Contribution to decisional human-robot interaction: towards collaborative robot companions

Muhammad Ali

INSTITUT NATIONAL DE SCIENCES APPLIQUÉES DE TOULOUSE
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Muhammad Ali

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Contribution to Decisional Human-Robot Interaction: Towards Collaborative Robot Companions

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sous la direction de:

M. Rachid ALAMI

Jury

M. Dominique DUHAUT, Professeur, Université de Bretagne-Sud,	Rapporteur
M. François CHARPILLET, Directeur de Recherche INRIA-LORIA, Nancy	Rapporteur
M. Abdel-Illah MOUADDIB, Professeur, Université de Caen Basse-Normandie	Examinateur
M. Daniel SIDOBRE, Maître de Conférence, Université de Toulouse III	Examinateur
M. Rachid ALAMI, Directeur de Recherche LAAS-CNRS, Toulouse	Directeur de Thèse

To my late father Qazi Fateh Muhammad Nizamani, his words of inspiration and encouragement in pursuit of excellence, will always guide me...

Abstract

Human Robot Interaction is entering into the interesting phase where the relationship with a robot is envisioned more as one of companionship with the human partner than a mere master-slave relationship. For this to become a reality, the robot needs to understand human behavior and not only react appropriately but also be socially proactive. A Companion Robot will also need to collaborate with the human in his daily life and will require a reasoning mechanism to manage the collaboration and also handle the uncertainty in the human intention to engage and collaborate. In this work, we will identify key elements of such interaction in the context of a collaborative activity, with special focus on how humans successfully collaborate to achieve a joint action. We will show application of these elements in a robotic system to enrich its social human robot interaction aspect of decision making. In this respect, we provide a contribution to managing robot high-level goals and proactive behavior and a description of a coactivity decision model for collaborative human robot task. Also, a HRI user study demonstrates the importance of timing a verbal communication in a proactive human robot joint action.

Résumé

L'interaction homme-robot arrive dans une phase intéressante où la relation entre un homme et un robot est envisagée comme un partenariat plutôt que comme une simple relation maître-esclave. Pour que cela devienne une réalité, le robot a besoin de comprendre le comportement humain. Il ne lui suffit pas de réagir de manière appropriée, il lui faut également être socialement proactif. Pour que ce comportement puisse être mis en pratique le roboticien peut s'inspirer de la littérature déjà riche en sciences socio-cognitives chez l'homme. Dans ce travail, nous allons identifier les éléments clés d'une telle interaction dans le contexte d'une tâche commune, avec un accent particulier sur la façon dont l'homme doit collaborer pour réaliser avec succés une action commune. Nous allons montrer l'application de ces éléments au cas d'un système robotique afin d'enrichir les interactions sociales homme-robot pour la prise de décision. A cet égard, une contribution à la gestion du but de haut niveau d'un robot et de son comportement proactif est montrée. La description d'un modéle décisionnel de collaboration pour une tâche collaborative avec l'humain est donnée. Ainsi l'étude de l'interaction homme robot montre l'intérêt de bien choisir le moment d'une action de communication lors des activités conjointes avec l'homme.

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Contents

Chapter 1

Introduction

Robots will soon be a part of our everyday lives. Instead of working alone in isolated industrial environments, their role will include interaction with humans. Increasingly, they are expected to work as our partners, such as, domestic assistants, teachers, health care workers, entertainment providers and even in the industrial milieu will require working closely with humans.

Robot as an interacting partner with the human raises several challenges, as a robot instead of acting as a tool to be used by the human becomes an interacting partner, requiring robot to have high level cognitive skills to act socially and collaborate appropriately, while taking into consideration the human at every level of interaction.

One important way to achieve the human level intricacy in the interaction by the robot is to equip it with the learning capabilities, though learning alone is not sufficient and will require long term interaction experience. Another way would be to bootstrap robot capabilities by building on available large repertoire of human human interaction knowledge. Rich literature in the socio-cognitive sciences on human-human interaction, provides a good inspiration for the roboticist.

In this work, we will study elements of human-human interaction in the context of a collaborative activity, with a focus on how the human successfully collaborate to achieve a joint action. And will show application of some of these elements in a robotic system to enrich its social human robot interaction aspect of decision making.

In this respect, a contribution to the managing of robot high-level goals and proactive behaviors is shown and a description of a coactivity decision model for a collaborative human robot task given. Also, a brief HRI user study demonstrates the importance of timing a verbal communication action in a proactive human robot physical joint action.

1.1 Motivation

Human-Human collaboration has been essential for the progress of the human race, in fact human beings as a species would not have existed were it not for our ability to engage in the joint action with others, which is crucial for participating in collaborative activities (require forming shared intentions and having shared goals) [Sebanz 09, Tomasello 05], figure 1.1 shows examples of human human collaboration. As it has played important role in developing social connections between human beings [Marsh 09], thus, making man a social animal and creating a social setup to support the development of societies.

Similarly, a Companion Robot will also need to collaborate with the human in his daily life and will require a reasoning mechanism to manage the collaboration and also, handle the uncertainty in the human intention to engage and collaborate. In this context, we will demonstrate the coativity decision model for human robot collaboration and qualitatively analyze it.

(a) handshake between JFK and Khrushchev 1961

(b) performance of a symphony

Figure 1.1: a) A simple handshake after saving the world from a potential disaster b) Performing a symphony: a collaborative activity with multiple participants

Human's are good at predicting others' behaviors and use it to proactively guide their respective behavior [Moshe 07], and even children have this built in characteristics to show curiosity [Carlton 98] and proactively help others in need [Warneken 06] (Figure 1.2, shows a child helping a person in need).

(a) Child detecting a person in need

(b) Child, picking up the object for the person in need

Figure 1.2: Child showing a proactive behavior and helping a person in need, from [Warneken 06]

As robots move towards being co-operative and social, the challenges of incorporating the basic ingredients of such behaviors are becoming prominent. Robots require similar capabilities to be able to collaborate with humans. Moreover, besides being able to collaborate, behaving proactively in a human centered environment is one of the desirable characteristics for a social robot [Salichs 06]. In this context, we will explore what are the basic expected proactive behaviors from a companion robot and propose a framework to achieve these behaviors.

Also, humans are good at anticipating partner's action and better time their own action accordingly [Sebanz 06] to achieve seamless coordination in a collaborative activity. Similarly, the robot would need to time its actions for a smooth human robot collaboration experience. In this context, we show a HRI user study that highlights "when" aspect of a communicative act in the human robot collaboration.

1.2 Contributions

In this work, we have proposed a number of contributions to help ameliorate decisional aspects of the human robot collaboration which may serve as a platform for building complex social behaviors in a companion robot.

The presented work serves to:

- identify important proactive behaviors for social human robot interaction
- exploit and adapt a temporal framework to recognize situations, where the robot can take initiative, and the architecture to support the proactive robot companion behavior.
- provide a framework for managing high-level robot goals.
- utilize the coordination aspect from the Human-Human collaboration to help develop a "coactivity" decision model for the human robot collaboration.
- analyze and suggest improvements in the "coactivity" decision model.
- highlight "when" aspect of a communicative act in the human robot collaboration.

1.3 Thesis Organization

This document consist of the following chapters:

Chapter 2 presents the relevant concepts in the collaboration, highlighting joint action part in a collaborative activity, from the point of view of human human socio-psychological studies. The key aspects involved in a collaboration are distinguished, for example, shared task representation, action prediction, coordination mechanisms, and joint attention etc.

Chapter 3 gives the general human robot interaction concepts, with focus on collaboration and showing initiative (showing proactive behavior). We identify the important proactive robot behaviors; "being aware", "curiosity", and "helping human" etc. We, also, give examples of initiative taking behaviors from the literature. A brief introduction of uncertainty in human robot collaboration is given, with description of related work on the models of human robot collaboration.

Chapter 4 describes the relevant robotic platforms and software support components, supporting the HRI research development in general and more specifically, helping us to build and test our system.

Chapter 5 shows, how high level robot goals are managed, which is important for a system capable of generating multiple competing goals. These goals, can either be given by the human through multimodal dialog or proactively generated. The system architecture is adopted to generate these proactive behaviors and the results are demonstrated on a robotic platform.

Chapter 6 shows the coactivity decision model developed for the human robot collaboration. Which is shown through a working example on the robotic platforms and is also, qualitatively analyzed. The improvements in the model are proposed and a new task instantiation with improvements is described.

Chapter 7 highlights, *when* aspect of a communicative act in a proactive human robot joint action. A HRI user study is shown, which describes *when* a verbal action be interleaved with a physical robot action.

Finally, in chapter **8**, we will make some general conclusions and give perspectives on future work.

Chapter 2

How do we do it? Collaboration in the Humans

Collaboration is an essential feature of human social interaction [Tomasello 05]. It is a process, where two or more people work together to realize a shared goal. It is an important aspect of human cooperative behavior, where individuals combine their capabilities to achieve a task which, either individual is unable to achieve on its own or is difficult for a single person to do. For example, a simple task of carrying a dining table may be achieved by a single person with some difficulty (by pushing etc.) or two person's can collaborate to lift and carry it together more easily.

In this chapter, we will present various studies in philosophy, cognitive sciences and social psychology related to collaboration, giving background theories (cognitive representation of joint intentions), and key features that makeup a successful collaboration with a focus on the joint action in collaboration.

2.1 Collaborative Activity

The collaborative activity can be seen as a social interaction where individuals cooperate to perform individual acts in pursuit of a shared goal requiring intricate coordination. For example, two individual preparing a dinner together, one of two may cut the vegetable and other's action may consist of cooking the vegetables and result of their combined actions may help achieve the task of the preparing the dinner. Collaboration invlovles, participants employing specific mental representations (joint intention theory), and it unfolds via, communication, mutual support, commitment to shared goal, meshing subplans, mutual beliefs, etc.

How do individuals engage in collaborative activities is a question which philosophers have tried to address for a long time. General philosophical approach has been to use the joint intention notion (collective intention or we-intention) [Bratman 92, Searle 90, Tomasello 05, Tuomela 05, Gilbert 09, Pacherie 11], i.e., participants in a joint collaborative task form joint intentions to achieve a shared goal. Development psychologists show that even young children have understanding of joint intentions in the collaborative activities [Warneken 12].

Besides planned human human collaboration, neuro-cognitive and behavioral psychology studies [Knoblich 11, Sebanz 06, Pacherie 06] show that joint action can also emerge through interactions without participants sharing intentions [Vesper 10] and it can be as basic as social motor coordination in the form of entrainment [Knoblich 11]. On a developmental note, young children apparently start participating in the collaborative activities prior to their ability to represent and share the goals of a partner [Brownell 11], although, they have the understanding of other's intentions [Warneken 12] but lack the required commitment for a joint goal [Hamann 12].

2.1.1 Joint Intention in Collaborative Joint Activity

Collaborative activity involve both, individual and joint actions with the partner. The joint actions implicate joint intentions and are essential for understanding the coordination in a collaborative activity. A joint intention to perform a particular action is a joint commitment to achieve a shared goal. Individual and joint intentions can be differentiated as follows [Warneken 12]:

Individual intention = I intend to bring about goal x by means of y. Or You intend to bring about goal x by means of y.

Joint intention = We intend to bring about goal x by means of me doing $y1$ and you doing $y2$.

[Bratman 09b, Bratman 09a], gives an important account of joint intentions and shows that the main building block of the joint intention are:

1. Intentions on the part of each in favor of the joint activity.
2. Interlocking intentions: each intends that the joint activity go in part by way of the relevant intentions of each of the other participants.
3. Intentions in favor of meshing subplans: each intends that the joint activity proceeds by way of subplans of the participants that are co-realizable and can be consistently agglomerated.
4. Disposition to help if needed: given that the contribution of the other participants to the joint activity is part of what each intend, and given the demands of means-end coherence and of consistency that apply to intentions, each is under rational pressure to help others fulfill their role if needed.
5. Interdependence in the persistence of each participant's relevant intention: each continues to intend the joint activity if and only if (they believe) the other participants continue to so intend.
6. Joint-action-tracking mutual responsiveness: each is responsive to each in relevant subsidiary intentions and in relevant actions in a way that tracks the joint action.
7. Common knowledge among all participants of all these conditions.

From above, [Bratman 92, Bratman 09b, Bratman 09a] identifies three essential features required in a collaborative joint activity (calling them shared cooperative activities, i.e., SCAs) and taken together they are characteristic of joint collaborative activity, these features are:

- Mutual responsiveness: In *SCA*, each participating agent attempts to be responsive to the intentions and actions of the other, knowing that the other is attempting to be similarly responsive. Each seeks to guide his behavior with an eye to the behavior of the other, knowing that the other seeks to do likewise.

- Commitment to the joint activity: In *SCA*, the participants each have an appropriate commitment (though perhaps for different reasons) to the joint activity, and their mutual responsiveness is in the pursuit of this commitment.

- Commitment to mutual support: In *SCA*, each agent is committed to supporting the efforts of the other to play her role in the joint activity.

Joint Activity Tracking and Mutual Responsiveness:
Mutual responsiveness is analyzed in terms of interlocking intentions and meshing sub-plans. In a joint collaborative activity, the intentions of the participants interlock in the sense that each agent intends that the collaborative activity go in part by way of the relevant intentions of each of the other participants. Furthermore, collaborative activity proceeds by way of sub-plans of the participants that mesh in the sense that they are co-realizable and that there be common knowledge among the participating agents of all these conditions.

In a Human-Robot collaboration activity, the robot not only needs to be responsive to human actions but also needs to keep track of the partner mutual responsiveness and commitment to the over all task. In the next section a brief description of the joint action in a collaborative joint activity is given.

2.2 Joint Action

Joint actions are inherent part of our daily (joint) activities, ranging from a handshake to the performance of a symphony [Clark 96]. Though these actions are performed seamlessly by humans but they require intricate coordination in time and space. A joint action is defined as "a social interaction whereby two or more individuals coordinate their actions in space and time to bring about a change in the environment" [Sebanz 06, Knoblich 11]. Joint action gives unique sense of agency for the human engaged in it, which depends on the type of joint action and the role played by the human [Pacherie 11].

2.2.1 What is It? Joint Action Formation in Human Human Collaboration

"Being able to coordinate one's actions with others in time and space means that the scope of potential products of action dramatically increases" [Clark 96]. Joint Action is a complex whole that builds on diversely rich cognitive capabilities requiring not only effective communication but coordination as well.

Research in Psychology [Knoblich 11] shows, that, the coordination for the Joint Action between participants can be :

- *Planned*

- *Emergent*

Planned

In joint cooperative actions humans sharing same goal intend to act together and therefore coordinate their actions to achieve their collective goal, for example two children working together to lift a pumpkin, figure 2.1. Planned coordination in a joint action, involves representations of the shared goal and agent's own part in achieving it. It requires shared task representation in the form of joint intentions and taking into account the joint perceptions, such as in the form of perspective taking and joint attention [Knoblich 11]. However, at minimum a planned coordination can be represented as a joint action outcome, one's own part in it and representation regarding how other agent can support to bring about that outcome [Vesper 10].

Emergent

Multiple individual acting in similar ways may involve in a emergent coordinated joint action. For example, in the game of "Tug of War", figure 2.1, each individual team member pulls the rope and their individual strength combines in attempting to pull the other team such that the marking on the rope closest to their opponent crosses the centre line. In the emergent coordination, coordinated behavior is independent of any joint plans or common knowledge and is result of perception-action couplings that make multiple individuals act in similar way, because their common processes are driven by the same cues and motor routines [Knoblich 11]. Spontaneous coordination may occur between individuals, for instance, pedestrians often fall into the same walking patterns [van Ulzen 08], who have no plan to perform actions together (as well as can occur during planned joint actions). The different sources of an emergent coordination are: entrainment, common affordances, perception action matching, and action simulation [Knoblich 11].

2.3 How Do We Do It? Joint Action Mechanisms in Human Human Collaboration

Joint action has multiple dimensions [Pacherie 11]:

- Number of participants: minimum 2 and maximum upto millions (e.g. protests, military coalitions),
- relationship among participants: Hierarchical (military) vs egalitarian (team members),
- extent and form of the division of labor among co-agents and thus to extent to which roles they play are specialized,
- nature of interaction among participants: virtual interactions (teleworking) or physical interactions (assembly task),
- nature of association formed by the participants: transient vs long-term,
- regulated by norms: Some joint actions depend on complex institutions and involve activities regulated by norm while others not.

Following are essential attributes of a Joint Action [Knoblich 11]:

- *Shared Task Representation/Task sharing*

(a) children working together to lift a pumpkin

(b) Tug of war, Ireland 600kg team in the European Championships 2009

Figure 2.1: Joint Action: a) planned coordination, and b) emergent coordination.

- *Joint Perceptions*
- *Action observations: Monitoring other's actions*
- *Action Simulation*
- *Action coordination*
- *Entrainment*
- *Affordances*
- *Action Prediction: Common Predictive Models, Action Simulation*

2.3.1 Shared Task Representation

Studies in the Neuro cognitive science show that individuals form shared task representations [Kilner 04, van Schie 04], as it helps individuals to plan ahead, in anticipation of others action instead of just reacting to others actions [Sebanz 06].

Shared task representation involves forming the necessary joint intentions and representation of one's own and partner's actions in the joint action. It provides the agents the flexibility in engaging in a joint action, as it specifies in advance the individual role for each agent, for instance, the robot is going to hold the table and the human is going to place wooden legs in the table in collaborative table assembly task. Also, it supports the relevant action monitoring and prediction processes and consequently enables real time interpersonal coordination [Pacherie 06, Knoblich 11]. Therefore, the ability to form shared representations of a task is the cornerstone of social cognition [Sebanz 06].

2.3.2 Joint Perception

Joint perception are important while planning a joint activity, it means taking into account coactor's perceptions into one's own representation of the other's task. Which includes perspective taking, i.e., by taking the other's perspective in situations where coactors' perspectives on a jointly perceived environment differ such as when two humans sit face to face looking at objects to be arranged on the table. It may can consist in inferring what other partner can or cannot perceive in situations where perceptual access to objects in the environment differs between agents [Brennan 09, Shintel 09].

Joint perception helps in establishing perceptual common ground between agents, facilitates monitoring coactors task and aids in coordination by adapting one's task accordingly [Clark 96]. *Common Ground:*" the sum of [...] mutual, common, or joint knowledge, beliefs, or suppositions" [Clark 96].

Forming joint perceptions may need acquiring joint attention, i.e., ability to direct one's attention to where a coactor is attending. It provides a basic mechanism for sharing representations of objects and events [Tollefsen 05, Frischen 09]. Therefore, for a successful joint action an accurate perception of peripheral actors as well as accurate predictions regarding the consequences of these actions is necessary [Bekkering 09].

2.3.3 Coordination in Joint Action

It takes *coordination* for people to do things together, no matter how simple, and it takes *communication* to achieve that cooperation [Clark 05]. One of the important feature of a joint action is how individuals adjust their actions to those of another person in time and space. It can not be just supposed that by sharing the task representation with partners, a seamless coordination will follow [Sebanz 06]. Also, important is to incorporate means of communication to instill coordination.

[Clark 05], describes two main means that govern coordination in the everyday joint activity:

- Linguistic means
- Material signals

Linguistic Means:

Clark ([Clark 96, Brennan 09]) epitomizes language as a form of joint action. Humans use language to achieve day to day activities and dialogue is often used to coordinate joint activities and is structured in particular, by the commitments people make in agreeing to engage in joint goals [Bangerter 03]. Therefore, verbal communication is the chief means employed in the human human interaction to coordinate joint activities. Though, it is not the sole means used, it can be used either alone or in conjunction with material signals to communicate.

Material Signals:

Besides verbal communication, humans also use extensively the material signals. Material signals mean communicative acts like pointing, gestures, actual placement of objects etc. Pointing and gestures communicate "*directing-to*" action between the individual in a joint activity, taking action to direct participants to focus attention to objects, events, place or themselves. Similarly in "*placing-for*" signal, participants place themselves, objects or actions in places/sites for the other to interpret.

People direct addressees to either to: other objects, locations, events using pointing, touching (touching at a location or object), exhibiting (showing object to draw attention) or poising (using object to point at something) in directing-to signals [Clark 05].

Similarly, in placing-for signals, for example placing an object, can be considered as direct preparation for the next steps in a collaborative activity and making actions public, which is an effective way of establishing common ground and also, an effective means of coordinating actions [Clark 05].

Material signals are used usually to sustain the joint activity, for instance, with pointing or with placement, and involves creating three phases of signals: Initiation, Maintenance, and Termination. For example sustained pointing, has three phases, each with its own characteristic interpretation [Clark 05]:

- Phase 1: Initiation, 'I now want you to attend to this'
- Phase 2: Maintenance, 'I continue to want you to attend to this'
- Phase 3: Termination, 'I now consider your attention to this to be complete'

Material signals as a whole serve as a communicative process where the transmitter and receiver establish joint attention to the signal itself, identifying what is being addressed, and interpreting transmitter's intention [Clark 05].

2.3.4 Action Simulation

Humans are good at predicting others' action, one way they do it is by simulating others actions. They match the observed action with internally performed actions and apply predictive models internally to predict timing and outcome of others actions, such process is called as action simulation [Sebanz 09]. Here, agents own internal model help guide her own actions in real time to predict other's actions [Wolpert 03]. This ability is crucial, as it helps predict what other is going to do in a collaborative activity.

2.3.5 Prediction in Joint Action

Coordination on how a joint action will be performed can be done effectively using verbal communication [Clark 96]. However, sometimes it requires more than just the verbal communication to coordinate, for example, in the game of football or to drive in heavy traffic. The football players or drivers need to predict other's actions (and relevant intention) to be proactive and coordinate their actions. Simulating others action can help in anticipating partner's actions.

Simulating other's action guided by shared task representation allows one to predict other's action and to imagine other's action when other's actions is not directly observable (for example, in tennis, partner's return volley may not be observed) and this simulation occurs when partner is perceived as an intentional actor [Sebanz 09].

Three critical aspects about others actions that predictions can deliver are: "what", "when", and "where" [Sebanz 09];

- The *what* aspect: It is important for predicting the type of action the other will perform and the relevant intention behind it. For example, if the task is two people assembling a toy, the partner will need to infer *what* object to look for, needed for assembling the toy.

- The *when* aspect: It is critical in the collaborative activities and important for the actions requiring temporal coordination. It is crucial for acting synchronously or in turns. For example, in the assembling a toy task, the partner will need to predict, *when* to provide the object needed by the other partner.

- The *where* aspect, Sharing space and attention: predicting where an action will happen is also important for coordination between actors helping to effectively manage the shared space, ranging from collision avoidance, to knowing that they are attending to the same object. In the toy assembling task example, the partner should predict *where* to handover object in the common space and detect if partner is attending to the object or not and help to reduce partner's physical and cognitive effort.

For a successful joint action an accurate perception of peripheral actors as well as accurate predictions regarding the consequences of these actions is necessary [Bekkering 09]. Joint action also requires attending to, objects and events together, which is important for the joint attention ability [Sebanz 09].

2.4 Joint Attention

Joint attention (figure 2.2 shows an example of joint attention) is a vital skill need for social competence in the humans. It develops around the age of 12-18 months in infants [Moore 01, Tomasello 00]. Children and adults that are unable to follow, engage and react to joint attention find difficulty in handling social situations and have impaired relationships as it affects the development of social skills and social interaction with people.

Figure 2.2: Joint Attention between a baby and her mother.

Joint attention is in simple term defined as the fact that two (or more) persons are looking at the same object [Butterworth 95]. Looking simultaneously is only one aspect of the whole mechanism [Tomasello 95] and there should be a "correspondence" between the persons involved in the interaction through a communication channel (the object) and there should be "mutual knowledge among them [Tomasello 95, Baron-Cohen 95b, Warreyn 05].

Tomasello [Tomasello 99] divides the joint attention in three types: check attention, following attention, and direct attention

1. *Check Attention:* Paying attention to the partner or to the object that he/she explicitly shows.

2. *Follow Attention:* Follow the gaze or the pointing direction of the partner.

3. *Direct Attention:* Influencing on the partner attention, with voice, eye gaze or pointing gestures.

Joint attention helps to create a type of perceptual common ground, serving two important functions:

- initiation of coordinated action (for instance, when individual follows other partner's gaze to an object to be manipulated),

- maintaining the coordination, once individuals are already engaged in a joint action (as when two people jointly attend to an obstacle while carrying an object together).

Joint attention implies that both actors know that they are both attending to the same object or location or event. It is important building block for developing social skills, for instance, *theory* *of mind*: ability to attribute belief, goals, perception, feelings and desires to themselves and others [Whiten 91], requires advance level joint attention skill [Baron-Cohen 95a]

In next section, we will explore a developmental joint attention model.

2.4.1 Joint Attention: A development Model

A development definition, from psychological research, is given by Tasker and Schmidt [Tasker 08]: "Formally, joint attention is defined as the use of communicative acts such as eye contact, person-object-person gaze shift, affective expression, and gestures to draw and direct a social partners attention to an object or event with the communicative intent of sharing the experience affiliatively or for the purpose of explanation, information, and clarification or affective contact in a spirit of mutual awareness and *cooperative understanding* or *confidence and confiding* in the intimate relationship between mother and child."

[Tasker 08] gives the operational definition of the joint attention using behaviour chains (see figure 2.3 1a and b)and describes a relevant developmental model of the joint attention (see figure 2.4 a).

The sequence or chain of behaviours required for the events of established joint attention (EJA) and consummative joint attention (CJA) to be coded is the following:

1. Initiation Act: the child or mother initiates engagement with the other for the purpose of attaining and then directing the others attention to an object, event, or activity;

2. Initiatory Response Act: the recipient responds behaviourally (e.g., through an orienting) or communicatively (verbally or nonverbally) within 5 seconds of the initiation act and the duration of this response is at least 3 seconds in order to establish evidence that the partners attention has been captured.

3. Response to Initiatory Response Act: the initiating partner then directs a communicative act or behaviour toward the recipient (for instance, a look to the recipients face) as evidence that the initiating partner is aware of the recipient partners attention toward his/her self and to the object, event, or activity, and therefore the recipient partners response is not rather on-looking behaviour or "passive joint attention".

4. Established Joint Attention (EJA): the mother and child now visually focus on the object or event of shared attention and communicatively and attentionally engage one another and the object through, for example, the exchange of smiles, vocalizations, verbalizations, for a minimum of 3 seconds. At this point, joint attention is considered to be established, and established joint attention (EJA) is recorded.

5. consummative joint attention (CJA): joint attention that is sustained or continues on from EJA through a sequence of two or more contingent and coordinated on-topic exchanges displayed by mother and child within 3 seconds of one anothers preceding response constitutes an episode of consummative joint attention (CJA).

6. Termination Act: a termination act produced by either the mother or child and results in the loss of the social partners attention for more than 3 seconds from the shared focus or topic of attention.

   Termination acts include:

a

CIA → MR1 → CR1 → MR2 ▶ EJA → Inside JA → MT/CT → Repair Act → Regained JA
→ Repair Act → Termination of JA
→ Termination of JA (no repair act)

CIA = Child Initiation Act; *MR1* = Maternal Response to CIA; *CR1* = Child Response to MR1; *MR2* = Maternal Response to CR1; *EJA* = Established Joint Attention; *CT* = Child Termination Act; *MT* = Maternal Termination Act; *JA* = Joint Attention.

b

MIA* → CR1 → MR1 → CR2 ▶ EJA → Inside JA → MT/CT → Repair Act → Regained JA
→ Repair Act → Termination of JA
→ Termination of JA (no repair act)

* MIA/MIA II
MIA = Maternal Initiation Act (Attention-Directing); *MIA II* = Maternal Initiation Act II (Follow-In); *CR1* = Child Response to MIA/MIA II;
MR1 = Maternal Response to CR1; *CR2* = Child Response to MR1; *EJA* = Established Joint Attention; CT = Child Termination Act;
MT = Maternal Termination Act; *JA* = Joint Attention.

Figure 2.3: (a) Joint attention behaviour chain following the display of a child initiation act. (b) Joint attention behaviour chain following the display of a maternal initiation act.Joint Attention between a baby and her mother, from [Tasker 08].

- physical movement away from the object, event, or activity of joint attention focus;
- greetings or other signals of leave-taking, termination, or cutoff
- statements and other acts that attempt to change the topic to another topic and other attention-directing behaviours that interrupt an established topic (e.g., show/offer-gestures)
- gaze aversion or looking around his/her the interaction or social partner and other active attempts by the child to distance him/herself or physically disengage from the mother such as arching of his/her back, squirming, turning, or looking around his/her surroundings or using part of his/her own body.

7. Repair Act: After establishment of Joint Attention, if either partner receives a termination act, he/she can apply a response act to the termination act within 5 seconds to regain joint attention.

It is a process oriented definition of joint attention, defining how to establish joint attention (EJA). EJA may terminate with an empty episode of joint attention (when joint attention is

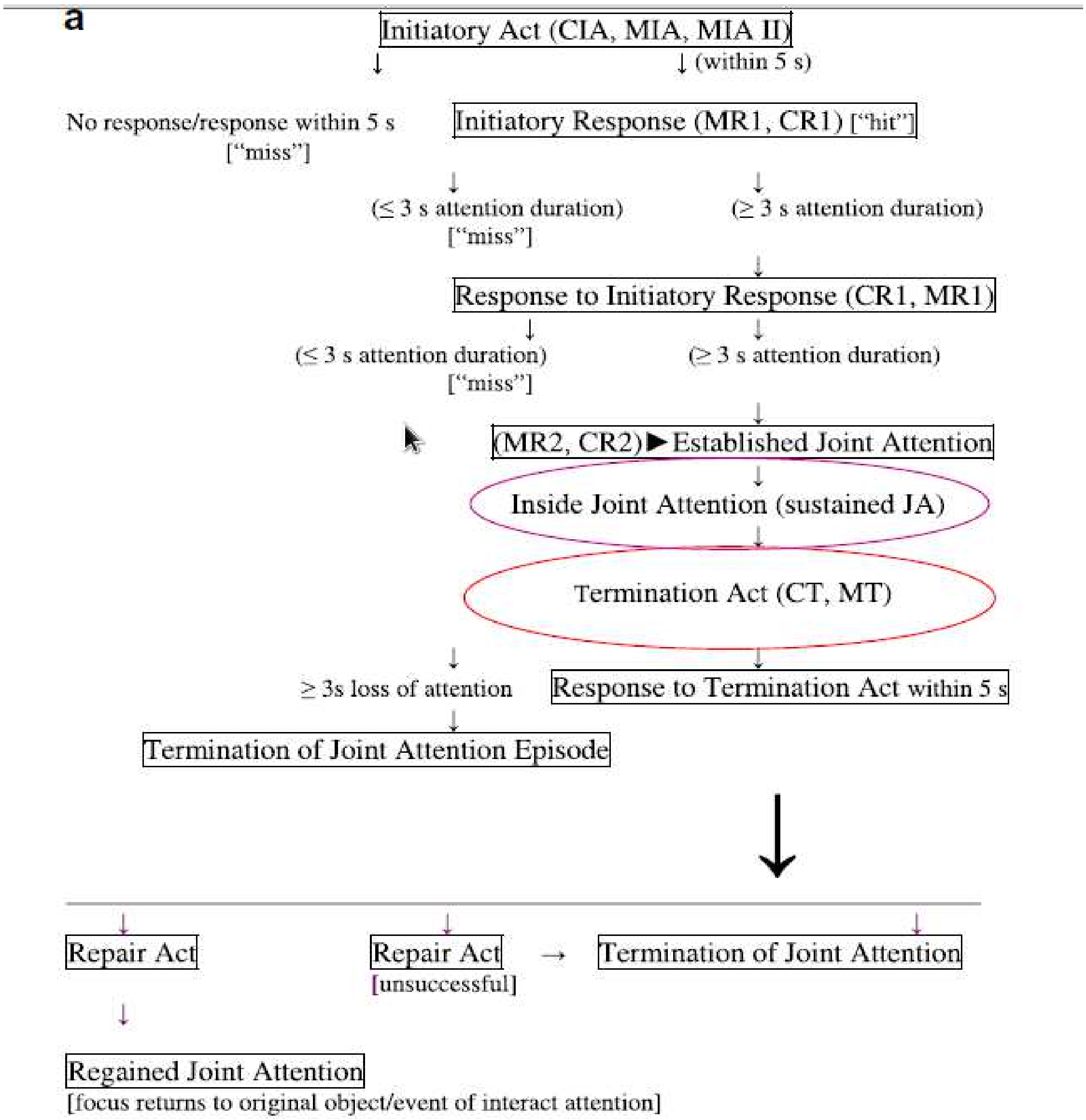


Figure 2.4: (a) A reconceptualization of joint attention in hearing mother-hearing child dyads (from [Tasker 08]).

lost within or less than one communicative exchange after EJA) or it may continue, marking an extended or sustained joint attention episode [Tomasello 86]. The social partners then engage in mutual activity and cooperatively participate in the task for unspecified duration of time, depending on the task complexity [Tomasello 86].

Joint attention has proved to be a basic ability for survival purposes in humans and it is present even on primates like chimpanzees [Tomasello 08]. Joint/Shared attention is one of psychological abilities in human to human interaction that a robot must have for an effective human-robot interaction.

2.5 Summary

This chapter gives general background on philosophical, psychological and cognitive sciences concepts of the human human collaboration and what are its important building blocks. These studies show that collaborative joint activity can be complex, requiring planned coordination and explicit monitoring to achieve a task.

Key essential aspects of a successful collaboration are:

- Establishing joint attention and engaging a partner in a collaborative task.
- Monitoring, using a combination of action simulation and action prediction, is important for relevant task progress and showing proactive behaviors.
- Using the coordination devices for a successful collaboration. Which include verbal and material signals (gestures, pointing, etc.).
- "When" part in a joint action is important, i.e., timing of an action is also critical.

So, for a seamless social human robot collaboration, robots will need to incorporate these characteristics to be able to successfully collaborate with humans.

Chapter 3

Towards Human Robot Collaboration

3.1 Introduction

Robots have come a long way from their successful industrial work to improve productivity, doing hazardous and monotonous tasks. They are increasingly being employed to assist humans outside the industrial milieu, in places such as homes [Parlitz 07], hospitals, elderly care centers [Pineau 03a, Wada 06], and even providing assistance to astronauts in the outer space [Bluethmann 03]. Robot companions can help tackle the problem of aging population in the developed world. A robot can allow the elderly to maintain their independence by performing daily living tasks and also interact in a safe and friendly manner. This can help reduce the health care costs and improve the quality of life for the elderly.

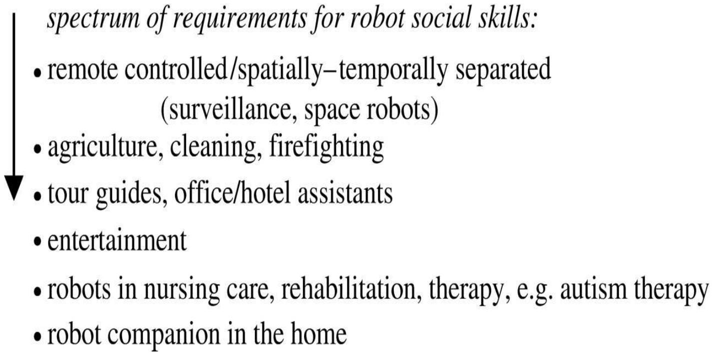
In this chapter, description of the research in Human robot interaction, with a focus on human robot collaboration and proactive robot behavior is given.

3.2 Human Robot Interaction

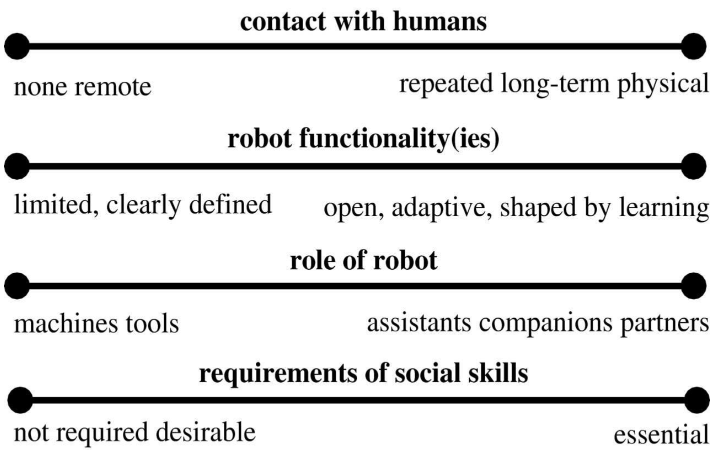
Traditionally, autonomous robots have been employed in areas where little or no interaction is required, such as; automobile industry, inspecting oil wells, search and rescue operations or for exploring planets. These robots are usually tele-operated and supervised by a human operator. Recent additions of service robots, like, vacuum cleaning robots, and autonomous lawnmowers, into the everyday human environments, have increased their contact with a common person, though, no high level interaction is involved with the human. The service robots are now evolving to acquire more important roles, such as, assistants, hospital workers or elderly care helpers, where social interaction is an important part of robot activity.

The required level of social skill varies with the task, and role the robot has in the interaction. [Dautenhahn 07], shows the increasing requirements for social skills in different robot application domains from remotely controlled to a robot companion in the home (as shown in figure 3.1(a)) and gives different evaluation criteria for the required social skills, depending on the contact with the human, the functionality required or role of robot (shown in figure 3.1(b)).

Figure 3.1(a) shows a list of different application domains, where increased level social skills are required. For example, a surveillance robot is not required to be social, unless it needs to



(a) Increasing requirements for social skills in different robot application domains.



(b) Evaluation criteria to identify requirements on social skills for robots in different application domains. Contact with humans ranges from none, remote contact (e.g. for robots operating in deep-sea environments) to longterm, repeated contact potentially involving physical contact, as is the case, for example, in assistive robotics. The functionality of robots ranges from limited, clearly defined functionalities (e.g. as vacuum cleaning robots) to open, adaptive functions that might require robot learning skills (e.g. applications such as robot partners, companions or assistants). Depending on the application, domain requirements for social skills vary from not required (e.g. robots designed to operate in areas spatially or temporally separated from humans, e.g. on Mars or patrolling warehouses at night) to possibly desirable (even vacuum cleaning robots need interfaces for human operation) to essential for performance/ acceptance (service or assistive robotics applications).

Figure 3.1: WHAT SOCIAL SKILLS DOES A ROBOT NEED? from [Dautenhahn 07]

cooperate with other human partners, whereas a robot companion will require a complex set of cognitive and social skills to be acceptable for humans [Dautenhahn 05, Dautenhahn 07].

Human robot interaction model can also be classified according to a mental model a human has of the robot [Breazeal 04]:

- robot as tool.
- robot as cyborg extension.
- robot as avatar.
- robot as sociable partner.

In the first case, the human uses the robot as a tool for performing a task and views it as such, requiring task specific supervision. In the second case, the robot is part of the human body, for example, a prosthetic arm. In the third case human views robot as self projection to communicate with some one else from far-away. Finally, the last one represents the robot as a sociable partner and in this case humans expect an interaction experience with the robot, similar to interacting with other humans. This requires understanding of these similar cognitive skills in the humans and their adaptation for the human robot interaction.

3.2.1 Social Human Robot interaction

In socially interactive robots the social interaction plays a key role, different from other robots that involve conventional HRI, such as those used in teleoperation scenarios [Fong 03a]. Social human robot interaction involves robots acting as co-workers, partners, assistants or companions, with the human. This requires having not only skills to carryout tasks but also require peer-to-peer interaction skills and the flexibility to drive interaction with the different humans.

Some key attributes [Dautenhahn 07] the socially interactive robots need to have: express and/or perceive emotions; communicate with high-level dialogue; learn models of or recognize other agents; establish and/or maintain social relationships; use natural cues (gaze, gestures, etc.); exhibit distinctive personality and character; and may learn and/or develop social competencies.

Robot do not necessarily need to have all the social skills and can be regarded by the human partners as acting socially. Robots can be socially situated, i.e., robots are able to separate humans from other agents (based on sensor information) and interact with the environment. The social interaction emerges from the robot being situated in and responding to its environment and thus may not have any model of social intelligence or human like appearance [Dautenhahn 07].

A robot companion, will need to behave socially and require some set of social skills to be able to achieve tasks for and/or with the human and interact with them.

3.2.2 Robot as a Companion for the Human

It has been the long lasting goal of AI to create intelligent robot companions that can live and share the space with humans. They are envisioned as service robots to be used in the homes and their principal expected role is that of an assistant [Dautenhahn 05]. [Dautenhahn 07] define a robot companion as follows:
"A robot companion is a robot that (i) makes itself useful, i.e. is able to carry out a variety of tasks in order to assist humans, e.g. in a domestic home environment, and (ii) behaves socially, i.e. possesses social skills in order to be able to interact with people in a socially acceptable

manner."

Show Initiative:

A robot companion's main role would be to assist the human in certain tasks by identifying and responding to his or her needs. The robot will need to demonstrate a socially acceptable and comfortable behavior towards the human. Also, important for a companion robot is to take initiative and be proactive if necessary, and is an important characteristic of a social robot [Breazeal 03]. For example, if an elderly human intends to read a book and will require his or her reading glasses, then the robot can either wait for his explicit command or can take initiative and bring the glasses to the human. In this way the robot companion can proactively help the human and be cooperative.

Show Ability to Collaborate:

Collaboration and teamwork is an integral part of human human cooperation, in fact, one of the reasons for the human intelligence evolution [McNally 12]. Robot companions could be very good at autonomous tasks, but the main difficulty will arise when it will need to cooperate and collaborate with a human during a social human robot interaction. Human robot collaboration will be essential for any robot assistant and important part of the interaction experience. The collaboration can be as simple as handing over an object to the human and can be more complicated, such as, the robot being a coworker with the human in a factory.

3.3 Robot Initiative Taking

Humans from very young age show proactive behavior and take initiative. Children show curiosity and proactively interact with the environment, which leads to learning and the acquisition of knowledge [Carlton 98]. This curiosity, driven by intrinsic motivation, is linked to higher learning and achievement in children [Stipek 02, Pintrich 02].

[Breazeal 02, Breazeal 03] describes that a social robots is a robot that proactively engages with humans in order to fulfill internal social aims. Therefore, it is important for a companion robot to take initiative and be proactive. This requires robot to:

- identify the proactive behavior to achieve,
- recognize relevant situation to take initiative,
- create and manage relevant robot goal,
- to have a plan or a recipe for the relevant task,
- to supervise the relevant task execution and its monitoring.

Besides, another form of proactive robot behavior would be to respond to human emotional states and show empathy, for example, if a human is moving randomly in the room and every now and then passes in front of the robot then robot probably can infer that he/she is in distress and needs some kind of counseling. It is important for the acceptation of a robot companion in the context of a long term interaction with the human [Duhaut 10]. Next, some existing examples of robot initiative taking are given:

3.4 Robot Initiative Taking Examples

Work related to proactive robot behavior initially began with mixed initiative approaches. In mixed-initiative approach focus is on initiative shifts between human and robot, and is related to robot tasks. Mixed-initiative (also called facilitated initiative [Few 06]) based on operator modalities [Curtis W. 06, Bruemmer 07] use a control architecture that allows robot to have different levels of autonomy. It can be in tele-operated, safe mode, shared control, collaborative task mode (CTM) and totally autonomous mode. Robot can take varying degree of "initiative" based on the mode chosen, the current context and even the difficulty of the task at hand. For example robot takes initiative and leads in navigation tasks in CTM mode.

A planner based mixed initiative approach is used in search and rescue scenario by [Finzi 05]. Its architecture is based on model based execution monitoring (activities model defined) and a reactive planner monitors task execution using that model. If the human operator changes execution order, planner responds by proposing a new execution order to him.

[Adams 04] uses an affect based mixed-initiative interaction approach using human robot interface. Robot responding to changes in human operators emotions (detecting drowsiness, inattentiveness etc) can take initiative from or may offer it back to human. [Acosta 08] describes emotion based planning for mixed initiative interaction.

In [Schmid 07], the robot takes initiative and acts proactively for removing ambiguity in the human intentions. Its architecture consists of intention recognition using "Dynamic Bayesian Networks" and a task planner for task execution. Planner executes robot tasks for correctly inferred intentions and for ambiguous intentions planner selects an action from a table (defined by the programmer) to induce human response and remove ambiguity.

In ROBOCARE project [Cesta 07b, Cesta 07a], the robot shows proactive behavior based on activity monitoring and the activities are defined as a schedule. The constraint violations in the schedule trigger system initiative and perform some action. The action is in the form of an alarm or a verbal action, giving suggestions to the person being assisted.

Also, [Hanheide 10] use a plan based goal generation and management framework for an exploration task. In this, the robot explore an area and planner generates possible goals for its exploration which are then accepted or discarded by a filtration layer.

In our context, proactive behavior is not based on constraint violations [Cesta 07b],or governed by operator modality [Curtis W. 06, Bruemmer 07] or planning based [Finzi 05, Schmid 07].

Our system aims at multi-layered proactive behavior, it consists of a whole system from detection of robot goals (for itself and as well as for human goal) using the Situation Assessment module, their management through task agenda. Then, a task planner provides planning mechanism that plans taking into account human preference and capabilities and finally, an execution and monitoring system takes into account human at every level of interaction.

Also, important are the affect based approaches [Adams 04, Acosta 08] as they are more suited for initiative taking in close human robot interaction scenarios. A framework with dynamic priority assignment capability can be useful to enhance the management of high level robot goals, for example, [Hanheide 10] framework can be exploited for improving our framework.

In the next section, a description of human robot collaboration is given.

3.5 Human Robot Collaboration

Some times a robot and a human will work together and collaborate. They can even share a common goal. Therefore, the robot becomes not just an assistant but a partner and helper. The robot may also ask human help when needed, using his advice and decision making skills, as appropriate [Fong 03b]. Humans and robots must be able to coordinate their actions so that they interact productively with each other, rather than just sharing the same space. The human robot collaboration models are inspired from the human human collaboration models [Green 08], for example, joint intention theory, joint attention etc.

Joint Intention Theory

One of the important underlying concepts of collaboration is the agents forming joint intentions regarding the goal. The joint intention theory developed by Levescque and Cohen deals with the collaborating agents forming joint persistent goals [Levesque 90, Cohen 98], using the notion of commitment and intention in the joint goal. Commitments are goals maintained over time, resisting capricious abandonment.

Agents can count on the commitment of other members, first to the goal, and then, if necessary, to the mutual belief of the status of the goal. This implies important need for a mechanism of coordination in the robot decision making to continue the collaboration and end it when required. The coordination in turn requires need for the *communication* between the agents.

Human Robot Joint Attention

Joint attention is an important part of the human human collaboration, it is the basis for establishing the joint intention between the agents and important for showing engagement in a collaborative task. Agents form a plan to achieve a shared intention and the plan includes the goal and the means to achieve it [Tomasello 05]. The attention is the intentionally directed perception [Tomasello 95], that helps agent realize its action plan efficiently. A robotic companion will need to check the human perceptual focus of attention for both successful collaboration and for the safe achievement of the task.

Engagement in the Human Robot Collaboration

Engagement is a key process in human robot interaction [Sidner 05], which helps identify and monitor partner commitment in the interaction. [Rich 10] endows engagement with four types of connection events:

- Directed Gaze: One person looks and points (optionally) at some object or group of objects in the environment.
- Mutual Facial Gaze: Initiator looks at responders face and responder's looks at the initiator's face.
- Adjacency Pair: Utterance with minimal overlap by each of two speakers, such as first utterance initiates second utterance, for example, question answer pair.
- Backchannel: Responders directs the conversation with a short verbal or gestural communication, for example, yes, no or nodding etc.

Towards Coactivity

[Johnson 10] propose the notion of coactivity for the human robot collaboration. Coacitvity means designing collaboration as a task involving joint actions not just robot autonomous actions, and there is underlying interdependence between them. These joint actions, also called the group participatory actions [Clark 96], due to their interdependence, require a collective obligation on the participants. The relevant obligations [Van Diggelen 10] or joint commitments in a collaboration are necessary to model, as they support the notion of reciprocal actions in a collaboration. This favors an implicit compulsion to engage in and maintaining the interaction. Therefore, it is important to describe the collaboration in terms of "coactivity".

Uncertainty Management in Human Robot Collaboration

Human robot collaboration involves a robot interacting with a human in real environments, requiring robustness and seamless interaction. However, a robot's observation capabilities are limited as the real world is only partially observable and events flow is non deterministic, increasing the uncertainty with respect to the observed human behavior and the intention behind it and ambiguity surrounding his/her engagement in the interaction. The robot needs to decide which of all possible actions should be done next, based on all observations so far and on some fixed background knowledge.

The Partially Observable Markov Decision Process (POMDP) [Kaelbling 98] provides a mathematical framework for modeling sequential decision-making under uncertainty and is an extension of the Markov Decision Problem (MDP). POMDPs help model various real world decision making process, for example: DEC-POMDP [Beynier 10] offers a rich framework for cooperative sequential decision making under uncertainty, distributed POMDPS [Kwak 11] for multi-agent teamwork, [Nair 05] Hybrid BDI-POMDP based framework for multiagent Teaming, etc.

POMDPs are more particularly, useful to model multiagent collaboration as they allow uncertainty in the agents observations in addition to the agents actions. Agents must therefore maintain a probability distribution over the set of possible states, based on a set of observations and observation probabilities. A decision about which action is most favorable for the collaboration can be derived from a policy, mapping it to any possible belief distribution, using the probabilities of events flow into the future and maximizing the associated reward.

Next, a brief description of the related work for the models of collaboration is given.

3.6 Models for the Human Robot Collaboration

POMDPs are being used extensively in HRI [Broz 11, Karami 09, Karami 10, Karami 11a, Fern 07a, Armstrong-Crews 07, Rosenthal 11b, Rosenthal 11a, Mouaddib 10] in various contexts, like modeling uncertainty in speech recognition [Schmidt-Rohr 08b, Schmidt-Rohr 08a], switching model between verbal and non-verbal HRI [Matignon 10], assistive robotics [Taha 08, Pineau 03b, Fern 07b], (cost-based Markov process is also used [Hoffman 07]), social robotics [Broz 08, Broz 11] and also to seek help from Human Observation Providers [Rosenthal 11a].

One class of such research concerns the human robot social interactions where the intention of the human is represented as an unobservable part of the POMDP state space. Human intention can be inferred from his observed actions by modeling human behavior in the POMDP transition function [Broz 11] and the focus is on behaving socially while pursuing its own goal. Our focus is on deriving a policy for robot collaborative behavior and the social aspect comes from higher level task planner [Alami 05].

Another class of HRI research concerns planning for asking the human for help where the human is considered as information provider. In Oracular Partially Observable Markov Decision Processes (OPOMDP) [Armstrong-Crews 07], it is supposed that human is available permanently to provide the information. Whereas, in HOP-POMDP (Humans Observation Provider POMDP) [Rosenthal 11a] and MI-MDP (Mixed Markov Decision Processes) [Mouaddib 10] studied the likelihood that the human is available. [Rosenthal 11b] used, "Learning the Model of Humans as Observation Providers" (LM-HOP) POMPDs to learn the accuracy of human availability.

Similar to the model we have used, in [Fern 07b] POMDP model is used for selecting assistive actions after estimating the possible human goals by using the Q-function values of a representative optimal human MDPs. They infer these values in a heuristic to approximately solve the POMDP. The resulting policy chooses an assisting action when there is no goal ambiguity, and select $no-operation$ action when the belief is highly ambiguous. Policy is derived by solving Q-MDP whereas, in the model we have used, policy is obtained by solving POMDP (as coactivity tasks are divided in small problem to be tractable) and also with our approach the policy of the robot takes into consideration dynamic nature of environment in which a human can act while robot is perfomring an action whereas in their model human action is only expected after robot chooses a $no-operation$ action.

In the model we have used the uncertainty about human engagement, is managed by using policy derived via rational HMDs(Human Makov model) [Karami 11b]. It helps to engage or re-engage the human in the collaborative activity. Also, it helps to end a collaborative activity in case the human has left or is not cooperating. Whereas [Rich 10, Holroyd 11] use engagement as an explicit robot task, using notion of connection events to support engagement with the human. [Holroyd 11] describes a way to generate the connection events for human robot collaboration, using *turn fragments* encoded in a EBML (extension Behavior Markup Language BML [Vilhjálmsson 07]). These turn fragments are consumed by turn policy and reference policy components, which help generate robot initiated connection events. Also, included in their system are *Response Policy* and *Maintenance Policy*, helping robot to respond to the human initiated connection events and maintain the connections during engagement. In essence, the connection events are generated for the engagement using a predefined policies specific to the task.

3.7 Summary

In this chapter, important aspects related to human robot social collaboration were given. These aspects are desirable in a socially acceptable robot companion. It includes the robot taking initiative whenever possible, especially where it can provide help to the human partner. Also, important in the human robot collaboration is, taking into account inherent uncertainty in the human robot interaction. This, requires the use of coordination devices; such as, communication to reduce the ambiguity in the human intention and engage/re-engage human in the collaborative task. Some examples regarding robot initiative taking mechanism from literature are described and also, shown relevant models of human robot collaboration.

Chapter 4

Experimental Robotic Platforms and System Architecture

4.1 Introduction

Robotic research needs support platforms: robotic platforms to actually test and run the systems developed and software platforms to build these systems. First, we will present our robotic platforms: Jido and PR2 Robot and then the different capabilities on these platform supporting the overall HRI Research. These experimental platforms have been developed and obtained in the context of two major European projects: COGNIRON [1] and CHRIS (Cooperative Human Robot Interaction Systems)‘[2], the aim being, develop robots that can cooperate with humans and enable safe human-robot interaction.

The software support capabilities are also, important for having a meaningful interaction with the humans; the robot requires a robust multi-component system in software as well as at hardware design level. This system should be efficient, flexible but also easily extensible. These components range from human detection and tracking to the human aware navigation and manipulation, necessary for the human robot interaction.

4.2 Description of Robotic Platforms

The integration of work and experimentation plays an important role in the research and requires supporting platform and software architecture. The work in this manuscript was integrated on the evolving platform of Jido (Figure 4.1) and on PR2 robot (Figure 4.2). Jido has evolved over the years, therefore some earlier work was demonstrated on Jido equipped with a Mitsubishi PA10-6C arm and later that was replaced with a Kuka LBR-IV arm. First, a short description of the robotic platforms is given, and then, software components of the platforms are presented.

4.2.1 JIDO

Jido is developed at LAAS-CNRS for conducting research on human-robot interaction. It is an evolving service robot (Figure 4.1), currently has a lightweight manipulator KUKA-LWR-IV arm, with seven degrees of freedom, mounted on a non-holonomic Neobotix platform. Earlier, Jido had

[1] www.cogniron.org/
[2] http://www.chrisfp7.eu

a Mitsubishi PA10 arm, having six degrees of freedom. The arm end effector was either a Schunk SAH hand or three finger gripper. The robot also has two stereo vision cameras and custom mounted Microsoft's Kinect sensor. Computing power is provided by four computers.

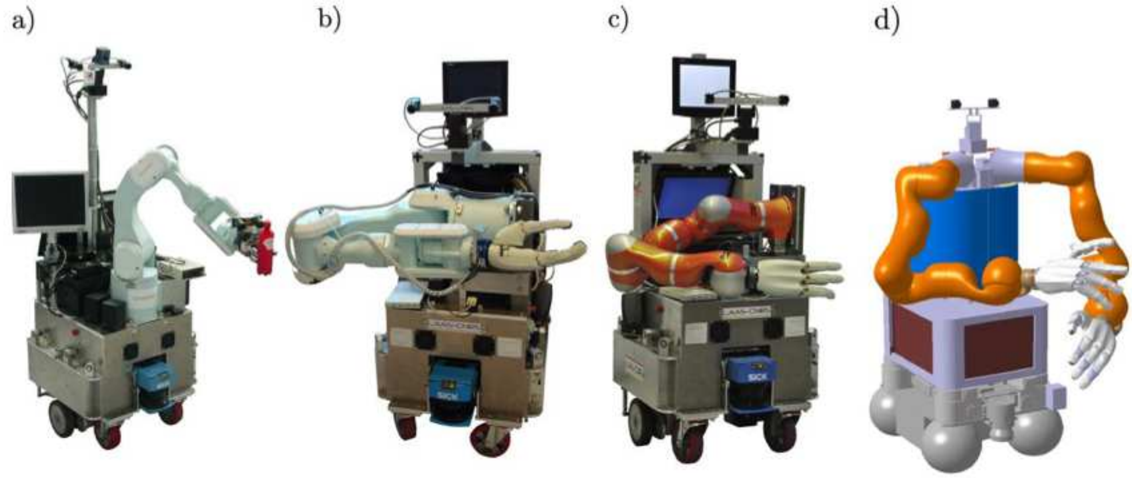


Figure 4.1: Jido, its evolution over the years: a) Jido with Mitsubishi PA10 arm and a gripper b) Jido with Mitsubishi PA10 arm and Schunk SAH hand c) Jido with KUKA-LWR-IV arm d) JIDO II: Future Jido with two KUKA-LWR-IV arms.

4.2.2 PR2

PR2 (Personal Robot 2) [3], Figure 4.2, is a robotic platform developed by Willow Garage. It supports an open architecture (user's can modify hardware of the robot) and uses ROS (Robot Operating System) [4], which helps the different teams working with ROS and using PR2 exchange and share their work. PR2 has two back drivable arms, with seven degree of freedom, attached to a torso mounted on a mobile base. It is also equipped with a wide range of sensors, Microsoft kinect, and cameras mounted on the head attached to the torso, camera on the arm for calibration and laser scanner, etc.

4.3 Architecture

4.3.1 LAAS Architecture

The LAAS architecture [Alami 98] for autonomous system was developed incrementally over many years and is implemented on all mobile robots at LAAS-CNRS. It is a three-levels architecture which consists of functional, decisional and executive layer (figure 4.3):

[3] http://www.willowgarage.com/pages/pr2/overview
[4] http://www.ros.org/

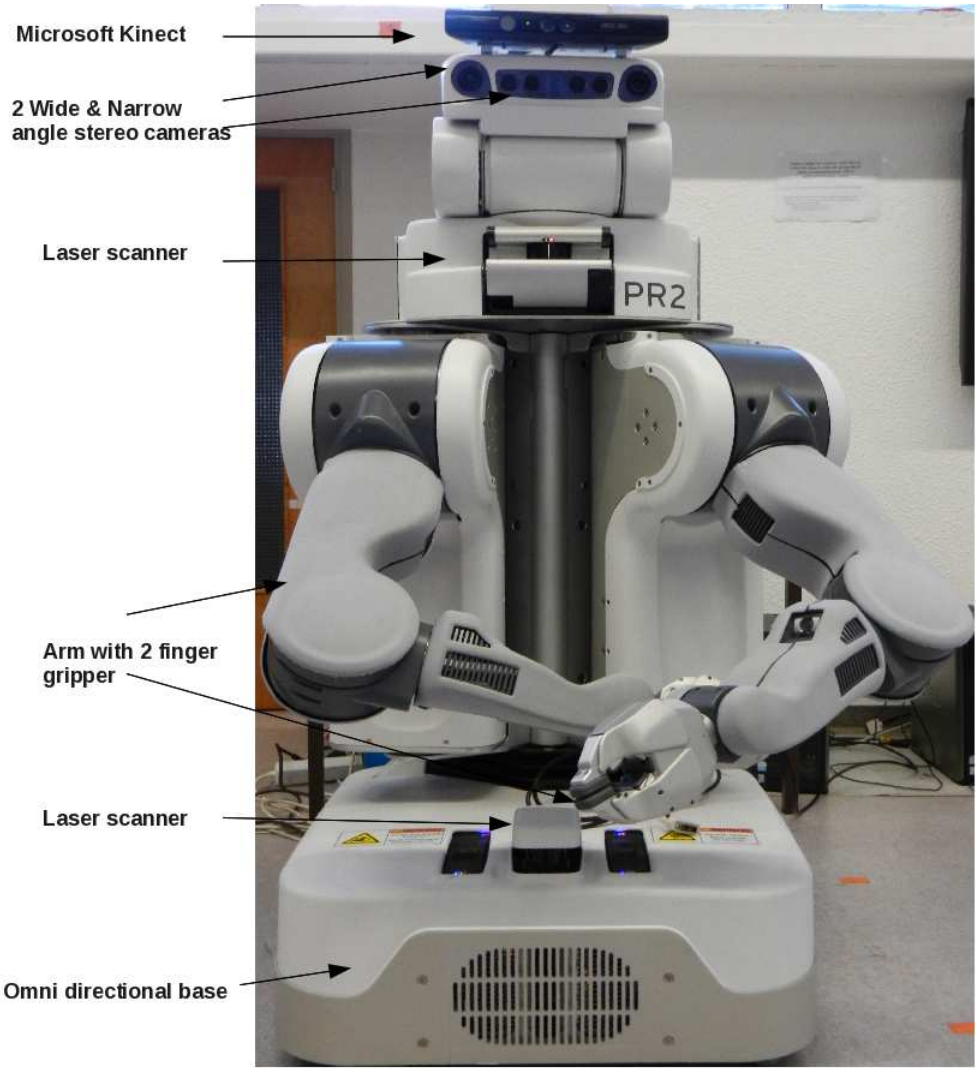


Figure 4.2: PR2 robot and its various sensors

- Decisional layer: This layer provides decision capabilities to the robot. It is the top most level which produces routine capabilities such as: to produce task plans, recognize situations, execution, etc.. it includes:
  - A procedural reasoning system OpenPRS [Ingrand 96] is connectd with lower levels to which it sends requests that will initiate actions (sensor/actuators) at lower levels to which it sends queries that will initiate actions (sensors /actuators) and is responsible for the action supervision and reacts to the events from lower levels or operator commands.
  - A high level task planner and / or a plan library,
  - A knowledge base.

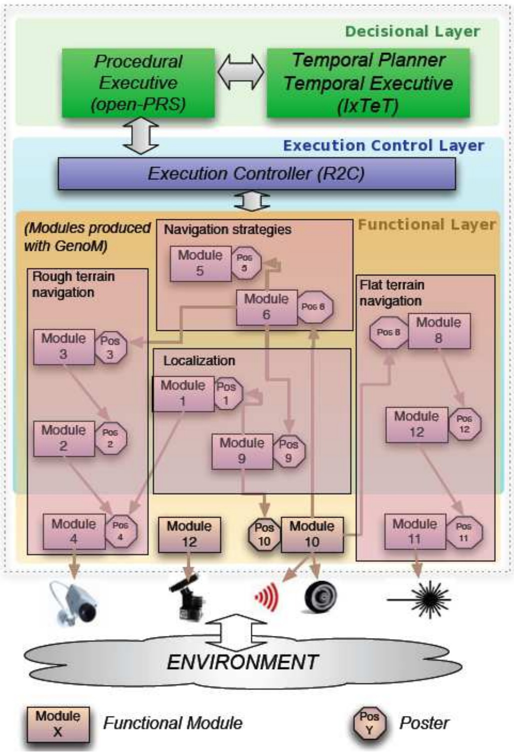


Figure 4.3: Illustration of the LAAS architecture [Ingrand 07].

- The Functional layer: This layer contains the perception and action functional components of the robot. Control loops and data interpretation are encapsulated into GenoM [Fleury 97] modules. The modules have direct access to the robot hardware. These modules are activated by requests sent by the decisional layer, according to the task to be executed. They send reports upon completion and may export data in posters to be used by other modules. This layer provides a level of modularity and generality that eases integration of modules.

- The execution control: It is the interface between the decisional and the functional layer.

4.4 System Support Components

The software architecture on Jido is based on the LAAS architecture [Alami 98] with various functional level modules supporting the higher level decision making and execution. The system architecture used for the proactive robot behavior (chapter 5), is shown in figure 4.4. Figure 4.5, shows the software components used on the current robotic platforms (JIDOKUKA, PR2) and figure 4.6, shows their relevant instantiation.

The functional layer is composed of modules, some of which are specific to the hardware on the platform and others more general purpose (reusable on other robots, for example, PR2):

- Sensing Functions (related to perception)

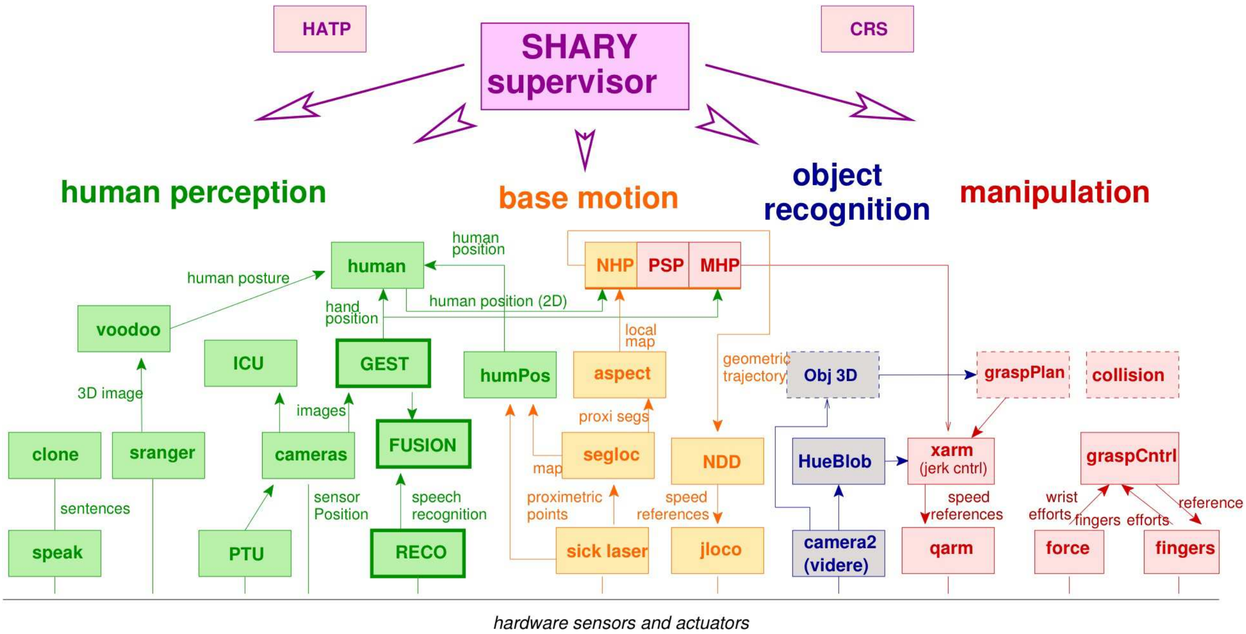


Figure 4.4: The architecture adapted for proactive robot behavior. Higher level decision components (SHARY, HATP), and other modules of the functional layer.

- SICK module: for localizing the robot in the environment, using SICK Laser scan data;
- Module MOCAP: Marker based detection and tracking of the objects in the environment using Motion Capture system;
- Module NIUT: 3D Human body parts tracking using Microsoft Kinect data Rights;
- Module VIAM: Stereo Camera image acquisition;
- Viman module: Tag based Object identification and localization

- Actuator Functions (control modules)
  - JLOCO module: allows you to control the robot platform;
  - Sahand module: Controls Schunk SAH anthropomorphic hand;
  - LWR module: Controls the arm, it is the interface with the Kuka arm.

Currently, the main intermediary placeholder for knowledge are: SPARK [Sisbot 11], for managing the geometric knowledge and ORO [Lemaignan 10], for managing symbolic knowledge. Both play important role in the higer level reasoning support [Alami 11]. A brief description of both follows:

SPARK:

SPARK (Spatial Reasoning and Knowledge [Sisbot 11]), figure 4.7, the geometric reasoning component, plays a central role in our architecture and is responsible for geometric information gathering and symbolic facts production and inference based on geometry. SPARK maintains all

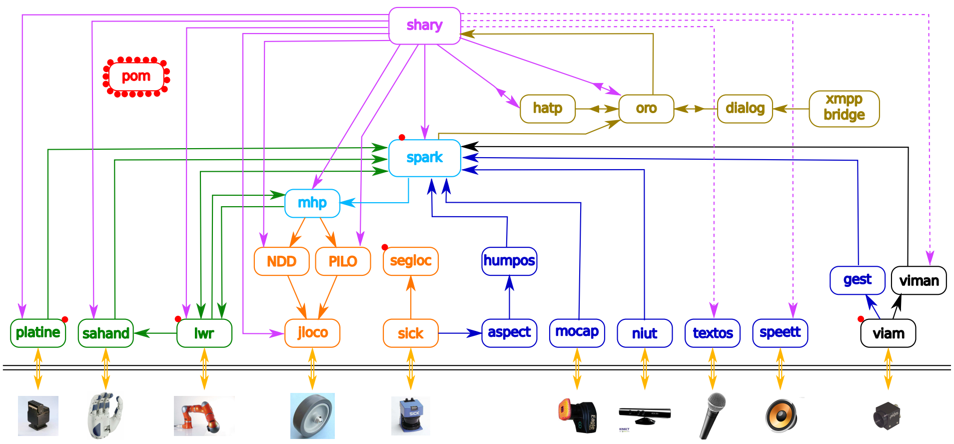


Figure 4.5: The whole architecture. Higher level decision components (SHARY, HATP, ..), symbolic and geometric knowledge module (ORO, SPARK) and other modules of the functional layer.

geometric positions and configurations of agents, objects and furniture coming from perception and previous or a priori knowledge.

SPARK generates symbolic relations between objects and agents by using perspective taking and spatial reasoning and also can produce different facts (like Agent Mightabilities [Pandey 10]), for example Human visibility (what objects are visible to the agent) or reachability (what objects are reachable for the agent). These facts are then stored in ORO.

ORO:

The facts produced by SPARK are stored in *ORO*. Open Robots Ontology [Lemaignan 10] (ORO), figure 4.8, is a central symbolic knowledge base. It stores independent knowledge models (as ontologies) for each agent (the robot and the humans it interacts with). The robot architecture components (like the executive layer or the situation assessment component) can then store the agents beliefs in specific models. Each of these models is independent and logically consistent, enabling reasoning on different perspectives of the world that would otherwise be considered as globally inconsistent (for instance, an object can be visible for the robot but not for the human). A component can for instance subscribe to events of kind "[?agent isVisible true, ?agent type

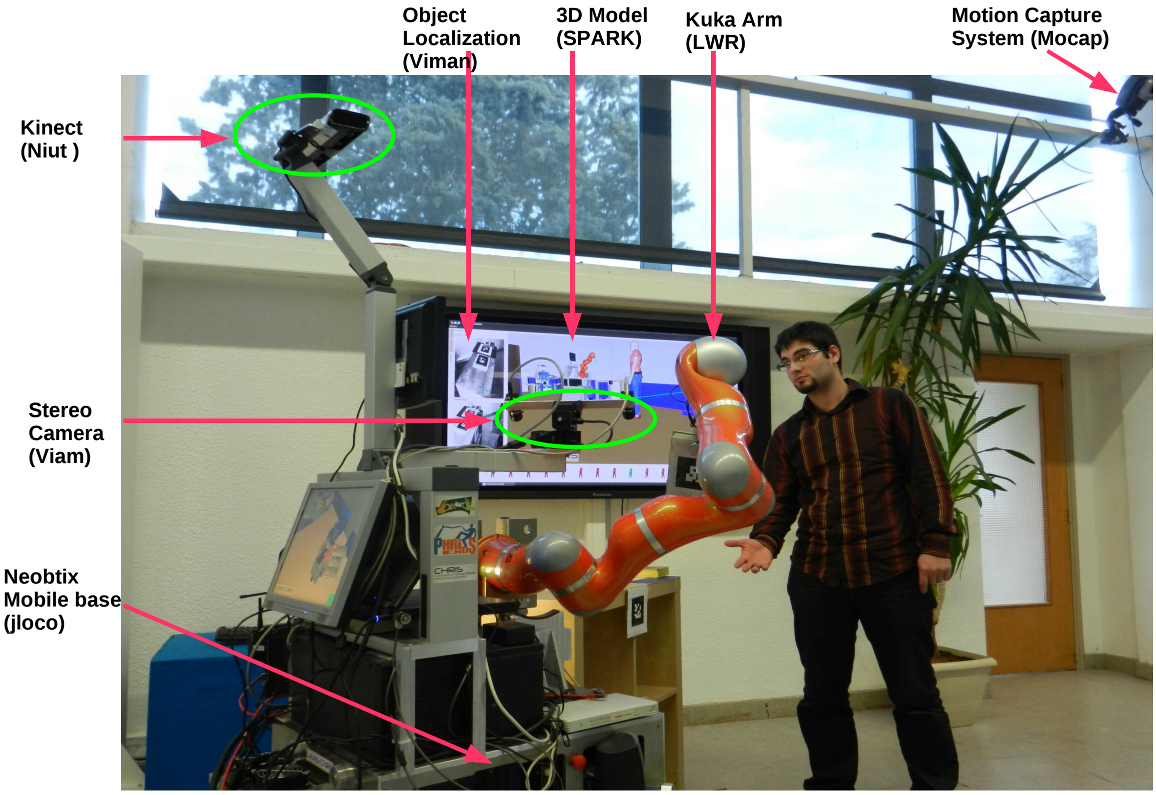


Figure 4.6: Software components and their relevant input sensors. Also, SPARK 3D environment representation with objects, the human and the robot is displayed on the screen.

Human]". As soon as SPARK produces the event, detected by the perception layer, human in the robots field of view and accordingly updates the knowledge base, the executive layer would be triggered back. The event framework also takes advantage of the inference capabilities of ORO. Thus an event can be indirectly triggered if its triggering conditions can be inferred to be true.

Also, important for the human robot interaction is the robot navigation and manipulation with the objects. Therefore module "MHP", integrates a human aware motion planner [Sisbot 08], with intelligent robot placement [Marin-Urias 08] and a manipulation planner [Gharbi 08].

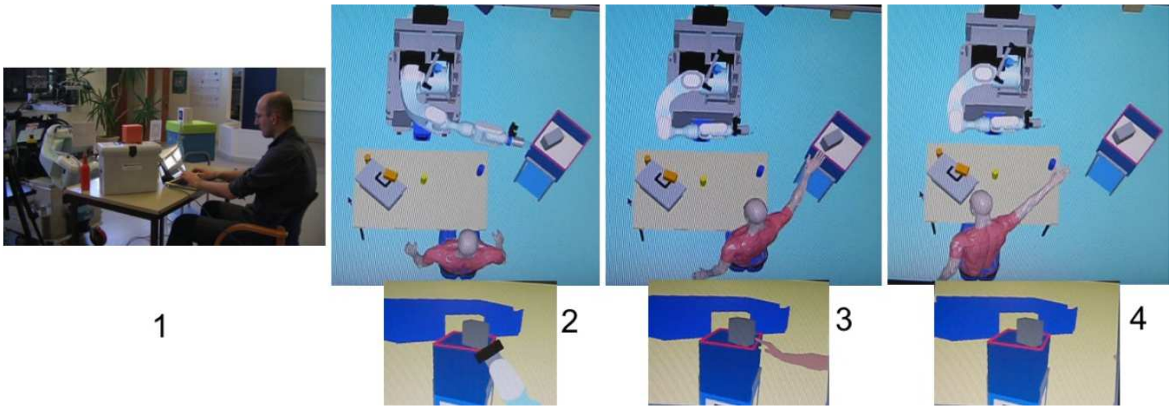


Figure 4.7: SPARK: An example illustrating the reachable relation. The relation is computed from the perspectives of both the robot and the human. The computed posture at each step is illustrated with a global view of the scene (top), and from a closest view (bottom), taken from [Sisbot 11].

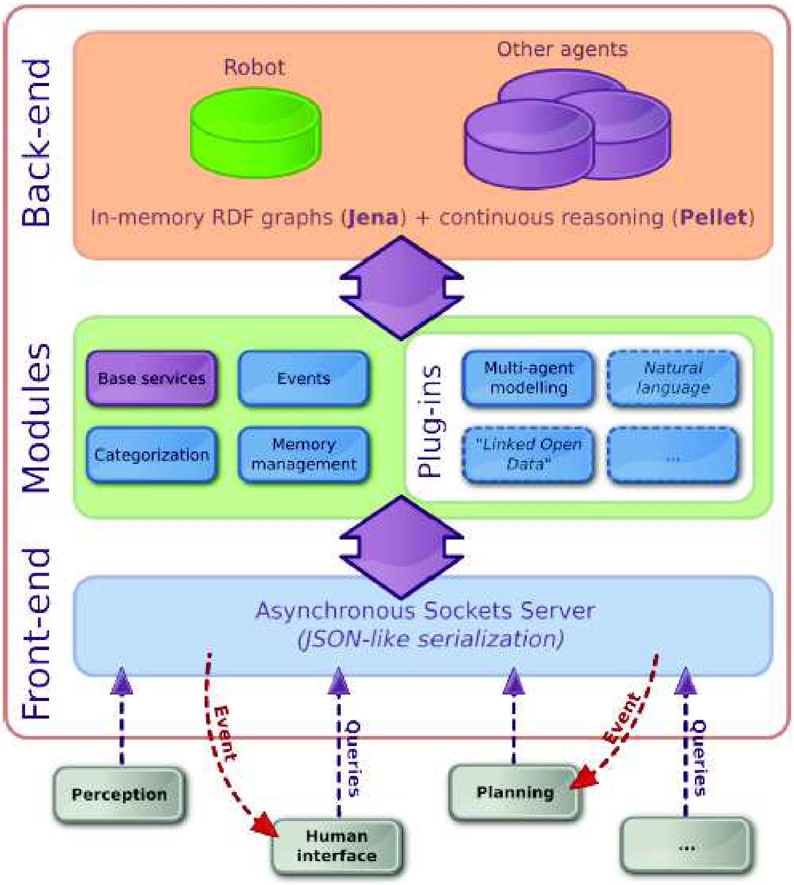


Figure 4.8: Overview of the ORO architecture, taken from [Lemaignan 10].

4.5 System Architecture Supporting Human Robot Interaction

A control architecture dedicated to robot decision and action in a human context (Figure 4.4) provides the basic support mechanism for the robot to be proactive for robot related as well as human related tasks.

The decisional layer consists of:

- **HATP:** A task planning system that is able to synthesize socially acceptable robot plans that may involve human-robot collaborative action.
- **SHARY:** which constitutes the decisional kernel. It is based on an incremental context-based task refinement in a human context.

We will now explain the different parts of this architecture.

4.5.1 Human Aware Task Planner - HATP

HATP [Alili 09] is a planner designed for heterogeneous Agent interactions, in our case humans and robots. It is based on hierarchical task planning [Ghallab 04] and integration of behavior rules, which orient robot decision and produce social plans. HATP has also its own language [Alili 08], which allows us to model human preference, ability and capacity.It describes the fact that the human needs Glasses by a boolean attribute associate to the entity "Human" called "needGlasses" it has the true value if human needs the glasses and false otherwise. The human model is complemented with the action description which takes into account the fact that the action is performed by the human or by the robot. It takes inspiration from human interaction to establish rules for a right social behaviors in human robot interaction. Six types of social rules has been defined [Alili 08]:

- Undesirable states
- Undesirable sequences
- Bad decompositions
- Effort balancing
- Timeouts
- Crossed links

HATP planning process is composed of two threads. One thread is responsible for the plan refinement [Montreuil 07] and a second thread is responsible for plan evaluation. The second one is based on the Analytic Hierarchy Process (AHP) [Forman 01], it gives to the plan evaluation a total control on the plan quality because it combines the penalty added by the rules violations with the costs of actions. Both of them integrate human model. For example we can model the human desire to be involved in the task and the fact that he/she has physical handicap. In this situation HATP will produce plans involving the human in the task that respect his/her capability. Otherwise it produces plans with as least as possible human involvement.

Here, the main HATP performances is its ability to take into account human actions and to produce social plans, its capacity to handle contingencies, and also the possibility for HATP to start planning from a partial plans [Alili 08] (It gives the robot the possibility to analyse human plans and correct or complement them for proactive behaviour).

4.5.2 SHARY

SHARY'S [Clodic 07a, Clodic 08]originality, as a supervision system, lies in its ability to take into account not only the task achievement but also communication and monitoring needed to support interactive task achievement in a flexible way. SHARY allows to define a task or a hierarchy of tasks linked to more or less elaborated "communication policies" that enable to execute tasks given the possibility to deal with contingencies that could occur during its execution (or even to stop the task in case of unexpected events).

A communication scheme, for a given joint task, represents all possible turn taking steps and synchronization between the robot and its human partner [Clodic 07b]. Each time a state is visited the corresponding task recipe or atomic task is launched.

From a practical point of view, a communication scheme is a finite state automaton. Its states are communication acts expressed by the robot through dialog or by an expressive motion. Its transitions are communication acts directly expressed by the human or inferred from her/his behavior by monitoring tasks.

It has some generic communication scheme with a defined set of communication acts that are mandatory in the framework of task achievement [Clodic 07c]. This set takes inspiration from Joint Intention Theory ([Cohen 91]) that states that each partner should be informed of the beginning, realization and ending of a joint task.

While executing a specific task this generic communication acts will be instantiated as an act_X_task with a recipe, an execution state, etc. For example, when the robot is proposing to give the human an object, it is realizing the act_X_task defined by the `Give Object` task and the `ASK-TASK` act.

Task Recipe: Task recipes are methods that compute the partially ordered list of subtasks of an act_X_task. This sub-task tree contains both a set of tasks needed for the achievement of the act_X_task but also a list of tasks required for monitoring the execution. Recipes can be scripts, i.e. provided by the programmer, or can be synthesized by a planner such as HATP [Montreuil 07] presented previously.

4.6 Discussion

The HRI research requires not only good robotic platforms but also needs supporting system software components. These components provide a vital support mechanism for the successful integration of the system and help achieve real time initiative taking and collaborative scenarios with the human. Also, these components are part of global architecture, an instance of the laas architecture, that help systematize their different role, i.e., whether decisional or functional etc. The software developed for our robotic platforms are opensource[5] and managed via robotpkg [6].

[5]http://www.openrobots.org
[6]http://homepages.laas.fr/mallet/robotpkg/

4.7 Summary

In this chapter, we presented various experimental robotic platforms used in our experiments. Also, described the important software components providing support for building robot decisional capabilities. These include; robot perception abilities (detecting and localizing itself, objects and humans in the environment), robot actuation capabilities (base motion, head motion and moving arms etc.) and more importantly robot capacity to: build 3D environment, manage symbolic knowledge and do motion planning. We also, described the system architecture providing crucial support for decisional human robot interaction.

Chapter 5

Managing Goals and Proactive behavior

5.1 Introduction

The Human brain proactively generates on-line focused predictions on what is relevant in a pertinent situation rather than passively 'waiting' to be activated by sensations. The primary role of these predictions is to guide our actions, plans and thoughts [Moshe 07].

Humans from very young age show proactive behavior and take initiative. Children show curiosity and proactively interact with the environment, which leads to learning and the acquisition of knowledge [Carlton 98]. This curiosity, driven by intrinsic motivation, is linked to higher learning and achievement in children [Stipek 02, Pintrich 02]. Also, 14 month old children engage in cooperative behaviors and *proactively* provide help for others, by getting objects for a person in need or by pointing to provide information [Warneken 06, Warneken 07, Liszkowski 06]. As the children become older, autonomy becomes more important, for regulating one's own behavior and to govern the initiation and direction of one's actions [Ryan 91].

As robots move towards being co-operative and social, the challenges of incorporating the basic ingredients of such behaviors are becoming prominent. Behaving proactively in a human centered environment is one of the desirable characteristics for a social robot [Salichs 06]. Initiative taking is one of the important characteristics of a companion robot, "helping it work towards a relationship of trust and confidentiality with the human and makes its interaction different from a master slave metaphor of human robot relationships" [Dautenhahn 07].

Proactive behavior can be tackled at different levels of abstraction and through various perspectives. It can be manifested at a low level in a physical human robot joint actions, for example, the robot proactively moving its hand to a location where a possible object handover may occur. Proactive behavior helps reduce human effort [Pandey 11].

We are essentially interested here in the identification and selection of different proactive behaviors, i.e., decide **what** to do, with the aim to facilitate human-robot interaction. The behaviors identified in 5.4 will serve as a template for generating high level proactive robot behavior and managing the robot goals accordingly. The other important aspect for the robot proactive behaviors is to: decide **how** to do, i.e. synthesis of different proactive behaviors (for example, as described in [Pandey 11]) and is not in the scope of work covered here.

In this context, we have adapted the control architecture dedicated to robot decision and action in a human context (Figure 5.1) to enhance robot capacity to be proactive for robot related as well as human related tasks. An explanation of the the different parts adapted in this architecture is given next.

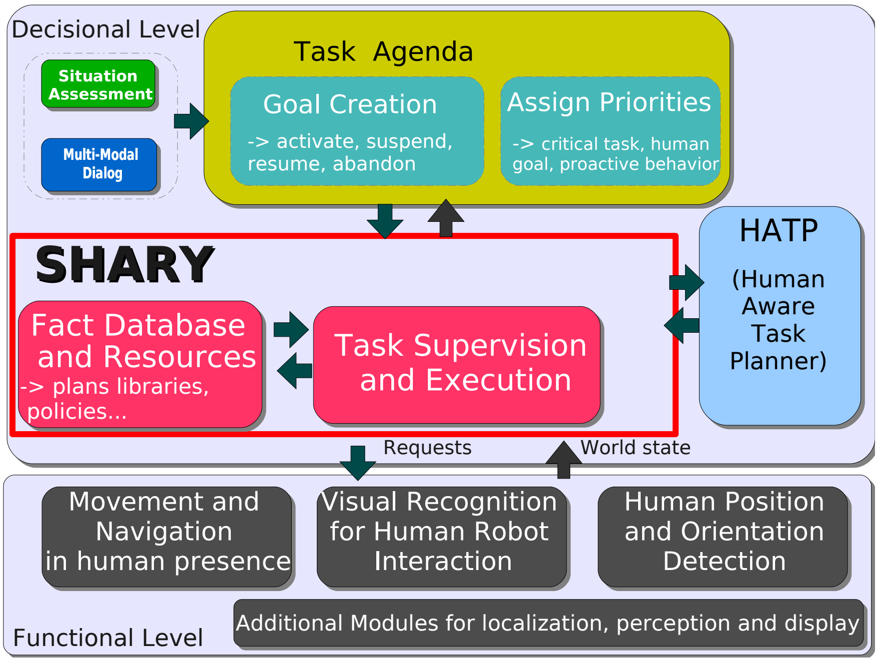


Figure 5.1: Architecture adapted for the supporting proactive human robot interaction: The decisional layer consists of four components: SHARY, which is in charge of task supervision and execution; HATP, is in charge of high level task planning; and Task Agenda, which manages high-level robot goals in a human; and a situation assessment system is in charge of the interpretation activity of the persons in the robot vicinity.

For a robot to be proactive an important requirement is: to recognize the relevant opportunity to take initiative. In this context the next section gives description of relevant situation assessment system that we used to recognize situations and for initiating the relevant goal.

5.2 Situation Assessment

For a companion robot to be able to take initiative and support the proactive behaviors, it needs to recognize the relevant situation and then decide whether to take initiative or not and to execute the pertinent task, representing the relevant behavior. The relevant situations are modeled as chronicles [Ghallab 96] and the Chronicle Recognition System (CRS) [Dousson 07b] (developed by [Dousson 96]) is used for their monitoring and the relevant situation assessment. CRS, provides the advantage of co-relating the events in a chronicle temporally and achieving the recognition of the situations on the fly.

After a scenario has been recognized, the Situation Assessment modules triggers a relevant OP [1], which in turn adds the related goal in the Task Agenda. Task Agenda manages the high

[1]Operation Procedure of PRS, which is a recipe for achieving tasks/goals

level goals and generates new task executions according to a pre-ordered priority. After that the scheduled task is executed by the supervisor, which can either choose a relevant task recipe if available or request a high level task plan from the task planner. CRS has not been previously used to recognize the human activity in the vicinity of the robot for the situation assessment.

5.2.1 Chronicle

A chronicle represents an observable part of the evolution of the supervised system. More specifically, a chronicles is:

- a set of patterns of observable events
- with temporal constraints between their occurrence dates.

Figure 5.2 shows an example chronicle evolution for a human making breakfast, with different events and the temporal constraints between the events.

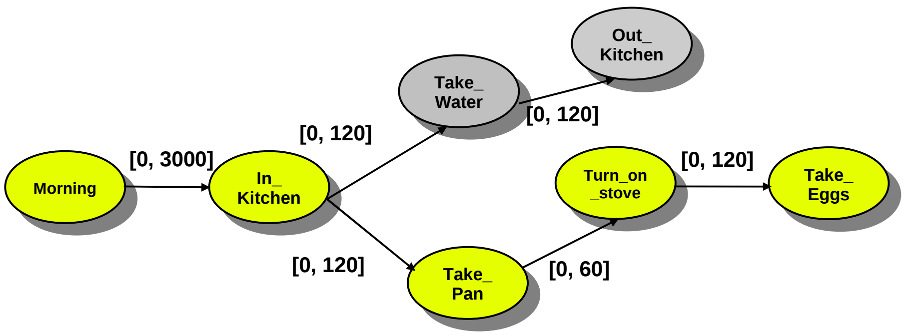


Figure 5.2: Chronicle evolution for the Human making breakfast.

Events in a Chronicle:

In a chronicle, an event can be represented either as a message or as an attribute. The "signal" events are called "message", for example: in the event(Location [?Human,in_kitchen], t1), the "Location" is a message and can take a number of values defined in the domain.

The "Change" events in a chronicle are called "attribute", for example: in the event(time_of_day:(night, morning), t2), "time of the day" is a change event (at a certain time, time changes from the night to the morning).

Also, absence of events between two time points can be represented using a "noevent" predicate, for example: noevent(Location [?Human,out_kitchen], t1,t4). This represents the fact that the between intervals $t1$ and $t2$ the human never leaves the kitchen. Similarly, the persistence of a fact can be represented by a "hold" predicate. For example, hold(Location [?Human,in_kitchen], t1,t4) represents the fact that the human remains in the kitchen during the time interval $t1$ and $t4$, and does not leave.

A "definition domain" D is associated to each message or attribute; for Location message, we have two domains one for Human = {H1, H2, H3}, and the other representing his current place = {in_kitchen,out_kitchen, living, bedroom}. Similarly, the state of day time is given by attribute time_of_day has domain day_time = {morning, noon, afternoon, evening, night}.

We will show how an activity is modeled for the situation assessment using CRS next.

5.2.2 Activity Modeling for the Situation Assessment with CRS

The human activity can essentially be related with temporal events. These temporal events can be used to monitor the activity evolution and model changes via chronicles. For example, in breakfast cooking scenario of figure 5.2, we can define the following events for this chronicle: human takes frying pan from kitchen-shelf, turns on the stove, and gets eggs from the fridge. Then we need to define temporal constraints on these events, for example, these events can happen between 3 - 5 minutes and these events should occur in the morning. A goal can be added to the task agenda by the Situation Assessment modules on the recognition of the scenario Making_Breakfast.

Also, we can divide situations into sub-situations, as it will simplify the modeling and integration of the events into multiple scenarios. For example, the chronicle (MakingBreakfast) can be part of another scenario, for example, "SetBbreakfastTable", the robot can start setting the table for the breakfast while the human finishes making breakfast.

```
chronicle MakingBreakfast {
event(WP_Locatoin[?h1,In_Kitchen],t1)
event(WP_InKitchen[?h1,Take_Pan],t2)
event(WP_InKitchen[?h1,Turn_on_Stove],t3)
event(WP_InKitchen[?h1,Take_Eggs],t4)
hold(WP_TimeOfDay:Morning,(t1,t4))
t2 - t1 in [200,500]
t2 < t4
t3 - t1 in [100,1000]
t3 < t4
t4 - t1 in [0,11000]
```

when recognized emit event(WP_TakingMeal[Making_BreakFast],t4)
}

5.2.3 Advantage of Using CRS for the Situation Assessment

The CRS gives us advantage of easy and effective modeling of the activities to test our architecture for different proactive behaviors. We have defined many scenarios based on presence or absence of human activity around robot. These scenarios are so modeled to enable the system to take initiative and show collaborative behaviors. CRS has not been used *previously in this context*.

The main advantages of CRS are:

- It handles time explicitly:
  An activity recognition system should not only take into account uncertainty surrounding an event but also important is the temporal constraints between the events. Human activity is inherently temporal in nature. Events in the activity are temporally co-related though their ordering can change.
- It can monitor modeled scenarios on the fly, by matching observations to modeled events and temporal constraints propagation.
- It can maintain several hypothesis (chronicles), that is, complete tree of instances of partial chronicles currently taking place.
- It can easily integrate several events in different scenarios and keep their window of relevance with respect to each scenario.

The main advantage being to use multiple chronicles to cover the uncertainty surrounding the activities to monitor (an activity can be done by various different ways) and is feasible in terms of memory usage (memory consumption is linear) [Dousson 07a] and complexity [Dousson 07b], allowing for real-time processing. It can be advantageous to use a combination of chronicles (allowing explicit temporal reasoning) with an uncertainty based systems, for examples, Hidden Markov Model based or Dynamic Bayesian Networks based systems.

5.3 Managing Goals

A companion robot working in a human environment will require an effective goal management strategy to manage high-level robot goals and their associated tasks. These goals may be given by, either a human, or generated by the robot proactively. Moreover, a robot can have multiple goals competing at the same time given by more than one human. We have defined a *Task Agenda* to manage the incoming robot goals. Figure 5.3 shows the schematic working of the goal management.

The goal management involves the following important steps:

- Goal Creation
- Goal Validation
- Goal Priority Assignment

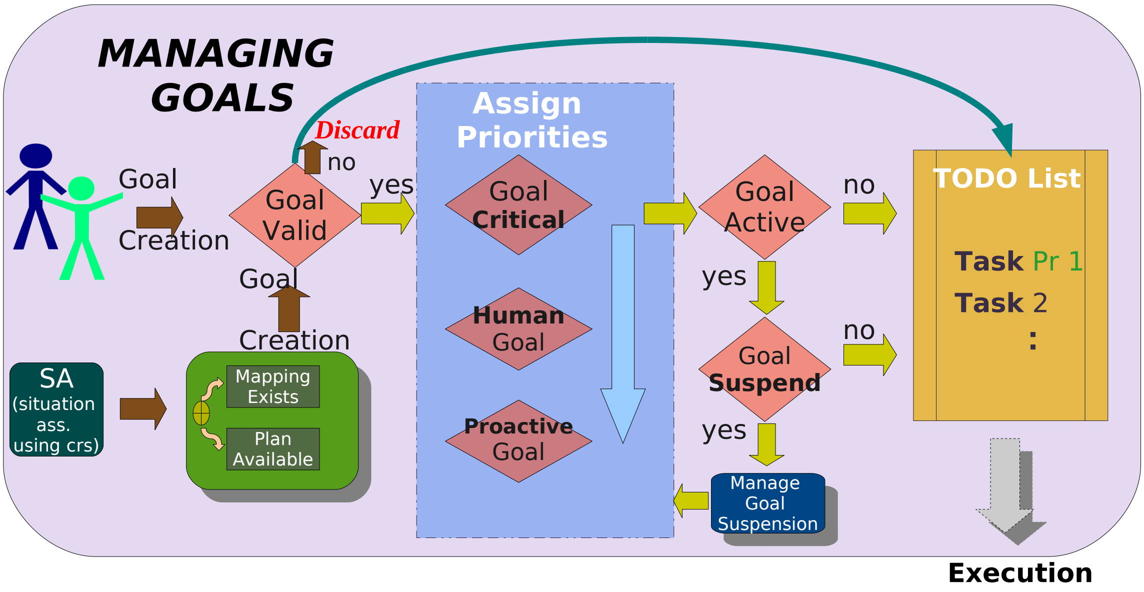


Figure 5.3: Managing Robot Goals

- Goal Activation Suspension
- Goal Related Task TODO List

Goal Creation

The human can assign goals to the robot, which arrive in the task agenda via a multimodal dialog module. Also, the robot can recognize situations using *Situation Assessment* (essentially used to interpret activity of the persons in the robot vicinity) and relevant robot goal to take initiative and show proactive behavior (explained in section 5.5). Multiple goal creation is possible as a companion robot serving in the home might have more than one human in the environment giving goals; similarly, the robot can recognize multiple scenarios to show proactive behavior. The supervisor, SHARY, can start executing relevant proactive behavior either using an existing task recipe or using a relevant plan from the HATP.

Goal Validation

The Task Agenda checks the goal validity by verifying that, if a goal related task already exists, either in the TODO List or currently being executed. For example, a human may ask again the robot to serve a drink and while the goal "serve the human a drink" might already exist. In this case, the goal and relevant task is added only once.

Goal Priority Assignment

Tasks are then scheduled based on priority and on the current context. A Fixed-priority preemptive [Audsley 95] based assignment is used, i.e., the priorities for the tasks are predefined but a high level task can preempt a low level task. As a general rule, human given goal has *higher priority* than the robot initiated goal supporting a proactive behavior. Also, a "critical" task/activity has the highest priority.

Critical Task

A task that, if not accomplished, results in a serious adverse effect upon the human safety, the robot survivability, or a mission accomplishment. For example, the robot could perform a critical task, such as reminding a person to take medications or providing security to an unattended infant before serving a drink to the human (initially a high priority task). Critical tasks should be defined and can be learned.

In our context, we defined higher priorities for the task related to the human given goals and assigned lower priorities to the task generated via robot's initiative taking proactive behavior. Within these priorities, there is an ordering on priorities.

Goal Activation or Suspension

Task Agenda needs to manage the activation of the new goal and/or suspension of a lower priority existing goal or resumption of an already suspended goal. It uses a task queue for scheduling goal related tasks, and is able to suspend an ongoing task in order to execute tasks with a higher priority. Suspending a task means canceling the task execution and keeping the goal in its current TODO list.

For example, Task agenda receives a new goal from the Situation Assessment-"Need to Interact" goal, and currently there exists the goal "Need to Explore". The task agenda will preempt and stop that goal and put it back into the waiting list. Now "Need to Interact" will be added as a high priority goal and it will be executed by launching a respective exec-task in the supervisor. Task agenda may also need to abandon a goal in the TODO list, if it becomes irrelevant later (for example, if the human leaves then no need to execute the task "Need to Interact").

Goal Related Task TODO List

The Task Agenda maintains several TODO lists that specify the goal related robot tasks. These tasks are high level tasks, for example: serve-a-drink, explore-new-objects, throw-bottle-in-the-garbage, and cleanup-a-table. In response to inputs from Situation Assessment or dialog, the Agenda adds a high-level goal into the appropriate TODO list if the goal is not already present. There can be several ACTIVE, INACTIVE, SUSPENDED goals in the TODO list.

In summary, the role of the Task Agenda is to maintain an ordered list of high-level tasks and embed a mechanism that permits the robot to exhibit a proactive behavior, for instance, taking the initiative to serve a drink or to behave as a curious robot that decides to acquire information about the state of the environment (e.g. exploration of objects placed on a table by the human).

5.4 Basic Proactive Behaviors Expected From A Companion Robot

A companion robot can be designed to achieve different tasks. It can be programmed achieve these tasks by following the human commands. In this case, the robot relationship will only be that of master-slave. Whereas, it is important for a companion robot to show proactive behavior [Breazeal 02, Breazeal 03]. For that, it is necessary to find relevant important proactive behaviors. The behaviors we are interested to have are the following:

- Being-aware of Human in the vicinity: seek to engage in an activity
- Curiosity, to increase its knowledge of the world
- Autonomy with responsibility
- Cooperate and participate in human task

In the following sections, a brief description of these behaviors is given.

5.4.1 Being-aware of the Human: Seek To Engage

For stimulating an appropriate reaction from the potential human interaction partners, it is necessary for the robot to show an observable, intentional "being-aware" behavior. In a general HRI context, the assumption of being confronted with an interested interaction partner can be supported by the resulting human behavior, like pausing or turning towards the robot, and looking at the robot.
[Ito 04] show that eyes play key role in human-human communication. [Yoshikawa 06] investigated the in influence of establishing eye-contact between robot and human user. They argue that eye-contact, is not merely "looking at each other", rather is an important process in itself to convey the partner's intention. Also, through dialog, robot can greet, introduce itself, and give information about the ongoing task or activity. Initiation of verbal utterances to engage the potential interested listeners, present in the robot proximity, will only make sense after establishing the eye-contact with them.

Consequently, a being-aware behavior of the robot for potential human interaction partners is desirable. Where, on finding an interested human in the vicinity of the robot, the robot tries to establish the eye-contact with the human and greets with verbal utterances (like "Hello I am Jido", etc.). It is important for the "being aware" behavior to have relevant memory module, so that, the robot does not repeat the behavior to same person again and again.

5.4.2 Curious Robot: Building Its Knowledge About World

Curiosity is the desire to learn or know about anything. Intuitively, to achieve its goal the robot may gain from spending some time on building a predictive world model, by exploring its environment and learning about the consequences of its actions in particular contexts [Schmidhuber 06]. Such activity, commonly referred to as curiosity, is an important skill for a social robot assistant. Though this behavior has its limits as the robot needs to take into account human partner's privacy, preferences and safety.

This will help the robot to build a predictive world model after watching human activity in the environment and have an upto date model of the world and can use this knowledge in the execution of future tasks. For example, if human asks the robot to give him an object and if this object was placed by him earlier on the work place, the robot can immediately get the object for his partner without needing to explicitly ask the human where the object is and without requiring to explore and search the environment for the object.

The curiosity behavior also be very intricate, requiring detection of salient events and defining which knowledge to acquire or what to learn, etc.

5.4.3 Autonomy With Responsibility

One other way a robot can be supportive to its human companion is through proactively seeking intervention without human requiring to give explicit commands. Not only must the robot focus on the task, but additionally, the robot must identify the needs and shortcoming of the human partner. For example, a human partner can forget to give a task "to do the housework" to the robot and leave the house (with the room cluttered, the kitchen sink filled with dishes or the stinky "poubelle" lying around). If a robot assistant can autonomously detect such situations and act autonomously to clean up and arrange the house then it will make life a lot easier.

Our focus is on detecting such a situation and having the robot execute relevant autonomous task without asking the human partner.

However, in the long term such autonomous decisions will require a responsibility in terms of autonomy. Sheridan's proposed levels of automation in human computer decision-which range from the human deciding on a task and assigning it to the computer, to the computer deciding on a task and performing the task without input from the human [Sheridan 92]. Of these levels, following three can be the guiding principles for a social assistant robot:

- Computer chooses an action and performs it if human approves;
- Computer chooses an action and performs it unless human disapproves;
- Computer chooses an action, performs it, and informs human;

Such as that the robot can apply gradual shifts in levels of autonomy so as to acclimatize with human partner's preferences, each level shift should occur on the approval of previous behavior and thus will help in building the trust with the human partner.

5.4.4 Cooperate and Participate in a Human Task

[Warneken 07] show that children from the age of 14 months show social cooperative behavior and provide help for others, like, getting the objects for a person which are out of his reach or holding a door open for someone whose hands are occupied. Also, children as young as 12 months old, point to provide information for others, in order to indicate the location of the object the person is looking for [Liszkowski 06].

Similarly, a robot will be expected to act and provide the assistance proactively to the human partner. It can provide help by acting, or can provide helpful information or can even just give reminders (like for monitoring elderly people [Cesta 11]). For that, the robot needs to recognize situations where it can participate in a ongoing human task and provide help. Which in turn can help it gain trust and acceptance as a useful assistant.

5.5 From Events To Proactive Companion Behavior

The proactive behavior modeled in our system is based on the behaviors explained already (section 5.4) are:

- Interact
- Explore
- Clean
- Help

We modeled these robot behaviors for various human activities using the Situation Assessment module. Which receives the relevant facts from the supervisor and on the recognition of a situation adds a relevant goal in the Task Agenda through an associative task recipe [2]. The system work flow is shown in figure 5.4

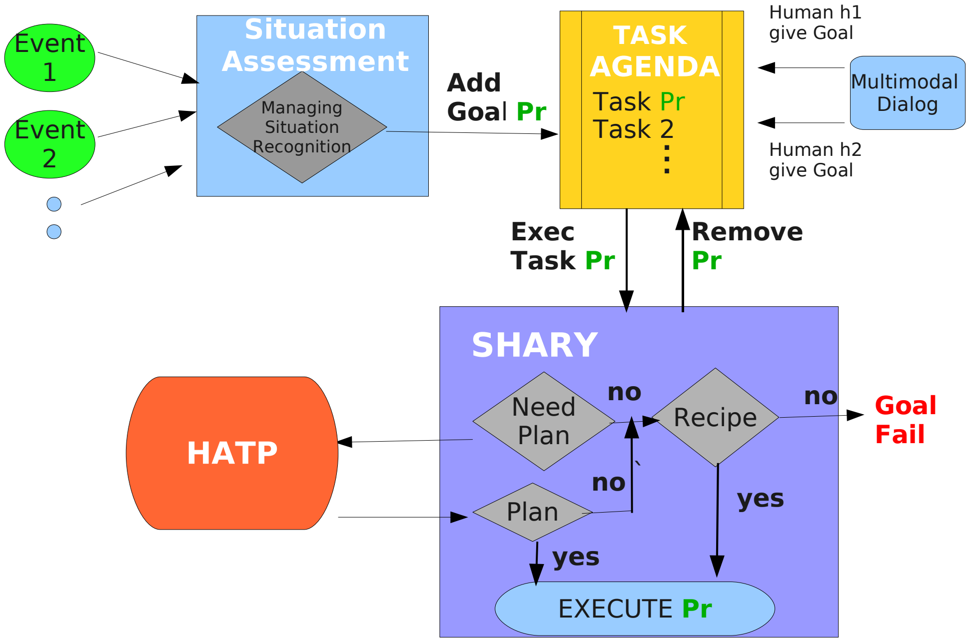


Figure 5.4: System work flow: From Facts to the Proactive Companion Behavior

[2] Recipe can be a script, i.e. provided by the programmer, to execute a task

5.5.1 Modeled Human Facts

Proactive behavior Modeling requires defining the important events to be monitored by the robot and these events contain predicates, defined by the facts generated in the knowledge base. The facts are either produced directly through functional modules or inferred by the supervision system. These events should account for different cues like (distance, head pose, gaze, etc.) that a model of Social Engagement (SME) should have and which has a basis in psychological or cognitive theories of the perception of social attention [Michalowski 06].

The supervisor receives the facts on the humans present in the environment, and maintains a facts database. The information on the human was generated through different modules; "humPos": laser based human detection and tracking, "gest": human head and hand detection and tracking, "icu": human face detection, "zone": to track human location and facts were fused by the module "human". The Supervisor also produces facts by inference and notifies any change in the the facts to the Situation Assessment module. Following are the main human fact types that are monitored:

- Presence
- Proximity
- Location
- Zone
- Look Direction
- Motion
- Posture

Presence:
This fact represents presence or absence of the human in the robot environment, i.e., human $isPresent \in \{true, false\}$. The Situation Assessment module gets notified on each human presence or absence (indicating human has left) and can integrate multiple human instances.

Proximity:
Proximity, represents human distance with respect to the robot or the relative object. The basic facts are: human isFar, isNeartoInteract, and isNear. Human proximity for verbal interaction can simply be that the human is at medium distance in the vicinity of the robot (from $0.57 - 0.60$ meters), or human is near the robot or work area (within 0.5 meters) using [Walters 09] distance measure.

- isFar: is far from the robot (or the work table, etc.)
- isNeartoInteract: human is at a medium distance from the robot and the robot can address the human verbally
- isNear: robot can collaborate physically with the human, for example, exchange objects with the human.

Location:
It represents the human location with respect to the robot, whether the human location is facing

the robot or not. Location is given by the fact $isInFront \in \{true, false\}$. Though, the new situation assessment system provides more elaborate information: isInfront, isAtBack, isRightOf, isLeftOf or a combination of these (isInFront and isRightOf).

Zone:
Zone, represents the current human position in the environment. The basic facts used were: InLivingArea, InWorkArea, InShelfArea, and InRobotArea.

- InLivingRoomArea: The human is in the living area zone, a living space with sofas and a coffee table in the environment.
- InWorkArea: The human is in the designated work zone defined around the table with objects.
- InShelfArea: The human is in the zone defined around the shelf.
- InRobotArea: The human is in the zone around the robot.

More elaborate information with respect to the human distance from the robot using proxemics [Hall 68] is also inferred by the supervisor. These are:

- PersonalZone: zone in the immediate vicinity of the robot and human presence should inhibit robot from moving torso or arms
- InteractionZone: zone near the robot, where it can interact with the human. For example, handover an object to the human or the human can give an object to the robot.
- SocialZone: social zone is an area larger than the interaction zone, in it robot can address the passer by and call for help.
- PublicZone: Out side social zone, People within this zone usually do not exert significant influence on the robot behaviour and require no special attention.

Look:
This fact shows, whether the human is looking at the robot or not. It is important for knowing where the human's current focus of attention is.

Motion:
This fact represents human motion, i.e., whether the human is moving or not and is instantiated by $isMoving \in \{true, false\}$

Posture:
Human hasPosture represents current human posture, i.e., either sitting or standing.

In the work presented in chapter 6, these facts are generated through more sophisticated situation assessment algorithms in the module SPARK and knowledge is maintained in ORO.
For the robot to be able to detect the situations where it can interact and establish joint attention or disengage from the interaction with the human partner, it needs to detect events and correlate them in a meaningful way.

5.5.2 Facts to Situation Assessment

The human facts are used as predicates in the chronicle events and combined in a chronicle model, section 5.2, with temporal constraints on them for the relevant *Situation Assessment*.

Need to Interact:

It is important for a robot to show an observable, intentional "being-aware" behavior. It will help stimulate appropriate reaction from the human in the environment. This kind of behavior will help engage people in elderly care centers or elderly homes. The relevant modeled behavior is, called as "Need to Interact", where, the robot recognizes an opportunity to interact and starts interaction with a person in the vicinity of the robot.

The facts for the *need to interact* scenario include: Human Presence in the environment (present or absent), proximity with the robot which can simply be that the human is in the vicinity of the robot (For example, [Walters 09]'s distance measure for Human Robot Proxemics could be used to ascertain proximity), human pose with respect to the robot (isLocated: infrontOf, behind, onLeft, onRight), zone (human in the robot area), looksAt (whether looking at the robot or not: focus of attention information), human motion information (whether moving or not), and his posture (sitting or standing or other).

The occurring or non-occurring of these events alone is not sufficient to recognize the opportunity to interact or even to disengage from the interaction mode. The events need to be true for a certain duration and event ordering (temporal) is also important. For example, a human may just be passing in front of the robot and consequently, the key event "human near the robot" may occur and be valid only for a short duration, without maintaining the event for a reasonable duration or without putting a temporal constraint on the event, it may cause a false positive recognition of *need to interact*. The event durations can be arbitrarily chosen by the programmer from experience, or a value derived from human development psychology can be used: for example, 3 seconds can be used as a duration for attention related events ([Tomasello 83] describes that both the mother and child visually focus on the referent object or activity for a minimum of 3 seconds in a joint attention task) and can also be learned and adapted for an individual human partner.

An example scenario is described in table 5.1, showing the important events and their temporal correlation for the *need to interact* scenario.

Table 5.1: Need to Interact: Summary of pertinent events and their temporal relevance

Facts	Necessary	Duration (sec)	ordering constraint	Time	Relevance
Present	yes	Maintain	always	Day	Presence
Proximity	yes	3	yes	Day	Distance
isLocated	yes	3	no	Day	Pose
zone	yes	3-10	no	Day	zone
looksAt	yes	3	yes	Day	Gaze
Motion	yes	Maintain	yes	Day	Attention
hasPosture	no	2	no	Day	Posture

The constraint "always" is a strict ordering constraint, for example, human must be present in the environment before all other facts. Whereas, the "yes" means, there may or may not be a constraint between facts, for example, the fact human 'nearby must precede the fact human "looksAt" the robot. Also, "no" indicates there is no constraint on the fact and between other facts.

Besides human related facts and temporal (or ordering) constraints them, also relevant is the time of the day. Whether it is day time (morning, afternoon, evening) or night it can help vary the scenario. If it is day time then robot can interact or if it is night time then it can either ignore or alert the human partner (in case human nearby is an unknown person).

After the recognition of *need to interact* situation, a relevant goal is added to the task agenda by the Situation Assessment and if no other higher priority goal exists the supervisor will start execution of the relevant task.

Need to Explore

It is important for the robot to explore its environment for having an up-to-date world model, especially if it detects new human activity in the environment. We have modeled this behavior as "need to explore", where, on detecting human activity around a work place, the robot can act curious and explore the environment of the work place and update its knowledge regarding it.

Similar to *need to interact*, the important facts include: human presence, human proximity to the work place, human motion, isLocated, looksAt, and posture. These facts are then transformed into the events of a relevant chronicle.

Scenario: The robot detects a person in the environment. Afterwards, the person arrives in the proximity of the workplace (for example, here also [Walters 09]'s distance measure for the physical interaction could be used) and is in front of the workplace and in other cases can be on left or on right. Then, the person stops moving and places the object on table, and afterwards turns and looks away from the workplace. Table 5.2, describes the respective events and their temporal corelation for this scenario.

Table 5.2: Need to Explore: Summary of pertinent events and their temporal constraints

Facts	Necessary	Duration (sec)	ordering constraint	Time	Relevance
Present	yes	Maintain	always	Day	Presence
Proximity	yes	3-120	yes	Day	Distance
zone	yes	3-120	no	Day	zone
isLocated	yes	3	no	Day	Pose
looksAt	yes	3-10	may	Day	Gaze
Motion	yes	3-120	yes	Day	Attention
hasPosture	yes	Maintain	no	Day	Posture

After the recognition of *need to explore* scenario, a relevant goal is added to the task agenda and if no other higher priority goal exists the execution of the relevant task will begin. The robot will move towards the workplace and start exploration, and on finding the new objects on the workplace update its knowledge. This new knowledge can help robot to better act on the human given goals. For example, if the human asks the robot to give an object and if the robot has the knowledge about the object then it can go and fetch the object without a need to, search the object or ask the human.

Need to Clean

For the robot to be a useful assistant it needs to recognize situations to do housekeeping. The relevant behavior is modeled as *need to clean* in our system. In this case, the robot not only needs to detect whether human has left but also, whether it has already served the human. An example scenario would be: the human is sitting in the living area, and asks the robot for an object. Afterwards, robot can act curious and do housekeeping of the living area. Robot activates monitoring after giving the object to the human and can act in two situations. First, the human leaves and is absent for some time and the robot acts to clean the coffee table. Second, the human is still in the living area but some time has passed so, the robot goes to clean the coffee table, though it will ask the human permission in this case.

In this scenario, the facts include: human is "present", is in living area "zone", and human "hasPosture" sitting. Afterwards, relevant events are defined for these facts in a relevant chronicle.

Also, included as events are sub-chronicles "picked_object" and "given_object" (therefore no duration required), which represent the scenarios where the robot picks an object and then serves the human. Table 5.3, describes the respective events and their temporal corelation for the relevant scenario to recognize. Though, in other cases a subset of these events can be sufficient to recognize the scenario, here, we give an example of a possible situation.

Table 5.3: Need to Clean: Summary of pertinent events and their temporal constraints

Events	Necessary	Duration (sec)	ordering constraint	Time	Relevance
Present	yes	300-500	yes	Day	Presence
Zone	yes	300-500	yes	Day	Zone
picked_object	yes	na	yes	Day	Pose
given_object	yes	na	yes	Day	Pose
hasPosture	yes	300-500	no	Day	Posture

On recognition of *need to clean* scenario, a new goal is added to the task agenda, and if no other higher priority goal exists the execution of the *need to clean* task will begin. Robot will move towards the coffee table and on detecting the given object, picks the object and throws it in the trashbin. There is no strict constraint on the human presence, the human can leave and then the robot can do the relevant task or if the human is present and after some time has passed then the robot can do the relevant task.

Need to Help

In this behavior, robot detects that human is going to do a task and that robot detects a situation where it can cooperate and help the human partner, for example, robot detects that human is going to read a book and that he will need his reading glasses (a preference defined in the task planner) and robot knows where the glasses are.

The robot detects such situations by using following facts: human presence, zone his/her location in the environment (living room), proximity (near bookshelf), his/her posture (sitting, standing), motion (moving, stopped), isLocated (e.g., inFrontOf bookshelf) and looksAt (bookshelf, human, workplace, otherway). These facts are then described as events, with their temporal occurrence defined, in a relevant chronicle. Table 5.4, describes the respective events and their temporal corelation for the *need to help* scenario. This is a possible example, some other subsets of events are also possible.

Table 5.4: Need to Help: Summary of pertinent events and their temporal constraints

Facts	Necessary	Duration (sec)	ordering constraint	Time	Relevance
Present	yes	Maintain	always	Day	Presence
Proximity	yes	3-120	yes	Day	Distance
zone	yes	3-120	no	Day	zone
isLocated	yes	3-120	no	Day	Pose
looksAt	yes	3-120	no	Day	Gaze
Motion	yes	3-120	yes	Day	Attention
hasPosture	yes	Maintain	no	Day	Posture

The events have temporal constraints on them but there is no strict ordering between the events, i.e., event are not necessarily sequentially ordered in a chronicle. Also, these tables represent important events partially as some events will be repeating in a chronicle, for example, in the scenario *need to help* scenario the human will be leaving the "living room" zone, then entering the "bookshelf zone" and then enter some other zone etc.

On the recognition of this scenario, a new goal is added to the task agenda and if no other higher priority goal exists the execution of the *need to help* task will begin. For activating this behavior, the decision is dependent on the high level task planner finding a relevant plan. This, will be shown via an example later.

The relevant state changes in the facts are sent to the Situation Assessment, section 5.2, by the supervisor. The Situation Assessment using CRS integrates these events on the fly, monitors the system evolution and on recognizing the relevant chronicle it adds a relevant goal into the task agenda, section 5.3.

5.5.3 Proactive Behavior Execution and Monitoring

On receiving the goal from the Situation Assessment, task agenda manages the respective goal execution as described in section 5.3. It will check if this goal requires collaboration with the human partner, in which case the task agenda will request a decision from the high level task planner. The task planner responds with a collaborative plan, where the robot can intervene in the human task and cooperate. Then the supervisor starts executing the relevant robot plan to help the human.

In other cases, the supervisor will launch the relevant task recipe to execute the proactive behavior. In both cases, the supervisor will start monitoring tasks as well for successful task completion. The supervisor informs the task agenda on successful or failed completion of a relevant behavior, which in turn removes that goal from the agenda.

An Architecture Adapted to Human Robot Interaction and Initiative taking

Key components required in a companion robot architecture include: a high level task planner, a supervisor for the task execution and monitoring, a task agenda which manages competing goals for each agent, a knowledge base to store information and a mechanism to infer or recognize on going human activity helping robot to determine when to intervene in these activities if needed.

In our case, we adapted the existing system architecture for supporting proactive robot behavior [Ali 09], as shown in figure 5.1, by adding the Task Agenda (section 5.3) to manage robot high level goals and modeling robot proactive behavior scenarios in the form of chronicles in the Situation Assessment module (section 5.2). The actual robot proactive behaviors are not possible without the help of HATP (section 4.5.1), a high level task planner and SHARY (section 4.5.2), for the successful task execution and monitoring.

In the next section, we give some working examples of the proactive behavior shown by our robot.

5.6 Examples of Proactive Robot Behaviors

(a) A "living-room" (b) 3D model used by the robot

Figure 5.5: Robot working environment.

The system has been implemented and integrated on a fully equipped mobile manipulator called Jido and tested in the experimental environment, shown in figure 5.5. It simulates a living-room with different objects of everyday human life (tables, chairs, etc.). The robot goal is to assists human in his daily life and the robot is able to perform a number of tasks: serving a drink, cleaning the table, and maintaining an updated knowledge of the state of the world (detecting and tracking persons in the room, detecting and recognizing new objects placed on tables by the persons).

Our robot has its functional level rich set of capabilities, such as, safe motion planning [Madhava Krishna 06], navigation [Sisbot 07b], manipulation [Sisbot 07a], perspective placement [Marin 08] in presence of humans as well as perception of human activities [Burger 08] and face tracking [Germa 07]. The challenge for the system is to perform these tasks showing proactive robot behavior and also interleaving it with social behavior when interacting with the human.

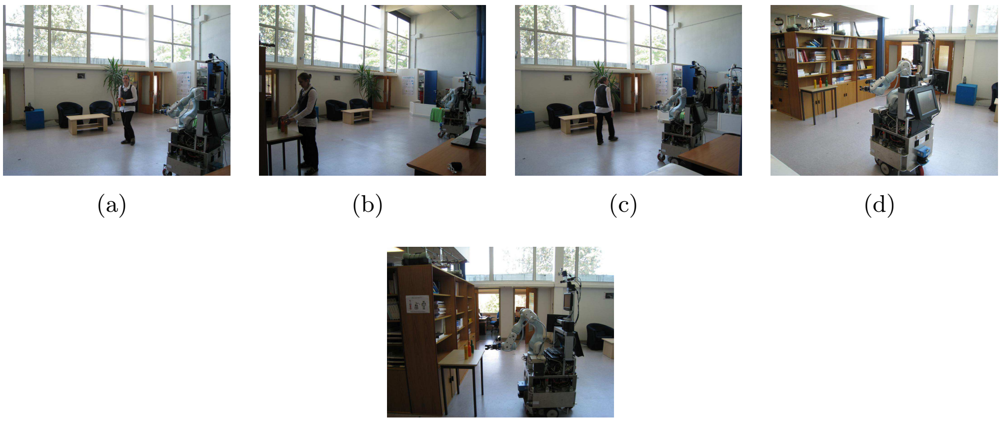
Illustrative examples of Jido capabilities are presented in the sequel. A human living room furnished environment (Coffee Table,Cupboard Table chairs, Cupboard, Chairs) and objects (Glasses for reading, Books, Bottles, 2 Glasses for drink) is the setting for the examples.

The examples will focus on three different kind of proactive robot behavior:

Example 1: proactively generate new tasks involving robot

As mentioned in section 5.3 the Task Agenda implements the ability for the robot to manage its high-level goals. New tasks can be obtained via dialog or can be generated via Situation Assessment based on the recognition of chronicles representing human activity. In the task Agenda there are some modes dedicated to the achievement of a family of tasks. These modes are defined such as "clean", "serve" and also "curiosity". While in this mode the robot will try to achieve tasks to keep an updated world model of objects on the table if the robot had inferred possible changes through Situation Assessment module.

In this example human comes near the table and stays there for some time and leaves. When this situation is recognized, Situation Assessment module sends an "Update Knowledge" (indicating uncertainty of the table state) goal to the Task Agenda. And when robot is not doing a more prioritized task it goes and looks at the table to find current table state. This helps robot keep an up-to-date world model of objects on the table. Figure 5.8 illustrates the example described.



(a) (b) (c) (d)

(e)

Figure 5.6: Example 3: proactively generate new tasks involving robot. A person approaches the table near the cupboard and stays still for a moment before leaving. This induces the fact that the person might have put or taken bottles. Jido takes the initiative to approach the table and to update its knowledge using its perception functions.

Example 2: Recognize situation to coachieve human goal

In this scenario we will see the capacity of the system to generate a pro-active behavior to help human achieve his/her goal. Robot observes the environment via Situation Assessment module and if it receives a relevant scenario recognition from the CRS, that corresponds to human goal, it transmits this human goal to the task Agenda. In this example, Jido observes human going near the bookshelf, taking the book and sitting on the sofa. Situation Assessment module receives the relevant situation recognition from CRS, that the human wants to read and adds this task to the Agenda which puts it on the top of the list after analysis. Shary sends a planning request to HATP for the relevant task execution. HATP starts planning, taking into account human preference, ability and capacity (like John wears glasses where as Jack does not) finds a plan where human should have his reading glasses (Assuming an ambient camera system through which jido knows that human is not wearing glasses) because one of the precondition of the **to read** task is to have reading glasses. SHARY checks if there is some thing to do and executes HATP plan if there is. Figure5.8(a) shows the system activities flow for this example. In this example, human is not wearing glasses was assumed and the robot served an object in place of the "reading glasses" (as the robot currently, can not pick glasses).

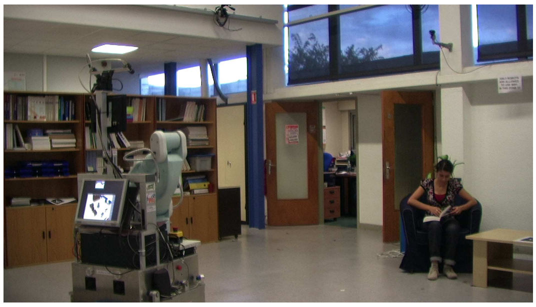
Example 3: Need to clean the table

In this scenario, Jido has already served the human partner. Here, already sub-chronicles robot "pick_object" and "human_served" are true, and as there is no_event human leaving living room with in duration defined, the situation Need to clean is recognized. The task consists in Jido cleaning the living-room table by picking up the bottle and throwing it into the trash. This goal is added to the Task agenda, and HATP finds a plan to clean the table.

Figure 5.9 illustrates the plan produced by HATP for normal execution as well as a snapshot of a current task refinement decomposition performed by SHARY.

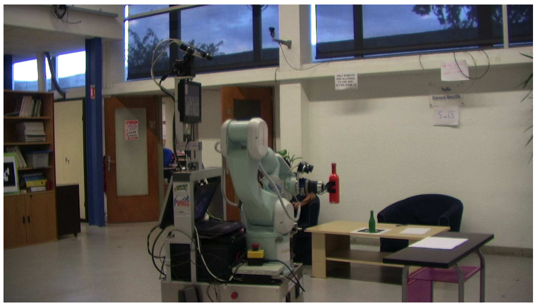
Here, human robot interaction experience can be enhanced, i.e, robot can compute human affordance and reduce hisher effort by proactively moving robot hand to a location where a possible object handover may occur. In this context, multi-perspective taking proactive motion planner [Pandey 11] can be used, for example, as shown in figure 5.10. Also, important is the timing of the robot ASK action, i.e., when should robot ask the human; before moving its arm, during arm motion or after arm motion has finished. This question is addressed in a HRI user study in chapter 7.

(a)

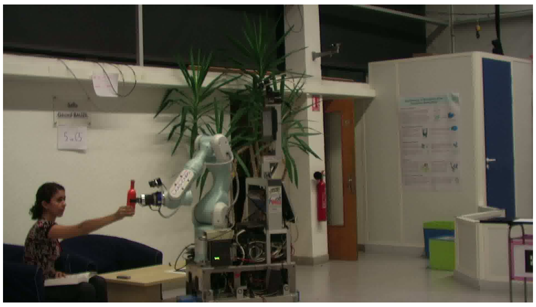


(b)

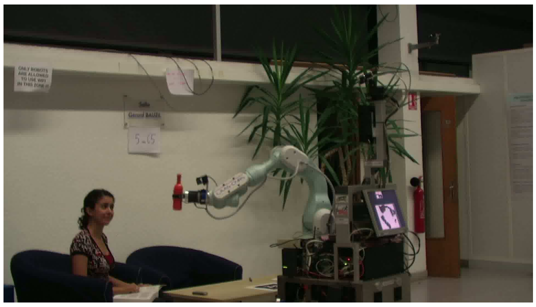
(c)



(d)



(e)

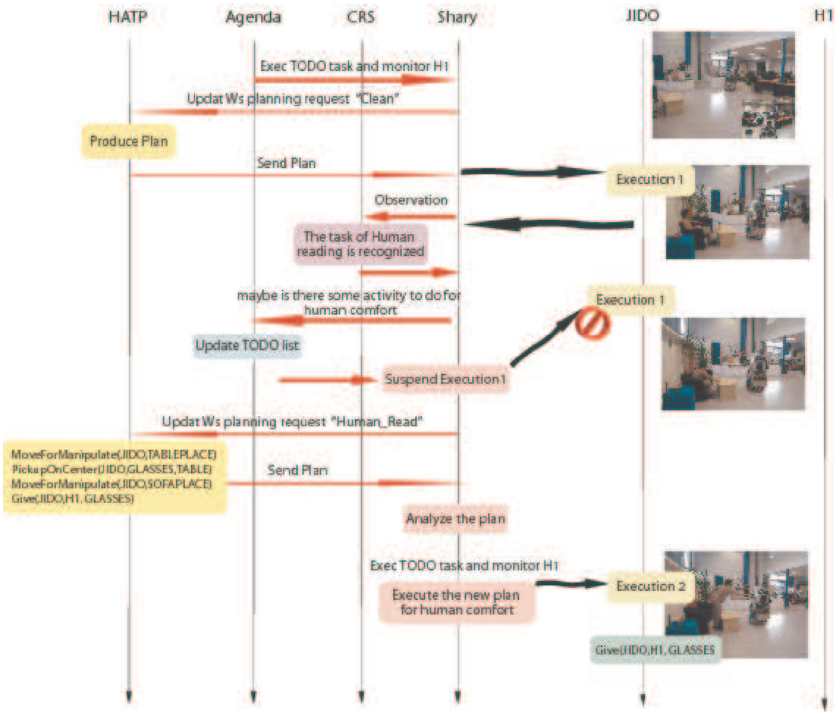


(f)

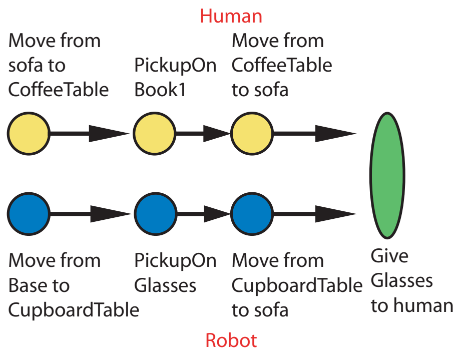
(g)

(h)

Figure 5.7: Robot recognizing situation and predicting to help and forming a handover joint action

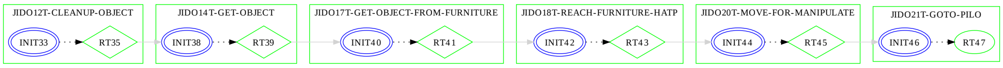


(a) The robot observes human activity and infers might do reading task, triggers SHARY OP, SHARY sends a planning request to HATP, HATP replies by a plan, SHARY analyses the plan and if there is a robot task for helping human, adds it to Task Agenda

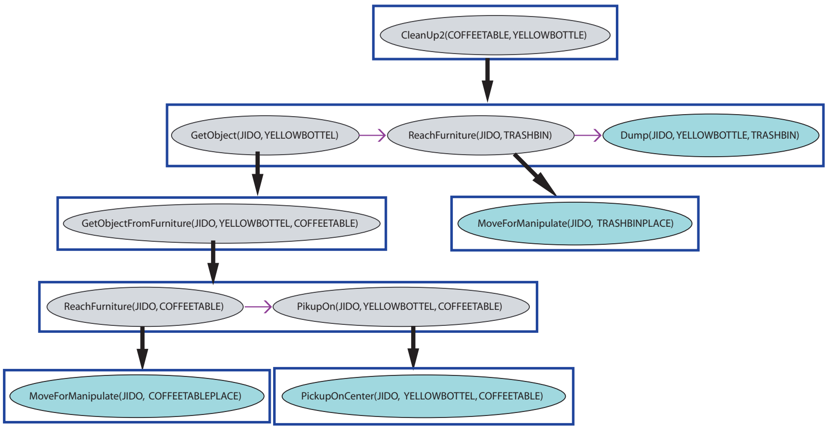


(b) HATP produced plan it is a plan with two streams on for human for its past and future action and an other for robot action

Figure 5.8: Example 3: act proactively to achieve human goal The general flow of activities in the system



(a) Current execution task stack in SHARY: Boxes are tasks, circles and diamonds shapes are act_X_tasks (`RT` is the abbreviation of `REALIZE-TASK`), gray arrows represent decomposition links and dotted arrows are transitions between act_X_tasks inside a communication scheme. Blue color corresponds to *achieved* tasks and acts while green color means that they are being executed.



(b) Hierarchical plan from HATP for the `clean-up` task

(c) Snapshot from the experiment

Figure 5.9: Example 3: Clean the table Achieving `clear-up(yellow-bottle)` consists mainly in achieving its act_X_task `RT` or its plan HATP as well. The HATP plan stops at a given abstract level in task decomposition (5.9(b)). Consequently, SHARY needs to further refine these tasks corresponding to the leaves in the HATP plan tree. This is illustrated in 5.9(a) for `MoveForManipulate` task.

Figure 5.10: Robot proactively moving its arm to ask for human help to get the not reachable object

5.7 Discussion

We have identified the basic proactive behavior required in a robot companion and shown, how a robot companion can generate proactive behavior and take initiative. This, requires robot recognizing the opportunity to act and perform intricate goal management, as it can become necessary to manage multiple goals from both the humans and the robot generated ones. For the situation assessment, i.e, recognizing the scenario that require robot initiative taking, we modeled multiple relevant chronicles for each scenario. The chronicles help relate the events temporally and have not been previously applied to scenario recognition for the human robot interaction. The temporal constraints for some events were described by trial and error. Whereas, for some events, for example, focus of attention in need to interact scenario, a value from behavioral psychology could be used.

The human activity is essentially difficult to model as a human can approach an activity differently. For example, in a cooking scenario, there can be several different ways a human can start the activity. One way, we handled this uncertainty is by defining multiple chronicle for a same situation (which has been the case in the examples described). Complexity does not increase significantly due to multiple chronicles as we used CRS for the Situation Assessment, which is quite efficient in handling many chronicle instances [Dousson 07b].

Although, this will help in some cases but will be difficult to manage in case of modeling a large scale human activities around the house, work and leisure related. A future solution would be learning chronicles for different human activities. Another, solution would be modeling the inherent uncertainties in human actions, for example, using partially observable markov decisional models or dynamic Bayesian models and use these in combination with the chronicles.

Also, the robot could incorporate human initiative taking, human can provide the robot information through multi-modal dialog, for example: human instead of handing over the object can make it accessible to the robot and then inform the robot (a basic working example is shown in the Appendix B).

In our case, the robot always took initiative and showed proactive behavior. Deciding on whether to take an initiative or whether to ask for permission or to inform about an initiative is not easy. As some could be reluctant about a robot showing a proactive behavior, whereas, others could be very enthusiastic and possibly bothered that the robot asks permission each time it wants to take initiative. We could also imagine that the individual preference of a particular person evolves both in a very short term (emergency situations, human emotional state, recent dialogues and actions) and in a longer term (people gradually becoming more confident or conversely more suspicious or annoyed). The challenge would then be to make this preference evolve according to context and interaction memory. Therefore, robot needs to be equipped with a learning capabilities to acquire these preferences.

5.8 Summary

In this chapter, we have presented a system; to manage high level robot goals and to show proactive robot behavior. We have identified the expected proactive robot behaviors, described the relevant scenario recognition process, and described the mechanism to create and manage robot goals. We have also shown the instantiation of different proactive behaviors through working examples.

Chapter 6

A Co-activity Decision Model for Human Robot Collaboration: A Qualitative Analysis

6.1 Introduction

Robots employed in the human environments, whether, as a service robot or as a coworker will need to collaborate and work with the human partner. Collaborative activity can be as simple as the robot taking an object from the human or can be as complex as collaborating in a large shared project, for example, building a ship. In any case, robot needs to take into consideration the human intention and monitor it both towards task achievement and human engagement in the task. As such, for successfully achieving a task will require to choose an optimal policy, that, includes action prediction based on a rational human behavior, and taking into account uncertainty surrounding the human behavior.

In this chapter, a decisional frame work that supports the human robot collaborative activity is proposed and is illustrated through some working examples.

6.1.1 Supervision in Human Robot Interaction

Robotics research has started focusing on the challenge of integrating robots in the human centered environment, which requires a new degree of task supervision and autonomy for the robot. Specifically, the human robot interaction requires the explicit consideration of the human at all levels, from low level arm motion to higher level task planning. Robot has to determine all the possible action outcomes taking into consideration relevant context and at the same time, take into consideration, the human. Therefore, its behavior needs to be pro-social and proactive, rather than, only reacting to the human commands.

6.1.2 Supervision in a Collaborative Human Robot Interaction

In a collaborative task the robot has to co-achieve a task with a human while sharing the same space and the activities of both agents could be quite intricate. It is a challenge, in such a case, to deal with this intricacy in an efficient, pertinent and acceptable way (with respect to the human). The robot should be responsive and should make the right choice at each step. For a robot to collaborate successfully with its partner it particularly needs to coordinate the joint actions, principally through communication, and as well as using activity monitoring. Specially, monitoring partner attention or lack of it is important for the joint action in the collaboration.

When the robot has to interact and collaborate with another partner (human or another robot) to achieve a task, it will have to produce set of actions required for the successful realization of that task, these actions may also involve joint actions, some times also called coactive actions [Johnson 10]. The robot may follow a set of predefined steps to achieve the task, for example, the robot goal of "give_object" to a person will have a handover_object task, move the arm with the object to the person, wait until the person takes object, return the arm to its original position. However, what happens if the collaborative partner does not follow exactly the protocol? He might receive a call or some other event might divert his/her attention, the robot accepts it or it abandons the task immediately or wait indefinitely. Therefore, robot needs to take into account all the ambiguities, related to the evolution of human intention in the context of the task and react appropriately. This will require intricate monitoring of partner's involvement in the task, for example, not only the robot moves the arm towards the partner in the proximity but at the same time monitors his/her attention towards: the robot and the task.

Also, important for successful realization of the collaborative joint activity is the coordination [Knoblich 11], which requires communication either through verbal means or via material signals (pointing, gestures, etc.) [Clark 05]. Robot should inform the partner 'step by step' robot intention relevant to the task. For example, if the partner receives a phone call and his/her attention is diverted, robot if doing a handover task, can stop the arm and move the arm to a wait pose, indicating to the partner that the robot is waiting. Such intentions, in this case, can not be realized in open loop without giving the human the information either through 'dialog' or through material signals ([Clark 05]), i.e., moving the arm in a wait position. The overall execution should be comfortable and should not restrict the human or prevent him to suspend momentarily or even abandon the task whenever he/she wants.

Therefore, the robot not only has to achieve its own actions and coordinate with the human actions but also be vigilant and monitor the human activity and mood. In this context, the term and concept of "coactivity" [Johnson 10] is fully pertinent and there is a need to devise models and decision schemes to implement this notion of coactivity in a Human Robot Interaction (HRI) framework. The work presented here, builds on the capabilities for collaborative task achievement developed previously that uses communication acts to support collaborative task achievement [Clodic 07c] and is inspired from joint intention theory [Cohen 91] and more particularly the work of Clark [Clark 96] on teamwork. It did not take into account the aspects related to the uncertainty in the human intention, a robust real-time generic decisional framework which explicitly includes these aspects is described next.

6.2 Coactivity Decision Model for Human-Robot Collaboration

Human's collaborating on a task form shared intentions, establish joint commitments and keep track of other partner's intentions. When one collaborating partner's shows lack of interest and shows an ambiguous intention regarding the joint task, the other partner tries to reengage and infer commitment to the task (even 3 years children understand the joint commitment in a collaborative activity and try to reengage the partner in the task [Grafenhain 09].

Consequently, a coactivity decision model (CDM) for supporting Human robot social collaboration should include establishment of joint activity; forming shared intention and joint commitments between the human and the robot for the co-activity task. To form shared intentions [Tomasello 05] both human and robot need to establish joint commitment related to the task, i.e., they need to monitor, influence and coordinate their behavior in order to engage in a collaborative task [Kaplan 06]. Therefore, robot needs to keep track of human commitment to the task and detect ambiguous human intentions pertaining to the collaboration.

We model the problem as a Coactivity Decision Model [1], using POMDPs (Partially Observable Markov Decision Process), where the hidden state of the human corresponds to the human intention of continued collaboration or not. A key feature of this approach is that it explicitly reasons about the ambiguity of human intention, and includes potential actions policy for re-engaging the human partner, providing the flexibility in achieving the collaborative task.

Next, the coactivity decision model is described, followed by description of working instance and a framework for its execution is demonstrated. Also, shown are the limitations of the coactivity decision model and given suggestions to enhance the model.

6.2.1 Coactivity Decision Model

The proposed Coactivity Decision Model (CDM) is based on an augmented POMDP model [Karami 11b]. Its novel feature is the integration of the observed human states, using Q-values (library of human action values, section 6.2.2) of simulated Human MDPs (Markov Decision Process), which are then evaluated to determine human intention towards collaboration with the robot.

Formally, the CDM is a tuple $\langle S, A, Z, T, O, R, b_0 \rangle$, where

- S is a set of states,
- A is a set of actions,
- Z is a set of observations,
- T is a set of transition probabilities,
- O is a set of observation probabilities,
- $R : A, S \to \mathbb{R}$ is the reward function,
- b_0, is the initial belief state.

[1] This is a joint work with Abir Beatrice KARAMI

The States

A state $s \in S$ represents variables about the robot, the human and the task itself.

$$S = S_r \times S_h \times S_t$$

The states are; the robot states S_r, the human states S_h, and the task state S_t. The robot states S_r include robot states pertaining to the achievement of collaborative task, for example, robot near enough to collaborate or robot arm in a state, where, partner can take the object. The human's states S_h include physical human's states regarding the collaborative task; the human presence or location in the interaction zone, and any other task relevant information about the human, that, can help the robot differentiate the scenario where the human is engaged and interested to collaborate from the scenario where the human engagement is lost. The human engagement in the task is non observable, therefore, would be a hidden variable. Finally the task state s_t represents the state of progress of the collaborative activity.

The initial belief state b_0, represents the initial uncertainty of the human interest in the collaborative task. For example, in case where human has started a collaborative task it will be less and in case, where, the robot initiates a collaborative task will be more. The belief state $b(s)$ is then updated at each time-step after applying the robot's current action and the observing the corresponding human states (indicating the action taken by the human).

The Actions

The CDM set of actions A includes two basic group of actions; one group of actions A_t, are the actions related to the actual task achievement and second group of actions A_c, are the coordination actions that help repair lost human engagement regarding the task collaboration. The set of actions in a CDM is defined as following:

$$A = A_t \cup A_c$$

The coordination actions serve as a coordination device, i.e., they are means of communication (either verbal or through material signals, pointing, physical arm motion etc.) to draw the human attention towards task, or ask the human to engage and collaborate in the task. A negative human reaction, observed through S_h, to a robot coordination action will increase the uncertainty regarding the human interest in the continuation (or participation) of collaboration with the robot and finally, may help end the shared task.

The other group of actions, serve as to achieve the robot's part of the task and are task dependent. For example, moving the robot arm to a rest pose after taking the object.

The Observations

The set of observations Z, represent the human states (concerning his actions) related to the shared task, the robot states pertaining to task achievement, and observations related to the information about the advancement of the task.

The Transition Function

The transition function $T(s, a, s') = pr(s'|s, a)$ (equation 6.1) memorizes the last applied step value of hidden state variable ($engagement$) with a maintain probablity. Where $s, s' \in S$ and $a \in A$.

$$T(s,a,s') = pr(s'|s,a) = \begin{cases} pr(s'_{cr}, s'_h, s'_t|s,a) * \text{maintain} & \text{if } engagement = engagement' \\ pr(s'_{cr}, s'_h, s'_e|s,a) * (1 - \text{maintain}) & \text{if } engagement \neq engagement' \end{cases} \quad (6.1)$$

The Observation Function

The observation function O gives the probability of observing the human state (corresponding to his/her action) $z \in Z$ knowing the robot performed an action $a \in A$ and the system ended in state $s' \in S$.

The function has a deterministic effect on the hidden state ($engagement$), given via equation 6.2 , by evaluating human states, using human action Q-Values (section 6.2.2), towards possible $engagement$ values. λ is a normalizing factor, s^h and s'^h are Human MDP states (section 6.2.2) derived from s and s' respectively.

$$pr(z|a, s') = \lambda Q_{engagement}(z, s^h) \text{ where } pr(s'^h|s'^h, z) > 0 \quad (6.2)$$

The Reward Function

The CDM reward function is simple, it rewards the robot actions that help achieve human collaborative states and perform task successfully. It penalizes the robot impertinent coordination actions when human is already collaborating with the robot. However, it rewards the pertinent coordination actions, where, human needs to re-engage in the collaboration. A reward function that includes two levels of coordination actions; soft coordination actions (low level verbal cues), and strong coordination actions (more emphatic verbal reminders) is given below.

$$R(s,a) =$$

$$\begin{cases} penalty_1 < 0 & \text{if } (engagement = engaged \text{ and } a \in \{ps, pl, pt\}) \\ penalty_2 < penalty_1 & \text{if } (engagement = engaged \text{ and } a \in \{sps, spl, spt\}) \\ reward_1 > 0 & \text{if } (engagement \neq engaged \text{ and } a \in \{ps, pl, pt\}) \\ reward_2 > reward_1 & \text{if } (engagement \neq engaged \text{ and } a \in \{sps, spl, spt\}) \end{cases}$$

To assure the balance between the penalties and rewards of different coordination actions (soft and strong) in different situations, engaged or not interested busy human, trials showed that the values of $penalty_1$; $penalty_2$; $reward_1$ and $reward_2$ can be found by solving the following equations:

$$v_1 * reward_1 + (1 - v_1) * penalty_1 \leq v_1 * reward_2 + (1 - v_1) * penalty_2 \forall v_1 \in [0.6, 1]$$

$$v_1 * reward_1 + (1 - v_1) * penalty_1 \geq v_1 * reward_2 + (1 - v_1) * penalty_2 \forall v_1 \in [0, 0.6]$$

where the value of v_1 represents the probability that the human is occupied and (1 - v_1) represents the probability that the human is engaged.

6.2.2 The Rational Human MDPs for the Library of Q-values

Inferring the intention behind human actions is a very difficult task due to various reasons, for example, human emotions or unforeseen situations that are not perceivable for the robot. A better solution would be to assume with some probability that the human will act rationally towards task achievement and then plan accordingly, taking into account related uncertainty.

Therefore, using a rational human model, human actions towards task collaboration or towards non-collaboration (in case human is not in a position to continue with the task) can be simulated to derive an optimal policy. Simulating human actions this way is reasonable, as we have seen in the behavioral psychological studies (chapter 2), humans also use action simulation to predict others action. Therefore, Q-values give expected cost of human executing the observed action, represent by the related state observed in the model, and then acting optimally. Social and Behavioral psychological studies can help create Q-value library regarding human actions for different collaborative tasks. In a long run robot would need to adapt to each human behavior with respect to the task by incorporating learning mechanisms.

Human MDPs

For modeling the rational human behavior, the robot will need to incorporate information regarding the human goal, human states, the environment, and possible human actions whether towards goal or away from it. This information is represented as a MDP, i.e., Human MDP (this is from [Karami 11b] is a tuple $\langle S, A, T, R\rangle$. Where, S is a set of states, A set of actions, T is a transition function and R is a reward functions.

The human and the robot can perform several shared tasks, and can also have many shared sub-tasks in a collaborative task. Therefore, the robot needs to take into account all the possible human intentions HI with respect to all the possible tasks.

A Human-MDP model ($MDP^h{}_hi$) represents respective possible human intention:

$$MDP^h{}_hi = \langle S^h{}_hi, A^h{}_hi, T^h{}_hi, R^h{}_hi\rangle \forall hi \in HI$$

The all human states and actions are evaluated towards all possible task, therefore these are unified as following:

$$S^h = \bigcup_{h_i \in HI} S^h{}_hi, A^h = \bigcup_{h_i \in HI} A^h{}_hi$$

The unified Human MDPs model is represented as:

$$MDP^h{}_hi = \langle S^h, A^h, T^h{}_hi, R^h{}_hi\rangle \forall hi \in HI$$

When creating the Human-MDP $MDP^h{}_hi_1$, states in S_hi_2 are set to default values and are not affected by the $MDP^h{}_hi_1$ and similarly, the actions in the A_hi_2 do not affect the $MDP^h{}_hi_1$. The reward function for each is defined such that it affects similarly the models.

In this way, we can have a library of human MDPs, i.e., one human MDP per human intention. For example, human "engaged" and human "busy" can be two possible human intentions during a collaborative task (there can be many more). The Human-MDP models for a human *engaged* and *busy* will be similar except for the reward function.

$$MDP^h_{engaged} = \langle S^h, A^h, T^h, R^h_{engaged}\rangle, \qquad MDP^h_{busy} = \langle S^h, A^h, T^h, R^h_{busy}\rangle.$$

The state $s^h \in S^h$ holds human states, task states and a state that represents the robot 'communication' action to coordinate (tryengage) the human to successfully achieve the task. Therefore,

$$S^h = S_h \times S_t \times tryengage$$

Where, $tryengage \subset A_c$ represents the fact that the robot's last action was to repair the engagement with the human. A Human MDP state $s^h \in S^h$ is created from the POMDP state $s \in S$ and the last applied robot action, if it was a coordination action. The set of actions A^h includes all possible human actions that are related to the task achievement and can be received by the POMDP model as observations. The transition function T^h transitions the human and task variables depending the problem to solve.

Q-values Integration

The augmented POMDP integrates observed human states ($z \in Z$) (representing human actions) with respect to the last robot action applied. This integration takes as input the Q-value of a human action, corresponding to the human state observed. The Q-values (or human action values) give estimate of human's policy for the collaboration, help the robot to decide, in the next time-step which action take, whether to execute a co-achieve action or a coordination action is required to re-engage the human. Also, where last robot action was a coordination action, then Q-value will help determine the human engagement level and eventually to end the task. A library of Q-values is generated offline, through 'Human-MDPs', using classical value iteration algorithm [Puterman 94].

Here, we describe the two example Human-MDPs from number of possible HMDs for representing respective human intensions: one assuming human is already "engaged" and interested in the task, therefore, rationally will act towards successful collaboration and second assuming human is "busy" and not interested in the collaboration, therefore, rationally inclined towards actions retracting from collaborative task.

These Human-MDPs are used to show: how to generate the library of human action values (Q-values). Each of the Human-MDPs calculates an optimal policy of a simulated human with respective intentions.

The resulting library can be accessed to know the value of the human action toward one possible intention ($Q_{engaged}(s^h, a^h), Q_{busy}(s^h, a^h)$). The library of Q-values is used in Equation (6.2) to calculate the observation function of the Coactivity Augmented POMDP model.

The part of the observation function concerned about this integration is the perceived human state representing the human action performed Z_h. The observation function gives the probability of observing z knowing the couple (s, s'). It gives the probability of observing an human state z, related to the action performed, and matching with the relevant task intention. As the human is assumed rational, this probability can be obtained using Q-values. The Human MDP states s_h corresponding to the observed human state are obtained via the POMDP state s, by choosing the common subset in both.

The transition function is calculated for all states and the estimated human intention $s_h i$ can transition with equal probability $\frac{1}{possibles'_h i}$ to any possible intention including the same:

$$pr(s'|s,a) = pr(s'_{cr}, s'_h, s'_t|s,a)_{cr}, s'_h, s'_t|s,a) * \frac{1}{possibles'_h i} \tag{6.3}$$

Memorizing the belief concerning the human intention

Model can be augmented with a Memory property, this will help retaining the calculated belief regarding human intention. The robot can keep the estimated human belief for longer duration and proactively further engage in case of previously cooperating but unsure human. However, it will take more time to "forget" an inadequate belief leading to a less then optimal robot behavior.

For memory property, in the transition function, a variable $maintain \in [0,1]$ is introduced. The higher the maintain probability, higher the probability that the human will keep his intention ($s'_h i = s_h i$) and smaller the maintain probability ($\frac{1-maintain}{s'_h i}$), higher the probability the human changed his intention ($s'_h i \neq s_h i$). Following equation represents the modified transition function with the memory property:

$$pr(s'|s,a) = pr(s'_{cr}, s'_h, s'_t|s,a)_{cr}, s'_h, s'_t|s,a) * \frac{1}{possibles'_h i} \tag{6.4}$$

$$pr(s'|s,a) =$$

$$\begin{cases} pr(s'_{cr}, s'_h, s'_t|s,a) * \text{maintain} & \text{if } (s'_h i = s_h i) \\ pr(s'_{cr}, s'_h, s'_e|s,a) * \frac{\text{1-maintain}}{possibles'_h i \neq s_h i} & \text{if } (s'_h i \neq s_h i) \end{cases}$$

In the next section, we present an example of human robot collaboration and use it to illustrate how a CDM can be instantiated. We note that the chosen variables and calculated functions are example related, however, the general CDM model presented in this section which is based on an augmented POMDP can be used for similar human robot collaboration tasks where coordination robot actions are needed.

6.3 Illustrative Scenario: Handing Over an Object

Human robot collaboration, in case of joint physical actions, will usually involve robot handing over an object to the human. The human may ask for the object from the robot or the robot can detect a situation where it can hand over the object to the human. The handing over an object may seem trivial, just moving the arm and human takes the object, but can be quite intricate as human can change his intention or loose his/her focus of attention and become busy. So, it requires monitoring of the human engagement in the task and relevant human behavior for successful task achievement. A possible task control flow for the handover_task is shown in figure 6.3, showing how intricate the $handover\_task$ can be. In the next section, a coactivity decision model for handing over an object is described.

6.3.1 Coactivity Decision Model for a $handover\_object$ task

In order to illustrate how Coactivity Decision Model (CDM) can be instantiated, an instance of a simple handing over an object task is adopted. The robot is assumed to hand over an object to a person, that has previously asked the robot to give the object. The object will be given while the human is sitting on the chair, the robot will ensure human engagement in

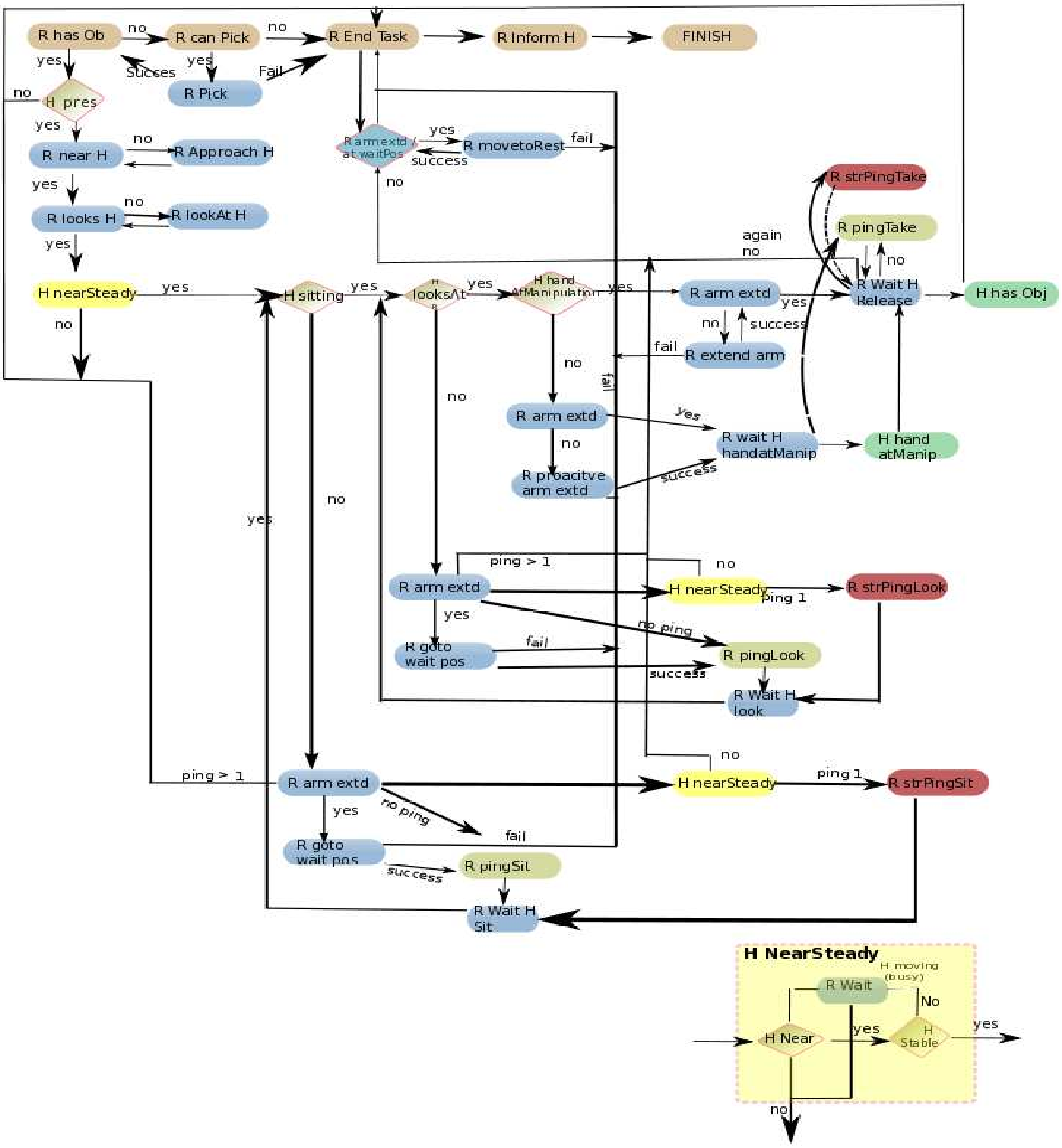


Figure 6.1: Control flow for handing over of an object.

the task by assuring that human focus of attention is on the robot and is aware of the robot intention of handing over the object. Also, robot will persuade human to sit on the chair and move its arm to a position that is socially acceptable and safe for the human. Finally, the robot should release the object on detecting human intention to take the object and is ready to receive it.

States

For the handing object task, a state in $s \in S$ represents the robot, the human and the task states. $S = S_r \times S_h \times S_t$.

The state of the robot are:

$$S_r = hand\_position \times hand\_situation$$

where, hand_position $\in$ { initial, wait, extended } and hand_situation $\in$ {not_ready, ready}.

The robot hand position which can be in initial position (close to the robot), wait position (middle) and the extended position (close to the human). The waiting position permits the robot to wait for new information about the human to better decide whether to go back to its rest position or to extend its arm to handover the object. The robot's hand situation represent the fact that the robot's hand is ready to release the object or not.

The state of the human includes: $humanpresence, looking, andengagement.$

$$S_h = presence \times looking \times engagement$$

where, presence $\in$ {sitting, nearby, far_away}looking $\in$ {at_robot, otherway} and engagement $\in$ { engaged, busy}.

The human presence state, who can be near and sitting on a chair, standing close or far away from the robot interaction region, The human looking direction, representing human focus of attention, which can be looking at the robot or looking elsewhere. Finally, the non-observable (hidden) state representing human engagement concerning the collaborative task, which can be engaged to achieve the task or is busy. In our task we will represent two human intentions only: "engaged" and "busy" and use as a platform to represent further relevant human intentions in the future.

The task state represents the agent which is currently holding the object,

$$S_t = object\_holder$$

where, object_holder $\in$ { robot, human }.

As it is assumed that human has initiated the task, the initial belief state is selected with a higher probability that human is engaged and interested in the task. However, the engagement state value will evolve over course of robot interaction with the human. In case ($engagement = engaged$), the final state includes ($hand\_postion = initial, objec\_holder = human$) and in case the ($engagement = busy$), the final state is represented by ($hand\_postion = initial,$ $objec\_holder = robot$).

Actions

The soft level coordination actions include **ping-sit** (ps), **ping-look** (pl) and **ping-take** (pt). The strong level includes **strong-ping-sit** (sps), **strong-ping-look** (spl) and **strong-ping-take** (spt). The ping-sit and strong-ping-sit actions are to ask the human to sit on the chair. Ping-look and strong-ping-look are to ask the human to look at the robot which is a sign of awareness and acceptance of the task advancement. Ping-take and strong-ping-take are to ask the human to take the object from the robot hand. The robot would try to ask the human to take the object (pt/spt) once the human is sitting on the chair and is engaged and the robot hand is already extended.

The task actions include, physical actions concerning the robot's hand/gripper positions, which are: move hand to wait position, move hand back to initial position, extend hand to a give position, move hand back to wait position, release the object from robot handgripper or do nothing.

$$A_t = \{move\_wait, back\_to\_initial, extend, back\_to\_wait, stop, release\}$$

The coordination (A_c)actions to coordinate and re-engage the human in the task are: soft level actions and strong level actions.

$$A_c = \{ps, sps, pl, spl, pt, spt\}$$

The soft level actions are; ping sit (ps), ping look (pl), and ping take (pt) and the strong level actions are; strong ping sit (sps), strong ping look (spl), and strong ping take (spt). These respectively ask human to cooperate and sit on the chair, look at the robot and take the object. Accordingly, the set of robot's actions is defined as:

$$A = \{move\_wait, back\_to\_initial, extend, back\_to\_wait, stop, release, ps, sps, pl, spl, pt, spt\}$$

Observations

The observations are related to the general human presence, human awareness of task through his focus of attention, robot awareness of human taking the object and the observation related to the task progress. The human presence observations include : human entered in the robot visibility space and is nearby the robot (ob_nearby), human is in the robot interaction area and sitting (($ob\_sitting$)) and human left the robot visibility space and is far from the robot ($ob\_farAway$). The human focus of attention observations are: human looking at the robot (($ob\_looking\_at\_robot$) or looking elsewhere(($ob\_looking\_away$). The observation regarding robot hand be ready (ob_hand_ready) to release the object on detecting human taking. Finally, task progress related observation consists of object status with the human ($ob\_object\_with\_human$).

$$Z = \{ob\_nearby, ob\_sitting, ob\_farAway, ob\_looking\_at\_robot,\\ ob\_looking\_away, ob\_hand\_ready, ob\_object\_with\_human, ob\_nothing\}$$

These observation come through different robot modules and are then integrated in the model. Also, it is possible to have more than one observation at each time step.

Transition Function

The actions $(goWait, backInitial, extend, backWait)$ are considered as deterministic actions and accordingly their transition is deterministic. For example:

$$pr(handPosition' = extended | hand\_position = wait, a = extend) = 1$$
$$pr(handPosition' = wait | hand\_position = extended, a = back\_to\_wait) = 1$$

The following states can change values at each transition: $presence$, $looking$ and $hand\_situation$. This represents the change in the current state caused by the possible received observation. Also, the robot's action release can transition the value of the state $object\_holder$ from $robot$ to $human$ or transition the system to a fail state.

Observation Function

The observation function gives the probability of observing the human state z, corresponding to a human action, knowing the robot did action a and the system ended in state s'. The function has a deterministic effect on the non hidden human related variables of the state, those are ($presence$, $looking$, and $object\_holder$). For example: $pr(z = ob\_sitting | a, presence' = sitting) = 1$. However, the effect of the observation (the human action) on the non observable hidden state $engagement$ is given by equation 6.5 , using an evaluation of human actions Q-Values (§6.4) toward possible $engagement$ values. λ is a normalizing factor, s^h and s'^h are HMDP states (section 6.4) derived from s and s' respectively.

$$O(z, a, s') = pr(z|a, s') = \lambda \text{ average AVF}(z, s^h) \qquad (6.5)$$
$$\forall s^h \in S^h \text{ where } pr(s^h, z, s'^h) \neq 0$$

Reward Function

To avoid disturbing the human, the model penalizes all weak and strong ping actions when the human wants the object and showing willingness to share the task. A small reward is given for weak and strong pings when the human is not showing engagement to the task. A penalty is assigned when the robot's hand is extended and the human is occupied, this encourage the robot to go back to wait position when the human is occupied. For final states, a small reward is assigned for $backInitial$ action when the human leaves the visibility space and a higher reward for the same action when the object is released to the human. Reward functions are parametrized manually

$$R(s, a) =$$

$$\begin{cases} p_1 < 0 & \text{if } (engagement = engaged \text{ and } a \in \{ps, pl, pt\}) \\ p_2 < p_1 & \text{if } (engagement = engaged \text{ and } a \in \{sps, spl, spt\}) \\ r_1 > 0 & \text{if } (engagement = busy \text{ and } a \in \{ps, pl, pt\}) \\ r_2 > r_1 & \text{if } (engagement = busy \text{ and } a \in \{sps, spl, spt\}) \\ p_3 < p_2 & \text{if } (handPosition = extended \text{ and } !wantsOb) \\ r_1 > 0 & \text{if } (presence = farAway \text{ and } a = backInitial) \\ r_3 \gg r_2 & \text{if } (objectOwner = human \text{ and } a = backInitial) \end{cases}$$

6.4 Human MDPs for the Handover Task

As described in Section 6.2.2 the Human MDP include states, actions, transition function and a reward function.

States S^h:

The Human MDP states include human's states, task's state and a state that represent the fact that the robot tried to repair the engagement with the human using coordination actions. Therefore,

$$S_h = presence \times looking \times pinged \times object\_holder,$$

Where, $(looking, presence, object\_holder)$ have the same values as described earlier and pinged represents type of coordination action the robot applied, if last applied action was a coordination action.

$$ping \in \{ps, sps, pl, spl, pt, spt, no\_ping\}$$

Actions A^h:

The possible human actions that are received by the POMDP model as observations are:

$$A^h = \{sit, stand, go\_away, look\_at\_robot, look\_away, take\_object, do\_nothing\}$$

Transition Function T^h:

The Human MDP state variables $presence$, $looking$ and $object\_holder$ transition deterministically according to the associated human actions:
$\{sit, stand, go\_away, look\_at\_robot, look\_away, take\_object\}$. However, the variable $pinged$ has the possibility to change to any possible $pinged$ value uniformly. Not possible future ping values are , for example, scenario such as, where, the robot trying to induce the human to sit ($pingSit$) while he is already sitting.

Reward Function:

For the HMDP of a simulated human who is interested and collaborating to take the object, the function rewards actions in favor of collaborating and well receiving the object from the robot. Such actions presents the intention of the human of taking the object as in sitting on the chair and looking at the robot, whether by himself or induced by the robot coordination action. However, the R_{wants} function penalizes all actions that show disinterest of the human in taking the object as looking away from the robot or standing or leaving the scene. The following summarizes all situations:

$$R_{wants}(s^h, a^h) =$$

$$\begin{cases} r_1 > 0 & \text{if } (pinged = nothing \text{ and } \\ & a^h \in \{sit, lookAtRobot, takeObject\}) \\ r_2 > r_1 & \text{if } (pinged = pt \text{ and } a^h = takeObject) \\ r_3 > r_2 & \text{if } (pinged = spt \text{ and } a^h = takeObject) \\ r_4 >= r_3 & \text{if } (pinged = pl \text{ and } a^h = lookAtRobot) \\ r_5 > r_4 & \text{if } (pinged = spl \text{ and } a^h = lookAtRobot) \\ r_6 >= r_5 & \text{if } (pinged = ps \text{ and } a^h = sit) \\ r_7 > r_6 & \text{if } (pinged = sps \text{ and } a^h = sit) \\ p_1 < 0 & \text{if } (a^h = lookOtherway) \\ p_2 < p_1 & \text{if } (a^h \in \{stand, doNothing\}) \\ p_3 < p_2 & \text{if } ((a^h = goAway) \text{ or } \\ & (pinged <> nothingmboxanda^h = doNothing)) \end{cases}$$

For a simulated human that is *not* interested, to take the object, the function rewards actions in favor of not collaborating. Such actions presents the interest of the human and his unwillingness to take the object as in not looking at the robot or leaving the scene. The function also penalizes actions that shows the human interest in collaborating especially responding properly to the robot guidance/pings.

$$R_{busy}(s^h, a^h) =$$

$$\begin{cases} r_1 > 0 & \text{if } (a^h = lookOtherway) \\ r_2 > r_1 & \text{if } (a^h \in \{standUp, doNothing\}) \\ r_3 > r_2 & \text{if } ((a^h = goAway) \text{ or } \\ & (pinged <> nothingmboxanda^h = doNothing)) \\ p_1 < 0 & \text{if } (pinged = nothing \text{ and } \\ & a^h \in \{sit, lookAtRobot, takeObject\}) \\ p_2 < p_1 & \text{if } (pinged = pt \text{ and } a^h = takeObject)) \\ p_3 < p_2 & \text{if } (pinged = spt \text{ and } a^h = takeObject) \\ p_4 <= p_3 & \text{if } (pinged = pl \text{ and } a^h = lookAtRobot) \\ p_5 < p_4 & \text{if } (pinged = spl \text{ and } a^h = lookAtRobot) \\ p_6 <= p_5 & \text{if } (pinged = ps \text{ and } a^h = sit) \\ p_7 < p_6 & \text{if } (pinged = sps \text{ and } a^h = sit) \end{cases}$$

6.5 Coactivity Decision Model: Integration and Qualitative Analysis

To evaluate and assess the Coactivity Decision Model (CDM); it has been integrated in a collaborative task supervision system, a part of Laas architecture [Alami 98], as shown in figure 6.2. The collaborative task supervision system, includes coactivity decision model and other components that aid, and complement its functioning.

First, CDM integration and execution is described, then a general system evaluation is done, followed by the description of supporting components (added to enhance the overall collaborative task achievement) and finally, CDM model is proposed for taking the object from the human.

6.6 System Integration

Currently, CDM is integrated as a part of collaboration task system and is as such initialized at the outset with $handover\_object$ task. The collaborative task supervision system is envisioned as a supervision and monitoring framework for achieving collaborative tasks with the human. Which will be mainly accomplished through CDM.

Correctly perceiving a human in the vicinity of the robot is very critical for a successful human robot collaboration. Therefore, a description regarding perception of the human is given next.

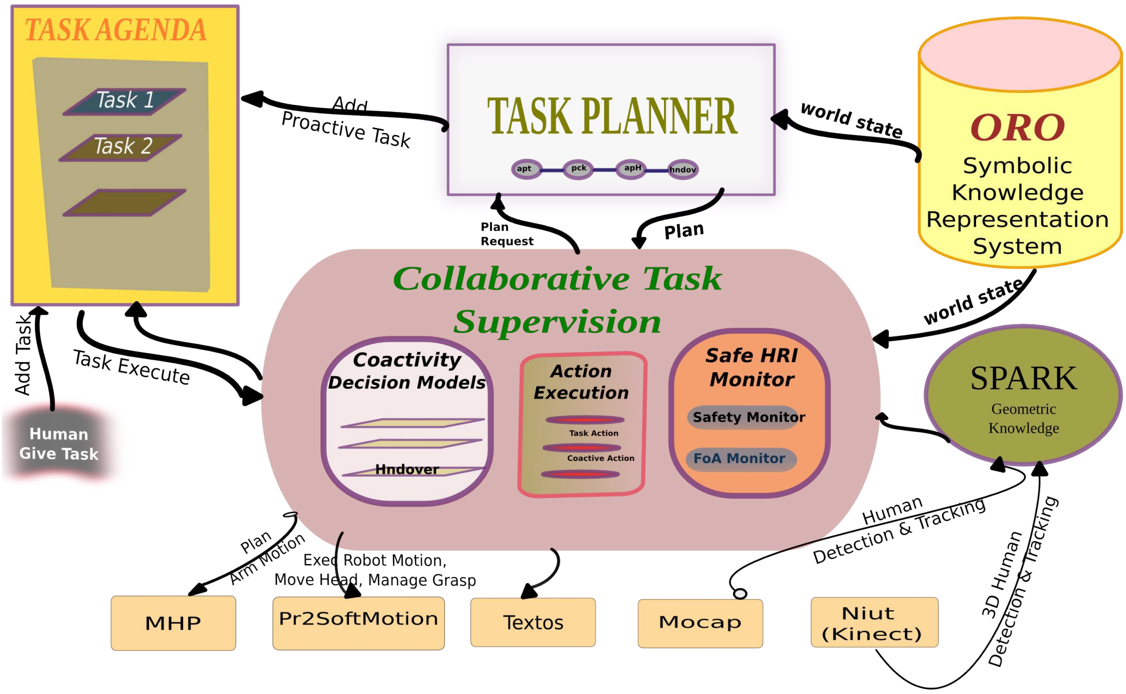


Figure 6.2: System Architecture

6.6.1 Human Observations

For a fluent human robot collaboration accurately observing the human is very important. In our system, the human observations are given by two highly accurate detection and tracking system; one is the marker based human motion tracking using *Mocap* module, and other is the 3D human tracking system using Microsoft Kinect. Originally, only Motion capture system was used to track the human and later on the Kinect was added to enhance the overall human observation capability. To give meaning to the human observations, the SPARK module fusions the information coming from both these modules and uses geometric reasoning tools to produces symbolic knowledge. This knowledge is then communicated to the ORO, the symbolic knowledge reasoner. SPARK not only has the information on the human, but as well as has information on the objects and other agent's (for example, robots) in the environment and also, displays the whole environment in 3D. Figure 4.6 shows the human in the environment and his detection in 3D on the wall screen. More, detailed description of these components is given in chapter 3.

The main human observations inferred by the system are:

- $isPresent \in \{true, false\}$
- $isMoving \in \{true, false\}$
- $human\_head\_isMoving \in \{true, false\}$
- $human\_torso\_isMoving \in \{true, false\}$
- $human\_right\_hand\_isMoving \in \{true, false\}$

- $human\_right\_hand\_pose \in \{extended, rest\}$
- $human\_left\_hand\_isMoving \in \{true, false\}$
- $human\_left\_hand\_pose \in \{extended, rest\}$
- $hasPosture \in \{sitting, standing, unknown\}$
- $looksAt \in \{robot, object_1, object_2, .., object_n\}$
- $proximity \in \{near, farFrom\}$
- $isLocated \in \{leftOf, rightOf, behindinFrontOf\}$

The CDM, is principally updated based on the human observation related to; the human is present in the environment ($isPresent$) and his posture ($hasPosture$), his proximity to the robot ($proximity$), and whether he is looking at the robot or not ($looksAt$). The rest of the human observation are also important and will be added to the CDM, currently these are used to ensure safe human robot collaboration through various monitors. Besides these, various other human abilities are also observed, for example, the object visible and reachable for the human in the environment and can be incorporated based on the collaborative task.

Temporal Model Updates:
These observations are given by ORO and the CDM is updated as soon as collaborative task supervisor receives a valid update from the ORO, for example, human $standsup$. The collaborative task supervisor validates the update regarding the human loss of focus, as the human can just momentarily look away and look again the robot. In case, there is no immediate update, the CDM is updated periodically. This periodic update helps to avoid the robot stagnating and helps repair the human engagement in the task via coord actions or eventual cancellation of the task if required.

6.6.2 Action Execution

For a successful collaboration, the robot not only need to be able to make right decisions but need to correctly execute these decisions. This requires the robot to have effective action execution mechanism. Following are the principal action employed by the supervision system:

- move_arm actions
- gripper actions
- move_head actions
- verbal actions

The principal actions related to the CDM, are move_arm and verbal coordination actions.

move_arm actions:

The move_arm actions require, moving the robot arm to a particular position. The position can range from moving the robot arm to a rest pose to moving it to a pose that is comfortable for the handing over object with the human. This is accomplished through a motion planner that produces the human-friendly motion [Sisbot 10], validated through user studies [Dehais 11], and is integrated in **mhp** module. The supervision system gives a motion planning request to the **mhp** module and then executes the relevant arm trajectory (if a motion plan is found) using a low level control module (**pr2SoftMotion** on the PR2 robot and **lwr** on the JIDOKUKA robot). The supervision manages the all the requests, and on detecting a failure, informs the human and cancels the task.

gripper actions:

The gripper actions include, close, open, $grab\_on\_contact$ and $release\_on_contact$. The supervision system, launches $release\_on\_contact$ action only when the robot arm is at give pose. Therefore, as soon as the human tries to take the object and makes contact with the object, automatic object release will happen due to $release\_on_contact$ action.

Moving Head Actions:

The supervision system, internally keeps track of the human and points the robot head using move_head request towards the human. This is important when the robot verbally addresses the human, to make him more comfortable.

Verbal Actions:

The supervision system, receives the respective verbal actions from the CDM, which are translated to a text using a fixed mapping. This text is then passed to a text to speech module **textos**, which produces an audible speech for the human.

The supervision system on receiving an action from the CDM, whether a task related physical action (requiring arm manipulation) or coordination action (requiring communication with the partner), maps it to the relevant action execution mechanism.

Next, coactivity decision model is illustrated through some example scenarios.

6.7 Coactivity Decision Model Illustration

The coactivity decision model (CDM) is illustrated for a handover collaborative task. The $handover\_task$ can also be a sub-task within a global robot goal of $give\_object$ to the human. This goal can come from the human, for example, through a verbal command or the robot can proactively decide to $give\_object$, for example, when the robot recognizes a human need and finds a relevant plan to decide to intervene in the human task.

Following different example cases will demonstrate the working of the CDM for the $handover\_task$ on our robotic platforms:

The Standard Cooperative Case

In this general scenario, the robot starts handing over the object in a state where, the human is comfortable and steady to receive the object, i.e., the human is nearby, sitting and has the focus of attention (looking) at the robot. Figure 6.3 illustrates the CDM achieving the $handover\_object$ task on the PR2 robot (Figure 6.5 shows $handover\_object$ task on the JIDOKUKA robot).

In this scenario, the interacting human has asked the robot to give an object, which the robot has already picked. As the human is sitting and looking at the robot, CDM selects $extend$ action and the robot moves arm to hand over object. Supervisor detects the human taking the object, releases the object and updates the CDM, i.e., object is with the human. Consequently, CDM selects $move_initial$ action and successfully ends the task. Figure 6.4 shows respective states observation and action evolution over time for this example.

The Standard Cooperative Case, human busy

In this example scenario (assumed the human has given the command), the human starts initially in a cooperative situation and then as the robot is handing over the object, the human looks away from the robot, i.e., the human looses its focus of attention, the CDM selects $move\_Wait$ action and the robot moves arm to a wait pose indicating to the human it is waiting. Afterwards, the human stands up, so the action selected by the CDM, is $ping\_sit$. As the human sits again, CDM starts handing over the object again. This scenario is shown in figure, 6.6 and in figure 6.7is graph shows respective system evolution for this example.

The Non Cooperative Case, Human Busy

In this the example, the human is initially standing and not focusing on the collaborative task. The human is less cooperative and reluctantly starts collaborating after the robot coord actions, for example, the robot asking the human to sit. The human sits but then again becomes busy and stands up, therefore the robot cancels the task as the observations lead to the high probability, that, the human is not interested in the collaborative task. This scenario is shown in figure, 6.8 and in figure 6.9 shows the CDM state observation and the action selected over time.

6.8 Ensuring Safety in Human Robot Collaboration and Improving Action Execution

The fundamental concern in human robot collaboration, especially in close physical collaboration, is how to ensure the safety to the human partner. In this regard, Asimov [Asimov 54] also identified it as a grand challenge, also known as 1st law of robotics:
A robot may not harm a human being, or, through inaction, allow a human.

As it is the case, in any non-deterministic collaborative decision model, there is always a chance that the robot action selected by the CDM may not be safe. Therefor, the robot should under all circumstances ensure safe and comfortable task execution and achievement with the human partner. So, for example, when the human looses his/her focus of attention (as in the figure 6.10) it should retract its arm first to a safe pose and then do a other things. This remains an important issue in the coacitivty decision model as some times it selects another action instead of a rendering task safe for the human first.

Similarly, the human can start moving abruptly and be in a unstable pose, for example, as shown in in the figure, 6.11. In this example, the robot is handing over the object but the human looses focus of attention and is moving, and unstable. Coactivity model after the update selects pingLook and then pingSit action, and the robot arm is still moving. This can be inconvenient

(a) Human Sitting and Looking at the Robot

(b) Robot extends arm to handover the object

(c) Human extends hand and grabs the object

(d) Robot on detecting human intention to take the object, releases the object

Figure 6.3: Handing over an object to a person.

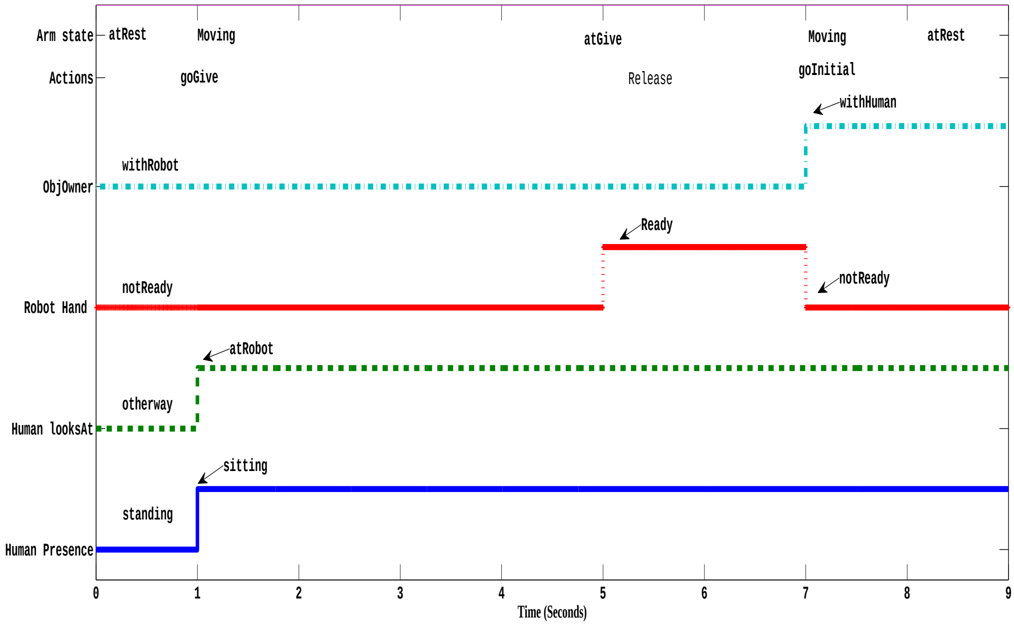
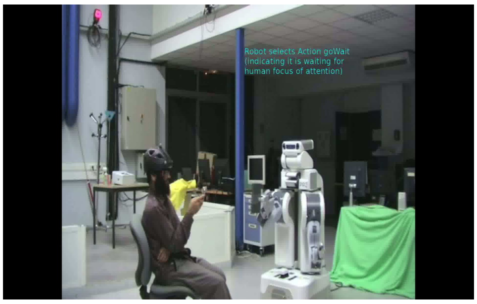


Figure 6.4: Handing over an object to a person: The state observations received and the action selected by the CDM over time is shown here. Initially, the human state is sitting and looking at the robot and the object is with the robot (actual observations starts after 1st second). CDM selects the *extend* action, moves arm to a give position. When the robot hand state changes to *Ready*, on detecting the human grabbing the object, a *Release* action follows and object is then inferred to be with the human.

Figure 6.5: JIDO handing over an object to a person.

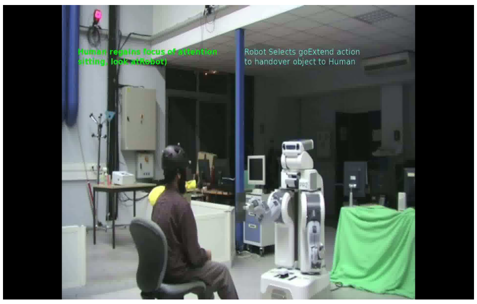
(a) Human Sitting and Looking at the Robot, CDM selects *extend* hand action

(b) Human looks away and robot hand is extended



(c) Human still looking away and CDM selects *move_wait* action

(d) Human stands up and CDM selects *ping_sit* action



(e) Human Sits and Looks at the Robot, CDM selects *extend* hand action

Figure 6.6: Handing over an object to a busy person, standard case:

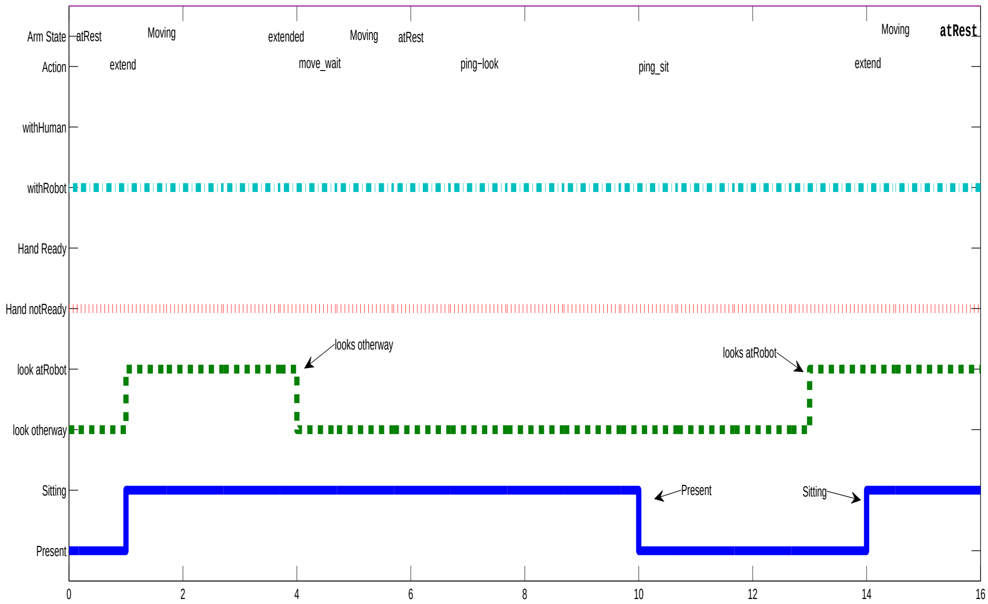


Figure 6.7: Handing over an object to a busy person, standard case. The state observations received and the action selected by the CDM over time is shown here for a human who becomes busy. Initially, the human state is sitting and looking at the robot and the object is with the robot (actual observations starts after 1st second). CDM selects the *extend* action, moves arm to a give position, but the human starts looking other way. CDM selects *move_wait* action. Finally, the human state changes to present (standing and near the robot). CDM selects *ping_sit* action, and when the human state changes to *sitting* again then CDM selects *extend* action to handover the objec.

(a) Human is standing, the robot asks human to sit

(b) Human sits but not looking at the robot

(c) Human sitting and looking at the robot, the robot extends the arm

(d) Human looks away from the robot

(e) Human stands up, the robot cancels the task

Figure 6.8: PR2 handing over an object to a busy person, non-cooperative case.

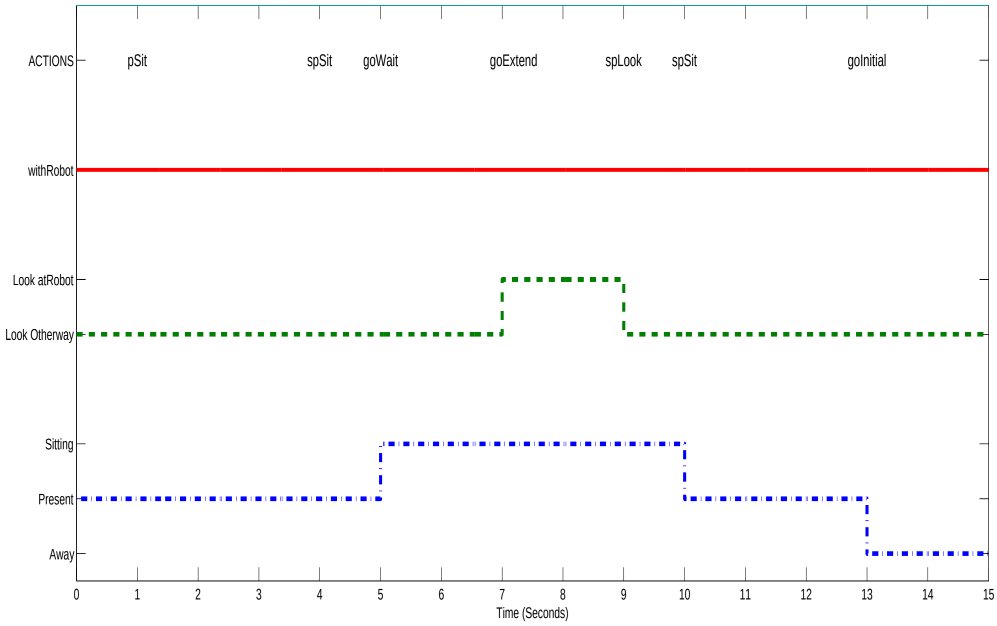


Figure 6.9: PR2 handing over an object to a non-cooperative person. The state observations received and the action selected by the CDM over time is shown here. The human is *present* and looksAt *otherway* at the start, CDM selects *ping_sit* coord action, to initiate the human to sit, the human state remains same, so, CDM selects *strong_ping_sit*, causing the human to sit though still looking away, so, CDM selects *move_wait* action, indicating to the human it is waiting. Afterwards, the human looks_at, the robot, CDM selects *extend* action. Meanwhile, the human state changes to looks_away and to *present*. CDM selects coord actions: *strong_ping_look* and *strong_ping_sit* respectively and finally selects *move_initial* action to cancel the task.

and may cause injury to the non attending human and requires model to act immediately and stop the arm first (currently is managed internally).

Figure 6.10: PR2 handing over an object to a person, safety issue case (Human lost FoA): This image shows that the human has lost the focus of attention and the robot arm stays extended and the robot asks the human to focus on the task instead of stopping arm motion and moving arm to safe pose.

6.8.1 Safe HRI Monitors

One of the important issue is monitoring the human focus of attention and the human pose stability during the task, so as to make collaborative activity safe and comfortable for the human partner. The Safe HRI monitoring, corresponds to the effective safe progresses of the task, both in terms of observing the human focus of attention for the task and his/her physical attentiveness. For this purpose, two monitoring modules; focus of attention and the human physical stability monitor were added.

Focus of Attention Monitor:

The Focus of Attention (FoA) Monitoring process, checks the human focus of attention during the task execution, for correct task execution and is important from safety consideration, as a human can suddenly loose focus and during the robot arm movement it can be critical.

In this case, the human head starts turning or the obot only receives the event: the human looks "otherway", then monitor starts watching both the human and the robot actions. This Look $Otherway$ state is not updated immediately, as it can be an one OffGaze [Hinte 11] and the robot waits to confirm that the human has lost focus of attention. In the case, where the human loss of FoA is confirmed (through a simple temporal verification), for example, the human

(a) Robot starts moving arm and human starts moving is unstable

(b) robot arm still moving and human is standing up

(c) human passes by the robot arm, which is still moving

Figure 6.11: PR2 handing over an object to a person, safety issue case (Human Unsteady).

looks other way for more than half a second, then any robot arm movement is stopped and arm moved to a wait pose. This process is shown in the figure 6.12.

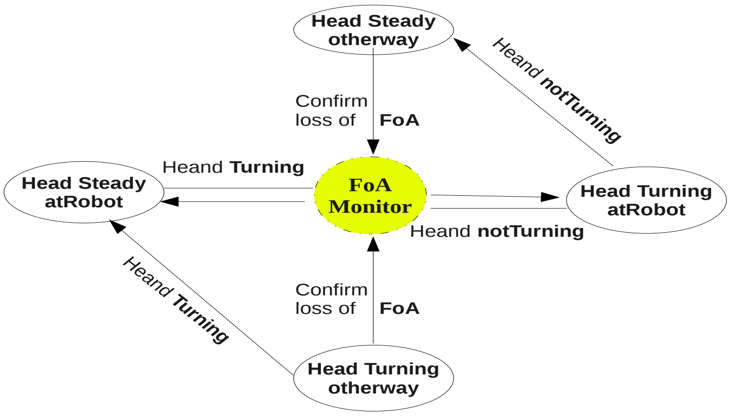


Figure 6.12: Activation of Focus Of Attention Monitor process when the human looks away and his/her head is unsteady.

Human Stable Pose Monitor:

This functions similar to FoA monitor, but here we focus on the sudden human movements, the human can be looking at the robot but moving at the same time. For example, when the human stands up suddenly, then the robot will monitor the human movements and if confirmed then stop the arm motion and move it to a safe wait pose.

A problem may arise due to safe HRI monitor stopping the arm motions to ensure safety, as currently there is no explicit arm_state monitoring in the CDM. This issue can be resolved using an expected state model for the action execution.

6.8.2 Improving Action Execution Using Expected State Model

In general, actions are directly mapped to the incoming actions selected by the Handover CDM, i.e., when the supervisor receives a task related action from Handover CDM, it is added to the queue and then begins its execution. For example, when an action $goGive$ is selected, the supervisor first sends a motion planning request and then sends motion execution request and all the while verifying its successful execution.

Currently, there can be a problem concerning the action selected by the Handover CDM, in lieu of current no explicit robot arm state monitoring in the model and also, due to non handling of multiple action in a single set. This causes problem, when the human looses focus of Attention or when the human posture is unstable, as in that case the FoA monitor or Safety Monitor will stop the arm and move the arm to a wait pose. Consequently, Handover CDMs internal representation would show arm at a give pose and the handover CDM could issue a non-pertinent action. For example, when the human becomes steady and regains Focus of Attention, the handover CDM could issue:*pingTake* action. In this case, arm could actually be at *wait pose state*, therefore would be inappropriate for the human.

Expected State Model for the Actions:

This issue can arise any non-deterministic system, one way to solve it would be, to use an *Expected state model*. An expected state model, is an intuitive automaton of the possible state transitions for each action. For example, expected state model for the $PingTake$ action is shown in the figure 6.13).

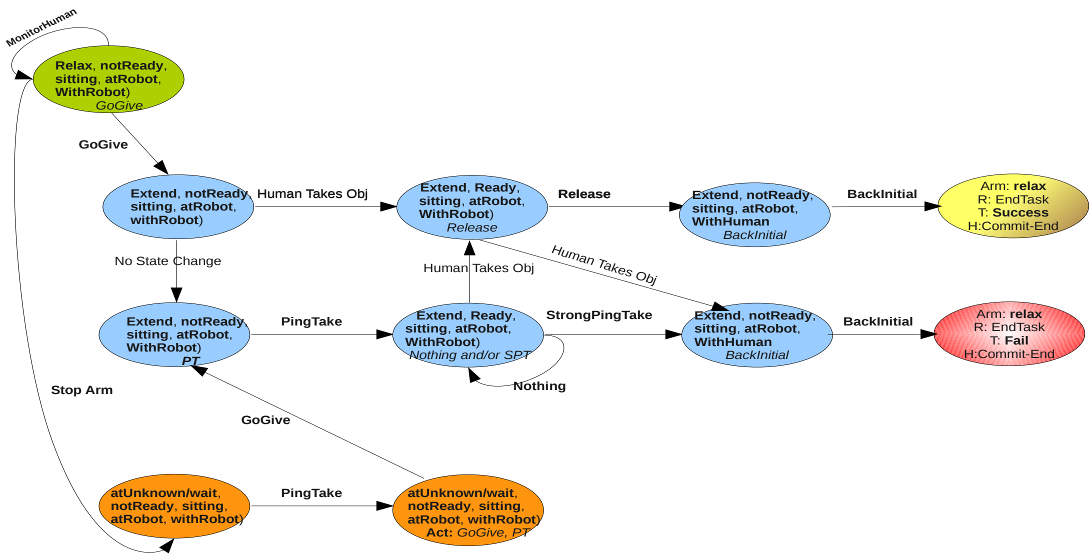


Figure 6.13: Expected Human State Model, for determining the correct robot action for the pingTake Action.

This helps determine, the correct robot action, and correct constraint on the actions, both non-pertinent coord action and the action selected, by correlating the observed states with the expected one.

For example, in above case, when the handover CDM selects the action *pingTake* and arm state is *atWaitPose*, then using Expected state model, first *goGive* action is selected and only then, *pingTake* action is executed. Similarly, when action selected is any other coactive action, for example, $pingSit$ or $pingStrongSit$ or $pingLook$ or $pingStrongLook$, then it verifies the correct arm state first and subsequently execute these coactive actions.

A constraint can be defined as:
$\text{Const}_{ij} := \langle observedstates, expectedstates, co-achieveactions, coactivityactions\rangle$ for example: PingTake := $(wait \wedge extended \wedge PingTake) \Rightarrow GoGive$

Although, this could be feasible if the number of possible such rules from actions and states database is small in number, whereas, with large data set of the actions and states deriving rules can become cumbersome. A better way would be to learn such set of rules.

Learning Action Constraints The action rules helping to determine the correct action constraint from the observed and expected states can also be learned from the available data and in future could even incorporate online learning methods.

Here, we used about 20 data sets from live runs constituting about 7 attributes and 115 instances. The attributes used for learning were: $armstate, handstate, humanstate, lookstate,$ $wantsObj, objOwner, andaction$. These attributes take different values and are same as previously described, for example, the attribute action is: $Actions = \{goInitial, backInitial, goWait,$ $backWait, goExtend,\ stop,$
$release, nothing, ps, sps, pl, spl, pt, spt\}$.

An example, data set is:
$relax, notReady, sitting, atRobot, yes, withRobot, GoGive$
$extended, notReady, sitting, atRobot, yes, withRobot, PingTake$
$extended, notReady, sitting, atRobot, no, withRobot, StrongPingTake$
$extended, notReady, sitting, atRobot, no, withRobot, Nothing$
$extended, notReady, sitting, atRobot, yes, withRobot, PingTake$
$extended, notReady, sitting, atRobot, no, withRobot, StrongPingTake$
$extended, notReady, sitting, atRobot, no, withRobot, Nothing$
$extended, notReady, sitting, atRobot, no, withRobot, BackInitial$

Using the random tree classifier in the weka data mining tool [Hall 09], the best classifier for $PingTake$ (or $StrongPingTake$) was arm_state, in fact following represents the tree classification in the order for the actions:
$armstate = extended, handstate = notReady, wantsObj = yes, humanstate = sitting,$
$lookstate = atRobot, objOwner = withRobot,$
where as we can exclude $wantsObj$ as it is a hidden variable.

Similarly, the best association rules found using "predictive Apriori" method in the weka data mining tool [Hall 09] for $PingTake$ action are:

1. $armstate = extended, handstate = notReady, lookstate = atRobot, wantsObj = yes$ $objOwner = withRobot \wedge action = PingTake$
2. $armstate = extended, handstate = notReady, humanstate = sitting,$ $lookstate = atRobot, wantsObj = yes\ objOwner = withRobot \wedge action = PingTake$

A general rule for $PingTake$ and $StrongPingTake$ can be drawn easily:
$(PingTake \vee StrongPingTake) \Rightarrow (armstate = extended \wedge$
$humanstate = sitting \wedge lookstateatRobot \wedge handstate = notReady)$

A better to handle some of the above problems would be to enhance the coactivity decision model (CDM), so as to make supervision more robust.

6.9 Improving the Coactivity Decision Model for the Handover Object Task

Current coactivity decision model for the handover needs improvements to be really effective and reliable for the human robot collaboration. Some of these improvements we envisage to add are:

Increasing Number of States:

Increasing the number of states will enrich the model and help improve the action selection and also, make the interaction safe. For example, in the current CDM, the robot hand position is not taken into account explicitly, i.e., it is not updated for the CDM. This can cause problems, for example, if the robot arm was stopped midway and moved to $wait\_pose$, for safety consideration, during the motion for $extend$ action, selected by the CDM, then in the model hand_position is at the $give$. So, when the human is ready to take object and arm is actually at $wait$, the action selected could be wrong (like $ping\_take$) and would be inconvenient for the human partner.

Following new states would enhance the model:

Robot states:
add at_unknown, $hand\_position \in \{initial, wait, extended, at\_unknown\}$
Human States:
add Human; looks_at Robot Hand, $is_moving(trueorfalse)$,
$hand\_extended(trueorfalse), hand\_moving(trueorfalse)$

These states will help achieve task in a more flexible way, for example, if the human wants to take the object standing (as shown in the figure 6.14) then the human can simply look at the robot hand (looksAt $Robot\_hand$). The human can even extend hand to take the object and the robot can **handover** the object to the human by moving its arm towards the human hand directly.

Task State: add in object_holder with_unknown,
There can be a situation where, the robot can detect that the object is no longer in its hand and that the human did not take the object either, i.e., object was dropped. Therefore, the robot can cancel the task early and inform the human partner about the problem.

Multiple Actions:

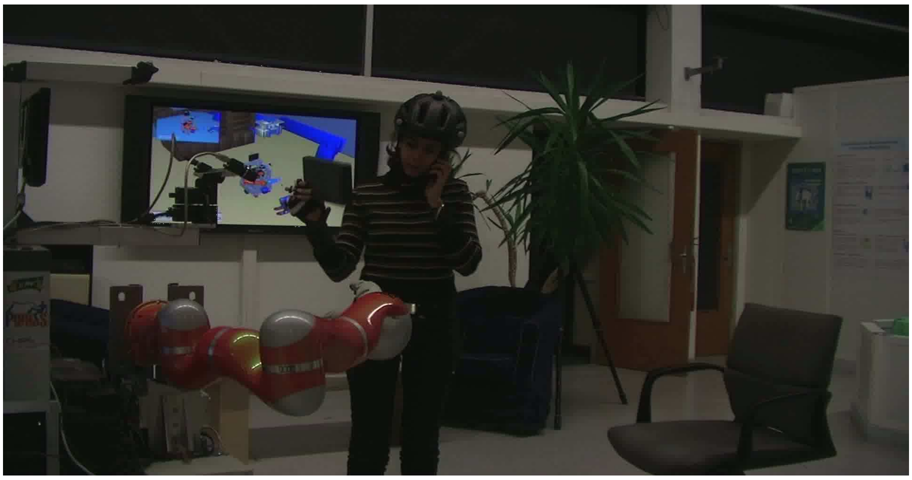
Model should be extended to allow for the multiple actions, for example, first move_wait and then ping_take are selected and issued as a single action array. This can help ensuring the safety and integrating safe HRI monitoring process directly into the model.

Selecting Appropriate Initial Belief Depends on Goal Initialization:

The supervisor should be able to select initial belief, for both cooperative case and non-cooperative case. For example, in the case the human has given the command the start belief could be 95%, that is, the human will collaborate. In case, where the robot selects a proactive task, the initial belief could be 50%, that is, the human is perhaps interested in collaboration.

(a) Human is standing and extending hand

(b) Human takes the object



(c) Object is with the human

Figure 6.14: Example: Handing over an object to a person standing. In this example, handing over of the object to a person standing is shown.

Current coactivity decision model for the handover task needs to be enhanced to accommodate the human preferences, as some humans require more reminding to re-engage (elderly, person with dementia, or children in a class etc.) and others get irritated with little reminding, and to take into account social conventions. Known limitation is the lack of general transition model, which is due to difficulty in acquiring models using learning methods [Broz 11] as there will be large variation in data (each person approaches a task his/her own way).

Coactivity decision model is useful for a collaborative task, however, there is a need to validate further system using user study. Coordination actions not only include verbal cues to induce coactivity behavior in the human partner but can also include $gestures$, like the robot moving its arm to a wait pose and indicating to the human that, the robot is waiting for his/her action. Coordination actions can be reused in other tasks for inducing collaboration while the actions used to achieve a task will vary from task to task.

6.10 Robot Taking Object from the Human

A robot will not only require to handover the object to the human but may also need to take the object from the human. Human can handover the object by explicitly asking the robot to take, for example, "Hey robot, take this object and put into the trash". The robot could also, proactively move hand towards the human [Pandey 11] and ask for the object as shown in figure 6.15.

6.10.1 Coactivity Decision Model for Taking Object from the Human

The CDM for the robot $take\_object$ task, is similar to the CDM for the handover_object task with some additional states and actions. It is assumed that the object is *not reachable* for the robot and is *reachable* for the human. Also, for detecting the human give, it is assumed the human will place the object in the robot hand.

States

States are similar to the $handover$ coactivity task as the $take\_object$ can be considered as reversal of roles for both agents, i.e., now the human will do the $handover\_object$ task but with some uncertainty on his willingness to collaborate with the robot, when the robot proactively asks help. Here, important is the human hand position, allowing the robot to determine the human intention to collaborate.

For the take object task, a state in $s \in S$ represents the robot, the human and the task states. $S = S_r \times S_h \times S_t$. The state of the robot are:

$$S_r = robot\_position \times robot\_looking \times hand\_position \times hand\_situation$$

where, robot_position $\in$ { near, far } and robot_looking $\in$ { at_human, at_hand, at_object, otherway } and hand_position $\in$ { initial, wait, extended } and hand_situation $\in$ { not_ready, ready }.

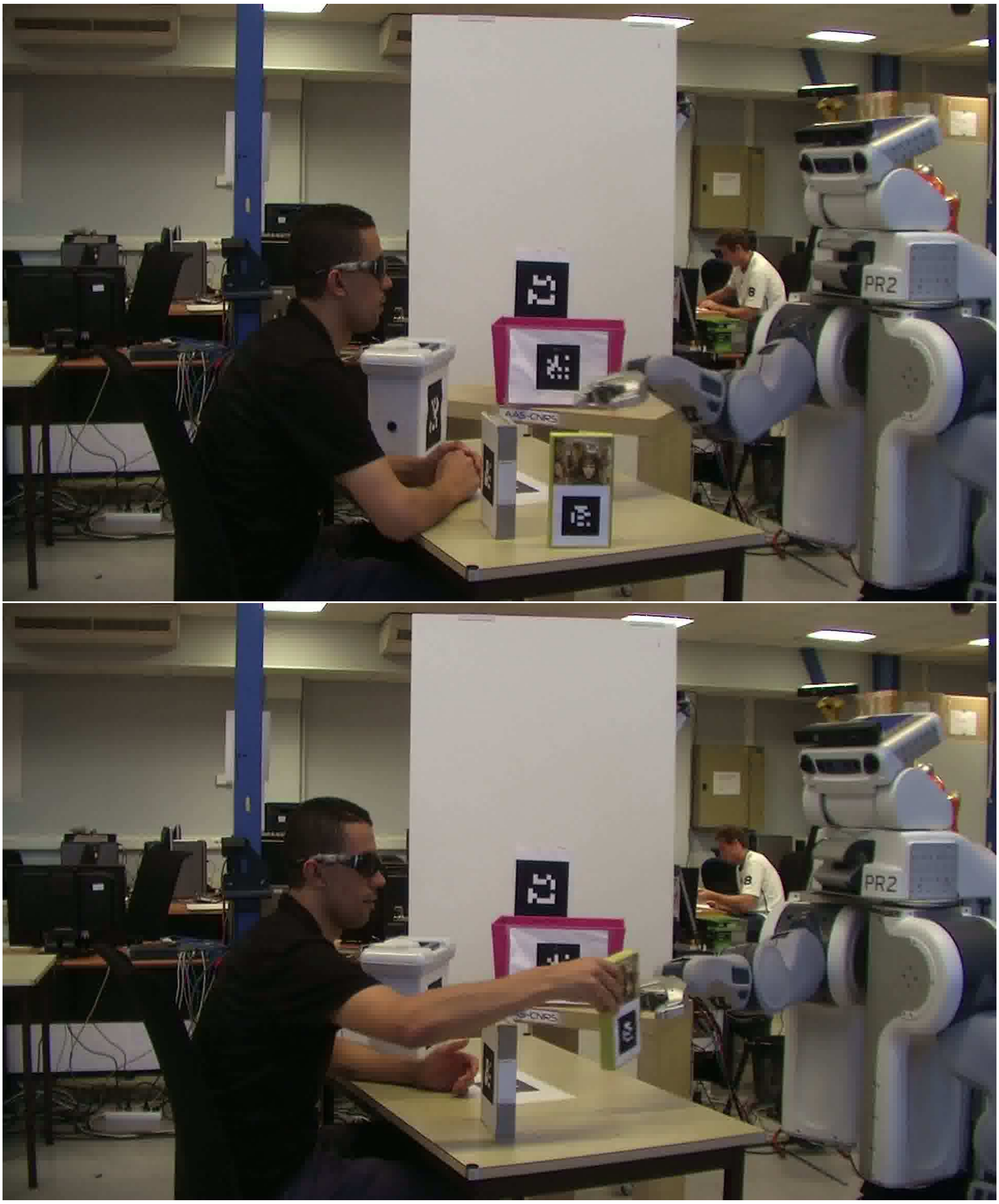


Figure 6.15: In this example, the robot has proactively extended the hand to take the object from the human.

The robot position is the robot location with respect to the human, the task is only possible when the robot is near the human. The robot $looking$ state will help to establish a *mutual focus of attention* (with the human) or a *directed attention* (at the object) or will help to indicate the robot focus of attention. For example, the robot should look at the human first, i.e., establish a *mutual focus of attention* and then look at the object when asking for the object, i.e., signal its *focus of attention*. In case where the human initiates the task, the robot looks at the human when the human asks the robot help. The robot hand position which can be in initial position (close to the robot), wait position (middle) and the extended position (close to the human). The waiting position permits the robot to wait for new information about the human to better decide whether to go back to its rest position or to extend its arm to take the object. The robot's hand situation represent the fact that the robot's hand is ready to take the object or not.

The state of the human includes:

$$S_h = presence \times human\_moving \times hum\_hand\_position \times looking \times engagement$$

where, presence $\in$ { sitting, nearby, far_away },human_moving $\in$ { true, false },
hand_position $\in$ { rest, extended } looking $\in$ { at_robot, at_object, otherway } and
engagement $\in$ { engaged, busy }.

The human presence state, can be near and sitting on a chair, standing close or far away from the robot interaction zone, The human looking direction, representing the human focus of attention, which can be looking at the robot, at the object or looking elsewhere. Finally, the non-observable (hidden) state representing the human engagement concerning the collaborative task, which can be engaged to achieve the task or is busy.

The task state represents the agent or the entity which is currently holding the object,

$$S_t = object\_holder$$

where, object_holder $\in \{robot, human, table\}$.

In the case, where the human initiates the task, the initial belief state is selected with a higher probability that the human is engaged and interested in the task and in the case, where the robot initiates the task the initial belief states is selected as 0.5. However, the engagement state value will evolve over course of the robot interaction with the human. In case $(engagement = engaged)$, the final state includes $(hand\_postion = initial, objec\_holder = robot)$ and in case the $(engagement = busy)$, the final state is represented by $(hand\_postion = initial, objec\_holder = humanortable)$.

Actions

The coordination actions include, verbal communication devices: **ping-ask-help** (ph), **ping-look** (pl) and **ping-give** (pg) and the material signals: **lookAt** (objecthuman), i.e., look at the object, look at the human. Also, would be added in future is, pointing, an important coordinating device.

The task actions include, physical actions concerning the robot's handgripper positions, which are: move hand to wait position, move hand back to initial position, extend hand to a take position, move hand back to wait position, take the object from the human hand by closing the gripper on detecting the object, and approach (navigate to) the human if necessary.

$$A_t = \{move\_wait, back\_to\_initial, extend, back\_to\_wait, stop, take, approach\}$$

The coordination (A_c)actions to coordinate and re-engage the human in the task are:

$$A_c = \{ph, pl, pg, lookAt\}$$

Therefore, the set of robot's actions A is defined as:

$$A = \{move\_wait, back\_to\_initial, extend, back\_to\_wait, stop, take, ph, pl, pg\}$$

Observations

The observations are related to the general human presence, the human awareness of task through his/her focus of attention, the human stability, the human hand pose, the robot awareness of the human giving the object and the observation related to the task progress. The human presence observations include : the human entered in the robot visibility space and is nearby the robot (ob_nearby), the human is in the robot interaction area and sitting (($ob\_sitting$)) and the human left the robot visibility space and is far from the robot ($ob\_farAway$). The human focus of attention observations are: the human looking at the robot (($ob\_looking\_at\_robot$) or (($ob\_looking\_at\_object$) or looking elsewhere(($ob\_looking\_away$). The observation regarding the human postural stability (ob_moving) or (ob_not_moving). The observation of the human hand ($ob\_hum\_hand\_extended$) or ($ob\_hum\_hand\_atrest$). The observation regarding the robot hand be ready (ob_hand_ready) to take the object on detecting the human handing over the object to the robot hand. Finally, task progress related observation consists of object status with the robot ($ob\_object\_with\_robot$) or with the human ($ob\_object\_with\_human$) or on the table ($ob\_object\_on\_table$).

$$\begin{aligned} Z = \{&ob\_nearby, ob\_sitting, ob\_farAway, ob\_looking\_at\_robot, ob\_looking\_at\_object, \\ &ob\_looking\_away, ob\_moving, ob\_not\_moving, ob\_hum\_hand\_extended, ob\_hum\_hand\_atrest, \\ &ob\_hand\_ready, ob\_object\_with\_human, ob\_object\_with\_robot, ob\_object\_on\_table, ob\_nothing\} \end{aligned}$$

These observation also represent the probable action taken by the human, whether helpful for the collaboration or otherwise. Different modules generate these observation through sensor inputs and are then integrated in the model and the changes in the state observations can also be more than one at each time step.

Transition Function

Similar to the handover CDM, the actions ($goWait, backInitial, extend, backWait$) are considered as deterministic actions and accordingly their transition is deterministic. For example:

$$pr(handPosition' = extended | hand\_position = wait, a = extend) = 1$$
$$pr(handPosition' = wait | hand\_position = extended, a = back\_to\_wait) = 1$$

The following states can change values at each transition: $presence$, $looking$, $hum\_hand\_position$ and $hand\_situation$. This represents the change in the current state caused by the possible received observation. When the robot initiates the task and the object is on the table, then non observation of $object\_on\_table$, would help transition of $object\_holder$ from $table$ to $human$. Also, the robot's action take on detecting the human placing the object, can transition the value of the state $object\_holder$ from $human$ to $robot$ or transition the system to a fail state.

Observation Function

The observation function gives the probability of observing the human state z, corresponding to a human action, knowing the robot did action a and the system ended in state s'. The function has a deterministic effect on the non hidden human related variables of the state, those are ($presence$, $looking$, and $object\_holder$). For example: $pr(z = ob\_sitting|a, presence' = sitting) = 1$. However, the effect of the observation (the human action) on the non observable hidden state $engagement$, similar to handover CDM, is given by equation 6.5 , using an evaluation of the human actions Q-Values (section 6.10.3) toward possible $engagement$ values. λ is a normalizing factor, s^h and s'^h are HMDP states (section 6.10.3) derived from s and s' respectively. Here, we repeat the equation for clarity:

$$O(z, a, s') = pr(z|a, s') = \lambda \text{ average AVF}(z, s^h)$$
$$\forall s^h \in S^h \text{ where } pr(s^h, z, s'^h) \neq 0$$

Reward Function

Similar to the $handover$ coactivity model penalizes all the coacitvity actions when the human is already collaborating. A small reward is given for all the coactive actions and penalty is assigned to the collaborative achievement actions, when the human is busy.

$$R(s, a) =$$

$$\begin{cases} p_1 < 0 & \text{if } (engagement = engaged \text{ and } a \in \{ph, pl, pg\}) \\ p_2 < p_1 & \text{if } (engagement = engaged \text{ and } a \in \{lk(obj, human)\}) \\ r_1 > 0 & \text{if } (engagement = busy \text{ and } a \in \{ph, pl, pg\}) \\ r_2 > r_1 & \text{if } (engagement = busy \text{ and } a \in \{, lk(obj, human)\}) \\ p_3 < p_2 & \text{if } (handPosition = extended \text{ and } !wantsOb) \\ r_1 > 0 & \text{if } (presence = farAway \text{ and } a = backInitial) \\ r_3 \gg r_2 & \text{if } (objectOwner = human \text{ and } a = backInitial) \end{cases}$$

6.10.2 The HMDs for Taking object from the human

The Human MDP include states, actions, transition function and a reward function.

States S^h:

The Human MDP states include human's states, task's state and a state that represent the fact that the robot tried to repair the engagement with the human using coordination actions. Therefore,

$$S_h = presence \times looking \times pinged \times object\_holder,$$

Where, $(looking, presence, object\_holder)$ have the same values as described earlier and pinged represents type of coordination action the robot applied, if last applied action was a coordination action.

$$ping \in \{ph, pl, pg, no\_ping\}$$

Here, the sub-coord actions, looking at the object or looking at the human (lk) are not included as there helping coordination action for the verbal reminders.

Actions A^h:

The possible human actions that are received by the POMDP model as observations are:

$$A^h = \{sit, stand, go\_away, look\_at\_robot, look\_at\_object, look\_away, hum\_moving, hum\_notmoving, hum\_hand\_atrest, hum\_hand\_extended, obj\_holder\_human, give\_object, do\_nothing\}$$

Transition Function T^h:

The Human MDP state variables $presence$, $looking$, hum_hand_pose and $object\_holder$ transition deterministically according to the associated human actions $\{sit, stand, go\_away, look\_at\_robot, look\_at\_object, look\_away, obj\_not_on\_table, give\_object\}$. However, the variable $pinged$ has the possibility to change to any possible $pinged$ value uniformly. Not possible future ping values are , for example, scenario such as, where, the robot trying to induce the human to look ($pingLook$) while he is already looking.

Reward Function:

For the HMDP of a simulated human who is interested and initiates the collaboration to give the object, the function rewards actions in favor of collaborating and well receiving the object from the human. Such actions presents the intention of the human of giving the object as in standing or sitting, hand extended and looking at the robot. However, the R_{wants} function penalizes all actions that show disinterest of the human in giving the object as looking away from the robot or leaving the scene. The following summarizes all situations:

$$R_{wants}(s^h, a^h) =$$

$$\begin{cases} r_1 > 0 & \text{if } (pinged = nothing \text{ and} \\ & a^h \in \{sit, lookAtRobot, hum\_notmovinghum\_hand_extend, giveObject\}) \\ r_2 > r_1 & \text{if } (pinged = pg \text{ and } a^h = giveObject) \\ r_3 >= r_2 & \text{if } (pinged = pl \text{ and } a^h = lookAtRobot) \\ p_1 < 0 & \text{if } (a^h = lookOtherway) \\ p_2 < p_1 & \text{if } (a^h \in \{hum\_hand\_extend, doNothing\}) \\ p_3 < p_2 & \text{if } ((a^h = goAway) \text{ or} \\ & (pinged <> nothingmboxanda^h = doNothing)) \end{cases}$$

In the case, where the robot initiates the collaboration, the HMDP of a simulated human who is interested and collaborating to give the object, the function rewards actions in favor of collaborating and well receiving the object from the human. Such actions presents the intention of the human of giving the object as in standing or sitting, hand extended and looking at the robot, whether by himself or induced by the robot coordination action. However, the R_{wants} function penalizes all actions that show disinterest of the human in giving the object as looking away from the robot or leaving the scene. The following summarizes all situations:

$$R_{wants}(s^h, a^h) =$$

$$\begin{cases} r_1 > 0 & \text{if } (pinged = nothing \text{ and} \\ & a^h \in \{sitstandnear, lookAtRobot, hum\_hand\_extend, giveObject\}) \\ r_2 > r_1 & \text{if } (pinged = ph \text{ and } a^h = hum\_hand\_extend, obj\_holder\_human) \\ r_3 > r_2 & \text{if } (pinged = pg \text{ and } a^h = giveObject) \\ r_4 >= r_3 & \text{if } (pinged = pl \text{ and } a^h = lookAtRobot) \\ p_1 < 0 & \text{if } (a^h = lookOtherway) \\ p_2 < p_1 & \text{if } (a^h \in \{hum\_hand\_atrest, doNothing\}) \\ p_3 < p_2 & \text{if } ((a^h = goAway) \text{ or} \\ & (pinged <> nothingmboxanda^h = doNothing)) \end{cases}$$

For a simulated human that is *not* interested, to give the object, the function rewards actions in favor of not collaborating. Such actions presents the interest of the human and his unwillingness to take the object as in not looking at the robot or leaving the scene. The function also penalizes actions that shows the human interest in collaborating especially responding properly to the robot guidance/pings.

$$R_{busy}(s^h, a^h) =$$

$$\begin{cases} r_1 > 0 & \text{if } (a^h = lookOtherway) \\ r_2 > r_1 & \text{if } (a^h \in \{hum\_hand\_atrest, doNothing\}) \\ r_3 > r_2 & \text{if } ((a^h = goAway) \text{ or} \\ & (pinged <> nothingmboxanda^h = doNothing)) \\ p_1 < 0 & \text{if } (pinged = nothing \text{ and} \\ & a^h \in \{sitstand, lookAtRobot, hum\_hand\_extend, obj\_holder\_human, giveObject\}) \\ p_2 < p_1 & \text{if } (pinged = pg \text{ and } a^h = giveObject)) \\ p_3 <= p_2 & \text{if } (pinged = pl \text{ and } a^h = lookAtRobot) \\ p_4 <= p_3 & \text{if } (pinged = ph \text{ and } a^h = hum\_hand\_extend, obj\_holder\_hum) \end{cases}$$

6.10.3 Analytical Discussion

The proposed $take\_object$ task, has not be implemented currently, includes additional states: that help detect the human focus of attention, whether on the object (before taking object he/she will look at the object), or on the robot (should further be distinguished into the human looks at the robot head and looks at the robot hand for giving the object) or can look elsewhere if busy. For the human safety monitoring, the human states related to the human motion (moving/not moving) are added. Also, added the human hand state (extended/not extended) can further help monitor task progress. The $take\_object$ is currently not implemented and its implementation will also include multiple action execution, i.e, the relevant CDM would give more than one action if multiple human states changes. For example; if the robot arm is moving and the human looses his/her focus of attention then the CDM can give two actions for execution: move_arm_wait and ping-look.

The CDM could also be used for another different task, for example, for the robot guide task. In this task the robot shows around a visitor in the building. The human will follow the robot (maintain his/her intention to follow), the robot will move and monitor the human for his/her engagement (human states: present, proximity, location, orientation, motion etc.). The robot can use different coordination actions; can stop and wait, can verbally call the human etc. When the human retracts from the task (stops, discuss with another person, enters a room, receives a phone), the guide CDM can select the relevant coordination actions and help the robot act to re-engage the human.

6.11 Discussion

Here, we have shown a coactivity decision model (CDM) for human robot collaboration [KARAMI on]. The coactivity decision model manages the collaboration with a human in a human robot collaborative activity. It manages the uncertainty in the human intention to engage and collaborate when the human becomes busy. In this case, the model describes and utilizes coordination devices to induce collaboration from the human. This model needs further enhancement; for example, it should include engagement generation capabilities and should also ensure safe interaction with the human.

The Coactivity Decision Model described here gives a basic template to achieve a collaborative task; it manages the uncertainty in the human intention to engage and collaborate, especially when the human becomes busy and his focus shifts from the task on hand, and at the same time employs the necessary steps to achieve the collaborative task.

Important aspect of the proposed framework is the coordination devices, which not only help coordinate the collaborative activity but also, help clarify relevant human intention towards the task. It uses the the idea of rational HMDs ([Karami 11b]), to track the relevant human intention using the currently observed human action, inferred via the observed states. If the human engagement probability reduces, then the supervision system uses coordination action, derived from an optimal policy using the HMDs, to reinforce the engagement. Eventually, if human lacks the relevant motivation to continue then the task is stopped.

In this model, only two of the possible human intentions: "engaged" and "busy" were used, where as, human can have various other task related intention and each can be represented using related HMDs. For example, a rational HMD can monitor human future intention using his/her task agenda and help co-relate with his/her current task related intentions. The robot on detecting human "busy" intention can verify through the "Agenda" intention that if human is busy doing something. In this way it can avoid bothering the human. Another interesting case can be that during the collaborative activity, the robot can determine (using "Agenda" intention monitoring HMD) that, the human is forgetting something important (Call his wife) and can actually, suspend the current collaborative task and remind the human.

The notion of engagement is implicit in our work, whereas, [Holroyd 11]'s work focuses on generating the connection events (section 3.5) for the engagement. Which are generated using the turn fragments provided by the collaborative layer. In our work, coordination actions obtained using rational HMDs, not only provide a mechanism to maintain the engagement, using verbal and material signals, but also, help determine relevant human engagement in the task. [Holroyd 11] currently, provides a simple framework for maintaining the engagement, which constitutes of robot maintaining the gaze with the human partner, where as, the CDM explicitly uses coordination action to maintain the engagement with the human and also takes into account relevant uncertainty in the human intention. Also, the collaborative aspect is more tightly coupled, as the optimal policy is derived from the rational human behavior.

The overall system ensures the safe human robot interaction both extrinsically, using explicit human safety monitors and intrinsically, embedding the safety in the policy, for example, stopping a ongoing robot physical action when observed human state is: loss of the human focus of attention. Also, offline learning from the data helped improve the action execution. In future, learning can be done online and can also help system adapt to various humans.

An important future work is to have an explicit mechanism to establish a joint attention with the human, which is essential in attributing the human being engaged in the task. A basic framework for establishing the joint attention is proposed in the Appendix A, inspired from a behavioral psychological model, and can be used to enhance the CDM.

Another useful enhancement would be the addition of *Time* in the CDM, it will help model to quickly end the task in case of unnecessary long partner response time. Time-State Aggregated POMDPs [Broz 08] can be useful for this.

Timing of the verbal coordination actions is also important when employed in conjunction with the task related actions, it is discussed in detail in the next chapter. Need to investigate similar models for other tasks involving collaborative human-robot navigation and object manipulation, to see how it can scale up. Also, it does not accommodate human preferences and take into consideration social conventions, as some human's may not like robot interference when busy.

6.12 Summary

The contribution here, focused on a set of robot decisional abilities that are necessary to endow a robot with the capacity to achieve a task in collaboration with a human. We have proposed to formalize it as so called "coactivity decision model" using an augmented POMDP which helps robot achieve joint activity task with the human, taking into consideration human engagement in the activity, a working example of model is shown. Such model opens opportunities for learning to adapt to human behavior during interaction.

Chapter 7

Communicative Act Placement in a Proactive Human Robot Joint Action

7.1 Introduction

One important aspect of human robot interaction is the verbal communicative act. Verbal communication plays an important role in the establishment of joint intention and commitments between the human and the robot. It can also be used to clarify ambiguous intention, as shown in the co-activity decision model (6), where the robot prompts the human to clarify the his/her intention or to ask the human for his/her help to achieve a robot task, as shown in figure 5.6. In this case, robot can be proactive and ask the human help and also, do a proactive physical action (for example, moving arm to take the object) to reduce the human effort. Therefore, it is important that the robot appropriately place and time the verbal action [Kopp 04, Salem 11].

In this chapter, first, a brief description of the proactive robot behavior in the context of a physical joint action with the human is given, and then using a HRI user study, we will show when to execute communicative act, i.e, when to interleave verbal communication with respect to the proactive robot reach action.

7.2 Verbal Communicative Act and Proactive Behavior in Human Robot Collaboration

Humans readily anticipate partner's action in a physical joint action during a collaborative activity and determines "where" a action should preferably take place [Sebanz 09]. Our robots are equipped to instantiate solutions for different proactive behavior, for example, proactively moving its arm to take an object from the the human or verbally indicating to the human partner where to make an object accessible for the robot [Pandey 11]. A HRI user study done in our lab demonstrates that people prefer the robot proactive reach behavior [Pandey 12].

Some of these proactive behaviors have been demonstrated in a global clean the table scenario, in which, the robot is given goal to clean the table. We have created a script to plan the solution for the high level task: clean the table. An example scenario has been shown in figure 7.1. Figure 7.1

(a), initial world state is shown, with the 4 objects to pickup from the table and put into the trash bin. Whereas, some objects are commonly reachable and visible by the robot and the human and other objects are exclusively reachable either by the human or by the robot. Figure 7.1 (b)to (e) shows the PR2 robot executing the actions, which the robot can perform by itself, i.e. picking and putting into the trash bin the two objects reachable to it. Then it requests the human to give the toycube (object 3 in figure 7.1 'a') while reaching out proactively. Figure 7.1 (f) shows the human is giving the object when the robot has proactively reached out to take. Figure 7.1 (g) shows that after taking the object, the robot is requesting the human to make the GREY_TAPE accessible with the proactive suggestion that the human can put it on the box. Figure 7.1 (h) the robot putting the object in the trash bin, while the human is making the object accessible by putting it on the box. Subsequently, the robot picks and places the GREY_TAPE into the trash-bin and returns to the interaction pose.

An important question arises, in case of proactive reach by the robot for taking object from the human (for example, in sub-figure (f) 7.1, the human is giving the object with the proactive reach by the robot,), when should robot verbally request the human:before starting proactive reach, after finishing the proactive reach or during proactive reach.

7.3 HRI Study: When the Verbal Action Should Occur

Below, we will briefly explain the results of preliminary user studies regarding when the robot should execute the verbal request relative to synthesized proactive reach out action in a proactive give task. In this aspect we did a HRI study with a group of users. The users were exposed to the different behaviors of the robot and were given the questionnaires to complete at the end of interaction, see figure 7.3.

7.4 Experimental Methods

7.4.1 Participants

Overall there were 30 participants in HRI study for the robot proactive behavior, of which 10 were exposed to the different verbal communicative acts interleaving. The 10 participants ranged in age from 26 to 33 years of age ($M = 29.3$, $\sigma 2.58$), 8 of the participants were male and rest were females. Participants consisted of a mixture of graduate students, researchers, and non-academic persons. Only 2 of the participants had regular exposure with the robots and rest had very little (N = 3) or no exposure at all (N=3).

7.4.2 Experimental Design

Scenario Setup:

The participants were seated across a table from the robot, see figure 7.2. Three objects were placed on the table, a box and two video cassettes, accessible for the participants and not reachable for the robot. Robot left arm was explicitly placed at a side pose, so that participants not expect it to move and the right arm is in a rest pose. The participants were asked to wear

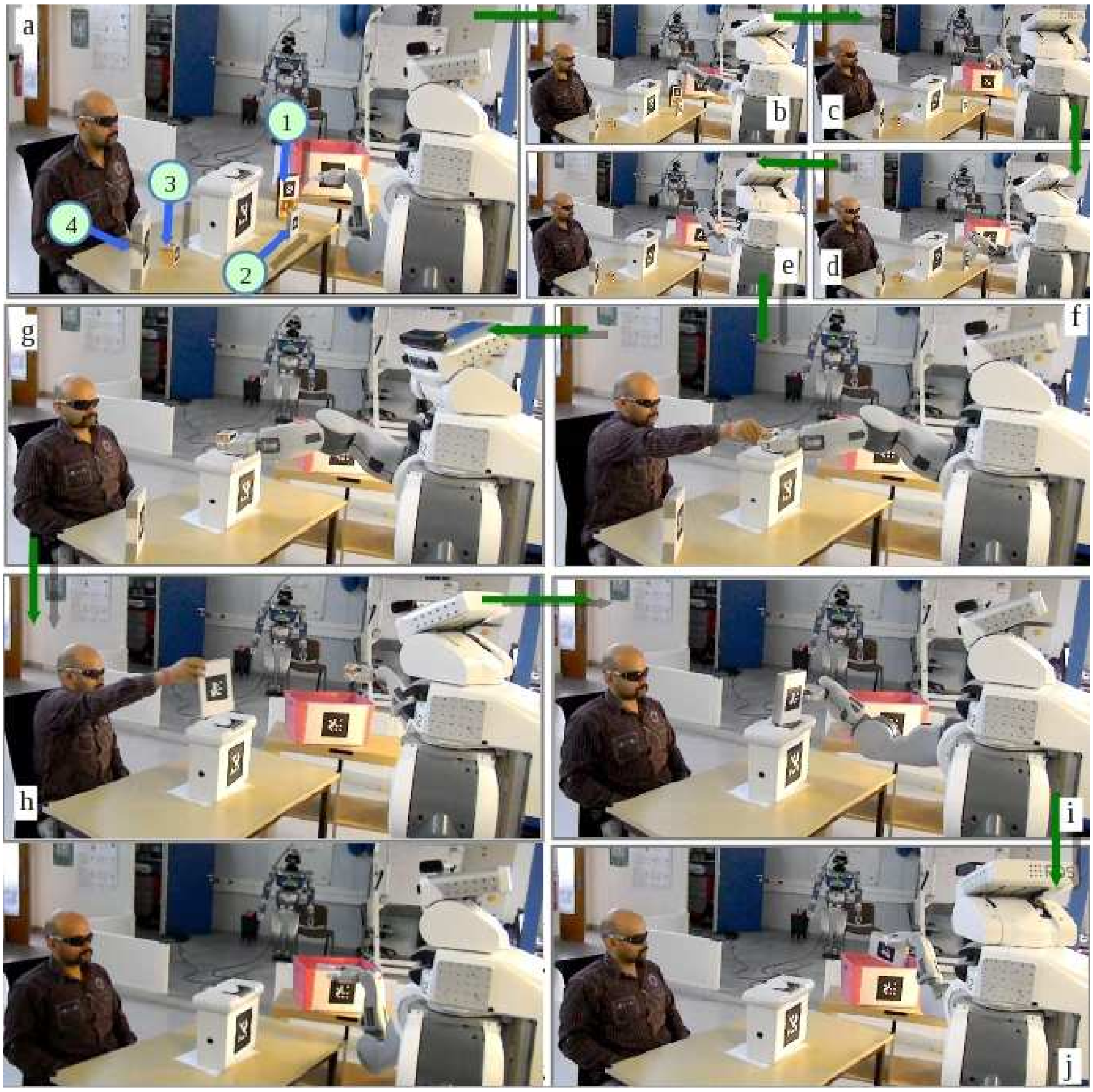


Figure 7.1: Execution of 'Clean the table' task with integrating proactive behaviors of the robot. In 'a': Initial scenario is shown, the robot goal is to clean the table by putting all the 4 objects in the trashbin. From 'b' to 'e': the robot is putting 2 objects, which are directly reachable to it, in the trash bin. In 'f': The robot verbally requests the human to give the toycube (3rd object in a), and the robot proactively reaching to take it. In 'g' After taking the object, the robot requests the human to make the remaining object, GREY_TAPE accessible to it, proactively through verbal communication action indicates where the human can put the object, so that robot could take it. In 'h': The robot is putting the toycube into the trashbin and meanwhile the human makes GREY_TAPE accessible to the robot. Rest of the images show robot picking and placing the GREY_TAPE into the trashbin and returning to interaction pose.

glasses with motion capture markers to track head orientation and were asked to sit near the objects on the table. The participants were either seated directly in front, figure 7.2(a) or on the side, figure 7.2(b), with respect to the robot. The scenario physical setup is shown in the figure 7.2.

Task:

In this HRI study, principal task chosen was the robot asking for the help from a human for getting a not-reachable object, while executing a proactive reach behavior (except in one case where robot did not execute the proactive reach). The participant had to respond to a number of spoken requests from the robot depending on the interaction behavior chosen and the order of the requests was changed for each participant. Following were the four interaction behaviors :

1. **Behavior A**: Robot asks to give the object and does not move its hand.
2. **Behavior B**: Robot first asks to give the object and when it finishes speaking then moves its hand.
3. **Behavior C**: Robot starts moving its hand and then asks for the object while continuing moving its hand.
4. **Behavior D**: Robot first moves its hand and then after stopping it asks to give the object at the end.

Behavior A is non-proactive and B-D are variants of proactive reach-out behavior from the perspective of when to move hand relative to the request to give the object.

The command spoken while looking at the subject: *"Hi, I need your help! Could you please give me the object"*. In case of behavior A, or in case, where the proactive behavior was the initial behavior, the object name was pronounced by the robot, for example" give me the Yellow Tape." and in the rest the object name was not used.

An example interaction is as follows:

- The robot looks at the object
- The robot looks at the subject
- The robot proactively reaches towards the object
- The robot: "Hi, I need your help! Could you please give me the object"
- The robot looks again at the object
- The participant reaches the object, picks the object and handovers to the robot
- The robot: "Thanks"
- The robot moves its arm to the rest position.

After the 1st interaction have been completed, the experiment setup is rearranged and next behavior interaction is executed and the process is repeated until the final interaction is completed.

(a)

(b)

Figure 7.2: HRI Study scenario, showing two setups: a) The participant sitting in front of the robot, and b) The participant sitting on the side.

7.4.3 Study Protocol

We took a Wizard of Oz approach [Dahlback 93] to the design of this experiment, allowing the experimenter to exert the necessary level of control over the order and timing of interactions during the course of the experiment. Using a predefined script and preset timings for each exchange between the robot and the participant, allowed to insure that each participant would have the same experience with respect to the behavior and the experiment setup chosen.

Each participant completed short interactions with the robot and were exposed to each of the four behavior defined above. The duration of each of these interactions was approximately half a minute long, allowing participants to complete the entire interaction portion of the experiment in less than five minutes.

The scripts were run by the experimenter and operated all of the necessary actions from one screen with the keyboard. Between each of the interactions, the experimenter changed the experiment setup, by re-arranging the objects on the table and instructing the participant regarding his/her new location.

When a participant entered the robotics room, he or she was seated in front of the robot. For each participant the experiment setup was selected at random and similarly, the behavior chosen were also randomized, to avoid setup or behavior bias. After being seated, the participant were told that the robot will interact with him/her and no further instruction regarding task were given. The instruction were explained in the following way:
"You are going to interact with the robot and you will be exposed to four different behaviors. You will be required to complete a survey questionnaire later."
The interaction then proceeded as described in the Task section above. At the conclusion of the interaction with the first behavior, the table setup is rearranged and the participant then completes the next interaction. These steps are then repeated until the final interaction with the fourth behavior. At the conclusion of the four interactions, participants were asked to complete a questionnaire about their experiences. This questionnaire took participants approximately ten-fifteen minutes to complete on average.

7.4.4 Questionnaire

The questionnaire given to the participant at the conclusion of the interactions consisted of twelve questions. These questions were designed to measure the participants expectation about the robot proactive behavior. First three questions were adapted to measure, using five-point liker scale, which behavior reduces the participant's confusion regarding, intention of the robot, where and when to exchange object with the robot. Question five-eleven, measure participants general preference regarding the task, for example, which over all behavior is favoured by the participant etc. The questionnaire concluded with participants gave general feedback regarding the experiment and interaction. The entire questionnaire is reproduced in Appendix C.

7.5 Results

The data collected from the experiment was analyzed with respect to the behaviors that were laid out earlier. Note that behavior A is non-proactive and B-D are variants of proactive reach-out behavior from the perspective of when to move hand relative to the request to give the object. The order of showing these behaviors was random for a particular user and there were two relative positions of the users with respect to the robot as shown in fig 7.3 (c) and (d).

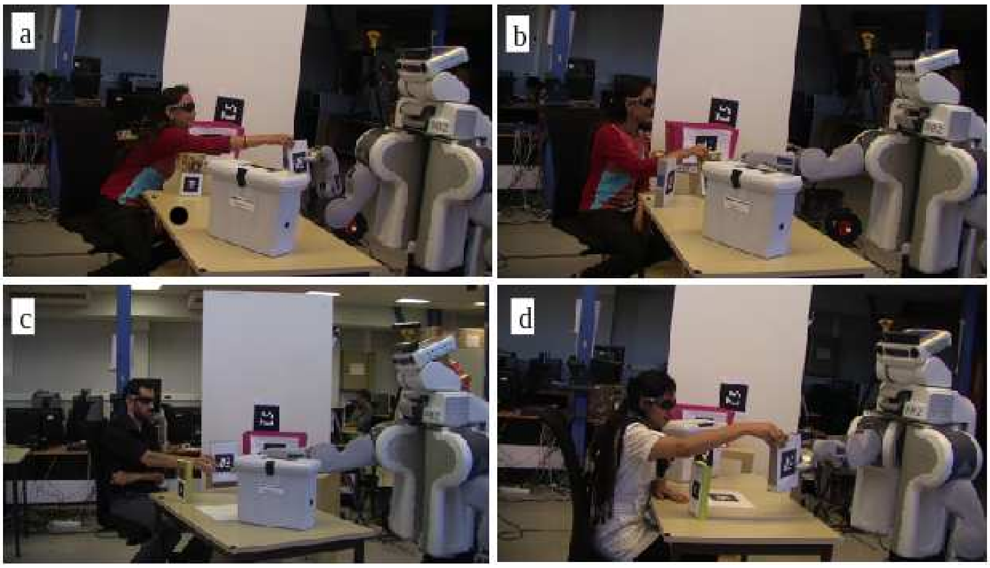


Figure 7.3: Users in the give object task study.

7.5.1 When to Execute Verbal Request

Table 7.1 shows the user preference regarding the temporal relation between the verbal request to give the object and the proactive reach out arm motion for the behaviors B, C and D. It shows the importance of relative timing of the communicative act. Also, in table 7.1 we see, that most of the users preferred behavior C that is integrated arm movement and verbal expression (interleaved near the end part of the motion) and that the verbal communication coming after the proactive arm motion is also accepted. It also, shows that almost all users unanimously do not prefer the behavior B. This suggests that the robot should speak after initiating the proactive reach out behavior. Results are in conformity with the findings in [Louwerse 05], which shows that aligned speech and gestures (e.g. pointing, etc.) results in less confusion and faster detection of the target for the hearer. Such robot behavior, i.e., interleaving of the robot communication act will also support the joint attention; as user gaze will be guided by robot arm motion trajectory towards the target in synchronization with the target identification. Therefore, the verbal communicative act serves as, not only to ask for the human help but, to clarify the robot intention to the human.

Table 7.1: User preferences about When to reach out relative to the verbal request to Give the object

Behavior	user prefer (percent)
A	0
B	0
C	70
D	30

Table 7.2: Overall preferences about each behavior

Behavior	user prefer (percent)
A	0
B	10
C	50
D	40

7.5.2 Video Analysis

Video analysis, also showed that the participants were able to localize well the object when the verbal request occurred after robot finished proactive reach or when it was made after robot started moving the arm. When, there was no proactive reach the participant had confusion localizing the object, even though the robot explicitly named the object. Similarly, participants were confused when robot first made the verbal request and then moved its arm.

This confusion was evident in the videos recorded, as shown in figure 7.4. In this case, the robot first asked the human for help and to give the object (behavior B). Then, the robot start moving its arm to do a proactive reachout. Although, the human understood the command and took the right object, the resulting motion of the arm caused confusion. The human tried to give the object during the motion (in future coactivity decision model can take this into account to take or handover object whenever the human wants). Finally, when the arm stopped moving then the human correctly handover the object to the robot. Here, timing a of the verbal action was critical as the human understood the task but had problem how to achieve the task.

The human had less confusion; when the robot arm had stopped moving and then asked for the help (behavior D) or, when the robot started moving its arm and then asked for the human help (behavior C), as shown in figure 7.5. In this case, the human waited for the robot the finish moving its arm and then gave it the object.

7.6 Discussion

The HRI user study demonstrated importance of timing a verbal communicative act, i.e., "when" to interleave verbal communication with respect to the proactive robot reach action. People attributed the robot behavior of moving arm first and then asking for the help, either after robot motion has finished or has nearly finished, as being most appropriate. This is perhaps due to the fact that when the robot moves its arm towards the object, it creates a kind of gesture (like pointing etc.) that helps clarify the object visually. Also, as the robot arm has stopped it makes it easier for the human to handover the object.

In the case, where the robot asks for the help first and then, moves its arm to take the object. First, the human needs to identify object using verbal cue only, second, the human needs to figure out how to handover the object and finally, wait for the robot arm to finish moving. This, probably causes confusion for the human and subsequently, the users attributed this robot behavior as causing more confusion. Perhaps if the robot is able to handover object dynamically, i.e., before the motion finishes, the results could be different.

This study needs to be enlarged further to solidify these results and also, another long term study could help answer the reasons for the confusion or the lack of it.

(a) Robot ask human to give the object

(b) Human takes the object to give

(c) Human tries to give the object is confused when robot starts moving its arm

(d) Finally, robot finishes the motion and human hands over the object

Figure 7.4: Confusion: In this case, robot first asks the human to give the objet (Behavior B) and then starts moving the object causing confusion for the human.

(a) Robot starts moving the arm and then asks the human

(b) Human takes the object and hands it over to the robot

Figure 7.5: NO confusion: In this case, robot starts moving the arm and then asks the human to give the objet (Behavior C). The human waits for the motion to finish, takes the object and hands it over to the robot.

7.7 Summary

We have performed a preliminary level of user studies and found the results encouraging and supporting our intuition and hypotheses. The study showed how important is to time a verbal action in the context of human robot collaboration. We feel the need of further user studies from the perspective of long-term human-robot interaction in the context of high-level tasks. This study may provide starting point for further research directions that then need to be investigated in more depth.

Chapter 8

Conclusions and Perspectives

Human robot collaboration has a long way to go, however, we can bootstrap it using vast available knowledge from human-human collaboration studies. In this work, we distinguished a comprehensive list of behaviors/characteristics that are desirable in a robot, that will act as a companion or assistant in human centered environments.

We have identified the basic proactive behavior required in a robot companion and shown, how a robot companion can generate proactive behavior and take initiative. This, requires the robot recognizing the opportunity to show proactive behavior and requires intricate goal management, as it becomes necessary to manage goals coming from both the human and the robot generated ones. For recognizing the scenario that require robot initiative taking, we modeled multiple relevant chronicles for each scenario. The chronicles help monitor the human activity in the vicinity of the robot and create robot goals. The work has been demonstrated on real robotic platform by adapting the existing system architecture accordingly. It shows the systems capability and provides the basis for building complex social behaviors.

The other important aspect we have shown is a coactivity decision model (CDM) for human robot collaboration. This model manages the collaboration with the human and handles the uncertainty in the human intention to engage and collaborate. In this case, the model describes and utilizes coordination devices to induce collaboration from the human.

We have also done a HRI user study showing "when" the robot should ask, i.e., when the speech action should occur during a human robot joint action task, essential for a smooth human robot collaboration experience. This study's results are in conformity with the socio-psychological studies.

In summary our contributions enable the robot to:

- Manage high level robot goals and display important proactive behaviors.
- Coachieve a collaborative task with the human, by taking into consideration the ambiguity around human collaboration, and use the coordination devices to induce collaboration if necessary.
- Help decide "when" to place a communicative act in a collaborative task involving physical human robot interaction, especially in the context of the proactive robot reach behavior.

Perspectives and Future Work

Managing Goals and Proactive Robot Behaviors:

Enriching and defining more relevant facts for the situation assessment is important, for example, in a breakfast making activity we can add many more rich facts: pick oil bottle, pour oil, put salt, etc.

Currently, a limitation in using chronicles for the scenario recognition is the need to build large library of chronicles by a programmer using his experience. A way to improve on this limitation would be to use chronicle learning [Cordier 00] and adapt it for human robot interaction context, for obtaining new chronicles. Besides, other probabilistic approaches for interpreting human activity [Beetz 10, Chung 08, Duong 05] can be augmented with temporal context.

Goal management being fixed task priority prohibits natural and rational behavior. It needs to be more dynamic, should take into many factors, for instance, task progress. For that plan monitoring will be important, and Situation Assessment using CRS can be useful for this, by synthesizing robot plans into chronicles. Also, work from [Hanheide 10] can be exploited for improving our goal management framework.

Also, important is to find further robot proactive behaviors that will enhance long term human robot interaction experience. For example, robot acting proactively to protect a child or to help respond to a emergency situation.

In our case, the robot always took initiative and showed proactive behavior. Deciding on whether to take an initiative or whether to ask for permission or to inform about an initiative is not easy. The challenge would then be to make the relevant human preferences evolve according to context and interaction memory. Therefore, robot needs to be equipped with a learning capabilities to acquire these preferences.

Coactivity Decision Model:

We would like to extend this work to have:

- More coordination devices, such as; pointing, gestures and other material signals.

  Having more coordination device, for example, robot pointing to an object while speaking will help enrich the collaboration experience, as the saying goes " the more the merrier"

- Explicit engagement generation capabilities

  An important future work is to have an explicit mechanism to establish a joint attention with the human, which is essential in attributing the human being engaged in the task. In this respect a [Tasker 08]'s framework from development psychology can be adapted to enhance the model.

- Mechanisms to adapt to different human partners.

  Also, important is to adapt to different human partner or even to different human behaviors. It will require defining more HMDPs by taking into account the human preferences and learning HMDPs can also be useful in this context.

- More task goals considerations.

  Need to investigate similar models for other tasks involving collaborative human-robot navigation and object manipulation, social guide, etc. to see how it can scale up.

- Addition of *Time* in the coactivity decision model

  As it will help model to quickly end the task in case of unnecessary long partner response time, Time-State Aggregated POMDPs [Broz 08]can be useful for this.

This work provides only a basis for selected social interaction by robots. It needs to extended to include complex social interaction for enhanced user experience and validated by HRI user studies. A long term HRI user study is needed to further concretize our hypothesis on the communicative act timing in physical HRI.

Appendix A

Human Robot Joint Attention Model for a Collaborative task

For the human and robot to interact and work collaboratively, it is important to establish joint attention related to the task. Which requires mutual they need to monitor, influence and coordinate their behavior in order to engage in a co-activity task [Kaplan 06].

Here, we define a model for establishing the joint attention and describe a general framework for establishing the joint attention between agents, adopting from the the Tasker& Schmidt's [Tasker 08] operational definition of joint attention, ref 2. Which is suitable for a human robot framework, as it gives basic ingredients regarding sharing activity related attentional focus, between a mother and a child, and also important from development robotics perspective.

A joint attention framework should have following characteristics:

- Initiation Act
- Response Acts
- Termination Act
- Repair Act
- Established Joint Attention (EJA)

- Initiation Acts: An initial robot or human action for beginning a collaborative task, for the purpose of attaining and then directing the others attention to an object, event, or activity, and signals the agent intention of the task engagement. It can be a physical action, for example: orienting head towards the shared object, or can be a verbal utterance, for example: "Let's us begin constructing the table".

- Response Acts: The recipient responds with an appropriate action in response to the partner's previous action (for example, in response to an initiation act) and is pertinent to the task. The response act should occur in a temporally valid window so as to avoid other agent waiting indefinitely and or ending task too early. It is also constrained on previous partner action and agent available resources. Response Act can be, for example, agent orienting its head towards object or alerting response such as behavioural stilling or communicatively (verbally or non-verbally).

- Termination Act: Either partner can perform a non-pertinent action or not respond to a partner action for long time or perform a specific termination action, signaling end of the joint attention and possible disengagement from the interaction.
- Repair Act: After establishment of Joint Attention, if either partner agent receives a termination act, she can apply with a relevant repair act (response act) to the termination act within a certain time frame to try to regain partner attention and reengage in the co-activity.
- Established Joint Attention (EJA): Joint attention can be considered established between agents, at least after three joint attention related act exchanges and though can vary depending on the joint task. For example, first agent initiates an act, partner agent responds and first agent responds to the partner response act.

Next, we describe a frame work for establishing joint attention between agents using above notions and show its instantiation through a example, with a human and a robot.

A.1 A Frame Work for Establishing Joint Attention Between Agents

Suppose there are two collaborating social partners, $SAg1$ (e.g. a Human) and $SAg2$ (e.g. a robot). They can do various tasks, for example, a possible list of tasks $(\mathbf{tsk})$, is:

- give_object
- take_object
- hand_over_object
- clean_table_together

For achieving these tasks, each social agent has a recipe of action library $ActL_{SAg}$ to select actions, for example, "lookAt(x)" , "pointAt (x)" actions, Therefore, $ActL_{SAg1}$ and $ActL_{SAg2}$ are set of actions available to social agents $SAg1$ and $Sag2$.

This act library can be subdivided as:

- a verbal dialog repository $\boldsymbol{DialogAct}$ (e.g., Hello, I need your help),
- an initiating action's library $\boldsymbol{IActL}$, for indicating the start of the collaborating activity (e.g., lookAt(x), pointAt(x), or a relevant DialogAct),
- a response action's library $\boldsymbol{RActL}$, for responding to partner's stimulus actions (e.g., lookback, lookat(x), where x is a share object, or verbally ok)

We assume a one to many mapping function from,

$mapRAction(Act_{SAg1}, RActL_{SAg2}) \rightarrow RactL_{SAg1}$, where $Act_{SAg1} \in RactL_{SAg1}$ and a similar mapping exists for $SAg2$
$mapRAction(Act_{SAg2}, RActL_{SAg1}) \rightarrow RactL_{SAg2}$, where $Act_{SAg2} \in RactL_{SAg2}$, though relation is one to many but the relevant action selection will be based on action preconditions and is task/domain dependent

- a termination action's library ***TActL***, for an action that corresponds to end the joint attention during collaborative activity(e.g., lookawy, standup, leave or verbally bye),
- a repair action's library ***RpActL***, a subset of actions in RActL (RpAct $\subseteq$ RActL) mapping responses to the termination actions in TactL (e.g., for partner termination action "standup", repair action, dialog "please sit down"),

Also, the responses to actions have to occur in a certain time limit for the joint attention to be established and collaborating activity continues without negligence. For example:

- Response Time Limit, ***trsp***, can be for example, 5 seconds, robot should lookat the shared object, e.g. cassette in response to human looksAt cassette within this limit (can vary depending on task and the action),
- Valid Termination Action Time Limit, ***vtr***, can be 1 second (depends on task and the action),
- Response Duration, some response actions will be maintained for the time, ***rsd*** (e.g. lookAt Human for 3 sec), to make sure partner agent understands the agent intention to cooperate.

Agent $SAg1$ is interested in doing a joint task with $SAg2$, needs to establish joint attention ($ejaSAg1SAg2$) first for successful task execution, DoCoactivityTask().

Monitoring: Attentional Process The attentional process monitoring part can be directly part of Co-activity task model, including monitoring partner agent's (for robot, monitoring human's) ambiguous intention that can be termed as a termination act from the partner and subsequently agent will execute a repair act, for example, a communicative act (verbal or non-verbal).

A.2 Some Examples of the Possible Human-Robot Joint Attention

Here, we describe two examples, that show how the framework will establish joint attention in different co-activity tasks between the human and the robot.
Human Wants the Robot to Follow his Gaze

This is a simple task, where the human wants the robot to follow his/her gaze (useful if the human wants to teach the robot about the objects in the environment). The relevant establishment of the joint attention can go as follows:

1. Human Initiating Actions: looksAt Robot and then looksAt GREY_TAPE (each for at least 3 seconds)
2. Robot response actions: looksAt Human and then looksAt object (within 3 seconds of human looksAt at GREY_TAPE and looksAt human 1st for 1 second and then a GREY_TAPEfor 3 seconds)
3. Human then looksAt WALLE_TAPE

Algorithm 1 Framework for establishing joint attention

1. **if** $e \in ActL_{SAg1}$ **then**
2. Let SAg2 perform an appropriate action from $mapRAction_{SAg2}(e, RactL_{SAg2}) = rsp_{SAg2}$
3. Wait until fact corresponding to $mapRAction_{SAg1}(rsp_{SAg2}, RActL_{SAg1})$ becomes $true$ upto $trsp$ seconds,
4. **end if**
5. **if** time elapsed $\geq trsp$ seconds **then**
6. Goto 1
7. **else**
8. Let SAg2 perform a relevant action from $mapRAction_{SAg2}(rsp_{SAg1}, RactL_{SAg2}) = rsp_{SAg2}$
9. DoCoactivityTask() // JA_SUCCESS, Successful in establishing the joint attention so do task
10. **end if**
11. **while** true **do**
12. Wait until the fact corresponding to a $tact_{SAg2}$ becomes $true$, where $tact_{SAg2} \in TActL_{SAg2}$
13. Wait until the fact $tact_{SAg2}$ becomes $false$ upto vtr seconds
14. **if** time elapsed $\geq vtr$ **then**
15. // $tact_{SAg2}$ was a valid termination act
16. Let SAg1 perform an appropriate repair action from $mapRAction_{SAg1}(tActL_{SAg2}, RpActL_{SAg1}) = rpact_{SAg1}$

$$\begin{aligned} S_t = object\_holderwhere, \\ object\_holder \in \{robot, human\} \end{aligned} \tag{A.1}$$

17. Wait until the fact $tact_{SAg2}$ becomes $false$ upto trsp seconds
18. **if** time elapsed $\geq trsp$ **then**
19. Break
20. **end if**
21. **end if**
22. **end while**

4. Robot then looksAt WALLE_TAPE

5. Robot registers joint attention established and will now follow human gaze.

Robot Needs Human Help:
Here, the robot needs the human help to take_object, GREY_TAPE, from the table and proactively moves arm towards the object and asks the human for help. The relevant joint attention establishment can be as follows:

1. Robot Initiating Actions: looksAt the Human and then says "Hello"

2. Human: looksAt the robot (within 3 seconds of robot verbal utterance)

3. Robot: then looksAt GREY_TAPE

4. Human Either looksAt GREY_TAPE or keep looksAt the robot

5. Robot registers joint attention established and will now begin the joint task

Robot can establish necessary joint attention required for forming the shared intention with respect to a co-activity task with the human and start executing the task. Robot can then use task recipes to execute the high level task plan, describing actions to execute with respect to an expected human behavior. Hand coded recipes will lead to some problems, that programmer will need to hand code recipes for every task and importantly problem can arise where, the human behavior will deviate from the expected norm described in the recipes, causing ambiguity for the robot and task failure.

Appendix B

Implementation of Speech Interface

There arise situations in the human robot interaction where proactive human intervention, in term of physical intervention or through verbal action, can help the robot achieve a task and help it avoid failure. For example, the human can inform about the location of the object: "object isOn coffee table" or a robot might be repeatedly failing to pickup/throw an object from table/into a trashbin and the human can tell it to place itself little further right or left of its current placement: "turn right or move forward".

Therefore, the human should be a proactive partner and help the robot and for that an effective speech interface is necessary, here we will describe a basic communication structure which can be used as a foundation for the further improvement.

B.1 Type of Possible Human Communication

As the communication from the human can vary very widely, from direct goal related commands ("give me the object" etc.) to back channel utterance in a conversation ("uhh", "yes" etc), we need to define what kind of dialog robot supervisor will handle, so a basic structure of dialog input from the human was defined to which robot should react.

The human input speech format for the relevant communication iss predetermined and is processed by the module $SPEET$, which converts the speech to the relevant text using fine state grammar. Then an $interpreter$ module transforms the text recognized to the relevant human communication orders. These orders are directly mapped to a relevant supervisor OPs, managing their execution.

Supervisor manages following type of the human communication towards the robot:

- Task (Goal) Commands
- Action commands
- Information from the Human
- Task related confirmation

Table B.1, shows the summary of the incoming human communication.

Each information from human is treated as meta-goal which is added in the fact database, besides taking initiative and updating robot knowledge about the world, like object x is reachable

Table B.1: Dialog managed from the Human: Summary of managed incoming dialog from the human

Dialog	Example	Plan
Task related:		yes
Give	"Jido Give me the orange bottle"	
Take	"Jido Take the red cup"	
Pick	"Jido Pick the green bottle from Shelf"	
Throw (dump)	"Jido Throw the orange cup"	
Clean	"Clean the table"	
Action related:		No
Go	"Jido Go to the shelf"	
Move	"Move Forward (or backword)"	
Turn	"Turn Right (left)"	
Localize	"Localize itself"	
Information related:		yes
IsOn	"Green cup isOn Shelf"	
Reachable	"Red cup is reachable"	
Visible	"Blue bottle is visible"	
Different commands:		
yes, no, stop, restart, suspend, resume ...		

now, human can also proactively ask robot to move or turn the robot, making it closer or further away from the object in case of a failure.

Task commands
Task commands are the goal related commands that human can give to the robot for achieving a relevant task.

Action commands The human can ask robot to do a specific action, for example, move back or move forward etc.

Information The human can proactively give information to the robot, for example, inform the robot that the object is reachable for the robot (perhaps previously not reachable for the robot).

Different Task Related Orders Human can give confirmation/cancellation regarding success/failure of a task achievement.

B.2 Examples of Possible Human Communications

1. Task Commands related to different Goals:
   Jido:
   - GIVE ME (The) YELLOW BOTTLE or CUP
   - TAKE (The) Green Bottle or Cup
   - Pick Up (The) Red Bottle or Cup

- Dump (The) Blue Cup or Bottle
- CLEAN (The) Shelf or Table
- Go to (the) Shelf or Table or (Right/Left) Chair
  for example:
  (a) JIDO Give me (the) Green Bottle
  (b) JIDO Take (the) Orange Cup
  (c) JIDO Dump (Yellow) Bottle
  (d) JIDO Clean (the) table or shelf

2. Action Related Commands
   - GO Back or Forward
   - Turn Left or Right
   - Close or Open Fingers

   for example, "Command Go Forward or Back"

3. Human Giving the Information Proactively
   - Reachable: "Object" is "Reachable" for example, Green Bottle is Reachable"
   - Visible "Object" is "Visible" for example, Orange cup is Visible"
   - isOn "Object isOn (the) "furniture" for example, "Red or Blue.. Cup or Bottle is on (The) Table or Shelf"
   - NoObject
   - Human Location for example, "Human or John is on Left or Right Chair"
   - No Human "Human is not here" or "There is no one"

4. Task related confirmation
   - Yes or No or OK
   - Yes Resume or Restart
   - cancel or stop
   - Task Done (Achieved or Impossible)

Appendix C

User Study Questionnaire

Name:

Sex:

Age: (optional)

Earlier Exposure to Real Robots : (NOT At all, A little, Very often)

==

You have just been exposed to following 4 behaviors of the robot in the order marked inside ***[ ]***.

Behavior A: Robot asked to give the object and did not move its hand. ***[ ]***

Behavior B: Robot first asked to give the object and when the robot finished speaking then moved its hand. ***[ ]***

Behavior C: Robot first started moving its hand and then asked for the object during moving the hand. ***[ ]***

Behavior D: Robot first moved the hand and then after stopping it asked to give the object at the end. ***[ ]***

Please reply to the following questions:

1. I understood the robot's intention that it wanted to take which object:

	(strongly disagree)	(somewhat disagree)	(no opinion)	(somewhat agree)	(strongly agree)
Behavior A:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior B:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior C:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior D:	[ ]	[ ]	[ ]	[ ]	[ ]

2. I had no confusion regarding ***where to give*** the object to the robot

	(strongly disagree)	(somewhat disagree)	(no opinion)	(somewhat agree)	(strongly agree)
Behavior A:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior B:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior C:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior D:	[ ]	[ ]	[ ]	[ ]	[ ]

3. I had no confusion regarding ***when to give*** the object to the robot

	(strongly disagree)	(somewhat disagree)	(no opinion)	(somewhat agree)	(strongly agree)
Behavior A:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior B:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior C:	[ ]	[ ]	[ ]	[ ]	[ ]
Behavior D:	[ ]	[ ]	[ ]	[ ]	[ ]

4. Overall I prefer that robot should move its hand when it wants me to give some object:

   Yes [ ]

   No [ ]

5. Overall I prefer that robot should speak whenever it wants me to give some object:

   Yes [ ]

   No [ ]

6. Moving and speaking both components are important for the robot whenever it wants me to give some object.

   Yes [ ]

   No [ ]

7. Overall the speaking and moving the arm timing was more preferable to me in the case:

   Behavior B: [ ]

   Behavior C: [ ]

   Behavior D: [ ]

8. The robot seems to be more 'aware' about me, my capabilities and possible confusions in behavior

   A: [ ]

   B: [ ]

   C: [ ]

   D: [ ]

9. The robot has better communicated its 'capabilities' to me in behavior:

A: [ ]

B: [ ]

C: [ ]

D: [ ]

10. The robot seems to be more 'supportive' to the task and to me in behavior

A: [ ]

B: [ ]

C: [ ]

D: [ ]

11. Overall I prefer the behavior

A: [ ]

B: [ ]

C: [ ]

D: [ ]

12. If you wish to comment on: any of the behaviors. If you prefer to have any other behavior, which should be somewhere within A and D. Why do you like or dislike a particular behavior. Your comments will be helpful to improve overall robot's behavior and decision making.

==========Thank You for your time and honest evaluation=============

List of Figures

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