An Improved Artificial Fish Swarm Algorithm Based On Chaotic Search And Feedback Strategy

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Abstract—Artificial Fish Swarm Algorithm (AFSA) is a kind of swarm intelligence algorithms, which has the features of not strict to parameter setting, insensitive to initial values, strong robustness and so on. But the precision can not be very high and artificial fish (AF) often suffers the problem of being trapped in local optima. Especially when the objective function is a multi-model function, this problem is more prominent. Since chaotic mapping enjoys certainty, ergodicity and stochastic property, chaotic search can serve as a kind of method for global optimization. Feedback can also act as a strategy to lead the movement of AF. In this paper, chaotic search and feedback strategy are introduced into AFSA to overcome the shortcoming above. The experimental results show that the improved AFSA can obtain better results than the standard AFSA.

Keywords- AFSA, chaotic search, feedback strategy, multi-model function

I. INTRODUCTION OF AFSA

Optimization is a very important subject in practical application. Traditional optimization algorithm becomes more and more difficult to carry out when it is applied to solving some NP-hard problems. Intelligent optimization algorithm has unique advantage to solve these problems. Artificial Fish Swarm Algorithm (AFSA) which will be discussed in this paper is one kind of intelligent optimization algorithms.

AFSA was issued by Xiaolei Li in 2002 [1]. The AFSA is generated from long observation of fish swarm in nature, using the swarm intelligence and combining with the artificial intelligence. The basic idea of AFSA is to imitate the fish behaviors such as praying, swarming, following with local search of fish individual for reaching the global optimum; it is random and parallel search algorithm.

Fish usually swim freely in the water and will reach the place with a lot of food finally, so we can simulate the behaviors of fish based on this characteristic to find the global optimum. The basic behaviors of AF include: AF_Prey, AF_Swarm, AF_Follow, AF_Move and AF_Evaluate.

According to the current environment condition (the value of objective function and the condition of the AF), AF evaluates the results of the four behaviors described above and chooses one to execute. The four behaviors is the core of the AFSA. AF_Prey is the convergence basis of AFSA. AF_Swarm and AF_Follow accelerate the speed of convergence. AF_Move guarantees the global convergence of the AFSA.

AFSA can be used in optimization applications as the optimized variables are continuous or discrete. The paper [3] applies AFSA to the clustering Algorithms. The paper [4] applies AFSA to wavelet threshold algorithm optimization. More applications of AFSA can be seen in the paper [2]. AFSA can get satisfactory results in a lot of optimization applications.

AFSA has many advantages such as tolerance of initial values and parameters setting, requiring less for the objective function, rapid to search the global optimum. However, due to the random step length and random behavior (AF_Move), AF converges slower and slower when AF gets close to the optimal solution and we can’t get high precise result at last. Particularly, when AF falls into the local optimal solution, it can not escape from the local optimal solution easily.

Some search strategies can be added to AFSA to improve the performance of AFSA. The process of chaotic search corresponds to the ergodic process of chaotic trajectory which can avoid the AF being trapped into the local optimum point. Therefore, this paper provides a new method, which introduces chaotic mapping with certainty, ergodicity and stochastic property into AFSA so as to improve the global convergence.

The information that AFSA has got so far can be used to lead the movement of the AF. The steps, visual distance and the behavior choice can adjust adaptively to feedback information. The paper [5] proposes an improved AFSA in which the information of global best AF is added to the behaviors of the AF. In this paper the record in bulletin board is used as feedback information to improve the performance of the AFSA.

II. INTRODUCTION OF CHAOTIC SEARCH

Chaos is a common nonlinear phenomenon in our lives. The dynamic properties of chaos can be shown as following: (1) Chaos is highly sensitive to the initial value. (2) Certainty: Chaos is produced by the certain iterative formula. (3) Ergodicity: Chaos can go through all states in certain ranges without repetition.

Chaos is similar to randomness. But experimental studies assert that the benefits of using chaotic signals instead of random signals are often evident even though a general rule
can not be formulated [8]. So the performance of chaotic search is better than random search. Due to the easy implementation and special ability to avoid being trapped in local optima, chaos has been a novel optimization technique and chaos-based searching algorithms have aroused intense interests [9].

Chaotic search includes the following major steps:

1. The variable in solution space is mapped to the chaotic space.
   \[ cx_j = \frac{x_j - x_{\text{min},j}}{x_{\text{max},j} - x_{\text{min},j}} \]
   \[ x_{\text{max},j} \quad \text{and} \quad x_{\text{min},j} \] are the maximum and minimum value of the jth dimension variables.

2. Produce chaotic variables of next generation using chaotic mapping.

3. The chaotic variable is mapped back to the solution space.
   \[ x_j = x_{\text{min},j} + cx_j(x_{\text{max},j} - x_{\text{min},j}) \]

Chaos optimization is realized through chaos variables which can be obtained by many ways. Here the Logistic Mapping Method [7] is selected. The equation of Logistic Mapping is shown as follows:

\[ Z(k+1) = \mu \ast Z(k) \ast (1-Z(k)) \]

\( \mu \) is the control parameter. When \( \mu = 4 \), the equation above is in chaos state, which means all values between 0 and 1 except the fixed point (0, 0.25, 0.5, 0.75, 1) are produced randomly by iteration. Furthermore with its sensitivity to the initial value, n chaotic variables of different orbits can be obtained in the iteration after setting n different initial values between 1 and 0 to \( Z(k) \) in equation above.

III.  AFSA WITH CHAOTIC SEARCH AND FEEDBACK

A. Feedback Strategy

Bulletin board is used to record the optimal value that the procedure has got so far in the standard AFSA. The record in bulletin board can be used as feedback to guide the movement of the AF. We define a new behavior for AF: AF_Togbest. This behavior can be described as following: AF swims towards the global optimum position in the bulletin board. AF will execute this behavior in a certain probability.

If AF can not find a better position than the current position after evaluating AF_Pray, AF_Swarm and AF_Follow, AF will execute the AF_Move in the standard AFSA. AF_Move gives AF more chances to move randomly. So AF can avoid being trapped in local optima and find the global optima at early stage of the optimization process. But at the later stage of the optimization process, AF_Move causes that AFSA can not get high precise solution and reduces efficiency.

So a small change is made. A feedback probability \( P_{fb} \) is set. AF_Move will be executed with the probability of \( P_{fb} \) and AF_Togbest will be executed with the probability of \( 1 - P_{fb} \). A larger value is given to \( P_{fb} \) at first and \( P_{fb} \) decreases linearly gradually. So AF_Move will have greater probability to execute at early stage of the optimization process and AF_Togbest will have greater probability to execute at later stage of the optimization process. So the improved AFSA can not only guarantee the global convergence but also guarantee the precision and efficiency.

B. AFSA with Chaotic Search and Feedback Strategy

The ergodicity characteristic of chaos can act as a mechanism to avoid the AF being trapped into the local optima. Introducing chaotic search to AFSA can enrich the searching behavior of AF and avoid the AF staying in local optimum position for a long time, which can improve the global convergence and search efficiency. AFSA is applied to performing global exploration and chaotic search is applied for exploitation and modified the best AF resulted by AFSA.

The algorithm for AFSA with chaotic search and feedback can be summarized as follows:

Step1: Initialization, including the position of the AF, the AF_Total, step, visual, the feedback probability \( P_{fb} \), the attenuation coefficient \( \alpha \) and so on.

Step2: Calculate fitness value of the AF and the best AF will be included in the bulletin board.

Step3: AF execute AF_Pray, AF_Swarm, AF_Follow and evaluate the results of the three behaviors. If the result is better than the current condition, AF goes forward a step in that direction and the algorithm turns to step 5.

Step4: AF choose to execute AF_Move with the probability of \( P_{fb} \) and to execute AF_Togbest with the probability of \( 1 - P_{fb} \).

Step5: The best AF executes the chaotic search.

Step6: Update the bulletin board.

Step7: \( P_{fb} = \alpha \ast P_{fb} \).

Step8: If the stopping criterion is satisfied, then stop and output the result; else go to Step3.

IV. SIMULATION RESULTS AND ANALYSIS

To verify the validity of the improved AFSA, some simulation experiments are carried out. We analyzed the optimization ability of improved AFSA by the application of two standard testing functions which are both multi-model function. Two standard testing functions are shown as following:

function 1: minimize
\[ f(x,y)=\frac{-20}{0.09+(x-6)^2+(y-6)^2}+x^2+y^2, \]
subject to \(-20 \leq x, y \leq 20\)

function 2: maximize
\[ f(x,y)=-x \ast \sin(\sqrt{|x|})-y \ast \sin(\sqrt{|y|}), \]
subject to $-500 \leq x, y \leq 500$

Function 1 is a typical deceptive function. It has two optimum points: $(x_1, y_1) = (0.0233, 0.0233)$ and $(x_2, y_2) = (5.9976, 5.9976)$. $f(x_1, y_1) = -0.2785$, $f(x_2, y_2) = -150.2514$, $(x_2, y_2)$ is the global optimum point. Function 2 is the 2-D Schwefel’s function. It is deceptive in that the global minimum is geometrically distant, over the parameter space, from the next best local minima. Therefore, the search algorithms are potentially prone to convergence in the wrong direction. The global minimum: $(-420.9687, -420.9687) = 837.9658$.

All the parameters of the improved AFSA are the same as the standard AFSA. The parameters: the number of AF is 20, the circular times is 200, the try number is 10, the crowd factor $\delta$ is 0.2, the feedback probability $P_{fb}$ is 0.95, the attenuation coefficient $\alpha$ is 0.98 for both function 1 and function 2. The step is 2 and the visual is 4 for function 1, the step is 50 and the visual is 100 for function 2.

A. Experiment 1

The AF are distributed randomly in the solution space initially. If the result is less than -140 for function 1 or more than 837 for function 2, we think the algorithm converges to the global optimum value successfully. The experimental result of the standard AFSA and improved AFSA after testing 20 times is listed in Table 1 and Table 2.

Table 1 and Table 2 list the results of function 1 and function 2 respectively. From Table 1 and Table 2, we can see that the convergent speed, the precision and the average convergence generations of the improved AFSA is better than the standard AFSA. They explicitly tell us that the improved AFSA achieves better performance by comparison with the standard AFSA.

B. Experiment 2

We choose functions 2 to test AF’s ability of escaping from the local optimum value. Figure 1 shows the local optimum point of function 2. There are lots of local optimum points in function 2. $(-420.9687, -420.9687)$ is the global optimum point. The AF are distributed around one of the local optimum point (300, -420.9687) in the solution space initially. The initial positions of the AF in the improved AFSA are set as the same as in the standard AFSA. The circular times is 500, the feedback probability $P_{fb}$ is 0.99, the attenuation coefficient $\alpha$ is 0.99 and the other parameters are the same as above.

Figure 2 shows the initial distribution of AF in both the standard AFSA and the improved AFSA. Figure 3 and Figure 4 shows the distribution of AF in the standard AFSA and the improved AFSA respectively after 500 times iterations.

All the AF are distributed around the local optimum point (300, -420.9687). The distance between AF and the nearest optimum point to the AF is more than 100. The visual distance of the AF is 100. AF can not see other optimum point except the local optimum point (300, -420.9687). So the AF are still trapped in the local optimum point in the standard AFSA after 500 times iterations. Owing to the ergodicity characteristic of chaotic search, AF can escape from the local point quickly. Because of the feedback strategy, most AF can reach the global optimum point although they are distributed in the local optimum point. The improved AFSA improves the ability of AF to flee from the local optimum point and to converge globally by the comparison of Figure 3 and Figure 4.
Figure 4. The final distribution of the AF in the improved AFSA

V. CONCLUSIONS

Artificial Fish Swarm Algorithm is a new kind of swarm intelligence optimization algorithm, which has lots of advantages in solving the optimization problems. But there is something need to be improved too. In this paper, an improve AFSA with chaotic search and feedback strategy is proposed. By means of simulation testing, the performance of the improved AFSA is superior to the standard AFSA.

<table>
<thead>
<tr>
<th>Table 1. EXPERIMENT RESULT OF FUNCTION 1</th>
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<tbody>
<tr>
<td>The Worst The Best The Average Convergence Rate Average Convergence Generations</td>
</tr>
<tr>
<td>Standard AFSA -0.2784 -148.9170 -145.2376 8/20 59.6</td>
</tr>
<tr>
<td>Improve AFSA -148.4480 -150.2461 -150.2374 20/20 51.3</td>
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<tr>
<th>Table 2. EXPERIMENT RESULT OF FUNCTION 2</th>
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<tr>
<td>The Worst The Best The Average Convergence Rate Average Convergence Generations</td>
</tr>
<tr>
<td>Standard AFSA 709.3136 837.9600 837.7983 6/20 69.5</td>
</tr>
<tr>
<td>Improve AFSA 837.9154 837.9647 837.9536 20/20 16.7</td>
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REFERENCES


