TELKOMNIKA, Vol. 11, No. 9, September 2013, pp. 5517~5522
ISSN: 2302-4046

Bionic Intelligent Optimization Algorithm based on MMAS and Fish-Swarm Algorithm

Jingjing Yang*[1], Benzhen Guo[1], Jixiang Gou[2], Xiao Zhang[1]
[1]School of information Science & Engineering, Hebei North University, Zhangjiakou 075000, Heibei, P.R.China, +86-313-8041735
[2]School of information Science & Engineering, Lanzhou University, Lanzhou 730000, Gansu, P.R.China, +86-931-8913746
Corresponding author, e-mail: r78z-yang@126.com[1], 1792295399@qq.com, yjr78z@gmail.com[2]

Abstract

With large number of ants, the ant colony algorithm would always take a long time or is rather difficult to find the optimal path from complex chapter path, further more, there exists a contradiction between stagnation, accelerated convergence and precocity. In this paper, we propose a new bionic optimization algorithm. The main idea of the algorithm is to introduce the horizons concept in the MMAS fish swarm algorithm, so it would take shorter time to find the optimal path with numerous ants, and the introduction of the concept of fish swarm algorithm congestion level would enable the ant colony find the path of global optimization with a strong crowding limit which avoids the emergence of local extreme and improves the accuracy and efficiency of the algorithm.

Keywords: *MMAS, artificial fish swarm algorithm, vision, congestion level*

1. Introduction

The ant colony algorithm (Ant Colony Optimization ACO) was proposed in 1991 by the Italian scholar Dorigo M et al. It is an evolutionary algorithm based on swarm intelligence bionic with the characteristics of groupment, robustness, collaboration and rapidness [1, 2]. However, due to the fact that ant initial motion is random, when the population size is too large, it becomes very difficult or even impossible to find an optimal path in a short period of time, furthermore, with time going on, it is easy to fall into local minima later, amounting to less than the global optimum. The MMAS (MAX-MIN Ant System) is an improved ant colony algorithm put forward by the German researchers Stuetzle T. The difference between the improved algorithm and the traditional ant colony algorithm is that each iteration allows only the best performing ant to update path pheromone, which will help to prevent premature convergence [3, 4].

Artificial fish swarm algorithm (Artificial Fish Swarm Algorithm, AFSA) [5] is proposed by Li Xiaolei and Qian Jixin in 2002. The algorithm has the ability to overcome local minima to obtain global extreme, but AFSA has a faster convergence just in the early time, the convergence speed will become slower later, sometimes even stop the process of convergence, so it is difficult to get an accurate optimal solution with the only hope to find the the solution domain [6, 7] of the optimal solution.

In this paper, we analyzes the characteristics of MMAS and fish swarm algorithm and find the similarities of the optimization mechanism between these two algorithms, combined with the advantages of both methods, we proposed a new hybrid bionic optimization algorithm which can better improve the optimization efficiency of the algorithm.

2. MMAS Algorithm and Fish Swarm Algorithm

2.1. MMAS Algorithm

Assume that the number of ants in the colony m, the distance between any path i and j is $d_{ij}\left(i, j=1,2,\ldots,n\right)$, $b_i\left(t\right)$ stands for the number of ants of point i at time t , $m=\sum_{i=1}^{n} b_i\left(t\right)$. $\tau_{ij}\left(t\right)$ is the residual amount of information of path ij ant time t. The value of $\tau_{ij}\left(0\right)$ is 0, the direction

Received April 19, 2013; Revised June 12, 2013; Accepted June 27, 2013

of movement of ant $k\left(k=1,2,...m\right)$ is determined based on the amount of information on each path, $p_{ij}^{k}\left(t\right)$ indicates the probability of ant k choosing the path ij at time t, parameter $\rho\left(0<\rho<1\right)$ is a factor represents information residual, $1-\rho$ is a coefficient which can signify the content of the pheromone evaporation (i.e., the degree of the passage of information). Each ant should behave to meet the following conditions:

1) Choose the next path with the corresponding probability based on the concentration of the hormone in the path.
2) No longer select the path traversed and store this point with a data structure, called tabu list to control it, the taboo list stored all the paths until the moment t and taboo the ant to find the optimal value again before access them after N interactions.
3) After the completion of the first iteration, according to the length of the path to release the corresponding concentrations of pheromone.

2.1.1. Pheromone Update Rules and Restrictions [8]

(1) Update only the best performing ant pheromone

$$\tau_{ij}\left(t+1\right)=\left(1-\rho\right)\tau_{ij}\left(t\right)+\rho\Delta\tau_{ij}^{best} \tag{1}$$

in the above equation, $\Delta\tau_{ij}^{best}=\frac{1}{L^{best}}$.

(2) The pheromone restrictions: set a upper and lower limits for the pheromone: $\tau_{\min}$、$\tau_{\max}$ and $\tau_{\min}\le\tau_{ij}\left(t\right)\le\tau_{\max}$, in order to avoid premature convergence. If $\tau_{\max}\le\tau_{ij}$, then $\tau_{\max}=\tau_{ij}$ else if $\tau_{ij}\le\tau_{\min}$, then $\tau_{ij}=\tau_{\min}$, and equation $\tau_{\min}>0$ should be assured. While researching, set the maximum pheromone to be an estimated maximum limit, and S is a global optimal solution:

$$\lim_{t\to\infty}\tau_{ij}\left(t\right)=\tau_{ij}\le\frac{1}{1-\rho}\cdot\frac{1}{f\left(S\right)} \tag{2}$$

If got global optimal solution, then refresh $\tau_{\max}$, try to get a dynamic value of $\tau_{\max}\left(t\right)$.

$$\tau_{\min}=\frac{\tau_{\max}\left(1-P_{dec}\right)}{\left(\bar{\tau}-1\right)P_{dec}}=\frac{\tau_{\max}\left(1-\sqrt[n]{P_{best}}\right)}{\left(\bar{\tau}-1\right)\sqrt[n]{P_{best}}} \tag{3}$$

In the above equation, $P_{dec}=\sqrt[n]{P_{best}}=\frac{\tau_{\max}}{\tau_{\max}+\left(\bar{\tau}-1\right)\tau_{\min}}$. The selection of maximum and minimum pheromone value is determined by the average path length. By setting a path pheromone concentration to ensure it is not too high to avoid premature stagnation, and the same way to avoid reducing the possibility of finding a new path.

2.1.2. Transition Rules

The probability of selecting path ij for ant k at time t can be calculated with the following equation:

$$p_{ij}^{k}\left(t\right)=\begin{cases}\dfrac{\left[\tau_{ij}\left(t\right)\right]^{\alpha}\left[\eta_{ij}\left(t\right)\right]^{\beta}}{\sum k\in allowed_{k}\left[\tau_{ik}\left(t\right)\right]^{\alpha}\left[\eta_{ik}\left(t\right)\right]^{\beta}} & j\in allowed_{k}\\ 0 & otherwise\end{cases} \tag{4}$$

With $allowed_k = \{0,1,\cdots n-1\} - tabu_k$ to provide all the possible paths an ant could select.

2.2. FISH Swarm Algorithm

The main behaviors of fish swarm include foraging behavior, swarming behavior and following behavior.

Foraging behavior: assuming the current state of the artificial fish swarm is X_i, randomly select a state X_j within its sensing range, for the maximal value, if $Y_i < Y_j$, move a step forward the direction, else randomly select a state X_j, determine whether it meets the forward conditions or not. Try repeatedly for several times, if it does not meet the conditions forward, randomly move one step.

Swarming behavior: assuming the current state to be X_i, explore the number of partners n_f and central location X_c in current neighborhood $d_{ij} < Visable$. If $\frac{Y_c}{n_f} > \delta Y_i$, meaning that the partners have more food and the cluster is less crowded, so move one step toward the direction of the center of partners, otherwise implement the foraging behavior.

Bulletin board: Record the status of the individual artificial fish. Each artificial fish individual in the optimization process will examine whether the individual state is better than the state of the bulletin board when the optimization is completed, if the state of the bulletin board is better than the individual state, the bulletin board state will be changed to their own state, thus making the bulletin board to record the history optimal state.

Its behavior mechanism is to select behavior to make the biggest act in the optimal direction forward, if fail to make the next state behavior better than the current behavior, take a random behavior.

3. A New Hybrid Bionic Optimization Algorithm

3.1. Thought of the Algorithm

MMAS fish swarm algorithm belongs to swarm optimization algorithm, when the number of individuals reach a certain extent, the entire population will exhibit some intelligent behavior. The ant colony is to find the optimal paths, while fish swarm is to find a food source. The similarities between them are as following:

1) For ant colony algorithm, $\tau_{ij}(0)$ is equal everywhere at the beginning, all ants randomly selected path; While the fish swarm algorithm will try to select a state X_j randomly.

2) Ant colony algorithm will perform the convergence of the algorithm according to the update of pheromone, namely $\tau_{ij}(t+1)$. The more pheromones, the more ants. Fish swarm algorithm perform converges based on clusters and rear-end behavior. Generally, for artificial fish, where there is most water, there is most food, that is, the optimal solution domain. The larger the number of artificial fish is, the more it is likely to attract more artificial fish. So the clusters and rear-end behavior of ants is similar to secrete pheromones behavior of fish stocks.

When the number of ant colony is very large, the movement of most ants are random, so in this article, we introduced vision concept before each iteration of the fish-swarm algorithm. When ant k update pheromone to choose path ij with largest $p_{ij}^k(t)$, if there exists a better path in all paths within vision, that is $d_{visual}(t) < d_{ij}(t)$, then the ant will try to select $iVisual^{best}$ again, or, ij is the final choice.

At the beginning of the algorithm, ant colony algorithm is easy to fall into local convergence, so in this paper, we introduce a parameter δ, a degree of congestion of the fish swarm algorithm concept, which can avoid premature self-aggregation pheromone at early time, which not only prevents premature ant colony redundant convergence, but also improves the ability of global optimization.

3.2. Main Steps of the Algorithm

Take the traveling salesman problem (TSP) [9] as example, the main steps of the algorithm are as following:

Step 1: Set initial time t = 0, put m ant into n cities randomly, the initial concentration of pheromone for each path is $\tau_{ij}(0)=0$;

Step 2: Set S = 1,(s is the subscript of the tabu list), store the initial city number of Kth ant into $tabu_k(s)$ which stands for the Sth city the current ant is traveling in.

Step 3: The probability of ant k shifting from position i to position k is:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum k\in allowed_k\left[\tau_{ik}(t)\right]^{\alpha}\left[\eta_{ik}(t)\right]^{\beta}} & j\in allowed_k\\ 0 \qquad otherwise & \end{cases} \tag{5}$$

Equation $allowed_k=\{0,1,\cdots n-1\}-tabu_k$ indicates all the cities the ant could choose, α and β are two parameters represent the pheromone the ant accumulated while moving, and generally $\eta_{ij}(t)$ equals to $\frac{1}{d_{ij}}$.

Step 4: Ant k fist inspect at position i, the vision value is d_{visual}, which will find a path ix randomly and then compare $p_{ij}^{k}(t)$ with the largest path ij, if $d_{ij}<d_{ix}$, then choose path ij, else, choose path ix.

Step 5: When the ant moving as the above path, calculate the congestion μ_{ij} with the following equation:

$$\mu_{ij}=\frac{2\tau_{ij}(t)}{\sum\limits_{i\neq j}\tau_{ij}(t)} \tag{6}$$

If $\mu_{ij}<\delta(t)$, we know that the path is not that crowded, then the ant will move from path i to path j according to this path, else, in the feasible neighborhood the ant will re-select a sub-optimal path. $\delta(t)$ is the threshold ant time t which will update according to the equation $\delta(t)=1-e^{-ct}$.

Step 6: After n iterations, update the pheromone,

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\rho\cdot\Delta\tau_{ij}^{best} \tag{7}$$

In the above equation, $\Delta\tau_{ij}^{best}=\frac{1}{L^{best}}$. Each iteration process just update the best performing ant pheromones to avoid searching too concentrated mainly adopting pheromone smoothing mechanism to adjust the concentration of the pheromone, in accordance with the proportion updated.

Step 7: One cycle to update the bulletin board, the cycles of the optimal path. Until the next cycle if there is a better path than the value, then update the bulletin board again.

Step 8: Repeat Step 2 to Step 7 until convergence as a path or a specified number of times.

Step 9: The algorithm terminated with the output of optimal solution.

4. TSP Instance Simulation

In order to test the effectiveness of the algorithm, take the traveling salesman problem Oliver 30 as an instance of the calculation.

The parameter settings are as followings: n=100, try_number=10, α=1, β=5, ρ=0.1, NC_max=200, Q=100, δ=0.6. The algorithm is realized with Matlab7.0, the configuration of the PC is: Pentium Dual-core E5400, 2GRAM.

Optimization curve and the shortest path is shown in Figure 1.

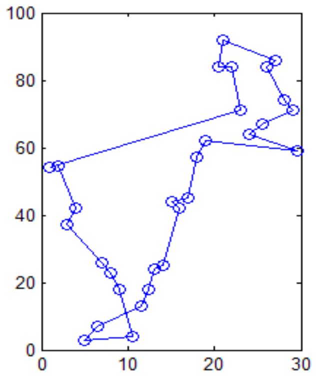

Figure 1. The Optimizing Curve of the Improved Algorithm

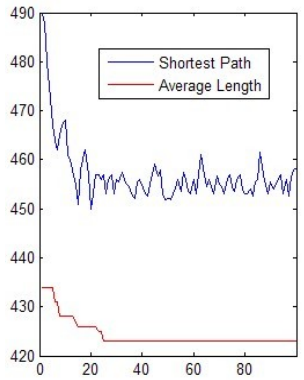

Figure 2. The Average Length and the Shortest Path of the Improved Algorithm

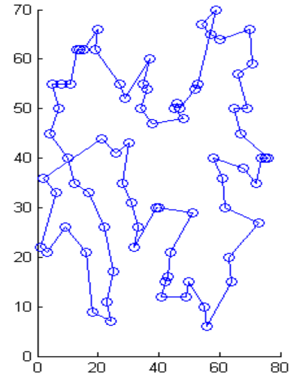

Figure 3. The eil76 Path of the Improved Algorithm

As the data show in the above figure, standard optimal solution is 423.7406; the integer distance for 420. The algorithm of his paper achieves a optimal distance of 423.2071, slightly better than the optimal solution which improved the accuracy of the algorithm.

To further validate the merits of the improved algorithm compared with other algorithms, we take the TSP problem eil76 (76 cities) as example.

Table 1. Comparison of the Proposed Algorithm with other Algorithms

Algorithm	Maximum length	Minimum length	Average length
AFSA	588.14	554.32	570.27
ACO	565.16	545.97	553.04
SA	570.42	548.26	564.67
MMAS	561.38	544.08	551.83
Proposed Algorithm	556.29	543.86	549.04

5. Conclusion

Bionic algorithm based on MMAS fish swarm algorithm were introduced in the concept of vision and congestion of the fish swarm algorithm enabling the ant colony optimization to better avoid local minima and improve the efficiency of the algorithm. However, MMAS require relatively high about parameters compared with AFSA. The improved algorithm of this paper is mainly based on ant colony algorithm, so parameters would have a direct impact on the results of algorithm. How to make the most appropriate choice of parameters or choose a an algorithm which has least requirements about parameters to perform organically integration of intelligent algorithms and design efficient and more adaptive algorithm used to solve the actual problem is what we must continue to do with the following research work.

Acknowledgement

This work was supported by the National Science and Technology Support Program (No. 2012BAJ18B08) of Ministry of Science and Technology.

References

[1] Dorigo M, Maniezzo V, Colorni A. Positive feedback as a search strategy. Technical Report 91-016, Dipartimento di Electronica, Politecnico di Milano, IT. 1991.
[2] Colorni A, Dorigo M, Maniezzo V. *Distributed optimization by ant colonies*. Proceedings of the First European Conference on Artificial Life. Elsevier. 1992; 134-142.
[3] Stutzle T, Hoos H. *Improvements on the ant system: Introducing MAX-MIN ant system*. Proceedings of the International Conference on Artificial Neural Networks and Genetic Algorithms. Wien: Springer Verlag. 1997; 245-249.
[4] Stutzle T. *MAX-MIN ant system for Quadratic Assignment Problems*. Technical Report AIDA-97-04, Intellect Group, Department of Computer Science, Darmstadt University of Technology, Germany. 1997.
[5] Wang Cuiru, Zhou Chunlei, Ma Jianwei. *An Improved Artificial Fish-swarm Algorithm and Its Application in Feed-forward Neural Networks*. Proceedings of 2005 International Conference on Machine Learning and Cybernetics. Piscataway, USA: IEEE Press. 2005: 2890-2894.
[6] Jiang Mingyan, Yuan Dongfeng. *Wavelet Threshold Optimization with Artificial Fish Swarm Algorithm.* Proceedings of 2005 International Conference on Neural Networks. Piscataway, USA: IEEE Press. 2005: 569-572.
[7] CR Wang, CL Zhou, JW Ma. *An improved artificial fish-swarm algorithm and its application in feedforward neural networks.* Proc. of the Fourth Int. Conf. on Machine Learning and Cybernetics. 2005; 2890-2894.
[8] Thomas stutzle, Holger Hoos. *MAX-MIN ant system and local search for combinatorial optimization problems*. Proc. Of 2nd Int. On Metaheuristics. Wien: Springer-Verlag. 1997.
[9] Chiong R. Nature-Inspired Algorithms for Optimisation, Springer. 2009; 536.