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Conceptual Imitation Learning: An Application to Human-Robot Interaction

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Abstract

In general, imitation is imprecisely used to address different levels of social learning from high level knowledge transfer to low level regeneration of motor commands. However, true imitation is based on abstraction and conceptualization. This paper presents a conceptual approach for imitation learning using feedback cues and interactive training to abstract spatio-temporal demonstrations based on their perceptual and functional characteristics. Abstraction, concept acquisition, and self-organization of proto-symbols are performed through an incremental and gradual learning algorithm. In this algorithm, Hidden Markov Models (HMMs) are used to abstract perceptually similar demonstrations. However, abstract (relational) concepts emerge as a collection of HMMs irregularly scattered in the perceptual space. Performance of the proposed algorithm is evaluated in a human-robot interaction task of imitating signs produced by hand movements. Experimental results show efficiency of our model for concept extraction, symbol emergence, motion pattern recognition, and regeneration.

Keywords: Imitation, Concept Learning, Incremental Learning, Hidden Markov Model.

1. Introduction

Imitation is one of the main methods of social learning. There are also other types of social learning which are somehow similar to imitation like mimicking or sampling, but according to Arbib (2002); Breazeal and Scassellati (2002); Inamura et al. (2004), imitation is discriminated from others by abstraction, conceptualization and symbolization. In fact, perfect imitation is accompanied by comprehension and generalization which are attained by abstraction. Hence, skills can be represented in a generalized symbolic level which is desired for high level cognitive tasks (Billard et al., 2008). In addition, abstraction helps for efficient memory management, handling the huge real world search spaces (Inamura et al.,

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2004), and quick knowledge transfer from an agent to another agent or from a situation to another situation (Kadone and Nakamura, 2006a).

In robotics, imitation is a powerful paradigm (in time or energy) to teach complicated tasks to complex robots like humanoids. In addition, imitation provides a natural and implicit mechanism for training a robot which is a key point in human-robot interaction (HRI). Recently, symbolization and conceptualization has drawn attention in robot learning by imitation (Inamura et al., 2004; Kadone and Nakamura, 2006a; Samejima et al., 2006; Kadone and Nakamura, 2006b; Takano and Nakamura, 2006; Krichmar and Edelman, 2002; Mobahi et al., 2007). However, the majority of previous works are dedicated to form concepts based on similarity in perceptual characteristics, and there is not enough work to find abstract concepts which share functional properties. We think that although perceptual categorization is necessary to abstract demonstrations in imitation, however, there exist skills or knowledge which cannot be transferred merely from perceptual information, like internal intents of the teacher or functional meaning (or effect) of the actions.

In this work, we propose an incremental and gradual learning algorithm for concept acquisition, generalization, recognition and regeneration of spatio-temporal demonstrations. This is an interactive algorithm in which the agent receives reinforcement signal from the teacher. So, it can form concepts based on functional characteristics of demonstrated behaviors. Perceptual abstraction of demonstrations is fulfilled stochastically by Hidden Markov Models (HMMs). However, an abstract (relational) concept is obtained as a collection of HMMs which might represent different perceptual features. Generated HMMs are stored in two different memories, long-term memory (LTM) and Working memory (WM), based on their contents. In the proposed algorithm, the concepts and proto-symbols emerge automatically without explicit human intervention. Also, the algorithm is invariant to the order of incoming demonstrations and acquires the concepts in parallel. Finally, the whole model can make an interface between skill representation in symbolic level and trajectory level which is a significant challenge of integrating discrete symbolic AI planning research and continuous control of robotic systems (Geib et al., 2006). The last note is that the cognitive terms (e.g., LTM and WM) used throughout this paper are based on our previously proposed bio-inspired model for conceptual imitation (Mobahi et al., 2007). However, as the biological counterparts are not presented here, we do not make any claims about the work as a cognitive model.

This paper is organized as follows. Section 2 discusses related works on imitation and abstraction. In section 3, some basics and theories about concepts are reviewed. In addition, conceptual imitation is elaborated, and an approach is introduced to teach a concept oriented agent. Section 4 describes the proposed algorithm for learning and recall phases. In section 5, an experimental scenario is introduced to evaluate performance of the model. Also, results of the experiments, including abstraction, recognition, and generation of concepts are presented in this section. Finally, conclusions are drawn in section 6.

2. Related Works

In the recent years many researchers have addressed the problem of imitation and abstraction. Samejima et al. (2006) proposed an imitation learning model with symbolization of motion patterns. The imitation process was accomplished through a motion recognition and control approach using some controller and predictor modules. However, in the proposed model, abstraction was based on perceptual similarity, and also the sequence of symbols was given to the agent by communication.

Kadone and Nakamura (2006a,b) introduced an incremental algorithm to learn human motion primitives. Their model was able to automatically segment, abstract, memorize, and recognize demonstrated motions, using associative neural networks. However, like previous works, the obtained symbols were categorized based on perceptual information.

HMMs have been extensively used for development of imitation models in the last decade (Inamura et al., 2004; Takano and Nakamura, 2006; Kulic et al., 2008; Billard et al., 2006; Calinon and Billard, 2004; Calinon et al., 2005; Lee et al., 2008). In fact, HMMs have shown the ability for abstraction, generalization, recognition and generation of spatio-temporal signals. They can deal simultaneously with the statistical variations in the dynamics and the statistical variations in the observations. Consequently, HMMs can provide a unified mathematical model for learning from imitation. In the previous research on imitation learning based on HMM, some issues have been proposed and solved gradually. In the early works, demonstrated motions of different behaviors were grouped manually (or clustered offline) and next trained with distinct HMMs in an offline manner. So, the number of HMMs which represented different behaviors was also determined a priori. In addition, the models lacked a mechanism for motion generation through HMMs. However, in the advanced works, algorithms were proposed for incremental and autonomous acquisition and learning of human motions from continuous demonstrations (Kulic et al., 2008, 2007). Furthermore, several methods introduced to generate smooth motions from HMMs (Inamura et al., 2004; Kulic et al., 2008; Billard et al., 2006; Calinon and Billard, 2004; Calinon et al., 2005). For example, Kulic et al. (2008) developed an algorithm for incremental and autonomous learning, symbolization, recognition, clustering and hierarchical organization of whole body motion patterns, using Factorial HMMs. They also provide an algorithm for greedy motion generation. However, in all previous works, abstraction and symbolization are based on similarity in perceptual space, and the proposed approaches cannot tackle with abstract (relational) concepts.

The closest work to ours is proposed by Mobahi et al. (2007, 2005) who introduced a bio-inspired model to acquire abstract relational concepts from imitation, using reinforcement learning. However, unlike our procedure which is suitable for sequence of observations (e.g., human motion), their proposed algorithm is only applicable for concept acquisition from single observations. Moreover, our algorithm makes a stochastic scheme to represent the concepts and also encodes the acquired knowledge into proto-symbols which are more meaningful and informative for both recognition and regeneration.

3. Conceptual Imitation

3.1 Concepts

As the aim of this paper is to extract abstract concepts out of demonstrations, some general basics about concepts are firstly reviewed. According to representational theory of mind, concept is a mental representation of world in agent's mind. It can be an abstract idea, object, or event generally defined as a unit of meaning or knowledge (Zentall et al., 2002). This unit is constructed based on other units which describe some characteristics about the concept. In fact, these physical and/or functional characteristics make principles to categorize perceptions from world into concepts. For concept acquisition in natural environments, three points are desired (Davidsson, 1994). First, concepts should be learned gradually as experience of the agent is increasing during the lifetime. Second, the concepts should be learned in parallel to cope with the diversity in type and order of incoming knowledge. Finally, like any learning procedure, it is very favorable to learn fast. Concepts are categorized into three levels of abstraction, namely, perceptual, relational, and associative (Zentall et al., 2002). Perceptual concepts are formed based on similarity of instances in perceptual space. Relational concepts are formed not only by perceptual similarity but also by external information. However, in associative concepts, physical similarity is not important, but shared functional characteristics of the concepts are influential. An illustration of three types of concepts is provided in Figure 1.

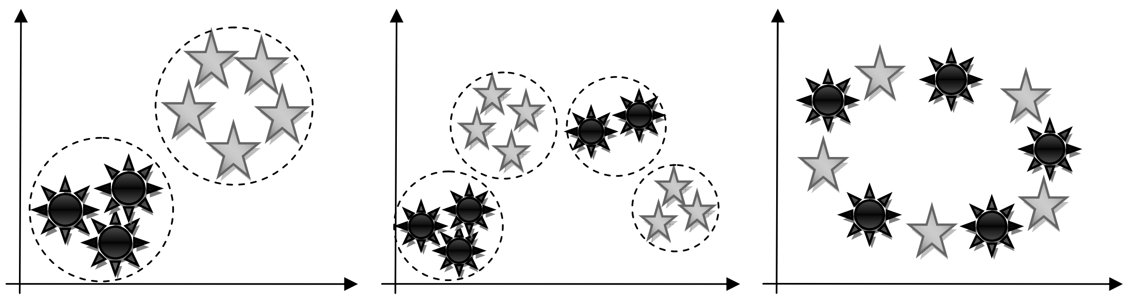

Figure 1: Three types of concepts (from left to right): Perceptual, Relational, and Associative.

An important problem with a concept is how to represent it. Three theories are proposed by Kruschke (2005) to represent the concepts: exemplar, prototype, and rule theories. In exemplar theory, all instances of a concept are memorized. In prototype theory, a summary of instances are derived to represent various instances of a concept. This theory is more abstract and efficient to come up with limitations in memory. Finally, rule theory uses a match/mismatch process or boundary specification to represent concepts.

3.2 Problem Description

In this work, we want to devise an algorithm for autonomous extraction and learning of relational concepts from imitation. In this way, demonstrated spatio-temporal behaviors are abstracted based on similarity in both perceptual and functional space. To this end, we favor to represent concepts by prototypes. Actually, the ideal situation is when we have the least number but the most general prototypes to understand a concept. Consequently, in the face of new demonstrations, the previously learned concepts can be recognized using generated proto-symbols, and there is no need of learning the behavior (motor commands to perform the behavior) from scratch. Also, behaviors which are associated with the same concept can be used alternatively in place of each other according to robot's comfort or affordance.

The real world is full of spatio-tempral experiences with relational concepts. For example, there are several perceptually different behaviors which represent "respect" among people like saluting, removing hat, lowering head, bending down, etc. In fact, all these behaviors have the same meaning (i.e., respect) for the observers. In addition, there might be different actions that make the same effect in the environment. For example, there are different body gestures that make people laugh. In real world, we are facing with instances of these concepts permanently. A robot which is an inhabitant of the human environment will also faces similar experiences during colocation and interaction with the human over its entire lifespan. Hence, there should be an incremental and gradual mechanism to learn and acquire these concepts.

3.3 How to Teach Relational Concepts?

As described in part 3.1, relational concepts cannot form merely from perceptual observations, and external information should be also provided. This information can unify perceptually scattered prototypes which represent the same concept. However, it is interested to have a simple process to transfer external information from the naive teacher to the robot. One solution to this problem is same/different judgment. In this method, the learning agent is exposed to two stimuli. It should decide whether they are associated with the same or different concept. Based on correctness or incorrectness of the answer, the agent receives a reward or punishment signal from the teacher. In this work, a similar approach is used. First, the learning agent observes the teacher's demonstration. In response to the teacher, the agent guesses concept of the demonstrated behavior. Next, it reproduces a behavior which is linked to that concept in its mind. Now, the teacher issues a reward or punishment signal according to correctness or incorrectness of the learning agent's response. In this way, the learning agent gradually develops abstract concepts to increase its reward. Eventually, the agent will be able to correctly classify novel demonstrations of the learned concepts.

4. The Proposed Algorithm

In this algorithm, HMMs are used for abstraction and symbolization of spatio-temporal perceptions. As a result, relational concepts are represented by HMM exemplars and prototypes which might encode different perceptual information but demonstrate the same functional properties. People unfamiliar with HMM should refer to Rabiner (1990). Also, to find the algorithms for motion generation through HMM, one might see Inamura et al. (2004); Kulic et al. (2008); Billard et al. (2006).

4.1 Learning Phase

The learning algorithm is an iterative procedure where a cycle is repeated whenever a new demonstration is perceived. To have better understanding about the learning algorithm, assume we are at the middle of execution where some concepts have been formed, and some prototypes and exemplars have been stored in the agent's memory. In our algorithm, an exemplar is an HMM made up of only one demonstration. However, prototypes are HMMs formed by consolidating perceptually similar exemplars in the memory. Accordingly, we categorize the exemplars and prototypes in two different sets, namely Working Memory (WM) and Long-Term Memory (LTM), respectively. The HMM exemplars and prototypes which are stored in the LTM and WM are associated with symbolic concepts according to the illustration in Figure 2.

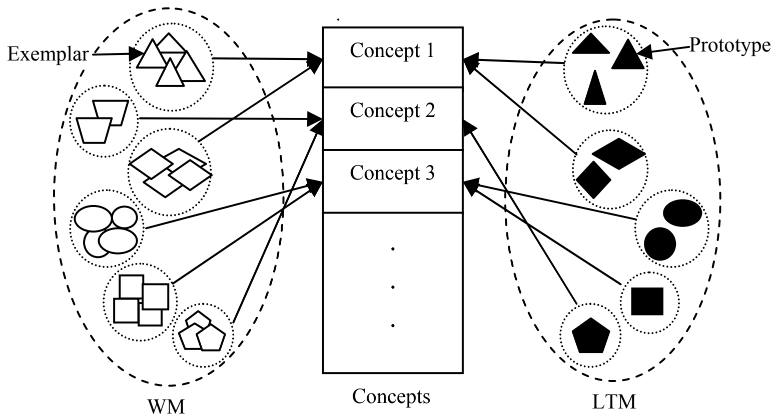

Figure 2: Associative memory of exemplars, prototypes, and concepts.

Now, assume that a novel demonstration is perceived by the robot. First, Likelihood of this perception ($\mathbf{x} = x_1 x_2 \cdots x_T$) is computed against the HMM prototypes in the LTM, using forward algorithm. Next, the HMM prototype with the highest likelihood is considered, and the concept associated with this HMM is selected according to (1) and (2):

$$i = \arg\max_{m \in LTM} P(\mathbf{x}|\lambda_m), \tag{1}$$

$$k = c_i. \tag{2}$$

Where elements of C (e.g., c_i) are simple functions that maps a prototype index (e.g., i) to a concept index (e.g., k). Then, the action for that concept (i.e., y_k) is produced, and reinforcement signal (reward or punishment) from the teacher is received. Now, it is crucial to specify three processes of concept acquisition in the learning algorithm (Schank et al., 1986): when to make a new concept, when to modify a concept, and how to modify a concept. The scheme of these procedures are as follows.

If reinforcement of the teacher is positive (reward) and the likelihood of the catching prototype is high enough, the only thing to do is to strengthen that HMM prototype by the new spatio-temporal perception. In this case, a modified form of re-estimation formulas suited for multiple observation sequences can be used (Rabiner, 1990). The algorithm works by over-weighting HMM prototypes in order to consider the fact that they are built from multiple sequences. To evaluate whether the likelihood is high enough or not, the following criteria is used. If the log likelihood of the absorbing HMM is greater than the minimum log likelihood of that HMM's contents (i.e., perceptions previously encoded in the HMM), the HMM prototype will be appropriate to be updated by the new perception. We call the aforementioned minimum log likelihood value ll_min which is adjusted whenever a new

HMM prototype is generated or modified. Note that if the reinforcement signal is rewarding but the log likelihood of the absorbing HMM is less than ll_min, the perception is encoded as a new HMM exemplar, stored in the WM, and linked to the rewarding concept.

However, if the reinforcement is negative (punishment), the other concepts are tried in an order based on the likelihood of their HMM prototypes in the LTM. Whenever a concept is tried, its index is stored in a set of tried concept indices, namely C_{tired}. This process repeats until the reinforcement signal of the teacher becomes positive. It means that the new demonstration belongs to the concept which receives reward from the teacher. Then the robot modifies this concept exactly the same as explained above, by updating absorbing HMM prototype (if log likelihood is greater than ll_min) or making a new HMM exemplar (if log likelihood is less than ll_min).

After all above, if the new demonstration is associated with none of the concepts which have representations (HMM prototypes) in the LTM, the agent should search in the WM. This is the case when instances of a concept have been observed previously, but they have not been consolidated into HMM prototypes yet. In this case, the likelihood of the new perception is computed against the HMM exemplars associated to the concepts which do not have representations in the LTM (so, they have not been tried yet), using forward algorithm:

$$P\left(\mathbf{x}|\lambda_m\right), m \in WM, c_m \notin C_{tried}. \tag{3}$$

Consequently, the concepts are tried (i.e., their associated actions are produced) in an order based on the likelihood of their HMM exemplars in the WM. If a concept is rewarded, the new perception is encoded into an HMM as an exemplar, stored in the WM, and linked to that concept.

The last case is when all the concepts are tried, but no reward is issued by the teacher. In this case, a new concept is generated. Also, the perceived signal is encoded into an HMM, stored as an exemplar in the WM, and connected to the new concept. In some experiments, it is favourable to have only one motor representation for each concept, for example because of difficulty in generation of motor commands at each demonstration (like our experiment where the robot's inverse kinematics is not known). In this case, we can generate or learn motor programs for a concept whenever a new concept emerges, and store these motor commands or their encoded information in the memory. In this paper, we use motor babbling to generate appropriate motor commands for each concept (cf. 4.2).

Following the procedure explained so far, the WM is overpopulated with exemplars after a short time. So, we must have an abstraction and consolidation mechanism to merge HMM exemplars and make HMM prototypes which are stored in the LTM. For this purpose, whenever an exemplar is stored in the WM of a concept and the number of exemplars associated with that concept exceeds a threshold number (Num_{th}), then a clustering process gets started on both the HMM exemplars and prototypes of that concept. In this work, we use a mechanism similar to the algorithm proposed by Kulic et al. (2008) to cluster HMMs based on the pseudo-distance:

$$D\left(\lambda_1, \lambda_2\right) = \frac{1}{T}\left[\log P\left(O^1|\lambda_1\right) - \log P\left(O^1|\lambda_2\right)\right], \tag{4}$$

where λ_1 and λ_2 are two HMM models, O^1 is an observation sequence generated by λ_1, and T is the length of O^1. Finally a symmetric distance is defined as:

$$D_s = \frac{D(\lambda_1, \lambda_2) + D(\lambda_2, \lambda_1)}{2}. \tag{5}$$

Now that the distances between HMMs are specified, an agglomerative algorithm which performs a complete link hierarchical clustering is used to construct new prototypes. Final clusters are selected based on two criteria, i.e., surpassing the minimum number of elements and falling behind the maximum distance measure. Maximum distance measure is defined according to mean and standard deviation of the distances between all the HMMs in the concept:

$$D_{cutoff} = \mu - K_{cutoff} \cdot \sigma. \tag{6}$$

After this operation, if new clusters are produced, corresponding HMM prototypes are trained with their associated elements in the clusters, using Baum-Welch algorithm or modified re-estimation formulas explained before. These consolidated prototypes are stored in the LTM. Pseudocode for concept learning algorithm is provided in Figure 3. In the pseudocode, New_L, New_W, and New_C are functions to make new prototypes, exemplars, and concepts.

4.2 Motor Babbling

As demonstrations are perceived by the robot's visual system, these perceptual motion trajectories or the generalized motion patterns generated by HMMs should be transformed to motor space for imitation. To this end, we should use a mechanism for hand-eye coordination. If inverse kinematics of the robot is given, it can be simply used to make motor programs; otherwise (e.g., for the robotic marionette in our experiment), it should be learned. It is known that this knowledge is acquired by human (during infancy) for a large part through motor babbling. Actually, infants try to learn sensory-motor system of their body by performing random primitive movements and following those with interesting effects. So, for the purpose of hand-eye coordination by motor babbling we use the algorithm introduced by Ajallooeian et al. (2009a). This algorithm is summarized as follows. First, a number of temporary goals are determined on the visual path of the teaching trajectory. Robot starts with an initial joint configuration and makes small perturbations in its joint variables. In this way, the end-effectors sweep all the temporary goals gradually. Next, the visuomotor information at temporary goals is piled up and a mapping form sensory space to motor space is learned with a feedforward neural network. For more details, the reader is referred to Ajallooeian et al. (2009a).

4.3 Recall Phase

In the recall phase, there is no more external information by the teacher. So, the robot should use the acquired knowledge in the learning phase to classify concept of each novel demonstration and produce appropriate motor actions to realize that concept. For this purpose, HMM prototypes in the LTM are used. So, the likelihood of the perceived motion patterns against HMM prototypes is obtained through forward algorithm. Next, HMM

1: x:= **Sense**()
2: $C_{tried} = \phi$
3: $i := \underset{m \in LTM\ ,\, c_m \notin C_{tried}}{ArgMax} P(\mathrm{x}|\lambda_m)$
4: **if** (i is not null)
5: $k := c_i$, $\mathrm{y} = \mathrm{y}_{\mathrm{k}}$, $C_{tried} = C_{tried} \cup c_i$
6: **Perform** (y)
7: R := Get_Reinforcement()
8: **if** ($R > 0, \log P(\mathrm{x} \mid \lambda_i) \geq ll\_min_i$)
9: update λ_i with x
10: **else if** ($R > 0, \log P(\mathrm{x} \mid \lambda_i) < ll\_min_i$)
11: $p :=$ **New_W**(), $c_p := k$
12: **Try_Clustering** (k)
13: **else if** ($R < 0$)
14: go to line 3 and repeat the steps
15: **else if** (i is null)
16: $j := \underset{m \in WM\ ,\, c_m \notin C_{tried}}{ArgMax} P(\mathrm{x}|\lambda_m)$
17: **if** (j is not null)
18: $k := c_j$, $\mathrm{y} = \mathrm{y}_{\mathrm{k}}$, $C_{tried} = C_{tried} \cup c_j$
19: **Perform** (y)
20: R := **Get_Reinforcement**()
21: **if** ($R > 0$)
22: $p :=$ **New_W**(), $c_p := k$
23: **Try_Clustering** (k)
24: **else if** ($R < 0$)
25: go to line 16 and repeat the steps
26: **else if** (j is null)
27: find y^* through babbling such that Perform(y^*)=x
28: $p :=$ **New_W**(), $q :=$ **New_C**(), $c_p := q$, $y_q := y^*$

Try_Clustering(k)
1: **if** (number of exemplars linked to $k > Num_{th}$)
2: cluster the elements linked to concept k
3: **for** clusters satisfying criteria for making new prototypes
4: $p :=$ **New_L**(), $c_p := k$

Figure 3: Psuedocode of the concept learning algorithm for each demonstration.

with the largest likelihood is chosen, and eventually, the observed motion is recognized as one of the learned concepts by selecting the concept associated with this HMM. Now, the generalized motion pattern is generated by the selected HMM and transform into motor commands through motor babbling. However, if the motor program of each concept (or its encoded representation) is stored in the memory during learning phase, this information can be used to retrieve appropriate motor commands. Finally, the robot uses these motor commands to realize the concept. The last note is that if there is no prototype in the robot's LTM (e.g., because of immature learning), the robot employs the aforementioned process on the HMMs in the WM.

5. Experimental Studies

To test the proposed algorithm for imitation learning in a human-robot interaction task, we set up an experiment which might be called conceptual hand gesture imitation. In this experiment, five people are asked to draw six signs by moving their hands in the air. Signs are "Heart", "Rectangle", "Infinity", "Tick", "Arc", and "Eight". The subjects can freely start hand movements from any point, but they have to keep their hand in the view field of the robot's camera. Each sign might be produced with different types of hand trajectories. For example, one subject might sketch the Tick sign from left to right and another one from right to left, but the meaning of both sketches is the same for the subjects. In our experiment, we have one type of perceptual representation for the signs Rectangle and Infinity but two representations for each remaining sign. These demonstrations are incrementally provided to the robot. Samples of demonstrated hand motion patterns are provided in Figure 4.

Figure 4: Samples of demonstrated signs by the subjects.

The robot is a robotic marionette controlled by 8 servo motors that pull the attached strings. The teacher uses same/different judgment explained in section 3 to provide external information for the robot. More precisely, the teacher issues a rewarding signal if his demonstrated action and the robot's response have the same meaning for the teacher, and a punishing signal if they do not have the same meaning. As previously noted, in our experiment different perceptual representation of hand trajectories pertaining to one sign have the same meaning for the teacher. Hence, each sign is considered as a distinctive concept which might have irregularly scattered representations in the robot's visual space. The robot should understand that these perceptions belong to one concept and imitate that concept. Note that this problem can be simply solved if we find the overall hand movement, take it as a complete shape, and use algorithms for shape classification (Ajallooeian et al., 2009b). However, instead, we are interested to use sequence of hand movements as perceptual data. The first reason is to define an experiment to evaluate our conceptual imitation model which is suited for relational concepts. The second reason is that tracking hand movement can help to use dynamics of incoming samples in the waveform of a trajectory to identify the gesture faster and more confidently.

5.1 Hand Detection and Tracking

For hand detection, we use a saliency based model of visual attention. It is a biologically inspired bottom-up model proposed by Itti et al. (1998). In this model the image is filtered and subsampled to make a Gaussian pyramid. The pyramid levels are decomposed into channels from which feature maps are constructed. Accordingly, this model can be used to select specific objects by weighting feature channels. Details of image processing and saliency operations for hand motion extraction from video are described by Ajallooeian et al. (2009b). In this study, we also take advantage of Kalman filtering to track the hand motion path (Emanuele and Alessandro, 1998). Therefore, more accurate and smoother trajectory is achieved for hand.

5.2 Results

The experiment was conducted in a natural room environment, i.e., no artificial background or other simplifications were used. Perceptions are visual information derived from video frames of demonstrations. Hand motion path is extracted through visual attention model in part 5.1. Finally, trajectory of changes in the hand location specified in the camera coordinate is considered as the input to the learning algorithm. It means that the task space is selected as the relative displacement in the hand trajectory. So, the perception is invariant to the translations in the camera coordinate. Total number of demonstrations in this experiment was 210, including 43 demonstrations for Heart (22 for type 1 and 21 for type 2), 23 demonstrations for Rectangle, 20 demonstrations for Infinity, 42 demonstrations for Tick (21 for each type), 42 demonstrations for Arc (21 for each type), and 40 demonstrations for Eight (20 for each type). We employed our proposed algorithm to learn the concept of demonstrated hand gestures. In the concept learning algorithm, we chose $K_{cutoff} = 0.5$, $Num_{th} = 3$, and the number of states for HMMs was set to 10. For initializing state distribution of HMMs (i.e., mean and covariance of the state), a rough clustering of the data is performed, and then a Gaussian Mixture Model (GMM) is estimated by Expectation Maximization (EM), using the k-means clusters at initialization. Minimum number of elements to form a new cluster (HMM prototype) was set based on the following rule. There should be at least one prototype and one exemplar or three exemplars in a candidate cluster to make a new prototype. We used k-fold cross validation with $k = 5$ to evaluate the performance of our algorithm for abstraction and recognition of the concepts. So, the experiment was repeated five times with different combinations of demonstrations for training and test.

Results of this experiment are summarized as follows. The reinforcement (average of five experiments) of the teacher over the learning procedure on the training data is illustrated in Figure 5. More accurately, this plot shows the first reinforcement of the teacher for each incoming demonstration. Note that due to the discrete nature of reinforcement (1 for reward, and -1 for punishment), the result in the figure is smoothed with a window length of 10 to clearly reflect the expected behavior. The reason that reinforcement is falling at the first demonstrations is that there are not enough prototypes in the LTM at the beginning. However, after a while, all concepts are perceived for at least one time. From this moment, number of exemplars for the concepts is getting increased by each new demonstration. Hence, consolidation is performed more efficiently, and consequently more informative prototypes are produced.

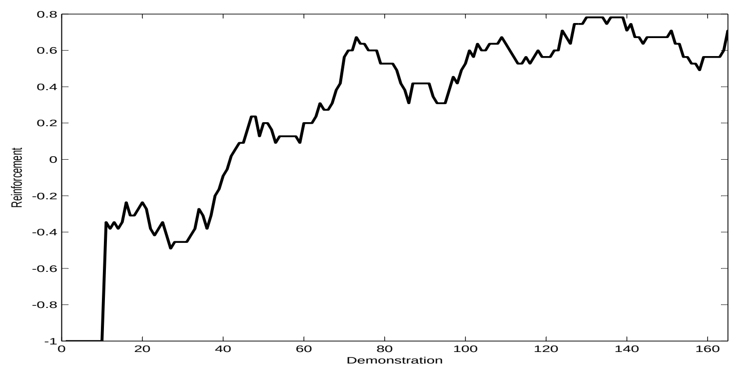

Figure 5: Reinforcement over demonstrations.

Figure 6 shows the average smoothed size of the WM and the LTM during learning. Number of HMM prototypes produced at the end of the learning process of each experiment is listed in Table 1. In most cases, the algorithm finds the same number of HMM prototypes as the number of types which perceptually represent each sign. In all, however, there are always one or two prototypes more than what is expected. For example, in the first experiment, three prototypes emerge for the Eight sign, but there are two types of perceptual representation for that in the task. This outcome is because of the fact that the features making perceptions out of demonstrations are not scale invariant, but the subjects can freely sketch the signs. We also illustrate the proto-symbol space of HMMs (Takano and Nakamura, 2006) for the fifth experiment in Figure 7. This space is constructed based on distances between all pairs of HMM prototypes and classical multidimensional scaling method (Seber, 1984). Distance between each pair of HMMs is obtained according to (6). In Figure 7, the first and second principal coordinates of multidimensional scaling are used to visualize dissimilarity of HMMs in the proto-symbol space.

To summarize performance of our proposed method, recognition accuracy of the algorithm for classifying the concepts in the test data is provided in Table 2. This table also shows some statistics about the number of generated exemplars and prototypes in the WM and the LTM. In addition, Table 3 demonstrates the average confusion matrix for this experiment. Finally, an example of signs (Infinity) produced by the robotic marionette through babbling algorithm for hand-eye coordination is demonstrated in Figure 8.

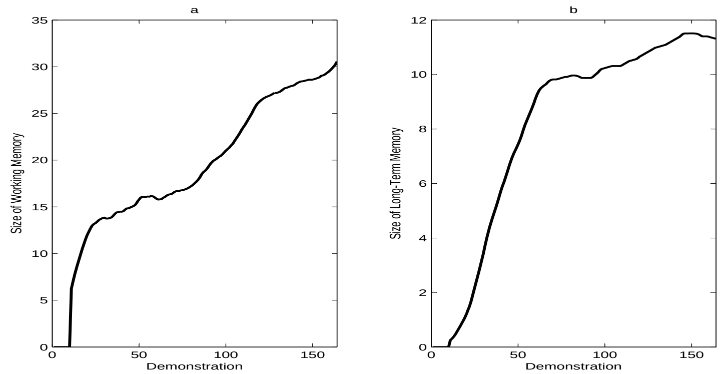

Figure 6: Load in (a) working and (b) long term memory.

Experiment no.	Heart	Rectangle	Infinity	Tick	Arc	Eight	Total
1	2	1	1	2	2	3	11
2	2	2	1	3	2	2	12
3	3	1	2	2	2	2	12
4	2	1	2	2	2	2	11
5	2	1	2	2	2	2	11

Table 1: Number of HMM Prototypes Generated for each Concept

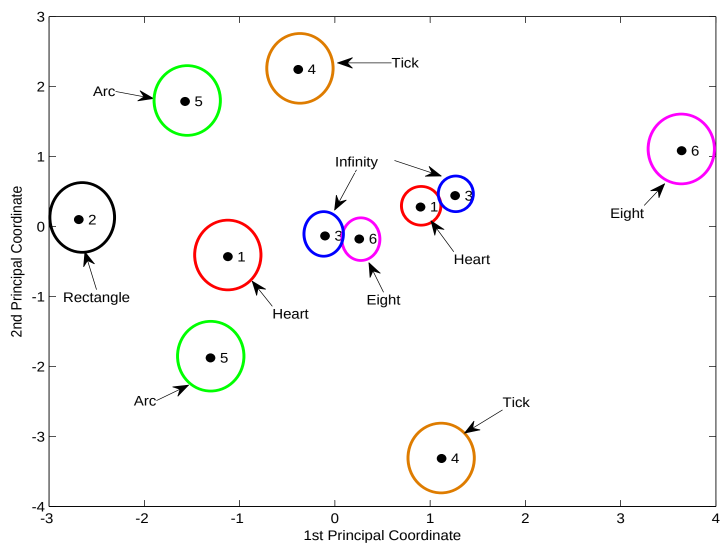

Figure 7: Proto symbol space of HMMs in the LTM for the fifth experiment.

Accuracy		Size of WM		Size of LM	
Mean %	Std %	Mean	Std	Mean	Std
88.30	4.78	32.40	8.73	11.40	0.55

Table 2: Statistical Information for the experiment with 5-fold cross validation

Concept	Heart	Rectangle	Infinity	Tick	Arc	Eight
Heart	97.50	0.00	0.00	0.00	0.00	2.50
Rectangle	5.00	87.00	4.00	0.00	0.00	4.00
Infinity	15.00	0.00	80.00	0.00	0.00	5.00
Tick	2.22	0.00	0.00	97.78	0.00	0.00
Arc	6.94	6.67	11.67	0.00	72.50	2.22
Eight	5.00	0.00	0.00	0.00	0.00	95.00

Table 3: Average Confusion Matrix for the experiment with 5-fold cross validation

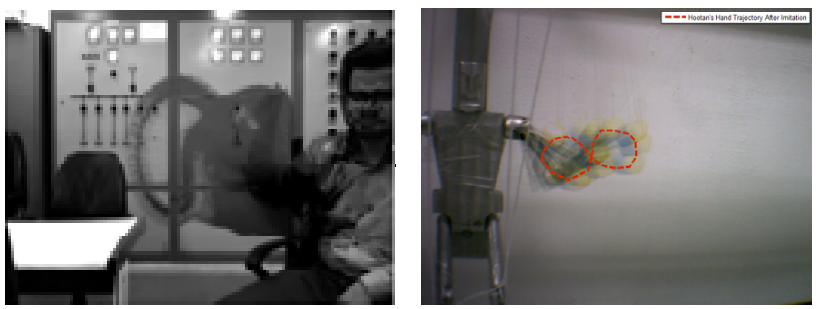

Figure 8: An example of hand-eye coordination with the robot.

6. Conclusion

In this study, we introduced a model for conceptual imitation. The main contribution was to devise an incremental and gradual learning algorithm for autonomous learning and acquisition of relational concepts from demonstrations, using reinforcement signals and interactive teaching. HMMs were used to abstract spatio-temporal demonstrations into stochastic perceptual prototypes and exemplars. Consequently, relational concepts formed as a collection of irregularly scattered HMMs unified based on their functional properties. This abstraction leads to efficient memory management, generalization of acquired information, ease of knowledge transfer, and flexibility of choice between different alternatives. Finally, we evaluated the algorithm in an experimental scenario, namely conceptual hand gesture imitation. The experiment was conducted on a robotic marionette. Results showed that our algorithm is successful for acquisition of concepts, emergence and self-organization of prototypes, recognition, and regeneration of conceptual behaviors.

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