

Article

Improved Multi-Scale A* and DWA Algorithm for USV Path Planning Integrating MMG Maneuvering Constraints

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Abstract

To balance safety, real-time performance, and dynamic feasibility in path planning for unmanned surface vehicles (USVs) operating in complex aquatic environments, the study proposes a hybrid planning framework that integrates a multi-scale A* algorithm with the Dynamic Window Approach (DWA) under Maneuvering Modeling Group (MMG) dynamic constraints. Global path optimization incorporates target-oriented neighborhood expansion, obstacle risk constraints, and a maneuverability cost function to comprehensively evaluate path length and collision risk, thereby enhancing the efficiency of the hybrid global-local planning framework. Local trajectory prediction strictly couples the MMG USV motion model with the DWA algorithm. Real-time optimization of these dynamically constrained trajectories ultimately achieves proactive and safe evasion of dynamic obstacles. Compared with the traditional A* + DWA method, the proposed hybrid method reduces path length and computational time by 5.09% and 31.93%, effectively suppressing abrupt heading changes during dynamic obstacle avoidance. This paper provides an efficient path planning strategy that conforms to USV maneuvering constraints for autonomous navigation and dynamic obstacle avoidance.

Keywords: multi-scale A* algorithm; DWA; MMG model; path planning; dynamic obstacle avoidance

1. Introduction

Driven by the continuous growth in demands for marine resource development and maritime traffic safety monitoring, the autonomous navigation of USVs in complex waters has become a research hotspot in the field of path planning [1]. The current path planning methods mainly include graph search methods, sampling-based methods, and optimization-based intelligent algorithms [2]. Hu et al. [3] optimized the heuristic function of the traditional A* algorithm by introducing a Voronoi field-based risk function, which overcomes the defect of conventional algorithms failing to balance water depth and safe obstacle distances. Li et al. [4] integrated an improved A* algorithm with DWA using a 5×5 neighborhood safety expansion and an exponentially weighted heuristic. This method reduced the path length by 20.18% and effectively improved planning efficiency. However, this hybrid algorithm struggles to satisfy the dual requirements of global optimality and dynamic obstacle avoidance. Xu et al. [5] and Yuan et al. [6] improved the unidirectional A* search to a bidirectional search and combined it with an improved DWA, reducing the running time by 52.52% and improving the comprehensive performance of the hybrid algorithm, but path planning in complex marine environments requires fine environmental



Academic Editor: Xinqiang Chen

Received: 17 June 2026

Revised: 20 July 2026

Accepted: 22 July 2026

Published: 27 July 2026

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modeling capabilities. Liu et al. [7] utilized potential energy values as the node search cost instead of traditional binary grids, simultaneously quantifying safety costs and target proximity during node evaluation. Song et al. [8] improved global search efficiency and static obstacle avoidance by integrating collision-risk evaluation into a multi-scale A* method; however, its coupling with vessel maneuvering dynamics and local dynamic obstacle avoidance remains limited.

The solving efficiency of traditional graph-search methods heavily depends on grid resolution under complex maritime conditions and multiple constraints. Sampling-based methods replace exhaustive grid traversal with random sampling, but their convergence efficiency remains low. Liang et al. [9] and Hu et al. [10] improved the RRT algorithm from the perspectives of sampling strategy and path smoothing. The improved algorithm enhances search directionality incorporating potential fields and heuristics, while suppressing redundant turns through a steering cost model. Consequently, it generates smooth trajectories conforming to maneuvering constraints with fewer iterations. Chen et al. [11] constructed a decision tree classifier based on the CART algorithm to address local dynamic obstacle avoidance. The classifier partitions the environment into five scenarios and adaptively adjusts evaluation weights to escape local optima. Furthermore, this approach integrates DCPA and TCPA into the evaluation function as obstacle avoidance decision criteria, effectively optimizing local dynamic obstacle avoidance. He et al. [12] investigated collision-avoidance path planning for multi-ship encounters by considering ship manoeuvrability and COLREGs, which provides an important reference for rule-aware and manoeuvrability-constrained maritime collision avoidance. To balance the mutual constraints between the obstacle avoidance safety margin and the economic cost of navigation, path planning needs to shift from single-objective to multi-objective optimization. Gao et al. [13] introduced the velocity potential field into the heuristic information of the ant colony algorithm. The modified algorithm utilizes a transition control factor to coordinate local guidance and global optimization. The path planner targets path length and carbon emissions as dual objectives and integrates speed constraints to generate smooth avoidance trajectories. Thus, it reduces the average path length by 4.3% and 2.9% compared to the genetic algorithm and the traditional ant colony algorithm. Chen and Mao [14] proposed an isochrone-based predictive optimization method that achieves smooth route convergence through a segmented grid strategy. A fuel-predictive heuristic cost replaces the traditional local greedy search. Real-ship navigation data demonstrates a 5% average fuel reduction. Smierzchalski and Michalewicz [15] incorporated path length, smoothness, and navigation time into the evaluation function. The evaluation framework introduces speed variables and time-varying constraints. An evolutionary algorithm generates an initial trajectory to achieve simultaneous optimization of safety and economy. Furthermore, the unified dynamic-static environmental model executes adaptive collision avoidance correction and real-time trajectory reconstruction under complex time-varying disturbances. A comprehensive evaluation system integrating multiple navigational metrics achieves the collaborative optimization of obstacle avoidance safety and navigation economy.

Multi-objective optimized trajectories are applied to autonomous ship navigation. Zhang [16] proposed a novel DVS guidance principle and a robust adaptive path-following control method, and utilized a low-frequency gain learning mechanism to enhance the path-following robustness of underactuated ships. Song et al. [17,18] utilized real-ship test data to execute nonlinear identification for a 4-DOF ship maneuvering model. This identification process effectively reduces modeling errors. Furthermore, Børhaug et al. [19] utilized precise modeling to develop a nonlinear line-of-sight (LOS) path-following strategy. The LOS guidance mitigates ship controllability constraints under low-speed conditions, with its tracking robustness further validated against wave-induced disturbances. Traditional

path-following methods fail to accommodate ship maneuvering characteristics in shallow waters. Guo et al. [20] and Zhang et al. [21] designed a robust adaptive event-triggered path-following control algorithm. The event-triggered controller simultaneously reduces control update frequencies and enhances shallow-water navigational robustness. In summary, existing studies optimize modeling, control, and planning aspects, but path planning optimization universally relies on standard kinematic frameworks. The integration of complex hydrodynamic constraints throughout the planning and collision avoidance process lacks in-depth investigation.

In complex marine environments, USV path planning faces severe impacts from environmental uncertainties, random dynamic obstacles, and navigational constraints, and must balance global path optimality with real-time responsiveness to local dynamic environments. Therefore, this paper proposes a collaborative multi-scale A* and DWA path planning method integrating nonlinear MMG characteristics. The optimized multi-scale A* node expansion mechanism transforms USV maneuvering limits into topological search weights. Correspondingly, the DWA algorithm utilizes maneuvering dynamic limits and nonlinear sideslip effects to reconstruct dynamic windows and trajectory evaluation metrics. This algorithmic reconstruction significantly enhances the autonomous collision avoidance performance of USVs in complex environments. The main contributions are as follows:

- (1) A multi-scale A* path planning method systematically incorporates MMG dynamic constraints. During the path search phase, the method introduces USV maneuvering constraints by utilizing a formulated cost function to explicitly quantify longitudinal velocity and yaw rate deviations. This integration deeply couples generated paths with USV motion characteristics.
- (2) An improved DWA trajectory prediction algorithm integrating the MMG model is formulated to evolve traditional kinematic prediction into dynamic prediction. This dynamic extension introduces USV maneuvering equations to recursively solve candidate trajectories, thereby improving the prediction accuracy in dynamic environments.
- (3) The design of a global-local collaborative framework achieves hierarchical coordination between path planning and dynamic collision avoidance (Table 1). The global layer generates paths and provides local target waypoints. Guided by these waypoints, the local layer incorporates static obstacles, dynamic obstacles, and water flow disturbances into a unified cost function, effectively balancing global path optimality and local navigational safety.

Table 1. Comparison between related studies and the proposed framework.

Related Studies	Difference from the Proposed Framework
Studies considering maneuverability constraints	Maneuverability is usually introduced as a local feasibility constraint or a post-processing criterion, whereas the proposed framework embeds MMG-based maneuverability costs into the global multi-scale A* evaluation function.
Improved DWA-based methods	Improved DWA methods enhance local obstacle avoidance, but most of them still rely on simplified kinematic prediction rather than MMG-based dynamic prediction of USV motion.
Proposed framework	MMG-based constraints are introduced into both the global multi-scale A* cost function and the local DWA prediction model, forming a unified hierarchical planning framework for dynamic USV obstacle avoidance.

2. Mathematical Modeling of the USV Motion

As a modular dynamic model extensively utilized in ship maneuverability analysis, the MMG model establishes its framework by decoupling the hydrodynamic forces exerted by the hull, propeller, and rudder [22]. This paper constructs a 3-DOF simplified motion model, selecting surge velocity (u), sway velocity (v), and yaw rate (r) as the state variables [23]. The model captures the fundamental characteristics of the USV's longitudinal, lateral, and yaw motions, while satisfying the computational efficiency requirements for path planning and trajectory prediction. The MMG equations of motion can be expressed as:

$$\begin{aligned}(m + m_x)\dot{u} - (m + m_y)vr &= X \\ (m + m_y)\dot{v} + (m + m_x)ur &= Y \\ (I_{zz} + J_{zz})\dot{r} &= N\end{aligned}\quad (1)$$

where m is the USV mass; m_x and m_y are the surge and sway added masses; I_{zz} is the moment of inertia in yaw; J_{zz} is the added moment of inertia in yaw. The variables X , Y and N respectively represent the surge force, sway force, and yaw moment acting on the USV. The coordinate system is illustrated in Figure 1.

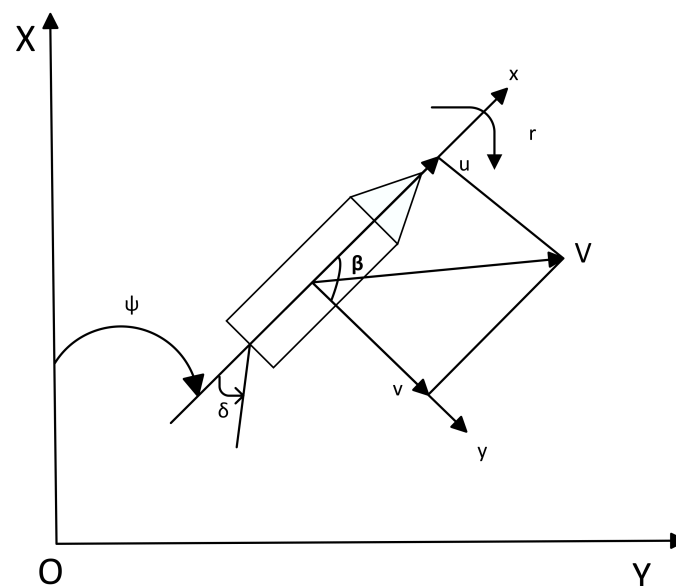


Figure 1. Coordinate system for USV motion.

3. Improvement of the Multi-Scale A* Algorithm

The cost function of the traditional A* algorithm is expressed as $f(n) = g(n) + h(n)$, where $g(n)$ represents the actual cost from the start node to the current node, and $h(n)$ is the heuristic cost from the current node to the target node. Paths generated based on this approach typically contain sharp turns or discontinuous headings, which USVs frequently struggle to execute given their inertial and maneuvering limitations [24,25]. To overcome these challenges, this study fuses environmental factors with USV maneuverability, developing an evaluation function that comprehensively accounts for distance, collision risk, and USV motion constraints. The flowchart of the improved A* algorithm considering MMG constraints is illustrated in Figure 2.

The evaluation function is formulated as:

$$f(n) = g(n) + \omega \cdot h(n) + \alpha \cdot R(n) + \beta \cdot C_{flow}(n) + C_{man}(n) \quad (2)$$

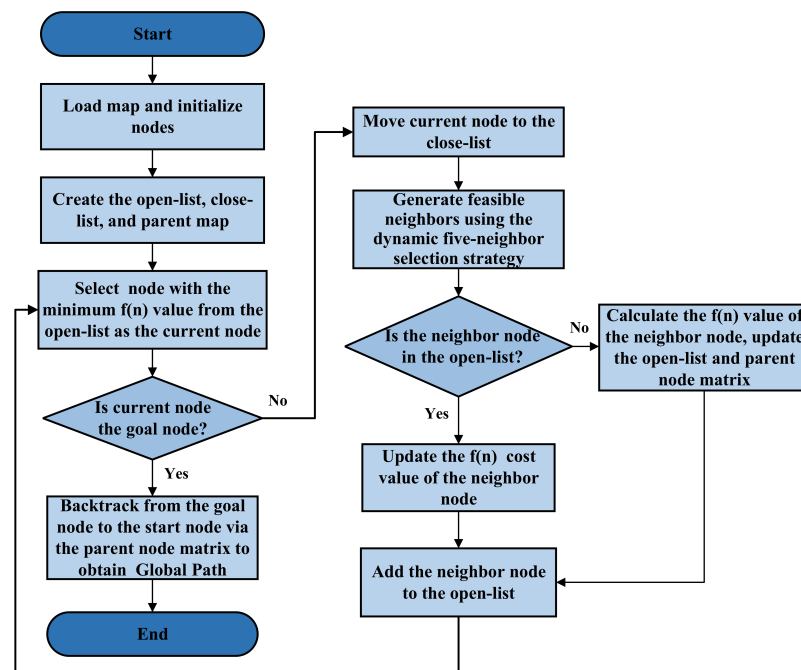


Figure 2. Flowchart of improved A* algorithm considering MMG constraints.

To ensure a consistent numerical scale in the composite evaluation function, each cost component in Equation (2) is first transformed into a dimensionless quantity before weighted aggregation. The path-length and heuristic terms are normalized by the map diagonal length, while the collision-risk and current-influence terms are normalized using characteristic scale values. The maneuverability term is defined by the normalized deviations of surge velocity and yaw rate from their reference values. The coefficient ω controls the heuristic term; α and β are the weighting coefficients for the collision-risk and current-influence penalties, respectively; and η and ζ regulate the surge-speed and yaw-rate deviation penalties. The weighting parameters are selected to preserve the dominance of path-length and heuristic terms, while using the remaining terms as auxiliary penalties for safety, current adaptability, and maneuvering feasibility. The coefficients in the global evaluation function were selected empirically in preliminary trials and then checked through a local sensitivity analysis.

To balance the search efficiency in open waters and the safety in obstacle-dense areas, this paper adopts an adaptive quadtree decomposition strategy to discretize the global geographic space. Based on this grid structure, the algorithm extracts obstacle distance information and introduces an exponential risk function to quantify the safety risks of the path nodes. The formula is expressed as follows:

$$R(n) = \gamma \cdot \left(e^{1/d_{obs}} - 1 \right) \quad (3)$$

In Equation (3), d_{obs} represents the Euclidean distance from the current node to the nearest static obstacle, and γ acts as the risk weight coefficient regulating the penalty intensity. As the clearance between a node and an obstacle diminishes, the collision risk approaches infinity, thereby imposing a severe penalty effect. Consequently, this function effectively guides the multi-scale A* algorithm to prioritize routes with sufficient safety margins, achieving proactive avoidance of static obstacles.

The motion characteristics of the USV are constrained by factors such as thrust, rudder angle, and hydrodynamic forces [26]. Traditional methods typically lack sufficient integration of these physical limitations during the global optimization phase, generating

geometrically unsmooth paths that severely compromise USV velocity stability. This paper integrates the MMG model constraints into the cost function of the multi-scale A* algorithm, quantifying the deviations of surge velocity and yaw rate from the USV's actual capabilities. This quantification guides the algorithm to generate executable paths free of sharp turns and abrupt heading variations.

With the reference variables set to the target velocity of the USV and the yaw rate during straight-line navigation, the maneuverability cost is formulated as:

$$C_{man} = \eta \cdot \left| \frac{(u - u_{ref})}{u_{max}} \right| + \zeta \cdot \left| \frac{(r - r_{ref})}{r_{max}} \right| \quad (4)$$

In Equation (4), η and ζ are the weight coefficients for the surge velocity and yaw rate, while u_{max} and r_{max} respectively denote their corresponding maximum limits. To guarantee global-local integrated coordination, the reference surge velocity u_{ref} is kept consistent with the target velocity of the DWA local planner, while the reference yaw rate r_{ref} represents the ideal state of straight-line navigation. During the search process of the multi-scale A* algorithm, u and r act as the expected surge velocity and the rate of heading change between adjacent search segments. By imposing penalties on expanded nodes that exhibit significant deviations from these reference values, this function effectively guides the algorithm to prioritize trajectories with smooth velocity transitions.

Recent research on ship carbon emissions and low-carbon shipping pathways has further indicated that route selection and environmental conditions are closely associated with navigation energy efficiency and emission reduction [27]. Water flow disturbances constitute the primary environmental constraint on the energy efficiency of USV navigation. Relying solely on discrete grid flow velocities in environmental modeling induces algorithmic cost discontinuities between adjacent nodes. The integration of low-frequency feature sampling and bicubic interpolation constructs a spatially continuous and smooth water flow field. Based on this continuous field, the water flow resistance cost is formulated as:

$$C_{flow} = k \cdot v_{current} \cdot (1 - \cos \theta) \quad (5)$$

Here, k is a normalization coefficient for the current-resistance term, whereas the contribution of this term in the global objective function is determined by β in Equation (2). Where $v_{current}$ is the current interpolated flow velocity, and θ is the angle between the water flow and the USV's motion direction. This formula ensures that downstream paths incur the lowest cost and upstream paths the highest. By integrating continuous flow field data, this cost term mitigates the impact of prevailing currents on path tracking, guiding the USV to prioritize energy-efficient downstream regions.

The traditional A* algorithm uses a fixed eight-neighborhood search strategy, which generates a large number of redundant search nodes in open areas. To address this issue, this study adopts a dynamic five-neighborhood selection strategy. At each expansion step, the azimuth from the current node to the target point is computed, and the five adjacent directions with the smallest angular deviation are retained as candidate nodes. This selective expansion reduces unnecessary node generation while preserving the connectivity of the multi-scale grid. The five-neighbor strategy is implemented as a directional pruning heuristic rather than a hard topological constraint. Because the candidate set is recomputed adaptively at each step and the search proceeds until the open list is exhausted, the strategy is designed to reduce redundant branching without compromising the completeness of the search on the discretized map. Integrating a direction-filtering module during the node expansion phase ensures compatibility with the existing multi-scale A* framework without altering its core data structure.

To further examine the influence of the proposed global planning modules, an ablation analysis is provided in Table 2. Variant A represents the baseline represents the traditional A* algorithm. Variant B incorporates the target-oriented neighborhood expansion strategy. Variant C further introduces the collision-risk constraint. Variant D adds the MMG-based maneuverability cost term on the basis of Variant C. Variant E denotes the complete proposed global planner, which combines the target-oriented neighborhood expansion strategy, the collision-risk constraint, and the MMG-based maneuverability cost term.

Table 2. Ablation results of the proposed global planning modules.

Varian	Length (m)	Time (s)	Turn	$l_{\min}$ (m)
Variant A	2016.73	39.74	9	8.42
Variant B	2162.28	49.54	7	31.84
Variant C	2140.52	47.86	6	46.37
Variant D	2122.38	43.76	5	48.91
Variant E	2116.19	42.30	4	50.28

Remark 1. The goal-oriented azimuth calculation explicitly restricts node expansion to kinematically favorable directions. This targeted elimination of redundant searches substantially minimizes computational overhead without sacrificing the inherent flexibility of the multi-scale framework.

Remark 2. The maneuverability cost function maps USV kinematic constraints onto topological search weights by quantifying the deviations in surge velocity and yaw rate. It penalizes expanded nodes that violate these constraints, forcing the global path optimization to strictly adhere to the hull's dynamic limits.

4. Improved MMG-DWA Local Path Planning Algorithm

This paper proposes an improved approach that integrates the MMG model with the DWA. In this framework, the DWA handles candidate velocity sampling and evaluation, while the MMG model governs trajectory prediction and dynamic response calculation. By maintaining continuous MMG state variables throughout the planning process, this framework enables the predicted trajectories to more accurately capture the USV's drift, steering lag, and maneuvering response characteristics. This mechanism effectively enhances the kinematic feasibility and tracking precision of the generated paths. The specific workflow of the MMG-DWA local path planning algorithm is shown in Figure 3 and described in detail as follows:

To achieve deep coupling with the MMG model, this paper maps and reconstructs the traditional kinematic velocity constraint space into a dynamic thrust and rudder angle control window. The formulation of this window accounts for the USV's mechanical limits, dynamic constraints, and safe braking requirements. Accordingly, the following constraint sets are defined:

$$\begin{aligned}
 V_s &= \{(v, \omega) \mid v \in [v_{\min}, v_{\max}], \omega \in [\omega_{\min}, \omega_{\max}]\} \\
 V_a &= \{(v, \omega) \mid v \in [v_c - a_v \Delta t, v_c + a_v \Delta t], \omega \in [\omega_c - a_\omega \Delta t, \omega_c + a_\omega \Delta t]\} \\
 C_r &= \{(T, \delta) \mid T = f_T(v), \delta = f_\delta(\omega), T \in [T_{\min}, T_{\max}], \delta \in [\delta_{\min}, \delta_{\max}], (v, \omega) \in V_s \cap V_a\}
 \end{aligned} \tag{6}$$

The variables V_s and V_a respectively represent the velocity limit window and the acceleration constraint window. Their intersection, denoted as $V_r = V_s \cap V_a$, defines the feasible velocity space. Additionally, $f_T(v)$ and $f_\delta(\omega)$ denote the dynamic mapping functions used to derive the candidate thrust T and rudder angle δ , subject to saturation limits.

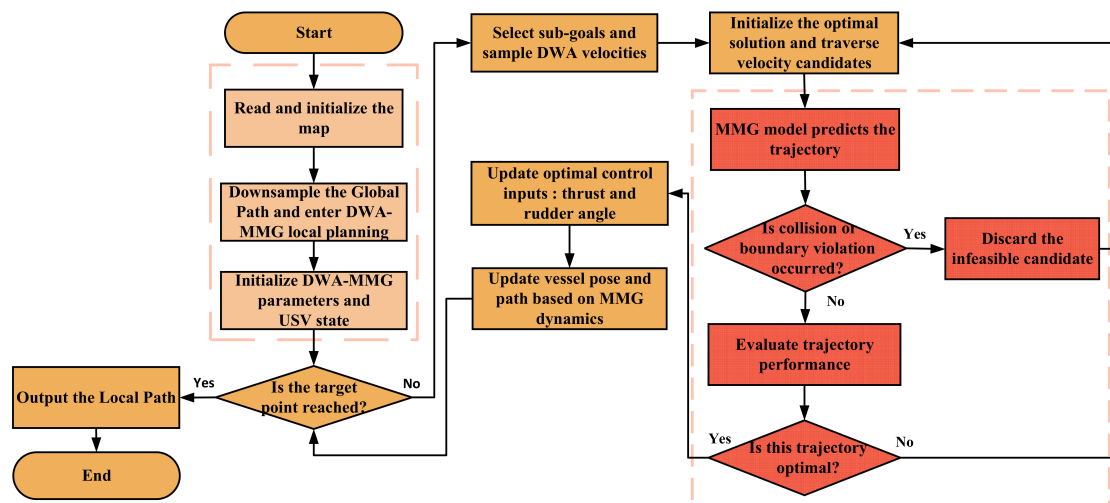


Figure 3. Flowchart of the hybrid MMG-DWA algorithm.

For the candidate velocity commands sampled at the decision layer, the aforementioned mapping functions are utilized to convert them into actual thrust and rudder angles. The system state is consequently expanded from a traditional three-dimensional geometric vector into a six-dimensional dynamic state vector $X = [x, y, \psi, u, v, r]^T$, comprehensively incorporating the surge velocity, sway velocity, and yaw rate. During the time-domain iteration, the MMG dynamic equations utilize the current motion states and control inputs to calculate the instantaneous acceleration components of the USV. Following the Euler integration of the velocity state, the sway velocity coupling term is incorporated to formulate the kinematic position equations as follows:

$$\begin{aligned} x_{t+\Delta t} &= x_t + (u \cos \psi - v \sin \psi) \cdot \Delta t \\ y_{t+\Delta t} &= y_t + (u \sin \psi + v \cos \psi) \cdot \Delta t \\ \psi_{t+\Delta t} &= \psi_t + r \cdot \Delta t \end{aligned} \quad (7)$$

Distinct from traditional methods that rely solely on surge velocity for position updating, the above equation introduces a sway velocity coupling term. This addition induces a drift angle during maneuvers, causing the predicted trajectory to shift inward. Consequently, the improved predictive model comprehensively captures three distinct physical processes: acceleration transition, progressive steering, and lateral sideslip. In the acceleration transition phase, solving the longitudinal dynamic equations yields the velocity response under applied thrust. This explicitly reflects the acceleration lag caused by the USV's inherent inertia, thereby overcoming the instantaneous velocity discontinuities prevalent in traditional kinematic models.

During progressive steering, the heading is updated through the integration of angular acceleration. This approach ensures that the turning segments of the predicted trajectory exhibit continuously varying curvature, accurately reflecting the inertial lag effect during the USV's turns. To account for lateral sideslip, incorporating the sway velocity coupling term compensates for the sideslip errors typical of standard kinematic models. The DWA evaluation results more closely align with the USV's actual spatial footprint during maneuvers, preserving a realistic safety margin for obstacle avoidance.

Traditional DWA evaluation functions primarily rely on the instantaneous spatial distance, limiting their ability to anticipate the movement trends of dynamic obstacles. Extending the standard DWA framework, the proposed evaluation function is designed as follows:

$$G(v, \omega) = \omega_{goal} \cdot G_{goal}(v, \omega) + \omega_{speed} \cdot G_{speed}(v, \omega) + \omega_{obs} \cdot G_{obs}(v, \omega) + \omega_{risk} \cdot G_{risk}(v, \omega) + \omega_{smooth} \cdot G_{smooth}(v, \omega) \quad (8)$$

In Equation (8), ω_{goal} , ω_{speed} , ω_{obs} , ω_{risk} , and ω_{smooth} denote the weighting coefficients for target tracking, speed preference, obstacle clearance, dynamic collision risk, and trajectory smoothness, respectively. In the local MMG-DWA evaluation function, the local target-tracking term G_{goal} is assigned the largest weight to ensure that the USV follows the global reference path. The dynamic-risk term G_{risk} is assigned a moderate weight to account for moving obstacles using TTC and predicted obstacle trajectories, while the smoothness term G_{smooth} suppresses abrupt changes in control commands. The speed term G_{speed} and the obstacle distance term G_{obs} are kept as secondary objectives, so that navigation efficiency can be considered without weakening the primary tracking objective. The coefficients in the local evaluation function were empirically tuned during the simulation setup to maintain the above priority structure among tracking, risk avoidance, smoothness, speed, and obstacle-distance terms.

The dual-index risk evaluation function G_{risk} incorporates Time to Collision (TTC) and the minimum encounter distance (D_d) to assess dynamic risk based on time urgency and spatial proximity. Let $p_{usv}(t)$ and $p_{obs}(t)$ respectively denote the position vectors of the USV and the obstacle at time t . The minimum relative distance between them within the prediction horizon is defined as:

$$D_d(v, \omega) = \min_{t \in [0, T_{predict}]} \|p_{usv}(t) - p_{obs}(t)\| \quad (9)$$

During the evaluation, the algorithm calculates the relative distance between the USV and dynamic obstacles. When the relative distance falls below the alert threshold, the corresponding time instance is recorded as the $TTC(v, \omega)$. A lower TTC value signifies a tighter critical margin for collision, which enforces stronger real-time constraints on the control strategy. Synthesizing the two aforementioned collision avoidance metrics, the dynamic risk penalty cost function is formulated as:

$$G_{risk}(v, \omega) = \frac{\mu_1}{TTC(v, \omega) + \varepsilon} + \frac{\mu_2}{D_d(v, \omega) + \varepsilon} \quad (10)$$

The parameters μ_1 and μ_2 in Equation (10) serve as adjustment weights, while a small positive constant ε is introduced to prevent denominator singularity. This formulation achieves a non-linear coupling of temporal and spatial dimensions, ensuring that a lower collision risk corresponds to a higher evaluation score. Consequently, the proposed algorithm is explicitly guided to prioritize obstacle avoidance trajectories characterized by safety margins and smooth maneuvering.

To illustrate the differences between the traditional DWA prediction mechanism and the proposed MMG-DWA prediction mechanism, schematic diagrams detailing their trajectory generation and evaluation processes are presented in Figures 4 and 5.

The curves in the figure represent five sets of candidate trajectories selected at the current time step, illustrating the USV's motion trends within the prediction horizon. Traditional DWA generates trajectories utilizing constant velocity commands throughout each prediction horizon, yielding candidate paths with divergent, arc-like profiles. By contrast, the proposed method integrates propulsion, steering, and hydrodynamic responses into the prediction process. This ensures the candidate trajectories exhibit continuous, smooth transitions that strictly adhere to the USV's inertial characteristics. Coupled with reinforced safety and smoothness constraints, the optimal trajectory achieves gradual curvature and steering stability while preserving target orientation.

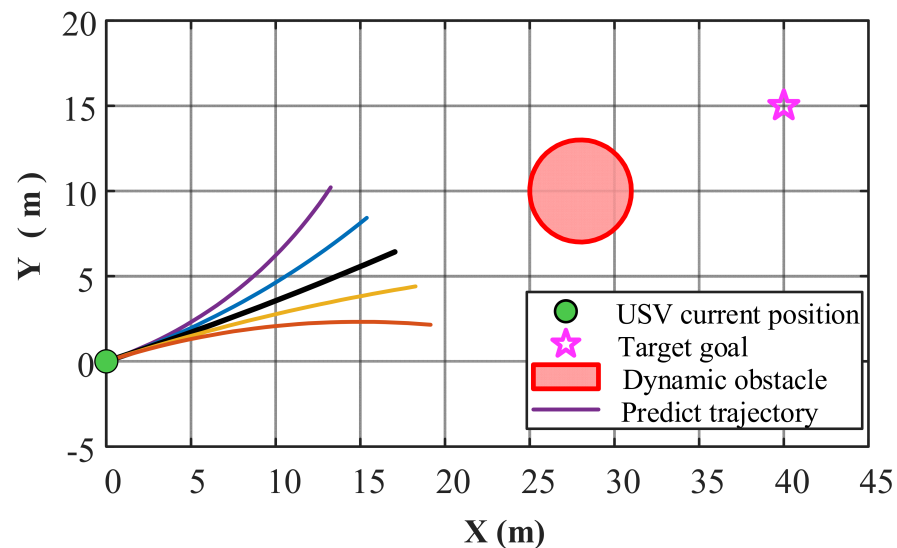


Figure 4. Traditional DWA kinematic prediction.

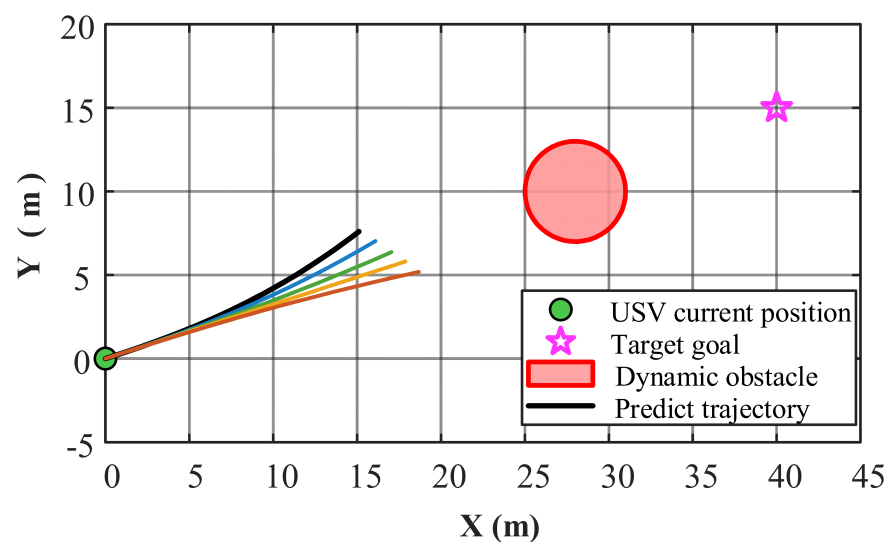


Figure 5. MMG-DWA dynamic prediction.

Remark 3. Integrating the sway velocity coupling term into trajectory prediction inherently suppresses velocity discontinuities. Dynamic prediction based on MMG equations accurately reflects the inertial lag during USV obstacle avoidance.

5. Simulation Experiments

To verify the effectiveness of the proposed global-local path planning method incorporating MMG constraints, this study establishes a simulation environment based on the Zhoushan Archipelago. The simulated USV has a length of 6.5 m and a mass of 800 kg. The rasterized map used in the simulations comprised 1783×1114 pixels, and the start and goal positions were set to [2500, 2500] and [3600, 3300]. A smooth synthetic current field was generated on a coarse grid and then interpolated over the computational domain using bicubic interpolation. The current speed was bounded within 0.5–2.0 m/s, and the current direction was constrained to $[0, 2\pi)$ at each grid point. By maintaining identical starting and ending points, dynamic obstacle scenarios, and parameter configurations, the comparative analyses evaluate global path planning performance and local dynamic obstacle avoidance capabilities. To explicitly compare the steering smoothness and path evolution between the improved MMG-DWA and the traditional algorithm, Figures 6 and 7 present representative

trajectory segments, where the solid blue curve denotes the USV trajectory, the dashed blue curve with arrows denotes the dynamic-obstacle trajectory and motion direction, the circles denote the obstacle boundary, and T1–T4 indicate successive obstacle positions. Figure 8 further illustrates the corresponding heading-angle and path-curvature responses for the same trajectory segment. To provide a quantitative comparison, four sampled kinematic indicators were calculated, including the maximum heading increment, mean heading increment, maximum curvature, and mean curvature variation, as shown in Figure 9. The main simulation and algorithm parameters are summarized in Table 3.

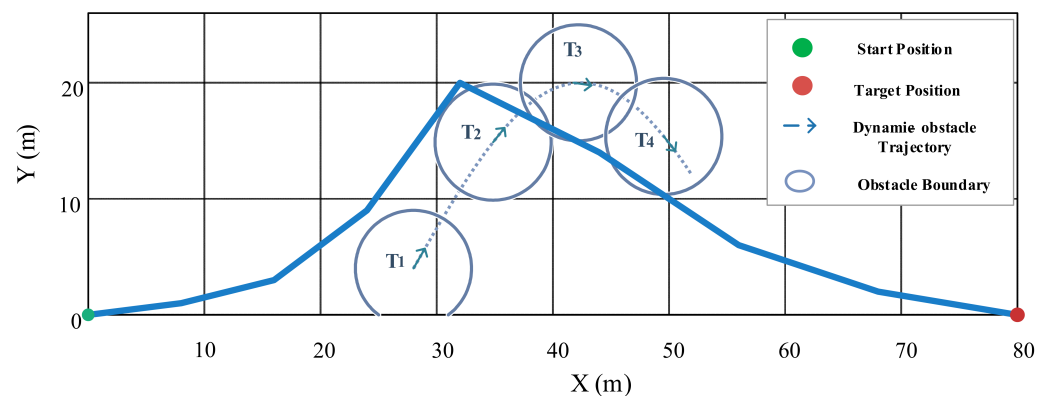


Figure 6. Dynamic obstacle avoidance trajectory of the traditional DWA algorithm.

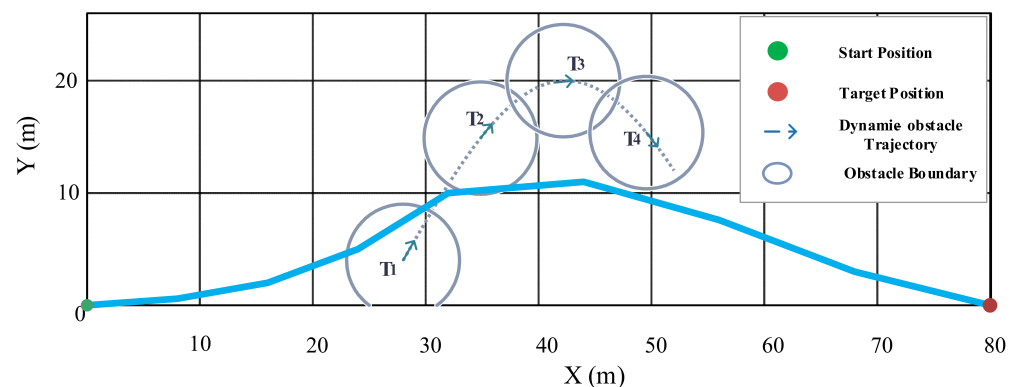


Figure 7. Dynamic obstacle avoidance trajectory of the improved MMG-DWA algorithm.

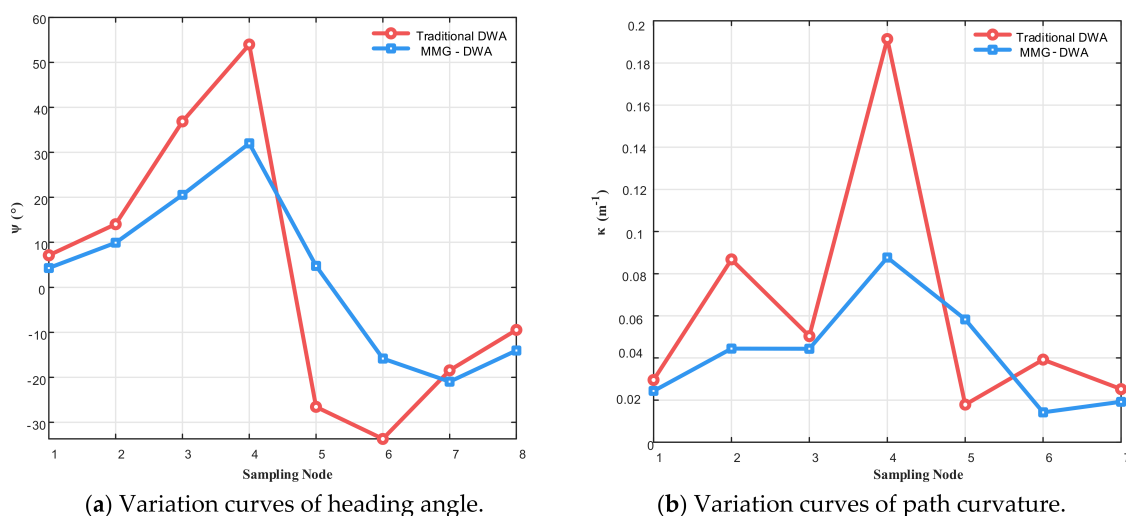


Figure 8. Comparison of kinematic parameters between traditional DWA and MMG-DWA algorithms.

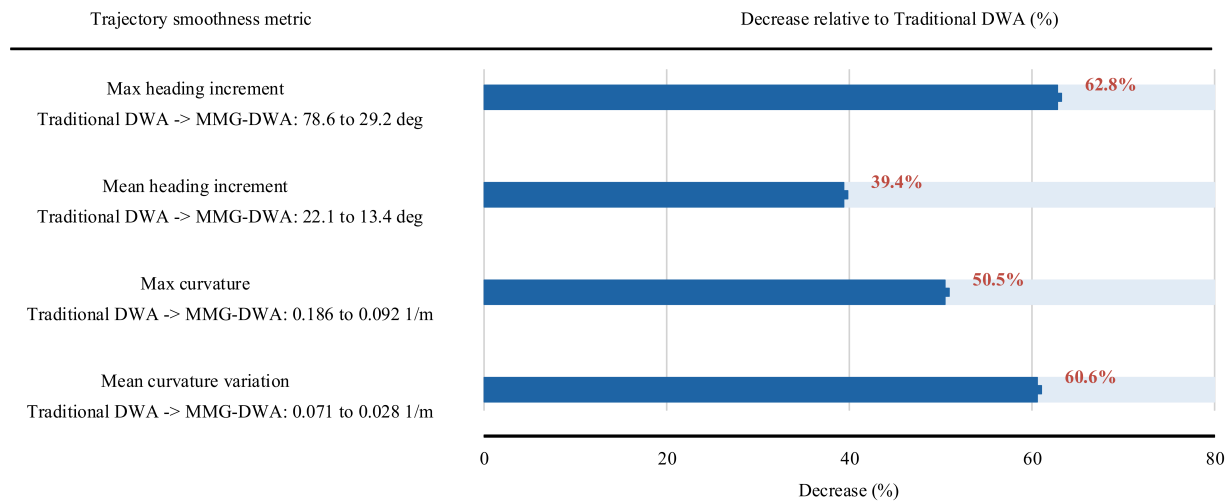


Figure 9. Quantitative comparison of trajectory smoothness between traditional DWA and MMG-DWA.

Table 3. Main parameters of the simulation environment.

Parameter	Value	Unit
Quadtree threshold	[10, 20, 50]	grid cells
Current speed range	0.5–2.0	m/s
Current direction range	$[0, 2\pi)$	rad
Number of dynamic obstacles	2	
DWA time step	0.1	s
DWA prediction horizon	3.0	s
USV surge speed range	0–5.0	m/s
USV yaw-rate range	−0.60–0.60	rad/s
Surge acceleration limit	1.0	m/s^2
Yaw-rate acceleration limit	3.0	rad/s^2
Safety distance	10	m

The results demonstrate that the traditional DWA algorithm produces drastic heading variations during dynamic obstacle avoidance, resulting in markedly abrupt trajectories. Constrained by a simplified kinematic model, it struggles to balance the USV's inertia and maneuvering hysteresis. This lack of kinematic continuity and dynamic adaptability renders it incapable of meeting the actual physical constraints of the USV. In contrast, the enhanced MMG-DWA algorithm generates a smooth and continuous trajectory. It steadily transitions back to the planned route post-avoidance, effectively preventing radical turns and system overshoot.

To analyze the control response performance of the improved algorithm in dynamic environments, Figure 10 captures the time-domain variations in the USV's 3-DOF planar motion states. As illustrated, the proposed algorithm maintains stable speed regulation and gradual heading transitions during obstacle avoidance.

To quantitatively evaluate the trajectory tracking accuracy in dynamic obstacle avoidance scenarios, the shortest Euclidean distance from the actual USV position to the global path is defined as the cross-track error metric, as illustrated in Figure 11. The improved algorithm effectively suppresses substantial error oscillations during dynamic avoidance maneuvers, thereby enhancing the smoothness and precision of path tracking.

The traditional DWA executes dynamic obstacle avoidance based solely on instantaneous distance, making it difficult to accurately anticipate the motion trends of obstacles. This deficiency causes the planned path to intersect with the obstacle trajectory, posing a potential collision risk. A comparative evaluation between the traditional A* + DWA method

and the proposed multi-scale A* + MMG-DWA method is illustrated in Figures 12–14. The findings reveal that the improved algorithm successfully predicts dynamic obstacle movements in advance, enabling the generation of an optimal collision avoidance trajectory.

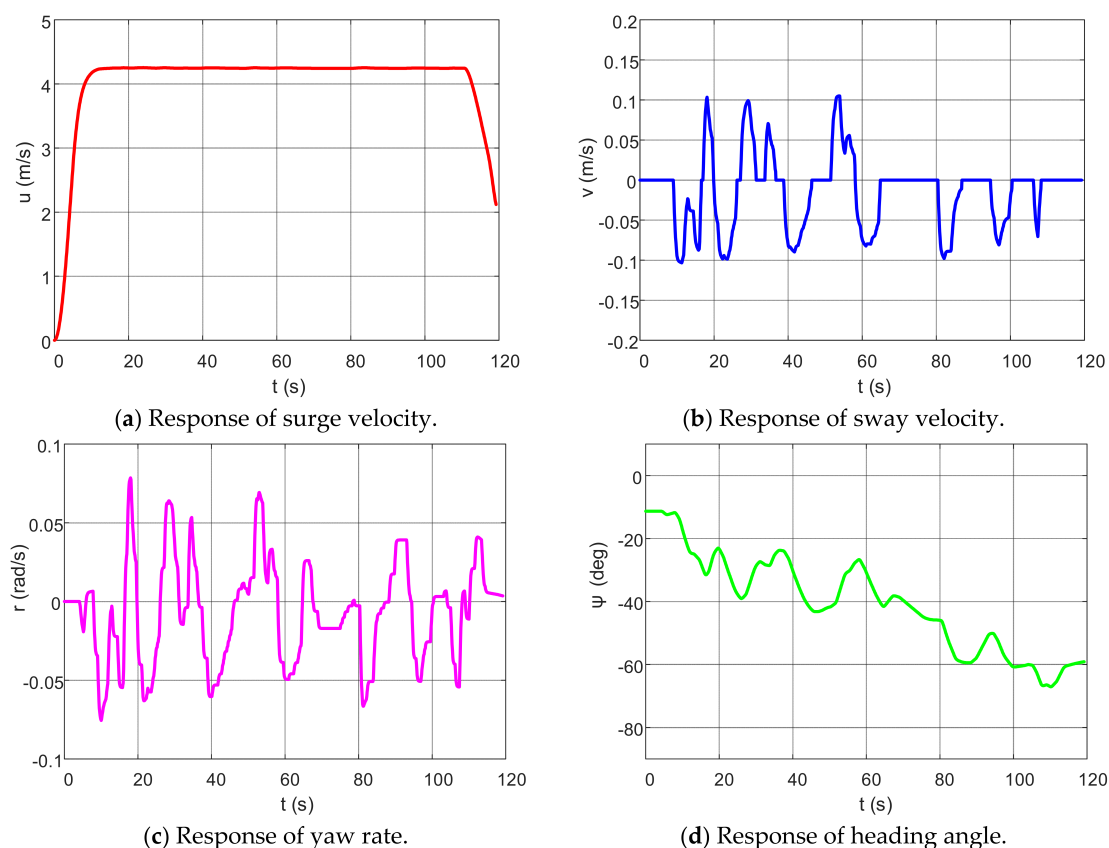


Figure 10. Time-domain response of the 3-DOF planar motion states.

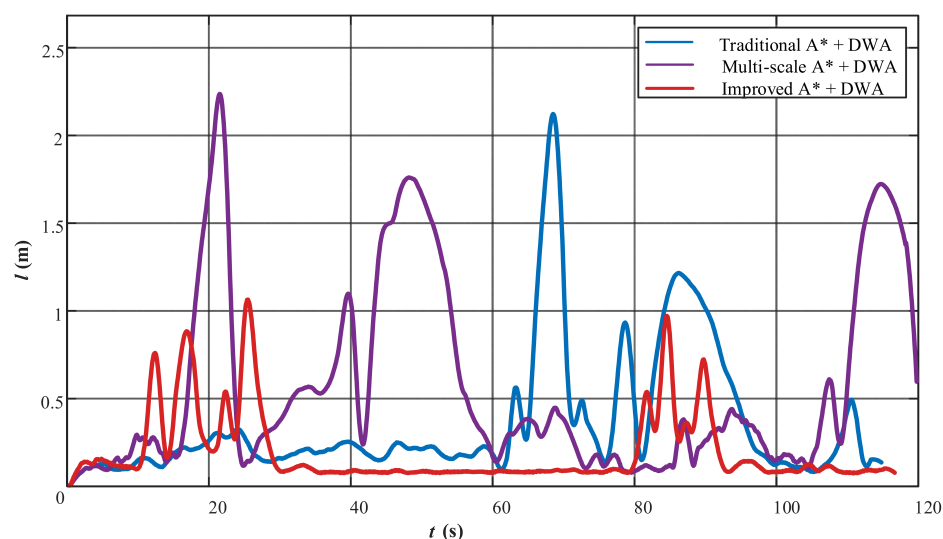


Figure 11. Comparison of cross-track errors.

The MMG model parameters used in the simulation are listed in Table 4. This study quantitatively compares the proposed hybrid algorithm with the traditional A*, the traditional DWA, and the traditional hybrid A*-DWA algorithm, as detailed in Tables 5–7. Table 8 presents the mean $\pm$ standard deviation results from 10 randomized trials, where

different current fields and dynamic obstacles were generated to evaluate the robustness of each method.

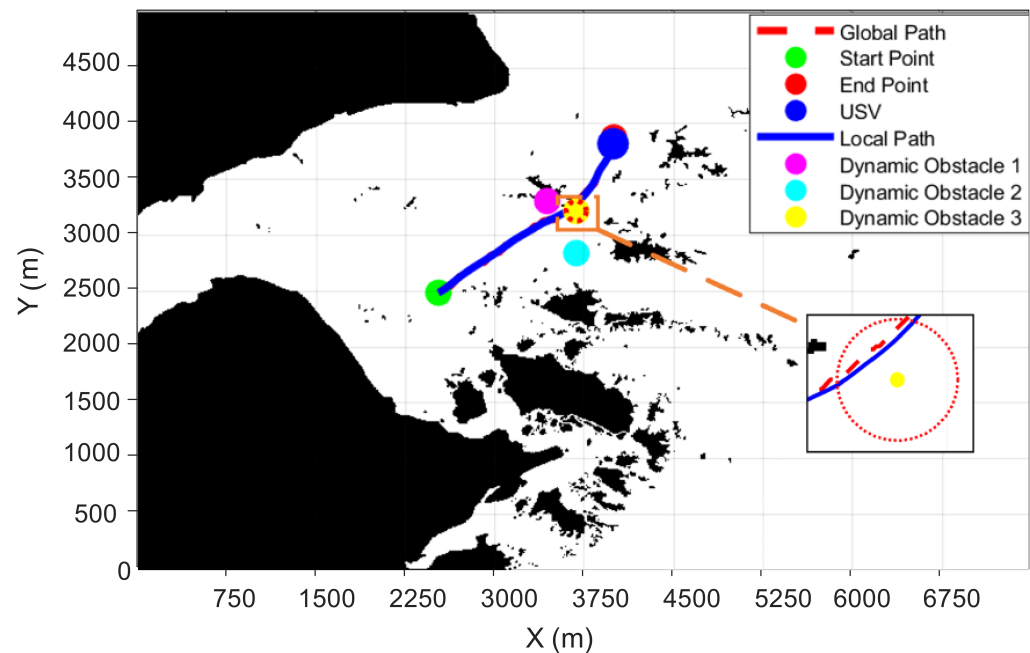


Figure 12. Obstacle avoidance trajectory of the traditional A* + DWA method.

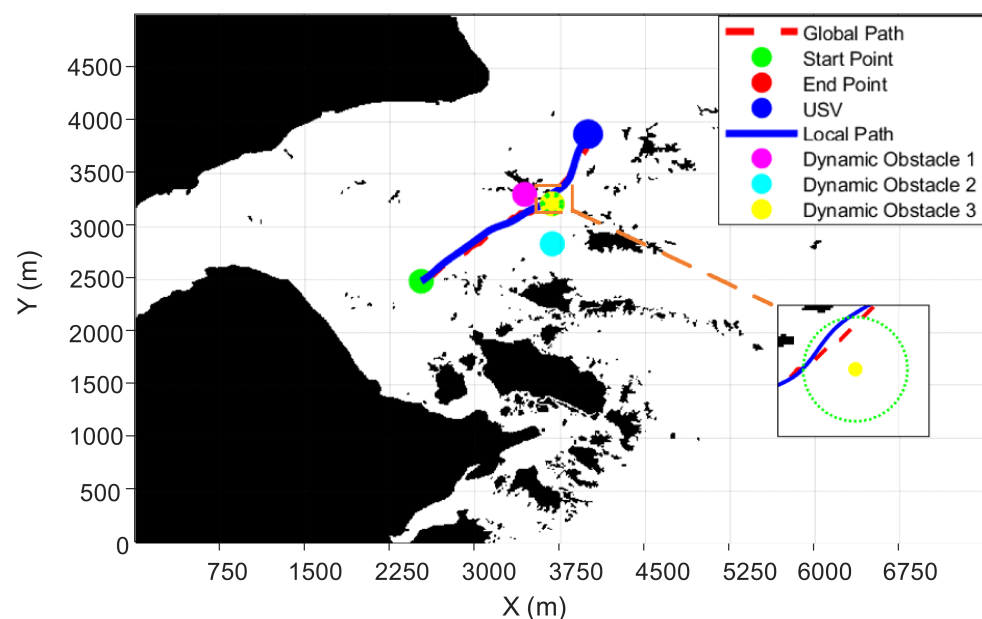


Figure 13. Obstacle avoidance trajectory of the proposed multi-scale A* + MMG-DWA method.

The proposed framework is mainly affected by the map resolution, the number of dynamic obstacles, and the prediction horizon of the local planner. In the global planning stage, the multi-scale grid representation reduces unnecessary searches in open-water regions and focuses finer resolution on complex regions near obstacles. In the local planning stage, the MMG-based trajectory prediction increases the cost of evaluating candidate control commands, but the prediction horizon and sampling resolution can be adjusted according to the onboard computational resources and real-time requirements. In conclusion, the proposed algorithm significantly improves the global search efficiency. These improvements were observed in the Zhoushan Archipelago simulation scenario described

above. Further validation under practical operating conditions is necessary to assess the influence of sensor noise, actuator response delays, and environmental disturbances on the proposed framework. In addition, validation using AIS trajectory data, hardware-in-the-loop simulations, or field tests will be considered to further evaluate the robustness of the proposed planner under real current, wind, wave, and perception uncertainties.

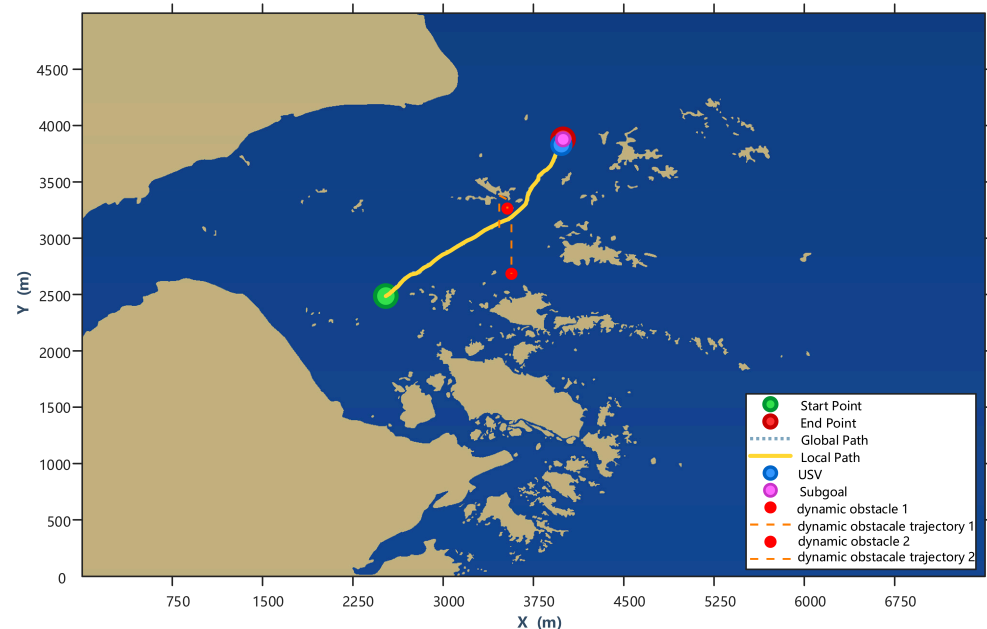


Figure 14. Global-local collaborative trajectory based on MMG constraints.

Table 4. Main parameters of the simplified MMG model.

Parameter	Symbol	Value	Unit
Length	L	6.5	m
Beam	B	2.2	m
Draft	d	0.8	m
Mass	m	800	kg
Surge added mass	m_x	120	kg
Sway added mass	m_y	360	kg
Yaw moment of inertia	I_{zz}	1500	$\text{kg}\cdot\text{m}^2$
Added yaw moment of inertia	J_{zz}	500	$\text{kg}\cdot\text{m}^2$
Maximum thrust	$T_{\max}$	1200	N
Maximum rudder angle	$\delta_{\max}$	± 35	deg

Table 5. Comparison of A* algorithm.

Algorithm	Planning Time (s)	Planning Path Lengths (m)
Traditional A* algorithm	39.74	2016.73
Multi-scale A* algorithm	49.54	2162.28
RRT* algorithm	49.10	2009.31
Improved A* algorithm	42.30	2116.19

Table 6. Comparison of DWA algorithm.

	Planning Time (s)	Planning Path Lengths (m)
Traditional DWA algorithm	38.24	2115.91
Improved DWA algorithm	10.77	2008.12
Percentage Decrease	71.83%	5.09%

Table 7. Comparison of A* + DWA algorithm.

	Planning Time (s)	Planning Path Lengths (m)
Traditional A* + DWA	77.98	2115.91
Improved A* + DWA	53.08	2008.21
Percentage Decrease	31.93%	5.09%

Table 8. Statistical comparison of navigation performance under randomized dynamic scenarios.

Method	Planning Time (s)	Planning Path Lengths (m)	Success Rate (%)
Traditional A* + DWA	77.20 ± 2.17	2114.86 ± 19.72	100
Multi-scale A* + DWA	65.49 ± 2.14	2133.11 ± 16.60	100
RRT* + DWA	61.81 ± 1.95	2016.52 ± 12.20	100
Improved A* + DWA	52.94 ± 1.34	2007.69 ± 11.29	100

6. Conclusions

The hierarchical architecture proposed in this paper maps the global path to local planning objectives in real time, solves the optimal control commands under MMG constraints, and generates smooth collision avoidance tracks. The main conclusions are as follows:

- (1) The proposed multi-scale A* algorithm integrates maneuvering characteristics. By adopting a goal-oriented mechanism and a motion deviation cost function, it suppresses abrupt course changes at path turning points, enabling the output global path to comply with the USV's low-level dynamic constraints.
- (2) The local collision avoidance strategy strictly constrains the velocity sampling space within the USV's dynamic limits. Integrated with a lateral sideslip compensation term and a nonlinear cost function, this approach guarantees the safe evasion of dynamic targets.
- (3) Through this hierarchical design, planning efficiency and maneuvering constraints are effectively unified. Optimization time and path length are both reduced, and maneuvering overshoot during dynamic avoidance is substantially suppressed. The resulting trajectories exhibit continuous curvature, which mitigates high-frequency oscillations in cross-track error.

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

Funding: This research was funded by the Applied Basic Research Program in the Field of Artificial Intelligence under the Liaoning Province Department of Science and Technology (Grant No.600024003), the Industry-University-Research Collaborative Education Project of Liaoning Province (Grant No. 790825206), the High-Level Talent Innovation Program of Dalian (Grant No. 2024RQ070), the Scientific Research Startup Fund for Introduced PhD Talents (Grant No. 100/11562520631).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ma, Y.; Hu, M.; Yan, X. Multi-objective path planning for unmanned surface vehicle with currents effects. *ISA Trans.* **2018**, *75*, 137–156. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Fu, X.; Qian, D. Research on automatic trajectory planning method of unmanned ships based on multi-objective optimization. *IEEE Access* **2023**, *11*, 129829–129839. [\[CrossRef\]](#)
3. Hu, S.; Tian, S.; Zhao, J.; Shen, R. Path Planning of an Unmanned Surface Vessel Based on the Improved A-Star and Dynamic Window Method. *J. Mar. Sci. Eng.* **2023**, *11*, 1060. [\[CrossRef\]](#)
4. Li, C.; Yao, L.; Mi, C. Fusion algorithm based on improved A* and DWA for USV path planning. *J. Mar. Sci. Appl.* **2025**, *24*, 224–237.
5. Xu, D.; Yang, J.; Zhou, X.; Xu, H. Hybrid path planning method for USV using bidirectional A* and improved DWA considering the manoeuvrability and COLREGs. *Ocean Eng.* **2024**, *298*, 117210. [\[CrossRef\]](#)
6. Yuan, X.; Tong, C.; He, G.; Wang, H. Unmanned Vessel Collision Avoidance Algorithm by Dynamic Window Approach Based on COLREGs Considering the Effects of the Wind and Wave. *J. Mar. Sci. Eng.* **2023**, *11*, 1831. [\[CrossRef\]](#)
7. Liu, C.; Xiao, F.; Ma, Y.; Chen, H.; Wu, Y.; Li, Z.; Guo, L. An enhanced RRT* algorithm with biased sampling and dynamic stepsize strategy for ship route planning in the high-risk areas. *Ocean Eng.* **2025**, *332*, 121466. [\[CrossRef\]](#)
8. Song, C.; Guo, T.; Sui, J. Ship path planning based on improved multi-scale a* algorithm of collision risk function. *Sci. Rep.* **2024**, *14*, 30418. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Liang, Z.; Yang, Y.; Huang, Z.; Zhou, S. USV path planning algorithm based on 20D-A* and IDWA algorithms under COLREGs. *Ocean Eng.* **2025**, *331*, 121389. [\[CrossRef\]](#)
10. Hu, W.; Chen, S.; Liu, Z.; Luo, X.; Xu, J. HA-RRT: A heuristic and adaptive RRT algorithm for ship path planning. *Ocean Eng.* **2025**, *316*, 119906. [\[CrossRef\]](#)
11. Chen, H.; Lin, Z.; Chen, Z.; Jian, J.; Liu, C. Adaptive DWA algorithm with decision tree classifier for dynamic planning in USV navigation. *Ocean Eng.* **2025**, *321*, 120328. [\[CrossRef\]](#)
12. He, Y.; Li, Z.; Mou, J.; Hu, W.; Li, L.; Wang, B. Collision-avoidance path planning for multi-ship encounters considering ship manoeuvrability and COLREGs. *Transp. Saf. Environ.* **2021**, *3*, 103–113.
13. Gao, P.; Zhou, L.; Zhao, X.; Shao, B. Research on ship collision avoidance path planning based on modified potential field ant colony algorithm. *Ocean Coast. Manag.* **2023**, *235*, 106482. [\[CrossRef\]](#)
14. Chen, Y.; Mao, W. An isochrone-based predictive optimization for efficient ship voyage planning and execution. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 18078–18092. [\[CrossRef\]](#)
15. Smierzchalski, R.; Michalewicz, Z. Modeling of ship trajectory in collision situations by an evolutionary algorithm. *IEEE Trans. Evol. Comput.* **2000**, *4*, 227–241. [\[CrossRef\]](#)
16. Zhang, G.; Zhang, X. A novel DVS guidance principle and robust adaptive path-following control for underactuated ships using low frequency gain-learning. *ISA Trans.* **2015**, *56*, 75–85. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Song, C.; Zhang, X.; Zhang, G. Nonlinear identification for 4-DOF ship maneuvering modeling via full-scale trial data. *IEEE Trans. Ind. Electron.* **2021**, *69*, 1829–1835. [\[CrossRef\]](#)
18. Song, C.; Guo, T.; Sui, J.; Zhang, X. Dynamic positioning control of large ships in rough sea based on an improved closed-loop gain shaping algorithm. *J. Mar. Sci. Eng.* **2024**, *12*, 351. [\[CrossRef\]](#)
19. Børhaug, E.; Pavlov, A.; Panteley, E.; Pettersen, K.Y. Straight line path following for formations of underactuated marine surface vessels. *IEEE Trans. Control Syst. Technol.* **2010**, *19*, 493–506. [\[CrossRef\]](#)
20. Guo, Q.; Zhang, X.; Han, X. Robust adaptive event-triggered path following control for autonomous surface vehicles in shallow waters. *Ocean Eng.* **2023**, *286*, 115571. [\[CrossRef\]](#)
21. Zhang, H.; Wei, Q.; Luo, Y. A novel infinite-time optimal tracking control scheme for a class of discrete-time nonlinear systems via the greedy HDP iteration algorithm. *IEEE Trans. Syst. Man Cybern. Part B (Cybern.)* **2008**, *38*, 937–942. [\[CrossRef\]](#)
22. Koike, H.; Dostal, L.; Sawada, R.; Miyauchi, Y.; Maki, A. A study on the implementation of nonlinear Kalman filter applying MMG model. *J. Mar. Sci. Technol.* **2023**, *28*, 733–745. [\[CrossRef\]](#)
23. Ebert-Uphoff, I. Introducing parallel manipulators through laboratory experiments. *IEEE Robot. Autom. Mag.* **2003**, *10*, 13–19. [\[CrossRef\]](#)
24. Petres, C.; Pailhas, Y.; Patron, P.; Petillot, Y.; Evans, J.; Lane, D. Path planning for autonomous underwater vehicles. *IEEE Trans. Robot.* **2007**, *23*, 331–341. [\[CrossRef\]](#)
25. Liu, C.; Mao, Q.; Chu, X.; Xie, S. An Improved A-Star Algorithm Considering Water Current, Traffic Separation and Berthing for Vessel Path Planning. *Appl. Sci.* **2019**, *9*, 1057. [\[CrossRef\]](#)

26. Sakakibara, S.; Kubo, M. Characteristics of low-frequency motions of ships moored inside ports and harbors on the basis of field observations. *Mar. Struct.* **2008**, *21*, 196–223. [[CrossRef](#)]
27. Chen, X.; Zhang, Y.; Feng, Z.; Zhang, H.; Biancardo, S.A.; Shang, W.L. Spatiotemporal ship carbon emission exploitation and low-carbon shipping pathway evaluation. *Appl. Energy* **2026**, *422*, 128334. [[CrossRef](#)]

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