NEW TYPES OF IEC APPLICATIONS AND LATEST RESEARCH ON REDUCING USER FATIGUE

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NEW TYPES OF IEC APPLICATIONS AND LATEST RESEARCH ON REDUCING USER FATIGUE

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ABSTRACT

We introduce our recent topics of interactive evolutionary computation (IEC) research. First, we introduce new types of IEC research unlike normal IEC-based system optimization: (a) estimation of IEC user's psychological scale or mental situation by analyzing the outputs of the system optimized by the user, (b) Extended IEC that optimizes a target system using IEC user's physiological data, and (c) IEC combined with evolutionary multi-objective optimization. Secondly, we describe how to realize an IEC simulator for repeated experiments under the same experimental conditions. Thirdly, we introduce research on reducing IEC user fatigue using a model of IEC user's evaluation characteristics.

1. INTRODUCTION

Interactive Evolutionary Computation (IEC) is an optimization technique that optimizes a target system based on human subjective evaluations. Most of IEC research aims to optimize target systems to obtain better system outputs for IEC users, and others aim to reduce IEC user fatigue to make the IEC technique practical. It has been widely applied to several areas, such as: graphic arts and animation, 3-D computer graphics lighting, music, editorial design, industrial design, facial image generation, speech processing and synthesis, hearing-aid fitting, virtual reality, media database retrieval, data mining, image processing, control and robotics, food industry, geophysics, education, entertainment, social system, etc. [18].

We introduce new types of IEC applications and some research on reducing IEC user fatigue in this paper taking account of this unbalanced research situation. Main objective of this paper is to raise interests of IEC researchers not only to major IEC-based system optimization research but also to wide variety of IEC research.

2. NEW TYPES OF IEC APPLICATIONS

2.1 Measuring Human Mind

IEC is an optimization method based on human subjective evaluation. Likely reverse engineering, we may measure the evaluation characteristics or mental conditions of an IEC user by analyzing the outputs of a system optimized by the IEC user's subjective evaluations.

Let us shift our view point from system optimization, which has been the main objective of IEC until now, to analyzing an IEC user whose psychological scale is used to optimize target systems. The IEC user's subjective evaluations are based on his or her psychological evaluation scale, and, in turn, the scale is reflected in the outputs of the system designed by the IEC user. We, therefore, may be able to observe the psychological scale or the mental health state of an IEC user indirectly by observing the system outputs. This view helps to expand IEC applications and show a new research direction.

One example of this approach is measuring mental dynamic ranges of schizophrenics [20]. It has been said that schizophrenics show narrow mental impression in the expressions of their faces or actions, but there was no way to measure the range. They were asked to make happy and sad impressions using an IEC-based 3-D CG lighting design system [2], psychological scale was calculated using analysis of variance (Figure 1), and dynamic ranges of happy-sad were calculated (Figure 2).

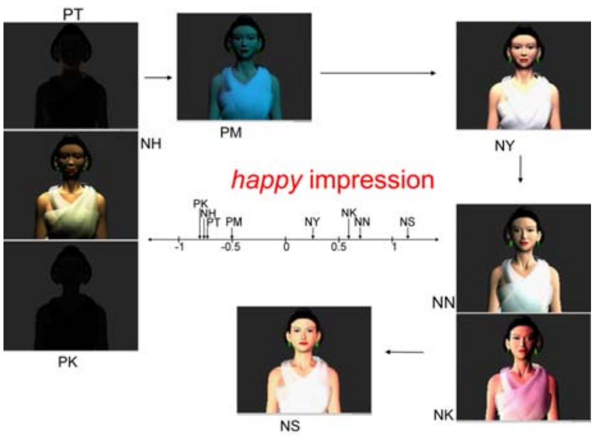

Figure 1. Happy impressions made by three schizophrenics and five mental-normal students. These eight images are put on a mental scale made by analysis of variance, and statistical significances with 1% risk are showed as arrows. Images with PK, PT, and PM were made by schizophrenics.

Figure 2. Dynamic rages of happy-sad of three schizophrenics, PK, PT, and PM, and five mental-normal students displayed in wider range order.

2.2 IEC with Physiology

The second new type of IEC research is adapting physiological data. Usually, IEC optimizes a target system based on IEC user's subjective evaluation, i.e. psychological evaluation. We may extend the evaluation from psychological one to physiological one.

Figure 3 is the framework of the Extended IEC [21]. When the outputs of an IEC target system are given to an IEC user, such as listening music, watching movies, or enjoying vibrations, some physical stimuli influence his/her physiology. Then, we may be able to drive his/her physiology by controlling the physical stimuli. Suppose that physiologists advise us the ideal physiological conditions of relax, exciting, or other target mental conditions. IEC framework may be able to direct the human physiological conditions to the ideal one by minimizing the error between measured physiological data and the ideal ones.

There were trials to apply the Extended IEC to control eight parameters of a vibration chair using physiological data of an extended IEC user on the chair [21] and to direct emotions of video movie viewers [22] though they have not been completed.

Other trial using physiological data is to guess IEC fitness by using eye-tracking of an IEC user [14]. Other physiological data such as EEG can be used to guess IEC user's evaluation or selection of better individuals.

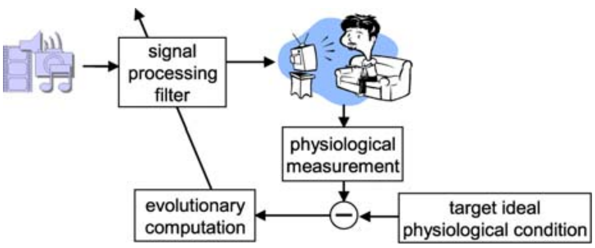

Figure 3. Framework of Extended IEC.

2.3 IEC+EMO

Evolutionary multi-objective optimization (EMO) is a growing research area in recent EC community, and the number of their publications increases rapidly. Their interest is shifting to more complex case, many-objective optimization.

There are a few number of IEC research combined with EMO. One is room layout design [3], and other is MEMS design [7]. Both design tasks have several restrictions and design objectives. For example, better MEMS design is requested to have performance within design specifications, smaller design area size, stronger stiffness, and others. IEC user evaluates individuals obtained through EMO search and increases their design performance.

3. Pseudo IEC User for IEC Simulation

Usually, we use human IEC users for evaluating IEC research. However, the drawback of this approach is that we cannot repeat evaluations under the same experimental conditions and cannot repeat many times, which is not suitable especially to develop methods for reducing IEC user fatigue. We need IEC simulators.

IEC simulation uses a fitness function as the same as normal EC but has two different points from the normal IEC: discretization and relativization. IEC users cannot evaluate system outputs in precise as a continuous fitness function does but evaluate them in *n* levels, where the *n* is a small number. They also compare individuals and evaluate them relatively in each generation. A pseudo-IEC user for simulation is designed to have a fitness function inside, calculate relative evaluation values in *n* levels, and output them as the simulated subjective fitness of the pseudo-IEC user.

Figure 4 shows a simple way to obtain the relative discrete fitness values. Suppose individuals shown as triangular marks distribute as the figure at a certain generation. To obtain relative fitness values in five levels, for example, the fitness interval between the best individual and the worst one is divided into five equally, and a discrete fitness value of each range is given to individuals in the range [23].

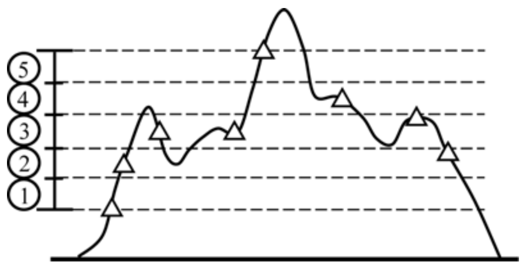

Figure 4. Calculation of relative fitness in five levels from a fitness function.

We can start IEC simulations now using the obtained pseudo-IEC user in this way. Designing a fitness function that is close to human evaluation characteristics for a given application task is a difficult task. We are using a Gaussian mixture model whose shape is parametrically controllable [5]. When we train a model of IEC user's evaluation characteristics using machine learning methods, it is necessary to consider introducing transformation from relative fitness to absolute one. We discuss it in section 4.2.

4. RESEARCH ON REDUCING IEC USER FATIGUE

4.1 Review

One of main problems for practical use of IEC is user fatigue [18]. To solve this problem, several approaches of IEC interface research have been presented, including learning an IEC user's evaluation characteristics and using it to predict their evaluation [8,9,11,12], improving IEC display interface and the input of user evaluation [12,13,17], accelerating IEC search [15,19], and active user intervention in EC search [4,16].

The approach of learning IEC user's evaluation characteristics during IEC evaluation process seems the most effective among them. Once an evaluation model of an IEC user is obtained, we may be able to find out better individuals through IEC simulation with many individuals and many generations as mentioned in section 3.

Tournament fitness is a considerable approach for improving IEC user interfaces. It was proposed as one of three competitive fitness methods [1] and was applied to IEC user interface [10]. The tournament fitness is a method to let a user choose better one from a displayed pair of individuals and give higher fitness according to the number of wins during a tournament. Although the total number of comparisons does not decrease, it is easier for an IEC user to compare two individuals than to compare whole individuals. More precise evaluation method was proposed earlier; it reflects the evaluation difference of a pair individual to the fitness as well as the number of wins during a tournament [6].

Other research topic of which author makes a point is EC operators for IEC. IEC must run with quite fewer numbers of individuals and fewer searching generations than those of normal EC, and we must find out the best EC operations that work well under such severe conditions. As this is a condition that researchers of normal EC do not use or even they cannot image, IEC researchers are expected to tackle this topic.

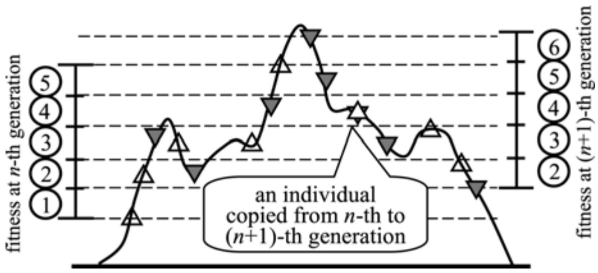

Figure 5. Conversion from relative fitness in each generation to absolute fitness for whole generations. White triangles and gray inverted triangles are individuals in the *n*-th and (*n*+1)-th generations, respectively. The difference of fitness values for the same individual copied from the next generation becomes the difference of fitness scales between two generations.

4.2 Predicting IEC User's Evaluations

If we can have a model whose output characteristics are similar to evaluation characteristics of an IEC user, we can simulate the IEC search of the user with many individuals and many searching generations behind a real interactive search of a human user and display better individuals obtained through the simulation even if the model is imperfect. So far, distance-based model, neural networks [9], and a fuzzy system [8] were used as learning models, but any learning models are applicable.

This approach has two difficulties; one is that we cannot obtain enough number of training data from an IEC user, and another is that we cannot use relative fitness values in whole past generations as they are or cannot expect better training performance if they are used. The first difficulty can be solved by only introducing learning models that work with less number of training data, and the second one can be solved by converting relative fitness values to absolute ones.

One of conversion method from a relative scale used in each generation to an absolute scale for whole generations is copying one or some individuals of the *n*-th generation to the next generation and correcting fitness of all individuals in the (*n*+1)-th generation (or all past fitness values until the *n*-th generation) based on the difference of fitness values between individuals commonly used in the *n*-th and (*n*+1)-th generations [23].

Figure 5 shows a concrete example to explain this conversion. Suppose that an individual evaluated as 3 point in five level in the *n*-th generation is copied to the (*n*+1)-the generation and is evaluated as 2 point. We can imagine that more number of better individuals are searched out in the (*n*+1)-th generation from the decreased evaluation to the copied the same individual. Here, we assume that an average evaluation value of all individuals in the (n+1)-th generation increases from that in the n-th generation and calculate absolute fitness values of individuals in the (n+1)-th generation by adding 1 point to their relative fitness values. When multiple individuals are copied to the next generation, an average difference of their fitness values is used to correct the relative evaluation scale used in the (n+1)-th generation. Although conversion noise is accumulated during repeating this simple conversion and decreases learning performance, still this simple method improved learning performance than just using whole past relative fitness for training an evaluation model [23].

4.3 Usage of Other IEC Users' Evaluation Models

Using evaluation characteristics models of other IEC users was proposed to accelerate IEC search [5]. Although the method mentioned in section 4.2 is expected to accelerate IEC search and reduce IEC user fatigue, this approach cannot be used until a learning method trains out the evaluation model of an IEC user. In the worst case, an IEC search may end when the model is made because of a few number of maximum IEC generations. One of solutions for this problem is to use other IEC users' models until the IEC user's own model is made.

An IEC user must evaluate all given individuals in normal IEC search (Figure 6 (a)); acceleration of IEC search using IEC simulation with a pseudo-IEC user is expected, but search speed is the same before the model is trained (Figure 6 (b)); we may be able to expect acceleration effect from the first IEC generation if the previously obtained other IEC users' evaluation models are similar to the said IEC user (Figure 6 (c)). One model whose evaluation fitness values are the most similar to those of the said IEC user is selected among all other IEC users' evaluation characteristics models in each generation; IEC simulation using the most similar characteristics to the said IEC user is conducted.

When the characteristics of other IEC users' models are similar to those of the said IEC user, we can expect acceleration of IEC search. However, by contraries, IEC search may become worse when they are not similar. We need to check if this method with other users' models is applicable before it is really applied.

Reference [5] proposed not only the method of introducing other IEC users' models but also a criterion to decide if we should/should not use the method through preliminary experiment. We applied the criterion to the three IEC tasks: MEMS design where it is expected that MEMS experts show similar evaluations, 3-D CG lighting design where it is expected that our evaluations to given design concepts are roughly similar, and logo mark design based on user's preference where the evaluation quite depends on users. As we expected before the experiment, the criterion showed that the proposed method is effective for the former two tasks but is ineffective to the third task through small preliminary subjective tests [5]. Thanks to the criterion, the method of introducing other IEC users' models became practical.

(a) Normal IEC.

(b) IEC with a user model.

(c) IEC with models of other persons and the user own.

Figure 6. IEC frameworks and searches with IEC and IEC user models in each generation: (a) normal IEC with only IEC search in all generations, (b) IEC simulation using an IEC user evaluation model is available once the model is trained., and (c) IEC search and IEC simulation with other IEC users' evaluation models run together until learning an evaluation model of the IEC user own ends.

5. CONCLUSION

We introduced new types of IEC applications and some research works on reducing IEC user fatigue to raise the interests of IEC researchers to different research directions. Many IEC research works have been done, but their majority is IEC optimization of target systems based on IEC user's subjective evaluations. Although it is an important for practical use of IEC, IEC research seems to be too biased to this direction. We hope that these topics become stimuli to IEC researchers and let them be interested in new IEC research directions and expand the coverage of the IEC technique.

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