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Route planning method of long-range unmanned ship based on improved ant colony algorithm

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Abstract

With the continuous development of science and technology, unmanned ship has gradually become a hot spot in the field of marine research. In practical applications, unmanned ships need to have long-range navigation and high efficiency, so that they can accurately perform tasks in the marine environment. As one of the key technologies of unmanned ship, path planning is of great significance to improve the endurance of unmanned ship. In order to meet the requirements, this paper proposes a path planning method for long distance unmanned ships based on reinforcement learning angle precedence ant colony improvement algorithm. Firstly, canny operator is used to automatically extract navigation environment information, and then MAKLINK graph theory is applied for environment modelling. Finally, the basic ant colony algorithm is improved and applied to the path planning of unmanned ship to generate an optimal path. The experimental results show that, compared with the traditional ant colony algorithm, the path planning method based on the improved ant colony algorithm can achieve a voyage duration of nearly 7 km for unmanned ships under the same sailing environment, which has certain practicability and popularization value.

Keywords: Improved ant colony algorithm, Long-range, Unmanned surface vehicle, Path planning

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1. Introduction

1.1. Research background and significance

Due to the rapid development of unmanned technology and maritime trade, Unmanned Surface Vehicle (USV), as a new type of intelligent underwater vehicle (JE Manley, 2008), has gradually become a hot spot in the field of marine research and industrial applications because of its safety, economic, practical and controllable characteristics compared with traditional ships. In recent years, with the continuous expansion of the scope of marine environmental monitoring (Hu Y. C., 2020) and target detection tasks and the enhancement of long-term trend, improving the endurance capability of unmanned ships has become a hot issue in the research of unmanned ships at home and abroad.

Based on the above background, this paper intends to improve the theoretical system in the field of path planning of unmanned ships on the basis of analysing it, and construct the shortest path from the beginning to the end that can ensure the smooth completion of operations of unmanned ships, so as to complete the maximum amount of operations with the least energy consumption. The amount of fuel saved through route planning can make up for the shortage of current unmanned ships in long-range directions. After the endurance of unmanned ship is improved, it will bring many benefits to broaden its application field, improve efficiency and safety, and is of great significance to the development of unmanned ship and further technological innovation.

1.2. Research status and trend of path planning

The path planning technology relied on for autonomous navigation of unmanned ships belongs to the autonomous decision-making technology, one of the six core technologies of unmanned ships. At present, one of the most common ways to classify path planning is to divide it into local path planning and global path planning according to the Angle from which an unmanned ship obtains obstacle information.

This thesis focuses on global path planning. Early global path planning mainly used A* algorithm (Wang Hongwei, 2010), so there are many researches on the improvement of this algorithm. However, in recent years, the path planning method based on biological heuristic algorithm rises rapidly in the field of path planning, and becomes a research hotspot. Intelligent algorithms represented by ant colony (LIU L, 2007), (TSOU M, 2010) and genetic algorithm (TSOU M et al, 2010), (SZLAPCZYNSKI R, 2012) simulate the survival, evolution and group behaviour processes of organisms in nature, and solve complex optimization problems by optimizing search. Although these algorithms have great potential, there are still some problems such as slow convergence in the early stage and easy to be limited to the local optimal solution. In order to solve the above problems, future path planning will be developed along the following three directions:

The first is to improve the existing algorithm. Each algorithm has its applicable environment, so that each algorithm can be constantly adjusted in a particular environment, so as to achieve the best results. Of course, this approach is not universal.

The second is algorithm fusion. This is the most potential algorithm improvement method, through the complementarity of advantages between algorithms indeed solved the single algorithm convergence speed is slow, easy to fall into the local optimal and other problems.

Finally, the algorithm research in high dimensional environment. At present, most path planning algorithms are based on two-dimensional environment, but with the practical popularization of unmanned ships, the traditional two-dimensional path planning will be subject to many limitations. Algorithmic problems that cannot be solved in a two-dimensional environment may make great breakthroughs in a three-dimensional environment.

1.3. Research contents and methods

The main content of this paper is to improve the endurance of unmanned ship as much as possible with the same energy consumption through reasonable path planning of unmanned ship. Firstly, canny operator is used to extract the information of navigation environment. On this basis, MAKLINK graph theory is used to construct the navigation environment model of unmanned ship. Finally, by limiting the selection of appropriate parameters and the Angle of searching nodes, introducing pheromone reward coefficient and penalty coefficient, the ant colony algorithm can be improved to further improve the endurance of ships.

2. Route planning of long-voyage unmanned ship

based on reinforcement learning with priority ant colony improvement algorithm

The path planning method of long-voyage unmanned ship mainly includes three steps: extraction of environmental information, environment modelling, finding feasible path and optimization. This chapter will analyse and describe the methods used in the above steps respectively.

2.1. Extraction of navigation environment information of long-voyage unmanned ship

Environmental information extraction is the basis of long voyage path planning for unmanned ships, which directly affects the search efficiency and path quality of the path planning algorithm. At present, most of the research focuses on the improvement of unmanned ship path planning algorithm. The extraction of environmental information, such as obstacles, starting points and destinations, is still limited to manual setting, which is not practical enough. In view of this, this paper proposes an environmental information extraction method which is different from the traditional obstacle information extraction, so as to restore the actual information of navigation environment to the maximum extent.

2.1.1. Method realization of navigation environment information extraction

Image edge extraction is a method for edge detection in computer vision. It can extract various types of edges from images and solve some problems existing in traditional edge detection methods.

Firstly, the image gets grayed and the image details are enlarged by image extension. After that, the gradient value of the pixel points is compared with the given high and low threshold, and the regions higher than the high threshold or lower than the low threshold are marked as strong edge and weak edge respectively, and whether to continue to be marked as edges can be determined according to the strong edge regions adjacent to them. Finally, the computed strong edge and the connected weak edge are combined to form the final edge image.

The image of imitation navigation environment is shown in Figure 2 after grayscale processing.

Figure 1: Imitation navigation environment image

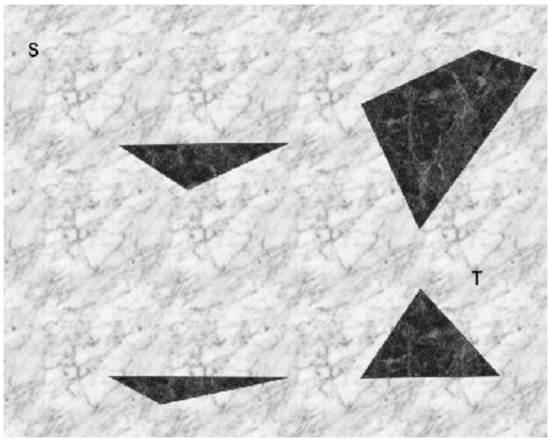

Figure 2: The image after grayscale processing

2.1.2. Navigation environment information extraction based on canny operator

Compared with other operators, canny operator has better edge positioning ability (Fengyun H et al, 2021). It can locate the pixel position and intensity value on the edge, making the detection result more precise and continuous. Therefore, this paper will extract the navigation environment information of unmanned ship based on canny operator.

Table 1: Methods of operator edge extraction based on MATLAB platform

Step	Program
1	I=imread('Imitation navigation environment image');
2	I=rgb2gray(I)；
3	imshow(I，[])；
4	title('Original Image');
5	cannyBW=edge(I, 'canny');
6	Figure;
7	imshow(Canny BW);
8	title(' Edge detection result ')

Edge extraction is carried out in Figure 2, and the extraction results are shown in Figure 3.

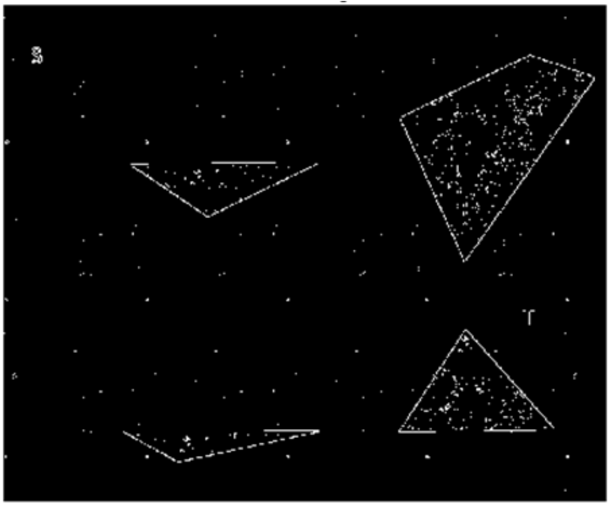

Figure 3: Edge detection results based on canny

Coordinate the edge points based on the source code. The final results are shown in Table 2. Since the extraction result is mirrored, be careful to swap the coordinates.

Table 2: Results of environment information extraction based on canny operator

Extract object	Vertex coordinates
Obstacle a	(40,140), (60,140), (100,140), (60,120)
Obstacle b	(50,30), (30,40), (50,40), (100,40)
Obstacle c	(120,160),(140,100),(180,170),(165,180)
Obstacle d	(120,40), (170,40), (140,80)
S	(20,180)
T	(160,110)

2.2. Modelling of long-voyage unmanned ship sailing environment based on MAKLINK graph theory

The environmental model that this paper needs to establish is the navigation environment of unmanned ship. Since the starting point and ending point of each voyage of an unmanned ship may change with different tasks, and the accuracy of its environmental information is highly required, MAKLINK graph theory is selected for environmental modelling. Figure 4 shows the processing of the environment space hypothesis (That is, without regard to fluid dynamics) and free space modelling of MAKLINK graph theory.

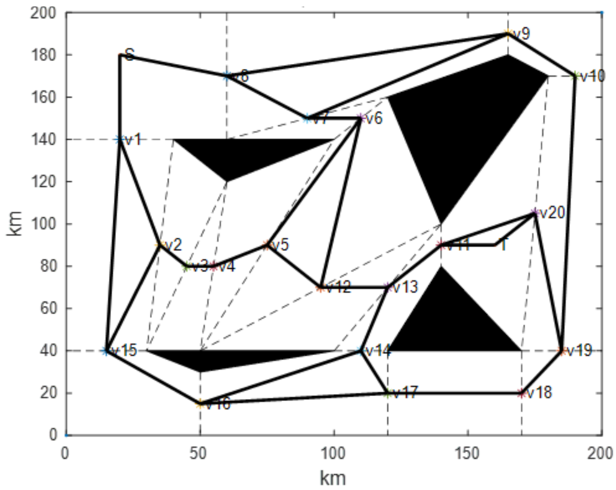

Figure 4: Environment modelling based on MAKLINK graph theory

2.3. Route planning for unmanned captain voyage based on improved ant colony algorithm

Path planning is one of the core technologies of unmanned ship operation. This chapter will determine the optimal path planning algorithm for unmanned ship operation through the data analysis of several intelligent algorithms and carry out the path planning of unmanned ship on this basis.

2.3.1. Comparison of intelligent algorithms for path planning

Genetic algorithm (GA), simulated annealing algorithm (SA) and ant colony algorithm (ACO), which are three typical intelligent algorithms, are often used to solve the path planning problem. Below, the above algorithms are used to conduct the simulation experiment of traveling salesman problem (TSP) respectively. The purpose of the experiment is to compare the effect of the algorithm through the experimental results and determine the most appropriate route planning algorithm for the operation of unmanned ships.

Thirty-one city experiments are randomly set, and the ant traversal results are shown in Table 3. It can be concluded that the ant colony algorithm is superior to other algorithms both in terms of the optimal path and the number of iterations to reach the optimal path. Therefore, ant colony algorithm is adopted in this paper to solve the path planning problem of unmanned ship.

Table 3: The results of each algorithm are compared

Algorithm	Shortest path /km	Mean path /km	Number of shortest path iterations

GA	20720.36	23305.91	500
SA	15997.28	16930.80	357
ACO	15600.03	16895.94	237

2.3.2. Priority ant colony improvement algorithm based on reinforcement learning

Ant colony algorithm has three obvious defects: first, the selection of initial parameter values has a great influence on the final path planning results; Second, the convergence direction of waypoints cannot be determined in time, and when waypoints transfer at the same time, the fit degree of each point is insufficient, which leads to the oscillation of the total distance (Ratanavilisagul C, 2022); Third, it is easy to fall into local optimal. This section will improve the basic ant colony algorithm in view of the above shortcomings.

(1) Selection problem for initial parameter values.

It is pointed out that when $\alpha \in [1,5], \beta \in [1,5]$, a relatively ideal solution can be obtained for the ant colony problem (ZHAN Shichang, 2003). Now, in the specific environment of unmanned ship navigation in Figure 1, we determine the optimal combination of α and β, through data analysis. First, set the initial parameter $\beta = 2$, $\rho = 0.1$, $Q = 1$, $N = 500$, m=15 and transform the value of α to obtain different optimal paths, as shown in Table 4.

Table 4: The impact of α on path planning of unmanned ships

Pheromone heuristic factor	Maximum value /km	Minimum value /km	Get the minimum number of iterations
$\alpha = 1$	347.8	194.8	467
$\alpha = 2$	307.6	187.8	173
$\alpha = 3$	269.3	183.1	332
$\alpha = 4$	266.3	198.9	365
$\alpha = 5$	262.6	197.1	400

Since the purpose of this paper is to maximize the endurance capacity of the unmanned ship, the α value corresponding to the shortest path should be preferred. In the case that there is little difference between the minimum values corresponding to $\alpha = 2$ and $\alpha = 3$, $\alpha = 2$ is finally determined in consideration of the rate of convergence.

When $\alpha = 2$, ρ, Q, N do not change, the value of β is transformed to observe the changes of the optimal path, as shown in Table 5.

Table 5: The impact of β on path planning of unmanned ships

Expectation heuristic factor	Maximum value /km	Minimum value /km	Minimum number of iterations
$\beta = 1$	368	203.7	325
$\beta = 2$	307.6	187.8	173
$\beta = 3$	343.4	191.7	183
$\beta = 4$	349.1	199	493
$\beta = 5$	345.5	205.7	222

Similarly, when $\beta = 2$, the path planning requirements of long-distance unmanned ships are best met. Finally, the parameters applicable to unmanned captain distance navigation obtained through the experiment are: $\alpha = 2$, $\beta = 2$, $\rho = 0.1$, $m = 15$, $Q = 1$, $N = 500$.

(2) Aiming at the problem that the convergence is not timely and the total distance oscillation is easy to occur.

An improved method is the improved Ant colony Algorithm (AACO) based on Angle first. The AACO algorithm divides the city into multiple directions, and introduces Angle information, so that the ants consider not only the pheromone concentration, but also the Angle difference with the previously selected city when choosing the next city, so as to make the ant colony search complete and balanced. AACO algorithm can be simply described as the following steps:

Firstly, the environment space is discretized on the basis of parameter initialization. Assuming that the environment modelling has been completed by MAKLINK graph theory, the link lines L_i in it are now divided by fixed length γ, the final equal parts are:

$$K_i = \begin{cases} Int(L_i / \gamma), Int(L_i / \gamma) = even \\ Int(L_i / \gamma) + 1, Int(L_i / \gamma) = odd \end{cases} \tag{1}$$

And then calculate the probability $S, P_0, P_1 \ldots P_n, T$ is already formed the mid–point of each link line, ants need from the current node P_{i-1} to choose the next node P_i. Different from the basic ant colony algorithm, in addition to considering pheromone concentration and path length, the AACO algorithm also needs to consider the Angle difference between nodes. As shown in Figure 5, as long as the Angle between the line between the current node P_{i-1} and P_i and the line between the starting point coordinate Sand the ending point coordinate T is minimum, ants are more inclined to move from P_{i-1} to P_i,than other nodes.

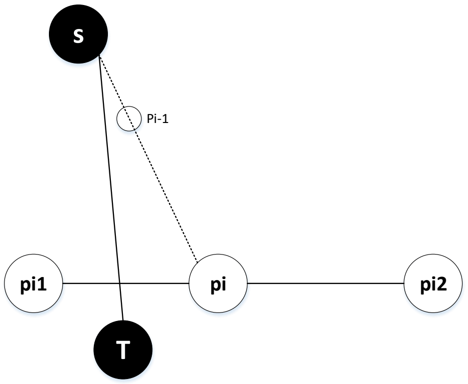

Figure 5: AACO Angle diagram

To determine the location of the P_i, the first to link line $P_{i1}P_{i2}$of discretization and introducing parameter h_i, at this time:

$$P_i = P_{i1} + \left(P_{i2} - P_{i1}\right) \cdot h_i, h_i \in [0,1] \tag{2}$$

The probability formula is:

$$P_{ij}^{k} = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \times \left[\eta_{ij}(t)\right]^{\beta}}{\sum_{s \in allowd_k} \left[\tau_{is}(t)\right]^{\alpha} \times \left[\eta_{ij}(t)\right]^{\beta}}, j \in allowd_k \\ 0, j \notin allowd_k \end{cases} \tag{3}$$

However, $\eta_{ij}(t)$ has changed from the inverse of the original path distance to:

$$\eta_{ij}(t) = 1/\left(\theta_{ij} + \varepsilon\right), \varepsilon \neq 0 \tag{4}$$

Finally, the pheromone concentration and angle are updated to prepare for the next round of city selection. After the number of cycles is reached, the cycle is terminated and the optimal solution is output.

(3) AACO algorithm is easy to fall into the problem that the local optimal solution cannot obtain the optimal path

In the second step, although AACO algorithm is an improved algorithm of ACO, it does not change the problem that all ant colony algorithms are prone to fall into local optimal solutions. To solve this problem, many scholars have adopted hybrid algorithms. This section will also introduce reward coefficient and penalty coefficient in reinforcement learning on the basis of AACO (Yang Jidong, 2019) to improve the convergence ability of AACO algorithm and prevent AACO algorithm from falling into local optimality.

Reward coefficient refers to the positive coefficient provided in an algorithm to encourage correct behaviour. When an effective action appears, the reward coefficient will provide it with a positive reward signal to increase the likelihood of continuing the action and continue to optimize its strategy in the next choice. In the ant colony algorithm, the reward coefficient is used to control the behaviour of ants in the solution space. Ants rely on pheromones and heuristic information to make decisions, and at each time step, they use this information to choose what to do next. If the optimal path after iteration is better than the path obtained in the previous generation, the reward coefficient will increase the pheromone concentration of the optimal path in the current generation.

The updated pheromone concentration of the original ant colony algorithm is:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t), 0 < \rho < 1 \tag{5}$$

After introducing the reward coefficient:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) + \Delta\tau_{ex}(t), 0 < \rho < 1 \tag{6}$$

Among them:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_K} \\ 0 \end{cases} \tag{7}$$

$$\Delta\tau_{ex}(t) = reward/\min\_lenth_{re} \tag{8}$$

$\min\_lenth_{re}$ is the path planning of the optimal solution.

The penalty coefficient is usually used to describe the degree of bad decisions in an algorithm. In general, the penalty is negative and is used to punish the algorithm for poorly performed, inappropriate actions or decisions. In ant colony algorithm, the penalty coefficient is often used to avoid the algorithm falling into the local optimal solution. For certain actions or decisions, if they do not move the ant closer to the target solution, then consider introducing a penalty coefficient. It is transformed into a mathematical model as shown in (9).

$$\Delta\tau_{ex}(t) = -penalty/\min\_lenth_{le} \tag{9}$$

where $\min_lenth_{le}$is the end of update after the four times of iterations.

In order to make the improved ACO algorithm achieve better results, the set value of the reward coefficient should be slightly larger than the penalty coefficient.

2.3.3. Implementation steps of optimal path of unmanned ship based on improved ant colony algorithm

The procedure flow chart of the algorithm for unmanned captain voyage path planning by using the improved ACO is shown in Figure 6:

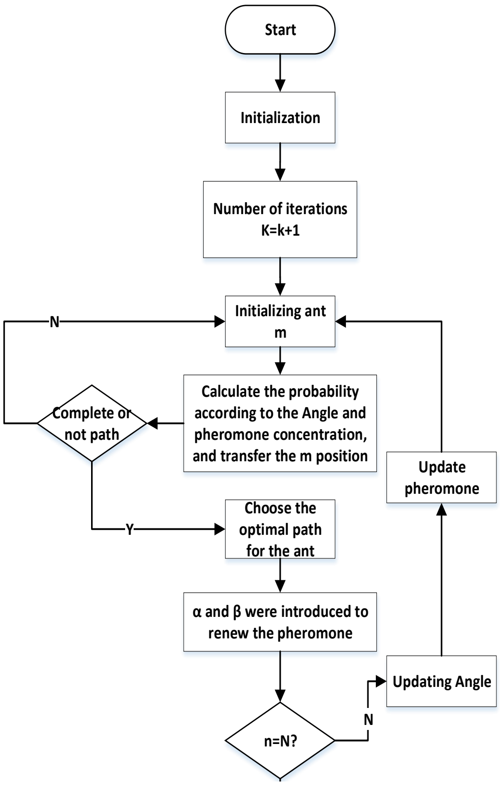

Figure 6: Improved ACO algorithm flow chart

In each iteration, each ant selects inputs in an "angle-first" fashion for the next set of viable nodes. That is, the feasible directions are selected in the order of the Angle with the current direction from small to large. If the Angle with multiple directions is equal, the feasible directions are selected in the order of distance from near to far and pheromone concentration from large to small.

Reach the maximum number of iterations to output the optimal solution; otherwise, the pheromone reward and punishment coefficients are cited to update the global pheromone concentration, update the Angle, and reset the state of all ants.

3.Route planning simulation of long-voyage unmanned ship based on improved ant colony algorithm

This chapter will take MATLAB as the simulation platform, by comparing the experimental results obtained by the traditional ACO algorithm and the improved ACO algorithm to illustrate that the method studied in this paper can improve the endurance of unmanned ship.

3.1. Parameter setting

The parameter Settings of this simulation experiment are shown in Table 6, which is a good parameter value obtained through the analysis in Section 2.3.3:

Table 6: Improve the parameter setting of ant colony algorithm

Parameter	Numerical value
α	2
β	2
Pheromone volatility ρ	0.1
Number of ants m	15
$reward$	2
$penalty$	1

3.2. Experimental procedure

(1) Randomly set an unmanned boat sailing area, as shown in Figure 7.

Figure 7: Unmanned ships navigate the waters

(2) Canny operator is used to extract coordinates of starting and ending points and vertex coordinates of obstacles, and the extraction results are shown in Table 7.

Table 7: Canny operator coordinate extraction results

Extract object	Vertex coordinates
Obstacle a	(40,140), (60,140), (100,140), (60,120)
Obstacle b	(50,30), (30,40), (80,80), (100,40)
Obstacle c	(120,160),(140,100),(180,170),(165,180)
Obstacle d	(120,40), (170,40), (140,80)
S	(20,180)
T	(160,110)

(3) According to the coordinates of obstacles and

starting and ending points, MAKLINK is used to conduct environment modelling, and the results are shown in Figure 8.

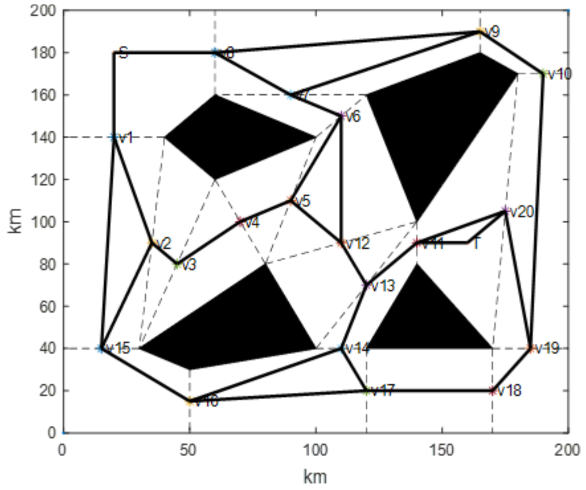

Figure 8: MAKLINK environment modelling results

ACO algorithm and optimized ACO algorithm are respectively used for path planning of unmanned ships. The simulation results are shown in Figure 9, Figure 10.

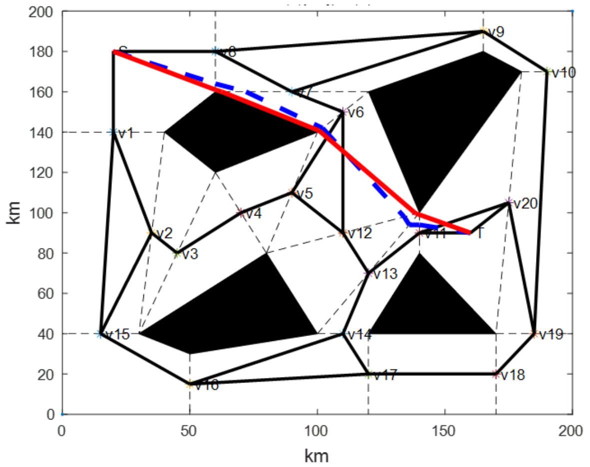

Figure 9: Path planning diagram of original (red) and improved (blue) ant colony algorithm

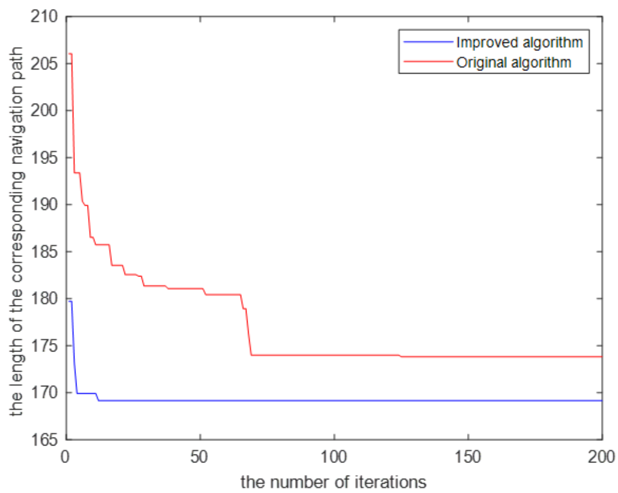

Figure 10: Comparison of path length and iteration times between original(red) and improved ant colony algorithm(blue).

3.3. Experimental results

The results of the original ACO algorithm and the improved ACO algorithm for unmanned ship path planning are shown in Table 8.

Table 7: Experimental result

Algorithm	Shortest path /km	The number of shortest path iterations reached
Original ACO algorithm	174.9902	64
Improved ACO algorithm	168.1513	12
Difference	6.8389	52

Both the path length obtained by the improved ACO algorithm and the number of iterations to reach the shortest path are far better than the original ACO algorithm: under the same sailing environment, the endurance of nearly 7 km unmanned ship is achieved, and the computing speed of the algorithm is also increased by five times. It can be concluded that the improved ACO algorithm can not only greatly improve the endurance capacity of unmanned ships, but also speed up the operational efficiency of unmanned ships.

4. Conclusion

Effective path planning is the most direct way to improve the endurance of unmanned ships. This paper mainly studies the path planning method of long-distance unmanned ship based on optimized ant colony algorithm, and on this basis, the simulation experiment is carried out. Experimental results show that the convergence speed of the improved ant colony algorithm based on reinforcement learning is five times that of the traditional ant colony algorithm, and it can effectively realize the endurance of unmanned ships.

But it still has some defects and deficiencies. Firstly, as the optimized ant colony algorithm is a heuristic optimization algorithm, it is sensitive to the setting of algorithm parameters and initial variables, so the stability and repeatability of its optimization results need to be further strengthened. Secondly, the optimization ant colony algorithm itself has the problem of difficult parameter adjustment, which requires many tests to find the optimal parameter value. Finally, although this paper proves the application advantage of optimized ant colony algorithm in long-range unmanned ship path planning through MATLAB simulation experiment, in practical application, the algorithm needs to be further improved in the face of more complex and changing marine environment, so as to improve the stability and practicability of path planning.

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