Application of Improved Fruit Fly Optimization Algorithm in Three Bar Truss

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Abstract. Fruit fly algorithm (FOA) is a new swarm intelligence algorithm based on fruit fly foraging behavior. It has the advantages of less adjustment parameters, fast running speed and easy to use. However, the original algorithm also has some problems, such as poor stability, low convergence accuracy and easy to fall into local optimization. Because the exponential function, logarithmic function and inverse proportional function have different variation characteristics, they have good parameter regulation performance. In order to improve the optimization performance of FOA, the above three mechanisms are introduced into the original algorithm. Firstly, the variable step size mechanism (exponential function) is applied in the initialization of FOA, which can improve the stability of FOA; Secondly, the logarithmic mechanism is used for iterative optimization to improve the optimization accuracy of the original algorithm; Thirdly, the disturbance coefficient (inverse proportional function) is used to replace the fixed step value, so as to improve the global optimization ability of the original algorithm. Therefore, this paper proposes a multi mechanism improved fruit fly algorithm (IFOA), which is to reduce the blindness and disorder in the optimization process and promote the optimization ability of the algorithm. Finally, 15 test functions and an engineering example are selected to simulate experiment. The results show that IFOA has better performance.

Keywords: Fruit fly optimization algorithm · Three bar truss · Disturbance coefficient · Test functions · Variable step size

1 Introduction

Swarm intelligence optimization algorithms have been developed over 20 years, they are applied for optimization problems widely. The Fruit Fly Optimization Algorithm belongs to one of them, it was proposed by Pan Wenchao in 2011. It is an intelligent swarm algorithm that imitates the foraging behavior of fruit flies [1]. Compared with other intelligent algorithms, it has the advantages of simple optimization mechanism, easy to understand, easy to implement program code and fewer parameters to be adjusted [2], etc. Therefore, FOA is widely used in the scientific and engineering neighborhoods, such as enterprise performance evaluation [3], gasification parameter optimization [4], support vector machine parameter optimization [5], GRNN neural network parameter

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optimization [6], PID controller design [7], power load forecasting [8], optimization of multidimensional knapsack problem [9], etc.

FOA is similar to other swarm intelligent optimization algorithms, the iterative optimization process is a random search, and all individuals are concentrated near the best individuals of the previous generation. If the optimal individual is not the global optimal solution, it is easy to cause the algorithm to fall into the local optimum, which affects the convergence accuracy and stability of the algorithm. So as to solve the above problems, some scholars have proposed many improved FOA algorithms and applied them in related neighborhoods. Liu Xiaoyue et al. proposed an improved FOA based on chaotic particle and swarm optimization [10]; Shi Wenfeng et al. introduced an optimization of unequal spacing grounding grid based on chaotic FOA [11]; Zhang Xiaoping introduced a study on multi-objective collaborative optimization of switched reluctance motor based on chaos FOA [12]. Jiang Feng et al. proposed a multivariate adaptive step FOA optimized generalized regression neural network for short-term power load forecasting [13]. Yu Helong et al. proposed an optimized deep residual network system for diagnosing tomato pests [14]. Gouda Ram et al. introduced a multi-objective crow search and FOA for combinatorial test case prioritization [15]. Gang Ding et al. introduced a segmentation of the fabric pattern based on FOA [16]. Lu Hongfang et al. proposed a short-term load forecasting of urban gas using a hybrid model based on improved FOA and support vector machine [17]. Qingyong Zhang proposed a short-term traffic forecasting model based on echo state network optimized by improved FOA [18]. Zhao Fuqing et al. introduced a hierarchical guidance strategy assisted FOA with cooperative learning mechanism [19]. Rabhi S et al. introduced an improved method for distributed localization in WSNs based on FOA [20].

To a certain extent, the above-mentioned improved fruit fly algorithm promotes the deficiencies of the algorithm, but the adopted mechanisms are relatively single. a multi mechanism improved fruit fly algorithm (IFOA) is proposed in this paper, the following is specific ideas: (1) In the initialization process of fruit flies, a variable step size mechanism with e function as the base is introduced to improve the problem of instability in algorithm optimization; (2) As the iterative optimization of fruit flies uses random search, the logarithmic mechanism is used to improve the optimization ability and accuracy of the algorithm; (3) In the iterative optimization process of fruit flies, disturbance coefficient is added to dynamically adjust the search step of the algorithm, which effectively balances the local search and global optimization capabilities of the algorithm, and enhances the ability of the algorithm to jump out of the local optimal solution.

The structure of this article is arranged as follows. Review of the original FOA is summarized in Sect. 2. In Sect. 3, the motivation and implement of the IFOA approach are described in detail. In Sect. 4, the proposed IFOA approach is tested by benchmark problems. In Sect. 5, the constrained optimization problem(the three-bar truss problem) is carried out and the simulation results are compared with other algorithms. Ultimately, the conclusion is drawn in Sect. 6.

2 Preparations

The Fruit Fly Optimization Algorithm (FOA) is a new method of seeking global optimization based on the foraging behavior of fruit flies. Fruit flies are superior to other species in sensory perception, especially smell and vision. The olfactory organs of fruit flies are very good at collecting various odors floating in the air, and they can even smell food sources 40 km away. Then, after flying to the vicinity of the food location, they can also use their keen vision to find the location where the food and companions gather, and fly in that direction.

The vital steps in FOA's searching for global optimization are as follows:

Step 1: Randomly initialize the position of the fruit fly population.

$$Init\, X_{-axis}, Init\, Y_{-axis} \tag{1}$$

Step 2: Give fruit fly individuals a random distance and direction to search for food with their sense of smell.

$$\begin{cases} X_i = X_{-axis} + Random\ Value \\ Y_i = Y_{-axis} + Random\ Value \end{cases} \tag{2}$$

Step 3: Because of the location of the food is unknown, so the distance from the origin is estimated firstly (*Disti*), and then the taste density judgment value is calculated (S_i), which is the reciprocal of the distance.

$$Disti = sqrt(X_i^{\wedge}2 + Y_i^{\wedge}2) \tag{3}$$

$$S_i = 1/Disti \tag{4}$$

Step 4: The taste concentration judgment value (S_i) is substituted into the taste concentration judgment function (or called *Fitness function*) to find the taste concentration ($Smell(i)$) of the individual position of the fruit fly.

$$Smell(i) = Function(S_i) \tag{5}$$

Step 5: Find the fruit flies with the highest taste concentration in the fruit flies group.

$$[\,bestSmell\ bestIndex] = \min(Smell) \tag{6}$$

Step 6: Keep the best taste concentration value and the coordinates of X, Y at this time the fruit fly colony uses vision to fly to this position.

$$Smellbest = bestSmell \tag{7}$$

$$\begin{cases} X_{-axis} = X\,(bestIndex) \\ Y_{-axis} = Y\,(bestIndex) \end{cases} \tag{8}$$

Step 7: Enter iterative optimization, repeat steps 2 to 5, and judge whether the taste concentration is better than the previous iteration taste concentration, if yes, proceed to step 6.

3 A Improved Fruit Fly Optimization Algorithm

3.1 Exponential Growth Step

Fruit fly population use a random initialization mechanism during the initialization process. This causes a problem, the quality of the algorithm's optimization result is too dependent on the quality of the initialization value. If the initialization value of the algorithm happens to be near the optimal value, the optimization speed and accuracy of the algorithm will be significantly improved. However, if not, it will greatly affect the optimization performance of the algorithm. It is detrimental to the search stability of the algorithm. To this, the improved fruit fly optimization algorithm uses e function as the base to update the search step size, and uses the monotonic increase of the exponential function to make the initialization of the algorithm more orderly and enhance the stability of the algorithm.

$$\begin{cases} X_{-axis} = lb + (ub - lb)^{*}\mathrm{e}^{rand()}; \\ Y_{-axis} = lb + (ub - lb)^{*}\mathrm{e}^{rand()}; \end{cases} \tag{9}$$

In the formula, lb is the lower limit, ub is the upper limit.

3.2 Logarithmic Optimization

A random search process is also used in the process of iterative optimization of fruit fly population. This disordered search method makes the search efficiency of the algorithm low, which directly leads to poor optimization accuracy and convergence speed of the algorithm. For these, the improved fruit fly optimization algorithm uses a logarithmic mechanism to iteratively optimize. Due to the increasing order of the log function, the iterative optimization process of fruit flies has become more orderly and efficient. Through the introduction of different mechanisms, the algorithm's search capabilities are diversified, and its optimization accuracy and convergence speed are further enhanced.

$$\begin{cases} X(i) = X_{-axis} + (ub - lb)^{*}\log(k^{*}rand()) \\ Y(i) = Y_{-axis} + (ub - lb)^{*}\log(k^{*}rand()) \\ (i = 1, 2, 3, \ldots\ldots, n). \end{cases} \tag{10}$$

In the formula, X_{-axis}, Y_{-axis} is the current optimal position of the fruit fly, k is the adjustment coefficient.

3.3 Disturbance Coefficient

The optimization mechanism of the fruit fly optimization algorithm is that other fruit flies learn from the optimal fitness fruit flies, and then other fruit flies use vision to fly to the optimal individual to find the optimal value. This makes the algorithm easy to fall into the local optimal risk. Therefore, in the iterative optimization process of the algorithm, a disturbance coefficient is added to dynamically adjust the search step of the algorithm. Avoid the algorithm skipping the global optimal value due to the long search step, or falling into the local optimal value due to the short search step. The disturbance coefficient is used to balance the local optimization and global search capabilities of the algorithm. The following formula is the specific expression of the disturbance coefficient, which is used to replace the fixed step length in the iterative process of fruit flies.

$$R = c_1 - ((c_1 - c_2) * (gen - sizepop))/Maxgen \tag{11}$$

In the formula, c_1, c_2 is a constant greater than 0, *gen* is the current iteration number, *sizepop* is the population number, and *Maxgen* is the maximum iteration number.

3.4 IFOA Algorithm

Based on the principle of the fruit fly optimization algorithm and the above-mentioned improvement methods, the specific steps of the improved fruit fly optimization algorithm proposed in this article are as follows:

Step 1: Initialize the *sizepop*, the maximum number of iterations *Maxgen*, the *dim*, and determine the X_{-axis}, Y_{-axis} according to formula (9).

Step 2: Estimate the distance between the fruit fly and the origin, and then calculate the taste concentration judgment value S_i.

Step 3: Substitute S_i into the taste concentration judgment function $Smell(i)$ to find the position of the fruit flies.

Step 4: Find the fruit fly individuals with the best taste concentration (adaptability) in the fruit fly population.

Step 5: According to the best fruit fly position, all fruit flies fly to the best position by vision.

Step 6: Update the position of the fruit fly population according to formula (10) and then perform iterative calculations, repeat steps 2 to 5, in the optimization process, judge whether the current optimal taste concentration is better than the previous iteration result, and judge whether the current iteration number is less than the maximum iteration number; if so, go to step 5, otherwise end.

Algorithm 1. Pseudo-code of IFOA

Initialization: $Maxgen, sizepop, dim, (lb, ub)$;
$X_{-axis} = lb$; $Y_{-axis} = lb$;
For $i = 1$ to $sizepop$
  $X_i = X_{-axis} + (ub - lb) * \exp(rand()); Y = Y_{-axis} + (ub - lb) * \exp(rand())$;
  $Disti = sqrt(X_i \wedge 2 + Y_i \wedge 2); S_i = 1 / Disti$;
  $Smell(i) = Function(S_i)$;
End for
  $[\ bestSmell \quad bestIndex\ ] = \min(Smell)$;
  $Smellbest = bestSmell$;
  X_{-axis}=X(bestIndex); $Y_{-axis} = Y(bestInedx)$;
  $R = C1 - ((C1 - C2) * (gen - sizepop)) / Maxgen.$
For $gen = 1$ to $Maxgen$
 For $i = 1$ to $sizepop$
  $X_i = X_{-axis} + R * \log(rand())$; $Y_i = Y_{-a\ is\ x} + R * \log(rand())$;
  $Disti = sqrt(X_i \wedge 2 + Y_i \wedge 2); S_i = 1 / Disti$;
  $Smell(i) = Function(S_i)$;
 End for
  $[\ bestSmell \quad bestIndex\ ] = \min(Smell)$;
 If $bestSmell < Smellbest$
   $Smellbest = bestSmell$;
   X_{-axis}=X(bestIndex);
   $Y_{-axis} = Y(bestInedx)$;
 End if
  $gen = gen + 1$;
End
End

4 Simulation Experiment and Result Analysis

4.1 Experimental Design

In order to verify the optimization performance of IFOA, FOA, Flower Pollination Algorithm(FPA), Moth-Flame Optimization Algorithm(MFO) and Bat Algorithm(BA) are selected to compare with IFOA algorithm in this paper. And 15 benchmark test functions are used to optimize simulation experiments of the minimum problem. The test function is shown in Table 1, the parameters settings of the IFOA and other algorithms are shown in Table 2.

Table 1. Fifteen test functions

ID	Equation	Bound	Dim	F(min)
Multi − mod*al* functions				
Griewank	$F1(x) = \sum_{i=1}^{d} \frac{X_i^2}{4000} - \prod_{i=1}^{d} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[−600,600]	30	0
Noncontinous−Rastrigin	$F2(x) = F2(y)(y_i = \{x_i, \lvert x_i\rvert < 0.5;$ $round(2x_i/2, \lvert x_i \ge 0.5\})$	[−5.12,5.12]	30	0
Drop − Wave	$F3(x) = -\frac{1+\cos\left(12\sqrt{x_1^2+x_2^2}\right)}{0.5\left(x_1^2+x_2^2\right)+2}$	[−5.12,5.12]	30	−1
Elliptic − UN	$F4(x) = \sum_{i=1}^{d} (10\hat{}\,(6(i-1)/(d-1)) *\hat{}\ 2)$	[−100,100]	30	0
Rastring	$F5(x) = 10d + \sum_{i=1}^{d} [x_i^2 - 10\cos(2\pi x_i)]$	[−5.12,5.12]	30	0
Schaffer N.2	$F6(x) = 0.5 + \frac{sin^2\left(x_1^2-x_2^2\right)-0.5}{\left[1+0.001\left(x_1^2+x_2^2\right)\right]^2}$	[−100,100]	30	0
Ackley	$F7(x) = -a\exp(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2)}$ $-\exp(\frac{1}{d}\sum_{i=1}^{d} \cos(cx_i) + a + \exp(1))$	[−32.768,32.768]	30	0
Powell	$F8(x) = \sum_{i=1}^{d/4} [(X_{4i-3} + 10X_{4i-2})\hat{}\,2$ $+5(X_{4i-1} - X_{4i}) \wedge 4 + 10(X_{4i-3} - X_{4i})\hat{}\,4]$	[−4,5]	30	0
Un − mod*al* functions				
Zakharov	$F9(x) = \sum_{i=1}^{d} x_i^2 + (\sum_{i=1}^{d} 0.5ix_i)\hat{}\,2 + (\sum_{i=1}^{d} 0.5ix_i)\hat{}\,4$	[−5,10]	30	0
Bohachevsky−Rotated	$F_{10.1}(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1) - 0.4\cos(4\pi x_2) + 0.7;$ $F_{10.2}(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1)0.4\cos(4\pi x_2) + 0.3;$ $F_{10.3}(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1 + 4\pi x_2) + 0.3.$	[−100,100]	30	0
Hyper − Ellipsoid	$F11(x) = \sum_{i=1}^{d} \sum_{j=1}^{i} x_j^2$	[−65.536,65.536]	30	0
Sum Squares	$F12(x) = \sum_{i=1}^{d} ix_i^2$	[−5.12,5.12]	30	0
Matyas	$F13(x) = 0.26(x_1^2 + x_2^2) - 0.48x_1x_2$	[−10,10]	30	0
Sphere	$F14(x) = \sum_{i=1}^{d} x_i^2$	[−5.12, 5.12]	30	0
Sum Power	$F15(x) = \sum_{i=1}^{d} [(\sum_{j=1}^{d} X_j^i) - b_i]\hat{}\,2, b = (8, 18, 44, 144)$	[0,4]	4	0

Table 2. Parameters of the IFOA and other algorithms' variants

Algorithm	Parameter
IFOA	$c_1 = 5.0$, $c_2 = 2.63$, $k = 10$, $Maxgen = 500$, $sizepop = 50$
FOA	$Maxgen = 500$, $sizepop = 50$
FPA	$p = 0.1, p \in [0, 1]$, $Maxgen = 500$, $sizepop = 50$
MFO	$Maxgen = 500$, $sizepop = 50$, $lteration = 1$
BA	$T = 1$, $Maxgen = 500$, $sizepop = 50$

4.2 Experimental Evaluation and Criteria

In the experiment, each algorithm runs independently 30 times, and the termination condition is set as the number of iterations reaches 500 times. To assess the effect of algorithm optimization, four criteria are given in this article as follow: (1) Optimize mean(*mean*), the expectation of the optimal value obtained after the algorithm has been run 30 times, to measure the average quality of the algorithm optimization; (2) Standard deviation (*std*), the standard deviation between the optimal value and the average optimal value obtained after the algorithm runs 30 times, to evaluate the stability of the algorithm optimization; (3) Global optimal solution (*best*), the global optimal solution obtained by running the algorithm 30 times. (4) The global worst solution (*worst*), the global worst solution obtained by running the algorithm 30 times.

4.3 Experimental Results and Analysis

Perform 30 independent tests on the two types of standard test functions in Table 1. The test comparison results are shown in Table 3. Among the fifteen groups of test results in Table 3, $F1$ $F8$ is the high-dimensional multimodal function test and $F9$ $F15$ is the high-dimensional unimodal function test. In addition, *best* represents the optimal fitness value, *worst* represents the worst fitness value, *mean* represents the average fitness value, *std* represents the standard deviation value. The experimental results are shown in Table 3.

Table 3. Test functions' results

Benchmark function	Method	IFOA	FOA	FPA	MFO	BA
$F1$	*best*	**2.16E-13**	7.56E-06	1.43E + 01	1.04E + 00	4.97E-01
	worst	**2.56E-13**	1.59E-05	8.24E + 01	7.30E + 00	5.95E + 02
	mean	**2.19E-13**	1.14E-05	4.05E + 01	4.21E + 00	4.85E + 02
	std	**7.06E-15**	1.90E-06	1.78E + 01	1.68E + 00	1.05E + 02

(*continued*)

Table 3. (*continued*)

Benchmark function	Method	IFOA	FOA	FPA	MFO	BA
$F2$	*best*	**2.89E-06**	3.46E-02	1.19E + 02	3.00E + 01	3.70E + 02
	worst	**2.93E-06**	1.89E + 02	2.04E + 02	1.99E + 02	4.68E + 02
	mean	**2.91E-06**	4.41E + 01	1.54E + 02	1.04E + 02	4.14E + 02
	std	**8.58E-09**	4.87E + 01	2.02E + 01	4.38E + 01	2.75E + 01
$F3$	*best*	**−1.00E + 00**	−9.36E-01	−1.00E + 00	−1.00E + 00	−9.97E-01
	worst	**−1.00E + 00**	−8.74E-01	−9.36E-01	−9.36E-01	−2.67E-01
	mean	**−1.00E + 00**	−9.33E-01	−9.74E-01	−9.94E-01	−6.88E-01
	std	**3.35E-09**	1.16E-02	2.40E-02	1.95E-02	1.77E-01
$F4$	*best*	**2.36E-06**	1.04E + 01	1.60E + 07	8.16E + 05	7.10E + 06
	worst	**3.07E-06**	3.40E + 02	3.71E + 07	1.76E + 08	4.22E + 09
	mean	**2.45E-06**	1.50E + 02	2.63E + 07	2.57E + 07	2.32E + 09
	std	**2.07E-07**	1.20E + 02	5.51E + 06	3.66E + 07	9.06E + 08
$F5$	*best*	**2.88E-06**	3.46E-02	1.26E + 02	7.27E + 01	3.86E + 02
	worst	**2.92E-06**	1.01E + 02	2.05E + 02	2.83E + 02	4.80E + 02
	mean	**2.90E-06**	8.25E + 00	1.62E + 02	1.52E + 02	4.39E + 02
	std	**9.52E-09**	2.55E + 01	1.95E + 01	4.23E + 01	2.46E + 01
$F6$	*best*	1.29E-14	5.15E-09	1.82E-06	**0.00E + 00**	6.89E-09
	worst	1.47E-14	1.63E-07	1.64E-02	**0.00E + 00**	4.40E-01
	mean	1.42E-14	5.63E-08	2.03E-03	**0.00E + 00**	2.50E-01
	std	3.79E-16	6.78E-08	3.19E-03	**0.00E + 00**	1.38E-01
$F7$	*best*	**1.36E-05**	1.01E-02	1.48E + 01	2.07e-01	1.94E + 01
	worst	**1.37E-05**	2.67E-01	1.82E + 01	1.94E + 01	2.09E + 01
	mean	**1.36E-05**	1.71E-01	1.71E + 01	6.57E + 00	2.06E + 01
	std	**2.05E-08**	1.01E-01	8.38E-01	7.93E + 00	3.02E-01
$F8$	*best*	**4.26E-07**	3.94E-03	7.97E + 01	7.87E-01	2.49E + 02
	worst	**4.43E-07**	5.87E + 01	1.95E + 02	4.91E + 03	2.12E + 04
	mean	**4.31E-07**	1.08E + 01	1.34E + 02	6.96E + 02	1.22E + 04
	std	**3.28E-09**	1.87E + 01	3.18E + 01	1.15E + 03	4.27E + 03
$F9$	*best*	**1.17E-05**	4.10E-01	5.97e + 01	1.40E + 02	2.48E + 01
	worst	**1.18E-05**	2.62E + 06	2.30E + 02	4.81E + 02	6.19E + 09
	mean	**1.77E-05**	7.88E + 05	1.45E + 02	3.27E + 02	6.84E + 08
	std	**3.73E-08**	9.34E + 05	3.68E + 01	9.80E + 02	1.40E + 09

(*continued*)

Table 3. (*continued*)

Benchmark function	Method	IFOA	FOA	FPA	MFO	BA
$F10$	*best*	3.34E-11	9.50E-05	1.24E-05	**0.00E + 00**	2.380E-03
	worst	4.83E-11	3.53E-03	2.25E-02	**0.00E + 00**	1.49E + 03
	mean	3.87E-11	1.02E-03	5.21E-03	**0.00E + 00**	1.71E + 02
	std	6.34E-12	1.38E-03	5.07E-03	**0.00E + 00**	2.76E + 02
$F11$	*best*	**1.30E-09**	2.64E-03	1.15E + 04	2.73E + 00	2.03E + 02
	worst	**1.31E-09**	2.29E-01	2.45E + 04	5.58E + 04	4.75E + 05
	mean	**1.30E-09**	1.11E-01	1.71E + 04	1.66E + 04	3.85E + 05
	std	**3.85E-12**	7.34E-02	2.87E + 03	1.76E + 04	8.16E + 04
$F12$	*best*	**2.18E-07**	2.18E-07	2.18E-07	2.18E-07	2.18E-07
	worst	**2.22E-07**	3.07E + 01	1.44E + 02	4.98E + 02	3.11E + 03
	mean	**2.20E-07**	6.63E + 00	1.10E + 02	1.01E + 02	2.52E + 03
	std	**9.03E-10**	1.10E + 01	2.18E + 01	1.40E + 02	5.05E + 02
$F13$	*best*	2.85E-12	1.16E-07	2.80E-12	**1.55E-98**	2.43E-05
	worst	4.02E-12	4.27E-04	1.07E-07	**8.28E-42**	6.50E-01
	mean	2.98e-12	4.51E-05	1.05E-08	**2.76E-43**	1.96E-01
	std	3.35E-13	1.19E-04	2.07E-08	**1.51E-42**	1.76E-01
$F14$	*best*	**1.46E-08**	1.74E-04	5.98E + 00	3.25E-04	6.64E + 00
	worst	**1.49E-08**	1.84E + 00	1.14E + 01	2.62E + 01	1.95E + 02
	mean	**1.46E-08**	4.32E-01	8.23E + 00	8.78E-01	1.68E + 02
	std	**6.11E-11**	6.59E-01	1.36E + 00	4.79E + 00	3.29E + 01
$F15$	*best*	1.64E-09	2.70E-06	4.51E + 01	**0.00E + 00**	2.39E + 01
	worst	**2.18E-09**	2.68E-01	2.08E + 06	65792	2.84E + 12
	mean	**1.83E-09**	1.77E-01	1.04E + 05	5.08E + 03	4.26E + 11
	std	**2.26E-10**	6.19E-02	3.84E + 05	1.67E + 04	6.72E + 11

From the comparative analysis of the experimental results in Table 3, IFOA basically ranked first in the eight high-dimensional multimodal function tests, and all indicators are better than the original algorithm. It can be seen from the standard deviation in the above table that the stability of the improved algorithm has been generally promoted, which shows that the variable step size mechanism and log logarithm mechanism have a good effect; It can be seen from the optimal value in the above table that the improved algorithm can basically approach the optimal value without local extreme value, which shows that the addition of disturbance coefficient can effectively improve the global optimization ability of the original algorithm. However, the optimization accuracy of MFO is higher than IFOA in the test of $F6$. Nevertheless, combined with the performance of this algorithm in other function tests, it can be seen that the stability of this algorithm is poor and the convergence accuracy is low; In the test of seven high-dimensional unimodal functions, most indicators of IFOA also ranked first. Compared with the original algorithm, the accuracy and stability are improved. Although the accuracy of MFO is higher than IFOA in the optimization results, the stability of this algorithm is poor and the performance index fluctuates greatly. To sum up, the improved algorithm shows good results in the test of high-dimensional multimodal function or high-dimensional unimodal function, which verifies the effectiveness of the improved strategy.

Then, this paper selects several representative functions to show their convergence curves and variance graphs. Figures 1, 2, 3, 4, 5, 6, 7, 8, 9 are the evolution curves of their average fitness values, and Figs. 10, 11, 12, 13, 14, 15, 16, 17, 18 are the standard analysis of variance graphs.

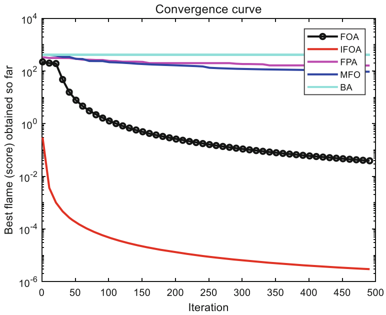

Fig. 1. Convergence curve for $F2$

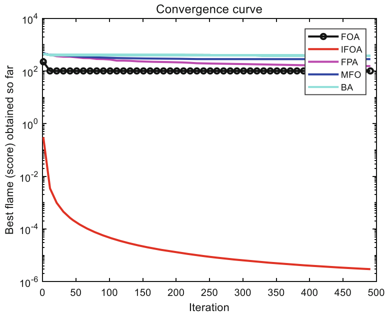

Fig. 2. Convergence curve for $F5$

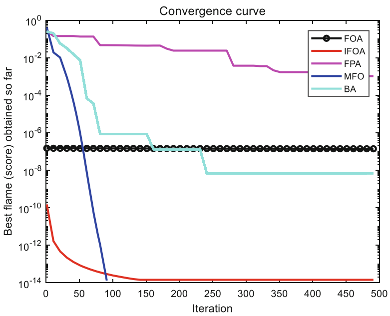

Fig. 3. Convergence curve for $F6$

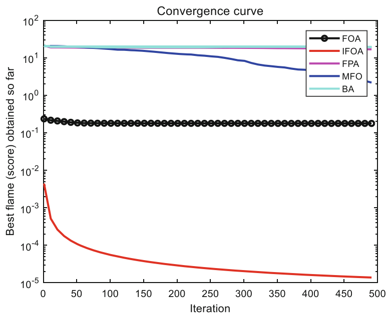

Fig. 4. Convergence curve for $F7$

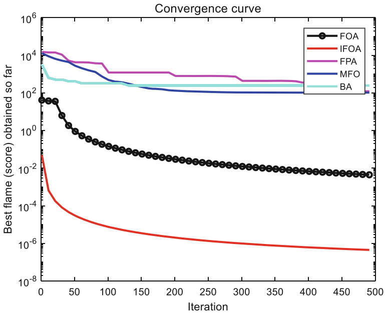

Fig. 5. Convergence curve for $F8$

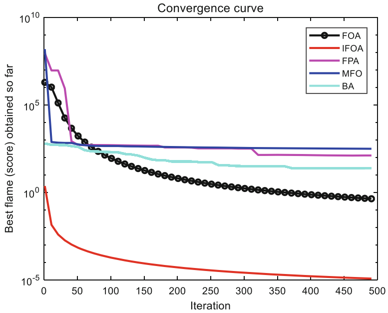

Fig. 6. Convergence curve for $F9$

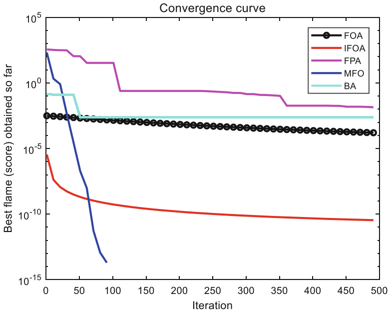

Fig. 7. Convergence curve for $F10$

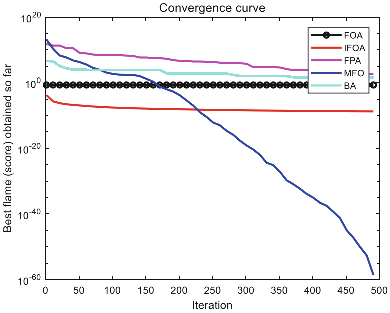

Fig. 8. Convergence curve for $F15$

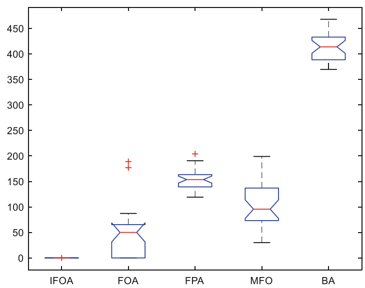

Fig. 9. ANOVA tests for $F2$

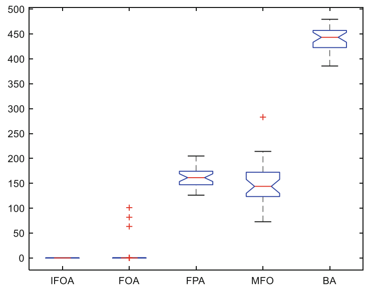

Fig. 10. ANOVA tests for $F5$

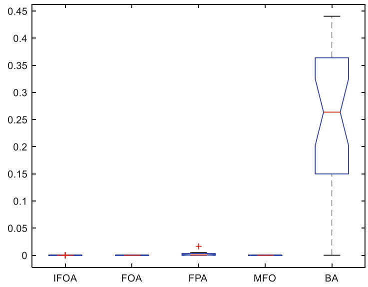

Fig. 11. ANOVA tests for $F6$

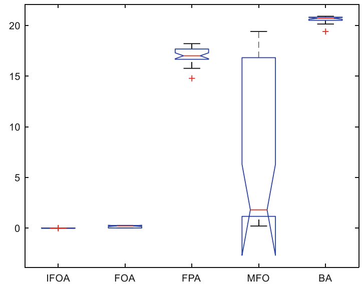

Fig. 12. ANOVA tests for $F7$

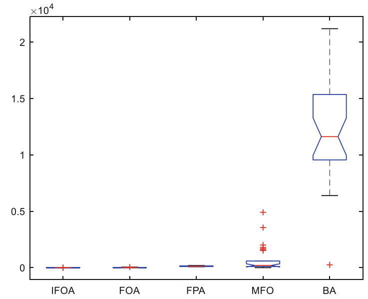

Fig. 13. ANOVA tests for $F8$

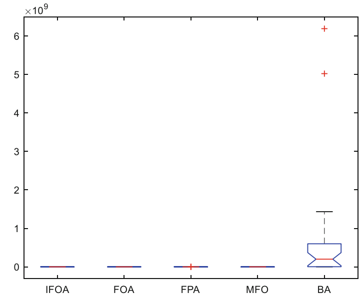

Fig. 14. ANOVA tests for $F9$

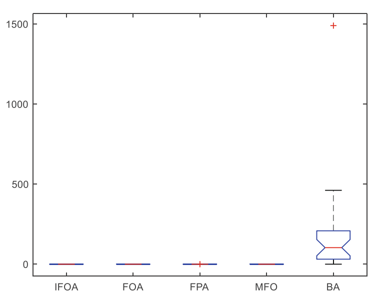

Fig. 15. ANOVA tests for $F10$

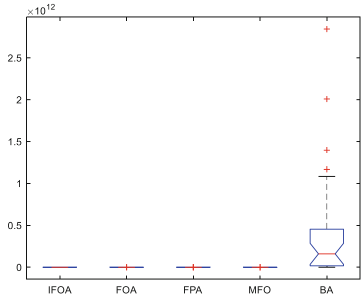

Fig. 16. ANOVA tests for $F15$

In order to visually verify the superiority of the IFOA algorithm performance, Fig. 1, 2, 3, 4, 5, 6, 7 and 8 respectively show the test results of the 5 optimization algorithms after running 30 times independently. The convergence graph of the tested standard functions $F2$, $F5$, $F6$, $F7$, $F8$, $F9$, $F10$, $F15$ is as above (in order to facilitate the display and observation of the evolution curve, all the tested functions' fitness is taken base 10 logarithm). By observing the convergence curve of the 4 high-dimensional multimodal functions (Fig. 1, Fig. 2, Fig. 3, and Fig. 4), it is easy to find that the convergence speed of the IFOA algorithm is faster than the other algorithms, and the search accuracy is higher. Figure 5, 6, 7, 8 show the convergence curve of the high-dimensional unimodal function. IFOA still maintains its advantage in these functions' test. Although MFO is faster than IFOA, it has less stability in Fig. 7. Whether it is a high-dimensional unimodal function or a high-dimensional multimodal function, IFOA still maintains a fast convergence rate, showing the superior stability and convergence of IFOA.

To further fully verify the effectiveness of the algorithm, Fig. 9, 10, 11, 12, 13, 14, 15, 16 show the standard deviation diagrams of the 8 standard functions tested by 5 optimization algorithms. By observing the standard deviation graph of each algorithm, it is more intuitive to observe that the IFOA algorithm has better stability and robustness. Among the tested functions, Fig. 9, 10, 11, 12 solve the high-dimensional multimodal function. The standard deviation of the IFOA algorithm is smaller than the other optimization algorithms except $F6$. The BA algorithm has the worst stability and the IFOA algorithm has the most stability. For the test standard deviations of high-dimensional unimodal functions in Fig. 13, 14, 15, 16, other optimization algorithms have different degrees of fluctuations. However, the IFOA algorithm still maintains stability, which shows that the IFOA algorithm has stronger robustness, better stability, and better portability.

Overall, it can be seen from Fig. 9, Fig. 10, Fig. 11, Fig. 12, 13, Fig. 14, Fig. 15, and Fig. 16 that whether it is a high-dimensional multimodal function or a high-dimensional unimodal function, the other four intelligent optimization algorithms all show certain fluctuations. In contrast, the IFOA algorithm still maintains strong stability and the optimization performance also has obvious advantages. Therefore, it shows that the IFOA algorithm proposed in this paper has more obvious strengths.

5 Application of IFOA in Structural Optimization Design

In order to test the effectiveness of IFOA in solving practical engineering problems, it is used to solve the engineering optimization problem in structural design, which is the three-bar truss problem.

The constraint variables of this problem are $g_1(x)$, $g_2(x)$ and $g_3(x)$, and the mathematical description of the problem is as follows (Fig. 17):

$$
\begin{aligned}
&Min.f(x) = (2\sqrt{2}x_1 + x_2) \times l \\
&S.t. \\
&g_1(x) = \frac{\sqrt{2}x_1 + x_2}{\sqrt{2}x_1^2 + 2x_1x_2}P - \sigma \le 0 \\
&g_2(x) = \frac{x_2}{\sqrt{2}x_1^2 + 2x_1x_2}P - \sigma \le 0 \\
&g_3(x) = \frac{1}{\sqrt{2}x_2 + x_1}P - \sigma \le 0 \\
&0 \le x_i \le 1,\ i = 1, 2 \\
&l = 100\,\text{cm},\ \text{P} = 2\ \text{kN/cm}^2,\ \partial = 2\ \text{kN/cm}^2
\end{aligned}
$$

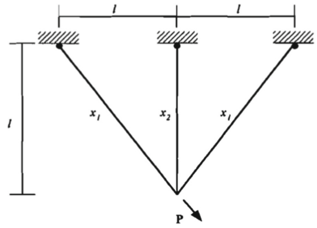

Fig. 17. Mathematical model of three-bar truss

For the above engineering problems, the IFOA is used to compare experiments with FOA, BA, and MFO in this paper. The experimental environment is the same as before, and Matlab R2017b is used for programming. The computer configuration is: Intel Core(TM) i5-6300hq, 2.3 GHz, 8 GB memory, Windows10 operating system. The algorithms are run independently 30 times (the number of iterations is changed to 1000, and the parameter settings of other algorithms are the same as above), and the result statistics are shown in Table 4 (NAN means not a specific data, the maximum value of the penalty function is set to infinity).

Table 4. Compared test result

Item	*Best*	*Worst*	*Mean*	*std*
FOA	2.643151e + 02	2.880574e + 02	2.728668e + 02	6.517315e + 00
IFOA	2.638973e + 02	2.639910e + 02	2.639335e + 02	2.668537e-02
BA	−Inf	3.130432e + 02	−Inf	NaN
MFO	2.638958e + 02	2.641057e + 02	2.639255e + 02	5.309939e-02

Through the analysis of the above data, it can be found that the improved fruit fly optimization algorithm has higher accuracy in engineering applications, can be closer to the optimal value, and obtain higher engineering accuracy. At the same time, the analysis of the standard deviation data of each algorithm shows that the stability of the IFOA algorithm is two orders of magnitude higher than the original FOA algorithm, and it is also higher than other algorithms. Therefore, the improved algorithm has higher stability. In summary, the improved fruit fly optimization algorithm has good practical application value.

6 Conclusion

A improved fruit fly optimization algorithm is proposed to solve constrained optimization problems in this paper, which broadens the application field of the FOA algorithm. The improved algorithm uses the variable step size mechanism to initialize the fruit fly population and enhances the algorithm's performance stability. At the same time, the log logarithm mechanism is used for population iteration to further increase the diversity of the fruit fly population solution space and improve the optimization accuracy of the algorithm. In addition, the disturbance coefficient is introduced in the iterative process to adjust the search step size of the algorithm, which effectively avoids the occurrence of premature convergence of the algorithm, and balances the global optimization and local search capabilities. 15 benchmark test functions are used to verify the feasibility and effectiveness of the algorithm in this article, the experimental results show that the algorithm in this article has faster convergence speed, higher convergence accuracy and strong optimization stability. Finally, the algorithm is used to solve engineering optimization problems and achieved good application results.

In the future work, we are trying to combine the fruit fly optimization algorithm with other intelligent algorithms in order to get a better improved fruit fly optimization algorithm. Moreover, the improved optimization algorithm will be applied to some practical problems, such as: 0–1 knapsack problem, pressure vessel, PID controller, etc.

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