Optimization algorithm of fireworks explosion based on elevator

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Abstract. The fireworks algorithm proposed in recent years. Compared with other traditional optimization algorithms, the fireworks algorithm has a strong ability to solve optimization problem. This paper improves the fireworks algorithm and proposes an elitism based fireworks explosion optimization algorithm (E-FWA). The E-FWA algorithm improves the explosion radius of fireworks algorithm and adds elite selection strategy to fireworks algorithm. A large number of experiments show that the elitism based fireworks explosion optimization algorithm can reduce the search time, improve the convergence of the algorithm, and avoid falling into the local optimal value.

1. Introduction
The fireworks algorithm establishes a mathematical model by simulating the aerial explosion of fireworks, and introduces random factors and selection strategies to form a parallel explosive search manner, and then develops a global probabilistic search method that can solve the optimal solution of complex optimization problems[1]. The numerous advantages of fireworks algorithm make it widely used in other problems, such as web service combination optimization[2], multi-objective scheduling optimization research[3], mobile robot[4], cloud computing multi-objective task scheduling[5]. However, fireworks algorithm also has many shortcomings, such as long search time and large amount of calculation, resulting in low efficiency of the algorithm. Aiming at these shortcomings, this paper improves the explosion radius and selection strategy of fireworks algorithm to make E-FWA algorithm have the advantages of good convergence, high search precision and fast search speed.

2. Original fireworks algorithm
The fireworks algorithm first generates a certain number of initial fireworks in the solution space, and the fireworks explode in a certain range, generating a certain number of sparks. Then select some fireworks or sparks with good fitness values by selecting strategies to continue the explosion as the next generation, let the fireworks fill the entire solution space. Through continuous explosion operations and selection operations, the fireworks continually iterate through the search until the global optimal value is found.

The formula to calculate the number of sparks produced by fireworks explosion is:

$$S_i = m \cdot \frac{Y_{\text{max}} - f(x_i) + \varepsilon}{\sum_{i=1}^{N}(Y_{\text{max}} - f(x_i)) + \varepsilon}$$

(1)
In formula (1), $S_i$ is the number of sparks produced by the $i$-th fireworks; $m$ is a constant used to control the total number of sparks produced; $Y_{\text{max}}$ is the maximum fitness value in the current population, that is, the worst fitness value; $f(x_i)$ is individual $x_i$ fitness value; $\varepsilon$ is a very small constant to keep the denominator from being zero.

The formula for calculating the range of fireworks explosion is:

$$A_i = \tilde{A} \cdot \frac{f(x_i) - Y_{\text{min}} + \varepsilon}{\sum_{i=1}^{N} (f(x_i) - Y_{\text{min}}) + \varepsilon}$$

In formula (2), $A_i$ is the explosion range of the $i$-th fireworks; $\tilde{A}$ is a constant used to control the explosion range; $Y_{\text{min}}$ is the minimum fitness value in the current population, that is, the most optimal fitness value; $f(x_i)$ is individual $x_i$ fitness value; $\varepsilon$ is a very small constant to keep the denominator from being zero.

After calculating the number of sparks and the explosion range, the displacement operation is performed on each dimension of the fireworks:

$$\Delta X^k_i = X^k_i + \text{rand}(0, A_i)$$

In formula (3), $X^k_i$ represents the position of the $i$-th individual in the $k$-th dimension; $\text{rand}(0, A_i)$ represents the uniform random number generated within the explosion range. The sparks generated by the explosion can be randomly distributed in the explosion range through displacement operation, which improves the search efficiency.

Gauss Mutation is carried out on fireworks to generate more sparks, and the calculation formula:

$$X^k_i = X^k_i \cdot g$$

$g$ is a random number of gaussian distribution with mean and variance of 1. The sparks generated within the explosion range were mutated by Gauss Mutation, allowing the population to become more diverse and reducing the probability of premature maturation. This ensures the parallelism and explosiveness of the algorithm. Then, through the selection strategy, select some fireworks or sparks as the next generation to continue the above operation. The farther away you are from other individuals, the more likely you are to be chosen to be the next generation.

Use Euclidean distance to measure the distance between any two individuals:

$$R(x_i) = \sum_{j=1}^{K} \| x_i - x_j \|$$

$R(x_i)$ represents the sum of the distance between individuals $x_i$ and other individuals; $K$ is the set of positions where the sparks are generated.

Calculate the probability that an individual will be selected to become the next generation:

$$P(x_i) = \frac{R(x_i)}{\sum_{j=k} R(x_j)}$$

3. E - FWA algorithm

Compared with the original fireworks algorithm, E-FWA algorithm modified two parts: improved explosion radius and added elite selection strategy. This improves the accuracy and stability of the algorithm.

3.1 Improve the explosion radius

In formula (2), we can see that, with the gradual increase of iteration times of fireworks algorithm, the fitness value of individuals in the current population is gradually decreasing. Then the optimal fitness
value of the individual in the current population may be equal to the global optimal fitness value, that is, formula (1) will become the following formula (7):

$$A_i = A \cdot \frac{\epsilon}{\sum_{i=1}^{N} (f(x_i) - Y_{\text{min}}) + \epsilon}$$

The numerator of formula (7) is close to zero, then the explosion radius of the fireworks is close to zero. Equivalent to the fire position of a fireworks in the current position is almost unchanged, recopying the last explosion, without any search, so this iteration is meaningless. This reduces the number of searches for the algorithm and increases the amount of running, reducing the efficiency of the algorithm.

Improved explosion radius formula:

$$r = \left(\frac{T - t}{T}\right)^k \cdot (r_{\text{initial}} - r_{\text{end}}) + r_{\text{end}}$$

$T$ represents the total number of iterations of the algorithm, $t$ represents the current number of iterations of the algorithm; $k$ is a constant that limits the decreasing radius, a large number of experiments show that the search effect is best when $k$ is 7; $r_{\text{initial}}$ is the radius of the first explosion of fireworks; $r_{\text{end}}$ is the maximum radius of the last fireworks explosion. In this way, the radius of fireworks explosion can be avoided to be zero, which reduces the operation time and times of the algorithm, and improves the search efficiency.

3.2 Add elite selection strategy

The original fireworks algorithm selection strategy is based on distance. The farther an individual is from other individuals, the higher the probability of being selected. This selection scheme not only increases the diversity of selection results, but also increases the time consumption of algorithm execution per generation. Therefore, the running time of the algorithm is not ideal in practical experiments.

In order to accelerate the selection of fireworks population to the next generation, an elite selection strategy is adopted in this paper, so that each individual in the population has a certain probability to be selected to the next generation, which is related to the individual’s adaptive value:

$$P(x_i) = \frac{f_{\text{max}} - f(x_i)}{f_{\text{max}} - f_{\text{min}}}$$

$f_{\text{max}}$ represents the maximum fitness value in the current population; $f_{\text{min}}$ represents the minimum fitness value in the current population. The smaller the fitness value of an individual in the population, the higher the probability of being selected as the next generation, otherwise, the individual will be abandoned. It is not difficult to find that individuals with the best adaptive value in the current population will be selected as the next generation fireworks with probability 1. This selection strategy improves the search efficiency of the algorithm and guarantees the diversity of the population.

4. Realization of the E-FWA algorithm

In this paper, the explosion radius is improved based on the standard fireworks algorithm, and elite selection strategy is added. With the increase of iteration times, the number of sparks generated by fireworks explosion increases, while the explosion radius decreases continuously, which makes the algorithm converge faster. This not only guarantees the search efficiency of the algorithm, but also guarantees the diversity of the algorithm.

The implementation steps of the E-FWA algorithm are as follows:

Step1: Initialize to determine the number of fireworks explosions $n$;

Step2: Calculate the explosion radius of each fireworks explosion according to formula (8)
Step 3: Calculate the number of sparks generated during each fireworks explosion according to formula (1);
Step 4: Perform displacement operation on each dimension of the fireworks according to formula (3);
Step 5: Perform a Gaussian variation operation on the fireworks according to formula (4);
Step 6: Elite the fireworks or sparks that have been generated according to formula (9), and select the appropriate individual to continue execution as the next generation;
Step 7: Determine whether the termination condition is satisfied, that is, whether the algorithm finds the global optimal value or reaches the maximum number of iterations. If not, repeat steps Step 2-Step 6 until the termination condition is met; if yes, end the operation and perform the next step.
Step 8: The algorithm ends and the optimal value is output.

5. Experiment
Particle swarm optimization (PSO) is a population intelligence algorithm proposed by Kennedy and Eberhart in 1995 on the basis of studying the group behavior of birds and fish [6]. The idea is derived from the theory of artificial life and evolutionary computation, which mimics the flight foraging behavior of birds and achieves the optimal group through collective cooperation of birds. PSO, a branch of evolutionary computing, is an iterative optimization tool. The system is initialized to a set of random solutions, and the optimal value is searched through iteration. The principle and mechanism of PSO are simple. It only updates the speed and position to continuously evolve to the global optimal solution. No gradient information is needed. Since its introduction, it has been discussed and improved by many researchers, and has been applied in more and more fields [7].

In order to prove the performance of E-FWA algorithm on the function optimization problem, an experimental comparison was made between E-FWA algorithm and PSO algorithm. Six test functions were used in the experiment. In E-FWA algorithm, the number of fireworks is set to 5, the optimized dimension is 30, and the number of iterations in the experiment is 1000. In PSO algorithm, the particle swarm size is 60, the optimized dimension is 30, and the number of iterations is 1000. Through matlab simulation experiments, the following conclusions are drawn through a large number of experiments:

| Algorithms | function | dimension | optimal value | iteration |
|------------|----------|-----------|---------------|-----------|
| PSO        | Sphere   | 30        | 1.972638      | 1000      |
|            | Griewank | 30        | 2.755043      | 1000      |
|            | Schwefel | 30        | 3.712166      | 1000      |
|            | RosenBrock | 30    | 0            | 1000      |
|            | Ackley   | 30        | 3.149497      | 1000      |
|            | Rastrigin| 30        | 39.33702      | 1000      |
|            | Sphere   | 30        | 0            | 1000      |
|            | Griewank | 30        | 0            | 1000      |
| E-FWA      | Schwefel | 30        | 0            | 1000      |
|            | RosenBrock | 30    | 21.87389     | 1000      |
|            | Ackley   | 30        | 0            | 1000      |
|            | Rastrigin| 30        | 0            | 1000      |

Experiments show that E-FWA algorithm is superior to standard PSO algorithm in Sphere function, Griewank function, Schwefel function, Ackley function and Rastrigin function. In order to further prove the advantages of E-FWA algorithm, this paper also compares four other sets of data: original fireworks algorithm, fireworks algorithm that only improves the explosion radius, fireworks algorithm that only improves the elite selection strategy, and E-FWA algorithm. The experimental data are as follows: the number of fireworks n=5; Dimension $d = 30$; The number of iterations of the algorithm
T=1000. Six test functions are used in the experiment. The experiment system is Windows10 system and matlab simulation experiment is used. The results are shown in figure 1-figure6.

Experiments show that E-FWA algorithm has advantages in convergence and search efficiency compared with other three algorithms. The explosion radius was improved and elite selection strategy was added to solve the problems of long running time and low efficiency of the original algorithm, and the population diversity of the algorithm was increased.

6. Conclusion
Aiming at the shortcoming of standard fireworks algorithm, which has many running times and large calculation amount, this paper proposes E-FWA algorithm to improve the explosion radius and add
elite selection strategy. As the number of iterations of the algorithm increases, the number of sparks generated by fireworks explosion increases, while the explosion radius keeps decreasing. A large number of searches are carried out in the solution space in a short time, which enables the algorithm to converge faster and ensures the search efficiency and diversity of the algorithm.

Acknowledgments
First of all, I would like to thank Mr. Yang kai for his daily instruction and help, which made me understand that I should have perseverance and patience to do research. Secondly, I want to thank my girlfriend Yiding Liu, who teaches me how to have a good attitude to deal with problems. Finally, thanks to Liaoning university of science and technology for cultivating me.

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