Route Optimization Method for Unmanned Surface Vehicles under Complex Sea Conditions

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Abstract: To address the composite requirements of route planning for Unmanned Surface Vehicles under complex sea conditions, which need to balance path optimality, motion feasibility, and obstacle avoidance, this study proposes a scenario-specific optimized route planning method. First, by reconstructing the cost function and optimizing the node expansion strategy, an improved A* algorithm is proposed, which significantly enhances the efficiency of its straight-line search in open waters. Second, by deeply integrating the ship kinematics model, introducing dynamic parameter adjustment and path smoothing strategies, an improved Hybrid A* algorithm is constructed, which enhances its safe obstacle avoidance capability in obstacle-dense areas. Furthermore, a hybrid planning strategy based on obstacle density for scene recognition and dynamic algorithm switching is designed in this paper. Simulation experimental results show that, compared with traditional algorithms, the proposed improved algorithms and hybrid strategy exhibit significant advantages in key performance indicators such as path length, search time, and success rate in high-obstacle areas. They can better adapt to the complex and variable marine environment, providing an effective technical solution for the autonomous and safe navigation of Unmanned Surface Vehicles.

Keywords: Marine Environment Adaptation; Path Planning; USV Route Optimization; Improved A* Algorithm; Improved Hybrid A* Algorithm

1. Introduction

USV technology is widely applied in fields such as marine exploration and disaster rescue, but the insufficient adaptability of path planning algorithms to marine scenarios has become the core bottleneck. The marine environment presents unique challenges such as dynamic obstacles and ship motion constraints. Although traditional path planning algorithms can ensure the geometric optimality of paths, they have inherent flaws:

Marine obstacle modeling is coarse: it fails to conduct refined modeling on the geographical boundaries of obstacles such as irregular islands and coral reefs, leading to the risk that planned paths may frequently cross shoals or land boundaries;

Neglect of ship motion constraints: the generated "right-angle turns" or "sharp turning paths" exceed the physical turning capacity of USVs, resulting in path infeasibility;

Therefore, developing a path planning algorithm that balances path shortestness, motion feasibility, marine environment adaptability, and computational efficiency serves as the core technical fulcrum for promoting the transition of USVs from laboratory research to practical engineering applications.

2. Related Work

Current research on USV path planning centers on two core objectives: algorithm adaptation to marine scenarios and meeting ship motion constraints. Domestic and international studies align with each other in technical directions, and the specific progress is as follows:

2.1 Basic Algorithm Construction Phase

Domestic and international studies all take classical path planning algorithms as the starting point, providing a core framework for subsequent optimization. Hart et al. proposed the A* algorithm by introducing the heuristic cost function $f(n)=g(n)+h(n)$, which achieved the balance between path optimality and search efficiency for the first time. However, this algorithm was originally designed for general scenarios and failed to consider the characteristics of large-scale continuous marine areas, irregular reefs, and other marine-specific features; its direct application is prone to the problem of redundant path turns [1]. Although the motion planning theory and sampling-based path generation method elaborated by Lavalle can solve high-dimensional motion constraint problems, they are focused on terrestrial robots. These methods lack sufficient adaptability to the three-degree-of-freedom (3-DOF) motions of ships, namely surge, sway and yaw, making it difficult to directly migrate them to marine scenarios [2].

2.2 Marine Scenario Adaptation and Optimization Stage

Domestic and international scholars have conducted research on algorithm improvement and data fusion targeting the navigation characteristics of USVs. Park et al. improved the Hybrid A* algorithm by introducing an obstacle penalty term, which enhanced the success rate of near-shore paths, but failed to consider the kinematic constraints of ships [3].Zhang Ming et al. improved the A* algorithm by adding a marine weight coefficient, shortening the path by 5%~8%, and Wang Jian et al. simplified the ship kinematics model to enhance feasibility, but neither of them addressed the risk of hull grounding [4,5]; Liu Kun et al. optimized obstacle modeling based on nautical charts, and Zhao Jianhu et al. improved the accuracy of nautical charts, but neither of them integrated the water depth data of shoals, resulting in the persistence of potential collision risks [6,7]. Although relevant foreign studies have focused on the coupling between motion constraints and path planning, they suffer from low modeling accuracy when dealing with irregular marine obstacles, which is likely to result in path collision risks. Chen et al. constructed a 3D environmental model based on S-100 electronic nautical charts, improving environmental adaptability by 30%; however, the increased complexity of data parsing has led to longer planning time [8].

2.3 Dynamic Environment and Multi-Objective Optimization Research Stage

Dynamic Environment and Multi-Objective Optimization Research Stage. Li et al. achieved dynamic obstacle avoidance based on Deep Reinforcement Learning (DRL) and trajectory prediction, but it suffers from insufficient generalization ability in ocean-going scenarios and high inference latency [9]. Zhang et al. proposed a distributed cooperative framework, reducing the cluster route crossing rate to 15%, but failed to balance the motion constraints of individual vessels and cluster efficiency [10].

In terms of adaptability to extreme sea conditions, Wang et al. incorporated current velocity and direction as constraint terms into the cost function of the Hybrid A* algorithm: by collecting real-time ocean current data, an interference model of ocean currents on ship tracks was established. In strong current environments with a flow velocity exceeding 2 m/s, the path deviation was reduced from 12 m to 5 m, meeting the engineering accuracy requirements; however, this model simplifies the vertical current component, and the path accuracy still needs to be improved in sea areas with significant upwelling and downwelling [11].

To sum up, although existing research has achieved certain progress, it still lacks an integrated planning framework that can adaptively switch optimization strategies according to the dynamic changes of the marine environment.

3. Principles of Path Planning Algorithms

The core of path planning is to find the optimal path from the start point s to the end point t in the gridded nautical chart $G=(V,E)$.Marine scenarios need to additionally satisfy two constraints: remaining within marine areas throughout the entire process and ship motion constraints. Below, we will focus on analyzing the path planning algorithm processes from the perspectives of the A* algorithm and the Hybrid A* algorithm.

3.1 A* Algorithm

Compared with basic path planning algorithms, the A* algorithm introduces the heuristic cost $h(n)$, with the total cost $f(n)=g(n)+h(n)$, and accelerates search convergence through heuristic information.

3.2 Hybrid A* Algorithm

The Hybrid A* algorithm is a path planning algorithm specifically designed for nonholonomic constraint systems. Its core breakthrough lies in deeply integrating the kinematic model into heuristic search, ensuring that the generated path meets the physical motion limits of the carrier.

To summarize, these two types of algorithms provide a clear problem-oriented direction for improvements in marine scenarios: the A* algorithm guides search through the heuristic function f(n)=g(n)+h(n) and achieves higher efficiency than general algorithms, but due to ignoring ship motion constraints, the generated path often contains non-navigable segments such as "right-angle turns"; the Hybrid A* algorithm integrates the ship kinematics model to address the issue of "path physical feasibility", however, its fixed parameters struggle to adapt to the complex marine scenarios of "long-distance open waters + short-distance obstacle-dense areas", resulting in reduced efficiency in long-path planning.

4. Optimization Method

To ensure that the path planning process is conducted within marine areas, it is first necessary to perform legitimacy verification on the input start point, end point, and intermediate nodes. Next, the marine areas will be divided into two categories: long-distance open waters and short-distance obstacle-dense areas. For long-distance open waters, the improved A* algorithm is adopted; for short-distance obstacle-dense areas, the improved Hybrid A* algorithm is used for appropriate path planning. The optimization implementation flow chart is shown in Figure 1.

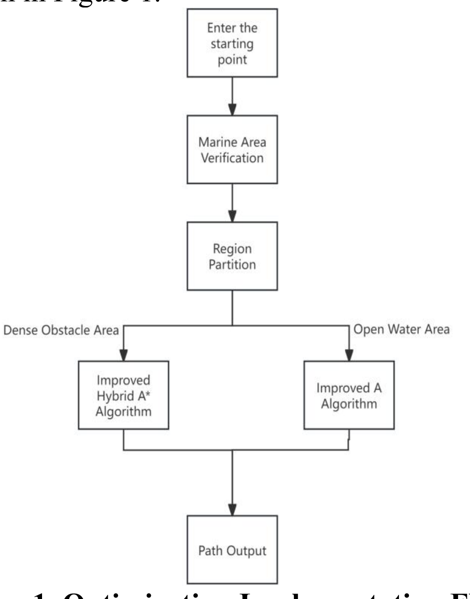

Figure 1. Optimization Implementation Flow Chart

4.1 Marine Area Verification Mechanism

Manual Node Verification: For the marine USV, its start point $s_{man} = (x_s, y_s)$ and end point $t_{man} = (x_t, y_t)$ must be within the boundaries of the nautical chart.Marine Area Discriminant Function: Define a binary function is_sea(x,y) to describe whether the coordinates (x,y) belong to a marine area:

$$\text{is\_sea}(x,y)=\begin{cases}1 & \text{if } 0\leq x,y<W\\ 0 & \text{else}\end{cases} \quad (1)$$

Real-time filtering at intermediate nodes: For the intermediate node n of the path, in addition to verifying $is\_sea\ (x_n, y_n) = 1$, it is also necessary to ensure that all four corner points belong to marine areas:

$$\forall\,(x_v,y_v)\in Vertices(n),\ is\_sea(x_v,y_v)=1 \quad (2)$$

Among them, $Vertices(n)$ denotes the set of the vessel's corner points, which is calculated based on the vessel's dimensions and heading angle:

$$\begin{cases}x_v=x_n\pm\frac{L}{2}cos\psi\mp\ \frac{W_s}{2}sin\psi\\ y_v=y_n\pm\frac{L}{2}sin\psi\pm\frac{W_s}{2}cos\psi\end{cases} \quad (3)$$

4.2 Improved A* Algorithm

Based on the characteristics of the A* algorithm, the optimization focus is placed on prioritizing adaptation to long-distance open waters to achieve the goal of "straight-line priority and efficient search".

Cost function reconstruction:Introduce the "weight coefficient ω for marine obstacle-free areas" to distinguish the heuristic costs between open waters and obstacle-dense areas, and the formula is optimized as:

$$f(n)=g(n)+\omega h(n) \quad (4)$$

Node Expansion Optimization:Cache movement vectors to reduce redundant calculations. For 8-directional movement, the expanded time complexity after caching is reduced from O(8) to O(1), with the mathematical expression as the set of movement vectors.

$$\text{Moves}(k) = \{(0, \pm k), (\pm k, 0), (\pm k, \pm k)\} \quad (5)$$

Path Smoothing Optimization:The process of quantifying the smoothing effect is as follows:

$$\eta=(1-\frac{N_{smt}}{N_{raw}})\times 100\% \quad (6)$$

4.3 Improved Hybrid A* Algorithm

The Hybrid A* algorithm integrates the heuristic search of A* and the ship kinematics model, making it suitable for carriers with motion constraints and better adaptable to short-

distance obstacle-dense areas. This paper simulates the position and heading angle changes of USVs through the ship kinematics model, and introduces a multi-stage parameter adjustment strategy. When search fails, parameters such as speed and steering angle are relaxed to find a suitable path in complex areas.
The planar motion of marine USVs can be simplified to a three-state model:

$$\begin{gathered} s = [x, y, \psi] \\ u = [v, r] \end{gathered} \tag{7}$$

Dynamic Parameter Adjustment:To adapt to the marine "short-distance reef-dense areas", the mathematical model is designed as follows:
The time step Δt determines the "time resolution" of state expansion, and the piecewise function is defined as:

$$\Delta t=\begin{cases} 0.4s & d>400 \text{ Pixel} \\ 0.3s & 200<d\leq 400 \text{ Pixel} \\ 0.2s & d\leq 200 \text{ Pixel} \end{cases} \tag{8}$$

In the code, the G cost of ShipNode includes distance and steering penalty, which is mathematically expressed as:

$$G(n_{next})=G(n_{curr})+\sqrt{(\Delta x)^2+(\Delta y)^2}+\lambda(2\Delta\psi) \tag{9}$$

Introduce the obstacle penalty, which is mathematically expressed as:

$$h(n)=\sqrt{(x_n-x_t)^2+(y_n-y_t)^2}+d\cdot\frac{c}{m} \tag{10}$$

5. Experimental Design and Result Analysis

5.1 Experimental Environment

The experiment adopted a binary electronic nautical chart with a resolution of 1000×600 pixels to simulate the complex marine environment with multiple reefs in China's South China Sea. The nautical chart distinguishes land from ocean using a grayscale threshold of THRESH=100: a pixel value of 255 represents a navigable marine area, and a pixel value of 0 represents a land obstacle. The nautical chart is shown in Figure 2.

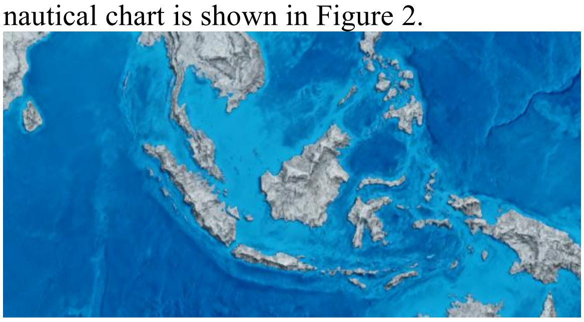

Figure 2. Experimental Ocean Chart

The parameters of the USV are set based on a self-developed unmanned boat model: the vessel length L=12 m, vessel width $W_s = 4$ m, maximum speed $v_{\max} = 6$ knots, maximum steering angular velocity $r_{\max} = 0.2$ rad/s, corresponding to a minimum turning radius $R_{\min} \approx 60$ m .

5.2 Experimental Results and Analysis

To verify the feasibility of the algorithms, the traditional algorithm, improved A* algorithm, improved Hybrid A* algorithm and hybrid HAA* algorithm are compared below in terms of three aspects: search path length, search time, and success rate in high-obstacle areas.
As shown in Figure 3, compared with the traditional A* algorithm, the path length of the improved A* algorithm increases slightly. This is because the "weight coefficient for marine obstacle-free areas" in its cost function sacrifices part of the shortest-path property when guiding the path away from potential risk areas. The improved Hybrid A* algorithm generates a smoother path through gradient domain path refinement, with a total length superior to that of the original Hybrid A* algorithm. The HAA* hybrid algorithm achieves a good balance between the two.

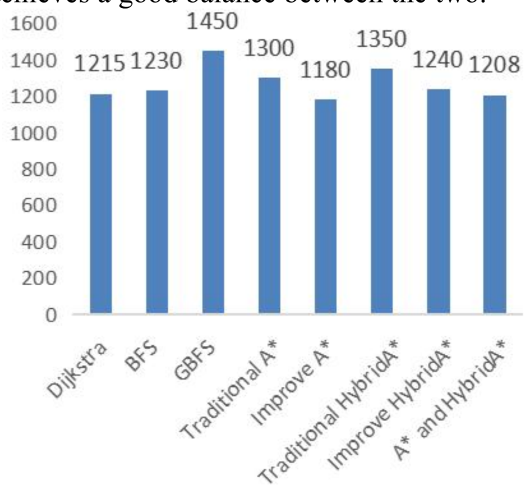

Figure 3. Comparison of Search Path Lengths for Multi-Algorithm

As shown in Figure 4, the improved algorithms achieve a significant improvement in efficiency through "search strategy optimization" and "computational redundancy reduction", without sacrificing path accuracy. In addition, the time performance of the hybrid algorithm is fully compatible with the real-time planning requirements of complex sea conditions, and it has greater flexibility than a single algorithm, especially in tasks involving "continuous switching of multiple scenarios".

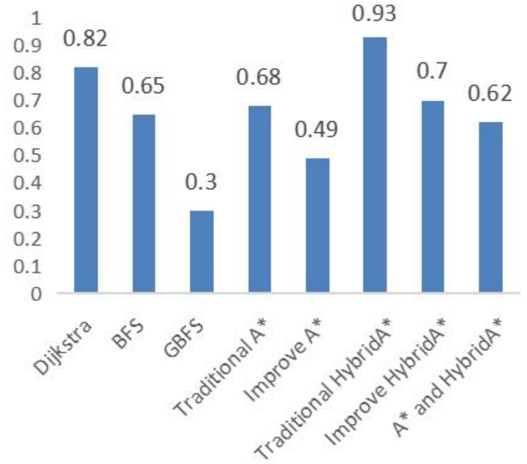

Figure 4. Comparison of Search Path Time for Multiple Algorithms

As shown in Figure 5, the success rates of the improved Hybrid A* and HAA* algorithms in high-obstacle areas are much higher than those of other algorithms. This directly verifies the key role of their deeply integrated ship kinematics model and refined hull collision detection mechanism in ensuring the physical feasibility of the path.

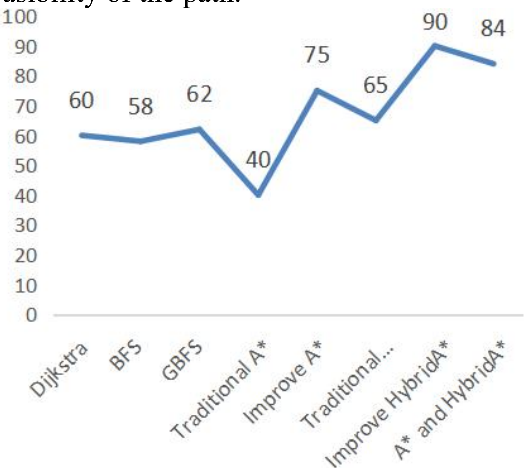

Figure 5. Comparison of Path Search Success Rates among Multiple Algorithms

In summary, combining the three core indicators of path length, search time, and success rate in high-obstacle areas, the improved A* algorithm, improved Hybrid A* algorithm, and their hybrid algorithm have all reached the level of engineering application in terms of performance through targeted marine scenario adaptation and motion constraint optimization, providing reliable technical support for USVs to move from the laboratory to practical operations.

6. Conclusion

This study focuses on the two core challenges of "marine environment adaptability" and "ship motion feasibility" in the path planning of marine USVs. Through scenario-based in-depth optimization and innovative integration of classic algorithms, three key achievements have been made as follows. An exclusive path verification and optimization system for marine scenarios has been constructed, and a threefold verification mechanism of "start-end point verification, intermediate node filtering, and hull collision detection" is proposed to ensure the entire path is located in safe sea areas. The marine-oriented improvement of classic algorithms has been realized: the improved A* algorithm achieves the best performance in open water scenarios by reconstructing the cost function and adopting bidirectional parallel search. The improved Hybrid A* algorithm greatly improves the success rate of paths in high-obstacle areas through dimensionality reduction of the motion model, dynamic parameter scheduling, and gradient domain fine-tuning, meeting the navigation requirements of reef-dense areas. Additionally, an attempt is made to combine the two algorithms to make up for their shortcomings, and a quantitative algorithm selection framework is established.

Future research will focus on three directions: "dynamic environment adaptability", "multi-ship collaboration", and "robustness under extreme sea conditions". Integrate real-time meteorological and ocean current data to optimize the ship kinematics model, thereby reducing path errors caused by wind, wave and current interference. Construct a multi-ship collaborative path planning framework and introduce distributed optimization algorithms to achieve conflict-free navigation of the cluster.

Conduct actual ship experiments on lakes and seas to verify the performance of the algorithm in real marine environments and further iteratively optimize model parameters.

Acknowledgments

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