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高木, 英行

Department of Acoustic Design, Kyushu Institute of Design

OHYA, Kimiko

Department of Acoustic Design, Kyushu Institute of Design

OHSAKI, Miho

Department of Acoustic Design, Kyushu Institute of Design

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Improvement of Input Interface for Interactive Genetic Algorithms and its Evaluation

Hideyuki TAKAGI

Kimiko OHYA

Miho OHSAKI

Kyushu Institute of Design, Dept. of Acoustic Design 4-9-1, Shiobaru, Minami-ku, Fukuoka 815, Japan

Phone : +81-92-553-4555, Fax : +81-92-553-4569, E-mail : takagi@kyushu-id.ac.jp

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Abstract— This paper proposes an input method that allows interactive GA operators to use discrete fitness values to reduce their psychological stress to input and evaluates its advantage and disadvantage. We investigate the influence of the quantization noise of discrete fitness values on convergence by simulations. The result shows that the quantization noise does not make convergence worse significantly. From the practical point of view, the proposed method and its variation that combines both discrete and continuous fitness values are evaluated using two subjective tests for the task of drawing a face. The results of the subjective tests show that our proposed method and its variation can reduce psychological stress of interactive GA operators significantly.

1 INTRODUCTION

1.1 Interactive GA

Interactive genetic algorithms (GA) is used to design systems based on human preference. Most applications of the interactive GA deal with drawing figures or creating images which are spatially presented. Although there are time sequential applications of the interactive GA, the number of the applications are not many[9, 1, 2].

The problem of the interactive GA is that the psychological burden of interactive GA operators is rather big. The interactive GA uses human evaluation characteristics as a fitness function and requires the human to evaluate GA individuals in each generation. It is difficult for humans to compare time sequential outputs such as acoustic signals, therefore the psychological burden of the operators is bigger than that when they compare outputs at the same time.

The psychological burden of the operators and the fluctuation of fitness values become bigger as the number of generation advances in time. It is difficult to express slight

difference of impressions between individuals as a value.

1.2 Input method of discrete fitness values

We have proposed an input method that allows discrete fitness values to be used as a new method of improvement of interactive GA interface to reduce the psychological burden of interactive GA operators.

It is psychologically difficult to distinguish and score objects which are slightly different. If we allow human operators to roughly score the given objects, the psychological stress for them could be reduced. The definition of discrete/continuous fitness values in this paper is a psychological definition. Suppose that we can easily evaluate given stimuli with several levels of quantized fitness values but cannot distinguish them with hundreds of levels of quantized fitness values. Then we say that the former is discrete and the latter is continuous.

There are several variations of realizing this proposed method from using only discrete fitness values to using free combinations of the discrete and continuous fitness values. The essential point of our proposal is to introduce the input method of discrete fitness values.

1.3 Advantage and disadvantage of the proposed method

The proposed method has both disadvantage and advantage. Due to quantization noise of discrete fitness value, the GA convergence may become poor, and elitist strategy sometimes does not work, because same highest scores are given to different GA individuals. We evaluate how this disadvantage is serious in the next section.

The advantage of this method is to be able to reduce the burden of interactive GA operators. In section 3, we evaluate how the proposed method can reduce human burden through subjective tests.

2 EVALUATION OF THE DISADVANTAGE OF THE PROPOSED METHOD

2.1 The effect of quantization noise in fitness values

To evaluate whether the quantization noise of discrete fitness values makes GA convergence worse, two simulations are conducted.

2.1.1 Simulation I: under the ideal condition

We compare the convergence characteristics of two input methods with precise fitness values: proposed method that deals with discrete fitness values and conventional input method that deals with continuous one.

This simulation uses the error between prepared searching target and GA individuals as score. Since fluctuation of human evaluation is not included in this simulation, this is an ideal case when human can evaluate individuals exactly.

Different fitness value steps ($n=15, 13, 11, 9, 7, 5, 3$) are used to evaluate our proposed method, because quantization noise becomes bigger as the number of the step becomes fewer.

One GA simulation is conducted till 1,000 generations, and the simulation is iterated 10 times with different initial individuals. The average convergence curve of 10 simulations is stored as the result of each fitness value step.

2.1.2 Simulation II: with considering the fluctuation of human's evaluation

Next, we simulate GA tasks using discrete fitness values method with considering the fluctuation of human evaluation. Fitness values that interactive GA operators score based on their psychological measure must fluctuate slightly. As this fluctuation is considered as noise in evaluation, the evaluation of quantization noise that is the disadvantage of our proposed method should be conducted under not the only ideal condition but also the condition with fluctuation noise.

Fluctuation characteristics is obtained previous to this simulation II. The characteristics is obtained from analyzing the deviation of human evaluation to same stimuli, drawing faces used in section 3.1. Random noise based on the obtained characteristics is added to fitness values in the simulation II to simulate human evaluating.

In this previous experiment, 3 sets of 20 drawing faces are used. The fluctuation of human evaluation might become smaller according to GA convergence. Therefore, 3 sets of faces generated in 1st, 10th, and 20th generations are used. To avoid memory effect, 3-generation sets are successively given, and 20 faces in each set are randomly and spatially displayed in each iteration. This iteration is conducted five times.

The final fluctuation characteristics is calculated by combining data in all generations, because the deviation

of scores in three generations are similar against our expectation. Figure 1 shows standard deviation of human evaluation for each fitness value and a fitness function that approximates the observed data with a quadratic function. Fluctuated fitness values are generated as $x + rand(f(x))$, where x is true fitness value, $f(x)$ is the quadratic fitness function, and $rand(a)$ generates uniform random value whose range is $[-a, +a]$.

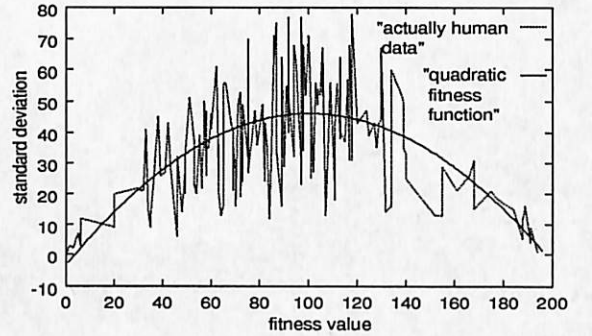


Figure 1: Human fluctuation of scoring and a quadratic fitness function as its fluctuation model.

2.2 The results of simulations and discussion

Figure 2 and 3 show the average convergence curve of simulations I and II, respectively. As human cannot use the interactive GA for many generations due to burden [5], practical number of generation, first 20 generations, are shown in the figures. There is no difference between discrete and continuous methods for all discrete fitness steps under both the ideal condition and the condition with fluctuation of human's evaluation.

From the both results of simulations I and II, the quantization noise dose not make convergence worse till the number of generations increases significantly.

To make sure whether the Figure 2 and 3 converge to local minimum, we change mutation rate when the convergence curve becomes flat, 300th generation. However, there is no significant difference on the convergences, which implies the convergences may reach to global minimum.

3 EVALUATION OF THE ADVANTAGE OF THE PROPOSED METHOD

3.1 Evaluation of convergence characteristics of discrete fitness values

To evaluate how the proposed input method is effective to reduce psychological burden, two subjective tests are conducted: the method of successive categories[3] and a variation of Seffé's method of paired comparison[8, 4].

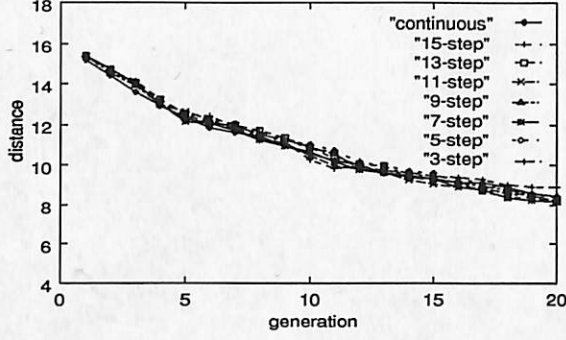


Figure 2: Convergence curve of simulation I under the ideal condition

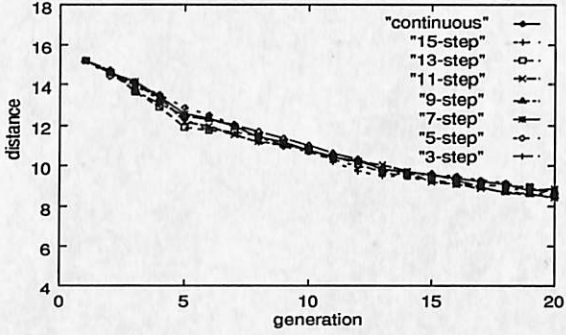


Figure 3: Convergence curve of simulation II with considering the fluctuation of human's evaluation

To compare our proposed method and the continuous fitness value method in different presentation ways, we select 4 conditions shown in Table 1.

3.1.1 Experiment I: Evaluation of discrete fitness value method

The effect of discrete fitness value method is evaluated using conditions 1, 2, and 3.

18 subjects are separated into 3 groups of 6 to avoid order effects. Different orderings of pairs to be compared are given to the three groups as follows. Each subject take a rest to forget any effects of combinations.

group A	1-2	3-1	2-3	rest	2-1	3-2	1-3
group B	3-1	2-3	1-2	rest	1-3	2-1	3-2
group C	2-3	1-2	3-1	rest	3-2	1-3	2-1

where the number in the table are in Table 1. For example, 1-2 means a combination of conditions 1 and 2.

Drawing a face is the task used in our interactive GA experiment. 5-step fitness values for the discrete fitness

Table 1: Conditions used in section 3.1. 'Combination' in input method means the combination of discrete and continuous input methods.

condition	input method	presentation
1	continuous	simultaneous
2	continuous	sequential
3	discrete	sequential
4	combination	sequential

value input method and 196-step fitness values for the continuous fitness value input method are used in this experiment.

3.1.2 Experiment II: Evaluation of a combination of discrete and continuous fitness value methods

We evaluate a variation of proposed method that allows both discrete and continuous fitness values. By analyzing the subjects' reports in experiment I, we found that the discrete fitness value input method increased operator burden when the operators wanted to input more precise fitness values than the quantized level of the input method allowed.

Then we think that a combination of discrete and continuous fitness value methods is more effective than either method. In this method, interactive GA operators can input precise fitness values after inputting fitness values roughly.

To evaluate the combination method as a variation of discrete fitness value method, we select conditions 3 and 4.

10 subjects are separated into 2 groups of 5 to avoid order effects. Different orderings of pairs to be compared are given to the two groups as follows.

group D	3-4	one week	4-3
group E	4-3	one week	3-4

where the number in the table are in Table 1. For example, 3-4 means a combination of conditions 3 and 4.

3.2 Experimental results and discussion

Table 2 shows the results of Seffé's method of paired comparisons for both experiment I and II.

The result of the method of successive categories for experiment I shows that condition 2 and condition 3 belong to different categories, respectively. It can be concluded from the results of the method of successive categories and Table 2 that the discrete fitness value input method significantly decreases operators' burden more than the continuous one does.

The result of the method of successive categories for experiment II shows that condition 3 and condition 4 belong to different categories, respectively. It can be concluded from the results of the method of successive categories and Table 2 that combination of continuous and discrete fitness value input method significantly decrease operator burden more than the discrete one does.

From the result of experiment I and II, we may expect that the combination method in time sequential display almost clears away the operators' burden caused by time sequential display.

Table 2: Statistical test for significant psychological differences obtained by Sheffé's method of paired comparisons.

a pair of conditions	2 vs. 3	3 vs. 1	3 vs. 4
test	significant	not significant	significant
result	($p < 0.01$)	($p < 0.05$)	($p < 0.01$)

4 CONCLUSION

To make the interactive GA practical, we have proposed a method for inputting fitness values that requires less human burden: discrete fitness value input method.

We have simulated GA tasks to evaluate the effect of quantization noise of discrete fitness values on convergence under two conditions: with and without fluctuation of human evaluation. Under each condition, the result has shown that the quantization noise does not make convergence worse.

Through subjective tests, we have shown that the proposed method can decrease the operator's burden more than the frequently-used continuous fitness value input method can. Furthermore, we have proposed a combination of discrete and continuous methods as a variation of

the original proposed method. The results of subjective tests have shown that the combination method decreases the burden when stimulus are presented sequentially same as that when stimulus are presented specially.

To make the interactive GA practical, we are going to continue improving not only input interface but also presentation interface [7, 6].

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