Behavior Generation of Humanoid Robots Depending on Mood

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Abstract. Personal robots, which are expected to become popular in the future, are required to be active in joint work and community life with human. Therefore, the objective of this study is the development of new mechanisms and functions for a humanoid robot to express emotions and to communicate naturally with human. We developed both the mental model from psychological point of view and the Emotion Expression Humanoid Robot WE-4RII (Waseda Eye No.4 Refined II) from engineered point of view.

In this paper, a co-associative memory model using mutually coupled chaotic neural networks was proposed and implemented in WE-4RII as its mental model. We confirmed that the robot could generate the behavior depending on its mood in response to a stimulus.

Keywords. Humanoid Robot, Neural Network, Mental Model, Memory

Introduction

Industrial robots have various functions, such as assembly and conveyance. However, an operator has to define the robot's behavior with very complex processes or methods. On the contrary, personal robots, which are expected to become popular in the future, have to be active in joint work and community life with human. Adaptation to partners or the environment and communication with partners are necessary for them. Therefore, the objective of this study is the development of new mechanisms and functions for the natural bilateral interaction between a robot and a human, e.g. expressing the emotions and personality, and generating active behaviors.

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Various communication robots are researched in robotics. Brooks at MIT has developed an expressive robotic creature that expresses facial expressions using its eyes, eyelids, eyebrows and mouth. It communicates with human by using visual information from CCD cameras [1]. Sony Corporation has developed the entertainment humanoid QRIO, which is 50 [cm] tall and has 50-DOFs. It can autonomously walk by using CCD cameras information on the head, and it can control its behavior with the homeostasis regulation mechanism [2][3].

We have produced emotional expressions and active behavior with the Emotion Expression Humanoid Robot WE-4 (Waseda Eye No.4) series, which have the face, neck, lungs, waist, 9-DOFs emotion expression humanoids arms and humanoid robot hands RCH-1 (Robo Casa Hand No.1) [4]. In addition, we have developed the mental model for humanoid robots in order to realize the communication with humans. A mental space with three independent parameters, mood, second order equations of emotion, robot personality, need model [5], consciousness model and behavior model have been introduced into the mental model.

On the other hand, many authors research new models for neural networks. In the Hopfield model, which is the most typical neural network, it is shown that the energy function decreases monotonically, and one energy minimum corresponds to one memory [6][7]. However, if the system falls into a spurious minimum, it cannot then escape from it. Therefore, several methods have been proposed to solve this problem by using chaos. Shimizu has proposed a chaotic neural network model, which consists of N Brownian particles [8]. It was found that the network retrieves all stored patterns and reversed patterns in the associative memory problem.

We have been researching a system of multiple harmonic oscillators interacting via chaotic force as a model of neural network [9]. We have investigated a system of mutually coupled neural networks, in which each neuron is connected only with the correspondent neuron in the coupled network. Storing the different pattern in two networks, we have found that each network retrieves not only the pattern stored in it but also the pattern stored in the coupled network.

In the previous mental model, the robot has showed just one behavior in response to a stimulus, though human behavior in response to a stimulus depends on the mood at the time. Therefore, we proposed a co-associative memory model using mutually coupled chaotic neural networks for generating the behavior to a stimulus depending on the mood. We implemented new mental model with memory model in the Emotional Expression Humanoid Robot WE-4RII (Waseda Eyes No.4 Refined II). In this paper, we describe in detail the new memory model.

1. Previous Mental Model

We have developed the mental model with the mental space with three independent parameters, mood, second order equations of emotion, robot personality, need model, consciousness model and behavior model for a humanoid robot to interact bilaterally with a human. First, we have defined the mental space consisting of the *pleasantness*, *activation* and *certainty* axes shown in Figure 1. The *Emotion Vector* **E** has been defined in the mental space as the robot's mental state as:

$$E = (E_p, E_a, E_c), \tag{1}$$

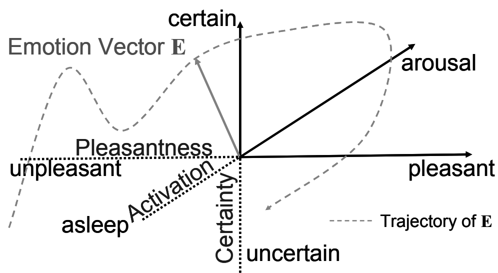

Figure 1. 3D Mental Space and Emotion Vector **E**.

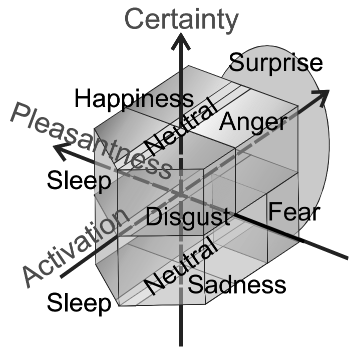

Figure 2. Mapping of Seven Different Emotions.

where E_p is the pleasantness component of emotion, E_a is the activation component of emotion, and E_c is the certainty component of emotion. We have mapped out seven different emotions in the 3D mental space as shown in Figure 2. The robot expresses the emotion corresponding to the region traversed by the Emotion Vector **E**. We have considered that the transition of a human mental state is expressed by similar equations to the equation of motion. Therefore, we have expanded the equations of emotion into the second order differential equation as shown in Eq.(2). Also three Emotional Coefficient Matrixes, the Emotional Inertia, Emotional Viscosity and Emotional Elasticity Matrixes have been introduced.

$$M\ddot{E} + \Gamma\dot{E} + KE = F_{EA}, \tag{2}$$

M : *Emotional Inertia Matirx*

Γ : *Emotional Vis*cos*ity Matirx*

K : *Emotional Elasticity Matirx*

F_{EA} : *Emotional Appraisal*

where the Emotional Appraisal F_{EA} stands for the total effects of internal and external stimuli on the mental state. The robot expresses different reactions to a stimulus by changing the Emotional Coefficient Matrixes.

The mental state is affected not only by emotion, but also by mood. Therefore, we have defined the Mood Vector **M**, consisting of a pleasantness component and activation component:

$$M = (M_p, M_a, 0), \tag{3}$$

$$M_p = \int E_p dt, \tag{4}$$

$$\ddot{M}_a + (1 - M_a^2)\dot{M}_a + M_a = 0, \tag{5}$$

where M_p is the pleasantness component of the mood and M_a is the activation component of the mood, respectively. Since we have considered the current mental state to influence the pleasantness of mood, M_p has been defined as the integral of the pleasantness component of the emotion (Eq.(4)). On the other hand, since the activation component of Mood Vector is similar to the human biological rhythm such as the internal clock, the Van del Pol equation has been applied to define M_a (Eq.(5)).

In addition, we developed the need model, which consists of the Appetite, the Need for Security, and the Need for Exploration, in order to generate actively a behavior for bilateral interaction with a human [5]. The need matrices N_t at time t and $N_{t+\Delta t}$ at $t+\Delta t$ are described by the Equation of Need:

$$N_{t+\Delta t} = N_t + P_N \times \Delta N, \tag{6}$$
$$P_N : \textit{Need Personality Matrix}$$
$$\Delta N : \textit{Small differences between two need states}$$

where ΔN is determined by the stimuli from the internal and external environment, P_N is a 3*3 matrix and stands of the personality for the need. In psychology, each need is independent, so P_N is a diagonal matrix. Especially, the appetite depends on the total spent energy (described as the sum of the basal metabolism energy and output energy):

$$\begin{aligned} \Delta N_A &= f(\Delta A) \\ \Delta A &= \Delta A_{BM} + \Delta A_{EA} \end{aligned}, \tag{7}$$

where ΔA means the variation in the energy spent by the robot, A_{BM} is the basal metabolism energy, and A_{EA} is the output energy.

However, the robot with the previous mental model has been able to determine just a single kind of recognition in response to a stimulus and has showed behavior corresponding to the recognition. On the contrary, humans recognize a stimulus and generate a behavior depending on their mood at the time. Therefore, we proposed a new memory model for recognition (memory retrieval) depending on mood in response to a stimulus, using mutually coupled chaotic neural networks.

2. Human Memory

Human memory is related to their mood by mood state-dependency and mood congruency [10]. Humans store Memory A when in a certain mood. They can easily retrieve Memory A if their mood becomes the same mood again. This is known as the *mood state-dependency*. On the other hand, a certain mood helps retrieving a memory corresponding to that mood (*mood congruency*). Basically, humans tend to retrieve pleasant memories if they are pleasant and conversely, unpleasant memories if they are unpleasant.

Moreover, human performance is related to their activation level [11]. If an activation level becomes too high or too low (i.e. superexcitation or bleariness), active human performance becomes impossible. The best human performance comes at a medium activation level.

In this paper, we proposed a co-associative memory model for generating various behaviors to a stimulus, whereby the robot retrieves a pleasant memory if it is pleasant and an unpleasant memory if it is unpleasant. In addition, we controlled the time for retrieving a memory by the activation component of the robot's emotion, in order to realize the connection between performance and activation level.

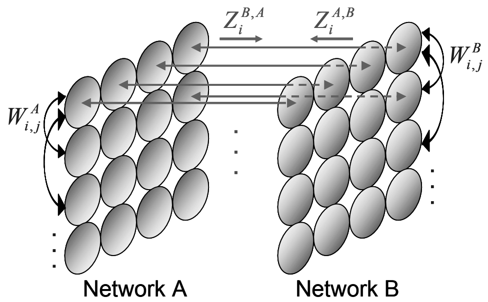

Figure 3. Coupling of Two Neural Networks.

3. Co-associative Memory Model

3.1. Mutually Coupled Chaotic Neural Networks

We proposed a system of mutually coupled chaotic neural network, which consists of many harmonic oscillators (neurons), as a co-associative memory model. The internal state of each neuron is represented as the position of the harmonic oscillator driven by the chaotic force. If the internal state of neuron i (i=1,2,…,N) in Network α (α=A or B) at time $t=n\tau$ is denoted by $x_i^\alpha(t)$, the time evolution of the neuron is provided by Eq.(8). $f(t)$ is the input from the surrounding neurons and itself, whose amplitude changes chaotically at time interval τ:

$$\ddot{x}_i^\alpha(t) + k\dot{x}_i^\alpha(t) + \omega_0^2 x_i^\alpha(t) = f_i^\alpha(t), \tag{8}$$

$$f_i^\alpha(t) = \frac{K}{\sqrt{\tau}} h_i^\alpha(n) \quad \text{for} \quad n\tau \le t < (n+1)\tau \quad (n=0,1,2,\cdots), \tag{9}$$

where, k, ω_0 and K are the damping constant, the eigen-frequency and the magnitude of $f(t)$, respectively. The factor $1/\sqrt{\tau}$ is needed to obtain a finite diffusion constant in the small τ limit [12]. $h(n)$ denotes the interaction among neurons. We coupled two networks by connecting neuron i in Network A(B) with neuron i in Network B(A) as shown in Figure 3:

$$h_i^A(n) = \sum_{j=1}^{N} W_{i,j}^A y_j^A(n) + Z_i^{A,B} y_i^B(n), \quad h_i^B(n) = \sum_{j=1}^{N} W_{i,j}^B y_j^B(n) + Z_i^{B,A} y_i^A(n), \tag{10}$$

$$W_{i,j} = \frac{1}{N} \sum_{s=1}^{P} \xi_i^s \xi_j^s, \tag{11}$$

where $W_{i,j}$ is the coupling constant from neuron j to neuron i and $Z_i^{A,B}$ ($Z_i^{B,A}$) is that from neuron i in Network B(A) to neuron i in Network A(B). ξ_i denotes the stored pattern vector and ξ_i takes +1 or -1. To store patterns in the network, we used the Hebb rule to determine $W_{i,j}$ as shown in Eq.(11). The self-coupling constant is equal to 1; $W_{i,i}$=1.

In Eq.(10), $y(n)$ denotes the output of the neuron and represents the nth iterate of a map. As an example of the map, we employed the Logistic map, whose bifurcation parameter $r(n)$ is modulated by the internal state of the neuron:

$$y_i^{\alpha}(n+1) = r_i^{\alpha}(n)(0.5 - y_i^{\alpha}(n))(0.5 + y_i^{\alpha}(n)) - 0.5 \quad (-0.5 \le y(n) \le 0.5) \tag{12}$$

$$r_i^{\alpha}(n) = 4 - b + b\cos^2 \beta x_i^{\alpha}(n) \quad (0 \le b \le 4) \tag{13}$$

where b and β are control parameters. *y(n)* changes chaotically or periodically according to the bifurcation parameter. Since the bifurcation parameter *r(n)* is modulated by the internal state of the neuron as shown in Eq.(13), the chaos is controlled by the neuron itself.

A new type of feed-back mechanism is included in this model. The internal state *x(n)* determines the bifurcation parameter *r(n)*, which, in turn, determines the dynamics of the chaotic output *y(n)*. The chaotic output then affects the dynamics of the neuron. Thus, the dynamics of the chaos is changed by the system itself. In particular, if we put the period of the harmonic oscillator 2.0, the neural network can retrieve the original and reverse patterns alternately, meaning this neural network can perform very well.

3.2 Co-associative Memory Model

In this paper, we defined "Apple" as the pleasant memory for "Red" and "Tomato" as the unpleasant memory for "Red". Of course, we can select other memories according to the robot personality. In the case of $Z_i^{B,A}$=0.0, if $Z_i^{A,B}$ becomes large the number of times in which Network A retrieves "Apple" increases and the number of times in which Network A retrieves "Tomato" decreases. Therefore, we introduced the mood state-dependency and the mood congruency by modulating $Z_i^{A,B}$ by the pleasantness component of the mood M_p. The robot retrieves "Apple" for pleasant mood and "Tomato" for unpleasant mood when it recognizes "Red". However, human retrieve the favorite food even if they are unpleasant by feeling hungry. We solved this problem by defining $Z_i^{A,B}$ as the sum of the pleasantness component of mood M_p and the Appetite N_A:

$$Z_i^{A,B} = M_p + N_A. \tag{14}$$

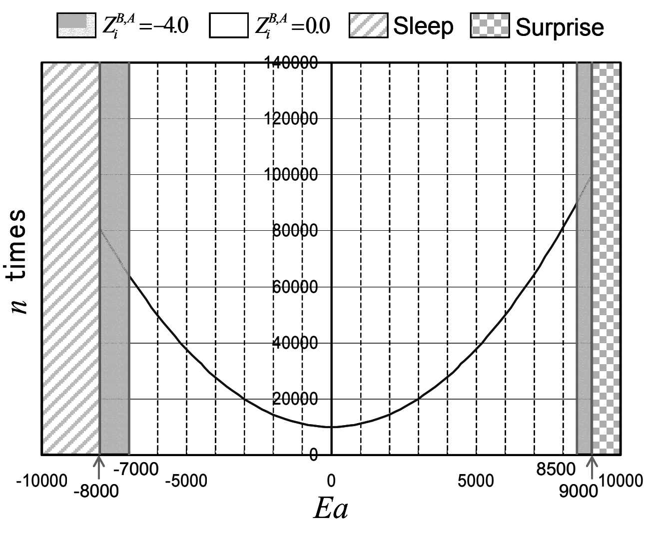

Figure 4. Relation between Performance and Activation Level.

In addition, we controlled the time for retrieving a memory by the activation component of the robot emotion E_a, in order to realize the connection between performance and activation level, as shown in Figure 4. The robot with suitable activation level can retrieve the memory corresponding to its mood soon. However, the robot needs time to retrieve the memory if E_a becomes too high or too low.

Moreover, we considered that a wrong memory is sometimes retrieved in case of too high or too low activation level. For $Z_i^{B,A}$=-4.0, Network A retrieves "Tomato" in almost smaller half region of $Z_i^{A,B}$ but sometimes retrieved "Apple." Reversely, Network A retrieves "Apple" in almost larger half region of $Z_i^{A,B}$ but sometimes retrieves "Tomato". Therefore, we defined that $Z_i^{B,A}$ is equal to 0.0 for suitable activation levels and to -4.0 for too high or too low activation levels.

4. Experimental Results

We evaluated a new co-associative memory model through implementation in the Emotion Expression Humanoid Robot WE-4RII as shown in Figure 5. We set the parameter values as K=14.0, k=0.1, ω_0=31.4, β=0.05, τ=0.1 and b=1.2, and the initial values as $x_i(0)$=25.0, $\dot{x}_i(0)$=0.0 and $y_i(0)$=0.2. Figure 6 shows the time evaluation of the emotion, the mood and the retrieved memory of WE-4RII. At first, we showed the red ball to the robot and the robot became unpleasant by being hit. It retrieved the unpleasant memory "Tomato" and shows the "Disgust" emotional expression. Next, the robot felt hungry since it moved considerably. Due to hunger, it retrieved the pleasant memory "Apple" in spite of unpleasant mood. After that, the robot can take the apple using its hand, and generate the behavior such as eating. If its hunger is satisfied, the robot becomes happy.

Moreover, we confirmed that it took only about 2[s] for the robot from looking at the red ball until retrieving a memory. On the other hand, the robot needed about 9[s] for memory retrieval, since the activation level became very high by being hit many times. At this time, sometimes the robot could not retrieve the memory, depending on mood.

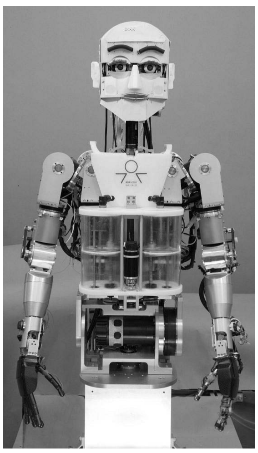

Figure 5. WE-4RII.

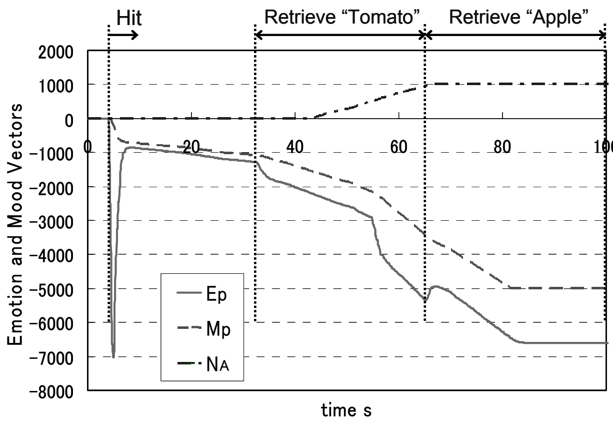

Figure 6. Experimental Results of Mood State-Dependency and Mood Congruency

5. Conclusions and Future Work

In this paper, we investigated the co-associative memory model including the mood state-dependency, the mood congruency and the connection between performance and activation level in order to generate a behavior depending on mood in response to a stimulus. This memory model was realized using mutually coupled chaotic neural networks, which consist of many harmonic oscillators (neurons) interacting via the chaotic force. We confirmed that the robot can retrieve the memory depending on mood in response to a stimulus and show the behavior corresponding to the memory by implementing this memory model in the Emotion Expression Humanoid Robot WE-4RII.

In the future, we will increase a number of retrievable memories. Furthermore, we will study a method for storing memories depending on mood.

Acknowledgment

Part of this research was conducted at the Humanoid Robotics Institute (HRI), Waseda University. The authors would like to express their thanks to Okino Industries LTD, OSADA ELECTRIC CO. LTD, SHARP CORPORATION, Sony Corporation, Tomy Company LTD and ZMP INC. for their financial support to HRI. The authors would like to thank Italian Ministry of Foreign Affairs, General Directorate for Cultural Promotion and Cooperation, for its support to the establishment of the ROBOCASA laboratory and for the realization of the two artificial hands. In addition, this study was supported in part by the Ministry of Education, Science, Sports and Culture, Grant-in-Aid for Young Scientists (B), 17700211, 2005. Also, this research was supported by a Grant-in-Aid for the WABOT-HOUSE Project by Gifu Prefecture. Finally, the authors would like to express thanks to ARTS Lab, NTT Docomo, SolidWorks Corp., Advanced Research Institute for Science and Engineering of Waseda University, Prof. Hiroshi Kimura for their supports to our research.

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