Interactive Evolution of Human-Robot Communication in Real World

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***Abstract*— This paper describes how to implement interactive evolutionary computation (IEC) into a human-robot communication system. IEC is an evolutionary computation (EC) in which the fitness function is performed by human assessors. We used IEC to configure the human-robot communication system. We have already simulated IEC's application. In this paper, we implemented IEC into a real robot. Since this experiment leads considerable burdens on both the robot and experimental subjects, we propose the human-machine hybrid evaluation (HMHE) to increase the diversity within the genetic pool without increasing the number of interactions. We used a communication robot, WAMOEBA-3 (Waseda Artificial Mind On Emotion BAse), which is appropriate for this experiment. In the experiment, human assessors interacted with WAMOEBA-3 in various ways. The fitness values increased gradually, and assessors felt the robot learnt the motions they desired. Therefore, it was confirmed that the IEC is most suitable as the communication learning system.**

***Index Terms*— Human-Robot Interaction, Communication Robot, Interactive Evolutionary Computation**

I. Introduction

In recent years, many companies and researchers have been developing many different kinds of robots, which are expected to contribute to our lives. These robots should be able to communicate with people, however the communication capabilities of current robots are poor when compared to humans.

Most communication robots are developed using 'model-based' techniques. They have their own models (scenarios) of communication, and can only communicate with people based on the models. Although these techniques are currently suitable to achieve the context sensitive communication, such as verbal communication, the variety of behaviors is physically limited.

Therefore, it is strongly required that the robots are able to adapt to the situations changing continuously. We think that evolutionary computation (EC) is suitable for learning communicative motions. In EC, various possible solutions are generated and tested. Since the diversity of behaviors can be kept high, it can prevent people from boredom throughout the learning experiment.

However, there is a potential problem, even if we use any kind of learning algorithms. It is a problem of *quantitative* evaluation. Though it is indispensable to evaluate the robot's behaviors, it is quite difficult to evaluate the robot's communicative behaviors *quantitatively* rather than *qualitatively*.

To solve this problem, we used interactive evolutionary computation (IEC), which is constructed of techniques of interactive learning and EC.

In this paper, we discuss how to implement IEC into a real robot system. In the next section, we describe IEC in detail. We also show a problem of IEC in communication learning. In section III, we propose the method of human machine hybrid evaluation (HMHE), which reduces human fatigue without decreasing population size. In section IV, we describe the robot we tested. We used a communication robot, WAMOEBA-3, which was designed as a platform robot for communication experiments. In section V, we describe the implementation of the IEC with HMHE is described in detail. In section VI, we describe the experimental setting. In section VII, we show results of this experiment and in section VIII, we discuss the results. Finally, we present our conclusion and describe our future work.

II. Interactive Evolutionary Computation

Interactive evolutionary computation (IEC) is an evolutionary computation whose fitness function is provided by human assessors. IEC, therefore, makes it possible to apply EC into human subjective optimization [5]. IEC has been applied to aesthetic areas, such as art, music, and so on. It has also been applied to robots [4] [13].

On the other hand, we aimed to use IEC for human-robot communication. Since we believe that communication can be learnt only via mutual interaction between a human being and a robot, our system consists of both of them. Therefore, in our experiment, assessors interact with a robot and simultaneously evaluate its response.

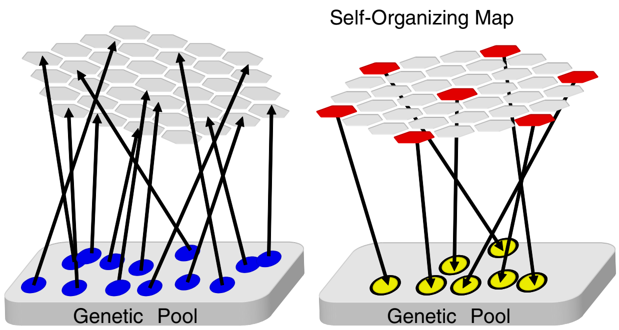
However, in our case, there are two problems. One is human fatigue, and the other is hardware error. IEC process takes very long time to learn, since the assessor must cooperate with a tireless robot to evaluate individuals. This is a burden for both human beings and a robot.

III. Human-Machine Hybrid Evaluation

To minimize human fatigue, we need to reduce the number of evaluation, that is, we should decrease the population size and generations. However, that usually results in the genetic pool's convergence which makes the assessors bored. One way to avoid the assessor's boredom is 'mutation' because it diverses the genetic pool. Since the mutation is a random process, however, mutation makes it difficult to refrec human assessor's preference.

To solve this problem, we proposed the human-machine hybrid evaluation (HMHE). In IEC with HMHE, an assessor tests only some selected individuals. As for the others, the system automatically estimates the fitness values of them based on the results the assessor tested before. With this method, we can increase the population size of the genetic pool without increasing the assessor's fatigue.

Moreover, to improve the HMHE, we deviced the selection method. If the selected genes have similar data to each other, the estimation of the method becomes poorer. In order to analyze the genes, we used a self-organization map (SOM) [6]. The SOM is an algorithm that is suitable for analyzing large multi-dimensional dataset. In the SOM, similar vectors are placed close to each other and dissimilar vectors are placed further away from each other. The individuals are selected using it as follows: first, the SOM is trained by the dataset of genes in the genetic pool (see Fig.1(a)). Next, seven genes are selected; each selected gene has the best matching dataset with each of the seven neurons placed at the positions shown in Fig.1(b). In this way, we can select individuals that have distant dataset of genes from each other, which is efficient for the estimation function.



(a) Training Period (b) Selecting Period

Fig. 1. Positions of selected genes on SOM

Our proposed algorithm is shown in Figure 2.

First, initial genes are generated at random. Next, some genes are selected using the SOM. Then, the selected genes are translated into pheno-type (parameters of a motion generator) and installed into a robot. An assessor interacts with the robot, and evaluates the gene individually. This sequence is repeated until all the selected genes are evaluated. Whereas unselected genes are automatically evaluated by the estimation function. Their fitness values are estimated on the basis of the Euclidian distance from the dataset of the genes given the assessor's subjective fitness values previously.

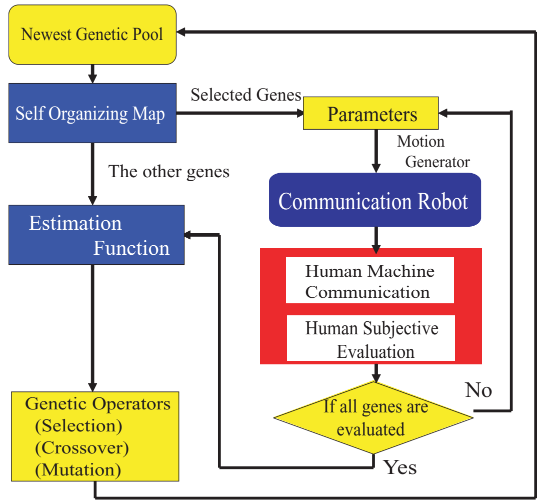


Fig. 2. IEC with HMHE

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

We have already confirmed efficiency of this algorithm in a simulation. The simulation confirmed that this algorithm can keep diversity of the genetic pool at a high level, and stop the fitness value's drops which is caused by the human boredom [11].

IV. WAMOEBA-3

As described above, our IEC experiment takes a considerable amount of time, because an assessor individually evaluates many individuals. Therefore, the robot must have a variety of behaviors to keep the assessor's interest. It also must be harmless for people and easy to maintain and customize. Another important feature that the robot requires is independency, that is, it can move without the cables for energy supply or control, because those cables are inconvenient when the robot moves dynamically.

In this paper, we used a communication robot named "WAMOEBA-3"(Waseda Artificial Mind On Emotion Base) (Fig. 3). WAMOEBA-3 is an independent, wheeled robot, with inbuilt batteries and a PC. Its upper body is similar to human ones and its size is similar to the average size of a Japanese child: 656 [mm] long, 825 [mm] wide, 1316 [mm] tall. It 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. The head is equipped with 2 CCD cameras and 2 ears. Each camera can independently move horizontally, and each ear can rotate horizontally, too.

WAMOEBA-3 is also equipped with an omni-directional vehicle for locomotion. The vehicle moves in any direction

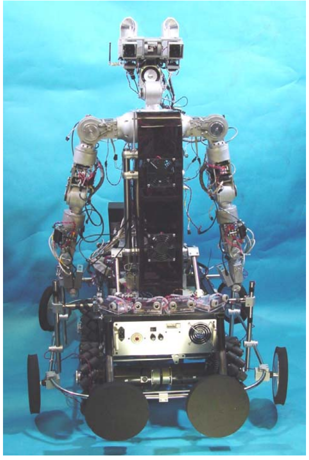


Fig. 3. WAMOEBA-3

without actually turning at any stage. It has 8 bumper sensors and 8 ultrasonic sensors on the vehicle.

TABLE I
SPECIFICATIONS OF WAMOEBA-3

Dimensions	mm	1316(H)×825(L)×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+1×2=3
	Ear DOF	2
	Neck DOF	3
	Vehicle DOF	3
	Arm DOF	6×2=12
	Hand DOF	1×2=2
Outside Sensors	Vision	CCD Color camera × 2 (10×Optical zoom, 4×Degital zoom)
	Sound input	microphone×2 (Directional hearing, Voice recognition)
	Sound output	Speeker(Voice synthesis)
	Distance	Ultra sonic sensor×8
	Collission	Bumper switch×8
	Joint stress	Torque sensor×14
Structural material		Extra super duralumin Titanium alloy(Ti-6Al-4V) aluminium(52S)
CPU		Pentium4(3.2GHz)
Micro Computers		VR5550-ATOM×5
OS		Linux
Battery		Lead-Acid Battery for EV

WAMOEBA-3 was developed as a platform for communication experiments. Therefore, we designed some devices which make it easy to maintain and customize. For example, sliding mechanisms are installed on the battery case and power supply unit to allow easy access.It has a distributed control system constructed of 5 microcomputers and a Dos/V PC. The control system contains enough space capacity to customize the robot in the future.

V. IMPLEMENTATION

Using HMHE and WAMOEBA-3, we were able to carry out an IEC experiment in a real world. In this section, we show how we implemented IEC into the robot.

A. Motion Generator of the Robot

The motion generation algorithm for WAMOEBA-3 was the motor-agent (MA) model. The MA model is a distributed control algorithm. Each actuator (or sensor) is regarded as an autonomous agent, and each agent collects data from another agents, and determines its own actions autonomously and independently. Therefore, the connections between the agents create a network in WAMOEBA's body, and the network topology stands on the robot's bodily structure [12].

Each actuator moves according to the output of the following equations.

The output of the motors is described in terms of angular velocity, and movement of the whole body is generated by integrating motions caused by input from the sensors, such as the rotary encoders, bumper switches, and so on.

$$\dot{\theta}_i = \sum_{j=0}^{n} \gamma_{ji}\alpha(\theta_j) + \sum_{k=0}^{m} \gamma_{ki}s_k + \delta\theta_i \qquad (1)$$

Here, θ is the joint angle of actuator, and s is the input from sensor. α is the function that determines the influence from the other actuators.The 3rd term is for the stability of the output of the function. α is given by the following function which changes based on the angle of another joint.

$$\begin{aligned} \alpha(\theta_j) &= \exp\left[-\omega_j\left(\theta_j - c_{const}\right)^2\right] \\ &\quad - \exp\left[-\omega_j\left(\theta_j + c_{const}\right)^2\right] \end{aligned} \qquad (2)$$

Here, c_{const} is the threshold, and ω is the degree of sensitivity of θ. If the value of ω is large, the change of the θ strongly influences the output of the function.

In this experiment, we used a very simple MA network, as shown in Figure 4. To simplify the experiment, the images captured using the cameras were not in use, and the joints on the arms and ears weren't used, either. Agents with actuation capabilities included the eye agents, the neck agents, and the omni-directional vehicle agent, and available sensors were the bumper switches, the ears (microphones), and the sonars (ultra sonic sensors). In this case, the eye agent autonomously determined its rotation direction and speed based on the angle of the neck joint and data from the ear sensors (microphones) and the bumper sensors. The neck agent determines its action based on the angles of both eye joints and 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 from the bumper and sonar sensors.

The characteristic behaviors achieved by this network were as follows.

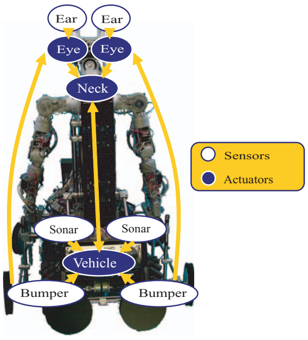


Fig. 4. Motor-agent network: blue circle and white circle represent motor-agents and sensor-agents respectively.

- If someone made a noise (shout, clapping), the microphones detected the sound's direction. Then the eyes and neck moved horizontally, and the vehicle moved to follow (or escape from) him/her.
- If someone touched the bumper sensors, the sensors detected the collision. Then the eyes moved up or down, and the vehicle moved.
- If someone came up to the robot, the ultrasonic sensors detected the person approaching. Then the robot moved.

B. Genetic Settings

The MA enables WAMOEBA-3 to move just reactively. However, the direction and amount of movements are based on human interpretation. Therefore, the connection weights between the agents (γ in Equation 1) were encoded into genes. The genes were encoded using numerical data, which are easy to analyze. The dataset dimension of a gene was 32. The probability of mutation was 0.3%. If a mutation occurred, the value of the gene was added by a random value.

We also used multi point crossover and elitisum (the best 40% individuals were preserved and made their offsprings).

C. IEC with HMHE

Since the period of the experiment is limited by human fatigue, we set the parameters according to the result of the simulation so that the experiment ends in at the most 3 hours. The population size was 30 and the experiment continued until the 7th generations. There were 37 neurons in the SOM network, and 1000 training cycles. The system also displayed the best individual from the previous generation, which made sure the learning progressed and eased an assessor's mind.

Without HMHE, each assessor must evaluate all the genes. Therefore, the assessor would have had to interact with 240 individuals. Since there must be almost the same genes in the genetic pool, this is an inefficient method. Using the HMHE, each assessor needed to evaluate only 56 individuals in total.

VI. Experiment

As described above, we've already made a simulation to confirm the effectivity of the HMHE. However, we thought that human-robot interaction in real world should be different from simulated one. In order to confirm the difference between the simulation and the real world, we made the behavior acquisition experiment using IEC with HMHE. In this section, our experimental settings are described in detail.

A. Experimental Subjects

Experimental subjects (assessors) were 6 students in our laboratory. They were young students (21-23 years old), and had some knowledge of computers and robots.

Before the experiments, we informed them the following.

- The robot's name is "WAMOEBA".
- The robot has bump sensors, ultra-sonic sensors, and ears. The robot's cameras and arms are not in use.
- Please tell us the total point of the robot's behaviors whenever you want.

They were simply informed of the robot's abilities, and were allowed to evaluate the robot's behavior freely.

B. Experimental Design

Usually, communication has its own specified task or goal (eg. escape from labyrinth). In our experiment, the task was "play", because communication robots like WAMOEBA-3 are expected to entertain or may be used in psycho-therapy in the near future [1]. Therefore, in this study, WAMOEBA-3 interacted with a human assessor to entertain him/her.

C. Environment

The experimental environment is shown in Figure 5. We used a conference room where there were no objects or obstacles. The assessors interacted freely with the robot, and evaluated its behaviors. Each individual started to move from the center of the room.

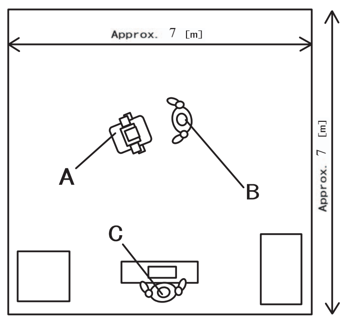


Fig. 5. Experimental environment: (A) WAMOEBA-3. (B) human assessor. (C) experimenter.

D. Evaluation

In this experiment, the robots' behaviors were evaluated using a scoring method. The assessors were able to evaluate the robot at any time. When they wanted to input a score, they said it to an experimenter and the experimenter inputted the score into a laptop.

We did not supply any evaluation criteria to the assessors. They gave their own subjective evaluation to the robot's behaviors.

E. Questionnaire Surveys

After the experiment, the assessors completed questionnaires to survey their impression of the experiment. Some of the questionnaire items used are shown as follows.

- Did you feel the WAMOEBA tried to communicate with you?
- How did you feel the WAMOEBA in the early generations?
- How did you feel the WAMOEBA in the last generation?
- How did you evaluate the robot's behaviors?
- Did your evaluation criteria change?
- Did you think the robot learnt?
- Were you satisfied with the result?

VII. Results

A. Interaction

Each individual interacted with a human assessor for an average of 3 minutes. The experiment took about 3 hours in total.

Figure 6 shows the typical interactions between a human assessor and WAMOEBA-3. The assessor clapped their hands or called the robot's name (Fig.6-a), kicked the bumper switches on WAMOEBA-3's vehicle (Fig.6-b), touched or pushed WAMOEBA-3's body or shoulders (Fig.6-c), and posed in front of the robot (Fig.6-d).

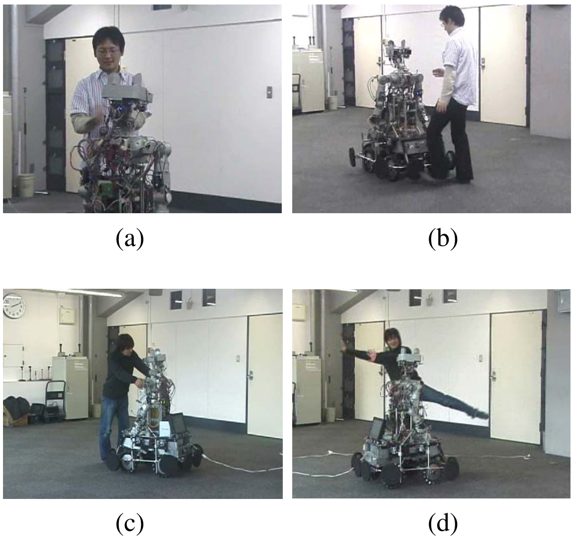


Fig. 6. Interaction: An assessor clapped his hands (a), kicked the bump switches (b), touched the robot's shoulders (c), and posed in front of the robot (d).

B. Acquired Motions

Figure 7 shows the population distribution of each genetic parameter and for each generation. In the graphs, horizontal and vertical axis respectively indicate generation and the data of each gene. Colored regions represent the population. If the population size of the gene has a specified data that is large, the assessor highly evaluated the genes in the previous generation. Therefore, we can see the acquired motions and the assessor's preference from the graphs.

Figure 7 a) shows the connection weight between the ear and eye agents. If the value is positive, WAMOEBA-3 turned

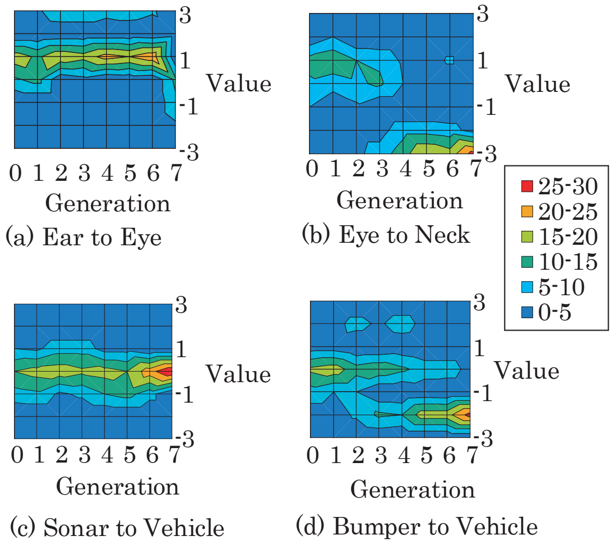


Fig. 7. Population distribution of each connection weight and generation: Colored region represents population of genes. These are examples from one assessor.

its eye in the direction of the sound. In this case, throughout the experiment, the population of the genes which had a value of 1 was the largest.

Figure 7 b) shows the connection weight between the eye and neck agents. If the value is negative, WAMOEBA-3 turned its head in the direction of the gaze. Until the 3rd generation, the population of 1 was the largest. However, from the 4th generation, the population of -3 increased drastically.

In Fig. 7 c) (the connection weight between the sonar and vehicle agents), the data of 0 was the most popular.

The connection weight between the bumper and vehicle, as shown in Fig. 7-d), shifted from 0 to -2 in 4th generation. This suggests that the vehicle started to move to avoid the obstacles.

C. Fitness Values

Figure 8 shows the average and maximum fitness values. The horizontal and vertical axis respectively indicate generations and fitness values.

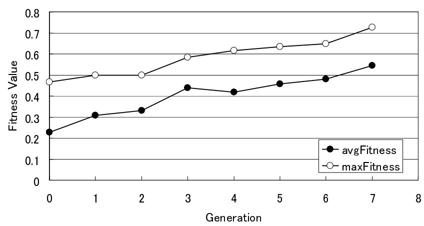


Fig. 8. Fitness Value

Both the average and maximum fitness values gradually increased. Although the variance is not indicated in Fig. 8, it remained constant throughout the experiment.

D. Questionnaire surveys

As for the results of the questionnaire, we obtained many comments from the subjects.

In earlier generations, they felt that the robot did not move dynamically, or moved wildly. On the contrary, WAMOEBA-3 moved actively and achieved motions the assessors desired in the last generation. They said that they scored high fitness values when the robot moved actively and safely. Most of the individuals which they scored high fitness values escaped from the assessors, or turned their head to the direction of the sound.

VIII. Discussion

At first, we discuss the interaction between humans and robot. Although the assessors were informed of the robot's capabilities, they interacted with the robot in a variety of ways. The assessors sometimes touched the robot's shoulders, though there were no sensors on the shoulders. They even posed in front of the robot although they knew that the cameras are not in use in this experiment. Considering these results, we determined that human-robot interaction has various and infinite ways, and it is quite difficult for developers to predict because the interaction is greatly affected by the behaviors of the robot as well as its form.

We should have prepared more sensors and actuations, so that we could provide more space for interesting communication (redundancy).

Then, we considered the acquired behaviors and assessor's evaluation. In earlier generations, the behaviors of the WAMOEBA-3 were small and slow because the absolute values of the initial genes were very small. In contrast, WAMOEBA-3 moved more dynamically in the last half of the experiment. In the final generation, most of the acquired motions seemed to be compliant and governable. For example, when the assessor stood in front of WAMOEBA-3, it moved backward.

The assessors may have placed importance on safety of both the robot and environment. The robots that rushed at obstacles were evaluated as low. However, these rushing robots were sometimes highly evaluated because the motion surprised the assessors and they scored accordingly. Therefore, the robot should be equipped with sensors that can distinguish human beings from other obstacles.

According to the questionnaire surveys, the assessors felt WAMOEBA-3 had learnt motions they desired. This can be also observed in the gradually increasing fitness value. Therefore, we determined that IEC with HMHE is effective for the real environment.

IX. Conclusion and Future Works

In this paper, we demonstrated that interactive evolutionary computation (IEC) is suitable for communication learning because fitness functions are performed by a human assessor. Using IEC, we configured the behaviors of a communication robot, WAMOEBA-3, and determined that IEC could be applied to the real robot.

In this experiment, future works of this project were also discussed. Since the human assessors interacted with WAMOEBA-3 in a variety of ways, the WAMOEBA-3 required more sensors. The visual impression of the robot is very important, so we should prepare all sensors in the next experiment.

We also believe that the results will not improve as long as the robot behaves reactively. We will develop a system that changes WAMOEBA's motions dynamically. In the former researches, we proposed an endocrine model for the robot system [9]. We think that this endocrine model could be configured using IEC.

Acknowledgement

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