DCMOGA: Distributed Cooperation model of Multi-Objective Genetic Algorithm

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1 DCMOGA

In the multi objective problems, the good Pareto optimum solutions should have the following characteristics; the solutions should be close to the real Pareto front, the solutions should not be concentrated but should be widespread and the solutions should have the optimum solutions of every single objective function.

"Distributed Cooperation model of Multi-Objective Genetic Algorithm (DCMOGA)" is a new mechanism of MOGA to derive the solutions that have the above characteristics. In DCMOGA, there are $N+1$ sub populations (islands) when there are N objects. One of these groups is the group for finding the Pareto optimum solutions. This group is called a MOGA group. One of the other groups is the group for finding the optimum of ith objective function. These groups are called SOGA groups. Any GAs and MOGAs can be applied in the SOGA and MOGA groups respectively.

The following steps are the procedure of the DCMOGA.

Step 1: All the individuals are initialized.

Step 2: These individuals are divided into $n+1$ groups. n of them are SOGA groups and each group has own objective function. One of them is a MOGA group that searches Pareto-optimum solutions.

Step 3: In each group, the solution search has been performed for several iterations.

Step 4: The elite archive and the Pareto archive are renewed in each group at every iteration.

Step 5: After the certain iterations, the solutions are communicated between the MOGA and SOGA groups. In this step, the solution M_i whose value of ith objective function F_i is best in the MOGA group is chosen. The solution M_i is sent to the group whose target objective function is ith objective function. On the other hand, the best solution S_i in the ith group of SOGA is sent to the MOGA group.

Step 6: The solutions M_i and S_i are compared. When $S_i > M_i$, some individuals of the MOGA group are added and the SOGA group are decreased. When $S_i < M_i$, some individuals of MOGA are decreased and SOGA are added.

Step 7: In this timing, the best individual of each SOGA group is compared with the individual that is the best in the last time. When all the best individuals in SOGA groups are the same as the ones in the last time, SOGA groups are expired and all the groups become MOGA groups.

Step 8: The terminal condition is checked. If the condition is not satisfied, the process is back to step 3.

In Figure1, the concept of the DCMOGA is illustrated.

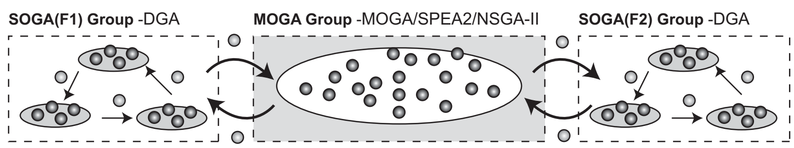

Fig. 1. DCMOGA (2 object functions)

2 Numerical Examples

To discuss the effectiveness of the DCMOGA, the DCMOGA is applied to several test functions and the Pareto optimum solutions are derived. Because of the limitation of the space, only the knapsack problem (KP750-2) and ZDT4 are discussed in this paper. The KP750-2 has 750 items and two objectives.

The DCMOGA is applied to Fonseca's MOGAs[3], SPEA2[1], and NSGA-II[2]. The results of these methods are compared.

To solve the test functions, the bit coding is used for representing the individuals. 750 bit length is used for the KP750-2. In the ZDT4, there are 10 design variables and 20 bit are used for each design variable. In the GA, the double point crossover and the bit flip mutation are applied. The population size is 250 for the KP750-2 and 100 for the ZDT4. The simulation is terminated when the number of evaluation is over 500000 for the KP750-2 and 250 for the ZDT4. All the results are from 30 trials. The description of the other parameters is omitted.

To compare the results that are derived by several algorithms, the figure of the derived Pareto optimum solutions and the two types of the coverage are used. The Coverage($\mathcal{C}$) and Coverage($\mathcal{D}$) are explained and used in the reference[1].

In Figure2, the results of the KP750-2 are shown. In Figure3, the results of the ZDT4 are shown.

From these figures, it is found that the DCMOGA can apply to MOGA, SPEA2 and NSGA-II. These algorithms can derive the wide spread Pareto solutions when the DCMOGA is combined.

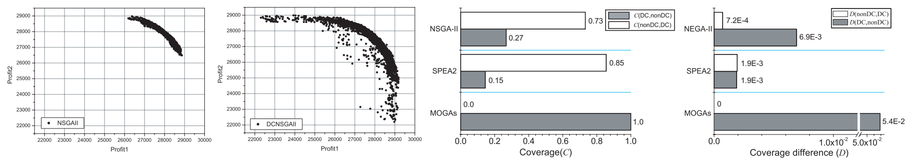

Fig. 2. Result: KP750-2

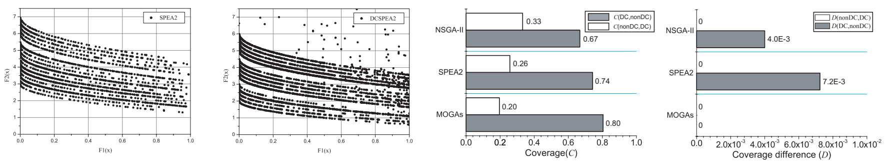

Fig. 3. Result: ZDT4

The DCMOGA was applied to other test functions and the same tendency of the results is derived. The DCMOGA has a mechanism to find the wide spread solutions. Therefore, it sometimes takes time to close to the Pareto front. From these results, it can be said that the DCMOGA is a useful mechanism for the multi objective GAs especially in the difficult problems.

Acknowledgement

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