New IEC Research and Frameworks

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Abstract We introduce recent research on new types of interactive evolutionary computation (IEC) applications and that on reducing IEC user fatigue. IEC is an optimization technique to embed IEC user's subjective evaluations based on his/her domain knowledge, experiences, and preferences into several designs and has been applied to wide varieties of applications in artistic, engineering, and others for these 20 years. The approach of almost them can be said as a system optimization based on IEC user's subjective evaluations. We review recent new research topics including an IEC as a tool for analyzing human mind, an IEC with physiological responses, and an IEC with evolutionary multi-objective optimization. We also introduce recent approaches for reducing IEC user fatigue by modeling user's evaluation characteristics and expanding an IEC framework.

1 Introduction

Interactive Evolutionary Computation (IEC) is an optimization framework consisting of a target optimization system, evolutionary computation (EC), and an IEC user, and it can be said that IEC is an EC whose fitness function is replaced with a human user. IEC is suitable for optimization tasks that are hard or almost impossible to be evaluated numerically or whose fitness functions are difficult to be designed. These tasks are, for example, fitting a hearing-aid to let its user satisfy his/her sound preference or designing cute motions of robot's behaviors. Although it is hard to evaluate these tasks quantitatively, we can apply IEC to them if we can evaluate them subjectively based on our domain knowledge, experiences, and preferences. We may say that IEC is a method for embedding our capability of global decision making, or *KANSEI* in general, into the process of optimization or design.

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IEC started from R. Dowkins's biomorph (1986). Its applications were biased to computer graphics in the former half of 1990's, but it was widely applied to several areas; they include artistic applications such as graphics, music, industrial design, or facial design, engineering applications such as acoustic and image signal processing, data mining, robotics, or control, and other applications such as geology, education or games [20].

One of recent remarkable features is the increase of its practical applications. The applications that aim practical real world applications include MEMS design with concrete fabrications [8], conceptual designing of software using Unifies Modeling Language [18], developing medicines [3, 10, 17], joint research of heading-aid fitting with hearing aid companies, Rion Co., Ltd. and Matsushita Communication Industrial Co., Ltd (in those days) [24], joint research of concept design of aircrafts with British Aerospace, engine control of Yamaha Motor Co., Ltd.

Other research direction is to aim practical IEC by reducing IEC user fatigue; it include reducing mental stresses of decision making for evaluation, fatigue of input operations, and boringness due to iterated evaluations. These approaches are categorized into (a) improving input/output interface, (b) accelerating EC convergence, (c) user intervening into EC search, and (d) making a model of user evaluation characteristics based on machine learning and simulating IEC with the model as a pseudo-IEC user.

The (a) is to improve the interfaces of inputting fitness values from an IEC user and displaying individuals to the user [20]. This kind of research includes evaluation of trade-off of more fitness levels that are precise but increase IEC user fatigue and fewer fitness levels that have their reverse characteristics, displaying individuals sorted by fitness to help IEC user's comparisons, multiple windows for displaying many individuals on a limited space of a PC display, a secondary window for displaying an enlarged image to check the detail of an individual, explicit display of an elite individual to help sequential comparisons with other individuals of sounds or movies, and others.

The (b) is to fasten EC convergence. It is an efficient approach for reducing the number of evaluations, but it must work well under the restricted conditions of fewer population size and fewer generation numbers. This kind of research includes acceleration of EC convergence on a simplified searching landscape roughly approximated by a simple unimodal function [21], developing optimization methods and EC operators that work well under the above mentioned restricted conditions of IEC, combination of IEC with normal EC using a fitness function, and others.

The (c) aims to reduce user's mental stress caused by boring iterations of IEC evaluations by letting an IEC user not only join to IEC evaluations but also intervene in EC search actively. It is also useful to accelerate IEC convergence. This kind of research includes reducing dimensions of a searching space by fixing the value of a certain optimization parameter when an IEC user thinks that its corresponding phenotype looks good if the relationship of its phenotype and genotype is one-to-one, adding a new searching point, i.e. an individual, based on visual guessing on the 2-D searching space that is mapped from an original n-D searching space [4], and others.

Refer the reference [20] for these descriptions without citations. We will describe about the (d) in section 3.1.

IEC has the below features:
(1) an optimization with fewer population size and fewer generation numbers,
(2) nevertheless, it is not so difficult to obtain satisfactory solutions,
(3) relative evaluations in general, and
(4) discrete n-evaluation levels.

The feature (1) is a restriction due to an IEC user fatigue for iterative evaluations. As mentioned, when we develop EC acceleration methods, it is essential that the methods must work well under this restrictions. This feature becomes a bottleneck for keeping enough number of training data for making a model of user evaluation characteristics that will be mentioned in the later of this paper.

The reason of the feature (2) is that any solutions are the same for an IEC user if he/she cannot distinguish them. It is easy to understand if we think that IEC searches global optimization *area*, while normal EC searches the global optimization point. For example, in our experience of IEC-based hearing-aid fitting using a commercial hearing-aids and real hearing-aid users, it frequently became difficult for the users to evaluate which sounds are good after five generations even if they can perceive the difference of the sounds themselves.

The reason of the feature (3) is that it is general for an IEC user to compare individuals relatively and then evaluate them. Since a normal EC generates offspring individuals using EC operations and fitness values of only its parent generation, it is not a problem to generate offspring using relative fitness. If absolute fitness values are used with fewer n-evaluation level of the feature (4), fitness values of almost individuals in early generations become poor and those in later generations become better, which reduces selection pressure and hinders IEC convergence.

The feature (4) causes quantization noise in fitness and may influence on IEC convergence. Unlike a fitness function, it is not easy for an IEC user to evaluate slight differences among individuals. This is a reason why rough evaluation levels, such as five-level or seven-level evaluations, are used for IEC. The ultimate level is one bit of *selected/unselected* used for simulated breeding that originates from a selection of artificial breeding. As the n-level evaluation rounds slight differences among real individuals and ignores them, subjective fitness values of an IEC user must include quantization noise. Even though it is said that genetic algorithms (GA) is robust for fitness noise or fluctuations in general, IEC convergence must be influenced badly by fitness noises: noises originating in reduced evaluation quantization levels, fluctuations of an IEC user's evaluations, and input inaccuracy. We may say that simulated breeding is the IEC with the most quantization noise in a sense. By contraries, psychological fatigue reduces in inverse proportion to the evaluation levels, and the simulated breeding requests fewer number of input operations, i.e. just clicking individuals without evaluating how good/bad they are. When we consider methods for reducing human fatigue discussed in section 3, we must think about the balance of IEC convergence speed and the easiness of operations and evaluations.

IEC simulators are useful for IEC research. Although IEC research should be evaluated with IEC users at the final stage, human users are not always the best for the IEC research. When we need to repeat experimental evaluations under the completely the same conditions, what we need is not human users who cannot provide us reliable objective data but an IEC simulator.

The IEC simulator looks similar to normal EC because the evaluation characteristics of an IEC user are replaced with a function. Their different point is whether the previously mentioned features (3) and (4) are included. The IEC simulator is designed by embedding a converter that converts values from a fitness function to relative and discrete fitness values into an EC framework. The evaluation characteristics of a pseudo-IEC user are expressed as those of a fitness function with the converter.

The converter equally divides the interval between the maximum and minimum fitness values into n and converts continuous fitness values to the relative and discrete ones of $1 - n$ points [25]. Since there may be multiple best individuals with the same best fitness value of n points, elite individual(s) are selected randomly among the best individuals when elite strategy is used.

Refer the reference [20] for general IEC tutorial and a survey of wide variety of IEC applications and research on reducing IEC user fatigue. In this paper, we introduce new type of IEC research that is not found in 1990's.

2 New Type of IEC Applications

2.1 As a Tool for Analyzing Human Mind

Since IEC optimizes a target system based on a user's subjective evaluation scale in mind, we may be able to analyze his/her psychological measure or mental characteristics by analyzing the optimized target system. We may say that it corresponds to reverse engineering of software.

From the IEC-based fitting of hearing-aids or cochlea implants, it is expected that new facts in audio-psychology or audio-physiology may be able to be found by analyzing the optimized characteristics of hearing-aids or cochlea implants. It was made clear that the best characteristics of hearing-aids fitted using voice and those using music were different [14, 24]. It means that human beings hear voice and music with different manners, and we should keep it in our mind as a new fact for hearing compensation. Cochlear implant fitting has conducted based on the common sense that the more electric channels and the wider dynamic range of each channel, the better. However, the cochlear implant fitted by IEC had fewer channels than conventional ones and dynamic ranges of some channels were quite narrower. Nevertheless, it was reported that a correctness ratio of cochlear implant user improved from about 45% with a cochlear implant fitted based on conventional method to 92% with that fitted by IEC [11]. This fact implies that there is unknown mechanism of audio-psychology/physiology, and therefore there are possibility that new knowledge in this area may be found.

IEC was applied to measure the mental dynamic range of *happy–sad* [22]. Three schizophrenics and five mental healthy students were asked to make *happy* impression and *sad* impression using the IEC-based computer graphics (CG) lighting design system [1]. More than 30 subjects evaluated these 8 CG of each impression using the Nakaya's variation [13] of the Sheffé's method for paired comparisons [19], and a psychological scale was constructed. An order scale of *happy–sad* was also calculated from the obtained two scales for *happy* and *sad* impressions. This experimental result showed that it was significantly harder for these three schizophrenics to design *happy* impression than mental healthy subjects, while there was no significant difference for designing *sad* impression. Although the number of experimental subjects is too few to conclude, the experimental result implies that the dynamic range of schizophrenics for *happy–sad* is narrower than that of mental healthy people, which matches the thoughts of some therapists based on their experiences. If it is confirmed through further research, there is a possibility that this IEC-based method can provide useful information for psychiatric diagnostics.

2.2 Extended IEC Based on Physiologic Responses

Extended IEC based on IEC user's physiologic responses is an extension of conventional IEC that is based on psychological evaluations.

The first trial use of physiologic responses was that IEC inputted IEC user's physiologic responses and optimized physical parameters of sounds, images, or movies to bring his/her physiological condition to a certain target condition, such as relaxed or stressed one. Movies and music move us. Although their stories or scenes may be the biggest factors for influencing our emotion, physical features such as colors, motions, switching scenes, sound volume affect our physiological responses, too. If we can control these physical features, we may be able to control the physiological responses of listeners or viewers.

IEC inputs the differences of physiological responses, such as blood pressure, heart rates, or breathe rates, between the targeted relaxed or excited condition and current measured ones as fitness. We form the framework of the extended IEC's loop that the EC optimizes the physical features of the stimuli to an IEC user based on his/her physiological inputs iteratively [23].

The second trial was to use eye tracking for inputting IEC user's subjective evaluations instead of a mouse or keyboard [15]. This approach is based on the assumption that an IEC user watches individuals of his/her interest longer than others. Although there are remained problems such as verifying the assumption, detecting individuals of the interest from eye trajectory that always moves, comparing the superiority of this method to other input methods, and others, eye tracking-based IEC has potential for the cases that we do not want to use intentional inputs or cannot use it, and when trajectory itself has useful information rather than detecting the individuals in which a user is interested.

2.3 IEC with Evolutionary Multi-objective Optimization

The number of items that we want to optimize is not always one. Multi-objective optimization methods are used for this case. The number of research on evolutionary multi-objective optimization (EMO) has increased rapidly in this decade.

When it is hard or impossible to quantify some of these optimization objectives, IEC is combined with the EMO. For example, the conventional EMO is available to find the best apartments whose room sizes, tenant fees, and distances to the nearest stations are wide, less expensive, and near, respectively, but it cannot be used when new searching conditions of beauty of room inside/outside and great views from a room besides the above quantitative optimization objectives. In this case, we need to combine subjective visual evaluation with the EMO.

IEC and EMO were applied to design MEMS (or micromachine). UC Berkeley and other teams have tried to replace conventional CAD-based MEMS design with EMO-based design to automate the conventional manual designing. The EMO approach tries to find out designs of a MEMS acceleration sensor whose spring stiffness is strong enough, resonance frequency is close enough to the specification frequency, and area size is small enough, for example. However, fabricated MEMS does not always show the same characteristics as a MEMS simulator shows. It happens when MEMS simulation does not use the finite element method that shows high precision but request high computational cost. Besides it, there is an essential reason that we cannot design fitness functions for all evaluation items, and therefore, manual designing method has not been able to be automated completely.

To solve this problem, IEC that optimizes MEMS design based on MEMS designer's experiences and domain knowledge was combined with EMO [8]. As experienced MEMS designers can evaluate total quality of MEMS designs by just glancing at them, we can accelerate designing MEMS by embedding their evaluation into EC search.

Architectural design is its other application. Architects design room floor layouts under several restrictions and objects, for example, requirements of architectural laws such as window sizes, the pass condition from an entrance to a veranda through only public spaces such as house passages, a living room, and a kitchen, a room shape condition that requests rectangular or similar one but allows slight irregular room shapes, conditions that each room size is close to the target specific size, and others. Besides them, there are qualitative objects in architectural designs such as architects' experiences and their sense of beauty, and preference of clients, and therefore IEC and EMO are necessary for supporting its designs [2, 6].

There are several combination ways of IEC and EMO: a method that IEC runs first and narrows searching areas from the global view point and then EMO search starts: a contrary combination that EMO searches Pareto solutions first, and then IEC fine-tunes the solutions: a method that EMO runs several generations behind an IEC user's evaluation at every IEC generation. There are comparative reports, but the best combination of IEC and EMO and its performance may depend on application tasks.

We introduced IEC+EMO research within an ordinary IEC framework that an IEC user evaluates the output of the target system and EC inputs user's evaluations and optimizes the target system. This type of research is few. Note that there are many EMO papers with confusing names of interactive EMO or similar ones, and they do not mean IEC+EMO but mean that a human being selects Pareto solutions based on his/her visual inspection. For example, we cannot distinguish which type of research the reference [16] is from its paper title, but it is the latter type of EMO research. They may be categorized in IEC of wide definition IEC [20].

3 Research to Reduce IEC User Fatigue

3.1 Leaning User Models and its Applications

(a) Learning User Models

Since inputs and outputs to an IEC user are outputs of the target system (exactly speaking, values of optimization variables from EC) and subjective evaluations to EC, respectively, computer can observe both of them. If the computer can learn the relationship between these inputs and outputs, we can make a model of an IEC user's evaluation characteristics. Once we obtain the model, we can estimate user's evaluation previously. We may be able to accelerate IEC convergence by using the model as a pseudo-IEC user, simulating IEC process with a big population size and many generations, showing the best m individuals that the pseudo-IEC user finds out to a real human IEC user. Furthermore, when we obtain the user's evaluation model, there is a possibility that we can know the optimization parameters or hidden factors to which an IEC user attaches much importance by analyzing the model. Once we know the user's evaluation factors, we may use them to accelerate an IEC convergence.

There are three major approaches to make a model of IEC user's evaluation characteristics, i.e. a prediction model of user's evaluation values: (1) distance-based models, (2) neural networks (NN) learning, and (3) fuzzy systems.

Predicting user's evaluations based on the distance-based model is similar to the case-based reasoning in knowledge engineering. Distances on a searching space from the individual with unknown fitness to individuals whose fitness values were known in past generations are calculated, the known fitness values are weighed with inverse of the distances and the average of the weighted known fitness values is used as the estimated fitness.

The advantage of this method is that costly learning is not necessary and estimated user's fitness can be calculated from a few individuals in past generations. This feature is quite preferable for IEC that searches with small population size. Its disadvantage is that its estimated fitness is not precisely obtained from Euclidian distances on a searching space when importance levels that an IEC user attaches to each of optimization parameters are different. In this case, we need to estimate the importance levels and calculate weighted Euclidian distances. If fitness values are not in proportion to distances in a searching space, nonlinear estimation methods, such as NN, are necessary for this distance-based model.

NN-based estimation is to learn the relationship between input and output data using a supervised learning, which methodology is easy to understand. This method works even when the contributions of optimization parameters to the total fitness are not equal or the relation between the parameters and the fitness is nonlinear. However, it is not easy to collect enough number of NN training data because the features of IEC are small population size and small number of searching generations. When enough number of training data is obtained after many generations, IEC may reach to the end of its search and the trained model may not be able to be used. There are several improvements for practical use of this NN approach, such as finding new NN that does not require many training data.

A fuzzy system that was off-line designed previously was used as a user model of evaluation characteristics [9]. The advantage of the off-line design is to use the model for predicting user's evaluation to accelerate IEC search from the first generation regardless the approaches of fuzzy systems or NN learning. The cases when the model is off-line designed are that same user applies IEC to the same optimization task or that the evaluation characteristics of multiple IEC users are similar. The case of the latter depends on application tasks; the variance of evaluations based on domain knowledge of multiple domain experts is small, while those based on user's preferences are big. Since evaluations for MEMS designs are based on experienced MEMS designers' domain knowledge and experts' evaluations are similar in general, the reference [9] could adopt this off-line method.

To obtain enough number of training data, just collecting fitness values in past generations is not good to learn user's evaluation characteristics because IEC fitness values are relative in each generation and therefore the best fitness in past generation may be worse than the worst fitness of the current generation. However, it is almost impossible to collect enough number of data for learning the user's evaluation characteristics without using fitness values in past generations.

The solution for this dilemma is to transform relative fitness values to absolute ones that can be compared over generations. One of the transformation is to evaluate the same individual in continuous two generations, assume the difference of the two fitness values to be the evaluation difference of two generations, and correcting all individuals of either of the two generation with the difference [25]. This simple transformation may accumulate transformation errors according to generations, but the simulation results showed that IEC with the prediction model was better than IEC without the model and that IEC with a prediction model trained with absolute fitness transformed by this simple method was better than that with relative fitness.

(b) Usage of Other Users' Evaluation Models

As described in the previous section, once an evaluation characteristics model of an IEC user is obtained, we can simulate IEC search with a pseudo-IEC user behind real user's evaluation. The IEC simulation can use big population size and many generations as much as computation time allows and provide the best m individuals, which helps to accelerate IEC convergence. This is a good approach to reduce IEC user fatigue. However, this method cannot be used in early generations until the model is leant. If many generations are necessary for training the model, this method may not be used well till the end of the IEC search.

One solution for this problem is to prepare models of several users' evaluation characteristics previously, choose the most similar model to the real IEC user in each generation, and use the chosen model instead of the model of the real IEC user until the real IEC user's model is learnt [5]. In each generation, all models of other IEC users evaluate all individuals as the same as the real IEC user does, and evaluation vectors of the real IEC user and each of other models are compared, and the other user's model whose evaluation vector is the closest to that of the real IEC user is chosen as the alternative of the IEC user's model.

We can expect the better performance of the IEC simulation from the first generation if the chosen other user model and the real IEC user's one are similar; if they are not similar, the IEC simulation works worse. It is convenient if we can check the similarity before we really apply this method.

We made the boarder of effective and ineffective clear through simulation. We made two mixture Gaussian models of evaluation characteristics of users A and B. The similarity between two models is changed gradually by changing the parameters of the B model, and the effect of IEC simulation is measured. At the same time, the fitness differences of two models are normalized by the n of evaluation levels to absorb the difference of the evaluation levels. From these experiences, we can estimate whether the method of using other IEC user's models works well by checking the differences of users' fitness values previously. This is, we show some individuals to several IEC users previously, normalize their fitness values, calculate the difference of normalized ones, and decide whether we use this method by checking the fitness difference is smaller than the boarder of effectiveness and ineffectiveness.

3.2 New IEC Frameworks

(a) Tournament IEC

In typical conventional IEC, all individuals are shown to an IEC user and relatively evaluated in n-evaluation levels. This relative evaluation by comparing all individuals is heavy load for an IEC user, and especially evaluating sound or movie individuals that we cannot compare spatially increases user's mental load as if a tramp concentration game. Its solution is a tournament IEC that does not request an IEC user to compare all individuals but pairs of individuals [7].

Tournament IEC makes pairs of all individuals randomly in each generation. The half of winner individuals at the first game go up to the second game, and this evaluation is iterated until one champion individual is obtained. Fitness is given to each individual according to the number of winning. The simplest way is to give the same fitness to all looser individuals at the same game. More precise fitting method takes into account the evaluation difference between an individual pair instead of 1 bit of win and loss. Thanks to taking into account the fitness difference, even if the second best individual is beaten by the champion individual at the first game, the second best does not become the worst looser [7]. This method corrects the fitness differences after a tournament game is over from the last game to the first game or its inverse order.

As the tournament IEC has less information than normal IEC that compares all individuals, its convergence may become slower than normal IEC. However, tournament IEC user's fatigue is improved largely thanks to paired comparison.

As the term of *tournament selection* is used in EC community, it is necessary to distinguish two *tournaments* when you survey IEC papers.

(b) Interactive PSO

Any individual-based optimization methods that do not request the information of a search space such as differential information can be used in an IEC framework. Since different optimization methods have different characteristics, we should investigate the best optimization method whose searching performance with fewer individuals and fewer generations is excellent for new IEC.

Particle swarm optimization (PSO) is one of such optimization methods. The comparative experiments of PSO and GA showed that PSO that uses space information for its velocity vector converges faster than GA for less complex benchmark functions such as DeJong's F_1 and F_2 but the PSO becomes worse than GA according to increasing complexity of benchmark functions [12]. As the landscape of IEC searching space is that of evaluation characteristics in IEC user's mind, it is hard to believe that the landscape is complex enough and fitness changes dramatically when values of optimization parameters change slightly. In many IEC applications, satisfied solutions can be obtained with smaller population size within fewer generations, and it is the proof that the IEC landscape is quite simple. Thus, we can expect that PSO is better than GA for IEC.

However, experimental comparison showed that interactive PSO is poorer than interactive GA for any simple benchmark functions unlike the comparison of PSO and GA. We analyzed the reason and found that fitness quantization noise that cannot be avoid due to the feature (4) mentioned in section 1 gave bad influence to the calculations of the global best and the local bests and the imprecise velocity vectors made the convergence of interactive PSO worse [12]. Less tolerance of PSO to fitness noise is a disadvantageous feature to use for IEC. In other words, if we can reduce the influence of the quantization noise, we can expect that interactive POS converges faster than interactive GA. We proposed some methods for improvements and showed that it was true [12].

4 Conclusion

We overviewed the features of IEC research mainly in 2000's following remarks for developing IEC techniques in this paper. Most IEC research is within the typical IEC framework; EC optimizes the target system based on IEC user's subjective evaluation. Besides them, new types of IEC research can be found in this decade, and we introduced such research: measuring a psychological scale of an IEC user by analyzing the system optimized based on his/her psychological scale, IEC based on physiological responses, and IEC+EMO. Other features of IEC research are several trials to reduce IEC user fatigue and the start of new type/framework of IEC research.

Author is thinking that IEC is one of tools that realize *Humanized Computational Intelligence* and there must be several approaches to realize it besides the IEC. We would like to continue to research toward this big framework.

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