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An Approach from Motion Generation/Recognition to Intelligence based on Mimesis Principle

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Abstract

The discovery of Mirror Neurons in human brain shows that the motion recognition and generation are executed by bidirectional computation model, and the model leads to symbol grounding system through embodied humanoids. We have proposed mirror neuron models based on Hidden Markov Models. In this paper, we propose a new method for usual models in order to be developed through behavior observation and generation.

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 on the background of such issues. Mirror neurons, 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], 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[3] that the language and brain had evolved each other.

In this paper, we propose 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.

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. The observer would then need to modify it from the performer's motion to fit it for his own body. The model is developed using Hidden Markov Models (HMMs). One issue is to identify appropriate motion primitives that enable both motion recognition and generation. This problem is to be solved using continuous Hidden Markov Models. The second issue is to acquire the time sequence of the motion primitives, which is to be done adopting discrete Hidden Markov Models. The acquired models are to be modified to fit for the observer's body. This is the third issue and to be discussed as a problem of database managements for HMMs.

2. Mimesis model which recognize others motion and generate self-motion

So far, many researcher have tackled with the issues between the imitation learning for humanoids and human intelligence[4]. In this section, we explain the outline of mimesis models with showing the difference between usual imitation models.

There are some suggestions that module struc-

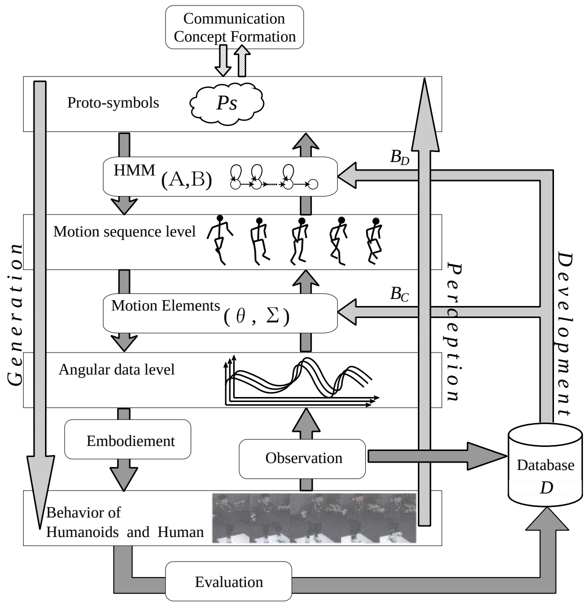

Figure 1: An outline of proposed mimesis model

ture of basic motions is needed for the symbolization and representation of complex behavior, such as Schaal's work[4]. In Kuniyoshi's approach[5], robots can reproduce complex behaviors from observation of human demonstration with the abstraction and symbolization, however, it is difficult to be applied to general recognition and reproduction process because of lack of dynamics point of view, that means the robots have to memorize the whole flow of basic behavior. Moreover, the basic behavior modules needed to be designed by developer. In an imitation learning framework MOSAIC which have been proposed by Samejima et al[6], plural dynamics and inverse-dynamics modules for the prediction and control of motion are implemented in order to imitate others' motion. However, a premise is set that sequence of symbol is given from others by communication, thus a certain representation model for dynamics of the whole body motion are needed.

We, here, propose an imitation framework which abstracts the dynamics of the motion as symbol representations, recognizes others' motions, and generates self-motions from the symbol representations. The realization of the framework leads to the implementation of the mirror neuron from engineering point of view.

2.1. Mimesis model based on Hidden Markov Models

The mimesis model consists of three processing; perception part, generation part and development part, as shown in Fig.1. 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. We call such symbol representation as "proto-symbols".

In the generation part, a sequence of motion elements is decoded from a proto-symbol. However, the generated motion patterns would be inappropriate for real humanoids. For the issue, we introduce the learning part where motion elements are modified based on a database consist of performer's motions and observer's motions.

Characteristics needed by the mimesis model is to integrate three functions; motion recognition, motion generation and symbol emergence of motions. 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 are performed probabilistically, then sequence of vectors are outputted during the transition as shown in Fig.2. 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). In this paper, DHMMs are adopted.

A parameter $\boldsymbol{\lambda}$ of HMMs is designed in order to be desirable to generate a motion sequence $\boldsymbol{O} = \{\boldsymbol{o}_{k_1}, \boldsymbol{o}_{k_2}, \ldots, \boldsymbol{o}_{k_T}\}(k_i \in \{1, 2, \ldots, M\})$ which belongs to a certain category, thus $\boldsymbol{\lambda}$ can be regarded as a representative of the category. In this paper, left-to-right type HMMs as shown in

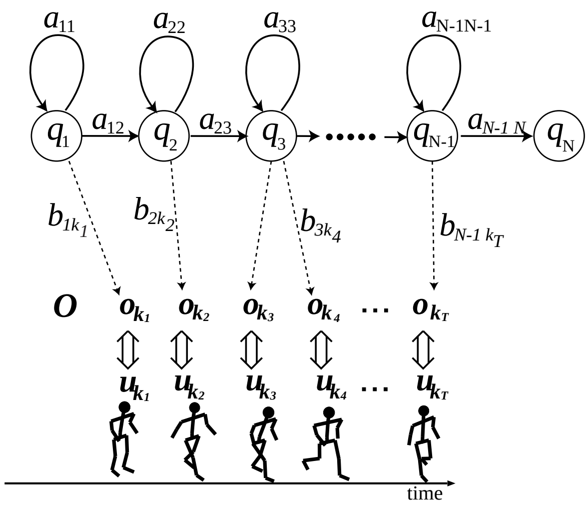

Figure 2: Motion Elements and Hidden Markov Models

Fig.2 are used whose initial distribution vector $\boldsymbol{\pi}$ have fixed vector as $(1, 0, \ldots, 0)$. The structure is fixed for each motion category, therefore a set of state $\boldsymbol{Q}$ and a set of output label $\boldsymbol{S}$ have not to be belongs to the representative of HMMs. Consequently, State transitions probability matrix $\boldsymbol{A}$ and output probability matrix $\boldsymbol{B}$ can be regarded as the representative of the HMM. Here, we define the proto-symbols $\mathcal{P}_{\mathcal{S}}$ as follow

$$\mathcal{P}_{\mathcal{S}} \stackrel{\text{def}}{=} \{\boldsymbol{A}, \boldsymbol{B}\}. \qquad (1)$$

A motion element is corresponded to a point in a state space which consists of like joint angle or torque. As the whole body motions are represented using finite motion elements, each motion element has a covariance matrix in order to occupy the state space, that is the covariance matrix means the charge area of each motion element. Therefore, motion elements are defined as follows

$$\boldsymbol{u}_i \stackrel{\text{def}}{=} \{\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i\} \qquad (2)$$

Due to the following equation

$$\boldsymbol{o}_i \stackrel{\text{def}}{=} \boldsymbol{u}_i, \qquad (3)$$

time series data treated by HMMs can represent the observed others' motions and generated self-motions.

An alternative of HMMs for such computation is the use of recurrent neural networks (RNNs). RNNs also memorize dynamics of patterns [7][8] [9]. The authors tested the use of RNNs for motion recognition and generation[8]. According to the result, the drawback of RNNs is in the low efficiency of computation RNNs would use a large set of parameters to memorize a few motion patterns. The parameters would requires a large computation to be adjusted.

3. Motion abstract, recognition and generation using HMMs

3.1. Creating proto-symbols through observation

In order to transfer the observed motion into a sequence of motion elements $\boldsymbol{O}$, motion are sampled as $\boldsymbol{\theta}$ for each short time period, then a motion element $\boldsymbol{o}_j$ is assigned for each moment where j is decided by executing following equation

$$j = \arg\max_i \frac{\exp\{-\frac{1}{2}(\boldsymbol{\theta}-\boldsymbol{\mu}_i)'\boldsymbol{\Sigma}_i^{-1}(\boldsymbol{\theta}-\boldsymbol{\mu}_i)\}}{\sqrt{(2\pi)^n|\boldsymbol{\Sigma}_i|}}, \quad (4)$$

where n is the number of dimension of the motion elements.

After that, a parameter of a HMM ($\{\boldsymbol{A}, \boldsymbol{B}\}$) which output the sequential elements plausibly is calculated and registered as a proto-symbol $\mathcal{P}_{\mathcal{S}}$. Humanoids gather several motion patterns as a stock of observed data for the learning. For the parameter estimation, Baum-Welch algorithm which is one of EM-algorithms[10] is used.

3.2. Motion recognition using proto-symbols

To recognize others' motion, a parameter $P(\boldsymbol{O}|\mathcal{P}_{\mathcal{S}})$ is calculated for each proto-symbol. This parameter indicates a probability that a motion pattern $\boldsymbol{O}$ is generated by a proto-symbol $\mathcal{P}_{\mathcal{S}}$. This value is called as likelihood, calculated by forward algorithm[10].

A proto-symbol which corresponds to input pattern should indicate high likelihood, and other proto-symbols ought to indicate low likelihood. In order to distinguish these likelihoods, following criterion is introduced.

$$R(\boldsymbol{O}) = \log \frac{\max\{P(\boldsymbol{O}|\mathcal{P}_{\mathcal{S}i})\}}{\text{second}\{P(\boldsymbol{O}|\mathcal{P}_{\mathcal{S}i})\}} \qquad (5)$$

Where second$\{\boldsymbol{x}\}$ means that the second highest value in the components of $\boldsymbol{x}$. Mimesis model recognizes the input motion without any confusion when the R indicates high value. In this case, the recognition result becomes $\mathcal{P}_{\mathcal{S}j}$, where

$$j = \arg\max_i \{P(\boldsymbol{O}|\mathcal{P}_{\mathcal{S}i})\} \tag{6}$$

when the R indicated low value, the recognition was failed and Mimesis model tries to shift to proto-symbol creation phase.

3.3. Motion generation using proto-symbols

Contrary to the easiness of sequential pattern recognition with calculating likelihood $P(\boldsymbol{O}|\mathcal{P}_{\mathcal{S}})$, it is difficult to generate time series pattern from a proto-symbol $\mathcal{P}_{\mathcal{S}}$ because there is no general algorithm to calculate $\max_{\boldsymbol{O}} P(\boldsymbol{O}|\mathcal{P}_{\mathcal{S}})$. Thus, we introduce general generation method using Genetic Algorithm (GA).

Owing to letting each gene be corresponded to each motion element and l be fixed length of motion sequence, $\boldsymbol{O}$ becomes a chromosome. Searching of the most plausible motion can be carried out with letting the the fitness value as likelihood $P(\boldsymbol{O}|\boldsymbol{A}, \boldsymbol{B})$[11]. Finally, motion patterns for humanoids are generated with transformation from the sequential motion elements to continuous time series data of joint angle.

There have been some researches in which time series of motion data were recognized using HMMs[12] [13], however, no research has been existed in which motion is generated from HMMs. Masuko et al[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 single HMM.

4. Development of mimesis model through repetition of motion observation and generation

The performance of motion recognition and generation is influenced by the characteristic of motion elements. If the motion elements had no relationship between the observed motion, the recognition process would be failed. Therefore, we adopted an approach that the system searches the best motion elements with an evaluation criterion whether the generated motion would be fit for the body and the recognition would be succeeded against familiar motion. Using the method, the humanoid can acquire adequate motion elements through repetition of motion perception and generation.

4.1. Introduction of Continuous HMMs and applying to mimesis model

On the CHMMs, output probability matrix $\boldsymbol{B}$ becomes probability density functions in CHMMs. Here, the density function is approximated with linear combination of Gaussian functions as follows.

$$b_i(\boldsymbol{o}) = \sum_{j=1}^{m} c_{ij}\mathcal{N}_{ij}(\boldsymbol{o}; \boldsymbol{\Sigma}, \boldsymbol{\mu}) \tag{7}$$

Where $b_i(\boldsymbol{o})$ is probability density function for output of continuous vector $\boldsymbol{o}$ at i-th state node, m is the number of mixture Gaussian functions, c_{ij} is mixture coefficient, $\mathcal{N}(\boldsymbol{o}; \boldsymbol{\Sigma}, \boldsymbol{\mu})$ is the Gaussian function with covariance matrix $\boldsymbol{\Sigma}$ and mean vector $\boldsymbol{\mu}$, and D is the number of dimension of continuous vector $\boldsymbol{o}$.

The characteristic of the CHMMs are decided by parameter $\{\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{c}, \boldsymbol{\Sigma}, \boldsymbol{\mu}\}$. These parameters are calculated using Baum-Welch algorithm .

Here, each mean vector of the Gaussian function is regarded as important representation of the observed motion. Therefore, we divide the parameters of CHMMs, and redefine the motion elements $\boldsymbol{u}$ as follows.

$$\boldsymbol{u}_i \stackrel{\text{def}}{=} \{\boldsymbol{\Sigma}_i, \boldsymbol{\mu}_i\} \tag{8}$$

In other words, the number of motion elements is as many as the number of mixture Gaussian components. An important issue is that the motion elements are automatically calculated by the Baum-Welch algorithm as well as mentioned in Sec.3.1..

4.2. Closing the mimesis loop for embodiment

Baum-Welch algorithm[10] for the design of motion elements can be expressed by following equations.

$$\mathcal{D} = \{\boldsymbol{O}^1, \boldsymbol{O}^2, \ldots, \boldsymbol{O}^r\} \tag{9}$$

$$\{\boldsymbol{A}, \boldsymbol{B}\} := \mathcal{B}_D(\mathcal{D}) \tag{10}$$

$$\{\boldsymbol{\mu}, \boldsymbol{\Sigma}\} := \mathcal{B}_C(\mathcal{D}) \tag{11}$$

where $\mathcal{B}_D, \mathcal{B}_C$ are operations using the Baum-Welch algorithm, $\mathcal{D}$ is a database consists of r observations as Initial database $\mathcal{D}^0$ consists of only observed others' motions, that is, motion elements and proto-symbols which have no relationship between learner's physical characteristic are acquired by above operations. Therefore, let the proto-symbols and motion elements be acquired with database manipulation during repetitions of motion recognition and generation as follows.

1. Generating a motion $\boldsymbol{O}$ from a proto-symbol $\mathcal{P}_{\mathcal{S}}$ and motion elements.
2. Judging whether the generated motion $\boldsymbol{O}$ is suitable or not.
3. Adding the motion to the database when the result of judge is good. $\mathcal{D}^{t+\Delta t} := \{\mathcal{D}^t, \boldsymbol{O}\}$
4. Acquiring the proto-symbols and motion elements using above Eq. (10)(11), and returns back to step 1.

For the evaluation at the step 2, two evaluation criteria were introduced; an inner evaluation for checking the characteristic of proto-symbol, and an outer evaluation for checking the aim and meaning of the motion from point of teacher's view. For the outside evaluation, we prepared following criterion.

$$E_\theta = \frac{1}{T}\int_0^T |\boldsymbol{\theta}_{in}(t) - \boldsymbol{\theta}_{out}(t)|dt \qquad (12)$$

Where $\boldsymbol{\theta}_{in}(t)$ and $\boldsymbol{\theta}_{out}(t)$ indicate the joint angle of an observed ideal motion and a generated motion. For the inner evaluation, recognition rate $R(\boldsymbol{O})$ explained in Sec.3.2. is used.

Considering above two criterion, following integrated criterion is used for the experiment

$$V = \alpha E_\theta + \beta R^{-1}(\boldsymbol{O}) \qquad (13)$$

where α and β is a certain constant. When the value V is larger than a certain threshold, the mimesis model judges that i-th motion data is suitable for recognition process, adds the motion data into database, and calculates the motion elements again. These constant and threshold is adjusted according to each experiment case.

Due to the distinction method, the influence of initial others' motion would be decrease, and the database would be gradually under the control of generated self-motions.

5. Experiments of motion elements acquisition

A humanoid used in experiments is shown in Fig.3. The humanoid has four degrees of freedom at each arm, six degrees of freedom at each leg, namely 20 degrees of freedom for the whole body. We have confirmed the performance of our method by experiments where the mimesis model observes humans' motion and generate motions for a real humanoid. Joint angle data for 20 DOFs are directly observed using the Behavior Capturing System[15]. The time period of each motion is about 2[sec] with sampling time 20[msec].

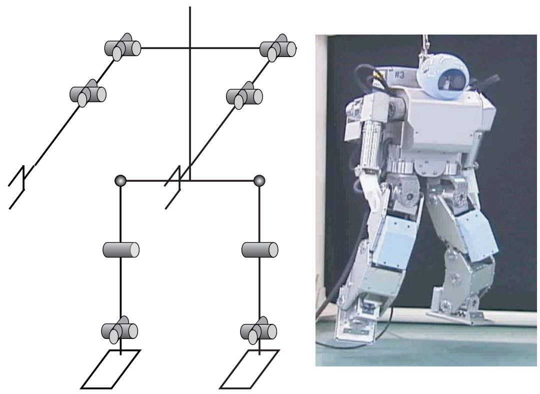

Figure 3: Humanoid HOAP-1

5.1. Experiments of motion recognition

for the motion recognition experiments, seven behaviors; (a) tennis swing (swing), (b) walking (walk), (c) Cossack dancing (dance), (d) kicking (kick), (e) backward walking (back), (f) crawling (crawl), are prepared as shown in Fig.4. The behavior from (a) to (e) were treated as already-known motions, the behavior (f) was treated as a unknown motion. Table 1 is the recognition result.

The value in the table indicate the logarithm of likelihood $P(\boldsymbol{O}|\boldsymbol{A}, \boldsymbol{B})$. Proto-symbols arranged length-ways indicate the target of the recognition, and behavior names arranged sideways indicate the proto-symbols already learnt. The value indicates larger, the target motion matches better with the proto-symbol. The value of a certain target motion against a proto-symbol which is corresponds to the motion indicates high, that is located on a diagonal line. The values of unfamiliar motion (unknown) against each proto-symbol are almost the same. Thus we see that the recognition process would be succeeded without mistake, when recognition rate R is set to about -1000 empirically.

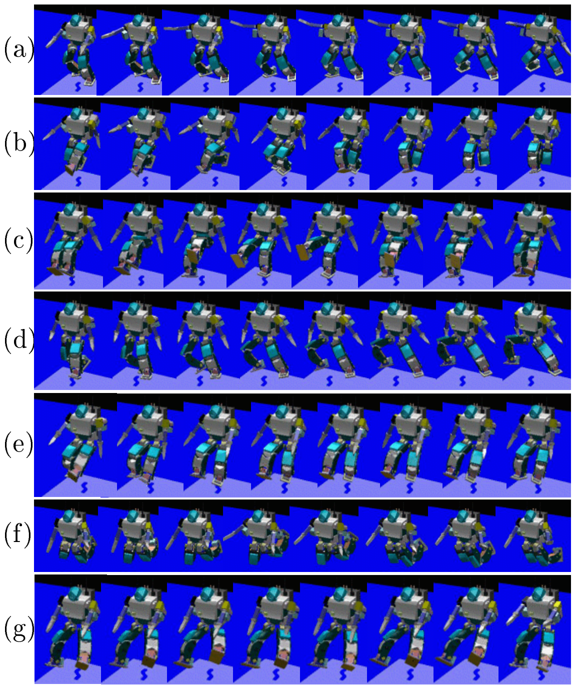

Figure 4: Target behaviors (a) tennis swing, (b) walking, (c) Cossack dance, (d) kicking, (e) backward walking, (f) crawling, (g) unknown behavior.

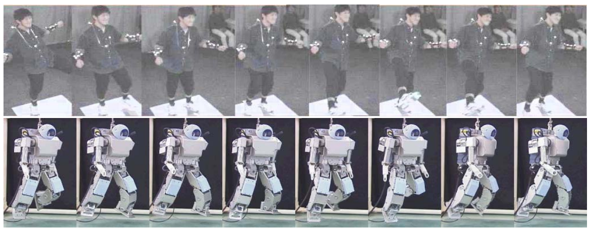

Figure 5: Original humans' performance (upper) and generated humanoid's behavior (lower).

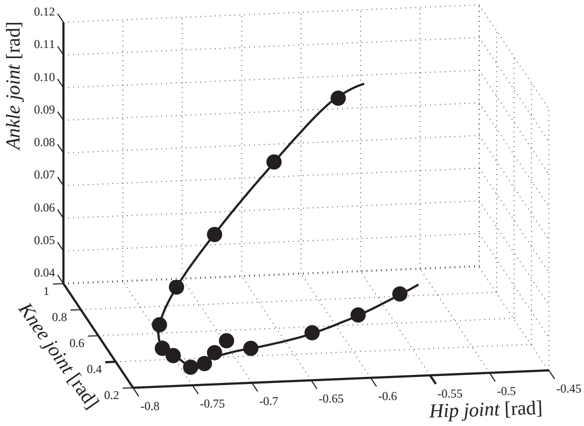

Figure 6: Acquired motion elements without loop structure

5.2. Experiments of motion generation

A target motion is stepping motion shown in Fig.5. Upper of the figure is original motion by the performer, lower one is generated motion on the humanoid. It is confirmed that an approximate motion is generated from HMMs.

The computational time for the generation process was about 1[sec] using Pentium-III 1[GHz] processor. The time is enough fast as the off-line pattern generator for humanoids.

5.3. Experiments of motion elements development based on embodiment

Here, we set up a situation where the joint angle limitation of the humanoid's knee is about 40[deg], less than humans' one. We investigated whether motion elements for the humanoid are acquired by observations of humans' motions under such a condition. In the experiment, 80 times loop are repeated as explained in Sec. 4.2.

Figure 5 shows the original motion which is performed by a human. Figure 6 shows the acquired motion elements from the performance when the joint angle limitation is not existed. A result with the limitation condition is shown in Fig.7. In these figures, three axes indicate hip joint (pitch), knee joint and ankle joint (pitch), as well as Sec.5.2. The curved line in the figures corresponds to the motion trajectory. The dots indicate acquired motion elements. As Fig.6 indicates, the motion elements are located near by the original motion trajectory. Comparing with the Fig.6, motion elements are gathered not only on the A area, but also on the B area in Fig.7. These motion elements located on the B area is acquired by the generated self-motions in the database, which fits for the humanoid embodiment. This result shows that the both motion elements are acquired; elements for the recognition of others' motions (A area) and ones for the generation of self-motion (B area).

5.4. Designing of HMMs

Here, We shall concentrate on the rest parameter, which decides the structure of HMMs. As the HMMs adopted in this paper is left-to-right type, parameter concerned with the structure is

Table 1: Recognition result of others' motion using HMMs.

Input Behavior	Proto-symbols						
	swinging	walking	dancing	kicking	backward walking	crawling	R
swing	-430	-3915	-4077	-3940	-4114	-4007	3485
walking	-3048	-225	-3071	-1646	-3099	-3019	1420
dance	-1656	-1603	-144	-1613	-1683	-1577	1433
kicking	-2543	-1574	-2562	-199	-2585	-2519	1374
backward walking	-2395	-2318	-2413	-2332	-202	-2372	2117
crawling	-4083	-3950	-3815	-3976	-4151	-488	3327
unknown behavior	-1915	-1853	-1928	-1865	-1946	-1896	11

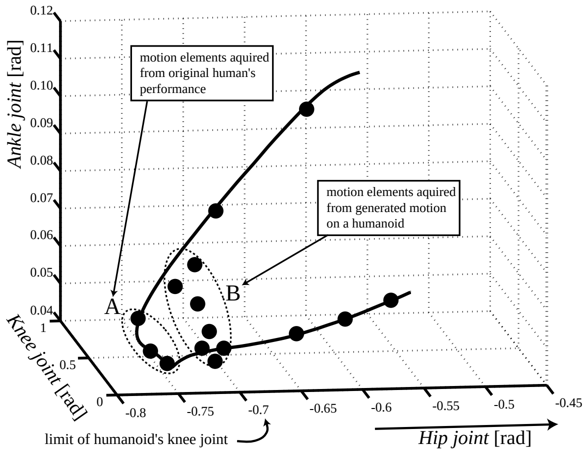

Figure 7: Acquired embodied self-motion elements using loop structure

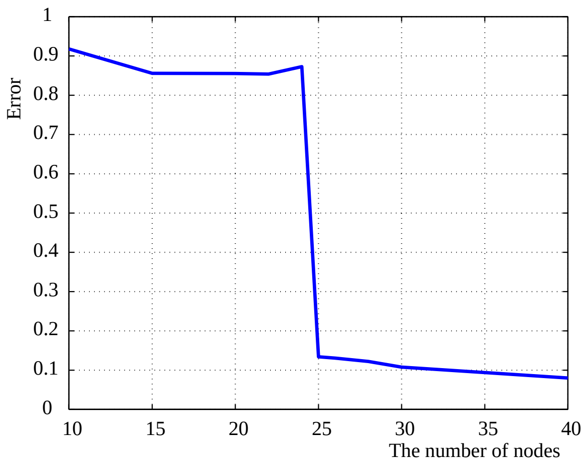

Figure 8: Error value E_θ and the number of nodes

the number of nodes. It is also possible to use the evaluation criterion explained in Sec.4.2. for investigation of the number of nodes, during the repetition of motion recognition and generation.

Swing motion is selected for the experiment. The error values E_θ are measured with changing the number of nodes from 10 to 40. The result is shown in Fig.8. As the diagram indicates, the error value decreases hardly where the number of nodes shift from 24 to 25. Figure 9 shows the generated motion pattern for four conditions; the number of nodes is 20, 24, 25 and 40, respectively. The diagram focused on the right shoulder's yaw joint. Solid lines indicate generated motion pattern, broken lines indicate original motion pattern. The diagram supports the result that the desirable number of nodes is above 25. Though there is a slight increase when the number of node is 24 in Fig.8, stochastic process of HMMs is the cause of this increase. As the error value can be regarded as monotone decreasing, the error E_θ is valid and simple method for the structure decision.

6. Conclusions

In this paper, we proposed a framework which begins from motion recognition/generation, symbolize the motion patterns, and leads to intelligence of humanoid based on mimesis theory. In our mimesis model, proto-symbols and motion elements are introduced with Hidden Markov Models in order to integrate following three ability using only one mathematical model; (1) abstraction of motion patterns and symbol representation , (2) generation of self-motions from the symbol representation, and (3) recognition of others' motions using the symbol representation. Through experiences, the feasibility of the mimesis model is cleared. Furthermore, we proposed an approach in which the development of motion elements is resulted as the management of motion database, and investigated the effectiveness through an experiment in which the learner's physical body condition is different from the teacher's one.

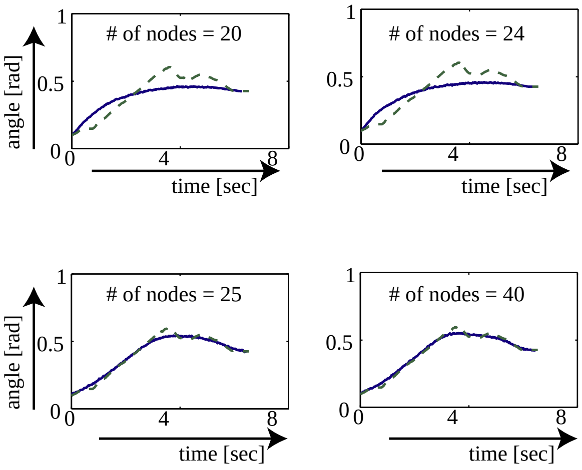

Figure 9: Generated motion (shoulder's yaw joint) for each number of nodes

The mimesis model is not simple method for motion recognition, generation, abstraction. The recognition process which transfers an observed others' motion into proto-symbol representation, and the generation process which transfers a proto-symbol representation into self-motions is implemented as opposite direction function by only one mathematical model. The most important characteristic is integration between imitation learning and symbol emergence is established with defining the bidirectional computation model as proto-symbols.

We think this result is the first step to connect symbol manipulation ability to the motion acquisition process using the mimesis model. One of the most important characteristics of the symbols representation is distance and similarity are able to be defined between each symbols. We try to define the distance between each HMM using hierarchical proto-symbol space in order to be able to extend for intelligence issues.

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