A firefly optimization algorithm based on multi-group learning mechanism

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Abstract

The evolution mechanism of the traditional firefly algorithm (FA) is analyzed, and the causes of premature convergence and easy to fall into the local optimal solution in the firefly algorithm are studied by using examples. A multi-group firefly optimization algorithm based on improved evolution mechanism is proposed. MFA_IEM): The firefly population is divided into multiple subgroups of different parameters, and the fireflies within each subgroup update the position and brightness according to the improved firefly algorithm. When the population falls into a local optimal solution, Gaussian mutation is used to improve the diversity of firefly individuals. The test results of several typical test functions show that the algorithm improves the convergence speed and optimization accuracy to some extent.

Keywords

Firefly algorithm,group intelligence,multiple groups, learning mechanism, Gaussian variation.

1. Introduction

In 2008, Cambridge scholar Yang [1] proposed a new group intelligence algorithm, Firefly Algorithm (FA). The Firefly algorithm is a heuristic search algorithm that inspires the behavior of fireflies glowing at night. In the clustering activities of fireflies, each firefly communicates with the companion to search for food and courtship by distributing fluorescein. The brighter the fluorescein, the stronger its appeal, and eventually many fireflies gather around some of the brighter fluorescein.

Literature [3] proposed a Multi-Group Firefly Algorithm (MFA) based on multi-group learning mechanism to enhance the diversity of firefly algorithm by dividing the firefly population into multiple sub-populations, and avoid the "premature" of firefly algorithm. status. This enhances the search space and diversity of the firefly algorithm; however, if multiple sub-populations converge together and fall into a local optimal solution, the learning mechanism of multiple groups will fail and fall into the local optimal solution.

Literature [4] proposed a new evolutionary model of Improved Evolutionism Firefly Algorithm (IEFA), which enhanced the optimal firefly's traction effect on other fireflies, effectively avoiding the firefly falling into the local part of the traditional algorithm. The dilemma of the solution; however, as the complexity of the function increases, the optimization efficiency of the algorithm will be affected.

In view of this paper, a multi-group firefly optimization algorithm based on improved evolution mechanism (MFA_IEM) is proposed. The simulation results show that the improved firefly algorithm can effectively avoid the algorithm falling into the local optimal value prematurely and has better optimization ability.

2. The Basic Theory of FA

The basic idea of the standard Firefly Algorithm (FA) is: Assume that the firefly population has a total number of individuals of m and a search space of N dimensions, the position of the i-th firefly in space is $x_i = (x_{i1}, x_{i2}, \cdots, x_{iN})$.

Each firefly is considered a solution to the N-dimensional solution space, and the firefly population is randomly distributed as an initial solution in the search space. The brightness of a firefly individual depends on the value of the objective function to be sought. The stronger the brightness of the firefly, the better the value of the objective function. Fireflies with strong brightness attract fireflies with weak brightness. If the brightness is the same, the fireflies move randomly. Through each generation of movement, the fireflies are finally gathered around the better fireflies, that is, multiple extreme points are found.

2.1 Standard FA basic idea

The Firefly algorithm consists of two elements: brightness and attractiveness. The brightness reflects the pros and cons of the location of the firefly. The higher the brightness, the better the position and the direction of its movement. The degree of attraction determines the moving distance of the individual, and is constantly updated by brightness and attractiveness to achieve optimization of the objective function.

Definition 1: Fluorescence brightness of the first firefly

$$I_{0i} = f(x_i) \tag{1}$$

Where $f(x_i)$ is the target fitness value of the location of the i-th firefly.

Definition 2: Relative brightness of fireflies:

$$\mathbf{I} = \mathbf{I}_{0i} \times e^{-\gamma r_{ij}} \tag{2}$$

Where I_0 is the maximum fluorescence brightness of the firefly, that is, the brightness at r=0, which is related to the objective function value. The better the objective function value is, the higher the brightness is; γ is the light absorption coefficient, because the fluorescence increases with the distance and The absorption of the medium is gradually weakened; r_{ij} is the spatial distance between fireflies i and j.

Definition 3: Attraction:

$$\beta = \beta_0 \times e^{-\gamma r_{ij}^2} \tag{3}$$

Among them, β_0 is the maximum attractiveness, that is, the attraction at r=0 (where the light source is).

Definition 4: Firefly Location Update:

During the optimization process, the firefly i is attracted by j, so that the formula for updating the position near the firefly j is:

$$x_i(t+1) = x_i(t) + \beta \times (x_j(t) - x_i(t)) + \alpha \times (rand - \frac{1}{2}) \tag{4}$$

Where $x_i(t+1)$ is the position after the t+1th movement of firefly x_i ; α is the step factor, which is the constant on [0, 1]; $\alpha(rand - 1/2)$ is the random disturbance factor, which is conducive to expanding the search area and avoiding the local optimal solution.

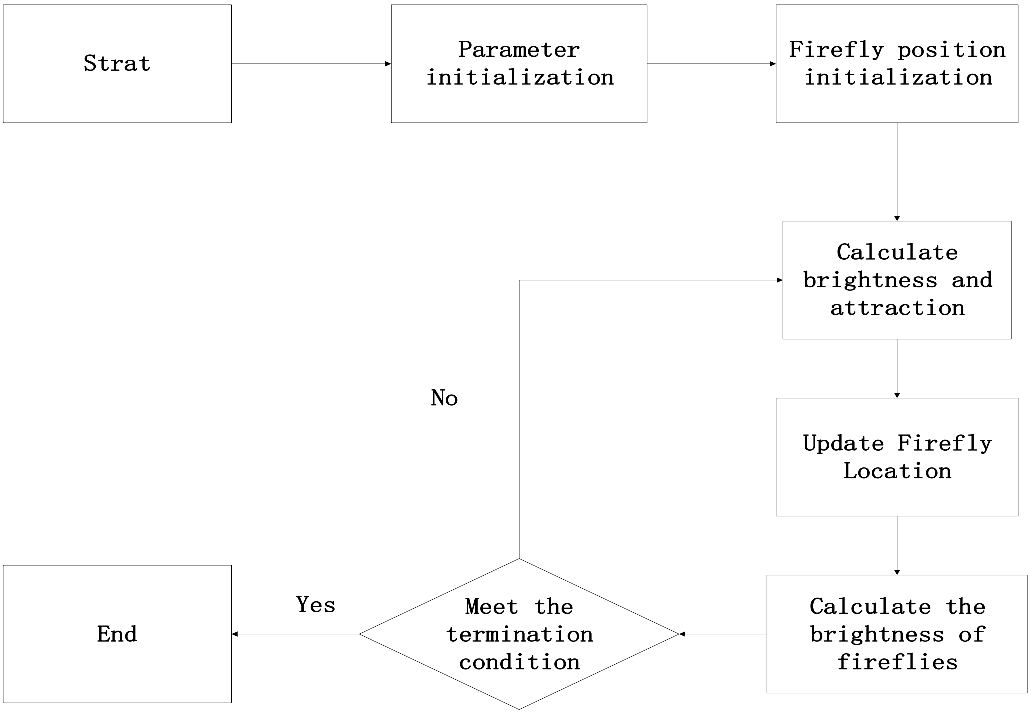

Fig. 1 Firefly algorithm flow

2.2 Optimization mechanism analysis

The following is an example of the Four Peaks function to analyze the optimization process of the firefly algorithm.

$$f_1(x) = e^{-(x-4)^2-(y-4)^2} + e^{-(x+4)^2-(y-4)^2} + 2e^{-x^2-(y+4)^2} + 2e^{-x^2-y^2} \tag{5}$$

The four peak points of the four-peak function shown in Figure 2 are points (-4, 4), (0, -4), (0, 0), (4, 4), respectively, where the theoretical maximum is 2. The global maximum point and the local optimal point of the function are taken in the peak point of the function.

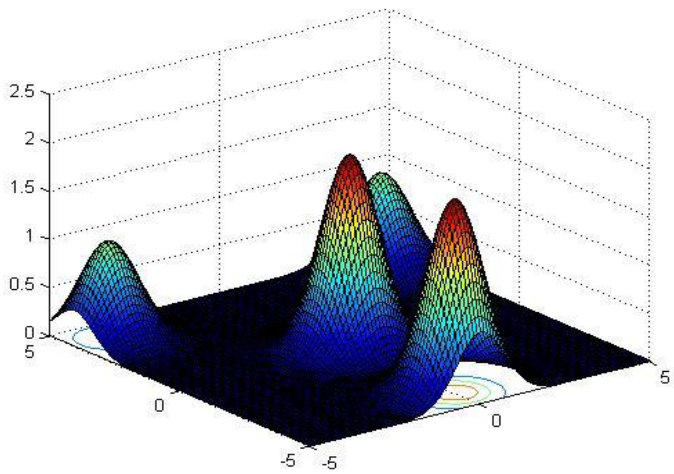

Fig. 2 Four-peak function

Table 1 Population, search space, halving firefly algorithm optimization four-peak function results

Serial number	Population size	Number of iterations	Optimal solution mean square error
1	100	50	6.22E-01
2	50	50	5.87E-01
3	25	50	4.73E-01
4	13	50	3.32E-01

It can be seen from Table 1 that in optimizing the Four Peaks problem, as the population size and search space synchronization are reduced to 1/2 of the previous population and 1/2 of the previous space, the number of iterations is unchanged, and the optimal solution The mean and variance show a significant downward trend, and the accuracy and convergence speed of the algorithm are obviously enhanced, indicating that the “group division and division” is better for the firefly algorithm.It can be seen from Table 1 that in optimizing the Four Peaks problem, as the population size and search space synchronization are reduced to 1/2 of the previous population and 1/2 of the previous space, the number of iterations is unchanged, and the optimal solution The mean and variance show a significant downward trend, and the accuracy and convergence speed of the algorithm are obviously enhanced, indicating that the “group division and division” is better for the firefly algorithm.

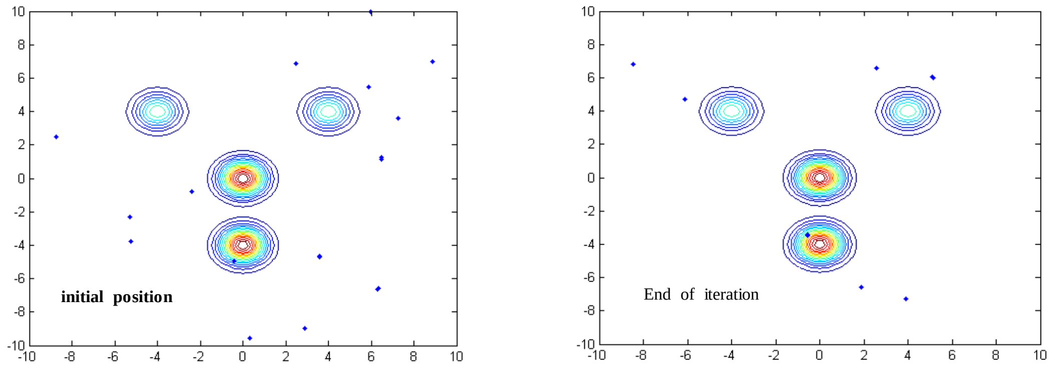

Fig. 3 Distribution of fireflies in the first group of experiments ([-10,10] interval)

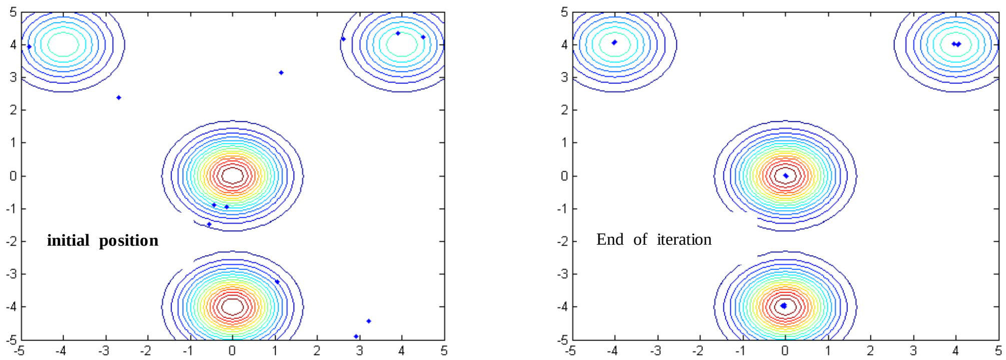

Fig. 4 Distribution of fireflies in the second group of experiments ([-5,5] interval)

It can be found from Fig. 3 and Fig. 4 that when searching in the [-10,10] interval, only the fireflies that are adjacent to each other are well-received, and the fireflies that are far away are less attractive and can only be near the initial position. Fluctuation becomes a "failed" individual. In the interval of [-5,5], since the fireflies are close to each other, the distance between the fireflies is relatively close, so the information exchange between individuals is relatively complete, and all individuals are quickly completed in mutual learning. Evolutionary process, find the global optimal solution.

3. Multi-group firefly algorithm based on improved evolutionary mechanism (MFA_IEM)

3.1 Multi-population learning mechanism

The standard firefly algorithm has a relatively fast evolutionary speed in the early iteration, but when it reaches the local optimal region, it tends to slow down or even stagnate. At this time, the firefly group will perform group oscillation around the local extreme point, that is, premature convergence occurs. In order to effectively improve the population diversity of fireflies and better accomplish the global optimization task, this paper first divides the firefly group into n subgroups, and the initial values of each subgroup are randomly distributed in the solution domain.

When it is found that the optimal value of a subgroup has not been updated three times in succession, it is judged that the subgroup may fall into local optimum and prematurely occurs. The subgroup will be perturbed using a Gaussian variation factor. The Gaussian distribution is an important probability distribution commonly used in engineering, and its probability density function is shown in equation (6).

$$f(x) = \frac{1}{\sqrt{2\Pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad -\infty < x < \infty \tag{6}$$

Where σ is the variance of the Gaussian distribution and μ is the expectation.

The fireflies in the subgroup are sorted according to the size of the pros and cons, and the firefly in the subgroup is used to replace the status of the firefly group in the last group, and the state of the firefly population is updated by Gaussian mutation, as shown in equation (7).

$$x_i = x_i + x_i \times N(\mu, \sigma) \tag{7}$$

Where a is $N(\mu, \sigma)$ random vector obeying a Gaussian distribution with a desired μ and a variance of σ.

The self-adjustment within the sub-group enhances the diversity of the fireflies, so as to help the sub-groups to jump out of the local optimum and improve the global search ability.

3.2 Adaptive variable step size mechanism

In order to prevent the firefly from falling into local optimum prematurely, as shown in equation (4), the disturbance item $\alpha(rand - 1/2)$ of the position update. When α takes a large value, it is easy to jump out of the local best, and better realize the task of global optimization. However, it is easy to generate oscillation phenomenon in the later stage of the algorithm operation; α is smaller and easy to fall into the local best. In order to better achieve the global optimization and improve the two-way requirements of convergence speed, this paper sets up an adaptive variable step size mechanism in the process of iterative optimization. The adaptive adjustment process of the step factor is as shown in equation (8).

$$\alpha(t) = 0.4/(1 + \exp(0.015 * (i - \mathrm{MaxGeneration})/4)) \tag{8}$$

Where: i is the current number of iterations, and *MaxGeneration* is the maximum number of iterations.

The larger α in the early stage can effectively improve the diversity of the firefly population, expand the range of the firefly's movement, and better find the global best. The decrease with the iteration α can effectively improve the oscillation phenomenon of the convergence process and effectively coordinate the convergence speed and accuracy.

3.3 Domain constraint

In view of the firefly crossover problem in the firefly algorithm, the idea of boundary variation is introduced to the cross-border firefly, which effectively overcomes the defect that the firefly easily falls into the local extreme value on the boundary, and at the same time, the diversity of the population is strengthened, and the algorithm is improved to some extent Global search capabilities.

Set to the lower limit of x_{min} search space and x_{max} to the upper limit of search space. Then the domain is constrained to the firefly individual by the following formula:

$$x_i = \begin{cases} x_{min} * (1 - c * rand), x_i < x_{min} \\ x_{max} * (1 - c * rand), x_i > x_{max} \end{cases}$$

After the mutation operation is performed on the individuals who cross the boundary, the individuals are distributed in the search space and no longer gather at the boundary, so that the algorithm not only preserves the diversity of the population but also improves the global search ability of the algorithm.

3.4 MFA_IEM algorithm flow

Input: Number of fireflies, number of iterations.

Output: The location of the optimal solution and the optimal solution.

BEGIN：

iter=1; /*Number of iterations*/

Parameter initialization, grouping firefly populations, initializing firefly position and initial fluorescence brightness;

For i=1 To n do /*n is the number of subpopulations*/

For j=1 Tom do /*m is the number of fireflies in the subgroup*/

If /*The firefly population within the subgroup has converged*/

Gaussian perturbation for firefly individuals caught in local optimum

Else

Improve the location update mechanism of the firefly algorithm;

Perform domain constraint on the updated firefly individual to determine whether the firefly individual in the population exceeds the search scope;

End

Sub-populations learn from each other

End

End

4. Experimental simulation and analysis

In this paper, two standard test functions are used to analyze and verify the convergence performance and optimization effect of the MFA_IEM algorithm, as shown below.

Four Peaks function

$$f_1(x) = e^{-(x-4)^2-(y-4)^2} + e^{-(x+4)^2-(y-4)^2} + 2e^{-x^2-(y+4)^2} + 2e^{-x^2-y^2} \quad (5)$$

The FourPeaks function is a multi-peak function with four minimum peaks in the [-5,5] interval, where the theoretical minimum is -2.

1) Ackley function

$$f_2(x) = 20 + e - 20e^{-0.2\sqrt{\frac{x^2+y^2}{2}}} - e^{\frac{\cos 2\Pi x + \cos 2\Pi y}{2}} \quad (9)$$

This function is a continuous cosine function obtained by moderately amplifying the exponential function superposition, and has multiple local advantages. In theory, the global minimum point of the function is at with a minimum of zero.

Table 2 Optimal fitness statistics

Function	Algorithm	Best	Worst
Four Peaks	FA	1.989999	0.024439
	MFA_IEM	1.999999	0.658515
Ackley	FA	-0.51119	-18.1516
	MFA_IEM	-0.00782	-15.4478

It can be seen from Table 2 that the worst value and the optimal value are better than the FA algorithm;It can be seen that the MFA_IEM algorithm has good adaptability and robustness.

In order to further understand the effectiveness of MFA_IEM, this paper is the best for MFA_IEM and FA.The evolutionary process of fitness values was compared and the results are shown in Figure5 and 6 .

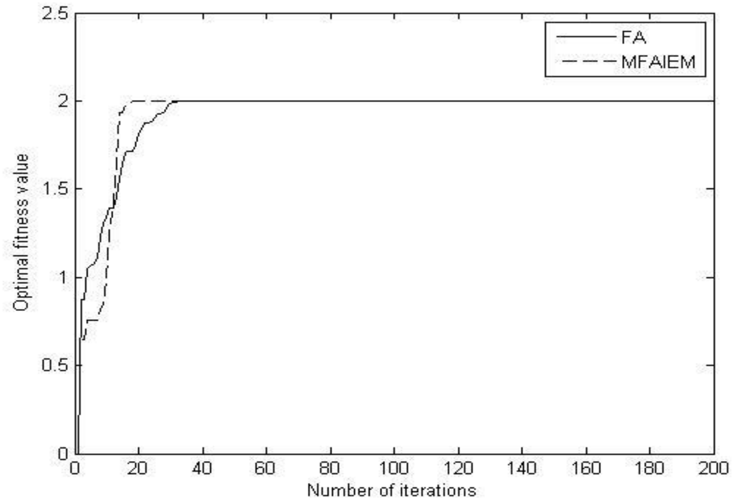

Fig. 5 Four Peaks function evolution fitness curve

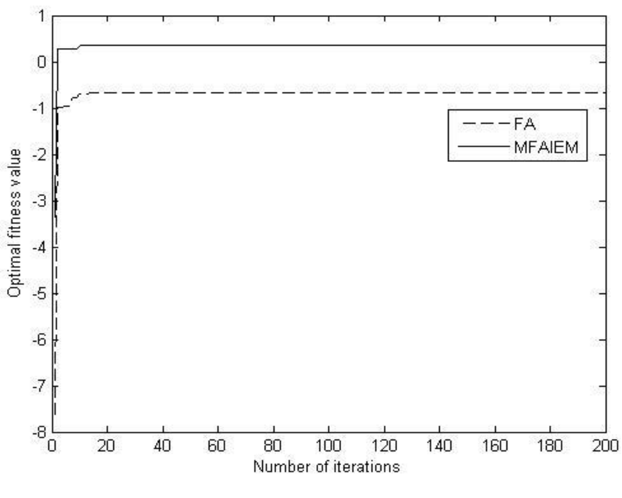

Fig. 6 Ackley function evolution fitness curve

As can be seen from the figure, MFA_IEM has fewer evolution iterations, faster convergence, and higher convergence accuracy. Driven by the multi-subgroup mutual learning mechanism, MFA_IEM is more likely to jump out of the evolutionary stagnation state. When evolution slows or stagnate, MFA_IEM can re-enter the evolutionary state of the firefly that has been hindered by Gaussian variability, and has a certain ability to evolve and recover, so as to better meet the comprehensive search requirements of local search and global precision. Better solution efficiency.

5. Conclusion

In this paper, the evolution mechanism of firefly algorithm is studied, and a multi-group firefly algorithm (MFA_IEM) based on improved evolution mechanism is proposed. The firefly algorithm with different mode parameters is added to increase the diversity of individuals. The performance comparison test of MFA_IEM is carried out by using several standard test functions. It can be seen from the experimental results that MFA_IEM can effectively improve the evolutionary stagnation problem of FA, and has a good solution effect in terms of global precision and convergence speed.

References

[1] YANG X-S.Nature-inspired meta heuristic algorithm [M].Luniver Press, 2008:81-96.

[2] YANG X S, DEB S. Eagle strategy using lévy walk and firefly algorithms for stochastic optimization [J].Studies in Computational Intelligence,2010,28(4):101-111.

[3] FU Q,TONG N,ZHAO Y.Firefly algorithm based on multi-group learning mechanism [J]. Application Research of Computers, 2013, 30(12)∶3600—3603.

[4] FU Q,TONG N,ZHONG C. Firefly algorithm based on improved evolutionism [J]. Computer Science,2014,41(3):228-231.

[5] SRIVATSAVA P R. MALLIKARJUN B, YANG Xin-she. Optimal test sequence generation using firefly algorithm[J]. Swarm and Evolutionary Computation,2013,8(1):44-53.

[6] GANDOMI A H, YANG Xin-she. ALAVI A H. Mixed variable structural optimization using firefly algorithm[J]. Computers&Structures,2011,89(23):2325-2336.

[7] SAYADI M K,HAFEZALKOTOB A.NAINI S G J. Firefly inspired algorithm for discrete optimization problems∶ an application to manufacturing cell formation[J]. Journal of Manufacturing Systems, 2013, 32(1)∶78-84. Q. D. Zeng, Q. E. Li: Progress in Civil Engineering, Vol. 32 (2012) No. 9, p. 3077-3080.

[8] YANG J, YE C. Novel firefly algorithm for solving jab shop scheduling problem [J]. Computer Engineering and Applications,2013,49(11):213-215.

[9] LIU C,YE C.Novel bio-inspired swarm intelligence optimization algorithm:firefly algorithm[J].Application Research of Computers,2011.28(9):3295-3297.