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Acquisition of Reactive Motion for Communication Robots Using Interactive EC

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***Abstract*— We've developed an emotional communication robot, WAMOEBA, using behavior-based techniques. We also proposed motor-agent (MA) model, which is an autonomous distributed-control algorithm constructed of simple sensor-motor coordination. Though it enables WAMOEBA to behave in various ways, the weight of the combinations between different motor agents is influenced by the preferences of the developer. We usually use machine-learning algorithms to automatically configure these parameters for communication robots. However, this makes it difficult to define the quantitative evaluation required for communication. We therefore used the method of interactive evolutionary computation (IEC), which can be applied to problems involving quantitative evaluation. IEC does not require to define a fitness function; this task is performed by users. But the biggest problem with using IEC is human fatigue, which causes insufficiency of individuals and generations for convergence of EC. To fix this problem, we use the prediction function that automatically calculates the fitness values of genes from some samples that have received the human subjective evaluation. Then we carried out the behavior acquisition experiment using the IEC simulation system with the prediction function. As the results of experiments, it is confirmed that diversifying the genetic pool is an efficient way for generating a variety of behavior.**

I. Introduction

In the 21st century, robots have potential uses in many areas, especially entertainment, healthcare, and nursing. Robots that work around human beings must be equipped with capability for human-robot communication. Most of the 'communication' provided by robots is based on scenarios designed by their developers. Certainly, model-based communication is at present the most practical and fastest way of achieving verbal and context-sensitive communication, but it is boring for users once they are familiar with the scenarios. Though robots may behave in various ways to keep users interested, the number of their behaviors is physically limited. As an autonomous generator of variety, emotion has attracted the attention of numerous researchers [1], but emotional models are still based on the subjective preferences of developers.

To create a more interactive robot, we have developed an emotional-communication robot WAMOEBA (Waseda Artificial Mind On Emotional BAse) whose emotional behaviors are based on evaluations of its own hardware condition [8]. Currently, we are developing WAMOEBA-3 (see Fig.1) that is designed to behave in a greater variety of ways than the WAMOEBA-2 series. It is a wheel-type independence robot with inbuilt batteries and control systems. It is 656-mm long, 825-mm wide, 1316-mm tall, and weighs approximately 105 kg. It is equipped with an omni-directional vehicle that is capable of moving in any direction without actually turning at any stage. It has two arms (6 degrees of freedom) and a head (4 degrees of freedom). Its two eyes move independently, which is useful for communication [9]. It has enough sensors of sufficient sensitivity to enable it to behave in various ways. The sensors used to acquire external information include microphones, ultrasonic range sensors, two CCD cameras, bumper switches, and so on. But two cameras are not used in the current experiment shown in this paper.

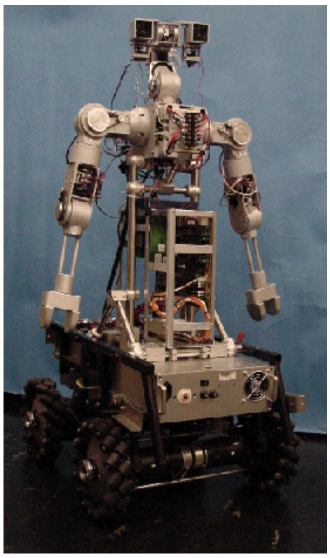


Fig. 1. WAMOEBA-3

We have also proposed a motion-generation algorithm called motor-agent (MA) model. MA model is an autonomous distributed-control algorithm. Each motor is regarded as an autonomous agent that connects with neighboring agents and collects information from sensors and other motors through a network in the robot. Each agent then determines its action autonomously according to the collected data. Though this algorithm enables WAMOEBA to behave in various ways, the weights of the combinations between agents are configured by the developer. Therefore, its behavior is influenced by the developer's preferences.

In this paper, we describe the method of using the evolutionary computation (EC) as a basis for installing behavior in a communication robot to automatically configure the weights of the MA network. First, we point out the problems for the human-robot communication learning and focus attention on a problem of evaluating the communication. As a prescription for it, we show the interactive evolutionary computation (IEC). Next, we describe some contrivances to acquire the variety of behaviors. In the communication learning system, there must be a mutual informational and physical interaction. Therefore we developed a simulator to investigate the interaction between a robot and a human being. According to the results of our experiment, we show that it is important for the communication learning of IEC to diversify the individuals in the genetic pool.

II. Learning problems for communication-robots

There are numerous learning algorithms, such as artificial neural networks (ANN), reinforcement learning, evolutionary computation (EC), and so on. We have to select the most appropriate algorithm for providing communication robots with various behaviors. We decided on EC because it is suitable for exploring a large search area, and can generate a number of possible solutions. An additional advantage of using EC is that it does not require models of the system and the environment.

When EC is used to optimize the behavior of a communication-robot, it is first necessary to define the fitness function. However, it is difficult to evaluate communicative behavior quantitatively, rather than qualitatively. No matter which learning method is selected, it is still necessary to explicitly define a method for evaluating communication.

Two methods have already been proposed to fix this problem. One involves using an evaluation model [2], and the other is an interactive learning system. The former method is based on building an evaluation model of a human being from trends shown by subjects. However, the phenomenon of communication is too difficult to build an explicit model of subjective human evaluation because there are mutual informational and physical interactions between people in communicative situations. The latter method incorporates a human being into the learning system instead of an evaluation function. This approach avoids the problem of complexity. Therefore, we decided to use interactive evolutionary computation (IEC), which combines evolutionary computation and an interactive learning system [5].

III. Interactive Evolutionary Computation

In conventional EC, each individual is evaluated using a given fitness function. IEC is an evolutionary computation; its fitness function is provided by users (see Fig. 2). It therefore enables EC techniques to be applied to problems of subjective optimization without an explicit model of human subjective evaluation. IEC has previously been applied to aesthetic areas, such as art, design, and music. In these areas, fitness functions cannot always be defined explicitly. With IEC, however, it is unnecessary to define them.

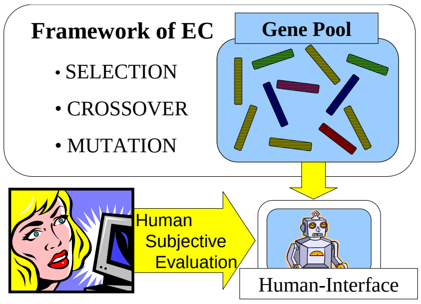


Fig. 2. Framework of IEC

IEC has also been applied to optimizing robot behavior. For example, in a study entitled "A Children's Game" [4], a robot controller was developed using an ANN; the connection weights in this ANN were developed according to children's preferences for robot locomotion. By repeating the selected locomotion on a simulator screen, IEC was able to generate the behavior that the children preferred. This study was aimed at developing a robot controller without programming. IEC has also been used to optimize the emotional expression of autonomous robots. Assessors observed the different movements of autonomous robots and chose the movements that seemingly mimicked the emotions, such as happiness, anger or sadness, that they were looking for [10].

Both of these studies used IEC to advantage in optimizing robot behavior. Our aim however, is to develop more communicative and interactive behavior. Therefore, our experiment required physical and informational interaction between human beings and robots.

IV. Introduction of IEC into Human-Robot Communication

A. Motor-Agent Network

We used MA model as the motion-generation algorithm for an robot. In this experiment, we used a very simple MA network, as shown in Fig. 3. Agents with actuation capabilities include the eye agents, neck agents, and the omnidirectional vehicle agent. Each agent determines its own actions autonomously and independently. The eye agent determines its rotation direction and speed autonomously according to the angle of the neck joint and data from the ear sensors. The neck agent determines its action according to the angles of both eye joints and the action of the omni-directional vehicle. The omni-directional vehicle determines 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.

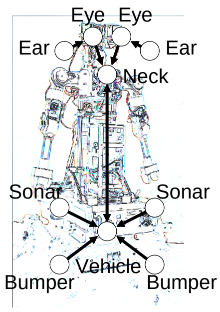


Fig. 3. Motor-Agent network

The output of the motors is described in terms of angular velocity, and movement of the whole body is generated by integrating the reflection motions caused by sensor input.

$$\dot{\theta} = \sum_{i=0}^{n} \alpha_i(\theta) + \sum_{j=0}^{m} \beta_j(s) + \delta\theta \qquad (1)$$

Here, α is a weight coefficient that shows the ratio from which the reflection motion is selected. α is given by the following function which changes according to an angle of another joint.

$$\begin{aligned} \alpha_i(\theta) &= \gamma_i \times \exp\left[-\omega_i\left(\theta_i - c_{const}\right)^2\right] \\ &\quad - \gamma_i \times \exp\left[-\omega_i\left(\theta_i + c_{const}\right)^2\right] \end{aligned} \qquad (2)$$

θ is an angle of joint, and c_{const} is a threshold. γ is the degree of influence of θ, and ω is the degree of sensitivity of θ. If the value of ω is large, the change in the sensor input influences α sensitively. β is also defined according to the sensor signal.

$$\beta_i(s) = \sum_{i} \gamma_i \times s_i \qquad (3)$$

s is the parameter changed according to the sensor inputs (e.g. the bumper switched).

B. Gene Expression

The γ values in Equation 2 and 3 are encoded to genes represented by numerical data, which are easy to analyze. Each connection in the motor-agent network has γ, and the dimension of datasets of a gene is 28. The probability of mutation is 0.5% for each element in datasets of a gene. If a mutation occurs in an element, it is updated by a random number generator. If the parent genes are close to each other, the probability of mutation increases to 50% to ensure that the genetic pool contains a variety of genes.

C. Evaluation Prediction

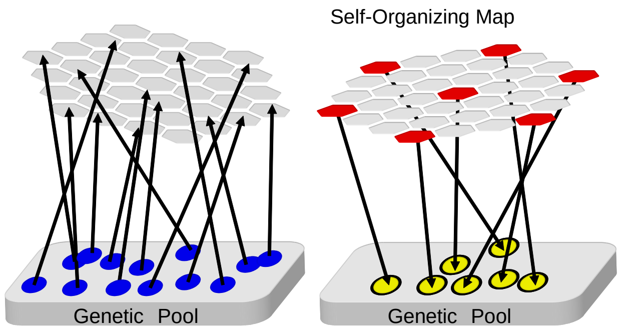
The biggest problem with applying IEC is human fatigue. Since assessors cooperate with a computer to evaluate individuals, the IEC process spends huge length of time. To minimize human fatigue, we need to reduce the number of individuals and generations. This results in poorer and slower EC convergence.

To solve this problem, we used a method for predicting the fitness values of genes [6].With this method, the assessor tests only some individuals that are selected from the genetic pool. And then the system predicts fitness values for the other genes. Fitness values of them are predicted on the basis of the Euclidian distance from the datasets of genes that an assessor gives his/her subjective fitness values before.

In usual prediction methods, the individuals evaluated by an assessor are selected at random. However, as a more efficient method to select individuals, we used a self-organization map (SOM) [3]. The SOM is an algorithm that is suitable for analyzing large multi-dimensional datasets. In SOM, similar vectors are placed close to each other and dissimilar vectors are placed further from each other.

The individuals are selected using the SOM as follows: first, the SOM is trained by the datasets of genes in the genetic pool (see Fig.4(a)). The number of neurons of SOM network is 37, and of training cycles is 1000. Next, seven genes are selected; each selected gene has the best matching dataset with each of seven neurons placed at the position shown in Fig.4(b). In this way, we can select the individuals that have distant datasets of genes from each other, which is efficient for the prediction system. Using this prediction system enables to increase the number of individuals in the genetic pool to 50.

The system also displays the best individual from the previous generation, which makes sure the progression of learning and eases an assessor's mind.



(a)Training Period (b)Selecting Period

Fig. 4. Positions of selected genes on SOM

Our proposed algorithm is shown in Figure 5. The newest genes are analyzed using the SOM algorithm. Then, selected genes are translated into individuals (motor-agent network) and interact with assessors, who then evaluat them. Genes that are not selected are automatically evaluated by the prediction system. When all the genes have been evaluated both automatically and manually, the EC applies genetic operators (selection, crossover, and mutation) to the gene pool and renewed the pool.

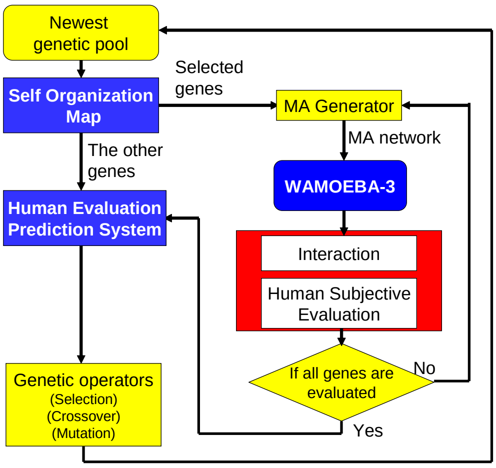


Fig. 5. Proposed Algorithm

V. Experiment

A. Interaction Simulator

We developed a simulator of WAMOEBA-3 in preliminary experiments to investigate the interaction between robots and human beings (see Fig. 6). In this paper, we discuss the problems, and techniques required to apply IEC to communication robots.

Fig. 6. Interaction simulator

In this experiment, two robots placed in a simulated environment interacted with each other. One was controlled by an assessor, and the other by a program (MA). To control the simulated robot, the assessor used a joystick with force-feedback capability. This enabled bilateral physical interaction.

The main interactions between the human-controlled robot and a program-controlled robot were as follows:

1) When physical contact occurs between a human-controlled robot and a program-controlled one in a simulated environment, the simulator generates force feedback effects for the assessor and sends information on the collision to the bumper agents of the MA. Then the bumper agents influence the action of the vehicle agent.
2) When the human-controlled robot makes sounds (when the assessor presses a button on the joystick), the ear sensors (microphones) capture the sound and the ear agents influence the eye motor agents.
3) When the ultrasonic range sensors of the program-controlled robot capture the human-controlled robot or the walls of environment, the sonar agents influence the vehicle agents.
4) The program-controlled robot stops moving when its battery level is too low. The human-controlled robot is equipped with an energy-charging gun which works by pressing a button on the joystick. If the human-controlled robot with the gun is close enough to the program-controlled one, it can recharge its battery also.

We used this experiment to examine the following aspects of applying IEC to the acquisition of various behaviors by communication robots.

1) Interaction Task
2) Presentation of Individuals
3) Evaluation
4) Dealing with the disadvantages of IEC

B. Interaction Task

Usually, a communication has its own goal (task). Assessors can evaluate how the task was achieved. In this experiment, however, since we wanted to acquire a variety of behaviors, we did not prepare communication tasks in advance.

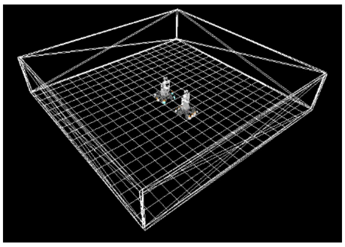


Fig. 7. Interaction environment

The environment is shown in Fig. 7. There are no objects, obstacles, or textures that could influence the assessor. There are only the two robots. The assessors interact freely with the program-controlled robot, and evaluate its behavior.

C. Presentation of Individuals

The IEC is usually applied to aesthetic areas such as design or art. In such cases, when an examinee evaluates individuals in the genetic pool, the static images of individuals are represented on the CRT screen at the same time. On the other hand, we use the IEC to acquire the behavior of the communication-robot. The communication is dynamic phenomenon that has duration of time, and it is spatially impossible to display. Therefore we have to display one by one. The examinee interacts with only one individual. On the simulator screen, the vision captured by the camera of the human-controlled robot is displayed, and an examinee evaluates the behavior of the robot.

D. Evaluation

In normal IEC, several individuals are shown on the screen at the same time, and the assessor then evaluates individuals by selecting or ranking them. In this experiment, robot behavior was evaluated using a scoring method because the assessors evaluated individuals one by one.

We did not supply any adjectives for the evaluation dialogue that took place at the end of each interaction because this would have provided the assessors with evaluation criteria that were influenced by the developer. Assessors were simply informed of the abilities of the robot and allowed to evaluate the behavior freely.

E. Behavior Acquisition Experiment with IEC

First, we made the behavior acquisition experiment using the IEC with the prediction function described in the section IV-C. It was carried out using the simulator described in the section V-A. We also carried out an experiment without using the prediction system. In the non-prediction system, IEC has only 7 individuals in the genetic pool.

F. Reevaluation Experiment with Paired Comparisons

After the experiment in using the IEC with the prediction function, we did a further experiment to check the successfulness of IEC learning. The experiment was carried out as follows:

1) Five individuals who had experienced learning were selected from the genetic pool.
2) The assessors evaluated the individuals using a paired comparisons method.
3) Priorities were calculated from the results of the comparisons.

Each assessor reevaluated the individuals in the genetic pool which was trained by him/her self. The paired comparisons method is one of the most famous decision making methods. The decision maker makes a comparison between two samples from the alternatives, and then he/she rates the priority of one of two. This process is carried out for each of the possible combinations. Finally, the priorities of the alternatives are calculated from the results of comparisons.

The paired comparisons method is expected to produce more accurate evaluations than the scoring method used in the first experiment. However it increases the human fatigue because the required number of the interactions and evaluations is as large as the number of the combinations between individuals that is to be evaluated. Therefore the number of individuals was more severely restricted and got down to five. The priorities were calculated from the geometric average of the judgments made by the assessor.

VI. Result

A. Behavior Acquisition Experiment

The behavior acquisition experiments took about 90 minutes on average. One evaluation of an individual took about 90 seconds (The assessors were five members of our laboratory staff).

Figure 8 shows the standard deviation of dataset of the genes. The vertical axis indicates the standard deviation and the horizontal axis indicates the generation. The line graph of 'non-prediction' represents the standard deviation of the IEC system without the prediction function, and the line graph of 'prediction' represents that of the IEC system with the prediction function. The standard deviation of the genes in the non-prediction system drops, but that of the prediction system remains high. This shows that variation in the genetic pool is maintained at a constant level with the prediction system.

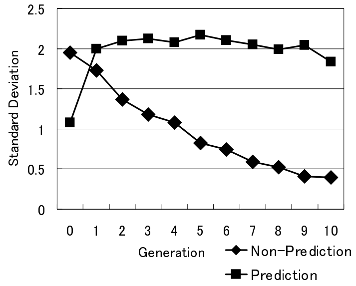


Fig. 8. Standard deviation of the genes represented(evaluated)

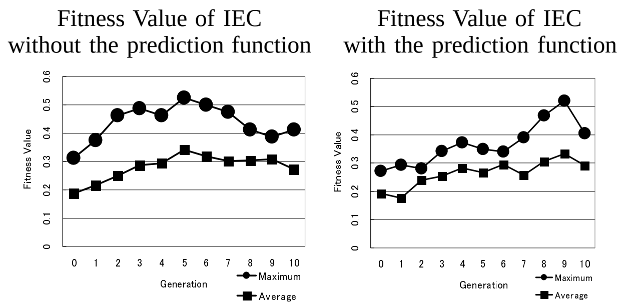


Fig. 9. Comparison of fitness value with or without the prediction function

Figure 9 shows an evolution process of experiments. Circle plots represent maximum fitness values in the population of each generations, and square plots represent population averages. In the early generations in the plots of the non-prediction system, the fitness values tended to increase, but from the fifth generation, the fitness value tended to drop.

In contrast, the values in the prediction system remained almost at an even level or increased.

B. Reevaluation Experiment

Figure 10 shows a graph of the priority values for individuals. The vertical axis indicates the priority value, and the horizontal one represents the order in which selected individuals were generated. The line graph represents the average priority; the variance in priority is also shown.

In early generations, the priorities of individuals increased. In later generations, the average priority stayed the same, but its variance increased.

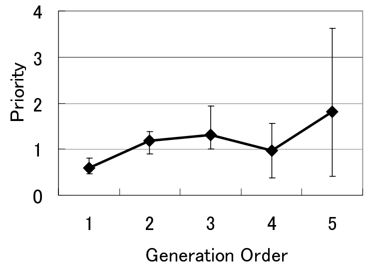


Fig. 10. Priority of individuals

VII. Discussion

In the early generations, though we had not set a task for the interaction or provided criteria for the evaluation, the assessors were able to interact with the robots and evaluate them. The learning capability of IEC was demonstrated in the reevaluation experiment. With the later generations, it was difficult to maintain or increase the fitness values.

Values dropped because the assessors changed their criteria for the evaluation and interaction due to their boring. When the criteria were changed, an assessor observed different aspects of the robots, and robots that had received favorable evaluations in previous generations were evaluated more critically. The change in the criteria was a result of the unstructured format of this experiment. We did not provide standards for the evaluation or a purpose for the interaction. In the reevaluation experiment, the increment in the variance of priorities might have been due to the changed criteria. In the later generations in the behavior acquisition experiment, the assessors evaluated the robots differently. For example, in the early generations, an assessor evaluated individuals looking at the movement of whole body vaguely, and in the latter generations, he/she paid attention to the head movement. This was why it was difficult to duplicate the evaluation in the reevaluation experiment.

However, using the prediction system we enabled the fitness values to be maintained at a constant level or to be increased. This system was effective in maintaining variety in the genetic pool. Even if the criteria was changed, the genetic pool contained various individuals that could produce individuals that could adapt to changes in interactions and evaluations. Therefore, even though the fitness values dropped, the genetic pool was able to adapt to the changed criteria and the fitness values recovered.

VIII. Conclusion and Future work

In this paper, we showed the property of using IEC to acquire various behaviors of communication-robot. And we applied IEC to configure the weights between agents in the WAMOEBA-3 MA network. Then we discussed the conditions to diversify the generated individuals (behaviors). Though we did not prepare the criteria for interactions and evaluations, IEC was capable of learning the behavior that the assessors preferred. In the latter half of the experiment, though it was difficult to keep increasing the fitness values because of changes to the criteria, the IEC prediction system effectively overcame this difficulty and increased the number of individuals in the genetic pool. This was why it is important for acquisition of various communicative behaviors to keep the variety of genetic pool.

We have two future works. First, to reduce human fatigue, we will try to refine the system. For example, to reduce assessors' effort in having to mentally compare current and past behavior, the system will enable assessors to replay the behavior of elite individuals whenever they choose.

Secondly, we will introduce greater diversity and complexity into the motion-generation function (MA) and emotional-behavior generator (endocrine system) we have already proposed [8].

We also need to do further work on the techniques required to apply IEC in the real world.

Acknowledgement

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