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Modeling of the development of the fetus cognitive map from the sensorimotor system

Eman Ahmed [a,b,*], Reda A. El Khoribi [a], Gamal Darwish [a], Alexandre Muzy [b], Gilles Bernot [b]

[a] *Faculty of Computers and Information, Cairo University, Egypt*
[b] *Laboratoire d' Informatique, Signaux et Systémes de Sophia-Antipolis (I3S) UNS CNRS, Université Côte d'Azur, France*

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ABSTRACT

The human cognitive map formation is still an open question. Based on biological facts, the cognitive map origin goes back to the age of the fetus human. In this paper, our aim is to provide a possible answer to that question. Accordingly, we present a theoretical model of the development of the cognitive map of a fetus human using its sensorimotor data. We define positions of the cognitive map as associations between high-level perceptions created from different sensory sources. We use a proposed method referred to as Frequency-based-means clustering algorithm to develop the perceptions that form the association map. Our proposed theoretical model is tested on simulated data. Results show that our model is a possible candidate for demonstrating how the cognitive map is formed. In addition, comparison with *k*-means clustering is presented and results show that the frequency-based-means clustering has a better performance than *k*-means clustering and is more suitable for this application.

1. Introduction

There is a sharp distinction between perception which is defined as the processing of sensory information that occurs at several levels) and cognition which is the judging of representational contents related to reasoning [16]. 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 the environment (i.e. a cognitive map) [9,1]. 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 environment 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 [18]. 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 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 [15]. There are many studies performed on high-level cognitive maps of adults 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. But, there are no studies done on the origin of the cognitive maps in the fetus stage despite that 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 him to reach different objects in the womb. Proprioception and perceptual learning affects the generation of a cognitive map. The influence of proprioception on human spatial cognition is investigated in [19] and it is found that proprioception can influence the time necessary to use spatial representations while other factors such as visio-spatial abilities can influence the capacity to form accurate spatial representations [20]. This was done by the study of the

* Corresponding author.
E-mail address: e.ahmed@fci-cu.edu.eg (E. Ahmed).

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navigation of blind individuals and comparing to the navigation and way finding in individuals without any visual impairments [10]. 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 are able to navigate easily after a number of trials [18]. These studies included the sense of touch with the proprioception. Some applications are made to help blind individuals move freely based on these findings [14]. Accordingly, the spatial positions can be represented in terms of proprioceptions and the sense of touch (i.e. pressure perception). Unlike vision and auditory senses, the proprioception development is not studied much due to the difficulty to measure its performance, but in [11], a study was presented to explain the proprioception development in children and it concluded that its precision improves with age. Recently, a study [12] highlighted that the sensorimotor system of the fetus plays an important role in forming the cognitive map. In addition, it is suggested that the sensorimotor data can be used to obtain higher level proprioceptions which provide the fetus with interpretation about his limbs positions in [2]. Perceptual learning is the discovery of new structure in sensory stimulation [13]. Although the sensory stimulation are the same, with repetitions, new structures start to appear which changes our perceptions. For instance, a student reading an article, s/he perceives more information each time s/he reads it. 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. Perceptual learning can be seen as a form of clustering as mentioned in [8]. In the same sense, the fetus starts by making random movements and the received sensory feedbacks are used for generating proprioceptions and perceptions about the environment. As noticed, no previous work built a model that integrates the sensorimotor system, the proprioceptions and perceptions with the cognitive map. Moreover, there was no study presented to model the cognitive map formation for the fetus. Working on the fetus is different from working on the adults. The fetus has no vision capability so it is not able to see objects in its environment and determine their places. Instead, it depends on its immature, developing proprioception and touch sensation rather than vision for recognizing objects and positions. Consequently, the fetus is able to identify positions and built his primary cognitive map using its proprioception and touch perceptions only. In this paper, we propose a theoretical model that shows how the sensory data obtained by the sensorimotor system can be used to make higher level perceptions and proprioceptions by using the frequency-based-means clustering algorithm, and how these, in turn, generate positions that form the cognitive map. We refer to the proprioceptions as length perceptions because proprioceptions can be seen as a form of perception regarding the self position. Section 2 demonstrates the suggested model. Section 3 illustrates how the proprioceptions and perceptions are obtained and developed through a proposed clustering method. Section 4 presents integrating the generated proprioceptions and perceptions to produce positions saved in the cognitive map. The simulation and the results are presented in Section 5 and the paper is concluded in Section 6.

2. From the sensorimotor system to the cognitive map

When the muscle moves, different sensory feedbacks are received from the body and from the environment. Sensory feedbacks from the body are received from the proprioceptors such as the muscle spindle and the golgi tendon organs whereas the sensory feedbacks from the interaction with the environment include the pressure felt by the tactile sensation [5]. All these sensory data are collected and processed. Accordingly, proprioceptions are produced from the sensory length and perceptions are generated from the sensory pressure. Next, all the obtained perceptions and proprioceptions obtained from different sensory neurons are collected in the mechanoreceptors-association-map where association links are created connecting the perceptions that exist together. The pairs of the proprioceptions and perceptions represent a position in the cognitive map.

3. The Generation of perceptions and proprioceptions using clustering

In the fetus stage, there is no knowledge about how it can identify its sensations, it starts learning on its own the process of creating perceptions. This can be seen as unsupervised learning. It may use clustering to group similar data together and separate them from different groups to identify its surrounding environment. Accordingly, its cognition ability increases with time as more clusters are formed. There are many adaptive clustering techniques in literature [4,21,7]. But, they can not be applied in our problem because the creation of clusters has no biological interpretation. As explained above, we hypothesize that fetus human develops its cognition through the repetition of certain values with time. Initially, the fetus groups all the sensory values it receives in one cluster. In other words, it considers it is at the same position even when the muscle length changes. When a sensory value is repeated a lot with time, its mind starts to distinguish it from the rest of values. This creates a new cluster for this value as the center of the cluster, the cluster members will be its similar values. The brain is not very precise and full of noise [3,17], so the center is updated to be the average value of the cluster member. The creation of a new cluster in our algorithm is based on that the frequency of a value starts exceeding either a pre-defined threshold or the maximum frequency of its cluster. In other words, the proposed clustering process groups similar values together until one of them becomes significantly repeated, hence, form a new cluster on its own and take its similar members with it. Through time, it is be able to recognize all the values incrementally by repeating its actions and receiving the same sensory values. The frequency-based-means clustering follows this idea. Assume we have a set of clusters C and a set of input length values L. For any cluster $c \in C$, we define $count(l(t))$ as the count of sample l at time t and $maxcount(c)$ as the maximum count in cluster c such that if $count(l(t)) \geqslant maxcount$, then $l(t)$ is expelled from the cluster and forms a cluster on its own. *Threshold* is a threshold value for the allowed frequency of the sample in any cluster such that If $count(L(t)) \geqslant Threshold$, then $l(t)$ is expelled from the cluster and forms a cluster on its own. For any input sample $l(t) \in L$ at time t, we use $dist(c_{center}, l)$ as the euclidean distance between cluster c

Table 1
Comparison between K-means clustering and the Frequency-based-means clustering.

Point of Comparison	K-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

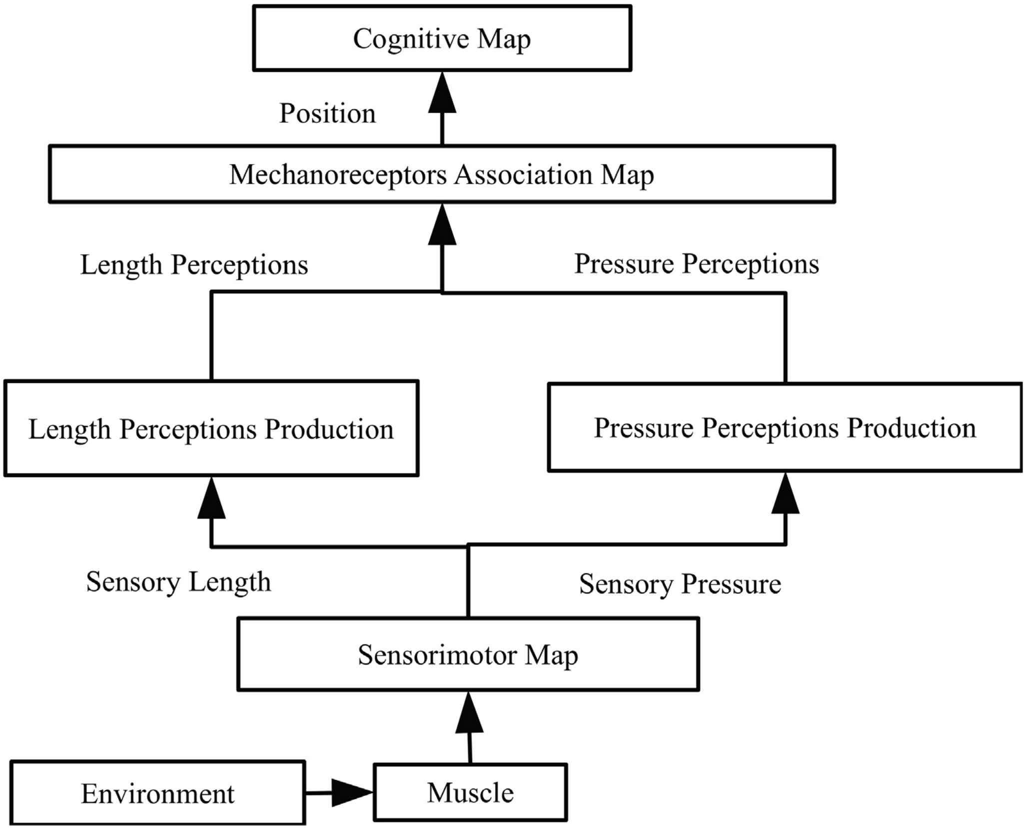

Fig. 1. The System Framework.

with center c_{center} and sample l to assign l to the nearest cluster. Fig. 2 describes the algorithm. We are using the frequency-based-means clustering to obtain perceptions over time. The cluster centers are referred to as the perceptions in our case. This way the human mind perceptions evolve with time; which represents cognition improvement. The frequency-based-means clustering algorithm can work on sequential online data. Its time of convergence is independent on the data values but it is dependent on the frequency of the data values and the repetition threshold that is chosen. Table 1 summarizes the main differences between the k-means clustering and the Frequency-based-means clustering algorithms. Fig. 1.

4. Creating the cognitive map

Depending on the collected sensory data, higher level perceptions are created. The perceptions obtained from different sensory neurons are associated in a map called a mechanoreceptors map. Different identified proprioceptions and perceptions that occur together are associated together. This association defines a position

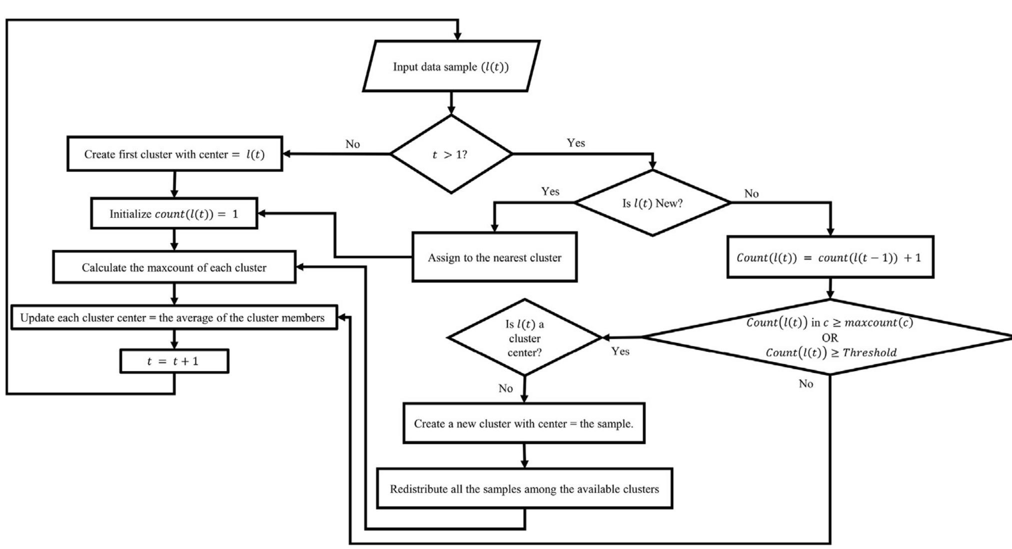

Fig. 2. Frequency-based-means Clustering.

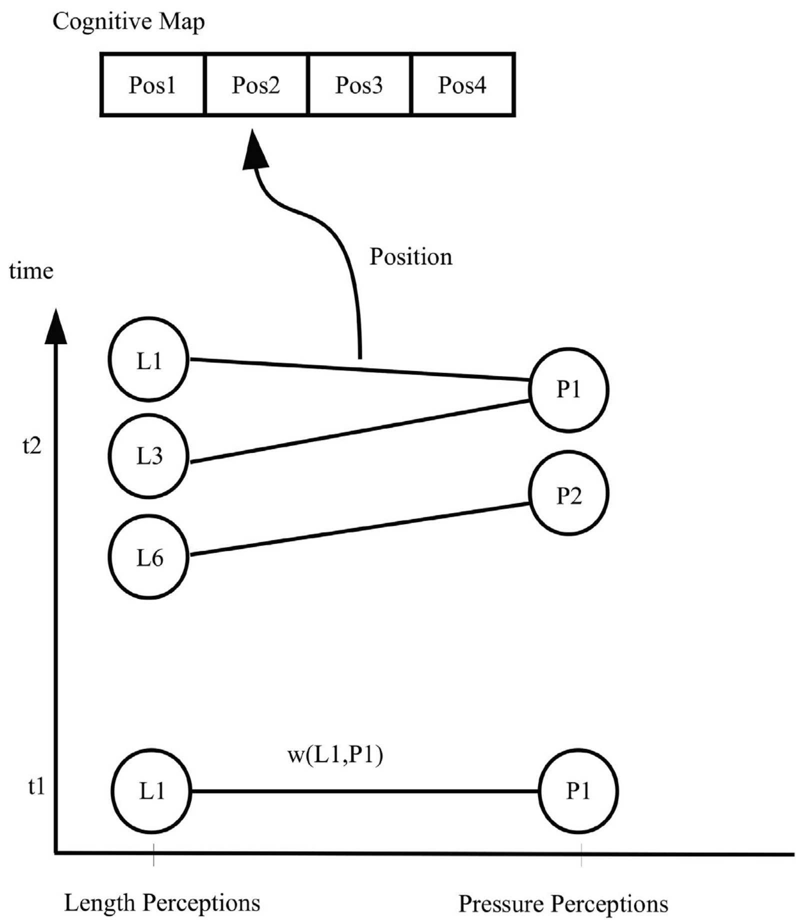

Fig. 3. The mechanoreceptors-association-map showing defined positions in the cognitive map. In time t = 1, only one position is defined between L1 and P1. At time t = 2, positions are formed for (L1,P1), (L3,P1) and (L6,P2) because they occured together many times. On the other hand, no positions are defined between L1 and P2 or L3 and P2 or L6 and P1 because they didn't exist simultaneously.

in the cognitive 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 will be 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. Fig. 3 demonstrates the association between length perceptions and pressure perceptions in the mechanoreceptors-association-map. The sensory length values form length perceptions and the sensory pressures form the pressure perceptions that reflects whether there is an object in the environment or not. Both the proprioceptions 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. 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_{LiPj}. When a command sequence (Q_t) results in perceptions L_i, P_j, then the weight is updated according to algorithm 1. When a pair of a length proprioception and pressure proprioception occurs at the same time, their link weight will 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's 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 resulted weights will be saved in memory for future use in making goal directed movements.

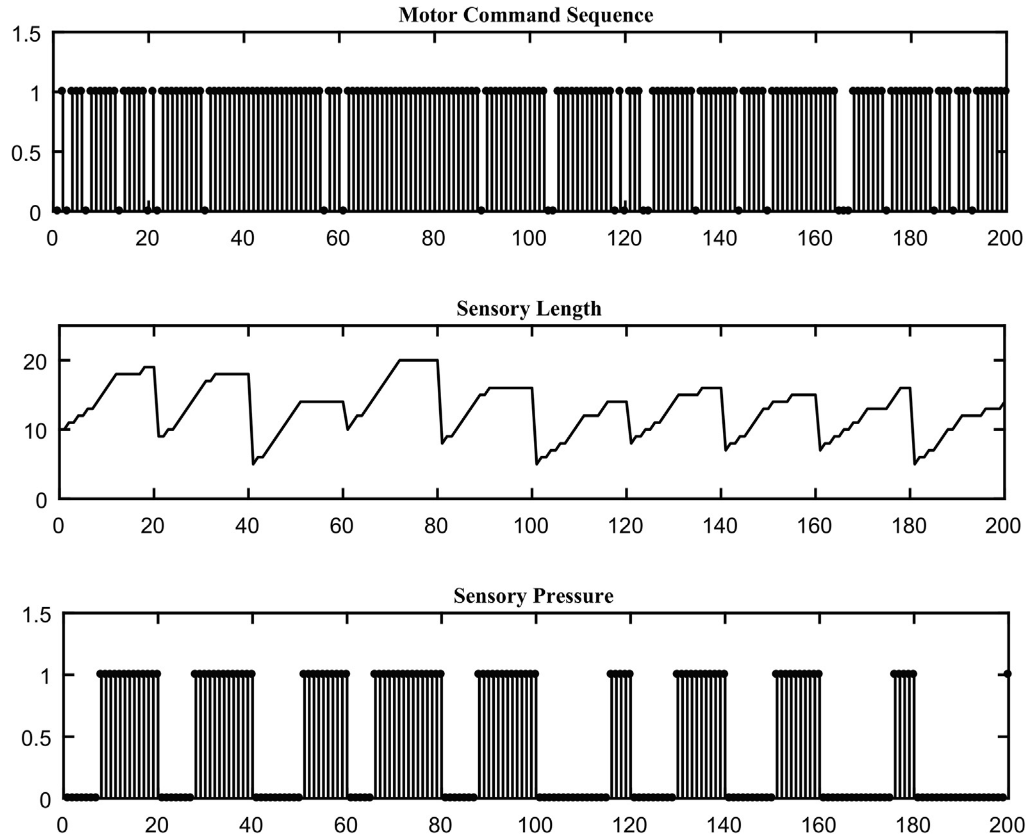

Fig. 4. An example of the generated data.

Algorithm 1: 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_{LiPj}: The connection weight between length value Li and pressure value Pj.
Begin
  Fort = 1: T
    Foreach $L_i \in L$
      Foreach $P_j \in P$
        If$(L_t == L_i) \wedge (P_t == P_j)$
          $w_{L_iP_j}(t)$=$w_{L_iP_j}(t-1)+1$
          $w_{L_iP_k}(t)$=$max(0, w_{L_iP_k}(t-1)-1)$
          such that $k \neq j$.
        EndIf
      EndFor
    EndFor
  EndFor
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.

5. Experimental setup

5.1. Data generation

To make a voluntary movement, command sequences are given to the motor neuron that controls the muscle and causes muscle contraction. There are involuntary movements that can also result in changing the muscle length. In the end, all muscle lengths will be covered, each with a certain frequency. We will explain in details the data generation for obtaining muscle lengths that corresponds to muscle movements, to be used in our experiment.

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

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

such that $t = 1$ refers to issuing a command with probability p and $t = 0$ implies the absence of command with probability $(1-p)$. We have used $p = 0.9$ to model the spontaneous large number of input command sequence to be given to the muscle. The generated sequence is of duration 20 for each movement. For 10 consecutive movements, the total duration of the generated sequences is 200.

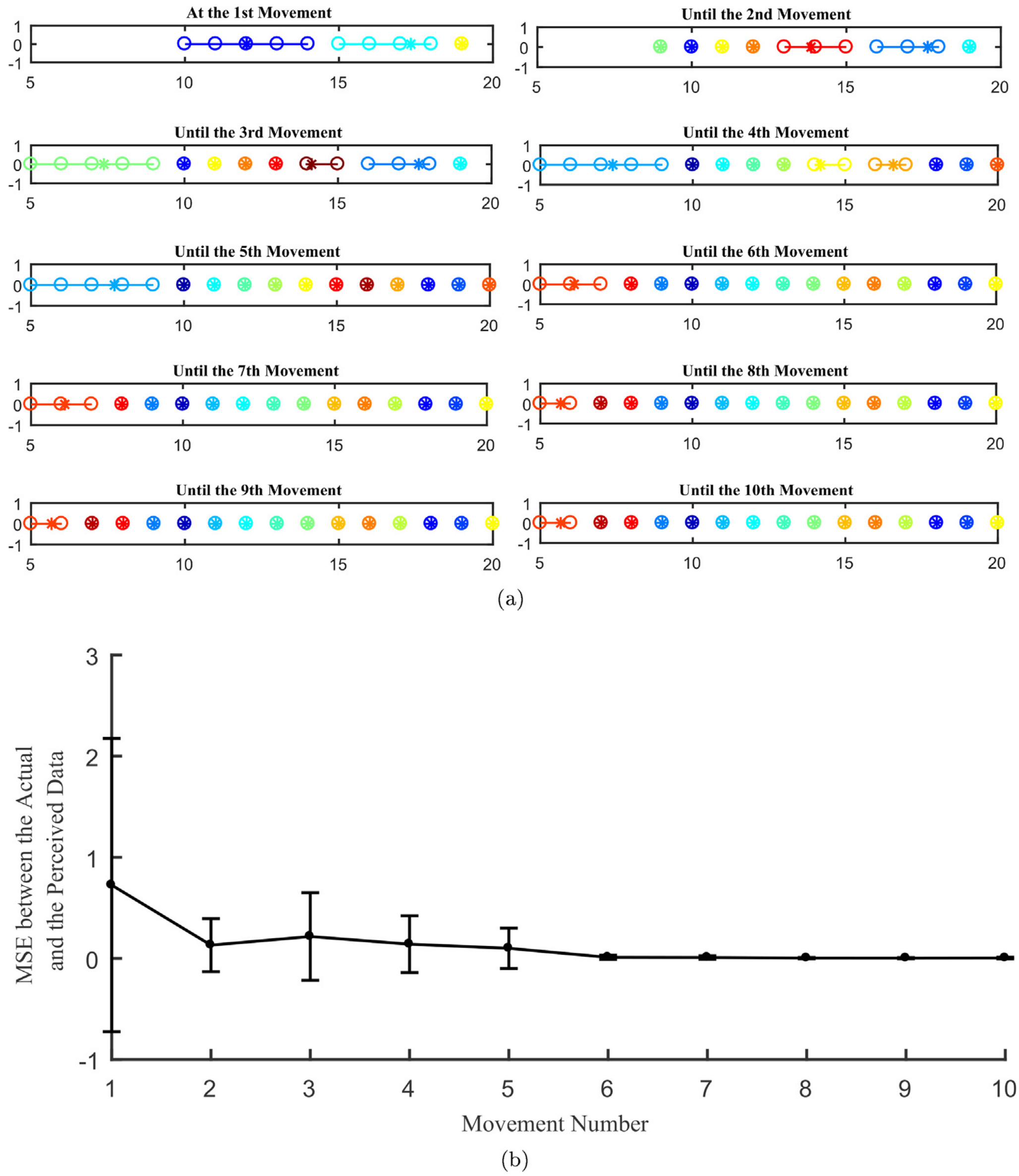

Fig. 5. An example of perceptions evolution across movements in one simulation. (a) The x-axis shows the sensory length values found per movement. Each color represents a cluster with cluster center marked by "x". Initially, all the obtained length values are assigned to one cluster. With the repetition 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.

5.3. The sensory data

It dictates the sensory length values are obtained after using a given command sequence. 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.

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

where x represents the fiber sizes. The contraction is given by a convolution function between the muscle and the command sequence:

$$contraction = Muscle \Theta Q \quad (3)$$

where Θ denotes the convolution operator and Q is that state sequence. The length sensory values are generated based on the fact 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:

$$length(t) = \begin{cases} length_{init}(t) & t \bmod T = 0 \\ length(t-1) + \Delta contraction & \Delta contraction > 0 \\ length(t-1) & \Delta contraction \leq 0 \end{cases} \quad (4)$$

The pressure appears when the fetus senses an obstacle (ex: his face) that brings a different sensation. Initially, when the fetus has low energy, his muscle won't be able to reach any obstacle and

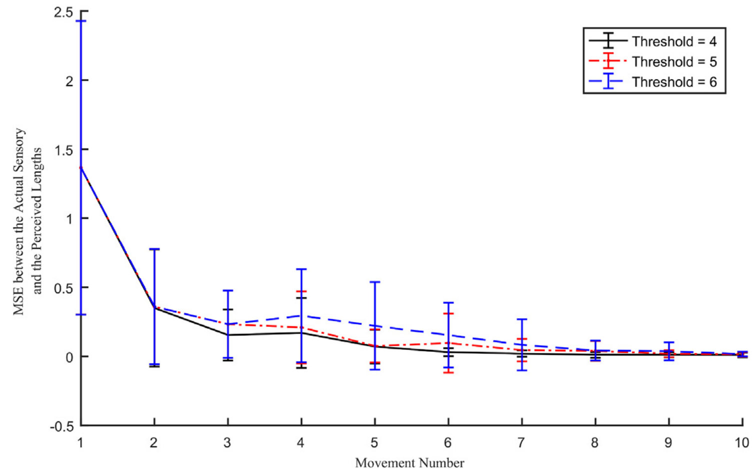

Fig. 6. Threshold effect in Frequency-based-means clustering algorithm. Mean Squared Error between the actual sensory length values and the perceived ones are shown when the input data are clustered using Frequency-based-means clustering using different threshold values. When the threshold decreases, more clusters are produced. Hence, the average approaches the cluster members resulting in smaller MSE.

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.

$$pressure(t) = \begin{cases} 1 & length(t) \geqslant Threshold_{length} \\ 0 & length(t) < Threshold_{length} \end{cases} \quad (5)$$

The generated sensory length have values from 5 to 20 and an object is assumed to be at $Threshold_{length} = 14$. Fig. 4 shows an example of the data generated for the motor command sequenc, the sensory length and the sensory pressure.

5.4. Performance measures

For comparing the performance of k-means clustering and the Frequency-based-means clustering, we calculates the intra-cluster distance in which the distance between the every point to the center of the cluster is measured. We use the Mean Squared Error (MSE) between every cluster member sample and the center of the cluster.

$$MSE = \frac{\sum_{[i=1]}^{N}\sum_{[j=1]}^{M}(\ell_i - c_j)^2}{MN} \quad (6)$$

where N is the number of samples in the cluster and M is the number of clusters. We apply this equation to the length such that ℓ is the sensory length and c represents a proprioception for each movement.

5.5. Simulation and results

Using the above mentioned equation, we have generated ten different simulated data. Frequency-based-means clustering is applied to the sensory length data to get length perceptions and to the sensory pressure data to get pressure perceptions. Fig. 5 depicts the resulted perceptions of one simulation for 10 consecu-

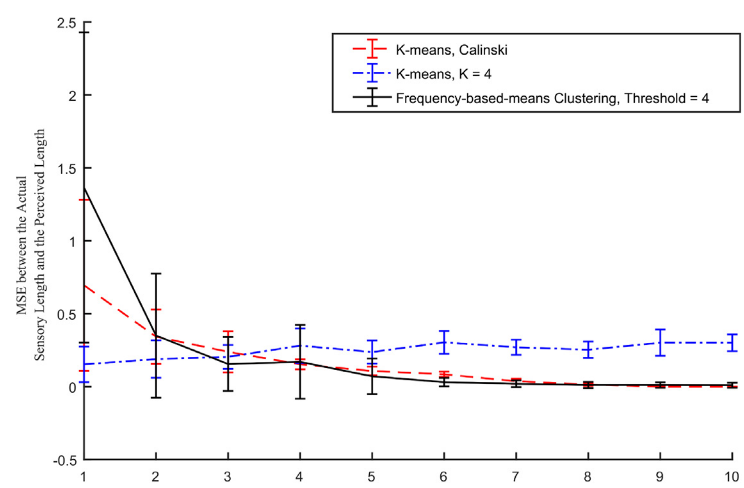

Fig. 7. Comparison between the performance of the Frequency-based-means clustering and K-means clustering. The results of generating perceptions for 10 movements obtained from 10 simulations are depicted for the frequency-based-means with a threshold values equal to 4, k-means with $k = 4$, and k-means where k is chosen by Caliniski 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 Caliniski 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.

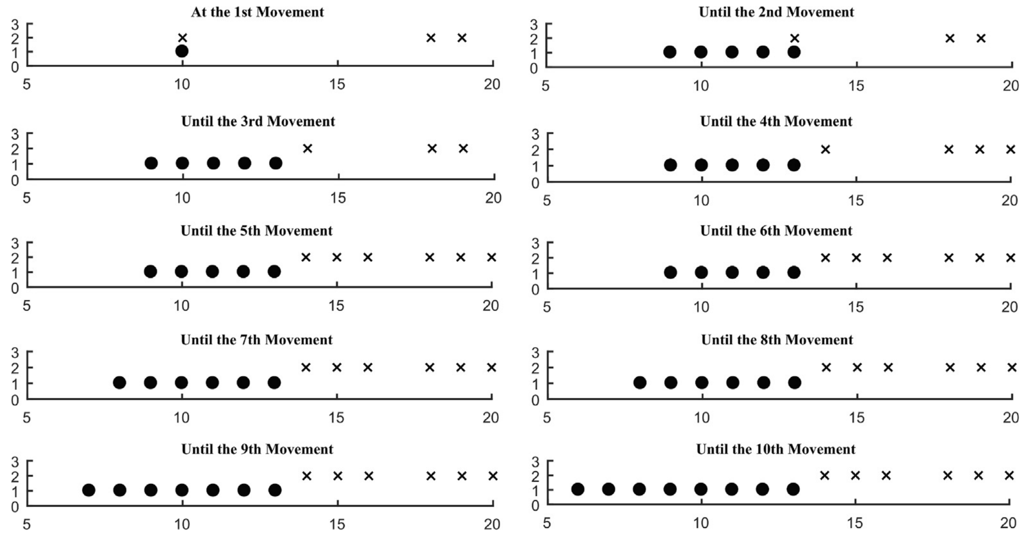

Fig. 8. An example of the mechanoreceptors-association-map. The x-asix represents the length perceptions and the y-axis represents the pressure perceptions.

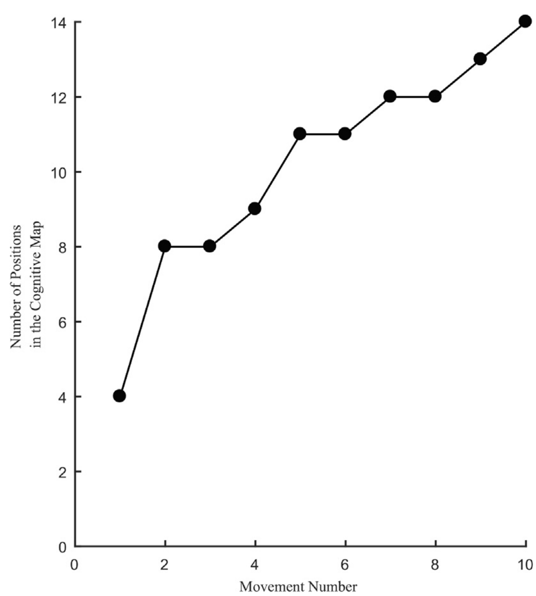

Fig. 9. An example of the resulting cognitive map.

tive movements upwards with repetition threshold equal to 4. It is shown how the perceptions approach the length values with time as more movements are produced. Fig. 6 demonstrates the effect of the threshold on the Frequency-based-means clustering. Using smaller thresholds results in faster clustering and lower mean squared error. We have repeated the experiments using k-means clustering where k is constant (chosen empirically as 4) or changing in an increasing order with the movements. In the latter, we chose the Calinski Harabasz index [6] as a criteria for choosing the optimal number of clusters. The input range was increasing with the number of movements. Results are presented in Fig. 7 and shows that the Frequency-based-means clustering has a comparable performance to k-means using the Calinski Harabasz index and is better than using a constant number of clusters. This result emphasizes that perceptions must be increasing with time. Otherwise, human cognition ability of his surrounding deteriorates. After getting the perceptions, the mechanoreceptors-association-map is created using algorithm 1 and is shown in Fig. 8. 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 perceptions 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. Fig. 9 demonstrates how the cognitive map is formed through consecutive movements. The number of positions of the cognitive map increases as more movements are done an as the mechanoreceptors-association-map is updated.

6. Conclusion and future work

We have investigated the problem of how the human mind builds cognitive perceptions from the sensory data provided by the body at the fetus stage. We have proposed a model that process the sensory data and built a mechanoreceptors-association-map which outputs positions in the cognitive map. The Frequency-based-means clustering algorithm is used to generate perceptions from the sensory data. A detailed study was presented for this clustering algorithm and comparison with k-means clustering is provided. 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. In addition, we have proposed an algorithm to build the mechanoreceptors-association-map and dynamically update its association links to mimic storing new positions and forgetting old positions. This work can benefit in the Biology field to help in understanding how the human gain his navigational skills. In addition, knowing which brain areas are responsible for each function can be useful in detecting the cause of any deterioration in movement or perceptions. This can help in the medical field to better understand the cause of many syndromes. On the other hand, the frequency-based clustering can be useful in numerous fields. It can be used in other biological applications such as modeling and tracking of gaining new skills or habits of a person or a group of people. It can also be used in a number of machine learning applications such as the recommendation systems by identifying new interests of any user and recommending goods that will interest him, in chaotic systems to identify an repeating patterns and in environmental applications that tracks natural phenomena in certain areas and identify any new phenomena that starts to exist.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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