Evolutionary Approach for Designing the Behavior Generator of Communication Robot

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Abstract: Our goal is to create the robot system which interacts with human users keeping their interest during a long period. We focus on the Interactive Evolutionary Computation (IEC) technique to achieve this goal. Although the IEC enables users to design various systems which reflect their subjective preferences, it forces users to evaluate a huge number of individuals in the genetic pool during the evolution period. To solve this problem, we propose a refined IEC technique, named Human-Machine Hybrid Evaluation (HMHE), which selects the representative genes for user evaluation and estimates the evaluation results of the other genes. It can increase the population size without increasing the users' evaluation processes. We carried out some simulations where a humanoid robot with our method interacted with a user. The experimental results demonstrated that the HMHE could continue to generate the various robot behaviors by adapting to the transition of user's subjective preferences.

Keywords: Evolutionary Computation, Communication Robot, Human-Robot Interaction

1. INTRODUCTION

In recent years, robots are expected to contribute to our lives as helpful staffs. They offer potential uses in many areas, especially in entertainment, healthcare, housekeeping and nursing.Those robots that work around people should be capable of communication with people not only to receive their commands but also to entertain or to take care of them [1]. However, most of the human-robot communication is based on scenarios (models) designed by developers. Though at present, the model-based communication is certainly the most practical and fastest way to achieve verbal and context-sensitive communication, the robot becomes quite boring, once users take notices of the scenarios.

On the other hand, to create more flexible and adaptive robot, the behavior based technique is focused on by many researchers [2]. In the technique, the behaviors of the robot are generated through the mutual interaction between the robot and the environment including human beings. Nevertheless, those behaviors are much influenced by the developers' own preference, so they sometimes appear questionable for users.

In this case, it is preferable for the robot to be readjustable, but the users usually do not have any programming techniques. Therefore the robots should have a machine learning function to configure the behavior automatically, such as artificial neural network, reinforcement learning, genetic algorithm.Moreover, the learning function generates the diversity of behaviors, which prevents users from boredom. So our goal is to create a communication robot which can adapt to the users preference in order to keep the users interested in the robot for a long period.

However, in order to learn the preference of a user, it is indispensable to evaluate how successful the interaction between the user and the robot was. Ishiguro et al. conducted some experiments of behavior adaptation using Policy Gradient Reinforcement Learning [3]. 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 easily varied, so the subjects sometimes behaved in the ways the experimenters did not expected.

To address the problem, in this paper, we propose a technique of applying the Interactive Evolutionary Computation (IEC) into a human-robot communication system. The IEC is a type of Evolutionary Computation like Genetic Algorithm (GA), but its fitness function is performed by users. When using the IEC, it is unnecessary to define the fitness function of the evolutionary computation. We also propose the human-machine hybrid evaluation (HMHE) to solve a problem of human fatigue.

The structure of the rest of this paper is as follows: In the next section, the IEC with HMHE is described in more detail. In section 3, we show the experimental settings. In section 4, experimental results are shown and we discuss them in section 5. Finally, we summarize this paper, and we show our future works.

2. IEC WITH HMHE

2.1 Interactive Evolutionary Computation

In the conventional Evolutionary Computation (EC), each individual is evaluated using a given fitness function. In the IEC, its fitness function is performed by users, that is, all of the pheno-types are evaluated by the users. It therefore applies the EC techniques to problems of subjective optimization without an explicit modeling of human subjective evaluation [4]. The IEC has previously been applied to aesthetic areas, such as art, design, and music [5] [6]. In these areas, fitness functions can not always be defined explicitly. With the IEC, however, it is unnecessary to define them.

The IEC has also been applied to optimizing behaviors of robots. For example, in a study entitled “A Children’s Game” [7], Lund et al. confirmed that the children could develop the robot’s controller by repeatedly selecting one robot from nine robots shown in the CRT display. This study’s aim was developing a robot controller without programming.

Since our goal is to develop more communicative and interactive behaviors, however, our experiment requires mutual interaction between a human and a robot. In such case, the human must interact with and evaluate the robot one by one. Thus, the human fatigue becomes a more crusial problem of this study.

2.2 Human Machine Hybrid Evaluation

In this study, the problem of the human fatigue can not be ignored. The longer the experiment is, the more bored a human gets. Therefore, we need to reduce the number of genes and generations to minimize the human fatigue, for these limitations make the EC’s learning capability poorer and slower.

To solve this problem, we developed a human machine hybrid evaluation (HMHE). The HMHE is an evaluation method that reduces the human fatigue by decreacing the number of mannually evaluated pheno-types. Using the HMHE, the human only needs to test some individuals that are automatically selected from the genetic pool. Then, the fitness values of the other genes are estimated on the basis of the distances from the data of all selected genes that the human gave his/her subjective fitness values before.

Our proposed algorithm is shown in Figure 1. First, the IEC process generates an initial genetic pool at random. Next, the process analiyzes the newest genes using the SOM algorithm [8].The SOM is an algorithm that is suitable for analyzing large multi-dimensional dataset. In the SOM, similar dataset are placed nearby and dissimilar ones are placed further from one another. The SOM is trained by the dataset of genes in the genetic pool (see Fig.2a), and then, seven genes that have the best matching dataset with seven neurons placed at the position shown in Fig.2b, are selected. Thus, we can select the individuals that have distant dataset of genes from one another. This is efficient for the HMHE because, if the selected genes are similar to one another, the fitness values of the other genes can not be estimated.

Then the selected genes are translated into phenotypes (parameters of controller) and installed into a robot. The robot interacts with a human and is evaluated by him/her. This process continues until all the selected genes are evaluated.

After that, the genes that weren’t selected are automatically evaluated on the basis of the fitness values of the selected genes. The fitness values are estimated as follows:

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

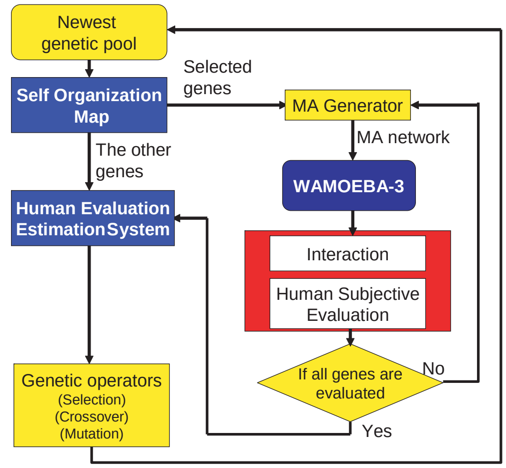
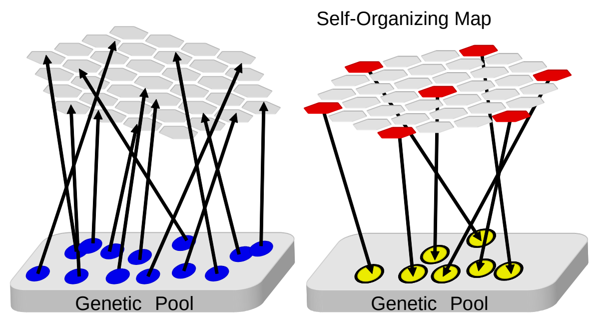


Fig. 1 Proposed Algorithm



(a) (b)

Fig. 2 The SOM algorithms in the HMHE: (a) Training period. The SOM is trained with all genes. (b) Selecting period. All vertice of angles and the center of the trained hexagon map are used to select the genes to be evaluated mannually.

$$\alpha_{ik} = 1 - \frac{\|\boldsymbol{r}_i^{manual} - \boldsymbol{r}_k\|}{\sum_{l=1}^{n} \|\boldsymbol{r}_l^{manual} - \boldsymbol{r}_k\|} \tag{2}$$

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). $\boldsymbol{r}$ is a dataset of a gene.

When all the genes evaluated both automatically and manually, the process applies genetic operators (selection, crossover, and mutation) to the genetic pool and generates more appropriate genes.

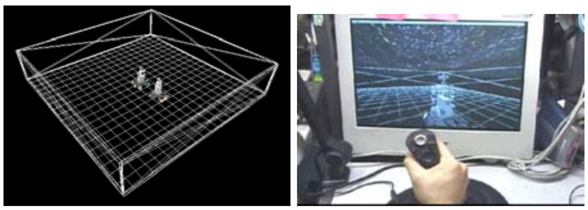
3. EXPERIMENTAL SETTINGS

In this section, we show the settings of the experiment that we made in order to confirm the efficiency of the HMHE. The experiment was carried out by using the simulator. Experimental subjects controlled a simulated robot and interacted with a robot controlled by a motion generator.

We also carried out an experiment without using the HMHE. In the plain IEC system (without the HMHE), the genetic pool has only 7 individuals in the genetic pool, in order to make the physical work load equal to the IEC with HMHE. The subjects were 8 members of our laboratory staff. They have high knowledge of the computers and robots.

3.1 Interaction Simulator

We developed a simulator to investigate for the human-robot interaction (see Figure 3). In this experiment, two robots are placed in the virtual environment. The experimental environment is shown in Fig.3a. There were no objects, obstacles, and textures that could influence subjects. There were only two robots. One was controlled by the experimental subject, the other was controlled by the program.



(a) (b)

Fig. 3 Interaction environment: The impression of the environment can influence the human mind. We didn't prepare any textures or background images in this experiment.

To control the simulated robot manually, subjects used a joystick with force-feedback function (Fig.3b). On the simulator screen, the vision captured by the camera of the human-controlled robot was displayed.The subjects interacted freely with a program-controlled robot, and if they were satisfied, they evaluated the robot's behaviors by using the same joystick. The score of the robot was from 0 to 1.

3.2 WAMOEBA-3

The robot which was displayed in the simulator was WAMOEBA-3 which is a wheeled, independent robot with inbuilt batteries and control systems (see Fig.4). It is 656-mm long, 825-mm wide, 1316-mm tall, and weighs approximately 105 kg. Its upperbody has two arms (6 degrees of freedom) and a head (4 degrees of freedom). Two eyes can move independently, which is useful for communication [11], and its vehicle is an omni-directional vehicle capable of moving in any directions without actually turning at any stage. It has microphones, ultrasonic range sensors, two CCD cameras, bumper switches.

3.3 Motor-Agent Network

In this study, as a motion generator, we used a Motor-Agent (MA) model we previously proposed [11]. In the MA model, all actuators are regarded as autonomous agents that determine their own actions autonomously and independently according to the information collected through the informational network.

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

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

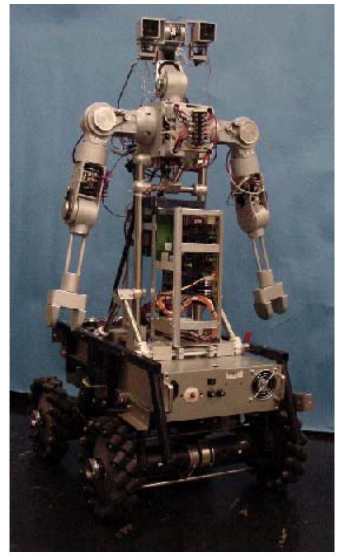


Fig. 4 WAMOEBA-3

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

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

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.

In this experiment, we prepared a very simple MA network, as shown in Figure 5. Agents with actuation capabilities included the eye and neck agents, and the omni-directional vehicle agent. The eye agent determined its rotation direction and speed autonomously according to the angle of the neck joint and data from the ear sensors and bump sensors. The neck agent determined its action according to the angles of both eye joints and the action of the omni-directional vehicle. The omni-directional vehicle determined its translational motion on the basis of input from the bumper switches and ultrasonic range sensors, and its rotational motion on the basis of input from the angle of the neck joint as well as the input of the sensors. The image captured by the cameras were not in use in this experiment.

The examples of the interactions between the human-controlled robot and the program-controlled robot are as follows:

1. When physical contact occurred between the human-controlled robot and the program-controlled one in a simulated environment, the simulator generated force feedback effects for the subject. Then the bumper agents in-

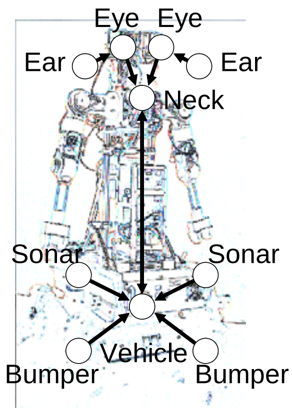


Fig. 5 Simple MA network: The actual MA network is constructed with all of the possible connections. However, in this study, we used very simple network for simplicity.

fluenced the action of the vehicle agent, and the robot moves.
2. When the human-controlled robot made sounds (when the subject pressed a button on the joystick), the ear sensors (microphones) captured the sound and the ear agents influenced the eye motor agents.
3. When the ultrasonic range sensors of the program-controlled robot captured the human-controlled robot or the walls of environment, the sonar agents influenced the vehicle agents.
4. The program-controlled robot stopped moving when its battery level was too low. The human-controlled robot was equipped with an energy-charging gun which worked by pressing a button on the joystick. If the human-controlled robot with the gun was close enough to the program-controlled one, it could recharge its battery.

3.4 Genetic Settings

To evolve the robot's controller, we must encode its parameters into geno-type. In this experiment, the ω values in Equation 5 were encoded into the geno-type represented by numerical data, which are easy to analyze. Each connection in the MA network has ω, and the number of components of dataset of a gene was 28.

We used the roulette wheel method and elitism where the 40 % genes which had high fitness values were preserved.

The probability of mutation was 1%, and multipoint crossover was used. If a mutation occurred, the value of a selected location was incremented by a small number randomly extracted from a distribution centered around zero (biased mutation).

3.5 Questionnaire Surveys

During the experiments, we suveyed some questionnaires to confirm the subjects' workload. The surveys were carried out every three generations. The questionnaire items we used were developed by Haga et al. [12]. Actually, the questionnaire was made to confirm the workload of motormans, but the circumstance of this experiment is very similar to that of motormans' (see Fig.3b), so we thought that it is applicable to confirm the mental and physical workload of these experiments. The questionnaire is made of 14 items;

1.	You needed to concentrate.
2.	You were satisfied with your work.
3.	You did not have incentive to work.
4.	You wanted to rest.
5.	You felt heavy-eyed.
6.	You did not have any consolable time.
7.	You got bored.
8.	You were nervous.
9.	You did your best.
10.	You could not concentrate.
11.	You wanted to stop working.
12.	You were almost asleep.
13.	You were pressed for time.
14.	You wanted to evade from work.

Experimental subjects score [0, 100] on each items. After suveying them, we categorized them into seven subdivisions, such as "difficulty", "busyness", "difficulty of concentration", "boredom", "sleepiness", "tiredness", and "sense of accomplishment". Each category has two questionnaire items and the sum of the scores of the two items was the total score of the category.

4. RESULTS

The behavior acquisition experiments took approx. 120 minutes on average. One evaluation of an individual took approx. 100 seconds.

The acquired behaviors could be categorized into two types, one to evade from the subject, the other to get close to him/her. The subjects preferred dynamic behaviors that seemed to make sense.

Figure 6 shows the standard deviation of dataset of the genes which were evaluated by the subjects. The vertical axis indicates the standard deviation and the horizontal axis indicates the generation. The line graph of 'IEC' represents the standard deviation of the prain IEC system, and the line graph of 'IEC with HMHE' represents that of the IEC with HMHE. As shown in the graph, the standard deviation of the genes in the plain IEC system dropped. In the same way, that of IEC with HMHE also dropped but kept higher level than that of the plain IEC. This shows that diversity of the genes in the genetic pool could be maintained at higher level, using the HMHE.

Figure 7 shows the evolution processes of experiments. During the experiments, the fitness values had been increasing. However, that of the IEC with HMHE had been higher than the plain IEC.

Figure 8 shows the result of the questionnaire surveys. We could observe the significant differences in 'tiredness', 'boredom', and 'difficulty of concentration'. The IEC with HMHE showed higher performance than the prain IEC. We couldn't observe the significant differences between them in the other categories.

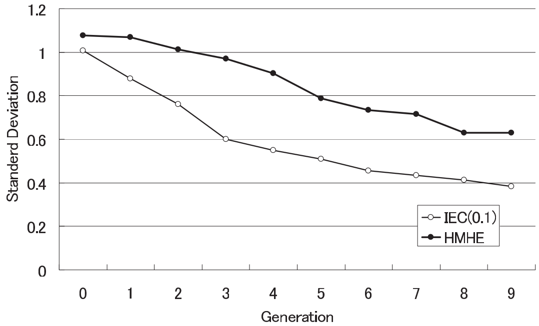


Fig. 6 Standard deviation of the displayed genes

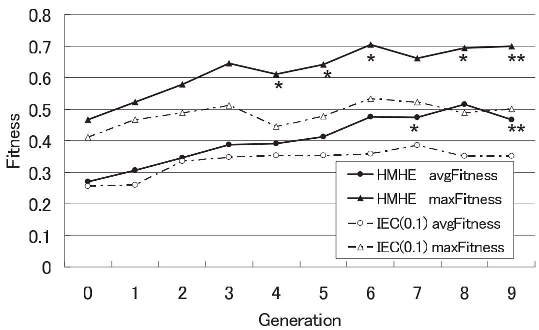


Fig. 7 Comparison of fitness value with or without the HMHE: Opened circles and opened triangles respectively represent average and max fitness values of the IEC without HMHE. Closed circles and closed triangles represent average and max fitness values of the IEC with HMHE.

5. DISCUSSION

In such experiment, to keep the fitness values increasing is quite difficult, because, as the experiments were continued, they had changed their criteria for their evaluation and interaction due to their boredom, and robots that had received favorable evaluations in previous generations were evaluated differently. Using the HMHE, though we could gain only the diversity of the genetic pool, the fitness values increased more quickly. This was becauase the genetic pool contained various individuals to adapt to the changes in interactions and evaluations, even if the criteria was changed.

In the usual EC, if we want to gain the diversity of the genetic pool, the mutation ratio is highly set a priori. However, high mutation ratio make the human impression worse because the IEC can not reflect the results of the human's selection. On the other hand, since the HMHE can increase the number of the genes, it can not only gain the diversity but also reflect the assessor's preference.

The effectiveness of the HMHE could also be confirmed in the questionnaire results. We could not observe any significant differences in ‘difficulty of the work’, ‘busyness’, and ‘sense of accomplishment’. Since the HMHE can work only for the diversity of the genetic pool, it was not concerned to the difficulty of the work.

On the contrary, the HMHE showed the advantages in ‘boredom’, ‘tiredness’, and ‘difficulty of concentration’. If the communication robot can provide various behaviors, it will prevent the humans from their boredom. Therefore they could concentrate on the experiments.

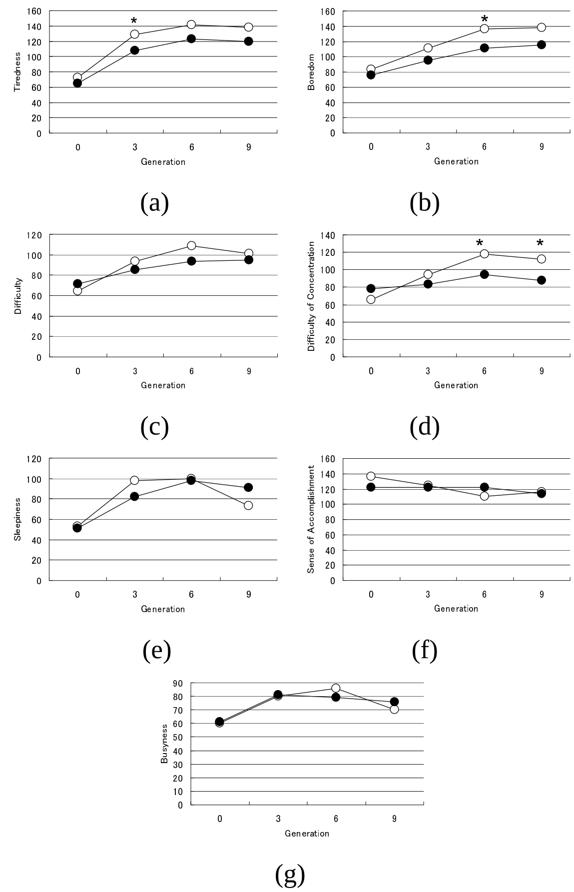


Fig. 8 Questionnaire results: Opened circles and closed ones respectively represented the plain IEC and IEC with HMHE. (a)Tiredness. (b)Boredom. (c)Difficulty of work. (d)Difficulty of concentration. (e)Sleepiness. (f)Sense of accomplishment. (g)Busyness.

6. CONCLUSION AND FUTURE WORK

In this paper, we proposed to use the IEC to acquire various behaviors of communication-robot. As the result, the IEC was capable of learning the behavior that the subjects preferred, though we did not prepare the criteria for interactions and evaluations. The IEC with HMHE increased the number of individuals in the genetic pool, and effectively overcame the difficulty of continue the experiment. Therefore, it is thought that to keep the variety of genes in the genetic pool is very important in order to evolve communicative behaviors.

We have already applied the IEC into the real robot, WAMOEBA-3 (Fig.4) [15]. In the real world, the behaviors both of the robot and of humans are quite complicated. As the results, the fitness values were gradually increased. However, to realize longer-term communication, it is thought that more dynamic behavior adaptation is favourable. The Evolutionary Computation can also provide some degrees of adaptability, but it is very slow. So, the learning function that enable the robot itself to adapt to the user's preference is required now. We are now focusing on the reinforcement learning whose reward system evolves by the IEC.

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