NEIGHBORHOOD CULTIVATION GENETIC ALGORITHM FOR MULTI-OBJECTIVE OPTIMIZATION PROBLEMS

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ABSTRACT

In this paper, a new genetic algorithm for multi-objective optimization problems is introduced. That is called "Neighborhood Cultivation GA (NCGA)". In the recent studies such as SPEA2 or NSGA-II, it is demonstrated that some mechanisms are important; the mechanisms of placement in an archive of the excellent solutions, sharing without parameters, assign of fitness, selection and reflection the archived solutions to the search population. NCGA includes not only these mechanisms but also the neighborhood crossover. The comparison of NCGA with SPEA2 and NSGA-II by some test functions shows that NCGA is a robust algorithm to find Pareto-optimum solutions. Through the comparison between the case of using neighborhood crossover and the case of using normal crossover in NCGA, the effect of neighborhood crossover is made clear.

1. INTRODUCTION

Recently, the study of evolutionary computation of multi-objective optimization has been researched actively and made great progress [1, 2]. The many approaches have been introduced and genetic algorithm (GA) is a main approach among them [1]. GA can derive a set of Pareto-optimum solution in one trial, since GA is one of multi point search methods.

In the past years, several new algorithms that can find good Pareto-optimum solutions with small calculation cost have been developed [1]. Those are NSGA-II [1], SPEA2 [2], and so on. These new algorithms have the same search mechanisms; those are preservation scheme of excellent solutions that are found in the search, allocation scheme of appropriate fitness values and sharing scheme without parameters.

We proposed the parallel model of multi-objective GA that is called DRMOGA [3]. In this model, we discussed the difference of the parallel models between single objective problems and multi-objective problems. We also proposed the neighborhood crossover and showed the effectiveness of the neighborhood crossover through the numerical examples.

In this paper, we propose a new GA for multi-objective optimization problems. That is called Neighborhood Cultivation GA (NCGA). NCGA includes not only the mechanisms of NSGA-II and SPEA2 that derive the good solutions but also the mechanism of neighborhood crossover. Through the numerical experiments, the effectiveness of NCGA is discussed. In the experiments, the results of NCGA are compared with those of NSGA-II, SPEA2 and non-NCGA (nNCGA). nNCGA is the same algorithms as NCGA but without neighborhood crossover.

2. MULTI-OBJECTIVE OPTIMIZATION PROBLEMS BY GENETIC ALGORITHMS

Genetic Algorithm is an algorithm that simulates the heredity and evolution of living things [1]. Since GA is one of multi point search methods, an optimum solution can be determined even when the landscape of the objective function is multi modal. In multi-objective optimization, GA can find a Pareto-optimum set with one trial because GA is a multi point search. As a result, GA is a very effective tool especially in multi-objective optimization problems. Thus, there are many researchers who are working on multi-objective GA and there are many algorithms of multi-objective GA [1, 2, 3, 4]. These algorithms of multi-objective GA are roughly divided into two categories; the algorithms that treat Pareto-optimum solution implicitly or explicitly [1]. The most of the latest methods treat Pareto-optimum solution explicitly.

The following topics are the mechanisms that the recent GA approaches have.

1) Reservation mechanism of the excellent solutions
2) Reflection to search solutions mechanism of the reserved excellent solutions
3) Cut down (sharing) method of the reserved excellent solutions
4) Assignment method of fitness function
5) Unification mechanism of values of each objective

These mechanisms derive the good Pareto-optimum solutions. Therefore, the developed algorithm should have these mechanisms.

3. NEIGHBORHOOD CULTIVATION GENETIC ALGORITHM

In this paper, we extend GA and develop a new algorithm that is called Neighborhood Cultivation Genetic Algorithm (NCGA). NCGA has the neighborhood crossover mechanism in addition to the mechanisms of GAs that are explained in the former chapter. In GAs, the exploration and exploitation are very important. By exploitation, an optimum solution can be found in a global area. By exploration, an optimum solution can be found around the elite solution. In NCGA, the exploitation factor of the crossover is reinforced. In the crossover operation of NCGA, a pair of the individuals for crossover is not chosen randomly, but individuals who are close each other are chosen. Because of this operation, child individuals that are generated after the crossover may be close to the parent individuals. Therefore, the precise exploitation is expected.

The following steps are the overall flow of NCGA where

P_t : search population at generation t
A_t : archive at generation t.

Step 1: Initialization: Generate an initial population P_0. Population size is N. Set $t = 0$. Calculate fitness values of initial individuals in P_0. Copy P_0 into A_0. Archive size is also N.
Step 2: Start new generation: set $t = t + 1$.
Step 3: Generate new search population: $P_t = A_{t-1}$.
Step 4: Sorting: Individuals of P_t are sorted with along to the values of focused objective. The focused objective is changed at every generation. For example, when there are three objectives, the first objective is focused in this step in the first generation. The third objective is focused in the third generation. Then the first objective is focused again in the forth generation.
Step 5: Grouping: P_t is divided into groups which consists of two individuals. These two individuals are chosen from the top to the down of the sorted individuals.
Step 6: Crossover and Mutation: In a group, crossover and mutation operations are performed. From two parent individuals, two child individuals are generated. Here, parent individuals are eliminated.
Step 7: Evaluation: All of the objectives of individuals are derived.
Step 8: Assembling: The all individuals are assembled into one group and this becomes new P_t.
Step 9: Renewing archives: Assemble P_t and A_{t-1} together. Then N individuals are chosen from $2N$ individuals. To reduce the number of individuals, the same operation of SPEA2 (Environment Selection) is also performed. In NCGA, this environment selection is applied as the selection operation.
Step 10: Termination: Check the terminal condition. If it is satisfied, the simulation is terminated. If it is not satisfied, the simulation returns to Step 2.

In NCGA, most of the genetic operations are performed in a group that is consisted of two individuals.

The following features of NCGA are the differences of the recent major algorithm like SPEA2 and NSGA-II.

1) NCGA has the neighborhood crossover mechanism.
2) NCGA has only the environment selection and it does not have the mating selection.

4. NUMERICAL EXAMPLES

In this section, NCGA is applied to the some test functions. The results are compared with those of SPEA2 [2], NSGA-II [1] and non-NCGA (nNCGA). nNCGA is the same algorithm of NCGA without neighborhood crossover.

4.1. Test Functions

In this paper, we use two continuous functions and a knapsack problem. These problems are explained as follows. In these equations, f denotes an objective function and $g(g \geq 0)$ indicates a constraint.

$$ZDT4: \begin{cases} \min & f_1(x) = x_1 \\ \min & f_2(x) = g(x)[1 - \sqrt{\frac{x_1}{g(x)}}] \\ & g(x) = 91 + \sum_{i=2}^{10}[x_i^2 - 10\cos(4\pi x_i)] \\ & x_1 \in [0,1],\ x_i \in [-5,5],\ i = 2,\ldots,10 \end{cases}$$

$$KUR: \begin{cases} \min & f_1 = \sum_{i=1}^{n}(-10\exp(-0.2\sqrt{x_i^2 + x_{i+1}^2})) \\ \min & f_2 = \sum_{i=1}^{n}(|x_i|^{0.8} + 5\sin(x_i)^3) \\ & x_i[-5,5],\ i = 1,\ldots,n,\ n = 100 \end{cases}$$

$$KP750-2: \begin{cases} \min & f_i(x) = \sum_{i=1}^{n} x_i \cdot p_{i,j} \\ s.t. & \\ & g(x) = \sum_{i=1}^{n} x_i \dot{w}_{i,j} \leq W_j \\ & p_{i,j}\text{(profit value)} \\ & w_{i,j}\text{(weight value)} \\ & 1 \leq j \leq 2 \end{cases}$$

ZDT4 was use by Zitzler and Deb [1]. This test function is a multi-model function. KUR was used by Kursawa [1]. It has a multi-modal function in one component. At the same time, there are interactions among the variables in the other component. KP750-2 is a 0/1 knapsack problem and it is a combinatorial problem [1, 2]. There are 750 items and two objects.

4.2. Parameters of GAs

In this paper, to discuss the effectiveness of the algorithm, simple methods are applied for all the problems. Therefore the bit coding is used in the experiments. Similarly, one

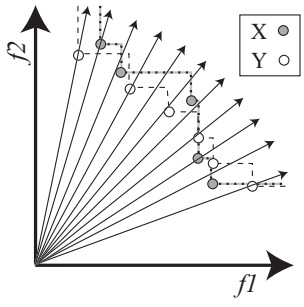

Figure 1: Sampling of the Pareto frontier lines of intersection

point crossover is used for the crossover and bit flip method is used for the mutation. The length of the chromosome is 20 bit per one design variable for the continuous problems and 750 bit for the knapsack problems. In the continuous problems, population size is 100. The simulation is terminated when the generation is got over 250. In the knapsack problems, population size is 250. The simulation is terminated when the generation is exceeded 2000.

4.3. Evaluation methods

To compare the results derived by each algorithm, the following evaluation methods are used in this paper.

4.3.1. Sampling of the Pareto frontier lines of intersection

This comparison method is presented by Knowles and Corne [4]. The concept of this method is shown in figure 1. In this figure, two solutions sets of X and Y that are derived by the different methods are illustrated.

At first, the attainment surfaces defined by the approximation sets are calculated. Secondly the uniform sampling lines that cover the Pareto tradeoff area are decided. For each line, the intersections of the line and the attainment surfaces of the derived sets are obtained. These intersections are compared. Finally, the Indication of Lines of Intersection (I_{LI}) is derived. When the two approximation sets X and Y are considered, then $I_{LI}(X, Y)$ indicates the average number of the points that X are ranked higher than Y. Therefore the most significant outcome would be $I_{LI}(X, Y) = 1.0$ and $I_{LI}(Y, X) = 0.0$.

In order to focus on only the Pareto tradeoff area as defined by the approximation sets and to derive the intuitive evaluation value, the following terms are considered.

- The objective values of approximation sets are normalized.
- The sampling lines are located in the area where the approximation sets are existed.
- Many sampling lines are prepared. In the following experiment, 1000 lines are used.

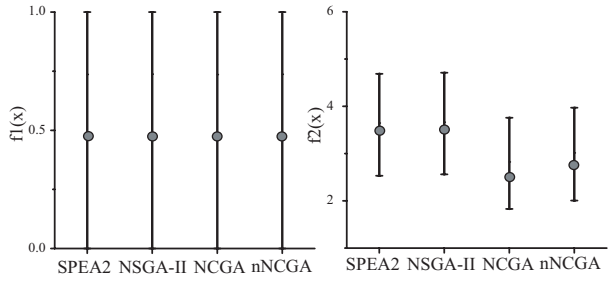

Figure 2: Max-Min values of ZDT4

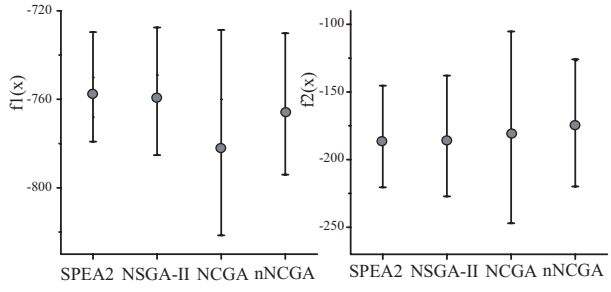

Figure 4: Max-Min values of KUR

4.3.2. Maximum, Minimum and Average values of each object of derived solutions (MMA)

To discuss the expanse of the solutions, the maximum, minimum and average values of each object are considered.

4.4. Results

Proposed NCGA, SPEA2, NSGA-II and nNCGA (NCGA without neighborhood crossover) are applied to test functions. 30 trials have been performed and all the results are the average of 30 trials.

4.4.1. ZDT4

The results of I_{LI} and MMA of ZDT4 are shown in Figure 2 and 3 respectively.

From figure 2 and 3, it is found that NCGA derived better solutions than the other methods. According to right figure in figure 2 , NCGA could get the best accuracy of the solutions.

And these results show that nNCGA could get almost the same quality solutions as NCGA gets. NCGA and nNCGA don't perform Mating selection, but only perform environmental selection. NCGA and nNCGA are different from SPEA2 and NSGA-II in this respect. As this problem is multi-model function, strong selection should let solutions centralize, and perform bad effect on solutions search.

4.4.2. KUR

In this problem, there are 100 design variables. Therefore, a lot of generations should be needed to derive the solutions.

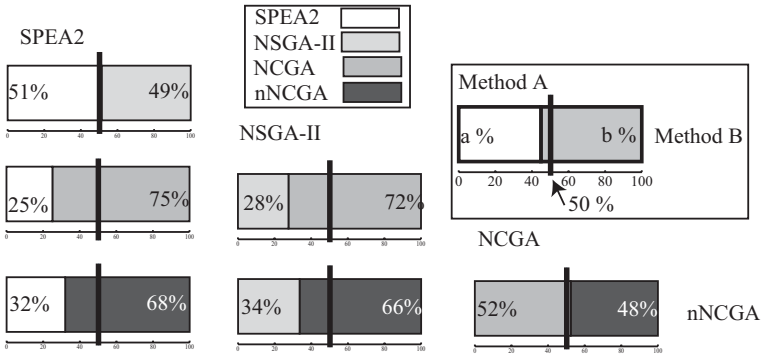

Figure 3: I_{LI} of ZDT4

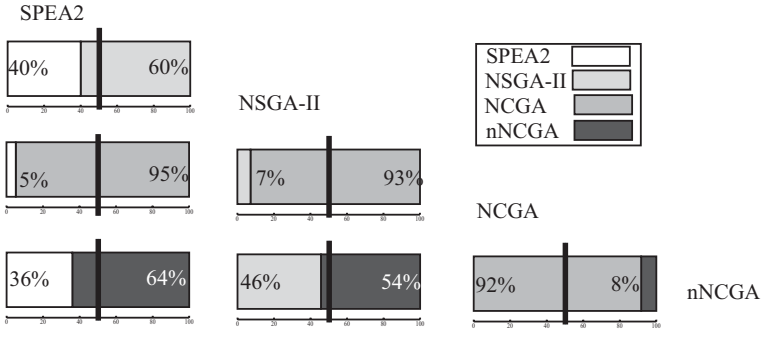

Figure 5: I_{LI} of KUR

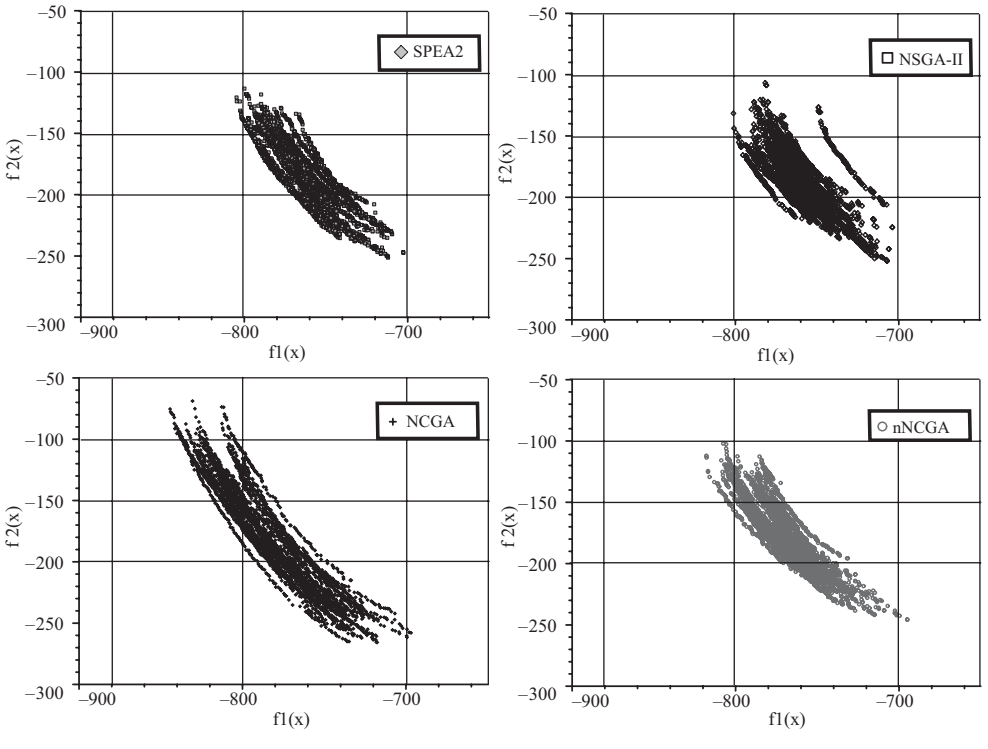

Figure 6: Pareto optimum individuals(KUR)

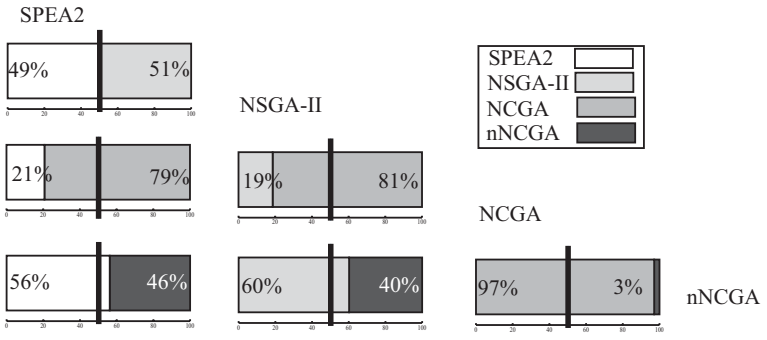

Figure 7: I_{LI} of KP-2

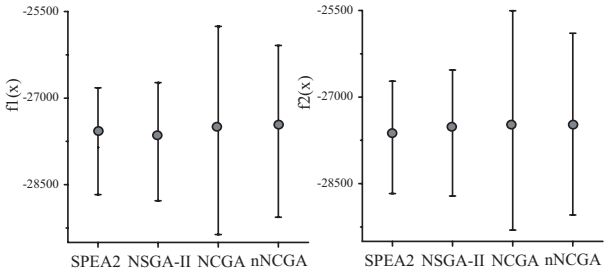

Figure 8: Max-Min values of KP750-2

The results of I_{LI} and MMA are shown in figure 4 and 5. Figure 6 indicates Pareto solutions in KUR. In this figure, all the Pareto-optimum solutions that are derived in 30 trials are plotted.

It is clear from the figure 5 that NCGA derived better solutions than the other methods. The solutions of NCGA are also wider spread than those of the other methods. In comparison with nNCGA, NCGA can get better solutions obviously. Therefore, the mechanism of neighborhood crossover acts effectively to derive the solutions in this problem.

4.4.3. KP750-2

KP750-2 is the knapsack problem and it is very difficult to search the real Pareto-optimum solutions. The results of I_{LI} and MMA are shown in figure 7 and 8.

From figure 8, NCGA found the wide spread solutions compared to the other methods. According to figure 7, the accuracy of the solutions of NCGA is better than those of the other methods. And nNCGA derived worse solutions than those of SPEA2 and NSGA-II, but NCGA could get better solutions than these methods.

5. CONCLUSION

In this paper, a new algorithm for multi-objective problems is proposed. The proposed algorithm is called ”Neighborhood Cultivation Genetic Algorithm (NCGA)”. NCGA has not only important mechanism of the other methods but also the mechanism of neighborhood crossover selection.

To discuss the effectiveness of the proposed method, NCGA was applied to test functions and results were compared to the other methods; those are SPEA2, NSGA-II and nNCGA (NCGA with no neighborhood crossover). Through the numerical examples, the following topics are made clear.

1) In almost all the test functions, the results of NCGA is superior to that of the others. From this result, it can be noted that the proposed NCGA is good method in multi-objective optimization problems.
2) Comparing to NCGA and NCGA without neighborhood crossover, the former is obviously superior to the latter in all problems. Therefore, the results emphasize that the neighborhood crossover acts to derive the good solutions.
3) Comparing to SPEA2 and NSGA-II, two methods have almost the same ability to find Pareto optimum solutions.

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