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Path Planning of Maritime Intelligent Ship based on Improved Ant Colony Algorithm

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Abstract

In this paper, grid modeling is carried out for the navigation environment of intelligent ships, and each grid is marked. Then, statistical analysis is carried out for the adaptive parameters α and β of ant colony algorithm to solve the optimal parameters.Then the pheromone volatile factor ρ is improved, and the updating coefficient of the volatile factor is designed to improve the pheromone volatile function, so that the volatile factor can adapt to the change.Thus, the running speed of the algorithm is improved, the iteration times of the algorithm is reduced, the shortest optimal path is solved, and the possibility of falling into the local optimal is reduced.Finally, the simulation results show that the improved ant colony algorithm is feasible and effective.

Keywords

Improved ant colony algorithm,path planning, parameter optimization, inspiring factor.

1. Introduction

In the era of big data, ship intellectualization has become an inevitable trend in the field of ship manufacturing and shipping.Intelligent ship is an important field in the development of navigation, which represents the future direction of ships and is related to the transformation and upgrading of the shipping industry.With the continuous development of science and technology, the navigation control technology of intelligent ships is becoming more and more mature, and path planning technology has become the core and key of safe, autonomous and intelligent navigation.

As for path planning, many scholars have made corresponding researches.Literature [1] improves the performance of ant colony algorithm by improving heuristic function and pheromone volatile factor.Reference [2] overadjusts the pheromone heuristic factor and the expected heuristic factor, and adaptively changes the volatility coefficient to reduce the iteration times of the algorithm.Literature [3] proposed new local pheromone updating mechanism and global pheromone updating mechanism, and introduced appropriate "mutation" operation in global pheromone updating to reduce the possibility of algorithm falling into local optimal.Literature [4] proposes an improved heuristic function based on path length, turn times and slope smoothness, which are jointly influenced by three factors.In reference [5], the weight parameters and of pheromone and heuristic information were improved to solve the problem of slow convergence speed caused by pheromone shortage in the early stage of ant colony algorithm, and the two parameters were dynamically adjusted.In literature [6], the evaluation function of A* algorithm was introduced to improve and adjust the heuristic function and pheromone updating mode of ant colony algorithm, so as to reduce the possibility of it falling into "self-locking".In reference [7], the traditional ant colony algorithm is prone to fall into the local optimal and has a slow convergence rate in the search process, so the algorithm's convergence rate is accelerated by improving the updating mode of pheromone by referring to the Wolf distribution principle.

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2. Environmental Model

Modeling methods usually include free space method, topological method, raster method, etc. [8].Because the raster map is simple, effective and easy to implement, the raster method is used to model the navigation environment of intelligent ships.Take the 20*20 grid map as an example, as shown in Figure 1, each grid is numbered, the cell no. 20 is set as the starting position, and the cell no. 381 is set as the ending position. The intelligent ship sails from the starting point to the target point.In the figure, the black grid represents obstacles and the white grid represents barrier-free areas.

In this paper, using the grid method for intelligent ship motion environment modeling, path planning for intelligent ship encountered in the research of search easily plunged into local optimum and slow convergence speed, carries on the quantitative analysis of alpha, beta, to improve the rho, this paper proposes a pheromone update strategy, improve the convergence rate of the traditional ant colony algorithm, reduce the number of iterations, to solve the optimal path.Each grid coordinate (x,y) can be obtained from the following formula:

$$x = \mathrm{mod}(i, M) - 0.5. \tag{1}$$

$$y = M + 0.5 - ceil(\frac{i}{M}). \tag{2}$$

Where, M is the number of rows and columns of the raster map, and i is the raster number.

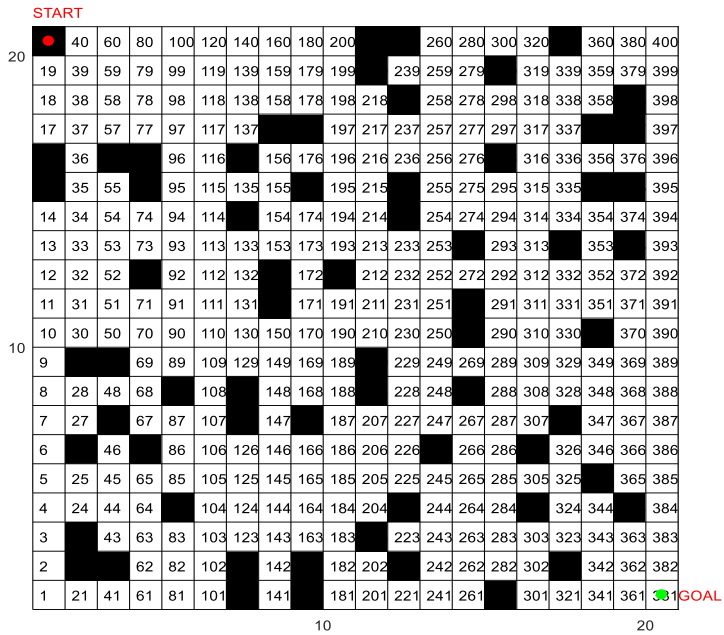

Figure 1. Grid environment modeling

3. Traditional Ant Colony Algorithm

Ant colony algorithm was first proposed by Marco Dorigo et al., in 1991. The basic idea comes from the principle of shortest path for ants to forage in nature.Ants search for food by releasing a pheromone hormone that makes it visible to other ants in the field.When there are more ants passing through a certain path and more pheromones, the probability of choosing this path is higher, leading to more and more large pheromones on this path, forming a positive feedback process.

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The mathematical model of the traditional ant colony algorithm is as follows: in the process of path searching, the ants transfer nodes according to the number of pheromones on the path and the distance heuristic information.The state transition probability of ant K from node i to node j at time t is shown in Equation (3) :

$$P_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\square\eta_{ij}^{\beta}(t)}{\sum\limits_{s\subset allowed_k}\tau_{is}^{\alpha}(t)\square\eta_{is}^{\beta}(t)}, & if\ \mathrm{j}\in\mathrm{allowed}_k \\ 0, & otherwise\end{cases}. \tag{3}$$

Among them, is the information heuristic factor for the relative importance of the trajectory, is the expected heuristic factor for the relative importance of visibility.Allowedk represents the set of nodes the ant can choose, and the next set of removable grids is represented by allowedk.$\tau_{ij}(t)$ refers to the information on the section (i, j) at the time of t, and the information on the initial part of each route is equal to $\tau_{ij}(0)$= constant;The pheromone concentration function was determined by $\tau_{ij}(t)$;$\tau_{ij}(t)$ is the distance heuristic function. The equation is expressed as follows:

$$\eta_{ij}=\frac{1}{d_{ij}}. \tag{4}$$

$$d_{ij}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}. \tag{5}$$

As the ant searches for a path, it releases pheromones that also evaporate.After the ant search path is cycled once, the pheromone update formula is shown in (6)(7) :

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}+\sum_{k=1}^{m}\Delta\tau_{ij}^{k}. \tag{6}$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t). \tag{7}$$

Where ρ represents the pheromone volatility coefficient and the value range is (0, 1).
The global pheromone update rules for global search are as follows:

$$\Delta\tau_{ij}^{k}=\begin{cases}\dfrac{Q}{L_K}, & if\ \mathrm{k\ move}\ from\ \mathrm{i}\ to\ \mathrm{j} \\ 0, & otherwise\end{cases}. \tag{8}$$

Where, Q represents the total amount of pheromones that affect the convergence rate of the algorithm to a certain extent.Lk represents the length of the road in this cycle.

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4. Improved Ant Colony Algorithm

Compared with the traditional ant colony algorithm, the ant colony algorithm is improved in two aspects: 1) Quantitative tests of information heuristic factor α and expectation heuristic factor β are carried out and the results are statistically analyzed to solve the optimal value that takes into account the shortest path and the least number of iterations.2) In the traditional algorithm, the pheromone volatile factor ρ is always unchanged. In this paper, the pheromone volatile factor ρ is set as a dynamic value to improve and update the ρ value in each iteration, so that the algorithm can achieve better performance and reduce the possibility of falling into the local optimal.

4.1. Improve Information Heuristics and Expectation Heuristics

In the traditional ant colony algorithm, the information heuristic factor α and the expected heuristic factor β are usually fixed values [1,9].However, in the practical application of the algorithm, the different values of α and β have α great impact on the performance of the algorithm. If the values of α and β are too large or too small, the algorithm will fall into the local optimum and fail to find the optimal path.In this paper, the shortest path and the least number of iterations are used as evaluation criteria to conduct statistical analysis on different Values of α and β, see Table 1-2.

Table 1. The influence of value β on algorithm performance

The value of β	Path length (cm)	Operation time (s)	Iterations
1	55.11	13.6501	10
2	43.77	12.0433	12
3	38.04	10.5613	13
4	44.87	12.7921	11
5	34.87	11.2789	11
6	30.63	11.3101	9
7	29.88	8.9701	10
8	29.21	10.9669	8
9	28.04	10.7017	6

Table 2. The influence of value α on algorithm performance

The value of α	Path length (cm)	Operation time (s)	Iterations
1	28.36	10.8109	26
2	31.12	11.3569	12
3	29.21	10.9669	8
4	30.38	10.5925	8
5	30.63	10.8421	6
6	30.63	11.0605	6
7	29.8	11.2321	6
8	32.63	11.3257	6
9	34.63	12.5269	6

Through comparative analysis, the value of was changed successively when the value of variable α was determined to be 3.It is observed that with the increase of β value, the path length decreases continuously and the number of iterations decreases continuously. Therefore,

the optimal value of expected heuristic factor β is determined as [7, 9].Let's make sure that β is equal to 8, and let's change the value of α.It is observed that as the value of α increases, the path length increases and the number of iterations decreases. Therefore, the optimal value of information heuristic factor α is determined as [2, 4].

4.2. Improved Pheromone Concentration Volatile Factor

In traditional ant colony algorithms, the pheromone concentration volatile factor ρ is a fixed value of (0,1) and remains unchanged.The traditional ant colony ignored the influence of pheromone concentration volatile factor on the performance of the algorithm, so it is necessary to improve the pheromone concentration volatile factor, so that it can adapt to the natural pheromone volatilization in the ant's actual pathfinding process, so as to improve the reliability of the algorithm.If the pheromone concentration volatile factor is set too high, it will cause the pheromone volatilization too fast, and it is difficult to find the best path.If set too small, it is easy to make the path fall into the local optimal.Based on the above problems, this paper proposes an improvement strategy for pheromone volatilization factor as follows:

$$\rho(t+1) = K * e^{P(t)-1}. \tag{9}$$

$$K = \frac{N}{N+t}. \tag{10}$$

Where: N represents the total number of iterations, t represents the current number of iterations, and K represents the update coefficient.

Since K is a positive coefficient less than 1, the volatile factor ρ gradually decreases and the pheromone volatilization rate gradually slows down during each iteration.This is consistent with the fact that as the number of ants passing through increases, the pheromone becomes more and more concentrated, and the volatilized rate also decreases relatively.When the volatilization rate of pheromone concentration decreases, it will play a stronger guiding role for the ant with the accumulation of pheromone concentration, thus speeding up the pathfinding process of the ant, improving the convergence of the algorithm, and reducing the iteration times of searching for the optimal path.

5. Analysis of Experimental Results

In order to verify the algorithm improvement strategy proposed in this paper, the intelligent ship path planning problem was simulated on MATLAB R2017A platform. Firstly, the simulation results of each group were compared quantitatively, and α and β were quantitatively analyzed.Then, the basic ant colony algorithm is taken as ρ comparison to verify the difference between the improved ρ in this paper and the traditional ant colony algorithm.

5.1. Improved Statistical Analysis of and Results

Quantitative experiments were carried out to determine the information heuristic factor A and the expectation heuristic factor β successively, and then the statistical results were visualized.The visual processing of quantitative analysis of α is shown in Figure 2. The influence of α value on ant colony algorithm can be intuitively seen. When α value is within the range of [2,4], the iteration times and shortest path of this algorithm are relatively optimal, and the algorithm has the best convergence.

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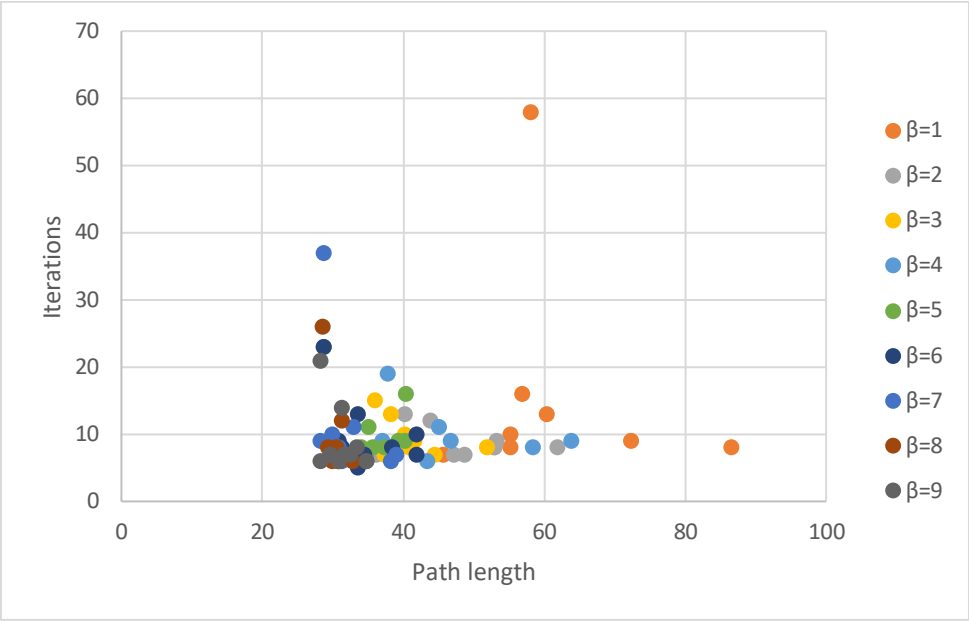

Figure 2. The influence of value α on algorithm performance

The visual processing of quantitative analysis of is shown in Figure 3. The influence of the value of β on ant colony algorithm can be intuitively seen. When the value of α is within the range of [7, 9], the number of iterations and the shortest path of this algorithm are relatively optimal.

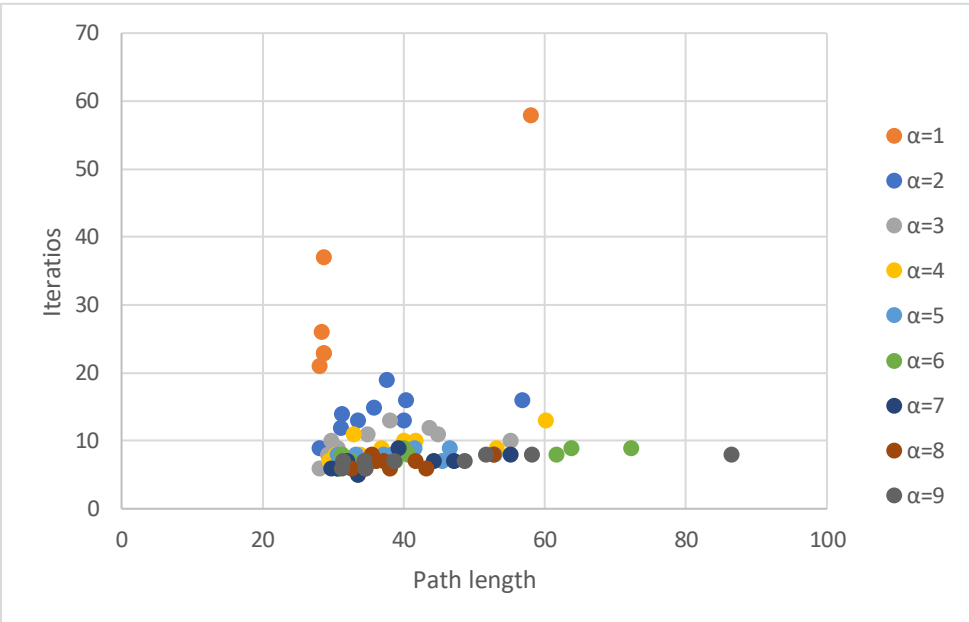

Figure 3. The influence of value β on algorithm performance

In MATLAB software, output algorithm convergence curve respectively.Figure 4 shows the convergence curve of the algorithm with α fixed value of 3 and changing the value successively.Figure 5 shows the convergence curve of the algorithm with fixed value β of 8 and changing value α successively.

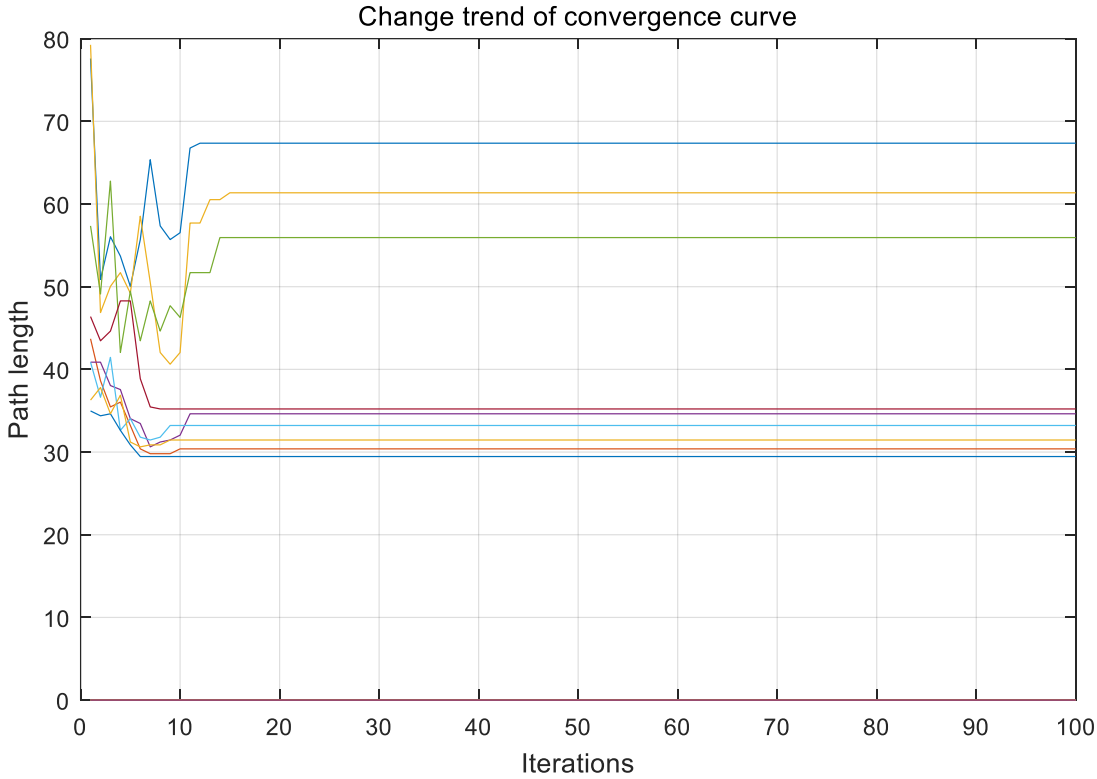

Figure 4. Algorithm convergence curve (α=3)

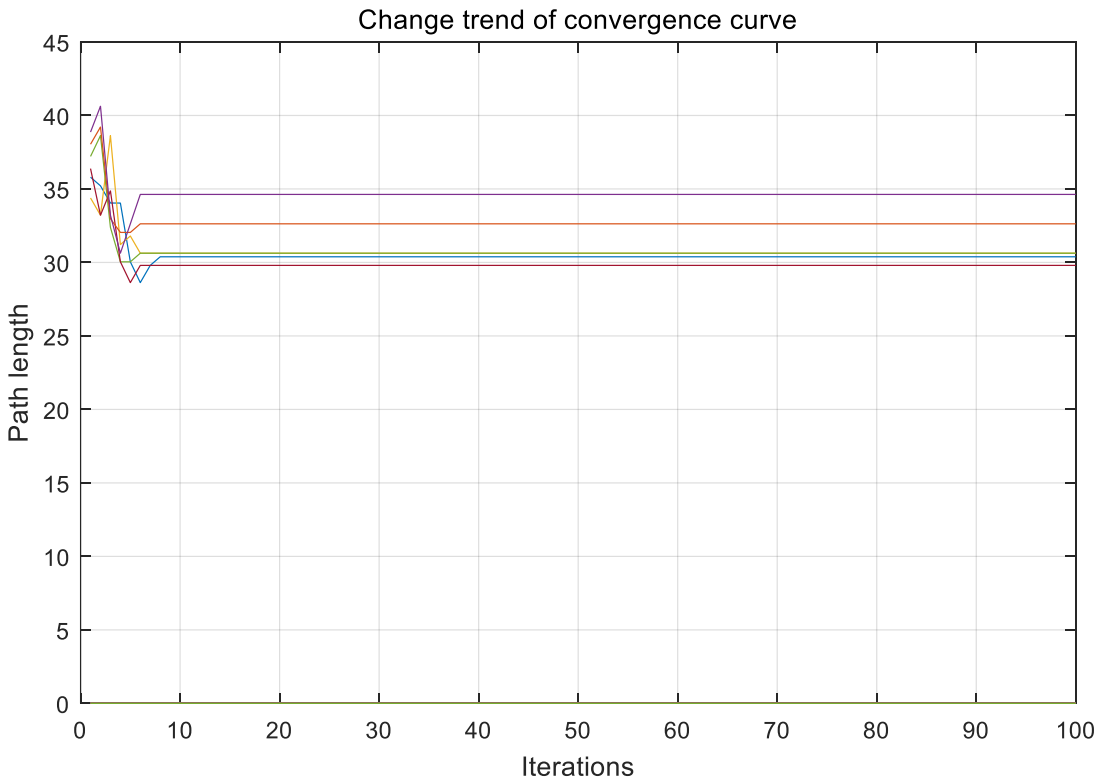

Figure 5. Algorithm convergence curve (β=8)

5.2. Improved Analysis of P Simulation Results

The algorithm in this paper is compared with the traditional ant colony algorithm in the 20*20 raster map. The number of ants with the same parameter is set to 50, the maximum number of iterations is 100, α=1, β=7, and the initial value of ρ is 0.7.Simulation experiments were

conducted for 10 times. The simulation path results of a certain experiment were shown in Figure 6-7, and the convergence curve of the algorithm was shown in Figure 8-9.

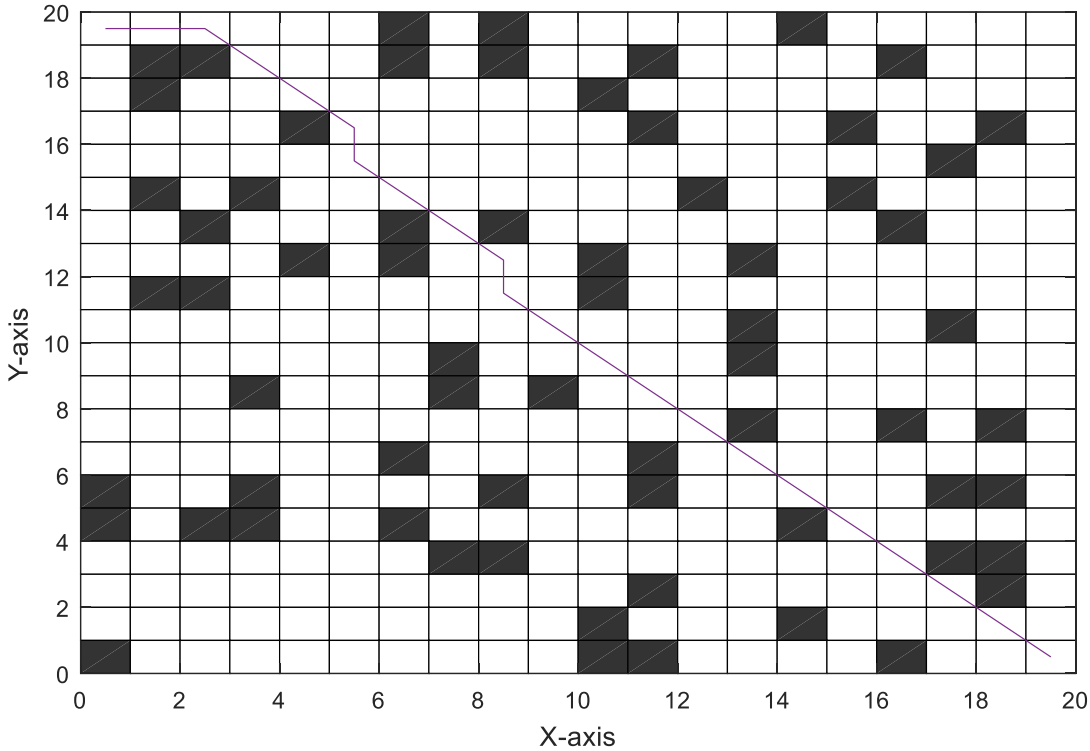

Figure 6. Traditional ant colony algorithm path planning

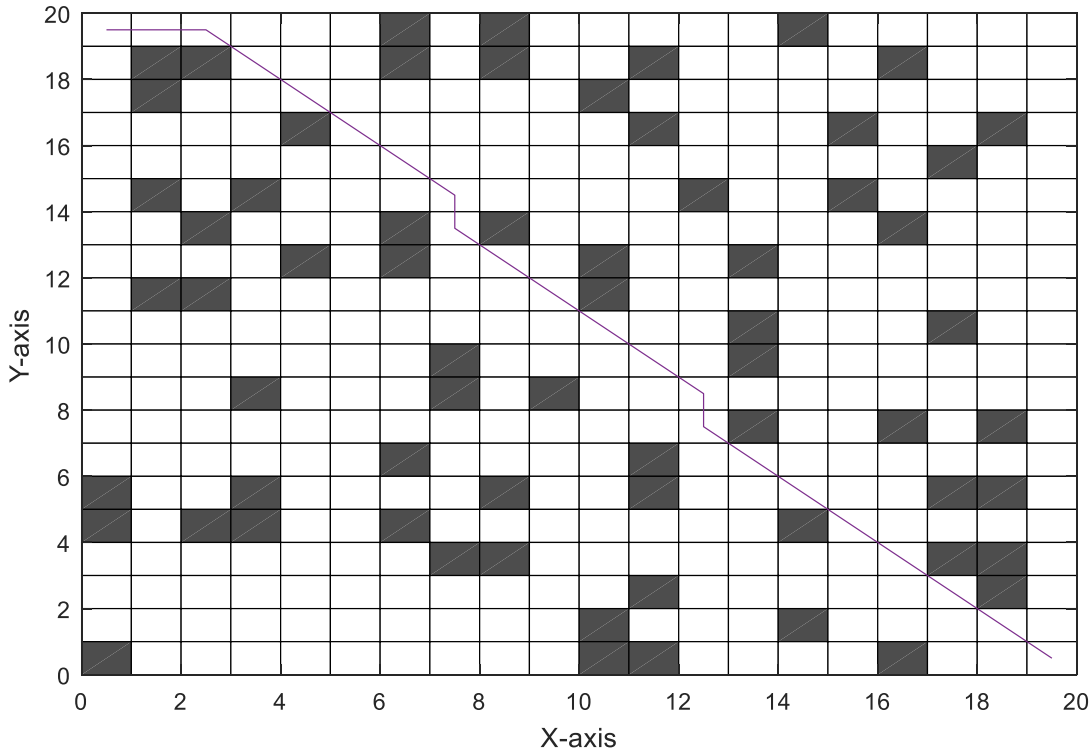

Figure 7. Improved ant colony algorithm path planning

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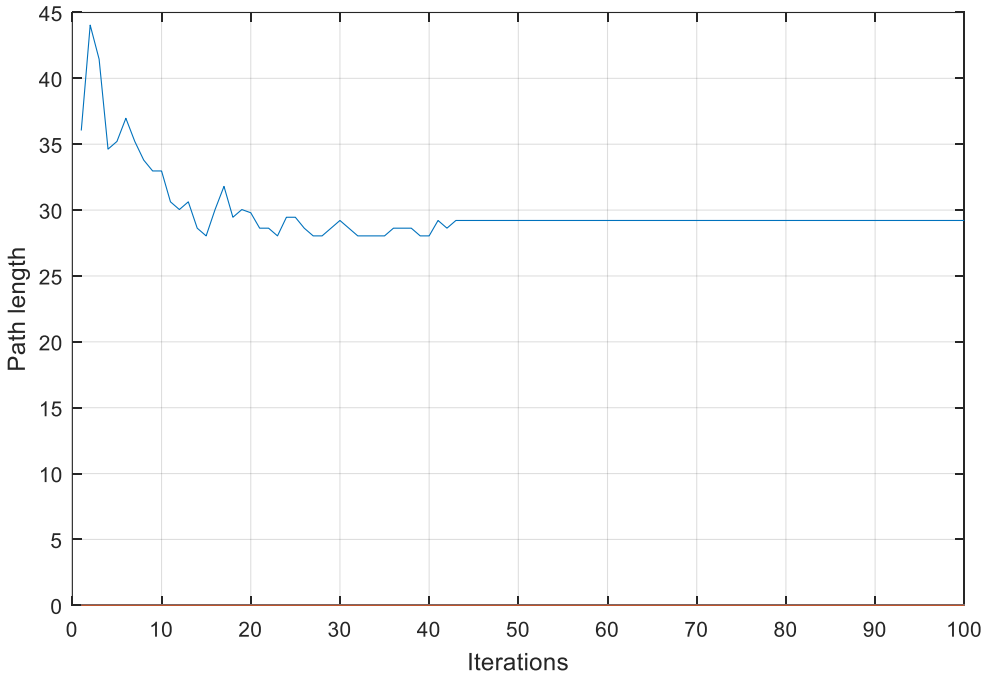

Figure 8. Convergence curve of traditional ant colony algorithm

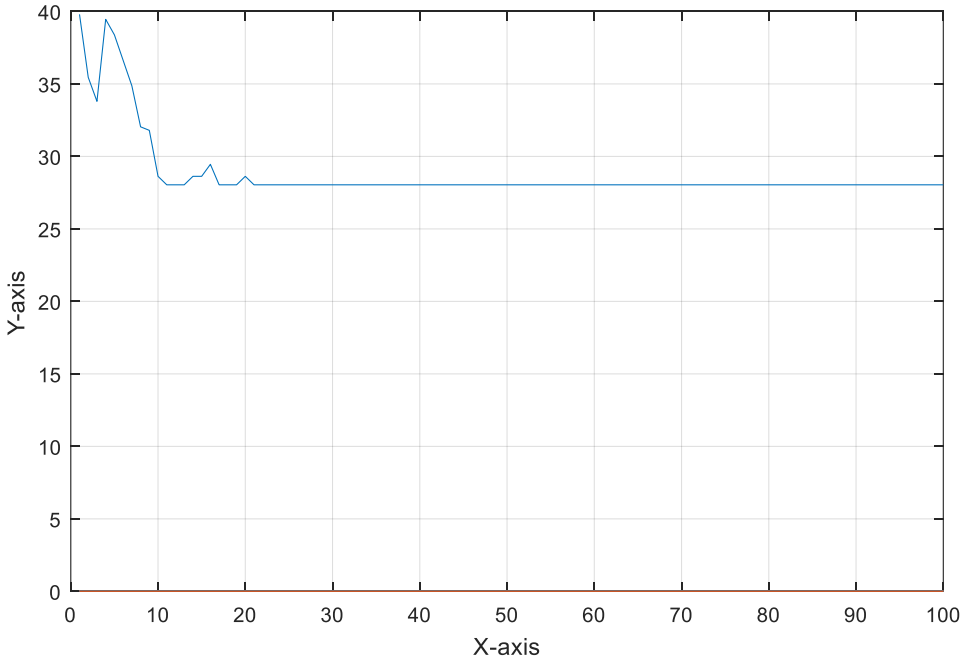

Figure 9. Improved convergence curve of ant colony algorithm

Table 3. The simulation results of traditional and improved algorithm are compared

Algorithm	Path length (cm)	Operation time (s)	Iterations
Traditional ant colony algorithm	28.04	14.0789	21
Improved ant colony algorithm	29.21	21.6345	43

From the analysis of simulation results, and Table 3 can be seen that the improved ant colony algorithm is compared with the traditional ant colony algorithm, to be able to use a shorter operation time, under the less iteration number search to a shorter path, to verify the algorithm

in this paper can improve the running time, reduce the number of iterations, the search for more the result of the short path.

In this paper, the statistical analysis of information inspiring factor α and expectation inspiring factor β to seek for the optimal parameters and the improvement of volatile factor improved the performance of ant colony algorithm greatly, making the algorithm not easy to fall into the local optimal solution.At the same time, the iteration times of the algorithm are reduced, the running time is reduced, and the performance of the algorithm is further improved.

6. Conclusion

In this paper, an intelligent ship path planning method based on improved ant colony algorithm is proposed.1) Conduct quantitative analysis experiments on information heuristic factor α and expectation heuristic factor β, and conduct statistical analysis and visual processing on experimental data, and finally work out the optimal parameter range.2) The pheromone volatilization concentration volatile factor ρ is improved to adapt to each iteration of the algorithm instead of always being a fixed value, which improves the running speed and reliability of the algorithm and enables the algorithm to obtain a shorter optimal path.

The simulation experiment was carried out on MATALB R2017A, and the simulation results were compared. It could be concluded that the algorithm presented in this paper had the advantages of faster convergence speed, faster running speed, fewer iterations and shorter paths than the traditional algorithm. The improved method in this paper improves the performance of the traditional ant colony algorithm.

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