Modeling of Goal-oriented Human Motion Evolution using Hidden Markov Models

Eman Ahmed[1,2], Reda A El-Khoribi[1], Alexandre Muzy[2], Gilles Bernot[2] and Gamal Darwish[1]
[1]*Faculty of Computers and Information, Cairo University, Giza, Egypt*
[2]*Laboratoire d' Informatique, Signaux et Systèmes de Sophia-Antipolis (I3S) UNS CNRS, Université Côte d'Azur, France*

Keywords: Fetus Human, Movement, Goal, Sensory-motor Loop.

Abstract: Humans have the ability to make many complex movements at the same time with full coordination through the whole body. This requires control of all body muscles. The body muscles are controlled by the Central Nervous System (CNS) which consists of the brain and the spinal cord through a group of neurons called the motor neurons. Each muscle is controlled by lower-level motor neurons called the motor neurons. A motor neuron controls a group of muscle fibers of the muscle such that when it is activated, this group contracts. Hence, a muscle movement occurs. Currently, many questions remain unanswered: How this system evolves to generate the complex movements? How to control the muscles to achieve a certain goal such as reaching a target position? and how a human becomes able to define goals in the first place? It is believed that the development of motion begins prenatally with spontaneous fetal movements. In this paper, we are trying to answer these questions by proposing a theoretical model of human learning of motion starting from being a fetus. Simulation is provided using computational intelligence and statistical methods.

1 INTRODUCTION

Human motion evolve during different stages starting from being a fetus till being an infant and then being an adult (Adolph, 2008). Most of the literature is focused on modeling the adult sensory-motor system such as how the human arm is able to reach a certain target and grab an object. Modeling of motor control using forward and inverse models have been studied extensively in the previous year (D.M.Wolpert and M.Kawatob, 1998).

However, working on adult models pre-assumes the adult being able to identify a goal and focus on how he will be able to achieve it. The question of how can a human identify a goal in the first place is not answered yet. To answer this, we believe we should go back to the fetus stage and model the evolution of the human motion.

The fetal human possesses an active central nervous system from at least the eighth week of development (Flower, 1985). Until then, his nervous system grows gradually. With his rapidly maturing nervous system, his nerves are connecting his brain to the rest of his body traveling from the the brainstem down to the spine finally extending to his torso and limbs. Using his developing muscles and reflexes, the fetus is able to move his 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, he may be able to hear mother's heart beat and voice, sucking his thumb. He starts feeling movements and his flexing arms and legs are soft and becoming stronger. After that, he may make movements in response to presses on the mother's belly as explained in (Viola Marx, 2015). He can feel his own face and anything within his reach, he will be experimenting and refining his sense of touch and grasp by touching the womb surrounding him and grasping his cord. Until this stage, eyelids may open as a reflex but he cannot see yet.

Accordingly, the fetus is able to make all these actions without his vision, he depends on other senses only, mainly the senses of touch and hearing.

The question now is how he becomes able to explore his body and his surrounding? how he is able to control his hand to touch and grasp? This brings us back to how a movement occurs through the brain and the muscular body.

For a movement to occur, this involves a muscle

Ahmed, E., El-Khoribi, R., Muzy, A., Bernot, G. and Darwish, G.
Modeling of Goal-oriented Human Motion Evolution using Hidden Markov Models.
DOI: 10.5220/0007391906050612
In *Proceedings of the 8th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2019)*, pages 605-612
ISBN: 978-989-758-351-3

contraction which is achieved by sending a command signal from the brain to the motor neurons controlling this muscle fibers to be activated causing contraction of the muscle. In response, a group of sensory neurons inform the brain with the changes that have occurred. This is done through a sensory-motor loop. Whether the sensory neurons feedback are sufficient to learn goals or not is another question that arises.

In this paper, we are trying to answer all the mentioned questions: how can a human identify a goal? how he becomes able to explore his body and his surrounding?. In other words, we are interested in understanding how a goal-oriented movement is developed and we believe this starts from the fetus stage by learning how to define different tasks and control his muscles to achieve them. With the help of a computational model, we provide a simulation at a high level of abstraction of how the movements may evolve during the fetus stage. The model is built upon the development of one muscle moving upward in a vertical direction.

In the next section, we provide a simplified biological explanation of how muscles work for achieving a movement. Section 3 gives a brief explanation on Hidden Markov Models. In section 4, a theoretical framework is demonstrated. The implementation of the framework is illustrated in section 5 using clustering and a hidden markov model. Simulation results are presented in section 6. The paper is concluded in section 7.

2 THE SENSORY-MOTOR SYSTEM

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 antagonist. Each antagonist muscle has a set of sensory neurons called proprioceptors that signal sensory information to the brain. The brain uses the sensory information to gain his awareness of the positions of the different limbs among the body (Heuer and Keele, 1996).

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.

To make a movement, the contraction of one muscle is required. A command signal is sent to activate the motor neurons controlling the muscle fibers of this muscle causing their contraction. Reference (Perruchoud et al., 2014) provides an abstract architecture for the sensory-motor loop with biological illustration.

There exist another class of receptors providing information about mechanical forces arising from the body itself, the musculoskeletal system in particular. These are called proprioceptors, roughly meaning “receptors for self.” The purpose of proprioceptors is primarily to give detailed and continuous information about the position of the limbs and other body parts in space. 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 (Purves D and et al., 2001).

Muscle contraction causes an increase in tension at the tendon and decrease in the muscle length. Consequently, it causes increase in the length of its antagonist muscle. The tension at the tendon is signaled by a proprioceptor referred to as Golgi Tendon Organ and it is activated as soon as there is tension. Tension is relaxed due to reflexes unless contraction occurs.

The 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 (Byrne and Dafny, 1997). Unfortunately, the proprioceptions are usually noisy and the brain is usually unable to perceive the precise proprioceptive values. However, the brain learns through the imperfect perceptions (Bays PM, 2007)(Prinz and Bridgeman, 1995).

3 HIDDEN MARKOV MODEL (HMM)

One of our main hypotheses is that humans learn from the most frequent actions at all stages. HMM is suitable for our problem in the sense that our brain learns through sequences of actions generated over time. Since the sensory neurons produce feedbacks to the brain in response to commands, the senses are observed. On the other hand, the commands are hidden as there are no sensory neurons that can describe the issued commands. Repetition of an action makes it a habit. Following the same concept, we hypothesize that the brain learns motion generation through the most frequently used commands.

An HMM model $\lambda = (Q, A, O, B, \pi)$, is characterized by the following components:

- $Q = q_1, q_2, \ldots, q_T$ a hidden sequence of T states, each one is drawn from a set of states $Z = \{z_1, z_2, \ldots, z_N\}$.

- $A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$ a transition probability matrix A, each a_{ij} representing the probability of moving from state i to state j, s.t. $\sum_{j=1}^{n} a_{ij} = 1 \forall i$.
- $O = o_1, o_2, ..., o_T$ a sequence of T observations, each one is drawn from a set of observations $X = \{x_1, x_2, ..., x_L\}$.
- $B = b_i(o_t)$ a sequence of observation likelihoods, called emission probabilities, each representing the probability of an observation o_t being generated from a state i.
- π is the initial probabilities of all the states.

Generally, HMM is used to solve one of the following problems:

1. Problem 1 (Likelihood): Given an HMM $\lambda = (\pi, A, B)$ and an observation sequence O, determine the likelihood $P(O|\lambda)$.
2. Problem 2 (Decoding): Given an observation sequence O and an HMM $\lambda = (\pi, A, B)$, discover the best hidden state sequence Q. We will use the Viterbi algorithm for solving this problem.
3. Problem 3 (Learning): Given an observation sequence O and the set of states in the HMM Q, learn the HMM parameters A and B. We will use Baum-Walsh Expectation Maximization algorithm for this problem.

More details about HMM can be found in (L, 1989).

4 THEORETICAL FRAMEWORK

4.1 Abstractions

Two abstractions have been used:

1. The pair of antagonist muscle is abstracted to be one muscle.
2. When a tension is generated by one muscle, the muscle spindle of the antagonist will be activated due to its stretching. In our abstract model, an increase in tension of one muscle will cause the increase in length of the antagonist muscle by the same amount. We will abstract both proprioceptors and treat them as being proprioceptors of one muscle due to the dependency relation between the length and the tension.

According to the above abstractions, our goal of reaching a target is reduced to getting a certain muscle length which is a function of muscle tension. Hence, our problem becomes a fetus who learns how to reach different tension levels of one muscle. We are going to use the term tension and proprioception interchangeably in the rest of the paper.

4.2 The Proposed Framework

The framework consists of three main blocks:

1. The Sensory-Motor Map Memory

   It is a memory recording all the commands that are issued and the corresponding sensory feedbacks referred to as proprioceptors.
2. 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 (Breed and Moore, 2012)(Fortin, 2008). We see that moving from one position 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 his body in the first place. From our point of view, the cognitive map comprises three main units:

   (a) Tasks Perception

   It is processing the input data from the sensory-motor map and getting perceptions. Tasks are then defined out of these perceptions.

   (b) Tasks Learning

   Each perceived task is to be learned in this unit using an HMM model. EM algorithm is responsible for getting the parameters that represent this task. The task parameters are saved in the cognitive memory.

   (c) Tasks Assessment

   After learning a task, the fetus is able to perform it whenever he likes. Initially, the task may not be learned well so the fetus will try to enhance his ability of doing it. The measure of performance will be measured in this unit.
3. The Internal Model

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

Figure 1 depicts the proposed system framework.

Our hypothesis is that the fetus passes through three phases to learn:

1. Phase I: Build the training set of commands and perceptions. We assume that the fetus makes

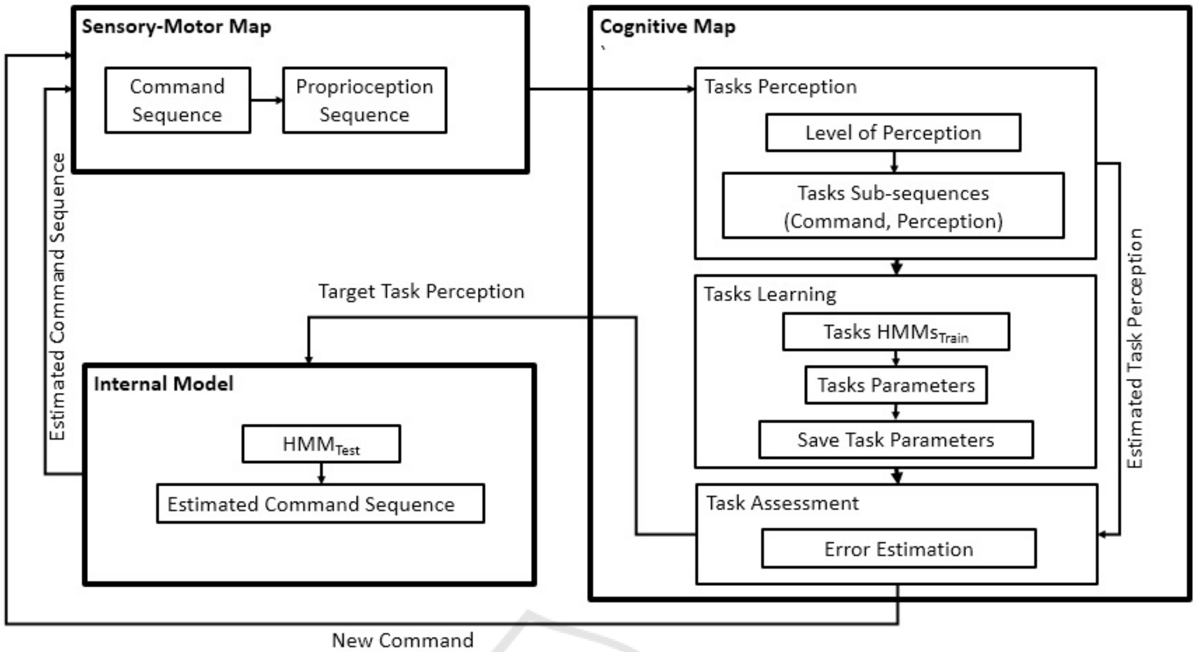


Figure 1: The proposed system framework. The sensory-motor map is responsible for building the training set of commands and perceptions, the cognitive map trains his cognition abilities using the recorded training set and the internal model helps the cognitive map to learn how to retrieve the commands to make intended movements.

movements that gets all the possible tensions in this phase.

- Generate random motor command that results in muscle contractions.
- Proprioception (tendon tension) is produced.
- Recording in sensory-motor map memory the association "this command sequence = these proprioceptions".

2. Phase II: Train his cognition abilities using the recorded training set.
   - Learn the relationship between the recorded commands and the recorded proprioceptions according to the level of perception of the fetus.
   - Get parameters that represent this relationship.
   - Record the parameters in memory.
3. Phase III: Try retrieving the commands to make intended movements.
   - Given a target perception, guess the estimated target command according to the parameters and issue it.
   - Get the corresponding estimated perception.
   - Compare the target perception to the estimated perception.
   - A new command is issued. It will increase the training sequence and will result in better estimation and may help in exploring greater proprioception values.

It is important to notice that one perception value can be achieved by different command sequences. Our model is based on two hypotheses: the first hypothesis is that the fetus will usually apply the command sequence that is most probable and the second hypothesis is that despite the noise, the original relationship between the commands and the accurate perceptions will be approximated.

We are going to use HMM for modeling the relationship between the command sequence and perceptions for one muscle such that phase II represents learning the relation between O and Q and get the mapping parameters as in HMM problem 3. Then, after the brain develops by learning and obtaining its mapping parameters, it starts gaining the ability of decoding (HMM problem 2) by choosing a target observation sequence and discover which commands should be issued to obtain it.

The details of implementation is presented in the next section.

5 IMPLEMENTATION

5.1 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 he gains more energy and becomes able to get stronger contraction.

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

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

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

5.2 The Proprioception

It dictates the sensory values are achieved using a given command sequence. As explained above, the proprioception represents the tension 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.

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

such that x represents the fiber sizes.

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

$$tension = Muscle \Theta Q \tag{3}$$

such that Θ denotes the convolution operator and Q is the state sequence.

Figure 2: Proprioception Values for each Sequence.

5.3 The Perceptions

Initially, the fetus is not able to distinguish precise proprioceptive (tension) values. Accordingly, clustering of similar proprioception values is performed using K-Means clustering. The clustering is applied to the proptioceptive values with small number of levels at first, then, the number of levels increases gradually as the fetus gains more abilities for distinguishing different tension levels. The perceptions are the cluster centers.

The perceptions represent the sequence of observations O such that $o_i \in X$ and $X = T$ where T is a vector of the clustered tendon tensions.

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

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

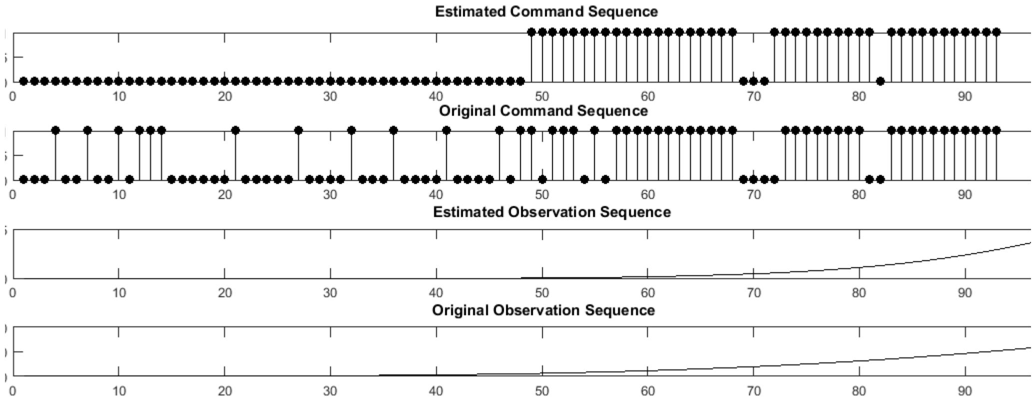
5.4 The Task

It is a notion that describes what a muscle can do in terms of changing its tension from one perceived values to another. All tasks are defined from the perceptions of the training set. The perceptions are divided into a combination of each two pairs of perceptive values in increasing order and all subsequences of moving between these pairs are collected to be the training set of this task.

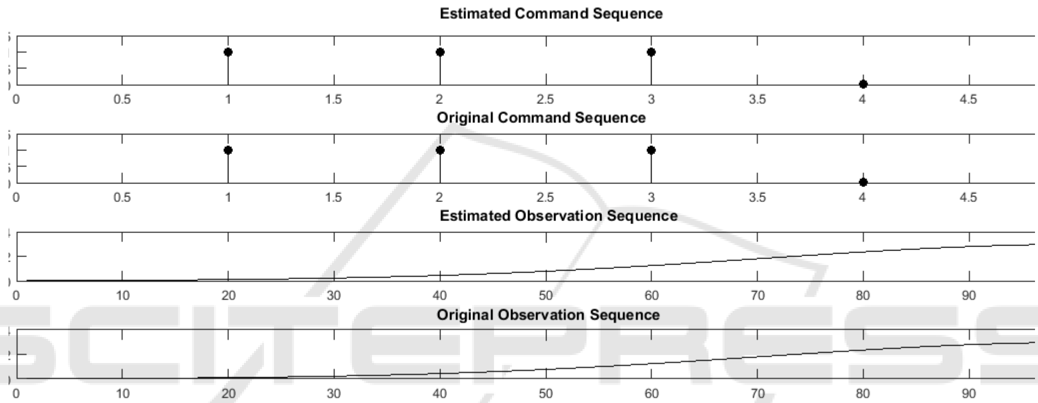
A Hidden Markov Model is built for each task and is trained using these sequences using Baum Walsh Expectation Maximization algorithm to get the transition and emission matrices from the collected sequences.

After the brain develops by learning the tasks and obtaining its mapping parameters, its starts gaining the ability of decoding (problem 2) by choosing a target observation sequence and discover which commands should be issued to obtain it.

Given a target perception sequence, the most probable command state sequence is obtained using the Viterbi algorithm.



(a) Two Clusters



(b) Four Clusters

Figure 3: The estimated sequences versus the original sequences of a HMM of 100 observation sequence for different number of clusters.

6 SIMULATION

Results show that the fetus is able to approximate the correct proprioceptive values over time by retrieving the required command sequence and by improving his perceptions to be able to identify more proprioceptive values.

Our simulation is based upon three stages, each stage is of duration 50 time units. Within each stage, we simulate the sequences that can be generated by the fetus according to his energy and the level of perception that should be increasing with time. We hypothesize that the energy is initially low and increase with time from the fact that the fetus can not do strong activities such as kicking in his early stage.

We apply our simulation on one muscle due to the fact that the abilities of the fetus changes over time, we built our simulation on a sequence that is growing with time. First, the simulation has a command sequence of 50 observations generated by Equation 1 with probability of firing equals 0.2 which is a small probability that mimic the low energy the fetus has at his early age. Despite that the resulted proprioceptive values are very low and the cognition will not be able to recognize any task to be learned, these are recorded in memory.

Next, another 50 observations are added with probability of firing equals to 0.8 where there is an increase in energy that makes the fetus more capable of doing stronger actions and hence, issues more commands. The corresponding proprioceptive values were calculated as in Equation 3.

Initially, the fetus can either sense a tension or not. This is simulated by clustering the proprioception into two large levels of perception as illustrated in Figure 3a. In this case, the fetus recognizes only one task moving between zero and a perceived tension value. We are only interested in learning moving from one

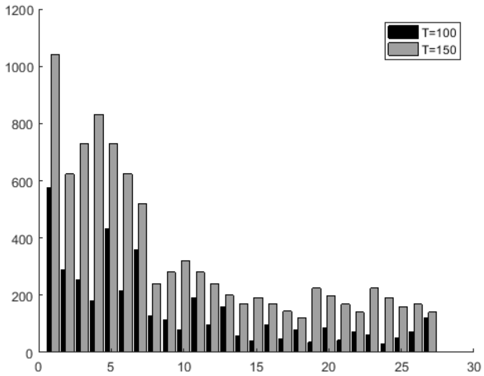


Figure 4: Number of sequences per task for 100 observations and 150 observations.

tension to another higher tension which involves issuing one or more commands. This is because moving from one tension to another lower tension is a trivial task as no command will be issued and it can be learned easily.

Second, fetus capability becomes stronger and he is able to issue more commands and reach greater tension values. Figure 2 shows the range of tension values that exist in sequences of duration 100 and 150, respectively.

Also, the fetus capabilities evolve by being able to distinguish different tension values. We simulated this by repeating the experiment with smaller step to get 4-clusters as depicted in Figure 3b. Hence, there are six tasks the fetus should learn.

The experiment is also repeated for 8-clusters.

The fetus will continue to experiment the tasks and more 50 observations with probability 0.9 are added which enhances the learning of the previous tasks.

Increasing the sequence length means increasing the proprioceptive values that are obtained. Accordingly, the perceptions will approximate more proprioceptive values. This make it necessary for the fetus to increase his level of perception to cover all the new values.

Figure 4 depicts the number of sequences available for each task during 100 observations and 150 observations.

Results show that the fetus is able to approximate the correct proprioceptive values over time by retrieving the required command sequence and by improving his perceptions to be able to identify more proprioceptive values as shown in Figure 5.

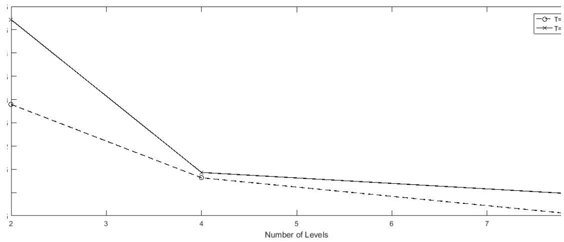


Figure 5: Mean Squared Error of all tasks for each quantization level for both sequences of T=100 and T=150 for unnoisy proprioceptions.

7 CONCLUSION

We have tackled the problem of understanding how human movements evolve since the age of the fetus. We proposed the first model that describes how a fetus learns to control one muscle to get an intended perception by giving it the essential command. The model passes through random stage where all commands issued are random and demonstrates how this converges to learning the appropriate relationship between commands and perceptions. We have proposed our model of applying k-means clustering to simulate perception development over time and we have shed light on the idea of how the human builds his own abilities of identifying goals which represented here reaching one perceived tension value from another. The simulation was done using Hidden Markov Model since its basics matches with our hypothesis that we learn from the most frequent actions which are represented as sequences. The model presented in this paper is a simple abstract model to illustrate the whole process. Further improvements are being done on this model to include more details. This work would benefit biologists to gain better understanding of the fetus stage and how the human movements develop, further, it may help them discover some early impairments in case of monitoring the fetus actions and responses over time. Moreover, it can be used in the robotics and humanoids field to explore more varieties.

ACKNOWLEDGEMENTS

The authors thank the NeuroMod institute (http://univ-cotedazur.fr/en/idex/projet-structurant/cauca) in Nice-Sophia Antipolis that funded this research.

REFERENCES

Adolph, K. (2008). *Motor and Physical Development: Locomotion.* Encyclopedia of Infant and Early Childhood Development.

Bays PM, W. D. (2007). Computational principles of sensorimotor control that minimize uncertainty and variability. *The Journal of Physiology.*, 578(Pt 2):387–396.

Breed, M. D. and Moore, J. (2012). Chapter 8 - movement: Search, navigation, migration, and dispersal. In Breed, M. D. and Moore, J., editors, *Animal Behavior*, pages 219 – 252. Academic Press, San Diego.

Byrne, J. H. and Dafny, N. e. (1997). *Neuroscience Online: An Electronic Textbook for the Neurosciences http://nba.uth.tmc.edu/neuroscience/*, chapter Chapter 1: Motor Units and Muscle Receptors, page Section 3. Department of Neurobiology and Anatomy, The University of Texas Medical School at Houston (UTHealth).

D.M.Wolpert and M.Kawatob (1998). Multiple paired forward and inverse models for motor control. *El Sevier, Neural Networks*, 11:1317–1329.

Flower, M. J. (1985). Neuromaturation of the human fetus. *The Journal of Medicine and Philosophy*, 10(3):237–251.

Fortin, N. (2008). Navigation and episodic-like memory in mammals. In Byrne, J. H., editor, *Learning and Memory: A Comprehensive Reference*, pages 385 – 417. Academic Press, Oxford.

Heuer, H. and Keele, S. W. (1996). *Handbook of Perception and Action Volume 2: Motor skills*, volume 2. ACADEMIC PRESS.

L, R., editor (1989). *A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition Proceedings of the IEEE*, volume 77 of *2*.

Perruchoud, D., Murray, M. M., Lefebvre, J., and Ionta, S. (2014). Focal dystonia and the sensory-motor integrative loop for enacting (smile). *Frontiers in Human Neuroscience*, 8:458.

Prinz, W. and Bridgeman, B. (1995). *Handbook of Perception and Action Volume 1: Perception*, volume 1. ACADEMIC PRESS.

Purves D, Augustine GJ, F. D. and et al., e., editors (2001). *Mechanoreceptors Specialized for Proprioception.* Neuroscience, Sunderland (MA): Sinauer Associates, 2 edition.

Viola Marx, E. N. (2015). Fetal behavioural responses to maternal voice and touch.