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OBSTACLE AVOIDANCE FOR SHIP NAVIGATION SAFETY COMBINING HEURISTIC SEARCH ALGORITHM AND IMPROVED ACO ALGORITHM

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Abstract:

The safety of ship navigation has always been a focus of attention in the field of maritime transport and navigation. In the complex marine environment, ships face a variety of obstacles, such as other ships, reefs, buoys, etc., which may pose a threat to navigation safety. Traditional obstacle avoidance methods mainly rely on the navigator's empirical judgement, but there are limitations and risks associated with this method. The standard ant colony optimisation algorithm tends to fall into local optimal solutions during path search, while the A algorithm is easily limited by the search space when dealing with large-scale problems. Therefore, the study proposes a method that combines a heuristic search algorithm and an improved ACO algorithm to improve the efficiency of obstacle avoidance for vessel navigation safety. Firstly, the standard ant colony optimisation algorithm is improved and applied to the study of obstacle avoidance paths for vessel navigation, and then the A* algorithm is effectively combined with the improved ACO algorithm to improve the performance of planning obstacle avoidance paths. Through simulation experiments and practical applications, the study verifies the capability of the obstacle avoidance planning model. The experimental results show that in simple environments, the hybrid algorithm reduces the path length by 3.8 and 5.5, and the number of iterations by 13.2 and 30.7 compared to Line-of-Sight and Particle Swarm Optimisation algorithms respectively. In moderately complex environments, the proposed algorithm reduces the average path length by 6.51 and 3.93 compared to Particle Swarm Optimisation and Line-of-Sight algorithms respectively. In complex environments, the proposed algorithm reduces the average path length by 15.7 and 12.4 compared to Particle Swarm Optimisation and Line-of-Sight algorithms, and reduces the number of iterations by 49 and 22.2, respectively. The study proposes a novel obstacle avoidance path planning method by effectively integrating the improved ant colony algorithm with the A* algorithm, which significantly improves the efficiency and accuracy of vessel navigation safety. The results show that the hybrid algorithm exhibits superior path planning capability in environments of varying complexity, and is able to quickly adapt to dynamically changing marine environments. This method not only provides a new solution for navigation safety, but also provides a theoretical basis and practical guidance for future autonomous navigation and decision-making of intelligent ships, which has important application value and promotion potential.*

Keywords: *ACO algorithm, A* algorithm, ship navigation, obstacles, path planning*

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1. Introduction

Ship navigation safety (SNS) has always been a focal point of concern in the field of maritime transportation and navigation. In the complex marine environment, ships face a variety of obstacles, such as other vessels, reefs, buoys, etc., which may pose a threat to navigation safety. Therefore, effective avoidance of these obstacles is crucial to safeguard SNS (Liu et al, 2023). The traditional obstacle avoidance (OA) method mainly relies on the experience of navigators and real-time judgment of the navigational environment, but this method has certain limitations and risks. As artificial intelligence technology has advanced, clever algorithms have become increasingly prevalent in open access (Wei, 2020 and Yu et al., 2021). A program called the Ant Colony Optimization (ACO) algorithm mimics how ants might search for food. Less accurate planning outcomes are produced by the standard ACO algorithm's propensity to settle into local optimal solutions during the path search process (Zhang et al., 2021 and Chen et al., 2021). The A* algorithm (A*A) is a heuristic search method that can locate the ideal answer within a constrained search space. Its benefits include great efficiency and accuracy. However, when dealing with large-scale problems, the A*A is easily constrained by the search space (Grifoll et al., 2022 and Wang et al., 2021). The work integrates the enhanced ACO algorithm with the A*A to increase the efficacy of OA for SNS. The work combines the A* and ACO algorithms after first refining the ACO method and applying it to the avoidance of navigation obstacles (ANO) path research. The goal of the project is to use the fusion algorithm to increase the quality and efficacy of OA for SNS. Additionally, it offers a path planning (P- P) strategy for SNS that is efficient and helps to raise the bar for marine transportation safety and effectiveness.

The first part of the study utilizes the improved ACO algorithm (IACOA) for P-P for OA on ships. The second part introduces the A*A based on the IACOA P-P and effectively combines the two algorithms as a way to improve the performance of the planning of OA paths. The third section uses real-world applications and simulated studies to confirm the OA P-P capabilities of the OA planning model. The experimental results are compiled in the fourth section, which also examines the benefits and drawbacks of the study's methodology.

2. Literature review

As maritime vessels become larger and routes become more intensive, the challenges to navigational safety are becoming more complex. Thus, it is essential to guarantee the maritime vessels' safety during navigation. OA is a significant area of research for ship navigation (SN), a process that involves SN. As artificial intelligence technology has advanced, OA has made extensive use of intelligent algorithms. Numerous professionals and academics have studied intelligent algorithms in OA for SN extensively in an effort to offer safer and more effective OA pathways for SN. Academics like Öztürk (2021) suggested a concrete visualization tool to improve the navigational safety of maritime traffic. The study utilized AIS data for feature extraction on the microscopic of the navigation channel, followed by the study of spatial position change. The results of simulation experiments demonstrated that the visualization tool was able to capture the characteristics of the data at the time of real accidents in a timely manner, which is a realistic guide for the safety of navigation of individual vessels and waters. However, research has only focused on capturing data features, and there is still insufficient research on how to further utilize these features for risk warning or optimizing navigation paths. Liu et al. (2022) constructed an evaluation model for a three-level hierarchical system. The model utilized the evidence-based reasoning method for the confidence distribution of the factors at different evaluation index levels, and the fuzzy theory was used to analyze the qualitative and quantitative indexes. The model's risk ratings were found to be in line with actual circumstances, according to the results, and they may be able to improve risk early warning systems and offer helpful suggestions for managing marine navigation safety. Insufficient discussion on the applicability and robustness of the model in complex navigation environments. To enhance the navigation safety ability and avoid collision, He et al. (2021) proposed a multi-ship encounter collision P-P method. Using a ship motion model and PID control, the study first created a real-time control system. Next, it created a scene recognition model, and by combining the two, it was able to determine the best collision prevention strategy. The outcomes showed that the P-P approach can considerably lower the likelihood of a vessel accident. This method still has certain shortcomings in terms of stability and response speed of real-time control systems. Twin neural network-based ship tracking was proposed by Liao H and other researchers to acquire the behavioral trajectory of the target ship (2020). The study used the correlation filtering method to first build a ship tracking module. Then, it used the twinning technique and the peak response method to detect shadows of other objects early on. The outcomes showed that the technique can greatly increase ship tracking's efficacy and punctuality. The performance of this method in complex sea areas and adverse weather conditions, as well as the difficulty of training and optimizing twin neural networks, have not been studied correspondingly.

To address this problem and increase ships' real-time P-P capacity, Gao et al. (2023) suggested an improved potential field ACO. In order to achieve real-time dynamic avoidance, the study first built a nonlinear planning model. It then integrated the artificial potential field method with the ACO. The outcomes showed that the algorithm can successfully solve the planning of the ship's avoidance path and effectively increase the accuracy of course prediction and collision prevention. The study did not conduct a reliable analysis of performance in extreme situations such as complex sea conditions and multiple vessel intersections. To enhance the deterministic and predictive capabilities of SN trajectory data, Zhang et al. (2020) suggested a ship trajectory reconstruction model based on node weights and edge weights of ACO. The model firstly constructed the a priori knowledge base and solved the optimal path (Opt-P) from the route trajectory, and then proposed a large-scale trajectory reconstruction method. The results demonstrated that the ship trajectory reconstruction model constructed by the study can significantly improve the prediction ability of route trajectories. But the complexity of research methods is relatively high, requiring a longer calculation time to make predictions. To guarantee the safety of SN and obtain the best possible navigation path, Chen G. and other academics (2021) presented a weather P-P approach based on the upgraded A-star algorithm. To find the best route, the approach first inflated the obstacles and then used the A*A to seek the node targets. According to the findings, the technique can successfully lower the number of nodes that the algorithm searches for. However, the A-star algorithm itself has limited adaptability to dynamic environments, so the algorithm can be further improved for obstacle avoidance research.

In domestic research, scholars pay more attention to the innovation and optimization of algorithms to adapt to complex and changing navigation environments, aiming to improve the autonomous decision-making ability and real-time response speed of ships in obstacle avoidance processes. Through simulation experiments and field tests, domestic research has verified the effectiveness of these algorithms in improving navigation safety and reducing collision risks. In contrast, foreign research focuses more on practical applications and system integration in the field of ship navigation safety obstacle avoidance. The research not only focuses on optimizing the performance of algorithms, but also aims to deeply integrate algorithms with ship navigation systems, sensor equipment, etc., to achieve intelligent decision-making and automated control during ship navigation. Foreign research also places greater emphasis on the fusion and processing of multi-source information to improve the accuracy and reliability of obstacle avoidance. Through comparison, it was found that domestic and foreign research is based on the actual needs of ship navigation safety, and obstacle avoidance capabilities are improved through algorithm optimization and technological innovation. Domestic research has shown outstanding performance in algorithm innovation, providing new solutions for ship navigation safety; However, foreign research focuses more on practical applications and system integration, providing strong support for the intelligent and automated development of ship navigation safety. Based on the above analysis, experts and scholars have proposed different research methods to adapt to the safety needs of ship navigation in different scenarios, but there are still certain shortcomings in the research. Based on this, it is of great significance to study the use of improved ACO algorithm and A * algorithm for obstacle avoidance in navigation. By effectively integrating the two algorithms, the ability of path planning can be improved. The research aims to provide a new solution for obstacle avoidance in ship navigation, promoting the safe and efficient operation of maritime traffic.

3. Modeling of navigation obstacles by combining the IACOA with the A* algorithm

The study suggests an ANO model architecture that combines the enhanced ACO algorithm with the

A*A to overcome the issues with conventional OA techniques. By leveraging the group intelligence optimization capability of the ACO algorithm and the quick path search capabilities of the A algorithm, the model seeks to offer a more secure and effective OA path for the SN.

3.1. Avoidance of navigation obstacles path based on IACOA

The environment and conditions of SN are growing increasingly complex due to the development and use of marine resources, and ANO has emerged as one of the most important factors in protecting SNS. Traditional ANO methods are often based on rules or mathematical models, which have certain limitations and shortcomings. On the other hand, the ACO algorithm is a colony intelligence optimization algorithm that can effectively handle complex and dynamic situations since it mimics the foraging behavior of ant colonies in the wild. When performing OA and P-P for SNS, it is not constrained by the traveling road due to the special characteristics of the marine environment. Meanwhile, the SN is also affected by the harsh environment such as wind, waves, fog, etc., which may lead to positional shifts during SN (Ai and Zhu, 2020; Yaun and Shi, 2021). Therefore, choosing an appropriate map model is essential for ANO research that uses the ACO algorithm. Through analyzing and summarizing the related SN OA research, it is found that the raster method shows simplicity in processing data information, and can transform environmental information into a network storage with binary image information. This method can effectively transform the marine environment into a computer-understandable map model, highlighting its unique advantages. Therefore, the raster method is chosen for the study to be used for the map model construction of ANO paths. Figure 1 depicts the schematic for ship collision detection in the case of ship avoidance obstacle P-P, where the study aims to simplify the computing process.

Following the establishment of ship collision detection, the distance between the ship's present position and its next position must be determined. At this point, the distance can be stated using Equation (1).

$$s = \sqrt{(-y_j + y_i)^2 + (-x_j + x_i)^2} \tag{1}$$

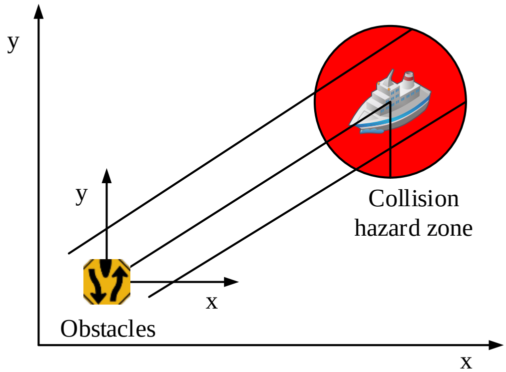


Fig.1. Schematic diagram of ship collision detection

In Equation (1), x_i, y_i denote the current position of the ship. x_j, y_j denote the next position of the ship. In the related ACO algorithm in ship OA P-P, the study found that the traditional ACO algorithm for OA path designers has the problems of easily falling into the local optimum and slow convergence. In order to solve these problems, the study improved the ACO algorithm. The reason that the IACOA is able to avoid the premature local optimum solution is that the study increases the stabilization factor, which improves the transfer probability in the P-P process. The transfer probability at this point can be expressed by Equation (2).

$$\begin{cases} P_{ij}^k(t) = \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta (stabled_j)^\gamma}{\sum_{j \in allowed_k} [\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta (stabled_j)^\gamma} \\ stabled_j = \dfrac{S_j - O_j}{S_j} \end{cases} \tag{2}$$

In Equation (2), $\tau_{ij}(t)$ denotes the value of pheromone concentration (PC) between region i and region G at the moment of t. j denotes the heuristic factor at this moment and $\eta_{ij}(t)$ is the heuristic function (HF). β is the desired atmosphere factor and $stabled_j$ denotes the stabilization factor. $allowed_k$ denotes the value of the passable region i of the kth ant, and γ denotes the value of the stabilization factor coefficient. S_j denotes the number of grids near the j search node and O_j denotes the number of obstacles present near the j search node. The HF can be expressed in Equation (3).

$$\eta_{ij}(t) = \frac{1}{\sqrt{(y^i - y^j) + (x^i - x^j)^2}} \tag{3}$$

Combined with the actual navigation of the ship can be found, the ship is sailing, its navigation is smooth and stable. Therefore, the study also needs to consider the actual sailing situation when performing P- P, and the avoidance path cannot have too much curvature or even deadlock situation. Based on this, the study adds a cornering factor to the ACO algorithm to increase the smoothness of the path, and the cornering factor can be expressed by Equation (4).

$$\omega_{ij}(t) = \omega_0 R \tag{4}$$

In Equation (4), $\omega_{ij}(t)$ denotes the corner HF from the current node i to the search node j. ω_0 denotes the corner parameter and R denotes the corner surrogate value. The inclusion of the cornering factor enables the algorithm to adjust the smoothness of the algorithm when searching for the next node, thus improving the ship P-P performance. After the ACO algorithm completes a global OA P-P, the ant colony will update the PC in the new environment where it is located. The study introduces a reward and punishment strategy in order to ensure that a stable Opt-P can be obtained at a later stage, and to improve the convergence speed and avoid the problem of local optimal solutions as a way of weakening the role of the positive feedback mechanism (Liang et al., 2020). The introduction of this strategy can compensate for the uneven distribution of pheromone in the neighboring better paths during the Opt-P search process, so as to ensure the smoothness of the path at the later stage. At this time, the global pheromone update rule can be expressed by Equation (5).

$$\tau_{ij}(n+t) = \Delta\tau_{ij}(t) + \Delta\tau_{ij}^*(t) + (1-\rho)\tau_{ij}(t) \tag{5}$$

In Equation (5), ρ denotes the volatilization coefficient of the PC of the ant colony during the search process. $\Delta\tau_{ij}(t)$ denotes the total amount of pheromone released by the ants on the path during a complete search cycle. $\Delta\tau_{ij}^*(t)$ denotes the reward and punishment strategy for global pheromone updating. The reward and punishment strategy at this time can be expressed by Equation (6).

$$\Delta\tau_{ij}^*(t) = \begin{cases} \sigma \cdot \Delta\tau_{ij}(t) & \text{Path length} \\ \dfrac{1}{\sigma} \cdot \Delta\tau_{ij}(t) & \text{Short path} \end{cases} \tag{6}$$

In Equation (6), σ denotes the value of the pheromone update parameter for the current Opt-P in global planning. The pheromone update of the ant colony is used to enhance the ACO algorithm for the analysis of OA in the SN path, effectively avoiding barriers and presenting the best way. Fig. 2 displays the flowchart of the best route based on the enhanced ACO algorithm.

3.2. Obstacle avoidance path combining A* algorithm and IACOA

By improving the ACO algorithm for the optimization of the Opt-P, the study conducted some experiments and found that the improved ACO still suffers from blind search at the beginning of the search. This will lead to a decrease in search efficiency (SE), a tendency to fall into local optimums and unstable results. To solve these problems, some heuristic information or optimization strategies can be considered to be introduced to guide the ACO to search more efficiently (Zhang et al., 2021 and Islam et al., 2023). By summarizing the heuristic search algorithms (HSA), the study introduces the A*A into the study of ship OA paths. The A*A is an HSA that uses an estimation function to determine the valuation of every potential passing point from the start point to the finish point. It then ranks those points in order to determine the Opt-P. Fig. 3 displays the flowchart of the A*A used to determine the Opt-P.

Combined with Fig. 3, the analysis reveals that the A*A has strong SE in the OA path protocol of SN. It can effectively decrease the complexity of the problem and the needless path search by just needing to search the state of a few obstacles. The evaluation function (EF) in the A*A is its most central part, which can be expressed by Equation (7).

$$f(n) = g(n) + h(n) \tag{7}$$

In Equation (7), $f(n)$ denotes the EF. $g(n)$ is the movement value from the path start point to the current point n. $h(n)$ denotes the movement value from the current point n to the end of the path, which is also the HF in the A*A. From the speculation of Equation (7), it can be concluded that the value of the EF taken by the A*A in the path search process has a direct relationship with the HF. The distance between the destination point and the path search's beginning point, in turn, affects the HF's value. The Manhattan distance is used as the HF in this study to make computation easier. Equation (8) can now be used to express the HF.

$$h(n) = |x_i - x_j| + |y_i - y_j| \tag{8}$$

It is being researched whether increasing the number of search nodes can enhance the fusion algorithm's outward expansion search capabilities, hence improving the performance of A*A in obstacle neighborhood search. In the A*A, there are 8 nodes to be searched and 8 moving directions. On this basis, the study incorporates the extra 16 nodes in the outer layer into the to-be-searched nodes of the algorithm as well. This can both expand the search range and improve the SE and accuracy of the algorithm (Yin et al., 2021 and Yu et al., 2020). The path search schematic of the ACO+A*A after expanding the search nodes is shown in Fig. 4.

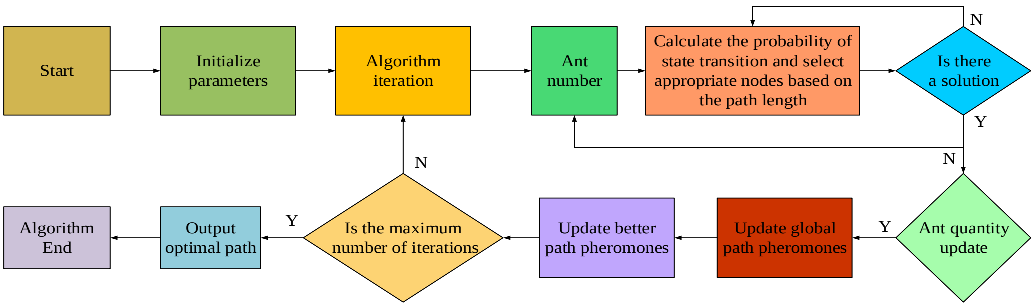


Fig. 2. Optimal path flowchart based on IACOA

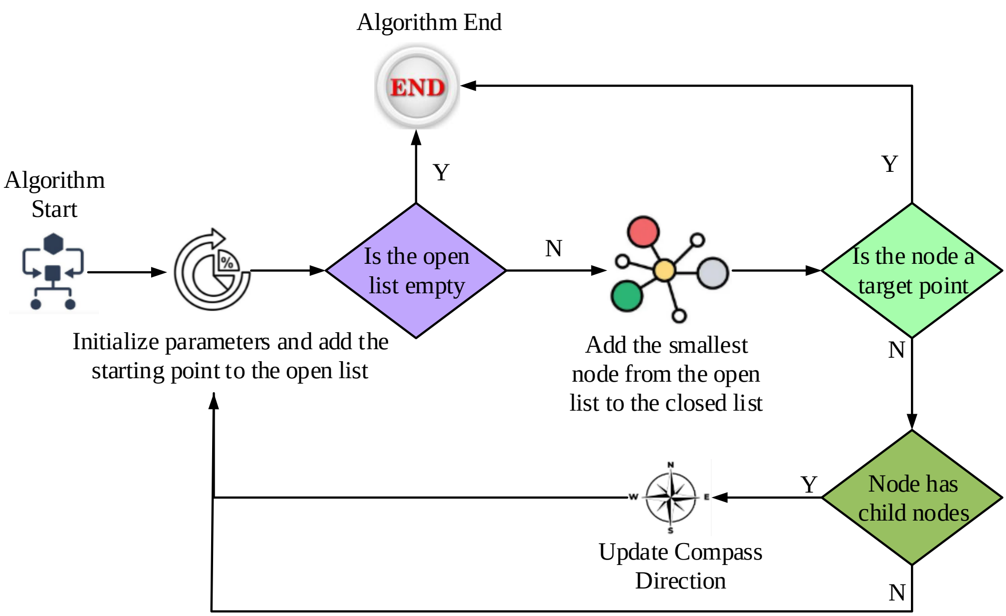


Fig. 3. The flowchart of A * algorithm for finding the optimal path

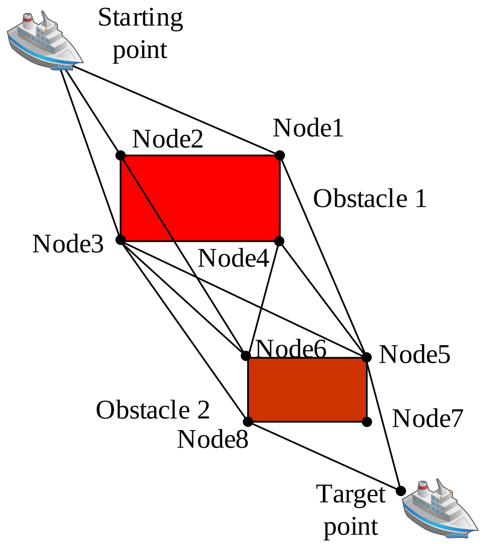


Fig.4 Schematic diagram of path search for ACO+A* algorithm after expanding search nodes

To specifically represent the relationship between the search nodes, search direction and the number of search outer extension layers, the study utilizes Equation (9) for representation.

$$\begin{cases} Q_a = 8 \times \dfrac{a(a+1)}{2} \\ D_a = 8a \end{cases} \tag{9}$$

In Equation (9), a denotes the number of layers added to the outward extended search of the current node. Q_a denotes the value of change in the unsearched nodes as the search layers increases. D_a denotes the value taken with the search direction as the number of search layers increases. On the basis of increasing search nodes, the IACOA is effectively integrated with the A*A so that the hybrid algorithm (HA) can first use the A*A to obtain an initial optimized path that avoids obstacles. Then the convergence speed of P-P in the OA process is improved by setting the pheromone for the initial optimized path. At this point, the setting constants at the initial stage of the algorithm can be expressed by Equation (10).

$$\tau_{ij}(0) = \left(Z \times M_j\right) + k \tag{10}$$

In Equation (10), Z denotes the ratio of the length between two nodes in the search area to the average value of the length of the search range in the area in which it is located. M_j is the node paths that are connected to the outside of the node is removed. k denotes the value of the multiplier of pheromone expansion. Z can be calculated using Equation (11).

$$Z = \frac{d_{ij}}{average \sum_{i,j \in n} d_{ij}} \tag{11}$$

In Equation (11), d_{ij} denotes the distance between the currently located node i and the next node j, and $average \sum_{i,j \in n} d_{ij}$ denotes the average value of the distance between the two points. After completing the pheromone update settings, the HF of the HA also needs to be reset. This helps to improve the SE, adapt to different problem scenarios, enhance the algorithm's generalization ability, and extend its application scope. The reset HF can be expressed by Equation (12).

$$\eta_{ij} = \frac{1}{d_{ij} + h_{jg}} \tag{12}$$

In Equation (12), h_{jg} denotes the value of the movement cost function from the unsearched node j to the target point g during the search process. By summarizing the above research, the OA path combining the A*A with the IACOA is shown in Fig. 5.

4. Performance analysis of ship obstacle avoidance path planning by fusing improved AOC algorithm with A* algorithm

To validate the performance of the HA constructed by the study using ACO and A*As in ship OA, the study uses particle swarm optimization (PSO) and line-of-sight (LOS) as comparison algorithms. The predicted depth magnitude and data magnitude during the path prediction process, as well as the change in depth magnitude before and after using the HA are also used as validation metrics for the performance.

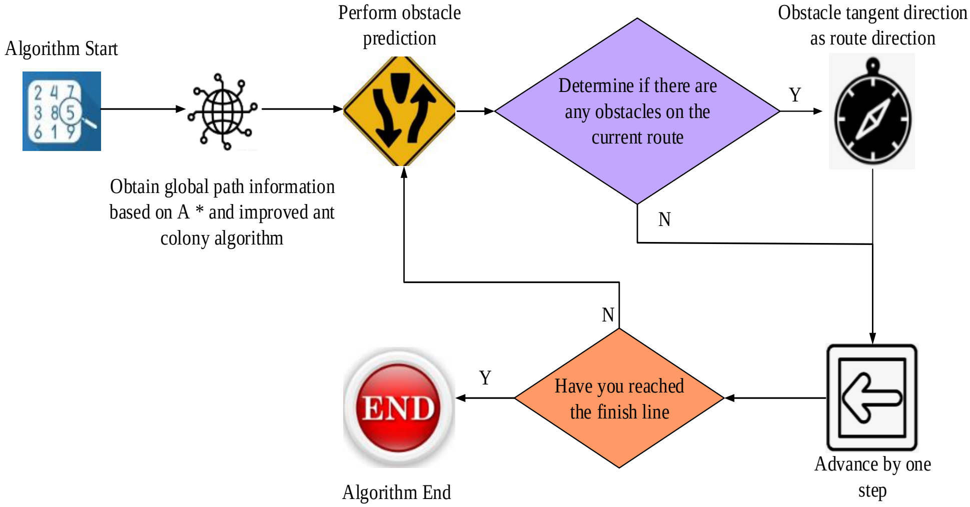


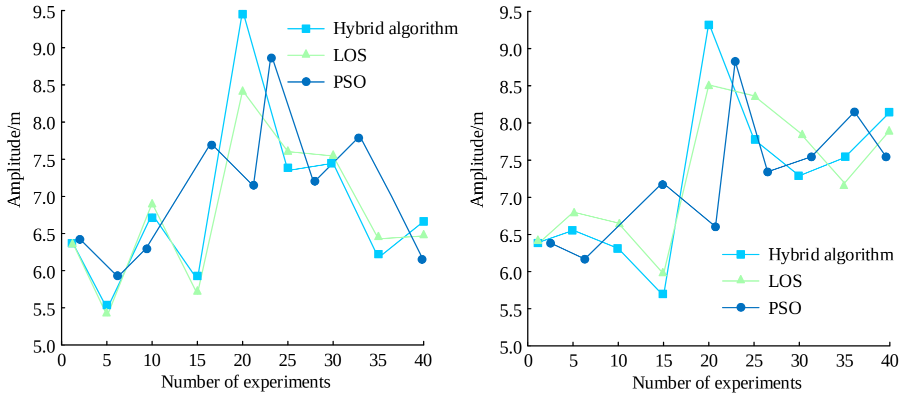
Fig. 5. A flowchart of obstacle avoidance path combining A * algorithm and IACOA

4.1. Performance analysis of HAs for path prediction in ship obstacle avoidance

Simulation experiments are carried out in a 20×20 raster map by the research to validate the performance of the fusion algorithm that fuses the enhanced AOC method with the A*A in ship overall area. The maximum number of iterations is set to 200, and the number of ants is set at 100. The study uses MATLAB software to compare PSO, LOS and HA as a way to verify the performance of HA in ship OA P-P. Meanwhile, the maps in the simulation experiments are set to three different types in MATLAB as simple, moderately complex, and complex, and simulation comparisons are performed using PSO, LOS, and HAs in these three map environments, respectively. The results of the comparison of path prediction depth magnitude and data magnitude are shown in Fig. 6.

Fig. 6(a) shows that the three algorithms have some differences in the prediction of P-P depth amplitude. The maximum and minimum values (Max-MinV) of the depth amplitude of the HA are 9.39 m and 5.37 m. The Max-MinV of the depth amplitude of the LOS algorithm are 8.41 m and 5.38 m. The Max-MinV of the depth amplitude of the PSO algorithm are 8.72 m and 5.91 m. In Fig. 6(b), the three algorithms have significantly larger amplitude values than the LOS algorithm and PSO algorithm in the prediction of the path prediction. prediction is significantly larger than that of LOS algorithm and PSO algorithm. The Max-MinV of the data amplitude of the HA are 9.23 m and 5.68 m. The Max-MinV of the data amplitude of the LOS algorithm are 8.52 m and 5.89 m. The Max-MinV of the data amplitude of the PSO algorithm are 8.65 m and 6.31 m. This indicates that the HA is significantly better at predicting and planning for the depth information of the navigation route, the size information of obstacles, and the depth and size information of the obstacles. More accurate and comprehensive obstacle information can be obtained. The study uses the error of depth magnitude and data magnitude before and after utilizing the HA as an indicator in order to further check the algorithm's inaccuracy in P-P. As shown in Fig. 7 is the result of the error comparison of depth magnitude and data magnitude before and after using the HA.

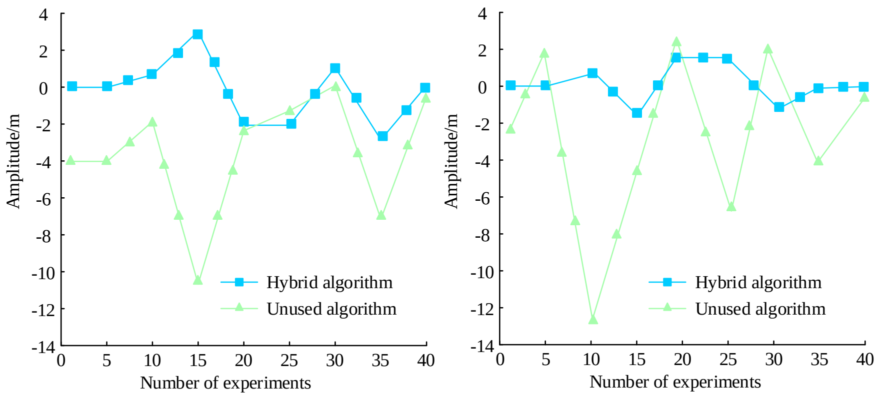
In Fig. 7(a), before using the HA, the error range of the depth magnitude is at [-10.45-2.91]. After using the HA, the error range of depth magnitude is reduced to [-2.46-2.87]. In Fig. 7(b), before using the HA, the error range of the data magnitude is at [-12.91-3.83]. After using the HA, the error range of data magnitude is reduced to [-4.52-2.46]. This shows that the smaller the error range of the magnitude, the stronger the P-P performance of the HA and the higher the accuracy.



(a) Comparison results of depth amplitude for path prediction using three algorithms

(b) Comparison results of amplitude of path prediction data using three algorithms

Fig. 6. Comparison results of path prediction depth amplitude and data amplitude



(a) Comparison results of depth amplitude errors in path planning

(b) Comparison results of amplitude errors in path planning data

Fig. 7. Comparison of errors in depth amplitude and data amplitude before and after using a HA

4.2. Effectiveness analysis of HAs in path planning simulation experiments for avoidance of navigation obstacles

Through simulation experiments on the three algorithms, the study confirms the efficacy and flexibility of the HAs application. MATLAB software is used for this purpose. The map environments used for simulation are set as three different types of simple, medium complexity and complexity in MATLAB, and the three algorithms are simulated and compared in these three map environments respectively. Figure 8 depicts the map environments utilized for the simulation at several degrees of complexity: Fig. 8(a) represents the simple environment, Fig. 8(b) represents the moderately complicated environment, and Fig. 8(c) represents the complex environment.

The SN beginning and finishing points are shown in Fig. 8 by the red square and red triangle grids, respectively. The starting and finishing coordinates of P-P on the map can be independently changed based on how obstacles are distributed throughout the map. As the HA requires more parameters to be set, the interrelationship between the parameters is more complicated. Therefore, several simulations are conducted to determine a set of better parameters, as shown in Table 1.

After the parameter settings are finished, 20 independent repetitions of simulation experiments are carried out in three different types of raster maps, respectively, to assure the accuracy and rigor of the results. The convergence curves and P-P comparison findings of the three methods in the basic environment are shown in Fig. 9.

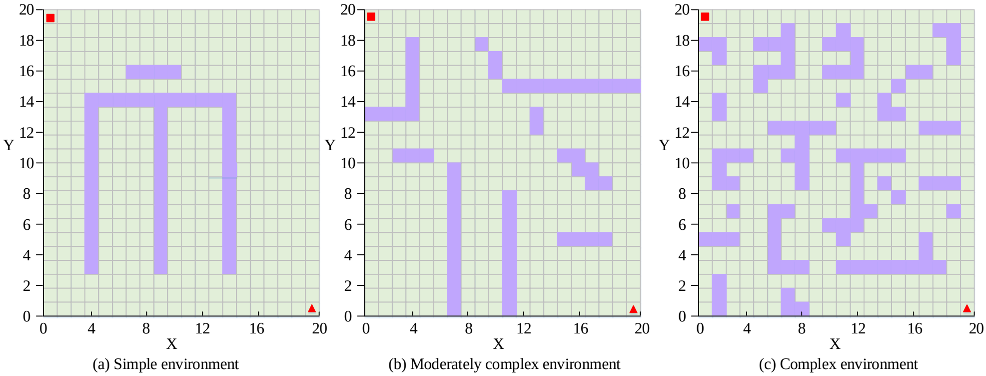


Fig. 8. Simulation maps with different complexities

Table 1 HA experimental parameter table

Parameter	Numerical value
Ant number m	100
Maximum number of iterations n	200
Pheromone factor α	5
Heuristic factor β	5
Total pheromone Q	100

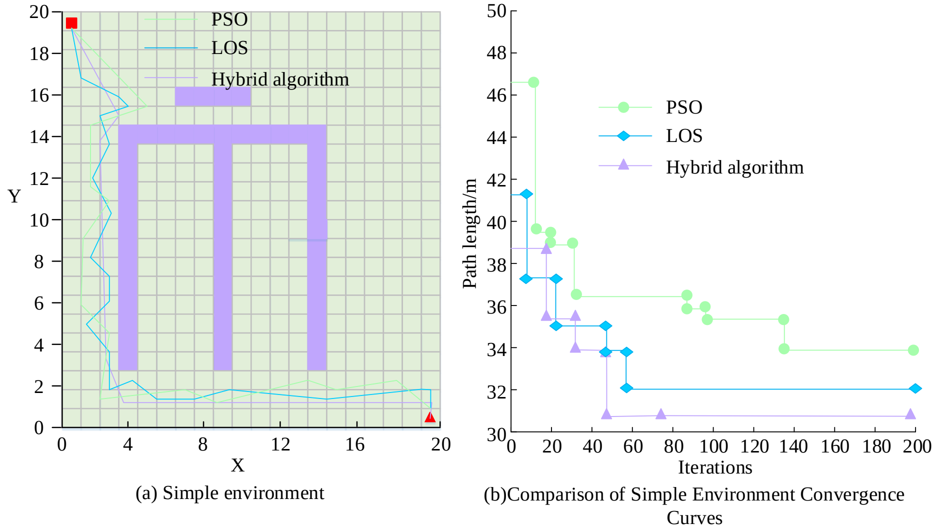
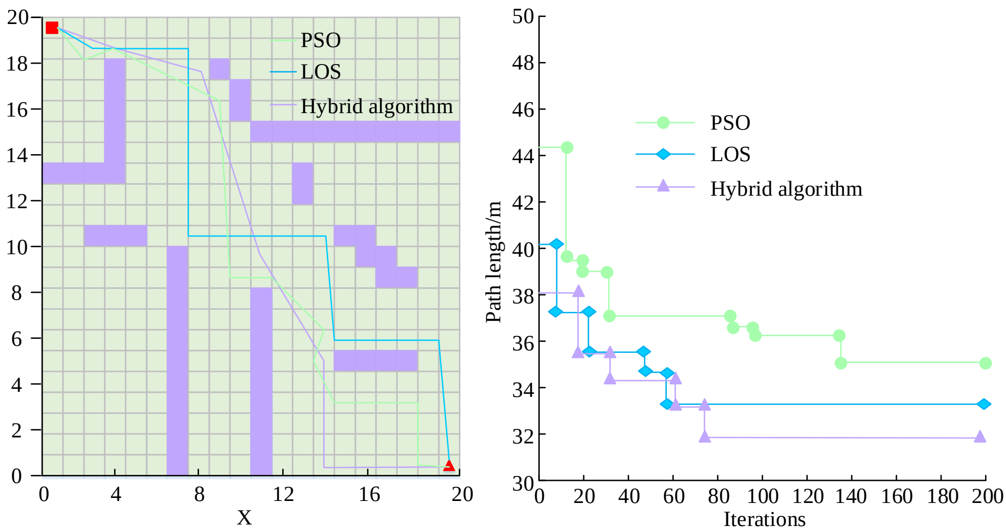


Fig. 9. Comparison results of path planning and convergence curves of three algorithms in a simple environment

From Fig. 9(a), the average path lengths of PSO algorithm, LOS algorithm and HA are 28.6, 26.9 and 23.1, respectively. The HA shortens the paths by 3.8, 5.5 compared to LOS and PSO algorithms. From Fig. 9(b), the average number of iterations of PSO algorithm, LOS algorithm and HA are 80.3, 62.8 and 49.6, respectively. This shows that, in comparison to the LOS and PSO algorithms, the average number of iterations of the PSO, LOS, and HA algorithms is 13.2, 30.7, and the number of iterations of the HA algorithm is decreased by 13.2, 30.7. This suggests that in a basic navigation context, the HA can greatly enhance the performance of SN OA. Fig. 10 displays the convergence curves and P-P comparison findings for the three algorithms in a moderately complicated environment.

In Fig. 10(a), the average path lengths of PSO, LOS and HAs in moderately complex environments are 29.67, 27.09 and 23.16, respectively. The HA reduces the average path lengths by 6.51 and 3.93 compared to PSO and LOS, respectively. The average PSO, LOS, and HA iterations is 129.5, 92.7, and 75.1, respectively, as indicated in Fig. 10(b). In comparison to the PSO and LOS stages, the HA iterations is lowered by 54.4 and 17.6, respectively. Fig. 11 displays the convergence curves and compared P-P outcomes of the three algorithms in a complicated setting.

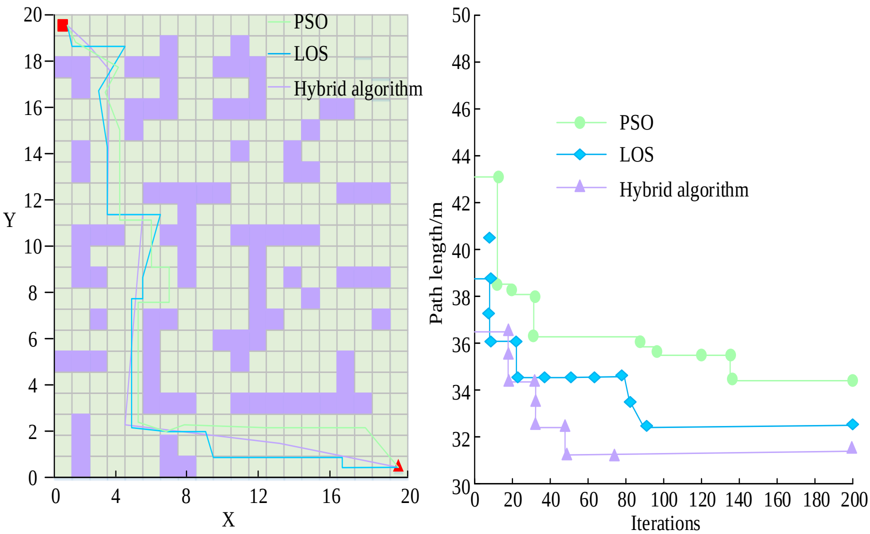
From Fig. 11(a), the average path lengths of PSO, LOS and HAs in complex environments are 41.6, 38.3 and 25.9. The HA reduces the average path lengths by 15.7 and 12.4 compared to the PSO and LOS phases. From Fig. 11(b), the average number of iterations of PSO, LOS and HAs are 119.5, 92.7 and 70.5. The iterations of the HA are reduced by 49 and 22.2 compared to the PSO and LOS phases, respectively. It is found that all the three algorithms are able to plan an OA path from the start to the end of the ANO path in simple, moderately complex and complex environments. However, the HA does not blindly conduct path search, and has better search results in the pre iteration period to quickly obtain the global optimal solution and find an Opt-P to avoid obstacles.



(a) Comparison of path planning in moderately complex environments

(b) Comparison of convergence curves in moderately complex environments

Fig. 10. Comparison results of path planning and convergence curves of three algorithms in moderately complex environments



(a) Complex environment

(b) Comparison of convergence curves in complex environments

Fig. 11. Comparison results of path planning and convergence curves of three algorithms in complex environments

5. Conclusions

To address the limitations and risks of traditional OA methods, the study effectively combines the IACOA with the A*A. The combination of the two algorithms can effectively utilize the group intelligence optimization capability of the ACO algorithm and the fast heuristic search strategy of the A*A to achieve a more efficient and accurate OA for SNS. The results indicated that in simple environments, the HA reduced the paths by 3.8 and 5.5, and the iterations of the HA decreased by 13.2 and 30.7 compared to the LOS and PSO algorithms. In moderately complex environments, the HA reduced the average path lengths by 6.51 and 3.93, and the iterations of the HA decreased by 54.4 and 17.6 compared to the PSO and LOS phases, respectively. In complex environments, the HA reduced the average path length by 15.7 and 12.4 and the number of iterations of the HA reduced by 49 and 22.2 compared to PSO and LOS phases, respectively. This suggests that the two algorithms work together to fully utilize the A*A's SE and enhance the ACO algorithm's path optimization capabilities, resulting in an improved and more accurate OA of the SNS. Although the study achieved significant results, there are still some shortcomings. Due to the limited experimental conditions, the study can only verify the performance in a simulated experimental environment, and the next step can be to apply the OA P-P method to actual sailing tests, so as to improve the practicality of the method.

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References

1. Ai, W. Z., Zhu, P. (2020) Navigation ship's drift angle determination method in curved channel. *Journal of Coastal Research*. 109(SI): 181-184. https://doi.org/10.2112/JCR-SI109-029.1.

2. Chen, G., Wu, T., Zhou, Z. (2021) Research on ship meteorological route based on A-star algorithm. *Mathematical Problems in Engineering*. 21(22): 1-8. https://doi.org/10.1155/2021/9989731.
3. Chen, Y., Bai, G., Zhan, Y., et al. (2021) Path planning and obstacle avoiding of the USV based on improved ACO-APF hybrid algorithm with adaptive early-warning. *IEEE Access*. 9(6): 40728-40742. https://doi.org/10.1109/ACCESS.2021.3062375.
4. Gao, P., Zhou, L., Zhao, X., et al. (2023) Research on ship collision avoidance path planning based on modified potential field ant colony algorithm. *Ocean & Coastal Management*. 235(5): 1-15. https://doi.org/10.1016/j.ocecoaman.2023.106482.
5. Grifoll, M., Borén, C., Castells-Sanabra, M. (2022) A comprehensive ship weather routing system using CMEMS products and A* algorithm. *Ocean Engineering*. 255(4): 1-15. https://doi.org/10.1016/j.oceaneng.2022.111427.
6. He, Y., Li, Z., Mou, J., et al. (2021) Collision-avoidance path planning for multi-ship encounters considering ship manoeuvrability and COLREGs. *Transportation safety and environment*. 3(2): 103-113. https://doi.org/10.1093/tse/tdab004.
7. Islam, A., Othman, F., Sakib, N., et al. (2023) Prevention of shoulder-surfing attack using shifting condition with the digraph substitution rules. *Artificial Intelligence and Applications*. 1(1): 58-68. https://doi.org/10.47852/bonviewAIA2202289.
8. Liang, C., Zhang, X., Han X. (2020) Route planning and track kee control for ships based on the leader-vertex ant colony and nonlinear feedback algorithms. *Applied Ocean Research*. 101(9): 1-18. https://doi.org/10.1016/j.apor.2020.102239.
9. Liao, H., Wang, W., Wang, S., et al. (2020) Multi-scale ship tracking based on maritime monitoring platform. *2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA)*. 15(9): 945-949. https://doi.org/10.1109/ICIEA48937.2020.9248235.
10. Liu, J., Jiang, X., Huang, W., et al. (2022) A novel approach for navigational safety evaluation of inland waterway ships under uncertain environment. *Transportation Safety and Environment*. 4(1): 29-39. https://doi.org/10.1093/tse/tdab029.
11. Liu, Z., Li, Y., Zhang, Z., et al. (2023) Spatial modeling and analysis based on spatial information of the ship encounters for intelligent navigation safety. *Reliability Engineering & System Safety*. 238(10): 1-26. https://doi.org/10.1016/j.ress.2023.109489.
12. Öztürk, Ü., Boz, H. A., Balcisoy, S. (2021) Visual analytic based ship collision probability modeling for ship navigation safety. *Expert Systems with Applications*. 175(8): 1-17. https://doi.org/10.1016/j.eswa.2021.114755.
13. Wang, A., Zhi, P., Zhu, W., et al. (2021) Path planning of unmanned surface vehicle based on a algorithm optimization considering the influence of risk factors. *2021 4th IEEE International Conference on Industrial Cyber-Physical Systems (ICPS)*. 4(9): 810-815. https://doi.org/10.1109/ICPS49255.2021.9468142.
14. Wei, Y. (2020) Design of ship navigation trajectory analysis and application system based on image processing technology. *Journal of Coastal Research*. 115(SI): 211-213. https://doi.org/10.2112/JCR-SI115-066.1.
15. Yin, J. K., Fu, W. P. (2021) A safety navigation method for integrating global path planning and local obstacle avoidance for self-driving cars in a dynamic environment. *Scientia Iranica*. 28(3): 1318-1328. https://doi.org/10.24200/SCI.2020.52417.2704.
16. Yu, H., Murray, A. T., Fang, Z., et al. (2021) Ship path optimization that accounts for geographical traffic characteristics to increase maritime port safety. *IEEE Transactions on Intelligent Transportation Systems*. 23(6): 5765-5776. https://doi.org/10.1109/TITS.2021.3057907.
17. Yu, J., Hou, J., Chen, G. (2020) Improved safety-first A-star algorithm for autonomous vehicles. *2020 5th International Conference on Advanced Robotics and Mechatronics (ICARM)*. 5(9): 706-710. https://doi.org/10.1109/ICARM49381.2020.9195318.
18. Yuan, M., Shi, H. (2021) An ant colony algorithm model for UAV sense and avoid based on ADS-B. *Journal of Northwestern Polytechnical*. 39(4): 761-769. https://doi.org/10.1051/jnwpu/20213940761.

19. Zhang, G., Wang, H., Zhao, W., et al. (2021) Application of improved multi-objective ant colony optimization algorithm in ship weather routing. *Journal of Ocean University of China*. 20(1): 45-55. https://doi.org/10.1007/s11802-021-4436-6.
20. Zhang, L., Zhang, Y., Zeng, M., et al. (2021) Robot navigation based on improved A* algorithm in dynamic environment. *Assembly Automation*. 41(4): 419-430. https://doi.org/10.1108/AA-07-2020-0095.
21. Zhang, X., Wang, J., Chen, Y., et al. (2020) Density-weighted ant colony algorithm for ship trajectory reconstruction. *International Journal of Shipping and Transport Logistics*. 12(1-2): 19-38. https://doi.org/10.1504/IJSTL.2020.105851.