Proto-Symbol Development and Manipulation in the Geometry of Stochastic Model for Motion Generation and Recognition

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Abstract. Humans' primitive skill of imitative learning is regarded as an origin of human intelligence because it is said that imitation is fundamental function for communication and symbol manipulation. He have proposed "mimesis model" in order to approach to a symbol emergence framework from behavior recognition/generation for humanoid robots. This "mimesis model" is able to abstract observed others' behaviors into proto-symbols, to recognize others' behavior using the proto-symbols, and to generate motion patterns using the proto-symbols based on a stochastic model. In this paper, we extend the mimesis model to geometric proto-symbol space which contains relative distance information among proto-symbols. We also discuss how to generate complex behavior by geometric proto-symbol manipulation, and how to recognize novel behavior using combination of the proto-symbols.

1 Introduction

Recently, the human behavioral science and the human intelligence have become conspicuous as a real research issue of robotics. Although the motivation of the artificial intelligence originated there, the physical limitations have forced or justified the researchers to carry on their research in a limited scope and scale of complexity. It ought to be the major challenge of contemporary robotics to study robotic behaviors and intelligence in the full scale of complexity mutually sharing research outcomes and hypotheses with the human behavioral science and human intelligence.

The discovery of mirror neurons[1] have been a notable topic of brain science which have been found in primates' brain and humans' brain, fire when the subject observes a specific behavior and also fire when the subject start to act the same behavior. Furthermore, it is located on Broka's area which has close relationship between language management. The fact suggests that the behavior recognition process and behavior generation process are combined as the same information processing scheme, and the scheme is nothing but a core engine of symbol manipulation ability. Indeed, in Donald's "Mimesis Theory"[2] [3], it is said that symbol manipulation and communication ability are founded on the behavior imitation, that is integration of behavior recognition and generation. We believe that a paradigm can be proposed taking advantage of the mirror neurons, with considerations of Deacon's contention[4] that the language and brain had evolved each other.

So far, we have proposed a mathematical model that abstracts the whole body motions as symbols, generates motion patterns from the symbols, and distinguishes motion patterns based on the symbols. In other words, it is a functional realization of the mirror neurons and the mimesis theory. For the integration of abstract, recognition and generation, the hidden Markov model (HMM) is used. One as observer would view a motion pattern of the other as the performer, the observer acquires a symbol of the motion pattern. He recognizes similar motion patterns and even generates it by himself. One HMM is assigned for a kind of behavior. We call the HMM as symbol representation.

Symbols are required to represent similarity or distance between each symbol. An example application is symbol manipulation based on the similarity or distance information. However, our conventional method have no way to represent similarity of relationship between each behavior. Therefore, in this paper, we extend the mimesis model to geometric symbol space which contains relative distance information among symbols. We also discuss how to generate complex behavior by geometric symbol manipulation in the symbol space, and how to recognize novel behavior using combination of symbols by known symbols.

2 Hierarchical Mimesis Model

2.1 Usual mimesis models and its defects

Figure 1 shows the configuration of usual mimesis models[5] [6]. The model consists of three processing; perception part, generation part and development part. In the perception part, observed motion patterns are analyzed into basic motion elements. Motion elements are low level physical parameter for short period of time, like joint angle, angular velocity or torque. Others' motion are represented by the sequence of the element, then the dynamics in the motion is abstracted as symbol representations, namely HMMs. We have call such symbol representation as "proto-symbols".

Here, one defect arises that the relationship between two similar behavior have been lost when the behavior transfered into proto-symbols. An aspect of the symbol is that semantic relation exists among symbols, contrary to the icons and labels which have no relation representation between each elements. To solve this defect, a hierarchy structure is needed in which the relation in the lower motion pattern layer will be kept in the higher symbol layer. We call such structure as "Hierarchical Mimesis Model". In following sections, we introduce an mathematical framework for the Hierarchical Mimesis Model.

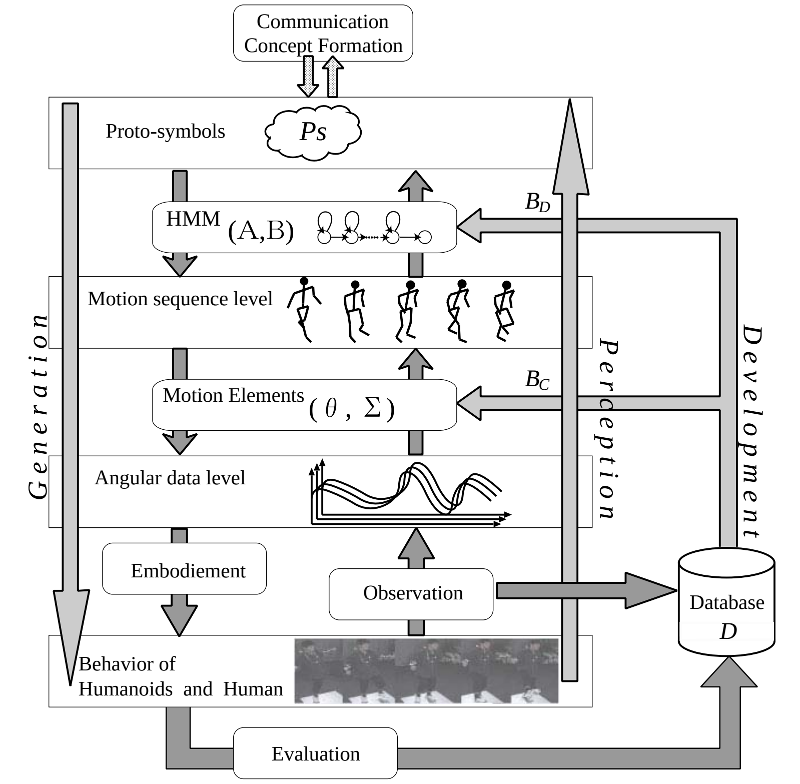


Fig. 1. Outline of Usual Mimesis Models

2.2 Hierarchical Mimesis Models

To construct such a hierarchical model, the mathematical framework ought to be had an ability to treat distance relationship between each behavior and symbol, and to structure the hierarchic. An conceptual image of such heirarchical mimesis model is shown in Fig.2. In the model, each proto-symbol is represented by continuous vector, that is, continuous proto-symbol space exists above the low level behavior pattern. Using the proto-symbol space, human's long term behavior are transfered into trajectory in the space. We can also abstract the trajectory as a symbol-like representation using the same HMM. In other words, hierarchical abstract framework can be established easily based on the HMM. Continous HMM is the adequate way to realize such a hierarchical structure.

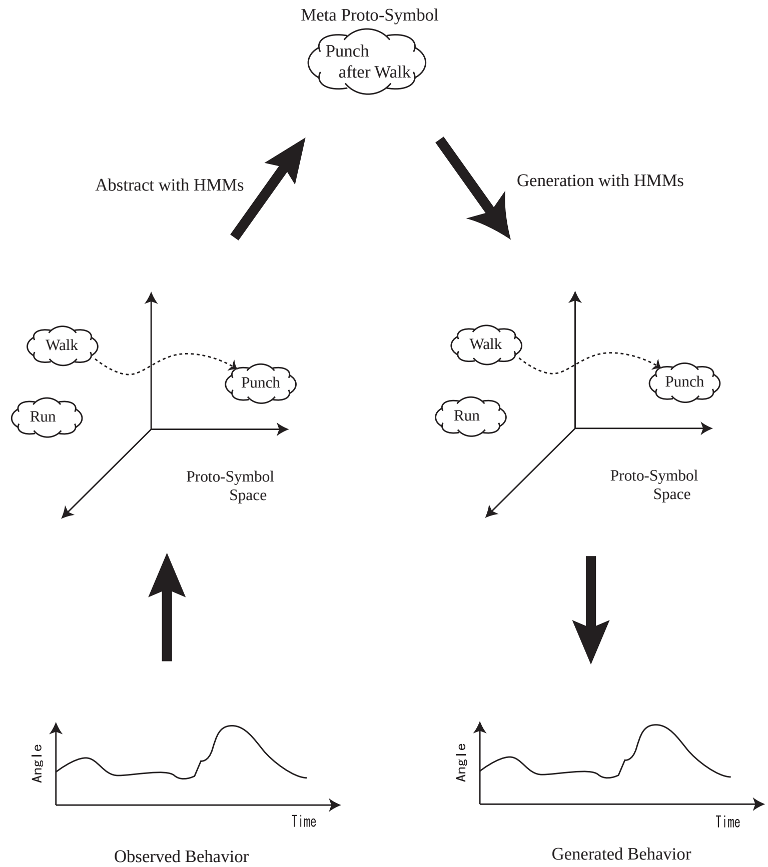


Fig. 2. Outline of Hierarchical Mimesis Model

3 Construction of hierarchical proto-symbol space

3.1 Continuous HMMs and humanoids' motion

We focused on Hidden Markov Models (HMMs) as mathematical backbone for such an integration. HMMs are one of stochastic processes which takes time series data as an input, then outputs a probability that the data is generated by the model. HMMs is most famous tool as a recognition method for time series data, especially in speech recognition field. HMMs consist of a finite set of states $\boldsymbol{Q} = \{q_1, \ldots, q_N\}$, a finite set of output vectors $\boldsymbol{S} = \{o_1, \ldots, o_M\}$, a state transition probability matrix $\boldsymbol{A} = \{a_{ij}\}$ (the probability of state transition from q_i to q_j), an output probability matrix $\boldsymbol{B} = \{b_{ij}\}$, and an initial distribution vector $\boldsymbol{\pi} = \{\pi_i\}$, that is a set of parameter $\boldsymbol{\lambda} = \{\boldsymbol{Q}, \boldsymbol{S}, \boldsymbol{A}, \boldsymbol{B}, \boldsymbol{\pi}\}$. In this framework, state transition and output processes

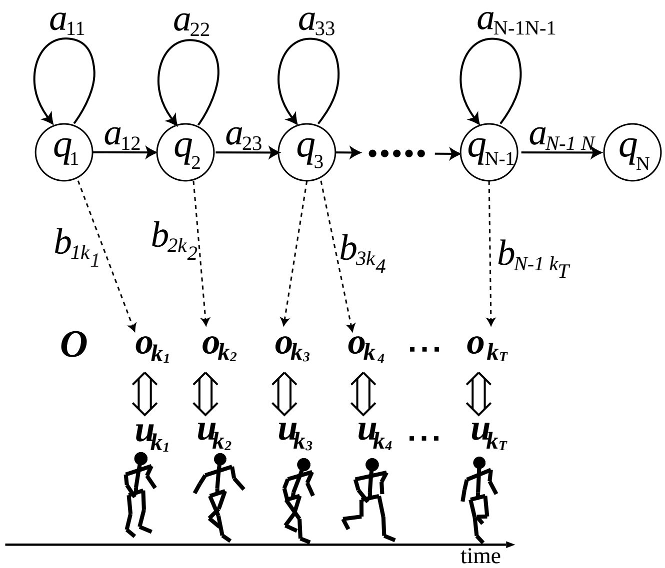


Fig. 3. Discrete Hidden Markov Models and Humanoids' Motion

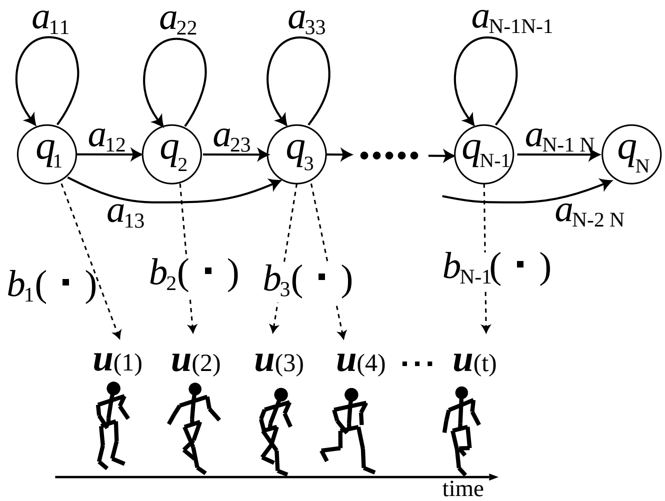


Fig. 4. Continuous Hidden Markov Models and Humanoids' Motion

are performed probabilistically, then sequence of vectors are output during the transition as shown in Fig.3. The vector may be a discrete label, or be a vector. In the case of label, the HMMs are called as discrete HMMs

(DHMMs). In another case of vector, the HMMs are called as continuous HMMs (CHMMs) as shown in Fig.4.

3.2 Definition of distance between HMMs

Through distance is needed for construction of space, distance between two HMMs is not able to be defined easily because it is stochastic model. For such stochastic modes, there is a method in order to express the distance information. In this paper, we adopt Kullback-Leibler information as the representation of distance between HMMs. To say strictly, the Kullback-Leibler information is not distance because it does not satisfy the property of the distance; triangle inequality and symmetry, therefore we call the Kullback-Leibler information as degree of similarity of the HMMs. The Kullback-Leibler information against two stochastic models p_1 and p_2 is defined as follows.

$$D(p_1, p_2) = \int_{-\infty}^{\infty} \left(p_1(x) \log \frac{p_1(x)}{p_2(x)} \right) dx \tag{1}$$

To apply the Eq.(1) to HMMs, following equation is usually used[7] .

$$D\left(\lambda_1, \lambda_2\right) = \sum_n \frac{1}{T_n} \left[\log P(y_1^T | \lambda_1) - \log P(y_1^T | \lambda_2) \right] \tag{2}$$

As the Eq.(2) does not satisfy the distance axiom, we use following improved information:

$$Ds(\lambda_1, \lambda_2) = \frac{1}{2} \left(D\left(\lambda_1, \lambda_2\right) + D\left(\lambda_2, \lambda_1\right) \right) \tag{3}$$

3.3 Construction of space based on similarity

In order to construct proto-symbol space from the distance information, multidimensional scaling (MDS) is used. MDS is a method that accepts distance information among elements and outputs position of each element in the generated space. Let the similarity between i-th element and j-th element as f_{ij}, the distance between i-th and j-th element as d_{ij}. MDS makes the following error to be minimum for the space construction.

$$S^2 = \sum_{i,j} (f_{ij} - d_{ij})^2 \tag{4}$$

In the case of HMMs, Kullback-Leibler information Ds is used for the similarity f_{ij}. Let the position of each HMMs as $\boldsymbol{x} = \{x_1, x_2, \ldots, x_n\}$ where n is the number of dimension of the space. Using least-squares method, each position $\boldsymbol{x}$ is calculated.

We confirmed the performance of the proposed space construction method against six kinds of motion shown in Fig.7. At first, we gave 10 dimensional vector for each $\{x_1, x_2, \ldots, x_n\}$. Figure 5 shows the constructed space and

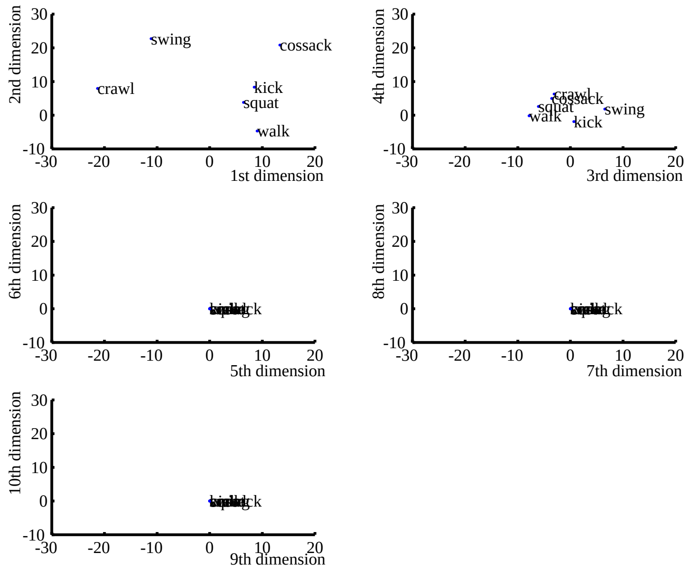


Fig. 5. Result of proto-symbol space construction

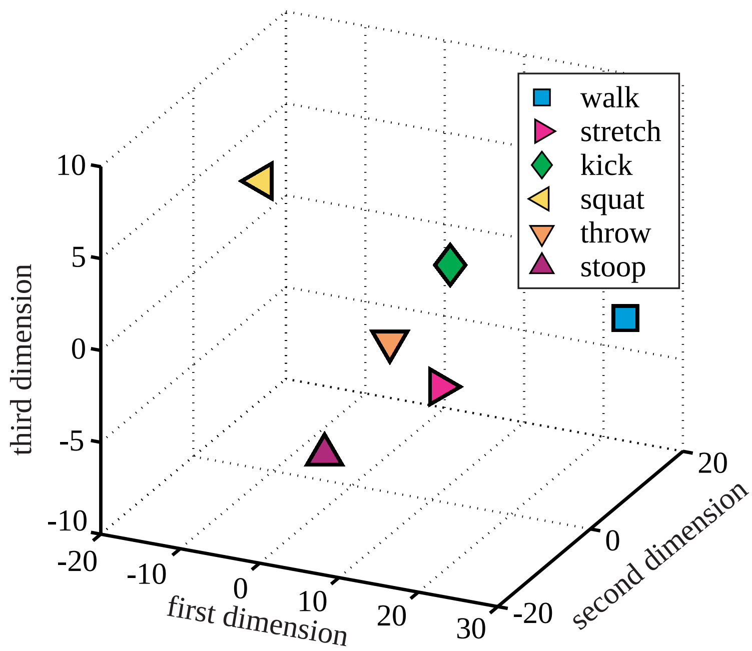


Fig. 6. Six motions in 3D proto-symbol space

(a)
(b)
(c)
(d)
(e)
(f)

Fig. 7. Six motions performed by human: (a) walk, (b) stretch, (c) kick, (d) squat, (e) throw and (f) stoop.

location of each proto-symbol (HMM). As the diagram indicates, from first to fourth dimensions are effectively used for the space construction, however, the rest of the dimension are not well used. Therefore, we adopted three dimensional proto-symbol space as shown in Fig.6.

4 Behavior Manipulation by Proto-symbol Manipulation

4.1 proto-symbol manipulation

In this paper, symbol manipulation is defined as following:

- Generation of novel behavior using known basic motions
- Recognition of novel behavior using known basic motions
- Abstract of novel behavior using know basic motions

From the view point on the proto-symbol space, above definitions can be interpreted as followings:

- Generation: creating a novel state point and motions using existing state point of proto-symbols.
- Recognition: recognize a novel sequence of state point, using existing state point of proto-symbols.
- Abstract: abstract of a novel sequence of state point into meta-proto-symbol.

A mutual conversion method between motion patterns and symbol representation in proto-symbol space have been established up to the previous section. In this section, proto-symbol manipulation method where generation and recognition of novel motion are defined by simple structure.

4.2 Generation of novel proto-symbol

Conventional motion generation

We have proposed a motion generation method using HMMs[8]. In this method, a sequence of joint angle vectors are generated from a HMM, then it is transformed into behavior pattern of a humanoid robot.

Figure 8 shows the generation result from six proto-symbols computed by human's performance shown in Fig.7. Each generated motion and original motion have similarities. This result shows the effectiveness of the conventional method, however, the method has limitation that generated motions are alwalys static within the bounds of known proto-symbols.

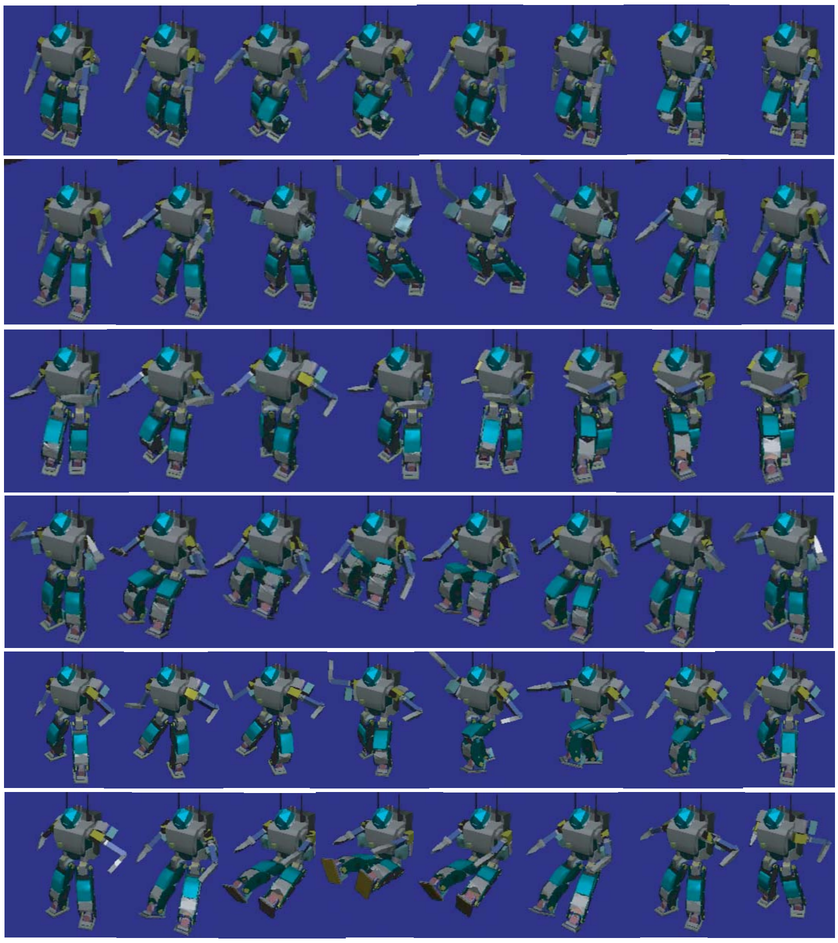
Novel motion generation using the proto-symbol space

Generation of a novel motion is equal to create a novel proto-symbol, that is, a state point on the proto-symbol space as combination of existing proto-symbols. To compute a novel state point from existing proto-symbols, the following composition regulation is used:

$$\begin{aligned} b_i(\boldsymbol{o}) = &\sum_{m=1}^{M} \alpha c_{im_A} N(\boldsymbol{\mu}_{im_A}, \boldsymbol{\sigma}^2_{im_A}) \\ &+ \sum_{m=1}^{M} (1-\alpha) c_{im_B} N(\boldsymbol{\mu}_{im_B}, \boldsymbol{\sigma}^2_{im_B}) \end{aligned} \tag{5}$$

$$a_{ij} = \alpha a_{ij_A} + (1-\alpha) a_{ij_B} \tag{6}$$

Eq.(5) and Eq.(6) is applied when a novel state point is located on a straight line connecting the two points (λ_A and λ_B). When a novel state point doesn't fall on any straight lines connecting existing proto-symbols, the parameter is



(a) (b) (c) (d) (e) (f)

Fig. 8. Six motions imitated by humanoid. Each motion from (a) to (f) is corresponds to each motion in Fig.7

composed according to the distance ratio among each known proto-symbol as follows:

$$
\begin{aligned}
b_i(\boldsymbol{y}) &= \sum_{m=1}^{M} \frac{1}{d_l \sum_l \frac{1}{d_l}} cN(\boldsymbol{\mu}_{im}^l, {\boldsymbol{\rho}_{im}^l}^2) \\
a_{ij} &= \sum_{m=1}^{M} \frac{1}{d_l \sum_l \frac{1}{d_l}} a_{ij}^l
\end{aligned} \tag{7}
$$

where d_l is the distance between a novel state point and known proto-symbol λ_l. Finally, law-level motion pattern is generated from the state point, using the method proposed in the paper[8].

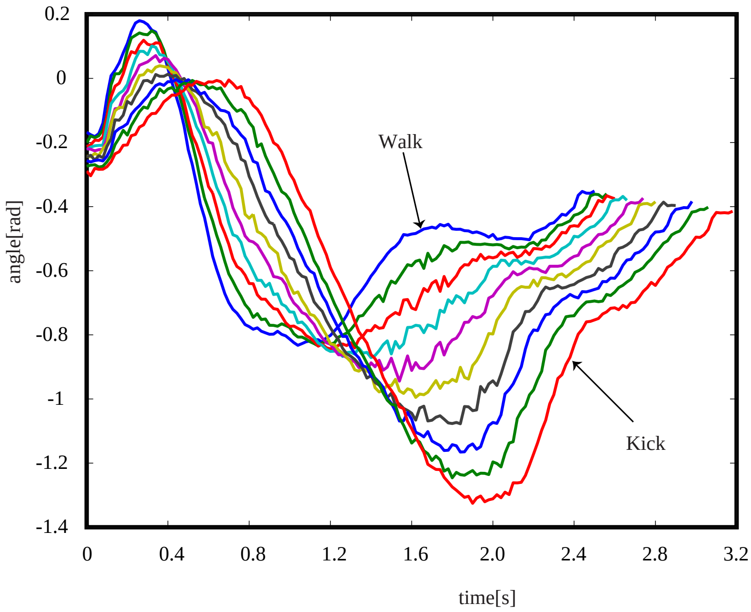


Fig. 9. Generated motion from a mixed HMM based on Eq.5 and Eq.6.

Figure 9 shows the result of motion generation by combination of walk and kick. The lines labeled as “walk” and “kick” correspond to normal generation. Eight lines between the “walk” and “kick” mean synthesis motion with changing the composition parameter α from 0.1 to 0.9. The result shows the effectiveness of composition strategy because the synthesis motion has a similarity to the morphing.

Novel motion generation from state sequence in proto-symbol space Furthermore, motion generation can be performed against the state transition sequence in the proto-symbol space. In this paragraph, a motion generation method in which a state transition sequence have been given.

Let be the state transition as $\boldsymbol{x}[1], \boldsymbol{x}[2], \ldots, \boldsymbol{x}[n]$. As a generation method in which a fixed state point is given in the proto-symbol space is introduced before, the continuous generation by transitional state points is equivalent to the average of motions which generated by those state points.

Figure 10 shows the outline of the generation process.

In step 1, motion patters are generated from each state point in the proto-symbol space using the proposed method[8]. In step 2, the time length of all motion patterns are set to the same value T_c in order to composition. In step 3 and 4, partial motion patterns are picked up based on the phase information

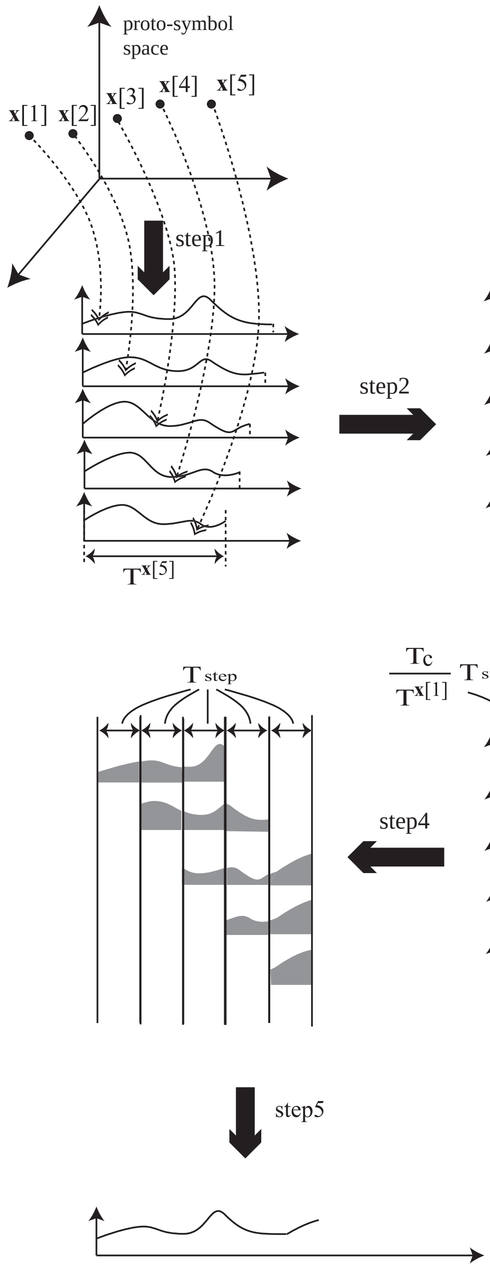


Fig. 10. Outline of motion generation from a sequence of state points

for each state point, that is, charging period of time for each state point. Finally in step 5, composite motion pattern are generated.

4.3 Recognition of novel motion based on proto-symbol manipulation

Novel motion recognition using the proto-symbol space
The recognition based on proto-symbol space is equivalent to compute a state point in the proto-symbol space. After the computation, the relationship between proto-symbols bring about the symbol representation of the novel motion.

Difference between observed motion $\boldsymbol{O}$ and each proto-symbol is represented as the likelihood $P(\boldsymbol{O}|\lambda_i)$. To convert the likelihood into distance information, the following equation

$$D(\lambda_k, \lambda_i) = \sum \frac{1}{T}\left(\log P(\boldsymbol{o}_k^T|\boldsymbol{\lambda_k}) - \log P(\boldsymbol{o}_k^T|\boldsymbol{\lambda_i})\right) \tag{8}$$

are used, however, the $P(\boldsymbol{O}|\lambda_{\boldsymbol{O}})$ is not able to be computed before the learning of the HMM $\lambda_{\boldsymbol{O}}$. Here, we introduce an approximation for the $P(\boldsymbol{O}|\lambda_{\boldsymbol{O}})$.

Table 1 shows the logarithm of the likelihood for each motion and proto-symbol. Diagonal values indicate about from 5 to 20, however, the rest show a very little value. According to the result, we had an assumption that a novel behavior also follows above empirical rule that,

$$\log P(\boldsymbol{O}|\boldsymbol{\lambda_O}) = 20. \tag{9}$$

Table 1. Likelihood of observed motion pattern for each proto-symbols

Observed Behavior	Proto-symbol					
	walk	stretch	kick	squat	throw	stoop
walk	15.00	-11609	-3978	-4501	-5471	-6736
stretch	-12833	19.03	-9329	-7864	-5985	-10126
kick	-4526	-9605	13.41	-2901	4985	4312
squat	-6624	-9248	-3239	7.05	-8278	-2021
throw	-8810	-6433	-7762	-9339	18.86	-13469
stoop	-8573	-10776	-4498	-1021	-10944	5.49

Novel motion recognition as state sequence in proto-symbol space
The outline of novel motion recognition as state sequence in the proto-symbol space is shown if Fig.11

In step 1, focusing on the period of time T_{span} in the observed motion pattern $\boldsymbol{O} = \begin{bmatrix}\boldsymbol{o}_1 & \boldsymbol{o}_2 & \cdots & \boldsymbol{o}_T\end{bmatrix}$. Let the cut off motion pattern be $\boldsymbol{O}_1 =$

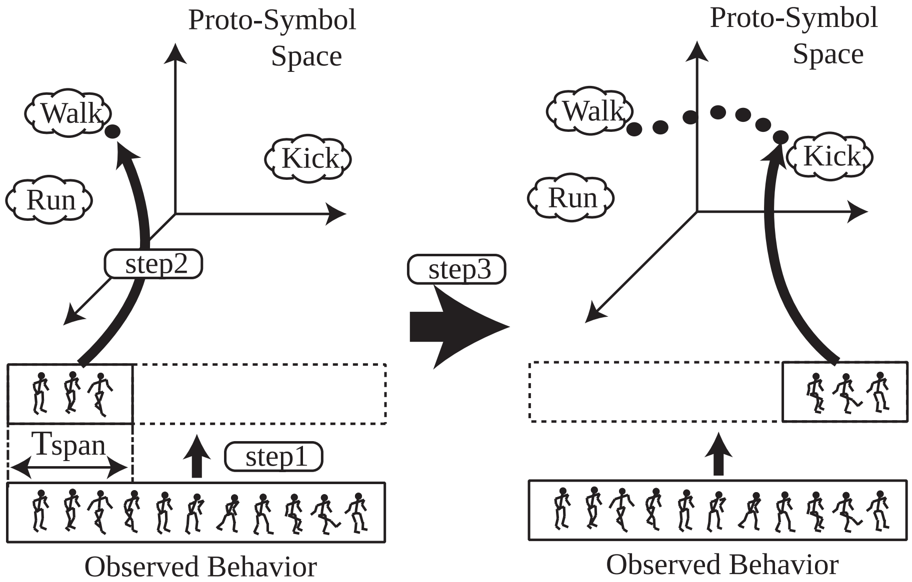


Fig. 11. Procedure of motion projecting in the proto-symbol space

$\left[\, \boldsymbol{o}[1] \;\; \boldsymbol{o}[2] \;\; \cdots \;\; \boldsymbol{o}[T_{span}] \,\right]$. In step 2, a state point is computed using mentioned method in the previous paragraph. Next, shift the focus point, and let the k-th focus point be

$$\boldsymbol{O}_k = \left[\; \boldsymbol{o}[1 + (k-1) \cdot T_{step}], \cdots, \boldsymbol{o}[1 + T_{span} + (k-1) \cdot T_{step} \;\right], \tag{10}$$

with increase the index as $k = 1, 2, \cdots, \frac{T-1-T_{span}}{T_{step}} + 1$. Finally in step 3, sequence of state point in the proto-symbol space is acquired.

5 Experiments

5.1 Recognition of novel motion

First, recognition in which motion patterns are transfered into a state point in proto-symbol space, was performed. Two novel motion "throwing with kicking" and "stretching with walking" are target motions. Figure 12 shows the result of recognition. The squares and triangles are known basic proto-symbols. The small dots indicates result state points. As the diagram shows, two dot marks are located on the line between each basic proto-symbol.

Next, a novel motion pattern is transfered into a sequence of state points in the proto-symbol space using the method mentioned in Sec.4.3. The target motion is "walking first, then shift to kicking". The result is shown in Fig.13.

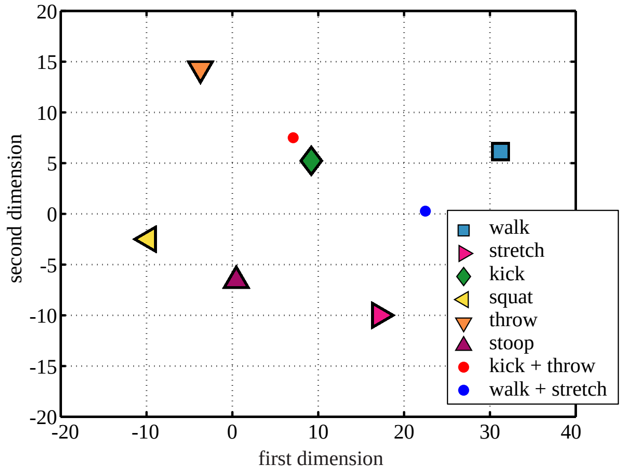


Fig. 12. A recognition result of novel motions

As the diagram shows, recognized dot marks starts from the proto-symbol of "walk", ends at the proto-symbol of "kick".

5.2 Generation of novel motion

In this experiment, we have investigate the motion output when a trajectory is given in the proto-symbol space. As a given trajectory, we prepared simple line trajectory from the "walking" state point to the "kicking" state point. Figure 14 is the result of motion output.

As the figure shows, motion of the humanoid is adequately controlled as the symbol manipulation in the proto-symbol space.

6 Discussion

6.1 Comparison with conventional research

Motion recognition using the HMM is famous method, thus many research are proposed for gesture recognition or behavior understanding [9][10] [11][12], however, no research has been existed in which motion is generated from HMMs. Masuko *et al*[13][14] have been proposed a speech parameter generation method using HMMs, however the generation process is not opposite direction of the speech recognition process. The most important characteristic of our method is that the motion recognition and motion generation process are integrated by only a HMM.

Acquisition and symbolization of motion pattern of robots have been discussed in Doya's research[15][16]. In their MOSAIC model, time-series data

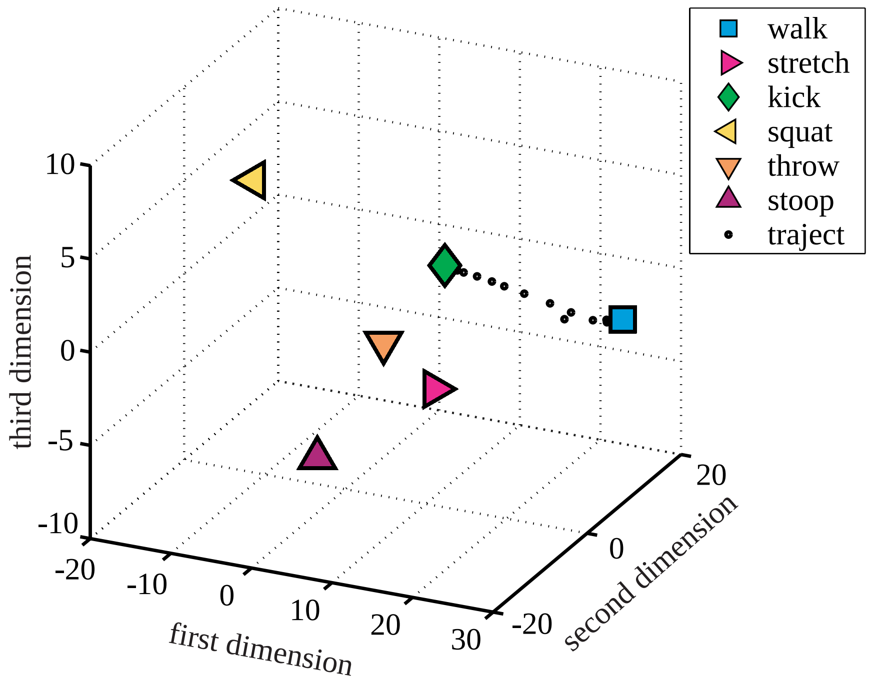


Fig. 13. A result of motion recognition in the proto-symbol space

are acquired as sequence of symbol representations, however, the symbol representation do not contains dynamics information in the time-series data. In contrast, our method, the proto-symbol representation contains dynamics information in motion patterns. Another different issue from Doya's research is that the single HMM is acts as recognition and generation model. In Doya's MOSAIC model, two modules; prediction module (for generation) and control module (for recognition), becomes a companion as motion primitive. We think that single HMM is smarter for abstract as symbol representation.

To integrate recognition process and generation process for time-series data, some dynamical approach have been proposed[17][18]. In these research, explicit dynamics like attractor is designed in order to abstract the time-series data. In conventional research, recurrent neural network is one of the effective way for the dynamics design [19][20] [21][22]. However, it is difficult to design symbol representation if these method was adopted as the dynamics representation. The HMM is effective for both dynamics representation and symbol representation.

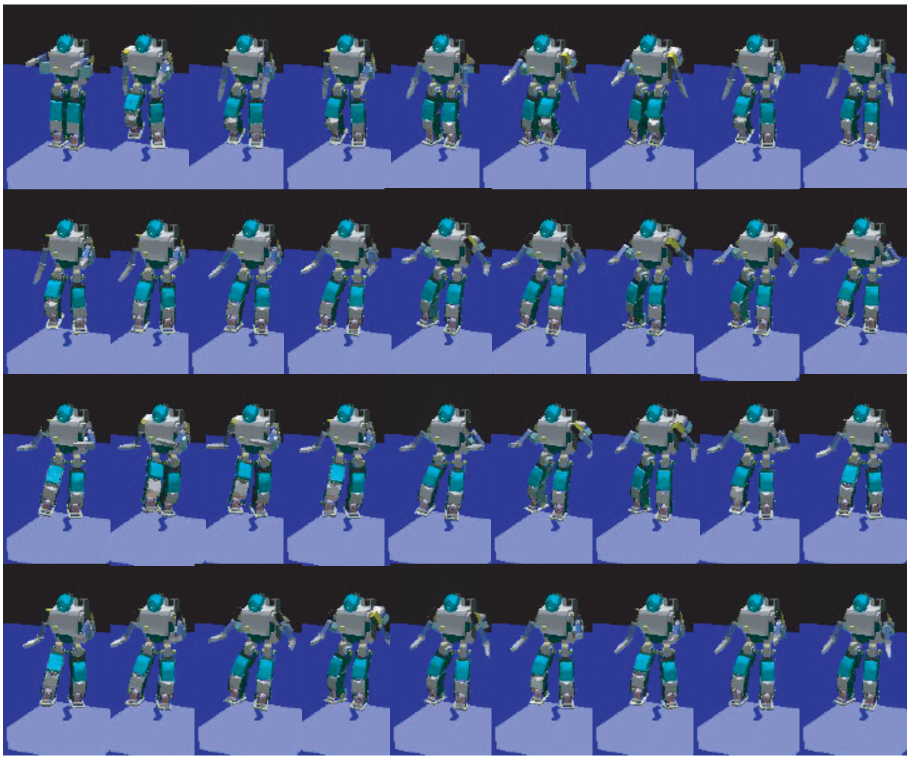


Fig. 14. Generated motion: from walking to kick

Symbol emergence had been tried in conventional research of artificial intelligence. The most difficult issue of the symbol emergence is how to manipulate the created symbol representation, contrary to the easiness of symbol creation. Deacon have proposed the symbol development model [4] as shown in Fig.**??**. In his theory, symbolic representation is developed from indexical level and iconic level. In the indexical level, simple relationship between a motion pattern and a symbol representation is established, however, relationship between each symbol and motion pattern is not considered. In the transitional level, relationship between each symbol is developed as token combinations, then the relationship between each motion pattern starts to be constructed. In the final level, logical relationship between symbol combined with the physical relationship between motion pattern. Our approach follows the development model. At the present moment, our method achieved the transitional level and is going to achieve the final symbolic level.

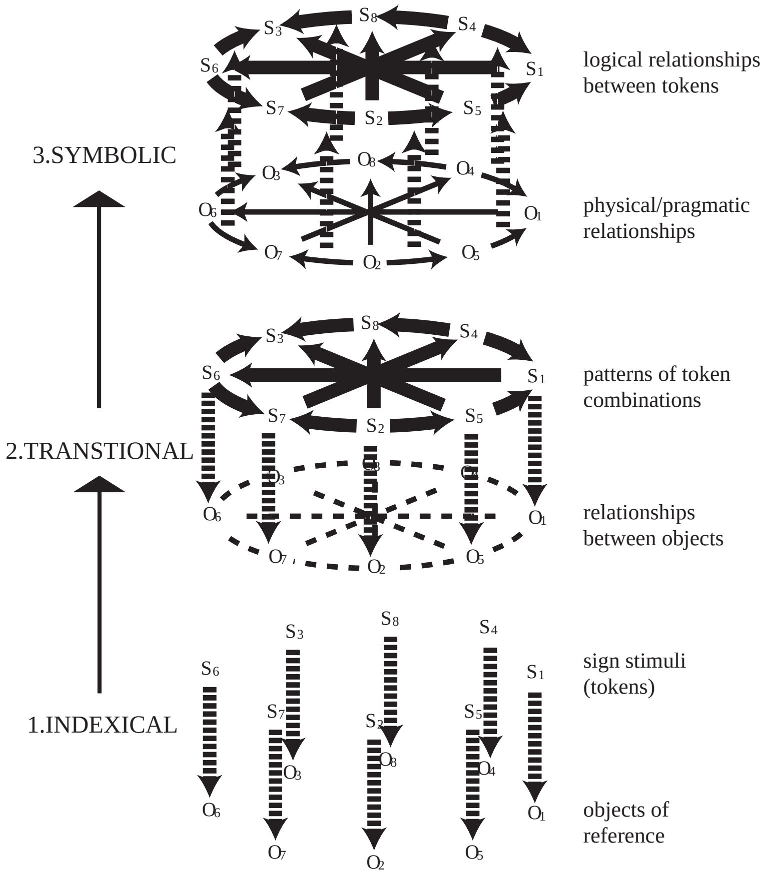


Fig. 15. Development of symbol representation from indexical level by Deacon. S indicates symbol, o indicates raw-level pattern like a motion patterns

7 Conclusion

To solve the defect of usual mimesis model, that is, impossibility of the symbol manipulation, we introduce hierarchical mimesis model. The hierarchical model is build on a continuous Hidden Markov Model and distance representation using *Multidimensional scaling method*. Continuous Hidden Markov Model enables the model to generate humanoids' motion naturally as contrary direction of the motion recognition. Multidimensional scaling method enables the model to describing the relationship between each proto-symbol, namely continuous HMM. Owing to the distance representation, symbol manipulation is achieved as geometric state manipulation. Through experiments, following ability is realized; (1) novel motion can be recognized as combination of known motion's proto-symbols, (2) novel motion can be generated by combination of known proto-symbols.

Remaining problem is the defectiveness of proto-symbol space. Even if the median point in the proto-symbol space between two proto-symbols generates natural motions, the characteristics of the motion is not always similar to the characteristics of real two motions. The most frequent cause is the proto-symbol space is not Euclid space. Toward the issue, we think that information geometry would achieve the desired effect.

Acknowledgement

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