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Human-Adaptive Robot Interaction Using Interactive EC with Human-Machine Hybrid Evaluation

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Using interactive evolutionary computation (IEC), we created human-robot interaction system that maintains user interest over time. Although IEC enables users to design systems reflecting subjective preferences, it forces them to evaluate a large number of individuals. The refined IEC techniques, we propose in this regard, human-machine hybrid evaluation (HMHE), lets users manually evaluate only representative genes, after which HMHE automatically estimates the fitness of other genes, thereby increasing a population without increasing user evaluation process. Experimental results showed that preferences easily change in interaction. We confirmed that HMHE maintains high diversity, while maintaining user interest.

Keywords: interactive evolutionary computation, human robot interaction

1. Preface

The increasing use of robotics in fields such as entertainment, medicine, nursing care, and psychotherapy, makes it necessary for such symbiotic robots to be able to communicate. Specifically, in interaction that requires maintaining user interest, particularly with entertainment robots, such robots must be able to automatically learn and adapt their behaviors to user preferences. In human-robot interaction learning algorithms such as neural networks are not suited for communication depending primarily on linguistic contexts, so it may be more practical to apply such learning algorithms to reactive communications. Introducing behavior-generating algorithms in searches, for example, could help keep users from getting bored by adapting to individual user preferences and continually changing robot behavior.

In attempting to realize such adaptive interaction, we focused on three issues:

- Diversity of interaction
- Changes over time in subjective preferences
- Evaluation of interactions

To address these issues, we used interactive evolutionary computation (IEC) in learning for communication robots, enabling them to learn directly from subjective user evaluation represented by genetic algorithms in which the fitness function is replaced by subjective human evaluation [1].

IEC requires deliberate user evaluation in learning, so gene pool populations cannot be increased too much, meaning that when IEC is applied to learning by communication robots, users must interact with all genetic-phenotype robot and provide them with evaluations. If a population is too large, it will overly burden users, but if it is too small, genetic data within a gene pool cannot be made diverse enough, preventing progress in learning.

As a trade-off among gene pool diversity, learning efficiency, and the burden on users, we propose human-machine hybrid evaluation (HMHE), which uses automatic evaluation referencing user evaluation in parallel with IEC and enabling population size to grow without adding to user fatigue.

In this paper, Section 2 details the three issues we are focusing on problems - diversity of interaction, changes over time in subjective preferences, and evaluation of interactions, and features in applying IEC to human-robot interaction. Section 3 discusses HMHE including an HMHE performances test using a mathematical model conducted prior to interactive experiments with users. Section 4 tells how to install HMHE in the interaction system. Section 5 describes experiment setup. Section 6 discusses experimental result. Section 7 mentions considerations. Section 8 Presents conclusions and projected work.

2. Problems in Communication Learning

Problems in learning with human-robot interaction involve diversity of interaction, changes over time in subjective preferences, and evaluation of interactions.

2.1. Problems Related to Diversity of Interaction

Maintaining the diversity of robot behavior to realize interaction keeping users interested requires multiobjective optimization of learning through dynamic selection of a solution among candidates rather than single-solution searching, since multiple types of behavior coincide with user preferences. In multiobjective optimization with ordinary GAs, gene pool clustering is first worked out, then parallel searching conducted for individual fitness functions. Since we do not know, however, how many evaluation items each fitness function consists of, it may be difficult to optimize GAs by changing evaluations for gene pools [2].

Regarding learning through dialogues with users, Inamura et al. used a Bayesian network in searching to adapt robot behavior to user instructions [3]. Although techniques using user instructions may be effective to avoid uncertainties in the real world, such a Bayesian-based technique requires behavior units designed prior to setting network nodes. For the technique we propose, robot behavior is described in terms of weight, etc., rather than behavior units, because behavior units, not yet differentiated, can continue to change variously by learning through interaction.

2.2. Changes in User Preference over Time

Regarding changes in user preference over time, changes in the evaluation axis caused by user boredom present a problem in learning in open-ended human-robot interactions in this study. If an interaction is long, interactions previously highly evaluated may be reevaluated lower as the evaluation axis changes over time, meaning that robots must learn continuously.

To cope with a dynamically changing fitness function, conventional GAs propose conducting a search while maintaining diversity or temporarily increasing a mutation ratio by detecting changes in fitness functions [4, 5]. HMHE as we propose it maintains diversity and enables well more effective adaptation by manipulating mutation ratios upon detecting worsening evaluations.

Ogata et al. used consolidated learning in interaction using recurrent neural networks (RNNs) [6]. Consolidated learning achieves adaptation without sacrificing currently acquired dynamics by learning instructor data together with current acquired dynamics as instructor data. Ogata et al. applied this to a navigation task in which humans and robots interacted and confirmed that such navigation learning was more than mere learning and was, in fact, highly varied creative process that generated mutual interactions between learning while maintaining consistency in output behavior, it may yet be difficult to apply RNNs to interactions with a high degree of freedom (DOF). The evolutionary technique we used is applicable to interactions with a high DOF even though searching time increase. Conservation of genes in a gene pool makes it possible to ensure some consistency in behavior.

2.3. Problems Related to Interaction Evaluation

Regarding how to evaluate success or failure of interactions in adaptation to user preferences, whatever learning algorithm might be used, it is necessary to evaluate behavior success or failure if learning is through behavior intensification or restraint, regardless of the learning algorithm used. In practice, it is difficult to determine whether a robot has succeeded or failed autonomously with user preference on its own account. Since user preference depends strongly on user subjectivity and on context information such as the relationship to the robot, the environment involved and past behavior, it is difficult to construct a model that quantitatively evaluates interactions regardless of circumstances.

Mitsunaga et al. used the perspective of personal space and optimized behavior parameters through intensified learning with human-robot distance and meeting of lines of sight set as the evaluation axis [7]. When psychological knowledge is relied on, learning is conducted based on a criterion of interaction success or failure based in turn on the user's unconscious feelings of pleasure or displeasure. Some users interacted completely differently, however, from how researchers expected, so a learning model with a much wider scope of application is needed.

2.4. IEC Application to Communication Robots

To solve our three issues, we propose applying IEC, as has been proposed in response to subjective human evaluation or individual differences, in fields such as computer graphics (CG), fashion design, and music [1, 8]. IEC directly using subjective user evaluation is also expected to address individual user differences, dynamic changes in evaluation indexes, etc. The fact that IEC generates different genes gives robots variety in their reactions to user behavior, which in turn lets users notice new interactions, leading to variations in interaction. Being able to retain a variety of genes at one time should enable robots to adapt to changing user subjectivity without disrupting learning and to acquire "intellectual" behavior with both of diversity and rationality, thus reducing user boredom.

IEC has a variety of advantages in optimizing robot behavior involving human interaction. Lund et al. proposed applying IEC to optimizing the controller for a dolly robot using neural networks [9], presenting plural obstacles and one robot in nine simulator domains so that users could select robots that would undertake behavior preferable to subjects. Their experiments confirmed that promotion of IEC with such selected individual robots as parents for subsequent generations could produce children with no programming capability who undertook desired behavior. Although this study coincides objectively with ours in robot adapting themselves to psychological user preferences, simultaneously presenting nine robots makes it difficult to introduce interactions with users.

We targeted one-to-one interaction between a subject and a robot, enabling robots complete with IEC to receive evaluations through interactions with users and to proceed with long-term interactions with users, responding to changing demands without boring subjects.

IEC involving one-to-one interaction is required to individually evaluate robots with different genes, which is tiring to users. The population size in a gene pool must thus be limited and the time required for users to evaluate robot behavior must be reduced. Populations that are too small, however, tend to cause early convergence, lower learning efficiency, deprive robots of diversified behavior, and, as a result, increase user boredom.

These issues could be dealt with using large mutation ratios to maintain diversity within a gene pool, but such ratios are the result of random searches, so mutation ratios that are too large cannot fruitfully reflect user intentions.

Applying IEC to human-robot interaction thus involves a significant trade-off in learning efficiency, burden on the user, and gene diversity.

3. Proposal

We start by detailing our proposed HMHE and then discuss HMHE performance tests using a mathematics model.

3.1. HMHE

To increase total population size without increasing the population size for user evaluation and fatiguing users, we developed human-machine hybrid evaluation (HMHE) with IEC in which users only evaluate the phenotype of representative genes in a gene pool, and evaluation of other genes is automatically calculated based on user evaluation of preselected representative genes. This enlarges the population size without burdening users.

Nagao et al., in a proposal lightening the burden on users in IEC, made genetic evaluations based on the distance from facial images of user choices stored in a buffer [10]. We targeted open-ended interactions and the need to respond to ever-changing subjectivity. As user subjectivity changes, previous evaluation results may prevent current interactions from being evaluated correctly, so we decided not to use records of evaluations but, instead, to use the evaluations of representative genes selected from current gene pools.

Our proposed algorithm is divided into five steps (**Fig. 1**).

Step 1 Generation of Initial Individual Genes

As in ordinary EC, initial genetic groups are generated at random (Step 1, **Fig. 1**). Information on each gene is expressed in real numbers.

Step 2 Selection of representative Genes

Representative genes are selected in gene pools out of the genetic groups generated (Step 2, **Fig. 1**). Any random selection of representative genes may result in the selection of genes with very similar data, lack of availability for properly evaluating other genes, and possible induction of boredom in users. We used a self-organizing map (SOM) as a tool to analyze genetic data at selection. The SOM analyzes multidimensional data. Numerous elements arranged in the SOM correspond to data on the same dimension with sample data – in this case, vectors of genes – distant data is arranged at a distant location and data at a short distance, at a near location, on the recognition layer of the SOM and thus self-organizing [11]. Despite its simple algorithm, the SOM analyzes multidimensional data and is visualized to help adjust parameters used for analysis, which is why we used the SOM to analyze genes in this algorithm.

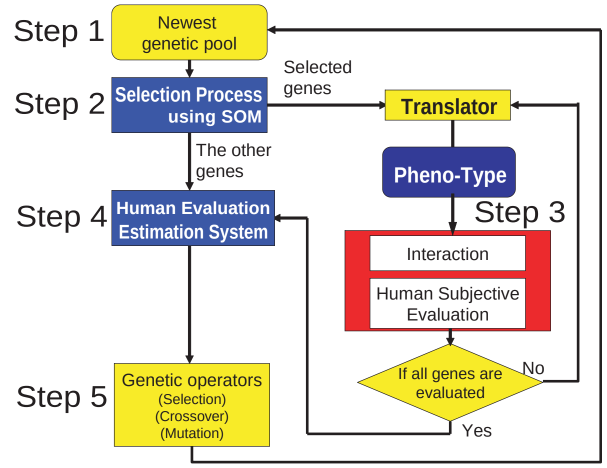


Fig. 1. Proposed Algorithm.

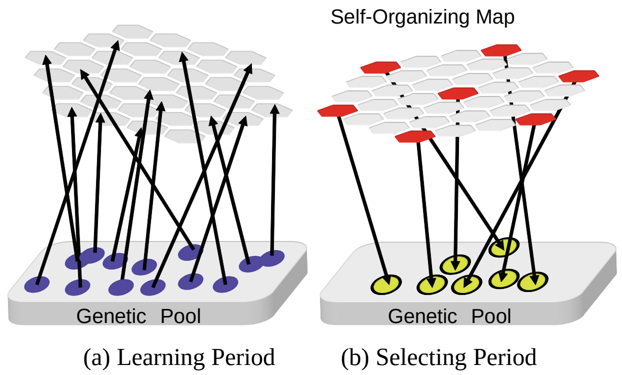


Fig. 2. Selection of Representative Genes Using an SOM.

Figure 2 shows the selection of representative genes using the SOM. In HMHE, SOM learning is first conducted for all genetic data in a gene pool. Element data on the recognition layer of the SOM is self-organized and near data arranged at a near location and distant data at a distant location. Elements at plural distant points on the SOM are selected and genes with data closest to such selected elements are selected as representative genes. The selection of elements on the SOM for selection of representative genes may vary with the SOM used, but visualization enables developers to make interactive adjustments and facilitates design. Phenotypes (robot behavior) presented to users are diversified to avoid "boredom."

Step 3 Interaction

Only genes selected above are translated as a behavior-generating algorithm representing the phenotype and introduced to a robot. Users interact with robots and make their own subjective evaluations (Step 3, **Fig. 1**).

Step 4 Automatic Evaluation Estimation

After all selected genes are evaluated, the fitness of other genes is automatically estimated (Step 4, **Fig. 1**). In automatic evaluation, the fitness of representative genes obtained by manual evaluation is weighted based on the distance between data on genes evaluated and data on representative genes. Evaluation expressions are as follows:

$$E_i^{auto} = \sum_{k=1}^{n} \alpha_{ik} E_k^{maunal} \quad \ldots\ldots\ldots\ldots \quad (1)$$

$$\alpha_{ik} = 1 - \frac{\|\boldsymbol{r_i} - \boldsymbol{r_k^{manual}}\|}{\sum_{j=1}^{n} \|\boldsymbol{r_i} - \boldsymbol{r_j^{manual}}\|} \quad \ldots\ldots\ldots \quad (2)$$

where E_i^{auto}, a calculated evaluation value of gene i, the weighted sum of E_k^{manual}, evaluation values of representative genes as obtained by users, and n indicates the number of individual genes evaluated by users. Weight α_{ik}, the ratio of distance between evaluated gene i and representative gene k to the sum of distances between evaluated gene i and all representative genes, is calculated using Eq. (2), where $\boldsymbol{r}$ denotes data on individual genes: $\boldsymbol{r_i}$ refers to evaluated gene i and $\boldsymbol{r_k^{manual}}$ and $\boldsymbol{r_j^{manual}}$ to representative genes k and j.

Step 5 Generation of New Gene Pools

Once evaluation is completed, next-generation gene groups are generated by applying genetic operators such as selection, crossover, and mutation (Step 5, **Fig. 1**).

In HMHE, where the majority of evaluation processes can be programmed and population size enlarged without fatiguing users so as to ensure diversity in a gene pool, user boredom is avoided by increasing diversity in robot behavior.

3.2. Performance Tests

To determine searching capabilities of the IEC using HMHE in application to human-robot interaction, we conducted performance tests using a mathematics model, detailed below.

3.2.1. Tests

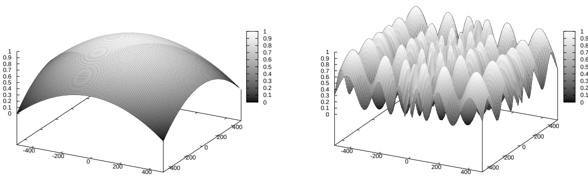
We used a mathematics model in the performance test of HMHE for simplification. Mathematics modeling of human preferences is not really possible. Noting that several behaviors, not just one behavior, of robots coincide with user preferences, we used the polymodal Schwefel function, together with a single-modal sphere function, to compare searching efficiency.

$$f_{sphere}(\boldsymbol{x}) = \sum^{n} (x_i)^2. \quad \ldots\ldots\ldots\ldots \quad (3)$$

Schwefel in n dimensions is a polymodal function expressed as follows:

$$f_{schwefel}(\boldsymbol{x}) = \sum^{n} sin(\sqrt{|x_i|}) \quad \ldots\ldots\ldots \quad (4)$$

where $\boldsymbol{x}$ denotes an n-dimensional vector and x_i the i^{th} element of vector $\boldsymbol{x}$ (**Fig. 3**). The ordinate is inverted through division by 1 after being normalized to $[0,1]$ to establish uniform criteria for subsequent tests so that the higher the evaluation, the higher the degree of adaptability to the environment.



(a) Sphere Function (b) Schwefel Function

Fig. 3. Surf Plots of Functions used in Tests.

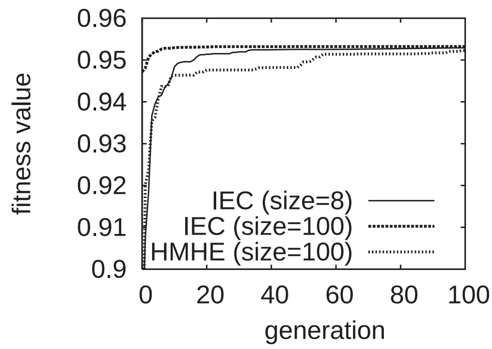


Fig. 4. Results of Sphere Function (Two-Dimensional).

We tested these two functions when HMHE is used (population size: 100) and not used (population size: 8 and 100). For the population size in a gene pool, HMHE would allow unlimited use of all population size in any test with HMHE including this performance test, but too large a population would take too long for calculation in SOM learning and further induce user fatigue. Since our preliminary test showed that HMHE performance could be evaluated even for a 100-population size, we used a population of 100 for EC using HMHE and also for EC not using HMHE for comparison. In this performance test and subsequent test evaluation with HMHE on a population size of eight (8), evaluations without HMHE were done on the same population size for comparison. Since both functions were two-dimensional, the gene type was expressed as a sequence of real values, and phenotype, also by two dimensional vectors (x_1, x_2).

Next-generation genetic groups were generated based on elite conservation strategy: 40% of genes survive into the next generation and the remaining 60 % is generated from parent genes selected from the surviving 40 % through roulette by fitness. Searching was conducted without using crossover by applying mutation to a gene locus (array element) within the chromosome. For HMHE, a hexagon map with sides of four elements (total elements: 37) was used for the SOM. With the distance between genes being Euclidean, eight genes consisting of genes near seven points, i.e., the center of the map and six vertices of the hexagon, and a representative gene of the previous generation were selected as representative.

3.2.2. Results

Figure 4 shows the transition of fitness values in a sphere function (abscissa: generation; ordinate: fitness),

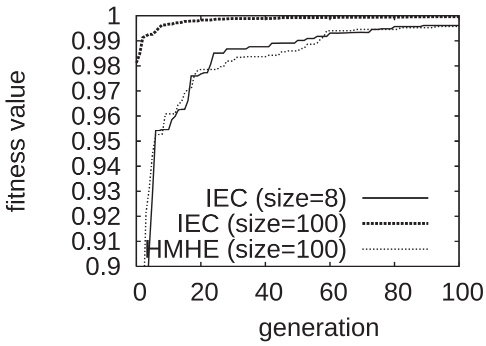
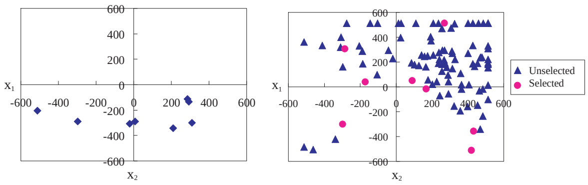


Fig. 5. Results of Schwefel Function (Two-Dimensional).



(a) IEC (size = 8) (b) IEC+HMHE (size = 100)

Fig. 6. Genetic Data by Two-Dimensional Schwefel Function.

representing average maximum fitness in ten trials under each condition. For the sphere function, HMHE was inferior in performance in the initial search for IEC (size = 100) and IEC (size = 8).

For the polymodal Schwefel function, HMHE showed performance equivalent to IEC with size = 8, although far inferior to IEC with size =100 (**Fig. 5**).

Figure 6 shows genetic data of generation 100$^{\text{th}}$ obtained by optimizing genes as two-dimensional real number vectors using the Schwefel function (abscissa: genetic data x_1; ordinate: genetic data x_2), and round and triangular plots in **Fig. 6(b)**, HMHE-selected and unselected genes. This confirms that increased population size in using HMHE extends the search range and that gene selection by the SOM presents to users genes distant from each other (**Fig. 6(b)**).

3.2.3. Discussion

Test results show that HMHE is inferior in performance to an ordinary IEC with the same population size. When IEC is applied to human-robot interaction, however, what matters is search capabilities in limited evaluation time in view of user fatigue. For us, it is therefore more important to compare the case of the same number of evaluations rather than that of the same population size.

A comparison of the two cases under the same condition, i.e., HMHE and conventional IEC with population size = 8, shows that conventional IEC is superior to HMHE in the single-modal sphere function. Ordinary IEC increases fitness monotonously, but HMHE uses representative genes for evaluation to calculate fitness based on similarity to representative genes and cannot searching unless representative genes are extreme.

Behaviors that users prefer in interaction between users and robots is so diversified that it presents polymodality.

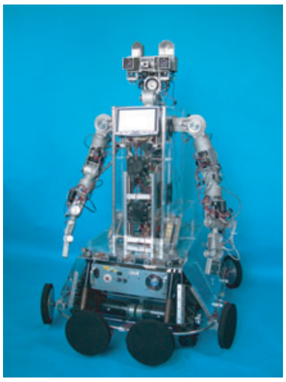


Fig. 7. WAMOEBA-3.

For the polymodal Schwefel function, IEC using HMHE closely matches conventional IEC in performance. Using HMHE enables much wider searching than conventional IEC and ensures dispersion of genes presented to users.

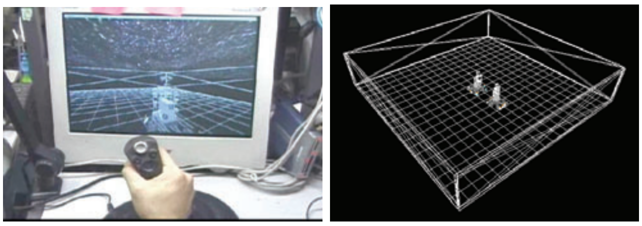
While IEC using HMHE ensures diversity in solutions and a very wide search range, uncertainties in the estimation of fitness for unselected genes may lead to poorer learning convergence. In interaction with users, however, learning convergence will not depend on evaluation axis transition, so it is more important to maintain the diversity of genes that will enable continuous learning during interaction.

4. Mounting in Interaction System

We implemented our proposed HMHE into interaction system using a simulator to validate the effectiveness of our proposal in user-robot interactions. For experiments, we used a simulator to verify behavior of the Waseda Artificial Mind on an Emotion Base (WAMOEBA-3), arranging two robots in virtual space inside the simulator and a user manipulating one of the two robots interacting with the other robot complete with a behavior-generation algorithm.

4.1. WAMOEBA-3

We developed WAMOEBA-3 (**Fig. 7**), a platform for experiments in human-robot communications. WAMOEBA-3 is 1316 mm high, 825 mm wide, and 656 mm deep, i.e., about the height of an elementary school student. We consider it advantageous in communication for a robot to be humanoid, so WAMOEBA-3 has two arms with 6 DOF and a head with 8 DOF, plus several sensors. The head has two CCD color cameras, two microphones, and one speaker. Each camera and auricles (ears) turn left and right independently and represent a direction of attention in each mode. We used an omnidirectional vehicle to move WAMOEBA-3, enabling small slewing radii and omnidirectional movements to enhance safety in interaction with users. The vehicle has ultrasonic sensors, contact switching sensors, etc., enabling the robot to move, measure distances to users, and evade walls and other obstacles.



(a) Subject's View (b) Environment

Fig. 8. Simulator and Environments in Virtual Space.

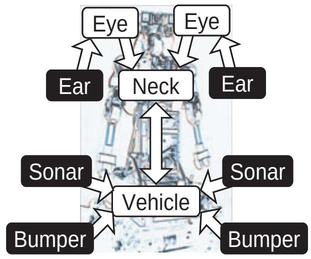


Fig. 9. Motor Agent Network for Experiments.

4.2. Interaction Simulator

In experiments, we used a simulator to verify WAMOEBA-3 activity (**Fig. 8**). Inside the simulator, there were no solid textures or obstacles that would psychologically affect users, apart from the two robots. One robot has a behavior-generation algorithm and users manipulate the other robot using a joystick with force feedback to interact in virtual space. Users can get the robot to move around or turn its head by manipulating the joystick, and can have the robot speak by pushing a button. Potential contact with a wall or robot is presented via force feedback.

4.3. Behavior Generation Algorithm

The behavior generation algorithm for WAMOEBA-3 used motor agents, an autonomous distributed behavior generation algorithm[12]. This algorithm generates reflexive behavior in a communication robot such as WAMOEBA-3. Each motor in the motor agent determines its own direction of turning and velocity, based on the weighted sum of sensor information collected from the network.

Equation (5) determines the output of each motor:

$$\dot{\theta}_i = \lambda_i \sigma_i(x_i) - \delta_i \theta_i \quad \ldots\ldots\ldots \quad (5)$$

$$\sigma_i(x_i) = \exp\left[-\gamma_i (x_i - c)^2\right] - \exp\left[-\gamma_i (x_i + c)^2\right] \quad \ldots \quad (6)$$

$$x_i = \sum_{m=0}^{j} \omega_{ji} s_j \quad \ldots\ldots\ldots\ldots \quad (7)$$

where $\dot{\theta}_i$ indicates the output angular velocity of the i^{th} motor agent, the first member commands calculated based on information from the sensor network, δ_i in the second member a constant for stabilization, σ_i a sigmoid function as defined by Eq. (6) having two gentle steps where a negative value is given to $x < 0$ and a positive value to $x > 0$, γ_i is the more steps a function has and the wider the dead zone near $x = 0$; x_i is the sum of values obtained by multiplying sensor network information by a coupling coefficient as determined by Eq. (7), ω_{ji} coupling strength with the i^{th} motor agent and the j^{th} sensor, and s_j indicates normalized input of the j^{th} sensor such as an encoder or switch.

Motor agents must define a network of motors and sensors connected by weighted coupling to collect information from sensors (**Fig. 9**).

Below are examples of interaction in the motor agent network.

- Touching touch sensors around the vehicle turns the robot toward an object or a user, or turns it inversely while making the vehicle move back and forth or left and right. The camera also turns in each direction.
- If a user speaks, the camera and head move.
- A user standing near the robot triggers the ultrasonic sensor and makes the vehicle move back and forth or left and right.
- Following the movement of the camera and head, the vehicle turns in the same or opposite direction.

4.4. Genetic Description and Evolutionary Computation Parameters

To optimize a controller consisting of the above motor agents by IEC, ω in Eq. (7) corresponding to the network's coupling strength was input to gene, while parameters such as γ, functional-linearity values, were made constant. Each parameter was described using real numbers, and genes were arrayed using real values with 27 dimensions consisting of coupling strength of 27 connections: from a microphone to a camera, from a camera to the head for turning, from a camera to the head for up-down movement, 12 connections between four ultrasonic sensors and three vehicle movements, and 12 connections between four touch sensors and three vehicle movements.

Experiments used crossover realized by random exchanges of array elements so that robot behavior parameters on genes, concentrated in the head, vehicle, etc., would be propagated all together within each group. If mutation occurred whose ratio was set at 1 % for each array element, random values were added. Of parent genes selected by roulette, individuals having 40 % epistatic genes are inherited by the next generation in what is called elitism.

4.5. HMHE Setup

The number of individuals was set at 50 so that learning time taken by the SOM during experiments was about 10 seconds in view of preliminary experiment results.

For the SOM, for which quadrangular and hexagonal neighborhood functions are generally used, we used the hexagonal neighborhood function setting the number of neurons on the cognitive layer to 37 (4 elements on one side of a hexagonal map) based on results of preliminary experiments on learning time and convergence on the cognitive layer.

We used a Euclidean distance to define the distance between genes used for learning by the SOM and estimation of fitness values.

5. Evaluation Experiments

Using the interaction system above, we conducted evaluation experiments among users, who were nine of our university students. In experiments, which are based on (1) conventional IEC (population size = 8) alone and (2) IEC using HMHE (population size = 50, 8 evaluations), 10 attempts at evaluation were conducted from generation 0 of an initially generated gene pool to generation 9. Since sequential effects cannot be ignored in these experiments, the user sequence was changed for each experimental condition. Once experiments were completed, we conducted a t-test for each sequential condition with no significant difference between the two condition.

We also surveyed users during and after experiments to determine their work loads, as detailed in the sections that follow.

5.1. Experimental Setup

Information given to users before experiments was as follows:

1. The robot has a microphone fitted in its ears and can react to sound.
2. The counterpart robot does not use a camera.
3. The robot's arms do not move.
4. Ultrasonic sensors on the robot recognize distance to objects or walls.
5. Switches on the vehicle detect contact.
6. Score the robot presenting interesting behavior out of a total of 100 points (perfect score).

Users then did a trial experiment for one generation to ensure that they understood the experimental flow, and practiced operating the simulator. After a break, users conducted experiments.

When we apply IEC to a survey on impressions made by robots, questions should be prioritized based on a single fitness value based in turn on a weighted sum, but it is difficult given individual differences among users, to set priorities in advance. Based on the task load index (NASA-TLX), users should determine their own priorities of items such as mental demand, physical demand, time demand, self-performance, effort, and frustration. In this study, involving a large number of experiments, however, evaluations were based on a single evaluation axis given the burden on users determining priorities. Users were allowed to input evaluation values at any timing.

Table 1. Survey Questions (after Haga et al.).

Item	Details
1	Concentration was needed.
2	Work was done as desired.
3	Motivation was lacking.
4	I wanted to take a break.
5	I became sleepy.
6	I was too busy to rest.
7	The work was boring.
8	I felt tense.
9	I worked very hard.
10	I could not concentrate on the work.
11	I wanted to stop the work before it was finished.
12	I felt like going to sleep.
13	I was pressed for time.
14	I wanted to get away from the work.

5.2. Questionnaire

To determine user work loads, we surveyed evaluations for every three generations after completion of evaluation of generation 0. For questions, we used the burden survey proposed by Haga et al. [13] (**Table 1**).

Users gave each question (14 in total) to 5 points. The 14 items were classified into the following seven pairs: items 1 and 8 (difficulty); items 6 and 13 (busyness); items 3 and 10 (difficulty in concentration); items 7 and 14 (boredom); items 5 and 12 (sleepiness); items 4 and 11 (tiredness); and items 2 and 9 (accomplishment). The points given to each pair yielded a score for each category.

In these experiments, we used the above burden survey, initially developed to measure the work load of a train operator, because it presented an environment similar to simulator operation.

6. Experimental Results

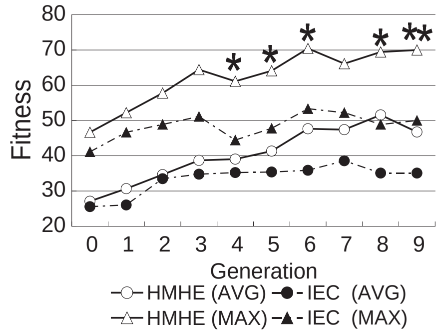
Evaluation by a single user took about 100 seconds and one user spent about two hours in evaluation.

6.1. Fitness Value Transition

Fitness values by IEC alone tended to stagnate in growth in generation 5 and after, while HMHE-combined IEC maintained growth, meaning combined use of HMHE in IEC showed higher fitness than conventional IEC later on in experiments (**Fig. 10**).

6.2. Diversity in Interaction

The interaction system we used in experiments dealt with the following interactions: a user walking around a robot observes whether the counterpart robot turns toward



(* $P < 0.05$ (* $P < 0.01$)

Fig. 10. Fitness Value Transition.

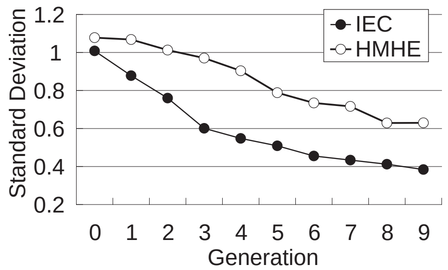


Fig. 11. Standard Deviation of Genetic Data Presented to Users.

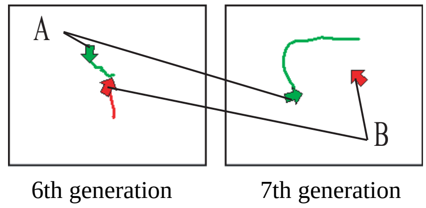


Fig. 12. Changes in Interaction between Generation: A indicates the movement path of the robot manipulated by the user and B, the movement path of the preprogrammed robot.

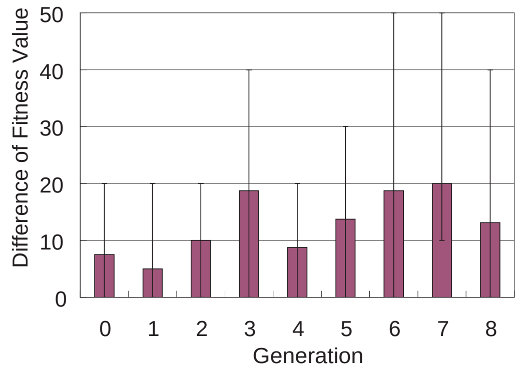


Fig. 13. Variations in Fitness Values of Most Elite Individual between Generations.

the user; the user observes robot reactions to the user's speech; the user observes how the robot reacts when the user touches the robot.

6.3. Maintenance of Gene Diversity by HMHE

We analyzed the maintenance of gene diversity by HMHE (**Fig. 11**). Standard deviation (S_D) was calculated using the following equation:

$$S_D(\boldsymbol{x}) = \sqrt{\frac{\sum_{i=0}^{n}(x_i - \bar{x_i})^2}{n}} \quad \cdots\cdots\cdots \quad (8)$$

where x_i indicates the i^{th} element of vector $\boldsymbol{x}$, part of genetic data, and $\bar{x_i}$ the average of all x_i for all genes in the gene pool.

Compared to IEC alone, we confirmed that use of HMHE with IEC ensured that genetic data remained dispersed during experiments.

6.4. Changes in User Evaluation Axes

In an example of robot movement output by the simulator (**Fig. 12**), robot A is manipulated by the user and robot B is programmed. Two types of movement indicate interactions for individuals with the same gene in different generations. For generation 6, the user observed robot behavior at a constant distance from the robots approaching the user. For generation 7, the user walked around robots from the counterpart robot's right side as soon as the experiments started and observed robot reactions to user speech. As a result, the robot won 90 points in evaluation in generation 6 but scores dropped to 50 in generation 7.

We analyzed changes in fitness values by users. In experiments, users were presented with seven individual robots with genes selected by the SOM for HMHE and the best individual robot in the previous generation to determine how the best individual robot in the previous generation was evaluated in the next generation (**Fig. 13**). This represents an average absolute value of differences in fitness values for the most elite individual between preceding and subsequent generations, excluding the value marked by one of the nine users that noticeably differed from others. This represents whether interactions by the most elite individual in each generation were evaluated highly or lower in the next generation, and thus is a good indicator of changes in user evaluations. Results for changes in fitness values were widely dispersed, particularly between generation 3-4 and 6-7.

6.5. Survey Findings

In survey findings by generation for combined use with HMHE, scores for tiredness in generation 3, for boredom and difficulty in concentration in generation 6, and for difficulty in concentration in generation 9 were significantly lower (**Fig. 14**). No significant differences were seen, however, in categories such accomplishment, difficulty, busyness, and sleepiness.

7. Discussion

7.1. Maintenance of Diversity in Interaction

HMHE was developed for and implemented in a communication robot to avoid user boredom by maintaining

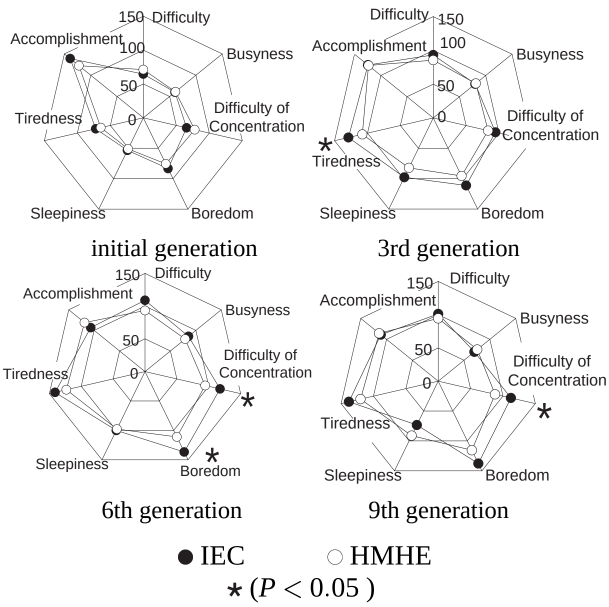


Fig. 14. Comparison of Survey Findings.

diversity in the gene pool. In comparison to conventional IEC by a simulator, use of HMHE significantly increased fitness values in the later part of experiments (**Fig. 10**). Differences in fitness values thus appeared to reflect changes in evaluations by users, i.e., their degree of boredom.

Effects of HMHE are due to the maintenance of diversity in the gene pool (**Fig. 11**). The ability to retain different genes in a gene pool at all times thus appears to have enabled a variety of behaviors to be presented to users.

7.2. Changes in Evaluation Axes of Users

A detailed look at the transition of fitness values among generations (**Fig. 10**) showed that timing when fitness values dropped coincided with changes in evaluation axes between generations 3-4 and 6-7 (**Fig. 13**), apparently indicating that users were so bored with monotonous experiments that they used different evaluation axes between generations 3-4 and 6-7, resulting in decrease in overall fitness values. Changes in evaluation axes are inevitable in an interaction experiments.

HMHE appears to cope with changes in evaluation axes of users by increasing the population size, meaning that even if evaluation guidelines of users are changed, it is possible to produce genes closely approximating new evaluation guidelines as long as diversity within a gene pool is maintained. This is why fitness values did not decrease in the later part of experiments.

7.3. Calculating Distances between Genes in HMHE

Survey findings confirmed the effectiveness of HMHE in handling psychological burdens such as boredom, so no differences were recognized in items such as difficulty and accomplishment in learning effects. Accomplishment used in these experiments refers to accomplishment of a robot in learning, i.e., whether a robot comes to behave as desired by a user. Effects of HMHE are limited to the avoidance of user boredom and do not directly affect accomplishment in learning.

Why an increased number of genes did not improve accomplishment lies in the method for calculating distance between genes. In HMHE, fitness values are automatically calculated by the program assuming that genes closer to each other will receive similar fitness values, whereas in interaction between robot and users, distance between genes as parameters for a robot does not always coincide with distance between user evaluation of interaction. In these experiments, we used genes expressed as real numbers and Euclidean distance, which, however, requires further consideration.

According to user opinions of interaction, some coupling strength in the motor agent network, e.g., touch sensors on the back, used in these experiments does not directly affect overall impression, but others do affect such considerations significantly, e.g., those related to vehicle and head movement. This suggests that effects can be improved by calculating distance using weighted elements rather than simple Euclidean distance, with weights acquired during learning.

7.4. HMHE Effects and Scope of Application

Although the interaction system using IEC with HMHE does not greatly improve learning efficiency, it requires only a small number of evaluations while retaining the diversity of genes in individuals presented to users. Results of evaluation experiments showed significant improvement in boredom and tiredness, but not in accomplishment of learning by interaction. It also could cope with changes in evaluation axes during long-term experiments.

This suggests that in adaptive interaction using IEC, the trilateral trade-off of learning efficiency, number of evaluations, and diversity should be addressed by prioritizing the diversity of behavior and lightening the burden on users rather than learning efficiency so that user do not become bored in long-term interaction.

This interaction, which places less emphasis on learning efficiency, can be better applied to areas that require long-term interaction, rather than to tasks whose accomplishment is related to serious problems such as user safety. The system used in these experiments cannot output behavior that takes contexts into consideration and are limited in application to communication based on reactive behavior. We consider it possible, however, to develop communication that adapts to time series interactions by combining the system with a behavior generator such as a recurrent neural network that deals with time series information.

8. Conclusions and Projected Work

We have proposed HMHE in which subjective user evaluations are used together with automatic calculation of fitness values for coping with problem of user boredom and tiredness arising when IEC is applied for acquisition of behavior by a communication robot. Application of IEC to human-robot interaction involves the problem of balancing learning efficiency, user boredom due to early convergence, and tiredness due to increased population size. To cope, HMHE is programmed to automatically calculate fitness values of remaining genes by referencing subjective user evaluations. Results of performance tests and simulation showed that HMHE effectively reduces user tiredness and boredom, although no significant improvements were seen in learning efficiency.

Our results suggest that the trilateral trade-off of learning efficiency, gene diversity, and burden on users can be better addressed by emphasizing the maintenance of diversity and the reduction of burden on the user rather than pursuing learning efficiency. HMHE, which generates a variety of genes with a small number of evaluations, proved effective in enabling the above balance.

In repeated experiments using actual robots with IEC, we confirmed that IEC with HMHE proceeds with learning by adapting itself to users' changing preferences [14]. We are planning to conduct experiments over a longer term.

The system we used has a number of shortcomings: Since no dynamic changes are incorporated in genes of phenotype robots, users will be bored quickly and shortened time of evaluations by users may prevent users from evaluating robots appropriately. To overcome such shortcomings, we have introduced intensive learning into robot behavior generation algorithms and optimized reward functions by IEC. This is expected to create adaptability of IEC on a group level, and learning efficiency of IEC and diversity of behavior on an individual level, thereby lengthening user interaction time.

The behavior generation algorithm we used is a simple reactive-behavior generator that cannot deal with time series information. We are therefore planning to introduce a behavior generator that deals with context information, such as a recurrent neural network.

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References:

[1] H. Takagi, "Interactive Evolutionary Computation:Fusion of the Capabilities of EC Optimization and Human Evaluation," Proc. of the IEEE Special Issue on Industrial Innovations Using Soft Computing, Vol.89, No.9, 2001.

[2] H. Kitano, "Genetic Algorithm 2," Sangyou-Tosho, pp. 72-87, 1995 (in Japanese).

[3] T. Inamura, M. Inaba, and H. Inoue, "Acquisition of Probabilistic Behavior Decision Model based on the Interactive Teaching Method," Proc. of the Ninth Int. Conf. on Advanced Robotics (ICAR'99), pp. 523-528, 1999.

[4] J. J. Grefenstette, "Genetic algorithms for changing environments," Proc. of 2nd Parallel Problem Solving from Nature, pp. 137-144, 1992.

[5] H. G. Cobb, "An investigation into the use of hypermutation as an adaptive operator in genetic algorithms having continuous, time-dependent nonstationary environments," NRL Memorandum Report 6760, 1990.

[6] T. Ogata, S. Sugano, and J. Tani, "Open-end Human-Robot Interaction from the Dynamical Systems Perspective -Mutual Adaptation and Incremental Learning, Advanced Robotics," VSP and Robotics Society of Japan, Vol.19, No.6, pp. 651-670, July, 2005.

[7] N. Mitsunaga, C. Smith, T. Kanda, H. Ishiguro, and N. Hagita, "Robot Behavior Adaptation for Human-Robot Interaction based on Policy Gradient Reinforcement Learning," Proc. of the 2005 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2005), pp. 1594-1601, 2005.

[8] J. A. Bildes, "GenJam: A Genetic Algorithm for Generating Jazz Solos, Proc. of Int. Computer Music Conference (ICMC94), pp. 131-137, 1994.

[9] H. Lund, O. Miglino, L. Pagliarini, A. Billard, and A. Ijspeert, "Evolutionary Robotics - A Children's Game," Proc. of IEEE Int. Conf. on Evolutionary Computation (ICEC '98), pp. 154-158, 1998.

[10] M. Nagao, M. Yamamoto, K. Suzuki, and A. Ohuchi, "Evaluation of the Image Retrieval System Using Interactive Genetic Algorithm," Journal of Japanese Society for Artificial Intelligence, Vol.13, No.5, pp. 720-727, 1998 (in Japanese).

[11] T. Kohonen, "Self-Organizing Maps," Springer-Verlag, Berlin Heidelberg, 1995.

[12] T. Ogata and S. Sugano, "Emotional Communication Between Humans and the Autonomous Robot which has the Emotion Model," Proc. of IEEE Int. Conf. on Robotics and Automation (ICRA'99), pp. 3177-3182, 1999.

[13] S. Haga, "Theory and Measurement of Mental Workload," Japan Publishing Service, 2001 (in Japanese).

[14] Y. Suga, Y. Ikuma, D. Nagao, T. Ogata, and S. Sugano, "Interactive Evolution of Human-Robot Communication in Real World," Proc. of IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS2005), August, 2005.

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