A Divisive Multi-level Differential Evolution

Huifang Zhang[1,2], Wei Huang[1,2(✉)], and Jinsong Wang[1,2]

[1] Tianjin Key Laboratory of Intelligent and Novel Software Technology, Tianjin University of Technology, Tianjin 300384, China
[2] School of Computer and Communication Engineering, Tianjin University of Technology, Tianjin 300384, China
huangwabc@163.com

Abstract. It is generally accepted that the clustering-based differential evolution (CDE) algorithm exhibits better performance in comparison with the standard differential evolution. However, such clustering method mechanism that is only based on input data may lead to some limitations such as premature convergence. In this study, we propose a divisive multi-level differential evolution algorithm (DMDE) to alleviate this drawback. The proposed divisive method is based not only input data but also the output fitness. In particular, DMDE becomes the conventional CDE when the output fitness in not considered in the process of clustering. Several benchmark functions are included to evaluate the performance of the proposed DMDE. Experimental results show that the proposed DMDE exhibits a promising performance when compared with CDE, especially in case of high-dimensional continuous optimization problems.

Keywords: DE · Divisive · Clustering · Parameter adjustment

1 Introduction

Generally, a global optimization problem can be formed as follows:

$$\begin{aligned} & \min f(x) \\ & s.t. \, x \in S \end{aligned} \tag{1}$$

Where S is a feasible region, $S = \{x \in \Re^n : g_i(x) \leq 0, i = 1, 2, \ldots, p\}$, $f(x)$ is the objective function and $f(x) : \Re^n \rightarrow \Re$. The general form of global optimization problem contains other types of constraints. Theoretically, it is very difficult to determine that whether or not a local optimum is the same as a global optimum when solving the optimization problems.

Differential evolution (DE) initialized by Storn and Price [1] is a classical evolutionary algorithm (EA) for global optimization, which is a kind of heuristic random search algorithm based on group differences. It has some trail vector generation strategies and three important control parameters, i.e., population size, scaling factor, and crossover rate. But usually by trial and error to find the suitable to solve the current problems of strategy and control parameter require high computational costs [2]. Thus

K. Li et al. (Eds.): ISICA 2017, CCIS 874, pp. 98–110, 2018.
https://doi.org/10.1007/978-981-13-1651-7_8

the algorithm CODE [2] proposed the random combination of various strategies and parameters to enhanced search capabilities of DE. Furthermore, the adaptive algorithm [3] proposed a parameter adaptive strategy, which makes the parameters need to be adapted to the optimization of the population to solve the problem of high computation costs. Recently CDE algorithm [4] use one-step k-means clustering acts as several multi-parent crossover operators to utilize the information of the population efficiently. But there also have a series of shortcomings to be solved. The clustering of the population belonging to the pure random process and the control parameters is set in advance, which can't change with the optimization process of population.

Here we proposed a new clustering based differential evolution, namely Guide Clustering-based differential evolution (DMDE). The population is first divided into two categories according to the fitness values of individual, so as to provide a guide to the second classification of the population, and to avoid the blind and random of the second clustering. According to the relationship between individuals of the two categories to analyze population state, then fine tune the control parameters, thus overcoming the shortcoming of control parameters can't be adaptive to changes. It makes the population in each generation to be able to match the current status of the control parameters. And, the clustering method of CDE algorithm is used to carry out the second classification to achieve the further optimization of the population.

The rest of this paper is organized as follows. Section 2 introduces the related study DE and CDE. Section 3 describes the detail descriptions of DMDE algorithm. In Sect. 4, the CDE algorithm is compared with DMDE algorithm through 20 benchmark functions. Experimental results are also discussed. At last, Sect. 5 mainly focuses on the summary and outlook.

2 Related Study

2.1 Differential Evolution

Differential Evolution (DE) [5] is a stochastic optimization algorithm based on swarm intelligence. It has the unique ability of memory, so that it can dynamically track the current search situation, to adjust its search strategy [6]. Therefore it has a strong global convergence and robustness. Like other evolutionary algorithms, DE consists of mutation, crossover and selection operators [7–9].

Mutation Operator: Assume that NP represents population size, N stands for the solution dimension, $P \subset R^N$ and the individual i can be formed as a vector of G in the space of a real solution in the following way $P_i^G = \left(P_{i1}^G, P_{i2}^G, P_{iN}^G, \ldots,\right)$, $\forall i \in \{1, 2, \ldots, N\}$.

DE mutation operator generates a corresponding temporary individual u_i^G. As shown in the variation formula (2). DE randomly selects three individuals from the contemporary population as the parent to generate the variant u_i^G.