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A generation alternation model for user-system cooperative evolutionary computation

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Abstract: User-System Cooperative Evolution (CEUS) is an Evolutionary Computation (EC) method to optimize quantitative and qualitative criteria. In previous work of CEUS, the whole population update is performed at every generation, and the user hardly observes all individuals. This paper proposes a generation alternation model designed for CEUS. The proposed model allows a user to find widely varied individuals in addition to the best individuals by replacing just one individual in a population for each generation, and consequently contributes user's idea generation by enhancing divergent thinking.

Keywords:
user-system cooperative evolution, generation alternation model, interactive evolutionary computation, genetic algorithm

1 INTRODUCTION

Interactive Evolutionary Computation (IEC)[1] faces a dilemma that general Evolutionary Computation (EC) algorithms require much trial and error but IEC can not use a large population and can not iterate so many generations due to user fatigue. To resolve this dilemma, the authors have proposed a method that is a fusion model of IEC and Non-Interactive EC (nIEC)[2]. In this paper we call the above method Cooperative Evolution by User and System (CEUS).

CEUS aims to incorporate user heuristics and/or preference into EC search dynamically. To achieve this, CEUS comprises following two essential functions.

1. CEUS optimizes both qualitative and quantitative objective functions simultaneously:
   CEUS can be regarded as IEC with domain knowledge that can be used to evaluate solutions, or as EC with a qualitative objective function. Designing a fitness function is crucial to find good solutions in real-world problems. But ideal function may not be sufficient to solve such real world problems, and ambiguous complementary subfunctions may be necessary to obtain practical quasi-optimal solutions. Incorporating ambiguous criteria such as user preference particularly makes it difficult to design the fitness function. Various real world problems can therefore be modeled as the problem involving explicit and ambiguous criteria.

2. CEUS has a mechanism to adopt user heuristics and preferences and to estimate user preferences from past user operation:
   To promote the effective use of EC, it is crucial to use large population size and to conduct a search long enough. But excessive user operations must be avoided. CEUS therefore allows a user to dynamically switch the role of EC at any time during the search. For instance, the user lets the system search for a solution like nIEC, and observes the search progress. Whenever the user finds an interesting individual, the user can stop the search, evaluate it, and add a genetic operation to it.

In previous work of CEUS, the whole population update is performed at every generation, and the user hardly observes all individuals. Only the best individuals can be seen by the user because it cannot be updated so frequently except the earlier stage of the search. Varied individuals with a moderate fitness value can be hardly found by the user because such individuals change and are replaced by new ones immediately. Consequently, although CEUS shows good performance to find a solution which can be expected by the user, CEUS was not effective to help the user find unpredictable, varied solutions.

This paper proposes a generation alternation model designed for CEUS. The proposed generation alternation model allows a user to find widely varied individuals in addition to the best individuals by replacing just one individual in a population for each generation. Consequently, the proposed model contributes user's idea generation by enhancing divergent thinking.

Experimental study showed that the proposed generation alternation model helped a user find various solutions not only the best individuals in the population.

2 USER-SYSTEM COOPERATIVE EC

Fig. 1 shows the process flow of CEUS. A typical CEUS search style is that the system searches for solutions by itself at the early stage of the search, and after the system produces some promising individuals the user chooses adequate one

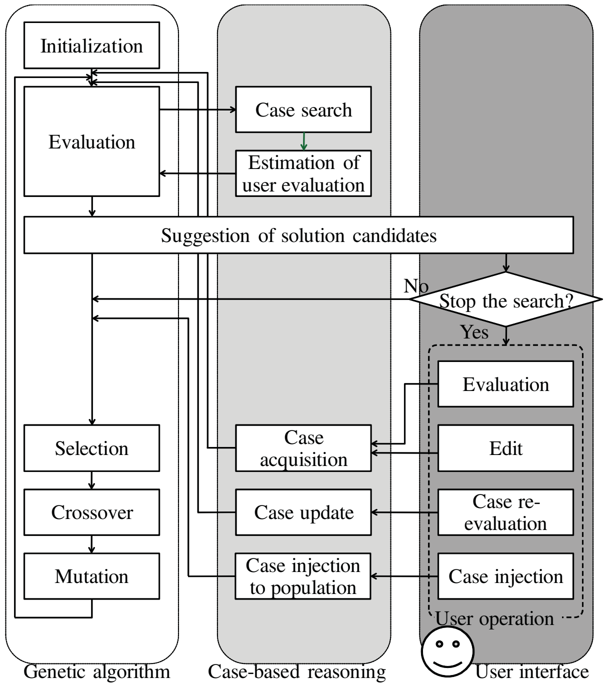


Fig. 1. Process flow of CEUS.

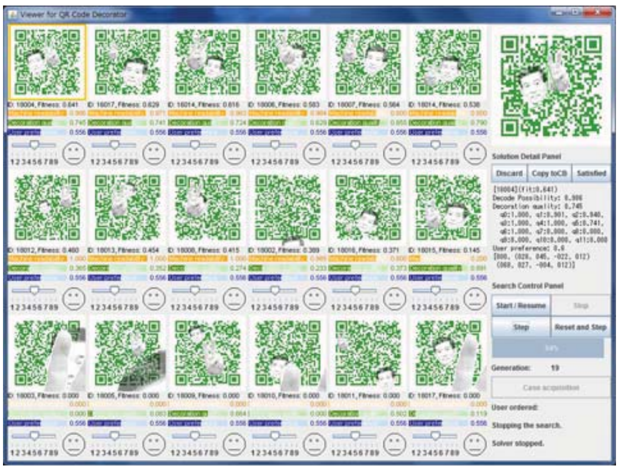


Fig. 2. User interface.

or directly revise them in order to enhance search intensification. nIEC search improves the population based on the chosen or revised individuals.

In CEUS, the user does not have to evaluate individuals at every generation. Unless the user stops the search, the system keeps searching for a solution. Although the user is allowed to concentrate on observing individuals reproduced by the system, it is hard to watch all individuals because the system grinds out individuals. CEUS proposed in [2] adopt simple GA (SGA), and most of individuals are replaced by new offsprings except top elites at every generation.

Therefore, to observe changes on the top elites and a few good individuals is the lowest the user can do. The user can not afford to watch other various individuals, and the user often passes over unpredictable and moderately good individuals. It is important to observe such individuals so that CEUS enhances the user's divergent thinking.

3 PROPOSED GENRATION ALTERNATION MODEL

The generation alternation model for CEUS proposed in this paper aims to increase the chance to discover unpredictable, good solutions. The proposed model is based on the following ideas:

1. **Minimize the gap between generations.**
   Just like Minimal Generation Gap (MGG)[3], one of the generation alternation models to prevent premature convergence, the proposed generation alternation model minimizes the gap between generations. The proposed model replaces only one individual at every generation, whereas MGG replaces two.

2. **Design some rules to choose a parent to be removed and an offspring to be added.** The proposed model generates as many offsprings as population size, and replaces one of the parents by one of the offspring. The parent and the offspring are chosen by rules in order to adjust the balance between search exploitation and exploration based on user preference.

Table 1 shows the generation alternation rules. Rules which have the smaller rule id have the higher priority. R_6 and R_7 are applied by random if none of R_1 to R_5 can be applied.

To esteem user operation and reflect it to the search, R_2 and R_3 removes individuals that are ranked as the minimum priority. R_4 enhances the local search based on user preference.

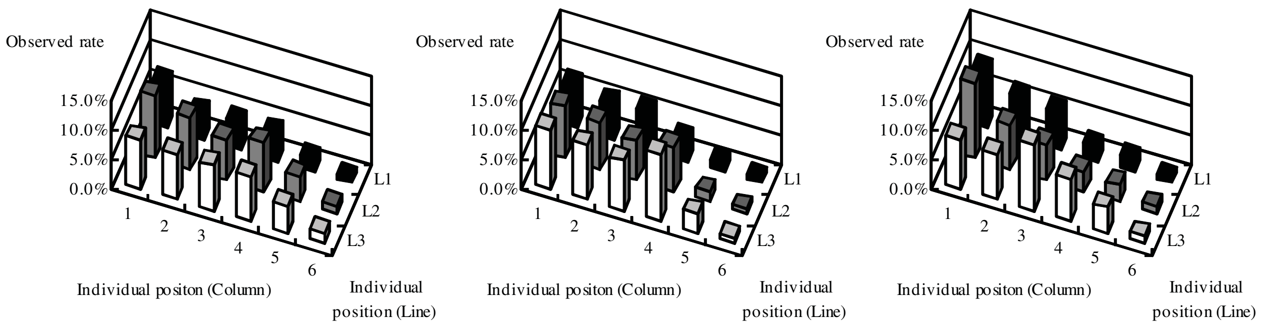
Although the proposed model can keep diversity by changing only one individual at every generation, bad individuals are hardly removed from the population. R_5, R_6 and R_7 are designed to shake out those individuals.

4 EVALUATION

To verify the effectiveness of the proposed generation alternation model in CEUS, the proposed method is compared with the previous work for CEUS[2] and MGG based method. A two-dimensional barcode decoration problem is used [2]. The problem has three objective functions: machine readability R, decoration quality Q, and user preference P. The readability R and decoration quality Q are quantitative criteria, and fitness F can be calculated by the following

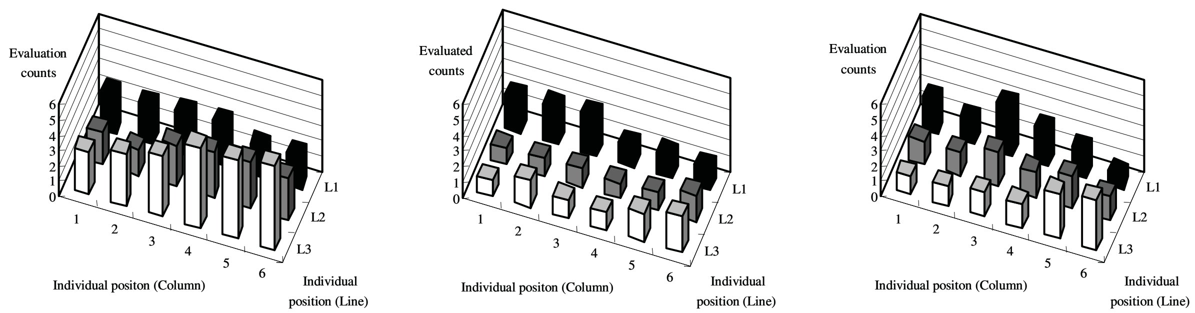
Table 1. Generation alternation rules.

ID	Antecedent	Consequent	
		Deleted	Added
R_1	The parent P_ρ having higher density than T_ρ exists.	P_ρ	Farthest offspring from P_ρ
R_2	Both parent P_0 whose preference was set to 0 and parent P_1 whose preference was set to 1 exist.	P_0	Nearest offspring to P_1
R_3	P_0 exits.	P_0	Farthest offspring from P_0
R_4	Parent P_1, which are evaluated in the current generation, exists.	Parent with the worst preference	Nearest offsping to P_1.
R_5	Fitness of the best offspring O_{best} is greater than the fitness of the best parent P_{best}.	By roulette selection based on inverse fitness value	O_{best}
R_6	—	The worst parent P_{worst}	Offspring O_δ with the maximum improvement from the previous generation
R_7	—	P_{worst}	The nearest offspring to P_{worst}



(a) Previous method (Update all) (b) MGG (c) Proposed method (Update one)

Fig. 3. Eye-tracking results.



(a) Previous method (Update all) (b) MGG (c) Proposed method (Update one)

Fig. 4. Number of evaluated individuals for each individual position.

equation involving weights $w^{(p)}$, $w^{(q)}$, and $w^{(r)}$.

$$F = R^{w^{(r)}} \times (1 - w^{(p)}) \cdot Q^{w^{(q)}} \times w^{(p)} \cdot P \qquad (1)$$

A system used in this experiment that can show 18 individuals with three lines and six columns as shown in Fig. 2. In this system individuals are sorted by the fitness and placed from top-left to bottom-right.

In this experiment, we tracked user eyes to clarify how the user can see widely varied individuals. Ten examinees tested the above three methods in random order, and answered a questionnaire.

Fig. 3 shows the eye tracking results, and Fig. 4 shows the averaged number of evaluated individuals by the examinees for each individual position. Fig. 3 reveals that individuals in right side columns were hardly watched, and that there was not so much difference between lines in all methods.

According to the questionnaire result, some examinees felt that the proposed model helped to find unpredictable good solutions. Fig. 4 shows that MGG based method and the proposed method urged the examinees to evaluate individuals placed at the second and third lines in addition to elite individuals placed at top-left. Also in the previous method, individuals in the third position seemed evaluated frequently. But this is because the examinees tried to remove bad individuals with much evaluation cost.

There was no significant difference on satisfaction with derived solutions according to the questionnaire result. The fitness of the previous method indicated by "Update all" in Fig. 5 showed the best, and MGG and the proposed method indicated by "Update one" showed worse fitness values. In particular, there seems differences in preference shown in Fig. 5(b), but these results show just transitions of the best solutions and do not imply the satisfaction of the final solutions. Because readability and quality score values of the previous and proposed methods were almost the same, the difference on preference implies that the proposed method tried to reproduce diversified individuals.

5 CONCLUSION

This paper proposes a generation alternation model for CEUS aiming to discover moderately good and unpredictable individuals. Experimental results have shown that MGG and the proposed model helped uses to find such individuals, and that simple eye-tracking was not sufficient to clarify the effectiveness of generation alternation models.

In future we plan to design a simpler rule set, and to analyze the effectiveness of generation alternation models in CEUS.

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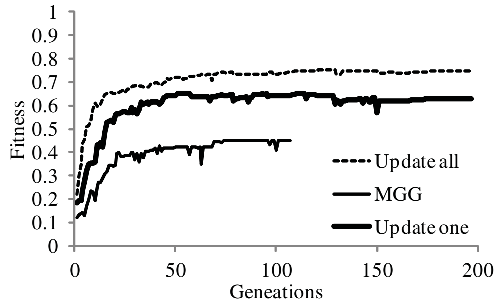
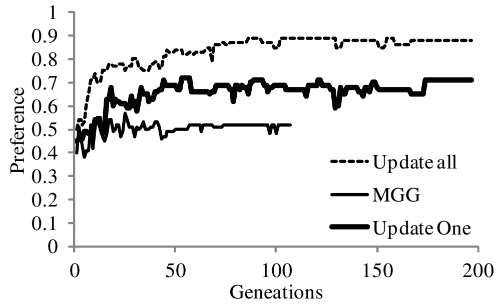
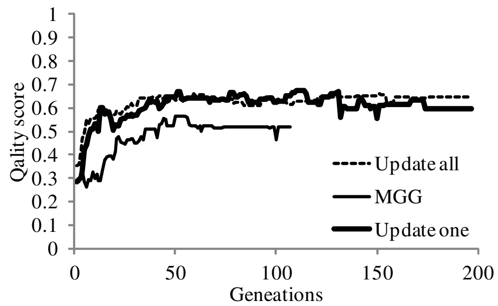


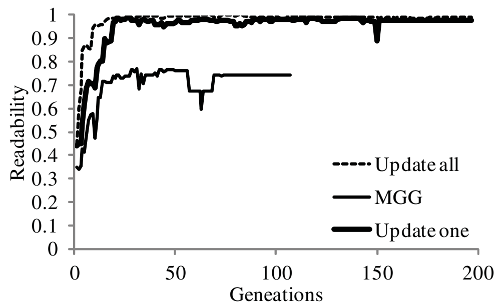
(a) Fitness transitions



(b) Preference transitions



(c) Quality score transitions



(d) Readability transitions

Fig. 5. Fitness transitions of the best individuals.

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