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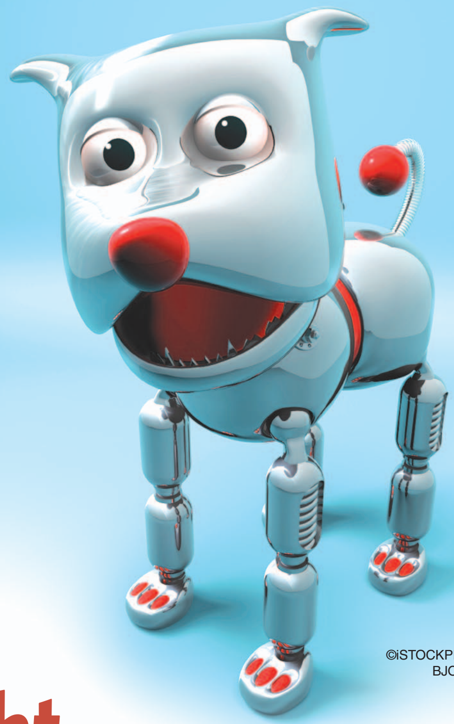

The Degree of Consideration-Based Mechanism of Thought and Its Application to Artificial Creatures for Behavior Selection

Abstract – To make artificial creatures deliberately interact with their environment like living creatures, a behavior selection method mimicking living creatures' thought mechanism is needed. For this purpose, there has been research based on probabilistic knowledge links between input (assumed fact) and target (behavior) symbols for reasoning. However, real intelligent creatures including human beings select a behavior based on the multi-criteria decision making process using the degree of consideration (DoC) for input symbols, i.e. will and context symbols, in their memory. In this paper, the DoC-based mechanism of thought (DoC-MoT) is proposed and applied to the behavior selection of artificial creatures. The knowledge links between input and behavior symbols are represented by the partial evaluation values of behaviors over each input symbol, and the degrees of consideration for input symbols are represented by the fuzzy measures. The proposed method selects a behavior through global evaluation by the fuzzy integral, as a multi-criteria decision making process, of knowledge link strengths with respect to the fuzzy measure values. The effectiveness of the proposed behavior selection method is demonstrated by experiments carried out with a synthetic character "Rity" in the 3D virtual environment. The results show that the artificial creatures with various characteristics can be successfully created by the proposed DoC-MoT. Moreover, training the created artificial creatures to modify their characteristics was more efficient in the DoC-MoT than the probability-based mechanism of thought (P-MoT), both in terms of the number of parameters to be set and the amount of time consumed.

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I. Introduction

Ubiquitous robot incorporating mobile robot (Mobot), embedded robot (Embot) and software robot (Sobot) was introduced for various services at any place and any time [1]. Mobot provides integrated mobile services in cooperation with Embot and Sobot. Embot is embedded in the environment to collect sensor data, and Sobot in a virtual world makes a decision. In recent years, pet-type Sobots were developed to be mounted on cell phones or computers as artificial creatures or synthetic characters. As they might behave like a real world creature, they could be used as an intermediate interface for interaction with a user [2]–[4].

To act like a living creature, the artificial creature should behave according to its desire in a certain situation. In this regard, there has been research on behavior

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selection methods using the control architecture for decision making of living creatures [5]–[8]. The architecture organized into perception, behavior, motivation and actuator modules was proposed for behavior selection [9]–[16]. The context and desire are generated respectively in the perception and motivation modules. In the behavior module, each candidate behavior is evaluated based on the desire and context, and the best one is selected. Then, the selected behavior is generated through the actuator module. Considering both deliberative and reflexive behaviors, a control architecture for probabilistic and deterministic behavior selections was proposed for artificial creatures [17]. The artificial creatures probabilistically select a behavior based on their internal state including motivation, homeostasis and emotion, and external sensor information as a deliberative behavior. A reflexive behavior that imitates animals instinct is selected deterministically using only external sensor information.

A two-layered confabulation architecture was proposed for behavior selection considering internal state and context using confabulation theory [18]. The confabulation theory illustrates the mechanism of thought of human beings [19]. The key idea is that each thalamocortical module is equipped with a large collection of input symbols of internal state and context, where the pairs of co-occuring symbols are connected by knowledge links. As a result of "thought process," one target symbol is selected among behavior symbols by confabulation. In this scheme, the knowledge link between co-occurring symbols is represented by conditional probability.

However, the human thought process is not based only on crisp numbers. Though such statistical information as conditional probabilities is an important part of the human thought process, it, generally, is not the dominant deciding factor. The personal biases, based on psychological and cognitive aspects of the human personality, and the environmental conditions have a dominant effect on the human thought process. For example, a person can be inclined towards a particular choice because of his/her optimism, belief, prejudice or some other personal or environmental aspect even though the statistical figures claim the feasibility of making some other choice. The effects of these personal biases on the human thought process and decision making were discussed in detail [20]–[22]. Besides, another real life characteristic that confabulation fails to effectively represent is the mutual interactions among wills or contexts ranging from redundancy (negative interaction) to synergy (positive interaction) [23].

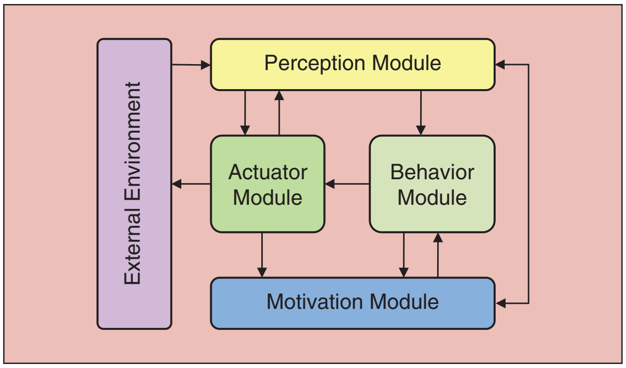

FIGURE 1 Schematic diagram of a typical conventional architecture for artificial creatures.

This paper proposes the degree of consideration-based mechanism of thought (DoC-MoT) and its application to the behavior selection method for artificial creatures. The human-like thought process which is affected by personal biases and prejudices based on psychological, cognitive or environmental grounds, is used to model the mechanism of thought for artificial creatures. The creatures' degrees of consideration (DoCs) for their internal wills and environmental contexts constitute the basis of the thought mechanism. In the proposed model, the DoCs for input (i.e. wills and contexts) symbols are represented by the fuzzy measures and the fuzzy integral is used for the global evaluation of the target (i.e. behavior) symbol on the basis of the partial evaluations over input symbols and their DoCs [24], [25]. The effectiveness of the proposed behavior selection method using the DoC-MoT is demonstrated by experiments carried out with a synthetic character "Rity," in a 3D virtual environment.

This paper is organized as follows. Section II briefly describes confabulation theory that explains the probability-based mechanism of thought (P-MoT) and proposes the DoC-MoT. Section III proposes a behavior selection method using the proposed DoC-MoT. Section IV presents the experimental results to demonstrate the effectiveness of the proposed method. The concluding remarks follow in Section V.

II. Modeling the Mechanism of Thought

An artificial creature, which acts like a real creature, mimics the real creature's thought mechanism. Fig. 1 shows a typical conventional architecture, which has two behavior generation paths: the deliberate generation and the reflexive generation [9]-[16]. In case of deliberate generation, a proper behavior is selected in the behavior module considering its desire and environmental context generated respectively in the motivation and perception modules, and the selected deliberative behavior is expressed through the actuator module. In reflexive generation, the sensor information in the perception module bypasses the motivation stage in order to take emergency measures. This reflexive behavior generation is inspired from the reflex actions in biological species. To generate the deliberative behaviors as a consequence of the thought process, the architecture should be embodied with a well-modeled mechanism of thought. In this section, the probability-based mechanism of thought (P-MoT) is briefly reviewed, and a novel model of the DoC-based mechanism of thought (DoC-MoT) is proposed.

A. The Probability-Based Mechanism of Thought (P-MoT)

The mechanism of thought is modeled by the confabulation theory based on probability [19]. To understand the mechanism of thought, the things to be understood first are: what forms a brain and how the brain functions. As muscles are composed of several individual fibers, the brain is formed of a number of well-connected neurons [26]. A set of connected neurons represents various symbols which are composed of input symbols (assumed fact symbols) and target symbols, such as "red," "sweet," as input symbols and "apple" as a target symbol, etc., where the symbols are grouped into "color," "taste," "word," etc. The links between the input and target symbols, e.g. the links between "red" and "apple" and between "sweet" and "apple" represent the knowledge about perceived entities, e.g. the "likeliness" of an "apple" to be "red" or the "likeliness" of an "apple" to be "sweet," and therefore, they are called the knowledge links. The knowledge links, such as "likeliness" in this example, are represented by conditional probabilities, and they describe the agent's degree of belief about the target symbol to possess the attributes specified by the input symbols.

With the knowledge links between input and target symbols, the cognitive information-processing is employed by confabulation as shown in Fig. 2(a). When some of the input symbols, e.g. a, b, c and d, are expressed (perceived), each target symbol receives input excitations by knowledge links from them. Since the strength of the knowledge link is represented by conditional probability, the total input excitation $I(z)$ for target symbol z, is calculated using Bayes' rule as follows [27]:

$$\begin{aligned} I(z) &= p(abcd\,|\,z)^4 \\ &= \left[\frac{p(abcdz)}{p(az)}\right]\left[\frac{p(abcdz)}{p(bz)}\right] \\ &\quad \times \left[\frac{p(abcdz)}{p(cz)}\right]\left[\frac{p(abcdz)}{p(dz)}\right][p(a\,|\,z)p(b\,|\,z)p(c\,|\,z)p(d\,|\,z)]. \end{aligned} \tag{1}$$

In general, the first four terms can be approximated as a constant number in any given situations as follows:

$$\left[\frac{p(abcdz)}{p(az)}\right]\left[\frac{p(abcdz)}{p(bz)}\right]\left[\frac{p(abcdz)}{p(cz)}\right]\left[\frac{p(abcdz)}{p(dz)}\right] \approx K. \tag{2}$$

Thus, $I(z)$ can be approximately calculated as

$$I(z) \approx K[p(a\,|\,z)p(b\,|\,z)p(c\,|\,z)p(d\,|\,z)]. \tag{3}$$

Once the total input excitations of all the target symbols are calculated, the target symbol with the highest input excitation is selected as a conclusion and this "winner-take-all" competition among target symbols is called confabulation.

B. The DoC-Based Mechanism of Thought (DoC-MoT)—A Novel Approach

Though the probability-based information processing, as described in the previous section, selects a behavior based on the multi-criteria decision making process considering both its desire and external context [18], there can be some exceptions where the thought process is largely affected by personal biases [21]. These biases generally occur due to psychological and cognitive aspects of personality. To tackle these issues, a novel approach that considers these personal biases, while selecting an

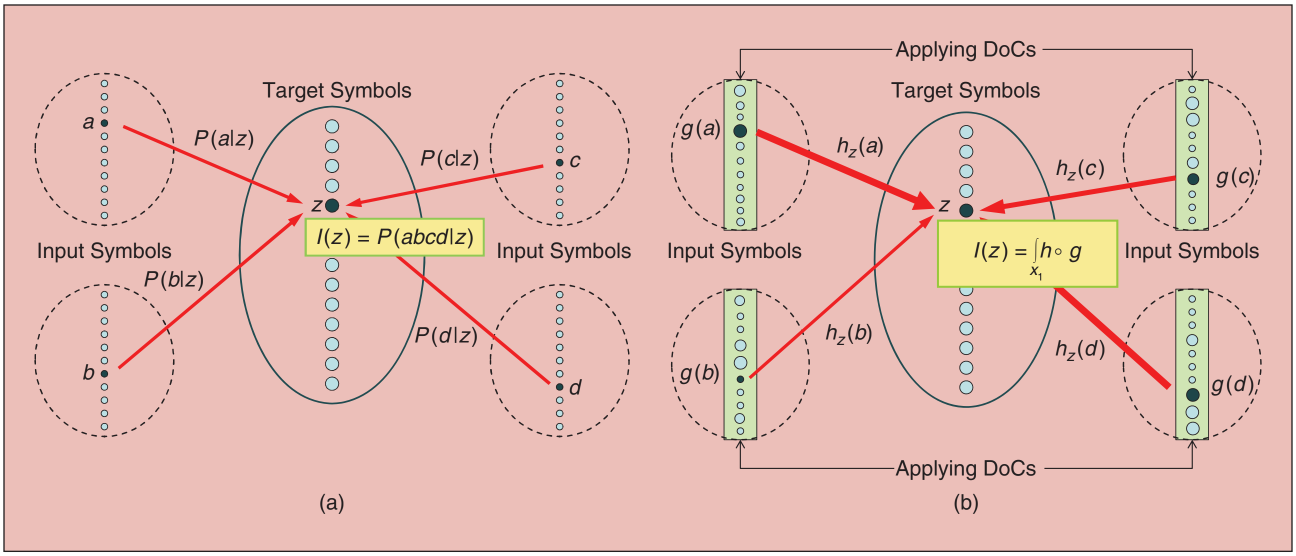

FIGURE 2 Modeling the mechanism of thought: The total input excitation for symbol z is represented by $I(z)$, calculated by confabulation in the P-MoT and by the fuzzy integral in the DoC-MoT. (a) The probability-based mechanism of thought (P-MoT) and (b) The DoC-based mechanism of thought (DoC-MoT).

TABLE 1 Fuzzy measure property and interaction degree.

FUZZY MEASURE PROPERTY	λ	ξ	SYMBOL RELATION
$g(A \cup B) > g(A) + g(B)$	+ inf	0	NEGATIVE CORRELATION
	$\vdots$	$\vdots$	
$g(A \cup B) = g(A) + g(B)$	0	0.5	INDEPENDENT
	$\vdots$	$\vdots$	POSITIVE CORRELATION
$g(A \cup B) < g(A) + g(B)$	−1	1	

appropriate behavior, is needed. One such approach, based on considering the creature's own DoCs and the decision making process for modeling a thought process, is proposed in this paper. These DoCs quantitatively define the creature's inclination towards a particular will or a context.

To represent the DoC for a criteria set, the fuzzy measure representation is preferred because besides representing the wills and contexts, it can also effectively represent the mutual interactions among them. The fuzzy integral based approach for global evaluation was considered because of its usefulness in the multi-information aggregation and the multi-criteria decision making [24]. Now, denote a set of symbols, e.g. input symbols for creature's wills and contexts, by $X = \{x_1, \ldots, x_n\}$ and the power set of X by $P(X)$. With these notations, the definitions of the Sugeno λ-fuzzy measure and the Choquet fuzzy integral are summarized in the following [25].

Definition 1 A fuzzy measure on the set X of symbols is a set function $g: P(X) \to [0, 1]$ satisfying the following axioms;

i) $g(\emptyset) = 0$, $g(X) = 1$;

ii) $A \subset B \subset X$ implies $g(A) \le g(B)$.

The Sugeno λ-fuzzy measure satisfies the following [24]:

$$g(A \cup B) = g(A) + g(B) + \lambda g(A) g(B), \tag{4}$$

where $g(A)$ and $g(B)$, $A, B \subset X$, represent the DoCs for the subsets A and B, respectively, and λ denotes an interacting degree index. To calculate the fuzzy measures more efficiently, ξ is used as an another interaction degree index [28]. If $0 \le \xi < 0.5$, (4) becomes a plausible measure, if $\xi = 0.5$, a probability measure, and if $0.5 < \xi \le 1$, a belief measure. Table 1 shows the relationship between two interaction degree indices. Note that if two symbols have positive (negative) correlation, i.e. $g(A \cup B) < g(A) + g(B)$ $(g(A \cup B) > g(A) + g(B))$, the global evaluation by the fuzzy integral over the symbols is to be underestimated (overestimated) [29]. The Choquet fuzzy integral which can be used in a discrete domain problem is defined in the following [30].

Definition 2 Let h be a mapping from finite set X to $[0, 1]$. For $x_i \in X$, $i = 1, 2, \ldots, n$, assume $h(x_i) \le h(x_{i+1})$ and $E_i = \{x_i, x_{i+1}, \ldots, x_n\}$. The Choquet fuzzy integral of h over X with respect to a fuzzy measure g is defined as

$$\int_X h \circ g = \sum_{i=1}^{n} (h(x_i) - h(x_{i-1})) g(E_i). \tag{5}$$

Using the definitions of the Sugeno λ-fuzzy measure and the Choquet fuzzy integral, the thought process of the proposed approach is realized as in Fig. 2(b). When some of input symbols, e.g. a, b, c and d, are expressed (perceived), each target symbol receives input excitations by both knowledge links and the DoCs for the input symbols. If the DoC for input symbol a is high, target symbol z is more strongly linked to a than other input symbols. This approach is called the DoC-MoT.

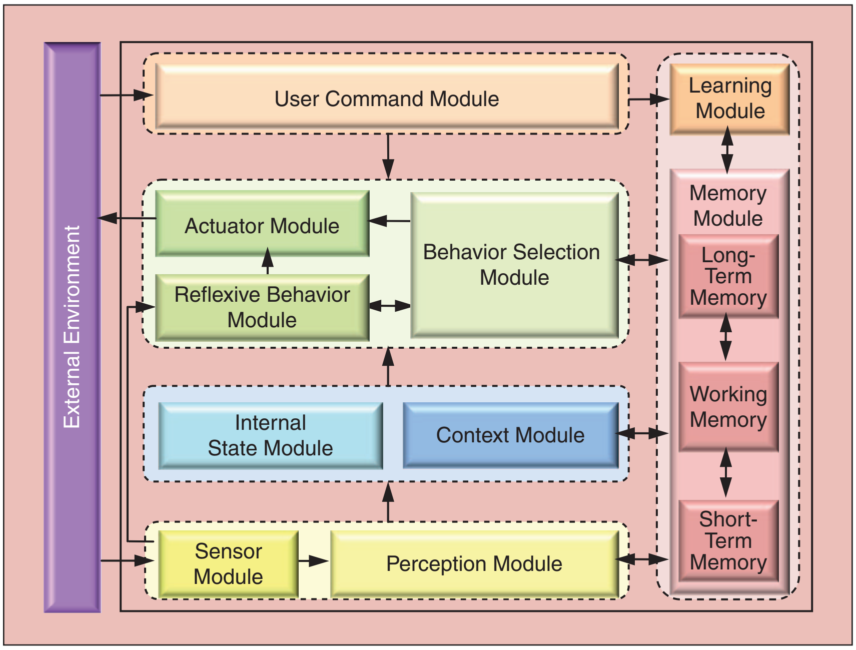

FIGURE 3 Overall architecture for behavior selection.

In the DoC-MoT, the fuzzy measures are employed to represent the DoCs for input symbols, e.g. $g(a), g(b), \ldots, g(X_1)$, where $X_1 = \{a, b, c, d\}$, and the fuzzy integral is used to globally evaluate each target symbol considering both the DoCs and the knowledge link strengths between the input and target symbols. The strengths are given by the partial evaluation values $h_z(a)$, $h_z(b)$, $h_z(c)$ and $h_z(d)$ of target symbol z over input symbols a, b, c and d. Then, the total input excitation $I(z)$ from input symbols a, b, c and d to target symbol z is calculated by the fuzzy integral, as follows:

$$I(z) = \int_{X_1} h \circ g. \tag{6}$$

III. Behavior Selection Method

In this section, the DoC-MoT is applied to the behavior selection problem. Fig. 3 shows the overall architecture of the proposed method, which is composed of 10 modules: sensor, perception, user command, context, internal state, learning, memory, behavior selection, reflexive behavior and actuator modules. The context module identifies a current environmental context using perceptions from the perception module, and the internal state module identifies a current will of an artificial creature. The memory module stores all the necessary memory contents including symbols of wills, contexts and behaviors. It also has the information on the DoCs for input symbols and the knowledge links between input and behavior (target) symbols. The DoCs are represented by the fuzzy measures and the knowledge link strengths are given by the partial evaluation values of behavior symbols over each input symbol. Considering the identified will and context, the behavior selection module selects a proper deliberative behavior by the fuzzy integral aggregating the partial evaluation values and the DoCs for input symbols. The reflexive behavior module selects a reflexive behavior using sensor information from the perception module. The learning algorithm to change the characteristics of artificial creatures is executed in the learning module. The key modules for behavior selection, namely internal state, behavior selection, learning and memory modules, are described [17], [18], [31], [32].

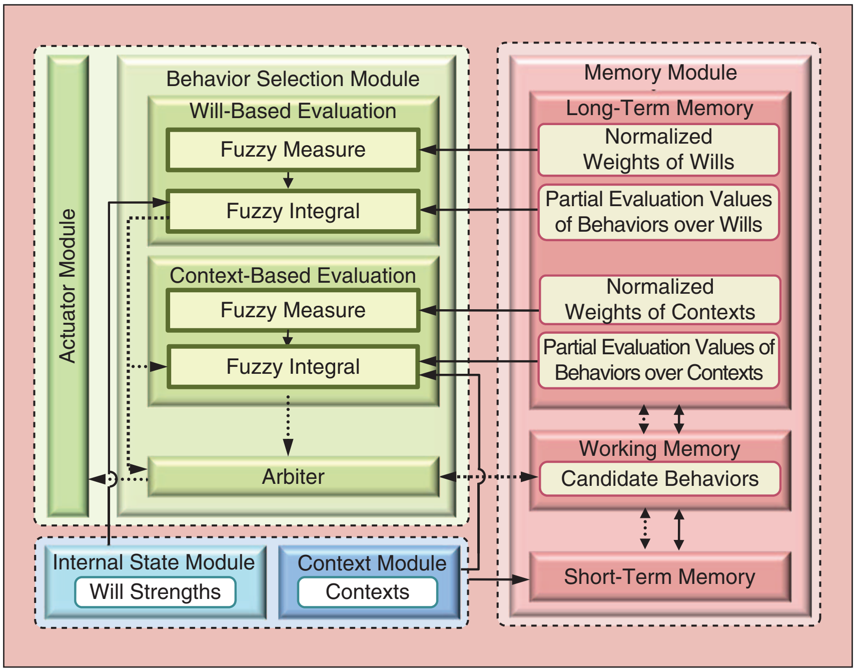

FIGURE 4 Block diagram of the behavior selection module. The solid arrows denote the movement of data related to wills and contexts, and the dotted arrows denote the behavior recommendation.

A. Internal State Module

The internal state module deals with the internal information including internal wills. In this module, the strength of the jth will, $\Omega_j(t)$, $j = 1, 2, \ldots, n$, where n is the number of wills, is updated by

$$\Omega_j(t+1) = \Omega_j(t) + \alpha_j(\overline{\Omega}_j - \Omega_j(t)) + S^T \cdot W_j(t) - \delta_{ij}(t), \quad (7)$$

where t is the time step, α_j is the difference gain, $\overline{\Omega}_j$ is the steady state value, S is the stimulus vector, W_j is the strength vector between stimulus and the jth will and $\delta_{ij}(t)$ is the amount of the change of the jth will strength caused by the previous ith behavior. The first adding term in (7) makes the j th will strength converging to the steady state value. For example, as time goes by without any stimulus, the will to play gets stronger and stronger, and finally it converges to the preassigned steady state value. The second adding term denotes the amount of the change of the jth will strength caused by external stimuli. If a user punishes an artificial creature, its "will to self-protect" gets stronger. The final adding term is the one caused by the previous behavior. If the previous ith behavior has a positive effect on the jth will (e.g. eating behavior and "will to eat"), $\delta_{ij}(t)$ is a positive value. If it has a negative effect on the jth will (e.g. kicking-ball behavior and "will to rest"), $\delta_{ij}(t)$ is a negative value. The calculated current will strengths are used in the behavior selection module.

B. Behavior Selection Module

In the behavior selection module, one proper behavior is chosen using the artificial creature's will strengths, environmental contexts and its DoCs for wills and contexts. Fig. 4 shows the block diagram of the behavior selection module. The solid and dotted arrows denote the movement of data related to wills and contexts and the behavior recommendation, respectively. Firstly, all the behaviors are evaluated considering its wills in a will-based evaluation. The normalized weights of wills are called up from a long-term memory to calculate the fuzzy measure values of all the related will sets. The will-based global evaluation value of each behavior is calculated by the fuzzy integral with respect to the fuzzy measure values of will sets, current will strengths and the partial evaluation values of behaviors over each will. Some proper behaviors to current wills are recommended to the next context-based evaluation stage and also to the arbiter for selection through a competition process. The recommended behaviors are re-evaluated considering external contexts in a context-based evaluation by the same manner of the will-based evaluation. After the context-based evaluation, the arbiter selects one behavior through competition. Then, it is actuated in the actuator module. The following describes in detail the procedure for the behavior selection process.

1) *Definition of Input and Target Symbols:* For the behavior selection to make the artificial creatures deliberately interact

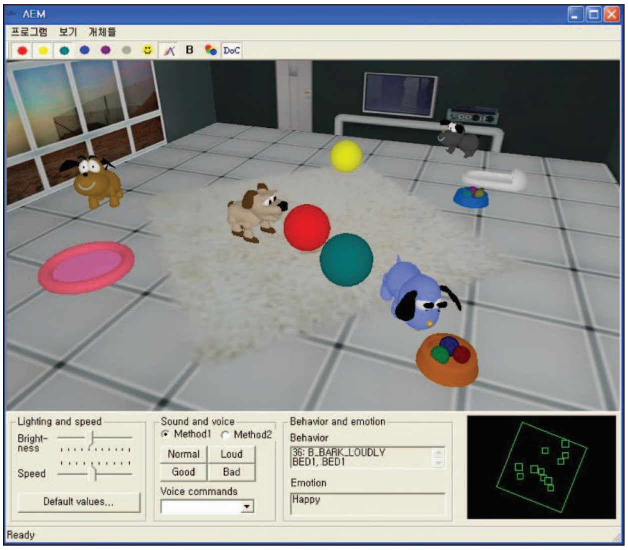

FIGURE 5 Screenshot of Ritys in the 3D virtual world.

with their environment like living creatures, input and target symbols should be first defined. In this paper, their internal wills and external environmental contexts are defined as input symbols, and their behaviors are considered as target symbols. The input and target symbols used in the experiments are provided in Section IV.

2) *Fuzzy Measure Identification of Will Set:* Let us denote a set of wills by $X_w = \{w_1, w_2, \ldots, w_n\}$, where w_j, $j = 1, 2, \ldots n$, represents the jth will. The number of subsets of X_w is 2^n, and to identify all the fuzzy measures of the subsets, $[(2^n - 2) \times (2^n - 3)]/2$ times of pairwise comparisons are needed [33]. Thus, in this paper, for the efficient identification, the following method is employed [34]. The example with detailed calculation process is described in Section IV.

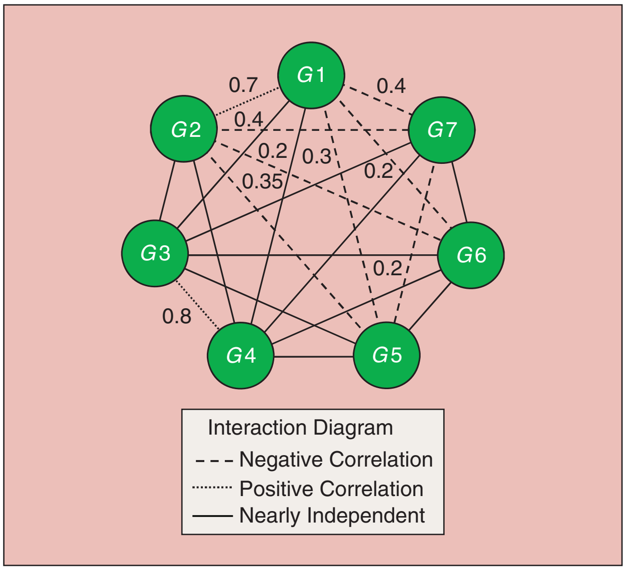

FIGURE 6 Interaction diagram of wills.

i) Normalized weights of will symbols

In ordinal analytic hierarchy process (AHP) eigenvalue method [33], the normalized weights of will symbols are calculated by the following ordinal AHP's pairwise comparison matrix (See Tables 5, 6, 7 and 8 in Section IV):

$$\mathbf{C} = \begin{pmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nn} \end{pmatrix}, \tag{8}$$

where c_{ij} represents the importance degree of the ith symbol compared to the jth symbol. c_{ii} is 1 and c_{ij} is given as $1/c_{ji}$. The normalized weight d_i^w of the ith will symbol w_i, $i = 1, 2, \ldots, n$, is calculated as follows:

$$d_i^w = \frac{\sum_{j=1}^{n} c_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}}. \tag{9}$$

ii) Interaction diagram

The interaction diagram of will symbols (Fig. 6 in Section IV) shows the interaction degree between two will symbols. If the two will symbols have negative correlation (e.g. "will to play" and "will to rest"), the interaction degree has a value between 0 and 0.5, as Table 1 shows. If the two will symbols have positive correlation (e.g. "will to seek shelter" and "will to self-protect"), the interaction degree has a value between 0.5 and 1. Otherwise, the two will symbols are independent, and the interaction degree has a value of 0.5. Therefore, the interaction degree between the ith and the jth will symbols ξ_{ij}^w lies in $[0, 1]$. Using the interaction diagram, the hierarchy diagram is constructed.

iii) Hierarchy diagram

The hierarchy diagram of will symbols (Fig. 7 in Section IV) represents hierarchical interaction relations among will symbols by clustering two closely-related will symbols. To estimate how much two will symbols are related, dissimilarity between them should be accounted. The dissimilarity $D_{\{G_p, G_q\}}$ between two clusters G_p and G_q, is defined as an average distance to other symbols as follows:

$$D_{\{G_p, G_q\}} = \frac{\sum_{G_r \in \Phi,\, G_r \neq G_p,\, G_r \neq G_q} \left[\xi^w_{\{G_p,\, G_r\}} - \xi^w_{\{G_q,\, G_r\}}\right]^2}{|\Phi| - 2}, \tag{10}$$

where Φ is a set of all clusters which can be a will symbol or a set of clustered will symbols, $G_p, G_q, G_r \in \Phi$ are clusters, $\xi^w_{\{G_i,\, G_j\}}$ is the interaction degree between will clusters G_i and G_j and $|\Phi|$ is the number of symbols of Φ.

Two will clusters that have the smallest dissimilarity are merged into one, and the interaction degrees among will clusters are recalculated. The interaction degree $\xi^w_{\{G_p,\, G_q\}}$ between two clusters G_p and G_q is calculated as

$$\xi^w_{\{G_p,\, G_q\}} = \frac{\sum_{(i,j) \in (E(G_p) \times E(G_q))} \xi_{ij}^w}{|E(G_p) \times E(G_q)|}, \tag{11}$$

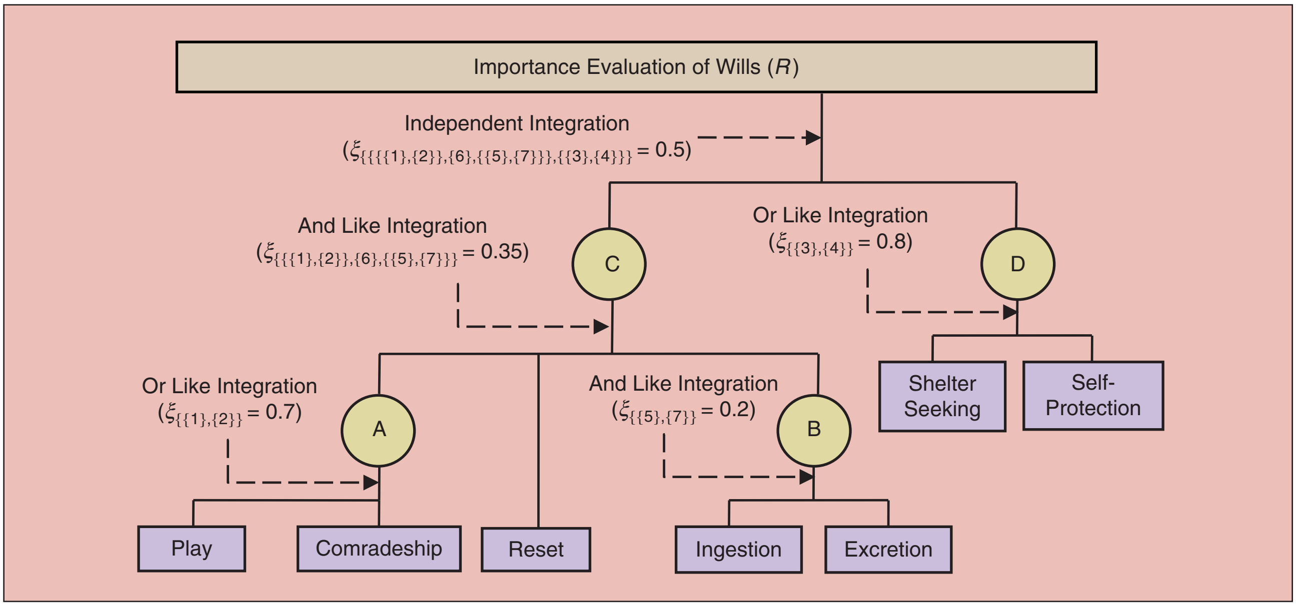

FIGURE 7 Simplified hierarchy diagram of wills.

where $A \times B$ is the direct sum and $E(G_p)$ is the function which picks up all symbols in the set G_p. The merging procedure is done until all groups are merged. Final structure of the hierarchy diagram is characterized by the interaction relations that are 'And like' or 'Or like' connections. The hierarchy diagram is simplified by re-merging two clusters if the difference between the interaction degrees of merged cluster and original clusters is less than 0.2 [34].

iv) Fuzzy measure identification

After getting the hierarchy diagram, a fuzzy measure $g(A)$, where $A \subset X_w$, is identified as follows:

$$g(A) = \phi_s\left(\xi_R^w, \sum_{P \subset R} u_P^R\right), \tag{12}$$

where R is the root level in the hierarchy diagram, ϕ_s is a scaling function [28] and u_Q^P is defined as follows:

$$\phi_s(\xi, u) = \begin{cases} 1, & \text{if } \xi = 1 \text{ and } u > 0 \\ 0, & \text{if } \xi = 1 \text{ and } u = 0 \\ 1, & \text{if } \xi = 0 \text{ and } u = 1, \\ 0, & \text{if } \xi = 0 \text{ and } u < 1 \\ \dfrac{s^u - 1}{s - 1}, & \text{other cases} \end{cases} \tag{13}$$

$$u_Q^P = \begin{cases} d_i^w, \text{ where } i \in Q & \text{if } |Q| = 1 \text{ and } i \in A \\ 0 & \text{if } |Q| = 1 \text{ and } i \notin A, \\ \phi_s^{-1}\left(\xi_P^w, \phi_s\left(\xi_Q^w, \sum_{V \subset Q} u_V^Q\right) \times T_Q^P\right) & \text{other cases} \end{cases} \tag{14}$$

where $s = (1 - \xi)^2/\xi^2$ and the value of $\phi_s^{-1}(\xi, r)$ is u, which satisfies $\phi_s(\xi, u) = r$. The conversion ratio T_Q^P from Q to P, is computed as

$$T_Q^P = \frac{\phi_s\left(\xi_P^w, \sum_{i \in Q} d_i^w\right)}{\phi_s\left(\xi_Q^w, \sum_{i \in Q} d_i^w\right)}, \tag{15}$$

where P is the upper level set and Q is the lower level set in the hierarchy diagram.

3) *Fuzzy Measure Identification of Context Set:* The fuzzy measure identification of the context set is achieved by the same manner as that of the will set. The normalized weight of each context is computed using the pairwise comparison method, and the hierarchy diagram of contexts is constructed from the interaction diagram of contexts. The fuzzy measure value $g(A)$ of the context set A is calculated by a scaling function ϕ_s in (13) using the normalized weights of contexts and the hierarchy diagram of contexts.

4) *Global Evaluation of Behaviors Over Wills:* Let us denote a set of behaviors by $X_b = \{b_1, b_2, \ldots, b_p\}$, where p is the number of behaviors and b_i, $i = 1, 2, \ldots, p$, represents the jth behavior. The global evaluation value $E_w(b_i)$ of the ith behavior b_i, $i = 1, 2, \ldots, p$, with respect to the fuzzy measure values of will sets and the knowledge links between b_i and wills, is computed by the Choquet fuzzy integral as follows:

$$E_w(b_i) = \int_{X_w} h \circ g$$
$$= \sum_{j=1}^{n} \{h_{ij}^w \cdot \Omega_j(t) - h_{i(j-1)}^w \cdot \Omega_{j-1}(t)\} g(A), \tag{16}$$

where $g(A)$ is a λ-fuzzy measure of $A \subset X_w$, identified by (12), $h_{ij}^w \in [0, 1]$ is the partial evaluation value of the ith behavior

b_i over the jth will, which denotes the knowledge link strength between the ith behavior and the jth will.

Once the behavior evaluation using current wills is done, some behaviors with a higher evaluation value b_i^r, $i = 1, 2, \ldots, l$, where l is the number of the recommended behaviors, are recommended to the next behavior evaluation stage to consider external contexts and also sent to the arbiter for selection through a competition among them.

5) *Global Evaluation of Behaviors over Contexts:* Let us denote a set of contexts by $X_c = \{c_1, c_2, \ldots, c_m\}$, where m is the number of contexts and $c_j, j = 1, 2, \ldots, m$, represents the jth context. The global evaluation value $E_c(b_i^r)$ of the ith recommended behavior b_i^r, $i = 1, 2, \ldots, l$, with respect to the fuzzy measure values of context sets and the knowledge links between b_i^r and contexts, is computed as follows:

$$E_c(b_i^r) = \int_{X_c} h \circ g = \sum_{j=1}^{m_p} \left(h_{ij}^c - h_{i(j-1)}^c\right) g(A), \tag{17}$$

where m_p is the number of activated contexts, $g(A)$ is a λ-fuzzy measure of $A \subset X_c$, identified by (12) and $h_{ij}^c \in [0, 1]$ is the partial evaluation value of the recommended behavior b_i^r over the jth activated context $c_j \in X_c$, which denotes the knowledge link strength between the ith recommended behavior and the jth activated context.

6) *Behavior Selection:* As the global evaluation of behaviors over current wills and external contexts is done by the fuzzy integral, the fittest behavior is selected through the following competition [18]:

$$E_a(b_s) = \max_j \left[E_w(b_j^r)\, E_c(b_j^r)\right], j = 1, 2, \ldots, l, \tag{18}$$

where b_s is the selected behavior with the highest global evaluation value among the recommended behaviors.

C. Learning Module

In this paper, learning based on reinforcement signals is employed for artificial creatures, which is motivated by the real pet-training scheme. The learning process is executed in real time using the patting and punishing signals from a user as reinforcement signals. As in a human thought process, the reward and penalty signals cause the change of the normalized weights of corresponding wills or contexts, and the normalized weights are used to compute the fuzzy measure values of will and context sets. Note that the artificial creature's DoCs are represented by the fuzzy measures calculated from the normalized weights.

After being rewarded (punished), the normalized weight of a will immediately increases (decreases) in proportion to the knowledge link strength between the will and the rewarded (punished) behavior. As an example, when the artificial creature excretes in the bedroom, it is punished, and then it notices that the excretion behavior causes a pain. Since the excretion behavior is strongly linked to "will to excrete," the normalized weight of "will to excrete" decreases. However, the normalized weight of "will to rest" is not changed, since "will to rest" is not related to the excretion behavior.

If the ith behavior is rewarded or punished, the normalized weight of the jth will d_j^w, $j = 1, 2, \ldots, n$, is changed by

$$d_j^w(t+1) = \begin{cases} d_j^w(t) + k_1 h_{ij}^w & (\text{reward}) \\ d_j^w(t) - k_1 h_{ij}^w & (\text{penalty}) \\ d_j^w(t) & (\text{otherwise}) \end{cases} \tag{19}$$

where $k_1 \in [0, 1]$ is the learning rate.

The knowledge link strength between will and behavior symbols is changed at the same time as the normalized weight of will is updated. When a reward or punishment is given to the artificial creature, the knowledge link strength $h_{ij}^w(t)$ between the jth will w_j and the rewarded or punished behavior b_i, is updated as follows:

$$h_{ij}^w(t+1) = \begin{cases} h_{ij}^w(t) + k_2(1 - h_{ij}^w(t)) & (\text{reward}) \\ h_{ij}^w(t) - k_2 h_{ij}^w(t) & (\text{penalty}) \\ h_{ij}^w(t) & (\text{otherwise}), \end{cases} \tag{20}$$

where $k_2 \in [0, 1]$ is the learning rate.

Eventually, it needs to realize that the excretion behavior "in the bedroom" is also a cause of the pain. Such a context as "in the bedroom" should be considered. In the case of context, however, it is not obvious which context has caused the reward or punishment. Thus, the normalized weight of context is changed if the context happens repeatedly more than once when doing the rewarded or punished behavior. As an example, after being punished repeatedly when it excretes in the bedroom, it notices that "place" is an important factor when excreting. Thus, the normalized weight of "place" increases. If the context c_j is recognized for the rewarded or punished behavior b_i, the normalized weight of the jth context d_j^c, $j = 1, 2, \ldots, m$, is changed by

$$d_j^c(t+1) = \begin{cases} d_j^c(t) + k_3 h_{ij}^c & (\text{reward/penalty}), \\ d_j^c(t) & (\text{otherwise}) \end{cases} \tag{21}$$

where $k_3 \in [0, 1]$ is the learning rate.

The knowledge link strength between context and behavior symbols is changed at the same time as the normalized weight of context is updated. When a reward or punishment is given to the artificial creature, the knowledge link strength $h_{ij}^c(t)$ between the recognized context c_j and the rewarded or punished behavior b_i, is updated as follows:

$$h_{ij}^c(t+1) = \begin{cases} h_{ij}^c(t) + k_4(1 - h_{ij}^c(t)) & (\text{reward}) \\ h_{ij}^c(t) - k_4\, h_{ij}^c(t) & (\text{penalty}) \\ h_{ij}^c(t) & (\text{otherwise}) \end{cases}, \tag{22}$$

where $k_4 \in [0, 1]$ is the learning rate.

Note that after learning, the normalized weights of wills and contexts are normalized and loaded into the memory because h_{ij}^{w} and h_{ij}^{c} are mappings from the will and context sets, respectively, to $[0, 1]$ by Definition 2.

D. Memory Module

The memory module consists of short-term memory (STM), long-term memory (LTM) and working memory (WM). In the STM, the sensory inputs from an environment are kept for a while and the information worthy of remembering is then transferred to the LTM. The LTM is a durable storage space for well-learned information. Memory contents in the LTM are the symbols of wills, contexts and behaviors, the partial evaluation values of behaviors over each will and context and the interaction degrees among input symbols. The WM keeps a limited amount of information for a limited period of time, such as the candidate behaviors during the global evaluation and the previous few contexts and behaviors when the artificial creature is rewarded or punished for learning.

IV. Experiments

To demonstrate the effectiveness of the behavior selection method using the DoC-MoT, experiments were carried out for "Rity," a synthetic character, which was developed in the 3D virtual world using OpenGL. Rity has 14 degrees of freedom for motions to express 40 behaviors and 7 wills as internal states, and it can perceive 9 contexts in its environment. In the environment, as Fig. 5 shows, there are food items, balls, a bed, a toilet and the fellow Ritys. The first goal of the experiments is to confirm that Rity's behaviors selected by the DoC-MoT are reliable. According to the knowledge links in memory, Rity behaves differently even in the same situation. The second goal is to create Rity with the desired characteristics through learning. The third goal is to show that the behavior selection method using the DoC-MoT is more effective compared to that using the P-MoT. Note that Rity which is a form of a dog and selects a behavior following the DoC-MoT, can give comfort to the user, since the user feels comfortable when Rity behaves as he or she has expected.

A. Experimental Setting

For practical experiments, 24 hours in the virtual world were scaled down to one hour in the real world. In every 2.5s, a proper behavior was selected by the proposed behavior selection method. The behavior generation frequency, which was used to check Rity's characteristics, was computed for each behavior from the experimental result gathered for one hour, i.e. one day in the virtual world. Note that the partial evaluation values of behaviors over each will and context, the strength vector between stimulus and wills and the amounts of will strength change by the previous behavior, were initialized by an expert, and the context on an object which appears in front of Rity, was randomly given to attain the reliable behavior generation frequency. A mouse click or double click was used for a reward or punishment, respectively.

B. Definition of Input and Target Symbols

In this paper, the Rity's wills were categorized into seven kinds based on the categorization of canine behaviors [9]. As shown in Table 2, there are twelve kinds of canine behaviors, but in the experiments, some inappropriate behaviors for Rity, i.e. sexual, miscellaneous motor and maladaptive behaviors, were excluded, and for simplicity, behaviors in the same category, e.g. epimeletic, et-epimeletic, allelomimetic and agonistic behaviors, were assumed to generate the same will, i.e. "will to have comradeship" as an assumed fact. Also, assumed facts on context were classified for "time (when)," "place (where)" and "object (what)." As Table 3 shows, nine assumed facts on context were defined. Note that among the assumed facts on a specific context, i.e. "when," "where" or "what," only one assumed fact from each category was activated at a time. Table 4 shows forty behaviors as target symbols.

C. Fuzzy Measure Calculation

As described in Section III, the fuzzy measure values of the will and context sets were calculated by the fuzzy measure identification method [34]. The detailed procedure of the fuzzy measure calculation of will sets is described in the following.

i) Normalized weights of will symbols

The normalized weight value of each will for four kinds of Ritys was calculated by AHP's pairwise comparison matrix, as

TABLE 2 Canine behaviors and assumed fact symbols on will.

CANINE BEHAVIOR	ASSUMED FACT
PLAY, INVESTIGATIVE (SEARCHING/SEEKING)	PLAY (W_1)
EPIMELETIC (CARE AND ATTENTION GIVING), ET-EPIMELETIC (ATTENTION GETTING), ALLELOMIMETIC (DOING WHAT OTHERS DO), AGONISTIC (ASSOCIATED WITH CONFLICT)	COMRADESHIP (W_2)
COMFORT-SEEKING (SHELTER-SEEKING)	SHELTER-SEEKING (W_3)
(ADDITIONAL)	SELF-PROTECTION (W_4)
INGESTIVE (FOOD AND LIQUIDS)	INGESTION (W_5)
(ADDITIONAL)	REST (W_6)
ELIMINATIVE	EXCRETION (W_7)
SEXUAL, MISCELLANEOUS MOTOR, MALADAPTIVE	(EXCLUDED)

TABLE 3 Assumed fact symbols on context.

CLASSIFICATION	ASSUMED FACT
TIME	MORNING (C_1) AFTERNOON (C_2) EVENING (C_3) NIGHT (C_4)
PLACE	BEDROOM (C_5) TOILET (C_6)
OBJECT	FOOD (C_7) COMRADE (C_8) TOY (C_9)

TABLE 4 Target symbols of behaviors.

b_1 STOP	b_{21} LOOK AROUND
b_2 SIT	b_{22} LOOK AT
b_3 CROUCH	b_{23} EAT CHEERFULLY
b_4 SHAKE HEAD	b_{24} EAT SLOWLY
b_5 LIFT ARM	b_{25} EXCRETE
b_6 WHINE	b_{26} URINE
b_7 GO BACK AND FORTH	b_{27} SLEEP
b_8 STEP BACK QUICKLY	b_{28} NAP
b_9 STEP BACK SLOWLY	b_{29} DIG QUICKLY
b_{10} WANDER QUICKLY	b_{30} DIG SLOWLY
b_{11} WANDER SLOWLY	b_{31} SCRABBLE QUICKLY
b_{12} MOVE CHEERFULLY	b_{32} SCRABBLE SLOWLY
b_{13} MOVE QUICKLY	b_{33} PUSH
b_{14} MOVE SLOWLY	b_{34} KICK
b_{15} FOLLOW AFTER CLOSELY	b_{35} BITE
b_{16} FOLLOW SLOWLY	b_{36} GROWL
b_{17} APPROACH	b_{37} BARK LOUDLY
b_{18} MOVE AROUND SLOWLY	b_{38} BARK
b_{19} MOVE AROUND QUICKLY	b_{39} BARK SOFTLY
b_{20} SNIFF	b_{40} HOWL

TABLE 5 The pairwise comparison matrix for wills of a normal Rity.

	W_1	W_2	W_3	W_4	W_5	W_6	W_7	NORMALIZED WEIGHT
w_1	1	1	1	1	1	1	1	0.143 (d_1^w)
w_2	1	1	1	1	1	1	1	0.143 (d_2^w)
w_3	1	1	1	1	1	1	1	0.143 (d_3^w)
w_4	1	1	1	1	1	1	1	0.143 (d_4^w)
w_5	1	1	1	1	1	1	1	0.143 (d_5^w)
w_6	1	1	1	1	1	1	1	0.143 (d_6^w)
w_7	1	1	1	1	1	1	1	0.143 (d_7^w)

shown in Tables 5, 6, 7 and 8, respectively. For a normal Rity, each will has the same importance, so all the normalized weights of wills were equal to 0.143. For a cheerful and outgoing Rity, "will to play" was set to be 10 times more important than "will to self-protect" and 9 times more important than "will to rest." As a result, the normalized weight value of "will to play" was 0.342, that of "will to self-protect" was 0.026 and so on. For an omnivorous Rity, "will to eat" was set to be 7 times more important than "will to play" and 4 times more important than "will to self-protect." Thus, the normalized weight value of "will to ingest" was 0.374 and so on. For a timid Rity, "will to self-protect" was set to be 8 times more important than "will to play" and 3 times more important than "will to ingest." Then, the normalized weight value of "will to self-protect" was 0.287 and so on.

In the following, the fuzzy measure values are calculated for the cheerful and outgoing Rity. The same procedure can be applied for the other Ritys.

ii) Interaction diagram

As defined, the number of wills was 7, and the interaction diagram of wills is shown in Fig. 6, where $X_w = \{G1, G2, G3, G4, G5, G6, G7\}$ = {Play, Comradeship, Shelter-seeking, Self-protection, Ingestion, Rest, Excretion}. The number on the line connecting two wills is the interaction degree (ξ) between them. If they have a negative correlation (dashed line), the interaction degree has a value between 0 and 0.5. If they have a positive correlation (dotted line), the interaction degree has a value between 0.5 and 1. Otherwise, they are independent of each other (solid line), and the interaction degree has a value of 0.5.

iii) Hierarchy diagram

To estimate how much two wills were related, the dissimilarity between them was accounted, and two wills that had the

TABLE 6 The pairwise comparison matrix for wills of a cheerful and outgoing Rity.

	W_1	W_2	W_3	W_4	W_5	W_6	W_7	NORMALIZED WEIGHT
w_1	1	3/2	6	10	3	9	3	0.342 (d_1^w)
w_2	2/3	1	5	8	2	7	2	0.255 (d_2^w)
w_3	1/6	1/5	1	2	1/3	2	1/3	0.060 (d_3^w)
w_4	1/10	1/8	1/2	1	1/5	1/2	1/5	0.026 (d_4^w)
w_5	1/3	1/2	3	5	1	3	1	0.137 (d_5^w)
w_6	1/10	1/7	1/2	2	1/3	1	1/3	0.043 (d_6^w)
w_7	1/3	1/2	3	5	1	3	1	0.137 (d_7^w)

TABLE 7 The pairwise comparison matrix for wills of an omnivorous Rity.

	W_1	W_2	W_3	W_4	W_5	W_5	W_7	NORMALIZED WEIGHT
w_1	1	1/2	1	2/5	1/7	1/4	1/3	0.045 (d_1^w)
w_2	2	1	2	2/3	1/5	1/3	1/2	0.083 (d_2^w)
w_3	1	1/2	1	1/2	1/8	1/4	1/3	0.046 (d_3^w)
w_4	5/2	3/2	2	1	1/4	1/2	2/3	0.105 (d_4^w)
w_5	7	5	8	4	1	2	3	0.374 (d_5^w)
w_6	4	3	4	2	1/2	1	1/2	0.187 (d_6^w)
w_7	3	2	3	3/2	1/3	2	1	0.160 (d_7^w)

TABLE 8 The pairwise comparison matrix for wills of a timid Rity.

	w_1	w_2	w_3	w_4	w_5	w_5	w_7	NORMALIZED WEIGHT
w_1	1	1	1/6	1/8	1/3	1/6	1/3	0.035 (d_1^w)
w_2	1	1	1/5	1/7	1/3	1/6	1/3	0.036 (d_2^w)
w_3	6	5	1	2/3	2	2	4	0.233 (d_3^w)
w_4	8	7	3/2	1	3	2	3	0.287 (d_4^w)
w_5	3	3	1/2	1/3	1	1/2	1	0.105 (d_5^w)
w_6	6	6	1/2	1/2	2	1	2	0.203 (d_6^w)
w_7	3	3	1/4	1/3	1	1/2	1	0.102 (d_7^w)

smallest dissimilarity were merged into one. For example, the dissimilarity between "will to play ($G1$)" and "will to have comradeship ($G2$)" was calculated as

$$D_{\{G1,\,G2\}} = \frac{\xi_{15}^w - \xi_{25}^w}{|\Phi| - 2} = \frac{(0.3 - 0.35)^2}{7-2} = 0.0005. \quad (23)$$

After calculating the dissimilarity, "will to seek shelter ($G3$)" and "will to self-protect ($G4$)" were merged into one, since they had the smallest dissimilarity. To merge another pair of wills, the interaction degrees among clusters were re-computed. For example, the interaction degree between $G1$ and $\{G3, G4\}$ was computed as $\xi^w_{\{G1,\{G3,G4\}\}} = (\xi^w_{13} + \xi^w_{14})/2 = 0.5$. The merging procedure was done until all wills were merged. Fig. 7 shows the simplified hierarchy diagram.

iv) Fuzzy measure identification

The fuzzy measure values of the will sets were computed by using the simplified hierarchy diagram (Fig. 7). As an example, the fuzzy measure value $g(A)$ of $A = \{G3\}$, for the cheerful and outgoing Rity, was calculated as

$$\begin{aligned} g(A) &= \phi_s(\xi_R^w, u_C^R + u_D^R) \\ &= \phi_s(0.5, u_D^R) \\ &= \phi_s(0.5, \phi_s^{-1}(0.5, \phi_s(0.8, 0.06) \times T_D^R)) \\ &= \phi_s(0.5, \phi_s^{-1}(0.5, 0.1635{*}0.3800)) \\ &= \phi_s(0.5, 0.0621) = 0.0621. \end{aligned} \quad (24)$$

The fuzzy measure identification of the context set was achieved by the same manner as that of the will set. Since the contexts, i.e. "time," "place" and "object" are independent of each other, all the interaction degrees among them were valued at 0.5, and the hierarchical diagram was an 'independent' integration of the three contexts. Therefore, the fuzzy measure value of the context set was the weighted sum of the normalized weights for the related contexts. The calculated fuzzy measure values of the will and context sets were used for behavior selection.

D. Experimental Results

i) *Experiment 1: Four Ritys with different characteristics*

Using the pairwise comparison matrices in Tables 5, 6, 7 and 8, four kinds of Ritys with different characteristics, i.e. normal, cheerful and outgoing, omnivorous and timid, were created, respectively. For each pairwise comparison matrix, the fuzzy measures of the will sets were calculated using a hierarchy diagram. Behaviors were selected as a result of global evaluation by the Choquet fuzzy integral of the knowledge links with respect to the fuzzy measures. Fig. 8 shows the mean and standard deviation of the behavior generation frequencies for the total number of selected behaviors, 1,440 per day, for each kind of Rity. Note that the error bar in Figures 8–14 denotes the standard deviation. For the normal Rity, the mean frequencies of stepping-back, eating, kicking and barking behaviors were about 7%, 9%, 17% and 11%, respectively. The most frequent behavior of the cheerful and outgoing Rity was "kicking a ball" of about 34%. For the omnivorous Rity, eating behaviors were dominant with over 17%. For the timid Rity, barking behaviors were dominant with over 27%, and stepping-back behaviors were about 15%. The standard deviation of each behavior generation frequency for four Ritys was less than 2%. These results show that by changing the weight of each will in the behavior selection method using the DoC-MoT, Rity could be created with different characteristics.

However, creating different characteristics of an artificial creature using the P-MoT is time-consuming and gives undesirable results in some cases, which can be achieved by two means: (1) changing all the conditional probabilities associated with the knowledge link strengths, and (2) applying the learning scheme to the initially created creature which has normal characteristics. For (1), the maximum numbers of pre-given parameters and parameters to be set to create different characteristics, in the two behavior selection methods were compared, as shown in Table 10. In general cases, the numbers of contexts and behaviors can be approximated by the number of wills and

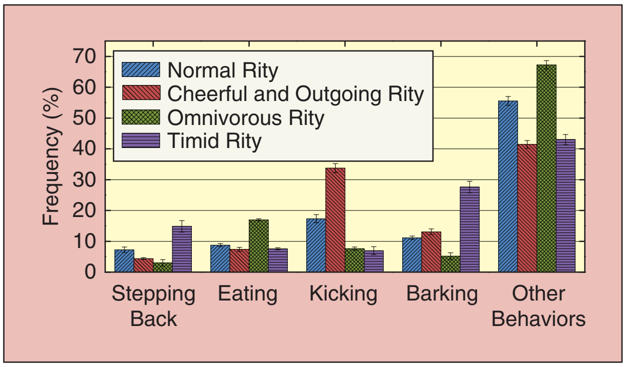

FIGURE 8 Behavior generation frequencies of four different Ritys.

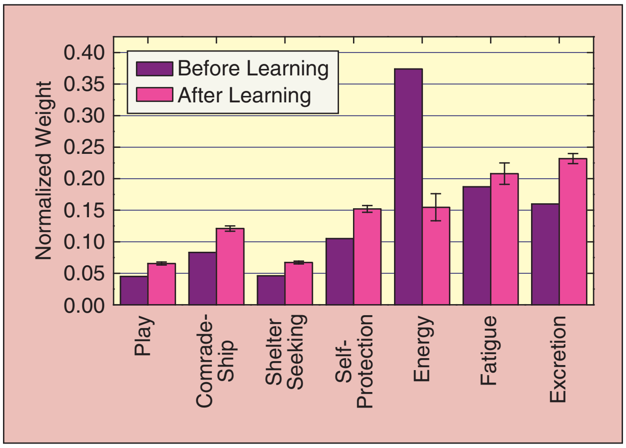

FIGURE 9 Change of the omnivorous Rity's normalized weights of wills.

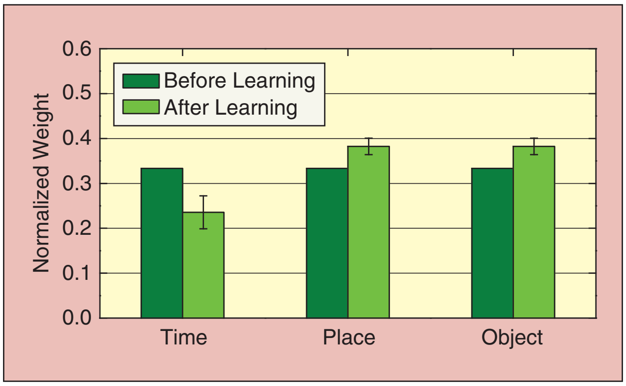

FIGURE 10 Change of the omnivorous Rity's normalized weights of contexts.

the square of the number of wills, respectively. With this approximation, we could say that the maximum number of parameters to be set to create different characteristics was considerably less in the behavior selection method using the DoC-MoT ($2n$) than that using the P-MoT ($2n^3$). Note that the number of parameters for normalized weights is n, since they may be given directly, without calculating by the pairwise comparison matrix.

As illustrated before, an artificial creature with different characteristics can also be created by applying learning scheme to a normal one in the P-MoT. In the experiment, a normal Rity, the behavior generation frequency of which was similar to that in the DoC-MoT, was initially created by changing all the conditional probabilities, and then its characteristics was changed to cheerful and outgoing, omnivorous and timid, respectively, through learning. To create a cheerful and outgoing Rity (a timid Rity), wandering, moving, following, moving-around, pushing and kicking behaviors were rewarded (punished). To create an omnivorous Rity, eating behaviors were rewarded. The mean and standard deviation of the behavior generation frequencies for each kind of Rity in the two behavior selection methods were compared, as shown in Table 10. The p-values were derived from an unpaired t-test to evaluate the difference between the behavior generation frequency distribution in the P-MoT and DoC-MoT.

For the normal Rity, the numbers of generated behaviors were 19 and 16 for the DoC-MoT and P-MoT, respectively. Among them, 14 behaviors had no significant difference in the means of the generation frequencies, since the p-values were larger than 0.05. In other words, the normal Ritys created by the DoC-MoT and P-MoT had similar characteristics. Nevertheless, for the cheerful and outgoing, the omnivorous and the timid Ritys, the distribution of behaviors (p-values less than 0.05) showed significant differences between the two behavior selection methods. Though the Ritys with P-MoT generated proper behaviors to their characteristics, i.e. kicking behavior for the cheerful and outgoing Rity, eating behaviors for the omnivorous Rity and stepping-back behaviors for the timid Rity, the behaviors which had not been generated by the normal Rity before learning, were not observed either in the other Ritys after learning. The generated behaviors from the changed Ritys by learning process were restricted to the behaviors which had been generated by the normal Rity. On the other hand, in Ritys with the DoC-MoT, slowly-following, quickly-moving and growling behaviors which had not been generated by the normal Rity, were observed after learning. This is because a reward or punishment in the P-MoT caused the change of the conditional probabilities of the specific rewarded or punished behaviors and the conditional probabilities related to the un-generated behaviors could not be changed. In the DoC-MoT, the change of DoCs during learning, can affect the

TABLE 9 The maximum numbers of pre-given parameters and parameters to be set to create different characteristics.

	BEHAVIOR SELECTION USING THE P-MOT		BEHAVIOR SELECTION USING THE DOC-MOT	
	# OF PRE-GIVEN PARAMETERS	# OF PARAMETERS TO BE SET TO CREATE DIFFERENT CHARACTERISTICS	# OF PRE-GIVEN PARAMETERS	# OF PARAMETERS TO BE SET TO CREATE DIFFERENT CHARACTERISTICS
KNOWLEDGE LINK STRENGTHS	$(n+m)*p$	$(n+m)*p$	$(n+m)*p$	0
NORMALIZED WEIGHTS	0	0	$n+m$	$n+m$
INTERACTION DEGREES	0	0	$n*(n-1)/2 + m*(m-1)/2$	0
TOTAL	$\approx 2n^3$	$\approx 2n^3$	$\approx 2n^3 + n^2 + n$	$\approx 2n$

n: the number of wills
$m(\approx n)$: the number of contexts
$p(\approx n^2)$: the number of behaviors

TABLE 10 Generated behaviors of four different kinds of Ritys.

BEHAVIOR	NORMAL RITY			CHEERFUL AND OUTGOING RITY		
	DOC-MOT	P-MOT	P-VALUE	DOC-MOT	P-MOT	P-VALUE
CROUCH	5.1 ± 1.7	7.2 ± 1.7	0.012	.	4.8 ± 2.8	< 0.001
SHAKE HEAD	0.1 ± 0.2	.	0.343	.	.	.
WHINE	0.1 ± 0.2	.	0.343	.	.	.
STEP BACK QUICKLY	6.6 ± 0.9	6.0 ± 1.5	0.304	3.6 ± 0.8	6.2 ± 3.0	0.025
STEP BACK SLOWLY	0.6 ± 0.0	.	.	0.8 ± 0.8	.	0.061
FOLLOW AFTER CLOSELY	6.8 ± 0.8	7.2 ± 1.3	0.385	.	10.8 ± 1.9	< 0.001
FOLLOW SLOWLY	.	0.1 ± 0.2	0.343	25.1 ± 1.7	.	< 0.001
MOVE AROUND QUICKLY	3.0 ± 1.4	6.6 ± 3.1	0.005	.	0.3 ± 0.3	0.037
EAT CHEERFULLY	6.5 ± 1.1	9.5 ± 0.2	< 0.001	5.6 ± 1.1	9.8 ± 3.6	0.005
EAT SLOWLY	2.3 ± 1.1	2.4 ± 0.0	0.736	1.8 ± 0.6	1.1 ± 2.2	0.372
EXCRETE	2.6 ± 0.8	1.0 ± 1.0	0.001	2.6 ± 1.2	0.9 ± 0.7	0.001
URINE	5.1 ± 1.0	4.6 ± 1.0	0.319	6.1 ± 0.7	4.2 ± 0.8	< 0.001
SLEEP	18.1 ± 0.6	18.5 ± 1.0	0.343	7.6 ± 0.8	17.5 ± 2.2	< 0.001
NAP	0.1 ± 0.2	.	0.343	.	.	.
SCRABBLE QUICKLY	6.6 ± 1.8	2.5 ± 1.4	< 0.001	0.1 ± 0.2	1.6 ± 2.1	0.046
KICK	17.3 ± 1.3	17.8 ± 1.6	0.431	33.8 ± 1.5	31.1 ± 12.0	0.505
BARK LOUDLY	2.9 ± 0.9	2.1 ± 0.8	0.053	3.4 ± 1.6	3.3 ± 0.8	0.849
BARK	3.3 ± 1.4	2.1 ± 1.1	0.054	9.7 ± 1.8	.	< 0.001
BARK SOFTLY	5.0 ± 1.4	3.8 ± 1.3	0.062	.	0.3 ± 0.4	0.104
HOWL	8.1 ± 1.5	8.6 ± 2.4	0.601	.	8.1 ± 3.1	< 0.001

BEHAVIOR	OMNIVOROUS RITY			TIMID RITY		
	DOC-MOT	P-MOT	P-VALUE	DOC-MOT	P-MOT	P-VALUE
CROUCH	11.4 ± 3.7	0.1 ± 0.2	< 0.001	0.3 ± 0.6	5.5 ± 1.6	< 0.001
SHAKE HEAD	1.2 ± 1.5	.	0.035	.	.	.
WHINE	1.3 ± 1.5	.	0.027	.	.	.
STEP BACK QUICKLY	3.0 ± 1.1	0.9 ± 1.2	0.001	10.8 ± 2.3	31.2 ± 2.3	< 0.001
STEP BACK SLOWLY	.	.	.	4.1 ± 1.7	.	< 0.001
MOVE QUICKLY	.	.	.	1.1 ± 1.4	.	0.029
FOLLOW AFTER CLOSELY	.	6.7 ± 0.6	< 0.001	0.3 ± 0.3	2.4 ± 1.8	0.004
FOLLOW SLOWLY	.	.	.	.	5.6 ± 2.2	< 0.001
MOVE AROUND QUICKLY	3.0 ± 1.1	3.0 ± 1.1	< 0.001	.	3.0 ± 1.1	0.148
EAT CHEERFULLY	15.0 ± 1.0	24.2 ± 0.5	< 0.001	0.4 ± 0.4	12.6 ± 0.0	< 0.001
EAT SLOWLY	1.9 ± 0.8	.	< 0.001	7.2 ± 0.4	.	< 0.001
EXCRETE	3.2 ± 1.0	1.0 ± 0.8	< 0.001	0.8 ± 0.5	0.9 ± 0.7	0.856
URINE	5.4 ± 1.4	4.4 ± 0.7	0.051	4.0 ± 0.9	4.8 ± 0.7	0.056
SLEEP	21.1 ± 1.3	21.0 ± 0.4	0.894	14.7 ± 3.4	8.2 ± 1.0	< 0.001
NAP	.	.	.	13.0 ± 4.9	.	< 0.001
DIG QUICKLY	.	.	.	1.3 ± 2.0	.	0.074
SCRABBLE QUICKLY	7.3 ± 1.7	6.7 ± 1.5	0.424	.	3.7 ± 1.9	< 0.001
KICK	7.6 ± 0.5	14.4 ± 0.6	< 0.001	6.9 ± 1.3	15.3 ± 0.4	< 0.001
GROWL	1.4 ± 1.2	.	0.005	5.5 ± 3.2	.	< 0.001
BARK LOUDLY	3.8 ± 1.1	.	< 0.001	0.3 ± 0.8	.	0.343
BARK	0.3 ± 0.4	0.1 ± 0.3	0.453	3.3 ± 1.0	9.1 ± 0.3	< 0.001
BARK SOFTLY	1.1 ± 0.5	0.4 ± 0.4	0.002	24.1 ± 2.5	.	< 0.001
HOWL	4.6 ± 2.6	20.0 ± 1.0	< 0.001	2.1 ± 2.3	.	0.019

The p-values were derived from an unpaired t-test.

global evaluation of un-generated behaviors as well. Hence, the behavior selection method using the DoC-MoT is more effective for creating Ritys with various characteristics than that using the P-MoT.

ii) *Experiment 2: Changing the characteristics of the omnivorous Rity by punishment*

Once the normalized weights of wills and contexts to repesent the DoCs for them, are implanted into the Rity's

The Rity's characteristics could be changed through the learning process.

memory, its characteristics is decided. However, it can be changed by learning process using (19), (21) and (22). In the experiment, a punishment from a user in a specific situation was used to lead to the memory change. The omnivorous Rity, as shown in Table 7, was a subject to be trained for one day. Since eating near a toilet was an inappropriate behavior for Rity, it was punished when it ate foods around the toilet.

The changes of the omnivorous Rity's normalized weights of wills and contexts are shown in Fig. 9 and Fig. 10, respectively. For the omnivorous Rity, "will to eat" was the strongest desire compared to other wills before learning. However, punishment when eating near a toilet, decreased the omnivorous Rity's normalized weight of "will to eat" from 0.37 to 0.15, whereas the normalized weights of other wills increased. As a result, "will to rest" became the strongest desire. In the case of contexts, the normalized weights of "time," "place" and "object" were the same before learning. However, after learning, the normalized weights of "place" and "object" increased, since the omnivorous Rity realized that the contexts, "toilet (place)" and "food (object)," were the causes of the punishment from a user. The normalized weight of "time" decreased.

Fig. 11 shows the behavior generation frequency of the omnivorous Rity around the toilet. After learning, behaviors related to eating decreased from about 25% of the total number of selected behaviors around the toilet, 400 per day, to about 11%, and behaviors related to excretion increased from about 20% to about 28%. These results show that the omnivorous Rity with the habit of eating anywhere could be trained not to eat around the toilet by punishment from a user. In other words, the Rity's characteristics could be changed through the learning process.

iii) *Experiment 3: Changing the characteristics of the timid Rity by reward*

In this experiment, a reward from a user in a specific situation was used to lead to direct the memory change. The timid Rity, as shown in Table 8, was a subject to be trained for one day. Assuming that cheerful and outgoing characteristics was

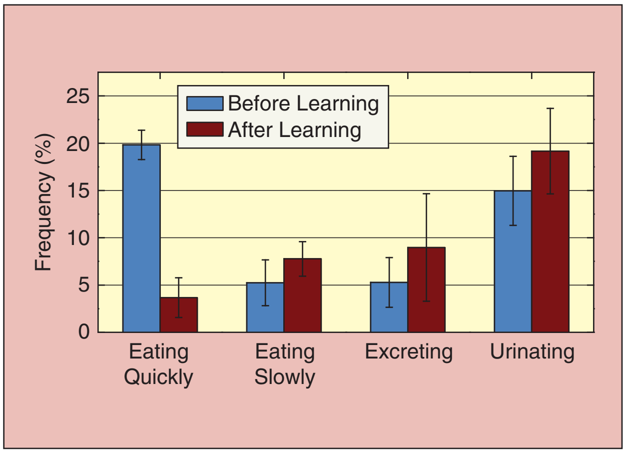

FIGURE 11 Change of the omnivorous Rity's behavior generation frequency around the toilet.

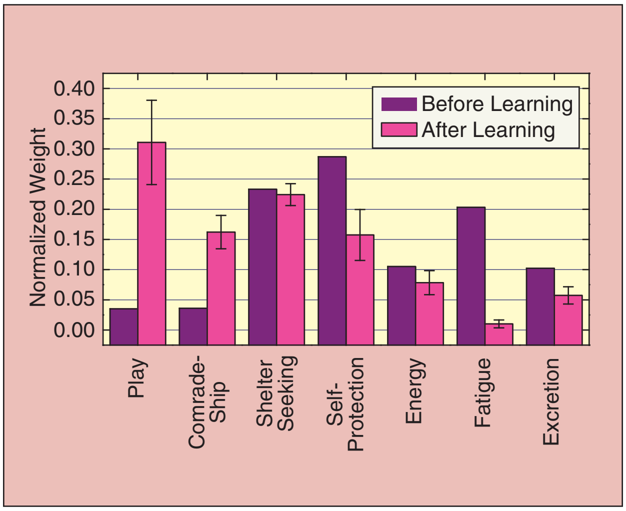

FIGURE 12 Change of the timid Rity's normalized weights of wills.

FIGURE 13 Change of the timid Rity's normalized weights of contexts.

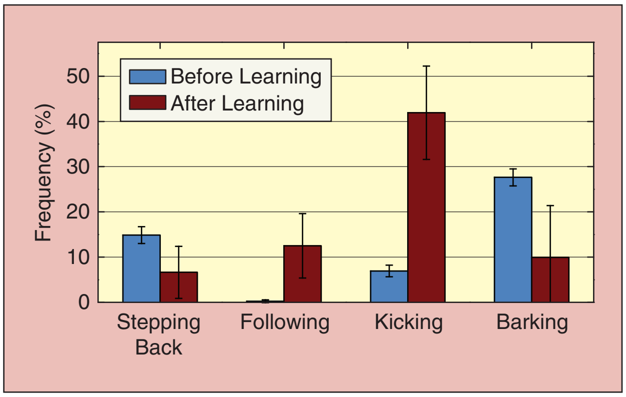

FIGURE 14 Change of the timid Rity's behavior generation frequency in the daytime.

more desired, the timid Rity was trained to be a desired one by giving a reward when it had done active behaviors, such as "kicking," "following," etc.

Fig. 12 shows the change of the normalized weights of wills after learning. For the timid Rity, "will to self-protect" was the strongest desire compared to other wills before learning. The reward when it had behaved actively caused the increase of the normalized weights of "will to play" and "will to have comradeship" from 0.035 to 0.311 and from 0.036 to 0.162, respectively, whereas the normalized weights of other wills decreased. As a result, "will to have comradeship" became the strongest desire.

Fig. 13 shows the change of the normalized weights of contexts after learning. Initially, the normalized weights of "time," "place" and "object" were the same. After learning, however, the normalized weight of "time" increased, since the reward was given mostly in the daytime, morning and afternoon. On the other hand, the normalized weights of "place" and "object" decreased because of the normalization process. Fig. 14 shows the behavior generation frequency in the daytime. After learning, the generation frequency of stepping-back behaviors decreased from 15% to 7% and that of barking behaviors from 28% to 10%. However, the generation frequency of kicking-ball behavior increased from 7% to 42% and that of following-comrade behaviors from 0.2% to 13% In summary, the timid Rity became cheerful and outgoing through the learning process.

V. Conclusion

This paper proposed the degree of consideration-based mechanism of thought (DoC-MoT) and its application to the behavior selection method for artificial creatures. Internal wills and external contexts, which account for the assumed facts, were defined as input symbols and behaviors were assigned as target symbols. The values of knowledge links between input and target symbols were represented by the partial evaluation values of target symbols over each input symbol. The DoCs for input symbols were described by the fuzzy measures, and the global evaluation of each target symbol was achieved by the fuzzy integral aggregating the DoCs and the partial evaluations in the memory. To demonstrate the effectiveness of the proposed method, experiments were carried out for an artificial creature "Rity." The behaviors considering both will and context were selected by the proposed method, and Rity was successfully trained to adapt their characteristics according to the user preferences. We believe that the DoC-MoT can also be used in robots to make them more responsive to the preferences of the human interacting with them.

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