Evolutionary Generative Process for an Artificial Creature's Personality

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Abstract—In this paper, an artificial creature is designed to have its own genome in which a specific personality is encoded. The genome is composed of 14 chromosomes each of which consists of three kinds of genes such as fundamental genes, internal-state-related genes, and behavior-related genes. To represent various types of personality, a large number of genes are needed. In this case, if gene values are assigned manually for the individual genome, it becomes increasingly difficult and time-consuming to generate a desired personality reliably and consistently. Considering this problem, this paper proposes an evolutionary process that generates a genome encoding a specific personality of an artificial creature. The process evolves a population of genomes such that it customizes the genome, which meets a simplified set of personality traits desired by the user. The evaluation procedure for each genome of the population is carried out in a virtual environment using a tailored perception scenario and a dedicated fitness function. An artificial creature, Rity, is developed in the virtual 3-D world created in a PC to demonstrate the effectiveness of the proposed process.

Index Terms—Artificial chromosome, artificial creature, artificial creature's personality, artificial genome, evolutionary algorithm.

I. INTRODUCTION

MUCH research in artificial life has been carried out to create artificial creatures, either simulated creatures or creature-like robots, with the aim of providing humans with entertaining interactions in real time. The creature-like robots have been developed as pet-type or humanoid robots [1]–[3]. Based on the design concept of sociable agents focusing on interacting with people [4], a robotic head [5] and a service robot with affective social intelligence [6] were developed. These robots are limited by their hardware in their realization in real world. On the other hand, the simulated creatures do not have such a limitation as they are created in the virtual 3-D world in a computer. The simulated ones include interactive creatures [7], autonomous agents [8], virtual creatures [9], synthetic characters [10], software robots (Sobots) [11], and 3-D avatars [12], etc. They have been developed by using numerous approaches

such as the behavioral action selection system [7], motivation-driven learning [13], the use of emotion or internal states to construct believable agents [14]–[16], and emotion defined in 3-D mental space [17].

These software agents have great potential for use in the entertainment industry. With a simplified model and evolutionary mechanism, they have been used as game characters in video gaming [18]–[26]. This application requires the software agents to be as simple as possible such that they can activate a proper behavior pattern during interaction with a user in real time. The software agents can be also used in the robot industry. A Sobot is one of the key components in building a ubiquitous robot, which incorporates Sobot, embedded robot, and mobile robot [27]–[29]. Sobot can move easily within the network and connect to other systems without time or geographical limitations. It has all the elements of being a robot, including self-adaptation, context-awareness intelligence, and seamless interaction, but only virtually. Thus, it can be used as a brain of a mobile robot and a continuous interface between physical world and the virtual world for greater convenience and flexibility in user interactions.

Considering the user interactions, the personality of the agents needs to be taken into consideration, as the personality is crucial in building a believable emotional agent. Having a diverse personality is important because, "Personality is the engine of behavior" [30]. It can be encoded as an inherited trait, which decides the behavior based on an internal state in response to the stimulus. It is characterized by the Big Five personality dimensions [31], [32]. This allows for the creation of diverse personalities for the agent, e.g., allowing it to express highly agreeable and at the other end of the scale, highly antagonistic characteristics. In spite of the importance of innate personality in deciding the behavior, the concretization of diverse personality has not been investigated to any great extent in previous research ventures, compared to that of artificial intelligence that is accumulated through experience and knowledge as posterior information during its lifetime by means of learning or interaction with human.

This paper presents computer-coded genomes as genetic representation of an agent to encode a specific personality. The genome is composed of multiple artificial chromosomes each of which consists of many genes that contribute to the representation of various types of personality. It provides primary advantages for the process of artificial reproduction, the ability to evolve, and the reusability among agents [34], [35]. However, the large number of genes allows for a highly complex system. If gene values are assigned manually for the individual genome, it becomes increasingly difficult and time-consuming to generate a desired personality reliably and consistently.

To overcome this problem, an evolutionary generative process for an artificial creature's personality (EGPP) is proposed. EGPP is a software system to generate a genome as its output for a specific personality, which is characterized by the manner of responses such as internal state changes and their concomitant behaviors to stimuli. It includes implementations of the artificial creature and its genetic representation, virtual environment, perception scenario, and evolutionary algorithm. Initialization of the genome population is performed by setting some parameters in the GUI. Evaluation procedure for each individual genome is carried out by implanting it into an agent and applying a series of stimuli to the agent and then measuring its fitness. The fitness is defined as a function of the difference between user-assigned preference values through GUI and the agent's responses to the stimuli, measured by the possession ratio of internal state and the frequency of behavior group. An artificial creature, Rity, is developed in the virtual 3-D world created in a PC to demonstrate the effectiveness of the proposed process.

This paper is organized as follows. Section II introduces an artificial creature, Rity, an internal control architecture, a genome, and a personality model. The genome is composed of a set of chromosomes consisting of the fundamental genes, the internal-state-related genes, and the behavior-related genes. Section III presents the proposed EGPP along with an evolutionary algorithm, a perception scenario, a fitness function, and a mutation operator. Experiments are carried out to demonstrate the performance and effectiveness of EGPP in Section IV. Concluding remarks follow in Section V.

II. ARTIFICIAL CREATURE

This section presents an internal control architecture, genetic representation, and personality model of an artificial creature, Rity, which resides in a 3-D virtual world created in a PC. The internal control architecture processes incoming sensor information and then eventually generates a proper behavior. The connection weights in between perception and internal state modules, and in between internal state and behavior modules are encoded in the genome, composed of a set of chromosomes, to represent the personality trait, which can be the inherited one [15], [16].

A. Internal Control Architecture

An artificial creature can be created as an agent that behaves autonomously, driven by its internal states, such as motivation, homeostasis, and emotion, responds to incoming sensor information, and interacts with humans or its environment in real time. This can be done by internal control architecture, which in this paper, is composed of seven core modules such as sensor, perception, attention, internal state, behavior selection, reflexive behavior, and motor modules, by imitating real creatures. Fig. 1 illustrates both the internal control architecture and a screenshot showing an artificial creature, Rity, in a virtual 3-D environment. Rity is a 3-D virtual pet with 12 DOF, which is developed in Visual C++ 6.0 and OpenGL, and works well on Pentium III machines or above.
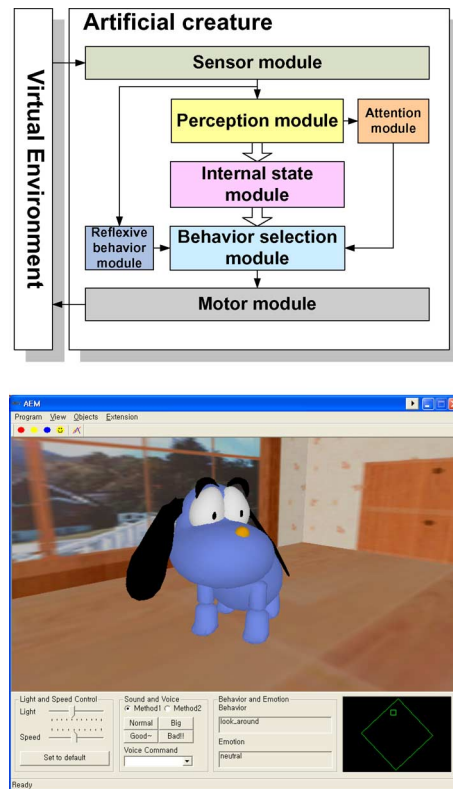

Fig. 1. Artificial creature, Rity. (a) Internal control architecture. (b) Screenshot of Rity in a 3-D virtual world.

Each module in the internal architecture is briefly described in the following. The sensor module consists of various virtual or real sensors such as touch, infrared, ultrasonic, vision, gyro sensors, etc., to sense the virtual or physical environment. The sensed data are forwarded to the perception module where they are classified as percepts (stimuli). At the same time, the attention module is triggered to select one attentional stimulus from the incoming stimuli. It should keep the attention of the stimulus until another bigger stimulus is received such that it prevents Rity from cycling through different stimuli and performing improper behaviors. Attention selection among stimuli is decided from

$$a = \text{Max}[pri(s_1), pri(s_2), \ldots, pri(s_y)]$$

where a is the attentional stimulus, $pri(\cdot)$ is the prespecified priority for a given stimulus, $\mathbf{S}^T = [s_1, s_2, \ldots, s_y]$ is the stimulus vector, and y is the total number of stimuli.

Rity can find objects, avatars' faces, or users' faces using virtual or real sensors such that it can interact with objects and avatars in a virtual environment or humans in the physical world using information through a mouse, a camera, or a microphone, with 47 perceptions. For example, single click and double click on Rity are perceived as "patted" and "hit," respectively, by Rity. Dragging Rity slowly and softly is perceived as "soothed," and dragging it quickly and wildly as "shocked." As Table I shows, these perceptions are classified in seven perception groups $\mathbb{A} = \{A_{po}, A_{ob}, A_{bt}, A_{ph}, A_{so}, A_{of}, A_{ba}\}$, where A_{po} is the perception group related to posture, A_{ob} obstacle,

TABLE I
LIST OF PERCEPTIONS AND THEIR GROUPS

Group	Perception	Group	Perception	Group	Perception
Posture (A_{po})	Power_On	Bright-ness/ Temp. (A_{bt})	Sudden_Lightness	Sound (A_{so})	Sound_Noisy
	Shaken		Sudden_Darkness		Sound_Normal
	Soothed		Glaring		Sound_Calm
	Shocked		Normal		Sudden_Loud
	Lifted		Dark		Sudden_Calm
	Fallen		Very_Dark		Voice
	Correct_Posture		Mild		Voice_Good
Obstacle (A_{ob})	Obstacle_Detected		Hot		Voice_Bad
	Distance_Near		Cold		Voice_Hello
	Distance_Mid	Pat/Hit (A_{ph})	Head_Patted	Object/ Face (A_{of})	Object1_Detected
	Distance_Far		Head_Hit		Object1_Close
	Sudden_Appearance		Body_Patted		Object2_Detected
	Sudden_Disappearance		Body_Hit		Object2_Close
	Cliff_Detected				Object3_Detected
					Object3_Close
					Face_Detected
					Face_Close
				Battery (A_{ba})	Battery_Low
					Battery_Normal
					Battery_Full

TABLE II
LIST OF INTERNAL-STATE-RELATED BEHAVIOR GROUPS

Related internal mode	Index	Internal state	Internal state related behavior group
Motivation	1	Curiosity	approach, observe, touch, chase, search_looking_around
	2	Intimacy	touch, eyecontact, glad, approach, show_me_face, hug_me, lean, chase, once_again, handshake
	3	Monotony	shake_arm_and_leg, snooze, look_around, stretch
	4	Avoidance	turn_and_ignore, look_away, move_backward, cover_eyes, kick, roar, head_down, hide_head, resist
	5	Greed	look_around, search_looking_around, search_wandering, collect, piss, roar, chase
	6	Control	show_me_face, hug_me, give_me_ball, once_again, complain_for_food
Homeostasis	7	Fatigue	refuse, rest, crouch, recharge, faint, head_down
	8	Drowsiness	yawn, sleep, snooze, lie, rest
	9	Hunger	complain_for_food, rumble, search_wandering
Emotion	10	Happiness	hurrah, dance_with_arms, mouth_open, shake_arms
	11	Sadness	hit_ground, head_down, be_ill, hug_me, weep
	12	Anger	shake_head, hit_head, roar, turn_and_ignore, look_away
	13	Fear	resist, hide_head, tremble, faint, move_backward
	14	Neutral	stop, lie, look_around

A_{bt} brightness/temperature, A_{ph} pat/hit, A_{so} sound, A_{of} object/face, and A_{ba} battery.

The internal state module consists of three units to deal with agent's internal states such as motivation, homeostasis, and emotion. The motivation unit represents an agent's desire to do something, which influences behavior selection. Homeostasis unit deals with an agent's hormone state. It also gives an effect to the agent on deciding a behavior. The emotion unit is to express an agent's behavior properly, representing an excited state of its mind [36]. The internal state module receives a stimulus information from a perception module, calculates each value of internal states as its response, and sends the calculated values to the behavior selection module to select a proper behavior. Motivation states are represented by the following vector:

$$\mathbf{M}(t) = [m_1(t), m_2(t), \ldots, m_p(t)]^T \quad (1)$$

where p is the number of motivation states. Each motivation state is updated by

$$m_k(t+1) = m_k(t) + \{\lambda_k(\overline{m_k} - m_k(t)) + \mathbf{S}^T \cdots \mathbf{W}_k^M(t)\}$$
$$k = 1, 2, \ldots, p \quad (2)$$

where $\mathbf{S}$ is the stimulus vector, $\mathbf{W}_k^M$ is the weight matrix connecting $\mathbf{S}$ to the kth motivation state, $\overline{m_k}$ is the constant to which the motivation state converges without any stimuli, and λ_k is the discount factor between 0 and 1. Similarly, the following update equations are defined for the homeostasis unit using its state vector $\mathbf{H}(t)$ and weight matrix $\mathbf{W}_k^H$, and also the emotion unit using its state vector $\mathbf{E}(t)$ and weight matrix $\mathbf{W}_k^E$, respectively

$$h_k(t+1) = h_k(t) + \{\lambda_k(\overline{h_k} - h_k(t)) + \mathbf{S}^T \cdots \mathbf{W}_k^H(t)\}$$
$$k = p+1, \ldots, p+q \quad (3)$$

$$e_k(t+1) = e_k(t) + \{\lambda_k(\overline{e_k} - e_k(t)) + \mathbf{S}^T \cdots \mathbf{W}_k^E(t)\}$$
$$k = p+q+1, \ldots, p+q+r \quad (4)$$

where $\mathbf{H}(t) = [h_{p+1}(t), h_{p+2}(t), \ldots, h_{p+q}(t)]^T$ and $\mathbf{E}(t) = [e_{p+q+1}(t), e_{p+q+2}(t), \ldots, e_{p+q+r}(t)]^T$.

The number of internal states generally depends on an agent's internal architecture. In Rity, the motivation unit is composed of six states ($p = 6$): curiosity, intimacy, monotony, avoidance, greed, and the desire to control. The homeostasis unit includes three states ($q = 3$): fatigue, hunger, and drowsiness. Five states

($r = 5$) such as happiness, sadness, anger, fear, and neutral are employed for emotion unit.

The behavior selection module is used to choose a proper behavior based on an agent's internal state. According to the internal state, various reasonable behaviors can be selected probabilistically by introducing a voting mechanism, where each behavior has its own voting value [2], [38]. Table II shows a set of behavior groups $\mathbf{B}_c^T = [\beta_1, \beta_2, \ldots, \beta_c]$, where $c = p + q + r = 14$ in this paper. It is classified on the basis of how much each behavior group is closely related to internal state. Each group has various correlated behaviors, which has the advantage of good consistency with the corresponding internal state. The procedure of behavior selection is described in the following.

1) Determine the temporary voting vector, $\mathbf{V}_{\text{temp}}$ using $\mathbf{M}$ and $\mathbf{H}$. The temporary voting vector is defined as follows:

$$\mathbf{V}_{\text{temp}}^T = (\mathbf{M}^T \mathbf{D}^M + \mathbf{H}^T \mathbf{D}^H) = [v_{t1}, v_{t2}, \ldots, v_{tz}] \quad (5)$$

where a superscript T represents a transpose of a vector, z represents the number of behaviors provided for Rity, and v_{ti}, $i = 1, \ldots, z$, is the temporary voting value. As there are six motivation states and three homeostasis states for Rity, $6 \times z$ matrix $\mathbf{D}^M$ and $3 \times z$ matrix $\mathbf{D}^H$ are the behavioral weight matrices connecting motivation and homeostasis to behaviors, respectively.

2) Calculate voting vector $\mathbf{V}$ by applying attention and emotion masks to $\mathbf{V}_{\text{temp}}$. Two masking matrices for attention and emotion prevent the agent from doing unreasonable behaviors. Behaviors, related to the current attention, are allowed for the candidates for selection, by suppressing the rest using an attention mask [15], [16]. An attention masking matrix $\mathbf{Q}^A(a)$ is obtained by the attentional percept a, which has its own masking value. The matrix is defined as a diagonal matrix with diagonal entries $q_1^A(a), \ldots, q_z^A(a)$, where $q_i^A(\cdot)$, $i = 1, \ldots, z$, is the masking value, which can be either 0 or 1. Similarly, an emotion masking matrix $\mathbf{Q}^E(e)$, where e is the dominant emotion, is defined. From these two masking matrices and the temporary voting vector, the behavior selector obtains the following final voting vector:

$$\mathbf{V}^T = \mathbf{V}_{\text{temp}}^T \mathbf{Q}^A(a) \mathbf{Q}^E(e) = [v_1, v_2, \ldots, v_z] \quad (6)$$

where v_i, $i = 1, 2, \ldots, z$, is the ith behavior's voting value.

3) Calculate the behavior selection probability $p(b_k)$ of behavior b_k, $k = 1, 2, \ldots, z$, which is calculated from the voting values as follows:

$$p(b_k) = \frac{v_k}{\sum\limits_{i=1}^{z} (v_i)}.$$

4) Select a behavior among various behaviors by the previous selection probability.

The probability proportional selection mechanism generates a reasonable and natural behavior. However, even if a behavior is selected by considering the internal state, there still exist some limits in providing the agent with natural behaviors. The reflexive behavior module, which imitates an animal's instinct, deals with urgent situations such that it makes up for the weak point in behavior selection module. For instance, as soon as an obstacle like a wall or a cliff is found, it makes the agent react to this situation immediately. Since it uses sensory information directly, its decision-making speed is much faster than that of the behavior selection module. In addition to behaviors, Rity has five facial expressions for happiness, sadness, anger, fear, and neutral state, one of which is expressed for the dominant emotional state. Finally, motor module incorporates virtual actuators to execute the selected behavior in the virtual 3-D environment.

Note that Rity's behaviors are preanimated and properly activated according to its perception and internal state. Rity shows a selected behavior for a predefined period of time in between 0.1 and 6.0 s to ensure sufficient time for behavior animation, and after finishing the behavior, it selects the next behavior. However, if a reflexive behavior is activated because of sudden environmental change, the execution of current behavior is interrupted. Since the behavior is selected for each perception and internal state based on the probability proportional selection mechanism, Rity's expressed behaviors are not continuous. This problem can be solved by introducing behavior assemblage that combines related behaviors in sequence [37].

B. Genetic Representation

This section presents a genetic representation of an artificial creature. The genetic encoding allows the pleiotypic and polygenic nature of the genotype such that a single gene influences multiple behaviors and also a single behavior is influenced by multiple genes in behavior selection. The artificial creature is made up of a genome, a set of chromosomes, $\mathbf{C}_k$, $k = 1, \ldots, c$, which has the capability of passing its traits to its offspring [35]. Each chromosome $\mathbf{C}_k$ is composed of three gene vectors: the fundamental gene vector (F-gene vector) $\mathbf{x}_k^F$, the internal-state-related gene vector (I-gene vector) $\mathbf{x}_k^I$, and the behavior-related gene vector (B-gene vector) $\mathbf{x}_k^B$, and is defined as

$$\mathbf{C}_k = \begin{bmatrix} \mathbf{x}_k^F \\ \mathbf{x}_k^I \\ \mathbf{x}_k^B \end{bmatrix}, \qquad k = 1, 2, \ldots, c$$

with

$$\mathbf{x}_k^F = \begin{pmatrix} x_{1k}^F \\ \vdots \\ x_{wk}^F \end{pmatrix}, \qquad \mathbf{x}_k^I = \begin{pmatrix} x_{1k}^I \\ \vdots \\ x_{yk}^I \end{pmatrix}, \qquad \mathbf{x}_k^B = \begin{pmatrix} x_{1k}^B \\ \vdots \\ x_{zk}^B \end{pmatrix}$$

where w, y, and z are the sizes of the F-, I-, and B-gene vectors, respectively.

Each agent has its own fundamental characteristics such as change rate in internal states. For example, an agent is easily motivated if it has larger values of constant $\overline{m_k}$ and discount factor λ_k in (2). These fundamental characteristics are encoded in F-genes. In this paper, constants and discounting factors in (2)–(4) are encoded as F-genes. Note that F-genes have no direct connection with perception and behavior selection modules. I-genes include genetic codes representing the weights of $\mathbf{W}_k^M(t)$ in (2), $\mathbf{W}_k^H(t)$ in (3), and $\mathbf{W}_k^E(t)$ in (4). These genes shape the relationship between perception and internal state. B-genes include genetic codes representing the weights of $\mathbf{D}^M$ and $\mathbf{D}^H$ in (5), and $\mathbf{Q}^E$ in (6), by which internal state and output behaviors are related. An artificial genome, $\mathbf{G}$, composed of a chromosomal set, is defined as

$$\mathbf{G} = [\, \mathbf{C}_1 \quad | \quad \mathbf{C}_2 \quad | \quad \ldots \quad | \quad \mathbf{C}_c \,]$$

where c is the number of chromosomes in the genome.

Rity is implemented by $w = 2$, $y = 47$, $z = 77$, and $c = 6 + 3 + 5 = 14$. y- and z-values correspond to the ability of perceiving 47 different types of percepts and of outputting 77 different behaviors as responses, respectively. The genome is composed of 14 chromosomes, where the first six $\mathbf{C}_1$–$\mathbf{C}_6$ are related to motivation: curiosity ($\mathbf{C}_1$), intimacy ($\mathbf{C}_2$), monotony ($\mathbf{C}_3$), avoidance ($\mathbf{C}_4$), greed ($\mathbf{C}_5$), and desire to control ($\mathbf{C}_6$), the next three $\mathbf{C}_7$–$\mathbf{C}_9$ are to homeostasis: fatigue ($\mathbf{C}_7$), drowsiness ($\mathbf{C}_8$), and hunger ($\mathbf{C}_9$), and the last five $\mathbf{C}_{10}$–$\mathbf{C}_{14}$ are to emotion: happiness ($\mathbf{C}_{10}$), sadness ($\mathbf{C}_{11}$), anger ($\mathbf{C}_{12}$), fear ($\mathbf{C}_{13}$), and neutral ($\mathbf{C}_{14}$). As each chromosome is represented by 2 F-genes, 47 I-genes, and 77 B-genes, Rity has $\nu = 1764$ genes in total.

Fig. 2 shows a genetic encoding, which includes all the related weights along with fundamental parameters. In the figure, the first part (F-genes) is composed of the fundamental parameters, the second part (I-genes) is composed of the weight matrices $\mathbf{W}_k^M$, $\mathbf{W}_k^H$, and $\mathbf{W}_k^E$ in order between perception and internal states and the last part (B-genes) consists of the weight matrices $\mathbf{D}^M$, $\mathbf{D}^H$, and $\mathbf{Q}^E$ in order between internal states and behaviors. The genes in Fig. 2 are originally represented by real numbers: F-genes range from 0.0 to 1.0, I-genes from -0.5 to 0.5, and B-genes from 0.0 to 1.0. F- and B-genes are normalized to brightness values from 0 to 255, which are expressed as black-and-white rectangles. The intenser the color is, the higher its value is. In addition to the positive normalization, I-genes may have negative values that are also normalized and shown as red–white rectangles in the same manner. The 2-D genetic representation has the advantage of representing essential characteristics of three types of genes intuitively, reproducing the evolutionary characteristics of living creatures, and enabling users to easily insert or delete other types of chromosomes and
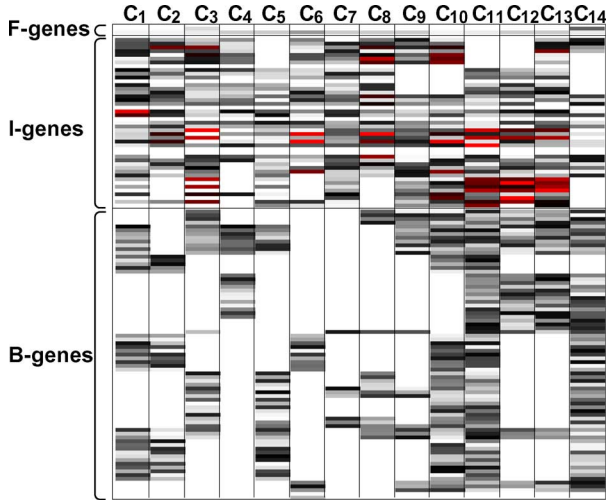
Fig. 2. Artificial genome of Rity. All genes are represented by real numbers and normalized to brightness values in this figure. The intenser the color is, the higher its value is. In addition, I-genes may have negative values which are also normalized and shown as red–white rectangles in the same manner.

genes related to an artificial creature's personality and other information.

C. Personality Model

To represent the personality, Big Five personality dimensions [31], [32] and MBTI [33] can be used. In this paper, Big Five personality dimensions are employed to classify agent's personality traits. They are classified as follows: extroverted (as opposed to introverted), agreeable (as opposed to antagonistic), conscientious (as opposed to negligent), openness (as opposed to closeness), and neuroticism (as opposed to emotional stability). For example, agreeable personality assumes strength in curiosity, intimacy, and happiness, and weakness in greed, desire to control, avoidance, anger, and fear. In contrast, antagonistic personality assumes weakness in curiosity, intimacy, and happiness, and strength in greed, desire to control, avoidance, anger, and fear.

Considering the personality traits, in this paper 14 internal states and their related behavior groups are provided. The preference values on each internal state and each behavior group for representing a certain personality model are assigned in between 0 and 1, respectively, by the user. Table III shows the assigned preference values for agreeable and the antagonistic personality models, where ψ_k^I and ψ_k^B are the values for kth internal state and behavior group, respectively. Note that they can be easily set by using slider bars in a GUI of the developed software system, as shown in Fig. 3.

III. EVOLUTIONARY GENERATIVE PROCESS FOR A PERSONALITY

This section presents an evolutionary generative process to generate a genome in which a specific personality is encoded. The process includes the implementations of the artificial creature, virtual environment, perception scenario, and evolutionary algorithm. The evolutionary algorithm is applied to a population

TABLE III
PREFERENCE VALUES FOR THE AGREEABLE AND ANTAGONISTIC PERSONALITIES

Internal State			Assigned preference values			
			Agreeable personality		Antagonistic personality	
Mode	State	k	ψ_k^I	ψ_k^B	ψ_k^I	ψ_k^B
Motivation	Curiosity	1	**0.8**	**0.8**	0.2	0.2
	Intimacy	2	**0.8**	**0.8**	0.2	0.2
	Monotony	3	0.5	0.5	0.5	0.5
	Avoidance	4	0.2	0.2	**0.8**	**0.8**
	Greed	5	0.2	0.2	**0.8**	**0.8**
	Control	6	0.1	0.1	0.7	0.7
Homeostasis	Fatigue	7	0.2	0.2	0.2	0.2
	Drowsiness	8	0.2	0.2	0.2	0.2
	Hunger	9	0.2	0.2	0.2	0.2
Emotion	Happiness	10	**0.8**	**0.8**	0.2	0.2
	Sadness	11	0.5	0.5	0.5	0.5
	Anger	12	0.2	0.2	**0.8**	**0.8**
	Fear	13	0.2	0.2	**0.8**	**0.8**
	Neutral	14	0.5	0.5	0.2	0.2

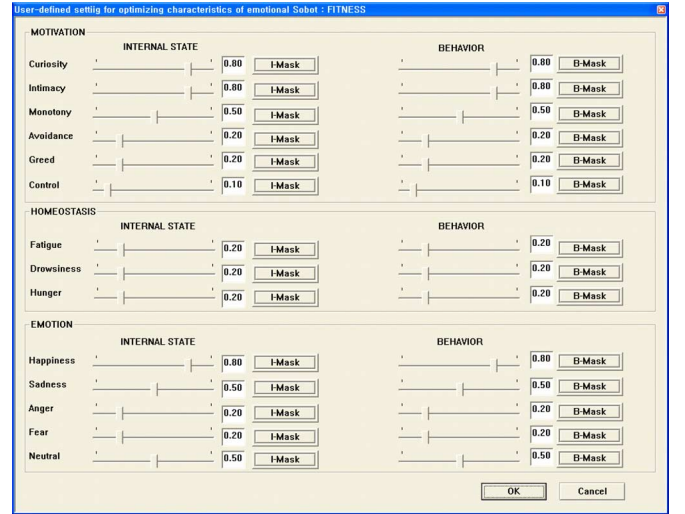The values mean user's desired preference and will be used for defining the fitness function.

Fig. 3. GUI window for setting the preference values of each internal state. If one clicks either 'I-Mask' or 'B-Mask' button, the gene masking is processed.

of genomes $\mathbf{G}_i^t$ $i = 1, 2, \ldots, n$, in the form of a 2-D matrix $P(t) = \{\mathbf{G}_1^t, \mathbf{G}_2^t, \ldots, \mathbf{G}_n^t\}$ at generation t, where n is the size of the population. $\mathbf{G}_i^t$ is defined as

$$\mathbf{G}_i^t = [\,\mathbf{C}_{i1}^t \quad |\mathbf{C}_{i2}^t \quad |\ldots \quad |\mathbf{C}_{ic}^t\,] = \begin{bmatrix} \mathbf{x}_i^{Ft} \\ \mathbf{x}_i^{It} \\ \mathbf{x}_i^{Bt} \end{bmatrix}$$

$$= \begin{bmatrix} \mathbf{x}_{i1}^{Ft} & |\mathbf{x}_{i2}^{Ft} & |\ldots & |\mathbf{x}_{ic}^{Ft} \\ \mathbf{x}_{i1}^{It} & |\mathbf{x}_{i2}^{It} & |\ldots & |\mathbf{x}_{ic}^{It} \\ \mathbf{x}_{i1}^{Bt} & |\mathbf{x}_{i2}^{Bt} & |\ldots & |\mathbf{x}_{ic}^{Bt} \end{bmatrix}.$$

The procedure of the evolutionary algorithm is illustrated in Fig. 4. The main parts of the procedure are described in the following.

```
Procedure EA
begin
          t ← 0
    i)    initialize P(t)
    ii)   gene-mask P(t)
    iii)  evaluate P(t)
    iv)   store the best genome Gb(t) among P(t)
    v)    while (not termination-condition) do
          begin
                t ← t + 1
    vi)       select P(t) from P(t − 1)
              by fitness proportional selection scheme
    vii)      alter P(t)
    viii)     gene-mask P(t)
    ix)       evaluate P(t)
    x)        store the best genome Gb(t)
              among Gb(t − 1) and P(t)
          end
end
```

Fig. 4. Procedure of evolutionary algorithm for an artificial creature's personality.

A. Initialization Process

A population of genomes is randomly initialized in the following ranges: I-genes $[-0.5, 0.5]$, B-genes $[0.0, 1.0]$, and constant values of F-genes for 3rd and 14th chromosomes (representing "monotony" and "neutral" states) $[0.0, 1.0]$. The rest of the constant values are set as 0. It means Rity's internal states shall be monotony in motivation and neutral in emotion when all states converge to initialized constant values. The discount factor in F-genes for kth chromosome is set as $1/(\psi_k^I + 1)$, where 1 in the denominator is added to avoid the division by zero. These F-genes are retained as the initial values during the evolution.

B. Gene Masking

Considering the big number of genes to be optimized, gene masking process (Fig. 3) is introduced, which is to isolate unnecessary genes such that improper internal states and behaviors can be inhibited. It consists of I-gene masking (I-masking) and the B-gene masking (B-masking). The masking process can be done by matrix operation. The matrix is a diagonal one of which element value is one of three masking values, $+1$, 0, or -1, which represent positive, zero, and negative masking, respectively. Positive masking makes the corresponding gene to positive value. Similarly, negative masking makes it to negative value. For example, as the perception of "shaken" or "head hit" would decrease the "intimacy" state, negative masking is used to the corresponding I-genes. Similarly, B-masking is required such that the agent can select a more appropriate behavior given a specified internal state and perception. Elements of the B-masking diagonal matrix take values either 0 or 1. Zero masking prevents the behavior from being selected, while positive masking retains the corresponding gene values. For example, "curiosity" state would not promote the behavior groups related to "fear" or "anger."

C. Perception Scenario

The perception scenario is a series of randomly generated events for a given time duration. It is sequentially applied to the agent and its internal states and behaviors are observed as internal and external responses, respectively. The responses are used to evaluate its genome for a specific personality by utilizing a fitness function at every generation. Each step in perception generation for the scenario is characterized by an event. To the user, the event represents a stimulus applied to the agent, and to the agent, it is a perception as a perceived information. The manner in which the stimuli are applied is customizable and characterized by the following quadruple [39]:

$$(\mathbb{A}, \mathbb{P}, t_s, T_s) \tag{7}$$

where $\mathbb{A} = \{A_1, A_2, \ldots, A_g\}$ is the set of all perception groups, each group includes correlated perceptions to an event, and g is the number of perception groups ($g = 7$ in Table I). $\mathbb{P} = \{p_1, p_2, \ldots, p_g\}$ is the set of generation probabilities for the groups. A perception in the selected group is randomly generated as an event, which occurs at discrete time for a random time period $t_s \in [t_{\min}, t_{\max}]$, where the minimum of $t_{\min}$ is the sampling time, ΔT. T_s is the duration length of the scenario.

Based on this formalization, the perception scenario is defined as a permutation of perceivable information of an agent for T_s. Note that care should be taken to ensure that illogically sequenced perceptions do not result. For example, a perception corresponding to the situation where an obstacle exists, is needed prior to the perception, ®sudden_disappearance⁻ of the obstacle.

D. Fitness Function

Considering the diverse range of personality, a well-designed fitness function is needed to evaluate genomes for a specific personality desired by user. The procedure of evaluation for each genome in the population has the following three steps: 1) a genome is imported into the agent; 2) a series of stimuli in a perception scenario is applied to the agent in a virtual environment; and 3) a fitness is calculated by evaluating its internal states and behaviors. Note that during the evolutionary process experiments, a genome is imported into the core engine of the agent to evaluate its personality (phenotype) without showing its 3-D graphics. According to the imported genome, it generates internal states and concomitant behaviors in response to stimuli. The fitness function can be designed by using the difference between the user assigned preference and the following two evaluation functions: one is to evaluate internal states and the other is to evaluate behaviors [see (10)].

1) Evaluation Function for Internal States: The internal state evaluation function is defined as the possession ratio of each internal state in response to a sequence of perceptions in a perception scenario during perception scenario time period T_s. The possession ratio of the kth internal state for T_s, $\Phi_{pk}^I(T_s, \mathbf{G})$, is defined as

$$\Phi_k^I(T_s, \mathbf{G}) = \frac{\left(\sum_{j=1}^{T_s/\Delta T} \alpha_k(j\,\Delta T, \mathbf{G})\right)}{\Phi^I(T_s, \mathbf{G})} \tag{8}$$

where $\Phi^I(T_s, \mathbf{G})$ is the sum of possession values of all internal states defined by

$$\Phi^I(T_s, \mathbf{G}) = \sum_{k=1}^{c} \sum_{j=1}^{Ts/\Delta T} \alpha_k(j\,\Delta T, \mathbf{G}) \tag{8a}$$

$\alpha_k(j\,\Delta T, \mathbf{G})$, $k = 1, 2, \ldots, c$, is the activation values of the kth internal states at time t for genome $\mathbf{G}$, c is a number of internal states and ΔT is the sampling time.

2) Evaluation Function for Behaviors: The behavior evaluation function examines the frequency of each behavior group in a set, $\mathbf{B_c^T} = [\beta_1, \beta_2, \ldots, \beta_c]$ in Table II for perception scenario time period T_s. The frequency of the kth behavior group for T_s is defined as

$$\Phi_k^B(T_s, \mathbf{G}) = \frac{f_k^B(T_s, \mathbf{G})}{\Phi^B} \tag{9}$$

where the dataset consists of $\Phi^B = \sum_{k=1}^{c} f_k^B(T_s, \mathbf{G})$ observations, with the behavior group β_k appearing $f_k^B(T_s, \mathbf{G})$ times for $k = 1, 2, \ldots, c$.

Using (8) and (9), the following fitness function is defined to minimize the differences between the user assigned preference values and the evaluated possession ratio of each internal state and the frequency of each behavior group

$$\Phi(T_s, \mathbf{G}) = N - \tilde{\Phi}(T_s, \mathbf{G}) \tag{10}$$

with

$$\tilde{\Phi}(T_s, \mathbf{G})$$
$$= \left[\sum_{k=1}^{c} |\tilde{\psi}_k^I - \Phi_k^I(T_s, \mathbf{G})| + \sum_{k=1}^{c} |\tilde{\psi}_k^B - \Phi_k^B(T_s, \mathbf{G})| \right] \tag{10a}$$

where the normalized preference values, $\tilde{\psi}_k^I$ and $\tilde{\psi}_k^B$, defined as

$$\tilde{\psi}_k^I = \frac{\psi_k^I}{\sum_{l=1}^{c} \psi_l^I}, \qquad \tilde{\psi}_k^B = \frac{\psi_k^B}{\sum_{l=1}^{c} \psi_l^B}. \tag{10b}$$

In (10a), $\Phi_k^I(T_s, \mathbf{G})$, is the possession ratios of the kth internal state in (8), $\Phi_k^B(T_s, \mathbf{G})$ is the frequency of the kth behavior group in $\mathbf{B_c}$ in (9), and N is a constant number to make a maximization problem.

It should be noted that user can easily set the relevant preference values ψ_k^I and ψ_k^B in Table III through the GUI (Fig. 3) for agent's personality by his/her preference, where each preference value is assigned in between 0 and 1. Since the user-assigned preference represents a desired personality, EGPP finds the I-genes and B-genes which meet the preference by utilizing the user-assigned preference values in the fitness function.

E. Mutation Operator

Since there are many genes to be optimized, it is difficult and takes a longer period of time to obtain the optimized genome by using mutation of normal distribution. To promote the performance, directed mutation is adopted, where the mean value is shifted according to the difference between the desired and evaluated values of the possession ratio of internal states. Note that a normal distribution in this mutation operator preserves the probabilistic search. For the pth I-gene of kth chromosome in ith individual, the mutation operator is defined as follows:

$$x_{ikp}^I = x_{ikp}^I + N(\mu_k^I, \sigma_k^I)$$
$$\mu_k^I = \gamma(\tilde{\psi}_k^I - \Phi_k^I(T_s, \mathbf{G}))$$
$$\sigma_k^I = \frac{\kappa\sqrt{\tilde{\Phi}(T_s, \mathbf{G})}}{\nu} \tag{11}$$

where $\tilde{\Phi}(T_s, \mathbf{G})$ is the difference term in fitness function, defined in (10a), γ and κ are the scaling factors for the mean and standard deviation of normal distribution, respectively, and ν is the number of genes. Similarly, the mutation operator for the B-genes can be defined with the difference between the desired and evaluated frequencies of the corresponding behavior group.
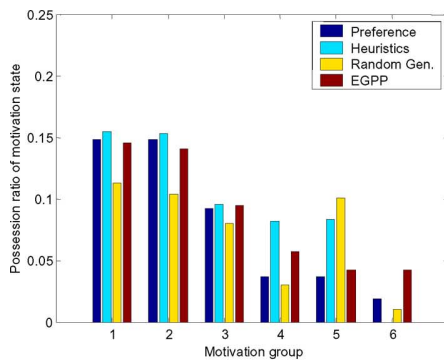
IV. EXPERIMENTS

The agreeable and antagonistic personality models for Rity were chosen to demonstrate the feasibility of the EGPP. By comparing the performance for the two contrasting personalities, the evaluation can be easily made concerning its ability to provide a consistent (the ability to exhibit reliably expectant behaviors) and uniquely distinct personality. Two perception scenarios to evaluate and verify genomes, respectively, were generated with the voting values $\{\tilde{v}_1, \tilde{v}_2, \ldots, \tilde{v}_7\} = \{0.5, 0.5, 0.5, 0.7, 0.5, 0.7, 0.5\}$ for seven perception groups, $A_{po}, A_{ob}, A_{bt}, A_{ph}, A_{so}, A_{of}$, and A_{ba}, in Table I. The perception scenario time period T_s was 500s. The selection probability for each perception group in (7) was calculated by $\tilde{p}_i = \tilde{v}_i / \sum_{j=1}^{7} (\tilde{v}_j)$, $i = 1, \ldots, 7$, and one perception in the selected group was randomly generated. The time duration for the selected perception was also randomly selected in between 0.1 and 10 s. The parameter setting of EGPP was applied equally in both cases of agreeable and antagonistic personalities. Preference values were given as those in Table III. The population size was 50 and the number of generations was fixed at 3000. $N = 1.5$ was used in (10), $\gamma = 0.05$ and $\kappa = 1$ were used in (11) and mutation rate was set to 0.05. It took about 12 h to generate a genome encoding a desired personality by Pentium 4, 2 GHz processor.
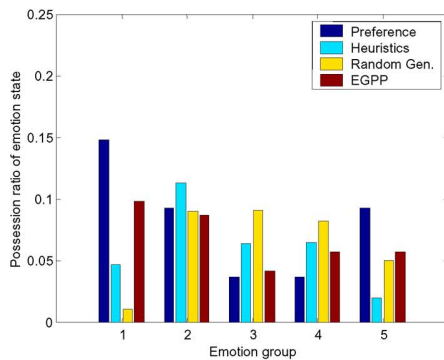
A. Generation of Genomes by EGPP

Experiments were carried out for agreeable and antagonistic personalities of Rity with three differently generated genomes: 1) one manually set by heuristics; 2) another generated randomly for the initial population; and 3) the other generated by EGPP. Figs. 5 and 6 show the comparison results among the three genomes for agreeable and antagonistic personalities, respectively. In the figures, (a) and (b) show each possession ratio of motivation and emotion internal states, respectively, (c) and
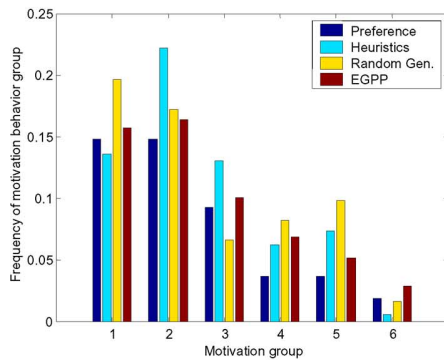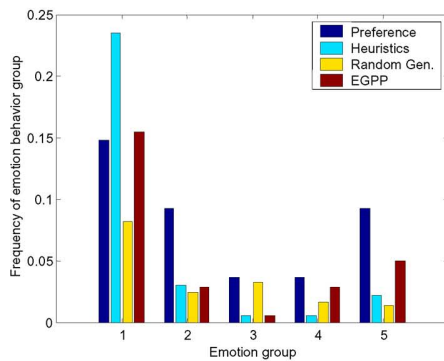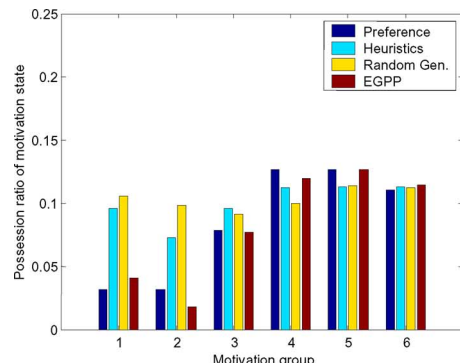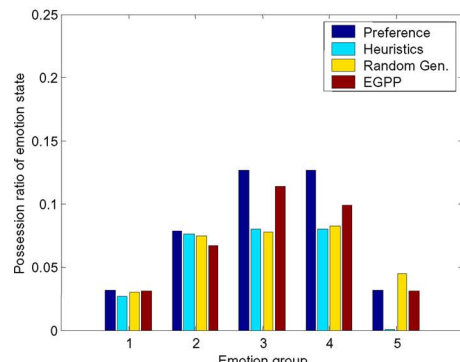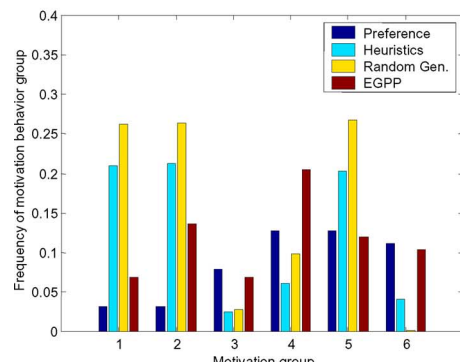
Fig. 5.   Comparison of possession ratio and frequency of behavior of generated genomes for agreeable personality. (a) Possession ratio of motivation state. (b) Possession ratio of emotion state. (c) Frequency of motivation behavior. (d) Frequency of emotion behavior. Bars in the graph represent: (1) normalized preference values, defined by user; (2) genome, manually set by heuristics; (3) genome, generated randomly; and (4) genome, generated by EGPP with random initialization.
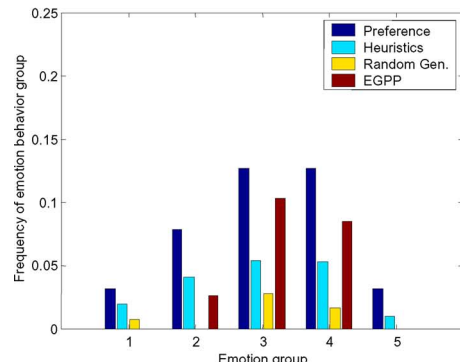
Fig. 6.   Comparison of generated genomes for antagonistic personality. (a) Possession ratio of motivation state. (b) Possession ratio of emotion state. (c) Frequency of motivation behavior. (d) Frequency of emotion behavior. Bars in the graph represent: (1) normalized preference values, defined by user; (2) genome, manually set by heuristics; (3) genome, generated randomly; and (4) genome, generated by EGPP with random initialization.
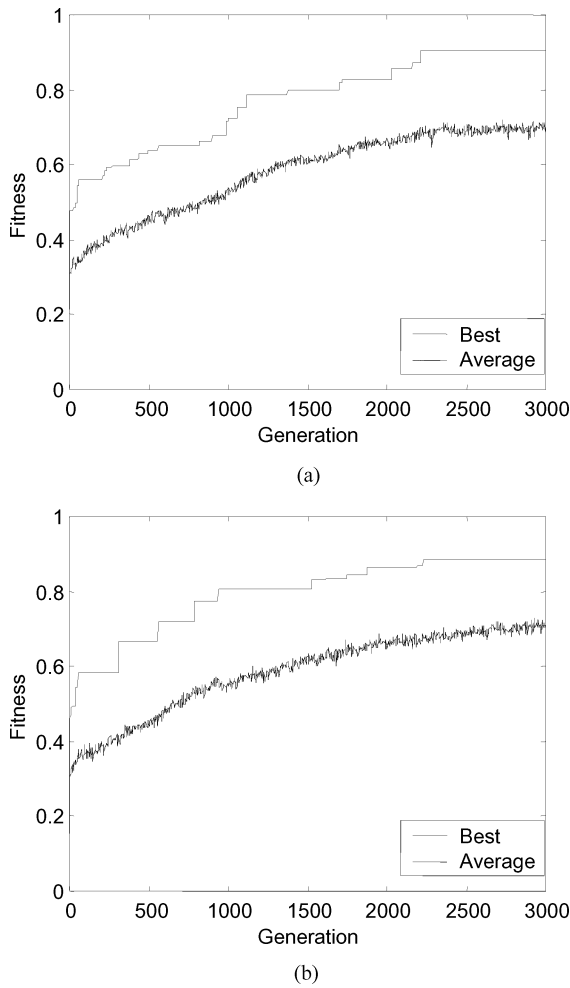
Fig. 7. Evolution process by EGPP. (a) Agreeable genome. (b) Antagonistic genome.

(d) show the frequency of each behavior group corresponding to the motivation and emotion states, respectively, and the first one in each item of the histogram is a reference value that is the normalized user-assigned preference value. Responses of homeostasis were similarly obtained.

It can be observed from the figures that the genomes manually set by heuristics, were not able to properly produce desired personalities. As expected, the randomly generated genomes showed the worst performance among the three. On the other hand, the genomes generated by EGPP exhibited reliably expectant internal states and behaviors representing a distinct personality. Note that EGPP, despite the random initialization, could generate the genomes showing similar traits as desired by the user-assigned preference values for both of the agreeable and antagonistic personality examples. The slight discrepancy between the obtained traits and the desired ones was due to the limited number of generations, the genetic operator, the probabilistic decision policy of resulting behaviors, etc.

Fig. 7 shows the evolution process of generating each genome for the agreeable and antagonistic personalities by EGPP, where a darker line is for the average fitness and the other line is for the best one. In the figure, a steady improvement in fitness along generation can be seen.

B. Verification of Evolved Genomes

Evolved genomes by EGPP were verified through the following procedure. Obtained agreeable genome A and antagonistic genome B were implanted into two artificial creatures, Rity A and Rity B, respectively. The perception scenario for verification, which was different from the one used for evolution in the previous section, was applied to them and observed their resulted internal states and behaviors.
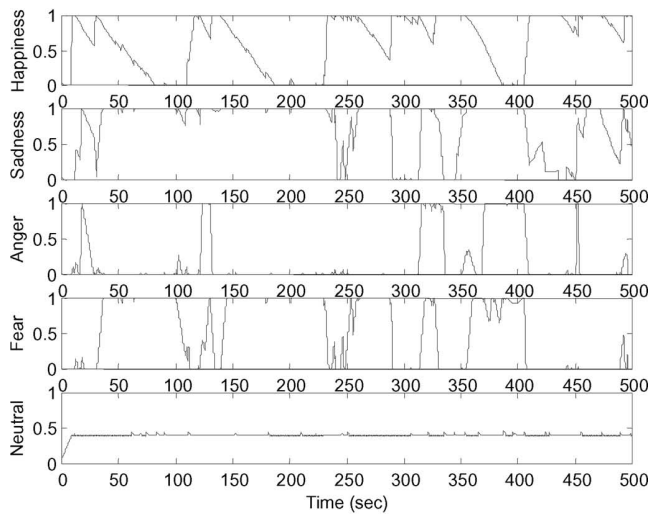
1) Verification on Internal State Responses: Figs. 8 and 9 show the experimental results on internal state responses when the verification scenario was applied to agreeable Rity A and antagonistic Rity B, respectively. Fig. 8(a) shows that the states of curiosity and intimacy have wider distribution than those of avoidance, greed, and desire to control in motivation for the perception scenario time period of 500 s. Fig. 8(b) shows that happiness state has the widest distribution among emotion states. Fig. 8(c) shows histograms of possession ratios calculated for each internal state by evaluation function (8). The horizontal axis represents the index of 14 internal states, where the vertical axis represents the possession ratios of internal states. The 1st, 2nd, and 10th internal states have high possession ratios, which indicate strong states of curiosity and intimacy in motivation and of happiness in emotion, while the 4th, 5th, 6th, 12th, and 13th internal states have low possession ratios, which indicate weak states of avoidance, greed, and desire to control in motivation, and of anger and fear in emotion.

In contrast, Fig. 9(a) shows that states of avoidance, greed, and desire to control have wider distribution than those of curiosity and intimacy in motivation for the same verification scenario. Fig. 9(b) shows that the states of sadness, anger, and fear have wider distribution than the happiness state in emotion. In Fig. 9(c), the 4th, 5th, 6th, 11th, 12th, and 13th internal states have high possession ratios, which mean strong states of avoidance, greed and desire to control in motivation, and of sorrow, anger, and fear in emotion, while the 1st, 2nd, 10th, and 14th internal states have low possession ratios, which indicate weak states of curiosity, and intimacy in motivation, and of happiness and neutral in emotion.

2) Verification on Behavior Responses: Figs. 10 and 11 show external output responses of agreeable Rity A and antagonistic Rity B, respectively, for the same verification scenario used for Figs. 8 and 9. Figs. 10(a) and 11(a) show the frequency of behavior groups. Fig. 10(a) shows that the frequencies of behaviors belonging to the groups such as "1—curiosity," "2—intimacy," and "10—happiness" are high. In contrast, Fig. 11(a) shows that the frequencies of behaviors belonging to the groups such as "4—avoidance," "5—greed," "12—anger," and "13—fear" are high. The indexes of five facial expressions, neutral, happiness, sorrow, anger, and fear are set to 0, 1, 2, 3, and 4, in Figs. 10(b) and 11(b). In Fig. 10(b), there are much more facial expressions of happiness than other kinds of facial expressions. In contrast, in Fig. 11(b), there are more facial expressions of sorrow and anger than that of happiness.
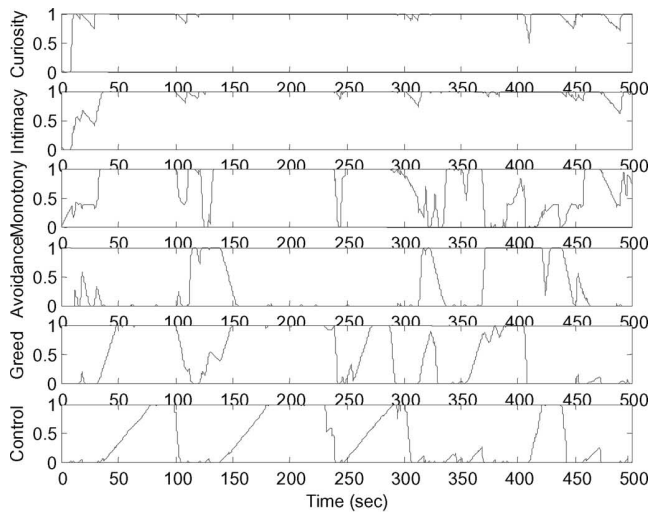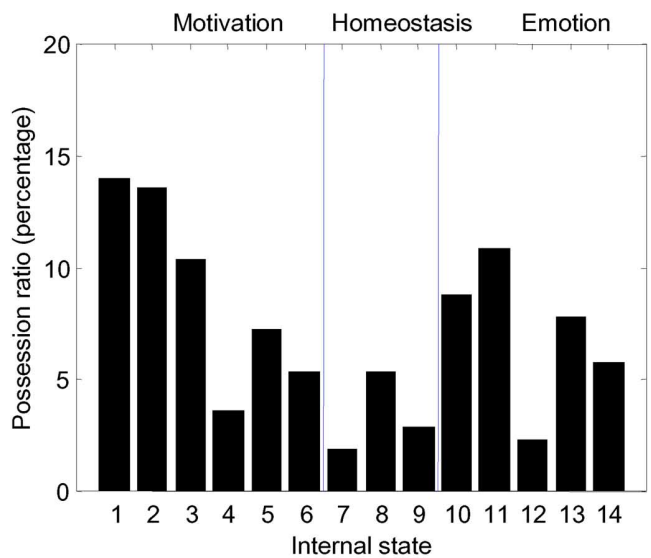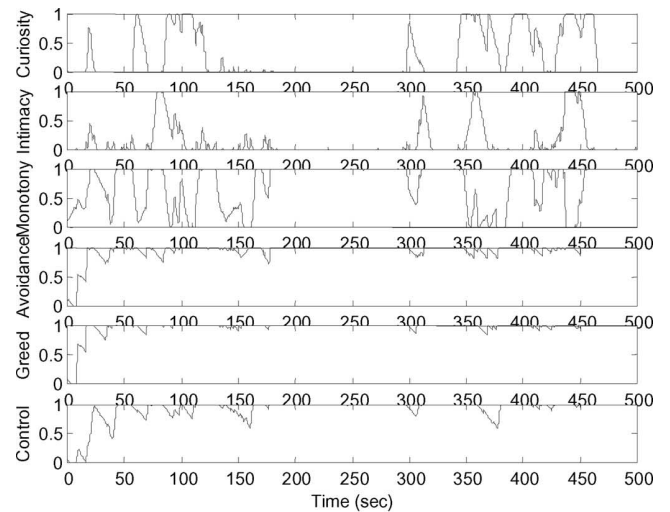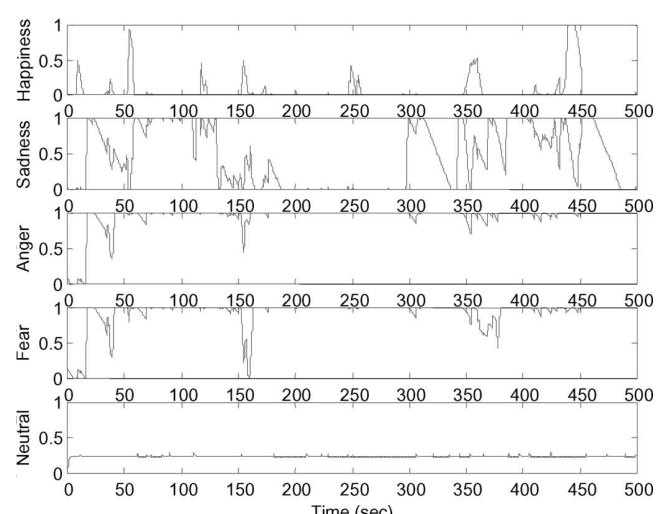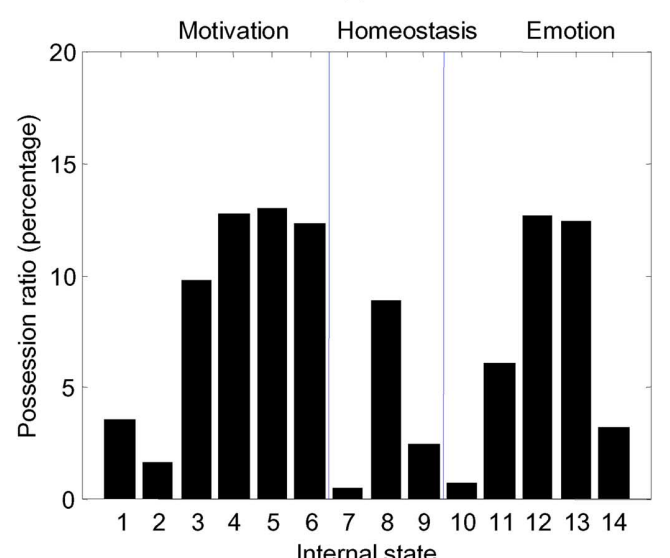
Fig. 8.   Internal state responses of agreeable Rity A to the verification scenario. (a) Motivation response. (b) Emotion response. (c) Possession ratio histograms calculated for each internal state.

Fig. 9.   Internal state responses of antagonistic Rity B to the verification scenario. (a) Motivation response. (b) Emotion response. (c) Possession ratio histograms calculated for each internal state.
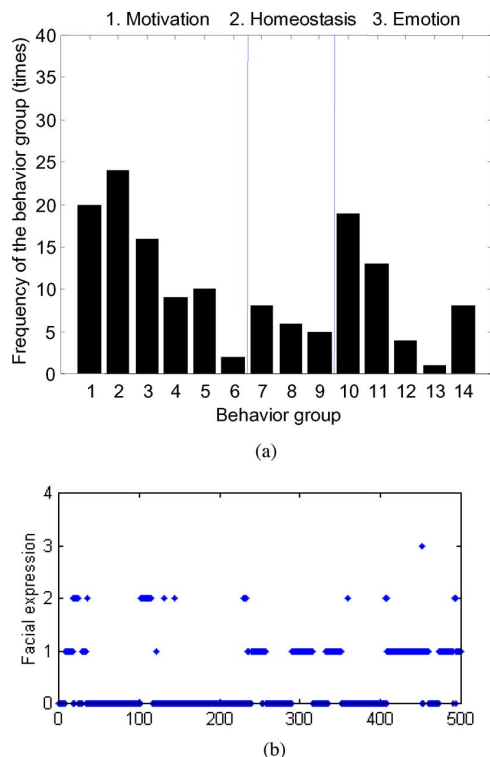
(a)

(b)

Fig. 10. External behavior responses of agreeable Rity A to the verification scenario. (a) The frequency of behavior groups, which corresponds to the number of occurred time during the scenario. (b) Facial expression response (The indexes of five facial expressions, neutral, happiness, sorrow, anger, and fear are set to 0, 1, 2, 3, and 4, respectively.).
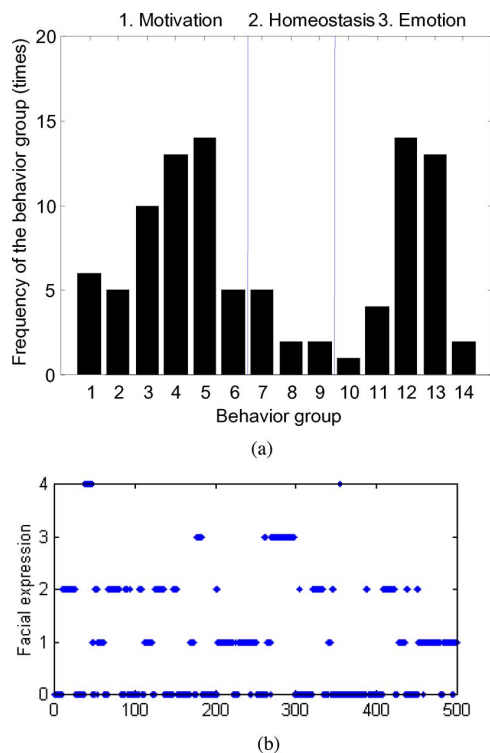

(a)

(b)

Fig. 11. External behavior responses of antagonistic Rity B to the verification scenario. (a) The frequency of behavior groups, which corresponds to the number of occurred time during the scenario. (b) Facial expression response (The indexes of five facial expressions, neutral, happiness, sorrow, anger, and fear are set to 0, 1, 2, 3, and 4, respectively.).

For both agreeable and antagonistic genomes, plausible artificial creatures, Ritys were observed for all internal states and behaviors simultaneously for the prescribed perception scenario. The obtained genomes defined consistent and distinct personalities for Ritys. These experimental results verify the effectiveness of EGPP as an evolutionary gene-generative mechanism for the personality desired by the user. Video clips of two Ritys are available at http://rit.kaist.ac.kr/home/ Artificial_Creatures_in_Virtual_Environment. The EGPP can also generate genomes for randomly generated personality preferences. Moreover, it can be used for generating genomes for specific personalities based on evolutionary multiobjective optimization [40].

V. CONCLUSION

This paper proposed an evolutionary process for generating a genome of an artificial creature representing a specific personality desired by user. The genome was composed of chromosomes in which genes were devised as basic building blocks to represent a simplified set of personality traits. The evolutionary process included a population of genomes, an evolutionary algorithm, a dedicated fitness function, a directed mutation operator, and a perception scenario randomly generated in virtual environment. A genome encoding the desired personality of an artificial creature was generated by the proposed evolutionary process. It was verified by applying another perception scenario for verification, which was different from the one used for evolution, to the agent and by observing the internal state and concomitant behavior as responses to a series of stimuli. Through the verification process, the effectiveness of the proposed process was demonstrated. Although in this paper two standard personality types such as the agreeable and antagonistic personalities were employed to test the feasibility of the proposed process, it can be also used to generate various types of personality each of which is encoded in a corresponding genome. This research will contribute not only to improve the capability of artificial creature for natural interactions with human beings but also to initiate the study of "The Origin of Artificial Species."

As a further work, the inherited information contained in the evolved genome as an innate personality, should be combined with the posterior information that is accumulated through experience and by means of learning or interaction with a human. To make the genome structure generalized, the types of perception, internal states, and behaviors should be classified and standardized, which also remains as another further work.

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