

Interactive GA for System Optimization: Problems and Solution

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Interactive GA for System Optimization: Problems and Solution

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This paper discusses how to make an interactive GA practical for system optimization based on human subjective. First, we points out that the problem of the interactive GA is that it forces human burden. Then, we propose methods that improve inputing and presenting interface. Through subjective tests and a simulation, we show how these proposed methods reduce human burden.

1 Introduction

Many optimization techniques have been proposed, and we have applied these techniques for system optimizations. Control tasks, adaptive signal processing, filter design, etc. are the typical system optimization tasks.

Most of these system optimizations have target specifications, and the auto-optimization techniques try to minimize the error between the given specification and the output of an actual system. Not only supervised approaches but also reinforcement approaches have similar sense. This is, most of auto-system optimizations have numerical goal.

When we cannot make a cost function to optimize a system, how should we optimize the system ? Suppose to optimize the parameters of a sound synthesizer to create sound that matches to the sound image *in my mind*, to optimize the parameters of computer graphics to create graphics that matches to *given design concept*, to adjust a hearing aid to its user's *hearing perception*, to control air condition or a vehicle to let people in a room or in a car *comfortable*. It is easy for human to judge the performance, but can we make a mathematical cost function that has similar evaluation characteristics for preference that human has ?

These system optimizations that have no numerical goal are our new challenging tasks. There are two approaches for this system optimizations; One is to make a precise model of human evaluation, and another is to combine human itself with auto-optimizing techniques. System optimization using an interactive GA (genetic algorithms) is the latter approach.

After surveying the interactive GA in the next section, this paper discusses problems of interactive GA, proposes two solutions that improve the interfaces of input and presentation, and evaluates them.

1.1 Interactive GA and its applications

Interactive GA is a GA that includes human as a fitness function. Human is good to evaluate systems with his/her sense from general points of view. Computer is good to searching solutions. The interactive GA combines the both strong points.

Figure 1 is a block diagram of the interactive GA for optimizing a sound synthesizer, CAD system, or CG system. The GA generates parameters of these systems. The system creates, for example, sound, drawing figures, or graphics according the parameters. A designer or interactive GA operator evaluates the outputs of the system and gives scores to them. The evaluation scores are feed-backed to the GA as fitness values. The applications of the interactive GA is not limited to the world of art but can be used for engineering purpose.

Interactive GA has been mainly applied to design images and figures. Some of them are: montage face image generation [3], designing shapes of bug biomorphs [11], creating images, evolving expressions that specify particular sequences of image-processing functions [10], combining interactive evolution with constructive solid geometry techniques to create computer renderings of 3-D forms ("virtual sculptures") [13], general-purpose interactive graphic layout system based on GA [7], the design of a double curvature concrete arch dam [8],

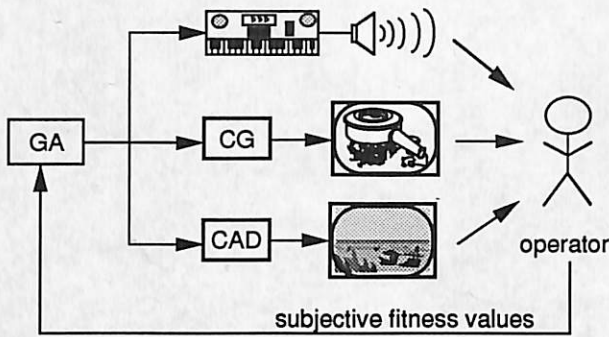


Figure 1: The diagram of the interactive GA for optimizing an example task: a sound synthesizer, computer-aided design, or computer graphics.

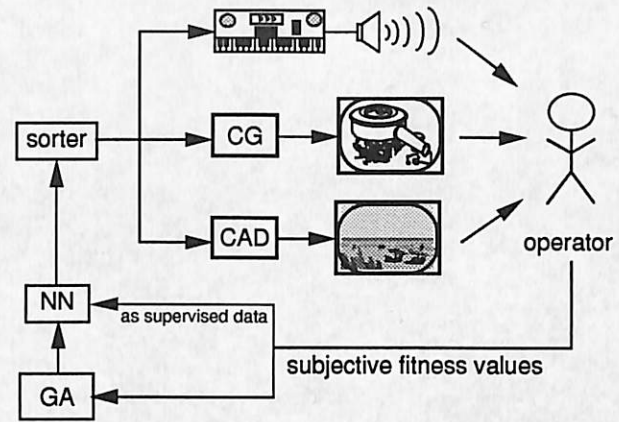


Figure 2: Interactive GA that involves an on-line learning type of NN that learns the characteristics of human evaluation. The NN inputs all individuals, i.e. system parameters, and gives fitness values instead of human, and a sorter sorts the fitness values and decides the display order.

line drawing and application to face drawing [1], and the decision supporting system for aesthetic design of cable-stayed bridges [6].

There are a few applications of the interactive GA to time sequential tasks, such as generating ad-lib melody of jazz that matches to given rhythm and base sections [2], generating rhythms of percussion instruments [4], and speech processing [15].

2 Problem of interactive GA

The biggest problem of the interactive GA is that the physical and psychological burden of interactive GA operators is rather big. It is hard for human to cooperate with machines for long time, while machines do not care about 1,000-iteration or 10,000-iteration searches. The reason why the interactive GA has been mainly applied to image and figure design is that it is easy and less burden for human to compare spatial displays than time sequential ones such as acoustic signal.

To make the interactive GA practical, we must develop techniques which reduce the burden of interactive GA operators. Tasks which cannot be solved without the interactive GA are waiting such techniques.

Some of solutions are to speed up the convergence time and to improve human interface. Speeding up the interactive GA is realized by generic speeding up techniques for general GA. Some of these techniques are several variations of selection, crossover, and mutation, and dynamic parametric GA. Improvement of its interface is a solution peculiar to the interactive GA. Its target is to develop several methods of input, presentation, and display.

This paper proposes input and presentation methods in sections 3 and 4 to reduce psychological burden of interactive GA operators.

3 Improvement of Input Interface

3.1 Proposal of input methods of discrete fitness values

We have proposed the input method that allows discrete fitness values (proposed method #1) and the combinational input method of discrete fitness values and contentious fitness values (proposed method #2) [12]. The latter idea came from the analysis of reports of the subjects who joined subjective tests. The definition of discrete/continuous of fitness values here is based on psychological sense.

The advantage of the proposed methods is to let interactive GA operators feel free to evaluate individuals which are slightly different. The disadvantage of the methods is that its convergence time may become longer due to imprecise fitness values.

Our simulation test has shown that fitness values without quantization error, i.e. the continuous fitness values input method, had converged better than that with quantization error, i.e. the proposed method.

Table 1: Statistical test for significance psychological differences obtained by the Sheffé's method of paired comparisons. P1, p2, A and B are fitness value input methods. P1 is discrete one (proposed method #1) with sequential display; P2 is combination of discrete/continuous ones (proposed method #2) with sequential display; A is continuous one with sequential display; B is continuous one with simultaneous display.

	A vs. P1	P1 vs. B	P1 vs. P2
test	significant	not significant	significant
result	($p < 0.01$)	($p < 0.05$)	($p < 0.01$)

However, this difference appears when GA generation goes far ahead, and there is no bad influence in the generations that human operators can accompany interactive GA [12]. As a conclusion, we can say that there is no problem in practical use.

3.2 Subjective tests and discussion

To evaluate the proposed input methods that use discrete fitness values, two subjective tests are used: the method of successive categories [5] and the variation of Sheffé's method of paired comparisons [9, 14].

Compared input methods in our subjective tests use 5-step fitness values for the discrete fitness value input method and 196-step fitness values for the continuous fitness value input method. These scores are inputted by a sliding bar on X-window using a mouse to avoid the influence of the difference of the number of keyboard strokes.

Drawing face is used as a task of our interactive GA experiment. Eyebrows, eyes, a nose, and a mouse are featured by 18 parameters of their angles and lengths. Subjects are requested to imagine certain image of face in their minds and to score the similarity between the face in mind and faces generated by the interactive GA.

Two presentation methods are used: time sequential and simultaneous presentations. The sequential presentation shows only one face at once, while the simultaneous presentation shows 20 faces spatially. The sequential presentation method is difficult for human operators, because they must compare the current given stimulus with the past stimuli remained in their memory. One of objectives of this research is to develop interfaces that the interactive GA can be practically used for sequential presentation of system outputs.

The result of the subjective test is shown in Table 1 [12]. From this table, it can be concluded that the discrete fitness value input method significantly decreases operator's burden more than the continuous one. Since operators need not care about slight differences among given similar the output of the target system, it results not only less burden but also shortening evaluation time in each generation.

We, also, may be able to conclude that it is easy and less burden for human to roughly score given similar system-outputs in the early stage and to precisely score them in latter stage.

4 Improvement of Presentation Interface

4.1 Simultaneous and time sequential presentations

When the outputs of a system made by all GA individuals are presented spatially at once, it is easy for human to compare and rate them. Furthermore, the output of system that are placed side by side are easier to compare than those placed here and there. Our facial drawing system based on an interactive GA has the function that sorts the given fitness values of drawing faces and re-presents them. Then, human operator can re-check his/her first evaluation easily by comparing faces side by side. Our psychological burden after the sorting is much less than that before the sorting. This implies an important hint to reduce human burden, which became the idea in section 4.2.

However, we cannot use this spatial comparison when the system-output is time sequential signal, e.g. sound or music. In the case of not only sound but also image output, sometimes same situation occurs; precise or big images must be presented on a CRT display one by one. When these system-outputs are time sequentially given to an interactive GA operator, he/she must compare the current given the output of the system with that in the past. This becomes psychological burden of the human operator.

Table 2: Correlation coefficients between the fitness orders that the NN in interactive GA produces and that human operator evaluates. k is the past generation number for training data.

# of generations used for training	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$	$k = 7$
NN trained with absolute measure	0.55	0.65	0.55	0.51	0.54	0.52	0.30
conventional interactive GA	average among $1 \leq k \leq 7 = 0.03$						

4.2 Proposal of embedding NN to learn human evaluation characteristics

If we can make a simulator of the human evaluation and embed it into the interactive GA, the simulator evaluates all individuals, sorts them in scoring order, and presents them according to the order before human operator evaluates the output of the system. Then, the outputs of the system are not presented randomly but in fitness value order. It must be a less burden presentation method for human. Even if in the worst case that the embedded simulator can not emulate the human evaluation characteristics, the presentation order becomes random, which is the case of the conventional method.

We have used a NN for the evaluation simulator. Figure 2 shows the proposed model to improve the presentation interface. The NN learns the characteristics of human evaluation using the system parameters and the subjective fitness values that the operator gives. The system parameters are individuals of the GA. The trained NN inputs new system parameters in the next GA generation and estimates fitness values to each individual by each. The sorter sorts the fitness values given by the NN and decides the sequential order of presentation to the operator.

If the NN has the same characteristics of human evaluation, the human operator need not change the order that is presented from the target system, at least. Even if the NN learning is not perfect and the operator need to change the order or give subjective fitness functions, the partial sorting order is more helpful than the random order that the conventional interactive GA produces.

4.3 Problems and performance

The questions to this proposed model may be:

1. whether a NN can learn the characteristics of human evaluation. Since human cannot keep fixed a completely same psychological measure, the subjective evaluation must be fluctuated. It corresponds to noise in training data.
2. whether a NN can learn with a few training data in high dimensional space. Suppose the interactive GA displays 20 system outputs that are composed of 15 parameters, and the NN use training data in past 3 generations. In this case, the number of training data is 45 in 20-dimensional space. From the sense of normal NN learning, it does not seem that the NN leans the evaluation surface in the 20-dimensional space.
3. even if the above two problems are solved, how the proposed model helps to reduce psychological burden of a human operator.

To evaluate the proposed model, we have conducted the following experiment. First, a human operator uses a normal interactive GA for the drawing-face system mentioned in section 3.2, and both all individuals and fitness values given by the operators are saved. Then, a NN is installed as in Figure 2. Unlikely the figure, the saved data are used instead of the GA and the human in Figure 2.

The dimensional number of searching parameter space is 18, and the number of training data sets is the number of GA individuals, 20. The NN is trained at every generation using past k -generation data sets; the number of training data is $20 \times k$ in 18-dimensional parameter space.

Table 2 shows the result. The absolute measure in the table means that operator tries to give subjective fitness values by keeping a same psychological measure for all generations. The presentation order made by the NN has similarity to that made by human with more than 0.5 of correlation coefficient, while the conventional interactive GA presents randomly.

4.4 Discussion

As the answer to the first question in the previous section, we can say that the NN leans some parts of the characteristics of human evaluation even if the human evaluation is fluctuated, experimentally. In other words,

the human fluctuation is not significantly big for NN training.

Why these good results have been obtained in spite of the second question? Our hypothesis is that the area where the NN is requested to learn is very narrow, while the total parameter space is big. The NN is re-trained every generations using past k -generation data. The trained NN is used for the next generation only. Since the offsprings in the $(n + 1)$ -th generation are mainly made by crossover of parents at the n -th generation, the subjective fitness values to the parameter sets at n -th generation must be very similar to that at the $(n + 1)$ -th generation. Therefore the learning area of the NN can be say relatively smaller. This hypothesis is our answer to the second questions.

The remained is the answer to the third question. This will be obtained through subjective tests for the interactive GA with and without a NN. This is the next step of our research.

5 Conclusion

To make interactive GA practical, we have proposed two methods of improving interfaces to reduce human burden. Through subjective tests and a simulations test, we have shown these proposed methods are effective to reduce human burden.

When we apply the interactive GA to tasks whose output must be presented time sequentially, it is difficult for human operators to evaluate, and human burden increases. The proposed methods help to reduce the burden and expand the practical application tasks of the interactive GA.

References

- [1] Baker, E. and Seltzer, M.: "Evolving line drawings," Graphics Interface'94 Proc., Banff, Alberta, Canada, edited by Wayne A. Davis and Barry Joe. Morgan Kaufmann Publishers, pp.91-100 (May, 1994).
- [2] Biles, J. A.: "GenJam: a genetic algorithm for generating jazz solos," Int'l Computer Music Conference (ICMC'94), Aarhus, Denmark, pp.131-137, (1994)
- [3] Caldwell, C. and Johnston, V. S.: "Tracking a criminal suspect through "face-space" with a genetic algorithm," 4th Int'l Conf. on Genetic Algorithms (ICGA'91), San Diego, CA, USA, pp.416-421 (July, 1991)
- [4] Damon, H.: "Generating rhythms with genetic algorithms," Int'l Computer Music Conference (ICMC'94), Aarhus, Denmark, (1994)
- [5] Dixon, W. J. and Massey, F. J.: "Introduction to statistical analysis," McGraw-Hill, New York, pp.342-343 (1951).
- [6] Furuta, H., Maeda, K., and Watanabe, E: "Application of genetic algorithm to aesthetic design of bridge structures," Microcomputers in Civil Engineering, Vol.10, No.6, pp.415-421 (1995)
- [7] Masui, T.: "Graphic object layout with interactive genetic algorithms," 1992 IEEE Workshop on Visual Languages, Los Alamitos, CA, USA, pp.74-80 (1992).
- [8] Parmee, I. C.: "The concrete arch dam: an evolutionary model of the design process," Int'l Conf. on Artificial Neural Nets and Genetic Algorithms, Innsbruck, Austria, pp.14-16 (April, 1993).
- [9] Sheffé, H.: "An analysis of variance for paired comparisons," *Am. Statis. Assoc. J.*, Vol.47, pp.381- (1952).
- [10] Sims, K.: "Artificial evolution for computer graphics," Computer Graphics, Vol.25, No.4, pp.319-328 (July, 1991).
- [11] Smith, J. R.: "Designing biomorphs with an interactive genetic algorithm," 4th Int'l Conf. on Genetic Algorithms (ICGA'91), San Diego, CA, USA, pp.535-538 (July, 1991)
- [12] Takagi, H. and Ohya, K., "Discrete Fitness Values to Improve Human Interface of Interactive GA," IEEE 3rd Int'l Conf. on Evolutionary Computation (ICEC'96), Nagoya, Aichi, Japan, (May, 1996) (will appear)
- [13] Todd, S. and Latham, W.: "Evolutionary art and computers," Academic Press, Harcourt, Brace, Jovanovich (1992).
- [14] Ura, S.: "An analysis of experiments of paired comparisons," Quality Control, Vol.16 pp.78-80 (1959) (in Japanese).
- [15] Watanabe, T. and Takagi, H.: "Recovering system of the distorted speech using interactive genetic algorithms," IEEE Int'l Conf. on Systems, Man and Cybernetics (SMC'95), Vol.1, pp.684-689, Vancouver, Canada (Oct., 1995)