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Eman Ahmed Sayed Ahmed

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# THÈSE DE DOCTORAT

Modélisation constructive des systèmes à événements discrets : Application aux organismes artificiels

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Laboratoire d'Informatique, Signaux et Systèmes de Sophia Antipolis (I3S)

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Faculty of Computers and Artificial Intelligence

Présentée en vue de l'obtention du grade de docteur en Informatique d'Université Côte d'Azur et d'Université du Caire en Egypte

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Soutenue le :  
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Cairo University  
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Information Technology Department

ÉCOLE DOCTORALE  
SCIENCES ET  
TECHNOLOGIES DE  
L'INFORMATION ET DE  
LA COMMUNICATION

UNIVERSITÉ  
CÔTE D'AZUR 

# Constructive Modeling of Discrete-Event Systems: Application to Artificial Organisms

Presented By:

**Eman Ahmed Sayed Ahmed**

*A thesis submitted to the*

**Faculty of Computers and Artificial Intelligence**

**CAIRO UNIVERSITY**

**And**

**UNIVERSITY OF CÔTE D'AZUR**

*In partial fulfillment of the requirements for the dual degree of Doctor of Philosophy in*

**Information Technology**

Under the supervision of

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...



**Titre : Modélisation constructive des systèmes à événements discrets: Application aux organismes artificiels ...**

---

**Résumé :** Les humains peuvent ressentir leurs muscles. Ils peuvent également reconnaître leur environnement et les objets qui s'y trouvent. Enfin, ils sont capables de se situer dans cet environnement et d'y atteindre des objets. Comment ces capacités sont acquises et interagissent les unes avec les autres au cours du développement ? Cette question demeure ouverte en biologie. Notre objectif est donc d'aider les biologistes à mieux comprendre comment un humain est capable de construire sa carte cognitive et d'effectuer des mouvements dirigés vers un objectif. Sur le plan développemental, l'acquisition des capacités sensorimotrices humaines débute avec le fœtus. Nous présentons ici un modèle théorique du développement de la carte cognitive d'un fœtus humain à partir de son système sensorimoteur. Le modèle intègre les proprioceptions des membres du corps et les perceptions de l'environnement et comment celles-ci coopèrent pour construire une carte cognitive. Cette carte est essentielle afin d'effectuer des mouvements dirigés vers un objectif et atteindre différents objets au sein de l'environnement. Nous proposons un nouvel algorithme de clustering appelé "Frequency-based-means", qui est utilisé pour obtenir les proprioceptions et les perceptions qui constituent la carte d'association. Des modèles de Markov cachés sont utilisés pour modéliser l'apprentissage et la production de mouvements.

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**Mots clés :** Cerveau, Cognition, Cognitive-map, Clustering, Foetus, Hidden Markov Models, Sensorimotor system

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**Title :Constructive Modeling of Discrete-Event Systems: Application to Artificial Organisms ...**

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**Abstract :**Humans can internally sense their muscles. They can also recognize their environment with its objects and are able to navigate through it easily to reach them. How these abilities are gained and interact each other is still an open question in biology. Our aim is to help biologists to understand how a human is able to build his cognitive map and make goal-directed movements. The origin of human capabilities goes back to the fetus stage. We present a theoretical model of the development of the cognitive map of a fetus human from his sensorimotor system. The model integrates the proprioceptions of body limbs and perceptions from the environment and how these cooperate to build a cognitive map, which in turn, is essential for making goal-directed movements to reach different objects in the surrounding environment. We propose a new clustering algorithm called "Frequency-based-means"; which is used to get the proprioceptions and the perceptions that form the association map. Hidden Markov Models are used to model movement learning and production.

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**Keywords :** Brain, Cognition, Cognitive-map, Clustering, Fetus, Goal-directed movements, Hidden Markov Models, Movement learning, Sensorimotor system



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## **In English**

Humans can internally sense their muscles. They can also recognize their environment with its objects and are able to navigate through it easily to reach them. How these abilities are gained and interact each other is still an open question in biology. Our aim is to help biologists to understand how a human is able to build his cognitive map and make goal-directed movements. The origin of human capabilities goes back to the fetus stage. We present a theoretical model of the development of the cognitive map of a fetus human from his sensorimotor system. The model integrates the proprioceptions of body limbs and perceptions from the environment and how these cooperate to build a cognitive map, which in turn, is essential for making goal-directed movements to reach different objects in the surrounding environment. We propose a new clustering algorithm called “Frequency-based-means”; which is used to get the proprioceptions and the perceptions that form the association map. Hidden Markov Models are used to model movement learning and production.

## **En français**

Les humains peuvent ressentir leurs muscles. Ils peuvent également reconnaître leur environnement et les objets qui s’y trouvent. Enfin, ils sont capables de se situer dans cet environnement et d’y atteindre des objets. Comment ces capacités sont acquises et interagissent les unes avec les autres au cours du développement ? Cette question demeure ouverte en biologie. Notre objectif est donc d’aider les biologistes à mieux comprendre comment un humain est capable de construire sa carte cognitive et d’effectuer des mouvements dirigés vers un objectif. Sur le plan développemental, l’acquisition des capacités sensorimotrices humaines débute avec le fœtus. Nous présentons ici un modèle théorique du développement de la carte cognitive d’un fœtus humain à partir de son système sensorimoteur. Le modèle intègre les proprioceptions des membres du corps et les perceptions de l’environnement

et comment celles-ci coopèrent pour construire une carte cognitive. Cette carte est essentielle afin d'effectuer des mouvements dirigés vers un objectif et atteindre différents objets au sein de l'environnement. Nous proposons un nouvel algorithme de clustering appelé "Frequency-based-means", qui est utilisé pour obtenir les proprioceptions et les perceptions qui constituent la carte d'association. Des modèles de Markov cachés sont utilisés pour modéliser l'apprentissage et la production de mouvements.

---

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# PUBLICATIONS

Eman Ahmed, Reda Abdel Wahab, Alexandre Muzy, Gilles Bernot, and Gamal Darwish. Modeling of goal-oriented human motion evolution using hidden markov models. In Proceedings of International Conference of Pattern Recognition Applications and Methods (ICPRAM 2019), February 2019.

Eman Ahmed, Reda Abdel Wahab, Alexandre Muzy, Gamal Darwish, and Gilles Bernot. Modeling of the Development of the Fetus Cognitive Map from the Sensorimotor System. Accepted to be published in the Egyptian Informatics Journal, El Sevier, 2020.



# CHAPTER 1

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## INTRODUCTION

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### 1.1 Domain

This PhD thesis focuses on creating models to elaborate how humans learn making goal-directed movements. It has been found that the fetus has adult-alike brain. The fundamental organization of brain networks is established in utero during the second and third trimesters of fetal development [6]. It has a complete nervous system which enables it to control all its muscles and make different movements. We are working based on a hypothesis that the fetus begins with doing some random movements that enables it to discover its abilities. The received sensory feedbacks are used to build a representation of its environment in a simple cognitive map. Then, it starts learning to change its limbs from one position to another. After that, it starts to specify goals and learns how to reach them. We are building an abstract theoretical model on the system level to be able to understand the process of goal-directed movements evolution based on biological facts found in literature. The modeling of functional areas of the brain is built, then computational intelligent techniques are employed to test our hypotheses using simulated data.

### 1.2 Definition of the Problem

Any human can sense the position of every muscle in his body. How this sensation is developed is unknown. In addition, s/he is able to identify her/his surrounding environment, navigate it easily and reach any position s/he wants. How the human acquired this skill is still an open question in biology. It seems that human mind can build a map of her/his

surroundings through which s/he can reach any position. But, what does the notion of “position” represent to the human mind? and how can s/he use it to navigate and reach different objects? These are the questions we are interested to answer in this work. From biology, we know that at the end of the fetus stage, the fetus has the same brain structure as the adult human brain. In addition, it is able to do primary moves such as sucking its thumb, kicking, and grasping its umbilical cord. These kinds of actions provoke the idea that the learning of movement starts at this early stage. Accordingly, we will use a constructive methodology to learn how the fetus human learns to make its primary movements using its sensorimotor system, how it will generate the “position” notion by its mind, then how it will integrate all this information to produce goal-directed movements to reach a target position or objects afterwards. For the sake of simplicity, we will model the *vertical movement from bottom to top* positions for one muscle only.

### 1.3 General Methodology

We have very few data on the fetus sensorimotor development. So, the goal of modeling the motion seems to be unreachable.

Nevertheless, in neurosciences it is usual to have very few data but to try to make models of the functions. For example, the measurements we can do inside the brain are far too poor to validate any model of the functioning of the brain.

Even if we don’t have enough data, what we can do is to check the *consistency of biological hypotheses* via the study of computational models or mathematical models which reflect these hypotheses and this allows to give advances in neurosciences. Investigating the consistency of hypotheses is useful for biologists.

The fact that the model is mathematical or computational facilitates the systematic checking of its consistency because every part of the model can be observed, or modified, during simulation. So, it is an indirect way to study complex systems where *operability* (the ability to put the real system in a given set of initial states) and *observability* (the ability to get enough information from the system to deduce in which state the real system is) of the states of the real systems is low.

This kind of approach, when we lack data, is an important scientific activity because it reduces the number of hypotheses to investigate experimentally, focusing on the most promising ones.

We will follow a methodology that is inspired from system-based modeling in computer science. This approach starts with a black box for which we partially know the external (input/output) behavior. Then according to the knowledge acquired about the system, we propose an internal structure of the black box that is able to reproduce the known external behavior. This internal structure can call for smaller black boxes and we iterate until we get consistent with the knowledge. This way, the model follows a constructive approach.

To choose a structure when we have a few knowledge we have to apply heuristics. One particularly important heuristic is the *Occam razor*. A complementary heuristic in this constructive approach is to use tools that are known to provide certain well-defined behaviors for example mathematical and computer science tools (e.g. Markov chains, machine learning algorithms, etc)

At the end of this constructive method, the model we obtained is by construction consistent with the biological hypotheses made about the problem. So, the study of this model is in fact a study of these hypotheses.

Due to the unavailability of real data about the fetus, we will use simulated data extrapolated from the knowledge about the children sensory motor development.

## 1.4 Thesis Organisation

The structure of the thesis is as follows:

**Chapters 2** provides the illustrations of the basics used in the thesis including biological background and machine learning background.

**Chapter 3** outlines previous work on understanding human cognition and movement development. This work is essential as it comprises some of the ground work, upon which this thesis is based.

**Chapter 4** briefly outlines our approach to build the model.

**Chapter 5-8** explain the details of each component of our model.

**Chapter 9** describes how the simulated data are generated.

**Chapter 10** presents the experimental setup and results

**Chapter 11** draws conclusions and contains a summary of the contributions of the work.



# CHAPTER 2

## BASICS

This chapter covers the basics required for our problem. These include basics in biology, modeling of discrete-event systems, mathematics and machine learning.

### 2.1 Biological Background

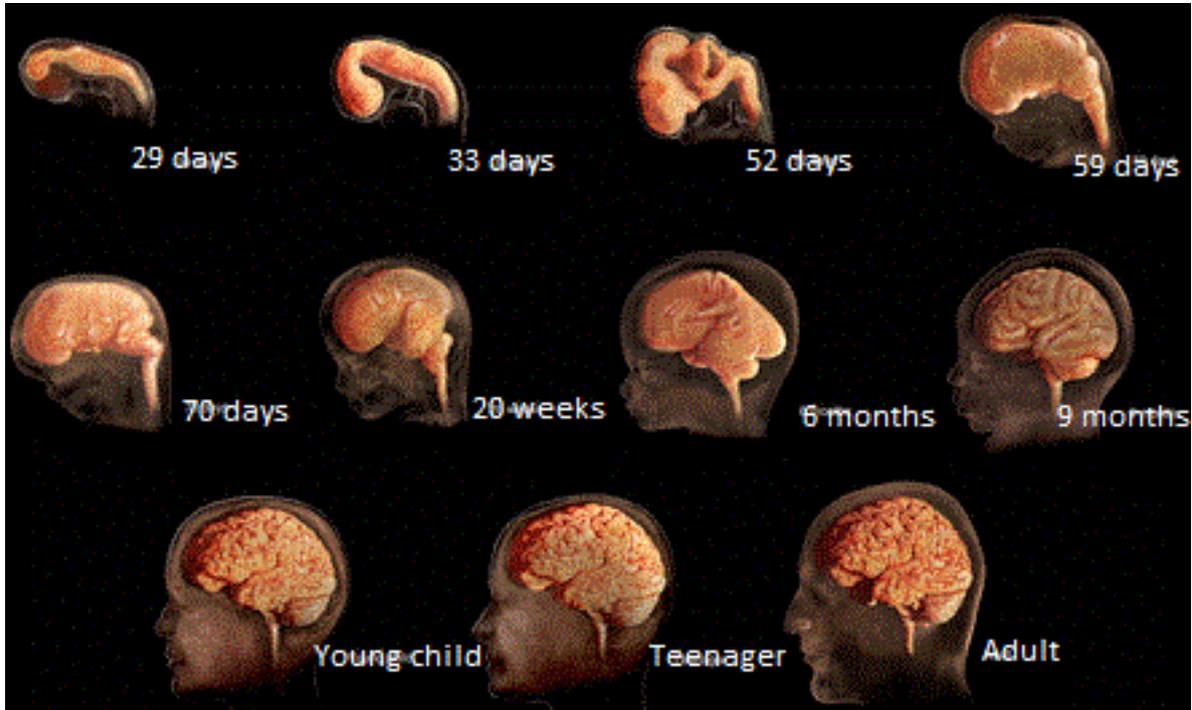
This section covers the basics for the brain structures that are needed in our problem and the communications between them through neurons. This is in addition to demonstrating the neurons involved in making movements and receiving sensory feedback from the body and the environment. It also provides an explanation for the body muscle structure and how it changes to make a movement.

#### 2.1.1 Brain Areas Development

The human brain passes through different stages during development: from the embryo to the fetus and the new born. The embryonic stage lasts until the 8th week of gestation while the fetus stage starts from the 9th week of gestation until the end of gestation. The brain begins in the third gestational week and continues to develop after birth. The brain regions develop incrementally during the stages as shown in Figure 2.1. By the end of the embryonic period the rudimentary structures of the brain and the central nervous system are established. The major compartments of the central and peripheral nervous systems are defined and primitive patterning of sensorimotor regions within the neocortex is established [7,8].

Neuron production in humans begins at embryonic day 42, and extends through midgesta-

tion in most brain areas [9,10]. Different populations of neurons form gray matter structures in many regions of the brain including hindbrain and spinal column, cerebellum, midbrain structures, deep subcortical nuclei and the neocortex.



**Figure 2.1** – *Brain structure development* [1].

The duration of pregnancy is usually divided into three trimesters; each lasts for three months. In the first trimester: 16 days after conception, the neural plate forms; it acts as the foundation of the baby's brain and spinal cord. It grows longer and folds onto itself, until that fold morphs into a groove, and that groove turns into a tube (the neural tube).

At around week 6 or week 7 of pregnancy, the neural tube closes and makes three sections known as the prosencephalon (forebrain), the mesencephalon (midbrain) and the rhombencephalon (hindbrain) [11]. After that, these areas are divided further.

It is widely accepted that the forebrain forms structures such as the cerebrum, the thalamus and the hypothalamus, the hindbrain forms other structures including the cerebellum. The spinal cord is formed just to the rear of the hindbrain. Some of these structures are involved in the sensorimotor development. The cerebrum is the biggest part of the brain, and it is responsible for thinking, remembering and feeling. This is where the cerebral cortex and its various lobes reside while the cerebellum is the area in charge of motor control. The cerebral cortex contains the somatosensory cortex responsible for collecting all the sensory data from different body parts, the motor cortex which is able to control different muscles by sending motor commands, and the association cortex which can blend different information to obtain higher level interpretation [12,13].

These regions continue to develop with time. The fetus develops its brain structures through

using them by interaction with its environment. The fetus lives inside the uterus (or the womb) surrounded by fluid.

It is connected to the placenta by the umbilical cord so that it can take in oxygen, nutrients, and other substances and eliminates carbon dioxide and other wastes. The fetal human possesses an active central nervous system from at least the eighth week of development [14]. With its rapidly maturing nervous system, its nerves are connecting its brain to the rest of its body traveling from the brainstem down to the spine finally extending to its torso and limbs. During the second trimester, using its developing muscles and reflexes, the fetus is able to move its limbs. The soft cartilage hardens into bones starting with arms and legs. The sensory system develops such that the brain dedicates special areas for smell, taste, hearing, vision and touch. At this stage, it may be able to hear mother's heart beat and voice, sucking its thumb. It starts feeling movements and its flexing arms and legs are soft and becoming stronger. After that, it may make movements in response to presses on the mother's belly as explained in [15]. By the end of the first trimester, it starts to wiggle its limbs and develop the sense of touch. It can feel its own face and anything within its reach, it will be experimenting and refining its sense of touch and grasp by touching the womb surrounding it and grasping its cord. Until this stage, eyelids may open as a reflex but it cannot see yet.

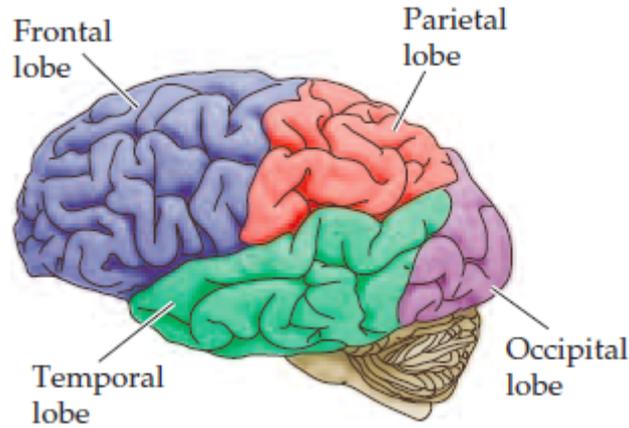
At the third trimester, there is a rapid development of neurons and wiring. At the same time, the cerebellum (motor control) is developing faster than any other area of the fetal brain [16]. This is coupled with the growing of the cerebral cortex that is responsible for thinking, remembering and feeling [17].

Though this important area of the brain is developing rapidly during pregnancy, it really only starts to function around the time a full-term baby is born and it continues to mature gradually in the first few years of life through the baby interaction with its surrounding environment.

We will explain below the brain regions that are involved in making voluntary movements and in cognition.

## **The Cerebrum**

The cerebrum is divided into two cerebral hemispheres namely right and left hemispheres. The left hemisphere controls the right side of the body, and the right hemisphere controls the left side of the body. Corpus callosum is the joining element which links the two hemispheres of the brain, which passes messages between the two hemispheres. Each cerebral hemisphere is divided into four regions called lobes that control senses, thoughts, and movements. The four lobes are the frontal, parietal, temporal and occipital lobes shown in Figure 2.2. The frontal lobe contains the motor cortex responsible for voluntary movements, the parietal lobe is in charge of sensations, the temporal lobe is for auditory information processing, and the occipital lobe is for vision processing.



**Figure 2.2** – *The Cerebrum Lobes [2].*

The outer layer gray matter of the cerebrum is called the cerebral cortex. According to the function, the regions of the cerebral cortex can be divided into three general categories, namely, motor, sensory, and associative. The motor cortex is generally associated with the movement of body parts and sensory cortex such as auditory cortex, visual cortex, etc. is associated with sensory organs. There is a portion of the cerebral cortex which is not occupied by motor and sensory cortices, known as the ‘association cortex’.

### **The Cerebellum**

The cerebellum has two hemispheres and consists of outer grey matter and inner white matter. Each cerebellum hemisphere consists of three lobes namely anterior, posterior and flocculonodular lobe. The cerebellum plays a fundamental role in motor functioning where a brain is giving signals to the rest of body parts to carry out a particular task. It is involved in motor learning, cognitive functions, maintenance of balance and posture, etc.

Figure 2.3 describes the overall organization of neural structures involved in the control of movement. Basal ganglia are group of neurons in the brain that are located deep beneath the cerebral cortex [18]. Upper and lower motor neurons connect the motor cortex and muscles. The upper motor neurons originate within the motor cortex and then travel down the spinal cord [19] and is responsible for the initiation of voluntary movement, the maintenance of muscle tone for support of the body against gravity, and the regulation of posture to provide a stable background to initiate voluntary activity [20]. The cell bodies of the lower neurons are located in the ventral horn of the spinal cord gray matter and in the motor nuclei of the cranial nerves in the brainstem. Lower motor neurons are used to control the muscles [2].

#### **2.1.2 Neurons and Muscles**

The brain consists of billions of neurons that act together to perform various tasks. A neuron has three main parts including the cell body (known as the Soma), the dendrites and the axon. The cell body contains the nucleus which has cell’s genetic material and controls cell’s

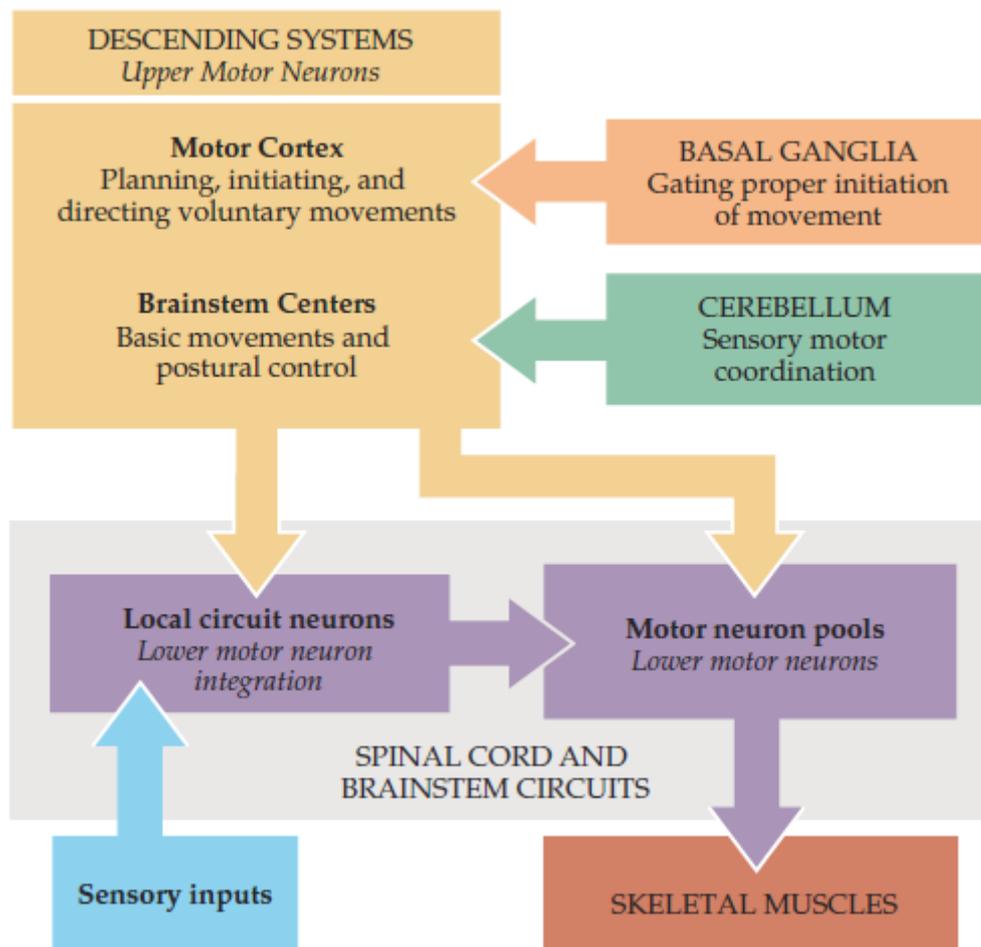


Figure 2.3 – Brain Connections [2].

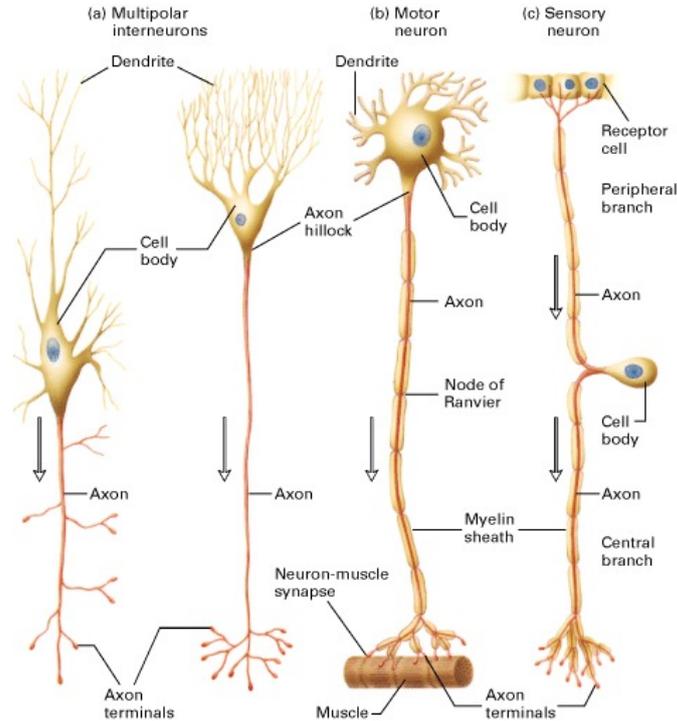
activities. Dendrites are tree-like structures that extend away from the cell body to receive messages from other neurons at specialized junctions called synapses. Once a signal is received by the dendrite, it then travels almost passively to the cell body. Every neuron has a single axon which looks like a long tail coming outwards the cell body and is responsible for transmitting messages from the cell through the axon tree-like structured terminals to the synapse. When input signals are received from the dendrites, they are collected by the cell body and can cause the neuron to “fire” sending action potentials through the axon [21].

Neurons use electrical impulses and chemical signals exchanged between different areas of the brain, and between the brain and the rest of the nervous system. They communicate with each other by firing action potentials which causes sending chemicals, called neurotransmitters, across the synaptic junctions between the axons and dendrites of adjacent neurons [22].

The neurons can be classified into three main classes which are the interneurons, the motor neurons and sensory neurons. Figure 2.4 shows the different types of neurons and their structures.

Sensory neurons are the nerve cells that are activated by sensory inputs from the environment. They are considered as afferent neurons because they communicate information from a stimulus to the brain or the spinal cord. Motor neurons are efferent neurons that communicate information from the brain or the spinal cord to body muscle. They are used to control muscles. Interneurons are used to transmit messages between the neurons.

Neurons structures can be classified according to the form and the number of dendrites extending from the cell body. Multipolar neurons have several dendrites. Bipolar neurons have only two processes: a single dendrite and an axon and Unipolar neurons lack dendrites and have a single axon, and are also sensory neurons. The majority of neurons in the spinal chord and brain are multipolar but bipolar neurons are found in the sense organs in the retina of the eye and in olfactory cells [23].

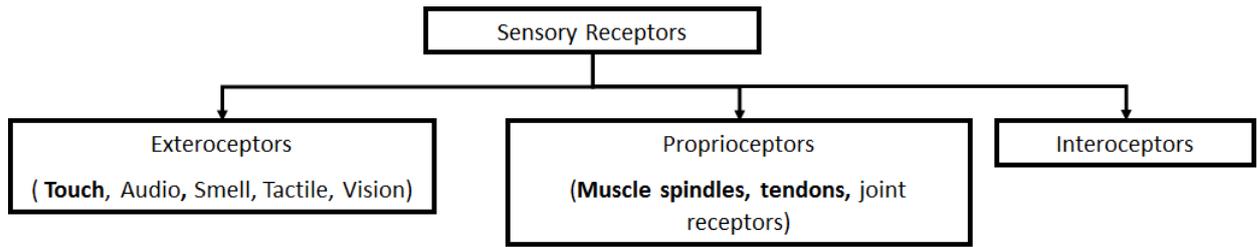


**Figure 2.4** – *Different Neuron Structures [24]. a) An interneuron as a multipolar neuron is shown having one cell body with a tree of dendrites and one axon. b) An example of motor neuron is depicted. It is also a multipolar neuron but its axon terminals are afferents to a muscle. c) A sensory neuron is represented as a unipolar neuron that has no dendrites but has two axons. This is because the input to a sensory neurons usually comes directly from axons of receptor cells in the body.*

Until recently, most neuroscientists thought we were born with all the neurons we were ever going to have. But, it has been found that the forebrains of male canaries get new neurons during the mating season. This was the same time in which the birds had to learn new songs to attract females. This was followed by other publications found that there is a generation of new neurons in the adult brain (neurogenesis) as in [25], [26], [27].

## Sensory Neurons

Sensory neurons are the nerve cells that are activated by sensory inputs from the environment which can be physical or chemical, corresponding to all our five senses. Thus, a physical input can be sound, touch, heat, or light. The neurons that are activated by touch stimuli at the skin surface are known as mechanoreceptors. They convey sensory signals from the body peripherals to the somatosensory cortex of the brain and can be further classified into proprioceptors, exteroceptors and interoceptors [28] [29]. The proprioceptors give detailed and continuous information about the position of the limbs and other body parts. They include muscle spindles and Golgi tendon organs. The major function of the muscle spindles is to provide information about the muscle length (the degree of muscle stretch) to the Central Nervous System (CNS) through “Ia” afferent axons while Golgi tendon organs, located at the tendons attaching the muscles to the bones, are specialized to signal changes



**Figure 2.5** – *Sensory Receptors Types*. It shows the sensory mechanoreceptors classified as exteroceptors, proprioceptors and interoceptors with examples of each type. The words marked in bold are the receptors that will be used in this thesis.

in muscle’s tension to the CNS through “Ib” afferent axons. They are distributed among the collagen fibers that form the tendons. On the other hand, the exteroceptors are sensory neurons that help in acquiring information about the surrounding environment. These include tactile, smell, hearing, taste and vision. For instance, the cutaneous (skin) pressure provides information from external stimuli as follows:

When an external stimulus is applied to the skin, it affects the ionic permeability of the receptor (sensory neuron) cell membrane which generates a depolarizing current producing a receptor (sensory neuron) action potential that reach to the CNS at the Somatic Sensory Cortex in the end. The CNS then interprets and triggers a command. The strength of the stimulus is represented by the rate of action potential discharge triggered by the receptor (sensory neuron) action potential.

Also, for Tactile stimuli, the accuracy with which it can be sensed differs from one region of the body to another. This is due to the fact that the number of sensory neurons (density) and the size of their receptive fields varies from one region to another.

Another type of sensory neurons is interoceptors, they give feedback to internal senses such as pain, hunger, etc.

Figure 2.5 summarizes the different types of the mechanoreceptors.

### 2.1.3 Motor Neurons

A motor neuron (or motoneuron) is a neuron whose cell body is located in the spinal cord and whose axon projects outside the spinal cord to directly or indirectly control effector organs, mainly muscles and glands. Motor neurons’ axons are efferent nerve fibers that carry signals from the spinal cord to the effectors to produce effects. Types of motor neurons are alpha motor neurons, beta motor neurons, and gamma motor neurons. For voluntary movements that require muscle contraction, alpha motor neurons are used to send command signals to the muscle to be contracted. Alpha motor neurons (also called alpha motoneurons) are large, multipolar lower motor neurons of the brainstem and spinal cord. They innervate extrafusal muscle fibers of skeletal muscle and are directly responsible for initiating their contraction. Alpha motor neurons are distinct from gamma motor neurons, which innervate intrafusal muscle fibers of muscle spindles. An alpha motor neuron and the muscle fibers it

innervates is a motor unit. A motor neuron pool contains the cell bodies of all the alpha motor neurons involved in contracting a single muscle [30].

#### 2.1.4 Muscles and Neurons

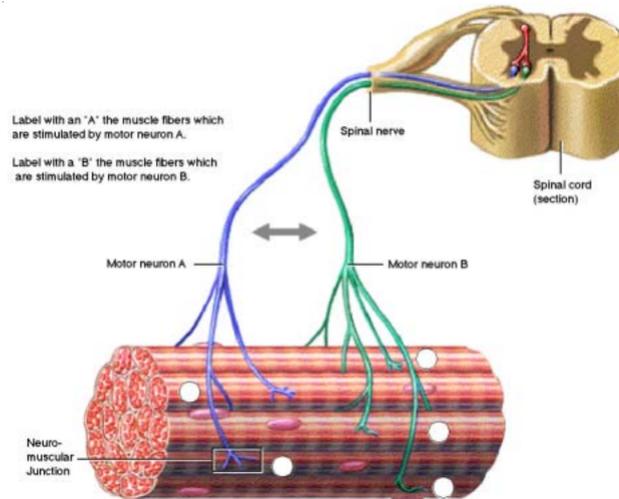
Muscles exist in pairs called antagonist muscles. One muscle performing an action is called the *agonist* and the other muscle performs the opposite action and is referred to as the *antagonist*. Each antagonist muscle has a set of sensory neurons called proprioceptors that transmit sensory information to the brain. The brain uses sensory information to gain its awareness of the positions of the different limbs among the body [31]. Among the proprioceptors is the Golgi Tendon Organ that signals the *tension* of the tendon and Muscle Spindle which provides the brain with muscle *length* information [32].

The brain can control any muscle contraction by activating the corresponding motor neurons. The pair of antagonist muscles are connected through tendons attaching them to the bones. One antagonist muscle contraction causes the extension of the other antagonist muscle in the pair. Muscle contraction causes an increase in tension at the tendon and decrease in the muscle length. Consequently, it causes an increase in the length of its antagonist muscle. The tension at the tendon is signaled by the Golgi Tendon Organ and it is activated as soon as there is tension. Tension is relaxed due to reflexes unless contraction occurs. Muscle Spindle activates when the muscle is stretched indicating the rate of change of muscle length and signals the new length after the stretch is finished [30].

Each muscle in the body is composed of muscle fibers, organized into groups called motor units. A *motor unit* is composed of a single motor neuron and all of the muscle fibers it stimulates as shown in Figure 2.6. When one motor neuron fires, all of the muscle fibers which are stimulated by that one neuron will contract. These motor neurons receive signals, from the motor cortex in the brain through the spinal cord and local nerves, when a movement is desired. The number of muscle fibers within a motor unit determines the degree of movement when that motor unit is stimulated. Motor units vary in size. Small motor units are used for precise, small movements; large motor units are used for gross movements.

In a motor unit, the amount of muscle fibers innervated by a motor neuron varies from fewer than 10 fibers for small muscles to more than 100 for larger muscles. The strength of a muscle contraction is determined by the size and number of motor units being stimulated. When stimulated, all the fibers innervated by the stimulated motor unit contract. To increase strength of contraction, more motor units are recruited to contract or equivalently, the frequency of the signal to contract (the rate of spikes forming the command to the motor neurons) is increased.

The signal from a motor neuron to its muscle fibers is a discrete time signal, it is a sequence of spikes at different times. If the time difference between two spikes becomes greater than or equals to an elapsed time, the muscle contracts then returns back to rest and after receiving



**Figure 2.6** – *Motor Units: When the nerve impulse gets down to the branches, it separates and goes down each branch. Only the muscle fibers that have neuromuscular junctions with one of the branches of that particular neuron will contract. Motor neuron A stimulates fewer muscle fibers than motor neuron B. When motor unit A is stimulated, the force of contraction is less than that generated when motor unit B is stimulated. [33]*

the next spike it contracts again with the same amount it did before. On the other hand, if the frequency of spikes is high, the successive muscle contractions sum up producing a faster contraction. The spikes from a motor neuron has a maximum frequency; exceeding it will not result in more contraction.

## 2.2 Fetus Behavior vs Human Behavior



**Figure 2.7** – *The fetus inside the womb [3].*

The fetus lives inside the womb as shown in Figure 2.7. As soon as its brain provides it with the ability to move, it starts making simple moves. These movements include the ability to suck its thumb, touch different parts of its body and grasp its umbilical cord. The new born can make these movements more strongly. The infant can move freely from one place to another but slowly. The child is able to move from one room to another and to go get the food from the kitchen when s/he desires. An adult can move from one address to

another and do more complex movements. Accordingly, the movements become more and more complex as the human develops. His environment also gets larger.

## 2.3 Discrete-Event Systems

A Discrete Event System (DES) is a dynamic system whose behavior is characterized by abrupt changes in the value of its state due to the occurrence of events [34]. Several modeling specifications have been proposed to model DES such as Discrete-Event Systems Specifications (DEVS); DEVS can be either an atomic model or a coupled model. Atomic models give a local description of the dynamic behavior of the studied problem, while the coupled models represent the different interconnections between a set of model elements [35,36].

Many biological problems can be modeled as Discrete-Event Systems. For instance, The NEURON simulation environment presented in [37] simulates networks of such artificial spiking neurons using discrete event simulation techniques in which computations are performed only when events are received. In [38], a formulation of the human motor decision-making problem as a discrete-event system is provided. Similarly, voluntary movements can be modeled as Discrete-Event System because the body state changes due to the occurrence of motor commands issued by the Central Nervous System (CNS) to muscles as explained in the previous section.

## 2.4 Learning Approaches

We are going to use machine learning techniques to implement our model. This section provides background about the machine learning techniques and their differences. It focuses on the unsupervised learning which is used in our implementation.

### 2.4.1 Machine Learning Techniques

In 1959, Arthur Samuel defined machine learning as a “*Field of study that gives computers the ability to learn without being explicitly programmed*”. With the evolution of computing and communication technologies, it became possible to utilize these machine learning algorithms to identify increasingly complex and hidden patterns in the data [39].

The process of learning begins with observations of data in order to find patterns in the data which will help in making better decisions in the future. Machine learning is an application of Artificial Intelligence whose primary aim is to allow the computers learn automatically without human intervention and adjust actions accordingly.

Machine learning techniques can be classified according to the type of learning into:

- Supervised: which involves using labeled training data that can be used by the system to infer a model function that can be used to label future data. It uses an error function to iteratively modify the model function so that it models the training data correctly, hence, assumed to make better prediction for the future data.

- Unsupervised: it involves unlabeled data. It studies how systems can infer a function to describe a hidden structure from unlabeled data. It is a simple and natural approach that depends on grouping based on similarity. It is used in many biological problems.
- Semi-supervised: fall somewhere in between supervised and unsupervised learning, since they use both labeled and unlabeled data for training. It is useful when the system has a small amount of labeled data and a large amount of unlabeled data and requires to label them. Usually, semi-supervised learning is chosen when the acquired labeled data requires skilled and relevant resources in order to train it or learn from it.
- Reinforcement learning: is a learning method that interacts with its environment by producing actions and getting errors or rewards. Trial and error search and delayed reward are the most relevant characteristics of reinforcement learning. This method allows machines and software agents to automatically determine the ideal behavior within a specific context in order to maximize its performance. Simple reward feedback is required for the agent to learn which action is best; this is known as the reinforcement signal [40].

Machine learning problems can also be classified into prediction, classification, clustering and regression. In our problem, we will use clustering which is an unsupervised machine learning approach that groups the data into clusters according to similarity [41]. The most famous clustering technique is  $k$ -means. In  $k$ -means clustering, the unlabeled data are grouped into  $k$  clusters according to the similarity measure which is the distance between each data sample and the cluster centers. Each data sample is assigned to the cluster of the nearest cluster center. This is the simplest and most commonly used clustering technique. Its drawback is that we have to pre-determine the number of clusters and the algorithm can result in different clusters each time it is run due to the usage of random seeds. Different criteria and metrics that calculate the value of  $k$  are used. These include the Elbow method which determines the  $k$  value by plotting the Sum of Squared Error (SSE) between the sample points in each cluster and the centroid of the cluster curve at different values of  $k$ , then finding the inflection point down. There are many adaptive clustering techniques in which the clusters can be formed and adapted according to the online data [42–44]. It refers to the problem of adapting the result of a clustering when the object feature set is extended. Examples of the adaptive clustering algorithms can be found in [45]. Among them are, the Adaptive Sample Set Construction. It is a heuristic technique that uses the distance measure to create clusters in addition to two parameters  $\theta$  (a fraction from 0 to 1) chosen according to design requirements and  $\tau$  which is the distance threshold. The first cluster center is chosen arbitrarily. A pattern is assigned to a given cluster if the distance from the sample to the cluster is less than  $\theta\tau$ . If that distance is greater than  $\tau$ , a new cluster is created. No decision will be made if the pattern falls in the intermediate region. After the training is complete, all patterns are assigned to the nearest class according to the minimum distance rule. Some patterns could be considered unclassified if their distances to all cluster centers are greater than  $\tau$ . In adaptive clustering techniques, the creation of the

clusters are based on statistical properties but they do not have biological interpretation.

## 2.4.2 Discrete Markov Process

### Observable Markov Model.

Consider a system that can be described at any time as being a state belonging to a set of  $S = \{S_1, S_2, \dots, S_N\}$  and each state  $S_i$  corresponds to an observable event. At a regularly spaced discrete times, the system can change its state by moving from the current state to a new one or even to the same current state according to a set of probabilities associated with the current state; this set is referred to as state transition probabilities  $A = \{a_{ij}\}$ . We denote the time instants associated with state changes as  $t = 1, 2, 3, \dots, T$ , and we denote the actual state at time  $t$  as  $q_t$ . The state transition probability  $a_{ij}$  from one state  $i$  to the next state  $j$  is given by:

$$a_{ij} = P(q_t = S_j | q_{t-1} = S_i), 1 \leq i, j \leq N \quad (2.1)$$

with the state transition coefficients having the standard stochastic properties  $\sum_{j=1}^N a_{ij} = 1$  such that  $a_{ij} \geq 0$ .

The output of this process at any time  $t$  is the observation  $o_t$  seen at the current state  $q_t$ .

### Hidden Markov Models

Suppose that there is a set of observations  $O = \{o_1, o_2, \dots, o_M\}$  from which one observation can be seen at any state  $q_t$  and that the choice of the observation is a stochastic process.

In this system, the output is a set of observations seen from a set of states at different times. Accordingly, there are two stochastic processes, the choice of the state and the choice of the observation within the state. As explained previously, the choice of the state depends on the state transition probability ( $A$ ) starting from an initial state specified according to initial probability distribution  $\pi = \{\pi_i\}$  such that:

$$\pi_i = P(q_1 = S_i), 1 \leq i \leq N \quad (2.2)$$

The observations output from state  $q_t = S_j$  has probability distribution  $B = \{b_j(k)\}$  known as the Emission probability distribution and is given by:

$$b_j(k) = P(o_{k,t} | q_t = S_j), \quad \begin{array}{l} 1 \leq j \leq N \\ 1 \leq k \leq M. \end{array} \quad (2.3)$$

In this setting, the states are hidden while the output observations are observable. That is why it is called a hidden Markov model (HMM).

Given a HMM model  $\lambda = (\pi, A, B)$  with set of hidden states  $S$  of  $N$  states and a set of observations  $O$  with  $M$  observations, the HMM can be used to generate an observation sequence as follows:

1. Set  $t = 1$ .
2. Choose an initial state  $q_1 = S_i$  according to the initial state probability distribution  $\pi$ .
3. Choose an observation  $o_t$  according to the emission probability distribution  $B$ .
4. Move to a new state  $q_{t+1} = S_j$  according to the state transition probability distribution  $A$ .
5. Set  $t = t + 1$  then return to step 3 if  $t < T$ ; otherwise terminate the procedure.

Additionally, HMM [46] is used to solve one of the following problems:

- Problem 1 (Likelihood): Given an HMM  $\lambda = (\pi, A, B)$  and an observation sequence  $O$ , determine the likelihood  $P(O|\lambda)$ . This is an evaluation problem of how well a given model matches a given observation sequence. It allows us to choose the model that best matches the observations.
- Problem 2 (Decoding): Given an observation sequence  $O$  and an HMM  $\lambda = (\pi, A, B)$ , discover the best hidden state sequence  $Q$ . It tries to uncover the hidden part of the model under an optimality criterion. The most widely used criterion is to find the single best state sequence (path). The *Viterbi* algorithm can be used for solving this problem.
- Problem 3 (Learning): Given an observation sequence  $O$  and the set of states in the HMM  $Q$ , learn the HMM parameters  $A$  and  $B$ . It is used to train the model by adapting its parameters to observed training sequence. *Baum-Walsh Expectation Maximization algorithm* can be used for this problem.

**Baum-Walsh Expectation Maximization** It is an iterative procedure that is used to find the maximum likelihood estimate of the parameters of a hidden Markov model given a training set of observed sequences. It is referred to as reestimation because in each step, the algorithm iteratively updates and improves the values of the HMM parameters using two main steps: the Expectation (E-step) and the Maximization (M-step). The algorithm is explained below in Algorithm 1.

---

**Algorithm 1** EM Algorithm

---

- Start with a random or preselected model  $\lambda$ .
- **E-step:** run  $O$  through the current model to estimate the expectations of each model parameter  $(\pi, A, B)$ .

- Forward procedure: calculate  $\alpha_i(T) = P(o_1 \dots o_T, q_T = S_i | \lambda)$

$$\alpha_i(1) = a_{0i} b_i(o_1)$$

$$\alpha_i(t+1) = \sum_{i=1}^N \alpha_i(t) a_{ij} b_j(o_{t+1})$$

- Backward procedure: calculate  $\beta_i(t) = P(o_{t+1} o_{t+2} \dots o_T | q_t = S_i, \lambda)$

$$\beta_i(t) = \sum_{j=1}^N a_{ij} b_j(o_{t+1}) \beta_j(t+1)$$

$$\beta_i(T) = 1$$

- Calculate  $\sum_{t=1}^T \gamma_i(t)$ : the expected number of transitions from  $S_i$ .

$$\gamma_i(t) = \frac{\alpha_i(t) \beta_i(t)}{P(O | \lambda)}$$

- Calculate  $\sum_{t=1}^T \xi_t(i, j)$ : the expected number of transitions from  $q_t = S_i$  to  $q_{t+1} = S_j$ .

$$\xi_t(i, j) = P(q_t = S_i, q_{t+1} = S_j | O, \lambda)$$

$$\xi_t(i, j) = \frac{\alpha_i(t) a_{ij} b_j(o_{t+1}) \beta_j(t+1)}{P(O | \lambda)}$$

- **M-step:** change the model to maximize the values of the paths that are used a lot by estimating parameters using the ratio of expected counts

$$a'_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i, j)}{\sum_{t=1}^{T-1} \gamma_j(t)}$$

$$b'_i(o_k) = \frac{\sum_{t=1}^{T-1} \gamma_j(t) p(o_t = k)}{\sum_{t=1}^{T-1} \gamma_j(t)}$$

- Repeat until convergence.
- 

**Viterbi Algorithm** There are several paths through the hidden states that lead to the given observation sequence, but they do not have the same probability. The Viterbi algorithm is a dynamic programming algorithm that allows us to compute the most probable path.

To find the best state sequence  $Q = \{q_1 q_2, \dots, q_T\}$  for the given observation sequence  $O =$

$\{o_1 o_2 \dots o_T\}$ , we will define  $\delta_t(i)$  as the highest probability along a single path that has  $t$  observations and ends in state  $S_i$  at time  $t$ , and is given by:

$$\delta_t(i) = \max_{q_1 q_2 \dots q_{t-1}} P[q_1 q_2 \dots q_t = i | o_1 o_2 \dots o_t | \lambda] \quad (2.4)$$

- By induction, we have:

$$\delta_{t+1}(j) = \left[ \max_i [\delta_t(i) a_{ij}] \right] \cdot b_j(o_{t+1}) \quad (2.5)$$

- By keeping track of the states that maximize equation 2.5, we will be able to retrieve the best state sequence. The whole algorithm is explained in Algorithm 2.

---

**Algorithm 2** Viterbi Algorithm

---

1. Initialization

$$\delta_1(i) = \pi_{si} b_i(y_1) \quad (2.6)$$

$$\Theta_1(i) = 0 \quad (2.7)$$

2. Recursion : calculate the Maximum Likelihood (ML) state sequence and their probabilities

$$\delta_t(i) = \max_{j=1}^N [\delta_{t-1}(j) a_{ij}] \cdot b_i(y_t) \quad (2.8)$$

$$\Theta_t(i) = \underset{j}{\operatorname{argmax}} [\delta_{t-1}(j) \cdot a_{ij}] \quad (2.9)$$

3. Termination: retrieve the most likely final state

$$\hat{P} = \max_j (\delta_T(j)) \quad (2.10)$$

$$\hat{S} = \underset{j}{\operatorname{argmax}} [\delta_T(j)] \quad (2.11)$$

4. State Sequence Backtracking : retrieve the most likely state sequences

$$S_t = \hat{\Theta}_{t+1} \left( S_{t+1}^\wedge \right) \quad (2.12)$$

such that  $t = T - 1, T - 2, \dots, 1$

---

HMMs have been successfully applied to problems including speech recognition, optical character recognition (OCR) and computational biology. In Computational Biology, it is used for modeling biological sequences such that a sequence is modeled as an output of a discrete stochastic process, which progresses through a series of states that are hidden. Each hidden state emits a symbol representing a basic unit of the modeled data, for example, in

case of a protein sequence, the basic unit is an amino acid.

## 2.5 Miscellaneous Basics

### Bernoulli Distribution

It is a discrete distribution having two possible outcomes ( $n$ ) labeled by 1 or zero which means success or failure, respectively. The success occurs with probability  $p$  and the failure occurs with probability  $(1-p)$  where

Therefore, Bernoulli distribution function is given by:

$$q_n = p^n (1 - p)^{1-n} \quad (2.13)$$

We will be using Bernoulli distribution to generate random binary sequences.

### Convolution

It is a mathematical operation on two functions that produces a third function that shows how the shape of one function is modified by the other, and it is given by:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau \quad (2.14)$$



# CHAPTER 3

## STATE OF THE ART

Many studies have been performed to understand how the human becomes capable of doing various tasks such as moving his body parts, navigating through his environment, generating intentions and making goal-directed movements. Some studies have focused on the sensorimotor system which investigates the relation between the sensory neurons, the motor neurons and the body muscles states. Other research is specialized in understanding the brain signals obtained from fMRI as a way to understand how the muscles are controlled and which brain areas are responsible for certain movements. Others are interested in modeling the human learning of motion with respect to producing motion, getting the sensory feedbacks and correcting the motion. Machine learning techniques have been used in some research such as using Self-Organizing-Maps (SOM) to generate joint angles from proprioceptors as in [47].

Even though the main regions of the brain are well-known, the function of each region is still undetermined especially when it comes to achieving a certain objective. For instance, how these regions contribute to make a goal-directed movement is still unknown. Some work has been done to understand the function of the brain structures and how they are functionally integrated. In [48], a general plan of the nervous system is presented. It proposes an idea about how the sensory nervous system, motor system and autonomic system work, and how they are all functionally integrated. Although the sensory data and the perceptions are usually noisy and the brain is usually unable to perceive the precise perceptive values, the brain learns through the imperfect perceptions [49, 50].

In this chapter, we present the recent research done for the sensorimotor system, the perceptions and perceptual learning, the cognition and the cognitive maps.

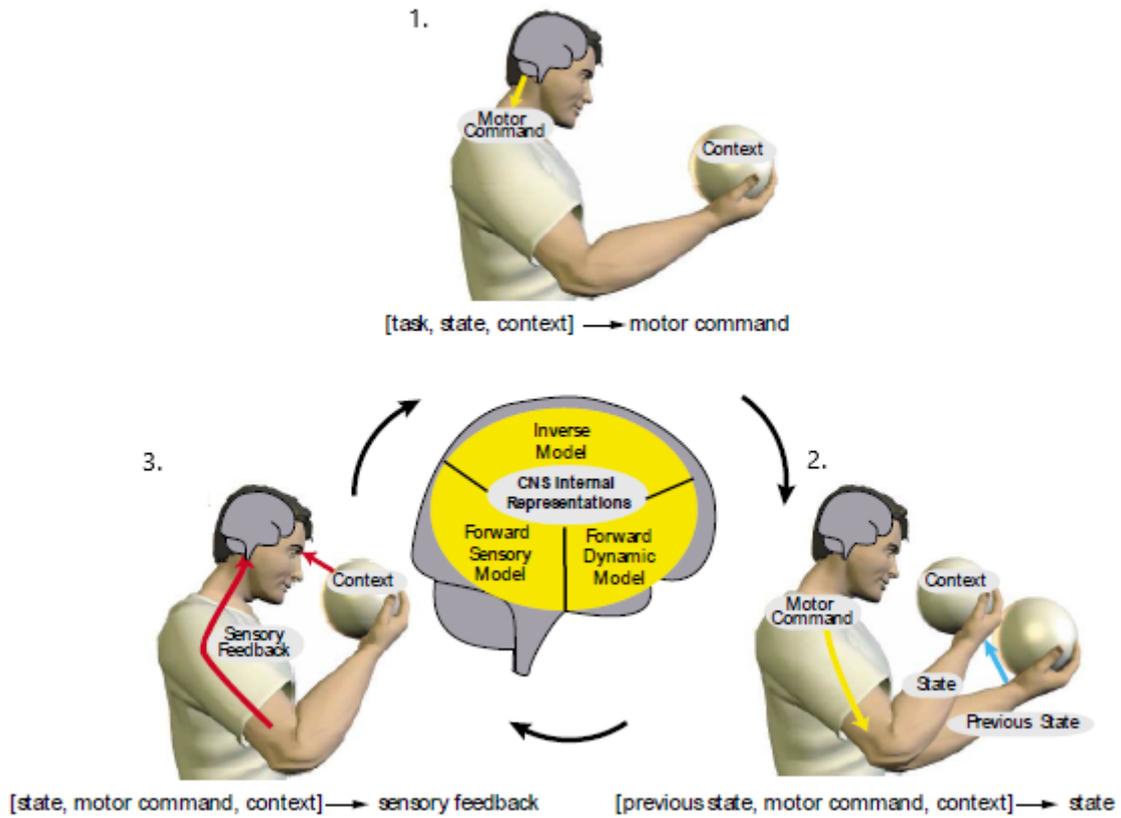


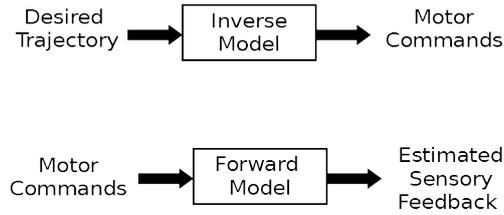
Figure 3.1 – The sensorimotor loop [4]

### 3.1 Sensorimotor System

The sensorimotor loop has been extensively studied in literature. Wolpert demonstrated that the sensorimotor loop can be divided into three stages, which govern the overall behavior of the sensorimotor system. The first stage specifies the motor command generated by the CNS given the state and a particular task. The second stage determines how the state changes given the motor command. The third closes the loop by getting the sensory feedback given this new state. These three stages are represented in the CNS as internal models, being the inverse model, forward dynamic model and forward sensory model respectively [4].

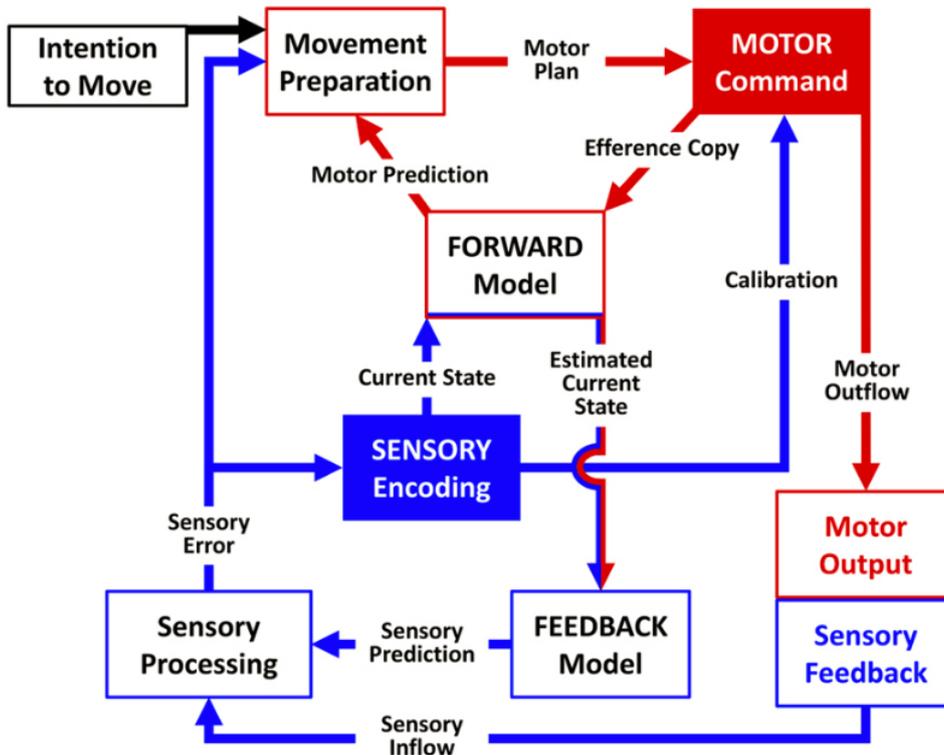
It is widely accepted that the cerebellum acquires and maintain internal models for motor control [51]. Cerebellar internal models can be forward models or inverse models. Forward internal models represents the causal relationship between actions and their consequences. The primary role of these models is to predict the behavior of the body and world, so they can be seen as predictors. A forward model transforms a motor command into a prediction of the sensory consequences of the movement. On the other hand, an inverse model computes the motor command required to achieve the desired state change of the body (i.e. reach the target sensory state) [52]. Figure 3.2 shows the difference between the inverse model and the forward model.

An abstract architecture for the sensorimotor loop is provided in Figure 3.3 with biological



**Figure 3.2** – *Inverse Model versus Forward Model*

illustration. This model provides a demonstration of the main building blocks that are needed to make a movement and get response [5]. It has included that there is an intention to move, for instance, to reach an object. A movement is prepared by issuing the necessary motor command to the target muscle which will change the target muscle state. At the same time, an efference copy of this motor command is given to a forward model which predict the next motor command sequence based on the actual current state of the sensory information. A feedback model estimates the sensory feedback to be received from the muscle after the movement. In addition to the output of the forward model, these predictions are used for making rapid decisions about the movement. The movement preparation generates a motor plan based on the intention, the motor prediction and sensory error. Some aspects are not covered in this model, these includes, the representation of the intention to our mind, how can the movement preparation be implemented, and what is the role of cognition in the performance of the sensorimotor system. In our system, we will try to answer these questions.



**Figure 3.3** – *SMILE sensorimotor loop* [5]

All the presented work are performed for child or adult sensorimotor systems. It is still unknown how the sensorimotor system originates and develops into this structure. Hypothesis of developmental psychology states that, in the first months of their life, infants perform exploratory/random movements referred to as motor babbling, in order to create associations between such movements and the resulting perceived effects [53]. Recent research [54] tracks the fetal origin of infants' sensorimotor behavior. It shows how observations on fetuses suggest that the fetus's first motor activity allows it to feel the space around it and to feel its body and the consequences of its movements on its body.

### 3.2 Perception and Perceptual Learning

Perception is the interpretation of sensory information [55]. Looking at some stationary rocks produces a perception that they are not moving from their position. However, a person who looks at a waterfall for a minute, and then looks away at the rocks, sees the rocks as moving even though they are not. This is a short-term change in perception that remains for few seconds before the original perception is retrieved. There are short-term changes and long-term changes of perceptions. Long-term changes in perception sometimes happen through exposure to stimuli, and without any instruction. Hence, perceptual learning can be a form of unsupervised learning [56]. Most aspects of our body and sensory organs, such as the spacing between our eyes and the length of our limbs, change as we age. Perceptual learning enables our perceptual systems to tune representations of our body and sensory organs and update these representations as we grow [57]. Perceptual learning is the discovery of new structure in sensory stimulation [58]. Although the sensory stimulation are the same, with repetitions, new structures start to appear which changes our perceptions. For instance, beginners in tennis do not have the same level of perceptions as experts. With practice, the perception of the flow of the ball itself will change, they will detect and distinguish features, differences and relations in the basic sensory information that were not previously registered at all. Similarly, experienced chefs are able to perceive structures in their sensory environment, i.e. they are able to easily detect ingredients in a given dish, where there was none before and that is invisible to those who do not have the same level of experience. Another example is a student reading an article, s/he perceives more information each time s/he reads it.

In both, neurobiology and in machine learning, learning has been considered to take place only at the cognitive level, i.e., either being processed in cognitive regions of the brain or handled by complex machine learning algorithms. However, many tasks in real life require humans to perform learning at the perceptual level. Learning was considered at the cognitive level where identification and categorization should be processed. However, perceptual learning is used to quickly discriminate between close colors, objects, odours or tastes that can make many categorization task possible. Thus, perceptual learning can be seen as a specific process that learns how to transform the data before the traditional learning task itself takes place [59]. As an example, the importance of perceptual learning

has also been shown in human for face recognition [60] and object recognition [61] using the visual system.

In [62], a study of the perceptual skills development for infants recognition of faces and spoken words is presented. It is shown that they follow similar trajectories; which supports the idea of development of the perceptual spaces representing the organization of the sensory information relating to all aspects of faces and spoken words. The paper concluded that the perceptual space is initially elaborated according to physical statistical properties in the infant's environment that lead to narrowing in discrimination of non-experienced stimuli during the first year of life for both faces and spoken words. Thus perceptual narrowing refers to developmental improvement in perception of often-experienced stimuli, reflecting the strengthening of neural pathways that are consistently stimulated.

Perceptual learning is used for skill learning which can take place both in sensory and in motor tasks. Sensory skill acquisition using perceptual learning tasks is measured by improvements in sensory acuity through practice-induced changes in the sensitivity of relevant neural networks [63]. Motor skill is a term used whenever a motor learning behavior improves along some dimension [64]. It is believed that motor skills have a direct relation with perceptual skills [65].

### 3.3 Perception and Proprioception

Proprioception predominates as the most misused term within the sensorimotor system. It has been incorrectly used synonymously and interchangeably with kinesthesia (the sense of limb movement), joint position sense, somatosensation, balance, and reflexive joint stability [66]. We will use the definition that is most commonly used in the literature which is the sense of "self" position, where self refers to the body muscles or joints [32] [67] [68].

The mechanoreceptors that are used to produce proprioception such as the muscle spindles and Golgi Tendon Organs (GTOs) are called proprioceptors [66]. Muscle spindles are considered as the principal proprioceptors [47, 69]. Unlike vision and auditory senses, the proprioception development is not studied much due to the difficulty to measure its performance, but in [70], a study was presented to explain the proprioception development in children and it concluded that its precision improves with age.

Proprioception map can be produced to identify different positions of each limb [71]. It remains unclear how visual, proprioceptive, and tactile modalities come together to create the structure of the hand-location map. Proprioception can be interacted with tactile information to produce haptic perception that helps us identify and grasp different objects [72] [73]. Since tactile pressure does not provide us with information about the muscle length position, it can not be considered as a proprioceptor. But, it enables us to identify whether there is an object or not at this muscle length. Hence, it is necessary for identifying positions in the cognitive map and it helps us in choosing goals.

The term proprioception is for an experience of the body itself whereas perception is for an experience of the environment surrounding the body. Now it is a fact that an environment implies something that is surrounded, and therefore an awareness of the environment implies an awareness of the body existing in the environment. Equally, an awareness of the body entails some feeling of its relation to the surroundings. So there can be no perception without an implied proprioception, nor can there be any proprioception without some awareness. The process of forming a perception begins with sensory experiences of the world. This stage involves the recognition of environmental stimuli provided through the five senses. It is to be noted that proprioception is a form of perception in which the sensory information is obtained from the body only [74].

### 3.4 Cognition

Cognition is a term referring to the mental processes involved in gaining knowledge and comprehension. These processes include thinking, knowing, remembering, judging and problem-solving. These are higher-level functions of the brain and encompass language, imagination, perception, and planning .

The study of how we think dates back to the time of the ancient Greek philosophers Plato and Aristotle. In his study of the mind, Plato proposed that people understand the world by first identifying basic principles stored inside themselves and then using rational thought to create knowledge. This viewpoint was later advocated by other philosophers such as Rene Descartes and linguist Noam Chomsky. This approach to cognition is often referred to as rationalism. Another approach to cognition is referred to as empiricism. This was introduced by Aristotle who believed that people acquire their knowledge through the observations they collect from the world. Later, thinkers including John Locke and B.F. Skinner advocated this point of view.

During the earliest days of psychology and for the first half of the twentieth century, psychology was largely dominated by psychoanalysis, behaviorism, and humanism. A formal field of study devoted solely to the study of cognition emerged as part of the “cognitive revolution” of the 1960s. The field of psychology concerned with the study of cognition is known as cognitive psychology [75].

One of the earliest definitions of cognition was presented in the first textbook on cognitive psychology published in 1967. According to Neisser [76], cognition is "those processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used". This means transforming the Sensory Inputs (sensations from the environment surrounding you such as the information that you see, hear, taste and smell) into signals that your brain can understand and act upon. For example, if we see an object flying through the air toward us, the information is taken in by our eyes and transferred as a neural signal to our brain. Our brain then sends out signals to our muscle groups so that we are able to respond and move out of the way before the object smacks us in the head [77].

The world is full of enormous amount of sensory experiences. To get a meaning out of all this incoming information, it is important for the brain to be able to reduce experience of the world down to the fundamentals (i.e. get a summary or the key points only). For instance, instead of remembering every detail about what the professor wore each day, where we sat during each class session and how many students were in the class, we focus your attention and memory on the key ideas presented during each lecture. The key points represent perceptions. Hence, perceptual learning and cognitive learning are strongly related [59]. However, there is a sharp distinction between perception (the processing of sensory information that occurs at several levels) and cognition (the judging of representational contents related to reasoning) [78].

Recently, many studies are performed to understand the fetus cognition development. In [79], the cognitive functions of the fetus are investigated. The human brain is designed to execute cognitive functions, such as perception, attention, action, memory and learning. It has been found that the fetal action planning is established by 22 weeks and investigations using four-dimensional ultrasound reveal that complexity of fetal motor action and behavior increases as pregnancy progresses whereas the fetus processes sensory stimuli at a cortical level starting from the 25 weeks of gestation.

### 3.5 Cognitive maps

Tolman proposed the term cognitive map, which is an internal mental representation (or image) of external environmental feature or landmark. He thought that individuals acquire large numbers of cues (i.e. signals) from the environment and could use these to build a mental image of an environment (i.e. a cognitive map) [80–82]. The cognitive map is a person’s spatial memory that store knowledge of the world and its events and processes [83,84]. A cognitive map consists of “positions”. By using this internal representation of a physical space they could get to the goal by knowing where it is in a complex of environmental features through different paths. Cognitive mapping is usually divided into building two internal representations: one for developing person to object relation (egocentric) and another for object to object relation (allocentric). Imperfections in encoding either relations can introduce imperfections in representations of environments in memory [85].

Burgess & O’Keefe considered that the cognitive map provides a Euclidean description of the surroundings from an allocentric reference perspective, informing on places in the environment, objects to be found in that places, and spatial relations, driving wayfinding, goal-directed behavior and exploration [86]. Some studies done on cognitive map consider it allows one to locate oneself in a familiar environment and to go from one place to another even through parts of the environment were never visited before. Others see that it is not a unitary integrated representation, but consists of stored discrete pieces including landmarks, route segments, and regions [87]. Although there are many studies performed on high-level cognitive maps whose purpose is to navigate to go from one route to another, how to link routes to go from one location to another, and how people have different abilities to form

cognitive maps. There are no studies done on the origin of the cognitive maps in the fetus stage.

The formation of cognitive maps are still unknown. Recently, a study [54] highlighted that the sensorimotor system of the fetus plays an important role in forming the cognitive map. They track the fetal origin of infants' sensorimotor behavior. Their observations on fetuses suggests that the fetus's first motor activity allows it to feel the space around it and to feel its body. This primitive motor babbling gives way progressively to sensorimotor behavior which already possesses most of the characteristics of infants' later behavior, for instance, repetition of actions leading to sensations, building intentions, getting motor control and oriented reactions to sensory stimulation. In this way the fetus can start developing a body map and acquiring knowledge of its limited physical and social environment.

The influence of proprioception on human spatial cognition is investigated in [88] and it is found that proprioception can influence the time necessary to use spatial representations while other factors such as visuo-spatial abilities can influence the capacity to form accurate spatial representations [89]. This was done by the study of the navigation of blind individuals and comparing to the navigation and way finding in individuals without any visual impairments [90]. It is found that the combination of both proprioception and auditory sense helps the blind individuals to build their cognitive map for the surrounding environment and they are able to navigate easily after a number of trials [85]. These studies included the sense of touch with the proprioception. Some applications are made to help blind individuals move freely, based on these findings [91]. Accordingly, the spatial positions can be represented in terms of proprioceptions and the sense of touch (i.e. pressure perception).

# CHAPTER 4

## THE PROPOSED FRAMEWORK

We will follow a methodology that is inspired from system-based modeling in computer science. This approach starts with a black box for which we partially know the external (input/output) behavior. Then according to the knowledge acquired about the system, we propose an internal structure of the black box that is able to reproduce the known external behavior. This internal structure can call for smaller black boxes and we iterate until we get consistent with the knowledge. This way, the model follows a constructive approach.

To choose a structure when we have a few knowledge, we have to apply heuristics. One particularly important heuristic is the Occam razor. Our knowledge is that the fetus learns by interaction with its environment using its sensorimotor system. The inputs to the sensorimotor system are the sensory feedbacks. These will represent the basic data upon which the knowledge is acquired. Using the repetitive received sensory feedbacks, it begins building perceptions as explained in previous chapter in sections 3.2, 3.3. Using perceptual learning, cognition will evolve making cognitive maps that represent an internal structure of the environment as illustrated in previous chapter in sections 3.4, 3.5.

We have made the simplest choices with high level of abstraction in the model implementation following Occam razor. For instance, our model focuses on the problem of moving the elbow upwards to reach different locations vertically at different speeds and get the corresponding sensation, binary sequences are used to represent the motor command signal sent from the CNS to the muscle. For movement learning and generation, we use HMM because it is simple and suitable for dealing with sequences. In addition, it has a probabilistic basis and enable us to get the most probable sequence. An inverse model is used to generate command sequences as mentioned in the previous chapter in section 3.1.

At the end of this constructive method, the model we obtained is by construction consistent with the *biological hypotheses* made about the problem. So, the study of this model is in fact *a study of these hypotheses*.

Due to the unavailability of real data about the fetus, we will use simulated data extrapolated from knowledge about the children sensory motor development.

## Definitions

Due to the availability of many definitions in literature for each part of our model as explained in chapter 2.5, the definitions chosen with respect to our model are demonstrated below. This provides better understanding for the model and alleviate any possible confusion.

- Sensorimotor map: is a map that associates the motor command to its corresponding sensory data 3.1.
- Perceptions: is the process of interpreting sensory information. We identify it as the interpretation of the sensory information coming from the environment and it is a cognitive process. For instance, the cutaneous pressure obtained by touching an object from the environment produces a perception that there is an object. In addition, different objects result in different pressures, so, we refer to these pressures as pressure perceptions 3.2.
- Proprioception: is a special form of perception in which the sensory information is obtained from the body only. For instance, it is the ability to interpret the sensory information from the muscle spindle as a self-position in space without any external information from the environment 3.3.
- Proprioceptors: are mechanoreceptors (sensory neurons) that are used to produce proprioception which is the self-position in space 3.3. We use muscle spindle to get the length information of the muscle. A muscle can have different length values, some of them are well-perceived and recognized as self-position for this muscle, we refer to these as length proprioceptions.
- Position: it is a proprioception when experienced from the body itself and is a perception when experienced from the environment. For instance, the position of a muscle is determined from the length of the muscle obtained by the muscle spindle. But, to make an interpretation about the state of that position (whether there is an object or not), other sensory data such as the tactile pressure is needed. In other words, the muscle position is a proprioception but when it touches an object in the environment, it creates a perception regarding that position (i.e. there is an object here). Hence, it is a pair of length (obtained from muscle spindle) and pressure (obtained by the tactile sensation of the surrounding environment) 3.3.
- Cognitive map: a map of positions 3.5. The fetus is able to move its hand to suck its thumb, which means it has the ability to recognize its mouth location and learn how to reach it. Similarly, it can grab its umbilical cord which means it is able to reach

it. From these simple moves, we believe that the fetus forms a simple cognitive map that enables it to reach different objects in the womb. We will focus on egocentric map which depends on changing the body position to go to an object rather than allocentric. It can be 1D in case of moving in one direction or 2D in case of moving vertically and horizontally. But, the structure of the cognitive map is not our concern in this work. We are more interested in the content of the cognitive map and how it can be expressed in terms of the input sensory data.

## 4.1 Simplifying Hypotheses

For the tractability and traceability of the model, we use four simplifying hypotheses in our model:

1. An increase in contraction of one muscle causes the increase in length of the antagonist muscle by the same amount during motion.
2. Due to the dependency relation between the length and the contraction during motion, we abstract the pair of antagonist muscles into one muscle and use the length proprioception.
3. After the muscle stops, the tension caused by contraction relaxes and decreases while the length remains the same.
4. The sensation of the environment is represented by the cutaneous pressure as either zero indicating the fluid pressure or one indicating an object.

## 4.2 Biological knowledge and hypotheses captured by the model

Based on the hypothesis developmental psychology, explained in section 3.1, that the infants depends on performing exploratory or random movements to create associations between such movements and the resulting perceived effects. We extrapolate the hypothesis that the fetus learns through two main phases namely, the Exploration phase and the Exploitation phase. The Exploration phase is the first phase that the fetus passes through to collect large amount of sensory and motor data by making random movements. During this phase, it makes vast amount of random movements without having any intention or goal. These random movements result in sensations collected through its body and sent to its mind. This helps it to develop its sensorimotor capabilities and their usage in making the cognitive map. On the other hand, in the Exploitation phase, the fetus has already gained some awareness and starts learn making intended movements. To make the transition from the Exploration phase to the Exploitation phase, it is necessary to have improved cognitive abilities such as differentiating between different sensations to various stimuli, linking these information in building the cognitive map of positions of the surrounding environment. This is in addition to being able to learn the relation between the motor skills required to move from one

position to another. After that, exploiting all these information to make a goal-directed movement can be done in the Exploitation phase. Both phases are explained as follows:

1. Exploration Phase: it is responsible for developing the sensorimotor map and helps in building a primary cognitive map.
  - (a) Issue a random command that activates a random motor neuron.
  - (b) The motor neuron sends a contraction signal to the muscle.
  - (c) Execution of the command (muscle contraction)
  - (d) Sense the perceived state (muscle length, tactile pressure), this state represents a position in the cognitive map.
  - (e) Learn and record the association : this motor command = these proprioceptions and perceptions  $(L, P) = \text{this position}$ .
  - (f) Repeat from (a) until the space is entirely covered.
2. Exploitation Phase:

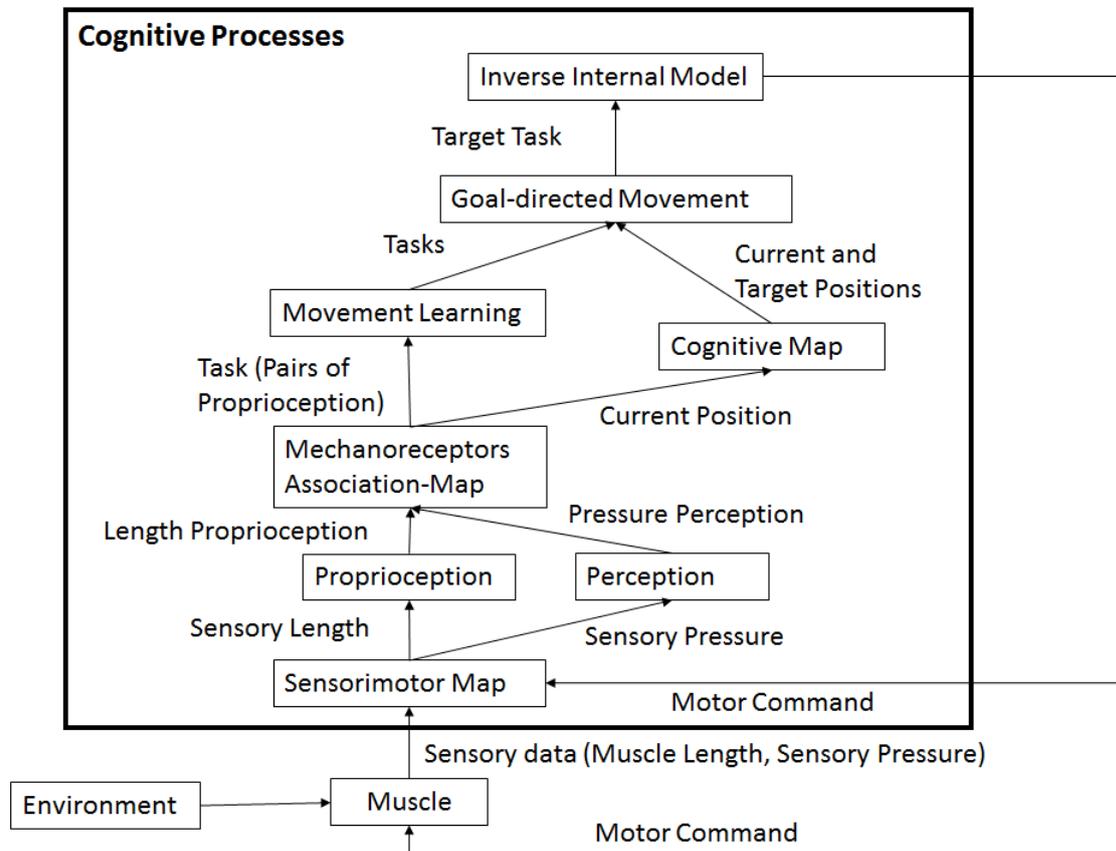
On the basis of the exploration phase, the fetus is now able to reach a given position stored in its cognitive map. To do so the fetus system uses the information from the cognitive map to build a specific internal model to program a given movement in a given context. For instance, it can choose to put its thumb in its mouth either quickly or slowly.

- (a) Build an intention (reach a given target state/position)
- (b) Build a motor program (build an internal model from the cognitive map: Given the current perceived state, if you want this position, so you want these perceived states, so you want this command)
- (c) Generate a motor command (stimulates one or more alpha motor neurons)
- (d) Execution (muscle contraction)
- (e) Get the perceived state (muscle length, tactile pressure)
- (f) Comparison of the target state and the perceived state, if there is a discrepancy, repeat from (b).

Passing through these phases, all the required building blocks for making a goal-directed movements are generated.

### 4.3 The Proposed Framework

This sub-section explains the proposed framework of the development of the human cognitive processes and the ability to make goal-directed movements.



**Figure 4.1** – *The System Framework.* The system works in bottom-top approach where the bottom represents the low-level processes and the top depicts the high-level processes. There are four main building blocks of our system. **1. The Environment** with which the fetus interacts and gets its exteroceptions in response to its actions such as the pressure in case of touching an object. **2. Muscle** it is the source of interaction of the body with the environment. **3. Cognitive Processes of the mind:** it includes, **a. Sensorimotor map:** it is a map that contains the command sequences issued by the brain to a muscle and the corresponding sensory information that includes both exteroceptions and proprioceptions such as the muscle length. **b. Proprioception:** it uses the length information in the sensory map to perform higher level processing. **c. Perception:** it uses the rest of the information in the sensorimotor map to perform higher level processing and generate perceptions from the sensory data. **d. mechanoreceptors-association-map:** it generates associations of the recorded proprioceptions and perceptions to generate the position concept. **e. Cognitive Map:** it represents all the positions identified by the mechanoreceptor association map. **f. Movement learning:** it learns how to go from one position to another. **g. Goal-directed movement:** it chooses the target task that should be done to move from the current position to the target position. **h. Inverse Internal Model:** it learns how to achieve a task that is specified by the goal-directed movement block and it learns how to generate the required command sequence to perform that task.

The system framework consists of three main building blocks shown in Figure 4.1:

1. The Environment

It is a representation of the locations of different objects around the fetus. It will be reflected as exteroceptors (pressure values) in the sensorimotor map.

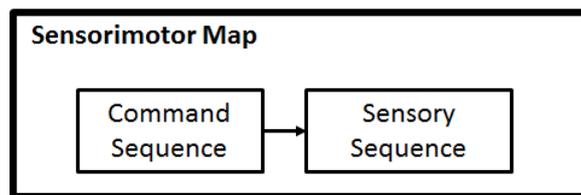
2. The Muscle

It is part of the body that interacts with the environment and allow the sensorimotor map to get updated. It provides the sensorimotor map with data about the motor command applied to it and the sensory feedback sent by its mechanoreceptors to the CNS.

3. The Cognitive Processes

- (a) The sensorimotor Map Memory

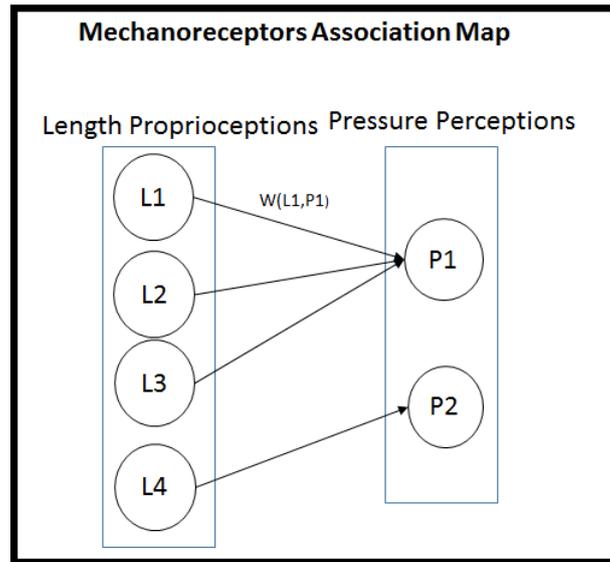
It is a memory recording all the commands that are issued and the corresponding sensory feedbacks from the body and the environment, referred to as proprioceptors and exteroceptors, respectively. It is shown in Figure 4.2.



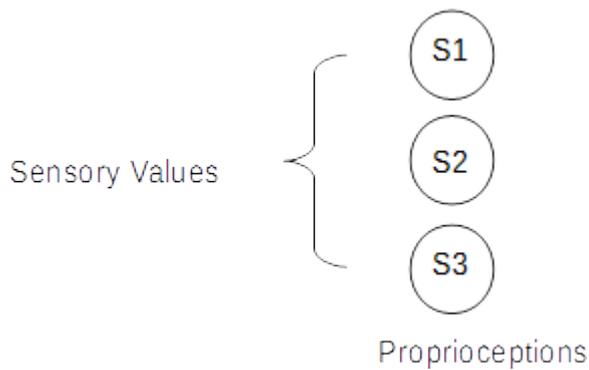
**Figure 4.2** – *The Sensorimotor Map*

- (b) Proprioception Generation

The input sensory data (sensory length from the muscle spindle) is converted into higher-level proprioceptions through time. Their numbers usually increase with time as the fetus reaches more sensory values as its physical abilities improve. It is implemented as a form of clustering where the number of clusters is dynamically increasing with repetition. Figure 4.3 shows how the proprioceptions corresponding to sensory values are depicted in the rest of the thesis.



**Figure 4.4** – *The mechanoreceptors-association-map*



**Figure 4.3** – *From Sensory data to Proprioception*

(c) Perception Generation

It is a cognitive process in which the input sensory pressures are grouped such that each group gives a sensation different from the other groups.

(d) The mechanoreceptors-association-map between length proprioceptions and pressure perceptions

As time moves on, more values for both length and pressure will be obtained from the sensory neurons. Hence, more proprioceptions are generated. Then, it will generate connections between the length and its corresponding pressure over time. Figure 4.4 demonstrates how the the relation between length and pressure perceptions.

(e) The Cognitive Map

In literature, the cognitive map is defined as a person’s spatial memory that store knowledge of the world and its events and processes [83] [84]. In other word, it is

a map of all the positions identified by our mind. The cognitive map is used to reach any of these positions which is the base of making goal-directed movements. We are interested in the Cognitive Map formed only from proprioceptions and pressure perceptions, vision will not be considered because it is not fully developed in the fetus stage.

(f) Movement Learning

Its objective function is learning how to change the muscle length from an initial value to a final value by generating the suitable command sequence.

We see that moving from one length to another can be seen as a task in a broader sense. Hence, we will use it to represent the cognition ability of the fetus of its body in the first place. From our point of view, the movement learning comprises two main units:

i. Tasks Perception

Tasks are then defined out of the length proprioceptions. They are transitions from one proprioception to another. A muscle movement means that its length is changed from initial to final length. Hence, the brain will learn the task of how to move from any initial length proprioceptions to a final length proprioception. The number of tasks depends on the number of proprioceptions. This means the number of tasks are increasing with time. The task  $Task(L_i, L_f)$  is a tuple of a motor command, initial length proprioception ( $L_i$ ) and final length proprioception ( $L_f$ ). Figure 4.5 shows how a task is defined from proprioceptions.

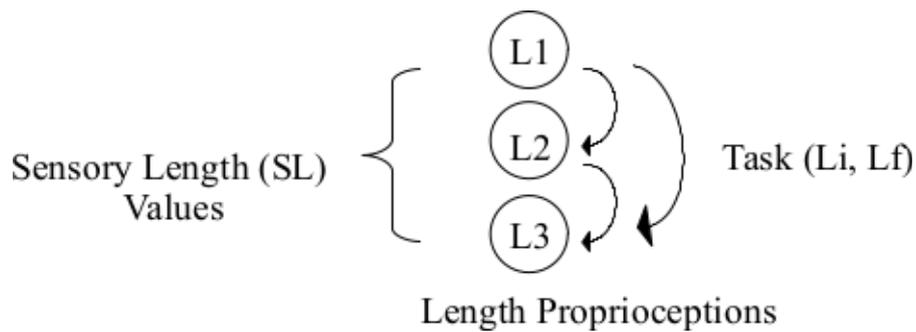
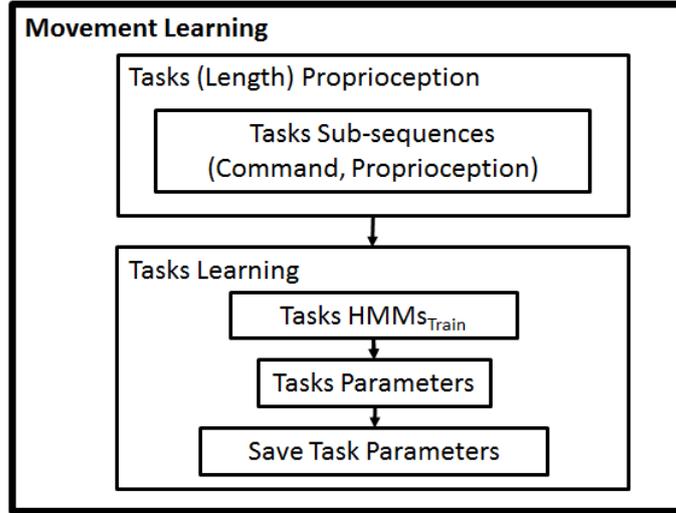


Figure 4.5 – Task

ii. Tasks Learning

Each perceived task is to be learned in this unit to get the parameters that represent this task. The task parameters are saved in the cognitive memory. This module is implemented using HMM. For learning a task to move from one initial length to another final length, all the sub-sequences that start at the specified initial length and end at the final length are collected with their



**Figure 4.6** – *Movement Learning*

corresponding command sequences. This forms the training set. HMM trains using this training set and gets parameters that corresponds to this task. It is to be noted that the command sequence may differ in these sub-sequences although they cause the change between the same lengths. This is due to the fact that to reach from one position to another can be done with different behaviors. This information is included in the motor command sequence and is taken into consideration in the learning process.

(g) Learning how to make a goal-directed movement

The fetus will combine the learned different movements and the learned relation between length and pressure to learn how to make an intended movement to reach a certain position referred to as a goal. Its objective function is to change the length from the current value to a new value and get the intended pressure as well. Accordingly, it will calculate:

- i. length proprioception Error

$$E_L = (L_t - L_a)^2 \quad (4.1)$$

where  $L$  refers to length proprioception,  $L_t$  is the target length and  $L_a$  is the actual length.

- ii. pressure perception Error

$$E_P = (P_t - P_a)^2 \quad (4.2)$$

where  $P$  refers to pressure perception,  $P_t$  is the target pressure and  $P_a$  is the actual pressure.

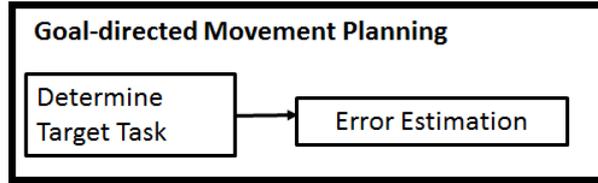


Figure 4.7 – *Goal-directed movement*

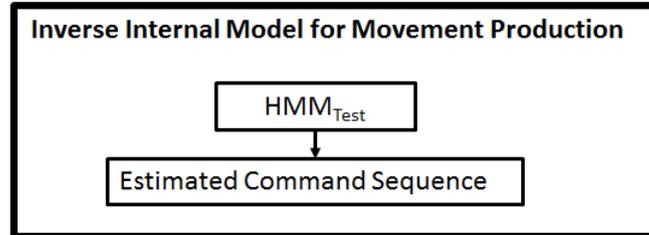


Figure 4.8 – *Inverse Internal Model*

(h) The Inverse Internal Model

When a fetus intends to accomplish a task, it will need to issue the corresponding command sequence. It will exploit the learned task parameters to estimate the command sequence. The internal model is responsible for applying the decoding (inverse model). HMM is used to estimate the command sequence using the Viterbi algorithm.

Figure 4.9 demonstrates the implementation of each cognitive process.

Our aim is to build a clear and simple model that can illustrate how the fetus human is able to move its muscle to go from one position to another either to reach an object or just to move freely. To achieve this aim, we need to go through different levels of processing in the mind. We will start from the low-level sensorimotor system to the high-level cognitive processes.

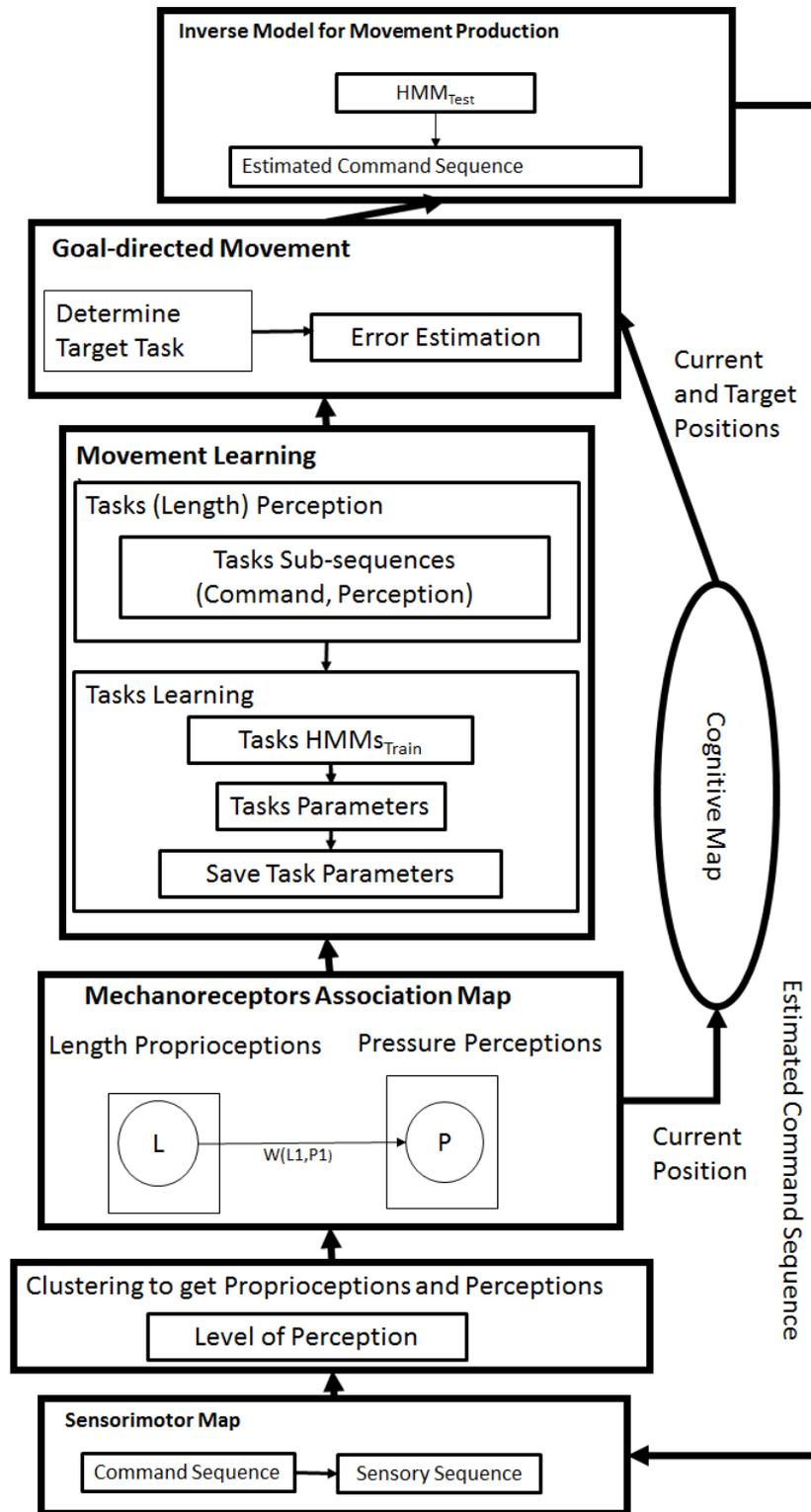


Figure 4.9 – The cognitive processes implementation



## CHAPTER 5

# GENERATION OF PROPRIOCEPTIONS AND PERCEPTIONS

Do we feel the exact sensory information sent from the body to our brain? The answer is no. We may sense our arm moving around, but we can not measure its length precisely. We can tell where it is approximately only. This is because our mind works with approximations and makes interpretations accordingly. Similarly, during your daily life, there is massive amount of information, but your mind does not preserve them all. For instance, moving in a street in one day, hearing a lot of noise and passing by different buildings. In the end of the day, our mind will not remember everything you have heard and will not remember all the buildings we have passed by. It will only remember the main things like the building we were going to, the people we have talked to. To save more information, they need to be repeated several times until they become recognizable and be stored in our memory.

Our mind processes the sensory information the same way as explained in previous section 3.3. It does not save every single value each time. Instead, it processes the incoming values and save the important information from them. For instance, the sensory information coming from a muscle spindle will be used to generate a sense about the length of that muscle (i.e. a proprioception). Each time a proprioception value is obtained, it will be saved in memory. In the same way, the tactile pressure information collected by touching different objects from the environment forms perceptions that are saved in memory. It is to be noted that proprioception is not recognized once being obtained, instead, it needs to be repeated several times to be saved in the memory as explained in previous section 3.2.

To summarize, getting proprioceptions and perceptions are cognitive processes that work on the input sensory data collected over time and saved in memory. It is to be noted that our mind is not accurate, the cognition is a high-level processing but is not very accurate. Hence, our mind is not supposed to identify the exact values of the sensory data, instead, it determines an approximation for them.

Since the proprioceptions are representations of the muscle lengths that are recognized cognitively by the mind and the perceptions are interpretation of different tactile sensations and separating them according to similarity, unsupervised learning seems to fit well for these representations. For proprioceptions, the sensory lengths are clustered to determine if they represent the same cognitive length or a different one. Similarly, for perceptions, the sensations are clustered to identify either we are touching the same object or a different one. Accordingly, a clustering algorithm should be used to generate proprioceptions and perceptions.  $K$ -means clustering seems to be a good candidate because it makes clustering using similarity and, at the same time, gives approximation for each cluster represented by the mean. Both proprioceptions and perceptions can be presented by these means. But, the shortcoming of the  $k$ -means clustering is the predetermination of the number of clusters ( $k$ ) which can not be biologically interpreted. Accordingly, we need to find a natural way for choosing the number of clusters.

The learning process evolves with time as inputs are presented. For example, adults learn new skills by practicing it through time. The learning process builds the human mind. The human mind is not the brain; the mind refers to the mental and cognitive processes while the brain represents a set of physical neurons. The mind is a higher-level structure that is built gradually using cognitive processes as the brain gets more inputs. In our problem, we model the production of proprioceptions and perceptions from the input sensory data.

As in the case of learning a new skill, in which a human learns gradually as inputs are presented, with repetition, we believe that a fetus human develops its cognition through the repetition of certain values with time.

Initially, the fetus will not be able to distinguish precise sensory values, due to its limited abilities that improve with time. We are interested in how this cognition ability increases with time. Our idea is based on that the most repeated value in a given cluster will dominate. It is not allowed that two values dominate together. So, in case another value in the cluster is repeated many times as the dominant value, it is expelled from the cluster and forms a new cluster on its own and take the similar values as its cluster members.

Applying this to our problem, at first, the fetus will group all the sensory values it receives in one cluster. When a sensory value is repeated a lot with time, its mind starts to distinguish it from the rest of values. This will create a new cluster for this value as the center of the cluster, the cluster members will be its similar values.

Through time, it will be able to distinguish all the values incrementally by repeating its actions and receiving the same sensory values. Since, the brain is not very precise and noisy, the center is updated to be the average value of the cluster members. Following this idea, we propose a new clustering technique referred to as, *frequency-based-means clustering*, explained in Figure 5.1. We use the frequency-based-means clustering to obtain proprioceptions and perceptions over time.

In this algorithm, the input is either a sensory length or a sensory pressure. If it is the first

time to receive an input, this input is considered as the center of the first cluster, the number of samples in this cluster becomes one and one is the maximum count in this cluster. When another input is received, it is compared to all the previous inputs, in case it is the old sample, the sample count is incremented. After that, the sample count is compared to the maxcount of the cluster and the repetition threshold. If it is greater than the maxcount or the repetition threshold, the sample will be expelled from the cluster and form a cluster on its own and take the similar samples as its cluster members; then the cluster center is calculated as the average of all cluster members. Otherwise, the cluster center will be updated to be the new average, the count and maximum count will be incremented. Otherwise, the sample is new, it is assigned to the cluster with the nearest cluster center with count equals to one. After that, the cluster center is updated.

The cluster centers are referred to as either the proprioceptions or perceptions (according to the input) in our case. This process will be applied to all the sensory information such as length and skin pressure.

This way the human mind perceptions evolve with time; which represents cognition improvement.

The sequence of observations  $O$  is formed of the perceptions  $o_i \in X$ .

By recording all this information, the fetus brain builds its training dataset. After that, it starts to learn the relation between  $O$  and  $Q$  and gets the mapping parameters as in problem 3 mentioned in previous section 2.3.

The fetus brain then learns different tasks where each task represents moving to a new perception value from the current perception value.

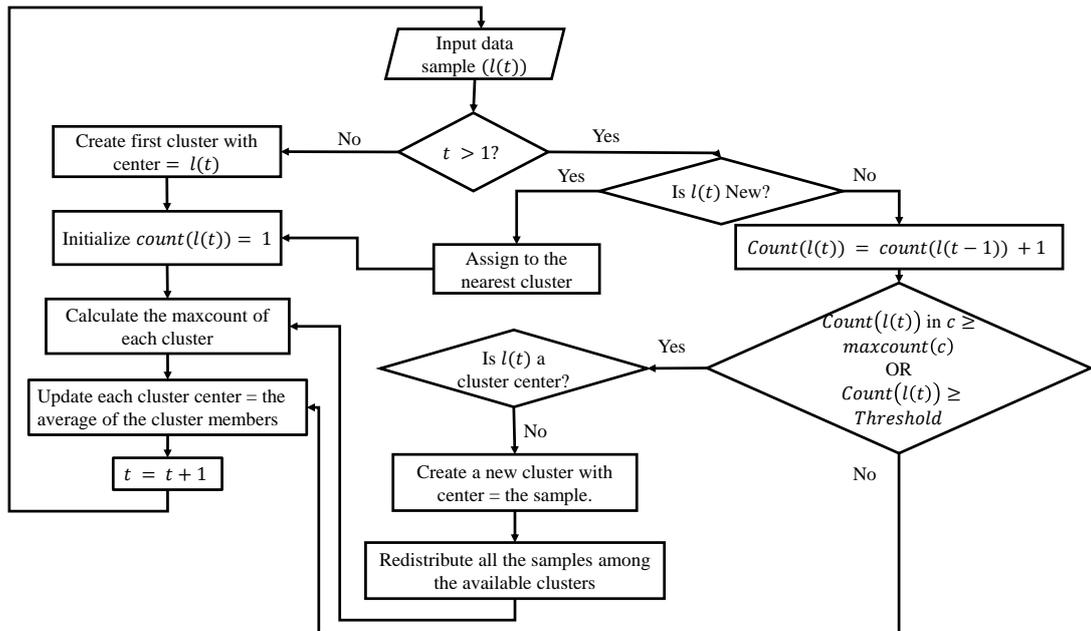


Figure 5.1 – Frequency-based-means Clustering

We present below an example that traces the frequency-based-means clustering algorithm using given sensory data.

### Tracing Example.

Assume that we have sensory data sequence in which one sensory value is input at each time  $t$  as shown in table 5.1. We provide the tracing of grouping them using the frequency-based-means clustering algorithm.

time $t$	sensory value
1	1
2	2
3	1
4	10
5	10
6	11
7	10

**Table 5.1** – *Input sensory values at different times*

1. At time  $t = 1$ :  
cluster 1 = 1  
cluster center=1  
count(1) = 1
2. At time  $t = 2$ :  
cluster 1 = 1, 2  
cluster center = 1.5  
counts = 1, 1, maxcount = 1
3. At time  $t = 3$ :  
cluster 1 = 1, 2  
cluster center = 1.3  
counts = 2, 1, maxcount = 2
4. At time  $t = 4$ :  
cluster 1 = 1, 2, 10  
cluster center = 3.5  
counts = 2, 1, 1, maxcount = 2

5. At time  $t = 5$ :

cluster 1 = 1, 2, 10

cluster center = 4.8

counts = 2, 1, 2, maxcount = 2

6. At time 6:

cluster 1 = 1, 2, 10, 11

counts = 2, 1, 2, 1, maxcount = 2

cluster center = 5.8

7. At time 7:

cluster 1 = 1, 2, 10, 11

counts = 2, 1, 3, 1

**count(10) > maxcount at time  $t = 6$  , Then form a new cluster with cluster center = 10 and redistribute the previous samples.**

cluster 1 = 1, 2

counts 1 = 2, 1

cluster center 1 = 1.3

cluster 2 = 10, 11

counts 2 = 3, 1

cluster center 2 = 10.25

The frequency-based-means clustering algorithm can work on sequential online data. Its time of convergence is independent from the data values but it is dependent on the frequency of the data values and the repetition threshold that is chosen. Table 5.2 summarizes the main differences between the  $K$ -means clustering and the Frequency-based-means clustering.

Point of Comparison	<i>K</i> -Means	Frequency-based Means
Requires Pre-determined Number of Clusters	True	False
Results may be altered from one run to another	True	False
Number of Required Parameters	1	1
Suitable for Online Input Data	False	True
Clustering Criteria	Distance-based	Distance-based
Type of data	Quantitative	Repetitive Quantitative data

**Table 5.2** – *Comparison between K-means clustering and the Frequency-based-means clustering*

It is shown that the proposed frequency-based-means clustering algorithm is suitable for online quantitative data that have repetitions. It does not require a predetermined number of clusters and evolves with time according to the chosen repetition threshold. It is used for creating perceptions and proprioceptions in our problem because they are acquired by repetitions as was explained in section 3.3.

# CHAPTER 6

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## CREATING THE MECHANORECEPTORS-ASSOCIATION-MAP

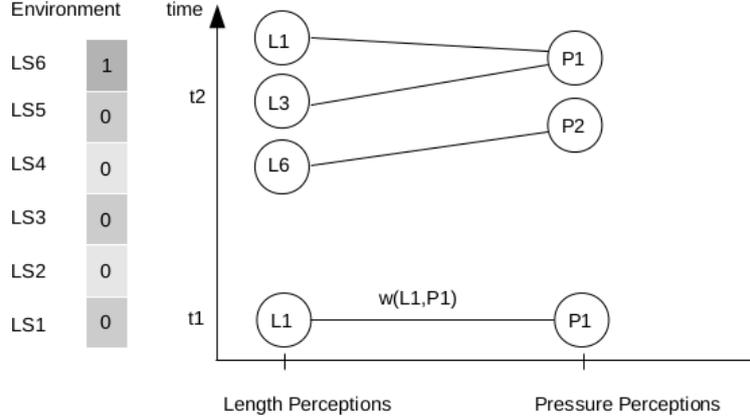
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As explained in previous chapter 1.4 in section 2.1, the cerebral cortex contains somatosensory cortex which collects all the sensory data from different sensory organs and the association cortex which blends different data to obtain higher-level interpretations. Based on this biological knowledge, we create a map referred to as a mechanoreceptors-association-map. According to the collected sensory data, higher level perceptions are created. The perceptions obtained from different sensory neurons are associated in the mechanoreceptors-association-map. The association links are dynamically updated with time as more cognitive abilities are acquired or as there is a change in the environment. Once an ensemble of perceptions are produced together, they are linked together using links with small weights. These weights are increased everytime this ensemble is repeated in order to strengthen the association between them. This way, the association link weights between different perceptions of an ensemble are proportional to the strength of the ensemble. This means that the perceptions that do not occur together should have zero weights for their association links.

In case of a dynamically changing environment, some ensembles may exist for some times then they no longer do. In that case, the association link weights of that ensemble should decrease gradually until they become zero.

Figure 6.1 demonstrates the association between length proprioceptions and pressure perceptions in the mechanoreceptors-association-map. The length proprioceptions are created from sensory length values and the pressure perceptions are formed from sensory pressures. Their integration reflects whether there is an object in the environment or not. Both the pro-

prioceptions and perceptions that occur together have association link created with weight greater than or equals to 1. If any proprioception does not exist simultaneously with a perception, their link weights are zeros.



**Figure 6.1** – Length-pressure perceptions Relation. (a) The muscle has sensory length values from LS1 to LS6. The environment represents the objects by tactile pressures at different proprioceptive lengths, zero means there is no object while one means there is an object at that proprioceptive length. (b) At time  $t_1$ , all the length sensory values received are perceived as one proprioception, the same is done for the pressure sensory values. This is because none of the sensory values is repeated as much as it is needed to be significantly noticed. At time  $t_2$ , three sensory length values (LS1, LS3, LS6) are repeated significantly to be proprioceptions. They form the main proprioceptions as clusters with the similar sensory received until this time without being significantly repeated. On the other hand, The pressure  $P_2 = 1$  is also repeated much to be a perception. This is when the fetus starts to feel this object and save this sensation in its memory. Notice the association link between L6 and P2 because they occur together. Each length proprioception is connected to all the pressure connections with weights equal to their occurrence together. The figure does not show the zero weights for simplicity.

These associations are updated through time when new perceptions are added or even deleted from one or more sensory neurons. For any length proprioception ( $L_i$ ) and pressure proprioception ( $P_j$ ), there is a associations ( $L_i, P_j$ ), with weight =  $w_{L_i P_j}$ .

When a command sequence ( $Q_t$ ) results in perceptions  $L_i, P_j$ , then the weight is updated according to algorithm 3. When a pair of a length proprioception and pressure proprioception occurs at the same time, their link weight increase by one unless it reached a maximum threshold to prevent domination. Similarly, the links between pairs of this length and other pressures will decrease. This is to model the case of dynamic environment where an object exists sometimes then disappears due to either its movement or the body movement. Accordingly, the object is not in the same previous place and does not correspond to this length anymore. Despite this change, the mind does not forget that this length corresponds to that pressure (of the object) instantly. It needs some time to forget this link. That is why the link weight decreases gradually by one each time this link is not correct until it reaches zero when it is assumed it does not exist anymore. The resulting weights are saved

in memory for future use in making goal directed movements.

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**Algorithm 3** The relation between length perceptions and pressure perceptions

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**Variables:**

$T$ : The final time.

$L$ : The set of length values.

$P$ : The set of pressure values.

$L_i \in L$ : Length value.

$P_j \in P$ : Pressure value.

$w_{L_i P_j}$ : The connection weight between length value  $L_i$  and pressure value  $P_j$ .

**Begin**

**for**  $t = 1: T$  **do**

**for** each  $L_i \in L$  **do**

**for** each  $P_j \in P$  **do**

**if**  $(L_t == L_i) \wedge (P_t == P_j)$  **then**

$w_{L_i P_j}(t) = w_{L_i P_j}(t - 1) + 1$

$w_{L_i P_k}(t) = \max(0, w_{L_i P_k}(t - 1) - 1)$

          such that  $k \neq j$ .

**end if**

**end for**

**end for**

**end for**

**End**

---

Hence, this architecture is dynamic as the number of perceptions changes with time until it reaches stability, when the change in weights is nearly constant and no new perceptions are created.



# CHAPTER 7

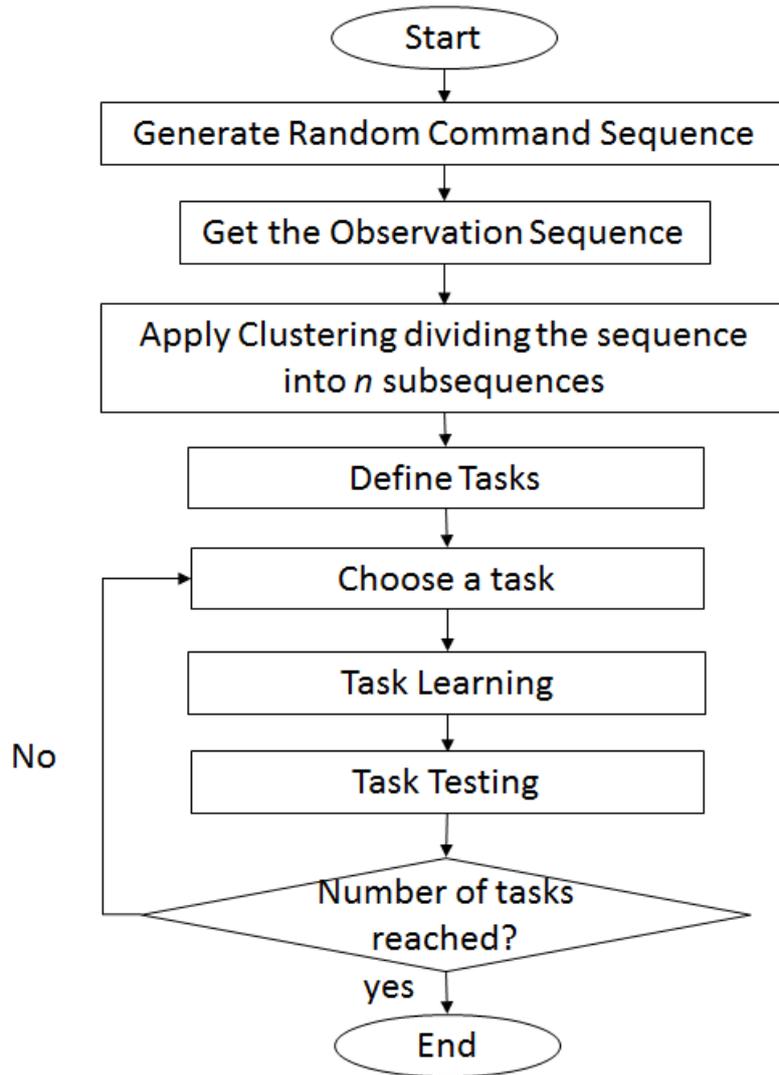
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## MOVEMENT LEARNING AND THE INVERSE INTERNAL MODEL

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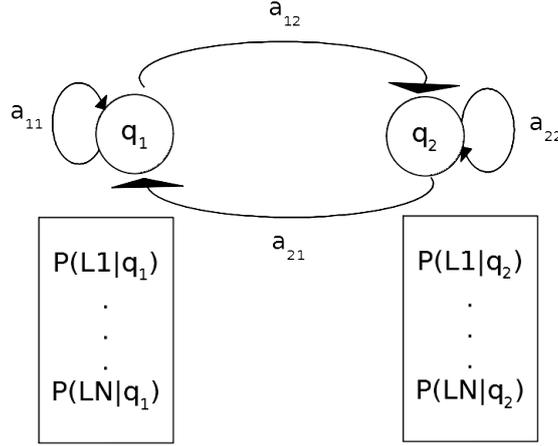
As illustrated in previous chapter 1.4, muscle fibers are innervated by motor neurons. Signal must be transmitted from the CNS to motor neurons in order to contract their muscle fibers. When muscle contracts, sensory feedbacks are sent from the muscle sensory neurons to the CNS. The coordination of this process forms the sensorimotor loop explained in section 3.1. In order to reach a position, a specific signal must be sent from the CNS to the motor neurons responsible for contracting the muscle. The production of this signal is a form of learning.

This chapter illustrates the process of learning to move a muscle from one position to another using HMM explained in previous section 2.4.2. This process is based on the previous cognitive processes of proprioception generation and building the mechanoreceptors-association-map which defines positions. Once the positions are determined, tasks can be defined such that a task is the transition from one proprioception to another. Accordingly, the number of defined tasks is proportional to the number of generated proprioceptions. It is important to note that the task is related to proprioceptions but is not related to perceptions. This is because it is focused on learning how to change the muscle lengths without any knowledge of pressures. Since we are interested in vertical movement upwards only, the tasks will be defined for pairs of proprioceptions with increasing order. For instance, a task is defined from  $L1$  to  $L2$  if and only if  $L1 < L2$ . Figure 7.1 shows how the tasks are obtained and used.



**Figure 7.1** – *Task Life Cycle*

Once the tasks are obtained, each task will be learned using HMM as shown in Figure 7.2. The command sequence represents the hidden state sequence  $Q$  such that any command  $q_t$  at time  $t$  represents whether there is a spike (1) or not (0).



**Figure 7.2** – *The structure of a HMM of one task.*

Accordingly, a HMM model  $\lambda = (Q, A, O, B, \pi)$ , is built for each task with the following characteristics:

- The set of hidden states  $Q = \{q_1, q_2\}$  is a set of 2 states corresponding to 1 or 0 commands.
- $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$  is a transition probability matrix  $A$ , each  $a_{ij}$  representing the probability of moving from state  $i$  to state  $j$ , s.t.  $\sum_{j=1}^n a_{ij} = 1 \forall i$ .
- $O = o_1 o_2 \dots o_T$  is a sequence of  $T$  observations, each one is drawn from the set of the defined proprioceptions  $X = \{x_1, x_2, \dots, x_N\}$ .
- $B = b_i(o_t)$  is the emission probability matrix of size  $2 \times N$  such that 2 is the number of the states and  $N$  is the number of the defined proprioceptions. Each cell represents the probability of an observation  $o_t$  being generated from a state  $i$ .
- $\pi$  is the initial probabilities of all the states.

To learn a task, we need to estimate its transition probability matrix ( $A$ ) and its emission probability matrix ( $B$ ). This is done using Baum-Walsh Expectation Maximization algorithm. The algorithm starts with a randomly chosen  $A$  and  $B$ , then it iterates through the E-step and M-step illustrated in chapter 1.4. Finally, it will converge to good estimates for  $A$  and  $B$ .

The estimated  $A$  and  $B$  act as the parameter of this task. They will be saved in the memory so that whenever a task is required to be done, its parameters will be retrieved from memory.

These parameters are used by the inverse internal model that is responsible for estimating the motor command sequence needed to make a task. In our model, this is implemented using the Viterbi algorithm which chooses the most probable sequence given the task parameters.



# CHAPTER 8

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## MAKING A GOAL-DIRECTED MOVEMENT

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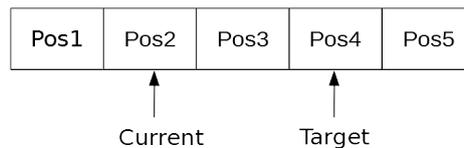
Voluntary movements can be done to change a limb position from one position to another by sending a motor command sequence to the limb muscles. The voluntary movements are said to be goal-directed when they are required to reach a position with some perceptions. For instance, reaching a certain object in the environment can be considered as a goal. In case of a fetus, there are some simple goals such as sucking its thumb as already mentioned in chapter 1.4. To achieve this, the fetus thumb has to reach the position of the mouth and feel the required sensation of its tongue. This simple goal requires recognition of the current proprioception and the current pressure perception (to say if the thumb is in the mouth or not), a cognition of different positions, the ability to identify a task of moving from the current to the target positions and to estimate the required motor command sequence then issuing the required motor command sequences using the sensorimotor system to the muscles. Other examples can be grasping the umbilical cord or touching the womb. Despite that the environment of the fetus is small and its goals are simple, they help in building the basic building blocks for making complex directed movements. For the infants and adults, the goals are more complex and may need making a plan for a series of movements. For example, reaching an object which is far away such as a food in the refrigerator in another room. This requires planning of many movements starting from knowing the way to the refrigerator from the current position, reaching there, then opening the door and taking the target food. Looking at such a complex goal, it can be divided into a series of motor commands given to many body muscles to move from one position to another until the target is achieved.

In this chapter, we demonstrate how goal-directed movements can be generated. In addition

to the sensorimotor system, each of the cognitive processes defined in the previous chapters play an important role in making the goal-directed movement.

### The role of the cognitive map

The cognitive map consists of positions identified by proprioceptions and perceptions, the goal is defined by choosing to reach one target position from the cognitive map according to the target perceptions. The cognitive map develops through time as more positions are produced. Figure 8.1 shows an example of a cognitive map that has five positions and depicts the current and the target positions.

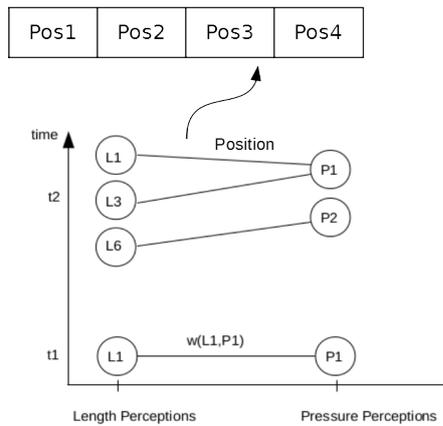


**Figure 8.1** – *The cognitive map. An example of a cognitive map with five positions showing the current position of the muscle and the target position required to be reached (the goal).*

### The role of the mechanoreceptors-association-map

Different identified proprioceptions and perceptions that occur together are associated together. This association defines a position in the cognitive map. The more proprioceptions and perceptions are obtained, the more positions are defined, the larger the cognitive map, the more goals can be chosen. Figure 8.2 shows how positions are represented by the association links between proprioceptions and perceptions. There can be proprioceptions and perceptions values that are not connected together because they did not exist together at the same time such as L1 and P1. In this case, there is no position defined at this length L1 with that perception P1.

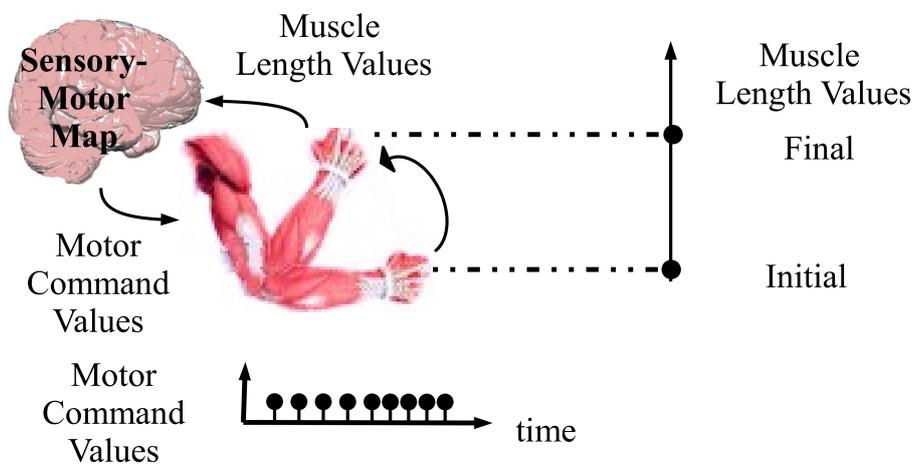
### Cognitive Map



**Figure 8.2** – The mechanoreceptors-association-map showing defined positions in the cognitive map. In time  $t = 1$ , only one position is defined between L1 and P1. At time  $t = 2$ , positions are formed for (L1,P1), (L3,P1) and (L6,P2) because they occurred together many times. On the other hand, no positions are defined between L1 and P2 or L3 and P2 or L6 and P1 because they didn't exist simultaneously.

### The role of the sensorimotor system

A muscle can contract and change its length based on command sequences sent to its motor neurons as shown in Figure 8.3. Accordingly, motor commands are essential for muscle movements which are, in turn, necessary to obtain different sensory data. We make the hypothesis that the fetus starts making a large number of random movements by issuing random motor commands in the Exploration phase in which it collected a vast amount of sensory data. These sensory data are the basic building blocks for making the cognitive map.



**Figure 8.3** – Moving a muscle from one position to another. The motor command sequences controls a muscle to change its initial length to reach the final target length.

## The role of the movement learning

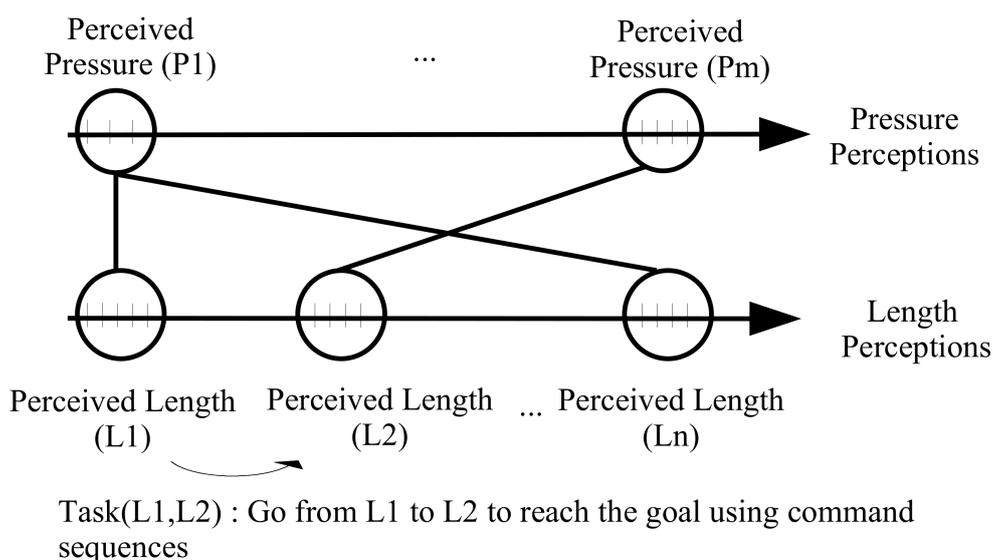
It learns the relation between positions and how to move from one position to another by identifying a task for each transition. It improves over time as more positions are generated and as their frequencies increase.

## The role of the inverse internal model

It translates the required movement from the current position to the target position into a sequence of motor commands and send it to the muscle. Figure 8.4 summarizes the definition of a goal and how it can be reached through proprioceptions and perceptions. These pairs of proprioceptions act as positions in the cognitive map. After a task is determined, the inverse model generates the corresponding motor command sequence and send it to the target muscle.

Goals:

- 1- Touch this object (object pressure).
- 2- Go from position 1 (assumed to be equal to L1) to position 2 (assumed to be equal to L2).



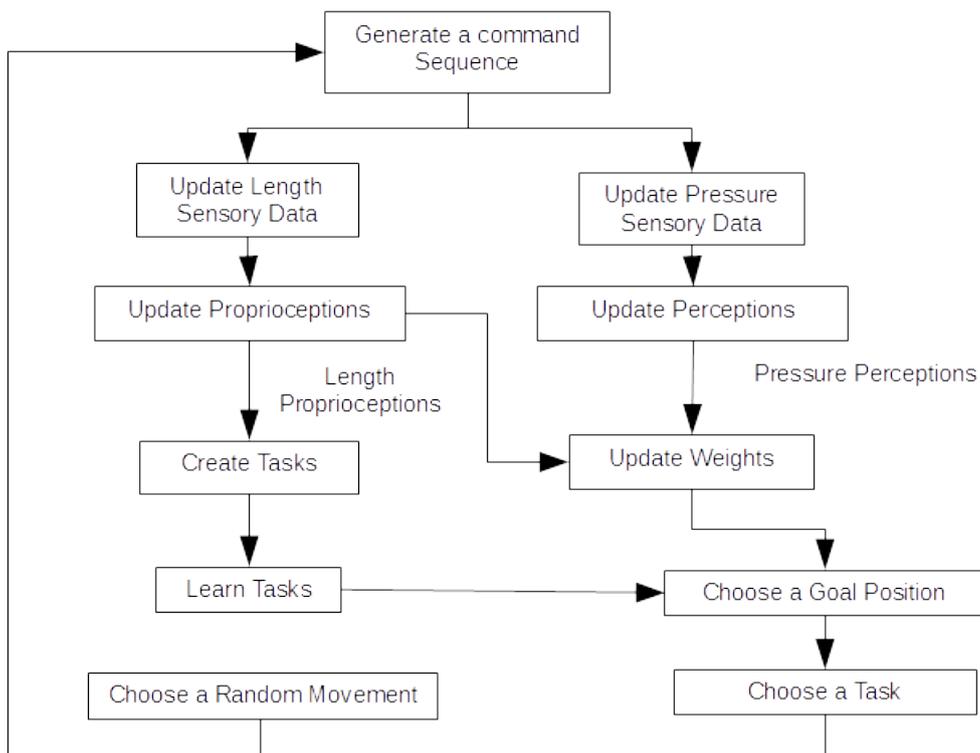
**Figure 8.4** – A summary of the goal-directed movement. Given a goal perceived pressure, the fetus should be able to get the length that is associated with this pressure according to its perception. This is depicted by the lines between the length and pressure perceptions. Then, a task of moving from the current length to the target length is defined. After that, a motor command sequence is generated to accomplish the task. The creation of perceptions is a cognitive process applied to the sensory data.

The development of this kind of movement requires the integration of all these cognitive processes. The developments starts from the early age of a fetus and continues improvement across the successive stages. The more the human capabilities increase, the more cognitive abilities it has, the more goals it becomes able to choose and learns to reach them.

We make the hypothesis that the fetus starts with interacting with its environment doing random movements produced by generating random command sequences. These command

sequences will result in receiving sensory data like length and pressure. After these sensory data are collected, primary proprioceptions and perceptions are generated. This is in addition to their associations. Then, the primary positions are sent to the immature cognitive map. Tasks are defined from the length proprioceptions and learned. The cognitive map size is proportional to the number of positions, which is proportional to the determined number of proprioceptions and perceptions. Accordingly, the more motor commands generated, the more sensory data obtained, the more proprioceptions and perceptions are produced, the more positions are defined from the association links, the larger the cognitive map. After some time, the fetus capabilities are enhanced and it is able to choose to either make a random movement or an intended movement based on a goal of reaching a target position or object from its memory.

Figure 8.5 demonstrates the whole process. At first random command sequence is generated, the sensory data are updated. Proprioceptions are produced from the length sensory data and perceptions are created from the pressure. Association links between the resulted proprioceptions and perceptions are developed with small weights. At the same time, tasks are formed and learned between pairs of proprioceptions. After some time, with the repetition of movements, the proprioceptions and perceptions increase, their links are strengthened. Hence, their corresponding positions are well-recognized in the cognitive map. Then, the fetus becomes able to choose a goal-directed movement choosing a target position to go to from the cognitive map. Based on its current position and the target position, a task to be performed is determined and the corresponding command sequence is issued.



**Figure 8.5** – *The Model of Learning How to make a goal-directed Movement. At any stage with a certain energy level, the fetus may try issuing either a random command movements or a goal-directed movements. This will generate a command sequence that will produce both proprioceptive length data and pressure data. Perceptions will be updated according to the newly added sensory data. Weights between length and pressure perceptions will be updated while tasks between length proprioceptions will be updated or even created and learned. The fetus may choose to either target a pressure proprioception goal and issue the required task or make any random action.*

# CHAPTER 9

## MODEL DATA GENERATION

Due to the unavailability of real data, we test our model using simulated data. The sensorimotor data are calculated by using equations from the literature [30]. We have used statistical and mathematical methods to obtain this data.

First, the command sequence is generated using Bernoulli distribution. Then, the proprioceptive length data are calculated using mathematical convolution. After that, the proprioceptions are produced and updated as more movements are done. A task between each pair of proprioceptions is defined as explained above. Figure 9.1 describes the whole process.

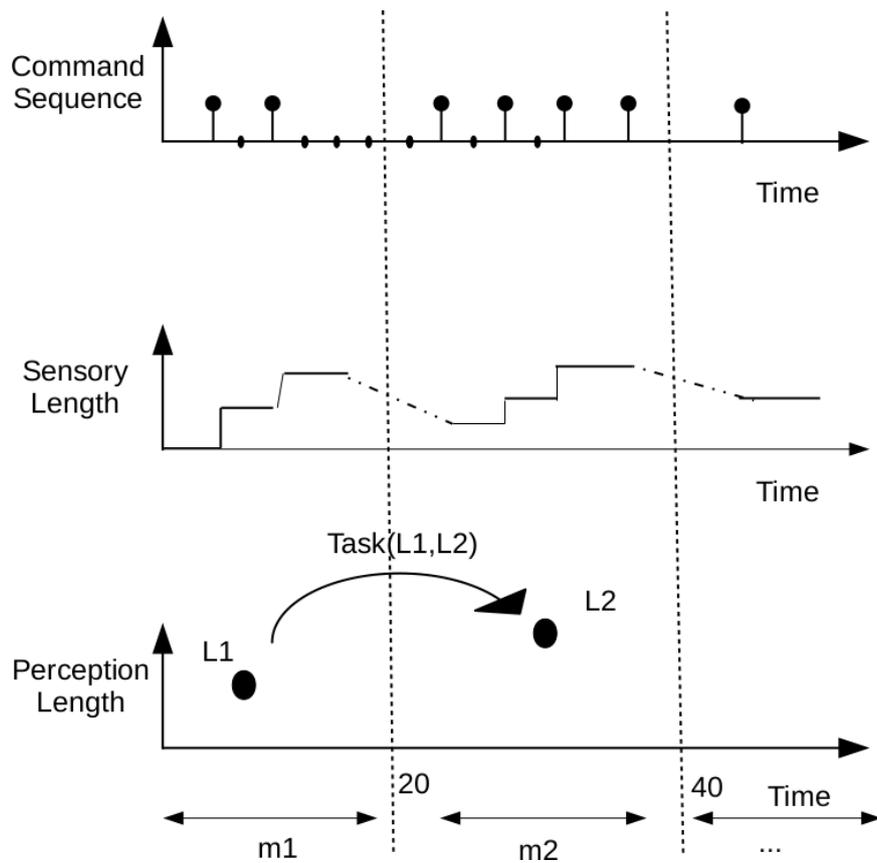
### The command sequence

Motor neurons fire when they receive a command so that the corresponding muscle fibers contract. Hence, there will be a spike coming out from the firing neuron when there is a command. Accordingly, the command sequence represents the hidden state sequence  $Q$  such that any command  $q_t$  at time  $t$  represents whether there is a spike (1) or not (0). In other words, a command state sequence is represented by a binary sequence such that 1 implies contraction and 0 implies no contraction.

Initially, the time between consecutive command signals is large and it decreases gradually as the fetus gets older as it gains more energy and becomes able to get stronger contraction.

The command state sequence  $Q$  is generated from a Bernoulli distribution given by:

$$q_t = p^t (1 - p)^{1-t} \tag{9.1}$$



**Figure 9.1** – *The Generated Data. First, the command sequence is generated. Second, the proprioceptive length data are calculated. Then, the proprioceptions are produced.  $m_1$  and  $m_2$  refer to the first and the second movements, respectively.*

such that  $t = 1$  refers to issuing a command with probability  $p$  and  $t = 0$  implies the absence of command with probability  $(1 - p)$ .

### The sensory data

It dictates the sensory values obtained after using a given command sequence. As explained above, this includes both the proprioception which represents the length and the exteroception which is pressure in our problem.

When a command is given to a muscle, a force is generated causing increase in its fibers tension. Muscles differ in terms of the number of fibers and size such that increasing them means the ability to get more force. Each muscle is represented by a Gaussian function with large variance for large muscles and small variance for small muscles.

$$Muscle = exp\left(-\frac{(x - mean)^2}{\sigma^2}\right) \quad (9.2)$$

where  $x$  represents the fiber sizes.

The contraction is given by a convolution function between the muscle and the command sequence:

$$contraction = Muscle \Theta Q \quad (9.3)$$

where  $\Theta$  denotes the convolution operator and  $Q$  is that state sequence.

The length sensory values are generated based on the fact that it increases by increasing the contraction and it is constant when the contraction is either constant or decreasing.

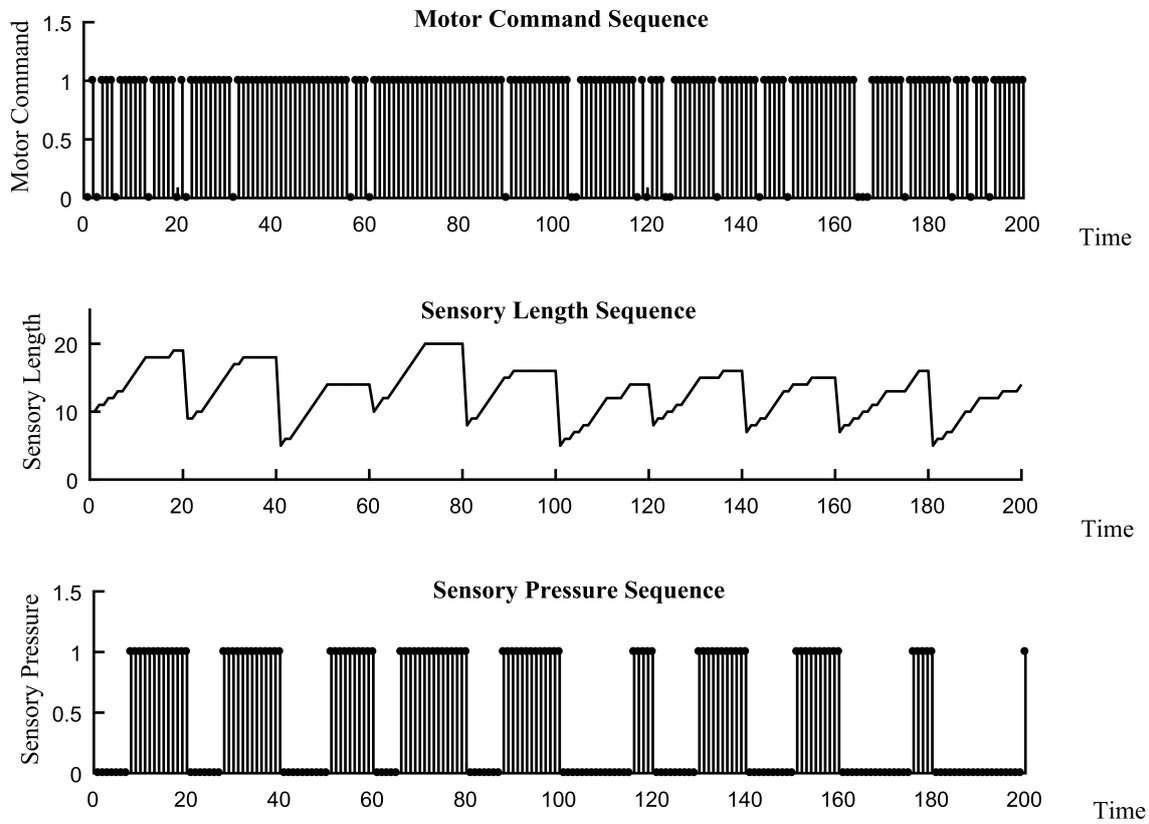
For an action with duration  $T$ , the length is given by:

$$length(t) = \begin{cases} length_{init}(t) & t \bmod T = 0 \\ length(t-1) + \Delta contraction & \Delta contraction > 0 \\ length(t-1) & \Delta contraction \leq 0 \end{cases} \quad (9.4)$$

The pressure appears when the fetus senses an obstacle (e.g. its face) that brings a different sensation. Initially, when the fetus has low energy, its muscle won't be able to reach any obstacle and hence, the pressure is zero. For simplicity, the pressure is modeled as either there is an object or not. The pressure is modeled as a unit step function .

$$pressure(t) = \begin{cases} 1 & length(t) \geq Threshold_{length} \\ 0 & length(t) < Threshold_{length} \end{cases} \quad (9.5)$$

Figure 9.2 shows an example of the data generated for the motor command sequence, the sensory length and the sensory pressure.



**Figure 9.2** – An example of the generated data. The x-axis represents the time units and the y-axis represents the motor commands, the sensory length values and the sensory pressure values from top to bottom, respectively. The x-axis is divided into 20 time units which is the assumed duration of one upward movement.

# CHAPTER 10

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## EXPERIMENTAL SETUP AND SIMULATION RESULTS

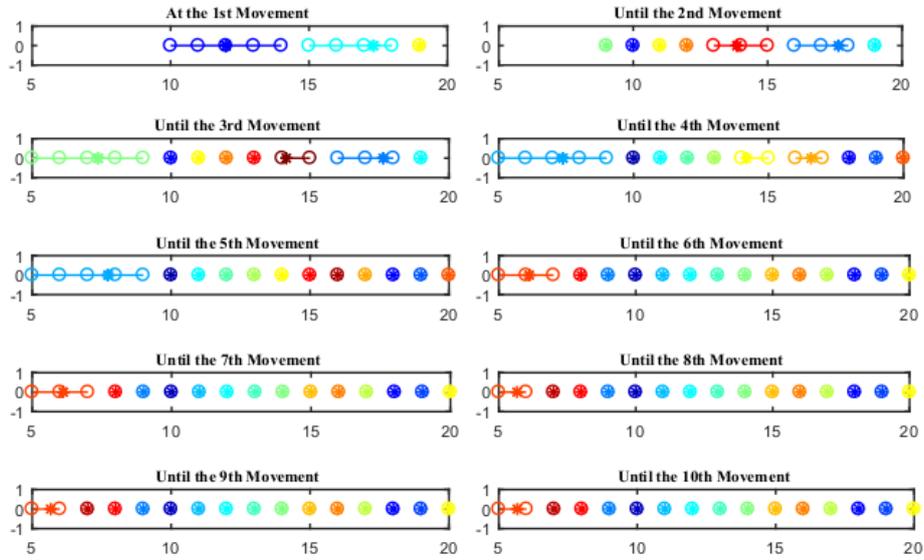
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We have modeled the movement learning evolution through a stage in which the fetus will be able to make movements by issuing commands with probability 0.9 using Bernoulli equation explained above. This probability was chosen empirically to reflect more movements are done upwards to get a wide range of sensory length values useful in our test. Choosing smaller probabilities will result in smaller range of length values obtained using convolution. In addition, our focus is on making voluntary movements so it is better to use high probability of issuing the commands. We assumed that the fetus will repeat moving its muscle upwards 10 times during this stage. So, the simulation is presented by 10 movements each has a duration of 20 time units. The number of movements and the duration of each movement are also chosen empirically to build our dataset with repetitive sensory length values to be used in getting the proprioceptions. Each movement will start at a random length starting with 5 which is the assumed minimum muscle length. It is to be noted that we are only interested in moving upwards using a voluntary movement. Accordingly, any change in length could have been done within these movements due to involuntary movements, reflexes or even voluntary movements in the opposite direction. Hence, we chose to start at random length values instead of a constant value. The Environment is modeled as either having an object or not at different lengths. If there is an object, the pressure is 1, otherwise, the pressure is zero. We have assumed that the object is static and is heavy (e.g. its face), so preprocessing is done to crop the lengths greater than the length at which the object is located, which is chosen as 14 in our experiment. It is a value chosen from the generated length values (from 5 to 20) less than the maximum value to describe the case when an object is placed at a

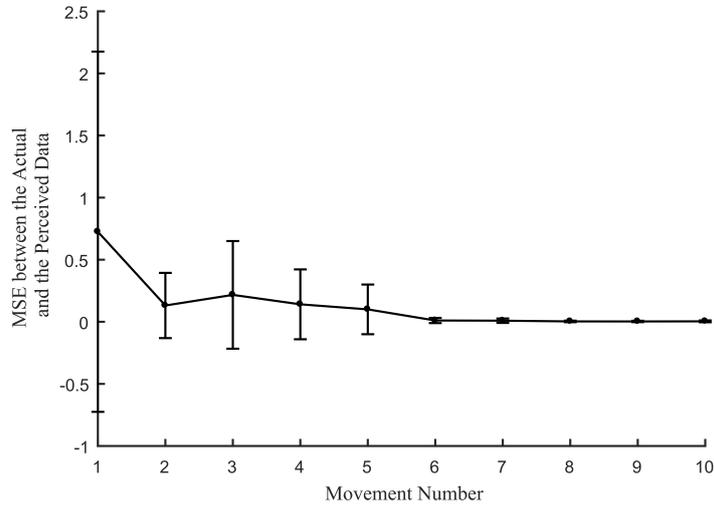
length value less than the maximum limit. The model runs incrementally as explained in the previous sections.

## 10.1 Experimental Results for getting the proprioceptions and perceptions

For getting the proprioceptions and the perceptions, we have used  $k$ -means clustering algorithm with  $k$  chosen using the Calinski Harabasz index criterion [92]. The interval given to the Calinski Harabasz index criterion was increasing with each movement by 1. Results have shown that increasing the number of clusters improves the performance which means that the number of clusters can reflect the enhancement of cognition level for proprioceptions and perceptions. Accordingly, we need to find a way of choosing  $k$  that is natural and can be interpreted biologically. This is provided by using the frequency-based means clustering which presents a way of evolution of cognition through increasing the number of clusters based on repeated feedbacks. Figure 10.1 shows how the input sensory data are clustered using the Frequency-based-means clustering and shows how the mean squared error decreases as movements increase; thus reflecting the fact that proprioceptions approach the sensory data. Figure 10.2 demonstrates how the threshold affects the performance of the clustering. When the threshold is low, the clustering process is fast and the mean squared error decreases fast. On the other hand, high threshold results in slow clustering and large clusters causes larger error. Figure 10.3 presents a comparison between the performance of the Frequency-based-means clustering and the  $k$ -means clustering using a constant value for  $k$  or using Calinski Harabasz index criterion. It shows that the Frequency-based-means clustering performs as good as the  $k$ -means using the Calinski Harabasz index whereas the constant  $k$  value has the worst performance. This result strengthens the idea that proprioceptions and perceptions must be increasing with time, otherwise, the human cognition capabilities deteriorate.

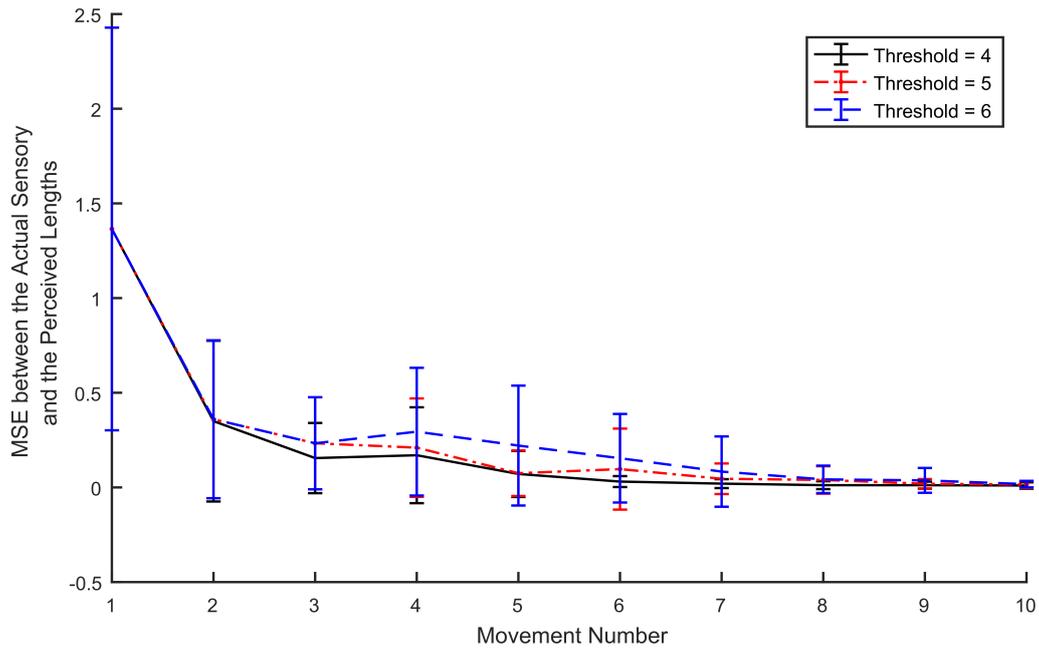


(a)

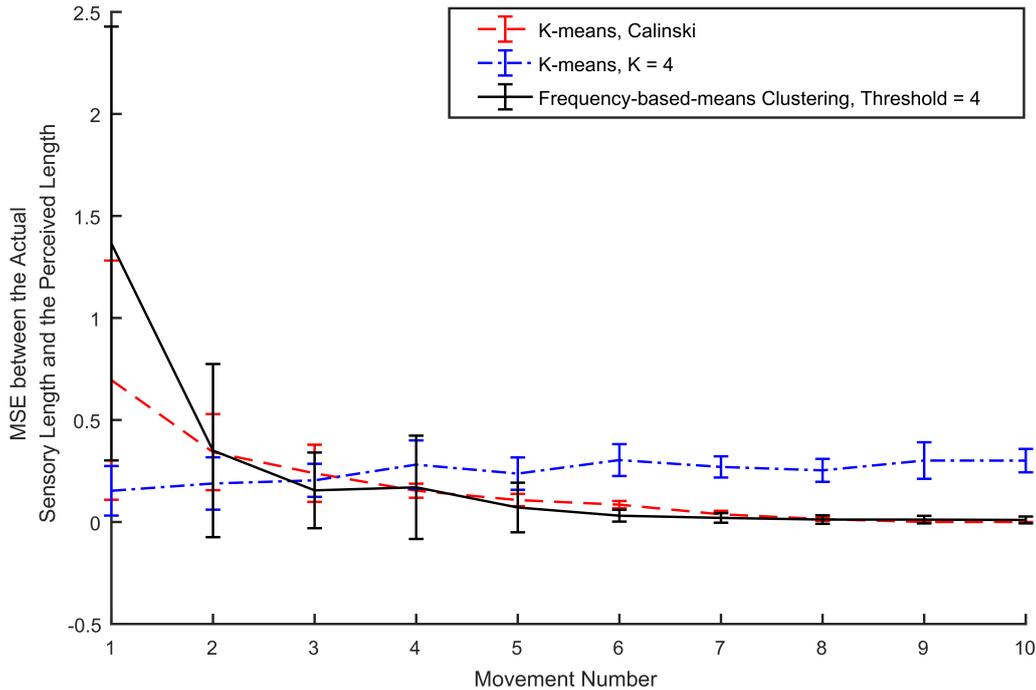


(b)

**Figure 10.1** – An example of perceptions evolution across movements in one simulation. (a) The  $x$ -axis shows the sensory length values found per movement. Each color represents a cluster with cluster center marked by “ $x$ ”. Initially, all the obtained length values are assigned to one cluster. With the repetition of length values, they will be recognized as perceptions, hence, the number of perceptions increases with time. Here, the presented maximum length is the assumed maximum muscle length. (b) depicts the mean squared error between the actual length values and the perceived length values as well as the standard deviation across all movements. From (a) and (b), It is noticed that some movements that have the same perceptions incorporate an increase in the error as seen in the 2nd and the 3rd movements. This is due to the inclusion of either new length values or old values that are larger than the recognized perceptions which increases the error as well as the variance, those will be discriminated with time.



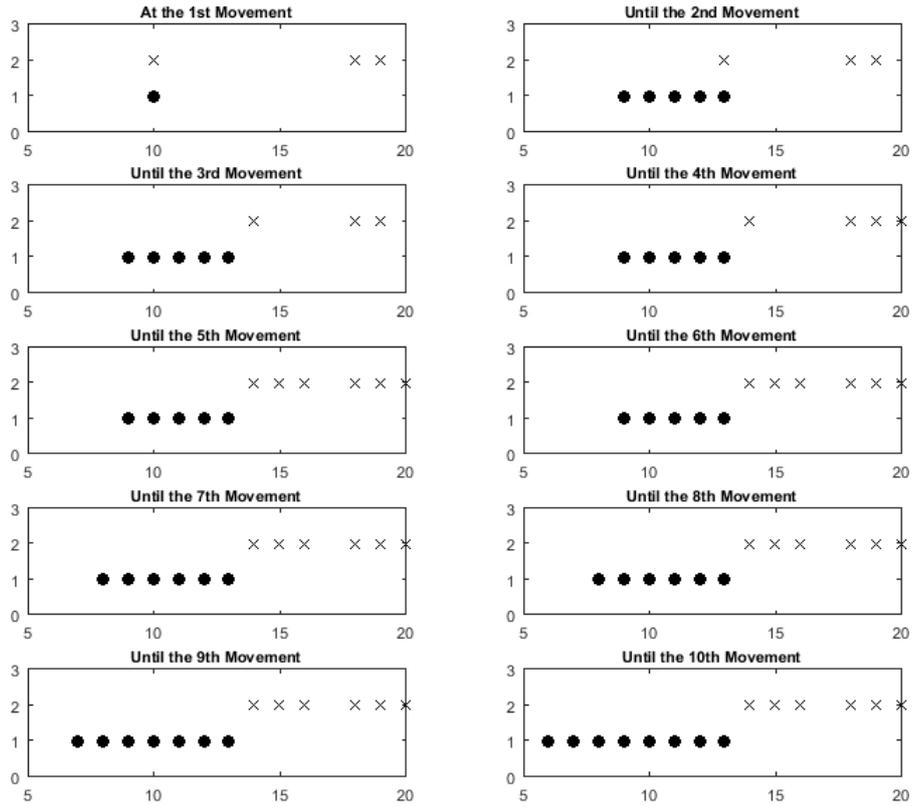
**Figure 10.2** – *Threshold effect in Frequency-based-means Clustering.* Mean Squared Error between the actual sensory length values and the perceived ones are shown when the input data are clustered using Frequency-based-means clustering using different threshold values. When the threshold decreases, more clusters are produced. Hence, the average approaches the cluster members resulting in smaller MSE.



**Figure 10.3** – Comparison between the performance of the Frequency-based-means clustering and K-means clustering. The results of generating perceptions for 10 movements obtained from 10 simulations and 10 LOOCV are depicted for the frequency-based-means with a threshold values equal to 4, k-means with  $k = 4$ , and k-means where  $k$  is chosen by Calinski Harabasz. Mean Squared Error is calculated between the actual sensory length values that are clustered and the perceived lengths in each case. The frequency-based-means clustering gets nearly similar results to the k-means with the Calinski Harabasz. The constant k-means has the worst performance because as the number of movements increase, more data are obtained and are distributed among the same number of clusters resulting in large clusters with increased intra-cluster distance. Accordingly, using a constant number of clusters is not suitable for data that increases with time and this demonstrates that perceptions must be increasing with time.

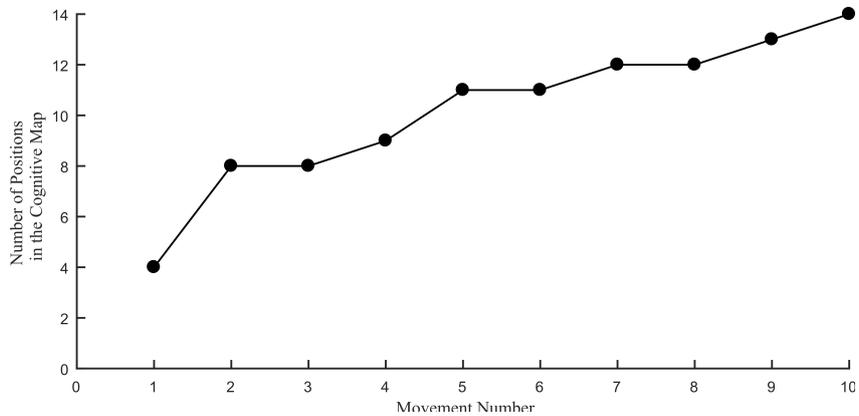
## 10.2 Experimental results of building the mechanoreceptor-association-map and the cognitive map

After getting the proprioceptions and perceptions, the mechanoreceptors-association-map is created using Algorithm 3 and it is shown in Figure 10.4. It can be seen that there can be a length having two pressure perceptions in early movements. This is due to the immature differentiation between the different proprioceptions and mixing different sensory values that have different sensations in one group. This will be solved in the next movements as the sensory values with the same sensations are grouped together and the old association links fade.



**Figure 10.4** – An example of the mechanoreceptors-association-map. The x-axis represents the length proprioceptions and the y-axis represents the pressure perceptions. Both the dots and the crosses depict the pressure perceptions at different length proprioceptions. Dots refer to one pressure perception and the crosses refer to another one.

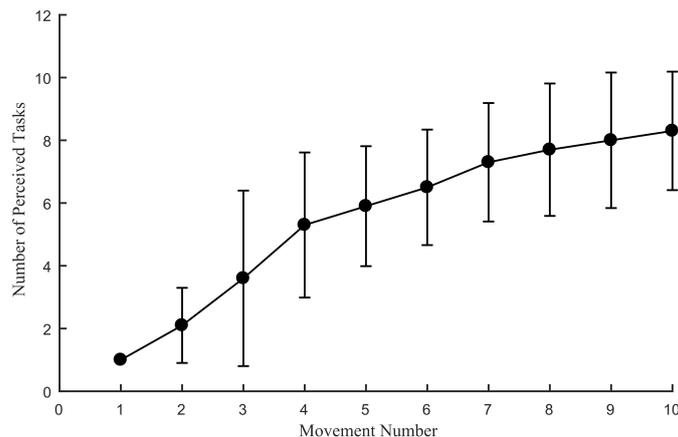
Figure 10.5 demonstrates how the cognitive map is formed through consecutive movements. The number of positions of the cognitive map increases as more movements are done and as the mechanoreceptors-association-map is updated.



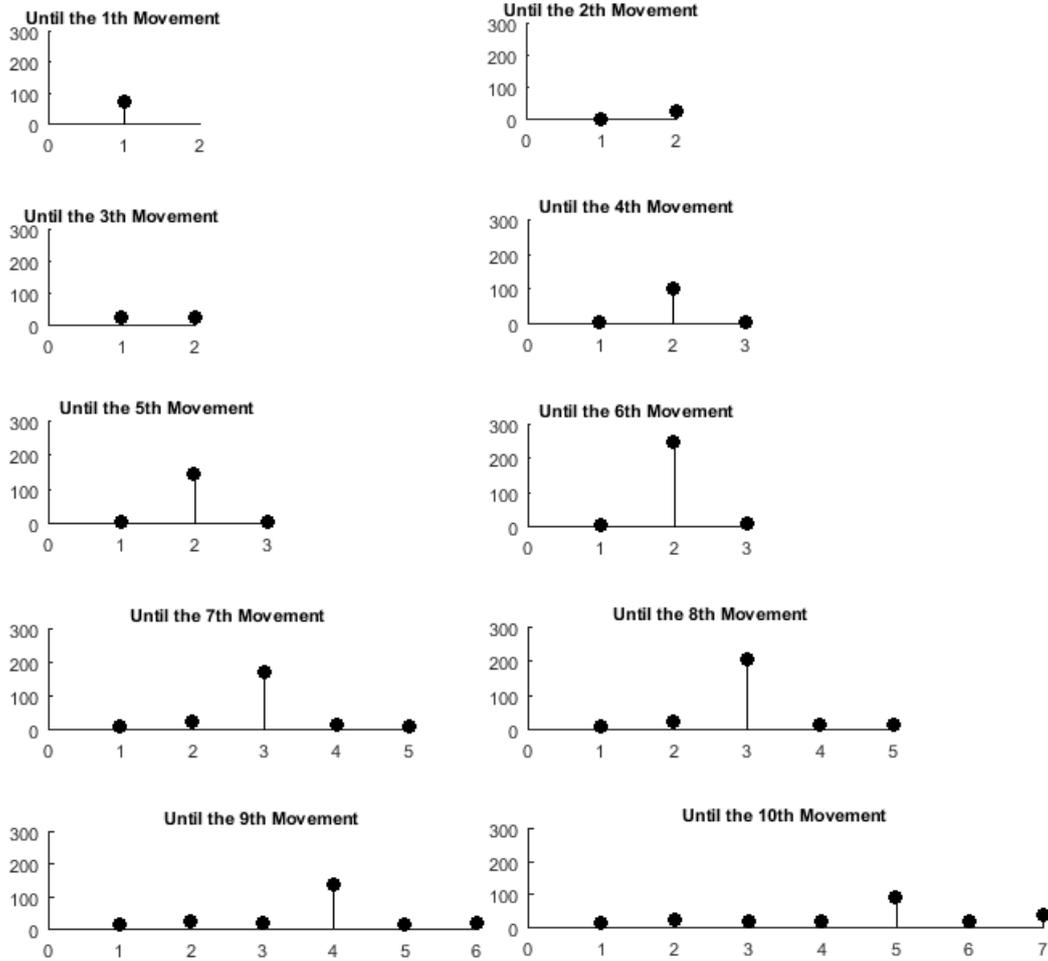
**Figure 10.5** – An example of the resulting cognitive map.

### 10.3 Experimental Results of the Movement Learning and the Inverse Internal Model Implementations

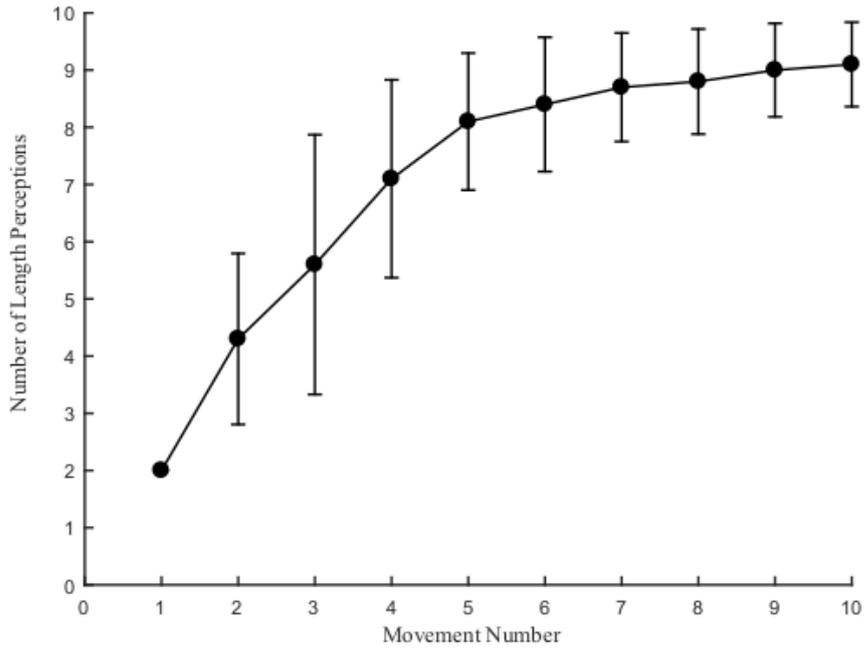
For producing the proprioceptions for lengths and the perceptions for pressures, we assumed that a sensory data must be repeated at least 5 times to be recognized as a proprioception or a perception and saved in memory. The value 5 was chosen because it is half the number of movements; consequently, the sensory value repeated that much can be distinguished as perceptions. The sensory length values are used to create length proprioceptions, this is shown by Figure 10.8. It is noticed that the number of perceived lengths increases with time as more movements are generated, which means increasing the proprioceptions and the sense of the self-position. From the created perceptions, tasks are defined to move from one proprioception to a higher proprioception. The number of tasks produced across different movements is demonstrated by Figure 10.6. All the sequences of each task are collected and used for training and testing its HMM model using 10-Leave One Out Cross Validation (LOOCV). An example of the change in the number of sequences per each task is depicted by Figure 10.7.



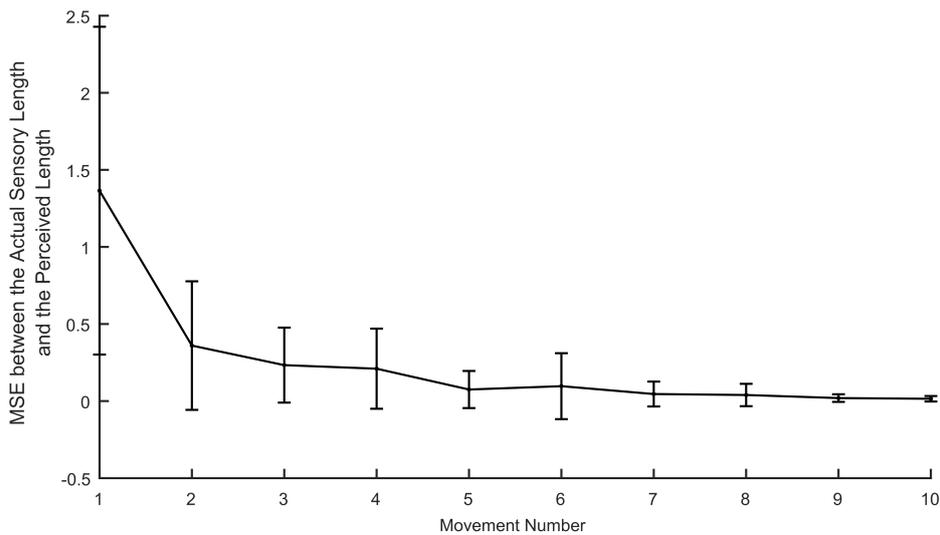
**Figure 10.6** – *Number of Perceived Tasks Versus Number of Repetition of Moving Upwards.* For the first three movements, no tasks are defined because there is only one perceived length. It is noticed that the number of tasks increases with the repetition as more proprioceptions will be recognized, hence, new tasks will be created. After sometimes, all the length domain is covered, so the number of tasks remains constant.



**Figure 10.7** – One Example of The Number of Sequences per Tasks for many Movements Upwards. The x-axis represents the task number and the y-axis depicts the number of sequences per each task. The figure shows that the number of tasks increases with the repetition of movements as well as the increase in the number of sequences per tasks at a constant the number of tasks as in the 5th, 6th movements and the 7th, the 8th movements. The increase in the number of sequences for a task will help in better learning.



(a)



(b)

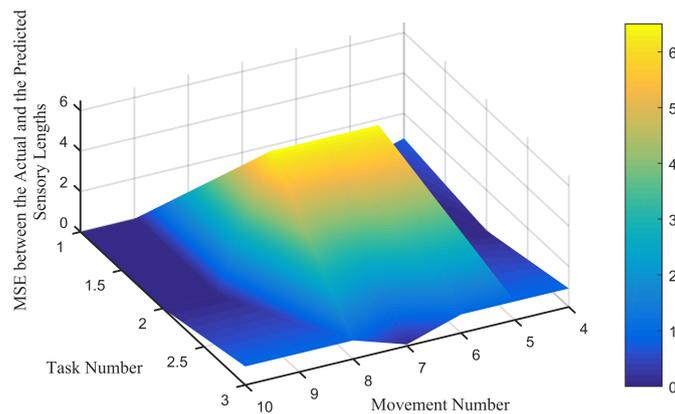
**Figure 10.8** – Perception Evolution across Movements for the 10 LOOCV runs. (a) Shows the mean and the standard deviation of the number of the defined length proprioceptions . Initially, all the obtained length values are assigned to one cluster. With the repetition of length values, they will be recognized as perceptions, hence, the number of perceptions increases with time. (b) Depicts the mean squared error between the actual proprioceptive length values and the perceived length values as well as the standard deviation across all movements. It is noticed that the proprioceptive length approaches the sensory length as more movements are generated as more proprioceptions are created. In addition, the standard deviation decreases.

Results shows that the perception approaches the correct senses as time increases due to the increase in the repetitions of movements and gaining more data. Accordingly, the pressure error decreases with time as well as the length errors. Figure 10.9 shows the HMM performance results for consecutive movements in one simulation. It depicts the results for

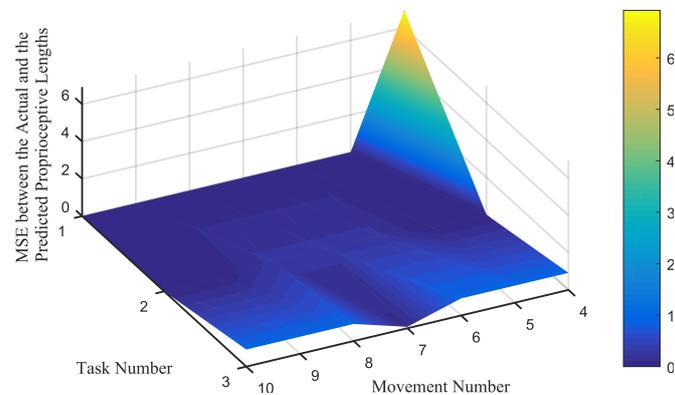
a subset of tasks defined from the 4th movement until the 10th. The HMM prediction of the suitable command sequence is enhanced as more movements are made. Hence, the HMM predicted command sequence will produce predicted proprioceptive length that is closer to the actual proprioceptive length as more movements are generated with time.

Figure 10.10 demonstrates the performance of the HMM according to different levels of perceptions defined by the clustering algorithm. The mean squared errors are also decreasing as more movements are made. The difference between Figure 10.9 and Figure 10.10 is that according to the perception, the fetus seems to reach the correct position while in fact it did not according to the proprioceptive length. This may result that it will not feel the correct pressures although his mind “thinks” that it is at the right length. The mean squared error between the actual proprioceptive length and the predicted perceived length is shown in Figure 10.11, in which it can be seen that the predicted perceived length will approach the actual proprioceptive length with time, as more movements are made.

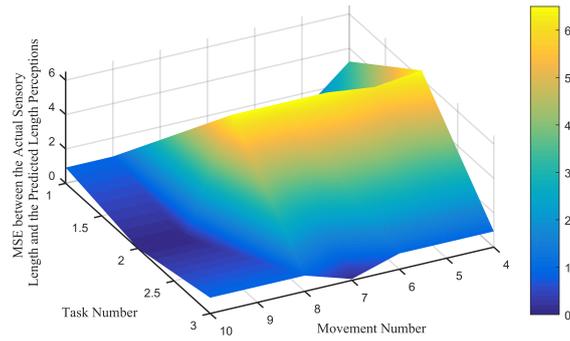
Figure 10.12 depicts the mean squared error for the sensed pressures, which also improves with time.



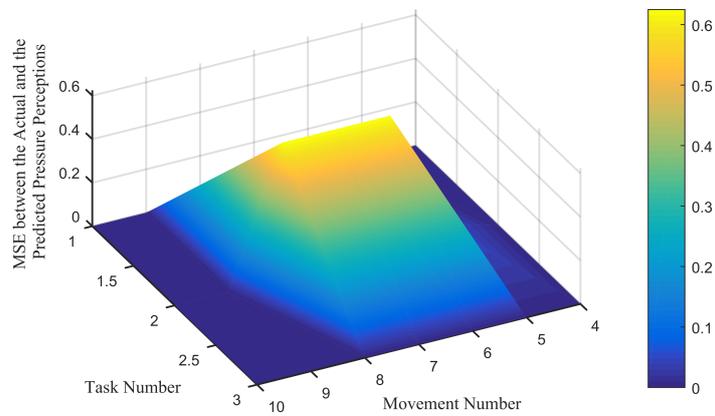
**Figure 10.9** – Mean Squared Error between the Actual and the Predicted proprioceptive lengths. It shows the performance of the HMM in predicting the state sequence that gets the actual proprioceptive length for different tasks. The prediction improves as more movements are made because more sequences becomes available for training the HMM.



**Figure 10.10** – Mean Squared Error between the Actual and the Predicted Perceived Lengths for a group of Tasks defined in one simulation.



**Figure 10.11** – Mean Squared Error between the Actual Sensory Length and the Predicted Perceived Length for a group of Tasks defined in one simulation.



**Figure 10.12** – Mean Squared Error between the Actual and Predicted Pressures of a group of Tasks defined in one simulation.



# CHAPTER 11

## CONCLUSION AND PERSPECTIVES

In this work, we are trying to answer questions such as, how does the human gain his ability to make goal-directed movements and navigate his environment easily?, how can he identify different objects in his environment? and what is a goal for a human in the first place?

From Biology and literature review, we know that the origin of the human sensorimotor system goes back to the fetus stage. The fetus is able to interact with his environment, which is the womb and its body. Accordingly, we build a theoretical model of how his cognition can improve during this stage and how he becomes able to make goal-directed movements such as grabbing his umbilical cord or sucking his thumb. We have used biological hypotheses that the fetus passes through two different stages; these are an exploration phase and an exploitation phase. In the exploration phase, it starts making random movements and save in his memory the corresponding sensory feedbacks. These form his data that are further processed into perceptions and then cognition. In the exploitation phase, it uses what is learned to make movements. We have used simplifying hypotheses to elaborate the idea and to build a simple tractable model. We abstracted the details of a movement into signals that are sent from the brain to the motor neurons. Similarly, the sensory feedbacks are represented by signals. We focus on the vertical movement upwards of the elbow using one muscle.

We have proved that this set of biological knowledge and our hypotheses are consistent, as the model exhibits sensible behavior, and are sufficiently complete as no additional hypotheses are required for the fetus to learn reaching different objects; which represent its goals.

Our model integrates the sensorimotor system and the cognitive map to make goal-directed movements. The sensorimotor system is the source of the data to be further processed into higher-level proprioceptions and perceptions using the proposed “Frequency-based-means clustering algorithm”. These, in turn, form cognitive map positions. In addition, a movement learning unit is used to learn the relation between the proprioceptions and motor commands, and an inverse model is used to generate the suitable commands to obtain target proprioceptions. We have used Hidden Markov Model (HMM) to model the movement learning and the inverse model.

## 11.1 Summary of results

We have proposed a modular structured system in which each module is responsible for a specific operation. We have eliminated confusion of biological terminologies found in literature such as the proprioceptions. In addition, the cognitive map terminology is given a broader sense than how it is expressed in the literature. Rather than focusing on its representation, we focused on its content which is made of positions and what they represent with respect to the sensorimotor system. A definition is given to the notion of “position” in terms of proprioceptions and perceptions obtained from the sensorimotor system. The cognitive processes are explained in details with a module responsible for each process. The role of proprioception in defining positions in the cognitive map is demonstrated. We have provided an explanation of how a goal-directed movement can be planned and accomplished using the information given by the cognitive map and the proprioceptions. In addition, we have shown the importance of an inverse internal model that issues command sequences according to its target.

## 11.2 Perspectives

We have built a modular model in which each module is responsible for a function. Results show that this model is valid based on the simulated data. This makes the proposed model a candidate hypothesis for the biologists who should further investigate it on real data as well as perform mapping of each module to the different brain areas. This will help them explain the cause of different impairments or shortage in many human biological functions. Understanding something in biology is usually a primary step for future progresses in many fields. Our problem can be useful for the medical field, it can provide us solutions to alleviate some syndromes and can explain the differences found between people regarding their muscular and mental abilities. The separation between proprioceptions, perceptions and cognition is useful in medical applications. Our model offers a “main structure” that should be more detailed once biological knowledge grows and it can be customized to other problems. For instance, in case a patient suffers from problems in proprioceptions, we can identify damaged areas in the brain. Similarly, people who can not remember their ways or those who can recognize them once they pass through, it will be their cognitive abilities to build their cognitive maps that can explain this, and any shortage can be found

in the region of the brain responsible for this task (the hippocampus). It can help predict autism in early stages and find solutions for it. In computer sciences, it gives new ideas to develop more intelligent and accurate systems that can be used in various applications. As an example, it can be used in the field of robotics for making enhanced humanoids whose perceptions and cognition abilities develop naturally. The proposed frequency-based means clustering algorithm can be used in applications that has online data, for example, it can be used in detecting areas that incorporate similar climate phenomena changes and decide whether these phenomena will be related to these areas or not. Additionally, it can be used in recommendation systems by identifying the new interests of users, which provide opportunities of making better, more-oriented, recommendations. This algorithm can only work on data that is characterized by having repetitions. As a future work, it will be extended to eliminate this limitation to be valid for use for a greater number of applications.

Despite that our model is based on one muscle but can be generalized to work with a group of muscles. As a future work, we should investigate how multiple muscles can cooperate together to reach positions in the cognitive map. This can be accomplished by choosing the appropriate length for each muscle of the limb. In addition, the model can be generalized to work on new born and infants which will require the inclusion of vision. Optimizations will be done to choose which tasks must be done to reach more complex positions. An analogy between the proposed simple cognitive map and higher-level cognitive maps can be useful in order to explain the fact that some people have better cognitive maps than others. For instance, positions can represent landmarks in real life and tasks can be going from one landmark to another. The choice of the sequence of tasks to go from a source to a destination is essential in that case. Reasons of failing to reach the destination can refer to a problem in the association map or proprioceptions.



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