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An Improved Differential Evolution for solving Large Scale Global Optimization

Sheng-Ta Hsieh[1], Shih-Yuan Chiu[2] and Shi-Jim Yen[2]

[1] Department of Communication Engineering, Oriental Institute of Technology, New Taipei City, Taiwan, R.O.C.
[2] Department of Computer Science and Information Engineering, National Dong Hwa University, Hualien, Taiwan, R.O.C.

fo013@oit.edu.tw

Abstract: Differential evolution (DE) is a population-based optimization algorithm. The members of population in DE are called parameter vectors. Due to more real-world optimization problems become increasingly complex. Algorithms with more ability and efficiency for searching potential solution are also increasing in demand. Thus, in this paper, an improved DE is proposed for solving large scale global optimization. The proposed method is incorporated with the population manager to eliminate redundant parameter vectors or to hire new ones or to maintain population size according to the solution searching status to make the process more efficient. The proposed method also involves mutation and cross-over for prevent the solutions from falling into the local minimum and enhance searching ability.

Keywords: Differential evolution, population manager, optimization, traveling salesman problem.

1 INTRODUCTION

Due to more real-world optimization problems become increasingly complex. Algorithms with more ability and efficiency for searching potential solution are also increasing in demand. In last four decades, more and more heuristic-based algorithms were proposed for solving numerical optimization, such as genetic algorithm (GA)[1] and particle swarm optimizer (PSO)[2], etc. In 1997, the concept of original differential evolution (DE) was proposed by Storn and Price [3].

Differential evolution (DE) is a population-based optimization algorithm. The members of population in DE are called parameter vectors. There are four common mutation strategies of DE were developed [4][5]and shown as follows.

1. DE/best/1

$$x_n^{child_i} = x_n^{best} + F\left(X_n^{r_1} + X_n^{r_2}\right)$$

2. DE/rand/2

$$x_n^{child_i} = x_n^{r_1} + F_1\left(X_n^{r_2} + X_n^{r_3}\right) + F_2\left(X_n^{r_4} + X_n^{r_5}\right)$$

3. DE/target/1

$$x_n^{child_i} = x_n^{i} + F\left(X_n^{r_1} + X_n^{r_2}\right)$$

4. DE/target to best/1

$$x_n^{child_i} = x_n^{i} + F\left(X_n^{best} + X_n^{r_1}\right)$$

In this paper, an improved DE is proposed for solving large scale global optimization. The proposed method is incorporated with the population manager control population size according to the solution searching status. Also, improved mutation and crossover are involved for prevent the solutions from falling into the local minimum and enhance searching ability.

2 PROPOSED METHOD

The first thing to apply DE for solving different applications is to decide several initial parameters of DE, such as population size. Having more chromosomes can extend the searching space and increase the probability of finding the global optimal solution, but it will require more time in each iteration. The problem is that, until now, there is no way to know what size of population is suitable for solving the current problem. Here, a population manager (PM) is introduced into DE to enhance its searching ability. The PM will increase or decrease population size according to the solution searching status. Thus, the population size in the proposed DE is variable.

2.1 Population Manager

The population manager will increase or decrease particle numbers according to the solution-searching status; thus, the population size in DE is variable. If the particles cannot find a better solution to update the global best solution, particles may be trapped into the local minimum during the searching process or need a competent guide to lead them toward the potential area. Thus, the information (experience) of existing particles may be too little to handle the current solution-searching procedures. Thus, new particles should be added into the population to speedup the solution searching progress.

On the other hand, if particles can find one or more solutions to update the global best solution, the existing particles may too many. For saving some time on finding the global optimal solution, the redundant particles should be expelled from the population to conserve their evolution time for speeding up the solution-searching progress.

2.2. Mutation

In general, mutation is adopted to generate new chromosomes, mutate one or more genes, to save chromosomes that fell into the local minimum using random process, and to explore other potential searching spaces.

In proposed method, mutation is to randomly select a dimension (d_1) of the chromosome i and to perturb it in the range between minimal and maximal solution of another randomly selected dimension (d_2). This will ignore other dimensions but can fine tune the solutions of specific dimensions one by one in the chromosome. To share searching ranges of selected dimensions among particles can generate more potential solutions. In this paper, the mutation rate is increase linearly from 0.001 to 0.01.

2.3. Crossover

In proposed method, crossover is consisted of two parts, one is the same as original DE, and the other is one-cut point cross-over. The activating rate of them is 50-50 in first iteration. After that, the activating rate it will depend on their child's survival rate in previous iteration.

The one-cut-point cross-over is to randomly select a cut-point of particle, and to exchange the right parts of cut-point from two particles. Then, linear combination at the cut-point is performed on particles to generate new solution.

3 EXPERIMENTS

In the experiments, the IEEE CEC 2008 test functions [6], which includes two unimodal and five multimodal functions, were chosen for testing four variants of DE [4][5] and proposed method. Each test functions are set as 500 dimensions and run 25 times and calculated their mean values and standard deviation. The maximum fitness evaluations (FEs) were set as 2,500,000.

The results five variants of DE approaches on the seven test functions with 500D problems are presented in Table I. The real optimal values are also listed on right column of Table I. The best results among the five approaches are shown in bold. From the results, the proposed method surpasses all other algorithms on functions 1, 2, 3, 5, and 6. The DE/best/1 performed better than the proposed on functions 1 and 7. The proposed method can efficiently find better solutions than other algorithms in the same FEs.

4 CONCLUSIONS

In this paper, the proposed method has been presented to solve large scale global numerical optimization problems. The proposed population manager strategy can adjust population size according to its current solution searching state to ensure better (potential) parameter vectors will join the evolution of DE. It also makes DE more robust, prevents parameter vectors from falling into the local minimum. The experiments show that the proposed method can get closer to optimal solutions, and it is more efficient than other variant of DE on the problems studied.

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Table I
Experiment Results of 500 Dimensions Problems and Their Optimal Values.

Methods / Functions	Proposed Method	DE/best/1	DE/target/1	DE/rand/2	DE/target to best/1	Real Optimal Values
f_1	**-4.5000E+02 ±3.9904E-05**	-4.4913E+02 ±5.1040E-01	-3.4633E+02 ±2.1536E+01	-4.4374E+02 ±9.1772E-01	-4.4987E+02 ±2.5957E-02	-450
f_2	**-4.1110E+02 ±1.7628E+00**	-3.6095E+02 ±3.3799E+00	-3.6802E+02 ±1.6044E+00	-3.7015E+02 ±1.2104E+00	-3.7109E+02 ±1.8678E+00	-450
f_3	**1.9389E+03 ±2.1301E+03**	2.7197E+03 ±4.8660E+02	2.0512E+07 ±7.0900E+06	3.4429E+04 ±1.0716E+04	3.0089E+03 ±4.6241E+02	390
f_4	-3.2995E+02 ±9.6550E-03	**-3.2996E+02 ±8.8627E-03**	2.0512E+07 ±7.0900E+06	3.1408E+03 ±1.3488E+02	-1.3606E+02 ±1.4043E+01	-330
f_5	**-1.7983E+02 ±1.7837E-01**	7.7221E+03 ±4.7561E+02	-1.5133E+02 ±4.7245E+00	-1.7592E+02 ±9.4683E-01	1.1096E+03 ±1.1584E+02	-180
f_6	**-1.4000E+02 ±3.0787E-04**	-1.3171E+02 ±4.2650E+00	-1.2070E+02 ±3.9538E-02	-1.2065E+02 ±7.7734E-02	-1.2096E+02 ±6.2450E-02	-140
f_7	-7.4025E+03 ±1.0097E+01	**-7.4042E+03 ±1.2252E+01**	-5.6549E+03 ±7.6434E+01	-4.7831E+03 ±1.2842E+02	-7.3251E+03 ±1.7702E+01	unknown