Two-Layered Confabulation Architecture for an Artificial Creature's Behavior Selection

Jong-Hwan Kim, *Senior Member, IEEE*, Se-Hyoung Cho, Ye-Hoon Kim, and In-Won Park

***Abstract*—This paper proposes a novel two-layered confabulation architecture for an artificial creature to select a proper behavior considering the internally generated will and the context of the external environment consecutively. The architecture is composed of seven main modules for processing perception, internal state, context, memory, learning, behavior selection, and actuation. The two-layered confabulation in a behavior module is processed by a will-based confabulation and a context-based confabulation consecutively by referring to confabulation probabilities in a memory module. An arbiter in the behavior module chooses a proper behavior among the suggested ones from the two confabulations, which is to be put into an action. To demonstrate the effectiveness of the proposed architecture, experiments are carried out for an artificial creature, implemented in the 3-D virtual environment, which behaves as per its will considering the context in the environment.**

***Index Terms*—Artificial creature, behavior selection, confabulation architecture, context awareness.**

I. Introduction

Many service robots and entertainment robots have been developed to help human beings in simple housework and share intimate interactions with them. Recently, software pet-type robots, which imitate an animal's spontaneity, have also been developed to be mounted into an actual hardware platform or an electronic device, i.e., a cell phone or a computer, for ubiquitous services [1]–[3]. An artificial creature can be used as an intermediate interface for interactions between a human and a service robot. It should hold outward appearances and knowledge including behavior patterns so that it can resemble a living creature and approach to the user with familiarity.

To generate a proper behavior when it faces a certain situation, there have been a lot of researches on control architecture. They mimic a decision mechanism of the real living creature, which considers its own desire to make a decision for a proper behavior [4]–[7]. Belief–desire–intention (BDI) architecture is provided for a rational agent, which consists of belief, desire, intention, and plan [8]. The architecture proposed in [9] selects the behavior using the state–action tuple. It creates the state from the result analyzed by using a percept tree that utilizes external sensor information. Cognitive architecture is also designed based on a multiagent system with three distinctive memory systems, namely spatio-temporal short-term memory, procedural/declarative/episodic long-term memory, and task-oriented adaptive working memory [10]. It selects an appropriate behavior using a machine consciousness model called self-agent.

Recently, confabulation has been studied, which imitates a human thought process. Confabulations, where millions of items of relevant knowledge are applied in parallel in the human brain, are typically employed in thinking. Confabulation as a thought mechanism is a process of making a plausible "spurious" memory from inexperienced facts in the brain using similar reminiscences in the past. Through this process, humans can generalize the past experiences and cope with the indirectly experienced situations [11]–[13].

In this paper, a behavior selection architecture based on two-layered confabulation is proposed. The architecture is composed of seven main modules for processing perception, internal state, context, memory, learning, behavior selection, and actuation [14]–[16]. This paper focuses on the behavior module along with the memory module and the learning module, which is to select a proper behavior. Note that the behavior module consists of two-layered confabulation submodule and arbiter. The two-layered confabulation submodule has two sequential layers in order to consider the internally generated will in an internal state module and the context of the external environment in a context module, respectively. The first layer calculates the cogency of each behavior using current internal states and confabulation probabilities in the memory module [17]–[19] and then recommends the most suitable behaviors to the second layer. The second one similarly calculates the cogency of the recommended behaviors considering the external context and referring to confabulation probabilities in the memory module. Finally, an arbiter in the behavior module chooses a fittest behavior among the recommended ones using cogency values from the two layers, which is to be put into action.

In the memory module, conditional probabilities between behaviors and each of the internal states and contexts are stored as memory contents, which are used in confabulations. All the memory contents are provided by an expert as an initialization process on plausible behaviors of the artificial creature. As it should continuously adapt to the varying environment or the user's preference, the memory contents should be updated through the learning module. Reinforcement learning as a training process is provided like a real pet training. The learning module updates memory contents according to the user-given reward or penalty signal.

The artificial creature is embodied by having real creature's characteristics using behavior sets and internal states. It can recognize the context of external environment using exteroception,

Manuscript received April 4, 2007; revised September 18, 2007. Current version published October 20, 2008. This paper was recommended by Associate Editor M. H. Lim.

The authors are with the Department of Electrical Engineering and Computer Science, Korea Advanced Institute of Science and Technology, Daejeon 305-701, Korea (e-mail: johkim@rit.kaist.ac.kr; shcho@rit.kaist.ac.kr; yhkim@rit.kaist.ac.kr; iwpark@rit.kaist.ac.kr).

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Digital Object Identifier 10.1109/TSMCC.2008.2001576

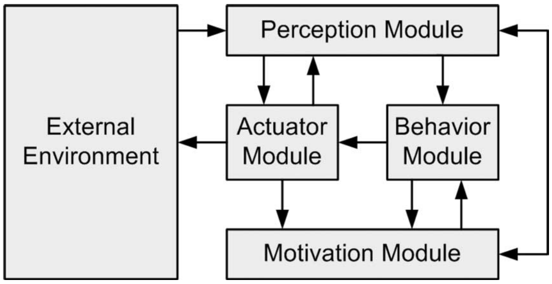

Fig. 1. Schematic diagram of a typical architecture.

and its will is produced by mimicking a real creature's interoception mechanism. The effectiveness of the proposed scheme is demonstrated by carrying out some experiments with an artificial creature implemented in the 3-D virtual environment, which can behave according to its will and context.

This paper is organized as follows. Section II introduces a typical control architecture of an artificial creature and basic idea of the confabulation theory. Section III proposes a novel two-layered confabulation architecture. In Section IV, experimental results are presented with an artificial creature implemented in the 3-D virtual environment. The concluding remarks follow in Section V.

II. Preliminaries

A. Typical Control Architecture for an Artificial Creature

In general, the architecture for an artificial creature mimics a decision mechanism of the real living creature, which faces a certain situation and considers its own desire to make a decision for a proper behavior. Fig. 1 shows a typical control architecture, where a proper behavior is selected in a behavior module considering its perception and motivation [4]–[7]. By using a perception module, the artificial creature finds out the situation of external environment. A motivation module has an influence on the behavior module for a proper behavior selection. The resulting behavior gets expressed through the motor module. Thus, it requires an adequate behavior selecting architecture between the perception module and the motor module.

To activate a behavior similarly as the real creature does, the behavior system should reflect the internal state such as motivation, homeostasis, and emotion. Also, the context of the external situation should be considered in order to select an appropriate behavior. If the behavior system is based on the priority between the context- and internal-state-based behaviors, and the context-based behaviors have higher priority, then the behavior considering the external situation (context) constrains the behavior reflecting the internal state. Thus, this kind of priority-based behavior selector is too deterministic to realize a deliberative behavior, which considers both external and internal states at the same time. Consequently, an architecture incorporating both the internal state and the external context is needed. In this sense, confabulation is adopted to imitate a human thought process.

B. Confabulation Theory

Bayesian and cogent confabulation techniques are used to represent the formal logic for inductive reasoning. These two methods reason by using the confidence to all conclusions. In the inductive reasoning, if the probability of a, b, c, and d are given as a partition of a sample space S and suppose that event E occurs, then the confidence of event E occurring is represented by using Bayesian posterior probability $p(e \mid abcd)$. In a cogent confabulation, on the other hand, the confidence of conclusion is represented as cogency $p(abcd \mid e)$. Cogency can be calculated using the Bayes' theorem as follows [11], [12]:

$$\begin{aligned} p(abcd \mid e)^4 = &\left[\frac{p(abcde)}{p(ae)}\right]\left[\frac{p(abcde)}{p(be)}\right] \\ &\times \left[\frac{p(abcde)}{p(ce)}\right]\left[\frac{p(abcde)}{p(de)}\right] \\ &\times [p(a \mid e)p(b \mid e)p(c \mid e)p(d \mid e)] \end{aligned} \tag{1}$$

where the first four probabilities can be approximated as a constant number in any given situations. In general, these assumptions are plausible approximations as follows:

$$\begin{aligned} &\left[\frac{p(abcde)}{p(ae)}\right]\left[\frac{p(abcde)}{p(be)}\right] \\ &\quad\times \left[\frac{p(abcde)}{p(ce)}\right]\left[\frac{p(abcde)}{p(de)}\right] \approx K \\ &p(abcd \mid e)^4 \approx K[p(a \mid e)p(b \mid e)p(c \mid e)p(d \mid e)] \end{aligned} \tag{2}$$

where K is a constant.

Once the first four probabilities are considered a constant, having the maximum cogency is equivalent as maximizing the probability $[p(a \mid e) \cdot p(b \mid e) \cdot p(c \mid e) \cdot p(d \mid e)]$ [11], [12]. This process is known as confabulation. In this paper, the confabulation process is applied to artificial creature's behavior selection.

III. Two-Layered Confabulation Architecture

The proposed two-layered confabulation architecture selects a behavior by consecutive confabulations on the internal states of an artificial creature and the contexts of its environment. Thus, it is expected to have more natural behaviors. As Fig. 2 shows, the architecture is composed of the following seven primary modules.

Perception module perceives the environment with virtual or real sensors.

Context module defines current situation such as "when," "where," "what," etc.

Internal state module defines motivation, homeostasis, and emotion.

Memory module holds confabulation probabilities for all behaviors to each of the internal states and contexts as memory contents.

Learning module learns from interaction with the user by updating the memory contents according to the user-given reward or penalty signal.

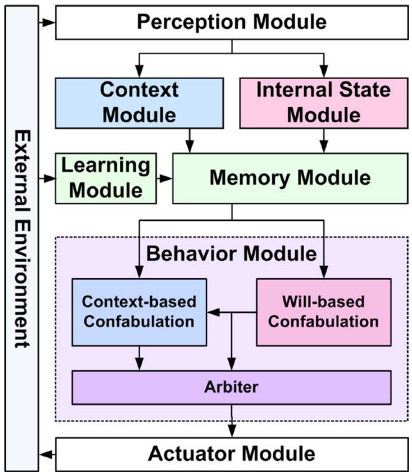

Fig. 2. Two-layered confabulation architecture.

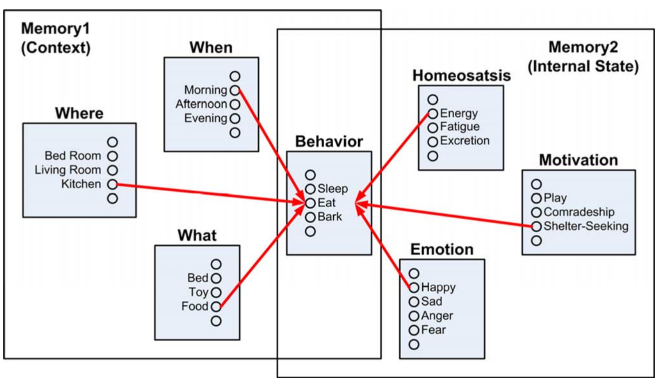

Fig. 3. Memory module for confabulation.

Behavior module selects a proper behavior for the perceived information.

Actuator module executes a behavior and expresses its emotion.

Perception, internal state, and actuation modules are the same as those in [14]. In this architecture, both internal state (or will) and context information are used for behavior selection, referring to the memory module that holds conditional probabilities between behaviors and each of the internal states and contexts as memory contents. The memory contents are referred to the confabulation process to select the most proper behavior considering both will and context at the moment. With the learning module, proper behaviors can be learned according to the changed situation or user's preference by updating the memory contents through reinforcement learning.

A. Memory Module

Cogent confabulation is employed to select the most adequate behavior based on memory contents, where all internal states, contexts, and behaviors are represented as symbols, and the knowledge is represented by each symbol's link in the memory module (Fig. 3). Many conclusion symbols (behaviors) are considered at the same time and the best likely symbol is projected as a conclusion.

The memory module consists of context memory and internal state memory, as shown in Fig. 3, where "when," "where," and "what" are considered to grasp the context from the environment, and motivation, homeostasis, and emotion are included in the internal state. In the figure, an arrow represents the link between a behavior and the current context and internal state by conditional probability. For example, the link between "eating behavior" and "in the kitchen" has the memory information given by a conditional probability $p_t(\text{kitchen} \mid \text{eating})$ at time t. A higher probability value is memorized for "eating behavior in the kitchen," as it is more adequate than "eating behavior in the bedroom."

All of the conditional probabilities, as memory contents, are initially assigned to the memory module by an expert, which is required as an initialization process. If inappropriate probabilities are given, plausible behaviors may not be expected, and thus, it requires careful settings and a learning module.

B. Behavior Module

Behavior module is to select a proper behavior and consists of three submodules: a will-based confabulation submodule, a context-based confabulation submodule, and an arbiter. The will-based confabulation submodule calculates the cogency of each behavior using current internal states, and then, recommends the most suitable behaviors to the context-based confabulation submodule. The context-based confabulation submodule similarly calculates the cogency of the recommended behaviors by considering the external context. Finally, the arbiter chooses the fittest behavior using the cogency values from the previous two confabulation submodules, i.e., the resulting behavior is recommended through the confabulation process.

1) Will-Based Confabulation: The set of the current internal states of an artificial creature, each from the internal state module, is given as assumed facts. The conclusion set corresponds to the artificial creature's behavior set. Confabulation is used to select the symbol of the next behavior in the conclusion set with the assumed facts. The confabulation process requires the behavior probability of each of the internal states, which is preserved in the memory module. The cogency of the will-based confabulation is computed using Bayes' rule as follows:

$$
\begin{aligned}
E_{\text{will}}(b_1) &= p(w_1 \mid b_1) \cdot p(w_2 \mid b_1) \cdot \;\cdots\; \cdot p(w_m \mid b_1) \\
E_{\text{will}}(b_2) &= p(w_1 \mid b_2) \cdot p(w_2 \mid b_2) \cdot \;\cdots\; \cdot p(w_m \mid b_2) \\
&\;\;\vdots \\
E_{\text{will}}(b_l) &= p(w_1 \mid b_l) \cdot p(w_2 \mid b_l) \cdot \;\cdots\; \cdot p(w_m \mid b_l) \qquad (3)
\end{aligned}
$$

where E_{will} is defined as a cogency value (expectation) of the behavior to the current will, $b_j, j = 1, 2, \ldots, l$, represents the jth behavior in the behavior set, $p(w_i \mid b_j)$ is the conditional probability between the ith will and the jth behavior, and l and m represent the number of behaviors and the number of internal states, respectively. Once cogency values between behaviors and current will are calculated, some of the behaviors with the highest cogency values are recommended to the next context-based confabulation submodule. Since most of the animals load up to four objects into working memory at one time [20], in the experiments of this paper, three behaviors were recommended to the next submodule.

2) Context-Based Confabulation: Assumed facts for the context-based confabulation are given as the set of current context from the external environment. The recommended behaviors from the will-based confabulation submodule form a conclusion set. In this paper, when, where, and what (time, place, and objects) are considered as contexts in a given situation. Similarly, the confabulation is to select the symbol of the next behavior in the conclusion set with the assumed facts, and the cogency can be calculated using Bayes' rule as follows:

$$\begin{aligned} E_{\text{context}}(b_1^r) &= p(c_1 \mid b_1^r) \cdot p(c_2 \mid b_1^r) \cdot \cdots \cdot p(c_n \mid b_1^r) \\ E_{\text{context}}(b_2^r) &= p(c_1 \mid b_2^r) \cdot p(c_2 \mid b_2^r) \cdot \cdots \cdot p(c_n \mid b_2^r) \\ &\vdots \\ E_{\text{context}}(b_k^r) &= p(c_1 \mid b_k^r) \cdot p(c_2 \mid b_k^r) \cdot \cdots \cdot p(c_n \mid b_k^r) \end{aligned} \tag{4}$$

where E_{context} is defined as a cogency value (expectation) of the behavior to the context, $c_i, i = 1, 2, \ldots, n$, represents the ith context where n is the number of considered contexts, $b_j^r, j = 1, 2, \ldots, k$, represents the jth recommended behavior from the will-based confabulation where k is the number of recommended behaviors. $p(c_i \mid b_j^r)$ is the conditional probability between the ith context and the jth recommended behavior. As mentioned before, the calculation is carried out only for the k recommended behaviors from the will-based confabulation submodule to compute the adequacy of each behavior, reflecting environmental situations.

3) Arbiter: The arbiter decides the final behavior among k candidates based on the results of the will-based confabulation $E_{\text{will}}(b_j)$ and context-based confabulation $E_{\text{context}}(b_j^r)$, where $j = 1, 2, \ldots, k$. The behavior is determined by the max-product operation as follows:

$$E_{\text{arbiter}}(b^s) = \max_j [E_{\text{will}}(b_j^r) E_{\text{context}}(b_j^r)], \quad j = 1, \ldots, k \tag{5}$$

where b^s is the finally selected behavior. The behavior having the highest value among the recommended behaviors is selected as the most suitable one. Using this method, the artificial creature can select a proper behavior fitted to the external situation and reflecting its internal desires if memory contents are properly set.

C. Learning Module

The memory-based learning is needed to train an artificial creature for a desired behavior to a specific context like a real pet training by tuning the corresponding memory content. In this paper, reinforcement learning is employed using feedback signals from a user. The user grants either a reward or a penalty by patting or hitting the artificial creature to teach a desired behavior at a given situation. When patting input is given at a particular situation, confabulation probability gets increased and vice versa for hitting input. The value of a reward/penalty should be decreased as the number of training signals increases due to the adaptation mechanism. In other words, the change of conditional probability becomes smaller as the creature adopts the users' feedback signals over a long period of time. Learning was achieved by the following equation:

TABLE I
ASSUMED FACTS OF WILL-BASED CONFABULATION

Internal State	Assumed fact
Motivation	Play (w_1)
	Comradeship (w_2)
	Shelter-Seeking (w_3)
	Pain (w_4)
Homeostasis	Energy (w_5)
	Fatigue (w_6)
	Excretion (w_7)
Emotion	Happy (w_8)
	Sad (w_9)
	Anger (w_{10})
	Fear (w_{11})

$$p_{\text{temp}}(c_i \mid b_j) = \begin{cases} p_t(c_i \mid b_j) + \{1 - p_t(c_i \mid b_j)\}\lambda & \text{(reward)} \\ p_t(c_i \mid b_j) - p_t(c_i \mid b_j)\lambda & \text{(penalty)} \\ p_t(c_i \mid b_j) & \text{(otherwise)} \end{cases} \tag{6}$$

where p_{temp} represents a temporal probability by interaction, $p_t(c_i \mid b_j)$ is the conditional probability between the ith context and the jth behavior, t is the number of training signals, and $\lambda \in [0, 1]$ is the learning rate. Reinforcement learning was attained only when several reward/penalty signals were frequently applied as input. Otherwise, learning might not be achieved easily. As the sum of all probabilities must be equal to 1, the following normalization process is needed:

$$p_{t+1}(c_i \mid b_j) = \frac{p_{\text{temp}}(c_i \mid b_j)}{\sum_{i=1}^{l} p_{\text{temp}}(c_i \mid b_j)}. \tag{7}$$

By this technique, confabulation probability is adjusted such that undesired behaviors can be restrained from being activated. In the following section, experimental results demonstrate the effectiveness of the proposed architecture.

IV. EXPERIMENTAL RESULTS

A. Experimental Environment

The interactive learning method and the proposed behavior selection architecture were applied to a synthetic character "Rity," which was developed using OpenGL in a 3-D virtual space. The sampling rate of computational model was set to 0.1 s. Rity has 14 DOF, 19 percept symbols, and 40 behaviors. Rity has virtual sensors such as a timer, vision, auditory, IR, touch sensors for the perception module, and the context module to be aware of the situation in its environment. More detailed descriptions on Rity are presented in [14].

Internal states of Rity were defined based on those of a real dog such as motivation, homeostasis, and emotion. Parameter values from (3)–(5) were set as follows: $l = 40$, $m = 11$, $n = 3$, and $k = 3$. The learning rate λ in (6) was set as 0.1. Note that three contexts on when, where, and what were considered in the experiments. The assumed facts for the will-based confabulation were classified in Table I.

TABLE II
ASSUMED FACTS OF CONTEXT-BASED CONFABULATION

Context	Assumed fact
Time (c_1)	Morning
	Afternoon
	Evening
	Night
Place (c_2)	Bed Room
	Toilet
Object (c_3)	Food
	Comrade
	Toy

Each element of motivation, homeostasis, and emotion has three states of high, mid, and low. Similarly, the assumed facts for the context-based confabulation were considered as in Table II.

In each experiment, all probabilities were initialized by an expert such as a developer or a user. Then, reinforcement learning was conducted by an interaction between the user and Rity. As user hits (mouse double click) or pats (mouse click) Rity, he/she can give either a reward or a penalty for reinforcement learning. In other words, the behavior probability gets either increased or decreased based on the user's stimulus. Rity is rewarded (punished) if the selected behavior is appropriate (inappropriate) to the given context. Since Rity has a virtual vision sensor that detects an object in the virtual environment, Rity can be aware of the kinds of detected objects and its place as contexts.

B. Experimental Results

The goal of the experiment is to create an artificial creature, which behaves as per its will, considering the context in a given situation. Context awareness enables it to carry out a proper decision in its environment. In order to evaluate the performance of the proposed architecture, the following four experiments were carried out.

1) Scenario of Reinforcement Learning: Eating behavior would never be carried out around a toilet. If Rity ate food at a location near the toilet, it was punished. Will was focused on energy (hunger) and context was focused on toilet and food in this scenario. The behaviors related to excreting were expected at the toilet. In Fig. 4, a probability value of $p(\text{toilet} \mid \text{eating})$ is plotted as the penalty is applied. When many reward/penalty signals were given as input in a short period of time, reinforcement learning could be attained. Otherwise, learning might not be achieved. The penalty value reduced as the learning count increased by (6). The learning process of this behavior was carried out for 4 min. The graph shows that it has a decreasing tendency according to the user's penalty. Since the user forbade eating behavior around the toilet, the probability of eating near the toilet became lower.

Every result of behavior frequency in Figs. 5–8 was observed for 15 min. Fig. 5 shows behavior frequency before and after reinforcement learning in the given context. In each situation, the frequency of the behaviors sum up to 100%. Only eating, excreting, and urinating behaviors are plotted in the graph, and the rest ones are classified as other behaviors. Before

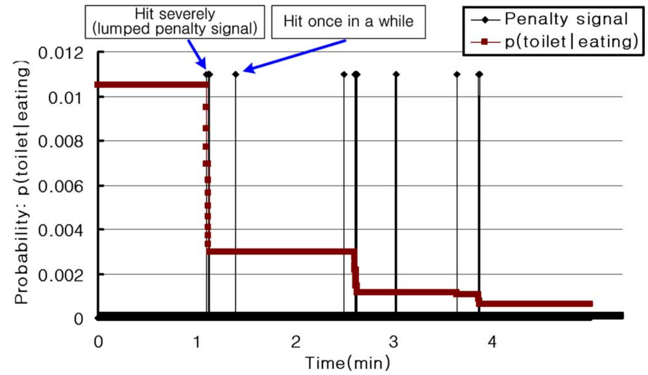

Fig. 4. Probability change when reinforcement learning was applied.

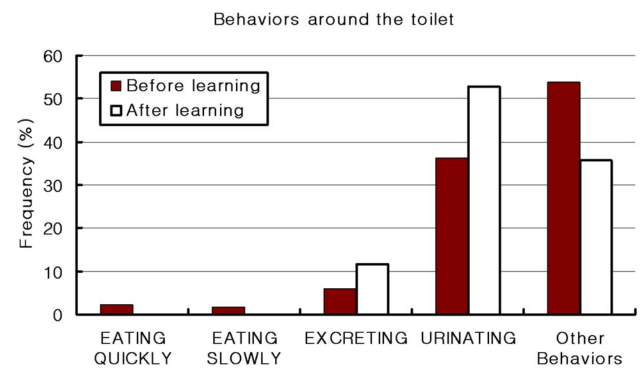

Fig. 5. Behavior frequency before and after reinforcement learning.

learning, Rity often ate food with the toilet in its vicinity. However, the frequency of eating behavior around the toilet was reduced after reinforcement learning. Thus, the user can teach Rity proper behaviors at a certain situation by reinforcement learning.

From the next experiment onward, behavior frequency after learning will be described in the subsequent graphs, according to the proposed two-layered confabulation.

2) Scenario for the Case of Strong Will: The scenario was that Rity was absolutely sleepy (will), and since the will was stronger than the context (bed), it would ignore the context and sleep at anywhere. It means that the behavior, which is not related to the context, would be selected if Rity has a strong will. In this experiment, will was focused on fatigue (sleepy) and context was focused on bed. The context changed between bed and other places as Rity moved around. The behaviors related to sleeping were expected to be activated. Fig. 6 shows that the sleeping behavior was generated at any location when Rity was absolutely sleepy. When it was only a bit sleepy, sleeping behavior was revealed mostly on the bed.

3) Two Scenarios for the Case of Strong Contexts: First scenario was that the influence of context (bed) was stronger than that of will (somewhat sleepy). In this case, it was expected that the behavior related to the given context (bed) would be chosen, though it was not much sleepy. Will and context were equally focused as in the experiment of the previous scenario. But the changed situation was that Rity was not so sleepy. In this case,

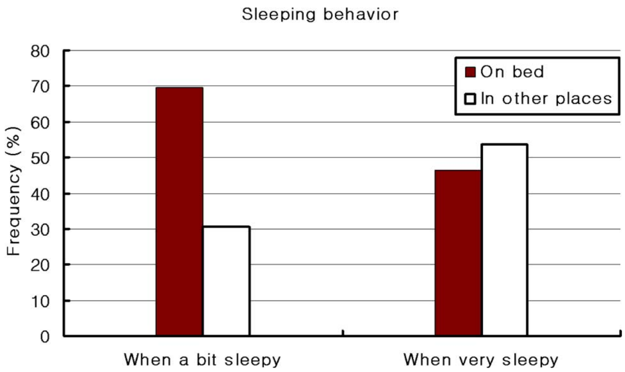

Fig. 6. Behavior frequency for scenario when Rity was absolutely sleepy and the context was a bed.

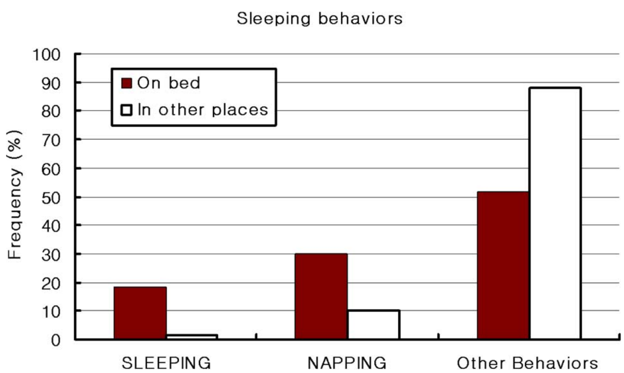

Fig. 7. Behavior frequency for scenario when Rity was not so sleepy and the context was a bed.

Rity would make a decision according to the dominance of will and context. In Fig. 7, the graph plots the frequency of the sleeping behaviors when the context was bed and the other places, respectively. The graph shows that the sleeping and napping behaviors were expressed by the effect of a bed in the vicinity even though Rity was not so sleepy. In other words, the frequency of the sleeping and napping behaviors was increased only if the context was the bed. This result came from the dominant context such as the bed.

Second scenario was that the influence of a context (toy) was stronger than that of will (desired to play). In this case, it was expected that the behavior related to the given context (toy) would be chosen, though it did not have much desire to play with anything. Thus, if a toy was in its vicinity, Rity would play with the toy. If no toy was in the surroundings, it would behave on its own. Fig. 8 shows the frequency of the playing behaviors. When Rity detected a toy in its neighborhood, it played mostly with the toy, pushing and kicking. If no toy was in the surroundings, it played alone, for example, digging the ground. This result shows that Rity considered the context and behaved in an adequate way while meeting its internal needs.

A video clip of experiments on the proposed architecture is available at http://rit.kaist.ac.kr/home/Two_Layered_Confabulation_Architecture.

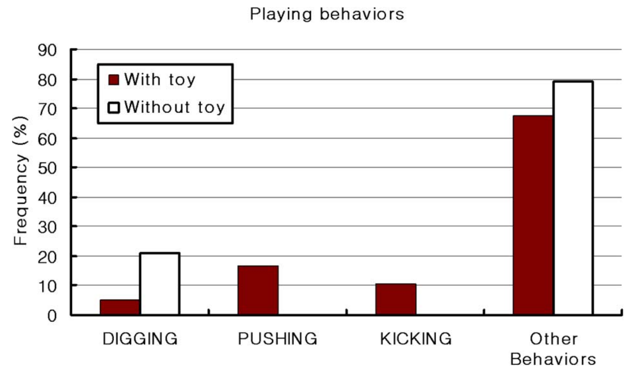

Fig. 8. Behavior frequency for scenario when Rity somehow desired to play and the context was a toy.

V. Conclusion

This paper proposed a novel two-layered confabulation architecture, which considers both internal state and context for the artificial creature's behavior selection. In the will-based confabulation, behaviors are selected considering the internal states such as motivation, homeostasis, and emotions. The selected behaviors are forwarded to the context-based confabulation to consider the contexts on "when," "where," and "what." The arbiter finally decides the most fitting behavior among the suggested behaviors from the two confabulation layers. A learning mechanism, which modifies the confabulation probabilities in a memory module using the user's reward and penalty inputs, was presented in order to train the artificial creature's behaviors like real pet training. The experimental results showed that the artificial creature could select the most adequate behavior to meet the context and reflecting its internal desires at the moment. By employing the proposed architecture, a virtual pet that has a function of emotional interaction is enough to be used as an entertainment robot. Moreover, an artificial creature can be used as an intermediate interface for interactions between a human and a service robot.

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Jong-Hwan Kim (S'85–M'88–SM'03) received the B.S., M.S., and Ph.D. degrees in electronics engineering from Seoul National University, Seoul, Korea, in 1981, 1983, and 1987, respectively.

Since 1988, he has been with the Department of Electrical Engineering and Computer Science, Korea Advanced Institute of Science and Technology, Daejeon, where he is currently a Professor. His current research interests include ubiquitous and genetic robotics.

Prof. Kim is an Associate Editor of the IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION and the IEEE COMPUTATIONAL INTELLIGENCE MAGAZINE. He was one of the Co-Founders of the International Conference on Simulated Evolution and Learning (SEAL). He was also the General Chair for the IEEE Congress on Evolutionary Computation, Seoul, 2001. His name was included in the *Barons 500 Leaders for the New Century* in 2000 as the Father of Robot Football. He is the Founder of The Federation of International Robot-Soccer Association (FIRA) and The International Robot Olympiad Committee (IROC). He is currently the President of FIRA and IROC.

Se-Hyoung Cho received the B.S. degree in electronical and electrical engineering from the University of Seoul, Seoul, Korea, in 2004, and the M.S. degree in 2007 from the Korea Advanced Institute of Science and Technology, Daejeon, where he is currently working toward the Ph.D. degree in electrical engineering and computer science.

His research interests include evolvable artificial creatures and ubiquitous robotics.

Ye-Hoon Kim received the B.S. degree in computer science and statistics from the University of Seoul, Seoul, Korea, in 2003, and the M.S. degree in information and communication from the Gwangju Institute of Science and Technology, Gwangju, Korea, in 2005. He is currently working toward the Ph.D. degree in electrical engineering and computer science at the Korea Advanced Institute of Science and Technology, Daejeon.

His research interests include evolutionary multiobjective optimizations and ubiquitous robotics.

In-Won Park received the B.S. degree in electrical engineering from the University of Toronto, Toronto, ON, Canada, in 2005. He is currently working toward the joint M.S.–Ph.D. degree in the Division of Electrical Engineering, Department of Electrical Engineering and Computer Science, Korea Advanced Institute of Science and Technology, Daejeon.

His research interests include ubiquitous robotics and reinforcement learning.