

A Review of Local Path Planning Algorithms for USV

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Abstract

The autonomous navigation system constitutes the core foundation for the operation of unmanned surface vessels (USVs), and local path planning algorithms serve as a key component within their autonomous navigation framework. This paper conducts a systematic review of local path planning algorithms commonly used in the current USV field, covering mainstream methods such as the A* algorithm, Dynamic Window Approach (DWA), Rapidly-Exploring Random Trees (RRT) algorithm, and Artificial Potential Field (APF) algorithm. It conducts an in-depth analysis of the basic principles, advantages, and limitations of each algorithm, and summarizes their applicable application scenarios. The study reveals that existing local path planning algorithms for USVs have demonstrated considerable practical value in simple navigation scenarios like open waters, yet they still face significant challenges when addressing complex situations. Specifically, these challenges are reflected in three aspects: insufficient adaptability to high-density unstructured navigation environments, lack of robustness under high-dynamic and strong nonlinear environmental interference, and limited planning efficiency in multi-constraint and multi-objective task scenarios. The research findings of this paper can provide a systematic reference for the theoretical innovation and engineering practice of local path planning technology for USVs.

Keywords

USV; Local Path Planning; Autonomous Navigation; Path Planning Algorithm.

1. Introduction

With the rapid advancement of intelligence and unmanned technologies in maritime transportation, unmanned ships have emerged as a prominent research focus and a critical direction for future development in the maritime sector. Autonomous navigation capability serves as the core guarantee for the safe and efficient operation of unmanned ships. As a key component of the autonomous navigation system, local path planning directly dictates ships' obstacle avoidance decisions and navigation trajectory quality in dynamically complex marine environments. Its algorithmic performance exerts a pivotal influence on the practicality and reliability of unmanned ships. In recent years, scholars worldwide have conducted extensive research on local path planning for unmanned ships, proposing a variety of algorithmic models with distinct characteristics. To systematically synthesize the research progress in this field, clarify existing technical bottlenecks, and identify future development directions, this paper presents a comprehensive review and analysis of current mainstream local path planning algorithms for unmanned ships. The autonomous navigation system constitutes the fundamental core for the operation of unmanned ships, while local path planning algorithms are integral to their autonomous navigation architecture. This paper systematically collates the commonly adopted local path planning algorithms in the current unmanned ship domain, encompassing mainstream methods such as the A* algorithm, Dynamic Window Approach (DWA), Rapidly Exploring Random Tree (RRT) algorithm, and Artificial Potential Field (APF) algorithm. It conducts an in-depth analysis of the basic principles, advantageous features, and inherent limitations of each algorithm, and summarizes their applicable application scenarios.

2. Current development status

In recent years, a growing number of scholars have conducted innovative optimization work based on traditional path planning algorithms, facilitating remarkable advancements in the field of local path planning for unmanned ships. To align with navigation requirements in real-world marine environments, researchers have significantly improved the practical applicability and operational reliability of these algorithms through multiple strategies [1], including the integration of International Regulations for Preventing Collisions at Sea (COLREGs) constraints, the incorporation of ship kinematic characteristics, and the integration of dynamic marine environmental features.

Current mainstream local path planning algorithms primarily encompass: the A* algorithm based on a graph search mechanism [2], the Dynamic Window Approach (DWA) that accounts for dynamic constraints [3], the Rapidly Exploring Random Tree (RRT) algorithm suitable for high-dimensional spaces [4], and the Artificial Potential Field (APF) algorithm characterized by physical field modeling [5]. These algorithms exhibit distinct features in terms of theoretical frameworks, performance advantages, and applicable scenarios. This chapter will systematically elaborate on their core operational mechanisms, conduct in-depth analysis of their technical merits and application limitations, and comprehensively summarize their current development status in the field of local path planning for unmanned ships.

2.1. A* algorithm

The A* algorithm is a classic path planning method based on graph search, with its core lying in the weighted combination of a heuristic function $h(n)$ and a cost function $g(n)$. Specifically, $g(n)$ represents the actual cost from the start node to the current node n , while $h(n)$ denotes the estimated cost from the current node n to the target node. Once the A* algorithm is initiated, it first adds the start node to the open list and calculates its cost function, then enters an iterative search process: in each iteration, the node with the minimum cost is selected from the open list for expansion. If this node is the target node, the path search is completed; if not, the node is moved to the closed list to avoid redundant processing, and all its adjacent nodes are checked simultaneously. The cost information of adjacent nodes is updated according to the cost function, or unprocessed adjacent nodes are directly added to the open list. This process of "node selection - expansion - list update" repeats continuously until the target node is found. Finally, a complete planned path is generated by backtracking from the target node to the start node. The evaluation function of the A* algorithm is as follows:

$$f(n)=g(n)+h(n) \quad (1)$$

Advantages of the A* Algorithm:

The A* algorithm offers significant advantages in ship local path planning. Leveraging an evaluation function that satisfies the "no overestimation of actual cost" criterion, it stably generates the shortest or minimum-cost path from the start point to the target point, aligning with the core requirements of efficiency and energy conservation for ship navigation. Meanwhile, the algorithm guides the search direction through heuristic information, drastically reducing invalid node expansion. In scenarios with moderate environmental complexity such as coastal waters and ports, its planning efficiency meets real-time requirements. It also exhibits excellent compatibility with the grid-based environmental modeling method commonly used in ship local planning, eliminating the need for complex model conversion and lowering engineering implementation difficulty.

Disadvantages of the A* Algorithm:

In marine environments, dynamic obstacles and ocean current changes occur frequently. However, the A* algorithm is a static planning method—once the environment changes, a complete search process must be restarted, leading to potential planning delays and difficulty

in addressing sudden collision avoidance scenarios. Additionally, when considering multi-dimensional ship states (e.g., position, heading, speed) or increasing grid resolution to adapt to complex sea areas, its search space expands sharply, resulting in a significant rise in computational cost that may exceed real-time control requirements. Furthermore, the algorithm does not directly incorporate ship motion constraints such as steering lag and minimum turning radius, so the generated path may contain sharp corners. This requires additional smoothing processing, increasing system complexity.

Building on the A* algorithm, scholars have developed various hybrid algorithms that have been widely applied in ship local path planning after improvements. Singh et al. [6] proposed a constrained A* algorithm considering ocean current interference, whose core goal is to compensate for the impact of ocean currents on local path re-planning while enhancing computational efficiency. Campbell et al. [7] presented a rule-corrected A* algorithm: it first excludes areas violating the International Regulations for Preventing Collisions at Sea (COLREGs) from optional grids, then recalculates only specific regions in the grid map, ultimately shortening the algorithm's computation time effectively.

The application scope of the A* algorithm in local path planning is relatively limited, with two core constraints: first, the algorithm itself incurs certain computation time; second, its ability to handle multi-dimensional constraints is insufficient. In high-dimensional state space scenarios, these shortcomings become more prominent—it not only faces a significant increase in computational complexity but also struggles to meet real-time requirements due to prolonged computation. These two issues collectively further narrow its applicable scenarios to a certain extent.

2.2. Dynamic Window Approach algorithm

The Dynamic Window Approach (DWA) is a sampling-based local path planning algorithm. Its core idea is to sample the velocity space within the constraints of the robot's kinematics, and select the optimal velocity combination through an evaluation function to generate a local trajectory that ensures safe obstacle avoidance. Owing to its advantages of high real-time performance and strong adaptability to dynamic environments, the algorithm has been widely applied in the field of mobile robots and has demonstrated unique merits in the local path planning of unmanned surface vessels (USVs). Unlike traditional static planning algorithms, DWA adopts an iterative process of "velocity sampling - trajectory prediction - evaluation and selection," enabling rapid responses to dynamic obstacles and sudden collision avoidance requirements in marine environments. This aligns well with the autonomous navigation scenarios of USVs in complex waters such as coastal areas and ports.

The operational logic of the DWA algorithm revolves around two core components: "velocity space constraints" and "trajectory evaluation and optimization." The specific process can be divided into four key steps:

Velocity Space Sampling:

Based on the USV's kinematic model (including maximum linear velocity, maximum angular velocity, acceleration limits, etc.), a set of linear and angular velocity combinations are discretely sampled within the feasible velocity space to form a candidate velocity window. Different from land robots, velocity sampling for USVs must additionally consider factors such as draft and hull inertia to avoid sampling velocities that exceed the vessel's actual maneuvering capabilities.

Trajectory Prediction and Constraint Checking:

For each sampled velocity combination, the navigation trajectory over a short period in the future is predicted using the vessel's kinematic equations. Simultaneously, environmental perception information is utilized to check whether the trajectory will collide with static or dynamic obstacles, and velocity combinations that violate safety constraints are eliminated.

Multi-Objective Evaluation Function Calculation:

A multi-dimensional evaluation function is designed to quantitatively score the remaining feasible trajectories. Common evaluation indicators include safety, goal-orientedness, smoothness, and velocity consistency. In different maritime scenarios, the priority of each indicator needs to be adjusted through weight coefficients. For example, in narrow waterway navigation, the weight of safety should be significantly higher than that of goal-orientedness.

Optimal Velocity Selection and Execution:

The velocity combination with the highest evaluation score is selected as the current control command to drive the USV to execute the local trajectory. After completing the planning of the current cycle, the algorithm re-collects environmental information and repeats the above process, realizing a closed-loop iteration of "perception - planning - control."

In the field of USV local path planning, scholars have carried out extensive research on improvement strategies targeting the inherent limitations of the DWA algorithm. QU et al. [8] pointed out that traditional USV path planning methods suffer from insufficient adaptability to dynamic environments and poor real-time response capabilities. To address these issues, they proposed an improved algorithm (DWA-RL) integrated with safe reinforcement learning. This algorithm innovatively uses the state encoding of the DWA algorithm as the observation input for reinforcement learning, effectively reducing the state space dimension. Meanwhile, by designing a safety reward function with collision avoidance constraints and adaptively adjusting key algorithm parameters, it ultimately achieves efficient local path planning of USVs under the interference of dynamic surges and ocean currents. CHEN et al. [9] focused on the poor environmental adaptability of the traditional DWA algorithm in USV path planning and proposed an improved decision tree fusion-based algorithm (DT-DWA). By embedding a decision tree classifier into the classic DWA framework and introducing dynamic characteristic parameters such as "encounter distance" and "encounter time," the algorithm achieves adaptive dynamic adjustment of motion weights through accurate evaluation of obstacle threat levels, thereby enhancing the adaptability of path planning in complex environments. The DWA algorithm, by integrating "dynamic window velocity screening" and "kinematic constraints," exhibits unique application advantages in USV local path planning tasks. Through real-time deduction of velocity combinations and optimal solution of the cost function, the algorithm can effectively incorporate vessel maneuvering characteristics and dynamic environmental parameters into the planning process, endowing it with strong environmental adaptability in dynamic collision avoidance scenarios. However, it should be noted that the DWA algorithm has inherent shortcomings such as limited global vision and insufficient ability to handle complex scenarios, which restrict its practical application in confined waters or complex task scenarios.

2.3. Rapidly-Exploring Random Trees algorithm

The Rapidly Exploring Random Tree (RRT) algorithm is a probability sampling-based path planning method. Its core idea is to randomly sample nodes in the state space and gradually construct a random tree extending from the start point to the target point, thereby achieving path search in complex environments. Characterized by strong adaptability to high-dimensional spaces and no need for global environmental modeling, the algorithm has been widely applied in fields such as mobile robots and autonomous driving. In the local path planning of Unmanned Surface Vessels (USVs), the RRT algorithm can effectively handle complex scenarios in marine environments, including high-dimensional state spaces (e.g., integrating multiple parameters such as position, heading, and speed) and dynamic obstacle distributions. It is particularly suitable for navigation environments that are difficult to model with traditional algorithms, such as open sea areas and complex reef zones.

The core process of the RRT algorithm is as follows: first, initialize the tree structure with the start point as the initial node; then randomly sample a node in the configuration space, find the nearest neighbor node of this sampled node in the constructed tree, and extend it with a fixed step size to generate a new node; after collision detection confirms that the path is collision-free, add the new node to the tree; repeat the above processes of sampling, nearest neighbor search, node extension, and collision detection until the new node is close to the target point; finally, generate a feasible path from the start point to the target point by backtracking the node connection relationship, as shown in the following figure:

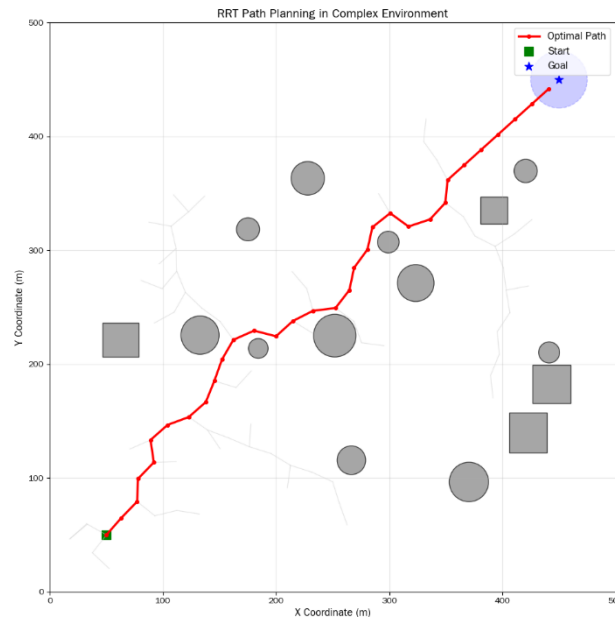


Fig. 1 RRT algorithm

The original Rapidly Exploring Random Tree (RRT) algorithm exhibits inherent limitations, including strong path randomness, low planning efficiency, and poor path smoothness. Directly applied to Unmanned Surface Vessels (USVs), it fails to meet the dual demands of navigation safety and economic efficiency in maritime scenarios. In recent years, targeting the dynamic marine environment and the unique constraints of ship motion, scholars have developed a range of targeted optimization strategies: Mao et al. [10] addressed the core issue of disconnection between traditional path planning search rules and actual ship maneuverability, proposing a state-prediction-based RRT motion planning algorithm; Hu et al. [11] tackled the traditional RRT algorithm's shortcomings (e.g., slow convergence, frequent path turns, and subpar planning quality) by developing a heuristic adaptive HA-RRT algorithm. Overall, leveraging its strengths of excellent search efficiency, broad applicability, and superior scalability in high-dimensional spaces, the RRT algorithm can effectively integrate multi-dimensional constraints (e.g., kinematics and dynamics) of USVs, thus gaining widespread adoption in various practical local path planning scenarios.

2.4. The Artificial Potential Field algorithm

The core of the Artificial Potential Field (APF) algorithm lies in abstracting the ship's navigation environment into a virtual potential field. The target point acts like a low-potential depression generating an attractive force that propels the ship toward it. Static obstacles such as islands and reefs, as well as dynamic obstacles like other navigating ships, behave like high-potential hills producing a repulsive force that prevents the ship from approaching. As a force-receiving object, the ship moves along the direction of the resultant force composed of the attractive and repulsive forces to complete local path planning. The key is to calculate the attractive force, repulsive force, and total resultant force through mathematical functions. The magnitude of the attractive force is usually proportional to the distance between the ship and the target point,

while the magnitude of the repulsive force is inversely proportional to the distance between the ship and the obstacle. Finally, the ship's navigation direction is continuously adjusted based on the direction of the total resultant force.

Advantages of the APF Algorithm:

Strong real-time responsiveness: The algorithm features a concise calculation logic. It only requires simple mechanical calculations for the positional relationships between the ship's current location, obstacles, and the target point, enabling rapid output of the resultant force direction. This adapts to the local planning needs of dynamic environmental changes during ship navigation. **Adaptability to multi-obstacle scenarios:** When there are multiple static or dynamic obstacles in the navigation area, the total resultant force of multiple repulsive forces and a single attractive force can be calculated through vector superposition, allowing quick path adjustments to avoid all obstacles. **Easy engineering implementation:** The algorithm's mechanical model is intuitive, and the relevant function formulas are simple. It can be combined with the ship's motion model to quickly complete code writing and practical deployment without the need for complex hardware support.

Disadvantages of the APF Algorithm:

Proneness to local minima: When the attractive force on the ship is offset by the repulsive forces from multiple obstacles, the total resultant force becomes zero. This causes the ship to stagnate and unable to continue path planning, a problem that is likely to occur in waters surrounded by multiple reefs. **Risk of target inaccessibility:** If there are obstacles near the target point, the strong repulsive force generated by the obstacles may offset the attractive force of the target point, making it difficult for the ship to reach the target location. **Susceptibility to path oscillation:** In scenarios such as narrow waterways, the ship may experience repeated adjustments in navigation direction due to frequent changes in the repulsive force of obstacles, affecting navigation stability.

In recent years, scholars have proposed various solutions for the local path planning of unmanned ships. HAN et al. [12] proposed a potential field-extended dynamic window algorithm. This algorithm innovatively couples the global path-guided potential field, shoreline grid repulsive potential field, and COLREGs repulsive potential field, and then combines it with the dynamic window algorithm to generate predicted trajectories that comply with dynamic constraints. This method effectively addresses the key issues of the traditional APF algorithm, such as rough environmental modeling and disconnection from motion constraints, providing a better solution for trajectory planning in related scenarios. Ma et al. [13] proposed an improved APF algorithm to solve the low path planning efficiency of sampling-based algorithms in dense environments. They integrated the APF with the RRT* algorithm to form the APF-RRT* algorithm. This algorithm constructs artificial potential fields for the start point, target point, reference path, and obstacles respectively by combining task and environmental prior information, and improves the random sampling step of RRT*. Under the guidance of the potential field, the sampling points are closer to the optimal path, and the number of invalid sampling points is significantly reduced. Ultimately, it outperforms mainstream sampling-based path planning methods in terms of convergence speed, sampling effectiveness, and time efficiency. GAN et al. [14] addressed the problems of path oscillation and discontinuous steering in the traditional APF algorithm for narrow inland waterway scenarios, designing a four-layer composite potential field model based on an elliptical ship domain. This model introduces a velocity repulsive potential field to characterize the movement trend of dynamic obstacles, and optimizes the curve trajectory generation mechanism by combining steering attraction points. It ultimately achieves path planning with continuous curvature that complies with inland waterway navigation rules.

The APF algorithm has been widely applied in the field of local path planning for unmanned ships due to its significant advantages of strong real-time responsiveness and easy integration of various constraints. By integrating precise environmental modeling, ship dynamic constraints, and maritime navigation rules, the improved APF algorithm has effectively made up for the inherent defects of the traditional algorithm. However, in dynamically time-varying environments, the design of the real-time potential field update mechanism, as well as how to avoid the algorithm falling into local minima in complex obstacle scenarios, remain core technical challenges that need to be addressed urgently.

3. Problems and Challenges

Although current USV local path planning algorithms have demonstrated certain practicality in simple scenarios such as open waters and static obstacles, as maritime mission scenarios evolve toward higher complexity, higher dynamics, and multi-constraints, existing algorithms still face many core problems and challenges in theoretical adaptability and engineering implementation, which can be specifically summarized into the following three aspects:

3.1. Insufficient Adaptability to High-Density Unstructured Environments

USVs often face high-density, irregularly shaped unstructured obstacle distributions in typical operating scenarios like coastal areas, ports, and reef zones, and existing algorithms have obvious shortcomings in adaptability to such environments: the A* algorithm sees a sharp reduction in effective grid passage area due to high-density obstacles, leading to a significant increase in computational time; the DWA algorithm relies on short-term trajectory prediction and is prone to falling into the "local optimal trap," where the current obstacle avoidance trajectory may lead the subsequent path into a dead end; the random sampling of the RRT algorithm generates a large number of invalid points in high-density obstacle areas, resulting in decreased node expansion efficiency and frequent path turns, which are difficult to meet the ship's smoothness requirements; the APF algorithm is prone to local minima due to the superposition of repulsive forces from multiple obstacles and gravitational imbalance, leading to ship stagnation or obstacle avoidance failure, and at the same time, the irregular shape of unstructured obstacles is difficult to accurately characterize through traditional geometric modeling, further reducing the accuracy of obstacle boundary perception and the reliability of obstacle avoidance decisions.

3.2. Lack of Robustness Under High-Dynamic and Strong Nonlinear Environmental Disturbances

The high dynamic and strong nonlinear characteristics of the marine environment pose severe challenges to the robustness of USV local path planning algorithms; the A* algorithm, as a static planning method, cannot update environmental information in real time and is prone to obstacle avoidance delays when facing sudden dynamic obstacles; although the DWA algorithm can handle dynamic obstacles, it does not deeply integrate environmental force disturbances such as ocean currents and wind waves, and it is difficult to offset the offset impact on the ship's actual trajectory only by adjusting speed constraints; the potential field function of the APF algorithm is mostly based on static environment assumptions, and the movement trends of dynamic obstacles are not effectively incorporated into repulsive force calculation, which easily leads to lag in obstacle avoidance actions.

3.3. Limited Planning Efficiency in Multi-Constraint and Multi-Objective Task Scenarios

Modern marine tasks performed by USVs often involve the coordinated optimization of multiple constraints and multiple objectives, and existing algorithms have obvious limitations

in planning efficiency and objective trade-off: from the constraint dimension, in addition to traditional obstacle avoidance constraints, it is also necessary to meet multiple constraints such as the International Regulations for Preventing Collisions at Sea (COLREGs), the minimum turning radius of the ship, and the task time window, and the ambiguity of rules for crossing encounters and overtaking in COLREGs makes it difficult to directly convert them into quantifiable constraint conditions for algorithms.

4. Conclusion

This paper systematically reviews mainstream algorithms in the current field of Unmanned Surface Vehicle (USV) local path planning, including A*, Dynamic Window Approach (DWA), Rapidly Exploring Random Tree (RRT), and Artificial Potential Field (APF) algorithms, conducts an in-depth analysis of each algorithm's core principles, advantages, limitations, and application scenarios, and further explores three core challenges in practical applications: insufficient adaptability to high-density unstructured environments, lack of robustness under highly dynamic and strongly nonlinear disturbances, and limited planning efficiency in multi-constraint and multi-objective scenarios; research shows that a single algorithm is difficult to fully meet the local path planning requirements of USVs in complex marine environments, so the future development of USV local path planning algorithms should focus on three directions—first, algorithm fusion and improvement to enhance adaptability to complex environments through complementary advantages across algorithms; second, environmental modeling and constraint embedding to construct a dynamic potential field model integrating wind, wave, and current disturbances, and realize accurate quantification of COLREGs rules by combining technologies such as fuzzy logic and Bayesian networks; third, intelligence and adaptive optimization to improve the trajectory prediction accuracy of dynamic obstacles using deep learning and achieve adaptive adjustment of multi-objective weights through reinforcement learning, ultimately achieving the goal of safe, efficient, and robust USV autonomous navigation—and the research results of this paper can provide a systematic reference for the theoretical innovation and engineering practice of USV local path planning technology, helping to promote the intelligent development process of USV equipment.

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