsed with the Supervi-  
 423 sor, and the recognized action, with the name and the arguments (e.g. “Peter” as agent,

424 “circle” as object, “A” as spatial location), is sent to the ABM, indicating that this ac-  
425 tion will happen. A snapshot of the OPC is then taken from ABM producing the state of  
426 the world before the named action. Again this illustrates how the human interaction al-  
427 lows the system to segment the perceptual flow, here to identify the beginning and end-  
428 ing for actions. Control is returned to the human who can then proceed and execute the  
429 action before given a signal to the system (“Done”). This triggers the end of the action,  
430 which is written into the ELM, and a second snapshot, this time after the action execu-  
431 tion, is then taken. Thus within the ELM there is a specification of the action and its  
432 arguments, and snapshots of the state of the world before and after the action. This pro-  
433 cedure is repeated several times for the same action (with different arguments) in order  
434 to have a set of data where statistical tools can be used for extracting regularities (or  
435 “rules”), as described in Section 3.

436 The characteristic regularity is that actions can be performed with any objects, but  
437 there is a “*from-to*” structure that to go to B you must be at A, to C you must be at B,  
438 etc. as illustrated in Figure 9. The ABM Reasoning module collects the statistics on the  
439 pre- and post-conditions of these movements, and generates a set of entries in the se-  
440 mantic memory “Context” entry, for each type of move, according to its initial and final  
441 location.

442 Once the pre-conditions and effect of actions have been extracted and made explicit  
443 in the semantic memory, the system can use them in order to produce the two PDDL  
444 files needed for reasoning. The first one, the domain file, is the list of all the known ac-  
445 tions, including preconditions and effects, arguments. The ABM Reasoning module be-  
446 gins by writing a “skeleton” of the PDDL, everything which does not change: the do-  
447 main (“*efaa*”), the requirements (“*:strips :typing :equality*”), the predicates (*isPresent*,

448 isAtLoc, Objects and Locations). Then the system iterates through the known actions  
449 that are stored in ContextualKnowledge class. For each action the system will write in  
450 the files the required components: action, parameters, precondition and effect, which are  
451 directly translated from the ContextualKnowledge of the Semantic Memory.

452 The action name is extracted by combining the verb (e.g. “add”, “move”) with the  
453 none-generalizable arguments (nothing for “add”, the location for “move”). That allows  
454 for the possibility that actions can have different rules according to the location to where  
455 an object is to be moved. The precondition for “move-B” is “isAtLoc obj A”, whereas  
456 the precondition is “isAtLoc obj C” for “move-D”.

457 Parameters are the arguments over which the action can generalize (e.g. object for  
458 “add” and “move”). One can perform these actions with different parameter values, and  
459 the rules will be the same (for add, the object is not present at first, and is present after,  
460 no matter what the object is).

461 Preconditions are extracted from the ContextualKnowledge class. The system checks  
462 for properties which are above an empirically determined maximum threshold for posi-  
463 tive conditions and below an inferior threshold for negative conditions, before the action  
464 is executed. These properties are the presence of the object (which has to be present for  
465 “move” but has not to be for “add”) and its location of (for “move-B” the object has to  
466 be in location A), as illustrated in Figure 10. The effects or post-conditions are deter-  
467 mined in the same way, except that instead of using the regularities before the action is  
468 done, the system computes over the data after the action’s execution.

469

```

;; STRIPS domain automatically generated by ABMReasoning, part of EFAA
(define (domain efaa)
  (:requirements :strips :typing :equality)
  (:predicates
    (isPresent ?obj)
    (isAtLoc ?obj ?loc)
    (Object ?obj)
    (Locations ?loc)
  )
  (:action add
    :parameters (?obj1)
    :precondition (and (not (isPresent ?obj1) ) )
    :effect (and (isPresent ?obj1) )
  )
  (:action remove
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) )
    :effect (and (not (isPresent ?obj1) ) )
  )
  (:action move-B
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) (isAtLoc ?obj1 A) )
    :effect (and (isPresent ?obj1) (not (isAtLoc ?obj1 A)) (isAtLoc ?obj1 B) )
  )
  (:action move-C
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) (isAtLoc ?obj1 B) )
    :effect (and (isPresent ?obj1) (not (isAtLoc ?obj1 B)) (isAtLoc ?obj1 C) )
  )
  (:action move-D
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) (isAtLoc ?obj1 C) )
    :effect (and (isPresent ?obj1) (not (isAtLoc ?obj1 C)) (isAtLoc ?obj1 D) )
  )
  (:action move-A
    :parameters (?obj1)
    :precondition (and (isPresent ?obj1) (isAtLoc ?obj1 D) )
    :effect (and (isPresent ?obj1) (not (isAtLoc ?obj1 D)) (isAtLoc ?obj1 A) )
  )
)

```

Extracted from ABM (based on reasoning from previous interaction with the human)

470

471 **Figure 10 : Domain file with actions learned by iCub for this game, with their precondition and effects.**

472

473 After the creation of the domain file specifying the known actions, the problem file  
 474 must be produced. The problem is defined by the current state and the goal that is to be  
 475 achieved. As for the domain extraction, the system begins to write the skeleton of the  
 476 problem file, with the problem name (“efaa-prob”) and the domain name (same as for  
 477 the domain file, “efaa”). The objects (all the locations and objects known by iCub) are  
 478 extracted by a SQL query to the ABM in order to have their name (circle, cross, A, B,

479 ...) and their types (object for circle and cross, location A and B). These pairs are added  
480 in the “init” section, along with the initial condition.

481 This PDDL creation is performed when the human asks iCub to reason about a situa-  
482 tion, i.e. to attain a particular world state. An OPC snapshot is taken, which correspond  
483 to the state of the world before iCub preforms the reasoning. This snapshot is obtained  
484 through an SQL query in order to extract all objects present or absent from the table and  
485 if present, their locations. This gives the system the initial situation, which is written in  
486 the problem file.

487 The “goal” part is produced from the human request to iCub to reason about a situa-  
488 tion, i.e. to attain a particular world state. Indeed, the human must specify to iCub that  
489 he wants something, and enumerate conditions he desires (or does not desire). These are  
490 extracted and put inside the goal (e.g. “I want the cross on D” gives “(isAtLoc cross  
491 D)”). An example of an automatically generated problem file can be seen in Figure 11.

```
492 ;; STRIPS problem automatically generated by ABMReasoning, part of EFAA
(define (problem efaa-prob)
  (:domain efaa)
  (:objects
    Ball circle cross eraser Square Toy
    A B C D
  ) ;; end :objects
  (:init
    ;;types
    (Object Ball) (Object circle) (Object cross) (Object eraser) (Object Square) (Object Toy)
    (Locations A) (Locations B) (Locations C) (Locations D)
    ;;init-conditions
    (isPresent cross) (isAtLoc cross A)
  ) ;; end :init
  (:goal
    (and (isAtLoc cross D)
    ) ;; end and
  ) ;; end goal
) ;; end define
```

493 **Figure 11 : example of a problem file for the game, including the initial condition and the goal to achieve**

494

495 Both the domain and problem PDDL files are now written. ICub can run the PDDL  
496 planner in order to know what actions he has to do if he wants to execute the human  
497 wishes. We use the LPG-td planner (Fern, Givan, & Siskind, 2002), with options to find

498 the best of 30 generated solutions, and a computation time limit of 2 seconds. Thus, the  
 499 system will take a maximum of two seconds or 30 solution files, from lower quality to  
 500 better quality before finding the best solution. After execution, the files matching “solu-  
 501 tionEFAA\_X.SOL” are searched, as X goes from 1 to the maximum number of solu-  
 502 tions, to identify the file with the best solution (if there is a solution). This file is  
 503 scanned until the actions are found. They are then put together, stored in a YARP “bot-  
 504 tle” and sent back to the Supervisor, which will launch the motor command of iCub to  
 505 execute them, one by one. As shown in Figure 12, we demonstrate that the system is  
 506 indeed able to learn the rules of the game, and to appropriately find solutions to sample  
 507 problems.

```

; Version LPG-td-1.0
; Seed 52616643
; Command line: lpg-td-1.0 -n 30 -cputime 2 -o domainEFAA.pddl -f problemEFAA.pddl -out solutionEFAA
; Problem problemEFAA.pddl
; Actions having STRIPS duration
; Time 0.05
; Search time 0.00
; Parsing time 0.03
; Mutex time 0.00
; Quality 3

Time 0.05
0: (MOVE-B CROSS) [1]
1: (MOVE-C CROSS) [1]
2: (MOVE-D CROSS) [1]

```

Automatically generated by PDDL planner

508

509 **Figure 12 : example of a solution file produced to solve the problem**

## 510 **5.2 Experiment 2: The Table of Hanoi**

511 We now consider a more strenuous test of the system. The Table of Hanoi (TaOH) is  
 512 based on the Tower of Hanoi (ToOH), adapted to the constraints of the ReacTable. In  
 513 particular this implies that objects cannot be stacked, but rather they can be placed in  
 514 zones, following the rules of the Tower of Hanoi, i.e. an object cannot be moved from  
 515 its current location if there is a smaller object at that same location (because in the  
 516 ToOH that smaller object would be on top). Also, an object cannot be moved to a loca-

517 tion if there is a smaller object at that location. Thus, the goal of the current experiment  
518 is to determine if the ABM and domain extraction functions are suitable for learning  
519 such rules, and if so, whether the system can learn these rules and then correctly play  
520 the TaOH.

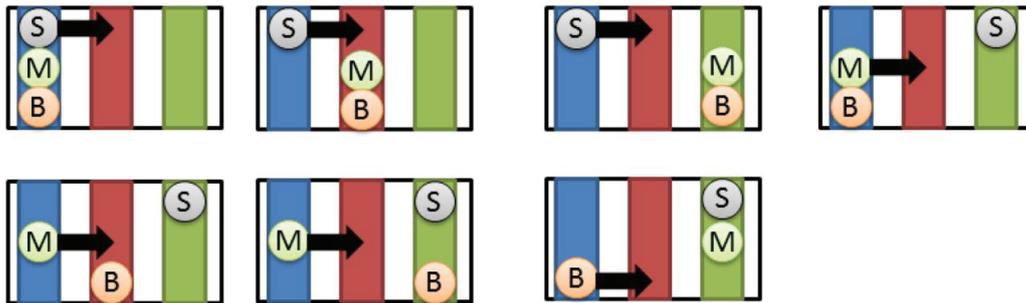
521 In the ABCD experiment, the system had to learn that the constraints on actions in-  
522 volve where objects come from and where they go, but there were no constraints on the  
523 objects themselves. The move-A action was demonstrated with different objects, thus  
524 there was high variability in the object parameter, and so the object identity was not  
525 considered as part of the action, but rather as a free parameter. Thus, the moves could be  
526 learned with one set of objects and generalized to another. In the Table of Hanoi exper-  
527 iment, the difference is that, as they are demonstrated, the actions will be location-  
528 generalizable instead of object-generalizable. The Hanoi moves have the same rules  
529 from one location to another (between the left, middle and right positions) but they de-  
530 pend on the object involved (small, medium, big), such that small can move to locations  
531 with the medium or big object, medium can move to the big object, and all objects can  
532 move to empty locations. Moreover, because the status of the different locations, the  
533 origin place (from) and the destination place (to) are particular and have to be managed  
534 instead of just working on fixed locations.

535 The human demonstration of these moves (HANOI-BIG ?FROM ?TO, HANOI-MEDIUM  
536 ?FROM ?TO, HANOI-SMALL ?FROM ?TO) is done in the same way as for Experiment 1,  
537 with only a modification to the lexical entries of the speech recognition grammar (for  
538 the new names of objects and locations). It should be noted that, because of the general-  
539 ization of learning, we need only to perform the moves from “Left” to “Middle”, and  
540 iCub will be able to generalize to other move locations. In particular, it has never seen

541 an actual Hanoi game, from the beginning to the end, only a set of illustrative moves.  
 542 We first teach iCub the locations left, right and middle by moving each of the three ob-  
 543 jects three times to each of the locations. This makes 9 moves per location, for a total of  
 544 27 moves, which is sufficient to allow the consolidation to extract the location defini-  
 545 tions.

546 It has to be noted that we used this minimal and predefined set of actions to show  
 547 that iCub can learn to solve TaOH without any need for seeing the actual solution, but  
 548 the same results can be achieved by observing a real attempt of TaOH realized by a  
 549 naïve subject.

550 These locations can then be used to demonstrate the moves that allow the system to  
 551 learn the rules governing how object positions influence legal moves.



552  
 553 **Figure 13 : Minimal set of moves to learn the rules for the Table of Hanoi. S,M, B stand for Small, Medium,**  
 554 **Big respectively. Colored areas correspond to left, middle and right locations.**

555 These moves are illustrated in Figure 13. The three moves executed with the small  
 556 object indicate that it can move from an occupied or a free position to a free position or  
 557 an occupied position, thus there are no constraints on where it can come from or go to.  
 558 This is revealed in the rule that is extracted from the SM illustrated in Table 1. For the  
 559 Medium object, the three demonstrations indicate that it cannot move from or to the  
 560 same location as the Small. Recall that when calculating the pre-conditions, the system  
 561 examines all possible relations between objects, and then looks for probabilities that

562 approach 0 (corresponding to a “never” or “not” condition, and probabilities that ap-  
563 proach 1 (corresponding to a positive constraint).

564 For building the domain, the procedure is exactly the same, except the fact that, in-  
565 stead of providing absolute locations intersected by object, through several reasoning  
566 layer (Figure 6) and due to the fact that the TaoH rules are objects but not location de-  
567 pendent, the ContextualKnowledge can generalize the actions of TaoH with two spatial  
568 concepts “from” and “to”. An example of a produced file is shown in Figure 14.

```
;; STRIPS domain automatically generated by ABMReasoning, part of EFPA
(define (domain efaa)
  (:requirements :strips :typing :equality)
  (:types location object)
  (:predicates
    (object ?obj)
    (location ?loc)
    (isAtLoc ?obj ?loc)
  )
  (:action hanoi-small
    :parameters (?from ?to)
    :precondition (and (isAtLoc small ?from) (location ?to) )
    :effect (and (not (isAtLoc small ?from)) (isAtLoc small ?to) )
  )
  (:action hanoi-medium
    :parameters (?from ?to)
    :precondition (and (isAtLoc medium ?from) (not (isAtLoc small ?from)) (not (isAtLoc small ?to)) (location ?to))
    :effect (and (not (isAtLoc medium ?from)) (isAtLoc medium ?to) )
  )
  (:action hanoi-big
    :parameters (?from ?to)
    :precondition (and (isAtLoc big ?from) (not (isAtLoc small ?from)) (not (isAtLoc small ?to)) (not (isAtLoc medium ?from)) (not (isAtLoc medium ?to)) (location ?to))
    :effect (and (not (isAtLoc big ?from)) (isAtLoc big ?to) )
  )
)
```

569 )

Extracted from ABM  
(Based on previous interactions with the human)

570 **Figure 14 : Domain file automatically produced from human interactions in a TaoH game.**

571  
572 To specify a problem or goal, the user can set the objects at the desired initial location  
573 (left location, for example), so that the system can determine the current state. The user  
574 can then explain the final state, in terms of the positions of the objects (e.g. that all three  
575 objects should be on the right location). This yields the automatic construction of the  
576 domain and goal. Figure 15 illustrates a domain and goal specification that was auto-  
577 matically generated from ABM (initial conditions) and spoken language interaction  
578 with the human (goal). Then the planner can be executed to generate a solution. The  
579 solution is presented in Figure 16. Again, the sequence of commands is then automati-  
580 cally transformed into the equivalent commands for iCub, then the problem is physical-  
581 ly solved.

582

```

;; STRIPS problem automatically generated by ABMReasoning, part of EFAA
(define (problem efaa-prob)
  (:domain efaa)
  (:objects
    small medium big
    left middle right
  ) ;; end :objects
  (:init
    ;;types
    (object small) (object medium) (object big)
    (location left) (location right) (location middle)
    ;;init-conditions
    (isAtLoc small middle) (isAtLoc medium middle) (isAtLoc big middle)
  ) ;; end :init
  (:goal
    (and (isAtLoc big left) (isAtLoc small left) (isAtLoc medium left)
    ) ;; end and
  ) ;; end goal
) ;; end define

```

Extracted from ABM (current situation)

Extracted from Speech Processing (Human expressing desires)

583

584 **Figure 15 : Example of a problem file produced in a TaoH game**

```

; Version LPG-td-1.0
; Seed 114675836
; Command line: lpg-td-1.0 -o domainEFAA_hanoi.pddl -f problemEFAA_hanoi.pddl -n 30 -cptime 2 -out solutionEFAA_hanoi
; Problem problemEFAA_hanoi.pddl
; Actions having STRIPS duration
; Time 0.03
; Search time 0.01
; Parsing time 0.02
; Mutex time 0.00
; Quality 7

Time 0.03
0: (HANOI-SMALL MIDDLE LEFT) [1]
1: (HANOI-MEDIUM MIDDLE RIGHT) [1]
2: (HANOI-SMALL LEFT RIGHT) [1]
3: (HANOI-BIG MIDDLE LEFT) [1]
4: (HANOI-SMALL RIGHT MIDDLE) [1]
5: (HANOI-MEDIUM RIGHT LEFT) [1]
6: (HANOI-SMALL MIDDLE LEFT) [1]

```

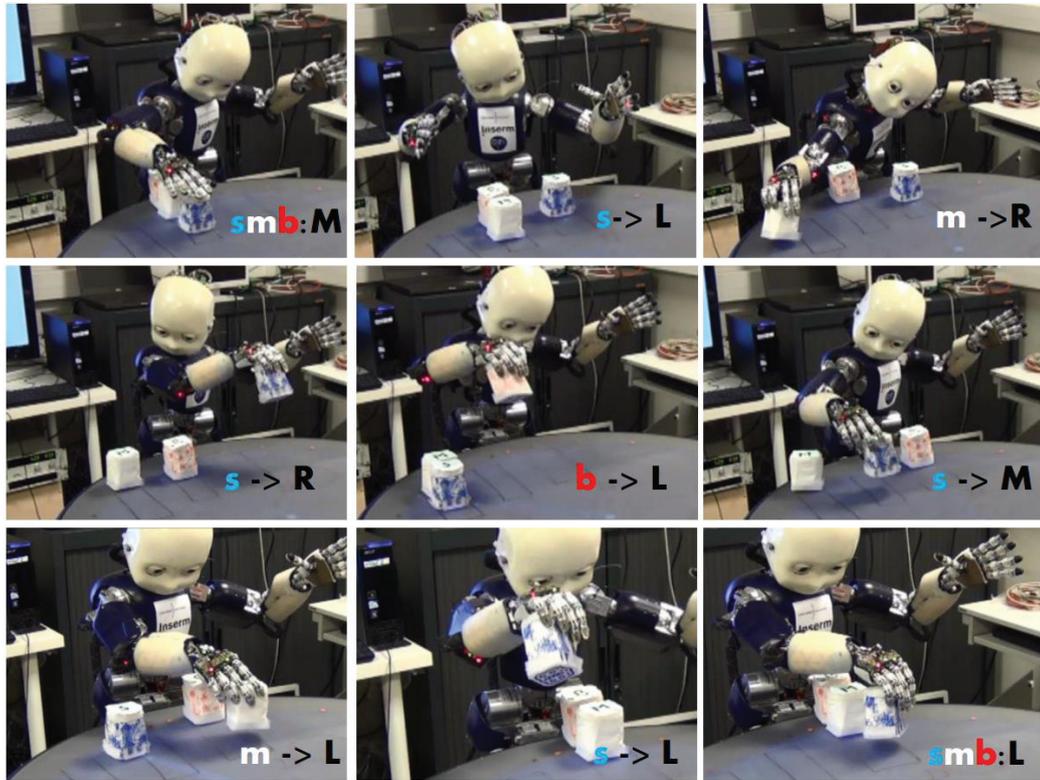
Automatically generated by PDDL planner

585

586 **Figure 16 : Example of a solution file produced in a TaoH game**

587 Figure 17 illustrates the performance of the solution that was generated. Here we see  
588 the completion of the embodied reasoning loop: Experience gained by interacting with  
589 the human allows iCub to learn the locations, and the rules about different objects and  
590 their ability to move to these locations based on the status of other objects in the context  
591 (i.e. the rules of the Hanoi game). Once this knowledge has been extracted it can be au-  
592 tomatically formatted into a PDDL description, which can then be executed on standard

593 robust planners. The plan is then automatically transformed into the corresponding se-  
 594 quence of physical actions that can be realized by iCub.



595

596 **Figure 17 :** iCub solving the Table of Hanoi. Initial state: small, medium and big objects at Middle position.  
 597 Goal state: small, medium and big objects at Left position. The problem is solved in 7 moves. (1) small to left,  
 598 (2) medium to right, (3) small to right, (4) big to left, (5) small to middle, (6) medium to left, (7) small to left.  
 599 The task is solved based on learning the rules of the game, without ever seeing a complete solution.

## 600 6 Discussion and Conclusion

601 Reasoning requires some form of inference engine, and equally important, a base of  
 602 structured knowledge from which the system can reason. In the current research, we  
 603 have conceived and implemented a framework for human-robot interaction, in which,  
 604 through interaction with the human, the robot acquires experience, and then organizes  
 605 this experience in order to create a structured knowledge base from which it can reason.  
 606 We demonstrate the functioning of the system with two experiments. In the second ex-  
 607 periment, from a small set of examples the system learns the rules for moving objects in

608 a Tower of Hanoi – like problem. The system then demonstrates that it can use these  
609 rules with a standard AI planner to solve arbitrary problems in the Tower of Hanoi do-  
610 main. This is of interest, as it illustrates a concrete example where real-world experi-  
611 ence, extracted from interaction with a human, can provide a knowledge base upon  
612 which a robotic intelligent system can reason to solve new problems.

613

614 When learning new actions, the identification of action parameters is one of the cen-  
615 tral problems that must be addressed. The difficulty is to determine what are the signifi-  
616 cant aspects of an action, and what can be ignored, potentially leading to “forgetting”  
617 data allowing the robot to remember only pertinent information (Broz, Nehaniv, Kose-  
618 Bagci, & Dautenhahn, 2012; Ho et al., 2009). For example, Siskind demonstrated how  
619 cross situational reasoning can be applied in this context during the acquisition of word  
620 meanings (Siskind, 1996). The same kind of statistics can be applied to learning the ar-  
621 gument structure of actions (Fern et al., 2002). In an effort to determine how to reduce  
622 the scope of what should be considered during learning, we previously determined that  
623 the focus can be placed on all objects whose state changes as a result of the action  
624 (Lallee et al., 2010).

625 The developing infant faces the same problem, which is, how to know what is the  
626 pertinent aspect of a given scene that should be learned. Extensive behavioral studies  
627 and observations suggest that in many interactions between adults caregivers and chil-  
628 dren, the adult creates a very focused context of joint attention with the child in order to  
629 supervise in a certain sense what the child will focus on (Rader & Zukow-Goldring,  
630 2012). This motivates us to allow the robot to have knowledge from the user about

631 when demonstrated actions begin and end, particularly when the user is also naming the  
632 objects.

633 In our previous research, iCub was learning about actions, and we introduced a bias  
634 such that actions would generalize over objects. By performing actions such as moving  
635 different objects from different starting locations to a fixed target location and calling  
636 that “move A to B”, the system detected the variability in the A argument, and thus  
637 learned that the move command could take arbitrary arguments for the object. The sys-  
638 tem thus learned to generalize over objects.

639 As we have seen, for objects in the Table of Hanoi experiment, the situation is differ-  
640 ent. Objects are not of a single form of equivalence class. Rather, there are specific rules  
641 associated with each object and its movement with respect to the presence and absence  
642 of other objects at the source and target destinations. Interestingly, these constraints are  
643 coded in the statistical structure of the data in the ELM, and they are extracted by the  
644 multi-level reasoning, to become reflected as pre- and post-conditions of the action rep-  
645 resentations in the SM.

646 A principal limitation of the current system is the restrained environment in which it  
647 is demonstrated. One can ask whether the current system could generalize to a much  
648 more open and high dimensional world, where the focus of interaction would not be so  
649 obvious. It has been stated by Levi-Strauss that the objective of man is to understand the  
650 world around him (Lévi-Strauss, 1979). Beneath this objective lies a set of tools for at-  
651 tempting to impose structure on the world. The degrees of freedom for the possible  
652 structures that could be imposed on the observables in the world is quite large, and in  
653 the absence of constraints, the resulting models or explanations can deviate substantially  
654 from the truth, or never converge. This is essentially related to issues of learnability in

655 language, where it has been claimed that the training data that the child is exposed to is  
656 so highly under-constrained, that there must be some highly specialized language spe-  
657 cific learning capability (reviewed in detail in (Dominey & Dodane, 2004)) along with  
658 human ‘pedagogy’ (Gergely & Csibra, 2005, 2006). However, in the presence of proper  
659 constraints, the problem changes, any typical interactions between infants and caretak-  
660 ers are characterized by behavior that creates joint attention around the object of inter-  
661 est, thus effectively reducing the search space to something very tractable. It has to be  
662 noted that, as joint attention need intentional understanding (Kaplan & Hafner, 2006)  
663 these notions works in a “transitive” way, and thus the intention of a human (extracted  
664 here from the reasoning part) helps the robot to engage in a joint attention episode with  
665 the agent and thus retrieve the most relevant visual information (Demiris & Khadhour, 2006; Ognibene, Chinellato, Sarabia, & Demiris, 2013).

667 This gives us hope that the current approach can scale. By including the human in the  
668 learning context, we exploit the notion that the human will perform this search space  
669 reduction, by making pertinent demonstrations, and by using language to identify the  
670 objects of focus. Still, we remain humble, as the current research is far from a user-  
671 study. Rather it serves as a proof of concept that through interaction with humans, cog-  
672 nitive systems can extract knowledge that serves as the basis for reasoning on future  
673 situations.

## 674 **7 Acknowledgements**

675 This research was supported by the EU FP7 EFAA and WYSIWYD Projects (FP7-  
676 ICT-270490 and FP7-ICT-612139).

677 **8 References**

- 678 Broz, F., Nehaniv, C. L., Kose-Bagci, H., & Dautenhahn, K. (2012). Interaction  
679 Histories and Short Term Memory: Enactive Development of Turn-taking  
680 Behaviors in a Childlike Humanoid Robot. *Computing Research Repository*.  
681 Artificial Intelligence; Adaptation and Self-Organizing Systems.
- 682 Cangelosi, A., Metta, G., Sagerer, G., Nolfi, S., Nehaniv, C., Fischer, K., ... Zeschel, A.  
683 (2010). Integration of Action and Language Knowledge: A Roadmap for  
684 Developmental Robotics. *IEEE Transactions on Autonomous Mental Development*,  
685 2(3), 167–195.
- 686 Carey, S. (2009). *The Origin of Concepts* (p. 608). Oxford University Press.
- 687 Carey, S., & Xu, F. (2001). Infants' knowledge of objects: beyond object files and  
688 object tracking. *Cognition*, 80(1-2), 179–213.
- 689 Cheng, P. W. (1996). From Covariation to Causation: A Causal Power Theory.  
690 *Psychological Review*, 104(2), 367–405.
- 691 Crangle, C., & Suppes, P. (1994). *Language and Learning for Robots. Center for the*  
692 *Study of Language and Information*.
- 693 Demiris, Y., & Khadhour, B. (2006). Content-based control of goal-directed attention  
694 during human action perception. In *ROMAN 2006 - The 15th IEEE International*  
695 *Symposium on Robot and Human Interactive Communication* (pp. 226–231).  
696 IEEE.
- 697 Dominey, P. F. (2003). Learning Grammatical Constructions in a Miniature Language  
698 from Narrated Video Events. In *25th Annual Meeting of the Cognition Science*  
699 *Society, Boston*.
- 700 Dominey, P. F., & Dodane, C. (2004). Indeterminacy in language acquisition: the role  
701 of child directed speech and joint attention. *Journal of Neurolinguistics*, 17(2-3),  
702 121–145.
- 703 Dominey, P. F., Mallet, A., & Yoshida, E. (2007a). Progress in Programming the HRP-  
704 2 Humanoid Using Spoken Language. In *Proceedings 2007 IEEE International*  
705 *Conference on Robotics and Automation* (pp. 2169–2174). IEEE.
- 706 Dominey, P. F., Mallet, A., & Yoshida, E. (2007b). Real-time cooperative behavior  
707 acquisition by a humanoid apprentice. In *2007 7th IEEE-RAS International*  
708 *Conference on Humanoid Robots* (pp. 270–275). IEEE.
- 709 Dominey, P. F., Mallet, A., & Yoshida, E. (2009). Real-time spoken-language  
710 programming for cooperative interaction with a humanoid apprentice.  
711 *International Journal of Humanoid Robotics*, 6(2), 147–171.

- 712 Dore, A., Cattoni, A. F., & Regazzoni, C. S. (2010). Interaction Modeling and  
713 Prediction in Smart Spaces: A Bio-Inspired Approach Based on Autobiographical  
714 Memory. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems  
715 and Humans*, 40(6), 1191–1205.
- 716 Doshi, F., & Roy, N. (2008). Spoken language interaction with model uncertainty: an  
717 adaptive human–robot interaction system. *Connection Science*, 20(4), 299–318.
- 718 Fern, A., Givan, R., & Siskind, J. M. (2002). Specific-to-General Learning for  
719 Temporal Events with Application to Learning Event Definitions from Video. *J.  
720 Artificial Intelligence Res.*, 103–129.
- 721 Gergely, G., & Csibra, G. (2003). Teleological reasoning in infancy: the naïve theory of  
722 rational action. *Trends in Cognitive Sciences*, 7(7), 287–292.
- 723 Gergely, G., & Csibra, G. (2005). The social construction of the cultural mind: Imitative  
724 learning as a mechanism of human pedagogy. *Interaction Studies*, 6(3), 463–481.
- 725 Gergely, G., & Csibra, G. (2006). Sylvia’s recipe: The role of imitation and pedagogy in  
726 the transmission of cultural knowledge. *Roots of Human Sociality: Culture,  
727 Cognition, and Human Interaction*, 229–255.
- 728 Gergely, G., Nádasdy, Z., Csibra, G., & Bíró, S. (1995). Taking the intentional stance at  
729 12 months of age. *Cognition*, 56(2), 165–193.
- 730 Gori, I., Pattacini, U., Nori, F., Metta, G., & Sandini, G. (2012). DForC: A real-time  
731 method for reaching, tracking and obstacle avoidance in humanoid robots. In *2012  
732 12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012)*  
733 (pp. 544–551). IEEE.
- 734 Gorniak, P., & Roy, D. (2004). Grounded Semantic Composition for Visual Scenes. *J.  
735 Artif. Intell. Res. (JAIR)* 21, 429–470.
- 736 Hayes-Roth, F. (1997, June 15). Artificial Intelligence: What Works and What Doesn’t?  
737 *AI Magazine*.
- 738 Helmert, M. (2009). Concise finite-domain representations for PDDL planning tasks.  
739 *Artificial Intelligence*, 173(5-6), 503–535.
- 740 Ho, W. C., Dautenhahn, K., Lim, M. Y., Vargas, P. A., Aylett, R., & Enz, S. (2009). An  
741 initial memory model for virtual and robot companions supporting migration and  
742 long-term interaction. In *RO-MAN 2009 - The 18th IEEE International Symposium  
743 on Robot and Human Interactive Communication* (pp. 277–284). IEEE.
- 744 Kalkan, S., Dag, N., Yürüten, O., Borghi, A. M., & Sahin, and E. (2013). Verb concepts  
745 from affordances. *Interaction Studies Journal*.

- 746 Kaplan, F., & Hafner, V. V. (2006). The challenges of joint attention. *Interaction*  
747 *Studies*, 7(2), 135–169.
- 748 Lallee, S., Lemaignan, S., Lenz, A., Melhuish, C., Natale, L., Skachek, S., ... Dominey,  
749 P. F. (2010). Towards a platform-independent cooperative human-robot interaction  
750 system: I. Perception. In *2010 IEEE/RSJ International Conference on Intelligent*  
751 *Robots and Systems* (pp. 4444–4451). IEEE.
- 752 Lallee, S., Madden, C., Hoen, M., & Dominey, P. F. (2010). Linking language with  
753 embodied and teleological representations of action for humanoid cognition.  
754 *Frontiers in Neurorobotics*, 4, 8.
- 755 Lallee, S., Pattacini, U., Boucher, J. D., Lemaignan, S., Lenz, A., Melhuish, C., ...  
756 Dominey, P. F. (2011). Towards a platform-independent cooperative human-robot  
757 interaction system: II. Perception, execution and imitation of goal directed actions.  
758 In *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp.  
759 2895–2902). IEEE.
- 760 Lallee, S., Pattacini, U., Lemaignan, S., Lenz, A., Melhuish, C., Natale, L., ...  
761 Dominey, P. F. (2012). Towards a Platform-Independent Cooperative Human  
762 Robot Interaction System: III An Architecture for Learning and Executing Actions  
763 and Shared Plans. *IEEE Transactions on Autonomous Mental Development*, 4(3),  
764 239–253.
- 765 Lallee, S., Warneken, F., & Dominey, P. (2009). Learning to collaborate by  
766 observation. In *Epirob, Venice, Italy*.
- 767 Lauria, S., Bugmann, G., Kyriacou, T., & Klein, E. (2002). Mobile robot programming  
768 using natural language. *Robotics and Autonomous Systems*, 38(3-4), 171–181.
- 769 Lévi-Strauss, C. (1979). *Myth and Meaning*. Routledge.
- 770 McDermott, D., Malik, G., Adele, H., Craig, K., Ashwin, R., Manuela, V., ... David,  
771 W. (1998). PDDL - The Planning Domain Definition Language. In *tech. report*  
772 *CVC TR-98-003/DCS TR-1165, Yale Center for Computational Vision and*  
773 *Control, Yale Univ., New Haven, Conn.*
- 774 McGuire, P., Fritsch, J., Steil, J. J., Rothling, F., Fink, G. A., Wachsmuth, S., ... Ritter,  
775 H. (2002). Multi-modal human-machine communication for instructing robot  
776 grasping tasks. In *IEEE/RSJ International Conference on Intelligent Robots and*  
777 *System* (Vol. 2, pp. 1082–1088). IEEE.
- 778 Metta, G., Sandini, G., Vernon, D., Natale, L., & Nori, F. (2008). The iCub humanoid  
779 robot. In *Proceedings of the 8th Workshop on Performance Metrics for Intelligent*  
780 *Systems - PerMIS '08* (p. 50). New York, New York, USA: ACM Press.
- 781 Mirza, N. A., Nehaniv, C. L., Dautenhahn, K., & Boekhorst, R. (2008). Developing  
782 social action capabilities in a humanoid robot using an interaction history

- 783 architecture. In *Humanoids 2008 - 8th IEEE-RAS International Conference on*  
784 *Humanoid Robots* (pp. 609–616). IEEE.
- 785 Ognibene, D., Chinellato, E., Sarabia, M., & Demiris, Y. (2013). Contextual action  
786 recognition and target localization with an active allocation of attention on a  
787 humanoid robot. *Bioinspiration & Biomimetics*, 8(3), 035002.
- 788 Payne, J. D., & Nadel, L. (2004). Sleep, dreams, and memory consolidation: the role of  
789 the stress hormone cortisol. *Learning & Memory (Cold Spring Harbor, N.Y.)*,  
790 11(6), 671–8.
- 791 Petit, M., Lalle, S., Boucher, J.-D., Pointeau, G., Cheminade, P., Ognibene, D., ...  
792 Dominey, P. F. (2013). The Coordinating Role of Language in Real-Time  
793 Multimodal Learning of Cooperative Tasks. *IEEE Transactions on Autonomous*  
794 *Mental Development*, 5(1), 3–17.
- 795 Pointeau, G., Petit, M., & Dominey, P. F. (2013a). Embodied Simulation Based on  
796 Autobiographical Memory. In N. F. Lepora, A. Mura, H. G. Krapp, P. F. M. J.  
797 Verschure, & T. J. Prescott (Eds.), *Biomimetic and Biohybrid Systems* (Vol. 8064,  
798 pp. 240–250). Berlin, Heidelberg: Springer Berlin Heidelberg.
- 799 Pointeau, G., Petit, M., & Dominey, P. F. (2013b). Robot Learning Rules of Games by  
800 Extraction of Intrinsic Properties. In *ACHI 2013, The Sixth International*  
801 *Conference on Advances in Computer-Human Interactions* (pp. 109–116).
- 802 Pointeau, G., Petit, M., & Dominey, P. F. (2014). Successive Developmental Levels of  
803 Autobiographical Memory for Learning Through Social Interaction. *IEEE*  
804 *Transactions on Autonomous Mental Development*, 6(3), 200–212.
- 805 Rader, N. de V., & Zukow-Goldring, P. (2012). Caregivers' gestures direct infant  
806 attention during early word learning: the importance of dynamic synchrony.  
807 *Language Sciences*, 34(5), 559–568.
- 808 Roy, D. K. (2002a). Learning visually grounded words and syntax for a scene  
809 description task. *Computer Speech & Language*, 16(3-4), 353–385.
- 810 Roy, D. K. (2002b). Learning words from sights and sounds: a computational model.  
811 *Cognitive Science*, 26(1), 113–146.
- 812 Shmuelof, L., & Zohary, E. (2005). Dissociation between ventral and dorsal fMRI  
813 activation during object and action recognition. *Neuron*, 47(3), 457–70.
- 814 Siskind, J. M. (1996). A computational study of cross-situational techniques for learning  
815 word-to-meaning mappings. *Cognition*, 61(1-2), 39–91.
- 816 Sutton, S., Ronald A., C., & Jacques De Villiers, Johan Schalkwyk, Pieter JE  
817 Vermeulen, Michael W. Macon, Y. Y. et al. (1998). Universal speech tools: the  
818 CSLU toolkit. In *ICSLP, vol. 98* (pp. 3221–3224).

- 819 Takács, B., & Demiris, Y. (2008). Balancing Spectral Clustering for Segmenting  
820 Spatio-temporal Observations of Multi-agent Systems. In *2008 Eighth IEEE*  
821 *International Conference on Data Mining* (pp. 580–587). IEEE.
- 822 Welke, K., Kaiser, P., Kozlov, A., Adermann, N., Asfour, T., Lewis, M., & Steedman,  
823 and M. (2013). Grounded Spatial Symbols for Task Planning Based on Experience.  
824 In *13th International Conference on Humanoid Robots (Humanoids)*. IEEE/RAS.
- 825 Wood, R., Baxter, P., & and Belpaeme, T. (2011). A review of long-term memory in  
826 natural and synthetic systems. *Adaptive Behavior*, *20*(2), 81–103.
- 827 Zacks, J. M., Speer, N. K., Swallow, K. M., Braver, T. S., & Reynolds, J. R. (2007).  
828 Event perception: A mind-brain perspective. *Psychological bulletin*, *133*, 273.
- 829

### 9.3.4 Living Machine : Embodied Simulation Based on an Autobiographical Memory

Authors : **Pointeau, G.**, Petit, M., and Dominey, P. F.

Title : "Embodied simulation based on autobiographical memory."

Journal : Biomimetic and Biohybrid Systems, pages 240-250. Springer.

Year : 2013

# Embodied Simulation Based on Autobiographical Memory

Gregoire Pointeau, Maxime Petit, and Peter Ford Dominey\*

Robot Cognition Laboratory, INSERM U846, Bron France  
{gregoire.pointeau,maxime.petit,peter.dominey}@inserm.fr

**Abstract.** The ability to generate and exploit internal models of the body, the environment, and their interaction is crucial for survival. Referred to as a forward model, this simulation capability plays an important role in motor control. In this context, the motor command is sent to the forward model in parallel with its actual execution. The results of the actual and simulated execution are then compared, and the consequent error signal is used to correct the movement. Here we demonstrate how the iCub robot can (a) accumulate experience in the generation of action within its Autobiographical memory (ABM), (b) consolidate this experience encoded in the ABM memory to populate a semantic memory whose content can then be used to (c) simulate the results of actions. This simulation can be used as a traditional forward model in the control sense, but it can also be used in more extended time as a mental simulation or mental image that can contribute to higher cognitive function such as planning future actions, or even imagining the mental state of another agent. We present the results of the use of such a mental imagery capability in a forward modeling for motor control task, and a classical mentalizing task. Part of the novelty of this research is that the information that is used to allow the simulation of action is purely acquired from experience. In this sense we can say that the simulation capability is embodied in the sensorimotor experience of the iCub robot.

**Keywords:** Humanoid robot, perception, action, mental simulation, mental imagery, forward model.

## 1 Introduction

One of the central capabilities that cognitive systems provide to living organisms is the ability to “travel in time,” that is, to imagine the future, and recall the past, in order to better anticipate future events [1]. This can be considered in the context that one of the central functions of the brain is to allow prediction [2, 3]. One of the most classical uses of prediction in the context of control is the forward model, which allows a system to predict responses to a motor command, and then compare the predicted and actual outcome. This notion has been extensively applied in the

---

\* Corresponding author.

neuroscience of motor control [4]. At a more extended time scale, a suitably detailed forward model can be used as a simulation system for allowing the system to image how things might have been, or how they might be in the future. This can allow perspective taking, as required for solving tasks in which one must take the perspective of another. In the “Sally – Anne” task, a child is shown a set-up with two dolls, Sally and Anne. Sally puts her ball in a basket, and then leaves. Meanwhile, Anne moves Sally’s ball into a box. Then Sally returns, and we can ask the child “where will Sally look for her ball?” Frith and Frith demonstrated [5] that before a certain age, children will “mistakenly” indicate that Sally will look in the box, the ball’s actual location, rather than in the basket, where she put it. They suggest that the ability to mentalize – to represent other’s mental states – relies on a system that has evolved for representing actions and their consequences. Such a capability to compare representations of others mental states with reality can form the basis for detecting that another agent is not telling the truth [6]. In the current study, we present a capability that allows the development of an internal simulation function, based on experience acquired by the agent, which allows the generation of mental simulations that can be used both in low level motor control.

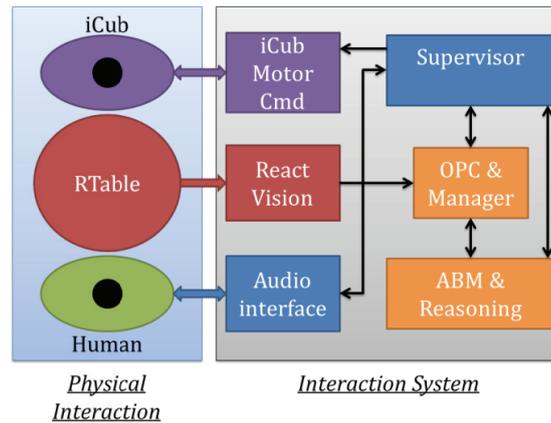
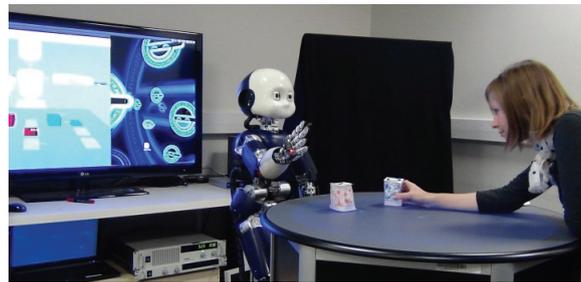
The Experimental Functional Android Assistant (EFAA) system functions in a domain of physical interaction with a human as illustrated in Figure 1. Objects are manipulated by the robot and the human in cooperative interactions, and thus it is important that the EFAA system can accurately perform these manipulations and keep track of the actual and predicted physical state of itself and the human in their shared space.

## 2 System Description

The system provides control for real-time human interaction with the iCub robot that is achieved by articulation of three software modules: Autobiographical Memory, `abmReasoning` and `OPCManager`. The two first modules (`AutobiographicalMemory` and `abmReasoning`) have been previously described [7, 8]. They provide the ability for the system to store the history of all interactions in the ABM, and to extract conceptual information from the ABM, including the meaning of spatial and temporal referencing terms. We will briefly describe these functions, and then focus on the `OPCManager` (`OPCM`). Our complete system is developed in the context of the emergence of a self of the robot (use of an autobiographical episodic-like memory and a reasoning based on the experience) but an important property of the self is the ability to mentally simulate and predict consequences of the actions of himself or of other.

Illustrated in Figure 1, the Objects Properties Collector (`OPC`), contains the world-related knowledge of the robot at the current time. Here, we use two different `OPCs`. One will be related to the “real” world (`realOPC`), and the second one to the “mental” picture of the robot and to his imagination (`mentalOPC`). The main purpose of the `OPCmanager` module will be to simulate in the `mentalOPC` activities previously learned through the joint action of the `AutobiographicalMemory` and the `ambReasoning`, then to observe the possible implication of these activities, and to compare this with the final state of the same activities in the real world.

In summary, we will focus on the coordinated interaction of the three modules: 1) Autobiographical Memory: Take a snapshot of the world at a given time, Store snapshots and manage them. 2) abmReasoning: Manipulate the data of the ABM, Summarize and generalize different levels of knowledge. 3) OPC Manager: Simulate action interaction in a mental OPC, and extract differences between realOPC and mentalOPC.



**Fig. 1.** Illustration of the iCub EFAA interacting with a human (Above), and System Architecture overview (Below). Human and iCub interact face-to-face across the ReactTable, which detects objects through the translucent surface, and communicates object locations via ReactVision to the Object Property Collector (OPC). The Supervisor coordinates spoken language and physical interaction with the iCub via spoken language technology in the Audio interface. The autobiographical memory ABM & reasoning system encodes world states and their transitions due to human and robot action as encoded in the OPC, and generates semantic representations. The OPC manager generates the representations of the actual and imagined states.

## 2.1 Autobiographical Memory and ABM Reasoning

The Autobiographical memory (ABM) is made up of an episodic memory and a semantic memory. The Episodic memory consists of 12 SQL tables, and stores the content of the OPC, with related contextual knowledge. The information will be: content of the realOPC, time, date, agent performing an action, semantic role of the argument of an action (i.e.: "ball": object, "north": spatial).

The Semantic Memory is made up of 12 SQL tables and stores the knowledge of the iCub related to different levels. Levels are: spatial, temporal, contextual, shared plan, behaviors. The semantic memory is constructed by extracting regularities from the episodic memory as human and robot actions cause changes to the states of objects on the ReacTable.

As such actions take place during the course of ongoing interactions, these events are stored in the episodic memory. The ABMreasoning function then extracts regularities that are common to experiences that are encoded in the episodic memory, to populate the semantic memory. The semantic memory thus includes the names and locations corresponding to locations taught by the human, and actions (e.g. *put an object at a location*) and their pre-conditions (e.g. that the object should be present) and post-conditions (e.g. that the *object* is now at *location*). Thus, through interaction, the system learns about the pre- and post-conditions of actions. This knowledge will be crucial in allowing the system to mentally simulate action.

## 2.2 OPC Management of Physical Reality and Mental Simulations

The OPC manager ensures the proper functioning of the realOPC and the mental OPC. The realOPC should maintain an accurate reflection of the physical state of the world. This state will be modified after the execution of actions. Thus, when the robot or the human perform an action of the type “put the triangle on the left”, the physical state changes that result from this will be that the triangle is at the north location. For the realOPC, these changes will occur as part of the normal functioning of the OPC as it is updated by perceptual inputs from the ReacTable. This corresponds to the update of an internal model (the realOPC) via perception (ReactVision inputs to realOPC).

The novel aspect concerns the updating and maintenance of the mentalOPC. The function `simulateActivity` will simulate an action by retrieving its pre-conditions and post-conditions from the Semantic memory, and then “executing” this action by checking that its pre-conditions hold in the mentalOPC, and then updating the mentalOPC so that the post-conditions now hold, and the pre-conditions are removed. Thus, we emphasize that mental simulation is based on experience, initially encoded in the episodic memory and then extracted in the semantic memory.

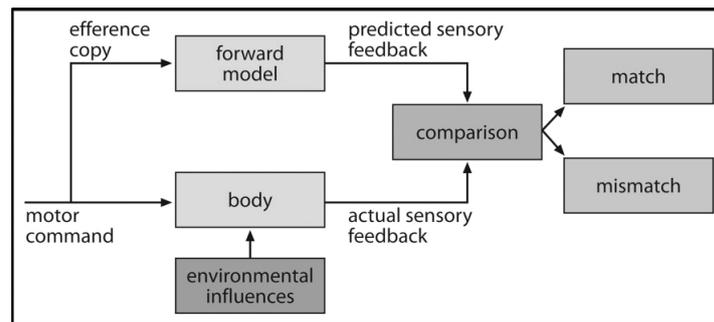
## 3 Experiments

Here we report on two experimental evaluations of the use of the real and mental OPCs in different contexts.

### 3.1 Forward Model in Grasp Control

A current problem in robotics is the use of feedback in motor control, for example, when a robot attempts to grasp an object and the grasp fails, feedback can be used to detect the failure [9]. Such a feedback control loop is illustrated in Figure 3. The motor command is sent to the forward model, and to the body, and the resulting predicted sensory feedback and actual sensory feedback are compared. If they match, the movement has been successfully completed, and if not, a failure is detected. We can use this method in the dispositive described above with the iCub. After experience producing the “put object at location” action, the system has acquired semantic information that the result of this action is that the object is now positioned at the specified location.

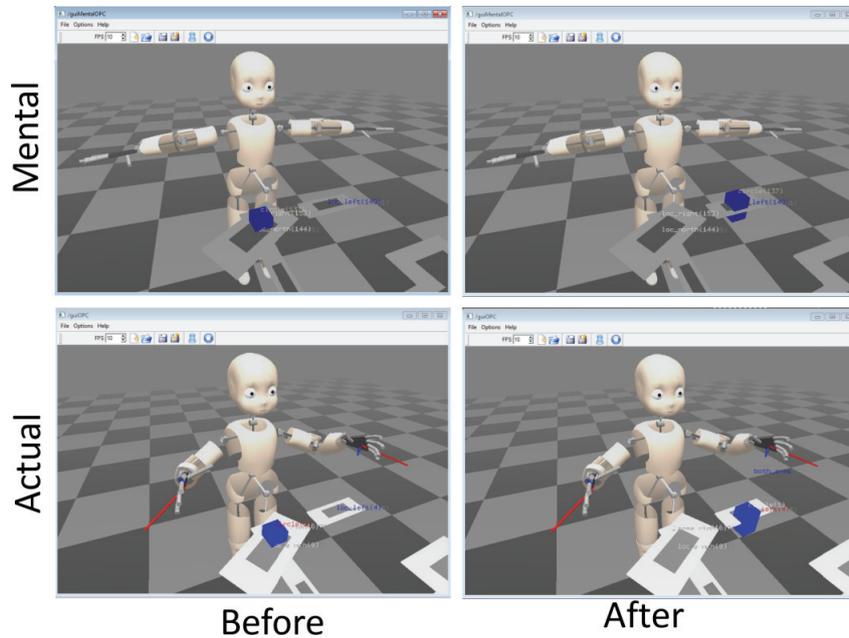
Functionally, the mentalOPC is used as the forward model. The “put” command is sent for execution to the ICubMotorCmd module, and it is also sent for simulation to the SimulatActivity function of the OPCmanager. The realOPC and mentalOPC can then be compared to assess the success of the action.



**Fig. 2.** Illustration of the forward model in the context of motor control. The motor command is sent to the motor command system and to the internal model. Subsequent comparison allows the system to determine if the grasp was correctly executed. Figure from [2].

Figure 4 illustrates the contents of the realOPC and mentalOPC before and after a successful “put circle left” action is executed by the iCub. The circle is indicated in the OPCs by a blue cube. In the Before panels it is at the “North” location near the robot’s midline, and in the After panels it is displaced to the robot’s left, to the location labeled Left. The diffOPC function produces a report indicating that there is no significant difference in the two positions, as illustrated in Table 1.

Figure 5 illustrates the mentalOPC and realOPC before and after “put cross left” action in which there is a physical disturbance during the execution by the iCub. In the lower right panel (Actual – After) we can observe that the representation of the cross object is not positioned on the localization “Left” in contrast to the predicted location that can be visualized in the upper right panel (Mental – After). During the execution a perturbation occurred and the put action resulted in a final positioning of the object that does not match with the predicted location. This mismatch is detected by the diffOPC function, as illustrated in Table 2.



**Fig. 3.** Mental image and actual physical state before and after a successful grasp and move action. The action to perform is to put the circle (the blue object) to the left of the robot in the delimited location..

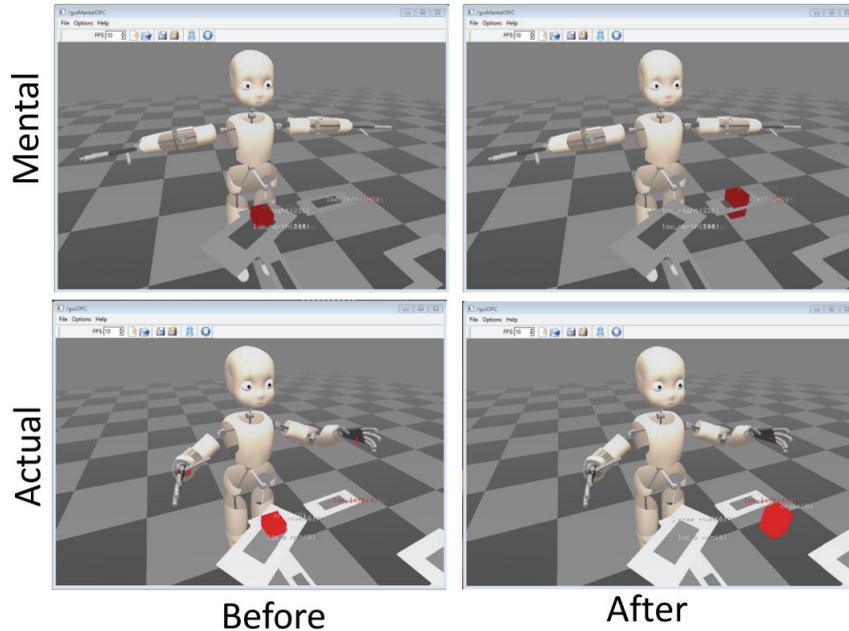
**Table 1.** Comparison from diffOPC function of realOPC and mentalOPC indicating no difference.

```

:circle
bot_position_x -0.025075
bot_position_y 0.016605
bot_orientation_z -0.048426
_position_x 0.112762
_position_y 0.180602

semantic differences
    
```

The detected mismatch can be used to allow the iCub EFAA to determine a corrective course of action. Our next step in this context will be to include experiments with this forward modeling capability integrated in the iCubMotorCMD so that failed actions can automatically initiate appropriate retrials.



**Fig. 4.** Mental image and actual physical state before and after an unsuccessful grasp and move action. The final state of the object in the actual condition is different from that in the mental simulation (forward model), thus indicating that the action failed. The action to perform is to put the cross (the red object) to the left of the robot in the delimited location.

**3.2 Simulating Other’s Beliefs in the “Sally Anne” Task**

Such mental simulation can also contribute to the ability of the robot to mentalize. Mentalizing is the ability to represent the mental states of others, traditionally referred to in the context of theory of mind (ToM) tasks [5]. A classic method to assay this capability to represent false beliefs is via the “Sally – Anne” task. In this task, the

**Table 2.** Results returned from diffOPC comparing realOPC and mentalOPC. The comparison indicates a significant difference, corresponding to the error in the execution of the action.

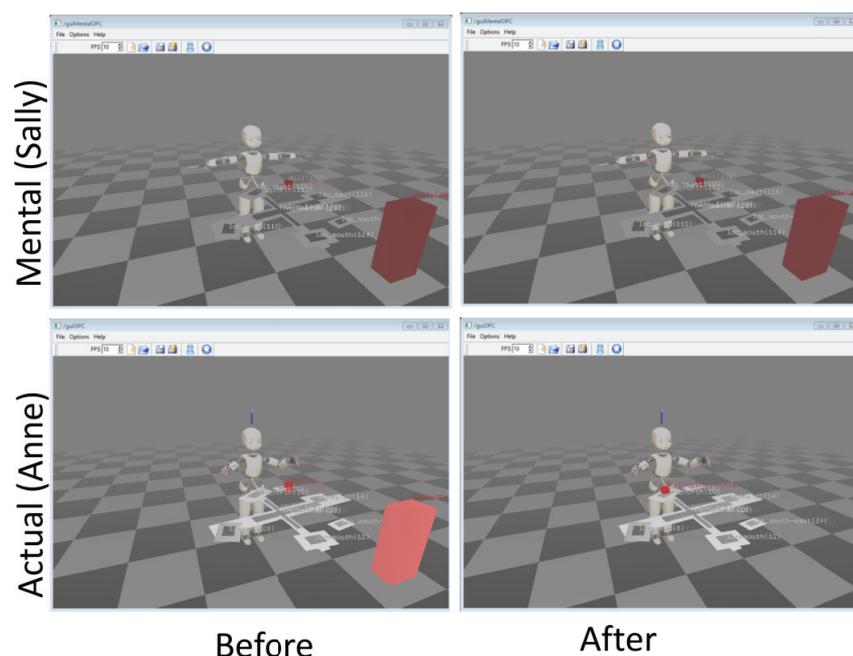
Entity : cross
robot_position_x -0.091195
robot_position_y -0.035511
robot_orientation_z 0.179689
rt_position_x 0.194235
rt_position_y 0.183612
Semantical differences :
Entity : icub
Beliefs removed:cross is left (mental-predicted)

child is shown a small stage with two dolls, Sally and Anne, and a toy ball. Sally puts her ball in a basket, and then leaves. Meanwhile, Anne moves Sally's ball into a box. Then Sally returns, and we can ask the child "where will Sally look for her ball?"

A long history of experimental research has demonstrated that the ability to perform tasks that require such representations develops over time, though the details of precisely when young children can perform such tasks depends significantly on the detail of how the task protocol is implemented, and children as young as 15 months of age can be demonstrated to represent the false beliefs of others [10].

We hypothesized that the mentalOPC can allow the iCub EFAA to resolve this problem correctly. The mentalOPC can be used to represent the initial state of affairs. The key element is that after Sally leaves, whatever happens in the mentalOPC - which is intended to represent Sally's perspective - should not change and should not be subject to the results of any actions that Sally does not actually witness.

The contents of the realOPC and mentalOPC in this context are represented in Figure 6. In this case, while the agent Sally is present, the toy is placed on the left. This is represented in the mentalOPC and the realOPC. In the After column, for the



**Fig. 5.** Contents of mentalOPC and realOPC in the Sally-Anne task. In the "Before" column is represented the contents of both OPC when the toy has been placed at the first location. The mentalOPC is the systems representation of what it and Sally have seen. In the "After" column, the Actual situation represents the contents of the realOPC after the toy has been moved. In that same column the mentalOPC represents the what Sally observed before she left. If this is maintained in memory, then it will persist after the world has been changed, and it can be used to mentalize about where Sally would look for the toy.

**Table 3.** Results returned from diffOPC comparing realOPC and mentalOPC. The comparison indicates a significant difference, corresponding to difference between the “false belief” attributed to Sally in the mentalOPC and the “true beliefs” attributed to Anne in the realOPC.

```

3 entities changed :
Entity : toy
  robot_position_x -0.034557
  robot_position_y 0.276599
  robot_orientation_z -0.042716
  rt_position_x -0.118581
  rt_position_y -0.252269
Entity : icub
  Beliefs added :toy is column toy is north (after)
  Beliefs removed :toy is left, Sally is isPresent (before)
Entity : Sally
The beliefs of Sally didn't change, because she wasn't here.
Her beliefs are : toy is left.

```

realOPC we see that Sally is no longer present, and the object has been moved to the North location. The mentalOPC is the same image as seen when Sally was present, and it is not updated. The ability to maintain this representation allows the system to recognize the mismatch between what Sally saw, and the actual state of the world.

Here we see that the use of the mentalOPC allows the system to “mentalize” about the belief state of another agent. This experiment has potential impact in the context of the ongoing debate on what is required for passing false belief tasks, and will be addressed in the discussion.

## 4 Discussion

The human cognitive system allows us to travel in time and space – we can imagine possible futures, and relive and analyze the past [1]. To do so, the system requires the ability to simulate itself and its activity in the world. We hypothesize that this simulation capability derives from the long evolved capability for forward modeling that was crucial for the ability of advanced primates to navigate through a complex world where real-time sensorimotor was crucial to survival. In the current research we demonstrate a developmental mechanism that could contribute to the emergence of such a simulation capability.

Through the accumulation of its own experience, the iCub EFSA can extract the regularities that define the pre- and post-conditions of its physical actions, and those of the human. This knowledge is then used to drive the mental simulation of action, which can actually operate faster than real-time, and generate predictions of expected outcome before the real movement is achieved. We demonstrate the functionality of this mechanism in two settings: Forward modeling in sensory-motor control, mentalizing in a false-belief task.

Learning forward models has been successfully applied in robotics [11, 12]. In the context of forward modeling, it is important for the system to detect that inconsistent

information is being provided. This can be important in the ongoing learning of the system based on experience. Thus, if the human says that it will perform an action, and then the system can detect a difference between the actual and predicted action, then it can mark this experience as suspect, and not include it in future learning, thus not contaminating experience with questionable content.

In the context of mentalizing and the false belief task, the current research has significant potential impact. There is an ongoing debate concerning the nature of the mental processes that are required to take the mental perspective of another agent. This includes discussion of whether distinct language capabilities are required [10]. Our research provides insight into this question, by illustrating how a simulation capability that is directly derived from experience can be used to provide an agent with the basic representational capabilities to perform the false belief task.

It can be considered that the mere notion of “autobiographical memory” presupposes that the system must have a first person perspective, from which that memory is situated. The notion of first person perspective is in fact a deep philosophical issue (see eg. [13]). From the perspective of the current research, we can say that the robot has taken steps towards achieving a minimal form of IPP in that it has developed an integrated representation of itself within the peripersonal space. This is also related to the notion of ecological self as defined by Neisser, which is the individual situated in and acting on the immediate environment [14]. What is currently missing with respect to these notions of self is a reflective capability, where the system reasons on a self-model as an integrated model of the very representational system, which is currently activating it within itself, as a whole [15].

In summary, the current research makes a significant contribution to the cognitive systems research. It allows the iCub EFAA system to autonomously generate an internal simulation capability based on its own personal experience. This simulation capability can operate at the level of physical control, and at high levels of cognition including mentalizing about the belief states of others. Our current research integrates this capability in the context of simulated situations models and language comprehension [16, 17].

**Acknowledgements.** This research has been funded by the European Commission under grant EFAA (ICT-270490).

## References

- [1] Vernon, D., Metta, G., Sandini, G.: A survey of artificial cognitive systems: Implications for the autonomous development of mental capabilities in computational agents. *IEEE Transactions on Evolutionary Computation* 11, 151–180 (2007)
- [2] Bubic, A., Von Cramon, D.Y., Schubotz, R.I.: Prediction, cognition and the brain. *Frontiers in Human Neuroscience* 4 (March 22, 2010)
- [3] Friston, K.: A theory of cortical responses. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* 360, 815–836 (2005)
- [4] Wolpert, D.M., Ghahramani, Z., Jordan, M.I.: An internal model for sensorimotor integration (1995)

- [5] Frith, C.D., Frith, U.: Interacting minds—a biological basis. *Science* 286, 1692–1695 (1999)
- [6] Singer, T.: The neuronal basis and ontogeny of empathy and mind reading: review of literature and implications for future research. *Neuroscience and Biobehavioral Reviews* 30, 855–863 (2006)
- [7] Petit, M., Lalle, S., Boucher, J.-D., Poiteau, G., Cheminade, P., Ognibene, D., Chinellato, E., Pattacini, U., Demiris, Y., Metta, G., Dominey, P.F.: The Coordinating Role of Language in Real-Time Multi-Modal Learning of Cooperative Tasks. *IEEE Transactions on Autonomous Mental Development* (2012)
- [8] Poiteau, G., Petit, M., Dominey, P.F.: Robot Learning Rules of Games by Extraction of Intrinsic Properties. In: *The Sixth International Conference on Advances in Computer-Human Interactions, ACHI 2013*, pp. 109–116 (2013)
- [9] Shirai, Y., Inoue, H.: Guiding a robot by visual feedback in assembling tasks. *Pattern Recognition* 5, 99–108 (1973)
- [10] Onishi, K.H., Baillargeon, R.: Do 15-month-old infants understand false beliefs? *Science* 308, 255–258 (2005)
- [11] Dearden, A., Demiris, Y.: Learning forward models for robots. In: *International Joint Conference on Artificial Intelligence*, p. 1440 (2005)
- [12] Metta, G., Fitzpatrick, P.: Early integration of vision and manipulation. *Adaptive Behavior* 11, 109–128 (2003)
- [13] Metzinger, T.: Empirical perspectives from the self-model theory of subjectivity: a brief summary with examples. In: Banerjee, R., Chakrabarti, B. (eds.) *Models of Brain and Mind: Physical, Computational and Psychological Approaches*, vol. 168, p. 215 (2008)
- [14] Neisser, U.: The roots of self-knowledge: perceiving self, it, and thou. *Ann. N. Y. Acad. Sci.* 818, 18–33 (1997)
- [15] Metzinger, T.: *Being no one: The self-model theory of subjectivity*. Bradford Books (2004)
- [16] Barsalou, L.W.: Simulation, situated conceptualization, and prediction. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* 364, 1281–1289 (2009)
- [17] Madden, C., Hoen, M., Dominey, P.F.: A cognitive neuroscience perspective on embodied language for human-robot cooperation. *Brain Lang.* 112, 180–188 (2010)

### 9.3.5 EPIROB : Emergence of the Use of Pronouns and Names in Triadic Human-Robot Spoken Interaction

Authors : **Pointeau, G.**, Petit, M., Gibert, G., and Dominey, P. F.

Title : "Emergence of the use of pronouns and names in triadic human-robot spoken interaction."

Journal : Development and Learning, 2014. ICDL 2014. IEEE 13th International Conference on.

Year : 2014

# Emergence of the Use of Pronouns and Names in Triadic Human-Robot Spoken Interaction

Grégoire Pointeau, Maxime Petit, Guillaume Gibert, Peter Ford Dominey  
Robot Cognition Laboratory, INSERM U846, Bron FRANCE  
Email:  [{name.surname}@inserm.fr](mailto:{name.surname}@inserm.fr)

**Abstract**—We present here a system capable of learning to extract the correct comprehension and production of personal pronouns and proper nouns during Human-Robot or Human-Human interactions. We use external 3D spatial and acoustic sensors with the robot iCub to allow the system to learn the proper mapping between different pronouns and names to their properties in different interaction contexts. The properties are Subject (*Su*), Speaker (*Sp*), Addressee (*Ad*) and Agent (*Ag*). A fast mapping system is used to extract correlation between the different properties. After a learning phase, the robot is able to find the missing property when only 3 out of 4 are known, or at least to discriminate which word cannot be used to be the lacking property. We present results from a set of experiments that provide some insight into aspects of human development.

**Index Terms**—Embodied robotic, functional language learning, real-time learning, fast mapping, human-robot interaction.

## I. INTRODUCTION

The future of social robotics will be written in the understanding of complex relations, where robots will interact not only with one user, but also with multiple agents. The classical learning of language through one-to-one spoken interactions has been studied for some time ([1]–[4]), but it has been shown that these interactions are insufficient to learn or use correctly personal pronouns [5]. According to Oshima-Takane, learning to use personal pronoun like “You” and “I” is done through observation and with the involvement of the student with several agents ([6], [7]). Gold and Scassellati have made several models using fast mapping for “You” and “I” [8]–[10], but here, we propose a system able to extend the learning from personal, to both personal and impersonal pronoun. This understanding is also an important step for the emergence of self [11].

If we want robots able to be in the middle of humans, behaving as one of them, we need these robots to understand human interactions. In fact, human interactions can be very complex and robots need a robust system able to understand and to acquire the knowledge of directed human interaction in order to be part of the interaction. The goal is not only to extract knowledge and to be able to create new knowledge, but also to use this knowledge at the proper moment for

example to understand the type of relationship between different persons. In the future, robots should be able to behave in a human environment, and to get clues about the different relationship between the people present like humans do. This is why we decided to focus about the development of children, and try to apply it to our system, to get a robot with the same developmental results.

To do so, we present here a fast mapping system able to understand the use of different pronouns during a classical interaction either dyadic or triadic. We use a fast mapping system between the use of a pronoun and the context in which it has been used to classify the different subjects of the pronounced sentences. The model is based on child development. The pre-required for the understanding of a triadic interaction is to be able to detect the *Sp* (*speaker*), *Ad* (*addressee*), *Ag* (*agent*) and *Su* (*subject*) of an action. Corkum & Moore [12] have shown that at about 9 months, children can detect the direction of an adult’s gaze. This age has been put in evidence by Tomasello [13] as the “*Nine month revolution*” and is the starting point of a full understanding of a complex interaction, including triadic interaction. Thus, this will be the starting point of our system. We will give the robot the possibility to detect these interaction properties.

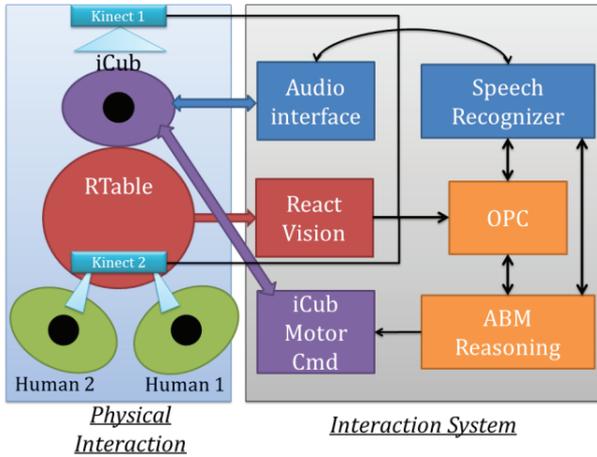
The section II will explain the method and system used (the physical and software architecture), the section III will explain the learning mechanism through fast mapping. The section IV will summarize the experiments and the conditions we tested, and the results obtained. Finally, we will have a discussion part (section V) about the results and limitations of the system and what are our next steps in this field of research, before concluding (section VI).

## II. METHOD AND SYSTEM USED

### A. Physical Architecture

In this section we will present the system we used for our work. The following study has been realized on the robot iCubLyon01 [14] at the INSERM Robot Cognition Laboratory in Lyon, France. The physical architecture is centered on the robot iCub, and the Reactable (an interactive table), to allow face-to-face physical interaction [15]. We use

a first Kinect above the head of the robot to detect the movements of the present agents. A second Kinect will be used to detect the orientation of each agent, and binaural microphones placed on each ear of the robot to localize the origin of the sound (see Figure 1). This second Kinect needs to be placed at less than 1m from the subject for good results. This is the reason of the use of 2 Kinects.



**Figure 1: Physical and software architecture of the system used.**

The software architecture is centered on an Objects Properties Collector (OPC) which can be considered as a working memory, and that represent the state of the world at a given time. In this OPC the contextual data from the different sensors will be stored and all this information will be stored in an episodic-like memory (ELM) and be parsed by a reasoning module (abmReasoning) to create some knowledge relative to the heard sentences, and store it in a semantic memory (SM). The ELM and SM will form the auto-biographical Memory (ABM). More information about ABM can be found in [16], [17].

### B. Software Architecture and Sensors

The audio interface and speechRecognizer used are based on Microsoft speech recognizer SAPI5.1. The system, given a grammar, can detect the semantic role of each word in a sentence. For example, we used sentences like: “Peter put the cross to the left” or “You point the circle”. In these sentences, the first word will be extracted as the subject (or pronoun), the second as a verb, and the last one as the object of the sentence.

The rigid head motion of several human partners can be estimated using the Random Forest algorithm developed by [18]. In fact, a depth camera (Asus Xtion) was placed on the Reactable close to the robot and facing the human partners. Given the depth image provided by the sensor, the Random Forest Head tracking algorithm provided the position and orientation of the human partners’ head movements at 30 Hz. This information was used to estimate where the visual attention of each partner was directed to.

The speaker’s location was determined using the acoustic signals coming from the binaural microphones placed in the robot’s ears. The acoustic signals were retrieved in real-time thanks to the Jack library (<http://jackaudio.org/>). The Interaural Intensity Difference (IID) was computed. In fact, sound coming from the right has a higher intensity in the right ear microphone than on the left ear one. This difference allowed us to determine if the sound was coming either from left or right. In the triadic setup, the robot was able to determine who the speaker was (see Figure 2).



**Figure 2: System running when the robot is interacting with 2 agents around the Reactable.**

### C. Method

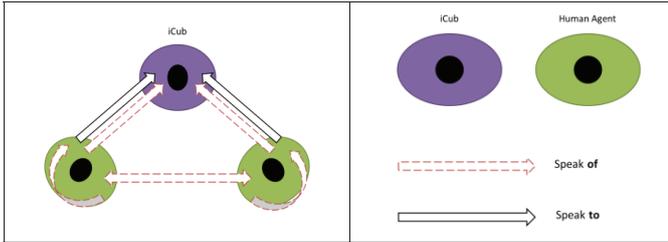
In our study, the robot will have a set of training data. For each set of learning data, we will use the pronouns: “I” and “You”, and the proper names: “Peter”, “Maxime” and “Grégoire” (will be referred as “known names”). “John” and “Mark” will never appear during the learning phase (only the testing phase) and will be referred as “unknown names”.

Then for each of the four possible modalities (*Sp*, *Ad*, *Ag*, *Su*) we give a random but doable (ie: *Sp* different of *Ad*) set of the three other modalities, and ask for the fourth one. For example, we will give the system: “*Su* = “I”; *Sp* = “Peter”; *Ad* = *iCub*” and the system should return: “*Ag* = “Peter””. Another example would be: we give the system: “*Sp* = “*iCub*”; *Ad* = “Maxime”; *Ag* = “Maxime” “ and the system should return: “*Su* = “You””.

We will test different learning conditions (that we can easily simulate see Section IV) in order to i) determine how the system learn with constrained conditions, potentially simulating constrained real solution and ii) investigating what kind of interaction is needed for the child to learn personal and impersonal pronoun use. We will test a set of 7 different conditions. These conditions involved two or three agents, the robot can be either spectator or actor. The precise conditions will be explicated in the section IV, at the beginning of each sub section. An agent can talk to someone or not, and an agent can talk about the action of someone (himself included) or not.

As we said earlier, Tomasello has shown in [13] that the child is not able before the “nine month revolution” to fully

understand a spoken interaction where he/she is not involved (neither speaker nor addressee). This is what Oshima-Takane calls the “Addressee Condition” [6], and will be summarized by:  $Ad = iCub$ . Another kind of condition that we tested is the case of «blind» children. The particularity of «blind» children is that they can only detect the actions related to them:  $Ag = iCub$  [19]. We will have two conditions with respectively two or three agents, where the  $Ag$  of the action is always the iCub. The Figure 3 is an example of a tested condition with the corresponding legend .



**Figure 3: Example of all available interaction for one of the learning conditions (left). Right: black arrows mean that the origin agent SPEAKS TO the target agent (origin =  $Sp$ , target =  $Ad$ ). Red arrows mean that the origin agent SPEAKS OF the target agent’s action (target =  $Ag$ ).**

### III. LEARNING MECHANISM

#### A. Data formalization

For each encountered interaction, we can have access to the four contextual properties of interest: Speaker ( $Sp$ ), Addressee ( $Ad$ ), Agent ( $Ag$ ) and Subject or Pronoun ( $Su$ ). We take the  $Su$  as higher level of property. For each  $Su$ , we build a cubic  $N^3$  matrix (three dimensions: one for  $Sp$ , one for  $Ad$  and one for  $Ag$ ), where  $N$  is the number of label encountered. A label can be any  $Ag$ ,  $Ad$  or  $Sp$  encountered (i.e.: “Maxime”, “Greg”...). A label corresponds to a way to refer to a person for the robot. In most cases, the label will correspond to the proper name of the person (e.g. *Peter*), but it can be something generic (e.g. *Agent\_5*). However,  $Su$  include personal pronouns (“I”, “You”) and proper names that have been used in a sentence. The matrix is then filled with the number of events encountered. The notation (1) gives us the number of events encountered with a particular set of  $Su$ ,  $Sp$ ,  $Ad$  and  $Ag$ .

$$M_{Su}(Sp, Ad, Ag) \quad (1)$$

For example, in the case of the sentence: “You point the toy”, where:  $Su = \text{“You”}$ ,  $Sp = \text{“Greg”}$ ,  $Ad = \text{“Maxime”}$ ,  $Ag = \text{“Maxime”}$ , we will add 1 in the matrix:  $M_{You}(Greg, Maxime, Maxime)$ , and for “John pushes the cross”, where:  $Su = \text{“John”}$ ,  $Sp = \text{“Peter”}$ ,  $Ad = \text{“Greg”}$ ,  $Ag = \text{“John”}$ , we will add 1 in the matrix:  $M_{John}(Peter, Greg, John)$ . We can expect to have only zero in the case of  $Sp$  is  $Ad$ , because we consider the case where one doesn’t talk to himself. In the case of the apparition of a new

label, the matrix will grow and fill the new case according to the number of utterances.

After the learning phase, we will have as many matrices as we have of different  $Su$ , and each matrix will be of size  $N^3$  with  $N$  the number of label encountered.

#### B. Fast Mapping

As we have seen earlier, the goal of the system is to retrieve the fourth property of an interaction, where the robot knows three properties. It can be used for the example when the robot sees Maxime moving ( $Maxime = Ag$ ), and want to explain the situation ( $iCub = Sp$ ) to Peter ( $Ad = Peter$ ). What  $Su$  should he use in this context ( $iCub = Sp$ ,  $Ad = Peter$ ,  $Maxime = Ag$ )? Another utilization could be when the robot hears Maxime speaking ( $Maxime = Sp$ ) while looking at the robot ( $Ad = iCub$ ), using the pronoun “You” ( $Su = \text{“You”}$ ), and the iCub wants to find who is the agent to know if he is concerned (context:  $Maxime = Sp$ ,  $Ad = iCub$ ,  $Su = \text{“You”}$ ).

To find a missing label ( $Sp$ ,  $Ad$ ,  $Ag$ ) or a respectively a pronoun ( $Su$ ), we list all the labels (resp. pronouns) known, and for each, we calculate a Chi Square associated to the corresponding situation (see Table 1). The p-value relative to the Chi-Square will give us some information about the distribution of event (context or no-context) given the label. If this p-value is strong, the two distribution are different and there is an effect of the context on the use or not of the pronoun. The score of the Chi Square will determine the likelihood to use (or not) a specific label or pronoun in a specific context. For a specific context, and a specific label (or pronoun) the Chi Square will be calculated with the data shown in the Table 1, where A is the number of sentences heard with this label (or pronoun) in this context, B is the number of sentences with a different label (or pronoun) is this context. C is the number of sentence with this label (or pronoun) in a different context and D the use of a different label (or pronoun) in a different context.

**Table 1: Table of fast mapping for a specific label/pronoun and a specific context**

	LABEL/PRONOUN	~LABEL/PRONOUN
CONTEXT	A	B
~CONTEXT	C	D

The Table 1 can correspond to the following situation: “Can I use this label (resp. pronoun) in this context?”. If the p-value associated to the Chi Square is above a threshold, the property is rejected. If the p-value is under this threshold, we add the distribution of the property to the score of the label (resp. pronoun) as shown in the pseudo code of the Figure 4.

```

GET THE SPECIFIC CONTEXT.
FOR EACH KNOWN LAB./PRON.:
{
IF: P-VALUE( $x^2$ ) < THRESHOLD
- DON'T CHANGE THE LAB./PRON. SCORE
ELSE:
- ADD TO THE SCORE OF THE LAB./PRON., THE DISTRIBUTION OF
THE PROPERTY: (A/C - B/D)
}
IF: ONE OR MORE LAB./PRON. HAS A SCORE > 0
- RETURN THE LAB./PRON. WITH HIGHER SCORE
ELSE:
- REMOVE LAB./PRON. WITH SCORE < 0

```

**Figure 4: Pseudo code corresponding to the searching part**

### C. Data Collection

In this section we will explain how we manage the collection of learning data. During an interaction with one or several agents around the Reactable, the different modalities will be retrieved as follows:

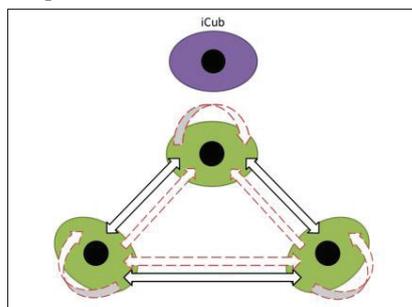
- **Sp**: We identify the speaker by using the binaural microphones placed on the iCub.
- **Ad**: As described in the section II-A, we use a Kinect to detect the orientation of the head of each speaker.
- **Ag**: We use the Kinect placed above the iCub to detect who is moving, or when the agent is the iCub, he will use proprioception (i.e. check if motors are moving).
- **Su**: The speechRecognizer is used to extract the subject of the sentence, and to return it.

All this contextual information is collected from the OPC, and stored in the ABM. Once all the information is in the ABM, the reasoning module can create the matrices. In the case of simulated data, each sentence is repeated 5 times in order to simulate the redundancy present in language

## IV. EXPERIMENTS AND RESULTS

In this section, we will present the 7 conditions tested and the results. Each subsection will detail one specific condition and the results obtained. We consider that the robot understands a subject when he can retrieve the *Ag* of the action with a *Su*, *Sp* and *Ad*, and that he has a correct use of a subject when given *Sp*, *Ad* and *Ag* he retrieves the correct *Su*.

### A. Triadic spectator



**Figure 5: triadic spectator condition. Three agents talk to each other, about each other.**

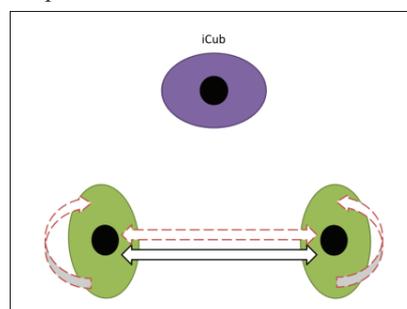
This first and “complete” situation is the one we recorded with real data and is the only condition where the sentences are not repeated (see Figure 5). We have three agents: Peter, Maxime and Grégoire. Each agent talks to the other two, about his own action, the action of the addressee, and the action of the third agent. We thus have a total of 18 different sentences. This is a case of “perfect” data without repetition. With this set of 18 sentences, the system is able to understand and to correctly use the pronouns “I” and “You” and also the use and the understanding of a known name (Peter, Maxime or Grégoire) but not of an unknown name.

UNDERSTANDING “I”	✓
CORRECT USE OF “I”	✓
UNDERSTANDING “You”	✓
CORRECT USE OF “You”	✓
UNDERSTANDING A KNOWN NAME	✓
CORRECT USE OF KNOWN NAME	✓

The learning data for this condition are summed up here:

Interaction	<i>Sp</i>	<i>Ad</i>	<i>Ag</i>	<i>Su</i>
1	Greg	Maxime	Greg	“I”
2	Greg	Maxime	Maxime	“You”
3	Greg	Maxime	Peter	“Peter”
4	Greg	Peter	Greg	“I”
5	Greg	Peter	Maxime	“Maxime”
6	Greg	Peter	Peter	“You”
7	Maxime	Peter	Greg	“Greg”
8	Maxime	Peter	Maxime	“I”
9	Maxime	Peter	Peter	“You”
10	Maxime	Greg	Greg	“You”
11	Maxime	Greg	Maxime	“I”
12	Maxime	Greg	Peter	“Peter”
13	Peter	Maxime	Greg	“Greg”
14	Peter	Maxime	Maxime	“You”
15	Peter	Maxime	Peter	“I”
16	Peter	Greg	Greg	“You”
17	Peter	Greg	Maxime	“Maxime”
18	Peter	Greg	Peter	“I”

### B. Dyadic spectator



**Figure 6: dyadic spectator condition. Two agents talk to each other, about each other.**

This condition refers to the iCub watching two persons talking to each other about each other (see Figure 6). The iCub is only spectator and in no way involved in the sentences. The agent uses only “I” and “You” and never an

agent's name. We used for this condition 4 different sentences repeated 5 times, for 20 training sentences. The results show that the robot can understand correctly the use of "I" and "You". That means that in the case where the robot wants to describe ( $Sp=iCub$ ) what he or his addressee does ( $Ag=iCub$  or  $Ag=Peter$ ) to someone ( $Ad=Peter$ ) he will correctly use the pronoun "I" or "You". The robot is also able to understand "I" and "You" in a sentence (ie: when we give the robot  $Su = "I"$ , resp.  $Su = "You"$ ,  $Sp$  and  $Ad$ , the robot assumes that the  $Ag$  is the  $Sp$  for "I" resp.  $Ag = Ad$  for "You".

UNDERSTANDING "I"	✓
CORRECT USE OF "I"	✓
UNDERSTANDING "YOU"	✓
CORRECT USE OF "YOU"	✓
UNDERSTANDING A NAME	✗
CORRECT USE OF A NAME	✗

### C. Triadic agent

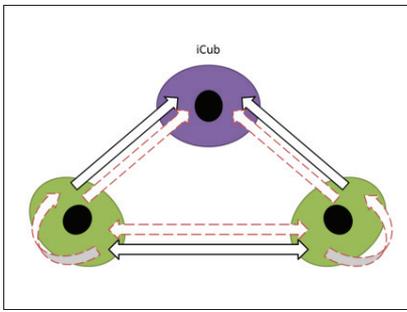


Figure 7: triadic agent condition. Two agents talk to each other and to the iCub about the three of them.

This condition is similar to the previous one (*Triadic Spectator*) but this time, one of the agent is the iCub, and does not speak (see Figure 7). We have thus not 18 but 12 different sentences that we repeated 5 times each for a total of 60 learning sentences. The results are similar to those for the triadic spectator, except that this time the robot is unable to use correctly the pronoun "I". When the robot is talking about him doing an action, he will prefer using "iCub" rather than "I" while for the other agent, he can use it correctly. But an interesting fact is that if we ask the robot who would be the agent in the case of a sentence said by the iCub using "I", the robot correctly understands that "I" refers to him.

UNDERSTANDING "I"	✓
CORRECT USE OF "I"	✗
UNDERSTANDING "YOU"	✓
CORRECT USE OF "YOU"	✓
UNDERSTANDING A KNOWN NAME	✓
CORRECT USE OF KNOWN NAME	✓

### D. «Blind» three agents

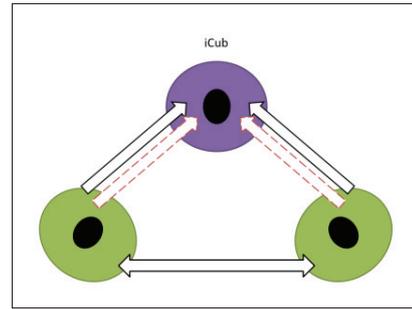


Figure 8: «blind» three agents condition. Two agents talk to each other and to the iCub, about the iCub's actions.

This condition is a triadic condition with the robot and two agents (see Figure 8). The two agents can only talk about the action of the robot ( $Ag = iCub$ ). In this condition one agent can talk to the other or to the iCub, about the iCub (third person). We have a set of 4 different sentences repeated 5 times for a total of 20 learning sentences. The results are that the robot understands and uses correctly "You" but not "I" (because he has never heard it). Also, the robot is confused with understanding and using the name "iCub". It could be the same as "he" or could just refer to "someone else".

UNDERSTANDING "I"	✗
CORRECT USE OF "I"	✗
UNDERSTANDING "YOU"	✓
CORRECT USE OF "YOU"	✓
UNDERSTANDING A NAME	✗
CORRECT USE OF NAME	✗

### E. «Blind» two agents

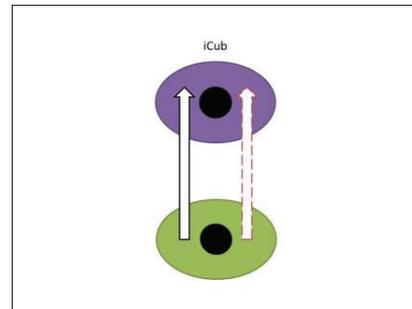
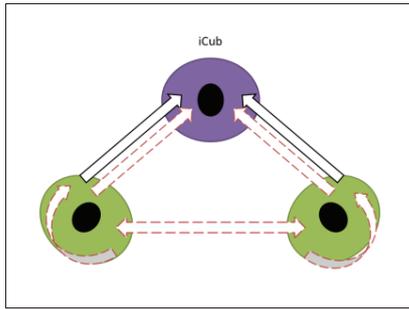


Figure 9: «blind» two agents condition. An agent talks to the iCub about the iCub's actions.

In this condition, we have only two agents: the iCub and a human agent (see Figure 9). The human only talks to the robot, about the robot. We have thus only one sentence possible ("You do ..."), repeated 5 times. With this learning data, as expected, the robot is unable to understand or use "I" or "You". Also, the robot doesn't acquire any knowledge about the use of any name.

UNDERSTANDING "I"	✗
CORRECT USE OF "I"	✗
UNDERSTANDING "YOU"	✗
CORRECT USE OF "YOU"	✗
UNDERSTANDING A NAME	✗
CORRECT USE OF NAME	✗

F. «Addressee» three agents

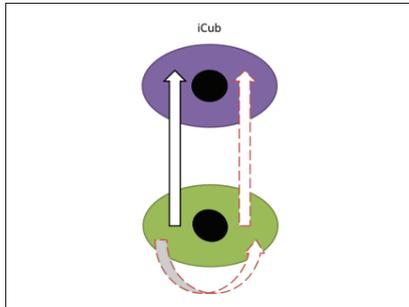


**Figure 10: «addressee» three agents condition. Two agents talk to the iCub about the action of everyone.**

In this condition, the robot is in presence of two agents (see Figure 10). The robot only perceives the sentences directed to him ( $Ad = iCub$ ). But an agent can talk of the action of a third person, while he is talking to the robot. We have a set of 6 different sentences (2  $Sp$ , talking to 1  $Ad$ , about 3 different  $Ag$ ), repeated 5 times, for a total of 30 sentences. The results are that the robot correctly understands and uses “*I*” and “*You*” and understand a known name as pronoun (ie: “*Peter does ...*”) but not an unknown name. In this condition, the robot never hears his own name.

UNDERSTANDING “ <i>I</i> ”	✓
CORRECT USE OF “ <i>I</i> ”	✓
UNDERSTANDING “ <i>You</i> ”	✓
CORRECT USE OF “ <i>You</i> ”	✓
UNDERSTANDING A KNOWN NAME	✓
CORRECT USE OF KNOWN NAME	✓

G. «Addressee» two agents



**Figure 11: «addressee» two agents condition. A agent talks to the iCub about the actions of both the human and the robot.**

In this condition, the robot is in presence of one other agent (see Figure 11). This human agent talks to the robot about the actions of both human and robot. We have a set of 2 different sentences (“*I do ...*” “*You do ...*”) repeated 5 times for a learning set of 10 sentences. One notable thing in this condition is that the robot fully understands and uses correctly “*I*” and “*You*”, even if he did not hear them in at least two different situations, where we could expect the robot to understand that, as a child does sometimes, his name is “*You*” and the name of the human is “*I*”. We will discuss it in the following section.

UNDERSTANDING “ <i>I</i> ”	✓
----------------------------	---

CORRECT USE OF “ <i>I</i> ”	✓
UNDERSTANDING “ <i>You</i> ”	✓
CORRECT USE OF “ <i>You</i> ”	✓
UNDERSTANDING A NAME	✓
CORRECT USE OF NAME	✓

V. DISCUSSION

The results we obtain with our cross validation system are primarily those that we expected based on child development. Indeed, we have seen that the case of a full triadic interaction observed by the robot provides the most information about the use of a personal pronoun (or proper noun). A fast mapping system allows the detection of the situation where a certain pronoun should be use. The learning phase (filling the matrices) and the working phase (finding the good lacking property) work in real time. The system is not greedy in computation or memory, but allows the understanding of an interaction with several agents, and to use correctly different subjects for a sentence according to the situation. However we can see a few limitations with our system.

The first limitation is the non-generalization of plural pronouns like “*We*” or “*They*”. This is in current development, and will need a processing of several  $Sp$ ,  $Ad$ ,  $Ag$  and not a one-to-one system as we have currently.

The second limitation is in the gender or social relation. One of our future research axis is to work on the discrimination of “*he*” and “*she*” but also more social relation has: parent/child professor/student. To do so, we will have to extend our matrix system for a more dynamical system extensible to more properties than the 4 that we have now ( $Su$ ,  $Sp$ ,  $Ad$ ,  $Ag$ ).

The third limitation is observed on the result that we obtained in the condition “«addressee» two agent”. The robot only witnesses a Human saying “*I*” when he refers to himself, and “*You*” when he talks to and about the iCub. We thus expected the robot to be confused between the use of “*I*” for  $Sp=Ag$  and when it refers to the Human, and vice versa for “*You*” and the robot. Why the robot does not think he is “*You*” and the Human is “*I*”? The answer, is because we put the same weight to each property. The simple properties like: “ $Ag=Human$ ” have as much weight as a property “double” like “ $Sp=Ag$ ”, or a property “triple” like “ $Sp\ fixed, Ad\ fixed, Su\ fixed$ ”. A “triple” property corresponds to an exact known situation, and a “simple” property to a simple fact. A “double” property is less intuitive: the robot searches a more complex correspondance between different contextual information. In our case, when the robot has to use “*I*”, he checks for example the case where he has to talk about his own actions: “ $Sp=Ag$ ”; “ $Ad!=Ag$ ”; “ $Ag=iCub$ ”. These three properties are true. The first two will be in favor of using “*I*” and the third one is in favor of “*You*”. Because each property has the same weight, the robot will choose to use “*I*”. With a bigger weight to the simplest properties, and for the exact known situation, we

could solve this kind of situation and recreate the ambiguity seen in children as shown by Gold and Scassellati [8].

The fourth limitation is the fact that the robot cannot generalize to an unknown name. Indeed, if one hears a sentence of the type: “Mark put something somewhere”, we know that *Mark* will be the agent of the action. We do so, because we know that *Mark* is not another unknown pronoun until now, but is a name. The robot does not know if what he hears is a name or a pronoun. The first time he hears *Mark*, he could try to analyze it as he would do for “*You*”. This is another limitation also experienced, until we reach the knowledge of all existing pronouns, and we categorize every other subject as a name, especially if we know that the word is a name.

With this system as a proof of concept, we can now in the future generalize the learning of the nomination of any agent according to the context. The future step in our work will lead to the good use or the good understanding of the appropriate word for a more complex interaction. For example, a child will address to his father with the word “*dad*”, while a friend will call him by his name. With this concept we will now be able to extract more advanced relationship between people, and also we will be able to use this knowledge for a better interaction. However, the first step that we showed in this study, is needed in order to develop more complex reasoning and knowledge.

## VI. CONCLUSION

We provide here a simple system to learn correctly different personal or impersonal pronouns, through fast mapping. A small amount of data is required in the memory to have the expected result and a good comprehension of different pronouns. Indeed 18 sentences are enough. This system is easily embodied and allows the robot to be more efficient in the case of a complex interaction (several agents present). We can free ourselves from the classical HRI with one robot, one human, to go to more realistic interaction, and a better understanding of the robot of the world in front of him. Even if the system is not yet totally accomplished, this first version is a good step forward for the robot in term of understanding other, and situating himself in a complex world made of several agents.

## ACKNOWLEDGMENT

This work was supported by WISIWYD (FP7-ICT-612139) and the ANR SWoOZ (PDOC01901) projects

## REFERENCES

- [1] D. K. Roy and A. P. Pentland, “Learning words from sights and sounds: a computational model,” *Cogn. Sci.*, vol. 26, no. 1, pp. 113–146, Jan. 2002.
- [2] L. Steels and F. Kaplan, “AIBO’s first words: The social learning of language and meaning,” *Evol. Commun.*, vol. 4, no. 1, pp. 3–32, 2001.
- [3] X. Hinaut, M. Petit, G. Pointeau, and P. F. Dominey, “Exploring the Acquisition and Production of Grammatical Constructions Through Human-Robot Interaction,” *Front. Neurobot.*, pp. 1–34.
- [4] P. Dominey and J. Boucher, “Learning to talk about events from narrated video in a construction grammar framework,” *Artif. Intell.*, vol. 167, no. 1–2, pp. 31–61, Sep. 2005.
- [5] K. Gold and B. Scassellati, “Grounded pronoun learning and pronoun reversal,” in *Proceedings of the 5th International Conference on Development and Learning.*, 2006.
- [6] Y. Oshima-Takane, “The learning of first and second person pronouns in English: network models and analysis,” *J. Child Dev.*, vol. 26, pp. 545–575, 1999.
- [7] T. Shultz, D. Buckingham, and Y. Oshima-Takane, *A Connectionist Model of the Learning of Personal Pronouns in English*. 1994.
- [8] K. Gold and B. Scassellati, “Using context and sensory data to learn first and second person pronouns,” in *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction*, 2006, pp. 110–117.
- [9] K. Gold, M. Doniec, and B. Scassellati, “Learning grounded semantics with word trees: Prepositions and pronouns,” *2007 IEEE 6th Int. Conf. Dev. Learn.*, pp. 25–30, Jul. 2007.
- [10] K. Gold and B. Scassellati, “Learning acceptable windows of contingency,” *Conn. Sci.*, vol. 18, no. 2, pp. 217–228, Jun. 2006.
- [11] A. Imbens-bailey and A. Pan, “The Pragmatics of Self- and Other-Reference in,” 1998.
- [12] V. Corkum and C. Moore, “The origins of joint visual attention in infants,” *Dev. Psychol.*, vol. 34, no. 1, pp. 28–38, Jan. 1998.
- [13] M. Tomasello, *The cultural origins of human cognition*. 2009.
- [14] G. Sandini, G. Metta, and D. Vernon, “The iCub Cognitive Humanoid Robot : An Open-System Research Platform for Enactive Cognition Enactive Cognition : Why Create a Cognitive Humanoid,” *50 years Artif. Intell.*, pp. 359–370, 2007.
- [15] G. Geiger, N. Alber, S. Jordà, and M. Alonso, “The reactable: A collaborative musical instrument for playing and understanding music,” *Her&Mus. Herit. ...*, vol. 4, pp. 36–43, 2010.
- [16] G. Pointeau, M. Petit, and P. Dominey, “Embodied simulation based on autobiographical memory,” in *Living Machines*, 2013, pp. 240–250.
- [17] G. Pointeau, M. Petit, and P. Dominey, “Successive Developmental Levels of Autobiographical Memory for Learning Through Social Interaction,” *IEEE Trans. Auton. Ment. Dev.*, vol. 0, p. in Press, 2014.
- [18] G. Fanelli, T. Weise, J. Gall, and L. Van Gool, “Real time head pose estimation from consumer depth cameras,” *Pattern Recognit.*, 2011.
- [19] K. Gold and B. Scassellati, “Using probabilistic reasoning over time to self-recognize,” *Rob. Auton. Syst.*, vol. 57, no. 4, pp. 384–392, Apr. 2009.

### 9.3.6 **Frontiers : Exploring the Acquisition and Production of Grammatical Construction Through Human-Robot Interaction**

Authors : **Hinaut, X.**, Petit, M., Poiteau, G., and Dominey, P.F.

Title : "Exploring the acquisition and production of grammatical constructions through human-robot interaction with echo state networks."

Journal : Frontiers in neurorobotics, 8.

Year : 2014

# Exploring the Acquisition and Production of Grammatical Constructions Through Human-Robot Interaction

*Xavier Hinaut<sup>1,2</sup>, Maxime Petit<sup>1,2</sup>, Gregoire Pointeau<sup>1,2</sup>, Peter F. Dominey<sup>1,2,3</sup>*

<sup>1</sup> Stem cell and Brain Research Institute, INSERM U846, 18 Avenue Doyen Lepine, 69500 Bron, France

<sup>2</sup> Université de Lyon, Université Lyon I, 69003, Lyon, France

<sup>3</sup> CNRS, France

(xavier.hinaut ; maxime.petit ; gregoire.pointeau ; peter.dominey)[@inserm.fr](mailto:)

## Abstract

One of the principal functions of human language is to allow people to coordinate joint action. This includes the description of events, requests for action, and their organization in time. A crucial component of language acquisition is learning the grammatical structures that allow the expression of such complex meaning related to physical events. The current research investigates the learning of grammatical constructions and their temporal organization in the context of human-robot physical interaction with the embodied sensorimotor humanoid platform, the iCub. We demonstrate three noteworthy phenomena. First, we demonstrate that a recurrent network model can be used in conjunction with this robotic platform to learn the mappings between grammatical forms and predicate-argument representations of meanings related to events, and the robot's execution of these events in time. Second, we demonstrate that this learning mechanism can function in the inverse sense, i.e. in a language production mode, where rather than executing commanded actions, the robot will describe the results of human generated actions. Finally, we collect data from naïve subjects who interact with the robot via spoken language, and demonstrate significant learning and generalization results. This allows us to conclude that such a neural language learning system not only helps to characterize and understand some aspects of human language acquisition, but also that it can be useful in adaptive human-robot interaction.

## 1. Introduction

### 1.1 Issues in language acquisition

The ability to learn any human language is a marvelous demonstration of adaptation. The question remains, what are the underlying mechanisms, and how do humans make the link between the form of a sentence and its meaning? Enormous debate has ensued over this question. The debate can be characterized with one end of the continuum, Piaget's constructivism, holding that language can be learned with general associative mechanisms,

and the other end, Chomsky's innatism, holding that the stimulus is so poor, that language could only be learned via a highly specialized universal grammar system (Piattelli-Palmarini, 1980). We and others have argued that linguistic environment is rich – in response to the “Poverty of stimulus hypothesis” (reviewed in (Peter F. Dominey & Dodane, 2004)). As the child is situated in the environment, it has access to massive non-linguistic information that can aid in constraining the possible meanings of phonemes, words or sentences that it hears (Peter F. Dominey & Dodane, 2004). In this context, social interaction is clearly an important factor that helps the child to acquire language, by focusing its attention on the same object or event as the person he is interacting with via joint attention. Joint attention permits one to considerably reduce the possible mappings between what is said and what is happening in the environment. Joint attention happens sufficiently often to assume it as one of the reliable ways to help the child to acquire language: for instance when playing a game, showing an object, ritualized situations including bathing and feeding, etc. (Carpenter, Nagell, & Tomasello, 1998; Peter F. Dominey & Dodane, 2004; Knoblich & Sebanz, 2008; Ricciardelli, Bricolo, Aglioti, & Chelazzi, 2002; Sebanz, Bekkering, & Knoblich, 2006; Tomasello, 2003; Tomasello & Hamann, 2012).

Despite the potential aid of joint attention, mapping the surface form onto the meaning (or deep structure) of a sentence is not an easy task. In a first step in this direction, Siskind demonstrated that simply mapping all input words to all possible referents allows a first level of word meaning to emerge via cross-situational statistics (Siskind, 1996). However, simply associating words to specific actions or objects is not sufficient to take into account the argument structure of sentences in language. For instance given these two sentences “Mary hit John.” and “John was hit by Mary.” which have the same meaning but with a different focus or point of view, how could a purely word-based system extract the exact meaning of the sentence? How could an infant determine who is doing the action (the *agent*) and who endures the action (the *object*)? As simple this example is, relying only on the semantic words, and their order in the sentence, will not permit to reliably distinguish the *agent* from the *object*.

To begin to answer this question, we consider the notion of grammatical construction as the mapping between a sentence's form and its meaning (A. Goldberg, 1995; A. E. Goldberg, 2003). Goldberg defines constructions as “stored pairings of form and function, including morphemes, words, idioms, partially lexically filled and fully general linguistic patterns” (A. E. Goldberg, 2003). Constructions are an intermediate level of meaning between the smaller constituents of a sentence (grammatical markers or words) and the full sentence itself.

Typical grammatical constructions could be used to achieve thematic role assignment, that is answering the question “Who did what to whom”. This corresponds to filling in the different slots, the roles, of a basic event structure that could be expressed in a predicate form like *predicate(agent, direct object, indirect object or recipient)*. A simplified summary of characterization of grammatical constructions can be seen in Figure 1.

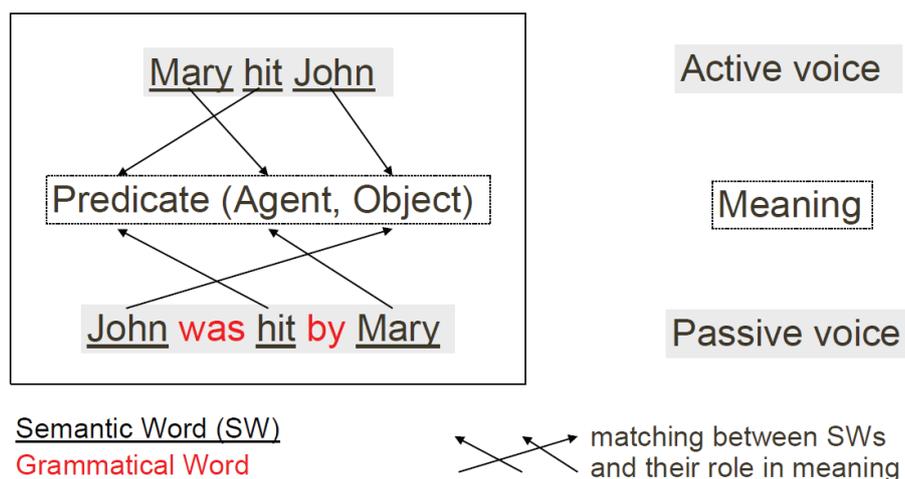


Figure 1: Schematic characterization of the thematic role assignment task. Solving this task consists in finding the adequate mapping between the content words (i.e. semantic words) and their roles in the meaning of a given sentence. This mapping is represented by the set of arrows (here three) for each sentence surface-meaning mapping.

Solving the thematic role assignment problem consists in finding the correct role for each semantic word (i.e. content word or open class word). It thus consists in finding the *predicate*, the *agent*, the *object*, and the *recipient* for a given action. In the preceding example this means that *hit* is the predicate, *Mary* is the agent and *John* is the object. How could one use grammatical constructions to solve this thematic role task for different surface forms as illustrated in Figure 1? According to the cue competition hypothesis of Bates and MacWhinney (E Bates & MacWhinney, 1987; E. Bates, McNew, MacWhinney, Devescovi, & Smith, 1982) the identification of distinct grammatical structures is based on combinations of cues including grammatical words (i.e. function words), grammatical morphemes, word order and prosody. Thus the mapping between a given sentence and its meaning could rely on the ordered pattern of words, and particularly on the pattern of function words and markers (P. F. Dominey, 2003; P. F. Dominey, Hoen, Blanc, & Lelekov-Boissard, 2003). As we will see in the Material and Method section, this is ~~the~~ assumption we make in the model in order

to resolve the thematic role assignment task, that is, binding the sentence surface to its meaning. In English, function words include “the”, “by”, “to” ; grammatical markers include verb inflexions “-ing”, “-ed” or “-s”. One interesting aspect of grammatical words and markers is that there are relatively few of them, compared to the potentially infinite number of content words (i.e. semantic words). Hence the terms “closed class” for grammatical words and “open class” for semantic words. As these closed class words are not numerous and are often used in language, it could be hypothesized that children would learn to recognize them very quickly only based on statistical speech processing. This argument is reinforced by the fact that such words or markers are generally shorter (in number of phonemes) than content words. This notion of prosodic bootstrapping (Morgan & Demuth, 1996) is reviewed and modeled in Blanc et al. 2003 (Blanc, Dodane, & Dominey, 2003).

### 1.1 Overview of the tasks

In this study we investigate how a humanoid robot can learn grammatical constructions by interacting with humans, with only a small prior knowledge of the language. This includes having a basic joint attention mechanism that allows the robot to know for instance what is the object of focus: this particular example will serve in the “scene description” task. We approach our simplified study of language acquisition via two conditions: language comprehension and language production. Both conditions will have two modes: a training mode, when the human acts as a kind of teacher, and a testing mode, where the human could test the language capabilities of the robot as in child-caregiver interactions. The experimental tasks will test the ability of our neural network model of language acquisition to understand and to produce meaningful language.

We have shown in previous studies that the neural model used (1) can learn grammatical constructions correctly generated with a context-free grammar (with one main and one relative clause), (2) can show interesting performance in generalizing to not learned constructions, (3) can show predictive activity during the parsing of a sentence and in some cases give the final correct parse before the sentence ended, and (4) that the neural activity may be related to neurophysiological human recording (Xavier Hinaut & Dominey, 2012; X. Hinaut & Dominey, 2013). We believe that these results demonstrate that the model may be suitable to a developmental robotic approach, extending our previous work in this domain (P. Dominey & Boucher, 2005a, 2005b).

Here we have four goals: (1) to determine if it is possible to use the model in an interactive fashion with humans, that is, to integrate this neural model in the robotic architecture and make it communicate and work in real-time with the other components of the architecture (speech recognition tool, etc.); (2) test the model in a productive manner, that is instead of “understanding” a sentence, it will be able to produce one, that is, to produce the sequence of words of the grammatical structure given the thematic roles and the sentence type (canonical or non-canonical); this has not been done in our previous experiments with the neural model; (3) in the comprehension task, test if the neural model can learn constructions that allow for commands that manipulate the temporal structure of multiple events. For instance to correctly respond to the sentence “before you put the guitar on the left put the trumpet on the right”. Finally, (4) we test the model with language input from naïve subjects, in order to determine if indeed this adaptive approach is potentially feasible in less structured environments.

In the Material and Methods section we will first briefly present the robotic platform and the interaction environment. We will then describe the two neural models used for the comprehension and production tasks. Finally, the integration of these components will be presented. In the Experiment section we will describe the experimental procedures for the *scene describer* task, and the *action performer* task. In Results section we will illustrate the functioning of the system in these two modalities, including figures illustrating the human-robot interactions, and figures illustrating typical neural activation recorded for both models. We then present the data and learning and generalization results for an extended experiment with 5 naïve subjects. In the last section, we will discuss the results and interesting aspects that the combination of a comprehension and production neural models provide. Training and testing data used in the experiments, and corresponding to the figures showing the output neural activity of the models are provided in Appendices section.

## 2. Material and Methods

### 2.1 iCub platform and interaction architecture

The platform that we used is the iCub, furnished by the FP6 EU consortium RobotCub (see Figure 2). The iCub (G. Metta et al., 2010) is a 53 DOF humanoid robot build by the Italian Institute of Technology (IIT) with the size of a three and a half year-old child. We use YARP (Giorgio Metta, Fitzpatrick, & Natale, 2006) as the robotic middleware with the Biomimetic Architecture for Situated Social Intelligence Systems (BASSIS architecture) built for the FP7 Experimental and Functional Android Assistant project (Petit et al., 2013).

The Supervisor module is implemented with the CSLU Toolkit (Sutton et al., 1998) Rapid Application Development for spoken language interaction. It uses the Festival system for speech synthesis (Taylor, Black, & Caley, 1998) and Sphinx II for spoken language recognition (Huang et al., 1993). The Supervisor provides a dialog management capability built as a finite-state system. This capability allows the user to guide the robot into the different states of behavior, but is distinct from the neural language model, described below. The Supervisor/Manager orchestrates the communication and exchange of data between speech recognition and synthesis, the neural models for language comprehension and generation, and the robot perception and action systems.

The ability of the iCub to perceive physical objects and their manipulation in the context of action performance and description is provided by the ReacTable, which detects objects on a translucent table based on detection of fiducial markers on the object bases, using an infrared camera (Bencina, Kaltenbrunner, & Jorda, 2005). The ReacTable thus provides data on the type and position of objects on the table with high precision. The ReacTable is calibrated into the motor space of the iCub, so that object locations can be used for physical interaction.

The motor control for iCub reaching, grasping and object manipulation is provided by DForC – Dynamic Force Field Controller – (Gori, Pattacini, Nori, Metta, & Sandini, 2012), based upon dynamic force control. The robot has a small set of primitive actions: put(object, location), grasp(object), point(object).

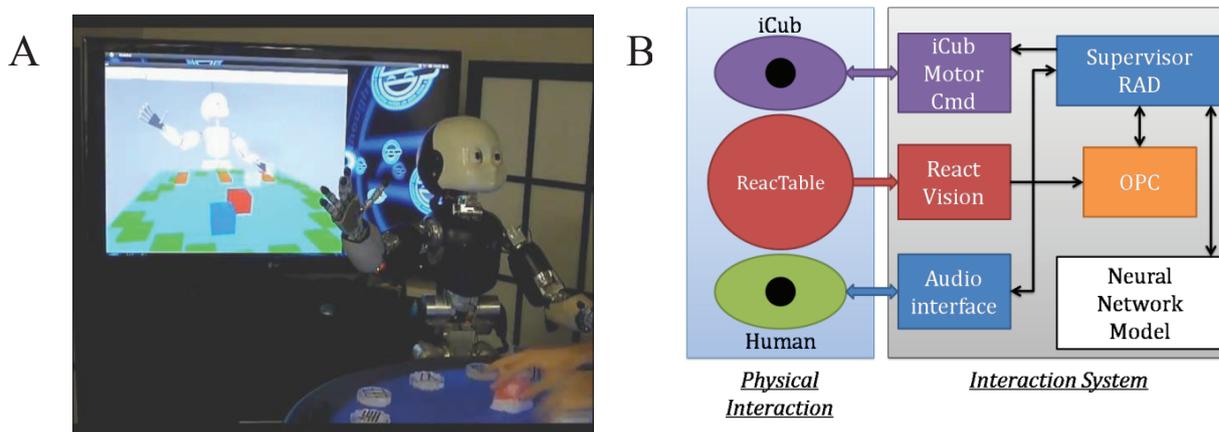


Figure 2: Robotic Platform. (A) iCub humanoid robot with the ReacTable. (B) System architecture overview. The Supervisor coordinates all interactions between the human and the different components of the system. When the human moves an object on the ReacTable, the coordinates are transformed into the robot space, and stored in the Object Properties Collector (OPC). For Action Performance when the human speaks, the words are recognized by the audio interface, then they are packaged and sent to the Neural Network by the Supervisor. Resulting commands from the Neural Network are processed and forwarded to the iCub Motor Cmd interface by

the Supervisor for execution on the robot. For Scene Description, the spatial relations between objects are taken from the OPC through the Supervisor and sent to the Neural Network together with the sentence type (canonical or non-canonical). The sentence generated by the Neural Network is sent to the Audio interface for speech synthesis, again under the control of the Supervisor.

## 2.2 Neural language model

The neural language processing model represents the continued development of our work based on the underlying concept of a recurrent network with modifiable readout connections for grammatical construction processing (P. F. Dominey, 2003; P. F. Dominey et al., 2003; Xavier Hinaut & Dominey, 2012; X. Hinaut & Dominey, 2013). As described in the context of grammatical constructions above, for sentence processing we have shown that the pattern of open and closed class word order could be used to correctly identify distinct grammatical constructions and extract their meaning for a small set of sentences. More recently we have demonstrated the extension of this ability to larger corpora from several hundreds of uniquely defined construction-meaning pairs, to tens of thousands distinct constructions including redundant and ambiguous meanings (X. Hinaut & Dominey, 2013).

The core of the language model is a recurrent neural network, with fixed random connections, which encodes the spatio-temporal context of input sequences. This sequence-dependant activity then projects via modifiable connections to the read-out layer. Modification of these read-connections by learning allows the system to learn arbitrary functions based on the sequential input. This framework has been characterized as Reservoir Computing (Lukosevicius & Jaeger, 2009; Verstraeten, Schrauwen, D'Haene, & Stroobandt, 2007), where the recurrent network corresponds to the reservoir, and has been developed in different contexts. The first expression of the reservoir property with fixed recurrent connections and modifiable readout connections, was developed in the context of primate neurophysiology, with the prefrontal cortex as the reservoir, and modifiable cortico-striatal connections as the modifiable readout (P. F. Dominey, 1995; P.F. Dominey, Arbib, & Joseph, 1995). Further development was realized in related systems including the Liquid State Machine (Maass, Natschlag, & Markram, 2002), and Echo State Network (Herbert Jaeger, 2001; H. Jaeger & Haas, 2004).

The model employed in the current research (X. Hinaut & Dominey, 2013) pursues this parallel between brain anatomy and the reservoir computing framework. Prefrontal cortex is modeled as a fixed recurrent network and striatum as a separate population connected to

cortex via modifiable synapses, corresponding respectively to the reservoir and readout. The reservoir is composed of leaky neurons with sigmoid activation. The following equation describes the internal update of activity in the reservoir:

$$x(t+1) = (1-\alpha)x(t) + \alpha f(W_{res}x(t) + W_{in}u(t+1)) \quad (1)$$

where  $x(t)$  represents the reservoir state;  $u(t)$  denotes the input at time  $t$ ;  $\alpha$  is the leak rate; and  $f(\cdot)$  is the hyperbolic tangent (tanh) activation function.  $W_{in}$  is the connection weight matrix from inputs to the reservoir and  $W_{res}$  represents the recurrent connections between internal units of the reservoir. In the initial state, the activation of all internal units of the reservoir is zero. The inverse of the leak rate ( $1/\alpha$ ) could be interpreted as the time constant of the system.

By definition, the matrices  $W_{in}$  and  $W_{res}$  are fixed and randomly generated. Internal weights ( $W_{res}$ ) are drawn from a normal distribution with mean 0 and standard deviation 1 and then rescaled to the specified spectral radius (the largest absolute eigenvalue of a matrix – here  $W_{res}$  –; This will be referred to as the *spectral radius* parameter). The input weight matrix  $W_{in}$  was first generated with values drawn chosen randomly between -1 and 1 with a 50% probability. The  $W_{in}$  matrix was then rescaled depending on the experiment (*input scaling* parameter). The density of the input connections is 100%.

The output vector of the system which models the striatum is called the readout. Its activity is expressed by the following equation:

$$y(t) = W_{out}x(t) \quad (2)$$

with  $W_{out}$  the matrix of weights from the reservoir to the readout (output). The activation function of readout units is linear: interestingly readout activity gives a pseudo-probabilistic response for each output unit. To train the read-out layer (i.e. compute  $W_{out}$ ), we use a linear regression with bias and pseudo-inverse method (Herbert Jaeger, 2001). This general model is applied in two distinct model instantiations. One model processes commands (sentences) and generates a predicate-argument representation of the meaning. The second describes observed actions, i.e. given a predicate-argument meaning as input, it generates a sentence describing that meaning. Thus, the comprehension system learns to map semantic words of input sentences onto an output that characterizes the role (action, agent, object, recipient) of each of these semantic words, based on the structure of grammatical words in the

sentence. The production system learns the inverse mapping, from the meaning (i.e. specification of the role of each semantic word) onto a sentence form.

### 2.2.1 Comprehension model for Action Performing task

The architecture of the comprehension model is illustrated in Figure 3.

**Preprocessing:** Before being provided as input to the neural model, the sentence must be transformed by extracting the open-class (i.e. semantic) words. The resulting grammatical form is characterized by the sequential pattern of closed-class (i.e. grammatical) words. This operation is performed by replacing all open class words by 'SW' markers (SW: semantic words). The semantic words removed from the sentence are stored in a working memory. The working memory acts as a first-in-first-out (FIFO) stack: the words will be retrieved in the same order in the output. For example, when semantic word 2 (SW2) is determined by the model to be the agent, the actual word corresponding to SW2 will be retrieved as the agent of the described action. The closed class words used were: 'after', 'and', 'before', 'it', 'on', 'the', 'then', 'you'.

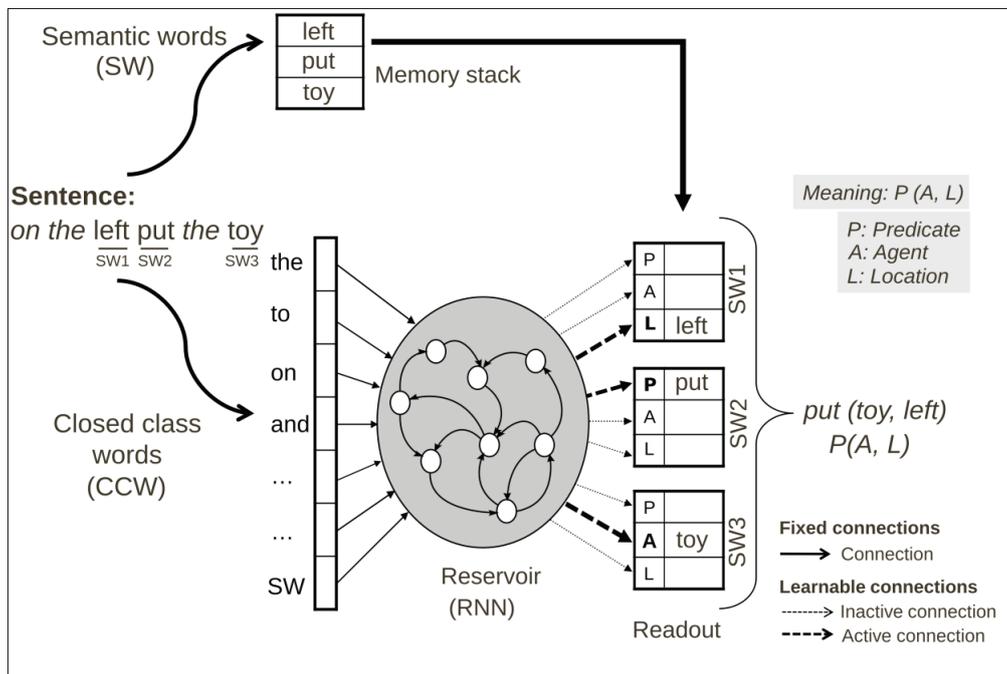


Figure 3: Neural comprehension model for the Action Performing task. Sentences spoken by the user are first transformed into grammatical forms, i.e. all semantic words (SW) are replaced by a *SW* marker. The reservoir is given the grammatical form word by word. Each word activates a different input unit. Based on training, the readout connections from the reservoir provide the coding of the meaning in the readout neurons, thus forming the grammatical construction as a mapping from grammatical form to meaning.

Reservoir parameters: The number of unit used in the reservoir is 100. The leak rate used is  $1/6$  ( $=0.1666\dots$ ). The *input scaling* was set to 0.75. The *spectral radius* is set to 1.

Sentence input parameters: Given an input sentence, the model should assign appropriate thematic roles to each semantic word. The presentation of inputs is illustrated in Figure 3. Sentences are represented in the input as grammatical forms, where specific instances of noun and verb words (semantic words – SW) are replaced by a 'SW' marker. Thus, a given grammatical construction can code for multiple sentences, simply by filling in the 'SW' markers with specific words. In this way of coding, the reservoir cannot distinguish between nouns or verbs, they have the same input neuron. This is an interesting characteristic when using the model within a robotic platform, because when a sentences are processed there is no need to do a preprocessing in order to classify words as nouns or verbs.

The total number of input dimension is 9; 8 for closed class words, 1 for the semantic word marker. Each word is coded as a square wave of 1 time step. There is no pause between successive word presentations (the use of pauses does not have significant influence on the results), but there is a final pause at the end of the sentence in order to inform the model that the sentence is finished; This final pause could be replaced by a dot, it would have the same function. An offset of the sentence was added at the beginning of the inputs if they were not of maximal length, in this way the correct final meaning is always given at the last time step.

Desired meaning output coding: Making the analogy with an infant who is learning language, we consider that the system is exposed to a meaningful scene while the input sentence is being presented. Thus, the system has access to the meaning starting at the beginning of the presentation of the sentence, and the desired output teacher signal is provided from the beginning of the first word until the end of the input. All the output neurons that are part of the meaning are clamped at 1, all other output neurons are clamped to 0. By forcing the outputs on from the onset of the sentence, we obtain predictive activation when processing (i.e. testing) a sentence after the learning phase. This can be seen in the results section in Figure 8, below (see (X. Hinaut & Dominey, 2011, 2013) for more details). The output dimension is 36 ( $=6*3*2$ ): 6 semantic words that each could have 3 possible thematic role assignment (predicate, agent or location), and each could have a role with at maximum 2 verbs.

Post processing: The activity of the output at the last time step is thresholded. For each SW, we take the role that has the maximum activation (if there are several). Each semantic word in the FIFO stack is then bound with its corresponding role(s). The full predicative

meaning is then obtained and written in the output data file in order to be processed by the Supervisor module, and then used to command the robot.

### 2.2.2 Production model for Scene Description task

We have described the functioning of the language model that learns to map input sentences onto a predicate-argument representation of their meaning. Now we consider the reverse case, where given a meaning, the model should produce a sentence. This model thus employs the same principals as the language comprehension model, but we now perform the reverse operation - from a meaning we want to generate the corresponding sentence (see Figure 4). It is important to recall that there are potentially multiple possible sentences for describing a given scene or meaning (as illustrated in Figure 1). To resolve this ambiguity, we provide additional input to the model, to indicate if we want a canonical (e.g. standard, active voice) or a non-canonical (e.g. passive voice).

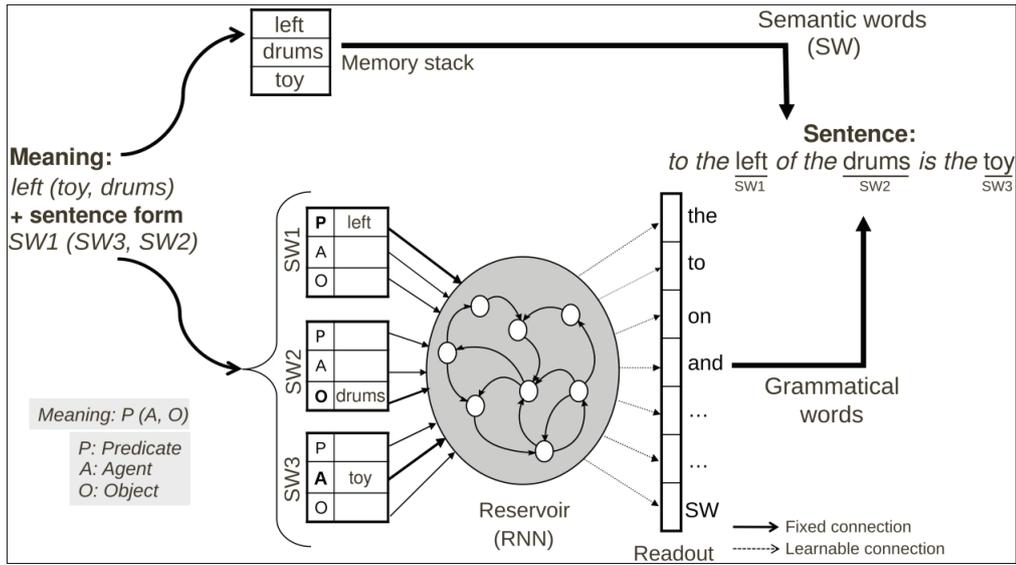


Figure 4: Neural production model for Scene Description task. The input has 2 components: (1) meaning format {Predicate(Agent, Object) - left(toy, drums)} corresponding to relation *toy to the left of drums*, and (2) construction format with {SW1 – Predicate, SW2 – Object, SW3 - Agent} which could be written in a compact way as SW1(SW3, SW2). The full input information could be represented as {SW1\_Predicate – left}, {SW2\_Object – drums}, and {SW3\_Agent – toy}. The system must find a construction that allows this mapping of SWs to thematic roles. The meaning is expressed as a predicate-argument representation P(A, O), with P predicate, A agent and O object. SW#\_θ: Semantic Word # has thematic role θ, with # the relative position in the sentence among all Semantic Words.

Preprocessing: The model is given the meaning and the sentence type desired (canonical or non-canonical) by the manager program. This information is converted in the corresponding coded meaning. The semantic words of the meaning are stored in the FIFO memory.

Reservoir parameters: The number of unit used in the reservoir is 500. The leak rate used was 0.75. The *input scaling* was set to 0.01. The *spectral radius* was set to 2.

Input and output coding: The coded meaning was given, for all the input units concerned, as a constant input activation set to 1. Remaining input units were set to 0. This is consistent with the output representation of the meaning in the first model presented in 2.2.1 (comprehension model). As illustrated in Figure 4 the desired mapping of the open class words onto thematic roles is specified by activating the appropriate input neurons. The input activation lasted during all the input presentation. The input dimension is the same as the output dimension of the comprehension model  $6 \times 3 \times 2 = 36$ : 6 semantic words that each could have 3 possible thematic role assignment (predicate, agent or object), and each could have a role with at maximum 2 verbs. Table 1 illustrates how different coded-meanings can be specified for the same input meanings. This allows us to specify in the input if the sentence should be of a canonical or non-canonical form.

	<b>Meaning</b>	<b>Sentence</b>	<b>Coded-meaning</b>
<b>Canonical</b>	left(toy, drum)	The toy is left of the drums	SW2(SW1, SW3)
<b>Non-Canonical</b>	left(toy, drum)	To the left of the drums is the toy	SW1(SW3, SW2)
<b>Double Canonical</b>	left(violin, trumpet); right(violin, trumpet)	The violin is to the left of the trumpet and to the right of the guitar	SW2(SW1,SW3); SW4(SW1, SW5)
<b>Double Non-Canonical</b>	right(violin, trumpet); left (violin, guitar)	To the right of the trumpet and to the left of the guitar is the violin	SW1(SW5,SW2); SW3(SW5, SW4)

Table 1. Representation and form of canonical and non-canonical sentences. Both examples have the same meaning. The sentences are different, and the mapping of semantic words onto the thematic roles in the meaning is different, as specified in the coded-meaning or sentence form. Both *Meaning* and *Coded-meaning* use the convention Predicate(Agent, Object). SW#: Semantic Word #, with # the relative position in the sentence among all Semantic Words.

Activation of the output units corresponds to the successive words in the retrieved construction. The closed class words used were: 'and', 'is', 'of', 'the', 'to', '.' (dot). The dot is optional and was not used for the experiments shown in Figure 9; it could be used in the future if several sentences has to be produced. The total number of output dimension is 7: 6 for closed class words and one for the SW marker.

The output teacher signal is as the following: each word is coded as a square wave of 5 time steps. Each word was separated with a pause of 5 time step. We used 5 time steps for each word and a pause of same duration between them in order to have an output activity that last a sufficiently long time; in this way each word could be detected more easily in the post-processing process. There is a final pause at the end of the teacher signal. All the teacher signals were of maximal length corresponding to the longest sentence.

Post processing: Once again, the output activity is first thresholded. Then each time an output exceeds the threshold, the corresponding word is added to the final construction (if the activity of this word last 4 or 5 time steps above the word it is considered only once). If several outputs are above the threshold, the word of maximal value is kept. Finally, the sentence is reconstructed replacing the SW makers with the semantic words kept in memory.

### 2.3 Integrated System

The system operates in real-time in a human-robot interaction. Figure 5 shows how the communication between modules is performed. Again, the system can operate in “action performer” (AP) and in “scene description” (SD) tasks, and the Supervisor module allows the user to specify which of these tasks will be used. The Supervisor interacts with the human through spoken language to determine if he wants to run the system in train mode – to teach the robot new <meaning, sentence> pairings – or in test mode – to use the corpus of pairings already learned by the robot –. Thus there is two tasks (AP or SD), each of which could be run in two execution modes (train or test). Details for AP and SD tasks are provided in the next section. Now we briefly describe train and test modes.

In train mode, the Supervisor generates incrementally one of the two training data files depending on the task (AP or SD). The human speech is transformed into text via the speech-to-text tool, and the meaning is given by the robotic platform: the <meaning, sentence> pairing is then written in the training data text file. In order to not populate the training files with bad examples in case of incorrect speech recognition, before writing the file the robot

ask the user for a checking (e.g. if it understood well the meaning). If the user wants the example to be added to the data file he answers “yes”, otherwise he answers “no”.

In test mode, the Supervisor processes the test example given by the user: in AP task the example is a sentence; in the SD task the example is a meaning (i.e. the user places objects in particular positions relative to the object of focus). This test example is a half-pairing of a complete sentence-meaning pair. First, the Supervisor generates a file containing the previously established training data, and the test example. It then launch the corresponding neural model (comprehension or production) depending on the task (respectively AP or SD). The neural model is trained with the training data, and then it processes the test half-pairing and generates the “missing half” in a text file. The Supervisor processes the file given by the neural model and executes the action in the AP task or produces the sentence in the SD task.

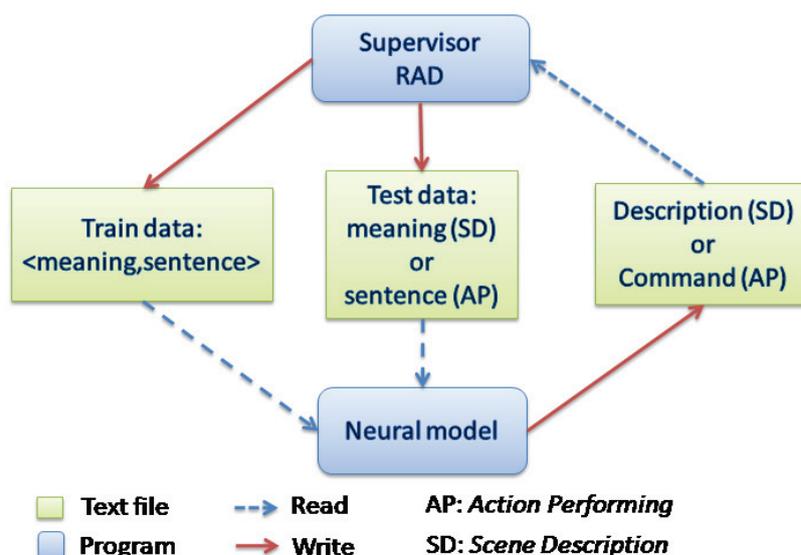


Figure 5: Communication between modules. The Supervisor manages the spoken interaction with the user and controls the robotic platform, providing different behaviors in SD and AP tasks. Depending on the mode selected by the user, train or test, it launches the neural model or not. In the train mode, pairs of <meaning, sentence> are stored in the train data file. In test mode, the sentence to be tested is written in the test data file, and both train and test files are sent as once to the Neural model. See Figure 2 for complementary information.

### 3. Experiments

We now illustrate in detail how the system works in two distinct modes: training and testing for the AP and SD tasks. An overview is provided in Table 1. In both tasks,

meanings are expressed in a predicate-argument form: for instance *put(toy, left)* (for Action Performing task; see Figure 3), or *left(toy, drums)* (for the Scene Description task; see Figure 4). During training, meaning is produced by transforming the events and relative position of objects into the respective action and scene meanings. This is achieved by analyzing the change in object positions on the ReacTable (in order to get scene meanings) and by interrogating the program generating random robot action (for action meanings). Spoken sentences are transformed from a speech record into a list of words (using the Sphinx II recognizer) and paired with the associated meaning to populate the training database. The training mode is responsible for building a corpus of <sentence, meaning> pairs which will be fed to the neural model in order to train it. The human is then invited to build the database by interacting with the robotic platform. The type of interaction is different according to the task, AP or SD, as indicated in Table 2. In testing mode, the human provides one component of a <sentence, meaning> pair, and gets the missing component of the pair in return.

	<b>Action Performer (AP)</b>	<b>Scene Descriptor (SD)</b>
<b>Training</b>	1. Robot generates random action(s) [meaning] 2. Human says a corresponding command [sentence]	1. Human arranges objects on the table [meaning] 2. Human describes the scene [sentence]
<b>Testing</b>	1. Human says a command [sentence] 2. Robot performs corresponding action(s) [meaning]	1. Human arranges objects on the table [meaning] 2. Robot describes the scene [sentence]

Table 2. Summary of events in Training and Testing modes for the Action Performer (AP) and Scene Descriptor (SD) tasks. In brackets is indicated the half-pairing generated corresponding to each event.

### 3.1 Experiment Scenario 1: Action Performing task

In the following X, Y and Z are arbitrary objects (e.g. guitar, trumpet, violin), and, L and R are different locations (e.g. left, right, middle). In the training mode, one or two random action(s) are generated by the iCub using available objects (e.g. <put X on the R>, <grasp Y,

point  $Z$ >, ...). This produces the *meaning*. At the same time, the human user observes and then says the order (i.e. command) which, according to him, should command the robot to perform the(se) action(s): this corresponds to the *sentence*. The <*sentence*, *meaning*> pair can thus be constructed. The robot continues to randomly select possible actions and execute them, and the user provides the corresponding command, thus populating the database with <sentence, meaning> pairs.

In testing mode, the system uses the data generated in the learning mode in order to fully interact with the human, whereas in the training mode the system is more passive. In the Action Performing task the human says a command to the robot (providing the *sentence*). This test sample is passed to the neural model (Figure 3). The neural model produces the corresponding *meaning*, which is sent back to the Supervisor which translates the meaning into the corresponding robot command(s). The robot then produces the desired action(s).

### 3.2 Experiment Scenario 2: Scene Description task

During the training phase for Scene Description task the user puts several objects on the table and specifies the focus object. Then he describes orally one or two spatial relations relative to the focus object (e.g. <the X is to the L of Y and to the R of Z>, ...), providing the *sentence*. The robot then uses the coordinates of the objects and the knowledge of the focus objects to find the relationships between the focus element and the other element(s) on the table, providing the *meaning*.

During the testing phase for the Scene Description task the user puts some objects on the table in a particular spatial relation, producing the *meaning*. This test example is passed to the neural model. The latter produces the corresponding *sentence* that is sent back to the Supervisor which produces the sentence via the audio interface (text-to-speech tool).

For both tasks during testing phase the data file that is transmitted to the neural model contains both the testing data and the training data. This permits to avoid executing the neural model each time one example is learned. Thus the model learns the whole data set and then applies this to the test data (on which it is not trained).

### 3.3 Experiment Scenario 3: Naïve Subject Action Performer task

In order to test the robustness of the system, we tested learning and generalization with data produced by 5 naïve subjects. In order to standardize the experiment we made a movie of a human performing a set of behaviors: 5 single actions and 33 double actions. For instance {point(guitar)} is an example of a single action: a corresponding sentence could be “Point to the guitar”; And {point(guitar), put(toy, left)} is an example of a double action: a corresponding sentence could be “Point to the guitar then put the toy on the left”. For each behavior (i.e. one scene of the movie), we asked the subjects to give a “simple” command, and then a more “elaborate” one corresponding to the observed action(s). The subjects looked at the same scene twice, once before giving a “simple” command (i.e. order), and once before giving an “elaborate” one. Subjects saw movies twice in order to obtain more spontaneous responses from them, instead of having to try to remember the movie scene and try to formulate the simple and elaborate commands in a row. This resulted in a corpus of 5 (subjects) x 38 (behaviors) x 2 (canonical and non-canonical) = 380 sentences. The <sentence, meaning> corpus was obtained by joining corresponding meanings to these sentences. First in order to assess the learnability of the whole corpus, where the training and testing data sets were the same. Then generalization capability was tested using “leaving one out” method (i.e. cross validation with as many folds as data examples): for each <sentence, meaning> pair, the model was trained on the rest of the corpus, and then tested on the removed <sentence, meaning> pair.

## 4. Results

### 4.1 Human robot interaction

The iCub robot learns in real-time from human demonstration. This allows the robot to (1) perform complex actions requested by the user, and (2) describe complex scenes. Here “complex” means multiple actions with temporal (chronological) relations. The system can for instance execute commands like: “Before you put the guitar on the left put the trumpet on the right.” We demonstrate how this form of temporally structured language can be learned and used in the context of human-robot cooperation.

In Figures 6 and 7, we can see images extracted during human-robot interactions for the two tasks. In Figure 6, the robot is performing the motor commands corresponding to the sentence “Point the guitar before you put on the left the violin.” (A) the robot is pointing the “guitar” (blue object), (B) the robot is finishing the displacement of the “violin” (red object). In Figure 7, the robot has to describe the scene relative to the object of focus: (A) the user sets the

object of focus in the scene, where other objects are already present; (B) the robot is describing the position of the focus object relative to the other objects.

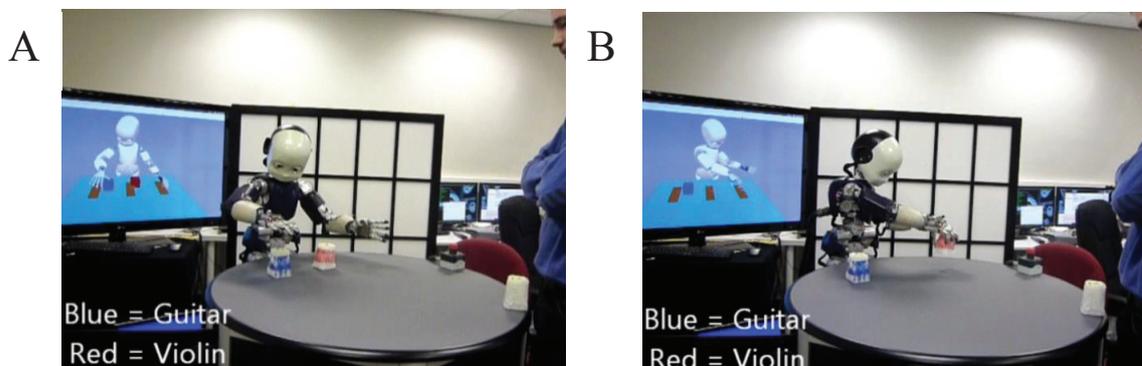


Figure 6. Action Performing task. The robot is performing the motor commands corresponding to the sentence “Point the guitar before you put on the left the violin.”: (A) the robot is pointing “guitar” (blue object), (B) the robot is finishing the displacement of the “violin” (red object).

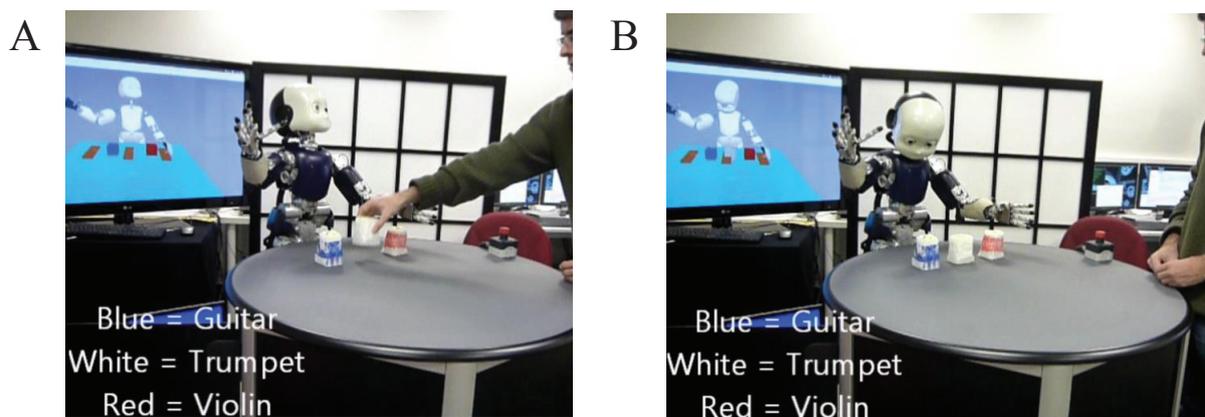


Figure 7: “Scene Description” condition. The robot have to describe the scene relative to the object of focus: (A) the user sets the object of focus in the scene, where other objects are already present; (B) the robot is describing the position of the focus object relative to the other objects.

In the following subsections we describe events and human-robot interactions during testing mode. They correspond to the transcript of parts of the videos for the Action Performer and Scene Descriptor tasks: movies are available in the supplementary materials.

#### 4.2 Trials for Execution of Action Performing task

For illustrating the Action Performer task, we will use the same initial positions for the objects across trials, and vary the oral description made by the user. The initial positions of objects are the following: the guitar is on the right and the violin is on the left. Absolute and relative positions are defined relative to the user. For the first trial, the action the user asked the iCub to perform was *put (violin, left)*. The user told the robot the non-canonical sentence 1 in Table 2. The robot then put the violin on the left. For trials 2, 3 and 4, the desired first action was *point (guitar)* and the second action was *put (violin, left)*. The robot first pointed to the guitar and then put the violin on the left. In this way, we could test for different ways of saying the same meaning but with different grammatical forms of sentences (i.e. with different grammatical constructions). For each sentence spoken to the robot, we indicate in Table 2 for clarification the type of sentence (canonical or non-canonical word order) and the order of actions (chronological or non-chronological order of actions).

<b>Example</b>	<b>Sentence</b>	<b>Type</b>
1	on the left put the violin	non-canonical
2	after you point the guitar put the violin on the left	canonical, chronological
3	before you put the violin on the left point the guitar	canonical, non chronological
4	point the guitar before you put on the left the violin	canonical & non- canonical, chronological

Table 2. Example sentences used during testing mode of Action Performer task.

#### 4.3 Trials for Scene Description task

For the Scene Describer task, the user was first asked to set the initial position of the objects (this is indicated by “set objects”). Then the user was asked to identify the focus object (“focus”). The latter is what should be in focus in the sentence, i.e. the subject (i.e. the agent in this case) of the sentence. After that, the robot asked the user if it should produce a usual (i.e. canonical) or non-canonical sentence. Then the robot processed all the information and described the scene by producing a sentence (“robot sentence”).

Trial	Set objects	Focus	Sentence Type	Robot Sentence
1	guitar middle	trumpet right	canonical	The trumpet is to the right of the guitar
2	trumpet middle	guitar left	non-canonical	To the left of the trumpet is the guitar
3	guitar left, trumpet right	violin middle	canonical	The violin is to the right of the guitar and to the left of the trumpet
4	guitar left, violin right	trumpet middle	non-canonical	To the left of the violin and to the right of the guitar is the trumpet

Table 2. Example trials for the Scene Describer task.

In order to get an appreciation for the near real-time behavior of the system, we examined experimental data logs and collected data from 22 experiments with the scene describer and from 66 experiments with the action performer.

The execution times for the Scene Describer task are recorded since the subject places the objects on the table, until the system responds with the description. This includes file transfer time from the Supervisor to the neural network model, and back, along with the model processing. Despite these delays, the total time of execution is around 30 seconds, which is near-real time performance. Likewise, for the action performer, processing of the spoken sentence by the model takes place within approximately 20 seconds, and then the execution of the actions by the robot is slower. This long time for executing actions is due to (a) safety limits on velocity, and the fact that (b) many of the commanded actions include two distinct actions. Still, from spoken command to completed action, the execution is less than a minute, again, within the bounds of near-real time performance.

Looking in more detail at the time used by actually running the neural network, we measured the time from sending the file to the network, to the time to retrieve the file containing the actions to be sent to the robot. For 66 trials of the AP task this required on average 6.02 seconds ( $SD \pm 0.33$  sec), and for 22 trials of the SD task the file transfer and neural network execution required 9.42 seconds ( $SD \pm 0.96$  sec). This can be considerably improved by replacing the file based communication with a client-server communication in the YARP framework.

#### 4.4 Neural output activity of the models

In this section we will illustrate the activity of the neural network model for the two tasks. One has to recall that the output of the neural network is used to generate the behavioral and spoken responses.

#### 4.4.1 Comprehension model neural activity for Action Performing task

In Figure 8 we illustrate the output activity for two example trials on the Action Performer task. From the beginning of the grammatical construction the read-out activity starts to change and is updated each time a new word is presented in input. This activity can be interpreted as an estimated prediction given the inputs thus far. These estimations are related to sentence forms statistics of the training corpus (see (X. Hinaut & Dominey, 2013) for details). In Figure 8A, the model correctly determines that there is only one meaning-predicate *put* (*trumpet, left*). We see that at the last time step the neural activations concerning the on-going predictions on a potential 2<sup>nd</sup> predicate-meaning all fall below the threshold of 0.5, and as a consequence only one predicate-meaning is considered.

In some cases, this activity can be used to know the correct response before the end of the sentence. In later experiments, this could potentially allow the robot to start moving the object before the end of the sentence. This is actually a behavior that seems natural in human interaction when one give the other a series of orders: when the first order is given the human can start to do the 1<sup>st</sup> action while listening to the rest of the orders (for instance when someone lists what has to be done for a cake recipe, while another one is making the cake).

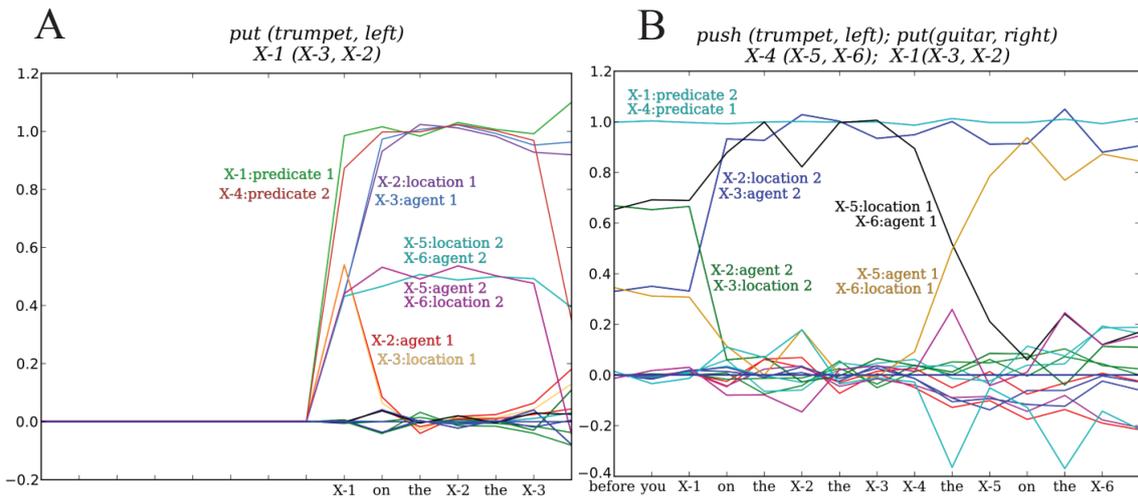


Figure 8: Example of output activity of the comprehension neural model for the “Action Performing” task. Each colored line indicates the pseudo-probability for each semantic word to have a given role (*predicate, agent, location*) for each of the two specified actions. (A) The input sentence was “put on the left the trumpet”. The 290

model correctly determines that there is only one meaning-predicate *put (trumpet, left)*. X-1, X-2, X-3 ... indicate the 1<sup>st</sup>, 2<sup>nd</sup>, 3<sup>rd</sup>, ... SW markers. For X-5 and X-6 plots are superimposed, as the output neurons “X-5:location2” and “X-6:agent2” have the same activity for this sentence. (B) The input sentence was “before you put on the right the guitar push the trumpet on the left”: the model correctly determines the two meanings in the right order *push (trumpet, left)* and then *put (guitar, right)*.

For the Action Performer task, we show the activity for sentences that were not learned (i.e. not seen beforehand): constructions shown on Figure 8 where not in the training data, but only in the test data. Even though the constructions were not pre-learned, the model was still able to correctly recognize them, demonstrating generalization capabilities. For more information on the model generalization performances see (Xavier Hinaut & Dominey, 2012; X. Hinaut & Dominey, 2013)

#### 4.4.2 Production model neural activity for Scene Description task

Figure 9 illustrates the readout unit activations for two different meanings and different sentence forms in the Scene Description task. In Figure 9A, the meaning given in input was *right (trumpet, guitar)* with the sentence form  $SW1(SW3, SW2)$ . The model correctly generated the sentence “to the right of the guitar is the trumpet”. In Figure 9B, the meaning given in input was  $\{right (violin, trumpet), left (violin, guitar)\}$  with the sentence form  $\{SW1(SW5, SW2), SW3(SW5, SW4)\}$ . The model correctly generated the sentence “to the right of the trumpet and to the left of the guitar is the violin”.

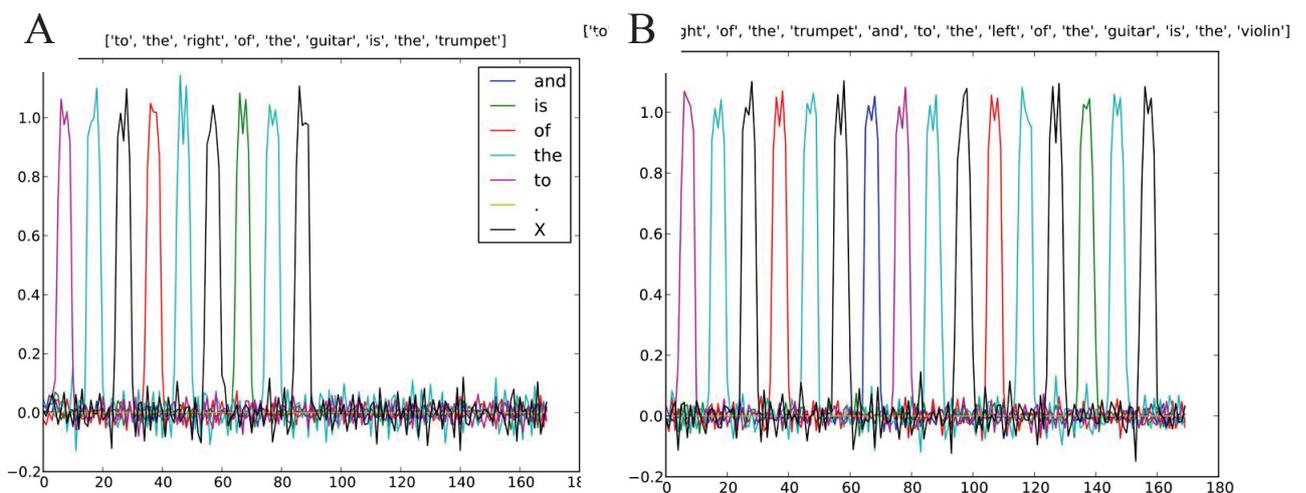


Figure 9: Output (read-out) unit activations of the production neural model in the Scene Description task. Each colored line represents a different read-out neuron. Each read-out neuron corresponds to a different word: either a grammatical word or a SW marker. On the x-axis is indicated the number of time steps. On the y-axis is indicated the neural activity for output neurons. X indicates the semantic word (SW) marker. (A) The construction found is “To the X of the X is the X”. The sentence correctly recovered after replacement of the SW markers is “To the right of the guitar is the trumpet”. (B) The construction found is “To the X of the X and to the X of the X is the X”. The sentence correctly recovered after replacement of the SW markers is “To the right of the trumpet and to the left of the guitar is the violin”.

These results indicate that the system works correctly in the SD and AP tasks, under controlled conditions. We should also evaluate the capacity of the system to accommodate less controlled conditions.

#### 4.5 Action Performing Training with Naïve Subjects

Here we report on the results of the Action Performer model, when trained and tested with a set of sentences from five naïve subjects. From the initial set of 380 sentences, 22 were eliminated from further analysis because they did not fulfill the minimal conditions in order to be processed correctly by the system: for instance (1) they did not describe the actions properly (e.g. “make a U-turn”: invention of new actions instead of using the atomic actions proposed), or (2) they did not refer to the objects by their name (e.g. “touch both objects”). The remaining corpus of 358 <sentence, meaning> pairs were included in the study (see supplementary material # containing included and excluded sentences). Examination revealed that several additional closed-class words were used by our subjects. They were used to define the set of possible inputs to the model. Here is the extended list of closed-class words: 'after', 'and', 'before', 'it', 'on', 'in', 'to', 'the', 'then', 'you', 'please', 'twice', 'both', 'objects', 'having', 'again', 'time', 'firstly', 'first', 'over', 'at', 'followed', 'once'.

The analysis of the naïve subject data proceeded in two steps. We first tested the learnability capability of the complete set of sentences: the reservoir was trained and then tested on the same set of sentences. Because of the increase in size and complexity of the training corpus compared to experiment 1, we increased the reservoir size to 2000 neurons. We created 6 instances of the model (i.e. different random generator seeds were used to generate the weight connections). Sentences are considered learnable if they were correctly learned at least once: if a sentence was successfully learned by one of model instances, it was considered as learnable. The results for this learnability capability is illustrated in the

“Learnability” column in Table 2. Only 25 sentences of the whole 358 corpus (i.e. 6.96%) were considered not learnable: thus the vast majority of utterances produced by the naïve users were exploitable and learnable; this confirms the viability of the approach.

	<b>Learnability</b>		<b>Generalization Error</b>	
Global	25/358 (6.96%)		40%	
	Single Action	Double Action	Single Action	Double Action
Simple Sentence	4/27 (14.8%)	2/151 (1.32%)	6/27 (22.2%)	38/151 (25.2%)
Elaborate sentence	0/16 (0%)	19/164 (11.6%)	8/16 (50%)	92/164 (60.4%)

Table 2. Learnability and generalization capabilities on the naïve subject data set. (left) Number of non-learnable sentences for different sentence categories. For each category, the number of non-learnable sentences is divided by the total number of sentences for that category, with the corresponding percentage in parentheses. Only 6.9% of sentences are not learnable: this indicates that most of the corpus is learnable. (right) Generalization error for different sentence categories. For any category the neural model is able to generalize to some not learned sentences. As expected, generalization performances are better for Simple sentences than for Elaborate sentences.

This learnability test is important to demonstrate the difficulty of the task, and it constitutes a preliminary step before looking at the generalization capability; because sentences that are not learnable have a priori no chance for being part of the group of sentences that the neural system could “understand” (i.e. generalize on) without learning them. Of course the “learnability” of a sentence is dependent of other sentences in the corpus: in this view, if one sentence is not learnable, it means that it is an outlier in this corpus. Here, an outlier is a sentence that have a grammatical structure different from other sentences. The majority of non-learnable sentences are Elaborate - Double Action sentences, but proportionally Simple - Single Actions have about the same rate of non-learnability. This “unexpected” high non-learnability of Simple - Single Actions could be explained by the fact that half of Elaborate - Single Action have been removed from the initial corpus: this category contains only 16 sentences instead of 27 for the Simple - Single Actions.

In a second step we tested the ability of the model to generalize to sentences not used in training. We used a standard “leaving one out” (L1O) method: the model is trained on nearly all sentences and then tested on the sentence left out of the training data. It corresponds to the

case were the robot-neural system has been taught hundreds of sentences and we want to test its ability to understand correctly a sentence given by a naïve user. This is considered more difficult than an usual 10-fold cross-validation as the learning system is more likely to have overfitted the data. Even if that test sentence has a grammatical structure different from those in the training set, the system could nevertheless generalize to this untrained structure in some cases. For this study, we used a reservoir with 1500 neurons. We runned 12 instances of the model. Of the 358 sentences, 144 failed the L1O test in all 12 simulations (i.e. for all 12 instances). We can consider that the corpus did not have sufficient grammatical information to allow generalization to these sentences. Of the remaining sentences, 18 succeeded in the L1O at least once, 14 twice, 7 three times, 28 were correctly processed in L1O four or more times, and 146 were correctly processed in all 12 L1O simulations. In Table 2, generalization errors for different sentence categories are provided in the left column. Considering the learnability results, which could lead to 14.8% error for Simple – Single Action category, the system have a good ability to generalize to unseen sentences. In particular, for the simple sentences (both single and double actions) the system is able to generalize to more than 75% of unseen sentences: this is an important result as in a natural conditions subjects will tend to produced spontaneously this type of sentences (that we categorized as “Simple”).

Some of the sentences that produced successful generalization are worth noting. Sentences (12), (27), (264) and (322) (see Table 3) illustrate the use of the impersonal pronoun “it” in various configurations of distinct constructions. Processed as a closed-class (i.e. grammatical) word, it indicates the appropriate role for the referent open class (i.e. semantic) element: the system is able to generalize correctly the function of the grammatical word “it” and bind to the correct role the semantic word it refers to. In a sentence like (12) (see Table 3) the semantic word 2 “circle” will be considered as the “object” of both actions, “grasp” and “point”. Sentence (19) illustrates a similar situation, where the closed class word “twice” informs the system that the same action is repeated two times. Thus, in a certain sense, the system has learned the non-trivial meaning of the word “twice”. The system also acquires non-trivial use of the temporal relatives “before” and “after”. In (229), (264) and (332), “before” is used in such a way that the first action appearing in the sentence is actually to be performed second. Thus in these situations, the presence of “before” results in a temporal inversion of the commanded actions. Interestingly, the system can also master a different use of “before” as illustrated in (258): here “before” does not result in an inversion, the order of actions in the sentence is preserved in the execution of actions. Sentences such a (322) illustrate how these different properties – “it” reference, “before”: inversion – can be

combined. Although the system has not been designed to reach this level of “interpretation” of close class words, it is able to generalize its use in not learned sentences. This ability of the system to work with non-predefined cases demonstrates its flexibility.

- |   |
|---|
| (12) grasp the circle and then point to it                              |
| (19) point to the cross twice   |
| (27) touch the triangle then move it to the left                        |
| (188) point to the circle after having grasped it                       |
| (229) before you touch the cross touch the triangle                     |
| (258) point the triangle before grasping the circle                     |
| (264) before grasping the triangle point at it                          |
| (322) before pushing the circle to the left please push it to the right |

Table 3. Example sentences produced by naïve subjects, and understood by the system.

## 5. Discussion

The current research makes several distinct contributions to language-based human-robot interaction. Previous research has used language to command humanoids e.g.(P. Dominey, Mallet, & Yoshida, 2007; Lallée et al., 2012; Petit et al., 2013), and to allow robotic systems to describe actions (P. Dominey & Boucher, 2005b). The current research for the first time demonstrates real-time acquisition of new grammatical constructions for comprehension and production that can be used respectively in commanding the robot and in asking the robot to describe the physical world. This is of interest both in theory and in practice. In theory, it demonstrates that the form-to-meaning mapping that we have employed in learning grammatical constructions can be used in both directions, to generate meaning from form, and to generate form from meaning. In practice, this means that the system can adapt to individual differences in the way users employ language to describe and request actions. The current research also addresses how language can allow for the coordination of multiple sub-actions in time, using the prepositions “before,” and “after.” Learning of these terms has a long history of research in child language development, and it poses an interesting problem because of the interaction with non-temporal event ordering and non-canonical syntactic structure (Carni & French, 1984). Our work can contribute to the debate by indicating that a system that is sufficiently powerful to handle canonical and non-canonical events in single event sentences can do the same in multiple event sentences in which order is expressed with

prepositions including “before” and “after”. Interestingly, the key assumption is that these prepositions are processed in the model as closed class or grammatical words, which can then directly contribute to the elaboration of the form to meaning mapping.

Because of this flexibility, the framework that we have developed potentially enables naive users to interact with the robot, indeed there is no "predefined" way of giving a command or description of an action such as *put (toy, left)* ; the user could say "put the toy on the left" or "on the left put the toy". In this way, we are able to escape from a 1-to-1 sentence-action correspondence: several sentences could indicate the same meaning.

Concerning the production model we partly escape the 1-to-1 sentence-action (or sentence-scene) limitation because we can specify if we want a canonical or non-canonical sentence type. We could specify more precise sentence type, for instance by specifying the semantic word of focus. But this problem could be tackled in a more general way. In order to be able to generate several sentences with the same meaning, we could consider 2 alternatives. (1) We could add feedback connections from the readout layer to the reservoir with the addition of noise either in the reservoir states or in these feedback connections. Thus the network would not produce every time the same pattern of words, but different ones. The noise would enable the network to be driven by one of the possible learned sentences (word patterns). (2) Use an additional self-organization map (SOM) based on the semantic words. During training this SOM will tend to organize words that appear in the same sentences in the same area of the map. During testing, the SOM activation will provide a supplementary input to the sentence production model in order to give a kind of "context" and enable the model to generate one pattern of words that is context relevant. In this way, if some sentence constructions are commonly used with certain semantic words, it will produce the more common sentences. Both alternative solutions may enable the production of constructions that were not learned, i.e. give the production generalization capabilities (like the comprehension model). Finally, the generation of different non-canonical forms allows the system to manipulate the grammatical focus while describing the same situation, as illustrated in Table 1.

The production model introduced here is able learn to produce grammatical constructions when given the meaning, coded in the same way that the comprehension model output is coded. This is the first time that we demonstrate that the input and output of the comprehension model could be reversed in order to do the “inverse” task (i.e. production instead of comprehension). This is an interesting property that may be useful in further understanding human language. Indeed, we have here a system that is able to do grammatical construction comprehension and production with a common coded meaning representation

(which corresponds to the output of the comprehension model, and to the input of the production model). We can imagine that the two models can be running in parallel, with the outputs of the production model connected to the inputs of the comprehension model. In this way, when the production model would be generating a sentence, the latter could be decoded in real-time and fed to the inputs of the comprehension model. Thus the comprehension model will reconstruct in real-time the meaning of the sentence produced by the production model. Consequently this would allow the system to check if the produced sentence is correct or not to the original meaning (i.e. input of the production model). A correction mechanism could be added to compensate when errors of productions are made. Such a correction mechanism appears to exist in human language behavior, as when one notices that they have produced a word instead of another in the middle of a sentence, they correct their sentence production in real-time accordingly. Detection of such a production error would likely be accompanied by specific brain response, as it is the case for the P600 event related scalp potential when an ungrammatical word or complex sentence is processed. In a previous study using our comprehension model (X. Hinaut & Dominey, 2013) we showed that a kind of instantaneous derivative of the output values – the sum of absolute change of all outputs – could be related with a P600-like event. In the reverse sense, the output of the comprehension model could be input to the production model, allowing the listener to predict the upcoming words of the speaker. Another alternative would be to combine both comprehension on production within a same model, with feedback connections from both discovered thematic roles and produced words: a unique reservoir would do both tasks at the same time; this would probably require an online learning algorithm.

The experiment with the naïve subjects is particularly interesting, as it provides the model with a form of “cognitive variability” in the language used, which goes beyond that employed when “insider” researchers interact with the robot. The use of the impersonal pronoun “it”, words like “twice”, the use of “before,” and “after,” in the diverse configurations allowed a test and finally an illustration of the adaptability of the language model. The good learnability of the sentences – 93% of the corpus is learnable – indicates that the naïve subjects can make really complicated sentences that may contain only partial information. The relatively robust generalization, particularly for the “simple” sentences (>75% generalization) indicates that the model was able to extract the relevant information from this relatively small (< 400 sentences) corpus; it also indicates that the naïve subjects are “playing the game,” i.e. they are attempting to speak in a reasonable way to the robot in the “simple” sentence condition. Future research

should assess how, as such corpora increase in size, generalization improves (for a given corpus complexity), as indicated in (X. Hinaut & Dominey, 2013).

## 6. Acknowledgments

This work has been financed by the FP7-ICT 231267 Project Organic and by the FP7-ICT-270490 Project EFAA. Neural model has been developed with Oger toolbox: <http://reservoir-computing.org/organic/engine>.

## 7. Video links

Video demonstration of the scene description in Experiment 1 can be seen at:

<http://youtu.be/AUbJAupkU4M>

Video demonstration of the action performer in Experiment 2 can be seen at:

<http://youtu.be/3ZePCuvgi0>

## Supplementary Material

SM1. File for Action Performer task with train and test data used for Figure 8.

Lines or end of lines after character # indicate commentaries that are not taken into account by the file parser. The coding is in the format “meaning; sentence”.

<train data>

#####

put trumpet left;put the trumpet on the left

put trumpet left;on the left put the trumpet

put trumpet left;put on the left the trumpet

put trumpet left;the trumpet put it on the left

grasp guitar;grasp the guitar

grasp guitar;the guitar grasp it

put trumpet left,put guitar right;put the trumpet on the left and then put the guitar on the right

put trumpet left,put guitar right;after you put the trumpet on the left put the guitar on the right

put trumpet left,put guitar right;put the trumpet on the left before you put the guitar on the right

put trumpet left,put guitar right;before you put the guitar on the right put the trumpet on the left

put trumpet left,put guitar right;put on the left the trumpet and then put the guitar on the right

put trumpet left,put guitar right;after you put on the left the trumpet put the guitar on the right

put trumpet left,put guitar right;put on the left the trumpet before you put the guitar on the right

put trumpet left,put guitar right;before you put the guitar on the right put on the left the trumpet

put trumpet left,put guitar right;put the trumpet on the left and then put on the right the guitar

put trumpet left,put guitar right;after you put the trumpet on the left put on the right the guitar  
put trumpet left,put guitar right;put the trumpet on the left before you put on the right the guitar  
put trumpet left,put guitar right;before you put on the right the guitar put the trumpet on the left  
put trumpet left,put guitar right;put on the left the trumpet and then put on the right the guitar  
put trumpet left,put guitar right;after you put on the left the trumpet put on the right the guitar  
put trumpet left,put guitar right;put on the left the trumpet before you put on the right the guitar  
put trumpet left,put guitar right;before you put on the right the guitar put on the left the trumpet  
#new sentences not in fig9 and 10

pointguitar,put trumpet left;before you put the trumpet on the left point the guitar  
pointguitar,put trumpet left;before you put on the left the trumpet point the guitar  
point guitar, grasp trumpet;before you grasp the trumpet point the guitar  
put trumpet left, point guitar;before you point the guitar put the trumpet on the left  
</train data>

<test data>  
before you grasp the cross put the circle on the right  
</test data>

#####

### SM2 File for Scene Description task with train and test data used for Figure 9

#####

<train data>  
left violin trumpet;the violin is left of the trumpet  
left violin trumpet;the violin is to the left of the trumpet  
left violin trumpet;to the left of the trumpet is the violin  
left violin trumpet,right violin guitar;the violin is to the left of the trumpet and to the right of the guitar  
left violin trumpet,right violin guitar;to the left of the trumpet and to the right of the guitar is the violin  
</train data>

<test data>  
right eraser cross , left eraser circle :N  
</test data>

#####

### SM3: Instructions given to the users.

#####

#### Introduction

Notre robot veut apprendre à parler. Pour l'instant il en est à un stade précoce. Il sait dire quelques phrases qu'il a appris par coeur qui lui permettent d'interagir un peu avec une personne, comme par exemple : « I see all the objects » ou « Set the relative objects ». Mais il n'est pas encore capable de faire le lien entre une phrase

qu'on lui dit et des actions (qu'il fait ou qu'il a vu faire) ou une description spatiale des objets les uns par rapport aux autres.

Votre but est de lui apprendre l'Anglais avec des phrases simples et des phrases « plus complexe » que celles qu'il connaît peut être déjà. Les phrases que vous allez dire au robot sont des ordres : vous allez dire au robot les actions qu'il doit utiliser. Car pour l'instant il ne connaît que de simples phrases apprises par cœur qui n'utilisent pas tout le potentiel du langage, c'est-à-dire de pouvoir décrire une même chose de plusieurs façons différentes. Pensez par exemple à la célèbre réplique du Maître de Philosophie à M. Jourdain dans le *Bourgeois gentilhomme* :

*Belle Marquise, vos beaux yeux me font mourir d'amour.*

*Ou bien: D'amour mourir me font, belle Marquise, vos beaux yeux.*

*Ou bien: [...]*

Ainsi vous pourrez faire des phrases de tous types, à la forme « active » et à la forme « passive » :

1. « Put the trumpet on the right », ou bien
2. « On the right put the trumpet »

Et aussi des phrases qui impliquent une ou deux actions à la fois :

- [1] « Put the drums on the right »
2. « Point the trumpet and on the left put the trumpet »

Vous pouvez aussi faire des variations chronologiques :

- « Before you grasp the toy put the trumpet on the right »
- « Put the drums on the right and then put the toy on the right »

Remarque : lorsque vous imaginerez les ordres, faites-le en pensant par rapport à **vos** droite / votre gauche, ceci afin de ne pas compliquer votre tâche.

On souhaite également apprendre un vocabulaire particulier au robot, correspondant à différents objets, positions ou actions.

### **Description de l'expérience même**

Vous allez visionner une vidéo comprenant 35 actions ou séquence (i.e. suite) d'actions répétées 2 fois. Il faudra appuyer sur pause (espace) à la fin de chaque scène et dire à l'expérimentateur l'ordre qui aurait pu permettre d'obtenir l'action. La première fois (X. Simple), contentez-vous de l'ordre le plus simple qui vous vienne à l'esprit. La deuxième fois, essayer de créer un ordre plus élaboré (X. Elaborate). Vous pouvez vous inspirer des exemples ci-dessus.

« X. » correspond simplement au numéro de la séquence.

Afin d'apprendre un vocabulaire particulier au robot, il est nécessaire de restreindre seulement le vocabulaire concernant les **actions**, les **objets** et les **positions** (de destination) que vous allez utiliser. Pour les autres mots (par ex. *you, the, on, it, then, after ...*) vous pouvez utiliser ceux que vous souhaitez, en les faisant varier autant que vous le désirez. Voici les différents mots de vocabulaire à utiliser :

- Pour les actions : **point, touch, grasp, push, put**
  - Pour les objets : **cross, circle, triangle**
  - Pour les localisations/positions (pour les destinations des actions push et put) : **left, middle, right**
- (Demandez à l'expérimentateur de vous montrer à quoi correspondent ces différentes actions, objets et localisation.)

Les positions (ou localisations) indiquées servent à indiquer au robot la position finale de l'objet (destination) seulement pour les actions push et put. Car étant donné que chaque objet est différent (cross, circle, triangle) il n'est pas nécessaire d'indiquer la position initiale de l'objet, il suffit d'indiquer simplement le nom de l'objet.

#####

## References:

- Bates, E., & MacWhinney, B. (1987). Competition, variation, and language learning. In B. MacWhinney & E. Bates (Eds.), *Mechanisms of language acquisition* (pp. 157-193). Hillsdale, NJ: Erlbaum.
- Bates, E., McNew, S., MacWhinney, B., Devescovi, A., & Smith, S. (1982). Functional constraints on sentence processing: a cross-linguistic study. *Cognition*, 11(3), 245-299.
- Bencina, R., Kaltenbrunner, M., & Jorda, S. (2005). *Improved topological fiducial tracking in the reactivation system*. Paper presented at the Computer Vision and Pattern Recognition-Workshops, 2005. CVPR Workshops. IEEE Computer Society Conference on.
- Blanc, J. M., Dodane, C., & Dominey, P. F. (2003). *Temporal processing for syntax acquisition: A simulation study*. Paper presented at the The 25th Ann Conf. Cog. Sci. Soc., Cambridge, MA.
- Carni, E., & French, L. A. (1984). The acquisition of 'before' and 'after' reconsidered: What develops? *Journal of experimental child psychology*, 37(2), 394-403.
- Carpenter, M., Nagell, K., & Tomasello, M. (1998). Social cognition, joint attention, and communicative competence from 9 to 15 months of age. *Monogr Soc Res Child Dev*, 63(4), i-vi, 1-143.
- Dominey, P., & Boucher, J. (2005a). Developmental stages of perception and language acquisition in a perceptually grounded robot. *Cognitive Systems Research*, 6, 243-259.
- Dominey, P., & Boucher, J. (2005b). Learning to talk about events from narrated video in a construction grammar framework. *Artificial Intelligence*, 167(1-2), 31-61.
- Dominey, P., Mallet, A., & Yoshida, E. (2007). *Progress in programming the hrp-2 humanoid using spoken language*. Paper presented at the IEEE International Conference on Robotics and Automation.
- Dominey, P. F. (1995). Complex sensory-motor sequence learning based on recurrent state representation and reinforcement learning. *Biol Cybern*, 73(3), 265-274.
- Dominey, P. F. (2003). *Learning grammatical constructions in a miniature language from narrated video events*. Paper presented at the 25th Annual Meeting of the Cognitive Science Society, Boston.
- Dominey, P. F., Arbib, M. A., & Joseph, J. P. (1995). A Model of Corticostriatal Plasticity for Learning Oculomotor Associations and Sequences *J Cogn Neurosci*, 7(3), 25.
- Dominey, P. F., & Dodane, C. (2004). Indeterminacy in language acquisition: the role of child directed speech and joint attention. *Journal of Neurolinguistics*, 17(2-3), 121-145.
- Dominey, P. F., Hoen, M., Blanc, J. M., & Lelekov-Boissard, T. (2003). Neurological basis of language and sequential cognition: evidence from simulation, aphasia, and ERP studies. *Brain Lang*, 86(2), 207-225.
- Goldberg, A. (1995). *Constructions: A Construction Grammar Approach to Argument Structure*. Chicago: University of Chicago Press.
- Goldberg, A. E. (2003). Constructions: a new theoretical approach to language. *Trends Cogn Sci*, 7(5), 219-224.

- Gori, I., Pattacini, U., Nori, F., Metta, G., & Sandini, G. (2012). *DForC: a Real-Time Method for Reaching, Tracking and Obstacle Avoidance in Humanoid Robots*. Paper presented at the IEEE/RSJ International Conference on Intelligent Robots and Systems.
- Hinaut, X., & Dominey, P. (2012). On-Line Processing of Grammatical Structure Using Reservoir Computing. In A. Villa, W. Duch, P. Érdi, F. Masulli & G. Palm (Eds.), *ICANN 2012 - Lecture Notes in Computer Science* (Vol. 7552, pp. 596-603): Springer Berlin / Heidelberg.
- Hinaut, X., & Dominey, P. F. (2011). A three-layered model of primate prefrontal cortex encodes identity and abstract categorical structure of behavioral sequences. *J Physiol Paris*, *105*(1-3), 16-24.
- Hinaut, X., & Dominey, P. F. (2013). Real-time parallel processing of grammatical structure in the fronto-striatal system: a recurrent network simulation study using reservoir computing. *PLoS One*, *8*(2), 1-18.
- Huang, X., Alleva, F., Hon, H.-W., Hwang, M.-Y., Lee, K.-F., & Rosenfeld, R. (1993). The SPHINX-II speech recognition system: an overview. *Computer Speech & Language*, *7*(2), 137-148.
- Jaeger, H. (2001). The "echo state" approach to analysing and training recurrent neural networks - with an erratum note'. *Bonn, Germany: German National Research Center for Information Technology GMD Technical Report*, 148.
- Jaeger, H., & Haas, H. (2004). Harnessing nonlinearity: predicting chaotic systems and saving energy in wireless communication. *Science*, *304*(5667), 78-80.
- Knoblich, G., & Sebanz, N. (2008). Evolving intentions for social interaction: from entrainment to joint action. *Philos Trans R Soc Lond B Biol Sci*, *363*(1499), 2021-2031.
- Lallée, S., Pattacini, U., Lemaignan, S., Lenz, A., Melhuish, C., Natale, L., et al. (2012). Towards a Platform-Independent Cooperative Human-Robot Interaction System: III. An Architecture for Learning and Executing Actions and Shared Plans. *IEEE Transactions on Autonomous Mental Development*, *4*(3), 239-253.
- Lukosevicius, M., & Jaeger, H. (2009). Reservoir computing approaches to recurrent neural network training. *Computer Science Review*, *3*(3), 22.
- Maass, W., Natschlager, T., & Markram, H. (2002). Real-time computing without stable states: a new framework for neural computation based on perturbations. *Neural Comput*, *14*(11), 2531-2560.
- Metta, G., Fitzpatrick, P., & Natale, L. (2006). YARP: yet another robot platform. *International Journal on Advanced Robotics Systems*, *3*(1), 43-48.
- Metta, G., Natale, L., Nori, F., Sandini, G., Vernon, D., Fadiga, L., et al. (2010). The iCub Humanoid Robot: An Open-Systems Platform for Research in Cognitive Development. *Neural Networks, Special issue on Social Cognition: From Babies to Robots*, *23*(8-9).
- Morgan, J. L., & Demuth, K. (1996). *Signal to syntax: bootstrapping from speech to grammar in early acquisition*. Mahwah, NJ: Lawrence Erlbaum.
- Petit, M., Lallée, S., Boucher, J.-D., Pointeau, G., Cheminade, P., Ognibene, D., et al. (2013). The Coordinating Role of Language in Real-Time Multi-Modal Learning of Cooperative Tasks. *IEEE Transactions on Autonomous Mental Development*, *5*(1), 3-17.
- Piattelli-Palmarini, M. (1980). *Language and learning: the debate between Jean Piaget and Noam Chomsky*: Cambridge Univ Press.
- Ricciardelli, P., Bricolo, E., Aglioti, S. M., & Chelazzi, L. (2002). My eyes want to look where your eyes are looking: exploring the tendency to imitate another individual's gaze. *Neuroreport*, *13*(17), 2259-2264.
- Sebanz, N., Bekkering, H., & Knoblich, G. (2006). Joint action: bodies and minds moving together. *Trends Cogn Sci*, *10*(2), 70-76.
- Siskind, J. M. (1996). A computational study of cross-situational techniques for learning word-to-meaning mappings. *Cognition*, *61*(1-2), 39-91.
- Sutton, S., Cole, R. A., De Villiers, J., Schalkwyk, J., Vermeulen, P. J., Macon, M. W., et al. (1998). *Universal speech tools: the CSLU toolkit*. Paper presented at the ICSLP.

- Taylor, P., Black, A. W., & Caley, R. (1998). The architecture of the Festival speech synthesis system [Electronic Version]. *Proc. Third ESCA/COCOSDA Workshop on Speech Synthesis, Jenolan Caves House, Blue Mountains, Australia, November 26-29, 1998. pp. 147-151.*
- Tomasello, M. (2003). *Constructing a language: A usage based approach to language acquisition.* Boston: MIT Press.
- Tomasello, M., & Hamann, K. (2012). Collaboration in young children. *Q J Exp Psychol (Hove)*, 65(1), 1-12.
- Verstraeten, D., Schrauwen, B., D'Haene, M., & Stroobandt, D. (2007). An experimental unification of reservoir computing methods. *Neural Networks*, 20(3), 391-403.

## 9.4 EFAA WYSIWYD Description of Work

### 9.4.1 EFAA DOW

Project acronym : EFAA

Project full title : " Experimental Functional Android Assistant (EFAA) "

Grant agreement no : 270490

Date of preparation of Annex I (latest version) : 2010-10-06

Date of last change : 2010-10-04

Pages : 12-14 /104

# WT3: Work package description

Project Number <sup>1</sup>	270490	Project Acronym <sup>2</sup>	EFAA
-----------------------------	--------	------------------------------	------

## One form per Work Package

Work package number <sup>53</sup>	WP3	Type of activity <sup>54</sup>	RTD
Work package title	Reasoning and Planning		
Start month	1		
End month	36		
Lead beneficiary number <sup>55</sup>	5		

## Objectives

The objective of this WP is to provide the system with the capability to exploit its previous experience in order to prepare for future experiences within the local peri-personal space. Thus EFAA shall maintain a spatially coherent representation of its relation to the task environment using a combination of cues derived from path integration and distal sensing based on our understanding of the neuronal mechanisms underlying spatial cognition. Using a reactive behavioral regulation system EFAA will optimize its distance and spatial relation to humans and objects with respect to the tasks involved. For this the iCub robot will be mounted on a simple mobile platform (see WP5). Within this context EFAA shall be able to learn and use action plans that represent the iCub and its interaction with object and with other agents. These plans will refer to the iCub in the context of an internal representation the self, and other agents and objects within peri-personal space. The flow of interactions, guided in part by these plans will be under the control of a limited spoken language interaction capability, extending our previous work in this domain . By maintaining an explicit autobiographical memory, the system will begin to develop an integrated model of itself. This will include representation of actions, their required initial conditions and resulting conditions. These capabilities will provide the basis for goal directed reasoning based on the sequencing of state-action-state links from the current state to the goal state.

## Description of work and role of partners

Task 3.1 Navigation and regulation of interpersonal distance.  
(Task Leader: UPF; Other Partners involved: IIT, INSERM)

In cooperation with WP1 we will implement an internal model in the form of physical simulation of the iCub and its peri-personal space, including manipulable objects, and other agents. This will be based on the existing open source simulation of the iCub . This representation will be updated using path integration and distal sensing, and will provide the basis for limited local navigation within the workspace for the iCub locomotion platform provided by Task 5.1. Navigation and interpersonal distance control will be developed using a well tested visual multi-person tracking system that will exploit tracking and proximity sensor data provided by Task 5.1. Existing spatial planning and navigation modules in the GNOSYS architecture will be taken as a starting point. The developed module will coordinate the acquisition of a spatial mental map of the environment by exploration, spatial planning, realization of spatial goals, and combined coordination of body movement with arm movements. The developed module will further act as a primitive action object for the reasoning system. Objects in the peri-personal space will be represented in the robot coordinate system such that they can be targets for motor actions including gaze, pointing and grasping.

Task 3.2 Interaction management via language  
(Task Leader: INSERM)

EFAA is interacting in space and time with other agents, and the practical control of the interaction will be managed via spoken language. In human cooperative interaction, language is used to create, recall and edit shared action plans. Moreover, during ongoing interactions, when it is necessary to get the interaction back on course, language is a principal tool for doing this. We have used language in this context of human robot cooperative interaction in several related studies. Will extend this use of language for interaction for EFAA, including the use of new grammatical constructions associated with the distinct spatial and temporal properties of the target behaviours. This will include experiments on object manipulation, compositional/hierarchical actions, and peri-personal spatial navigation. Interactions with the iCub will be under the global control of a

# WT3: Work package description

spoken-language based interaction capability, using the CSLU RAD system which exploits state of the art speech recognition and synthesis. Interaction dialogues will be implemented in a flexible manner that can be rapidly adapted to distinct scenarios specified in WPs 2 and 5.

**Task 3.3 Autobiographical memory and integrated cognitive model of self**  
(Task Leader: INSERM; Other Partners involved: UPF, Imperial)

Autobiographical memory will be implemented in the form of a continuous interaction history that encodes the temporal sequence of events that the robot has experienced throughout its existence. This includes perceived objects and events, actions generated by the robot, and observed as performed by other agents. In coordination with WP1, this autobiographical memory will provide part of the basis for the definition of self. In coordination with WP2, the interaction history will also provide the basis for recognition and extraction of repeating behavioural sequences that can form the basis of action plans.

**Task 3.4 Goal directed reasoning, executive control and attention:**  
(Task Leader: INSERM ; Other Partners involved: UPF, IIT, Imperial)

In WPs 1 and 2, actions will be linked with their initial and final states. As part of T3.3 the interaction history will encode behavioural sequences that link a succession of actions to a final goal. Within the contextual layer of the DAC architecture, these sequences encoded in the autobiographical memory will be operated upon by a probabilistic matching process so that the system can detect that it is in a potentially repeating subsequence, in order to anticipate future events. The same matching process will allow the system to detect behavioural sequences that have previously led to the current goal. In this context, mental simulation of action, and associated reasoning will be developed as an extension of related work by IIT in the EU GNOSYS project, and related work by UPF in rule learning within the DAC architecture.

**Task 3.5 Integration**  
(Partners: ALL)

Integration in this WP will take place at two levels. Level 1, this WP will interact directly with WP1 for the visuo-spatial interface necessary for T3.1; with WP2 for the language interaction and for the social learning that will contribute to the autobiographical memory; with WP4 for the memory and reasoning capability. The second level of integration within this task is in the context of integration of the functions developed in WP3 within the EFAA architecture in WP4. These are situated at the higher level of the architecture within the contextual level. Level 2 will interact with task 5.1 for the overall integration within the system architecture.

## Person-Months per Participant

Participant number <sup>10</sup>	Participant short name <sup>11</sup>	Person-months per participant
1	UPF	19.00
3	IIT	8.00
4	Imperial	4.00
5	INSERM	30.00
	Total	61.00

## List of deliverables

Delive- rable Number <sup>61</sup>	Deliverable Title	Lead benefi- ciary number	Estimated indicative person- months	Nature <sup>62</sup>	Dissemi- nation level <sup>63</sup>	Delivery date <sup>64</sup>
D3.1	Peri-personal spatial reasoning and spoken language interaction	5	11.00	R	PU	12
D3.2	Autobiographical memory and goal-directed reasoning	5	24.00	R	PU	24

306

# WT3: Work package description

## List of deliverables

Deliverable Number <sup>61</sup>	Deliverable Title	Lead beneficiary number	Estimated indicative person-months	Nature <sup>62</sup>	Dissemination level <sup>63</sup>	Delivery date <sup>64</sup>
D3.3	Integrated capabilities and demonstration	5	26.00	R	PU	36
Total			61.00			

## Description of deliverables

D3.1) Peri-personal spatial reasoning and spoken language interaction: Peri-personal spatial reasoning and spoken language interaction: Demonstration of robot capability to understand and produce spatial language in the context of manipulation of objects in the peripersonal space: Report comprising a manuscript submitted for publication, and video. [month 12]

D3.2) Autobiographical memory and goal-directed reasoning: Autobiographical memory and goal-directed reasoning: Demonstration of the ability to use autobiographical memory for reasoning about novel situations: Report comprising a manuscript submitted for publication, and video. [month 24]

D3.3) Integrated capabilities and demonstration: Integrated capabilities and demonstration: Report comprising demonstration of integrated capabilities [month 36]

## Schedule of relevant Milestones

Milestone number <sup>59</sup>	Milestone name	Lead beneficiary number	Delivery date from Annex I <sup>60</sup>	Comments
--------------------------------	----------------	-------------------------	--	----------

### 9.4.2 WYSIWYD DOW

Project acronym : WYSIWYD  
Project full title : " What You Say Is What You Did "  
Grant agreement no : 612139  
Version date : 2013-07-08  
Pages : 11-13 /131

# WT3: Work package description

Project Number <sup>1</sup>	612139	Project Acronym <sup>2</sup>	WYSIWYD
-----------------------------	--------	------------------------------	---------

## One form per Work Package

Work package number <sup>53</sup>	WP3	Type of activity <sup>54</sup>	RTD
Work package title	Verbal self and intentional communication		
Start month	1		
End month	36		
Lead beneficiary number <sup>55</sup>	5		

## Objectives

O3.1: To use existing state of the art spoken language technology to implement a platform for speech recognition and synthesis that provides a robust spoken language-based interface and is fully integrated with the WYSIWYD architecture.

O3.2: To design and implement efficient learning algorithms for cross situational binding of words and grammatical constructions to representations within the conceptual system, including the representation of self, driven by an intrinsic motivation to share mental states, and to validate these algorithms in the human-iCub-Reactable experimental setup where the human interacts with the robot via the learned vocabulary and grammatical constructions.

O3.3: To design and implement algorithms that allows the interface between grammatical constructions and the autobiographical memory in order to develop the narrative/conceptual self.

## Description of work and role of partners

### Task 3.1 Spoken Language Platform (Leader: INSERM, Participants: UPF) [M1-M24]

In this task we will develop and implement the spoken technology platform that will provide for the recognition and interpretation of human spoken language, synthesis of human-like language, and dialog management. We will use as a starting point our previous work linking spoken language to robot sensorimotor (Dominey, Mallet et al. 2007) and higher cognitive (Petit, Lallee et al. 2012) functions. Language technology will be provided by the state of the art off the shelf systems including Microsoft Speech Platform SDK 11, which provides an efficient and well documented environment. This technology platform will interface with the sensorimotor, body schema and self-other representations in WP1, the autobiographical self in WP2 and the intrinsic intentionality in WP4. In order to maximize recognition and understanding, recognition vocabularies and grammars will be specified for specific sub-tasks.

The primary aim of Automated Speech Recognition (ASR) is to demonstrate that a functioning ASR system can be implemented in a highly constrained situation but one that is feasible for real-world applications. Building on UPF's experience with multi-modal speech perception (Massaro 2012), and INSERM's experience with prosodic attitude discrimination (Blanc and Dominey 2003) we will exploit secondary aspects of speech to extract additional features from the spoken words, in order to label them with respect to their relevance to the context and thus driving the WR-DAC learning systems.

### Task 3.2 Learning Grammatical Constructions (Leader: INSERM, Participants: IMPERIAL, LUND) [M6-M30]

In this task we will implement algorithms for learning the mapping between linguistic utterances (words and sentences), and meanings represented in the conceptual system developed in WP4. Meanings will include representations of physical objects, agents, and actions. Word meanings will be learned by exploiting cross situational statistics (Siskind 1996; Yu and Smith 2007; Smith and Yu 2008) in the basis of which more extended grammatical constructions are learned through semantic bootstrapping (using acquired word knowledge to work out grammatical structure). This will be based on our work in learning word meanings, and the mappings between sentence structure and meaning that exploit cross-situational statistics, and semantic and syntactic bootstrapping [(Dominey and Boucher 2005), (Dominey 2002; Dominey and Boucher 2005; Dominey, Hoen et al. 2006)]. We will use recurrent neural networks, integrated in the WR-DAC architecture, to encode the grammatical structure of sentences which is then associated by linear regression with the conceptual

# WT3: Work package description

meaning structure (Dominey and Boucher 2005; Dominey, Hoen et al. 2006; Hinaut and Dominey 2012),. The result of this learning is an adaptive grammar learning system that will be used to extract meaning from human sentences, and to generate human understandable sentences based on meanings extracted from the conceptual system for human-robot interaction as in (Dominey and Boucher 2005). This task thus represents the interface between the spoken language processing in Task 3.1 and the conceptual representation in WP4, informed by our neuroscience studies of human language processing After learning the robot will be able to understand sentences such as “Why did you move the red block?” and generate a response such as “So that you could put it in the box.” The vocabulary and grammar can be cumulatively updated over the course of time, corresponding to lifelong learning. Learning experiments can “start from scratch”, but we will be particularly interested in cumulative learning over extended periods (weeks to months). Tools will be developed to allow incremental saving and restoring of intermediate learning states.

### Task 3.3 Narrative Self (Leader: INSERM, Participants: USFD, IMPERIAL, UPF) [M12-M36]

Language allows the individual to construct narrative of its own experience, which when assembled over extended time allows the construction of narrative or conceptual self (Neisser 1995; Gallagher 2000). In this task we will implement an interface between the language capabilities in Tasks 3.1 and 3.2, and the autobiographical memory (WP2), such that language based representations of the activities of the embodied self will be included in the autobiographical memory, allowing the development of the narrative self. The embodied self will be instantiated in the domain of the body schema development in interaction with WP1, where the conceptual space will have a direct correspondence to the sensorimotor space. This will then be extended to self in the context of interactions with others (Rochat 2009; Rochat 2011), the autobiographical self in WP2 and intentionality in WP4. Structuring of this narrative self is provided by the linking to the WR-DAC contextual sequential memory systems (WP5).

### Task 3.4 Integration (Leader: INSERM, Participants: ALL) [M1-M36]

This task will integrate the WR-DAC language system with the Interaction Engine and the Conceptual representation system within the WR-DAC Intentional Architecture, thus gaining access to the self, self-other and action representations from WP1, the autobiographical memory in WP2 in the context of the narrative self, and the conceptual system in WP4. As part of this integration, the WR-DAC language system will interact with the motor functions of the iCub via the whole-body aware action system in W6.

#### Person-Months per Participant

Participant number <sup>10</sup>	Participant short name <sup>11</sup>	Person-months per participant
1	UPF	6.00
2	USFD	6.00
3	IIT	0.00
4	Imperial	5.00
5	INSERM	47.00
6	LUND	8.00
Total		72.00

#### List of deliverables

Deliverable Number <sup>61</sup>	Deliverable Title	Lead beneficiary number	Estimated indicative person-months	Nature <sup>62</sup>	Dissemination level <sup>63</sup>	Delivery date <sup>64</sup>
D3.1	Intentional Communication for Goal-Directed Action	5	24.00	R	PU	12

# WT3: Work package description

## List of deliverables

Deliverable Number <sup>61</sup>	Deliverable Title	Lead beneficiary number	Estimated indicative person-months	Nature <sup>62</sup>	Dissemination level <sup>63</sup>	Delivery date <sup>64</sup>
D3.2	Intentional Communication applied to Self	5	24.00	R	PU	24
D3.3	Intentional communication and the autobiographical self	5	24.00	R	PU	36
Total			72.00			

## Description of deliverables

D3.1) Intentional Communication for Goal-Directed Action: This deliverable will report on the progress for development of the spoken language interaction platform, and its interface to the conceptual system representation and the body schema and goal directed actions in space, and the ability to learn and use grammatical constructions that allows intentional communication in the context of goal directed action. [month 12]

D3.2) Intentional Communication applied to Self: This deliverable will report on progress in development of the conceptual representation system applied to the internal structure of the WYSISYD representation itself, and the ability to learn and use grammatical constructions in the context of intentional communication with others about mental states. This will be complimentary to D1.2. [month 24]

D3.3) Intentional communication and the autobiographical self: This deliverable will report on progress in linking the intentional communication capability to the autobiographical memory and conceptual representation of self. This will be the demonstration of the “what you say is what you did” manifestation of the autobiographical self. [month 36]

## Schedule of relevant Milestones

Milestone number <sup>59</sup>	Milestone name	Lead beneficiary number	Delivery date from Annex I <sup>60</sup>	Comments
MS7	Prototype of the learned mapping of words & grammatical constructions to objects & actions in the co	5	24	Validation of successful performance for the learned mapping of words and grammatical constructions to objects and actions in the context of the learned self model, and in self-other interactions.

