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Mimesis Embodiment and Proto-symbol Acquisition for Humanoids

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Abstract

Mimesis is the primitive skill of imitative learning, one of the methods for recognition of others' behavior and construction of self behavior. Mimesis is thought an origin of human intelligence because this function is observed not only at humans but also at animals. When the mimesis is adopted as learning method for humanoids, convenience for designing full body behavior increase because bottom-up learning approaches from robot side and top-down teaching approaches from user side involved each other. Therefore, we have developed a behavior acquisition and understanding system for humanoids based on the mimesis. This system is able to abstract observed others' behaviors into conceptual symbols, to recognize others' behavior using proto-symbols, and to generate self motion patterns using the proto-symbols. In this paper, we mention the integration of mimesis loop, and confirmation of the feasibility on virtual humanoids.

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 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 autonomous humanoids. The demonstrations of HONDA P2 in the end of 1996 and the other models were widely publicized and accepted with a surprise even in the research community of robotics.

It was the time when the door opened to the human behavioral science and the human intelligence, 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.

Mimesis is the primitive skill of imitative learning and forms the foundation of skills understanding others' behaviors and constructing self behaviors. It is commonly observed for humans and the giant apes[1]. The group of animals coincides with those who live with full of social communications and manipulate symbols for the purpose. It is an recent hypothesis by Deacon[2] that the humans have developed the brains through co-evolution with the development of language, the ultimate symbol system. Therefore, the mimesis could be hypothetically thought the origin of intelligence of such animals. The discovery of "mirror neurons"[3] ,that activate not only when one observes an specific behavior of others, but also when one intends to act it, was suggestive. It implies that the basic functions for imitation was locally integrated in the hardware of the brain.

The contemporary technology, on the other hand, poses a grand challenge, namely to design the architecture of intelligence for complex machines such as the humanoids. The role of visual observation was studied by Kuniyoshi et al[4]. to extract reusable knowledge of tasks. The behavior pattern acquisition through the observation based learning was studied by Kawato et al[5]. for robotic manipulators and more recently for a humanoid. Schaal[6] and Mataric[7] discussed the issues between the imitation learning and the humanoids.

The authors' research goal is to bridge from the mimesis to the symbol manipulation through synthetic intelligence design for the humanoid robots. In this paper, we propose an architecture to realize the function of mimesis.

A sequence of other's motion was cut off and segmented from the ever-lasting sequence of motion with the help of the trainer. It is them decomposed using the probability neural network (PNN) such that its approximate is represented by a sequence of the innate primitive motions of the humanoid. The sequence of the primitives were modeled by the dynamics of a hidden Markov model (HMM).

An acquired HMM is used for the dual purposes. It can compute the likelihood when the humanoid observes a new sequence of motion, namely, how close it is to the one he had acquired. The HMM is also used to generate the acquired motion. However, the observed motion would be inappropriate for a self motion unless it is modified to be compatible with the physics of the humanoid. We consider it a process to close the loop of mimesis. Once a sequence of motion is acquired, the humanoid actually tries to generate it and mostly ends up with a failure. Then the observed motion must be modified to obtain a close motion that complies with the own physics. We propose closing the mimesis loop by using the Walking Controller[8], a computer simulation taking the full dynamics into account.

The proposed ideas are integrated to apply to the full body motion of the humanoids. The whole process of mimesis was tested for the motion-captured data of a human and used for the computation of a 26DOF humanoid.

When a set of HMMs for many sequences of motions are acquired, each of HMMs may be labeled. The labels, if we could design an appropriate structure of abstraction and association in-between, can be used as symbols to communicate. Although this design is still beyond the authors current developments, we would like to study in our future work to extend the architecture of mimesis in order to generate symbols.

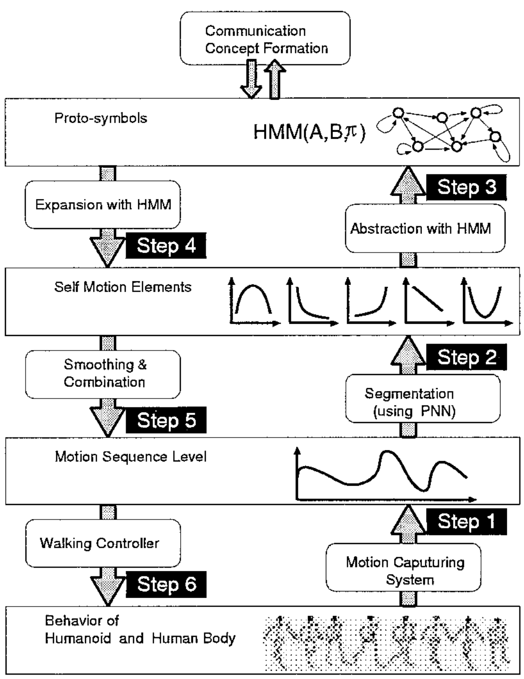

Fig. 1 : The mimesis loop for imitation learning

2 Mimesis loop using self motion elements and proto-symbols

2.1 Generation, abstraction, and recognition of whole body behavior

In feedback error learning proposed by Kawato et al[5], dynamics in a observed behavior is acquired and represented as a feed forward model. This model is able to abstract the dynamics, however, the consideration for symbolization is not well studied, therefore it is not able to be relevant to high order information processing such as recognition of behaviors. Schaal[6] et al have proposed a imitation learning method in which some abstracted modules referred as *primitive behavior* are prepared by developer in order to combine a complex behavior. There are some suggestions that this kind of modules is needed for the symbolization.

In Kuniyoshi's learning approach[4], the rule of sequence of behaviors is constructed by observation and symbolization of human's demonstrations. The approach can reproduce complex behaviors with the abstraction and symbolization, however, it is difficult to be applied to humanoid robots from lack of dynamics point of view.

Here, we propose a model which can abstract whole body motion into a certain symbols, generate motion patterns from the symbols, and recognize total behavior. The model is referred to as mimesis-loop with the precondition of the mimesis, as shown in Fig.1. We can reappear the mirror neuron explained before from a engineering point of view, when the dynamics is abstracted and represented as the symbols. In this paper, we introduce "proto-symbols" as this type of symbols, and "self motion elements" as basic motion patterns which compose the proto-symbols.

Mimesis loop consists of two phases. In the first half, observed motions are transformed into self motion elements by comparing, and are abstracted as proto-symbols. Observed motion patterns are analyzed into the self motion elements, and the sequence of the motion elements are abstracted into proto-symbols, regarded as a series of behavior. We adopted Hidden Markov Models (HMMs) for the description of the relation between sequence of motion patterns and proto-symbols.

HMM is one of stochastic processes which takes time series data as an input, then outputs probability that the data is generated by the HMM. This probability is referred to as likelihood, which enables the mimesis-loop to recognize others' behavior, and to generate humanoids' behavior, and to create proto-symbols. The detail application of the HMMs is explained in the next chapter.

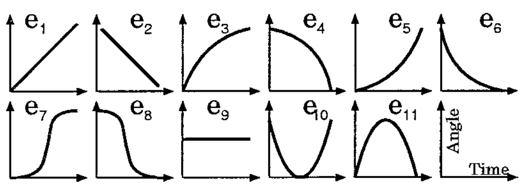

Fig. 2 : Self motion elements

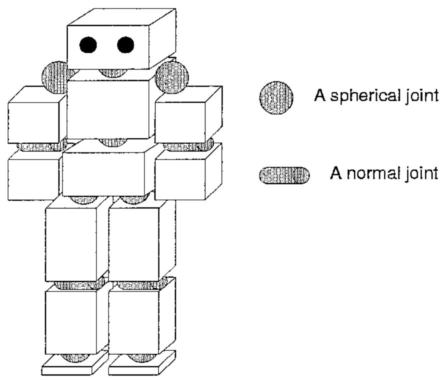

Fig. 3 : Configuration of degree of freedom

2.2 Definition of Self Motion Elements

Self motion elements mean the simple and primitive motion patterns like "moving the hand slowly" and "thrashing one's legs". To put it concretely, it is sequential joint angle pattern of each joint.

In this paper, we adopted 11 basic motion patterns

$$\mathbf{e} = \{e_1, e_2, \ldots, e_{11}\} \tag{1}$$

as the self motion elements, as shown in Fig.2. The horizontal axis indicates time, and vertical axis indicates joint angles. The self motion elements are partial piece of one joint motion. A whole body motion consists of the combination of the self motion elements.

The virtual humanoid used in this research has 28 DOFs as shown in Fig.3. A normal joint corresponds to one self motion elements, and a spherical joint corresponds to three self motion elements.

2.3 Definition of Proto-Symbols

When a dynamics included in the element combination is abstracted and represented as certain symbols, it is possible for the robot to recognize the others' motion and to generate whole body motions from symbols. We refer to the symbol as *proto-symbols.*

3 Abstraction of the whole body motion using proto-symbols

The abstraction of proto-symbols consists of two phase. At first phase, the robot observes others' motion and analyzes the motion into self motion elements. At second phase, the dynamics in the sequence elements are abstracted as proto-symbols using HMMs.

3.1 Analyzing observed motion into self motion elements

Properly speaking, it is better to analyze others' motion in the camera coordinate system into self motion elements in the body coordinate system. In this paper, we omitted the coordinate transformation process with the assumption that the robot observes others' motion in the absolute coordinate system.

At first, motion patterns are analyzed into motion segments using a border time on which the joint angle has big acceleration. Next, this segments are recognized as the self motion elements using Probabilistic Neural Network (PNN)[9]. PNN is a neural network model which uses radial basis function. This model classifies input patterns into prepared classes based on each feature vector. It has two advantage that it is tolerant toward noise, and it outputs the result with probabilities of the sureness of classification.

3.2 Abstraction of motion sequence using HMMs

Next, a HMM which can output the sequence of self motion elements plausibly, is generated. (corresponds to Step 3 in Fig.1) HMMs consists with three parameters; (1)transition probability matrix A_{ij} which means the probability of transition from status i to status j, (2)output probability matrix B_{ix} which means the probability of output x at the status i, (3) initial distribution probability π. The sequence of self motion elements correspond to the sequence of output symbol x. The proto-symbols are defined by the set of these three parameters as following:

$$P_s \stackrel{\text{def}}{=} \{A, B, \pi\} \tag{2}$$

The three parameters are calculated by Baum-Welch method in order for the system to output plausible output sequence.

Let n the number of self motion elements pieces, which is the analysis result of the observed motion sequence. In this case, the generated HMM has n states, the size of transition probability matrix A_{ij} is $n \times n$, and the size of B_{ix} and π is $1 \times n$.

In the case of an unknown motion input, the robot creates a new HMM. However, when an already-known motion is inputted, the robot must recognize the motion and output the result as the proto-symbols. HMMs are originally used for the pattern recognition, therefore, this kind of applications are easy to be realized.

4 Generation of whole body motion from proto-symbols

The generation of whole body motion consists with following two procedures.

1. Generating sequence of self motion elements from proto-symbols (Step 4 in Fig.1)
2. Transforming the self motion elements into joint angles and smoothing angle values. (Step 5 in Fig.1)
3. Compensating the whole body motion in order not to tumble using walking controller [8]. ((Step 6 in Fig.1))

4.1 Generation of sequence of self motion elements using HMMs

The target of this phase is to generate symbol sequence from HMMs and to transform them into self motion elements. When let the symbol sequence $\mathbf{O}$ as following,

$$\mathbf{O} = o_1, o_2, \ldots, o_T \tag{3}$$

$$o_i \in \mathbf{e} \tag{4}$$

the likelihood $P(\mathbf{O}|P_s)$ is used for description of the relation between motion patterns and the proto-symbol. Therefore, the generation is relevant to search a motion pattern which has the best likelihood among the entire patterns of $\mathbf{O}$.

There is an example of generating patterns using continuous mixture HMMs in speech synthesis field, however, it depends on the left-to-right models which is often used in speech recognition systems. The left-to-right models is not suitable for periodic motion such as human's behavior. Thus we propose a pattern generation method using normal discrete HMMs

Most simple way to search the best pattern is to scan the whole pattern space of the $\mathbf{O}$, and find the maximum likelihood. However, it is difficult to adopt this method because the size of the search space is 11^T when the length of motion sequence is T. Thus we have adopted generic algorithm (GA) for the searching.

In order to encode a motion pattern into a chromosome, T genes which correspond to 11 self motion elements are used, on the assumption that the number of motion sequence outputted by the HMMs is T. As the fitness of the chromosome, the likelihood of that the motion patterns are generated by the HMM, $P(\mathbf{O}|P_s)$ is used. It have also adopted translocatoin not simple crossover and mutation. It is suitable for the evolution to keep a series of behavior because the block of self motion elements indicates the series of behavior.

4.2 Motion modification using walking controller

The sequence data of all joint angles, namely the kinematic whole body motion of the humanoid is decided by the combination of outputted self motion elements from the HMMs. However, there is no guarantee that the whole body motion satisfies dynamics conditions because of the discontinuity of the whole body motion at the joint of motion elements. Additionally, difference of mass and moment of inertia between humanoids and human who was observed by the capturing system, has influence for stable walking. Thus transformation from the outputted motion into appropriate motion is needed for satisfying the dynamics conditions. In order to cope with this problem, we adopt the *Walking Controller*[8]. (This process is corresponds to Step 6 in Fig.1.)

This simulator controls angle of each joint of humanoid with modifying kinematic reference motion in order to compensate ZMP conditions. The simulator also outputs torque value to be needed and condition of contact between feet and a floor. It is possible to modify the self motion elements using these results in order that the humanoid creates its own embodiment parameters. This phase corresponds to the connection from the *Step 6* to the *Step 1*, for the completion of mimesis-loop.

5 Simulation of generating whole body motion

5.1 Simulation of motion abstraction

For the verification of the method, human's motion data have observed via motion capturing system. The capturing system can measures 28 joint angles of all DOFs with sampling time 33[ms]. Four walking data; person A, person B, tired man, and old man, have observed for verification experiments.

The captured walking motions are shown in from Fig.7 to Fig.10 From here, focusing on the angle of left knee, the time series of angle is as solid line shown

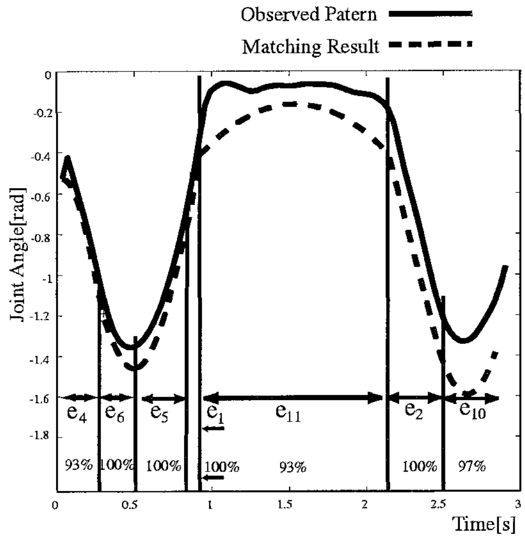

Fig. 4 : Segmented motion elements(left knee)

in Fig.4. The horizontal axis indicates time [sec], and the vertical axis indicates joint angle [rad]. The graph shows one and half cycle of the periodic walking motion. The circled number for each segment is the self motion elements, and the percentage is probability of PNN matching. The broken line indicates the angle time series constructed by the sequence of self motion elements, $\{e_4, e_6, e_5, e_1, e_{11}, e_2, e_{10}\}$.

5.2 Simulation of motion generation

We have practiced an experiment in which most plausible sequence of self motion elements is generated from the three parameter A, B, π which corresponds to proto-symbols. The condition of the GA is that the number of gene is 7, the number of chromosomes is 500, the crossover ratio is 0.9, the mutation ratio is 0.95, and elite selection was adopted. At about 500th generation, a sequence of self motion elements as same as shown in Fig.4 is generated. A calculation time is about 3[sec] on Pentium-III 600MHz, which is enough rapid to apply for motion generation based on symbolic communication between users.

A whole body motion transformed from the outputted sequence of self motion elements is shown in Fig.5. (This process corresponds to Step 5.) It is obvious that the generated motion pattern as same as the observed motion pattern, it also shown in Fig.4. The result of dynamic simulation of a humanoid is shown in Fig.6.

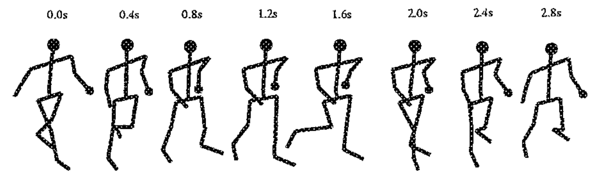

Fig. 5 : A generated motion

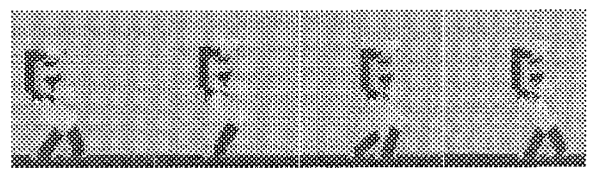

Fig. 6 : Result of walking controller

5.3 Recognition of others' motion

Here, we explain a method to recognize the observed motions using HMMs. Two proto-symbols, $P_s^{(a)} = \{A^{(a)}, B^{(a)}, \pi^{(a)}\}$ and $P_s^{(b)} = \{A^{(b)}, B^{(b)}, \pi^{(b)}$ was generated from observation of two walking behaviors by testee A and B. Another proto-symbols was generated from walking behavior when the testee was tired ($P_s^{(t)}$), and when the testee was an old man ($P_s^{(o)}$). After that, observes another walking behaviors of A, B, tired testee, and old testee, then executes the recognition process for each HMMs. The result is shown in Table 1. Each value indicates the likelihood of the motion generation. On the one hand, the likelihood of the walking pattern A generated by $P_s^{(a)}$ is 10^{17} times as large as the likelihood generated by $P_s^{(b)}$. On the other hand, the likelihood of the pattern B generated by $P_s^{(b)}$ is 10^{23} times as large as the likelihood generated by $P_s^{(a)}$. This result shows that the ratio of the likelihood is useful for the recognition. When an unknown behavior is inputted, it is possible to judge the novelty using certain threshold of the likelihood.

6 Summary and Conclusions

We focused on imitation learning and proposed mimesis-loop using self motion elements and proto-symbols. The feature of this system is that it is possible to realize following three function in the same model: (1)To abstract the dynamics of human's motion, (2)To generate natural motion patterns from the symbolized dynamics, and (3)To recognize others' behavior using proto-symbols. An abstraction method using PNN for analysis of the observed motion into self

Proto-symbols used in recognition	Input Behavior			
	Testee A	Testee B	Tired testee	Old testee
$P_s^{(a)}$	1.2×10^{-1}	5.4×10^{-31}	3.4×10^{-46}	6.1×10^{-18}
$P_s^{(b)}$	1.2×10^{-19}	2.8×10^{-8}	3.6×10^{-43}	4.8×10^{-14}
$P_s^{(t)}$	2.3×10^{-21}	5.4×10^{-32}	2.4×10^{-10}	8.7×10^{-14}
$P_s^{(o)}$	4.6×10^{-25}	5.4×10^{-42}	2.4×10^{-48}	2.3×10^{-1}

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

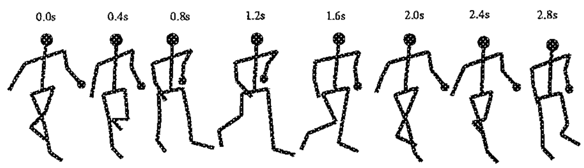

Fig. 7 : A walking motion of testee A

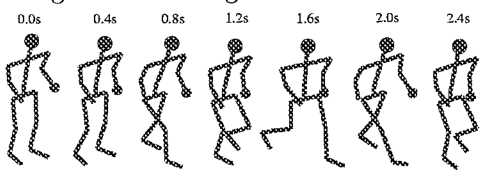

Fig. 8 : A walking motion of testee B

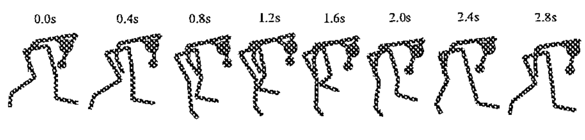

Fig. 9 : A walking motion when the testee was tired

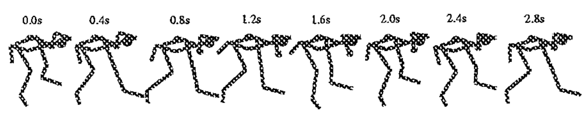

Fig. 10 : A walking motion by an old man

motion elements and HMMs for represent the motions' dynamics have explained. Also a generation method using HMMs and GA have explained.

Current difficulty is that a HMM represents not dynamics of whole body but dynamics for only one joint angle. There must be dynamics or correlative relationship between each joint, therefore it is not enough satisfied to express the whole body motion with leaving the current difficulty as it is. For the future works, we plan to introduce new self motion elements which can treat whole body motion. We also have a prospect of using results after passing the dynamics simulation as fitness of the GA, in order to generate natural motion from HMMs.

In this paper, the functions of the proposed system are the abstraction of others' motion and the reproduction of self motion. We plan to expand the system in order to refine the self motion by inputting the output self motion into the observation process as an other's motion. Finally, the research aims to realize humanoids which can communicates with human and makes plans using symbols.

Acknowledgement

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