Diversity-Based Multi-Population Differential Evolution for Large-Scale Optimization

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ABSTRACT

There are increasing large-scale optimization problems in science and engineering nowadays. This paper proposes a diversity-based multi-population differential evolution (DB-MPDE) to maintain the population diversity, which is crucial for the large-scale optimizations. The performance of multi-population algorithms is sensitive to the exchanged information involved in the migration process. In our proposed DB-MPDE algorithm, information of diversity between sub-populations is utilized to determine the exchanged information. Both diverse and similar exchanged information is involved. Diverse exchanged information helps a lot in maintaining population diversity and similar exchanged information could accelerate convergence speed. In this way, the balance between global search and local search ability of the proposed algorithm can be achieved. A set of 20 benchmark functions is used to test the proposed DB-MPDE algorithm. Results show that the proposed DB-MPDE outperforms some well-known multi-population DE approaches.

Keywords

Differential Evolution; Multi-Population; Large-Scale Optimization

1. INTRODUCTION

Differential evolution (DE) was proposed by Storn and Price and has shown excellent performance on various types of optimization problems. However, the performance of DE deteriorates rapidly as the dimensionality of the problem increases. There is ongoing research into multi-population differential evolution (MPDE) for enhancing the population diversity, which is crucial for the large-scale optimization problems. In MPDE, population is divided into several sub-populations which evolve on their own. During the evolutionary process, sub-populations can exchange information with any others. Various kinds of information exchanging approaches have been proposed for MPDE [3, 1, 4, 5].

In this paper, a diversity-based multi-population differential evolution (DB-MPDE) is proposed. Unlike the existing MPDE algorithms, the exchanged information between sub-populations is determined by measuring their diversity. Specifically, during the migration process, sub-populations choose the neighborhood to exchange information based on their diversity between each other. Exchanged information from the diverse neighborhood is used to enhance the population diversity and the one from similar neighborhood is helpful for fast convergence of the proposed algorithm. Experimental results show that DB-MPDE exhibits a significantly better performance with respect to its competitors.

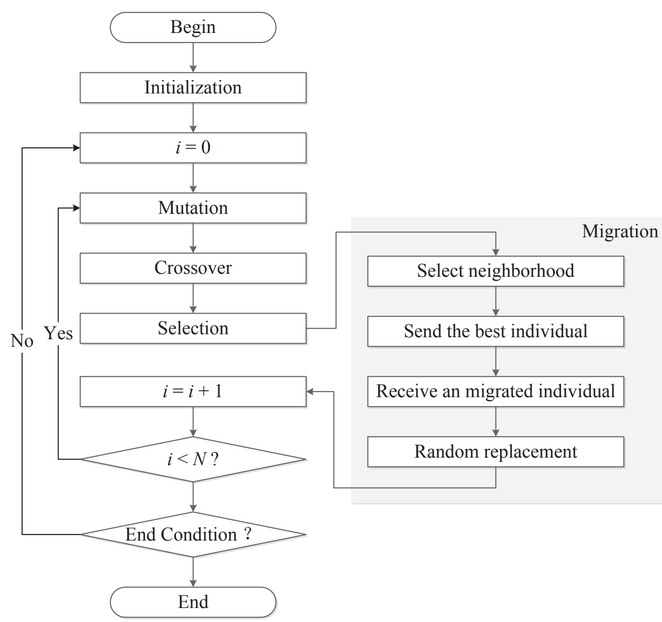

Figure 1: Flowchart of the proposed DB-MPDE algorithm.

2. DB-MPDE

The proposed DB-MPDE adopts a DE/rand/1/bin algorithm and a best-random migration strategy. The pseudo code of DB-MPDE is shown in Figure 1. The population is initialized and divided into N sub-populations. During the evolutionary process, mutation, crossover and update operators are carried out on the individuals in each sub-

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Table 1: Comparisons with well-known multi-population DE approaches.

Approaches	DB-MPDE		P-MPDE			PDE			DDE		
	Mean	**Std**	**Mean**	**Std**		**Mean**	**Std**		**Mean**	**Std**	
f_1	2.37E+02	6.21E+02	7.54E+02	3.20E+02	−	**8.31E+01**	3.68E+01	+	8.07E+02	6.47E+02	−
f_2	**5.74E+03**	2.85E+02	6.09E+03	2.99E+02	−	6.11E+03	3.01E+02	−	5.96E+03	2.53E+02	−
f_3	1.05E+01	9.18E-01	1.36E+01	1.19E+00	−	**9.92E+00**	9.01E-01	+	1.38E+01	1.12E+00	−
f_4	**9.44E+11**	3.48E+11	1.21E+12	3.18E+11	−	9.80E+11	2.52E+11	−	1.12E+12	3.18E+11	−
f_5	**6.98E+07**	2.36E+07	7.31E+07	1.71E+07	≈	7.97E+07	2.26E+07	−	7.36E+07	2.08E+07	≈
f_6	**1.97E+01**	1.34E-01	1.99E+01	2.12E-01	−	**1.97E+01**	1.57E-01	≈	2.00E+01	1.76E-01	−
f_7	**1.07E+05**	3.31E+04	1.51E+05	3.64E+04	−	1.15E+05	5.18E+04	−	1.52E+05	4.89E+04	−
f_8	**5.28E+07**	2.88E+07	8.46E+07	3.02E+07	−	5.61E+07	3.21E+07	−	5.45E+07	2.51E+07	≈
f_9	2.22E+08	1.40E+07	2.39E+08	1.44E+07	−	**2.18E+08**	1.38E+07	≈	2.26E+08	1.26E+07	≈
f_{10}	**5.79E+03**	2.97E+02	6.07E+03	2.48E+02	−	6.08E+03	2.64E+02	−	6.00E+03	2.19E+02	−
f_{11}	6.53E+01	7.21E+00	7.09E+01	7.40E+00	−	**6.31E+01**	7.53E+00	≈	7.11E+01	8.38E+00	−
f_{12}	**1.42E+05**	8.07E+03	1.60E+05	9.94E+03	−	1.45E+05	6.50E+03	≈	1.61E+05	9.64E+03	−
f_{13}	**6.33E+03**	2.84E+03	1.31E+04	4.50E+03	−	8.42E+03	3.83E+03	−	1.27E+04	7.42E+03	−
f_{14}	**6.08E+08**	2.32E+07	6.50E+08	3.12E+07	−	6.20E+08	3.48E+07	≈	6.20E+08	3.50E+07	≈
f_{15}	**5.52E+03**	1.70E+02	6.07E+03	1.88E+02	−	5.89E+03	3.07E+02	−	6.02E+03	2.56E+02	−
f_{16}	1.85E+02	1.00E+01	2.21E+02	1.49E+01	−	**1.84E+02**	8.31E+00	≈	2.16E+02	1.21E+01	−
f_{17}	**4.88E+05**	1.56E+04	5.10E+05	1.49E+04	−	4.91E+05	1.60E+04	≈	5.12E+05	1.64E+04	−
f_{18}	**1.22E+05**	1.84E+04	2.81E+05	7.85E+04	−	1.27E+05	1.16E+04	−	2.40E+05	2.54E+05	−
f_{19}	2.16E+06	9.75E+04	2.32E+06	1.09E+05	−	2.22E+06	1.29E+05	−	**2.09E+06**	1.13E+05	+
f_{20}	**1.11E+05**	2.71E+04	3.23E+05	1.33E+05	−	1.13E+05	1.70E+04	≈	2.04E+05	1.23E+05	−
−/≈/+			19/1/0			10/8/2			15/4/1		

population. At the end of each generation, sub-populations exchange their best individuals with others through a migration operator [3]. During the migration process, each sub-population in our proposed DB-MPDE first chooses the neighborhood based on their diversity. Specifically, the diversity between two sub-populations is measured by the difference of their search centers. The search center of sub-population i is defined as follows:

$$\mathbf{SC_i} = \sum_{i=1}^{NP} \mathbf{X_i} \times W_i \tag{1}$$

where $\mathbf{X_i}$ indicates the position of individual i, NP is sub-population size, and W_i indicates the weight of individual i and it is calculated as follows:

$$W_i = \frac{fit_i}{\sum_{i=1}^{NP} fit_i} \tag{2}$$

where fit_i is the fitness value of individual i. Then, each sub-populations sends its best individual to its neighborhood. Finally, it receives the migrated individual from the respective neighborhood and replaces a randomly chosen individual.

3. EXPERIMENTAL STUDIES

In this section, 20 benchmark functions in CEC2010 [2] are used to investigate the performance of the proposed algorithm on large-scale optimization problems. We compare the proposed algorithm with three existing multi-population approaches, namely, parallel multi-population differential evolution (P-MPDE) [5], parallel differential evolution (PDE) [3], and distributed differential evolution (DDE) [1].

For all the compared algorithms, population size NP is set as 300 and divided into $N = 10$ sub-populations. Each algorithm runs 25 times independently and the results are averaged. As shown in Table 1, the best results are marked in boldface. Overall, DB-MPDE achieves the best results in 14 functions over the 20 benchmark functions. Furthermore, based on the single-problem Wilcoxon signed-rank test, it is clear that DB-MPDE is significantly better than the compared MPDEs on the majority of the test functions.

4. CONCLUSION

In this paper, a diversity-based multi-population differential evolution (DB-MPDE) for large-scale optimization problems is designed. During the migration process of the proposed DB-MPDE algorithm, sub-populations choose their neighborhood based the degree of diversity between each other. A set of 20 benchmark functions is used to test the performance. Experimental results show that the proposed algorithm performs better than other well-known MPDEs.

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