

Introducing Recombination with Dynamic Linkage Discovery to Particle Swarm Optimization

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ABSTRACT

In this paper, we introduce the recombination operator with the technique of dynamic linkage discovery to particle swarm optimization (PSO) in order to improve the performance of PSO. Numerical experiments are conducted on a set of carefully designed benchmark functions and demonstrate good performance achieved by the proposed methodology.

Categories and Subject Descriptors

I.2.8 [Artificial Intelligence]: Problem Solving, Control Methods, and Search—*Heuristic methods*

General Terms

Algorithms

Keywords

Dynamic linkage discovery, building blocks, recombination operator, particle swarm optimization, genetic algorithm

1. INTRODUCTION

Particle swarm optimizer (PSO), introduced by Kennedy and Eberhart in 1995 [4, 5], emulates flocking behavior of birds to solve the optimization problems which is conceptually simple and can be implemented in a few lines of codes. On the other hand, genetic algorithms (GAs) introduced by John Holland [3, 2], are stochastic, population-based optimization algorithms loosely modeled after the paradigm of evolution. The two optimization techniques are both population-based that have been proven successful in solving a variety of difficult problems. However, both models have strength and weakness. Hence, a lot of studies on the hybridization of GAs and PSOs have been proposed and examined. Furthermore, some try to introduce the linkage concept to PSO and formulate linkage-sensitive PSO [1, 6].

In this paper, we propose a dynamic linkage discovery technique to effectively detect the building blocks of the objective function. Our method introduce the linkage concept and the recombination operator to the operation of PSO. The paper is organized as follows. Section 2 presents the method. Section 3 describes the test problems and the experimental results. Finally, section 4 concludes the study.

2. PSO WITH RECOMBINATION AND DYNAMIC LINKAGE DISCOVERY

The main purpose in this study is to enhance the PSO's performance by introducing the genetic operator with linkage concept. In order to make good use of linkage information, we design a special recombination operator. In the recombination process, there is a building block pool composed by selected individuals. Every offspring is created by choosing and recombining building blocks from the pool at random. We use this recombination process to generate the whole next population.

In the present work, we call the PSO combined with recombination and dynamic linkage discovery as PSO-RDL. In the proposed algorithm, we repeat the PSO procedure for a certain number of generations, we term such a period a *PSO epoch* in the rest of this paper. After each PSO epoch, we select the N best particles from the population to construct the building block pool and conduct a recombination operation according to the building blocks identified by dynamic linkage discovery. After the recombination process, the linkage discovery step is executed if necessary. We calculate the average fitness of the current epoch, compare the average with the one calculated during last epoch, and check if the improvement is great enough and thus decide that linkage configuration should changed or not. The complete flow of the algorithm are shown in Figure 1.

3. EXPERIMENTS

The test problems are proposed in the special session on real-parameter optimization in CEC2005. The description of test problems and parameter settings is provided in section 4.1. Section 4.2 shows the numerical results.

3.1 Test Problems

The newly proposed set of test problems includes 25 functions of different characteristics [7]. Due to the page restriction, we hereby present only the first 14 test problems results. Experiments are conducted on the 10- D problems. In this benchmark, the problem is considered solved when the error is $1e-6$ for problems 1-5 and $1e-2$ for problems 6-14. To conduct the experiments, the swarm size is set to 20, $0.8 \leq w \leq 0.9$, $0.5 \leq \bar{\varphi}_1 \leq 2.0$, $0.5 \leq \bar{\varphi}_2 \leq 2.0$, and V_{\max} restricts the particles' velocity, is equal to 25% of the initialization range. N , the number of particles selected for the recombination, is set to 25% of the swarm size. The threshold which decides the linkage configuration changed or not is set to 5% of the previous best fitness value.

Function	1	2	3	4	5
mean	6.821208E-15	8.185456E-14	4.555010E-04	6.985737E-10	1.455192E-13
Std	1.885282E-14	3.314516E-14	2.746542E-05	3.133031E-09	7.275960E-13
Function	6	7	8	9	10
mean	2.522122E-08	6.744376E-02	2.000148E+01	1.014857E+01	1.568052E+01
Std	1.101030E-07	5.439797E-02	3.008915E-03	5.233374E+00	5.519394E+00
Function	11	12	13	14	
mean	2.516470E+00	2.140760E-08	7.443845E-01	3.199979E+00	
Std	1.542868E+00	0.000000E+00	4.122971E-01	5.012267E-01	

Table 1: Best function error values achieved when FES = 1e+5 for functions 1-14.

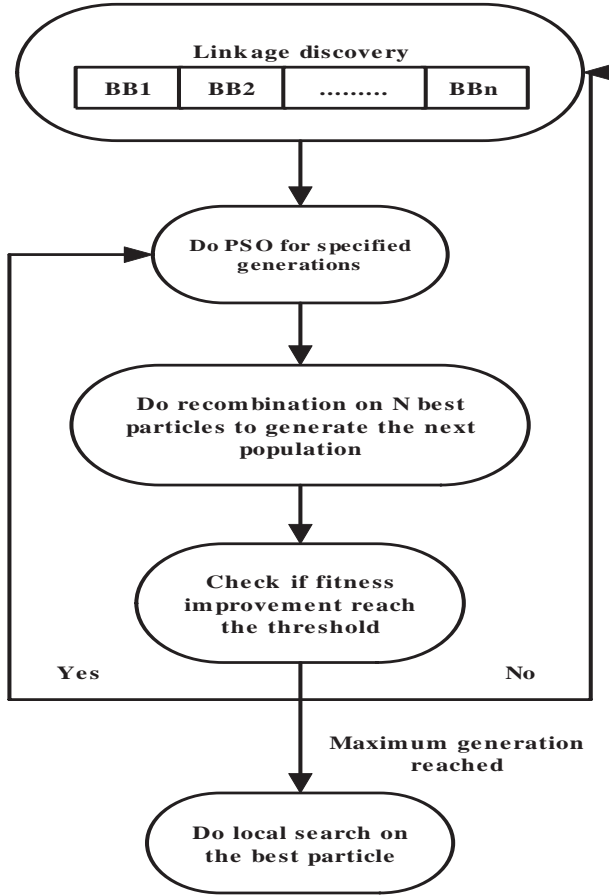


Figure 1: Flow chart of PSO-RDL

3.2 Experimental Results

The complete experiment results are listed in Tables 1. In the experimental results, PSO-RDL successfully solved problems 1, 2, 4, 5, 6, and 12. Moreover, comparable results are achieved in solving problems 3, 7, 8, 11, 13 and 14 when compared to the results achieved by other methods proposed in the special session on real-parameter optimization in CEC2005. Unfortunately, PSO-RDL failed to solve problems 9 and 10 due to the huge number of local optima.

4. CONCLUSIONS

In this paper, the present work on PSO-RDL gives us two observations. First, this work may shed light on the

existence of building blocks in real-parameter optimization problems. Secondly, according to the information obtained in this study, perhaps in a real-parameter optimization problem, the configuration of building blocks dynamically changes along with the search stage.

In this study, we introduce recombination with dynamic linkage discovery to PSO and consider the integration as a promising research direction. By combining the strength of different optimization models, we create the PSO-RDL algorithm with intriguing features and properties. We will continue to work on understanding and analyzing the real number optimization problem in order to design better evolutionary optimization algorithms in the future.

5. ACKNOWLEDGMENTS

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