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A Review of Path Planning Methods for Unmanned Surface Vehicles

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Abstract: Unmanned Surface Vehicles (USVs), as essential platforms for intelligent maritime operations, rely heavily on efficient and reliable path planning to achieve autonomous navigation. This paper systematically reviews major path planning methods for USVs, including global planning approaches based on graph search and intelligent optimization, as well as local planning techniques such as the Dynamic Window Approach, Artificial Potential Field, and Rapidly-Exploring Random Tree. A comparative analysis of these algorithms highlights their respective strengths and limitations, while summarizing key directions of academic improvements. By integrating existing findings, this review provides a structured perspective on the evolution of USV path planning methodologies and their practical implications. Finally, future perspectives are summarized, including AI-driven autonomous learning and generalization, multimodal perception and intelligent decision-making integration, distributed cooperation and large-scale swarm control, etc.

1. Introduction

USVs have emerged as critical enablers of intelligent maritime operations, offering advantages in persistence, safety, and cost-effectiveness over traditional manned vessels. Their successful deployment in tasks such as long-term ocean observation, search and rescue, and cooperative patrol relies heavily on robust autonomous navigation capabilities. Among the enabling technologies, path planning plays a central role, as it determines how USVs generate feasible and safe trajectories while addressing uncertain ocean environments, dynamic obstacles, and regulatory constraints.

In this context, path planning can be defined as the process of calculating an optimal path from a starting point to a destination under environmental constraints, typically requiring obstacle avoidance and the satisfaction of motion-related conditions such as kinematic feasibility and time efficiency. This process is often supported by a multi-dimensional evaluation framework that integrates geometric cost, motion compatibility, and safety redundancy, with coordinated analysis achieved through quantitative metrics and weight assignment. To this end, a wide range of algorithmic approaches, such as graph search, sampling-based, and optimization methods,have been developed.

To illustrate the fundamental concepts of path planning, Figure 1 provides a schematic diagram of global and local paths for an USV. Building on this, the overall framework of USV path planning methods is summarized in Figure 2, which highlights the classification into global and local planning approaches, along with representative algorithms in each category.

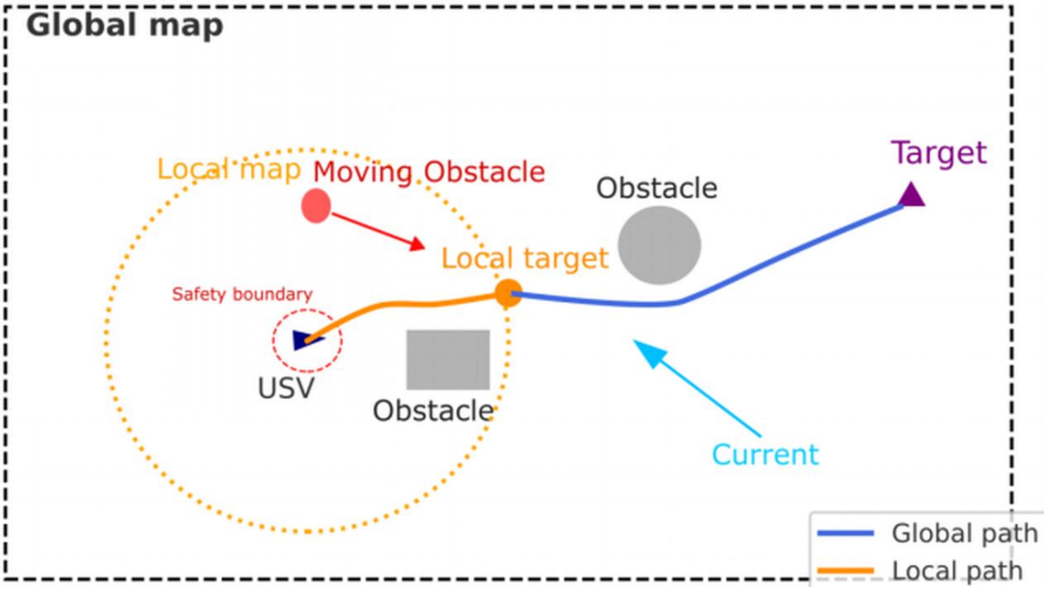

Figure 1 Illustration of global and local path planning for an USV.

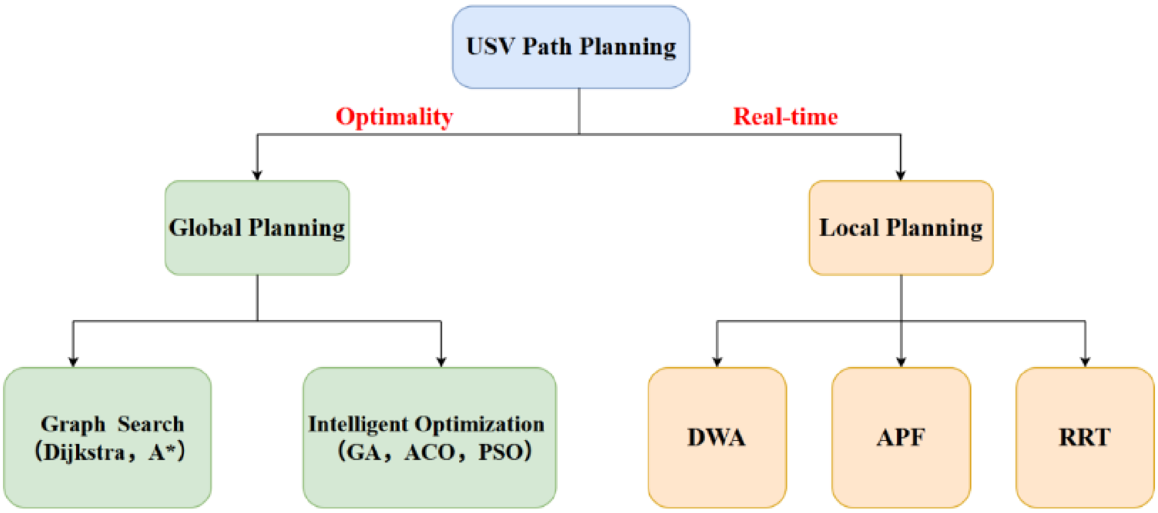

Figure 2 Framework of USV Path Planning Methods.

2. Global Path Planning

Global path planning provides unmanned USVs with globally optimal or near-optimal routes. It focuses on balancing computational efficiency with adaptability, while addressing constraints such as dynamic obstacles, energy consumption, and regulatory requirements. In this paper, global path planning is systematically discussed from the perspectives of graph search algorithms, intelligent optimization algorithms, and sampling-based methods, highlighting their advantages, limitations, and improvement trends.

2.1. Path Planning Based on Graph Search

Graph search algorithms are path planning methods based on graph theory, using node traversal and edge cost evaluation to explore the search space. Within a known topological map, they can generate collision-free paths from the start to the goal. Among them, heuristic methods (e.g., A*) and minimum-cost methods (e.g., Dijkstra) are effective in computing globally optimal solutions. A comparative analysis of Dijkstra and A* algorithms in terms of advantages, disadvantages, and recent improvements is provided in Table 1.

Table 1 Comparison of Dijkstra Algorithm and A* Algorithm in path planning.

Algorithm	Advantages	Disadvantages	Improvements in literature
Dijkstra	Strong global optimality; broad applicability	High computational complexity; low efficiency in large-scale environments	Energy-efficient optimization; environmental constraints integration; dynamic obstacle adaptation; multi-objective optimization
A*	Combines heuristic guidance with efficiency; guarantees optimality	Strongly depends on heuristic function; insufficient real-time capability in large-scale environments	Path smoothing; binary tree recursive search; hybrid A*–APF method; enhanced heuristic function; multi-vehicle cooperation

2.1.1. Dijkstra Algorithm

The Dijkstra algorithm, proposed by Dijkstra in 1959, is a classical shortest path search method characterized by strong determinism and broad applicability. However, when applied to large-scale graph searches, it suffers from limitations such as high computational complexity and insufficient efficiency. In recent years, improvements of the Dijkstra algorithm in the field of unmanned surface vehicles have primarily focused on: (1) energy-constrained optimization, (2) integration with environmental models, (3) adaptation to dynamic obstacles, and (4) multi-objective optimization.

Singh et al. developed a constrained Dijkstra algorithm for USV path planning that integrates static and moving obstacles as well as sea surface currents into the cost function, improving path feasibility in dynamic maritime environments. While effective in simulations, its scalability and real-time applicability to large-scale sea conditions remain unverified[1]. In another study, Niu et al. proposed an energy-efficient path planning algorithm for USVs that integrates Dijkstra search with Voronoi and visibility-based methods while explicitly modeling sea current effects and safety distances from coastlines. Simulations on ten mission scenarios demonstrated improved endurance and reduced energy consumption, although the method depends heavily on accurate prior environmental data and may face challenges in real-time dynamic conditions[2]. Xing and Wu et al. highlighted from a comprehensive perspective that the improvements of Dijkstra mainly focus on multi-objective optimization and adaptability to dynamic environments, while emphasizing its trend of integration with heuristic search methods[3-4].

2.1.2. A* algorithm

The A* algorithm, proposed by Hart et al., is a bounded-cost search method based on heuristic functions, which guarantees an optimal path under the condition of consistency. Compared with traditional search algorithms, A* exhibits advantages in terms of optimality and computational efficiency. However, its performance is highly dependent on the design of the heuristic function, and it often suffers from high search overhead and insufficient real-time capability in large-scale and complex environments.

Song et al. introduced a smoothed A* algorithm that incorporates curvature and continuity constraints to generate feasible USV trajectories with reduced backtracking and sharp turns, but its reliance on static grid resolution limits adaptability in dynamic environments[5]. To address this, Chen et al. proposed a cooperative hunting method for multi-USVs based on an improved A algorithm, introducing a path smoothing strategy considering the minimum turning radius and a binary tree recursive search to enhance efficiency, while also applying a biomimetic formation strategy to improve collaborative target capture in obstacle-rich environments[6].Sang et al. embedded artificial potential field (APF) constraints into the A* heuristic for formation navigation, balancing trajectory safety and efficiency, yet further validation under real-time multi-vehicle coordination remains needed[7].In summary, to meet the navigation requirements of USVs, researchers have proposed various improvements to the A* algorithm, mainly focusing on: (1) path smoothing, (2) intelligent integration, (3) cooperative extension, and (4) adaptation to dynamic environments.

2.2. Intelligent Optimization Algorithms

Intelligent optimization algorithms have become one of the most widely applied approaches for USV path planning in recent years, demonstrating strong global search capability and adaptability in complex and dynamic environments. Compared with traditional graph search methods, they perform more effectively in multi-objective, nonlinear, and uncertain scenarios. Representative algorithms include genetic algorithms, ant colony optimization, and particle swarm optimization, with research efforts primarily focusing on search strategy refinement, adaptive parameter adjustment, and hybrid integration with other methods. To highlight their respective strengths, weaknesses, and ongoing research directions, a comparative summary of GA, ACO, and PSO is provided in Table 2.

Table 2 Comparison of three intelligent optimization algorithms for USV path planning.

Algorithm	Advantages	Disadvantages	Improvements in literature
Genetic Algorithm (GA)	Strong global search capability; suitable for complex environments	Slow convergence; reduced accuracy	Improved convergence and smoothness; feedback mechanism for collision avoidance
Ant Colony Optimization (ACO)	High robustness; supports parallelism	Slow convergence; premature stagnation	Quantum ACO for faster convergence; optimized ACO for efficiency
Particle Swarm Optimization (PSO)	Simple design; few parameters	Premature convergence; weak adaptability in dynamic environments	Adaptive PSO for reliability; hybrid PSO for offshore areas

2.2.1. Genetic Algorithm (GA)

The Genetic Algorithm (GA), first proposed by Holland, is an evolutionary optimization method with strong global search ability, making it suitable for complex USV path planning. However, classical GA is often limited by slow convergence and reduced solution accuracy. Recent studies have sought to address these limitations. Xin et al. proposed an improved genetic algorithm (GA) for USV path planning that incorporates multi-domain inversion to increase offspring diversity and a secondary fitness evaluation to eliminate suboptimal individuals. This strategy enhanced convergence speed, robustness, and trajectory quality compared with conventional GA, but the method remains computationally expensive and has yet to be validated in real-world dynamic maritime environments [8]. More recently, Gao et al. incorporated a feedback mechanism into a GA framework to dynamically adjust crossover and mutation probabilities, thereby improving collision-avoidance efficiency and path stability under hybrid map constraints. Nevertheless, the algorithm's performance remains sensitive to parameter tuning, and its scalability in highly dynamic maritime conditions has not yet been systematically verified[9].

2.2.2. Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO), introduced by Dorigo in the 1990s, is a swarm intelligence algorithm based on pheromone-guided search, widely applied in path planning. Although ACO provides strong robustness and parallelism, it often converges slowly and risks premature stagnation. Recent research has focused on improving its efficiency and adaptability for USV applications. Xia et al. proposed an improved quantum ant colony algorithm (IQACA) for USV path planning that jointly optimizes path length, energy consumption, smoothness, and safety. The method achieved lower path costs and faster convergence than conventional ACO variants, though its effectiveness under real-time dynamic sea conditions remains unverified [10]. More recently, Cui et al. developed an optimized ant colony algorithm (OACA) for USV path planning that integrates energy consumption and turning costs. By adopting non-uniform pheromone initialization, weighted pheromone updating, and a penalty mechanism, the method accelerates convergence and avoids premature stagnation, achieving more reliable and energy-efficient global paths than conventional ACO approaches[11]. These advancements underscore the potential of ACO-based strategies to enhance convergence efficiency and solution quality, making them increasingly suitable for multi-objective and large-scale USV path planning.

2.2.3. Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) algorithm, developed by Eberhart and Kennedy, is a bio-inspired method valued for its simplicity and few parameters. Its major limitation lies in premature convergence, reducing applicability in complex marine environments. Recent advancements have sought to overcome these drawbacks. Zhao et al. proposed an adaptive particle swarm optimization (APSO) algorithm for unmanned vehicle path planning that integrates a map simplification strategy to reduce search space, three adaptive factors with Lévy flight for global–local balance, and a safety checking mechanism with dynamic obstacle avoidance. This approach achieved higher-quality global paths and stronger real-time obstacle avoidance than conventional PSO[12]. Wang et al. designed a bi-level hybrid framework for USV navigation in complex offshore areas, where an improved PSO with opposition-based learning, adaptive inertia weight, and variable step size was used for global optimization, while an enhanced APF handled local obstacle avoidance to overcome the local minimum problem. Simulations demonstrated more stable convergence and reliable collision avoidance than conventional PSO or APF alone, though the framework has yet to be validated in large-scale real maritime operations[13].

3. Local Path Planning

Local path planning enables USVs to adjust their trajectories in real time, ensuring collision avoidance and adaptability in dynamic maritime environments. Unlike global planning, it emphasizes rapid response, maneuverability, and compliance with navigation rules under local disturbances. In this paper, local path planning mainly focuses on representative methods such as the Dynamic Window Approach (DWA), Artificial Potential Field (APF), and Rapidly-exploring Random Tree (RRT), emphasizing their advantages, limitations, and recent improvements. A comparative summary of these representative local path planning algorithms is provided in Table 3.

Table 3 Comparison of representative local path planning algorithms.

Algorithm	Advantages	Disadvantages	Improvements in literature
Dynamic Window Approach (DWA)	Efficient in real time; considers dynamic constraints	Local minima; detours in dense environments	Non-uniform Theta* + DWA hybrid; bidirectional A* + DWA with COLREGs
Artificial Potential Field (APF)	Simple modeling; efficient and adaptive	Local minima; oscillations	Nonlinear potential functions; predictive APF; APF + deep RL; APF + A*
Rapidly-exploring Random Tree (RRT)	Efficient in high-dimensional spaces; simple implementation	Non-smooth paths; slow convergence	Dual-domain RRT*; RRT* + DWA; improved RRT for sea conditions; constrained sampling

3.1. Dynamic Window Approach (DWA)

The Dynamic Window Approach (DWA), first proposed by Fox et al. in the 1990s for mobile robots, has been widely adopted for USVs due to its ability to generate collision-free velocity commands under dynamic constraints. While efficient in real-time applications, it often suffers from local minima and detours in cluttered environments.

In early work, Lin and Fu applied DWA for real-time obstacle avoidance of USVs, demonstrating feasibility in cluttered environments but with limited robustness against dynamic obstacles[14]. To address this limitation, Han et al.proposed a dynamically hybrid framework combining non-uniform Theta* with improved DWA, enhancing global-local consistency and reducing the risk of local trapping[15]. Most recently, Xu et al. integrated bidirectional A* with DWA while explicitly considering maneuverability and COLREGs, achieving safer and regulation-compliant navigation, though its reliance on accurate maneuverability modeling may restrict generalizability[16]. These advancements show a chronological trajectory from feasibility demonstrations toward hybrid and regulation-aware frameworks, progressively improving robustness and practical applicability of DWA-based local planning in maritime environments.

3.2. Artificial Potential Field (APF)

The Artificial Potential Field (APF) method, proposed by Khatib, constructs a virtual force field through attractive and repulsive forces to generate feasible paths. It offers simple modeling, high efficiency, and adaptability but suffers from local minima, non-reachability, and oscillations. Recent advances have sought to overcome these drawbacks.

Xiao et al. introduced nonlinear modifications to APF attraction–repulsion functions, alleviating local minima and oscillations in USV navigation[17], while Song et al. extended APF with temporal prediction to achieve smoother trajectories and proactive avoidance of dynamic obstacles[18]. Building on this, Li et al. integrated APF with COLREGs compliance via deep reinforcement learning, enhancing navigational safety and rule adherence[19], and Yang et al. combined APF with A* under current-affected environments to improve robustness[20] . Recent improvements in APF mainly address: (1) optimization of attractive–repulsive force models, (2) predictive and temporal extensions, (3) integration with rule-based or learning frameworks, and (4) hybridization with global search algorithms.

3.3. Rapidly-exploring Random Tree (RRT)

The Rapidly-exploring Random Tree (RRT) algorithm, first introduced by Steven M. LaValle in 1998, is a sampling-based method that enables efficient path planning by incrementally building a tree through random sampling. It is widely recognized for its simplicity and effectiveness in high-dimensional spaces. Nevertheless, issues such as path smoothness, convergence speed, and sensitivity to sampling distribution remain. Current advancements in RRT-based methods are mainly oriented toward: (1) adaptive sampling strategies; (2) hybrid integration with other planners; (3) efficiency improvements through constrained sampling; and (4) enhanced robustness in dynamic and uncertain maritime environments.

Wen et al. proposed a dual sampling domain reduction RRT* that constrains tree expansion within feasible regions, thereby improving online safety and efficiency for USVs operating in dynamic maritime environments [21]. Building on hybridization, Zhang and Chen coupled RRT* with the dynamic window approach (DWA) to integrate global exploration with local trajectory feasibility[22], while Mao et al. refined RRT growth rules to enhance adaptability under complex sea states[23]. Complementarily, Yu et al. introduced cylindrical sampling constraints to reduce redundant exploration, significantly boosting computational efficiency[24].

4. Future Prospects

4.1. Integration of Global and Local Path Planning

To overcome the limitations of individual strategies, hybrid path planning that integrates global and local methods is essential. Global planning ensures long-distance optimality but lacks real-time adaptability, whereas local planning responds quickly to dynamic obstacles but suffers from local minima and path smoothness issues. Their seamless integration can improve the efficiency and robustness of USVs in complex maritime environments.

4.2. AI-Driven Autonomous Learning and Generalization

Future path planning for USVs is expected to rely increasingly on deep learning and reinforcement learning. These approaches can enhance adaptability in complex and dynamic environments. However, challenges remain in improving model generalization and interpretability to ensure reliability in unknown maritime scenarios.

4.3. Multimodal Perception and Intelligent Decision-Making Integration

The integration of path planning with multi-source perception data (e.g., vision, radar, AIS) is a key direction for future research. By fusing unstructured information through artificial intelligence, USVs can achieve perception–decision integration, thereby improving navigation safety and environmental adaptability.

4.4. Distributed Cooperation and Large-Scale Swarm Control

The development of multi-USV cooperation will increasingly shift toward decentralized and distributed intelligence. Future studies should focus on improving task allocation efficiency while enhancing robustness and self-organization in large-scale swarms, especially under communication constraints or uncertain environments. To better illustrate this concept, Figure 3 presents a schematic diagram of distributed cooperation and multi-task assignment within a USV swarm.

4.5. Cross-Platform Collaboration and Heterogeneous System Integration

Joint mission planning among heterogeneous unmanned systems, such as USVs and UAVs, will become an emerging trend. Research should explore cross-domain information fusion, real-time trajectory coordination, and cooperative task allocation to improve mission execution capabilities in complex maritime operations.

4.6. Deep Integration of Path Planning and Control

A future research priority is the development of unified frameworks that tightly couple path planning with motion control, considering vessel dynamics, environmental disturbances, and regulatory constraints. Efforts should emphasize reducing algorithmic complexity while ensuring real-time performance and robustness for practical applications.

4.7. Integration of Simulation and Real-World Trials

Current studies are largely confined to simulation validation. Future work should strengthen field trials and experiments under realistic sea conditions to facilitate the transition from theory to engineering practice. Establishing standardized testing platforms and evaluation systems will be crucial for practical deployment.

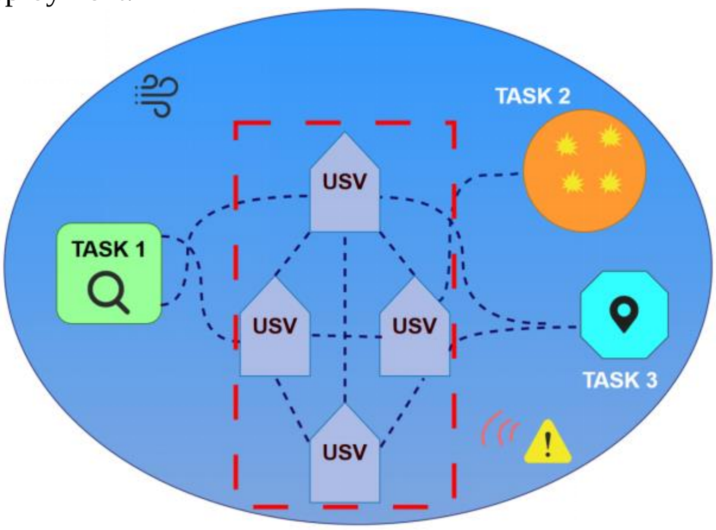

Figure 3 Distributed cooperation and large-scale swarm control of USV clusters.

5. Conclusion

The field of path planning for USVs still holds significant research potential and opportunities for innovation. Table 4 provides a detailed comparison of the two methods, global and local path planning, summarizing their main characteristics and potential improvements. In summary, subsequent research should rely on the complementary advantages of global and local planning, and through the deep integration of core technical directions such as artificial intelligence learning, multimodal perception, collaborative control strategies, cross-platform collaboration, and planning-control integration, build a path planning system that can achieve seamless connection between simulation research and actual sea trials, thereby accelerating the transformation of technologies in this field from the theoretical level to engineering practice.

Table 4 Comparison between global and local path planning approaches.

Dimension	Global planning	Local planning
Objective	Generate globally optimal or near-optimal path	Real-time obstacle avoidance and trajectory adjustment
Advantages	Strong global optimality; suitable for complex tasks	High real-time performance; strong adaptability in dynamic environments
Disadvantages	High computational cost; weak adaptability in dynamic environments	Risk of local minima; limited global awareness
Improvement trends	Integration with intelligent optimization and learning; multi-objective and energy constraints	Fusion with global search; incorporation of learning and rule-based mechanisms
Application scenarios	Long-distance navigation; mission allocation	Short-term avoidance; dense or cluttered environments

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