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Adaptive Human-Robot Interaction System using Interactive EC

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***Abstract*— We created a human-robot communication system that can adapt to user preferences that can easily change through communication. Even if any learning algorithms are used, evaluating the human-robot interaction is indispensable and difficult. To solve this problem, we installed a machine-learning algorithm called Interactive Evolutionary Computation (IEC) into a communication robot named WAMOEBA-3. IEC is a kind of evolutionary computation like a genetic algorithm. With IEC, the fitness function is performed by each user. We carried out experiments on the communication learning system using an advanced IEC system named HMHE. Before the experiments, we did not tell the subjects anything about the robot, so the interaction differed among the experimental subjects. We could observe mutual adaptation, because some subjects noticed the robot's functions and changed their interaction. From the results, we confirmed that, in spite of the changes of the preferences, the system can adapt to the interaction of multiple users.**

I. INTRODUCTION

In coming years, robots are expected to contribute much to our lives through nursing, house-keeping, and other areas. These robots should be able to communicate with humans effectively. Human-robot communication is not only for giving commands to the robot, but also for entertaining or relaxing the user, so communication should have variety and flexibility. However, most of robots can only communicate using the scenarios designed by their developers. Though scenario-based communication is practical for the context-sensitive communication like verbal communication, it lacks variety and flexibility.

On the contrary, we think that describing entire scenarios is not necessary for human-robot communication. We are interested in a behavior-based technique. Various, complex behaviors can be generated through interaction between a robot and its surroundings, including humans. Though a behavior-based technique is not yet suited to context-sensitive communication, such a technique would make human-robot interaction very flexible. However, even though entire scenarios are not described, a robot's behavior which corresponds to the specific sensory input is defined by the designer a priori. Ideally, to achieve user-friendly robot communication, the robot's behavior should be configured not by the designer but by the user. However, most of users do not have any programming skills, so it is desirable that robots should have functions that enable them to learn.

Therefore, our goal is to create a robot with user-adaptive communication. Using machine-learning algorithms, such as a neural network, reinforcement learning, and genetic algorithms, the robot can changes its behavior through interaction, which prevent users from boredom. However, those learning algorithm when using in the human-machine interaction have potential problem, that is, quantitative evaluation problem. Though it is indispensable for the learning algorithm to evaluate how successful the behavior was, the subjective evaluation of the interaction is quite difficult to model. For example, Ishiguro et al. conducted some experiments of behavior adaptation using Policy Gradient Reinforcement Learning [15]. In this experiment, they hypothised that a human's gaze, motion speed, and distance between a human and a robot indicate how well the interaction was. However, the human's evaluation and interaction are quite complicated and varied, so that the humans sometimes behave beyond the developer's expectation.

To address this problem, we introduced Interactive Evolutionary Computatiaon (IEC), a kind of evolutionary computation, such as a genetic algorithm. In conventional EC, designers have to define a fitness function that evaluates how successful genes are. On the other hand, the fitness function in IEC is performed by the user, so we do not have to model the user's preferences, and we can apply a machine-learning to the problems of human subjective preferences.

Moreover, IEC is able to keep the user's interest, because it can generate various behaviors using a diverse of the genetic pool. To improve this advantage, we developed an advanced evaluation technique called Human-Machine Hybrid Evaluation (HMHE). In HMHE, some representative genes are manually evaluated by the user, while the others are evaluated automatically using the results of the manual evaluation. This technique can increase population size of genetic pool without increasing human fatigue. We installed HMHE in a communication robot named WAMOEBA-3, and confirmed that the method will not bore the user [13]. However, in the former experiments, we told the experimental subjects the function of the robot, so the interactions were restricted.

In this paper, we show the further experiments in the real world. To realize various interactions, we installed extra sensors and actuators in the robot and did not tell experimental subjects anything about the robot before their interaction. Eventually, the interactions differed remarkably among the subjets, but the robot could adapt to their preferences. In the next section, HMHE is described in detail. Then, in section III, the experimental settings are described. In section IV, we show the experimetal results, and we discuss them in section V. Finally, we summarize this study and indicate areas for future work.

II. HUMAN-MACHINE HYBRID EVALUATION

Though IEC can be used to address preferences, it causes human fatigue. Since the user must evaluate all of the genes in genetic pool, the population size and generations are strictly limited. This limitation causes an early convergence problem, which bores the user. This is because the robot's behavior is simplified when the genetic pool converges. To solve this problem, the diversity of the genetic pool must be kept at a high level during interaction without increasing human fatigue.

We developed a Human-Machine Hybrid Evalution (HMHE) technique, where the genes are evaluated both manually and automatically. Figure 1 shows the flowchart of the HMHE.

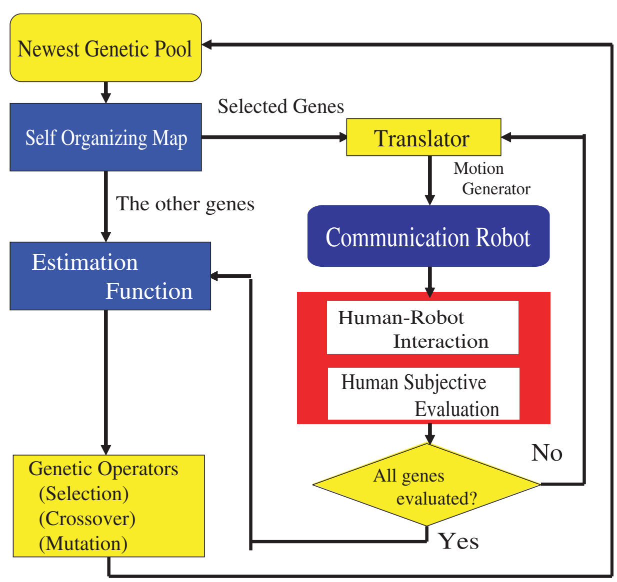
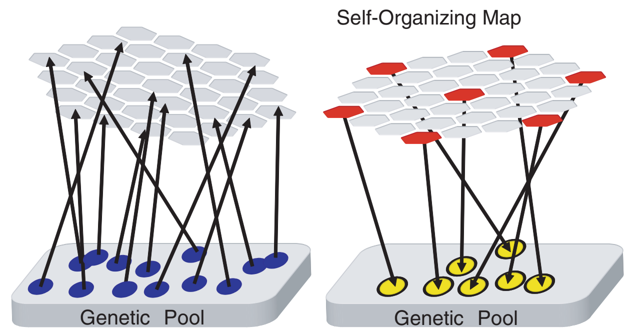


Fig. 1. Human-Machine Hybrid Evaluation

First, all of the generated genes are analyzed with a self-organizing map (SOM). An SOM is useful for analyzing a multi-dimensional dataset. In the SOM, the genes with a similar dataset are placed near each other, while dissimilar genes are placed away from each other. We used the SOM algorithm because the algorithm was very simple and if we define the distance between two dataset, it can eventually analyze a bunch of the sample dataset. Using the SOM, the various representative genes are selected as follows. First, the SOM is trained by the dataset of all genes in the genetic pool (see Figure 2(a)). Next, seven genes are selected; each selected gene has a best matching dataset among each of the seven neurons placed at the positions shown in Figure 2(b). Therefore, we can select individuals that have datasets of genes that are distant from each other, which is efficient for the estimation function.



(a) Training Period (b) Selecting Period

Fig. 2. Positions of selected genes on SOM

Then, each representative gene is translated into pheno-type (the robot's parameter), and the robot interacts with a user. Next, the user evaluates the robot's behavior. This sequence continues until all of the representative genes are evaluated.

After that, the fitness values of the other genes are estimated automatically. The estimation function is as follows:

$$E_i^{auto} = \sum_{k=1}^{n} \alpha_{ik} E_k^{maunal} \tag{1}$$

$$\alpha_{ik} = 1 - \frac{\|r_i^{manual} - r_k\|}{\sum_{l=1}^{n} \|r_l^{manual} - r_k\|} \tag{2}$$

Here, E_i^{auto} is the fitness value of gene i, and E_k^{manual} is the fitness value of gene k evaluated manually. n is the number of the genes evaluated by the user. α_{ik} is the weight, which is calculated according to the distance between genes i and k using equation (2). r is a dataset of a gene.

This technique can increase the number of genes without increasing human fatigue. Therefore, the system can maintain gene diversity and the users' interest.

We carried out some simulations to compare the HMHE to the conventional IEC [12]. In the simulation, the HMHE had a higher fitness value than the plain IEC.

III. EXPERIMENTAL SETTINGS

A. WAMOEBA-3

Our IEC experiment took a considerable amount of time, because each subject evaluates a number of genes. Therefore, the robot must have a variety of behaviors to keep the subject's interest, harmless to people, and be easy to maintain and customize. The robot must also be able to move without cables for power supply or control, because cables prevent easy interaction with humans.

We used a communication robot called the Waseda Artificial Mind On Emotion Base (WAMOEBA-3, Figure 3).

WAMOEBA-3 is an independent, wheeled robot, with built-in batteries and a PC. This robot was developed as a platform for communication experiments. Its upper body is similar to a human one and its size is about the average size of Japanese children: 825 mm wide, 1316 mm tall. WAMOEBA-3 weighs approximately 105 kg. It is equipped with two arms (7 degrees of freedom) and a head (8 degrees of freedom). Each joint has a torque sensor to measure the stress on the arm and head. WAMOEBA-3 is also equipped with an omni-directional vehicle for locomotion, which can move in any direction without actually turning at any stage. This is advantageous for both the variety of its behavior and for safety.

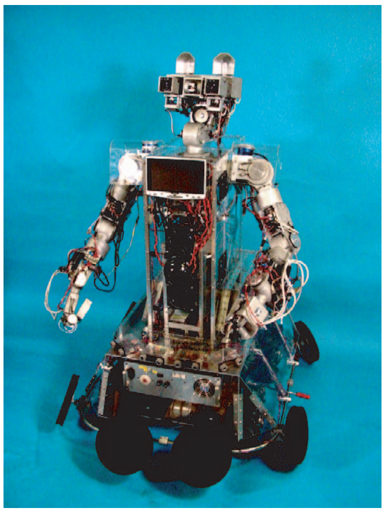


Fig. 3. WAMOEBA-3

The WAMOEBA-3 has also a lot of sensors. It has shoulder covers installed with 6-axis force sensors to detect touches on the shoulders. The head has two CCD cameras and two microphones. Each camera can independently move vertically and horizontally, and each ear can rotate horizontally, which enable the robot to indicate the direction of its attention. The vehicle has eight bumper sensors, three infrared sensors, and eight ultrasonic sensors. Table I shows the specifications of the WAMOBA-3 in more detail. We did not use all of the internal sensors, like the battery voltage or thermal sensors.

B. Robot Motion Generator

We used the motor-agent model (MA model) proposed in former studies as a motion generator of the WAMOEBA-3 [14]. The MA model is a distributed control algorithm in which all the actuators and sensors are linked to each other with connections. Each actuator autonomously collects sensor inputs through the network and determines its motion.

TABLE I

SPECIFICATIONS OF WAMOEBA-3

Dimensions	mm	1316 (H) x 825 (L) x 656 (W)
Total Weight	kg	105
Max speed	km/h	3.5
Payload	kgf/hand	5.0
Drive Time	hours	1.5
Drive Member	Camera DOF	1+1 x 2=3
	Ear DOF	2
	Neck DOF	3
	Vehicle DOF	3
	Arm DOF	6 x 2=12
	Hand DOF	1 x 2=2
Outside Sensors	Vision	CCD Color camera x 2 (x10 Optical zoom, x4 Degital zoom)
	Sound input	Microphone x 2 (Directional hearing, Voice recognition)
	Sound output	Speaker(Voice synthesis)
	Distance	Ultrasonic sensor x 8
	Human Body	Pyroelectric sensor x 3
	Collision	Bumper switch x 8
	Joint stress	Torque sensor x 14
	Shoulder	6-Axis force sensor x 2
Structural material		Extra super duralumin Titanium alloy (Ti-6Al-4V) aluminium (52S)
CPU		Pentium4 (3.2GHz)
Microcomputers		VR5550-ATOM×5
OS		Linux
Battery		Lead-Acid Battery for EV

Equation (3) shows the output decision of the actuators.

$$\dot{\theta}_i = \lambda_i \sigma_i(x) - \delta_i \theta_i \tag{3}$$

$$\sigma_i(x_i) = \exp\left[-\gamma_i (x_i - c)^2\right] - \exp\left[-\gamma_i (x_i + c)^2\right] \tag{4}$$

$$x_i = \sum_{m=0}^{j} \omega_{ji} s_j \tag{5}$$

Here $\dot{\theta}_i$ is the rotation velocity of the motor agent i. The first term of quation (3) is the calculation result from sensor inputs, and the second term is for the stabilization. σ_i is a sigmoid function defined by equation (4). Here, the γ affects the linearity of the function. If the γ is larger, the linearity is smaller. x is the summation of the inputs from the sensor network, defined by equation (5). ω is the connection weight between the agents, and s is the sensor input like the encoders or switches.

Using the MA model, the network has to be defined. We used the very simple network shown in Figure 4.

The characteristic behaviors achieved by this network are as follows.

- If someone waves his hand in front of the camera, the robot detects a moving region of the image, and the eyes move vertically or horizontally.
- If someone touches a bumper sensor placed on the vehicle, the vehicle either turns towards or away from him.

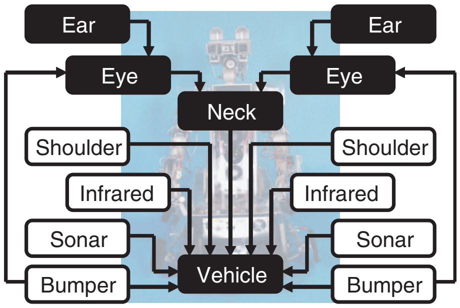


Fig. 4. Motor-agent network: filled boxes and open boxes represent motor-agents and sensor-agents, respectively. A motor agent has both an actuator and a sensor (encoder), and sensor-agent has a sensor only.

- If someone claps his hands or shouts, the robot's ears turn horizontally and the eyes move.
- If someone stands near the robot, the sonars measure the distance or the infrared sensors detect him, and the vehicle moves.
- If someone touches the shoulder covers, the vehicle moves.

C. Genetic Settings

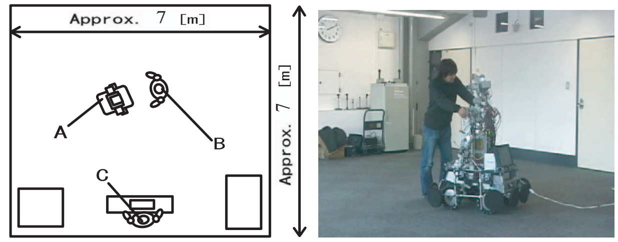
The MA model enables WAMOEBA-3 to move only reactively. However, the direction and amount of movements are based on human interpretation. Therefore, we configured the connection weights between the agents (ω in Equation (5)) with IEC. The weights were encoded into genes using numerical encoding, which is easy to analyze. The dimension of the dataset of each gene was 40. The probability of mutation was 0.5%. If a mutation occurred, the value of the gene was added by a random value. We also used multipoint crossover and elitism (the best 40% of the genes were preserved to the next generation). The population size was 30. The experiment continued until the 7th generation. Without HMHE, each subject had to evaluate all the genes (240 genes). Since there must be mostly the same genes in a genetic pool, evaluating all of them is not efficient. Using HMHE, each subject had to evaluate only 56 in total.

D. Interaction and Other settings

The experiment was carried out in a conference room in our university (Figure 5). The robot (Figure 5 (a)-A) and the subject (Figure 5 (a)-B) interacted with each other until he/she wanted to stop. After that, the subject evaluated how interesting the interaction was and gave a score to the experimenter (Figure 5 (a)-C).

The number of subjects was 10. 4 of them were the members of our laboratory, so they had more knowledge of robots than the others did. The others were also the students at our university, one female student was included in this group.

In former studies, the interactive experiments were conducted after announcing the robot's function, so the interaction was restricted [13]. In this study, we wanted to observe the mutual adaptation of both the robot and humans. Therefore, we did not tell the subjects anything about the robot to the subjects, so they could interact freely with the robot and evaluate it without bias.



(a) (b)

Fig. 5. Environment

After the 4th and 7th generations, we carried out a survey about the subject's impressions of the robot. The questionnaire items were as follows:

1) Is the robot friendly?
2) Is the robot funny?
3) Do you want to interact with the robot?
4) Do you feel a sense of unity with the robot?
5) Do you and the robot have similar behavior?
6) Is the robot interesting?
7) Can you communicate with the robot?
8) Does the robot do various behaviors?
9) Is the robot's reaction dynamic?
10) Can the robot communicate with you?
11) Is the robot sensitive?
12) Does the robot seem to be a living creature?
13) Is the robot boring?
14) Is the robot easy to interact with?
15) Is the robot warm-hearted?
16) Is the robot's bahviour normal?

IV. RESULTS

The experiment was continued until the 7th generation (including the initial evaluation). Each experiment took 1.5 hours on average. The longest time was 2.5 hours and the shortest was 46 minutes. Each pheno-types interacted with a subject for 1.5 minutes on average.

Figure 6 shows the average fitness values of all subjects' experiments. The fitness value tended to increase throughout the experiments. The diversity of the fitness value was kept during the experiment because HMHE could maintain a diversity of behavior.

Figure 7 shows the questionnaire results. We could see significant differences for "Friendliness," "Sense of Unity," and "Dynamic Reaction."

During the experiment, we shot videos and analyzed the interaction. We counted interaction such as touching the shoulders, waving hands, clapping hands, and so on. Figure 8 shows the percentage of interactions by body part. The horizontal axis and the vertical axis, respectively, indicate the experimental subjects and the percentage. Cool colors indicate proximal interaction like touching, and warm colors show

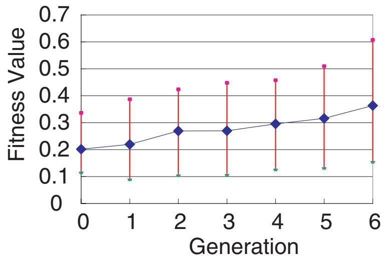
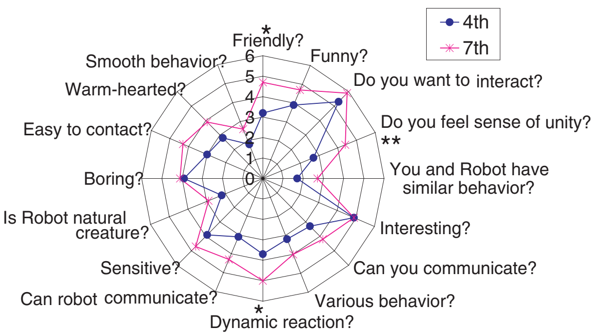


Fig. 6. Fitness Value (Average)



(★:$P < 0.05$ ★★: $P < 0.01$)

Fig. 7. Questionnaire Results

distant interaction like waving hands or clapping hands. The interaction greatly differs among the subjects.

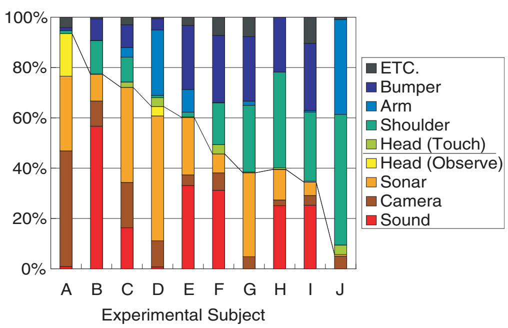


Fig. 8. Subjects' Interactions

V. DISCUSSION

We used IEC to create an adaptive interaction system. Since we did not tell the subjects anything about the robot, we could observe various kinds of interction in these experiments. However, the fitness values tended to increase in the experiments for almost all of the subjects. This may be because the robot had enough actuators and sensors to realize various kinds of interaction so IEC could adapt to the subject's preferences.

On the other hand, it is important to discuss the subjects' adaptation. They might have learnt through the interactions, and changed their behaviors. Therefore, in this section, we focus on the temporal changes of the interaction. Figure 9 shows the interaction of the subject J. The horizontal and vertical axes indicate the generation and the percentage, respectively, of J's interaction. The subject J was not a member of our laboratory, so he had less knowledge of the robot we used. This is an example of the proximal interaction; J continued to interact with the robot arms and shoulders. We did not use any controls on the arms. Though the arms moved like a doll's, J did not become bored of manipulating them. He also continued to push or pull on the robot's shoulders, and eventually the robot started to follow the pushing on the shoulders.

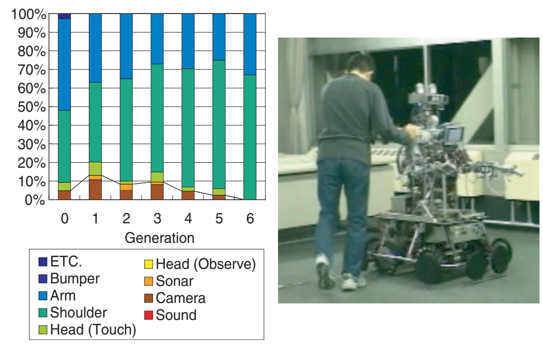


Fig. 9. Subject J (Interaction)

On the other hand, the subject D changed her interaction through the generations. Figure 10 shows the percentages of her interaction. The subject D was not a member of our laboratory, either. In the first generation, touching the robot's arms accounted for almost 50% of her interaction. However, in later generations, touching decreased and distant interaction increased.

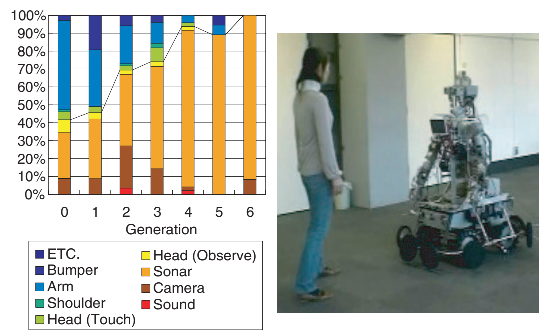


Fig. 10. Subject D (Interaction)

This is clearly because we did not prepare any control on the robot's arms. When D subject noticed that, she changed her interest to other parts of the robot. In the later part of the experiment, she tended to watch the robot's behavior, standing at a distance of about 1 meter from it. The best individual moved so that it stood directly in front of her.

Figure 11 shows the interaction of subject B. First he waved his hands in front of the cameras many times, but gradually he changed his interaction in the same manner as D.

In this experiment, we implemented moving area detection in the camera agents. Therefore, the robot was capable of de-

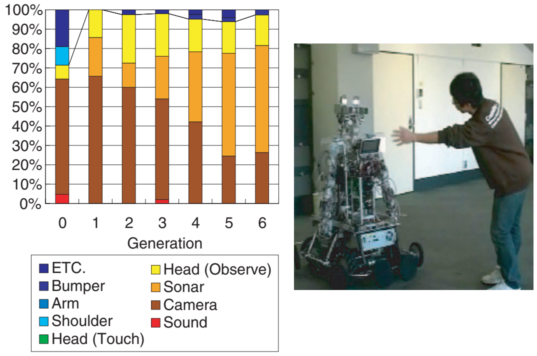


Fig. 11. Subject B (Interaction)

tecting his waving hands. Nevertheless, the subject B changed his interaction from using cameras to observing.

Figure 12 shows absolute values of the connection weights in the MA model. The circle plots represent the connection weights between the front sonar and the vehicle's sliding motion. The square plots represent the connection weights between the moving area detection and the eye motion. Throughout the experiment, the connection weights between the sonar and the vehicle were larger than those between the camera and eye motion. Therefore, the eye motion was smaller than the vehicle's. On the other hand, the vehicle motion was large and visible to the subject. As a result, the subject started to observe the robot's motion from a distance.

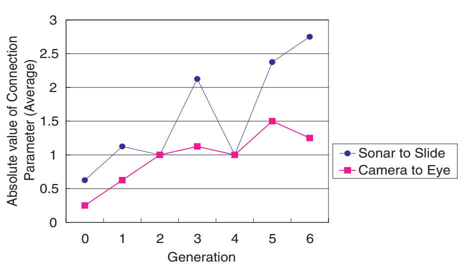


Fig. 12. Absolute values of connections

These subjects demonstrated that interaction changes during the experiments. Despite of the temporal changes of interaction, the fitness values of them increased.

VI. Conclusion and Future work

In this paper, we proposed an adaptive human-robot interaction system using Interactive Evolutionary Computation. Using IEC, a robot can configure its behavior according to the subjective evaluation of its user. We also proposed Human-Machine Hybrid Evaluation as an advanced technique of IEC. In the experiments, we did not tell the experimental subjects anything about the robot, so they interacted with the robot and evaluated it freely. In our results, we confirmed the adaptability of IEC. We also discussed temporal changes in the interaction. Despite the changes, IEC could adapt to their changing preferences.

To achieve longer-term interaction, we think that, to improve human-robot communication, we must change a robot's interaction more drastically. Using IEC, we can achieve this by increasing the mutation rate. A sudden change in the robot's behavior would make the interaction more interesting. We are hopeful that IEC will be achieve this eventually.

In our future work, we will improve the internal control algorithm to achieve more dynamic changes in the interaction. We have already tested some algorithms, but the number of parameters to be configured has increased. Therefore we are using incremental evolution techniques to configure a robot's behavior.

Acknowledgments

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