Multiple Swarm Intelligence Methods based on Multiple Population with Sharing Best Solution for Drastic Environmental Change

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ABSTRACT

This paper proposes the multiple swarm optimization method composed of some numbers of populations, each of which is optimized by the different swarm optimization algorithm to adapt to dynamically change environment. To investigates the effectiveness of the proposed method, we apply it into the complex environment, where the objective function changes in a certain interval. The intensive experiments have revealed that the performance of the proposed method is better than the other conventional algorithms (*i.e.*, particle swarm optimization (PSO), cuckoo search (CS), differential evolution (DE)) in terms of convergence and fitness.

CCS CONCEPTS

• **Mathematics of computing → Evolutionary algorithms**;

KEYWORDS

swarm optimization, multiple population, particle swarm optimization, cuckoo search, differential evolution

1 INTRODUCTION

Although many meta heuristics optimization algorithms have been proposed, the no-free-lunch theorem [3] suggested that there is no special algorithm that can derive a sufficient performance for all of the problems. This also means that one algorithm is not enough to find an optimal solution(s) or near optimal solutions in the case of dynamical environmental change, where the objective function changes from one to others. To tackle this problem, we focus on an advantage of optimizing multiple populations by different algorithms as an ensemble approach, and propose the multiple swarm optimization method composed of some numbers of populations, each of which is optimized by the different swarm optimization algorithm.

This paper is organized as follows. The next section proposes our method, and Section 3 shows the experimental results. Finally, our conclusion is given in Section 4.

2 PROPOSED METHOD

As described above, the proposed method is composed of some numbers of populations, each of which is optimized by the different swarm optimization algorithm. Although any combination of swarm optimization algorithms can be employed, the proposed method in this paper employs the following three different algorithms: Particle Swarm Optimization (PSO) [1], Cuckoo Search (CS) [4] and Differential Evolution (DE) [2]. As the reason for employing the these algorithms, they have different search capabilities, each of which can find some solutions that are hard to be found by other algorithms. To cope with the dynamical environment change, the proposed method has the following mechanisms.

• *Best solution sharing*
After PSO, CS, and DE in our method respectively find their own best solutions in their sub-populations, they are compared to determine the most best one among three best solutions. The worse solution in each sub-population is replaced with the the most best one. This mechanism promotes the exploitation of the good solution found by the other algorithm. If one of algorithm finds the good solution in the case of the dynamical environment change, other algorithms can utilize (start to search around) the found solution that is hard to be found by themselves.

• *Reference solution sharing*
PSO, CS, and DE in our method can select the solutions in the other sub-population of the other algorithms in the evolutionary process. For example, the offspring solution of the conventional DE is generated by the three candidate solutions in the population of DE, while the offspring solution of DE in our method can be generated by solutions from the other sub-populations. This mechanism increases the diversity of the solutions by getting out of the local optima which can be easily found within the single algorithm.

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3 EXPERIMENT

3.1 Problem

The objective function in our experiment changes in the order of *Ackley*, *Schwefel* and *Rosenbrock* every 5000 iterations (*i.e.*, generation), which means that the shape of functions changes in the order of the pointed shape (*Ackley*), the wavy shape (*Schwefel*), and the plate shape (*Rosenbrock*). More importantly, this experimental setting also drastically changes not only the fitness landscape (*i.e.*, the position of the multiple peaks) but also the number of local and global optima every environmental change. Note that all these functions are the minimization problem.

3.2 Experimental Settings

3.2.1 Comparisons. The experiment compares the performance of the proposed method (composed of the sub populations of PSO, CS, and DE) with that of the single (conventional) PSO, CS, and DE. Note that the population size of the proposed method is the same as that of the single PSO, CS, and DE for a fair comparison. When the (each) population size of the single PSO, CS, and DE is N, the (total) population size of the proposed method is also N, which are divided into the S number of the sub populations which size is N/S. When the number of population N is 90, for example, the sub populations of PSO, CS, and DE in the proposed method is 30.

3.2.2 Evaluation. In the experiment, the performance of the proposed method and the single PSO, CS, and DE are evaluated in terms of fitness and convergence, which evaluates how much better solutions can be found quickly. All results are calculated from the average of 5 trials.

3.2.3 Parameter Settings. For the parameter settings of PSO, we set them as follows: the inertia weight $w = 0.9$ and the trust weight $c_1, c_2 = 1.5$. For the parameter settings of CS, we set them as follows: the step size $\alpha = 0.01$, lambda $\lambda = 1.5$, the deletion probability $P_a = 0.25$. For the parameter settings of DE, we set them as follows: the scaling parameter $F = 0.8$, the crossover rate $CR = 0.5$. As the same parameter settings, we set them as follows: the population size $N = 90$, the function area range from $MinRange = -500.0$ to $MaxRange = 500.0$, and the $max\ iteration = 15000$.

3.3 Results

Figure 1 shows the fitness of PSO, CS, DE, and the proposed method, each of which is respectively represented by the blue, orange, green and red lines. In the figure, the vertical axis indicates the fitness while the horizontal axis indicates iterations. From the result shown in Figure 1, the following implications are found: (1) in the *Ackley* function as the first environment, DE and the proposed method can find the optimal solution, while PSO cannot find the optimal solution until 5000 interactions and CS is hard to improve its solution after 1800 interactions; (2) in the *Schwefel* function as the second environment, all methods get into the local optima, but the fitness of the proposed method is the smallest (*i.e.*, best) in comparison with that of PSO, CS, and DE; and (3) in the *Rosenbrock* function as the third environment, PSO and the proposed method can find the optimal solution, while DE cannot improve its solution and CS improves its solution very slowly.

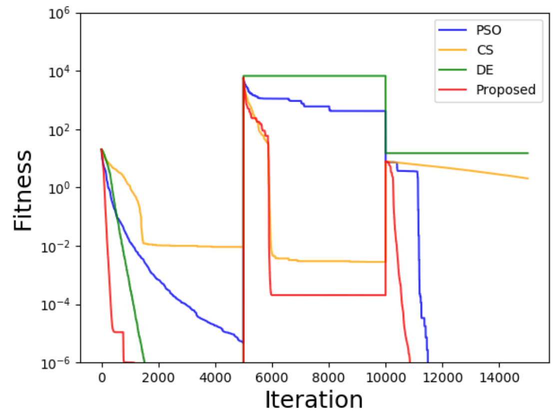

Figure 1: Fitness in dynamically change environment

The above implications suggest that the proposed method shows the good performance in all functions, meaning that the proposed method can find the smaller fitness and the speed of optimizing the solution is faster than the other conventional methods. Such features also suggest that the proposed method have a great potential of optimizing the solution in the dynamically change environment.

4 CONCLUSIONS

This paper explored the swarm optimization method for the dynamically change environment and proposed the multiple swarm optimization method composed of some numbers of populations, each of which is optimized by the different swarm optimization algorithm (PSO, CS and DE in this paper). To investigates the effectiveness of the proposed method, we applied it into the dynamically change environment, where the objective function changes in the order of *Ackley*, *Schwefel* and *Rosenbrock* every a certain iteration. The intensive experiments have revealed that the proposed method can keep to derive the good performance even in the dynamically change environment. Concretely, the proposed method can find the smaller fitness and the speed of optimizing the solution is faster than other conventional methods (*i.e.*, PSO, CS and DE) in such an environment.

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