Overview of Differential Evolution Algorithm

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Abstract

Explained the basic ideas and characteristics of the difference algorithm, according to the research status of the difference algorithm in the past five years, introduce the field of difference application and compare it with the evolutionary algorithm, and analyze the advantages and disadvantages of the difference algorithm. Many scholars have improved the differential algorithm and derived evolutionary algorithms with different characteristics. This article reviews the basic principles, characteristics, improvements and applications of the difference algorithm, and gives possible future research directions.

Keywords

Differential evolution algorithm; Function optimization; Global optimization.

1. Introduction

The differential evolution (DE) algorithm uses floating-point vector coding to perform random search in continuous space [1]. It is an effective and robust method with few controlled parameters and simple principles. It is used to solve micro, nonlinear, and multi-dimensional polarities. Values and high-dimensional complex functions can achieve parallel, random and direct alternate search, which is simpler and easier to understand than genetic algorithms. DE algorithm is based on group evolution, and solves the optimization problem through competition and cooperation between individuals in the population. It has the characteristics of information sharing within the population and the best solution for memorizing individuals. The difference algorithm is essentially a greedy idea. It is based on the real-coded genetic algorithm and has excellent preservation capabilities. Differential algorithms have been applied in many fields. In addition to constrained optimization problems, they also include: biological system modeling, pattern recognition, signal processing, decision-making and simulation multi-objective optimization problems, neural network training, system design, etc. Differential evolution algorithms have been successfully used in fuzzy control systems, robotics, power systems, function optimization, neural network training, combinatorial optimization and other commonly used application fields of evolutionary algorithms [2].

2. Differential development status and principle

2.1 Process Status

The DE algorithm has become one of the research hotspots in the field of evolutionary computing and control engineering. Although the DE algorithm system is not as mature as the genetic algorithm and other algorithm systems, the research progress of the DE algorithm has been increasing year by year, and the literature on the DE algorithm has been published in large numbers. According to the algorithm research in recent years. DE algorithm has a very excellent ability to find the best, and it is widely used in theoretical research and engineering practice, such as in photoelectric precision tracking system [3], robot scheduling problem [4], wind drive [5] and other fields.

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2.2 Differential Evolution Algorithm

Differential evolution algorithm is an algorithm for global optimization, that is, to solve the optimization problem through the cooperation and competition between individuals in the population. Its essence is a kind of greedy genetic algorithm based on real number coding to ensure the best quality. The difference algorithm is based on the concept of "survival of the fittest". At the same time, the differential evolution algorithm uses a parallel search method in the process of solving the problem. This method greatly reduces the time required to solve the problem. Compared with the genetic algorithm, the difference calculation uses a simpler structure, and tends to intelligently judge the adaptive conditions to generate a new generation of population, and finally select the global optimal solution through the adaptive condition judgment. The difference algorithm is based on the concept of "survival of the fittest".

2.3 Differential Evolution Algorithm Processing

Given control and differential parameters. Opulation initialize, evolution algebra i = 0. calculate the fitness value of each individual in the initial population to evaluate it. The termination iteration condition is that the maximum number of iterations is reached, and the output optimal solution is the optimal individual, otherwise, proceed to the next step. Perform mutation and crossover of individuals, and process boundary conditions to obtain experimental populations. Calculate the fitness value of the individual through the fitness value function, which is used to evaluate the population. Perform selection operations to obtain a new generation of population.i=i+1.as shown in Fig 1

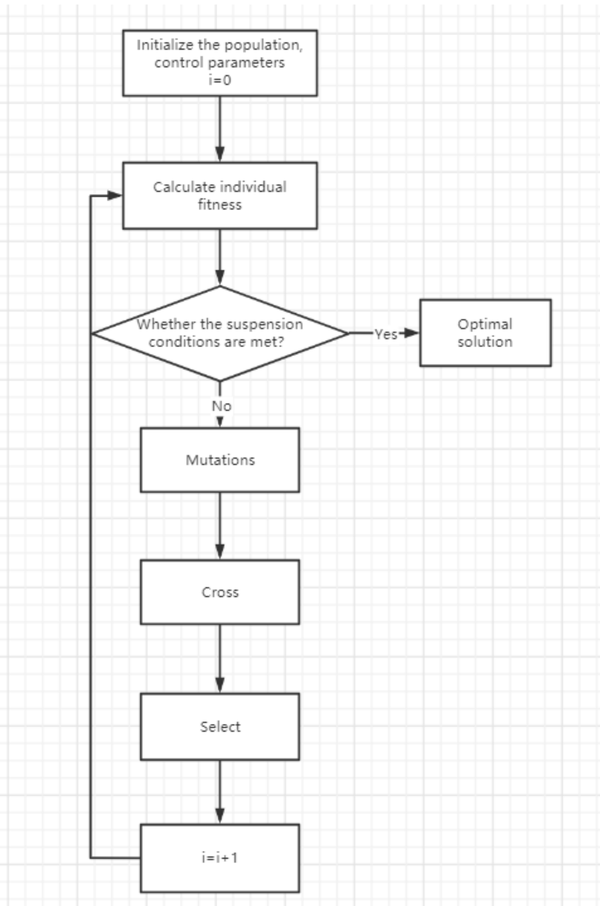

Figure 1. Difference algorithm process

2.4 Algorithm Features

The differential algorithm has strong adaptability. When the algorithm evaluates the entire population to find the optimal solution, even if the evolution mechanism is uncertain, there are certain dynamic

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changes, and there are requirements for adaptability, the DE algorithm can also perform well. Task. Evolution itself is to find the problem as a whole, so that the optimal solution can be easily found on a level. At the same time, the parallel search method can make the problem conversion speed faster, and the difference algorithm uses this method. Compared with the genetic algorithm, the DE algorithm requires a greatly reduced time for global optimization, and the original increment of the chromosome for the solution. Mutation, hybridization and selection of individuals are carried out to achieve chromosome generation and ensure the overall quality and quantity of chromosomes. Through continuous iteration and evaluation of fitness values, the best individual is the global optimal solution sought by the algorithm [3].

2.5 Performance Analysis

2.5.1 Defect

There are two main defects in the difference algorithm. When the first difference algorithm is looking for the optimal solution, it will stagnate somewhere and it will not get the global optimal solution, but the local optimal solution. When the DE algorithm search stagnation occurs, the stagnation feature can be described by the average distance between the G generation target individual and its center of gravity. The expression is shown in formula 1:

$$\mathrm{d}_G = (1/N_P)\sum_{1}^{N_P}\left\| x_{i,G} - \bar{x}_G \right\| \tag{1}$$

When the population is single, the optimal solution will also be the local optimal solution. This is similar to the purebred problem in genetic algorithms. When the parent and mother gene sequences are the same, the iterative population will not produce better offspring, making the algorithm unable to proceed. When the DE algorithm has search stalls, it can be described by the number of consecutive non-updates of the G generation target individual. The expression is shown in formula 2:

$$nu_{i,G+1} = \begin{cases} 0, f(u_{i,G}) \le f(x_{i,G}) \\ nu_{i,G+1}, others \end{cases} \tag{2}$$

2.5.2 Research on Improvement of Difference Algorithm

DE can be improved in three aspects, which are control parameter setting, evolution strategy selection, and mixing with other optimization algorithms. First, the parameters of the difference algorithm include population size, learning factor, mutation crossover probability, and number of iterations. The learning factor and mutation crossover probability parameters are usually controlled to optimize the difference algorithm. In [7] the performance was analyzed when the parameters of the DE algorithm changed, especially for real-valued functions. While the parameters in the DE algorithm correspond to different problems, there are also connections between the parameters, so the optimization of the DE parameters is not easy. Learning factor F. Generally, F is set to 0.6. If the algorithm stagnates during optimization, the final result is a local optimal solution, and the value of F should be adjusted. When the learning factor is too large, it means that the algorithm mutation crossover probability is high, which will make the algorithm unable to find the optimal solution in a short time, that is, it cannot converge; for the algorithm, the PCR value can improve the algorithm convergence speed, but if the PCR is too large, It will cause the algorithm to converge prematurely, and the solution obtained is a local optimal solution. A value between 0.3 and 0.9 for the scale factor F is usually a better setting. Second, the evolution strategy selection includes optimization of mutation link strategy, control parameter adaptation, and disturbance strategy [8]. The difference algorithm can be mixed and optimized with other algorithms. In [9], the difference algorithm and genetic algorithm are combined. Genetic algorithm uses floating-point number coding for optimization, and this paper uses real number coding, which not only reduces the complexity of the algorithm, but also improves the solution of the algorithm. Accuracy. It also increases the diversity of the population. Zhang et al. [10] proposed a hybrid algorithm DEMOEA based on multi-objective genetic algorithm NSGA-II and multi-objective differential evolution algorithm. In [11] proposed a multi-objective optimization DE

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(DEMORS) based on roughsets theory. In order to improve the diversity distribution of non-inferior solution sets, the algorithm introduces rough set theory for local search in the later search stage.

3. Multi-objective Differential Evolution Application

3.1 Multi-objective Differential evolution algorithm

According to the characteristics of the algorithm, the multi-objective difference algorithm is generally divided into two types [12]: Pareto-based approaches and non-Pareto-based approaches. Compared with other single algorithms, the Pareto-based multi-objective optimization difference algorithm is more convergent when solving high-dimensional problems, but the performance will drop sharply as the target dimensionality increases [13]. Parsopoulos [14] proposed a multi-objective differential evolution algorithm (VEDE) using vector evaluation in 2004. VEDE is inspired by the vector evaluation genetic algorithm (VEGA): consider the M subpopulations in the ring topology, and then use the objective function pair The population is evaluated, and each sub-population corresponds to the objective function of the multi-objective optimization problem. In the process of multiple cycles, each subgroup selects multiple better individuals as supplementary subgroups according to its own goals, and then exchanges information between each subgroup through the migration of the optimal individuals. This method helps keep the best individual on the target. At the same time, it verifies the four two-objective unconstrained optimization problems of VEDE and compares them with VEGA. Experiments show that the performance of the VEDE algorithm is better than that of VEGA.

3.2 Apply of differential evolution algorithm

In [15], in order to overcome the difficulty of selecting the weight of PID controller parameter adjustment function, the difference algorithm is improved. This algorithm can optimize multi-objectives without setting weights. The algorithm adopts an elite optimization strategy and optimizes the overshoot and rise time indicators of the step response of the control system according to the Pareto optimization principle. The simulation results show that the algorithm can obtain a large number of high-quality Pareto optimal solutions, and the quality of the solutions can replace other methods. In [16] designed a microgrid grid-connected system. The system is based on the actual load of users in a certain location, and uses a multi-objective differential evolution algorithm to optimize the accuracy, stability, and environmental pollution of the system, and obtain an ideal solution. According to the working characteristics of the DC blocking device, the literature [17] analyzes the influence of the DC current at the neutral point of adjacent transformers after installing the capacitor isolation device on the transformer, and proposes a multi-objective optimization method based on the field-circuit coupling model. Capacitor isolation device configuration method. Establish the transformer equivalent model and the soil layered model, combine the two to form an equivalent field-circuit coupling model, and use the finite element method to solve the DC current at the neutral point of each transformer. Under the condition of ensuring that the neutral point DC of each transformer is below the limit, the objective function is to establish an optimal configuration model with the smallest number of input devices and the smallest total neutral point DC of the entire network transformer. The effectiveness and superiority of the method are verified through simulation examples of DC transmission projects, thereby suppressing the DC bias phenomenon and saving costs. literature [18] conducted related research on the deployment of security stations, proposed an optimization model for the deployment of security stations, and proposed two optimization goals for the deployment of security stations, and then used a multi-objective differential evolution algorithm to optimize the two goals and simulate them. experiment. The experimental results show that the differential evolution algorithm effectively improves the two optimization goals of security station deployment and improves the deployment quality.in [19], aiming at the scheduling problem of the blast furnace gas (BFG) system in the steel industry, an improved multi-objective differential evolution algorithm (IMODE) based on dynamic Bayesian networks (DBN) and an improved algorithm BFG system scheduling method were proposed. Taking into account the dynamic characteristics of the BFG system and the output uncertainty of the time prediction model, the causality-based DBN algorithm is used to model the gas storage tank of the BFG system, which quickly reaches the desired value and has a large adjustment margin. optimize. Target. When optimizing scheduling, the particle crowding distance is introduced into the search mechanism of the multi-objective differential evolution algorithm to improve the search accuracy of the model. In addition, in view of the fact that the adjustment of a single user cannot make the gas tank operate safely, and at the same time, considering the difference in the adjustment ability of different consumption users, a multi-user adjustment scheme is proposed. In order to test the effectiveness of the proposed algorithm, experiments were carried out using the production data of the domestic steel company's blast furnace gas system. The results show that this method has a better effect than other methods in BFG system scheduling adjustment. In [20] mainly introduces the solution of nonlinear equations. The main methods of converting nonlinear equations into optimization problems are outlined. Then, aiming at the problems of the current algorithm, a multi-modal multi-objective differential evolution algorithm is proposed. The main improvements of the algorithm include population pre-selection mechanism and boundary selection method. These improvements can increase the diversity of decision space solutions. In order to verify the effectiveness of the multi-modal multi-objective differential evolution algorithm, 51 independent experiments were carried out on five test functions. Finally, compared with the results obtained by the four algorithms, it can be seen that the multi-peak multi-objective differential evolution algorithm has certain advantages in peak rate and success rate. In addition, by solving specific engineering examples, the effectiveness of the proposed algorithm is further verified. There is still a lot of room for improvement in current algorithms for solving nonlinear equation problems, especially in terms of success rate. The next step will continue to optimize the algorithm in order to better apply it to more complex engineering examples.

4. Research and Prospect

At present, DE algorithm is widely used in system optimization and solving static solutions. It is a more efficient optimization algorithm after genetic algorithm, but it also has various defects, especially it will stay at the local optimal solution, resulting in inaccurate optimization results. . The DE algorithm is affected by the diversity of the population. When the degree of population diversity is low or the diversity is lost, the results will also converge prematurely. Experiments show that the learning factor and objective function of the DE algorithm are improved, and the convergence speed of the function is improved. The accuracy of the optimal solution has been greatly improved, but there is no improved method to make the parameters in the algorithm fully adaptive. Compared with single algorithm optimization, hybrid optimization greatly alleviates the shortcomings of a single algorithm, but also brings different problems. The environment of hybrid optimization is relatively complex, the parameters change quickly, and the reliability of the algorithm is high. In the future, the adaptability of the difference algorithm to the environment in multi-objective optimization will continue to improve. At the same time, we should also consider how to control the degree of convergence of the algorithm to obtain the desired result of the experiment. For multi-objective optimization, environmental factors should also be considered [21], how to adapt to a changeable and dynamic environment, and the control of population size, evolutionary individual selection, and neighbor selection.

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