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Associative Computational Model of Mirror Neurons that connects Missing Link between Behaviors and Symbols

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Abstract

Behavior recognition process and behavior generation process have a close relationship in humans' brains. It is expected that humans' brains understand the meaning of behavior and create symbols through co-development of recognition and generation processes. In this paper, we propose a novel method for the integration of behavior patterns and symbols using associative memory in order to realize the co-development processing. In the model, behavior recognition process and generation process are practiced based on a mutual dynamics. We also confirmed the feasibility of the method on humanoid simulator.

1 Introduction

The research of humanoid robots has a long history and has accumulated a substantial amount of literature. The focus of early efforts was mostly on the dynamics, motion planning, and control of biped walk. Although it has not yet reached the level of complete solution with full of liability and adaptability, the hardware technology has been established for building the autonomous humanoids. The focus of humanoid research is now about to extend to the research on human-like intelligence.

The mirror neurons[1] are found in the frontal lobes of human and primate. They activate themselves not only when he/she observes a specific behavior of the others, but also when he/she intends to act the same behavior. Furthermore, the mirror neurons are located at neither motor field nor sensory field but broker's field which has close relationship with language field. It implies that the behavior perception process and behavior generation process might be integrated as an organization which has a close relationship between symbol manipulation.

In the field of cognitive science, a hypothesis of *mimesis*[2] also drawing attentions. Mimesis is the primitive skill of communicative intelligence with imitation learning; understanding the others' behaviors and constructing self-behaviors. Especially, the primates who cannot manipulate speech languages can make social communications through behavior imitation[3]. On the other hand, Deacon[4] advocates a hypothesis that the brains of humans have co-evolved with symbol communication, in other words, humans' high-degree intelligence cannot be realized without skill of symbol manipulation. As a consequence, a suggestion is arises that the origin of human intelligence results from the skill of imitation learning which is the strong combination of behavior perception and generation.

We believe that the theory of integration between behavior perception and generation leads to the breakthrough for the synthesis theory of artificial intelligence, like an embodiment of humanoids, symbol grounding problems, and so on. Although many humanoid researches treated the relation of imitation learning and intelligence [5][6][7][8], few arguments were made on the connection of behavior cognition and behavior performance. We have proposed an integration model for behavior perception and generation using Hidden Markov Models[9], however, the mathematical background of the system has a great gulf between the concept of mirror neurons. The goal of this paper is to provide a mathematical framework of *mimesis* as a computational model of *mirror neurons*, based on associative memory using recurrent neural networks.

In section 2, we describe the advantages and issues of time series data recognition and generation based on associative memory. In section 3, we propose a novel extension method for the associative memory which enables the system to memorize much more data and to decrease the calculation time. In section 4, we explain the mechanism of memorizing, generation, and recognition. In Section 5, experiment on the humanoid simulator is shown, and discussing the result in section 6.

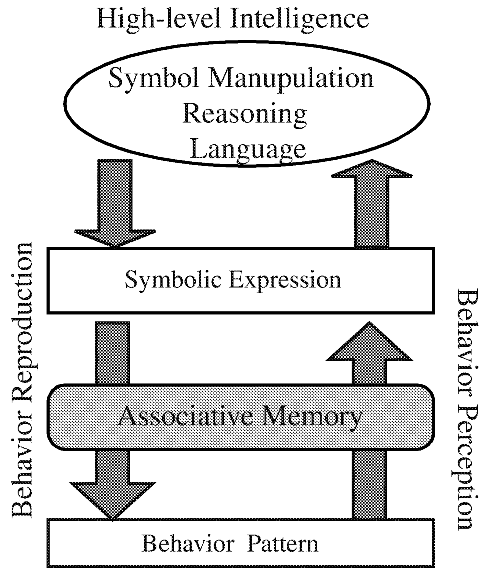

Figure 1: *Computational model of mirror neurons*

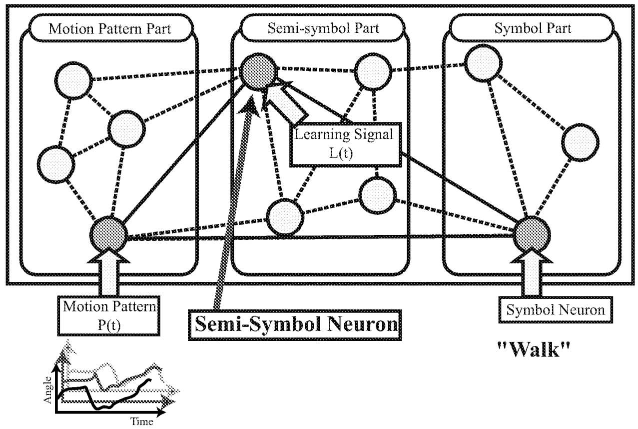

Figure 2: *A proposed associative memory*

2 Computational model of mirror neurons based on associative memory

2.1 Mimesis model which connects symbols and behavior

We have proposed a mimesis framework based on the Hidden Markov Models (HMMs)[9]. The outline of the framework is shown in Fig.1. In the mimesis model, observed behaviors are abstracted using by HMMs, and original behavior are reproduced from the same HMMs. Therefore, the HMM has been regarded as proto-symbols. The former corresponds to behavior perception, and the latter half corresponds to behavior generation. However, the model has two weak points as followings:

- The algorithm of behavior generation differs from the algorithm of behavior recognition[9]. This difference cases a problem that the real time behavior generation never achieved because of calculation for motion generation takes too much times.
- Proto-symbols are widely different from *symbols* like concept and language because the proto-symbols are defined as group of matrices and vectors which are parameter of HMMs.

To resolve these problems, it is desired not engineering algorithm like a searching method but simple dynamics rules, because they are fundamental feature of information processing in animals' brain. It is also desired that symbol representation should be not numerical value like vector and matrix but corresponded to physical phenomenon like neuron's fire. We introduce associative memory in order to satisfy these conditions.

2.2 Recognition and generation of sequential data using associative memory

In order to recognize time series data and to generate it, associative memory using recurrent neural networks have often used based on a suggestion from biology field that the humans' brain are doing such association process using simple dynamics.

Morita *et al* has proposed a time series data recognition method[10] and generation method[11]. This method has two advantages. First is that the recognition process and generation process are similar, thus it is easy to connect two processes as one model[12]. Second is that the neural networks can represent entrainments of the dynamics included in the target sequential data. However, this method unfortunately had some problems as follows:

1. Long length data cannot be memorized.
2. Target data must be represented as a certain fired pattern of several neurons, and almost all fired neurons should keep on being fired.
3. Symbol representation method was not implemented. Static activation pattern should be corresponded to symbol representation.
4. Calculation quantity is too big.
5. Recognition result wouldn't be output every moment, but be output at the end of behavior observation.

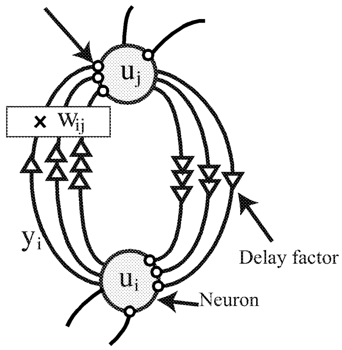

Figure 3: *Time delayed connections*

In this paper, we propose new methods that can resolve these problems. We also show how to combine the association system with the humanoid behavior control systems.

3 Extension of the associative memory

Outline of proposed associative memory is shown in Fig.2, which consists of three parts. First is *motion pattern part*, which receives and outputs behavior pattern. Second is *semi-symbol part* which located in middle layer of the network model. Third is *symbol part* which corresponds to the mirror neurons. From now on, we mention several features of the proposed model.

3.1 Neural networks with time delayed connection

The representation of human behavior is too large and complex for recurrent neural networks to be memorized because the large size of behavior representation causes explosion of the calculation quantity. Morita's model also cannot to cope with complex sequential data, for instance which has a sudden change of input pattern. Here, we introduce time delayed connection into the associative memory.

Each pair of neurons has two-way connections as shown in Fig.3. Signals are transmitted through several paths with time delay. HMM is often used for motion recognition with an assumption that the motion has been generated from Markov process, however, owing to the time delayed connections, non-Markov patterns can be treated.

This method has an advantages that it is easy to distinct similar patterns because the history of time series data is held in the model[13].

3.2 Introduction of semi-symbol neurons

One of the problems of the Morita's model is the inconvenience for rough and discontinuous sequence. We introduce semi-symbol neurons in order to resolve the problem. The semi-symbol neurons located between motion pattern part and symbol part as middle layer. Each semi-symbol neuron has connection between them, and the pattern neurons and symbol neurons don't have connections each other. It is needed to decide which neuron should be fired in learning phase.

The most suitable semi-symbol neuron is selected using following equation.

$$d_i = \sum_{k=1}^{p} \sum_{j=1}^{n} \frac{{}^k w_{ij} z_j(t - {}^k T)}{||{}^k w_i||} \tag{1}$$

A neuron which has the largest value of d_i is registered as a target semi-symbol neuron. The selection method has a feature of Self Organization Map[14].

The effects of the method is as followings.

- Smooth and continuous sequence can be formed
- The calculation quantity becomes be small, because the area decreases where is needed for the learning

3.3 Introduction of self-motion elements

The relation between inner potential value of pattern part and actual motion patters, namely the coding representation, is one of the factors which influent the ability of the mimesis model. For example when the inner potential indicates raw values like the joint angles directly, breakdown would easily occur because of the maximum of memorization quantity. Thus, we introduce motion elements which are basic pieces of motion pattern, for a short time length, such as bending a knee or stretching an elbow. A block of neurons in motion pattern is corresponded to a motion element following the sparse coding theory in which it is desired that single neuron is in charge of small information quantity. This approach enables the memorization capacity to be increase, and also enables the learning time cost to be decrease.

4 Mechanism of the associative memory

4.1 Memorization of behavior

When the system memorize a new behavior pattern, index of symbol neuron should be fired and time series motion data are given to the associative memory. Semi-symbol neuron for each moment selected using Eq.(1). Fire pattern, namely inner potential of the symbol neuron indicates 1.0 for all moment. Semi-symbol neuron for each moment also indicates 1.0. During the input, the weights between neurons are updated using following equation from (2) to (5).

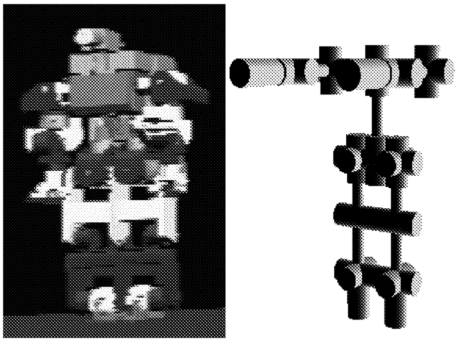

Figure 4: *Configuration of degree of freedom of the humanoid*

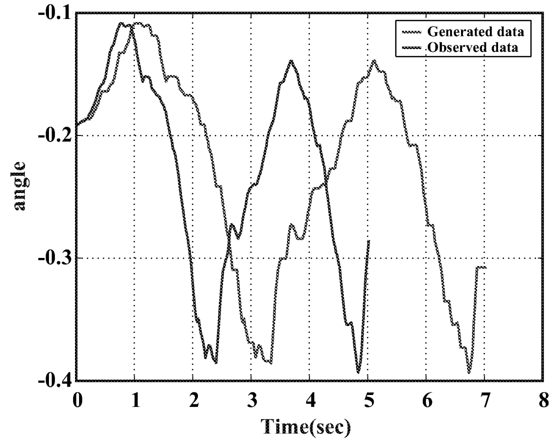

Figure 7: *Result of generation*

$$\tau \frac{d^k w_{ij}}{dt} = -{}^k w_{ij}(t) + \alpha_i z_i y_j(t - {}^k T) \quad (2)$$

$$\alpha_i = \alpha sgn(u_i) f(u_i, z_i) \quad (3)$$

$$y_i = \begin{cases} f(u_i) & y_i > 0 \\ 0 & y_i \leq 0 \end{cases} \quad (4)$$

$$f_w(u, z) = \frac{1 - e^{-cu}}{1 + e^{-cu}} \cdot \frac{1 + \kappa e^{c'(|u| - \beta|z|)}}{1 + e^{c'(|u| - \beta|z|)}} \quad (5)$$

where, τ is time constant, u_i is inner potential of neuron i, y_i is output value of neuron i, w_{ij} is weight value from neuron j to neuron i, z_i is learning signal which indicates potential value of neuron i ($z_i = 1$ when data is input for neuron i, z_i=0 when no data is input), T is time delay constant, α and $\beta(> 1)$ are adequate constant, f is output function of all neurons.

4.2 Behavior recognition and generation

The neuron dynamics in case of behavior generation and recognition is shown as follows;

$$\tau' \frac{du_i}{dt} = -u_i(t) + \sum_{k=1}^{p} \sum_{j=1}^{N} {}^k w_{ij} y_j(t - {}^k T)) + z_i \quad (6)$$

where τ' is another time constant, N is the number of neurons in a recurrent neural network, u_i is inner potential of neuron i, y_i is output value of neuron i, w_{ij} is weight between neurons i and j, z_i is learning signal of neuron i, T is time delay, f is output function of neurons, p is the kind of time delays.

During the input of recognition target patterns, inner potential of symbol neurons change every moment. Since there are several symbol neurons, a neuron which potential goes over a certain threshold is regarded as the recognition result. The recognition process can be done even if the pattern is not input fully, namely the online recognition. This characteristic is one of advantages of this model.

In the behavior generation phase, inner potential 1.0 is given to the target symbol neuron, and a motion element is selected whose inner potential becomes over threshold for every moment. Atractor dynamics in the RNN can generate sutable series of motion elements[15]. Finally total behavior is generated with combination of time series motion elements.

5 Experiment on humanoid

5.1 Design of mimesis model

For the design of motion elements, we captured real human's behavior using behavior-capturing system[16]. 20 angle joints which correspond to the joints of a target humanoid (Fig. 4) are focused and time series data for each joint are captured. Joint angle data are divided into four parts; right arm, right foot, left arm, and left foot , and segmented as motion elements for every 200[msec]. A human performed a sample behavior such as "swinging a hand" and "kicking" for 5[sec], then 25 elemtns for each part, that is 100 elements are generated from the sample behavior.

For the design of a recurrent neural network, 100 neurons for *motion pattern part*, 390 neurons for *semi-symbol part*, and 10 neurons for *symbol part* are assigned. As time delayed connections, three kinds of delays $T, 2T, 3T$ were set for each link between every two nodes.

5.2 Behavior generation experiment

We investigate performance of behavior generation ability for stepping behavior. As a result, a motion

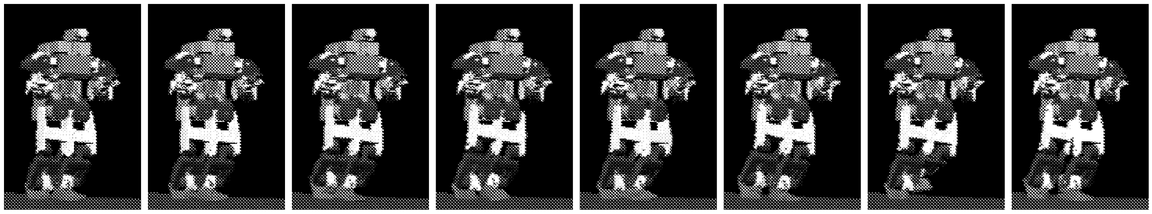

Figure 5: *Original motion on real humanoid*

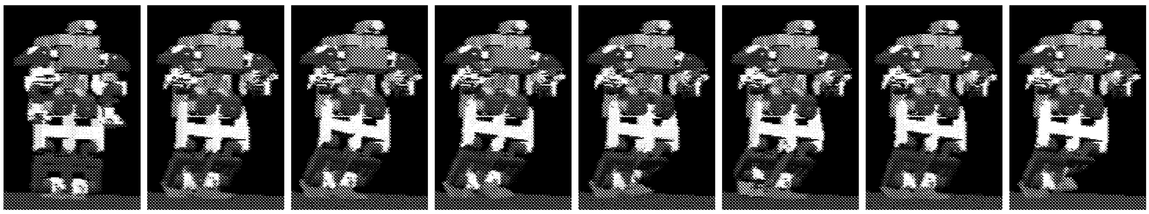

Figure 6: *Generated motion on real humanoid*

generated which is very similar to the original motion. Fig. 7 shows the generated data of knee joint angle. Fig. 6 shows a generated whole body behavior against a original behavior shown in Fig. 5.

As Fig.7 shows, the length of generated behavior is 7[sec] against the length of the original behavior is 5[sec]. This gap is generated because of the occurrence of futile time zone, when no specific neuron fires. The futile time zone is canceled after offline generation.

5.3 Behavior recognition experiment

Figure 8 and Fig.9 are the transition of inner potential of symbol neurons, where behavior pattern No.1 and No.2 were input respectively. The vertical axis indicates inner potential, the horizontal axis indicates time. The broken line indicates potential of the target symbol neuron, the solid line indicates the one of another symbol neuron. For the begging 1[sec], two symbol neurons show similar behavior, however, as the graph shows, the recognition was succeeded after 1.5[sec].

Fig.10 shows the result when behavior pattern No.1 and No.2 were input in rapid succession. Since the pattern No.2 is recognized even immediately after the input of pattern No.1, proposed associative memory is not influenced the initial state of the neural network. Figure 11 shows the result when incomplete pattern was input. In this case, a pattern whose 20% data was lost, was used as the input pattern. It is obviously that the associative memory can recognize the data, even if 20% of the pattern was lost.

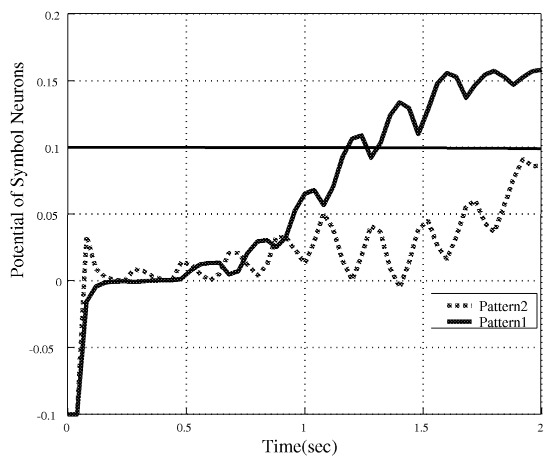

Figure 8: *Recognition result of behavior No.1*

6 Conclusion

In this paper, we proposed several improvements in order to create a computational model of mirror neurons which can integrate behavior recognition, generation, and memorization. We also confirmed the feasibility of the method through actually implemented framework and experiments on a virtual humanoid.

In proposed model, motion neurons are embedded, however sensory neurons also have relationship between mirror neurons. We plan to integrate this model of mirror neurons and symbol manipulation systems as future works.

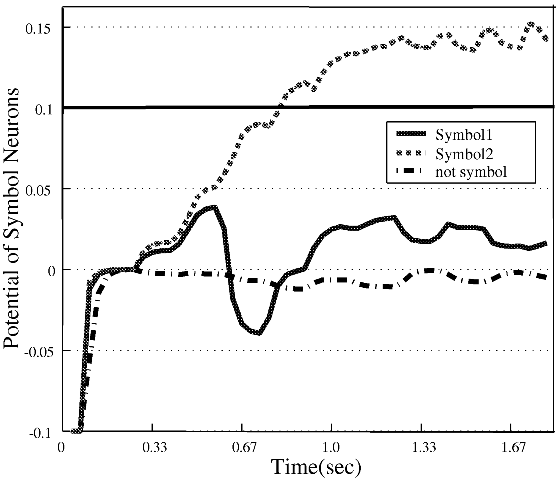

Figure 9: *Recognition result of behavior No.2*

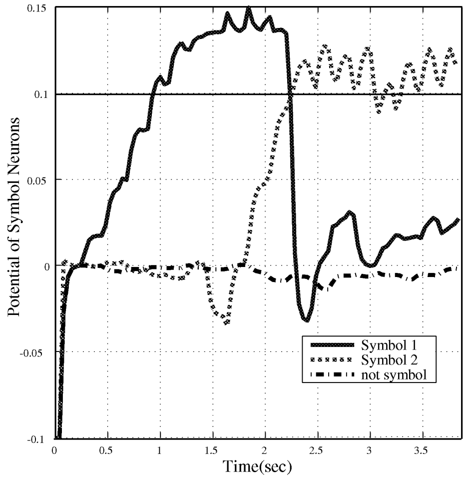

Figure 10: *Recognition result of behavior series No.1 and No.2*

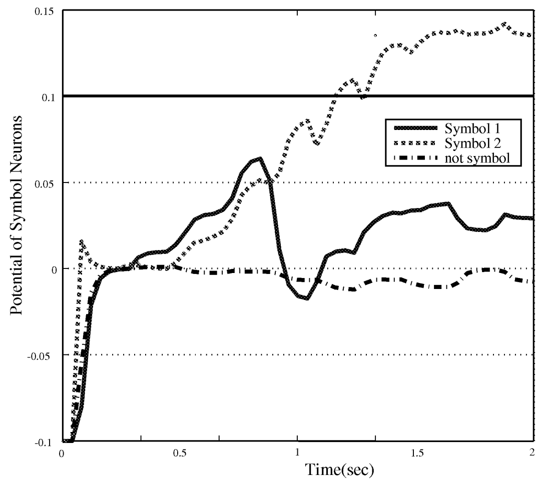

Figure 11: *Result of recognition (input behavior is similar to 2)*

Acknowledgments

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