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Improving the Performance of Predicting Users' Subjective Evaluation Characteristics to Reduce Their Fatigue in IEC

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Abstract Users' fatigue is the biggest technological hurdle facing Interactive Evolutionary Computation (IEC). This paper introduces the idea of "absolute scale" and "neighbour scale" to improve the performance of predicting users' subjective evaluation characteristics in IEC, and thus it will accelerate EC convergence and reduce users' fatigue. We experimentally evaluate the effect of the proposed method using two benchmark functions. The experimental results show that the convergence speed of IEC using the proposed predictor, which learns from absolute evaluation data, is much faster than the conventional one, which learns from relative data, especially in early generations. Also, IEC with predictors that use recent data are more effective than those which use all past data. *J Physiol Anthropol Appl Human Sci 24(1): 81–85, 2005* http://www.jstage.jst.go.jp/browse/jpa

Keywords: absolute scale, neighbour scale, users' fatigue, IEC

1. Introduction

Interactive Evolutionary Computation (IEC) is an optimization technology that adopts evolutionary computation (EC) for system optimization based on subjective human evaluation (Takagi, 2001). Simply, it is an EC technique where the evaluation function is replaced with a human user. Fig. 1 shows a general IEC system where a user sees or hears system outputs and the EC optimizes the target system to obtain the preferred output based on the user's evaluation. In this sense, we can say that the IEC is a technology that embeds human preference, intuition, emotion, and psychological aspects into the target system.

Over the past 10 years, the number of papers on IEC has increased and its areas of application have expanded to cover a wide variety of fields, such as computer graphics, music, artistic design (Smith, 1991), signal processing (Watanabe and Takagi, 1995), data mining (Terano and Ishino, 1998), virtual reality (Kamohara et al., 2000), Microelectrical Mechanical System (MEMS) design (Kamalian and Takagi, 2004), geophysical simulation (Wijns et al., 2003) and others.

However, because IEC users must evaluate each individual of each generation, users' fatigue is its biggest technological problem. Fatigue is therefore especially serious when the population size and number of generations is large. To make IEC technology more practical, we must improve the algorithm.

There are three approaches for reducing users' fatigue: improving the input interface, improving the display interface and accelerating EC convergence. Amongst these, predicting the IEC users' evaluation characteristics for fast convergence is one solution. If the IEC has a predictive function, it can increase the searching capability and quickly converge by using a large population size (m) equal to that of a normal EC while not increasing the users' fatigue because it displays only a few predicted individuals (n) that have higher fitness values, as shown in Fig. 2. Some research not only predicts users' evaluation values from the past evaluation data but also uses the predicted values for improving the display interface (Ohsaki and Takagi, 1998). Displaying individuals roughly in the order of human evaluation allows IEC users to evaluate them by comparing neighboring individuals, thereby reducing human fatigue.

There remain, however, unexplored methods for predicting users' evaluation characteristics. An IEC user's evaluation scale is not absolute over all generations but rather relative within each generation, i.e. the evaluation values from generations long past and from recent generations may be different even if the evaluation targets are the same. These differences become a kind of noise to the algorithm which learns and predicts the users' evaluation characteristics. Moreover, sometimes much older evaluation data can act like noise when the trend of the target changes.

To overcome this shortcoming, we propose the concept of "absolute scale" for mapping users' relative evaluation data to absolute ones, and another concept, "neighbour scale," for

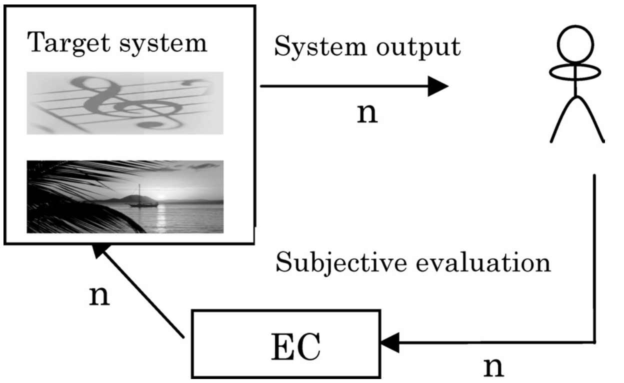


Fig. 1 General IEC system: system optimization based on subjective evaluation.

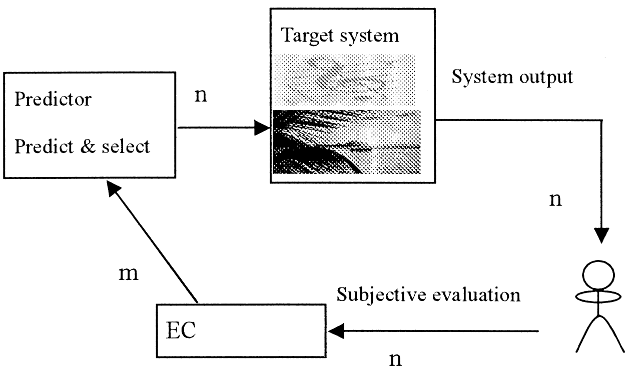


Fig. 2 IEC system with conventional predictor ($m \gg n$).

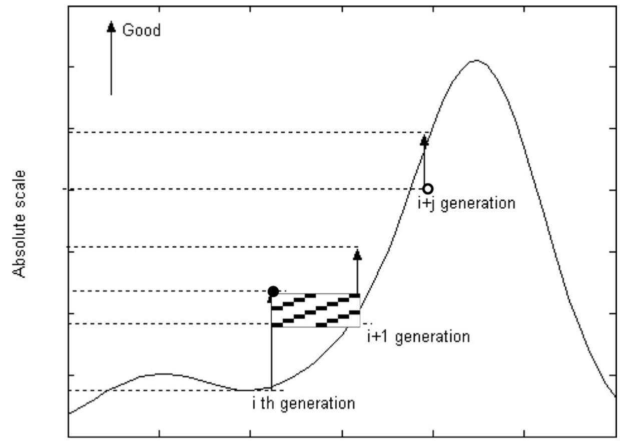


Fig. 3 Relationship between relative scale and absolute scale.

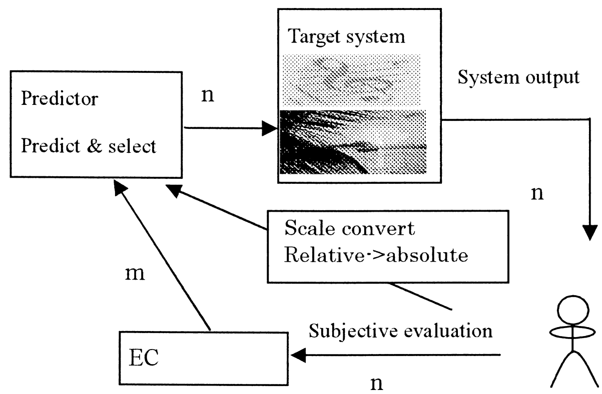


Fig. 4 IEC system with proposed predictor ($m \gg n$).

using only recent evaluation data. With these two concepts, only the absolute and recent data is used to learn users' characteristics. Since the noisiness of data is reduced, the performance of the users' evaluation characteristics predictor should be improved, and an acceleration of EC convergence is expected. This should, in turn, result in less fatigue for the users during their interaction with the system. The effectiveness of our approach is evaluated through simulation tests using two benchmark functions.

2. Method

Using relative evaluation values is easier and less stressful for IEC users, but it causes poor learning because the evaluation values from much older generations and much newer generations may be different even when the evaluation target is the same. For example, the best individual in ith generation is worse than the worst individual in $(i+j)^{\text{th}}$ generation, as shown in Fig. 3. These differences act as noise to the algorithm which learns the users' evaluation characteristics. To reduce this kind of noise, we propose a mapping from relative evaluation values to an absolute scale.

Given a set of individuals in the ith generation $\{x_j^i, j=1,...,n\}$, a user's evaluation values for these individuals are $\{f_j^i, j=1,...,n\}$. In order to change the user's relative evaluation to an absolute scale, the l individuals $\{x_j^i, j=1,...,l\}$ from the ith generation are remained in the next generation. These l individuals will have different evaluation values $\{f_j^{i+1}, j=1,...,l\}$ in the $(i+1)$ generation, since the user's evaluation is relative for each generation. Thus these relative evaluation values are mapped to absolute values according to Eq. (1).

$$f_j^{i+1}=f_j^{i+1}-\frac{\sum_{j=1}^{l}(f_j^{i+1}-f_j^{i})}{l} \qquad j=1,\dots,n \tag{1}$$

This means we use the average difference in evaluation between two neighboring generations to shift the relative scale to an absolute one. After mapping, these absolute evaluation data are used to learn the user's evaluation characteristic. Fig. 4 gives the framework of an IEC with our proposed predictor using an absolute scale. Here, a neural network (NN) is applied as the predictor. Although the mapping method described above is rough, it is very easy to implement and can reduce the noise caused by relative evaluation. We can expect that an IEC using the proposed predictor will converge more quickly than one which uses a conventional predictor.

Another aspect which should be pointed out is that sometimes evaluation values from much older generations also act as a kind of noise for learning a user's characteristics, especially when the target system is complex and recent trends are quite different from much older trends. To reduce this kind of noise, the predictor can learn from recent evaluation data instead of all past data.

3. Results

3.1 Experiment conditions

We evaluate how much the use of the proposed absolute scale accelerates the convergence of the EC search. The final validation of the system should be conducted using the IEC with the proposed predictor and subjective tests. However, since the IEC deals with subjective evaluation values that depend on the application task and the subject's perceived value of the task, we preliminarily evaluate the effect of the proposed method with a simulated subjective evaluation for the given task in this section.

The task here is to determine the minimum value of two benchmark functions, Hartman's function and Schwefel's function, as showed in Eq. (2) and Eq. (3), respectively. A Genetic Algorithm (GA) is used as one of the EC technologies. To simulate a human's relative evaluation, we first calculate the function values of each of the individuals in a generation according to Eq. (2) or Eq. (3), and then change these values to a scale with five degrees using uniform quantization. These five degrees correspond to a human's relative evaluation.

$$f(x) = -\sum_{i=1}^{4} c_i \exp\left[-\sum_{j=1}^{n} a_{ij}(x_j - p_{ij})^2\right] \quad 0 \le x_j \le 1 \qquad (2)$$

$$f(x) = \sum_{i=1}^{n} x_i \sin(\sqrt{|x_i|}) \quad 500 \le x_i \le 500 \qquad (3)$$

The performance measure is minimum value versus computation time. We compared three methods: one is an Interactive Genetic Algorithm (IGA) with the proposed predictor using an absolute scale, the second is an IGA with a conventional predictor using a relative scale, and the last is an IGA without a predictor. Furthermore, we evaluated the performance between an IGA with a predictor that uses all past data and one which only uses recent data. Table 1 shows the parameter settings of the IGA in the experiments.

3.2 Experiment result

The effectiveness of our proposal was estimated using two benchmark functions. To save space here, we will only give the experimental results for the Hartman function as an example, as shown in Fig. 5. The experimental results of Schwefel's function are similar. The results are as follows: Figs. 5 (a) and (b) clearly show that the IGA with the proposed predictor using an absolute scale converges much faster than not only the normal IGA without a predictor, but also the IGA using a conventional predictor with a relative scale; Figs. 5 (c) and (d) show that the IGA with a predictor using recent data converges faster than one using all past data; the difference in convergence speed between the proposed system using all past data and the proposed system using only recent data is smaller than that between the conventional predictor using all past data and only recent data.

Table 1 Experimental conditions of the GA

Parameters	Value
Population size	20
Crossover rate	0.7
Mutation rate	0.01
No. of generations	20
GA coding	Binary coding
Bit length	20

4. Discussion

Two conclusions can be drawn from the experiments above. One is that using an absolute scale can significantly improve the performance of the human subjective evaluation characteristics predictor. The other is that a predictor which uses recent data performs better than one which uses all past data. The proposed method using an absolute scale and a neighbour scale can therefore accelerate EC convergence and reduce IEC users' fatigue.

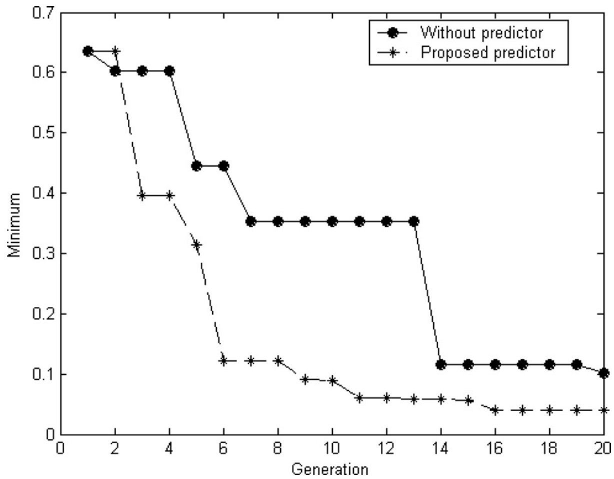
Since using an absolute scale dramatically reduces the noise in the data, the difference between the convergence speeds for the proposed method using all past data and the proposed method using only recent data was not as large as the difference for the conventional method using all past data and only recent data.

Accelerating the EC convergence significantly reduces human fatigue. Although any fast EC search methods are applicable, methods with quick convergence in early generations are especially useful for IEC. From Figs. 5(a) and (b), we can see that the proposed approach converges much faster than the conventional method in the first 6 generations. This implies that the proposal is expected to be a powerful tool for difficult IEC tasks.

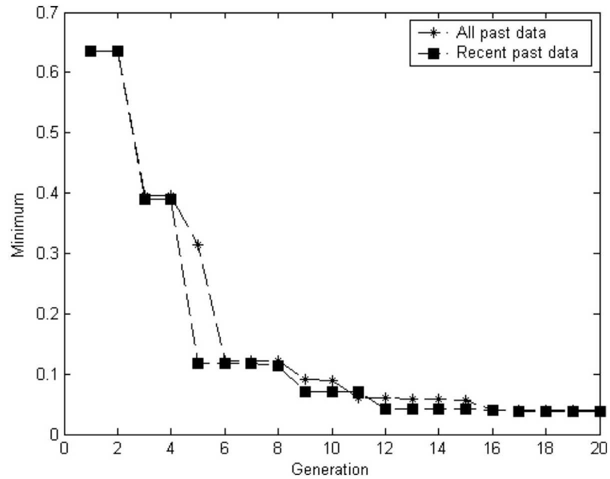
Our proposed mapping method is easy, but it is also rough; in the near future we will use some other mapping methods and we will also apply our proposed approach to some real tasks and do some subjective tests.

5. Conclusion

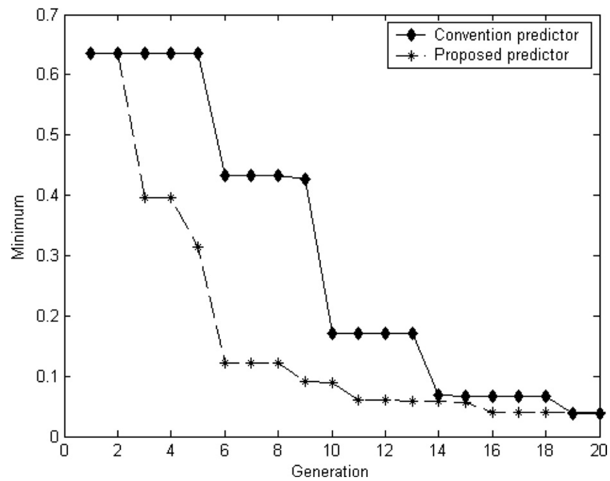
This paper introduced the ideas of "absolute scale" and "neighbour scale" to reduce data noise for predictors that learn IEC users' subjective evaluation characteristics. A concrete mapping method from relative evaluation data to absolute evaluation data and the technique of using only recent past data were proposed. Simulation results showed that the proposed



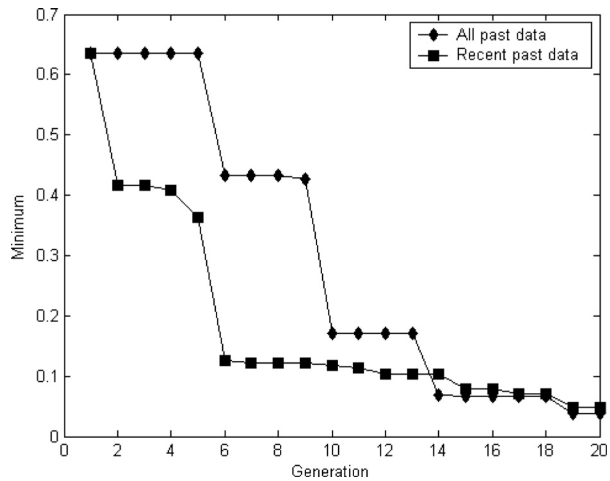
(a) Convergence characteristics for the normal IGA without a predictor and the IGA with the proposed predictor using an absolute scale.



(c) Convergence characteristic for the IGA with the proposed predictor using all past data and using recent data.



(b) Convergence characteristics for the IGA with a conventional predictor using a relative scale and for the IGA with the proposed predictor using an absolute scale.



(d) Convergence characteristic for the IGA with a conventional predictor using all past data and using recent past data.

Fig. 5 Convergence characteristics comparison.

predictor using absolute evaluation has significantly better prediction performance than conventional predictors, and a predictor using recent past data is better than a predictor which uses all past data. Thus the proposed approaches can hasten EC convergence and reduce IEC human fatigue.

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