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An Improved Artificial Fish Swarm Algorithm based on Hybrid Behavior Selection

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Abstract

The artificial fish swarm algorithm (AFSA) is a heuristic global optimization technique based on population which is easy to understand, good robustness, and not insensitive to initial values. The behavior of fishes has a great impact on the performance of the algorithm, such as global search and convergence speed. At present, there has no general research theory to select behaviors of fishes. In order to deal with this problem, we proposed an improved artificial fish swarm algorithm based on hybrid behavior selection. There are two mainly works in this paper. Firstly, we propose an improved algorithm based on swallowed behavior, which can greatly speed up the convergence. Secondly, in order to deal with the problems of easy to fall into local optimum value, we added breeding behavior to improve global optimization capability. The experiments on high dimensional function optimization showed that the improved algorithm has more powerful global exploration ability and faster convergence speed.

Keywords: *Artificial fish swarm, swallow behavior, breed behavior, function optimization*

1. Introduction

Optimization is a process of finding the extreme value of a function in a domain of definition, with various constraints on the variable values. Artificial fish swarm algorithm[1-2] is a class of swarm intelligence optimization algorithm based on the behavior of animals proposed in 2002 , the basic idea of the AFSA is to imitate the fish behaviors such as praying, swarming and following. AFSA [3] is very suitable for solving a variety of numerical optimization problem, making the algorithm quickly became a hot topic in the current optimization field.

Because of Simple in principle, good robustness and tolerance of parameter setting, AFSA has been applied successfully to all kinds of optimization problems such as image reconstruction [4], image segmentation [5], color quantization [6], neural network [7], fuzzy logic controller [8], multi robot task scheduling [9], fault diagnosis in mine hoist [10], PID controller parameters [11], data clustering [12-14] and other areas [15-19].

However, in the course of treatment the multi peak and the large search space function optimization problems, the convergence rate of AFSA algorithm is slow and easy to fall into local optimal solution. At the same time, the experiences of group members are not used for the next moves. In order to improve the optimization performance of the AFSA, many scholars have proposed some improved algorithm [20-23]. Although all the methods can

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improve the performance to some extent, but it still can not get satisfactory results for some of the functions. In this paper, we proposed a new method based on some new behavior.

This paper is organized as follows. Related work is described in Section 2. In Section 3 the background of AFSA is presented. The improved algorithm is presented in Section 4. In Section 5 some experimental tests, results and conclusions are given. Section 6 concludes the paper.

2. Related Work

In order to improve the performance of artificial fish swarm algorithm, researchers have made some attempts. In [20], the information of global best AF is added to the behaviors of fishes to AFSA which can improve the performance of the AFSA. Mingyan Jiang *et al.*, [21] reported a new leaping behavior which can improve the probability to leap out local extremes. Each fish can select a proper behavior to execute. In [22], crossover operator is used to increase the diversification of the artificial fishes based on their parents' characteristics. Edite *et al.*, [23] reported a new method with a set of movements, closely related to the random, the searching and the leaping fish behaviors.

Some researchers have tried to improve the performance of AFSA by combining different algorithm with AFSA. Huadong Chen *et al.*, [24] reported a hybrid algorithm to train forward neural network using a hybrid of artificial fish swarm algorithm and particle swarm optimization. In [25], a new algorithm is proposed for optimization in continuous and static environments by hybridizing cellular learning automata and artificial fish swarm algorithm. Experimental results show that proposed method has an acceptable performance. Zhaohui Chen *et al.*, [26] reported a hybrid algorithm by adding chaos to influence the update of the velocities of artificial fish which can improve the global optimization ability. In [27], an improved AFSA with adaptive visual is proposed to improve the performance of FCM outperforms. WEI Xiu xi *et al.*, [28] reported a hybrid algorithm based on particle swarm optimization and artificial fish swarm algorithm which owns a good globally convergent performance with a faster convergent rate.

A novel quantum artificial fish swarm algorithm [29] based on the principles of quantum computing is proposed which can improve the global search ability and the convergence speed of the artificial fish swarm algorithm. Kongcun Zhu *et al.*, [30] used the quantum rotation gate to update the position of the artificial swarm which can enable the AF to move and employ the quantum non-gate to realize the mutation to speed up the convergence. The experimental results show that the performance of QAFSA is significantly improved.

Mingyan Jiang *et al.*, [31] reported a simulated annealing artificial fish swarm algorithm which can obtain much better optimization precision and the convergence speed compared with basic artificial fish swarm algorithm.

3. Introduction TO AFSA

Supposed the state vector of artificial fish swarm is $X = (x_1, x_2 \cdots x_n)$, where $x_1, x_2 \cdots x_n$ is status of the fish. Visual is the visual distance, the artificial fish occurs only in the inner radius of the circle to the length of the field of vision various acts. The food concentration in this position of fish is expressed as $y = f(x)$, Where y is the objective function value. The distance between the artificial fish is $d_{i,j} = \left\| X_i - X_j \right\|$, i and j is a random fish. $Step$ means the maximum step size of artificial fish. δ is the degree of congestion factor.

Supposed X_v is the visual position at some moment. X_{next} is the new position. Than the movement process is represented as:

$$X_v = X_i + Visual \times rand(), \quad i \in (0, n] \qquad (1)$$

$$X_{next} = X + \frac{X_v - X}{\|X_v - X\|} \times step \times rand() \qquad (2)$$

Where $rand()$ produces random numbers between 0 and 1.

The basic behaviors of artificial fish are defined as follows.

3.1 Prey behavior

This is a basic biological behavior that tends to the food. Supposed the state of artificial fish is X_i, Select a state X_j within its sensing range randomly. If X_j superior to X_i, then move to X_j; on the contrary, selected randomly state X_j and determine whether to meet the forward conditions, repeated several time, if still not satisfied forward conditions, then move one step randomly.

$$X_j = x_i + Visual \times rand() \qquad (3)$$

If $Y_i < Y_j$, it goes forward a step in this direction.

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\|X_j - X_i^t\|} \times Step \times rand() \qquad (4)$$

3.2 Swarm Behavior

Supposed the current state of artificial fish is X_i ($d_{i,j} < Visual$), number of artificial fish is n_f, if $n_f < \delta$ indicates that the partners have more food and less crowded, if Y_c better than Y_i,then go forward toward the center of the direction of the partnership, otherwise prey behavior.

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\|X_c - X_i^t\|} \times Step \times rand() \qquad (5)$$

3.3 Follow Behavior

Supposed the state of artificial fish is X_i, explore its optimal state $X_{\max}$ from Visual neighbors , the number of partners of $X_{\max}$ is n_f, If $n_f < \delta$ indicates that near distance have more food and not too crowded, further move to the front of $X_{\max}$ position; otherwise perform foraging behavior.

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\left\| X_j - X_i^t \right\|} \times Step \times rand() \quad (6)$$

The artificial fish swarm algorithm is shown as algorithm 1.

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1). Initialize the parameters of artificial fish, such as $Step$, $Visual$, the number of exploratory try_number, maximum number of iterations ,and randomly generated n fishes;

2). Set bulletin board to record the current status of each fish, and select the optimal value recorded;

3). Implementation of prey behavior, swarm behavior and follow behavior;

4). Optimal value in bulletin board is updated;

5). If the termination condition is satisfied, output the result; otherwise return to step 2.

Algorithm 1. Artificial fish swarm algorithm

The flow chat of artificial fish swarm algorithm is shown as Figure 1.

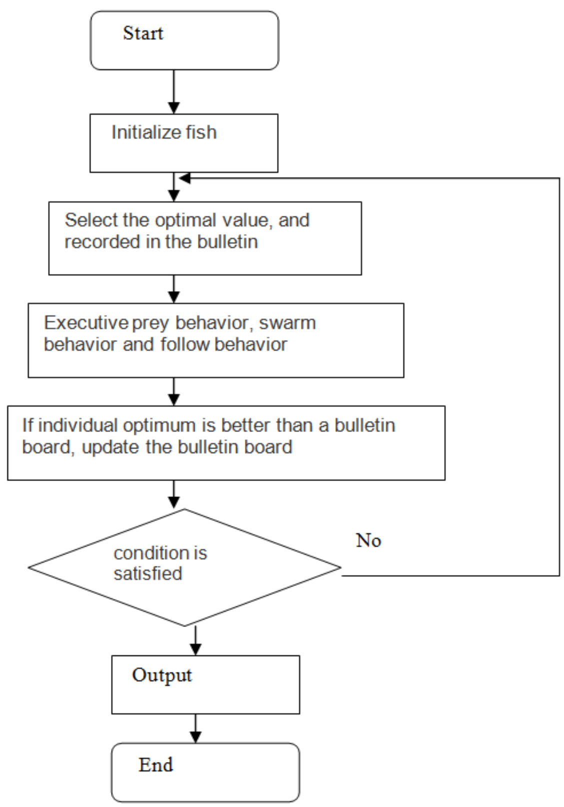

Figure 1. Flow chat of artificial fish swarm algorithm

4. The Improved Algorithm based on Hybrid Behavior Selection (IAFSA)

Artificial fish swarm algorithm has global search capability, but the convergence speed of later stages is too slow, a lot of artificial fish perform invalid search which waste of much time. So we propose an improved algorithm based on swallowed behavior.

The diversity of the population is used to describe the degree of dispersion of the fisher swarm. Diversity can be represented as $\alpha = [\alpha_1, \alpha_2, \cdots \alpha_n]$. Where a_i is adaptive diversity of ith artificial fish.

$$\alpha_i = \min(f, f_{avg}) / \max(f, f_{avg}), \alpha_i \in (0,1], i = 1, 2, \cdots, n \qquad (7)$$

Where f_{avg} means that the average fitness value of ith iterative, f is the fitness value of the current fish.

4.1 swallowed behavior

After a certain number of iterations (for example, half of the maximum number of iterations), If the diversity value of a fish is below the threshold, then the fish does not move, and the space of the fish is released.

$if\,(a_i > \mathrm{Threshold1})$ Perform swallowed behavior.

Where $\mathrm{Threshold1}$ is diversity threshold.

4.2 breeding behavior

Swallowed behavior can reduce the number of fish which can greatly reduce the elapsed time .But swallowed behavior may eat good fish which will lead to can not find the global optimum. So we propose an improved algorithm based on swallowed behavior.

$if\,(a_i < \mathrm{Threshold2})$ Perform breeding behavior.

Where $\mathrm{Threshold2}$ is diversity threshold .

Through the traverse of generated artificial fish, find the artificial fish $X_{\max}$ with the largest objective function value, if $Y_i < Y_{\max}$, then move one step to the largest fish of subclass $X_{\max}$,otherwise move one step to the center of subclass X_c .

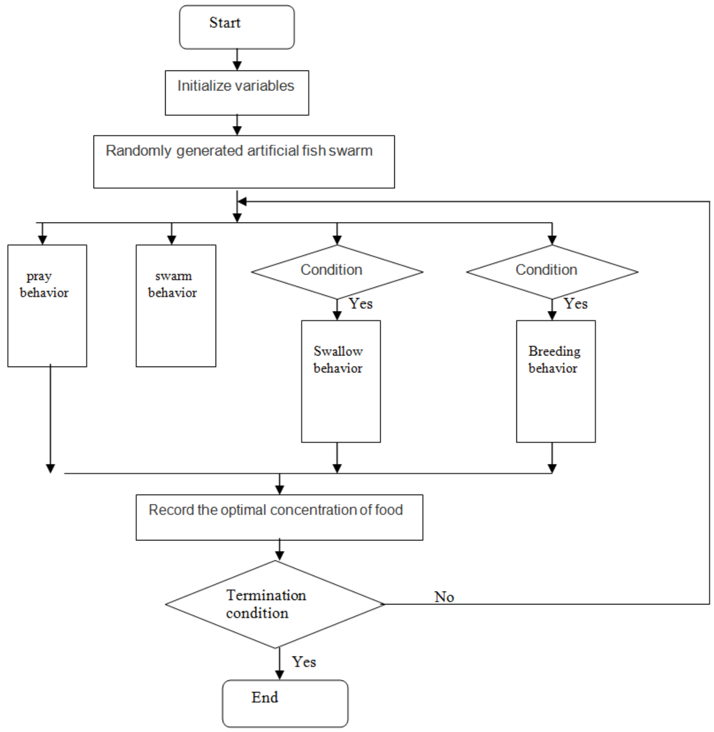

Figure 2. The improved artificial fish swarm optimization algorithm

The improved AFSA based on hybrid behavior selection is as follow:

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(1). Variable initialization;

Initialization population size, dimension, step, Visual, diversity threshold Threshold1 and Threshold2.

(2). Generate the initial artificial fish swarm;
(3).Each artificial fish update their location through prey behavior, swarm behavior and follow behavior;

(4). If the number of iterations is greater than half of the maximum number of iterations and $a_i > \text{Threshold1}$, perform swallowed behavior.

(5). If the number of iterations is greater than half of the maximum number of iterations and $a_i < \text{Threshold2}$, then perform breeding behavior.

(6). The threshold gradually reduced which can lead to the dispersion decreasing of fishes;

(7). Calculation of the fish food concentration and record the optimal;

(8). If the iteration is terminated, output the optimal value; otherwise return to step 3.

Algorithm 2. Improved AFSA based on hybrid behavior selection

The overall structure of the improved algorithm is shown in Figure 2.

5. Experimental Results

A set of unconstrained benchmark functions was used to investigate the effect of the improved algorithm which is shown in Table 1.

Table 1. Functions used to test the effects of IAFSA

Function	Function expression
Sphere function	$f_1(x)=\sum_{t=1}^{n} x_t^2$
Rastrigrin function	$f_2(x)=\sum_{t=1}^{n}(x_t^2-10\cos(2\pi x_t)+10)$
Griewank function	$f_3(x)=\frac{1}{4000}\sum_{t=1}^{n}(x_t-100)^2-\prod_{t=1}^{n}\cos(\frac{x_t-100}{\sqrt{t}})+1$
Ackey function	$f_4(x)=20+e-20e^{-0.2\sqrt{\frac{\sum_{t=1}^{n}x_t^2}{n}}}-e^{\frac{\sum_{t=1}^{n}\cos(2\pi x_t)}{n}}$
Shaffer's function	$f_5(x)=0.5+\frac{(\sin\sqrt{x_1^2+x_2^2})^2-0.5}{(1+0.001(x_1^2+x_2^2))^2}$

Sphere function is a single-peak function, we can find the optimal value is 0 through the analysis for function expression, the function image is shown as below:

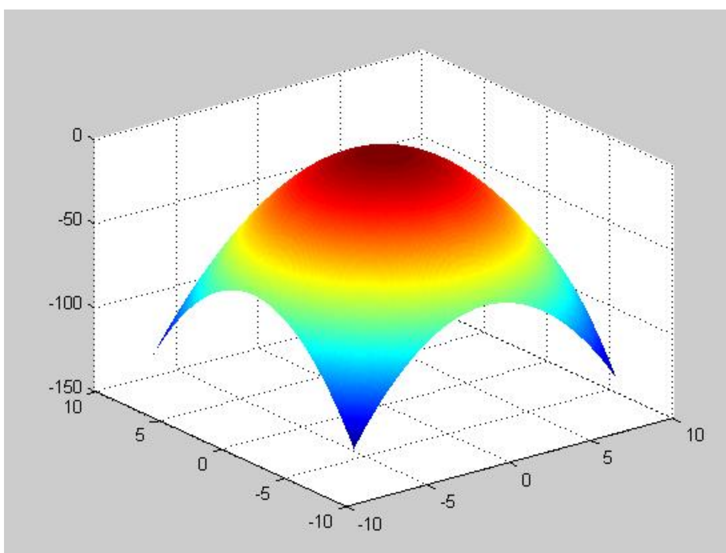

Figure 3. The image of Sphere function

Rastrigrin function is a multi-peak function, we can find the optimal value is 0 through the analysis for function expression, the function image is shown as below:

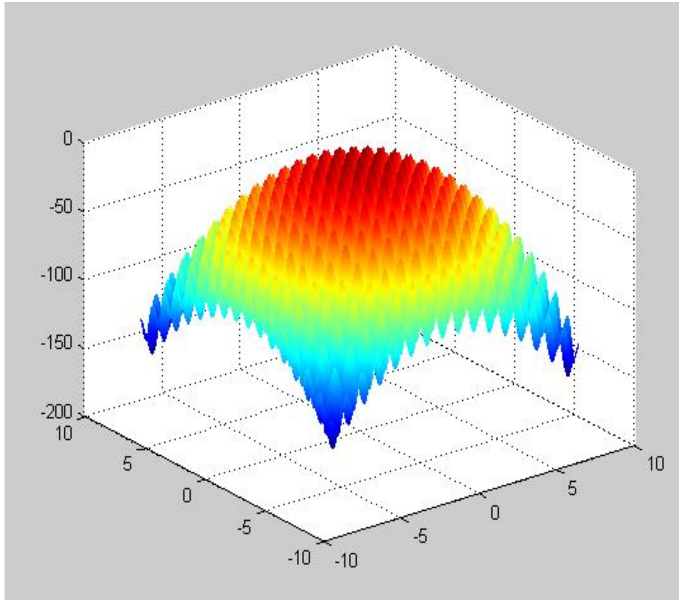

Figure 4. The image of Rastrigrin function

Griewank function is a multi-peak function, we can find the optimal value is 0 through the analysis for function expression, the function image is shown as below:

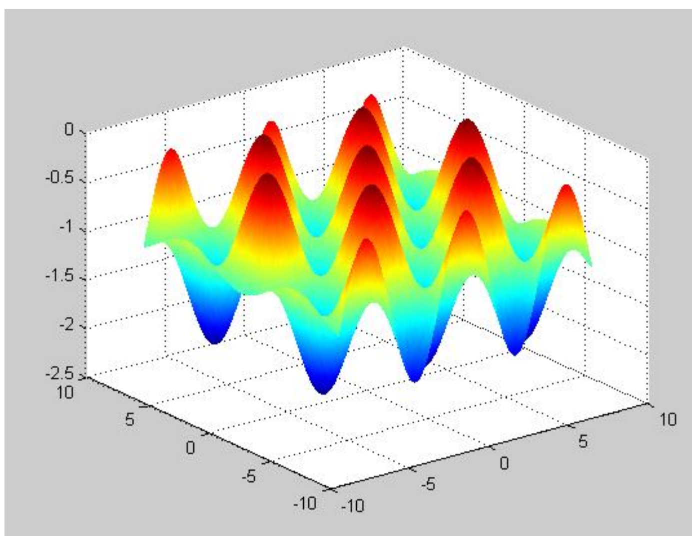

Figure 5. The image of Griewank function

Ackey function is a multi-peak function, we can find the optimal value is 0 through the analysis for function expression, the function image is shown as below:

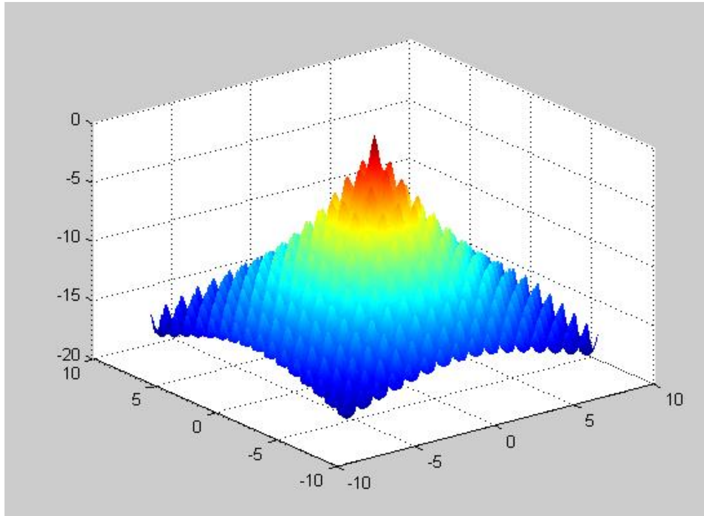

Figure 6. The image of Ackey function

Shaffer function is a multi-peak function, we can find the optimal value is 0 through the analysis for function expression, the function image is shown as below:

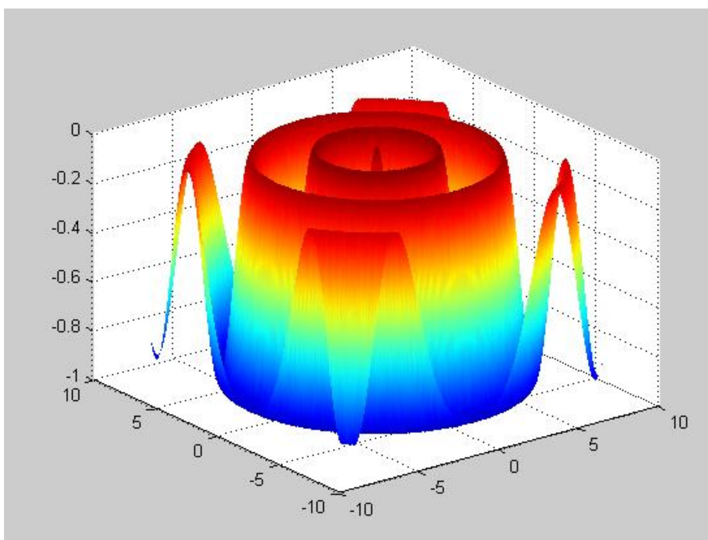

Figure 7. The image of Shaffer function

The results are shown in Table 2. Each point is made from average values of over 10 repetitions. The dimension of the test function is taken as 10 dimension.

Table 2. The performances of AFSA and IAFSA

Algorithm	AFSA		IAFSA	
	optimal	time(s)	optimal	time(s)
Sphere	0.10	2.83	0.0008	1.71
Rastrigrin	0.000258	2.325	0.000023	1.435
Griewank	0.000001	1.7	0.000002	0.983
Ackey	0.000702	1.841	0.000375	1.17
Shaffer	0.009716	1.79	0.009716	1.107

From Table 2, we can see no algorithm performs better than others for all five functions, but on average, the IAFSA is better than AFSA algorithm.

For Rastrigrin function and Ackey function, IAFSA algorithm can effectively improve the accuracy such that the optimal value obtained is much closer to the theoretical one compared with the standard AFSA algorithm. From the results of Griewank function, the accuracy of improved algorithm is not as good as the standard AFSA algorithm, but the difference is small and acceptable. For Sphere function and Shaffer function, there is no obvious superior algorithm.

For all the five function, there is a significant improvement as expected on the convergence time. The comparison of two methods with convergent curves is shown in Figure 8 to Figure 12.

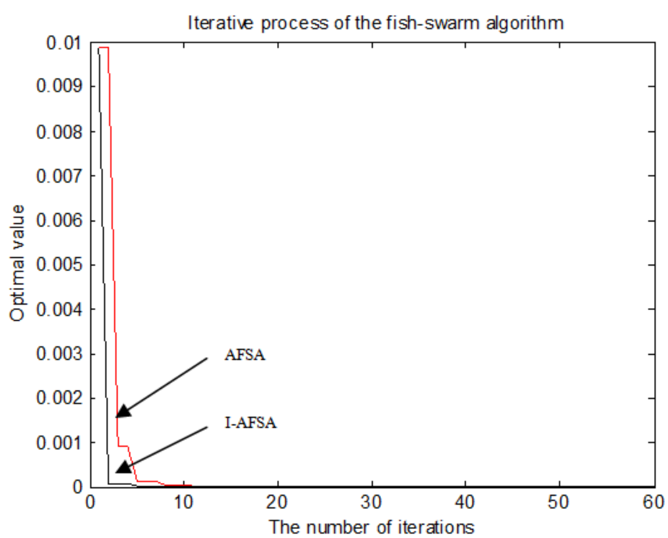

Figure 8. Sphere function

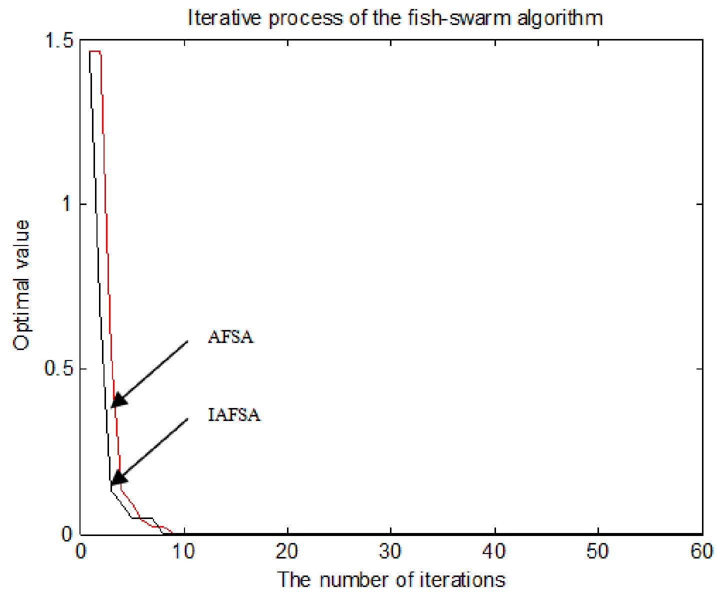

Figure 9. Rastrigrin function

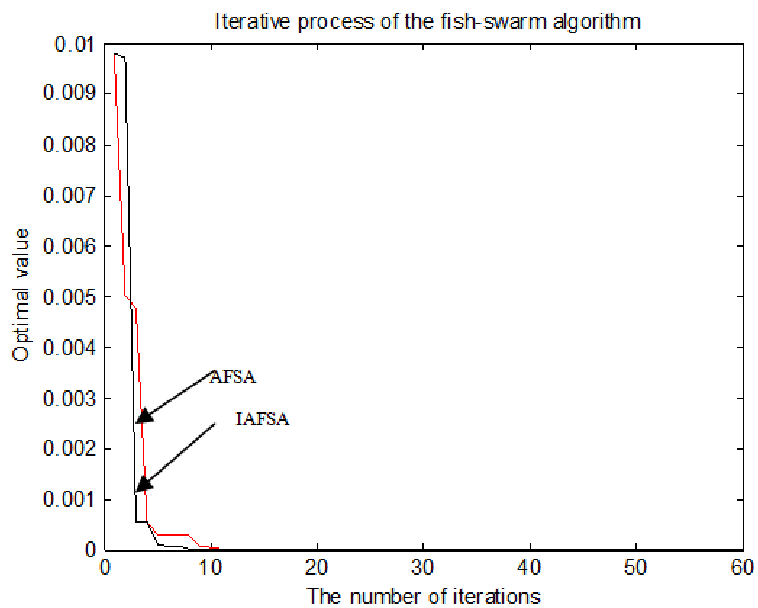

Figure 10. Griewank function

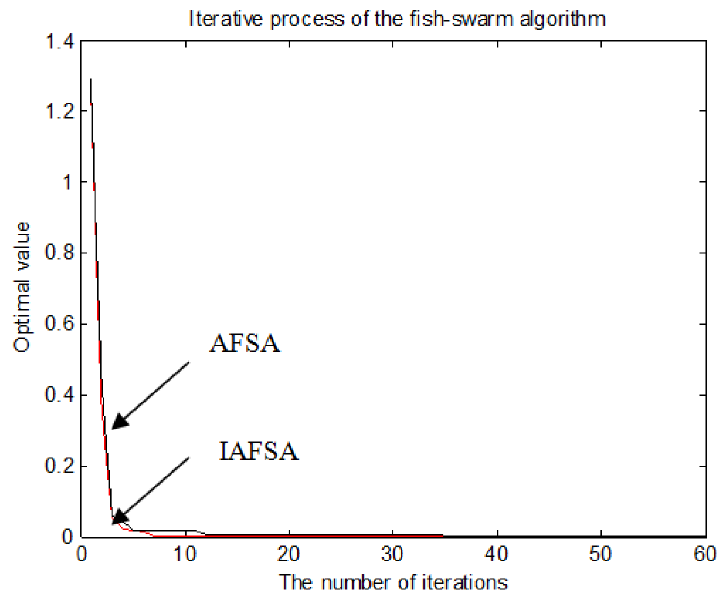

Figure 11. Ackey function

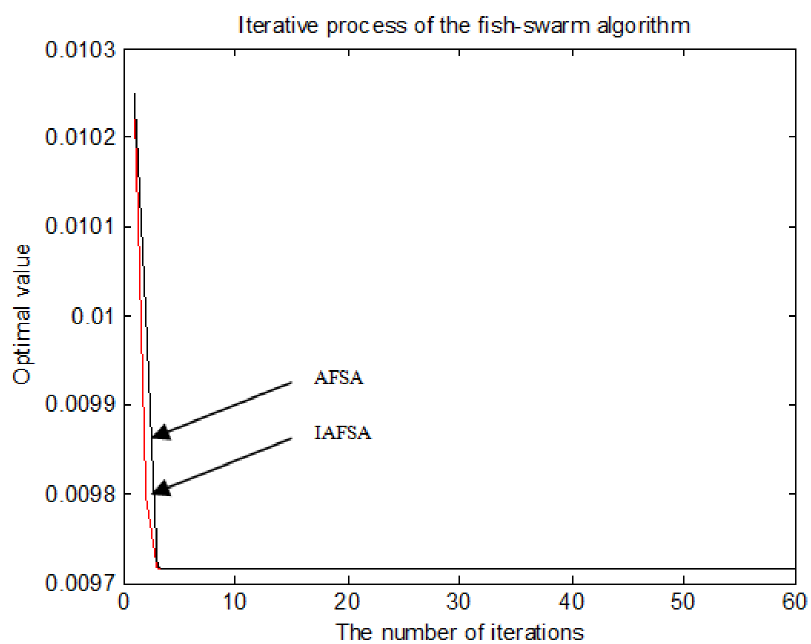

Figure 12. Shaffer function

The experiment results show the IAFSA algorithm has better result. Comparisons with AFSA, the IAFSA algorithm has both global search ability and fast convergence speed.

6. Conclusion

In order to improve the AFSO algorithm's stability and the ability to search the global optimum, we propose an improved algorithm based on swallowed behavior which can greatly speed up the convergence. At the same time, we added breeding behavior to improve global optimization capability. From the experiments on high dimensional function optimization, we can know the improved algorithm have more powerful global exploration ability and faster convergence speed, and can be widely used in other optimization tasks.

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