

# Active User Intervention in an EC Search

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**Abstract**— We propose two interactive evolutionary computation (IEC) methods that allow users to actively participate in an EC search. This is different from a conventional IEC in which the search and evaluation are performed by the EC and the user, respectively. The first method is one in which information obtained from an IEC search is explicitly incorporated into the EC search for the next generation using on-line knowledge embedding. The second is a method that introduces a 2-D visualization of an  $n$ -D searching space. The acceleration of EC convergence and the user interface were experimentally evaluated for both methods.

## 1 INTRODUCTION

Evolutionary computation (EC) has been widely used by researchers and engineers as an optimization technique. EC determines an optimal solution based on multiple evaluation values calculated by a fitness function.

It is difficult to design a fitness function for optimization tasks whose evaluation criteria are preferential or subjective, such as artistic design support in music, sound, or graphic creation. Although it is easy for a human to evaluate the output of a target system by observation, it is difficult to design a fitness function that models the subjective evaluation characteristics.

IEC is an optimization technology based on subjective human evaluation and is used for the aforementioned optimization tasks. It is an EC whose fitness function is replaced by human evaluation. Since the EC is a fitness-based search, it applies to a search of a psychological space, such as a preference space. In such a space, gradient information cannot be obtained and, therefore, we cannot use gradient methods.

The IEC has been mainly applied to the fields of art, engineering, education, and entertainment [6, 7, 8]. Artistic applications create computer graphics (CG), CG lighting, industrial design, music, and synthesizer timbre. Engineering applications include

speech and image processing, hearing aid fitting, virtual reality, database retrieval, data mining, control, and robotics. Newer education and entertainment applications include composition support, toy robot control, games, and therapy-related applications.

Although IEC is widely used, a significant problem still remains—IEC user fatigue. To address this problem, various methods to reduce the fatigue have been proposed [8]. Some IEC interface improvements have included the implementation of the discrete fitness value input method, the use of display methods based on predicting human evaluation, the avoidance of predictable non-musical melodies, the selection of the best  $N$  individuals from many individuals using a prediction function for human evaluation, the acceleration of GA (genetic algorithm) convergence for an IGA (interactive GA), and the combination of an IGA with a normal GA.

In this paper, we propose two methods that allow an IEC user to actively participate in an EC search. This is a different approach to reduce the human fatigue from the previously-mentioned trials; One is an on-line knowledge embedding method described in section 2 and another is a 2-D visualization of an  $n$ -D searching space proposed in section 3.

## 2 ON-LINE KNOWLEDGE EMBEDDING

### 2.1 Proposed method

When we have *a priori* knowledge of an IEC task, we are able to limit the searching space before the start of an IEC search. This reduces the searching space and accelerates EC convergence. Similarly, it is useful in an EC search if an IEC user's extemporaneous searching ideas are incorporated during an IEC operation.

The proposed on-line knowledge embedding method provides a mechanism for accepting such searching ideas, hints, or intentions during the IEC operation and allows the user to actively participate in the EC search and, hopefully, improve its convergence.

For example, when a user perceives that a certain facial feature of an individual will improve a search, we may be able to limit the searching space by fix-

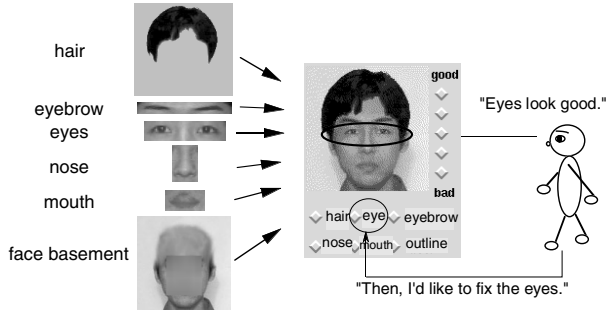


Figure 1: A face generated by combining six different facial feature images.

ing the parameter that expresses that feature. In our proposed method, applied to a montage system, a user selects and fixes an image of a facial feature during an IEC search as soon as they find an image similar to their target image.

This method is not applicable to every IEC task. It only applies when there is an intelligible relationship between the parameters of the searching space and their phenotype. For example, an IEC-based montage system whose phenotype and parameters have a one-to-one correspondence is a task suitable for the proposed method. However, an IEC-based filter design in which all filter coefficients relate to a filtered sound or image is not suitable.

## 2.2 Experimental task and condition

We applied the on-line knowledge embedding method to an IEC-based montage system to evaluate the proposed method [9]. Montage face image retrieval is a combinatorial optimization problem of facial feature images as shown in the left half of Figure 1. Our systems combine the six different facial feature images of 30 student faces. The possible number of synthesized faces is  $30^6 = 729$  millions.

Two montage systems are prepared for experimentally evaluating our proposed on-line knowledge embedding method and a conventional method without the on-line function. The montage system with our proposed method has six buttons assigned to each facial feature for each face window in order to embed a searching hint into the EC search as shown in the right half of Figure 1. For example, if an IEC user thinks that the impression of the eyes was similar to those in their memory, the user clicks the eye button to use the selected eyes for subsequent search generations. These eyes are used until the user pushes the button to release the eyes. The conventional method does not implement these six buttons.

The EC reduces the number of dimensions of the searching space from six to five. This constraint contributes to accelerating the searching convergence, which is expected to reduce human fatigue. However, at the same time, it could increase the operat-

ing time and human fatigue because of the increased number of button clicks or because of the increased concentration on certain facial features, respectively. We evaluate these effects in this section.

Subjects are required to generate a face that is similar to a given target face using the two montage systems by evaluating the 20 displayed faces in each generation. The evaluation criterion is how similar the impression of a generated face is to the target face. The operation time is also measured. The numbers of subjects, EC generations to operate, and repeated operations per system per subject in the subjective test are 14, 15, and 1, respectively. GA is used as one of the EC.

## 2.3 Result of evaluation

Table 1 shows the number of subjects who chose better montage system. By applying the sign test, we found the difference between 12 and 2 to be statistically significant.

Table 2 shows the number of subjects with their preferred montage system. By applying the sign test, we found the difference between 10 and 4 to be statistically insignificant.

Table 1: Subjective test result for the searching performance of our proposed on-line knowledge embedding method. The numbers of subjects who selected the face generated by each montage system as similar to the target face are listed.

	proposed system	conventional system	sign test
# of subjects	12	2	significant ( $p < 0.05$ )

Table 2: Subjective test result for the operability of our proposed on-line knowledge embedding method. The numbers of subjects who selected either montage system as easier to operate are listed.

	proposed system	conventional system	sign test
# of subjects	10	4	not significant ( $p > 0.05$ )

Table 3 shows the average numbers of 14 subjects that both montage systems determined as exact facial feature images in the 5th, 10th, and 15th generations. Since both systems generated 20 faces in each generation, the total number of facial images are  $120 = 6$  facial feature images  $\times$  20 faces. The statistical test has shown that the proposed method performs better at determining the correct facial feature images in three test generations.

Table 4 shows the average operating time of the two systems. The test result showed that the proposed method takes a significantly longer time per

Table 3: The average number of facial feature images in a generation that are exactly the same as those of the target face image. Since 20 faces are displayed in each generation and each face has six facial feature images, the number in table is out of 120.

	counted # of correct part-images		
	5th	10th	15th
	generation		
proposed system	12.5	14.1	17.7
conventional system	4.71	5.64	6.35
test for the averages	significant ( $p < 0.05$ )	significant ( $p < 0.05$ )	significant ( $p < 0.01$ )

Table 4: The average operation time until the 15th generation.

	proposed system	conventional system	sign test
minutes	22.9	16.8	significant ( $p < 0.01$ )

generation.

From Table 4, we can say that the operation time of the two systems becomes equivalent when the proposed system converges in 70% of the generations where the conventional system converges. Since Table 3 shows that the matching degree of the proposed system is three times that of the conventional system, we can say that the convergence time of the proposed system is faster than that of the conventional system.

From this discussion and the result in Table 1, we can say that the searching performance of the proposed method is quicker and more accurate.

Regarding operability, the statistical test shows that the difference between 10 and 4 was not significant. However, these numbers lead us to expect that the difference might become significant if we increase the number of subjects.

### 3 VISUALIZED INTERACTIVE EC

#### 3.1 Proposed method

The proposed visualized IEC is one that provides IEC users the distribution image of past individuals mapped from a  $n$ -D searching space to a 2-D space and allows the user to participate in an EC search. Although the 2-D space does not have all the information about the original  $n$ -D space, the visualization of the landscape of the searching space helps our observation and estimation of the area where the global optimum is located.

The visualized IEC is a searching method that combines different advantages of EC and human

searching techniques. EC directly and systematically searches the original  $n$ -D gene space based on EC operators, which is better than human searching techniques. However, humans have an excellent capacity to grasp an entire distribution of individuals in the 2-D space at a macroscopic level which cannot be interpreted by an EC.

In an IEC, the EC undertakes the searching role, and the IEC user undertakes the of the evaluator. In a conventional 2-D visualized-based search [2], the user searches and evaluates. Unlike these previous methods, in our visualized IEC, the human user and EC cooperate with each other in the search.

There are several mapping methods for 2-D visualization. Some are the principle component analysis of linear mapping, Kohonen’s SOM (self-organizing maps), NLM [5], Visor [1], TOPAS [2], and creating nonlinear mapping functions using genetic programming [10]. Some applications of 2-D visualization-based human searching include a 3-D CG design support system [4] and a violin sound estimator to design better violins [3].

#### 3.2 Experimental evaluation

We evaluate human intervention in an EC search by observing how well the 2-D map works for EC convergence using a toy task, modified Schaffer’s second function,

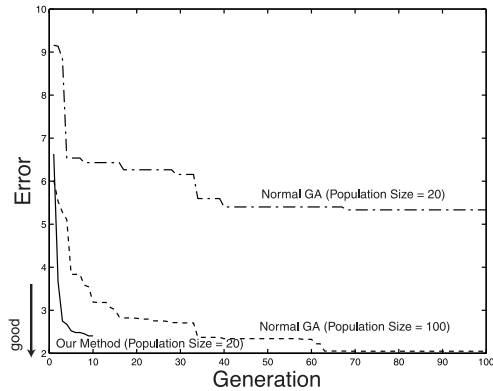
$$4 \sqrt{\sum_{i=1}^N x_i^2} \left\{ \sin^2 \left( 50 \sqrt[10]{\sum_{i=1}^N x_i^2} \right) + 1 \right\} \quad (1)$$

Since this task needs no human interactive evaluation, we did not evaluate IEC vs. Visualized IEC, but EC vs. Visualized EC, where we use a GA as one of the EC. SOM is used to map individuals from  $n$ -D space to 2-D space.

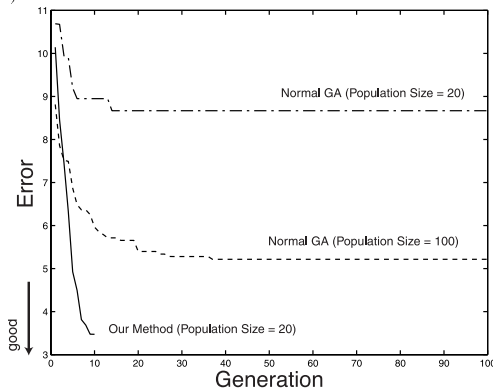
The convergence of three GAs are compared: GAs with 20 and 100 individuals and a Visualized GA with 20 individuals. An experimental user of the Visualized GA is allowed to select a maximum of three possible individuals in a 2-D space, and the best among three individuals is selected as a new individual, replacing the one of 20 individuals generated by GA. The GA parameters are: population sizes of 20 and 100, crossover rate of 0.9, mutation rate of 1/80, bit length of 16 bits, and evaluation to the 10th generation.

Figure 2 shows the error between the smallest values of the modified Schaffer’s functions, which is zero, and the best individuals in each generation. The convergence curves in the figures are the average of three trials of the Visualized GA and 10 trials of other 2 GAs.

The proposed method converges very well, while the given 3-D and 5-D searching spaces are too complex for the conventional GAs with 20 or 100 individ-



(a) Task is a 3-D modified Schaffer's function.



(b) Task is a 5-D modified Schaffer's function.

Figure 2: Comparison of convergence of Visualized GA and normal GAs for the modified Schaffer's function Eqn.(1) whose  $N$  is (a)  $N = 3$  and (b)  $N = 5$ .

uals to handle. In general, IEC users can operate 10 or 20 generations at most before giving in to fatigue. This experimental result implies that the proposed Visualized IEC is expected to be a powerful tool even for difficult IEC tasks.

We recognize that the number of subjects in this experiment is not sufficient to apply statistical tests to the obtained results, although visually, the difference of the result in Figure 2 is significant. We are now continuing this evaluation with more subjects.

#### 4 CONCLUSION

We proposed the on-line knowledge embedding method and the Visualized IEC to let IEC users actively participate in EC searching and aim for a fast EC convergence and less fatigue of the IEC users. We also evaluated these methods with human subjects and have found that they are useful in accelerating the IEC operation time and reducing human fatigue. Since there is nothing for the users of normal IEC to do except evaluating EC individuals as a human fitness function, these proposed methods are expected to reduce long IEC operation times due to a smaller population size of normal IEC and the fatigue prob-

lem of IEC users due to the slow searching.

This active intervention of IEC users may depend on the astuteness of their observation of each phenotype expression and the individual distribution on the mapped 2-D space. The next step of this research should be to reduce the amount the performance depends on humans and improve these proposed methods to show user-independent performance.

#### REFERENCES

- [1] König, A., Bulmahn, O., and Glesner, M., "Systematic Methods for Multivariate Data Visualization and Numerical Assessment of Class Separability and Overlap in Automated Visual Industrial Quality Control," 5th British Machine Vision Conference, pp.195–204 (1994).
- [2] König, A., "A Survey of Multivariate Data Projection, Visualization and Interactive Analysis," 5th Int'l Conf. on Soft Computing and Information/Intelligent Systems (IIZUKA'98), Iizuka, Fukuoka, Japan, pp.55–59 (1998).
- [3] König, A., Blutner, F. E., Eberhardt, M., and Wenzel, R., "An Acoustic Data Base Navigator for the Interactive Analysis of Psycho-Acoustic Sound Archives," 5th Int'l Conf. on Soft Computing and Information/Intelligent Systems (IIZUKA'98), Iizuka, Fukuoka, Japan, pp.60–63 (1998).
- [4] Marks, J., Andalman, B., Beardsley, P.A., et al., "Design Galleries: A General Approach to Setting Parameters for Computer Graphics and Animation," ACM SIGGRAPH'97, pp.389–400 (1997).
- [5] Sammon, J. W., "A Nonlinear Mapping for Data Structure Analysis," IEEE Transactions on Computers, vol. C-18, no.5, pp.401–409 (1969).
- [6] Takagi, H., "Interactive Evolutionary Computation: System Optimization Based on Human Subjective Evaluation," IEEE Int'l Conf. on Intelligent Engineering Systems (INES'98), pp.1–6, Vienna, Austria (Sept., 1998).
- [7] Takagi, H., "Interactive Evolutionary Computation – Cooperation of computational intelligence and human *KANSEI* —," 5th Int'l Conf. on Soft Computing (IIZUKA'98), pp.41–50, World Scientific, Iizuka, Fukuoka, Japan, (Oct., 1998).
- [8] Takagi, H., Unemi, T., and Terano, T., "Perspective on Interactive Evolutionary Computing," J. of Japan Society for Artificial Intelligence, vol.13, no.5 pp.692–703 (1998) (*in Japanese*).
- [9] Takagi, H., and Kishi, K., "On-line Knowledge Embedding for Interactive EC-based Montage System," 3rd Int'l Conf. on Knowledge-Based Intelligent Information Engineering Systems (KES'99), Adelaide, Australia, pp.280–283 (Aug. - Sept., 1999).
- [10] Venturini, G., Slimane, M., Morin, F., and Asselin de Beauville, J. P., "On Using Interactive Genetic Algorithms for Knowledge Discovery in Databases," 7th Int'l Conf. on Genetic Algorithms, pp.696–703 (1997)