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A Better Differential Evolution Algorithm and Its use for Solving Optimization Issues

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Abstract
The differentiation evolution (DE) algorithm's mutation strategy choice has a significant impact on the algorithm's exploration capacity, convergence correctness, and convergence speed. An enhanced differential evolution technique using opposition-based learning and neighbourhood mutation operators, specifically, was used to enhance these results. This paper develops NBOLDE. In order to suggest a new neighbourhood strategy, the new assessment parameters and weight factors are added to the neighbourhood model in the NBOLDE. To replace large-scale global mutation with local neighbourhood mutation that has a high search efficiency, a new neighbourhood mutation approach based on DE/current-to-best/1, called DE/neighbour-to-neighbour/1, is designed. The initial population is then optimized using a generalized opposition-based learning technique to determine which of the current and reverse solutions is the better fit, approximating the global optimal solution that can modify the convergence direction, speed up convergence, increase stability, and prevent premature convergence. The suggested NBOLDE is then contrasted with four cutting-edge DE variations using 12 benchmark functions that have both low- and high-dimensions.
The experiment's findings show that the suggested NBOLDE performs better when it comes to optimization and is able to solve difficult functions with large dimensions at a faster rate and with greater precision.
Keywords *Opposition-based learning, Global optimization, Selecting optimal parameters*

I. Introduction

Optimization problems in real life are becoming more and more complex, which show complex characteristics of nonlinearity, multiple constraints, high dimensions, discontinuities, and so on. It is difficult to solve these complex optimization problems by traditional optimization theories and methods. Therefore, it is necessary to seek efficient and robust new methods to solve complex optimization problems. In this context, various biological heuristic swarm intelligence algorithms have been proposed one after another, and new heuristic algorithms have continuously proposed, such as Whale Optimization Algorithm (WOA), Moth-Flame Optimization(MFO), Harris Hawk Optimization (HHO) (Heidari et al. 2019) and Slime Modulus Algorithm (SMA) (Li et al. 2020), and so on (Ren et al. 2021; Wang et al. 2019; Deng et al. 2020; Chen et al. 2020; Xu et al. 2019), which can effectively solve some practical complex problems. Then, various improved optimization methods of swarm intelligence algorithms have also been continuously proposed. These swarm intelligence algorithms and their improved optimization methods have been applied in many practical applications. For example, fruit fly optimization algorithm (FOA) is used for time series forecasting (Peng et al. 2020), particle swarm optimization (PSO) is applied to resource allocation (Deng et al. 2020), Backtracking Search Optimization Algorithm(BSA) solves the trade credit replenishment problem (Wang et al. 2020), Bayesian personalized ranking decline method effectively provides public services (Liu et al. 2020), chaotic multi-population whale optimizer enhances the support vector machine for medical diagnosis (Zhang and Jin 2020), and so on (Li et al. 2019; Xue et al. 2019; Liu et al. 2019, 2020; Wang et al. 2005; Chen et al. 2019; Zhao et al. 2020; Deb et al. 2020; Gao et al. 2020; Song et al. 2020).

Differential evolution algorithm

The DE algorithm uses the difference between individuals to guide this algorithm to search in the solution space. It mainly includes initialization population, mutation operation, crossover operation, selection operation, and so on. The main idea of the DE is to differentiate and scale between two different individual vectors in the same population, and add a third individual vector in this population to obtain a mutation individual vector, which is crossed with the parent individual vector with a certain probability to generate an attempted individual vector. Finally, the attempted individual vector and the parent individual vector are executed greedy selection, and the better individual vector is saved to the next generation.

The NBOLDE algorithm

The selection of the mutation strategy for DE directly affects the exploration ability, convergence accuracy and speed. Therefore, the new evaluation parameters and weight factors are introduced into the neighbourhood model to design a new neighbourhood mutation strategy (DE/ neighbour-to-neighbour/1) based on DE/current-to-best/1 mutation strategy. Then, the opposition-based learning is used to optimize the initial population and select better solution to amend the convergence direction. Finally, an improved differential evolution algorithm based on neighbourhood mutation and opposition-based learning, namely NBOLDE, is developed in this paper. In each generation of evolution, according to the fitness value, the top 30% individuals are randomly selected to the neighbourhood model and the information of high-quality individuals is fully used to generate mutation individuals through the neighbourhood mutation strategy (DE/neighbour-to-neighbour/ 1). In the selection stage of evolution, the opposition-based learning is used to optimize the initial population and select better solution between the current solution and reverse solution to quickly approximate global optimal solution and amend the convergence direction. The purpose of the proposed NBOLDE algorithm is to accelerate convergence and improve the search efficiency, enhance the stability of the algorithm, avoid to fall into the local optimum, and obtain better optimization capabilities in solving high-dimensional complex optimization problems.

Numerical experiments and analysis

In order to evaluate the optimization performance of the proposed NBOLDE algorithm, 12 benchmark functions are selected in here. Since the proposed NBOLDE algorithm is used for medium and high-dimensional problems, the lowdimensional benchmark functions are not selected. The expressions, value ranges and minimum values of 12 benchmark functions are shown in Table 1. For the 12 benchmark functions, f1, f4 are single peak functions, which are mainly used to evaluate the accuracy and convergence speed. f5, f8 are multimodal functions, which are mainly used to evaluate the global search stability. f9, f12 are functions with some special operations. For example, f9 is a round-down function, f10 is a function with noise added, and f11 and f12 are functions with absolute value. Each function was tested 30 times independently. The evaluation indexes include the best value (Best), the worst value (Worst), the median value (Median) and the standard deviation (Std.Dev).

Conclusions and future work

In order to improve the searching efficiency and convergence accuracy, enhance the stability and reduce time complexity for DE, a new neighbourhood mutation strategy based on DE/current-to-best/1, namely DE/neighbour-to neighbour/1, is designed in this paper. On the basis, an improved differential evolution algorithm with neighbourhood mutation and opposition-based learning, namely NBOLDE, is proposed. The NBOLDE uses the local neighbourhood mutation with high search efficiency to replace large-scale global mutation, and then opposition-based learning is used to optimize the initial population and correct convergence direction in order to accelerate the convergence, improve efficiency, enhance stability, and avoid to fall into local optimum. The effectiveness of the NBOLDE is tested on 12 benchmark functions. From the experimental results, it can be seen that for some simple functions of f1Sphere, f4Axis Parallel, f9Step, and f12Sum of different power, the proposed NBOLDE can accurately and quickly converge or approximate to the global optimal value under different dimensions. Therefore, the NBOLDE adopts the new neighbourhood mutation strategy to effectively reduce the impact of increasing dimensions on the optimization performance of the algorithm, and effectively improve the search efficiency and convergence accuracy of the algorithm.

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