Evolutionary Multi-Objective Optimization for Generating Artificial Creature's Personality

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***Abstract*— This paper proposes the evolutionary generation of an artificial creature's personality by using the concept of multi-objective optimization. The artificial creature has its own genome and in which each chromosome consists of many genes that contribute to defining its personality. The large number of genes allows for a highly complex system, however it becomes increasingly difficult and time-consuming to ensure reliability, variability and consistency for the artificial creature's personality while manually assigning gene values for the individual genome. Moreover, there needs user's preference to obtain artificial creature's personality by using evolutionary generation. Preference is strongly depend on each user and most of them would have difficulty to define their preference as a fitness function. To solve this problem, this paper proposes multi-objective generating process of an artificial creature's personality. Genome set is evolved by applying strength Pareto evolutionary algorithm (SPEA). To facilitate the individuality of generated artificial creature, complement of (1-k) dominance and pruning method considering deviation are proposed. Obtained genomes are tested by using an artificial creature, Rity in the virtual 3D world created in a PC.**

I. INTRODUCTION

A number of artificial creatures, called interactive creatures, autonomous agents, synthetic characters, software robots, or 3D avatars, have been being developed to entertain humans in real-time interaction. In general, an artificial creature has various virtual and physical sensors, which influence internal states such as motivation, homeostasis, emotion, etc., and then lead to a different behavior externally according to the internal states. These software agents have gained significant potential for application in the entertainment industry. Most of works, however, dealt with behavior selection and learning mechanisms in a fixed control architecture. The concept of evolution and genetic representation were not considered [1]–[7].

This paper focuses on the multi-objective evolutionary generative process of an artificial creature's personality by using its computer-coded genome in a virtual environment. The genome is composed of multiple artificial chromosomes each of which consists of many genes that contribute to defining the creature's personality. It provides primary advantages for artificial reproduction, the ability to evolve, and reusability among artificial creatures [8], [9]. The large number of genes also allows for a highly complex system. However, it is difficult and time-consuming to manually assign values to them for ensuring reliability, variability and consistency for the artificial creature's personality. Moreover, defining the objective of resulting personality is much difficult and it will vary as each user's preferring personality model. To overcome this problem, multi-objective generation of an artificial creature's personality is proposed.

The proposed process generates a set of genomes as its output, which characterizes various artificial creatures' personalities in terms of internal states and their concomitant behaviors. It acts to achieve genomes, which have non-dominated fitness by applying strength Pareto evolutionary algorithm (SPEA) [10]. The objectives are set as agreeable, antagonistic, extroverted, introverted, conscientious and negligent model by employing Big Five personality dimensions [11]. The proposed process is validated by implanting the evolved genomes into the artificial creature. In the experiments an artificial creature, Rity, developed in a 3D virtual world, was used.

This paper is organized as follows: Section II introduces an artificial creature, Rity, its internal control architecture, and the structure of the genome, which is composed of chromosomes including the fundamental genes, the internal state related genes, and the behavior related genes. Section III describes proposed generating process along with the personality model and evolutionary algorithm based on the SPEA. Experiments are carried out to demonstrate its performance and effectiveness in Section IV. Concluding remarks follow in Section V.

II. ARTIFICIAL CREATURE

This section introduces an artificial creature, Rity in a 3D virtual world, its internal control architecture, and its genome composed of a set of chromosomes [5].

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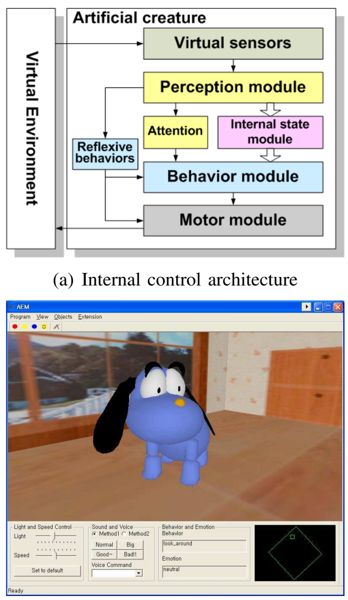
A. Artificial Creature, Rity

An artificial creature is defined as an agent which behaves autonomously driven by its internal states such as motivation, homeostasis, and emotion. It should be also able to interact with humans and its environment in real-time. Rity is designed to fulfill the requirements for an artificial creature. It represents itself visually on the screen as a dog and may interact with humans based on stimuli through a mouse, a camera or a microphone. The internal control architecture in this paper is composed of four primary modules, that is, perception module, internal state module, behavior selection module and motor module.



(a) Internal control architecture

(b) Screen shot

Fig. 1. Artificial creature, Rity in a 3D virtual world

A number of different techniques have been tried out by researchers to develop suitable reactive control architectures for robots [2] [3]. In this regard, considering the requirement to incorporate internal states onto Rity, it cannot be considered as a simple stimulus response system with behaviors being mapped to perceptions. The architecture employed in Rity follows up from work by Kim et al [5].

Perception module The perception module can recognize and assess the virtual environment and subsequently send the information to the internal state module. Rity has several virtual sensors for light, sound, temperature, touch, vision, orientation and time making a total of 47 types of stimulus information.

Internal state module

The internal state module defines the creature's internal state with the motivation unit, the homeostasis unit and the emotion unit. In Rity, motivation is composed of six states: curiosity, intimacy, monotony, avoidance, greed and the desire to control. Homeostasis includes three states: fatigue, hunger and drowsiness. Emotion includes five states: happiness, sadness, anger, fear and neutral. In general, the number of internal states depends on an artificial creature's architecture.

Each internal state is updated by its own weights, which connect the stimulus vector to itself and are also represented as a vector. For instance, motivation vector $\mathbf{M}$ is defined as

$$\mathbf{M}(t) = [m_1(t), m_2(t), \cdots, m_6(t)]^T \quad (1)$$

where $m_k(t)$ is kth state in the internal state module and the number of motivation states is 6. Each motivation state is updated by

$$m_k(t+1) = m_k(t) + \{\lambda_k(\overline{m_k} - m_k(t)) + \mathbf{S}^T \cdot \mathbf{W}_k^M(t)\} \\ k = 1, 2, \cdots, 6 \quad (2)$$

where $\mathbf{S}$ is the stimulus vector, $\mathbf{W}_k^M$ is a weight matrix connecting $\mathbf{S}$ to kth state in the internal state module, $\overline{m_k}$ is the constant to which the internal state converge without any stimuli, and λ_k is the difference gain. Similar update equations are defined for the homeostasis unit using state vector $\mathbf{H}(t)$ and weight matrix $\mathbf{W}_k^H$, and also the emotion unit using state vector $\mathbf{E}(t)$ and weight matrix $\mathbf{W}_k^E$, respectively.

Behavior selection module

The behavior selection module is used to choose a proper behavior based on Rity's internal state, which is influenced by stimuli. 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. The procedure of behavior selection is as follows:

1) Determine the temporal voting vector, $\mathbf{V}_{temp}$ using $\mathbf{M}$ and $\mathbf{H}$.
2) Calculate voting vector $\mathbf{V}$ by applying attention and emotion masks to $\mathbf{V}_{temp}$.
3) Calculate a behavior selection probability, $p(b)$, using $\mathbf{V}$.
4) Select a proper behavior b with $p(b)$ among various behaviors.

Motor module

The motor module incorporates virtual actuators to execute the selected behavior in the virtual 3D environment.

B. Genetic Representation

An artificial creature is made up of genome, a set of chromosomes, $\mathbf{C}_k$, $k = 1, 2, \cdots, c$, which has the capability of passing its traits to its offspring. 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

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

vector, I-gene vector, and B-gene vector, respectively.

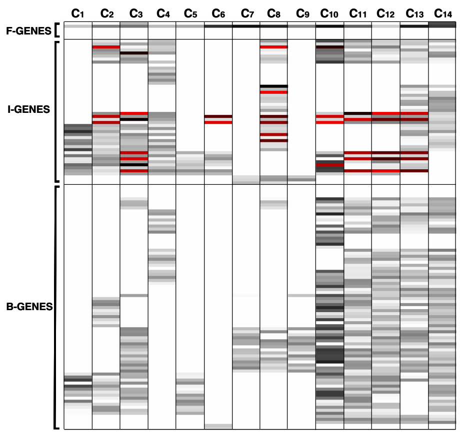


Fig. 2. Artificial genome of Rity

An artificial genome, $\mathbf{G}$, composed of a chromosomal set, is defined as

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

where c is the number of chromosomes in the genome.

III. Multi-Objective Evolutionary Generative Process for a Personality

To build a truly believable artificial creature, it is required to design an evolutionary generative process to generate individualized solutions representing plausible personalities. The process includes an implementation of the artificial creature and its virtual environment, its personality model, and an strength Pareto based evolutionary algorithm.

A. Personality Model

Big Five personality dimensions are employed and Rity's internal traits are classified for the corresponding personalty dimension. They are classified as follows: extroverted (as opposed to introverted), agreeable (as opposed to antagonistic), conscientious (as opposed to negligent), openness (as opposed to closedness), and neuroticism (as opposed to emotional stability) [11]. From these, agreeable, antagonistic, extroverted, introverted, conscientious and negligent personalities are chosen for the objectives of Rity to generate nondominated personality models.

Considering the personality traits, in this paper the preference values of each objective of personality models are assigned in between 0 and 1 as in Table I, where ψ^I_{lk} and ψ^B_{lk} are preference values of mth objective for kth internal state and behavior group, respectively. These values mean user's desired preference and will be used for defining each objectives.

Preference values in the table are denoted by

$$\begin{aligned} \mathbf{\Psi} &= [\mathbf{\Psi_1} \ \ \mathbf{\Psi_2} \ \ \mathbf{\Psi_3} \ \ \mathbf{\Psi_4} \ \ \mathbf{\Psi_5} \ \ \mathbf{\Psi_6}] \\ \mathbf{\Psi_1} &= \left[\begin{array}{cccc} \psi^I_{l1} & \psi^I_{l2} & \cdots & \psi^I_{lc} \\ \hline \psi^B_{l1} & \psi^B_{l2} & \cdots & \psi^B_{lc} \end{array} \right] \end{aligned} \tag{3}$$

TABLE I

Preference values for the agreeable, extroverted and conscientious personalities

Internal State		Assigned preference values: Agreeable	Antagonistic	Extroverted	Introverted	Conscientious	Negligent
Mode	State	ψ^I_{1k} ψ^B_{1k}	ψ^I_{2k} ψ^B_{2k}	ψ^I_{3k} ψ^B_{3k}	ψ^I_{4k} ψ^B_{4k}	ψ^I_{5k} ψ^B_{5k}	ψ^I_{6k} ψ^B_{6k}
Motivation	Curiosity	**0.5**	0.2	**0.8**	0.2	0.2	0.1
	Intimacy	**0.8**	0.2	**0.85**	0.2	0.2	0.1
	Monotony	**0.5**	**0.5**	**0.5**	0.2	0.2	**0.8**
	Avoidance	0.2	**0.8**	0.2	**0.8**	0.2	**0.8**
	Greed	0.2	**0.8**	**0.5**	0.2	**0.5**	0.2
	Control	0.1	**0.7**	**0.85**	0.2	0.2	0.2
Homeostasis	Fatigue	0.2	0.2	0.2	0.2	0.1	**0.4**
	Drowsiness	0.2	0.2	0.2	0.2	0.1	**0.4**
	Hunger	0.2	0.2	0.2	0.2	0.2	0.3
Emotion	Happiness	**0.8**	0.2	**0.65**	0.3	**0.65**	0.2
	Sadness	**0.5**	**0.5**	0.2	0.3	0.3	0.2
	Anger	0.2	**0.8**	0.2	0.3	0.1	**0.5**
	Fear	0.2	**0.8**	0.2	0.3	0.1	**0.4**
	Neutral	**0.5**	0.2	0.1	**0.7**	0.1	0.2

Procedure of multi-objective generative process
begin
    $t \leftarrow 0$
i)   initialize $P(t)$ and create the empty external nondominated set $P'(t)$
    do
    begin
ii)   gene-mask $P(t)$
iii)   evaluate $P(t)$
iv)   find nondominated members of $P(t)$ according to the compliment of (1-k) dominance and copy to $P'(t)$
v)   remove solutions within $P'(t)$ which are covered by an other member of $P'(t)$
vi)   if the number of externally stored nondominated solutions exceeds a given maximum N', prune $P'(t)$ considering deviation
vii)   calculate the fitness of each solution in $P(t)$ as well as in $P'(t)$
viii)   select solutions from $P(t) + P'(t)$ (multiset union), until the mating pool is filled
ix)   apply crossover and mutation operators
        $t \leftarrow t + 1$
    end
x)   **while** (**not** termination-condition)
end

Fig. 3. Procedure of SPEA for an artificial creature's personality

where $\mathbf{\Psi_1}$, $\mathbf{\Psi_2}$, $\mathbf{\Psi_3}$, $\mathbf{\Psi_4}$, $\mathbf{\Psi_5}$ and $\mathbf{\Psi_6}$ correspond to the preference values of agreeable, antagonistic, extroverted, introverted, conscientious and negligent personalities and c is 14 in this paper.

B. Procedure of Generative Process

Multi-objective generative process maintains a population of genomes, $\mathbf{G}^t_i$, $i = 1, 2, \cdots, n$, with the form of a two-dimensional matrix, $P(t) = \{\mathbf{G}^t_1, \mathbf{G}^t_2, \cdots, \mathbf{G}^t_n\}$ at generation t, where n is the size of the population.

Figure 3 illustrates the procedure of generative process in the following manner:

i) Preference values are assigned and genomes are initialized.

ii) Each $\mathbf{G}_i^t$ is masked by I-gene masking and B-gene masking, in order to generate reasonable behaviors. Masked genomes replace the original ones.

iii) The masked genome is implanted to the artificial creature, a series of perceptions is applied to it, and then each objective is evaluated.

iv) - viii) SPEA [10] is applied to evaluated genomes to find nondominated solutions. To facilitate the individuality of the artificial creature's personality, the compliment (1-k) dominance and the pruning method considering deviation are proposed.

ix) Some members of the new population undergo transformations by means of the crossover operators, $\mathbf{\Theta}_\chi^F$, $\mathbf{\Theta}_\chi^I$ and $\mathbf{\Theta}_\chi^B$, and the mutation operators $\mathbf{\Theta}_\mu^F$, $\mathbf{\Theta}_\mu^I$ and $\mathbf{\Theta}_\mu^B$, to form new genomes.

x) Steps ii)-ix) are repeated until the the termination condition is reached. This paper uses the maximum number of generations as a termination condition.

C. Gene Masking

To build a truly believable one with a specific personality, it is required for the artificial creature to have a proper genome which leads to generate plausible internal states and behaviors. In this regard, a gene masking process is needed to isolate unnecessary genes.

D. Perception Scenario

A series of randomly generated perceptions is applied to the artificial creature and its internal states and behaviors are observed. The perception scenario is designed using stimuli from the environment. Perception scenario 1 is used for evaluating genomes and perception scenario 2 is for verifying the selected genome.

E. Objectives

Considering the diverse range of personalities, a well-designed objectives are needed to evaluate genomes for a specific personality. The procedure of evaluation has the following three steps.

- Step 1: A genome is imported to the artificial creature.
- Step 2: A series of random stimuli in a perception scenario is applied to the artificial creature in a virtual environment.
- Step 3: A objective is calculated by evaluating its internal states and behaviors.

In Step 2, according to the imported genome it generates internal states and relevant behaviors in response to stimuli. The objective can be designed by using the difference between the user's preference and the following two evaluation functions: one is to evaluate internal states and the other is to evaluate behaviors (see (6)).

Evaluation function for internal states

For objectives, one evaluates the possession ratio of each internal state in response to stimuli in a perception scenario for perception scenario time T_s. The possession ratio of the kth ($k = 1, \cdots, c$) internal state for T_s, $\Phi_{pk}^I(T_s, \mathbf{G})$, is defined as

$$\Phi_{pk}^I(T_s, \mathbf{G}) = \left(\sum_{j=1}^{Ts/\Delta T} \alpha_k(T_s, \mathbf{G}) \right) / \Phi_p^I(T_s, \mathbf{G}), \qquad (4)$$

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

$$\Phi_p^I(T_s, \mathbf{G}) = \sum_{j=1}^{Ts/\Delta T} \sum_{k=1}^{c} \alpha_k(T_s, \mathbf{G}). \qquad (4.a)$$

Evaluation function for behaviors

Given a set of behavior groups $\mathbf{B_c}^T = [\beta_1, \beta_2, \cdots, \beta_c]$, one examines the frequency of each behavior group for T_s. The frequency of the kth behavior group for T_s is defined as

$$\Phi_{fk}^{BG}(T_s, \mathbf{G}) = f_k^{BG}(T_s, \mathbf{G}) / n_{BG}, \qquad (5)$$

where the data set consists of $n_{BG} = \sum_{k=1}^{c} f_k^{BG}(T_s, \mathbf{G})$ observations, with the behavior group β_k appearing $f_k^{BG}(T_s, \mathbf{G})$ times for k ($k = 1, 2, \cdots, c$).

Since the user's preference corresponds to the one of objectives, which are the basis of personality, multi-objective generative process finds the set of genes, those are the dominant according to these objectives.

Using (4) and (5), the objectives are defined as

$$\begin{aligned}\Phi_l(T_s, \mathbf{G}) = \rho \Bigg[&\sum_{k=1}^{c} (1/\tilde{\psi}_{lk}^I) |\tilde{\psi}_{lk}^I - \Phi_{pk}^I(T_s, \mathbf{G})| \\ &+ \sum_{k=1}^{c} (1/\tilde{\psi}_{lk}^B) |\tilde{\psi}_{lk}^B - \Phi_{fk}^{BG}(T_s, \mathbf{G})| \Bigg]\end{aligned} \qquad (6)$$

with the normalized preference value, ψ_{lk}^I and ψ_{lk}^B, defined as

$$\tilde{\psi}_{lk}^I = \psi_{lk}^I / \sum_{v=1}^{c} \psi_{lv}^I, \quad \tilde{\psi}_{lk}^B = \psi_{lk}^B / \sum_{v=1}^{c} \psi_{lv}^B \qquad (7)$$

where $\Phi_{pk}^I(T_s, \mathbf{G})$, is the possession ratios of the kth internal state, $\Phi_{fk}^{BG}(T_s, \mathbf{G})$ is the frequency of the kth behavior group in $\mathbf{B_c}$, and ρ a scale factor for the difference terms.

F. Complement of (1-k) dominance

To generate the artificial creature, the fitness is defined as,

$$\min \ \mathbf{\Phi}(T_s, \mathbf{G}) = \{\Phi_1(T_s, \mathbf{G}), \ldots, \Phi_6(T_s, \mathbf{G}).\} \qquad (8)$$

By the concept of original Pareto dominance, $\mathbf{G}_a$ dominates $\mathbf{G}_b$ if and only if [10]

$$\begin{aligned} \Phi_l(T_s, \mathbf{G}_a) &\le \Phi_l(T_s, \mathbf{G}_b), \quad \forall l \in \{1, \ldots, L\} \\ \Phi_l(T_s, \mathbf{G}_a) &< \Phi_l(T_s, \mathbf{G}_b), \quad \exists l \in \{1, \ldots, L\}. \end{aligned} \qquad (9)$$

A solution which is not dominated by any other solutions is called nondominated solution and the solutions that are nondominated within the whole solutions are denoted as Pareto optimal.

In this paper, there are 6 objectives and may cause drastically increased number of nondominated solutions. To reduce the number of nondominated solutions, there are some approaches to resolve this problem in the area of multi-objective optimizations. One approach is defining $(1-k)$ dominance by considering the number of improved objectives [12].

If we denote the number of better, equal and worse objectives as o_b, o_e and o_w , the following inequalities holds true:

$$\begin{aligned} o_b + o_e + o_w &= L \\ 0 < o_b, o_e, o_w &< L. \end{aligned} \tag{10}$$

Then, $\mathbf{G_a}$ is said to $(1-k)$ dominate $\mathbf{G_b}$ if and only if

$$\begin{aligned} o_e &< L \\ o_b &\geq \frac{L - o_e}{k+1}\ . \end{aligned} \tag{11}$$

Although applying $(1-k)$ dominance can reduce the number of nondominated solutions, this suppressed the individuality of generated artificial creatures, as shown in IV Experiments. This tendency is caused by the characteristics of problem specific objectives of this paper. To facilitate the individuality of obtaining solution, the complement of $(1-k)$ dominance is proposed.

If we define the set of nondominated solutions by original Pareto dominance, as P_{org} and the set by $(1-k)$ dominance, as $P_{(1-k)}$, then the set of nondominated solutions by proposed the complement of $(1-k)$ dominance, P_{comp} is defined as

$$P_{comp} = P_{org} - P_{(1-k)}. \tag{12}$$

G. Pruning method based on deviation

When the number of nondominated solutions exceeds a given maximum N', a clustering approach has applied to prune the nondominated solution. The average linkage method has applied to prune by measuring the distance in objective space as follows [13].

The distance is defined as

$$d = \frac{\sum_{\mathbf{\Phi}(T_s,\mathbf{G}_1)\in C_1, \mathbf{\Phi}(T_s,\mathbf{G}_2)\in C_2} ||\mathbf{\Phi}(T_s,\mathbf{G}_1) - \mathbf{\Phi}(T_s,\mathbf{G}_2)||}{|C_1| \cdot |C_2|} \tag{13}$$

where C is a cluster set which contains the nondominated solutions and each C is initialized to have each one nondominated solutions. After calculating all possible pairs of clusters, two clusters with minimal distance are chosen to combine into a larger cluster.

After clustering the nondominated solutions with cluster number less than N', a representative solution per cluster is selected. The average linkage method also use the distance by selecting minimal average distance between all other solutions in the cluster.

For the case of generating artificial creature, selecting minimal distance usually select creature of average individuality. To promote the possibility of having individualized creature, pruning method by considering deviation of solutions is proposed. Calculate the deviation of each objective for all

TABLE II

MULTI-OBJECTIVE OPTIMIZATION RESULTS. COMPARISON OF EACH OBJECTIVE AMONG THE RESULTING GENOME SET.

		$\Phi_1(T_s,\mathbf{G})$	$\Phi_2(T_s,\mathbf{G})$	$\Phi_3(T_s,\mathbf{G})$
Method 1	Avg.	314040	305440	291510
	Min.	**249530**	**240840**	**200190**
	Max.	398930	391790	418120
Method 2	Avg.	334780	348780	339730
	Min.	**235900**	**237620**	**205640**
	Max.	469110	495840	533050
Method 3	Avg.	315080	362560	334910
	Min.	**204520**	**213300**	**186000**
	Max.	471970	524700	553450
Method 4	Avg.	321670	353800	323310
	Min.	**218210**	**214820**	**192480**
	Max.	484740	504810	514390

		$\Phi_4(T_s,\mathbf{G})$	$\Phi_5(T_s,\mathbf{G})$	$\Phi_6(T_s,\mathbf{G})$
Method 1	Avg.	251780	275810	411620
	Min.	**213440**	**235360**	**305730**
	Max.	319060	339530	542980
Method 2	Avg.	284560	321360	436360
	Min.	**204050**	**256650**	**268910**
	Max.	408290	428840	659920
Method 3	Avg.	282250	315190	430590
	Min.	**175080**	**219470**	**249280**
	Max.	396080	421460	667310
Method 4	Avg.	285720	311520	439820
	Min.	**200270**	**230180**	**249060**
	Max.	391830	418600	656710

Method 1 : the multi-objective evolutionary generation based on the (1-k) dominance
Method 2 : based on the proposed complement of (1-k) dominance
Method 3 : using proposed pruning by deviation method to the original PARETO dominance
Method 4 : using complement of (1-k) dominance together with proposed pruning by deviation method
Avg. Min. Max. : average, minimum and maximum values of each objective among resulting non-dominated set.
Every data are calculated by averaging the results of 10 time runs.

members in cluster as

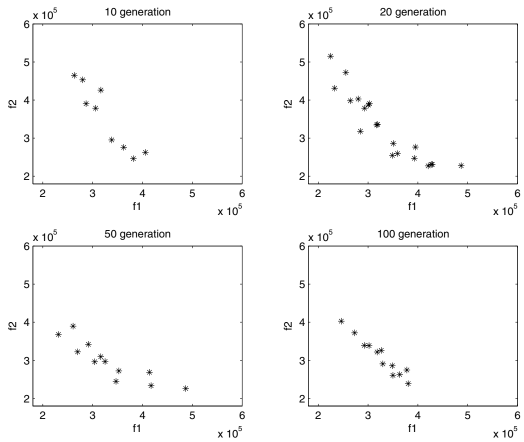
$$\begin{aligned} \Phi_l(T_s,\mathbf{G}_a) &= \overline{\Phi_l(T_s,\mathbf{G})} + \lambda_{la} * \sigma_l \\ \overline{\Phi_l(T_s,\mathbf{G})} &= \sum_{i=1}^{n} \frac{\Phi_l(T_s,\mathbf{G}_i)}{n} \end{aligned} \tag{14}$$

where, σ_l is the standard deviation of each objective for all population $\mathbf{G}_i$ and n is the number of population in a generation. In a proposed pruning method, the solution, which has minimum deviation λ_{la} for all $\mathbf{G}_a \in C$ and $0 \leq l \leq L$, is chosen as a representative solution for the cluster.

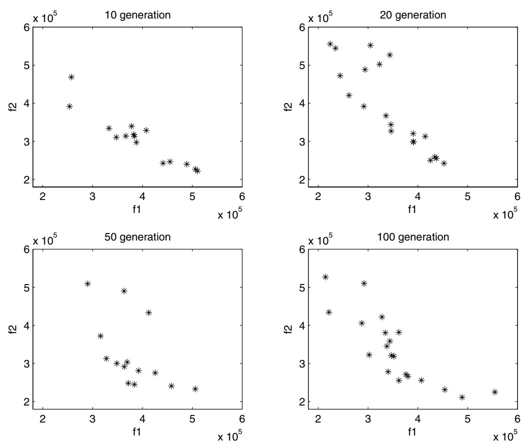
IV. EXPERIMENTS

A. Generating Genomes by generative process

The population size, N and nondominated set size, N_p were 100 and 20 and the number of generations was 200. The crossover and mutation rates for the I- and B-genes were set to (0.1, 0.05) and (0.2, 0.05), respectively. F-crossover and F-mutation rates were set to 0.0 to keep the assigned fundamental characteristics, because the 3rd gene (constant value) and the 4th gene (the difference gain) are the critical factors in F-genes that influence the evolved personality. Namely, either remarkably small difference gain or big constant value makes the corresponding internal state



(a) Method 1 : (1-k) dominance



(b) Method 4 : Complement of (1-k) dominance and pruning by deviation

Fig. 4. Comparison of Method 1 and Method 4, while objectives 1 and 2 at generation 10, 20, 50 and 100, were considered.

divergent in a perception scenario during the generative process.

In Table II, the average, minimum and maximum values of each objective among the resulting nondominated set are compared. The smaller value of one objective means better suited for corresponding personality or more individualized character. As shown in Table II, proposed complement of $(1-k)$ dominance and the pruning algorithm based on the deviation are well suited for generating the artificial creature's genome with individualized personality. Moreover, combining the two proposed dominance and pruning which corresponds to the Method 4, produces more improved performance.

Figure 4 shows the characteristics along generation of Method 1 and Method 4. As shown in Figure 4(a), $(1-k)$ dominance tends to produce stifled individuality, where solutions are far from both X and Y axis. Besides, as shown in Figure 4(b), among the nondominated solutions, genomes with smaller $\Phi_1(T_s, \mathbf{G})$ or $\Phi_2(T_s, \mathbf{G})$ are found. Proposed dominance definition and pruning method tends to preserve individuality of generating creatures' genomes.

V. Conclusions

To generate the artificial creature's personality, there needs user's preference to define desired one and evolving algorithm for the generation of preferable personality. Preference is strongly depend on each user and most of them would have difficulty to define their preference as a fitness function. To solve this problem, this paper proposes multi-objective generating process of an artificial creature's personality. Genome set is evolved by applying strength Pareto evolutionary algorithm (SPEA). To facilitate the individuality of generated artificial creature, complement of $(1-k)$ dominance and pruning method considering deviation were proposed. To demonstrate the effectiveness of the proposed scheme, experiments on artificial creature, Rity, were carried out and plausible results for the internal states and behaviors were obtained.

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