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Review

Route Planning Algorithms for Unmanned Surface Vehicles (USVs): A Comprehensive Analysis

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Abstract: This review paper provides a structured analysis of obstacle avoidance and route planning algorithms for unmanned surface vehicles (USVs) spanning both numerical simulations and real-world applications. Our investigation encompasses the development of USV route planning from the year 2000 to date, classifying it into two main categories: global and local route planning. We emphasize the necessity for future research to embrace a dual approach incorporating both simulation-based assessments and real-world field tests to comprehensively evaluate algorithmic performance across diverse scenarios. Such evaluation systems offer valuable insights into the reliability, endurance, and adaptability of these methodologies, ultimately guiding the development of algorithms tailored to specific applications and evolving demands. Furthermore, we identify the challenges to determining optimal collision avoidance methods and recognize the effectiveness of hybrid techniques in various contexts. Remarkably, artificial potential field, reinforcement learning, and fuzzy logic algorithms emerge as standout contenders for real-world applications as consistently evaluated in simulated environments. The innovation of this paper lies in its comprehensive analysis and critical evaluation of USV route planning algorithms validated in real-world scenarios. By examining algorithms across different time periods, the paper provides valuable insights into the evolution, trends, strengths, and weaknesses of USV route planning technologies. Readers will benefit from a deep understanding of the advancements made in USV route planning. This analysis serves as a road map for researchers and practitioners by furnishing insights to advance USV route planning and collision avoidance techniques.

Keywords: USVs; route planning algorithm; collision avoidance; real-world application; numerical simulation

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1. Introduction

Covering approximately 70 percent of the Earth's surface, the ocean is a vast domain studied by oceanographers—a multidisciplinary scientific branch that explores the geological, biological, chemical, and physical aspects of this dynamic environment [1]. USVs are extensively utilized for search, patrol, resource exploration, and various other tasks due to their compact size and affordable price [2,3]. Over the past few years, there has been a notable rise in the deployment of USVs and ground and air vehicles across diverse environments. These vehicles are predominantly autonomous, operating with varying degrees of self-governance. While discussions about autonomous vehicles usually focus on air or ground platforms, USVs are equally significant, albeit less prevalent and commercially adopted. As artificial intelligence technology continues to advance, the maritime transportation sector is striving to enhance safety, efficiency, and profitability. The most recent yearly assessment of marine accidents and incident reports has revealed that navigational accidents, including collisions, contacts, and groundings/stranding, account for 44 percent of all reported incidents [4]. The evolution of the shipping industry has always focused on improving navigation safety and enhancing transportation advantages. Enhancing the safety of vessel navigation has been a significant focus in the realm of marine transportation engineering and is a driving force behind the demand for USVs and their technological requirements. Each year, human mistakes or negligence, like inadequate lookout by the officer on watch (OOW), contribute to numerous marine accidents. The implementation of automated navigation effectively takes over the role of human pilots in managing vessel maneuvers and cargo transport, significantly reducing the likelihood of accidents caused by human error. Currently, autonomous technology is predominantly employed in USVs and submersible robots; however, fully autonomous navigation for cargo ships is not yet achievable. Collision avoidance navigation systems utilize various technologies and are subject to advanced research efforts. USVs must possess the capability to navigate independently and evade collisions with other ships or obstacles. In addition, they should exhibit behavior and functionality reminiscent of manually operated vessels. Hence, it is imperative that USVs are equipped with intelligent techniques for collision avoidance and route planning that ensure their secure operation in dynamic and intricate waterways [5]. The exploration of navigation systems for USVs began in the early 2000s [6]. Table 1 indicates the list of surveys conducted for USV route planning and avoidance of collisions.

Table 1. Previous reviews connected with route planning and prevention of collisions.

Review	Year	Main Focus
[7]	2006	This paper explores a pathway to attain the objective of complete autonomy in unmanned surface vehicles (USVs), including their ability to independently handle tasks, ensure survival, and navigate efficiently.
[6]	2009	This review examines the progress of obstacle avoidance methods and vessel navigation planning, specifically in situations where they come into close proximity.
[8]	2013	This research paper provides a comprehensive overview of an intelligent vessel's overall structure and is primarily grounded on current USVs. Then, attention pivots to the internal algorithmic methods necessary for modeling such a vessel as a hierarchical system.
[9]	2018	This research paper focuses on reviewing various path following and path tracking techniques commonly employed in the design of USVs. It particularly emphasizes situations in which the control system does not have a predefined position declared.
[10]	2020	This article presents the advancements in route planning research that focuses on the multi-modality constraint. The article further evaluates various research methods and classical algorithms that have been specifically used in USVs applications at each stage.
[11]	2021	This paper contributes to this endeavor by presenting a comparative analysis of modern algorithms for route planning and preventing collisions in USVs.
[12]	2022	This paper investigates the route planning algorithms used by USVs and their significance in regulating collisions and aims to uncover the approaches taken by researchers to address this matter.
[13]	2023	This study examines the existing algorithms and research findings in USV route planning; these includes global route planning, danger avoidance and local route planning with an approximation reaction, and route planning within clustered environments.

In recent decades, there has been a growing emphasis on the exploration and exploitation of ocean resources, leading to notable advancements and expansion within the marine robotics domain. Within this realm, USVs have emerged as a prevalent component and have actively undertaken missions such as source seeking in marine environments [14]. Path tracking serves as the foundational principle enabling USVs to execute diverse tasks, and the precision of tracking significantly influences task performance. The path tracking mechanism for underactuated USVs typically comprises a guidance law and a tracking controller. Specifically, the guidance law, exemplified by the line-of-sight (LOS) approach, transforms positional errors into a reference course, which acts as the input for the tracking controller. Engineers can select an appropriate path tracking method based on the attributes of the orientation sensors integrated into the USV. The course autopilot, utilizing the vehicle's course as feedback, can be directly integrated with the LOS law to establish a comprehensive path tracking controller. Course data, easily acquired from cost-effective GNSS receivers, include the course over ground (COG) and speed over ground (SOG), which is computed by determining the increment between the current position and the previous solution position. It is crucial to note that the reliability of the course feedback heavily relies on the accuracy of the positioning system [15].

Scholars from all around the world have undertaken substantial study of USVs, with a particular emphasis on route planning algorithms like the Dijkstra, A*, genetic, PSO, and other algorithms [16]. While simulation-based evaluations of collision prevention algorithms and route planning often yield reasonable outcomes, previous studies have encountered numerous challenges when attempting to implement these solutions on real vehicles. As our understanding of science and technology advances, scholars strive to organize and structure the current accomplishments in this field [17]. Numerous techniques have been devised to address local route planning and avoid collisions. Nonetheless, the majority of these methods have been applied exclusively in familiar surroundings and against stationary obstacles [18]. The primary objective of numerous practical engineering applications has been to find the most efficient route from an initial point to a desired destination. The cost-effective path of a USV can be assessed by considering factors such as travel time and energy usage. Particularly for long-distance or energy-intensive journeys, minimizing time and energy expenditure becomes crucial in route planning. Whether it involves transportation [19], cruising, or scientific exploration, vessels tend to favor the most economical path that significantly reduces both travel time and energy consumption [20]. Significant progress has been made in the field of path planning since the 1990s, with numerous successful endeavors and the development of promising algorithms [21]. These algorithms can be categorized into classical approaches as well as heuristic approaches [22]. Classical approaches follow strict procedures and, if possible, can obtain an optimal solution. On the other hand, heuristic approaches come into play when classical approaches become less effective, as they can still find a solution. Examples of heuristic approaches include genetic algorithms [23], simulated annealing, and evolutionary algorithms. The *Collision Regulations* (COLREGS) serve as the fundamental principle for water vehicles, making it imperative for the USV's route planning algorithm to accommodate these rules. This ensures that the USV does not pose any safety risks to other ships and safeguards its navigation security in public waters. Numerous studies have been conducted by researchers to develop route planning techniques that consider the guidelines set by the COLREGS [24]. In the contemporary era, simulation plays a crucial role in the development of systems across various engineering domains. Initially employed for addressing design challenges through numerical algorithms in the 1960s, simulation has evolved into the digital age and is seamlessly woven into the entire life cycle of a specific product. This integration spans design, testing, manufacturing, commissioning, operation, and decommissioning phases [25].

The main goal of this paper is to offer an organized examination of simulated and real-world applications of collision prevention and route planning algorithms in USVs. It also aims to compare the challenges faced during simulations with those encountered in actual implementations. This will help the readers to gain valuable insights into the bridge between theoretical understanding and practical implementation. The comparison allows for an assessment of algorithm robustness, adaptability to dynamic environments, and identification of practical challenges and solutions. Readers will learn how these algorithms perform in the face of real-world complexities, including dynamic obstacles and changing environmental conditions. The discussion of validation techniques, performance metrics, and industry use cases enhances readers' understanding of the implications for future research and development in the field of USV navigation. The arrangement of the paper is as follows: In Section 2, an overview of USV route planning is highlighted. In Section 3, the fundamental route planning and collision prevention algorithms utilized by USVs are presented. Section 4 presents the state-of-the-art in chronological order. Section 5 discusses the general overview of USV route planning algorithms, potential future research directions, and limitations that may hinder further advancements in this field. Lastly, Section 6 contains the final conclusions drawn from the study.

2. The Concept of USV Route Planning

The development status of USV route planning is considered an active research area and continues to evolve. Route planning addresses three primary challenges: firstly, accomplishing the task of moving from the initial point to the final destination; secondly, avoiding obstructions along the way; and lastly, selecting the ideal course, which can prioritize minimizing time or conserving control effort [8]. Intelligent ships often follow fixed routes for definite transportation tasks. Global offline route planning is employed in such cases and utilizes different algorithms, for example, A* and visibility graph to find paths grounded on a stationary or well known environment model. However, changes in the environment, such as the movement of other ships, fluctuating depth of the water, or altering scheduling responsibilities, present challenges for intelligent vessel routing. Figure 1 shows a comprehensive scientometric analysis that was conducted using VOS viewer and that focuses on the co-occurrence of keywords among authors within the academic literature spanning from the year 2000 to 2023, utilizing data extracted from the Web of Science database. The keywords used to get the data are 'USV route planning', 'USV collision avoidance', and 'USV path planning', from which relevant information was extracted to conduct the scientometric analysis.

One popular approach is to use AI algorithms and machine learning to create optimal routes for USVs. Researchers have used techniques such as reinforcement learning, genetic algorithms, and neural networks to develop intelligent route planning algorithms for USVs. In the literature [26], researchers have developed a revolutionary method to enable autonomous collision avoidance. Deep reinforcement learning (DRL) is a component of the distributed multi-USV navigation technology they have devised. This approach addresses the issue of collision prevention route planning even in the presence of limited information by combining the idea of reciprocal velocity obstacles (RVOs) with the DRL scheme. In general, the problem of route planning or mission planning involves creating viable paths or trajectories for a vessel to follow. The mission can be predetermined by a human operator or adjusted during the voyage either remotely or by the onboard crew. Successful USV mission planning requires a comprehensive approach that integrates collision avoidance measures, both locally and globally optimized route planning, compliance with COLREGS, rigorous risk assessment, and the ability to adapt to disturbances in the environment. These considerations collectively contribute to the safe and efficient execution of unmanned surface vehicle missions. Figure 2 shows the factors that needs to be taken into consideration during USV mission planning.

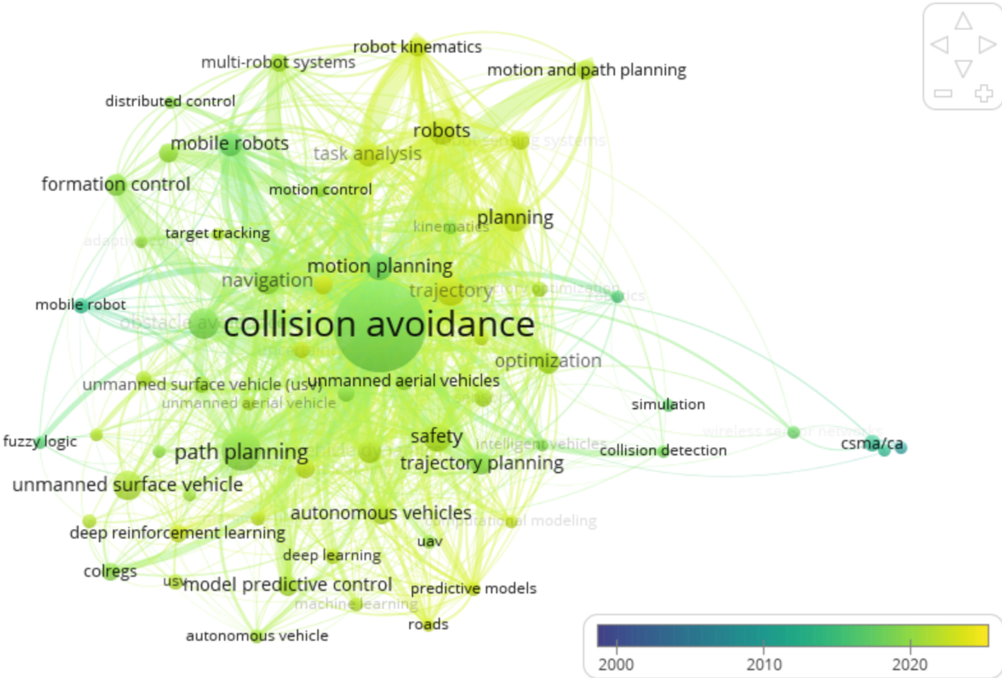

Figure 1. Temporal evolution of author keyword co-occurrence patterns (2000–2023) in Web of Science: a scientometric analysis using VOS viewer.

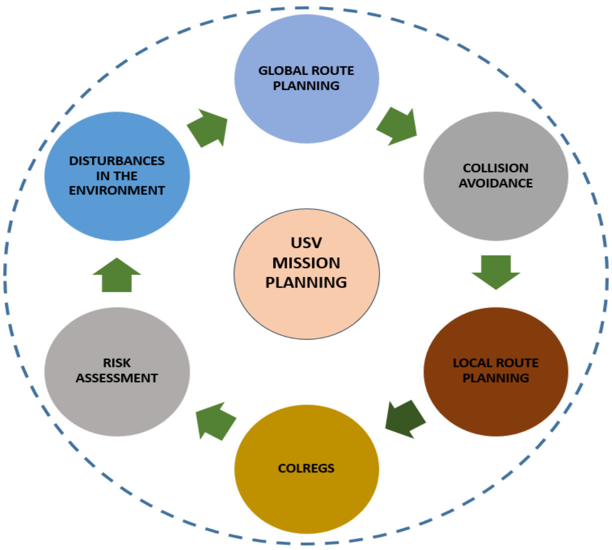

Figure 2. Various factors to consider when planning a USV's mission.

A crucial aspect in deploying USVs effectively in real-world maritime environments is the use of a route planning technique that prioritizes safety and efficiency. Therefore, the integration of both global and local route planning strategies is highly sought after to ensure optimal performance [27]. After reviewing the relevant literature, it becomes apparent that most papers classify route planning into two separate categories: local route planning and global route planning. Also known as deliberative route planning, global route planning entails finding a secure route from the starting point to the destination while bearing in mind obstacles that are already known and assuming a thorough understanding of the surrounding area. In contrast, local route planning, also referred to as reactive route planning, relies on information from vessel sensors to assess the immediate surroundings and prioritize avoiding dynamic obstacles. The aim is to generate a viable and safe path by emphasizing situational awareness. Local route planning is a dynamic process that uses positional and environmental data collected in real time to safely avoid hazards and follow the desired local route while being guided by the global path.

3. Fundamental Algorithms for USV Route Planning

In this section, primary route planning algorithms for USVs are introduced. Each method is thoroughly described, and we cover the underlying principles, advantages, disadvantages, environmental constraints, and potential challenges in practical implementations. Additionally, various application examples from diverse robotics domains are included for each approach. The implementation of USV route planning encounters two challenges. Firstly, there is a need to select an appropriate algorithm. Secondly, determining the type of algorithm to utilize poses a question. Figure 3 shows the categorization of algorithms for USV route planning, and Table 2 displays the initial utilization of some highly influential algorithms for route planning and collision prevention in the context of USVs. It is worth noting that Table 2 is not an exhaustive compilation but rather emphasizes key algorithms that have been widely used: either directly or in modified forms and sometimes in conjunction with other.

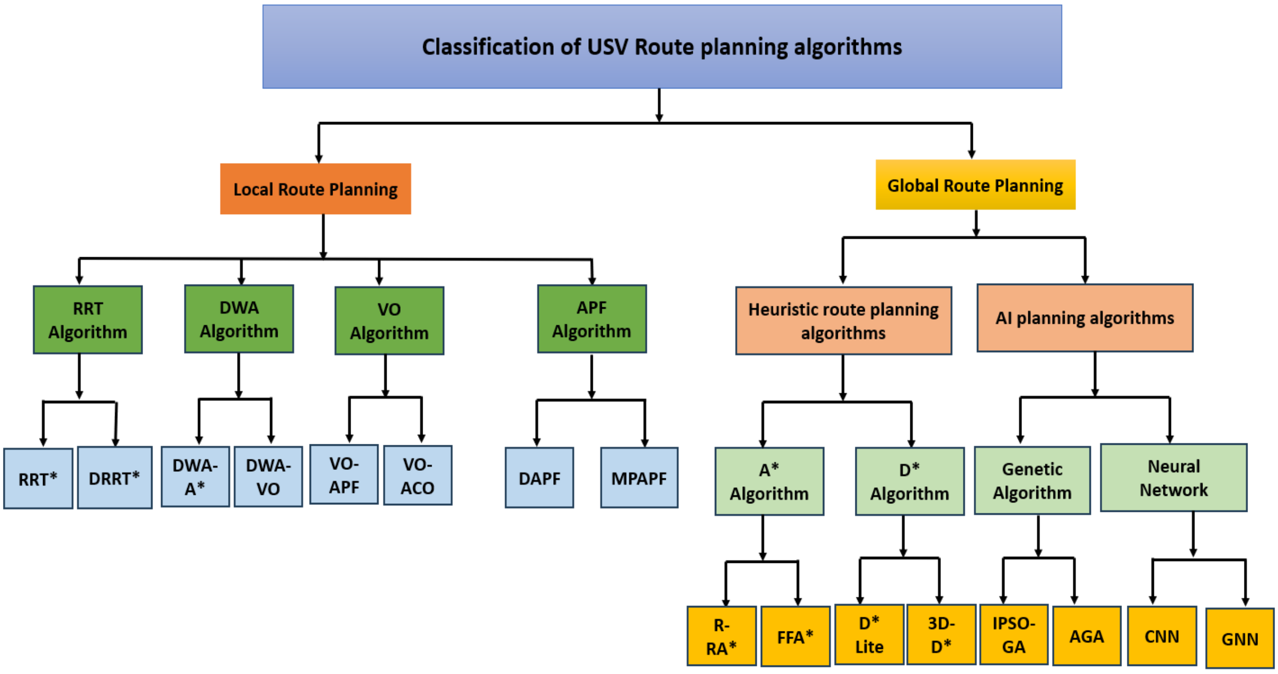

Figure 3. Classification of USV route planning algorithms.

Table 2. Chronological sequence of the initial application of prominent algorithms in USV guidance applications [11].

Name of Algorithm	Year
Genetic algorithm	1999
Fuzzy logic algorithm	2001
RRT algorithm	2008
A* algorithm	2008
Ant colony optimization	2010
Particle swarm optimization	2012
D* Algorithm	2014
Velocity obstacles	2015
Artificial potential field	2015
Deep reinforcement learning	2018

3.1. Local Route Planning Algorithms

In relation to USVs, the objective of local route planning is to evade unfamiliar dynamic or stationary obstacles. In this section, we review the prominent algorithms used in USV local route planning.

3.1.1. Rapidly Exploring Random Tree (RRT) Algorithm

The extensively growing random tree (RRT) algorithm was introduced by LaValle [28]. By utilizing an incremental forward sampling approach, he constructed a search tree and subsequently explored this tree structure to derive a path. Subsequently, as the number of sampled points increases, the algorithm persists at refining the path until reaching the target point or reaching the maximum allowable iterations [29]. The RRT* algorithm demonstrates progressive refinement, with the path becoming increasingly optimized as the iteration count rises. Although the RRT algorithm is a relatively efficient method that is capable of addressing route planning challenges involving non-holonomic constraints and offers substantial benefits for various aspects, it does not provide assurance of yielding a suitably optimized, feasible path. As a result, numerous enhancements to the RRT algorithm have focused on addressing the issue of path optimization, with the RRT* algorithm being one such endeavor. In [30], the authors introduced an innovative technique named PI-DP-RRT, which merges pre-existing automatic identification system (AIS) data and the Douglas–Peucker (DP) compression method for ship trajectory planning. In [31], the presented approach introduces a path planning strategy that incorporates the impact of environmental disruptions using a Virtual Potential Field RRT* technique. Initially, the virtual potential field RRT* technique was developed to chart the desired path, building upon the foundation of the RRT* algorithm. Subsequently, an anti-environmental disturbance technique was introduced that employs a deep recurrent neural network PI controller. This controller facilitates the unmanned surface vehicle (USV) in mitigating environmental disturbances and preserving its trajectory alignment with the intended path. In another article [32], to address the problem of conventional route planning methods having path search rules disconnected from the practical maneuvering capabilities of unmanned surface vehicles (USVs), a novel route planning approach called 'state prediction rapidly exploring random tree (spRRT)' is introduced. In the context of USV route planning, RRT algorithms face challenges in handling dynamic environments, high computational costs, sensitivity to parameter tuning, and limited adaptability to uncertainty. These limitations can hinder real-time decision making and optimal path generation. Consequently, further research is needed to enhance the efficiency, robustness, and adaptability of RRT-based methods for effective USV navigation. Figure 4 shows the working mechanism of the RRT algorithm.

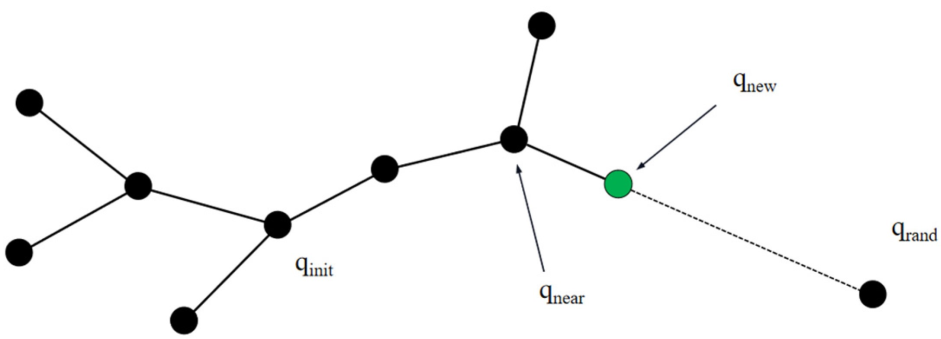

Figure 4. The working principle of RRT algorithm [33].

3.1.2. The Artificial Potential Field

This algorithm was first introduced by Khatib; the method was originally designed for mobile robot route planning to achieve smooth trajectories [34]. The core concept involves creating an attractive potential field towards the destination and a repulsive potential field around obstacles. By deriving a gravitational potential field function, the attraction force is gained, and the repulsion potential field function is derived out of repulsion. The algorithm enables real-time path planning for USVs and efficiently avoids dynamic obstacles, enhancing safety and cost-effectiveness. Path optimization techniques, as seen in the discrete artificial potential field (DAPF) method, enhance the calculation of secure routes in both stationary and dynamic obstacle settings, thereby improving overall path accuracy and efficiency. The model prediction strategy and artificial potential field (MPAPF) algorithm effectively tackles traditional APF constraints by addressing head-on and cross-encounter scenarios to ensure USV safety amid intricate conditions. Despite its rapid computation and path optimization techniques, it struggles with local maxima and has challenges with path smoothing, which impacts the quality of global paths, particularly in complex environments. Difficulties persist with identifying target points near obstacles, which hinders effective navigation. While advancements like map expansion improve local route adjustments, issues arise when obstacles are too close to target points, which affects overall navigation efficiency. The combined force, a summation of gravitational and repelling forces, governs the movement of the USVs [35]. A simulated field with minimal potential energy can be employed to visualize the course taken by a USV as it sets sail from its starting point towards its destination. The USV may deftly avoid high potential energy zones created by barriers by controlling the resulting force.

The APF method is advantageous because it is easy to implement and does not demand substantial computational power. This allows for real-time control of USVs and the ability to prevent collisions. However, the occurrence of local minima is a notable drawback [36]. Because the resulting force pressing on the USV is balanced in some circumstances, such as when it runs into a U-shaped obstruction, the algorithm may cause the USV to proceed in an endless loop instead of to its intended location. Additionally, because of the fluctuating impacts of opposing barrier gravitational fields, traveling between barriers that are closely spaced may be impossible or result in oscillation [37]. To address the issue of encountering local minima, additional methods are integrated with artificial potential fields (APFs), such as in [38]. In a study based on simulation [39], in order to achieve trajectory planning in real time for automated docking, a novel method known as the 'extended dynamic window approach' is presented. This approach utilizes potential fields and incorporates a nonuniform Theta* algorithm to explore global paths while considering potential obstacle risks, thereby avoiding the possibility of being trapped in a local minimum. Figure 5 shows the working mechanism of the APF algorithm.

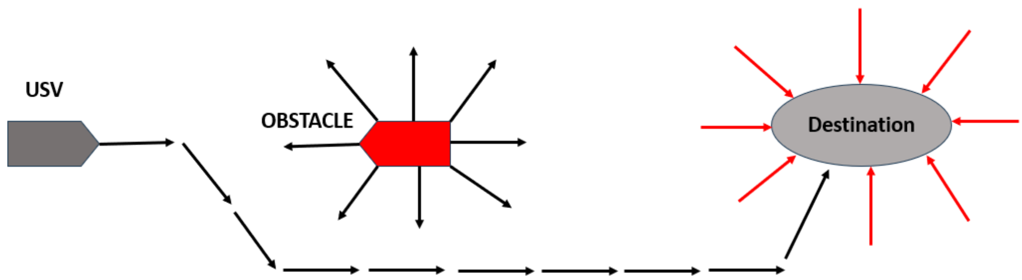

Figure 5. The working principle of APF algorithm

3.1.3. Velocity Obstacle

The concept of a velocity obstacle (VO) was initially introduced by Fiorini and Shiller in the year 1998 [40]. VO is a technique for guiding robots in dynamic surroundings by identifying velocities at which a robot would bump an obstacle in the future and should therefore be avoided. These velocities create constrained regions in the velocity space: forming cone-shaped areas specific to each obstacle. By choosing velocities outside of these cones, collisions can be reliably prevented assuming that the robot reaches the new velocity and heading instantaneously and that the obstacles maintain their current velocities and headings. The velocity obstacle (VO) approach and its enhanced iterations offer robust foundations for dynamic obstacle avoidance by integrating obstacle velocity characteristics and optimizing path length and fuel costs. Hybrid algorithms like VO-APF incorporate COLREGS rules and path optimization functions, augmenting safety and path efficiency. Combining the VO algorithm with the ACO algorithm provides globally optimal paths and effective dynamic obstacle avoidance. However, challenges persist for accurately predicting obstacle motion, which hinders effective avoidance strategies. Hybrid algorithms may struggle to generate globally optimal paths and avoid local optima, particularly in intricate environments. While collision avoidance systems improve performance, uncertainties about obstacle motion states can impact the accuracy of predicted information. Continued research is vital to refine these methodologies and address their limitations in navigating complex environments. According to [41], the utilization of velocity obstacle (VO) algorithms is essential for avoiding collisions with target ships that follow non-linear trajectories, as the algorithms are characterized by time-dependent velocities and probabilistic predictability. Specifically, linear velocity obstacle, probabilistic velocity obstacle, and non-linear velocity obstacle algorithms have been implemented to achieve this objective. In general, the existing methods for detecting potential ship collisions have two main concerns. Firstly, there is a possibility of either overestimating or underestimating the collision candidates. Secondly, the reliability of the results may vary depending on the parameter configurations used in these methods [42]. The velocity obstacle defines a collection of speeds; this set of speeds signifies that if the velocities of two objects fall within its range, a future encounter is predicted between them. This approach simplifies the detection of potential collision risks. The velocity obstacle has acquired significant recognition in recent years for anti-collision route planning [43]. It involves constructing a non-linear velocity obstacle zone by deliberating the foreseen trajectories of other vessels. Reference [32] introduces a time-discrete non-linear velocity obstacle technique to detect potential collisions. Built upon the non-linear velocity obstacle algorithm, it is assessed utilizing historical AIS data. Instead of analyzing traffic data at specific time points, it views ship encounters as processes. Case studies of single ship traffic encounters in waterway settings are conducted and detailed in the study.

3.1.4. Dynamic Window Approach Algorithm

The dynamic window approach algorithm is frequently employed as a technique for route planning and was first introduced by Dieter Fox, Wolfram Burgard, and Sebastian Thrun in 1997 in reference [44]. The dynamic window approach is an often-utilized technique for local route planning. Nonetheless, the conventional application of this algorithm often results in a path that circumvents the outer edges of densely populated obstacle regions. This elongates the distance traveled and brings the path in close proximity to dynamic obstacles [45]. The dynamic window approach is a method for local route planning that relies on sampling velocities. It involves generating several sets of velocities within the velocity space and then simulating the trajectory of the USV over a defined time span. The performance of these simulated trajectories is assessed using a predetermined evaluation function, allowing for the identification of the most favorable trajectory. Subsequently, the optimal speed associated with this trajectory is chosen for implementation [29]. In order to avoid the USV getting stuck in local low points following the evasion of dynamic obstacles, Ref. [46] proposed an improved dynamic window approach (IDWA) that adopts a dynamic selection process for the parent node as a local target. This is a departure from the DWA method, which adheres to a fixed sub-target along the global path. Additionally, to enhance the navigational efficiency of a USV, the IDWA incorporates the lowest cost of the path from the current cell to the goal, which enhances its functionality. This inclusion aids in the assessment of predicted trajectories. In [47], because previous research in this field had not completely taken into account the influence of oceanic environmental elements, which notably amplify the challenges to controlling USVs and the potential for collisions, this study therefore focused on investigating the effects of two specific oceanic environmental factors—waves and currents—recognizing their substantial impact on USVs. Moreover, they authors reconfigure a kinematic representation for a USV and revise the assessment criterion for a traditional and pragmatic local route planning technique grounded in the dynamic window approach (DWA). The DWA and its derivatives offer notable advantages, such as enabling real-time trajectory generation through the simulation of various velocity values and integrating a 'dynamic collision model' to anticipate future collisions, thereby enhancing operational efficiency by accounting for obstacle movement. Methods like DW-VG and DWA-VO bolster obstacle avoidance by incorporating virtual target points and prioritizing local obstacle navigation, respectively, thereby minimizing data inaccuracies and enhancing operational efficiency. Nonetheless, the DWA algorithms may encounter limitations in accurately discerning global obstacles, resulting in local optimization challenges. Despite attempts to mitigate these drawbacks and improve efficiency, there are persistent difficulties in fully adapting to both global and local maritime obstacles. While strategies like IDWA and the fusion of ACO and DWA aim to elevate navigation efficiency and obstacle evasion, the integration of intricate methodologies may impact real-time performance and introduce computational complexities.

3.1.5. Analysis of Algorithms for Local Route Planning

After a literature review of various algorithms for USV local route planning, considering both simulation and real-world scenarios, notable trends emerge, along with respective pros and cons. Among the algorithms listed, a significant portion, including APF-VO, MPAPF, Q-RRT*, IDWA, modified APF, VAPF, enhanced VO, APF, modified VO, and DWA, have primarily been verified through simulation. These algorithms offer several advantages, such as consideration of COLREGS, dynamic obstacles, and effective real-time execution. They are suitable for simulation environments, where controlled testing and validation are feasible. However, their limitation lies in the lack of direct validation in real-world scenarios, which may introduce uncertainty regarding their performance and robustness in practical applications.

Conversely, a few algorithms, such as P-RRT*, COLREG-RRT, and TD-NLVO, have been specifically validated in real-world scenarios, demonstrating their potential for practical implementation. These algorithms offer the advantage of real-world validation, which provides insights into the challenges of actual maritime environments and ensures more reliable performance. However, they may have limitations in terms of scalability or adaptability to dynamic environments.

Future advancements in local route planning algorithms for USVs could involve integrating advanced sensing technologies like LiDAR and radar for more accurate obstacle detection. Incorporating machine learning and artificial intelligence methods can enable algorithms to adapt dynamically to changing environments and enhance route planning decisions. Collaboration among USVs through information exchange can optimize route efficiency and mitigate congestion in shared waterways. Standardized protocols and communication frameworks should be developed to facilitate interoperability among different USV systems and navigation algorithms. Continuous evaluation and testing in diverse conditions are essential to validate algorithm performance and identify areas for improvement. These measures can significantly enhance the safety, efficiency, and adaptability of USVs in navigating complex maritime environments.

In future research, there is a critical need to bridge the gap between simulation and real-world validation. Algorithms should be rigorously tested and refined in both simulated and real-world environments to ensure robustness and reliability across various conditions. Moreover, researchers should prioritize developing algorithms that seamlessly transition from simulation to real-world implementation to address the complexities and uncertainties inherent in maritime environments effectively. Such efforts will contribute to the development of more reliable and adaptable USV local route planning algorithms that are suitable for practical deployment in real-world settings. Table 3 evaluates various algorithms used for local route planning while taking into account the elements determining the best possible route.

Table 3. Features of numerous algorithms employed for USV local route planning.

Ref.	Algorithm	COLREGS	Dynamic Obstacle	Static Obstacle	Effective	Smooth	Real Time	Simulation or Real World
[48]	APF-VO	Yes	Yes	No	Yes	No	Yes	Simulation
[49]	MPAPF	Yes	Yes	No	Yes	No	Yes	Simulation
[50]	Q-RRT*	No	Yes	Yes	No	Yes	Yes	Simulation
[46]	IDWA	No	Yes	No	Yes	Yes	Yes	Simulation
[51]	Modified APF	Yes	Yes	Yes	Yes	Yes	Yes	Simulation
[52]	P-RRT*	No	Yes	Yes	No	Yes	No	Real world
[53]	VAPF	No	Yes	Yes	Yes	Yes	Yes	Simulation
[54]	Enhanced VO	Yes	Yes	Yes	Yes	Yes	Yes	Simulation
[55]	COLREG-RRT	Yes	Yes	No	Yes	Yes	Yes	Real world
[56]	APF	Yes	Yes	Yes	Yes	No	Yes	Simulation
[42]	TD-NLVO	No	Yes	No	Yes	Yes	Yes	Real world
[57]	Modified VO	Yes	Yes	No	Yes	Yes	Yes	Simulation
[58]	DWA	Yes	Yes	No	Yes	No	Yes	Simulation
[59]	DWA-A*	No	Yes	No	Yes	No	No	Simulation

Yes = Considered, No = Does not consider, Simulation = The algorithm was verified by numerical analysis, Real world = The algorithm was verified in real-world scenarios.

3.2. Global Route Planning Algorithms

Global route planning involves a comprehensive offline approach that relies on available marine environment data (like the Electronic Chart Display and Information System (ECDIS) to gather insights about stationary obstacles within the USV's route. A global route planning algorithm gains a holistic view of the surroundings, constructs an environment model from the collected data, and conducts initial planning for the designated path [60]. In this section, we review the prominent algorithms used for USV global route planning.

3.2.1. The Dijkstra Algorithm

The Dijkstra algorithm was first introduced by Dutch computer specialist called 'Dijkstra' in the year 1959 [61] and is commonly known as the D* algorithm. The Dijkstra algorithm and its variations present benefits such as ensuring the identification of the nearest path within a graph, streamlining computation time, and offering tailored solutions for specific tasks like global route mapping. Nevertheless, these algorithms can be computationally demanding, particularly with large datasets, and may encounter obstacles in dynamic settings, resulting in diminished planning efficiency and heightened memory usage. Despite these limitations, Dijkstra algorithms retain their importance in path finding and optimization and are evolving continually to tackle practical complexities. The Dijkstra algorithm also has the capability to find the shortest distance between two given points in space and can also determine the shortest feasible route from a particular point to all other vertices. However, during the process of finding the shortest path, it performs calculations on unnecessary nodes that do not contribute to the shortest path. This leads to increased computation and reduced efficiency in searching for the desired path. In order to reduce the computational time for planning, reference [62] used an incremental algorithm and a new method for modeling dynamic obstacles. In response to the challenge of inadequate operational effectiveness, reference [63] suggested an enhanced Dijkstra algorithm that involves incorporating essential nodes and segmenting regions. This modification has proven effective for diminishing computation time and enhancing the algorithm's operational efficiency. In [64], the authors explore the application of the Dijkstra algorithm to address the challenge of devising motion plans for a USV navigating within a maritime setting. Their research expands the utilization of the Dijkstra algorithm within an environment characterized by both stationary and mobile obstacles. Furthermore, they delve into understanding how sea surface currents with varying strengths influence optimal route planning, considering both downstream and upstream effects. In another study [65], the Dijkstra algorithm was employed on the quad tree structure to identify a suboptimal path. Subsequently, a visibility graph was created that incorporated path waypoints through an enhanced line-of-sight algorithm. This facilitated visibility graph route planning. The new algorithm not only aids with devising paths that minimize the voyage period but also ensures a safe distance between the USV and the coastline.

3.2.2. The A* Algorithm

Cove introduced the A* algorithm in the year 1967 [66]. The A* algorithm was designed as a guided search technique to identify the shorter path between two nodes. This algorithm operates on a straightforward concept and generally outpaces the Dijkstra algorithm in terms of speed. The A* algorithm presents simplicity and speed advantages over the Dijkstra algorithm and guarantees optimal paths and enhances operational efficiency through heuristic search techniques. However, its dependency on heuristic functions can result in path smoothness issues if these functions are intricate or invalid. While variations such as the finite angle FFA* algorithm improve safety and route smoothness, they may extend computational time. Similarly, enhancements like the R-RA* algorithm trim route length and computational time but do not consistently yield globally optimal paths, indicating the ongoing challenge in refining navigation algorithms like A*.

In scenarios where these heuristic functions become intricate or unreliable, the algorithm may yield suboptimal path smoothness and continuity. Despite this drawback, such path irregularities do not adversely affect vessel navigation [38]. Currently, academic advancements to the A* algorithm encompass several key enhancements. Firstly, an expansion of the search scope to encompass a greater number of neighboring points aims to enhance path smoothness. Secondly, refinement of the heuristic function aims to decrease computation time. Lastly, efforts are directed towards minimizing raster computations to enhance overall efficiency. The A* algorithm is a widely used and effective search algorithm for route planning in various domains. It is a combination of the benefits of the D* algorithm (uninformed search) and an algorithm called best-first search (informed search), which utilizes heuristics. The A* algorithm guarantees optimal paths under certain conditions, making it suitable for a range of applications such as robotics, game AI, and graph traversal. In reference [67], an enhanced version of the A* algorithm has been introduced and was employed with the Springer USV. A novel path smoothing technique involving three route smothers is devised to enhance the quality of the generated route. This process effectively reduces unnecessary deviations in the path, eliminates superfluous waypoints, and results in a more continuous trajectory. Outcomes from both simulations and experiments illustrate that the refined A* algorithm surpasses the conventional approach in both sparse and cluttered environments that have been uniformly converted into raster formats. In another article [68], the research investigates an A* strategy for route planning concerning a USV within a boundary that is in a circular shape, which serves as a constraint as a safe distance in order to generate optimum waypoints. This addresses a challenge to orchestrating the movement of a USV within a maritime context. Diverging from existing studies employing graph-based techniques for USV navigation, this investigation broadens the application of the proposed A* method into environments that are complicated by both static and mobile obstacles as well as various current strengths. The study also examines the impact of different current intensities, considers partially dynamic environments, incorporates optimal waypoints while accounting for tailwind and headwind currents, and solves for both clockwise and counterclockwise directions.

3.2.3. Genetic Algorithm (GA)

In their study on cellular automata, J. Holland and his colleagues at the University of Michigan established the concept of the genetic algorithm in 1975 [69]. A genetic algorithm is a computational framework that emulates the evolutionary mechanism of Darwinian natural selection and genetic variation. The genetic algorithm (GA) offers versatility for solving complex problems with its broad approach to search methods. While it can enhance convergence rates and optimization processes, traditional GA suffers from slow processing speeds, limiting real-time usability, especially in dynamic environments. Variants like the adaptive genetic algorithm (AGA) show promise for collision avoidance with dynamic obstacles. However, challenges remain for achieving optimal solutions in changing environments, indicating the need for further improvement. Despite limitations, the genetic algorithm remains a powerful tool for addressing diverse optimization challenges. It begins with a set of initial solutions: either randomly generated or specifically chosen [70]. Through various genetic processes such as selection, crossover, and mutation, in every iteration, fresh individuals are generated. This iterative process continues until convergence is achieved, ultimately leading to the optimal solution [71]. The primary advantage of GA is its applicability to intricate problems and its general nature as a search method. Nonetheless, traditional GA has faced issues related to limited convergence, and optimization is dependent on the function being solved [72]. Given dynamic and new settings, a low-speed processor renders it unsuitable for route planning in real time. Improved crossover and variation operators, superior coding methods, and fine-tuned genetic parameters have been the focus of efforts to improve GA. In [73], by combining the concepts of initiating candidate sets through random testing and utilizing an adaptive probability set, an improved genetic algorithm is created to effectively address optimization problems within confined spaces. This approach enhances the algorithm's capability for global exploration. Additionally, considering the limitations posed by non-holonomic constraints, the rapid-discrete Clothoid curve method is employed to uphold and enhance the smoothness of the path trajectory. This, in turn, fosters seamless coordination between the planning and control components. In [74], given the complexities presented by dynamic and partially uncharted environments that change over time, an intricate framework for route planning is developed, which follows a hierarchical approach.

3.2.4. The Neural Network Algorithm

In 1944, McCulloch Pitts proposed the neural network algorithm [75]. It has evolved into what is now referred to as an artificial neural network (ANN). Additionally, this methodology is applied to enable navigation within unfamiliar surroundings [76]. An artificial machine learning technique known as a neural network (NN) is derived from a mathematical simulation of information handling as seen in the human brain. A neural network and its variations, like the artificial neural network (ANN), provide robust solutions for navigating unknown environments and ensuring safety, especially with methods such as the NN based on COLREGS and risk assessment. Algorithms like convolutional neural networks (CNNs) and residual convolutional neural networks (R-CNNs) improve real-time path planning and quality, even in dynamic settings. However, challenges include computational complexity, particularly with large-scale graphs or maritime USVs. Bio-inspired neural network (BINN) algorithms may struggle with producing smooth paths for USVs due to large turning angles. Despite limitations, adaptations like the full-coverage neural network (CCNN) streamline computation, enhance coverage efficiency, and achieve globally optimal paths while avoiding dynamic obstacles in USV path planning. Three tiers make up its basic structure: the input layer, intermediate hidden levels, and the output layer [17]. Each layer has neurons that are connected to every other neuron that can be found in its underlying layer, and their inputs are processed by using the connecting weights. The information coming from the input layer's neurons are then multiplied by weights before being sent as the input to the layers that are hidden, whereby each neuron is then given a bias value. The primary limitation of this algorithm is that it demands an extended training period to attain desirable outcomes [77]. In reference [78], to fulfill the demands of the coverage route planning task for USVs, a coverage route planning technique is presented. This method relies on an enhanced neural network inspired by biological processes. In addition to this, the approach incorporates the model of a template technique and a jump point exploration algorithm. These additions address the limitations of the initial algorithm, which struggles to fully encompass and navigate around obstacles when in close proximity to them. In another article [79], for the inaugural instance, a neural network algorithm called the 'complete coverage neural network (CCNN)' is introduced for route planning in USVs. This CCNN algorithm streamlines neural activity calculations, leading to a noteworthy reduction in computation time. Reference [80] explores the issue of tracking control for USVs when faced by uncertainties from both internal and external sources, alongside potential injection and deception attacks. A fresh approach to adaptive neural network tracking control is put forth. To solve control design difficulties, the methodology adopted incorporates the use of a backstepping design framework. In study [81], in order to mitigate the effects of time-fluctuating gain resulting from potential intrusion and subterfuge attacks, indirect adaptive neural approaches and single-parameter learning methods are used. Reference [82] introduced a specialized control scheme, known as 'robust adaptive neural network control', designed for achieving dynamic positioning in marine vessels. The objective is to ensure a predefined level of performance in the presence of model uncertainties, external disturbances, and input saturation. Figure 6 shows the architecture of a neural network algorithm.

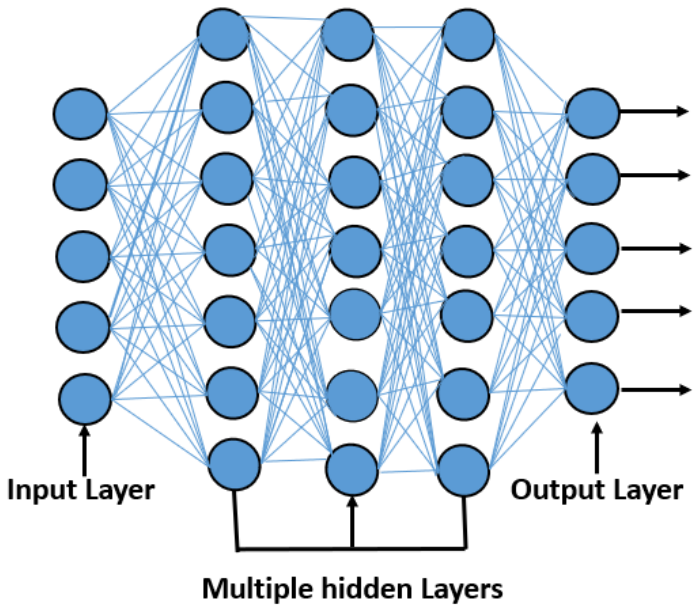

Figure 6. The architecture of a neural network

3.2.5. Analysis of Algorithms for Global Route Planning

Global route planning is very important in the aspect of USV navigation, as it ensures efficient and safe journeys across various environments. After reading the relevant literature on USV global route planning, a critical analysis of numerous algorithms reveals a diverse landscape of approaches with varied strengths and limitations and that consider both real-world and simulated scenarios. Among the algorithms listed, a significant portion have been verified through simulation, including DAA*, D*, adaptive GA, enhanced GA, improved ACO, A*, D* lite, and others. These algorithms offer advantages such as effectiveness, smoothness, and suitability for simulation. However, they often lack consideration of critical factors like COLREGS and dynamic obstacles, limiting their real-world applicability. On the other hand, algorithms like CCNN, AMPSO, GPGA, 3D-Dijkstra, CINN, and A* PS have been specifically validated in real-world scenarios: offering insights into practical implementation challenges. While these algorithms address COLREGS and dynamic and static obstacles, some may lack real-time capabilities, which could restrict their performance in dynamic environments.

Future improvements in global path planning algorithms can be achieved through several key strategies. Firstly, algorithms should focus on real-time adaptation to dynamically adjust to changing environments and obstacles. This involves enhancing data update mechanisms and integrating real-time sensor data for improved accuracy and safety. Secondly, the integration of machine learning techniques, like reinforcement learning, can enable algorithms to learn and adapt path planning strategies based on evolving conditions. Thirdly, adopting multi-objective optimization approaches can balance competing objectives and generate Pareto-optimal solutions. Hybrid approaches combining different algorithms' strengths can enhance overall performance and robustness. Efforts to improve scalability and efficiency in handling large-scale graphs and complex environments are crucial, as is the development of algorithms tailored to specific environments. Researchers need to ensure rigorous validation and testing for reliability and safety. By embracing these strategies, global path planning algorithms can become more adaptive, efficient, and effective across diverse domains.

In future research, there is a need to explore algorithms that seamlessly integrate real-time performance, smoothness, and handling of dynamic and static obstacles. Additionally, enhancing algorithms to comply more robustly with COLREGS while maintaining efficiency in real-world scenarios would be beneficial. Further research could also focus on developing algorithms that adapt dynamically to changing environments: ensuring safe and efficient USV navigation. By addressing these aspects, researchers can develop more adaptable and reliable USV global route planning algorithms suitable for practical deployment. Moreover, efforts should be made to ensure a balance between simulation and real-world validation to enhance the credibility and applicability of these algorithms in maritime navigation scenarios. Table 4 shows the features of diverse algorithms used for global route planning.

Table 4. Features of numerous algorithms employed for USV global route planning.

Reference	Algorithm	COLREGS	Dynamic Obstacle	Static Obstacle	Effective	Smooth	Real Time	Simulation or Real World
[83]	DAA*	Yes	Yes	Yes	Yes	Yes	Yes	Simulation
[61]	D*	No	No	No	No	No	Yes	Simulation
[53]	Adaptive GA	No	No	Yes	Yes	Yes	Yes	Simulation
[79]	CCNN	No	Yes	No	Yes	Yes	Yes	Real world
[84]	Enhanced GA	No	No	Yes	Yes	No	Yes	Simulation
[85]	Improved ACO	No	Yes	No	Yes	Yes	Yes	Simulation
[86]	AMPSO	No	No	Yes	Yes	Yes	No	Real world
[74]	GPGA	No	Yes	Yes	Yes	Yes	No	Real world
[87]	A*	No	No	Yes	Yes	Yes	No	Simulation
[88]	3D Dijkstra	No	No	Yes	Yes	Yes	Yes	Real world
[79]	CINN	No	Yes	No	Yes	Yes	Yes	Real world
[62]	D* lite	No	Yes	No	Yes	Yes	Yes	Simulation
[89]	A* PS	No	No	Yes	Yes	Yes	Yes	Real world

Yes = Considered, No = Not considered, Simulation = The algorithm was verified by numerical analysis, Real world = The algorithm was verified in real world scenarios

4. Current State-of-the-Art Methods in Chronological Order

After a thorough review on the existing literature within the realm of route planning and obstacle avoidance for USVs, a comprehensive categorization of these studies was conducted based on both their chronological order and the methodologies employed to assess the efficacy of the proposed algorithms. They are divided into four intervals: up to 2010, 2011–2015, 2016–2020, and from 2021 onward. The research was segmented into two distinct categories outlined as follows: the first classification comprises algorithms verified through numerical research, and the second classification incorporates algorithms applied in practical scenarios, which features USV control methodologies that have been introduced and assessed for their efficacy within authentic environments involving dynamic and static obstacles.

4.1. Up to 2010

The exploration of navigation systems for USVs began in the early 2000s [6]. In the early 2000s, basic route planning algorithms emerged incorporating grid-based and waypoint navigation methods. After reading papers related to USV route planning published before 2010, it is evident that algorithms validated through simulation offer a diverse range of approaches and methodologies. These algorithms encompass both local and global route planning strategies, each with its own set of advantages and disadvantages. Among the algorithms reviewed, the line-of-sight projection algorithm emerges as a local route planning method that focuses on dynamic obstacle avoidance and waypoint guidance. Its integration of components like dynamic LOS vectors and PID heading controllers provides comprehensive solutions. However, challenges related to scalability and performance in complex scenarios may arise. On the other hand, the A* graph-search algorithm and GODGZILA algorithm represent global route planning strategies and address COLREGS, environmental disturbances, and larger obstacles across various scenarios. While robust and versatile, their computational complexity and implementation difficulties may pose obstacles to practical deployment.

The rapidly exploring random tree algorithm shows promise in local path planning by offering compliance with COLREGS and dynamic obstacle avoidance. Nevertheless, its efficacy in intricate environments requires further investigation. Lastly, the Dijkstra algorithm, a classic method suitable for 2D scenarios, provides advanced graph-search capabilities but may face limitations in adapting to dynamic environments and complex terrains. While these algorithms contribute significantly to USV route planning, particularly in simulation settings, they also highlight the need for advancements to address scalability, regulatory compliance, real-world applicability, and computational efficiency in future research endeavors. Table 5 displays the compilation of algorithms that underwent validation through numerical research up until 2010.

Table 5. Summary of the algorithms that were confirmed through numerical studies until 2010.

Reference	Name of Algorithm	Main Features
[90]	Line-of-sight projection algorithm	• Waypoint guidance • Dynamic LOS vector • PID heading controller • Dynamic obstacles
[91]	A* graph-search algorithm And GODGZILA algorithm	• COLREGS • Environmental Disturbances • Larger obstacles • 2D and 3D scenarios
[92]	Rapidly-Exploring Random Tree algorithm	• COLREGS-compliant • Avoidance of dynamic objects • Realistic
[93]	Djikstra algorithm	• 2D scenarios • Advanced graph search

One can discover a real-world illustration of how collision avoidance algorithms are really applied in [94]. In this article, a system that controls and remotely monitors the USV is designed. This system incorporates an auto-navigation algorithm and a fuzzy algorithm to estimate the likelihood of collisions. To assess its effectiveness, the system undergoes simulator experiments and model tests in an inland water environment. Study [95] demonstrates the effective integration of collision avoidance capabilities into a functioning autonomous surface vehicle. The algorithms validated through field testing until 2010 offer a unique perspective on real-world applicability compared to those verified solely through simulation. Among them, the fuzzy algorithm provides real-time decision-making capabilities, which is crucial for safe navigation in dynamic environments, by assessing the time and distance of the closest point of approach. However, its performance under various environmental conditions and scalability to larger-scale operations remain unclear. Similarly, the LOS control algorithm, featuring nonlinear control for path following and applied in collaborative tasks by AUVs and ROVs, demonstrates advanced control techniques suitable for real-world testing on scaled models. Yet there is limited information on its performance in full-scale scenarios and under diverse environmental conditions. The visibility graph offers a systematic method for route planning, particularly in scenarios with complex obstacles, but is lacking clarity on its performance in dynamic environments and scalability to larger-scale operations. Table 6 lists the methods that had been used in actual applications as of 2010.

Table 6. List of algorithms that were validated through field testing until 2010.

Reference	Name of Algorithm	Core Features
[94]	Fuzzy algorithm	• Real time • The time of closest point of approach (TCPA) • The distance of closest point of approach (DCPA)
[96]	LOS control algorithm	• Nonlinear control for path following • Applied to perform tasks by AUVs and ROVs collaboratively • Tested on a scaled model of an autonomous cargo surface vessel
[97]	Visibility graph	• Graph-based approach • Visibility graph construction • Multiple obstacles

4.2. From 2011 until 2015

The algorithms validated by numerical research between 2011–2015 represent notable advancements in USV route planning and offer a mix of local and global path planning strategies. The DPSS algorithm generates COLREGS-compliant routes, utilizes an enhanced version of the A* algorithm, and considers both static and dynamic obstacles. The velocity obstacle (VO) algorithm demonstrates effectiveness at dynamic obstacle avoidance using relative coordinates. The curvature route planning algorithm introduces a three-dimensional graph with angular resolution and considers vehicle dynamics. In study [98], a grid environment model was utilized to enhance the ant colony algorithm in order to develop a global route planning method for USVs. In [99], while the A* algorithm is extensively utilized for path finding, it does not necessarily provide the shortest paths due to limitations to the potential headings of the paths. In an effort to overcome this drawback, the study introduces the finite angle A* (FAA*) method. Comparing these algorithms to those validated before 2010, it is apparent that advancements had been made in terms of compliance with regulations, dynamic obstacle avoidance, and the integration of advanced techniques such as neural networks. However, challenges related to computational complexity, scalability, and real-world applicability persist across both sets of algorithms. The algorithms validated between 2011–2015 showcase a deeper understanding of USV route planning complexities and offer more refined solutions to address dynamic and real-world scenarios. Moving forward, continued research efforts should focus on refining these algorithms, addressing scalability challenges, and ensuring their effectiveness in practical deployment scenarios. Table 7 presents a record of algorithms that underwent validation through numerical research from 2011 to 2015.

Table 7. Algorithms validated by numerical research between 2011–2015.

Reference	Name of Algorithm	Main Features
[100]	DPSS algorithm	• Generates COLREGS-compliant routes • Enhanced version of A* algorithm • Utilizes a goal direction vector • Static and dynamic obstacles
[101]	Velocity obstacle (VO)	• Uses relative coordinates as the basis for route planning • Avoids a variety of moving objects
[102]	Curvature route planning algorithm	• A three-dimensional graph with a 45-degree angular resolution • Considers the vehicle's dynamics • Modified version of the A* method
[103]	Logic-oriented neural networks	• It can be quickly and simply transformed into a set of logic expressions • Able to modify itself online based on a direct assessment of control accuracy

The algorithms validated in real-world scenarios between 2011–2015 exhibit notable advancements compared to those validated before 2010, particularly in terms of sophistication and adaptability. Prior to 2010, algorithms that focused on real-world validation tended to be less complex and often relied on classical methods for path planning, with a primary emphasis on regulatory compliance and basic obstacle avoidance. In contrast, the algorithms validated between 2011–2015 demonstrate a shift towards more sophisticated techniques, including hybrid path planning methods and AI-driven strategies. These newer algorithms prioritize real-time computation, dynamic obstacle avoidance, and scalability to handle complex navigational environments. For instance, the introduction of the Theta* algorithm showcases real-time computation capabilities and instant global path production, indicating a move towards more efficient and responsive navigation systems.

The algorithms validated between 2011–2015 place greater emphasis on handling multiple USVs and adapting to high-velocity scenarios, reflecting advancements in addressing dynamic maritime environments. The incorporation of modern techniques such as AI-driven collision avoidance algorithms further underscores the evolution towards adaptive and responsive navigation systems. In [104], field experiments are used to evaluate the effectiveness of four route planning behaviors that were developed automatically. The planner combines a local search approach based on the velocity obstacle concept with a global search based on a lattice structure to identify a trajectory that is both dynamically viable and complies to the nonlinear dynamics, nonholonomic limitations, and low-level control of each system. Reference [105] proposes a novel method that utilizes the Theta* algorithm to generate real-time paths for unmanned surface vehicles (USVs) taking into account both the angular rate and heading angle. Reference [106] proposes a brand-new, ground-breaking obstacle avoidance algorithm created especially for ultra-rapid USVs. The outcomes support the validity and dependability of the suggested algorithm for safely operating high-speed USVs (with speeds equal to or more than 20 knots) while successfully navigating obstacles. In [107], a novel route planning and navigation algorithm is proposed. The proposed algorithm utilizes the fast marching method as the primary algorithm to look for an ideal collision free path. In study [108], two objectives are discussed: route planning for USVs and the implementation of route planning on a real map. The proposed algorithm takes into account the size of the USVS. The route planning experiment was conducted on a realistic satellite thermal picture, and the results could be utilized by the USV. Table 8 shows some of the algorithms verified in field tests from the year 2011–2015.

Table 8. Algorithms used in real world scenarios between 2011–2015.

Reference	Name of Algorithm	Main Features
[104]	Velocity obstacle (VO)	• Multiple low-level USVs • High planning performance • COLREGS compliant
[109]	Fast marching (FM) algorithm	• Performs well in a challenging navigational environment • Capable of efficiently modeling the dynamic behavior of moving ships • Multiple USVs
[105]	Theta* algorithm	• Real time • Fastest computation • Tested on twin-hull type USV prototype • Can instantly produce a global path
[106]	Local reactive collision avoidance algorithm	• Takes into account the characteristics of high-velocity USVs • Able to steer USVs traveling at 20 knots or more • Can navigate safely in real maritime environment

4.3. From 2016 until 2020

The algorithms verified through numerical studies between 2016–2020 mark a significant leap forward in USV route planning strategies and introduce a diverse array of features and innovations. These include the two-level dynamic obstacle avoidance algorithm, which effectively combines velocity obstacle (VO) principles with improved APF techniques to handle multiple obstacles. However, challenges exist for its adaptability to highly dynamic environments and scalability to larger scenarios. The generalized velocity obstacle (GVO) algorithm emerges as a promising solution for various maritime environments, offering reliable collision prevention and minimal required evasive actions. Nonetheless, its effectiveness in complex scenarios and scalability require further exploration. The fast marching square algorithm facilitates safe navigation for multiple USVs but lacks sufficient validation in dynamic environments.

COLREG-RRT ensures compliance with regulations and identifies longer trajectories, yet its performance under dynamic conditions needs clarification. The optimized particle swarm (PSO) algorithm integrates dynamic factors like currents but faces challenges in computational complexity and scalability. The genetic algorithm seeks optimal routes but may generate suboptimal solutions due to random initialization and scalability issues. Comparing these advancements to earlier methodologies, trends indicate a shift towards sophisticated algorithms capable of handling dynamic maritime environments and compliance with regulations. While AI-driven techniques such as genetic algorithms and particle swarm optimization are increasingly integrated, challenges in scalability, real-world applicability, and computational complexity persist, driving ongoing research efforts in the field.

Reference [110] suggests an intelligent route planning algorithm and a collision avoidance control approach for the USV swarm in order to boost USV autonomy and mission effectiveness in confined waters. Study [111] shows early research findings from an original automatic obstacle avoidance technique for unmanned surface vehicles (USVs) based on COLREGS. The suggested method is basically a route-searching grounded algorithm termed the 'local-normal-distribution-based trajectory'. In [112], a reliable algorithm is proposed to conceal obstacles within convex hulls, which mostly includes clustering analysis of obstacle regions and the criteria for identifying edge points. In [113], an algorithm called 'angle guidance fast marching square' is proposed to make sure that the route generated is compliant with the dynamics of the vehicle and the restrictions to orientation. Study [114] employs a hierarchical framework utilizing a partially based minimum consensus (BMC) approach to address the route planning challenge for USVs. In [115], a novel approach for guiding unmanned surface vehicles (USVs) in an intelligent target search is proposed. The strategy consists of three main components: initial global route planning using preexisting knowledge, dynamic local route planning based on real-time data, and an enhanced obstacle avoidance algorithm called 'improved A*'. In [116], a novel algorithm is devised for energy-efficient route planning. This algorithm combines multiple techniques, including the Voronoi diagram, Dijkstra search algorithm, and visibility algorithm while also considering data on sea currents. Reference [117] proposed a novel approach for local route planning of unmanned surface vehicles to ensure collision avoidance. The proposed algorithm combines the velocity obstacle method and modified quantum particle swarm optimization. Reference [118] proposed a route planning algorithm that is based on the deep deterministic policy gradient technique, which is comprehensively compared to the traditional A* algorithm and the recently developed actor–critic algorithm. Through a series of simulation experiments, it can be observed that the deep deterministic policy gradient route planning algorithm achieves faster and more accurate optimal paths for USVs compared to the other two methods.

Comparing these advancements to earlier methodologies, trends indicate a shift towards sophisticated algorithms capable of handling dynamic maritime environments and compliance with regulations. While AI-driven techniques such as genetic algorithms and particle swarm optimization are increasingly integrated, challenges in scalability, real-world applicability, and computational complexity persist, driving ongoing research efforts in the field. Algorithms that were proven to work in simulated research between 2016 and 2020 are presented in Table 9.

Table 9. List of methods confirmed to work by numerical analysis between 2016 and 2020.

Reference	Name of Algorithm	Main Features
[48]	Two-level dynamic obstacle avoidance algorithm	• Combination of VO algorithm and improved APF • Multi-obstacles
[119]	Generalized velocity obstacle (GVO) algorithm	• Works properly in various maritime environments • More trustworthy and appropriate for preventing ship collisions at close range • Offer ships a minimal number of required evasive actions that comply with the rules
[120]	Fast marching square algorithm	• Multiple USVs • Practical safe navigation on genuine nautical chart
[55]	COLREG-RRT	• Identifies longer trajectories • COLREGS-compliant trajectories
[121]	Optimized particle swarm (PSO) algorithm in a modified form	• USV route control that also takes currents into account • Categorized as global route planning • Dynamic crowding distance
[122]	Genetic algorithm	• Optimal route with the least amount of trip time • Considers environmental loads • Random initialization

The algorithms confirmed to operate in real-world scenarios from 2016 to 2020 mark a notable evolution in USV route planning and showcase diverse characteristics and methodologies. These developments represent a significant stride forward in comparison to earlier periods. Before 2010, algorithms primarily focused on basic regulatory compliance and obstacle avoidance and often relied on classical methods for path planning. Subsequently, between 2011 and 2015, there was a discernible shift towards more sophisticated techniques, including hybrid approaches that integrated classical and AI-driven principles. The algorithms verified between 2016 and 2020 demonstrate a further refinement and specialization in navigation strategies. For example, the modified velocity obstacle (VO) algorithm considers specific rules (13–17) in the COLREGS and provides routes that circumvent these regulations (see Table 10). This demonstrates a move towards more nuanced regulatory compliance and adaptive decision making. Similarly, the time-discrete non-linear velocity obstacle algorithm, leveraging historical AIS data, effectively identifies potential collisions with high dependability, highlighting a focus on data-driven decision making and real-time situational awareness.

Challenges during this period likely include the need for robustness for handling dynamic and unpredictable maritime environments, scalability for coordinating multiple USV systems, and ensuring real-time responsiveness to changing conditions. The types of algorithms employed range from traditional methods, such as fast marching, to AI-driven techniques like predictive route planning using Kalman filters. There is also a notable combination of global and local path planning strategies, indicating a holistic approach to navigation that considers both macro- and micro-level factors. In study [123], a brand-new intelligent hybrid algorithm is implemented. A special method based on a self-organizing map (SOM) is developed and put into use with regard to the multitask allocation issue. The primary novelty is the development and incorporation of a flexible artificial repulsive force field within the SOM. In another study [124], the authors create a path-following algorithm based on broken lines. They run a wide range of numerical simulations and physical testing on their self-designed experimental platform for unmanned surface vehicles. Study [125] examines the potential application of advanced reinforcement learning techniques in the field of unmanned surface vehicles (USVs) and formation route planning. Table 10 lists the algorithms used in practical applications between 2016 and 2020.

Table 10. Algorithms confirmed to work in real-world scenarios from 2016 to 2020.

Reference	Name of Algorithm	Main Features
[126]	Modified velocity obstacle (VO) algorithm	• Considers Rules 13 to 17 in COLREGS • Provides a route that complies with the rules • Results of studies performed in real time at sea using the USV M-Searcher
[42]	Time-discrete non-linear velocity obstacle	• AIS (automatic identification system) historical data were used for testing • Effectively identifies potential collisions • Has high dependability when an approach is repeated
[127]	Fast marching method (FMM) and the self-organizing map (SOM)	• Task distribution among many USV systems • Plans multiple goals for many USV systems
[128]	Predictive route planning technique using Kalman filters	• Predicts the trajectories of moving ships • Assesses collision risk • Fast marching method • May effectively navigate situations with complex traffic

4.4. From 2021 to Date

Since 2021, there has been a notable evolution in USV route planning algorithms, characterized by a heightened emphasis on real-world applicability, adaptability, and efficiency. One prominent trend observed during this period is the integration of traditional path planning techniques with advanced AI-driven approaches. Algorithms developed in recent years leverage machine learning, reinforcement learning, and deep learning methods to enable USVs to make more informed and adaptive navigation decisions in dynamic maritime environments. This integration has led to enhanced collision avoidance capabilities, improved compliance with maritime regulations such as COLREGS, and increased robustness in handling complex navigational scenarios. Additionally, there is a growing focus on addressing challenges related to real-time performance, scalability, and interoperability with existing maritime infrastructure.

In order to address these challenges, current trends in USV route planning algorithms emphasize the combination of multiple techniques to mitigate weaknesses and enhance overall performance. Hybrid approaches that blend traditional path planning methods with AI-driven learning algorithms are increasingly prevalent. These approaches leverage the efficiency of traditional algorithms and the adaptability of AI techniques to create robust and versatile navigation solutions. Furthermore, there is a concerted effort to develop algorithms that seamlessly integrate with existing maritime systems and infrastructure to facilitate safe and efficient autonomous navigation in real-world environments. An emerging focus has been on enhancing precise navigation, which is accompanied by the refinement of algorithms to minimize navigation errors and the implementation of methods to track predetermined paths effectively [129]. Addressing the challenge of USV route planning amidst wave interference and navigating around unidentified obstacles remains a pertinent issue [130]. In study [131], in order to achieve autonomous collaborative formation control among underactuated USVs traveling in sophisticated ocean circumstances, a method utilizing dual model predictive control (DMPC) is developed. In another study [78], USV coverage route planning tasks are taken care of with the introduction of an improved biologically inspired neural-network-enhanced coverage route planning method. In study [132], a hierarchical framework that consist of two layers is proposed for route planning for multiple USV systems in complex marine environments. Study [133] proposes a technique that addresses the issue of obstacle avoidance when faced with a situation of encounter. In [134], a seamless collision avoidance system that enhances the efficiency of multiple USVs during ocean sampling expeditions is presented. In study [135], the optimal collision avoidance point (OCAP) method is proposed as a new approach for USVs to proactively prevent collisions. In [136], the authors tackle the issue of monitoring missions by employing a USV that is equipped with an onboard LiDAR system. This LiDAR system enables the USV to effectively surveil regions within its coverage radius. Table 11 provides a comprehensive compilation of algorithms that have been rigorously validated through numerical research conducted from 2021 onward.

Since 2021, there has been a discernible shift towards algorithms that undergo validation in real-world scenarios, indicating a commitment to ensuring the reliability and functionality of USV route planning solutions in actual maritime environments. These algorithms demonstrate a tangible effort to bridge the gap between theoretical development and practical implementation. Recent advancements in USV route planning algorithms validated in real-world scenarios highlight improvements in collision avoidance, efficiency, and adaptability. Algorithms validated in real-world scenarios exhibit distinct strengths and weaknesses that shape their practical applicability and effectiveness in autonomous maritime navigation. The strengths of these algorithms lie in their ability to offer reliable and safe route planning solutions amidst dynamic maritime environments. These algorithms, such as the improved APF method and the ACO-APF hybrid algorithm, demonstrate enhanced collision avoidance capabilities and compliance with maritime regulations like COLLREGS. They provide efficient and deterministic navigation solutions that ensure quick determination of optimal routes and safe traversal amidst obstacles.

However, these algorithms also exhibit certain weaknesses that warrant consideration. One notable limitation is the potential for computational inefficiency, particularly in scenarios involving complex navigational challenges or large-scale environments. Additionally, while these algorithms prioritize collision avoidance and compliance with regulations, they may encounter difficulties in handling uncertainties related to unknown static and dynamic obstacles. Ensuring real-time adaptability and scalability in dynamic environments remains a challenge, as does the effective mitigation of unexplored targets and local minima issues.

Table 11. Summary of the algorithms that were confirmed through numerical studies since 2021.

Reference	Name of Algorithm	Main Features
[137]	APF-DQN algorithm	• Able to handle COLREGS collision avoidance • APF algorithm was employed to improve the action space for DNQ algorithm as well as its reward function • DQN utilizes data acquired from virtual live sensors as its input information
[138]	AAFMS or the adaptive adjustable fast marching square	• FMS-driven approach has been enhanced to align route planning with the stipulations of the COLREGS • A fitness assessment function has been introduced to appraise the suitability of planned routes while accounting for heterogeneity among USVs • An anisotropic element has been incorporated into the FMS-driven approach to adapt the potential field in accordance with the varying characteristics of USVs
[139]	Deep deterministic policy gradient (DDPG) algorithm	• Reward system with numerous goals • Applying artificial potential field (APF) technology, a target USV avoidance strategy is developed • The use of ROS with Gazebo results in the creation of a 3D virtual reality simulator • Interception and avoidance issues are balanced using a multi-objective equilibrium • End-to-end learning is employed to acquire a tactic capable of intercepting evasive targets
[140]	Finite-time robust neural control algorithm	• Introduces an innovative real-time intelligent navigation strategy that adheres to collision avoidance regulations • Specific enhancements made to the artificial potential field (APF) ensure that the USV possesses robust collision avoidance capabilities in compliance with COLREGS • Finite-time adaptive controller reduces the computational workload, resulting in a lighter processing burden

Despite these weaknesses, algorithms validated in real-world scenarios represent significant progress in USV route planning. Their strengths lie in their practical applicability and effectiveness, which offers reliable navigation solutions for autonomous maritime vehicles. Moving forward, addressing the identified weaknesses and refining algorithms to enhance adaptability and scalability will be crucial for advancing the field of autonomous maritime navigation and ensuring safe and efficient operations in real-world environments. In study [141], a thorough reward function is described to prevent the RL-based controller from settling into a local optimum based on the job decomposition. RL-based controller effectiveness is evaluated by simulation and real-world USV path following. In another study [142], for multi-USV formation route planning, a dual-tier objective-driven hierarchical reinforcement learning system is recommended. The training of deep reinforcement learning for multiple agent procedures employs the upgraded APF approach. The efficiency of the suggested strategy is further examined by utilizing the NEU-MSV01 as an experimental platform and combining the parameterized line-of-sight guidance after a large number of simulated tests have been conducted. Table 12 displays the roster of algorithms utilized in practical, real-world applications since the year 2021.

Table 12. Algorithms confirmed to work in real-world scenarios from the year 2021.

Reference	Name of Algorithm	Main Features
[2]	Improved ACO-APF hybrid algorithm	• Utilizes a grid map for local and also global route planning • Capable of quickly determining the best course • Solves the issue of unexplored targets and the issue of local minima • Avoids unknown static and dynamic obstacles successfully
[35]	Improved APF method	• COLREGS compliant • Method can perform safe navigation well • Fast, effective, and deterministic • Dynamic collision avoidance
[74]	Adaptive elite GA with fuzzy inference (AEGAfi)	• Provides high-quality global paths • COLREGS-compliant local reaction is achieved • An innovative hierarchical route planning framework is introduced • A new meta-heuristic approach is suggested for addressing the global planning problem

5. Summary of Algorithms for Route Planning in USVs

In this section, we offer an overview of the results derived from our literature review. We present statistical information regarding the adoption of route planning and obstacle avoidance techniques. The measurable analysis includes the division of methods by those assessed through simulation tests and those validated in real-world scenarios and covers the time frame between 2000 and 2023. Furthermore, we classify these methods based on their focus on either local or global route planning. Following this, the subsequent portion of this chapter explores prospective avenues for future research and outlines the challenges that could hinder progress within this domain.

5.1. Summary

After conducting an extensive review of the literature pertaining to route planning and obstacle avoidance for USVs, it becomes apparent that there has been a significant upswing in research publications within this field, particularly over the past decade, as indicated in Figure 7. The increased prevalence of simulation tests for the development and integration of novel algorithms in domains of route planning and obstacle avoidance mirrors a corresponding rise in their practical utilization in motion control for USVs and real-world assessments. Over the last two decades, local route planning algorithms for USVs have undergone substantial evolution. From 2000 to 2010, the primary focus was on numerical research validation, and there were limited instances of practical implementation. Between 2011 and 2015, there was a modest uptick in real-world scenario validation. Remarkably, from 2016 to 2020, there was significant growth in both numerical research and practical validations, indicating an increasing interest in applying these algorithms in real-world contexts. This trend has continued into the 2021–2023 period, with a substantial increase in both types of validations. The data suggest a consistent shift towards greater practical application of local USV route planning algorithms (see Figure 8). Over the past two decades, the validation of global route planning algorithms for USVs has witnessed a notable transformation. In the early 2000s, the majority of these algorithms were predominantly verified through numerical research, and there were limited instances of real-world validation. However, from 2011 to 2015, there was a discernible shift towards an increased emphasis on real-world validation, though numerical research still played a significant role. This trend persisted into the 2016–2020 period, with an even more pronounced focus on practical testing. Starting from 2021, the dominant approach has been to validate global route planning algorithms in real-world scenarios, which underscores the growing importance of practical applicability and performance testing in the field. Figure 9 provides a visual representation of the trends in the validation approaches for global route planning algorithms within the context of USVs across specified time intervals; the figure aligns with the patterns previously discussed. When making comparisons between local and global route planning algorithms based on various criteria, distinct trade-offs come into view. Local route planning algorithms exhibit supremacy in terms of immediate COLREGS compliance, dynamic obstacle avoidance, real-time adaptability, and the generation of smoother paths, as can be seen in Figure 10. They excel at swiftly responding to changing environmental conditions, rendering them highly effective for real-time decision making and maneuvering in dynamic scenarios. In contrast, global path planning algorithms excel at effectively circumventing static obstacles by considering the entire route, making them suitable for known and intricate environments. Nevertheless, they may encounter challenges in real-time performance, particularly when rapid adaptations are necessary due to their computational demands. The selection between these algorithms pivots on mission-specific requirements: local approaches are favored for dynamic, time-sensitive situations, and global methodologies are favored for scenarios that demand meticulous static obstacle avoidance and long-range planning. Examining the evolution of USV development over the past two decades, it becomes evident that experiments carried out in real-world settings predominantly center around local route planning techniques. In scenarios validated through simulations, classical approaches often adopt the method of the artificial potential field, while within the algorithms for artificial intelligence, reinforcement learning and methods for fuzzy logic tend to be commonly observed, as can be seen in Figure 11. Conversely, for real-world applications, reactive behaviors constitute the most frequently employed approach, and algorithms for artificial intelligence are rarely featured in real-world scenarios, as can be seen in Figure 12. This limited adoption of artificial intelligence methods in real-world applications can likely be attributed to their extensive data requirements for training the AI system.

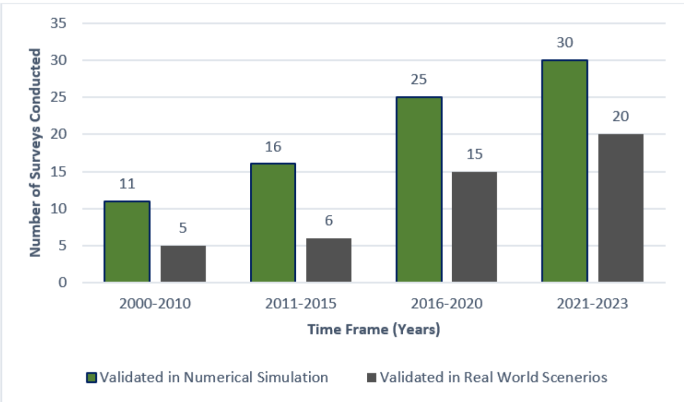

Figure 7. The quantity of papers published over the past 23 years concerning simulation techniques and real-world applications for control and obstacle avoidance systems for USVs.

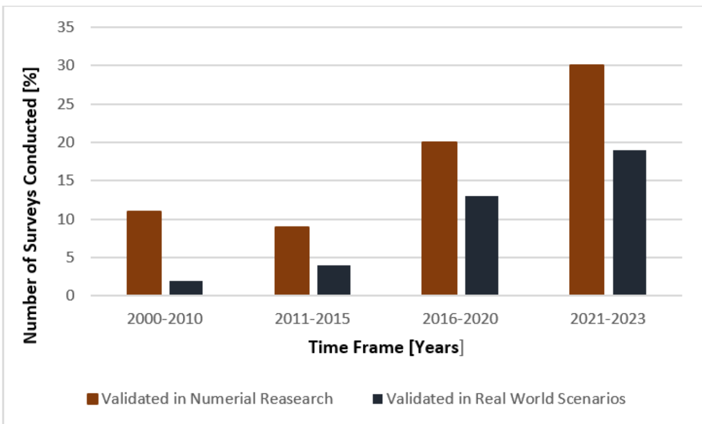

Figure 8. The number of publications released in the last 23 years addressing simulation methods and practical usage of local route planning algorithms used by USVs.

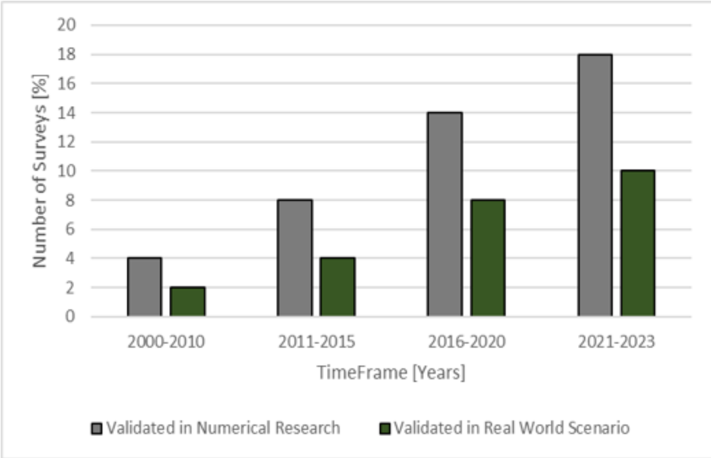

Figure 9. The number of publications released in the last 23 years addressing simulation methods and practical usage of global route planning algorithms used by USVs.

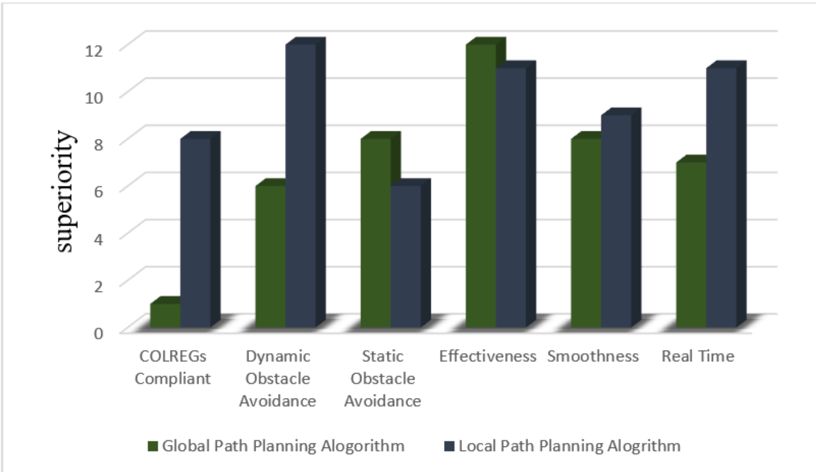

Figure 10. USV global and local route planning algorithm comparison matrix.

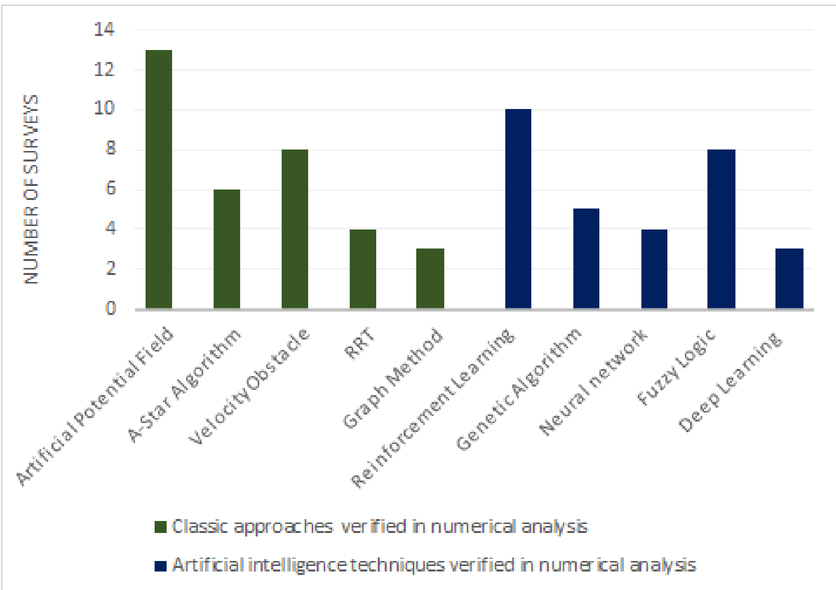

Figure 11. Classic and AI algorithms authenticated by numerical analysis.

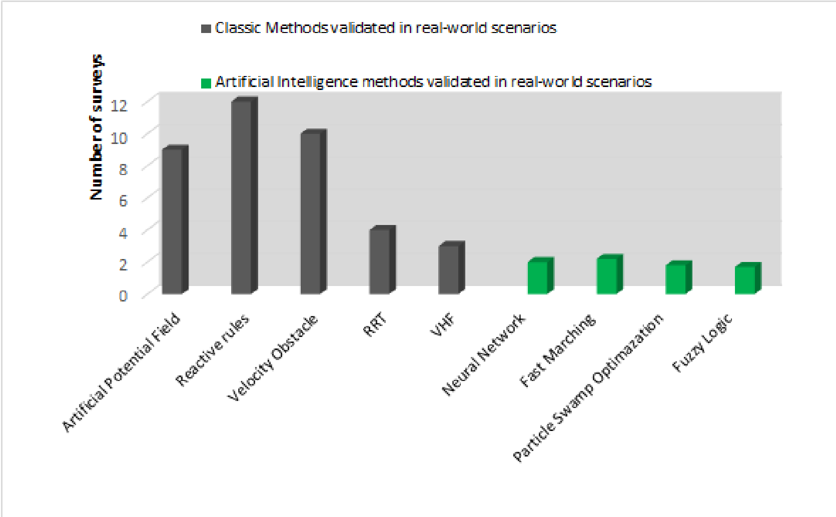

Figure 12. Classic and artificial intelligence algorithms validated in real-world scenarios.

5.2. Future Development

In the current decade, there are a multitude of proposed route planning and obstacle avoidance methods in the realm of USV technology. Despite these advancements, the practical application of effective systems for optimal route planning and obstacle avoidance in USVs remains limited. The judicious utilization of evolving technology is paramount for advancing collision avoidance and path planning systems for USVs. While some challenges in this domain have been successfully addressed, there remain unresolved issues that warrant extensive research in the foreseeable future.

- It becomes imperative to shift our focus towards practical implementations in order to leverage the insights gained from simulation studies. The ongoing progress of technology offers enhanced opportunities for more precise detection and navigation and increased computational speed.
- In numerous instances, the algorithms that have been developed fail to account for natural forces like wind, waves, or currents, thereby rendering the modeled environment incomplete and potentially leading to algorithm performance disparities when confronted with real-world conditions.
- While safety remains a paramount concern in vessel navigation, it is worth noting that not all solutions incorporate COLREGS as an integral component of their collision avoidance or route planning algorithms. Most algorithms need further improvement to incorporate COLREGS.
- Some algorithms exclusively address static obstacles while neglecting dynamic ones. Moreover, collision risk assessment often relies on only one or two factors, which does not offer a comprehensive understanding of the safety context within which the vessel operates. Consequently, there is a need for further enhancement to both the system of evaluating route planning and the assessment of collision risk models.
- Addressing the challenge of enabling USV groups to carry out numerous tasks while seamlessly integrating the avoidance of obstacles is a key issue to tackle in future. Enhancing the insight capabilities of the area of navigation and augmenting autonomous decision making are the vital components to resolve this challenge.
- The forthcoming trajectory of current route planning algorithms points toward a combination of multiple algorithms. This combination approach involves combining traditional optimization algorithms with emerging technologies like digital twins, deep reinforcement learning (DRL), and other algorithms for artificial intelligence. Such a direction embraces the potential to enable dynamic and real-time route planning.

6. Conclusions

Route planning stands as a dynamic and a very complex research field within the context of USVs and represents a pivotal technology for enabling USV autonomy within the maritime domain. This article offers both numeric and descriptive assessments of route planning and obstacle avoidance systems that have been subject to validation through either numerical simulations or real-world implementations. We have done a comprehensive survey and an analysis on the existing body of literature that encapsulates achievements, potential avenues for enhancement, and the obstacles that hinder the ongoing progress of USVs, with a specific emphasis on route planning and obstacle avoidance. The domain of route planning is categorized into two distinct branches: global route planning and local route planning. In Section 3, we delve into the strengths and weaknesses of various methodologies for global and local route planning. Future research should prioritize a dual approach encompassing simulation-based assessments and real-world field tests and aiming to appraise algorithmic performance across diverse scenarios and under varied conditions. Such evaluation systems could prove instrumental for scrutinizing the reliability, endurance, and adaptability of these methodologies as well as guiding the development of algorithms tailored to specific applications and requirements. Moreover, based on our analysis on the state-of-the-art, determining the optimal approach or combination of methods for collision avoidance presents challenges. Multiple strategies have proven successful in various circumstances, with hybrid techniques frequently demonstrating effectiveness. As indicated by our findings, three algorithms—artificial potential field, reinforcement learning, and fuzzy logic—are the most frequently evaluated in simulated environments and appear to hold significant promise for real-world practical applications.

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