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Ship path planning based on improved multi-scale A* algorithm of collision risk function

Chunyu Song, Teer Guo & Jianghua Sui

To improve the safety of ship navigation in complex sea areas and reduce planning time while achieving optimal path planning. The paper proposes an improved A* algorithm that incorporates ship collision risk assessment. The paper utilizes multi-scale raster maps to divide the sea chart in the context of complex sea areas, and combines the Line-of-sight (LOS) algorithm to solve the zigzag paths that may appear in this planning context. Moreover, in order to improve the efficiency of optimal path planning in the context of complex sea areas while ensuring path safety, the paper proposes a collision risk function to optimize the determination of the cost of A* algorithm nodes, thereby enhancing the heuristic function of the A* algorithm. The improved A* algorithm can consider both path length and collision risk to plan the optimal path and to enhance the overall quality of the planning results. To verify the advantages of the improved algorithm proposed in the paper, the Zhoushan Islands sea area with complex environment is selected as the planning background for simulation study. The results show that the improved algorithm with the introduction of the collision risk function reduces the path planning time, the number of expanded nodes, and the path length by 30%, 11%, and 5.8%, respectively, compared with the original algorithm, which can effectively reduce the computational burden of the algorithm. This study provides a relatively complete and scientific route planning strategy for the study of the safe navigation of smart ships in complex sea areas.

Keywords Optimal path planning, Improved A* algorithm, Collision risk function, Multi-scale nautical charts, Safety of navigation in complex sea areas

Nowadays, the development and application of intelligent ships is a field of considerable scope and potential. The study of intelligent ship technology has also become the focus of researchers. Moreover, as a pivotal technology in the domain of intelligent ships, the ship's path planning task has been a subject of intense scrutiny and investigation by numerous scholars[1]. The path planning task of the intelligent ship refers to the given starting point and end point of the ship. Make it find a suitable path that is safe to navigate, least time-consuming, and shortest distance under the constraints of the specified sea environment[2]. The core of path planning control is the selection of algorithms, and the commonly used path planning algorithms in the academic field include the artificial potential field (APF), model predictive control algorithms, deep learning algorithms, ant colony algorithm, Dijkstra's algorithm, and A* algorithm, etc. Bayat[3] aims at the mobile robot path planning problem in the presence of scattered obstacles, and constructs a synthetic potential field by the APF method to plan the optimal path to avoid the specified region. Wang[4] proposes an improved artificial potential field for the local minimum problem of the traditional artificial potential field method, and then designs the collision avoidance path for wave gliders. The above path planning algorithm can plan a smoother path and the algorithm is simple and robust, which facilitates the underlying real-time control. However, such methods suffer from the disadvantage of local optimization and the path planning effect depends on the gravitational field design.

Traditional path planning algorithms can effectively deal with local planning to avoid collisions, but still have limitations for global path planning tasks. And the research on path planning based on artificial intelligence (AI) provides new ideas for global intelligent obstacle avoidance and trajectory tracking control of ships. Lyridis[5] designed an improved fuzzy ant colony optimization algorithm to deal with path planning in dynamic environments, focusing on the movement of unmanned surface vessels (USVs) in complex environments that require multi-objective optimization and multi-modal constraints. Hsu[6] proposed an improved ant colony system algorithm to improve the global search capability for the problem of local path optimization in traditional path planning algorithms. Moreover, deep learning is a prominent algorithmic approach in the domain of AI-based path planning. It entails the utilization of neural networks to discern the intrinsic principles governing the

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behavior of path samples, thereby facilitating the generation of viable trajectories for maritime vessels. Wu[7] used convolutional neural networks and residual units to design a deep learning prediction algorithm and proposed a gridded path planning method by acquiring spatial-temporal characteristics of vehicular traffic. Gao[8] optimized the reward function, mesh structure, and observation state for the path planning problem of deep learning robots to achieve path planning for three-dimensional scenes. Guo[9] proposed an autonomous path planning model based on deep reinforcement learning, which effectively realizes intelligent path planning for USVs in unknown environments through deep learning algorithms. Above studies are conducted based on AI, which can adapt to the needs of environments with different levels of complexity and simple evaluation strategies. But there is the problem of overestimation due to excessive data volume and storage consumption as well.

The geometric model-based path planning algorithm is most popular and used by the scholars in path planning study nowadays. Unlike traditional path planning algorithms as well as AI-based path planning algorithms, these algorithms respond quickly to the environment and search for paths in a simple and straightforward manner. Deng[10] proposed a generalized Dijkstra's algorithm to solve the shortest path problem and improved it by fuzzy numerical mean integration for different traffic environments. Wang[11] proposed a three-dimensional Dijkstra optimization algorithm, which can effectively achieve the optimal path planning under non-rough sea conditions, and realize multi-objective voyage optimization. The above algorithm is simple to apply, but it also suffers from the disadvantages of many extended nodes and low search efficiency. The emergence of the A* algorithm effectively solves this problem, and the A* algorithm was first proposed by Peter Hart in 1968 based on Dijkstra's algorithm[12]. It retains the advantages of Dijkstra's algorithm and reduces the number of expansion nodes. Since the emergence of the A* algorithm, many scholars have continuously improved it to make its function increasingly perfect, and its application scenarios are also wider. Liu[13] solves the planning problem of smooth paths for robots by combining the A* algorithm, APF method, and the least squares algorithm, to avoid the planning algorithm from falling into the dilemma of local optimality. He[14] introduced the dynamic window method to improve the A* algorithm for the problems of low search efficiency, uneven paths, and inability to adapt to unknown environments. It makes the local part follow the global part and realizes the fusion of the two algorithms to meet the complex planning task. The above studies realized global path planning by combining the A* algorithm with the rest of the algorithms, while more scholars tried to improve the algorithm itself. Zhang[15] improved the heuristic function of the A* algorithm for the problem that the planning path of the A* algorithm contains unnecessary turning points and not smooth enough. Tang[16] considers the reliability of UAV flights in urban environments, introduces obstacle risk, death risk, and property loss risk to improve the A* algorithm, and designs a min-cost A* algorithm based on urban risk assessment.

Motivated by the above discussion, the authors introduce an innovative collision function into the improved A* algorithm, which is used for optimal path planning research in the context of stationary obstacles including land, reefs and shallow water areas. The traditional A* algorithm only considers the path length for node cost determination. However, when facing the scenario of many obstacles and dense distribution in the chart, it may lead to the wrong determination of the optimal path and has the limitations of long planning time and heavy computational burden. The introduction of the collision function ensures that the path is optimal, while considering the path length and collision risk relationship, which in turn guarantee the navigation safety and reduce the planning time. Meanwhile, the designed collision function architecture is simplified to reduce the computational burden of the algorithm. The main contributions of this paper are reflected in the following areas:

1. Multi-scale nautical charts are created to solve the problem of the equal-scale raster chart generating too many nodes in complex environmental waters, thereby increasing the computational burden of the algorithm.
2. Using multi-scale A* functions and constraining the curvature of paths with Bezier curves, thereby solving the problem of the zigzag path that occurs with the traditional A* function in the context of multi-scale nautical charts.
3. Analyzing the collision risk of ship navigation while introducing collision risk weight factor to design the collision function to further optimize the decision rule of node cost of A* algorithm. This addresses the issue of collision risk during optimal path planning in complex marine environments.

The remainder of this work was organized as follows: The second section presents an analysis of the principle of multi-scale nautical charts and introduces the concept of multi-scale connectivity charts in the context of the Zhoushan Islands. In "Path planning based on multi-scale A* algorithm" section, optimal path planning is conducted based on the established multi-scale nautical charts. To address the issue of zigzag planning paths under multi-scale nautical charts, a multi-scale A* algorithm is developed. In "Path planning with multiscale A* algorithms considering collision risks" section, a collision risk function is designed to further improve the multi-scale A* algorithm, and the basic indexes of the three A* algorithms are compared and analyzed. "Discussions" section contains a discussion and analysis of the full text of the work. "Conclusions" section concludes the entire work.

Establishment of multi-scale nautical charts

The scenario set up in this paper is the path planning of a ship traversing a complex sea area. Since there are many islands and reefs in the complex sea and densely distributed, the path planning needs to be carefully delineated on the charts to ensure the safety of navigation. Based on this condition, the authors apply the finite-depth quadtree algorithm for the segmentation of the chart. Compared with ordinary quadtree algorithms, finite-depth quadtrees provide flexible rasterized segmentation of charts by analyzing the obstacles present in the charts[17,18]. Consider the location and size of obstacles in the divided raster. If regions with dense distribution of obstacles, perform small raster divisions. And if the regions are without obstacles or the distribution of obstacles is sparse, perform a large raster division. Schematic diagram of a finite-depth quadtree structure is in Fig. 1.

When rasterizing a nautical chart, it is usually desired that each raster region be in the smallest possible size to improve the representativeness of regional nodes. However, too dense nodes will bring great difficulties to the algorithm calculation, so multi-scale nautical charts are used to divide the region to solve the problem[19]. The authors selected the sea area of Zhoushan Islands, Zhejiang Province, China, as the background of path planning for simulation verification, and its chart area is shown in Fig. 2.

As shown in Fig. 2, the selected Zhoushan Islands sea area has a more complex nautical chart environment, with both the relatively open area and the area of dense islands with a high risk of passage. The region is rasterized at multiple scales, taking the maximum division depth as 8 layers, and the rasterized multi-scale connectivity map is shown in Fig. 3.

The selection criteria for the obstacle area in this study are land and reef areas that are prone to collisions and shallow water areas prone to aground. The blue curve in the figure represents the obstacle edge, the contained area is defined as the obstacle region, and its contained nodes are all non-navigable obstacle nodes. The construction of multi-scale nautical charts with a maximum depth of 8 layers lays a feasible foundation for the optimal path planning task in a complex harbors' environment.

Remark 1 The authors construct multi-scale nautical charts with a maximum depth of 8 layers. The small-scale raster division of the dense obstacle distribution region and the large-scale raster division of the sparse obstacle region effectively reduce the computational load of the algorithm.

Path planning based on multi-scale A* algorithm

The traditional A* algorithm determines the optimal child node based on the move cost which can be expressed by Eq. (1). $g\left(S\right)$is the cost of the move corresponding to moving from the starting point to the intermediate point S, and $h\left(S\right)$ is the heuristic cost of moving from the intermediate point S to the end point[20].

$$F\left(S\right)=g\left(S\right)+h\left(S\right) \tag{1}$$

The application of A* algorithm for path planning is based on analyzing the connection relationship between nodes[20], thus it is not only applicable to uniform raster division, but also applicable to non-uniform raster division. However, uneven grids will likely result in different sizes between neighboring raster compared to uniform grids. Thus, applying the traditional A* algorithm to connect the center points of each mesh will lead to the appearance of extra zigzag paths, resulting in unnecessary resource loss and possible safety hazards at the same time. In the previous section, the authors used a corner of Zhoushan Islands to build a multi-scale raster map as shown in Fig. 3 to assist planning. It is proposed to set the starting point of the ship's path as (1650, 2500) and the end point as (5400, 600) to carry out the study of optimal path planning for ships crossing the complex sea area. The optimal path planning under the application of the traditional A* algorithm is shown in Fig. 4.

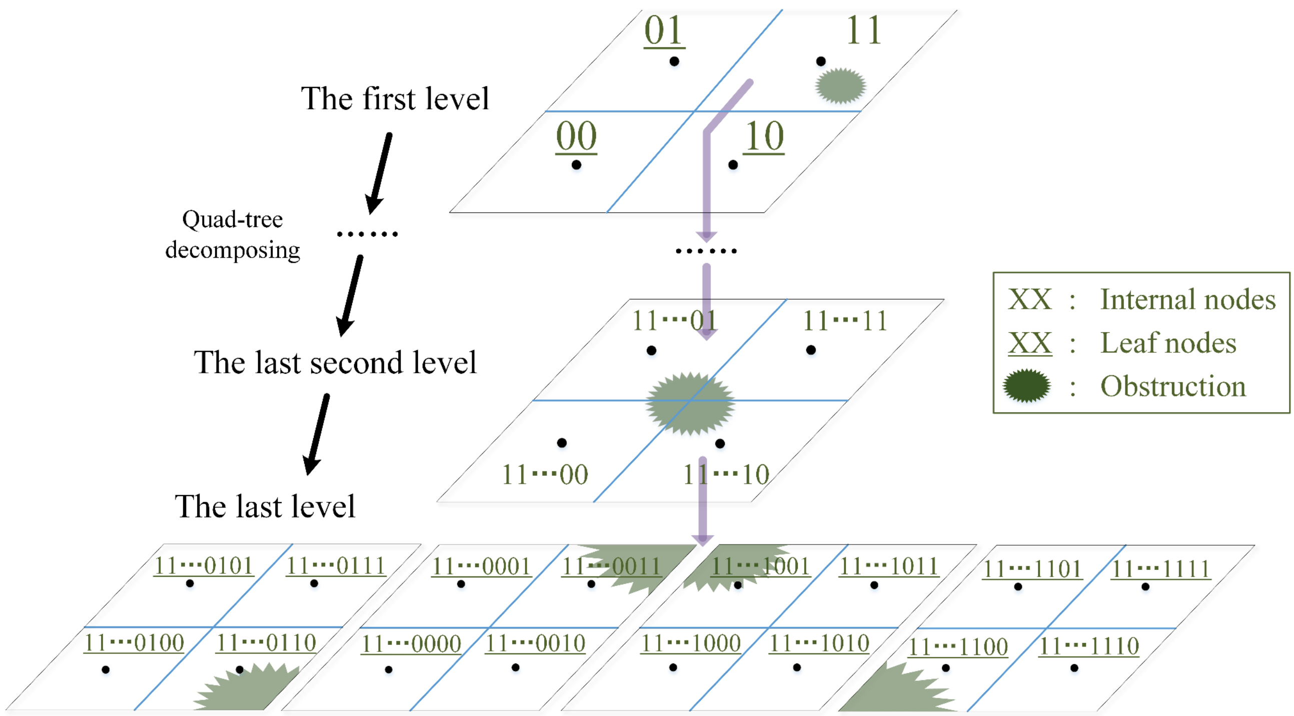

Fig. 1. Schematic diagram of finite-depth quadtree structure.

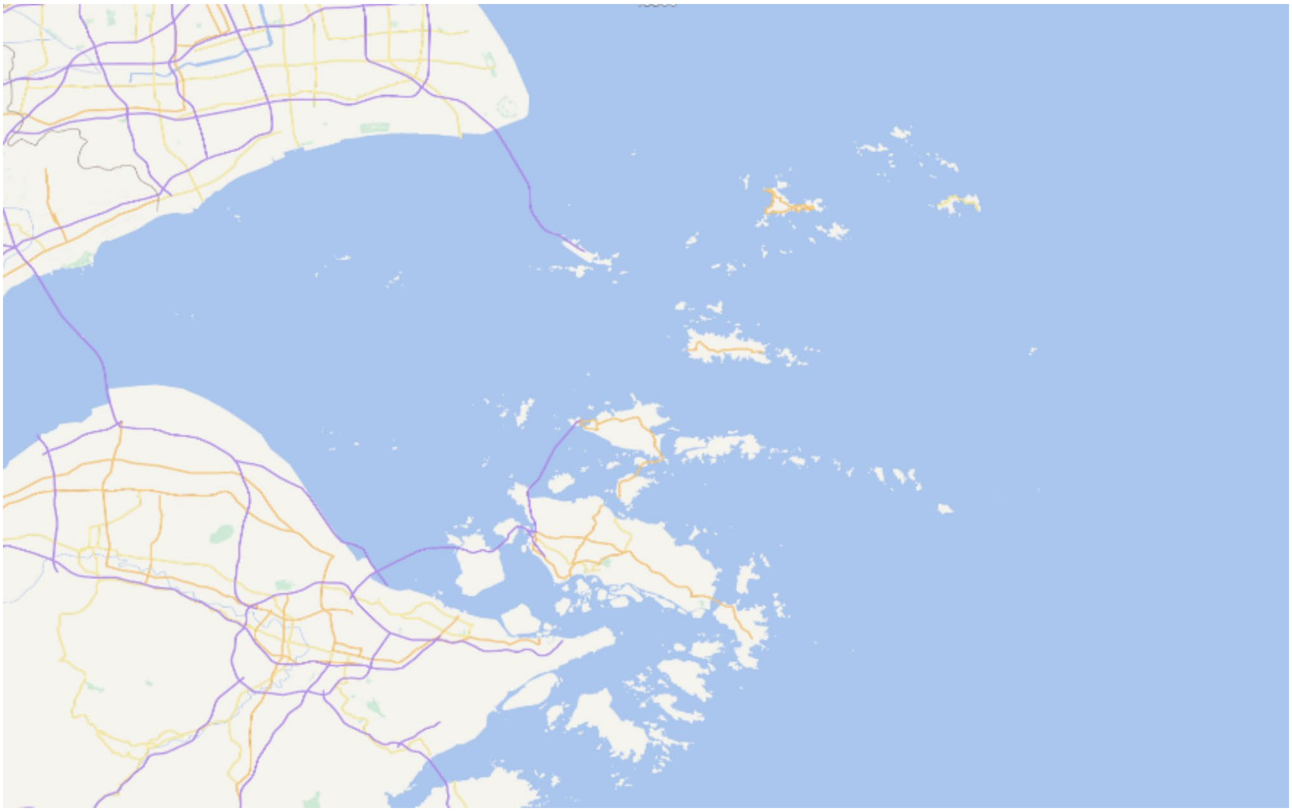

Fig. 2. A part of Zhoushan Islands simulation planning nautical chart background (The chart is cited on the Chart Online website, Copyright © 2010–2024 www.enclive.cn. Edited and modified in software MATLAB R2021b, © 1994–2024 The MathWorks, Inc., https://ww2.mathworks.cn/).

In Fig. 4, the simulation results show that the traditional A* algorithm plans the path by strictly traversing each expanded node on the optimal path, and the raster scale is not uniformly divided, so the planned path is dominated by zigzag lines. To solve this problem, the authors improve the traditional A* algorithm to be applicable to multi-scale nautical charts. By constructing a point node region near the current node, building search points around the edges of the region and searching neighboring regions. The neighbor nodes can be found in multi-scale nautical charts by deleting duplicate entries.

It is typically assumed that "path validity" between two nodes signifies that the connecting lines do not traverse the region encompassed by the obstructing node. However, the detection of a straight line is challenging to achieve within the program. In accordance with the LOS method, an improvement method is to use a series of continuous detection points on the LOS instead of the LOS itself. Furthermore, the LOS of the forward path can be discretized with a smaller step size $L$and the points after discretization are called detection points. If the detection point is within the same grid as the obstacle divided, the detection point is at risk of collision and is defined as a risk node, and the path can be judged to be obstructed. Find non-risk nodes and analyze the parents of their neighboring nodes, if unobstructed, assign the current node's parent node as the parent node of the adjacent nodes, and the process is repeated until the end[21]. The improved scheme of the multi-scale A* algorithm is shown in Fig. 5.

In addition, in order to make the path more consistent with the ship kinematics, the curvature constraints of the path are imposed by Bezier curves, which makes the planned path smoother in the turns[22,23]. The optimal path planning applying the multi-scale A* algorithm is shown in Fig. 6.

As shown in Fig. 6, the improved multi-scale A* algorithm effectively solves the problem of zigzag path planning. Under the curvature constraint, the planned path is smoother and more consistent with the actual ship trajectory. Combined with Figs. 4 and 6, the actual performance indexes of planning paths after the A* algorithm improvement are compared. Comprehensive analysis of the planning path lengths, planning times and the number of expanded nodes before and after the algorithm improvement is shown in Table 1.

Analyzing the performance indexes shown in Table 1, compared with the traditional A* algorithm, the multi-scale A* algorithm has an increased planning time, but its planning path length and the number of expanded nodes has been significantly improved. In addition, compared with the path planned by the traditional A* algorithm, the path planned by the multi-scale A* algorithm is smoother and more consistent with the actual path, thus making it the optimal path. Furthermore, it can be concluded that the evaluation criteria for the "optimal path" in this paper is: a path with improved path length and node number indicators while ensuring safety and conforming to the actual movement trajectory of the ship.

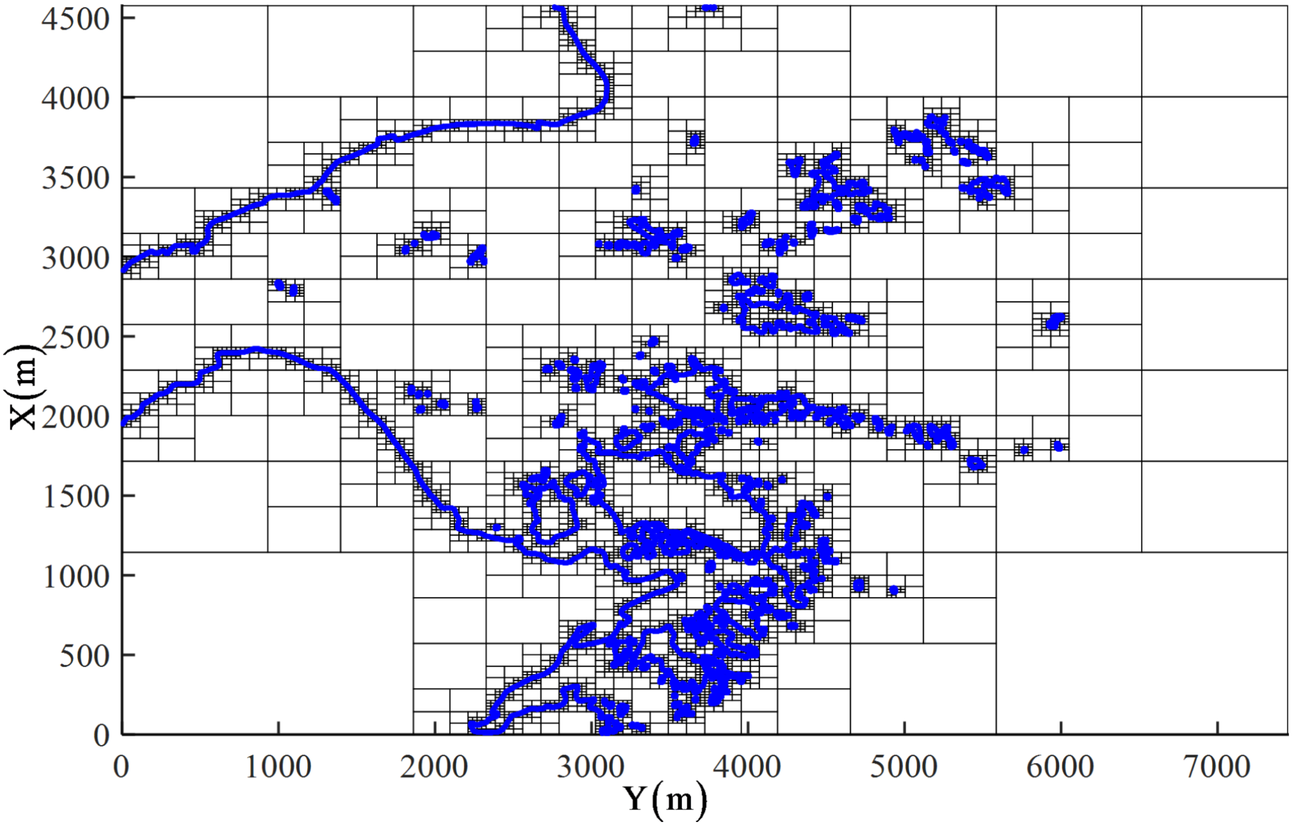

Fig. 3. Multi-scale connectivity map of Zhoushan Islands (maximum depth of 8 layers) (The chart is cited on the Chart Online website, Copyright © 2010–2024 www.enclive.cn. Edited and modified in software MATLAB R2021b, © 1994–2024 The MathWorks, Inc., https://ww2.mathworks.cn/).

Remark 2 The authors design a multi-scale improvement strategy to improve the traditional A* algorithm to solve the "zigzag path" phenomenon of the traditional algorithm under multi-scale nautical charts, so that the planned path is more consistent with the actual ship trajectory.

Path planning with multiscale A* algorithms considering collision risks

In the previous study, the authors applied the LOS algorithm as well as Bezier curves to improve the traditional A* algorithm. Then, the optimal path planning scenario of a ship crossing the sea area of Zhoushan Islands is considered, and the simulation effect is relatively well. In this section the authors will further improve the algorithm based on the multi-scale A* algorithm, introducing the collision risk function to design the A* algorithm. Chapter 3 mentioned that the A* algorithm determines the optimal child node based on a performance index. The performance metric refers to the total move cost $F(S)$ of the A* algorithm, which is determined by considering only the path length. The risk of ship collision is higher in more complex environments, that there are some limitations in determining the cost of movement by path length only[24,25].

To optimize the performance index and thus the strategy for determining the optimal child node, the authors optimize the heuristic cost of moving the current node to the end point. The detailed idea is to introduce collision risk weight factors and calculate the collision risk performance index of each expanded node by designing a collision risk function, which is combined into a heuristic function. The high collision risk weight factor of this node indicates its high collision risk, after which the node is discarded[26]. Conversely, it indicates that the node has a low risk of collision and can be included in the OPEN-List for subsequent planning tasks. At this point in the A* algorithm the path length and collision risk are combined when evaluating nodes by node cost. By adjusting the collision risk weight factor, the level of influence of collision risk on path planning can be controlled, thus obtaining both safe and efficient path planning results.

Design of collision risk function

Define the collision risk cost function $L(S)$, which is used to measure the collision risk in the path from the current node to the end point, the collision risk cost function is shown in Eq. (2).

$$L(S) = \varepsilon(S) + \lambda \sum_{n_i \in N(S)} \varepsilon(n_i) \tag{2}$$

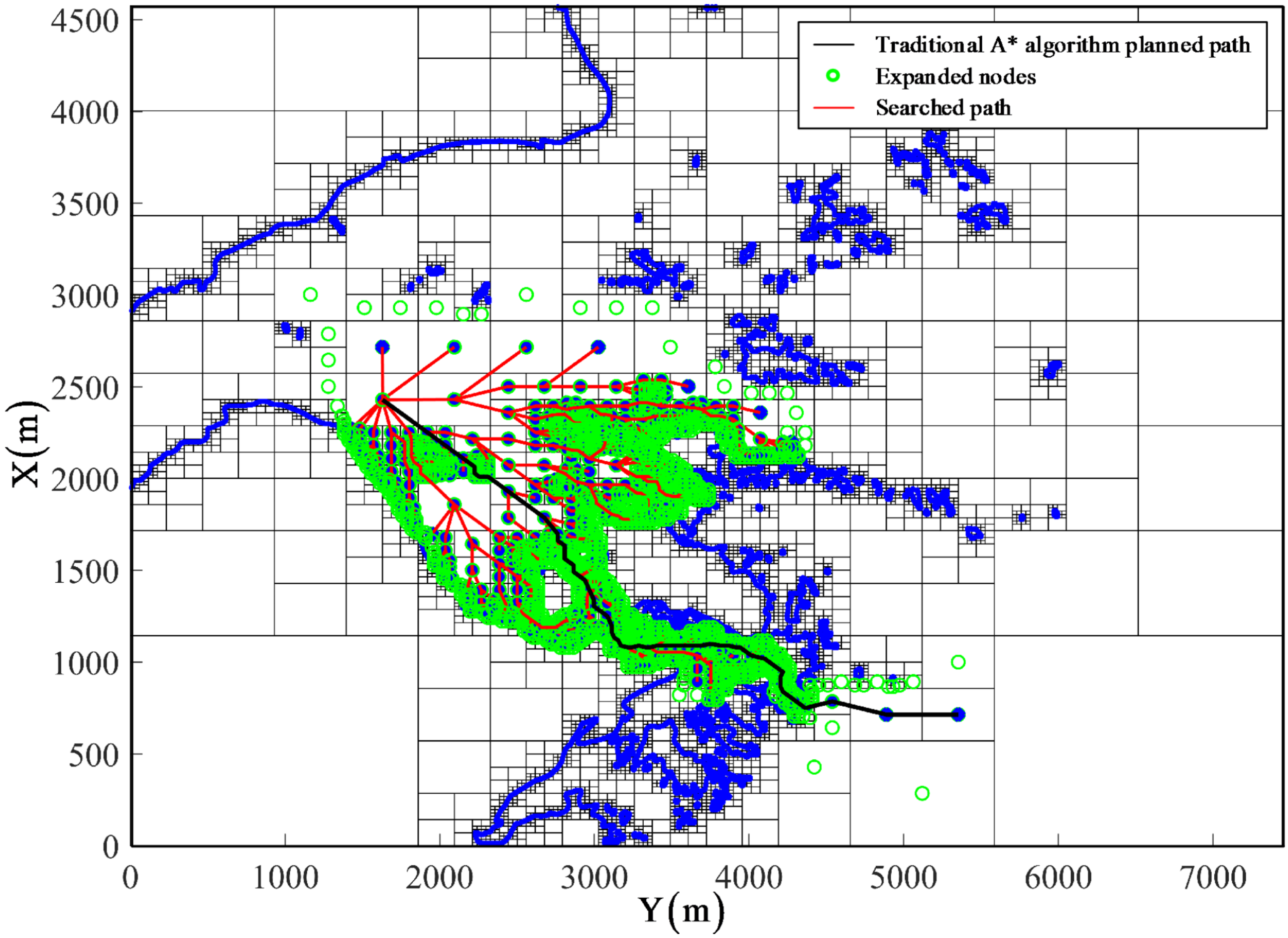

Fig. 4. Optimal path planning in Zhoushan islands under traditional A* algorithm.

where $\varepsilon(S)$ is risk weight for the current node. It is determined by the distance of such node from the obstacle, the closer it is to the obstacle the higher its risk and conversely the lower it is. $N(S)$ is the set of neighbor nodes n_i of the current node, $\varepsilon(n_i)$ is risk weights for neighbor nodes. The regulation parameter λ is determined by the contribution of the risk value of the neighbor node of this node to the total risk of the global path planning. In this study, the closer the area to an obstacle, the denser the grid division. Therefore, if there is an obstacle around the current node, the number of its neighbor nodes is relatively large, and the adjustment parameter is increased accordingly. On the contrary, if the current node is in open water, the grid division is sparse, the number of neighbor nodes is small, the risk of collision is low, and the adjustment parameter is reduced.

As the path planning progresses, the closer to the obstacle node, the greater the risk of collision. Since there are irregularly shaped obstacles, the risk near the obstacle node increases exponentially. The collision risk weight factor can be approximated by Eq. (3).

$$\varepsilon(N) = \mathrm{e}^{\frac{1}{r}} - 1 \tag{3}$$

where e is the natural constant, *r* represents the distance between node N and the neighboring obstacle node, as shown in Fig. 7. If there is an obstacle in the divided grid, the center of the grid is the obstacle node. Therefore, the closer to the obstacle node, the higher the risk of collision, and there is even a situation where the current node has already collided with the obstacle before it has even approached the obstacle node, so the risk weight factor of the current node grows rapidly as *r* decreases.

Combining the designed collision risk cost function with the traditional heuristic function results in a comprehensive heuristic function that considers collision risk and path length is shown in Eq. (4), and the move cost of the A* algorithm can be expressed by Eq. (5).

$$h'(S) = h(S) + \omega \cdot L(S) \tag{4}$$

$$F'(S) = g(S) + h'(S) \tag{5}$$

The weight parameter ω is determined by the weight between the current node path length and the collision risk weight factor. The collision risk weight factor is increased in areas with dense obstacles and decreased in areas

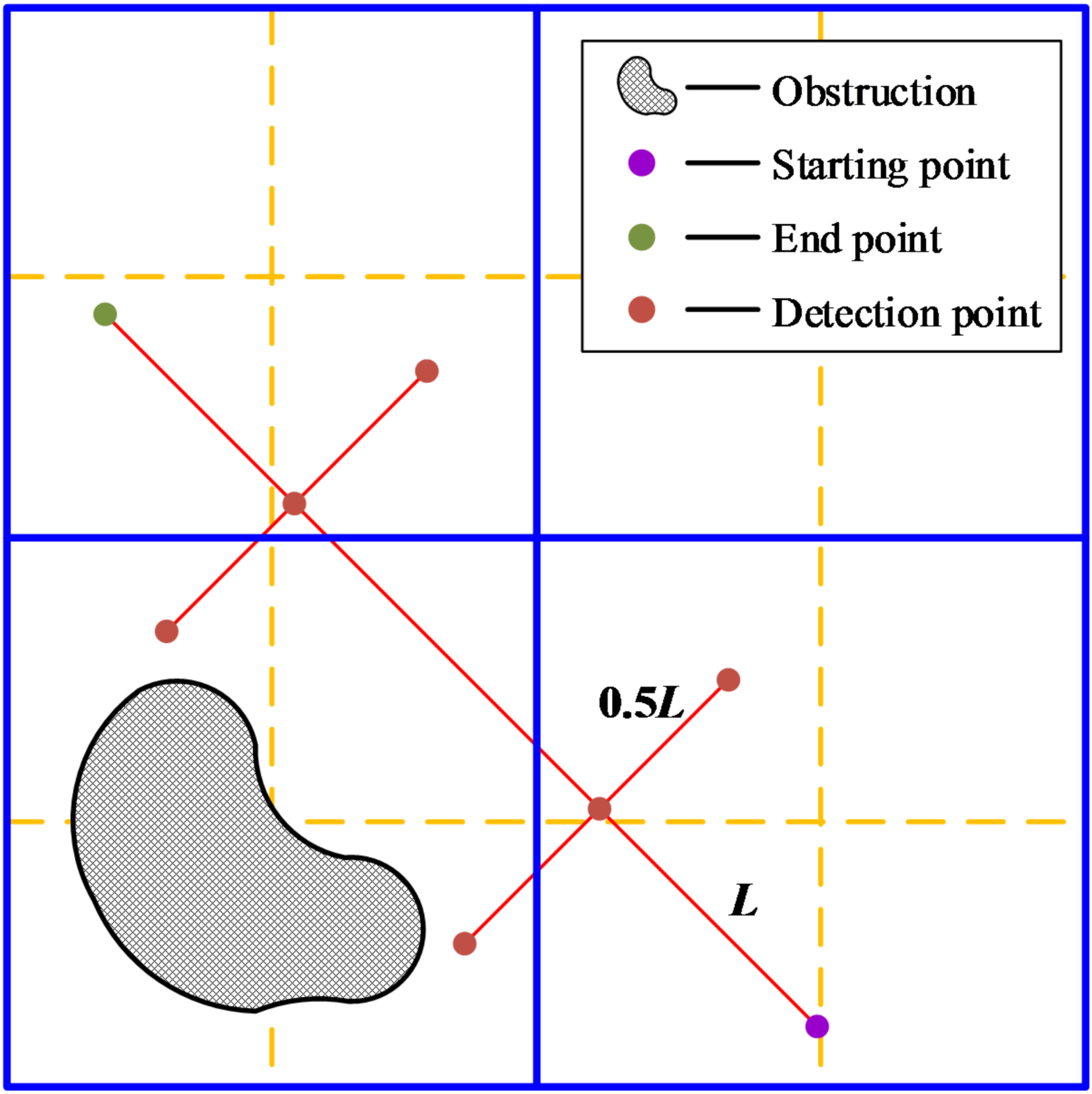

Fig. 5. Multi-scale A* algorithm improvement scheme.

with fewer obstacles. The overall technology roadmap of the A* algorithm considering collision risk is shown in Fig. 8, and the algorithm flowchart is shown in Fig. 9.

Path planning considering collision risk

After adding the effect of collision risk to the multi-scale A* algorithm, the same simulation conditions are selected for the simulation to verify the advantage of the improved algorithm over the original algorithm. Still taking the Zhoushan Islands as the planning background for the path planning study. It is proposed to set the starting point of the ship's path as (1650, 2500) and the end point as (5400, 600)to carry out the study of optimal path planning for ships crossing the complex sea area. The optimal path under the planning of the A* algorithm considering collision risk is in Fig. 10.

In the multiscale A* algorithm, the node cost considers only the path lengths. However, in the A* algorithm with collision risk weight factors, the collision risk cost can be added to the path length cost to form the total cost of the node. This time, the search process prioritizes low-risk nodes and produces paths with lower collision risk. Compared to the multi-scale A* algorithm mentioned in "Path planning based on multi-scale A* algorithm" section, the A* algorithm considering collision risk has a more significant improvement in terms of planning

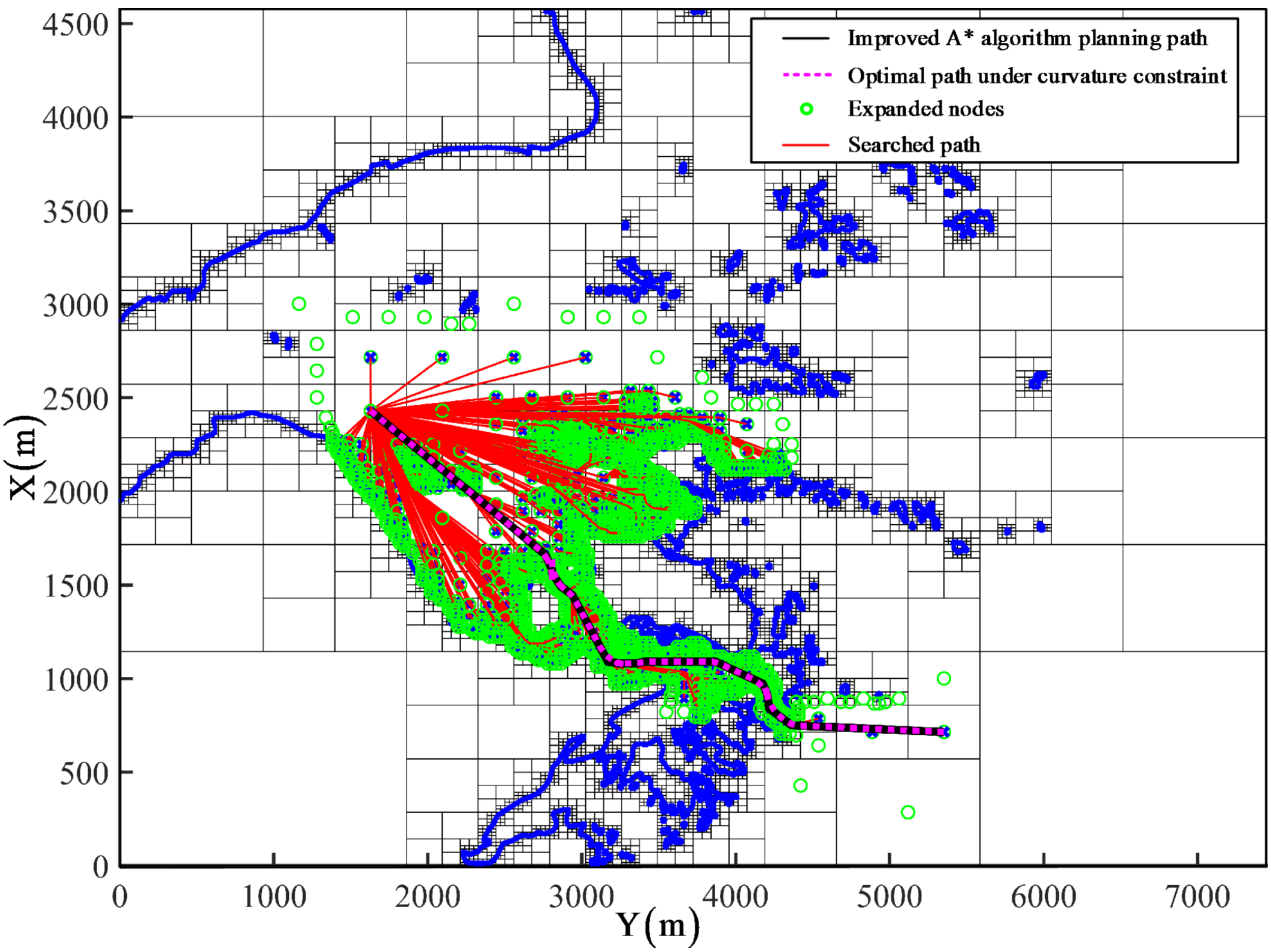

Fig. 6. Optimal path planning for Zhoushan Islands under multi-scale A* algorithm.

	Traditional A* algorithm	Multi-scale A* algorithm
Planning path lengths (m)	4457.404	4205.433
Planning times (s)	57.468	98.763
Number of nodes (pcs)	8053	7942
Optimal paths	No	Yes

Table 1. Comparison of performance indexes of A* algorithm before and after improvement.

path lengths, planning times, and number of expanded nodes. The comparison of the actual performance indexes of the algorithms is in Table 2.

Comparative analysis of Figs. 6 and 10, and Table 2 shows that the A* algorithm considering collision risk reduces the path length by 5.8% compared to the original algorithm, and reduces the planning time and the number of expanded nodes by 30% and 11% compared to the multi-scale A* algorithm, respectively. The multi-scale A* algorithm and the A* algorithm considering the collision risk both guarantee the "optimal path" of the path planning algorithm, thereby achieving optimal path planning and similar planning path lengths. However, the A* algorithm considering collision risk exhibits notable improvements in planning times and the number of expanded nodes, which can effectively reduce planning times and the computational burden of the algorithm. The greater the complexity of the sea space conditions involved in path planning, the greater the risk of collision. Therefore, the application of the A* algorithm for path planning, which considers the risk of collision, will result in a more pronounced effect. Furthermore, it demonstrates a robust capacity for generalization in path planning studies across diverse marine environments.

Remark 3 The authors innovatively designed a collision risk function to further improve the A* algorithm. Dynamically adjusting the weight factor of path length and collision risk between nodes, thus controlling the

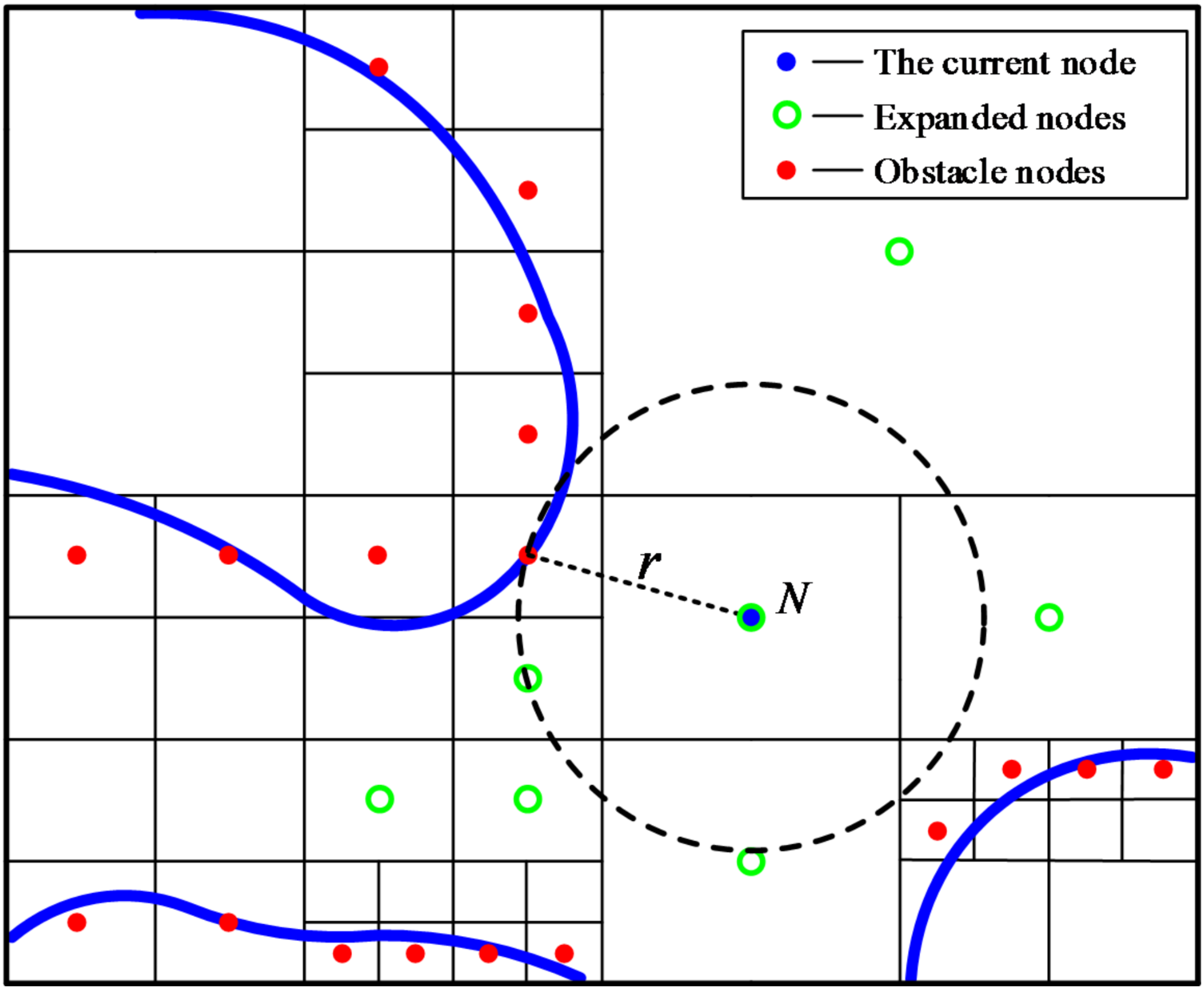

Fig. 7. The distance between the current node and the neighboring obstacle nodes.

influence level of collision risk on path planning. The improved algorithm has better generalization ability for different sea areas under various geomorphic conditions.

Discussions

This paper studies the optimal path planning problem for ships in complex environmental sea areas where shipwrecks, aground and collisions may occur. The optimal path is planned by constructing multi-scale nautical charts and utilizing an improved A* algorithm. In processing the nautical charts, this paper uses the "quadtree" algorithm for raster construction, which is the same as most studies nowadays. However, the difference is that most studies divide the raster into equal scales, while this paper adopts multi-scale raster division to avoid detailed raster division in large areas without obstacles, which increases the computational burden of the algorithm. For the selection of the path planning algorithm, the A* algorithm is used by most scholars due to the characteristics of its accuracy and efficiency. It is also constantly being improved by scholars since it is inspiring and extensible. Some scholars optimize global path planning by applying the A* algorithm in combination with the rest of the algorithms[13,14,27], and this kind of research can simplify the computation process while guaranteeing the path accuracy. In the process of combining different algorithms with the A* algorithm, the research on global path planning will be more refined in terms of breadth and depth, however, it does not improve the A* algorithm itself. In order to deepen the study of the A* algorithm itself, scholars have carried out more research. Some scholars have improved the heuristic cost by considering the obstacle information to improve the heuristic function of the A* algorithm, which improves the efficiency of the algorithm execution while reducing the number of turning points[15,16]. There are studies on predicted trajectories that decompose the predicted trajectories generated by the mathematical model into a series of waypoints on a grid map, and then execute the A* algorithm to search for methods to improve search efficiency and accuracy[28]. There is also literature on optimization of expanded nodes of A* algorithm, where the design function removes redundant nodes thereby reducing the computational burden of the algorithm and smoothing the planning path[29].

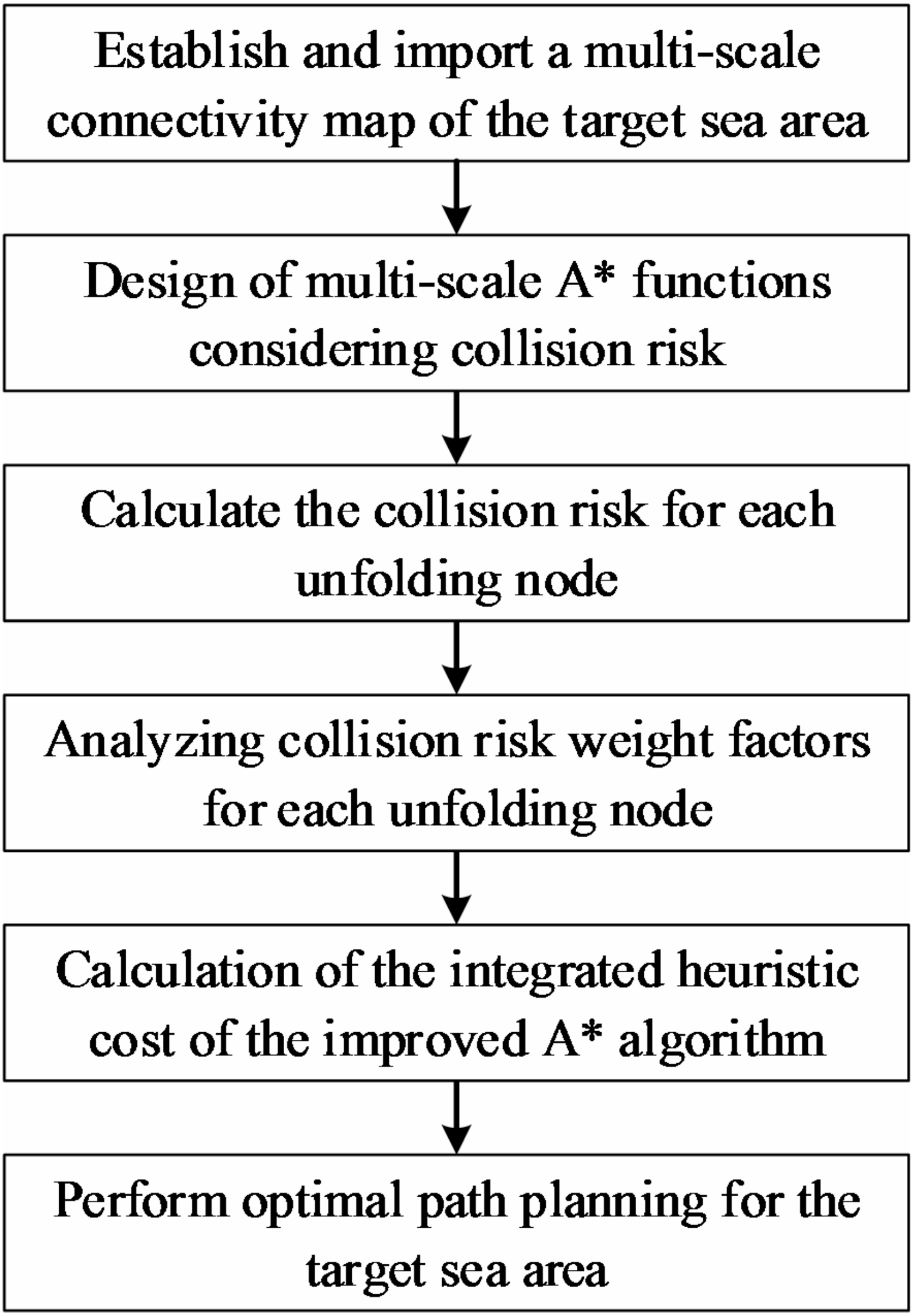

Fig. 8. Technology roadmap of A* algorithm considering collision risk.

Compared to the above existing studies, this paper also improves the A* algorithm by designing a comprehensive heuristic function. As compared to the traditional A* algorithm where only the path length is considered in the heuristic function, the combined heuristic function considers both the “path length” and the “collision risk”. Considering the characteristics of a complex environment with a sea area with many obstacles and a dense distribution, the author designs a collision risk function to optimize the heuristic cost of the A* algorithm, thereby further optimizing the A* algorithm’s measurement of the relationship between the “shortest path” and the “safe path”. This reduces the length of the planned path and the computational cost of the algorithm,

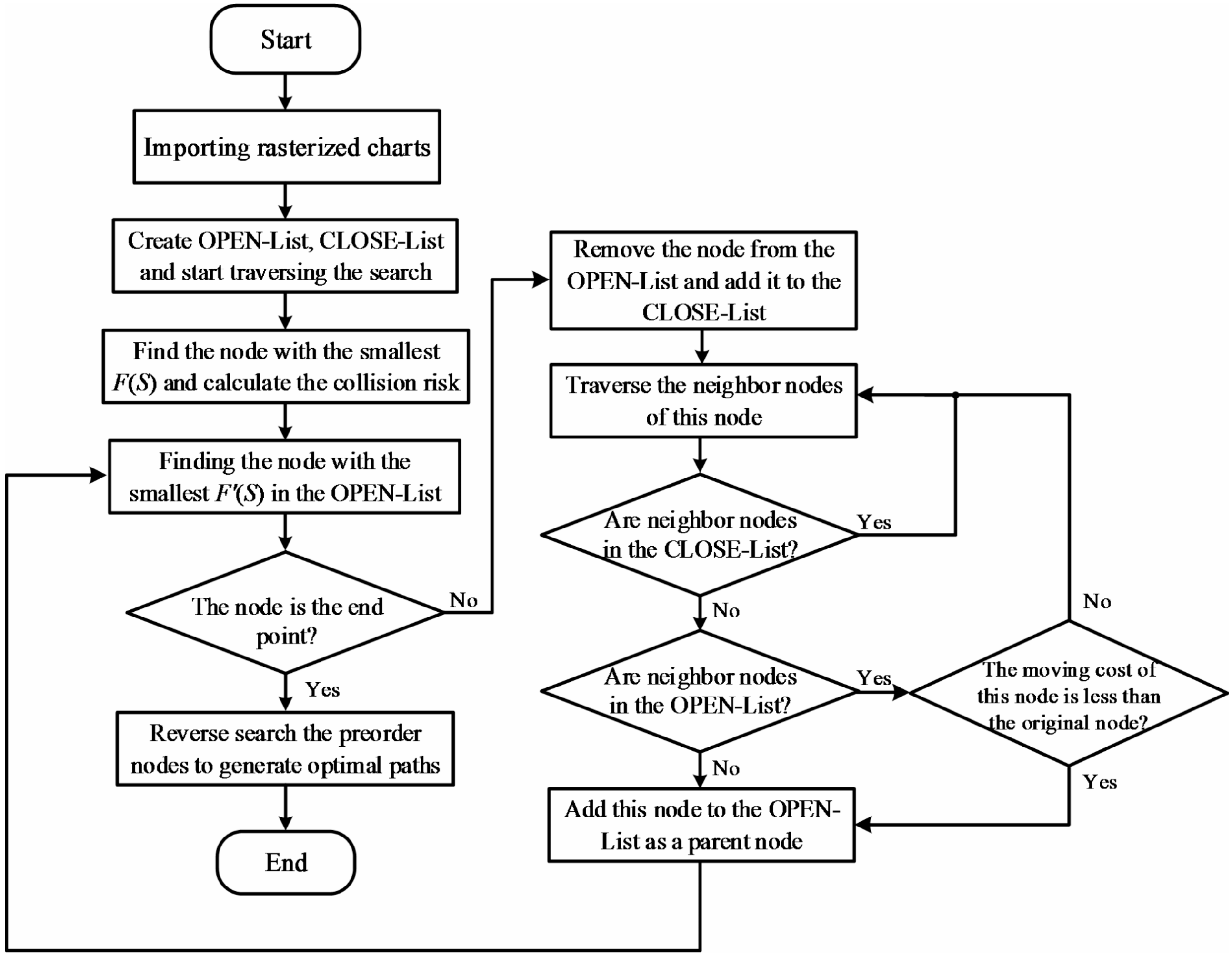

Fig. 9. Flowchart of A* algorithm considering collision risk.

while maintaining safety. In contrast to the earlier literature, this study equalized its parameters in different water environments with better generalization ability.

This paper presents research ideas for the construction of raster-based complex environment maps and the enhancement of the heuristic function of the A* algorithm. Additionally, it contributes to the research on the optimal path planning for the safe navigation of ships in complex sea areas. This paper also has some limitations that require further research. The algorithm is implemented without considering the interference of external sea conditions, and the simulation is conducted under ideal conditions. In addition, the paper's scope is limited to reefs, land, and shallow water areas in the selection of obstacles, with no consideration given to obstacles such as buoys and offshore platforms. This is since the position of these types of obstacles may be subject to change due to human intervention. It thus follows that the analysis of these types of obstacles, as well as other dynamic obstacles such as ships, necessitates the real-time updating of nautical chart data. This is a direction of further research for the author.

Conclusions

In this paper, the following conclusions are drawn through theoretical analysis and simulation experiments for the collision avoidance problem of ship navigation under complex geomorphic conditions:

1. Innovative design of a collision function by analyzing the collision risk of ship navigation, and combining it with the heuristic function of the A* algorithm optimizes the determination of node costs.
2. Applying the A* algorithm considering collision risk for path planning study, the proposed improved algorithm is proved to accomplish the optimal path planning task under complex sea space conditions by simulating the scenario of a ship crossing the Zhoushan Islands sea area.
3. Simulation of A* algorithm considering collision risk with conventional A* algorithm. Under the planning premise of guaranteeing the "optimal path", the improved algorithm considering the risk of collision has significantly improved all the practical performance indexes.

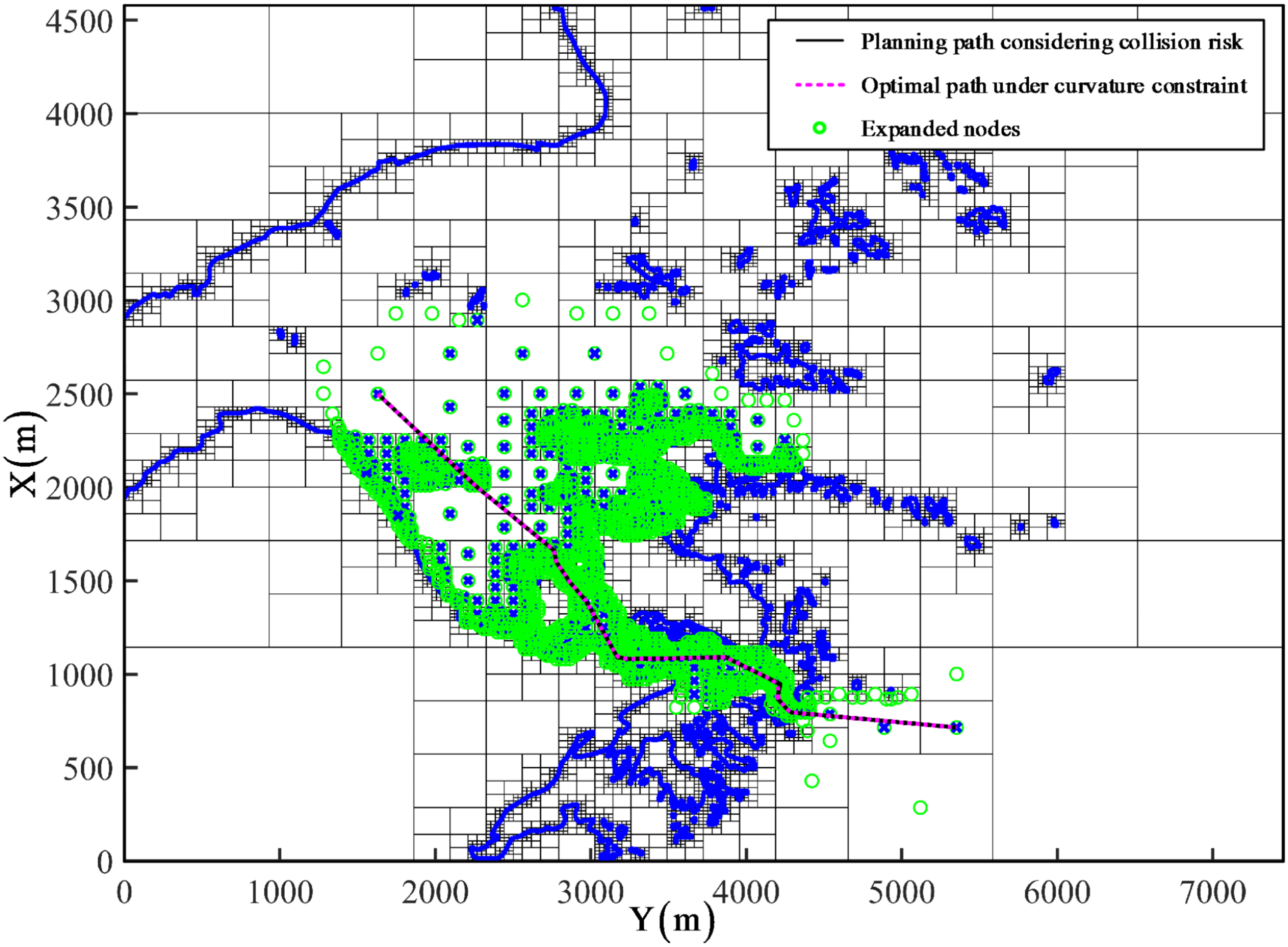

Fig. 10. Optimal path planning for Zhoushan Islands considering collision risk.

	Traditional A* algorithm	Multi-scale A* algorithm	The A* algorithm considering collision risk
Planning path lengths (m)	4457.404	4205.433	4197.796
Planning times (s)	57.468	98.763	69.073
Number of nodes (pcs)	8053	7942	7069
Optimal paths	No	Yes	Yes

Table 2. Comparison of performance indexes of three A* algorithms mentioned in the paper.

The proposed method in this paper provides an innovative point for the study of optimal path planning for safe navigation of ships in complex sea environments. In the future, the authors will also attempt to acquire collision risk information in the environment in real time and design autonomous collision avoidance algorithms for ships adapted to dynamic environments. To assist in the study of unmanned, autonomous and safe navigation tasks for smart ships.

Data availability
If you want to request the the experimental information and data presented from this study, please contact the corresponding author.

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Conceptualization, C.S.; methodology, C.S.; software, C.S.; validation, C.S. and J.S.; formal analysis, T.G.; investigation, T.G.; resources, C.S. and T.G.; data curation, T.G.; writing—original draft preparation, C.S. and T.G.; writing—review and editing, C.S. and J.S.; visualization, C.S.; project administration, J.S. and C.S.; funding acquisition, J.S.; All authors have read and agreed to the published version of the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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