An adaptive artificial fish swarm algorithm with elimination and clone mechanism

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Abstract

For the problem with imprecise optimal solution and reduced convergence efficiency of basic artificial fish swarm algorithm in the late, the adaptive functions of artificial fish's view and step were used to improve fish algorithm. On this basis, with the new concept of effective artificial fish proposed, the elimination and clone mechanism was used to increase the number of effective fish to solve the problem with artificial fish individuals scattered and the algorithm convergence efficiency dropped. The experimental results showed that the elimination and clone mechanism enabled the artificial fish to aggregate to the global optimum rapidly, which improved the algorithm convergence efficiency and stability. Finally, the comparative studies were carried on simulation among the basic artificial fish swarm algorithm (BAFSA), adaptive artificial fish swarm algorithm (AAFSA), basic artificial fish swarm algorithm with elimination and clone mechanism (ECAFSA) and the adaptive artificial fish swarm algorithm with elimination and clone mechanism (ECAAFSA). Simulation results showed that, the elimination and clone mechanism could increase the number of effective artificial fish significantly, which improved the convergence efficiency and stability of the algorithm.

Keywords: AFSA, elimination and clone mechanism, effective artificial fish, adaptive function

1 Introduction

In recent years, new heuristic algorithms, especially the metaheuristics absorbed the ideas of natural evolution and group collaboration set off a new upsurge of research in the global academic community once again, which attracted many scholars' attention and tracking. From of the last century, the genetic algorithm [1], simulated annealing [2], tabu search [3], artificial immune system [4], differential evolution algorithm [5], ant colony algorithm [6], particle swarm optimization algorithm [7] have appeared. Entering the new century, not only the traditional algorithms got more in-depth research and extension, but also the various novel heuristic algorithms, such as artificial fish swarm algorithm(AFSA) [8], bacterial foraging algorithm [9], frog leaping algorithm [10], Artificial bee colony algorithm [11], monkeys algorithm [12], etc. have emerged [13]. AFSA was proposed first by the Dr. Li Xiaolei in 2002, which was a swarm intelligent optimization method. The new bottom-up optimization mode-AFSA has been proposed by researching the characteristics of fish swarm behaviours, and simulating the autonomous body of the animal model and the mutual behaviours of fish population society. Advantages of AFSA include the simple evaluation index, just comparing the fitness of individual artificial fish and the robust parameters of algorithm.

2 Basic artificial fish swarm algorithm

Only the eusocial organism individuals with the social characteristics can produce the phenomenon of swarm intelligence when they make certain activities, such as insects, birds, fish, microorganisms and other biological. Artificial fish is an abstract from individual fish organisms, including the fish organisms behaviour characteristics and reactions to the environment, which can be regarded as the entities packaging with data and a variety of behaviours. Artificial fish can obtain the environmental information through its senses, and respond to the information accordingly, while artificial fish individuals can affect other one's individual behaviours through its own behaviour. Artificial fish perceive the environment, through its own "vision" to achieve, due to the biological fish visual system is more complex, the concept of the "view" is used for the bionics design of artificial fish vision. In living environment of fish the place contains more food, where often more individual fish exist. Imitating the biological fish's behaviours, prey, follow, swarm and other acts to constructed artificial fish model is the ideology of AFSA [14].

As shown in Figure 1, the current state of artificial fish is defined as $X = (x_1, x_2, \cdots, x_n)$, which the vastest view is expressed as $Visual$. On certain moment the state of the fish view point is expressed as

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$X_V = (x_{1V}, x_{2V}, \cdots, x_{nV})$ in its view. If the state X_V is superior to the state X, the artificial fish will move a step in the direction of state X_V, them its state changes to X_{next}. If the state X_V is not superior to the state X, the artificial fish will continue to try to select another new state. The more times artificial fish tries, the more comprehensively it understands environmental information of its view, which is beneficial to its own decisions of correct behaviour. Of course the number of the artificial fish's inspection can not increase indefinitely, which is inconsistent with the actual behaviour of the biological fish. Retained the artificial fish's uncertain local optimization is beneficial to the global optimization.

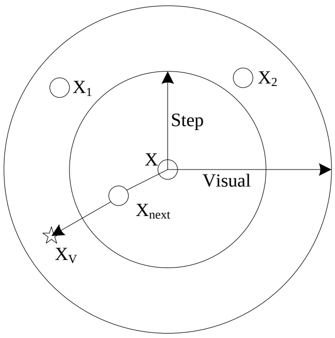

FIGURE 1 Artificial fish visual analogue

The basic parameters of AFSA include: the size of the artificial fish population N, view of artificial fish $Visual$, the largest moving step of artificial fish $step$, the largest number of attempts for prey behaviour of artificial fish try_num, crowding factor δ. In a d-dimensional search space there are N artificial fish. The state vector of artificial fish position is expressed as $X = (x_1, x_2, \cdots, x_d)$. The food concentration of artificial fish position is expressed as $Y = f(X)$, in which X is the search optimization variable of artificial fish state and Y is the function of fitness. The distance between two artificial fish is defined as $d_{i,j} = \|X_i - X_j\|$ [14-15].

3 Improvement of artificial fish swarm algorithm

The more large artificial fish population is, the more obvious features of swarm intelligence is, that makes the algorithm converge faster to get rid of local optimum capacity stronger. In the artificial fish optimization mode, the algorithm would complete, so long as any of a group of artificial fish reach the global optimum. Therefore, expanding the size of artificial fish population can increase the artificial fish density in the optimization space, which can improve the probability of artificial fish reach the global optimum, thus improving the convergence rate. However, increasing the size of the artificial fish populations will increase the computational complexity.

Perception scope of artificial fish is determined by the range of its view. The larger view can make artificial fish populations master the information on the surrounding environment adequately. The algorithm convergence rate will decrease when artificial fish view is narrow, and the algorithm convergence speed will increase when the field of view is vast. The larger step size is, the broadest range of view is, that is conducive to artificial fish rapid convergence. Later in the algorithm, if the step was still large, the artificial fish could not only miss the global optimal solution easily with too large step size, or get a solution with low accuracy, but also be prone to oscillate back and forth near the optimal solution. That was why it was difficult to approximate the optimal solution accurately. A small step size was in favor of local search for artificial fish, but the speed of searching global optimal solution was slower, and the algorithm was easy to fall into local optimum. The above analysis showed that, although the fish swarm algorithm is robust, simple and efficient, etc., the fish swarm algorithm has defects too, including imprecise optimal solution, contradictory parameters, difficult concentration of individual and the latter reduced convergence efficiency [15].

3.1 ADAPTION FUNCTIONS OF BASIC AFSA

In the process of the algorithm implementation, the optimal mode of artificial fish's view and step was that the view and step size was larger early, and decreased late. Therefore, the adaptive function for improvement must conform to this mode. Namely, during initial period of the algorithm the view and step maintained to be larger, and then with the algorithm running it decayed adaptively. At the initial stage of the fish algorithm, the vast view could induce artificial fish to find the global optimum, at the same time artificial fish could move closer to the global optimum quickly with the larger step size, so that made the algorithm converge rapidly. Late in the algorithm, artificial fish gathered around the optimum point in a crowded space with a big probability. If the view was still vast, the artificial fish could miss the point with the most abundant food, thus it would prey inefficiently.

Early in the algorithm, artificial fish could enhance the global search ability with a larger step size, which made the artificial fish move closer to a better solution and aggregate around the optimal solution as rapidly as possible. Along with the algorithm executing, the reductive step size made the artificial fish aggregate around the global optimum, reduce the probability of over the global optimal solution, and enhance the algorithm ability of local search in latter running stage. The main strategy for changing this contradiction was improving the view and step based on adaptive function [16-17]. The adaptive functions were constructed to modify the artificial fish's view and step, thus the adaptive artificial fish swarm algorithm (AAFSA) would be gotten. As equation (1) and (2) show K_V , K_S , V and S are the parameters of adaption functions. $iter$ indicates the current iterations. $f_V(iter)$ is the adaptive function of artificial fish's view, and $f_S(iter)$ is the adaptive function of its step. As equation (3) and (4) show, $Visual\_adap$ and $Step\_adap$ represent the improved artificial fish's view and step by adaptive functions.

$$f_V(iter) = \frac{K_V}{iner \wedge V}, \tag{1}$$

$$f_S(iter) = \frac{K_S}{iner \wedge S}, \tag{2}$$

$$Visual\_adap = Visual * f_V(iter), \tag{3}$$

$$Step\_adap = Step * f_S(iter). \tag{4}$$

3.2 IMPROVEMENT OF AFSA BASED ON ELIMINATION AND CLONE MECHANISM

First, the concept of effective artificial fish was defined before the elimination and clone mechanism was researched. Among all artificial fish, the artificial fish individual in global optimal vicinity was called the effective artificial fish. Through the adaptive improvement of view and step, the accuracy and convergence rate of the algorithm were improved. The distribution of artificial fish changed from the initial random form to the organized distribution, and the artificial fish concentrated in not only the vicinity of the global optimum but also the local optimum vicinity. In the process of optimization, a lot of artificial fish gathered in local optimal areas, which reduced the number of effective artificial fish, and resulted in the efficiency of the algorithm reducing. Even due to the role of adaptive parameters, the size of artificial fish view and step was too small, that made it could not get rid of local optima.

For these problems discussed above the elimination and clone mechanism was proposed to improve the fish algorithm. The fitness of each artificial fish would be estimated during the algorithm execution time, and the artificial fish would be ranked according to its fitness level. The artificial fish with the lowest fitness would be eliminated by a certain percentage, meanwhile the same proportion of artificial with the highest fitness would be cloned to replace the eliminated one, and the artificial fish population size remained unchanged.

In order to prevent the artificial fish populations tend to homogeneity, and impact on full understanding of the search space, the number of elimination and clone mechanism execution can be set at different stages of the algorithm, and the proportion of elimination and clone artificial fish can be adjusted. With the elimination and clone mechanism acted the artificial fish with low fitness are replaced by the ones with high fitness, it reduced the number of artificial fish in the vicinity of local optimal and increased the number of individuals in the vicinity of global optimum. The ratio of effective artificial fish was increased. The number of artificial fish increased in favour of optimizing efficiency. Therefore, on the premise of the constant number of the artificial fish populations, increasing the number of effective artificial fish can improve the efficiency of optimization, and make the algorithm converge fast [14], [18].

3.3 ALGORITHM STEPS

(1) Initializing the parameters of artificial fish (including the number of artificial fish N , artificial fish view $visual$, moving step $step$, maximum number of iterations $Iter\_\max$, times of attempt try_num , crowding factor δ , etc.).

(2) Generating N pieces of artificial fish randomly to construct the initial artificial fish swarm.

(3) The current value of iteration is set as $ITtimes = 0$, and the algorithm start.

(4) Prey behaviour, swarm behaviour, fellow behaviour and random behaviour are performed by each artificial fish then the fitness function value of these behaviours will be compared with each other. The behaviour with optimal fitness function value will be selected to perform. The view and step of artificial fish have been modified adaptively.

(5) Determined whether the execution condition of elimination and clone mechanism is satisfied. If the condition is required, then the elimination and clone mechanism will act.

(6) After each action all artificial fish compare their fitness to the bulletin board, if the fitness is superior to bulletin board, the bulletin board will be updated.

(7) Determining whether $iter$ has reached the maximum number of iterations $Iter\_\max$, if the maximum number of iterations is reached, the optimum will be output and algorithm ends, otherwise $iter = iter + 1$, and go to step 4.

4 Algorithm verification

4.1 SIMULATION OF ELIMINATION AND CLONE MECHANISM

Function F_1 has a single maximum at point (0,0), and some local extremums spread around the global optimum point.

$$F_1(x, y) = \frac{\sin(x)}{x} * \frac{\sin(y)}{y} \ , \ -10 \le x, y \le 10. \tag{5}$$

Simulation conditions: CPU Intel Core i3-2330M 2.2GHz, RAM 2G, operating system Windows7, simulation software Matlab_R2012a.

Parameter selection: total number of artificial fish $N = 50$, view $visual = 2$, moving step $step = 1$, maximum number of iterations $Iter\_max = 50$, times of attempt $try\_mun = 10$, the congestion factor $\delta = 0.618$, adaptive parameters of view and step ($K_V = K_S = 2, S = 0.9, V = 0.5$).

The function F_1 is taken for example to prove the validation of the elimination and clone mechanism. During the execution of the algorithm, the position variation trend of the artificial fish was studied comparatively, and the results showed in Figure 2, Figure 3, Figure 4, Figure 5, Figure 6, Figure 7, Figure 8, Figure 9 and Figure 10.

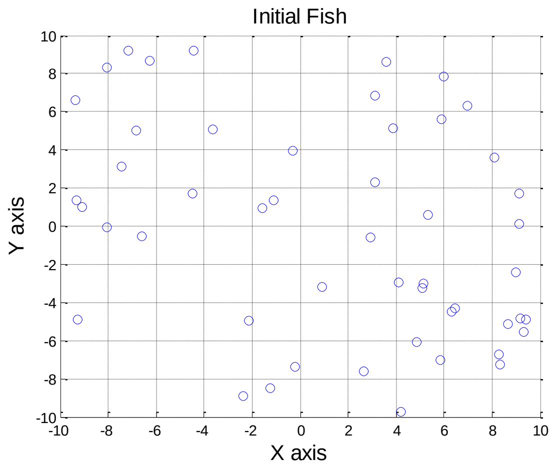

FIGURE 2 The initial random distribution of artificial fish

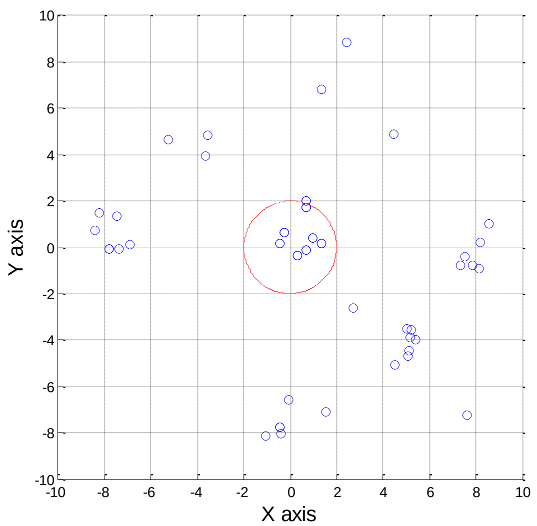

FIGURE 3 The distribution of artificial fish with elimination and clone mechanism after the second iteration

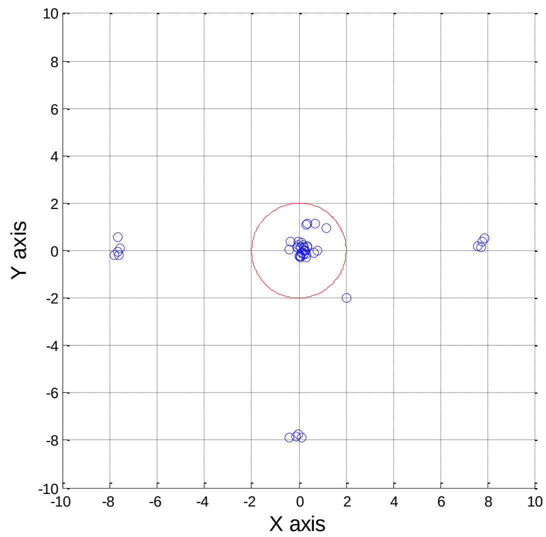

FIGURE 4 The distribution of artificial fish with elimination and clone mechanism after the fourth iteration

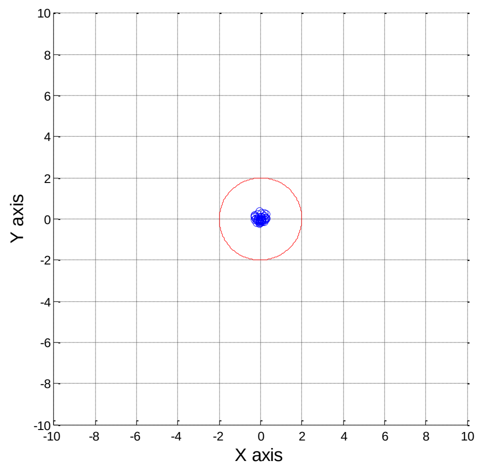

FIGURE 5 The distribution of artificial fish with elimination and clone mechanism after the sixth iteration

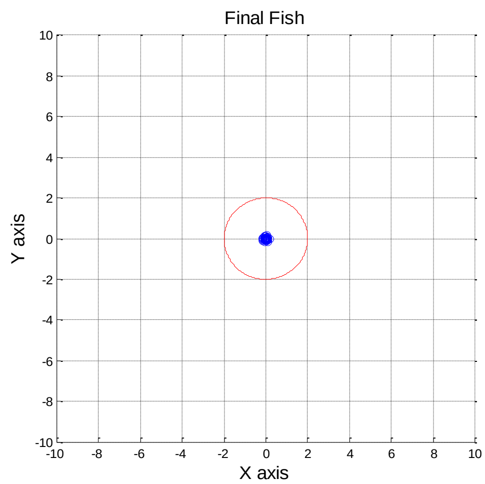

FIGURE 6 The final distribution of artificial fish with elimination and clone mechanism

As showed in Figure 2, at the beginning of the algorithm 50 artificial fish were initialized randomly, which distributed in two-dimensional coordinate system. The coordinate system range was set as [-10,10], [-10,10] inside. During the execution of the algorithm, due to the effect of elimination and cloning mechanism the artificial fish with low fitness were eliminated, and the number of artificial fish individual in the vicinity of local optimum reduced gradually. Meanwhile the artificial fish with high fitness were cloned, and the number of artificial fish in the vicinity of global optimum increased gradually, that increased the number of effective artificial fish. Ultimately under the action of elimination and clone mechanism, artificial fish gathered toward the optimal point (0, 0) gradually. The process varied gradually of the algorithm showed in Figure 3, Figure 4 and Figure 5. As shown in Figure 6, eventually all artificial fish gathered in the vicinity of global optimum (0, 0) with a small range.

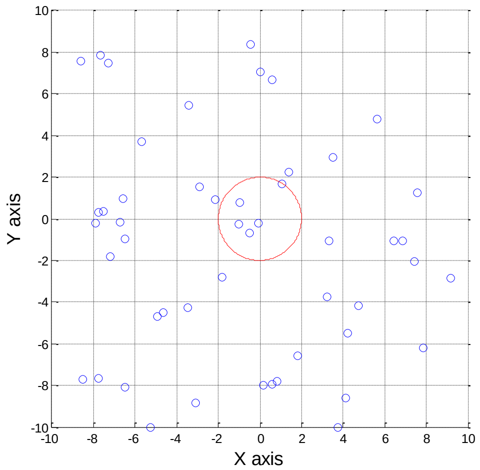

FIGURE 7 The distribution of artificial fish without elimination and clone mechanism after the second iteration

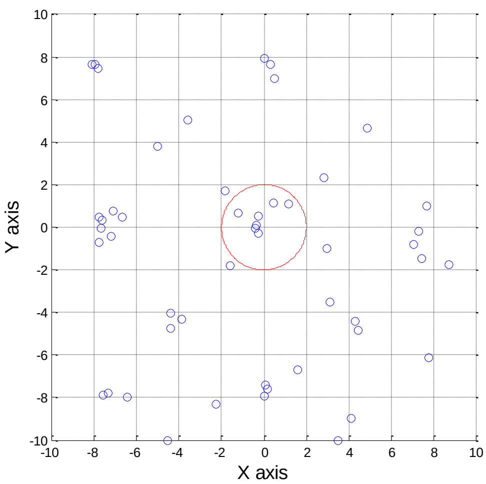

FIGURE 8 The distribution of artificial fish without elimination and clone mechanism after the fourth iteration

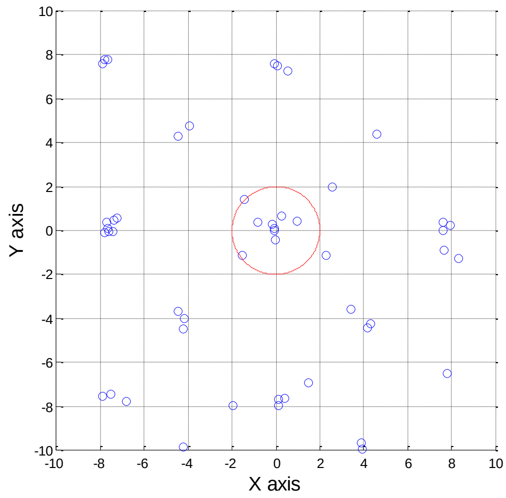

FIGURE 9 The distribution of artificial fish without elimination and clone mechanism after the sixth iteration

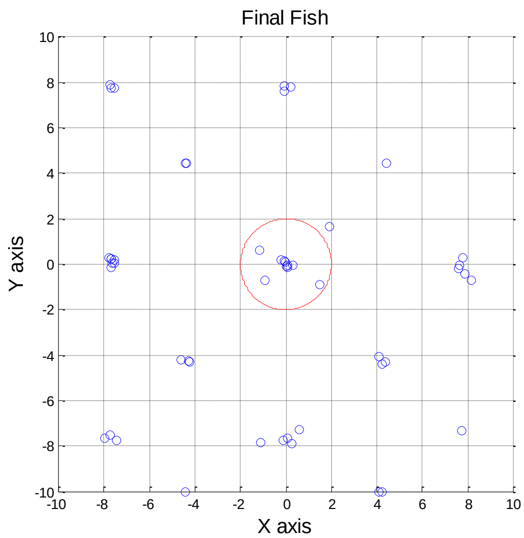

FIGURE 10 The final distribution of artificial fish without elimination and clone mechanism

As shown in Figure 7, Figure 8 and Figure 9, artificial fish gathered toward not only the vicinity of global optimum but also the vicinity of local optimum during the execution of algorithm, when the elimination and clone mechanism was not used. The number of effective artificial fish had decreased along with the execution of the algorithm. As shown in Figure 10, finally some artificial fish gathered in the field of global optimization and others in the local optimization.

4.2 THE RESULTS COMPARED OF DIFFERENT ALGORITHMS

Function F_2 is a typical local optimum problem, which obtains the global optimum value 3600 at point (0, 0). Several local minima points located on (-5.12, 5.12), (-

5.12, -5.12), (5.12, -5.12) and (5.12, .12) scatters around the global optimum, which obtain the local optimum 2748.7823. Function F_3 obtains the global optimum 0 at point (0, 0), which is a typical local optimum problem too. In order to make the results compare more obviously, the fewer number of iterations is tried to set, and simulation conditions are the same to the above.

$$F_2(x,y)=\left(\frac{3}{0.05+(x^2+y^2)}\right)^2+(x^2+y^2)^2, \quad (6)$$

$$-10\le x,y\le 10, \quad (7)$$

$$F_3(x,y)=0.5+\frac{\sin^2\sqrt{x^2+y^2}-0.5}{\left[1+0.001(x^2+y^2)\right]^2}, \quad (8)$$

$$-10\le x,y\le 10. \quad (9)$$

TABLE.1 Simulation results comparison

Function	Algorithm parameters	Algorithm	Worst	Best	Average	Time/s	Min times
F1	N=50, visual=2, step=1, try_num=10, Iter_max=15, δ=0.618, S=0.9, V=0.5, K_V=K_S=2	BAFSA	0.9928	1.0000	0.9982	0.291054	15
		AAFSA	0.9999	1.0000	0.99997	0.292608	7
		ECAFSA	0.9999	1.0000	0.99997	0.290419	4
		ECAAFSA	1.0000	1.0000	1.0000	0.300271	4
F2	N=100, visual=1, step=0.1, try_num=10, Iter_max=80, δ=0.618, S=0.9, V=0.5, K_V=K_S=2	BAFSA	3593.6	3599.9	3598.2	3.341346	73
		AAFSA	2748.8	3600.0	3511.6	3.063677	28
		ECAFSA	3599.7	3600.0	3599.9	3.688976	42
		ECAAFSA	3600.0	3600.0	3600.0	3.953595	5
F3	N=100, visual=2, step=0.2, try_num=10, Iter_max=80, δ=0.618, S=0.4, V=0.2, K_V=K_S=2	BAFSA	0.0097	8.2208e-06	4.9698 e-04	4.967201	31
		AAFSA	0.0097	4.4883e-07	4.9116 e-04	4.960826	51
		ECAFSA	0.0097	3.9832e-08	4.8793 e-04	4.955704	31
		ECAAFSA	1.5161e-04	4.1641e-11	7.5805 e-06	4.165586	55

The basic artificial fish swarm algorithm (BAFSA), the adaptive artificial fish swarm algorithm (AAFSA), the basic artificial fish swarm algorithm with elimination and clone mechanism (ECAFSA) and the adaptive artificial fish swarm algorithm with elimination and clone mechanism (ECAAFSA) had been verified respectively for 20 times by testing function, and the statistics results of simulation showed in Table 1. Table 1shows the optimal solution accuracy and the convergence speed are improved, after the algorithm has been modified with adaptive functions, so the AAFSA is superior to the BAFSA. The stability and the global optimum accuracy of the algorithm had been improved, and the global optimum less fluctuated, after the elimination and clone mechanism was used. On the basis of the adaptive functions, with the elimination and clone mechanism introduced, the optimum accuracy was obviously superior to the one of AAFSA, based on the same number of iterations. AS the simulation results show, the elimination and clone mechanism improved the performance of algorithm significantly, which was conducive to the improvement of the algorithm accuracy and stability.

5 Conclusions

Reviewing the research status of artificial fish swarm algorithm and its application, the AFSA is still a research focus of swarm intelligence optimization algorithm, but it also has some defections, such as the imprecise optimum and the late decreased optimization efficiency. With the adaptive functions of view and step, the accuracy of optimum has been improved, but the searching efficiency still needed to be improved. Thus, the elimination and clone mechanism has been introduced, which basic idea is increasing the proportion of artificial fish with higher fitness by increasing the number of effective artificial fish. With the elimination and clone mechanism acted, the artificial fish with low fitness have been eliminated during the execution of the algorithm, meanwhile the ones with high fitness have been cloned, which improved the fitness of overall artificial fish and the proportion of effective artificial fish. The elimination and clone mechanism made the number of effective artificial fish increase in the conditions of fixed artificial fish number, which improved the efficiency and stability of fish swarm algorithm.

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