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Review of Intelligent Ship Path Planning Algorithms

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Abstract

Intelligent ship route planning has become an important research direction in the field of shipping in recent years. This paper first provides an overview of the basic theory of intelligent ship route planning. Secondly, various intelligent ship route planning algorithms are introduced, including methods based on A* algorithm, artificial potential field algorithm, RRT algorithm, and reinforcement learning. These algorithms analyze information such as ocean environment, predict sea conditions and traffic conditions, and consider ship dynamics and navigation safety constraints to provide efficient and safe navigation routes for ships. Finally, this paper points out the key issues and future development directions in intelligent ship route planning. The continuous innovation and application of intelligent ship route planning algorithms will provide more intelligent and efficient ship transportation services for the shipping industry, promoting the sustainable development of the shipping industry.

Keywords: intelligent ship, algorithms of path planning, obstacle avoidance

1. Introduction

In recent years, China's national economy has sustained growth, with economic interactions with countries worldwide becoming progressively more frequent, indicating a year-on-year rise in the volume of foreign trade transactions. Maritime transportation, boasting unique advantages of high capacity, low cost, and minimal investment, holds a crucial position in China's foreign trade. With rapid technological advancements, particularly the integration of frontier technologies like artificial intelligence and big data, the intelligence of ships emerges as an inevitable trend in the evolution of shipbuilding and shipping industries. Presently, China has explicitly defined "enhancing the level of shipping intelligence, fostering the advancement of smart shipping and related strategic emerging industries, and achieving the enhancement of digitization, networking, and intelligence within shipping" as its core development goal and primary focus.

As a burgeoning trend within the shipping industry, smart ships, characterized by their increased autonomy and adaptability, are progressively emerging as pivotal for the transformation and enhancement of the national shipping and logistics sectors.

Ensuring the safe navigation and efficient operation of smart ships at sea requires a robust "brain" — an intelligent navigation decision-making system. This system gathers and analyzes crucial information, including the external environment and operational objectives, to provide smart ships with optimal navigation routes and collision avoidance strategies. Among these, path planning, as the cornerstone of the intelligent decision-making system, plays a crucial role. Path planning aims to dynamically assist smart ships in mapping out the most efficient navigation route based on real-time data to ensure both safety and operational effectiveness.

This article primarily delves into the key technologies and applications of intelligent ship path planning algorithms. Firstly, it introduces the fundamental theory of intelligent ship path planning, highlighting its pivotal role in enhancing ship navigation efficiency and safety. Then, it scrutinizes the principles, advantages, disadvantages, and applications of the primary algorithms for intelligent ship path planning. Finally, it addresses the key challenges of intelligent ship path planning and outlines prospects for future research directions (as shown in Figure 1).

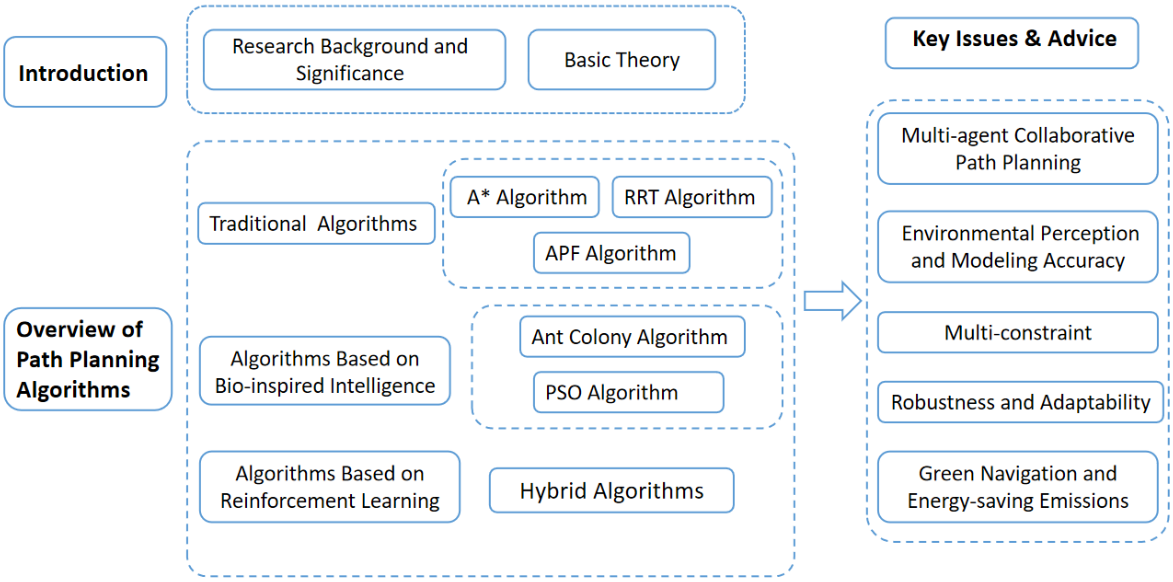

Figure 1. Overall Framework Diagram

2. Basic Theory of Intelligent Ship Path Planning

2.1 Overview of Intelligent Ship Navigation Strategies

Navigation strategy refers to a decision-making plan formulated by ships when navigating at sea based on factors such as objectives, conditions, and rules. Its primary aim is to guarantee the safe and efficient arrival of ships at their destination. Research on ship navigation strategy encompasses aspects such as route planning, speed regulation, collision avoidance decisions, weather prediction, and marine environmental factors. Among these, route planning stands as a core aspect of ship navigation strategy, encompassing considerations such as route selection, voyage calculation, and route optimization. Research methodologies primarily involve mathematical modeling, simulation experiments, and real-world sea trials. Mathematical models underpin research on ship navigation strategy, facilitating the modeling and analysis of ship navigation processes. Simulation experiments simulate ship navigation processes on computers to assess the effects of various navigation strategies. Meanwhile, actual sea trials serve to validate and refine research findings.

During the navigation process of intelligent ships, ships operate within three navigation states: (1) when no other ships are present, they are in the route planning state; (2) when other ships are present, and there is a risk of collision, collision avoidance decision-making is necessary; (3) after successfully avoiding collision and eliminating collision risks, the ship needs to return to the route planning navigation state. Therefore, ship navigation strategies can be delineated through three navigation states: route planning state, collision avoidance decision-making state, and restoration of route planning state.

With the advancement of technologies like artificial intelligence and big data, the application prospects for ship navigation strategies are extensive. For instance, by analyzing ship navigation data with big data, ship routes can be optimized to enhance transportation efficiency. Utilizing artificial intelligence technology can enable functions such as autonomous collision avoidance and navigation, thereby bolstering navigation safety.

2.2 Overview of Intelligent Ship Path Planning

During autonomous navigation, intelligent ships inevitably encounter unforeseen obstacles. To tackle this challenge, intelligent ships need to employ suitable path planning algorithms to navigate around obstacles. The path planning problem for intelligent ships essentially constitutes a multi-constrained optimization problem. It entails finding the optimal path from the current position to the target position while adhering to the operational performance of the ship and external environmental constraints. In this process, various factors such as distance, resource consumption, and time must be comprehensively considered. Additionally, constraints such as navigation restrictions and obstacles must be taken into account to ensure that the planned path is both feasible and safe. Path planning methods are primarily divided into two categories: global path planning and local path planning.

Global path planning utilizes pre-established environmental models of the starting and target points to chart an obstacle-free optimal path from the start to the endpoint. It typically does not consider the physical characteristics of the ship. In contrast, local path planning primarily addresses dynamic obstacles encountered during navigation, such as other ships. It relies more on real-time environmental information obtained by ship sensors to determine the optimal path to evade these obstacles. Throughout this process, the physical characteristics of the ship, such as attitude, turning radius, and maneuverability, are thoroughly taken into account.

In the path planning process, the optimization objective function commonly employs the distance-optimal function, aiming to identify the shortest path. Simultaneously, ensuring navigation safety is also a crucial objective function considered in the path planning strategy for intelligent ships. Path planning strategies for intelligent ships are integral components of smart shipping, capable of enhancing transportation efficiency, reducing fuel consumption, and emissions, thereby achieving sustainable development. In practical applications, factors such as maritime regulations and safety standards must be taken into account to ensure navigation safety and compliance.

3. Intelligent Ship Path Planning Algorithms

Presently, path planning algorithms for intelligent ships mainly categorize into the following three groups: traditional path planning methods, bio-inspired path planning methods, and reinforcement learning-based path planning methods.

3.1 Traditional Path Planning Algorithms

Traditional path planning algorithms rely on constructing geometric models of known environments to identify suitable paths. They primarily encompass algorithms such as A*algorithm, the artificial potential field method, and the RRT algorithm. These algorithms operate on relatively simple principles but may exhibit decreased efficiency when confronted with complex environments.

3.1.1 Ship Path Planning Based on the A* Algorithm

The A* algorithm, published in 1968, is a fusion of the Dijkstra algorithm and the breadth-first search algorithm (BFS). Leveraging a heuristic function, this algorithm can efficiently identify the optimal path. The heuristic function can be represented as:

$$f(n) = g(n) + h(n) \tag{1}$$

Here, *f(n)* represents the composite priority function of the node, taking into account the overall priority during node selection. *g(n)* denotes the cost function from the starting point to the current node; *h(n)* indicates the estimated cost function from the current node to the target node, namely, the optimal path heuristic value from the current ship position to the destination.

The A* algorithm, a heuristic approach based on graph search, stands as the most efficient direct search method for uncovering the shortest path in static road networks. It boasts advantages such as low computational complexity, straightforward patterns, and convergence to a globally optimal solution. Its integration into global ship path planning has garnered considerable attention from scholars worldwide. Scholars such as Kaklis, D. et al. (2024) utilized historical ship tracking data to extract maritime navigation trajectories and employed the A* algorithm to plan navigation paths, thereby notably reducing ship routes and cost-saving for the shipping industry. Researchers like Zhihuan, H. U. et al. (2024) integrated the A* algorithm with kinematic state space in the pre-docking stage, leveraging Reed-Shepp curves to generate optimal paths that guarantee kinematic feasibility and minimal collision risk. Xie, L. et al. (2019) proposed a global multi-directional A* algorithm, adapting the heuristic function based on the complexity of the surrounding environment to regulate the movement distance at each step. This adapted step pattern can broaden potential movement directions, significantly enhancing navigation safety. Sun Yaodong (2018) adopted a dual-layer path planning strategy using the A* algorithm and an improved potential field grid method to restrict and expand navigation angles to better reflect the maneuvering characteristics of ships.

To tackle challenges such as the significant computational complexity and extended running time of the A* algorithm, scholars have put forth various enhancement methods. Zhu Wenliang et al. (2023) proposed a circular distance method to optimize the A* algorithm, addressing issues such as the traversal of a large number of nodes in grid-dense scenarios and inefficient path searches, consequently reducing the time required to plan the globally optimal path. Li, H. (2023) introduced a segmented A* algorithm, partitioning the path into segments and implementing an adaptive heuristic function to automatically balance the magnitude difference between risk assessment values and estimated distances. This approach markedly curtails the expansion of redundant grids, enhancing the algorithm's efficiency and runtime speed. Zhen, R. et al. (2023) mitigated the limitations of the traditional A* algorithm by formulating a risk model that incorporates factors such as water flow, water depth, and obstacles. They devised a traffic model, turning model, and smoothing method to ensure adherence to COLREGs rules in the planned path, thereby facilitating ship tracking and control.

3.1.2 Ship Path Planning Based on Artificial Potential Field Method

The Artificial Potential Field method (APF) stands out as one of the most frequently utilized algorithms in local path planning. Its core concept revolves around employing a virtual force field, where the navigational environment of the ship is abstracted into this field. Obstacles generate "repulsive forces," steering clear of collisions, while target points produce "attractive forces," guiding ships toward the target to facilitate path planning. Similarly, in ship collision avoidance scenarios, the maritime area's navigational environment can be viewed as a virtual force field. Consequently, ships within this field experience simultaneous influence from both attractive and repulsive forces, continuously navigating toward the target point along the optimal path (as shown in Figure 2).

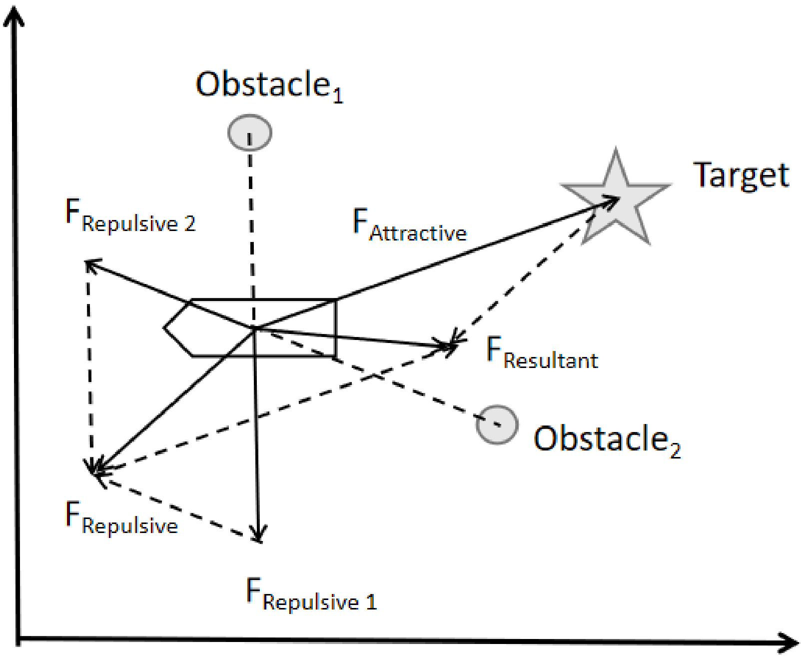

Figure 2. Force Analysis of Ships in Potential Field

Paths generated using the APF algorithm are typically smooth and safe. As a feedback control strategy, the APF algorithm demonstrates a certain level of robustness and is widely applied in ship path planning. Scholars like Du Xishen et al. (2022) analyzed ship maneuvering performance considering the configuration of ship thrusters and utilized the APF method to determine the ship's heading direction. By computing the potential energy, they determined the required thrust and torque of the ship, resulting in a ship motion trajectory that includes speed and heading information. Zhu Wubin (2022) proposed an APF collision model founded on collision risk evaluation, incorporating the spatiotemporal computation of ships to precisely evaluate collision risk and guide collision avoidance maneuvers.

However, during algorithm execution, it is susceptible to converging to local optima. When the target point is far away, the attraction is notably strong, while the repulsion is relatively weak, potentially resulting in collisions. Conversely, when obstacles are in close proximity to the target point, the repulsion is intensified, and the attraction is diminished, making it challenging to reach the target point. Numerous scholars at home and abroad have conducted extensive research to tackle this issue. Scholar Huang Dengjun (2021) enhanced the repulsive function within the traditional APF algorithm and introduced ship encounter identification methods to mitigate shortcomings such as susceptibility to local minima and inadequacy in meeting actual maritime applications. Zhang Qi et al. (2023) introduced escape forces perpendicular to the repulsive force from obstacles or the attractive force from the target point, enabling ships to break free from local minima and successfully reach the target point. Cheng Xide et al. (2024) introduced deflecting torques and enhanced the traditional APF method to ensure smoother turns when ships navigate through obstacles, with turning angles at each path meeting the constraints of ship maneuvering performance, thereby better satisfying the requirements of actual ship navigation conditions. Sun Shuo et al. (2023) proposed a radius-adaptive sub-target setting method and incorporated variable adjustment angles to modify the distance between sub-target points and obstacles, thus tackling issues like local minima and path oscillations during avoidance of large obstacles. Lyu, H. et al. (2024) developed a coupled model of dynamic and static obstacles, built a virtual potential field for the target ship constrained by COLREGs, and addressed the local optima issue of the traditional APF method. Lyu, H., & Yin, Y. (2018) introduced a hybrid APF method for path guidance, merging potential field and gradient methods. This includes path planning based on potential for static obstacles, gradient-based decision-making for dynamic target ships, and combined approaches considering prior paths and optimized waypoint selection to yield more reliable navigation paths.

3.1.3 Ship Path Planning Based on the RRT Algorithm

The Rapidly-exploring Random Tree (RRT) algorithm is a path planning algorithm well-suited for high-dimensional spaces. It circumvents space modeling by conducting collision detection on sampled points within the state space. Beginning from the initial point, it expands by employing a node expansion strategy to generate new nodes. Through multiple searches and expansions, the RRT algorithm locates the target point, successfully determining a path. It is especially adept at addressing path planning challenges with non-holonomic constraints. The schematic diagram of the extended RRT algorithm is shown in Figure 3.

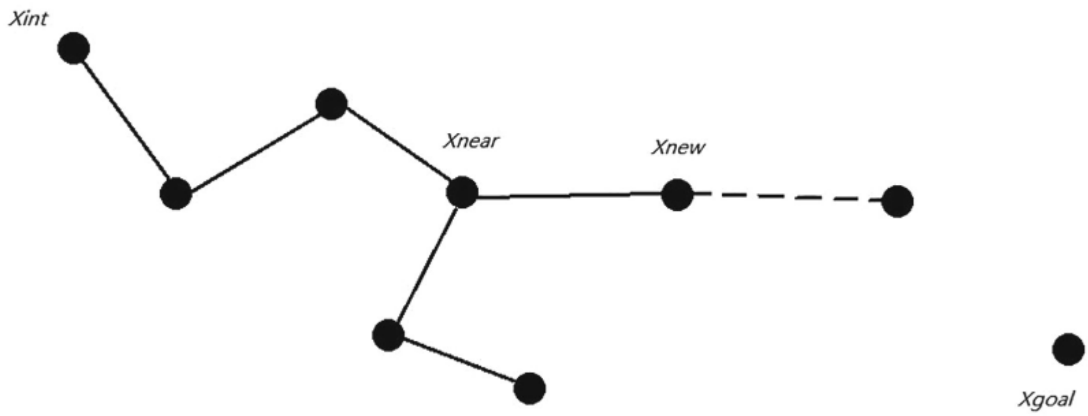

Figure 3. illustrates the extension of the RRT algorithm

Compared to other path planning algorithms, the RRT algorithm exhibits exceptional performance in addressing path planning challenges in high-dimensional spaces and with complex constraints, leading to its widespread application. While it may not be suited for dynamic environment path planning, it remains pivotal in static environments.

Scholars such as Zhang Xichao et al. (2023) transformed the target point problem into a target region problem and conducted target bias expansion based on the target point position. They redefined the sampling region using the initial path and enhanced the final feasible path through pruning and cubic spline interpolation methods. Zhang Jinfen et al. (2023) tackled the challenge of low search efficiency in complex water conditions by introducing a ship collision avoidance path planning model based on the adaptive step-size RRT algorithm. Mao, S. et al. (2023) integrated ship motion state information, accounting for complete dynamic constraints (position, heading angle, velocity, etc.), into the RRT path search rules to forecast reachable ship states, thereby amplifying search efficiency and minimizing costs. Cao, S. et al. (2022) enhanced the conventional RRT algorithm by incorporating path pruning and smoothing modules, ensuring a safe distance between moving ships and obstacles. Gu, Q., et al. (2023) clustered AIS data to create guidance regions, providing valuable guidance for targets. They improved the sampling strategy with biased sampling based on these regions to enhance convergence rate. Furthermore, they applied an enhanced DP algorithm for smoother and more practical path optimization, thereby boosting ship navigation safety and efficiency.

3.2 Ship Path Planning Algorithms Based on Bio-Inspired Intelligence

Path planning methods based on bio-inspired intelligence leverage principles from biological morphology evolution and collective intelligent behavior to design path planning algorithms. They exhibit exceptional adaptability, robustness, and global optimization capabilities, obviating the necessity for intricate environment modeling. However, this approach often entails complex and uncertain parameter settings, slow convergence speed, and high computational complexity. Commonly utilized bio-inspired path planning algorithms encompass the Bug algorithm, ant colony algorithm, particle swarm algorithm, and genetic algorithm, among others.

3.2.1 Ship Path Planning Based on Ant Colony Algorithm

The Ant Colony Algorithm is a global optimization heuristic algorithm inspired by the pheromone deposition behavior of ants during foraging. It treats paths between cities as a graph and involves deploying n ants to navigate within the graph. The algorithm's flowchart is depicted in Figure 4. Within this algorithm, ants deposit pheromones and exhibit distributed computation, positive feedback, and heuristic search characteristics, enabling them to effectively achieve global optimization.

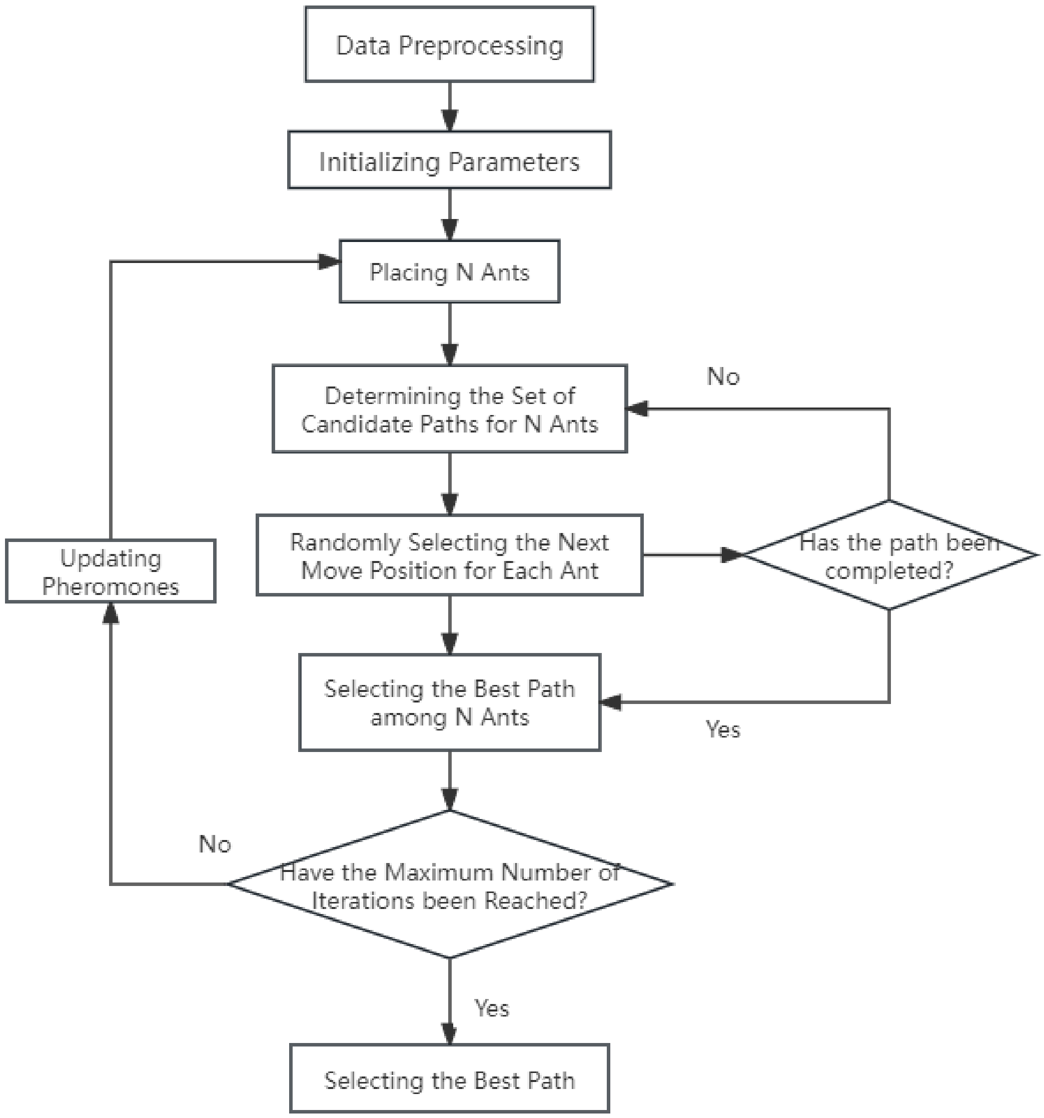

Figure 4. Flowchart of the Ant Colony Algorithm

Scholars Zhao Songying et al. (2022) introduced an ant colony algorithm featuring adaptive adjustments of state transition probabilities, adaptive updates of pheromone information, and corner handling strategies. This algorithm not only enhances convergence speed but also guarantees the smoothness and safety of the obtained path. Bai Xiangen et al (2022) introduced a bidirectional search algorithm, incorporating a turning function ω to smooth the path. They merged this approach with the bidirectional A* algorithm to optimize the search direction. Additionally, they refined the evaporation factor ρ based on the correlation between pheromone retention rules and the number of iterations, resulting in a notable improvement in the search efficiency and accuracy of the ant colony algorithm. Dong, L., & Gan, X. (2023) tackled the quality and diversity of paths during the optimization process by devising two process evaluation metrics. They suggested three enhancement measures: dynamically adjusting adaptive state transition rules using information entropy, dynamically controlling the number of ants involved in global update rules and their corresponding update values based on path quality, and improving the recombination mechanism to boost the performance of the ant colony system. Liu, H. (2023) et al. converted complex local maritime areas into grid format, employing the ant colony algorithm to generate optimal local routes. They subsequently integrated these local routes with the global flowchart to derive the optimal global route.

3.2.2 Ship Path Planning Based on PSO Algorithm

The fundamental concept of Particle Swarm Optimization (PSO) is to discover the optimal solution through collaboration and information sharing among individuals within a group (Chen Jun & Shen Qiqi, 2023). The PSO algorithm originated from the study of birds' foraging behavior, where a group of birds randomly searches for food. If there is only one piece of food in an area, the simplest and most effective strategy to find it is to search around the bird closest to the food (Yang Wei & Li Qiang, 2004). Compared to other evolutionary algorithms, PSO offers the advantages of easy implementation and fewer parameters. As a result, it has found extensive application across various domains, emerging as a vital tool for addressing optimization problems. However, the PSO algorithm exhibits certain drawbacks, including slow convergence speed and vulnerability to local optima. Consequently, numerous scholars have endeavored to enhance the PSO algorithm for global path planning.

Scholars such as Xu Xiaoqiang (2023) introduced an adaptive inertia weight updating and dynamic learning factor strategy to tackle issues with traditional PSO algorithms. This enables particles to adjust their inertia weight and learning factor as the iteration progresses, enhancing the algorithm's optimization capability and convergence rate. Additionally, they introduced the notion of a particle crowding factor to bolster the algorithm's capacity to escape local minima. Xue, H. (2022) integrated the PSO algorithm with the sine cosine algorithm to expedite the search for the optimal path while incorporating collision avoidance functionality. Akdağ, M. et al. (2024) integrated the dynamic safety domain based on ship maneuvering characteristics and potential collision scenarios with a multi-objective PSO algorithm to produce alternative trajectories. Additionally, they employed ratio analysis for multi-objective optimization with user preferences and the entropy weight method for automatic weight allocation, selecting the trajectory with the highest score as the final decision from the alternative trajectories.

3.3 Ship Path Planning Algorithm Based on Reinforcement Learning

Reinforcement learning has been applied in ship path planning and obstacle avoidance systems. Unlike deterministic methods, it can better accommodate influencing factors and facilitate real-time decision-making for actions. Such methods can be optimized by considering collision-free or collision-constrained scenarios to devise optimal strategies. Intelligent methods eliminate the need for manual rule-making and can encompass any deterministic decision branches, thus enhancing the comprehensiveness and safety of ship decisions. Deep reinforcement learning combines perception and decision-making capabilities, facilitating path planning and real-time obstacle avoidance in complex dynamic environments. Deep learning leverages vast amounts of multimodal information to acquire useful knowledge, thereby enhancing algorithm effectiveness. These algorithms have found extensive applications in the realm of path planning.

Scholars such as Yang Qisen et al. (2022) devised a potential-guided reward tailored for intelligent ship navigation tasks within complex dynamic environments. They integrated nautical charts and international maritime collision regulations into the modeling to enhance path planning and real-time obstacle avoidance capabilities. Zhang Daheng (2022), addressing the safety and obstacle avoidance requirements in autonomous ship path planning, proposed a local ship path planning method based on the Faster R-CNN image fusion algorithm to identify "feature radar targets" using deep learning technology. Y. Liu et al. (2023) proposed a cooperative search control method and a disturbance-resistant navigation control method based on reinforcement learning methods, combining the collaborative search control of multi-ship systems with disturbance-resistant navigation control to establish dynamic search and update task models. Guan, W. et al. (2024) proposed an intelligent navigation method using PRM and PPO algorithms, considering the collision avoidance behavior specified by COLREG regulations in the reward function to improve the autonomous navigation and collision avoidance decision-making capabilities of MASS. Wen, N. et al. (2023) devised an action evaluation network aligned with COLREGs and introduced an action selection network based on reward functions for diverse encounter scenarios, constructing a dual action selection strategy to effectively manage ship collision avoidance issues. Liu, L. et al. (2023) trained neural networks and Monte Carlo tree search, employing the AlphaZero algorithm to maximize cumulative reward values and derive optimal decision-making strategies, thereby enhancing navigation safety and efficiency. Chen, C. et al. (2019) simulated ship behavior within channels using the Nomoto model, transforming distance, obstacles, and restricted areas into reward or penalty signals to evaluate ship performance and control decisions. They applied Q-learning to acquire action-reward models and utilized the learned outcomes to autonomously guide ship motion, determining suitable paths or navigation strategies. Guo, S. et al. (2021) integrated environmental state data with the DQN algorithm, adapting it to real-world navigation settings and international maritime collision regulations. They refined traditional reward functions by assigning potential energy rewards to ship target points, incorporating reward zones around target points, and introducing risk zones near obstacles. These enhancements aimed to enhance ship navigation safety, efficiency, and autonomy.

3.4 Path Planning Algorithm Based on Hybrid Algorithms

3.4.1 Global and Local Hybrid Path Planning Algorithm

Global planning algorithms can derive the most efficient path for ships from start to finish, minimizing unnecessary diversions. However, they may not react in real-time to dynamic changes in the marine environment, such as sudden weather shifts or obstacles. Thus, integrating local planning algorithms enables real-time sensing and response to environmental changes. This allows for swift adjustments to local paths, ensuring safe navigation when encountering obstacles or emergencies. This hybrid approach combining global and local planning optimizes the overall route while bolstering real-time adaptability, significantly enhancing both the efficiency and safety of ship navigation. This methodology has garnered considerable attention in practical applications, offering robust support for the advancement of intelligent ships.

Researchers such as Yu, J. et al. (2019) devised their methodology based on modeling unknown terrain and water environments. They utilized the A* algorithm for global path planning and adopted the artificial potential field method for local path planning in uncharted regions. They introduced a self-learning A* algorithm to handle scenarios involving quadratic programming and situations where local paths cannot be generated. Zhang, L. et al. (2021) employed an enhanced artificial potential field method for global path planning and integrated an improved velocity obstacle (VO) method with the Closest Point of Approach (CPA) and COLREGS to derive local paths. This approach facilitates the identification of both global and local paths to avoid target ships.

3.4.2 Integrating Multiple Algorithms for Path Planning

Traditional path planning algorithms frequently fall short of meeting the necessary accuracy and specificity criteria when confronted with intricate, highly dynamic, and realistically simulated maritime environments. These algorithms are typically restricted by rigid search strategies or local optimizations, rendering them less adaptable to the ever-evolving challenges posed by navigation environments. In contrast, hybrid algorithms effectively surmount the limitations of traditional algorithms by intelligently amalgamating the strengths of various algorithms, fostering complementarity and collaboration among them. Consequently, in order to optimize ship navigation routes, experts and scholars have increasingly turned to employing these hybrid algorithms to meet the heightened demands imposed on path planning by contemporary navigation tasks.

Scholars like Wei, G.-A. (2023) tackled ship global path planning challenges by integrating key points to delineate a guiding path, consolidating the terminal heading range, and merging the A* algorithm with the DWA algorithm. Wei, X (2023) devised a target-oriented hierarchical reinforcement learning algorithm, integrating an enhanced artificial potential field algorithm during training to derive an optimal path planning and obstacle avoidance learning scheme for multiple ships within a deterministic perception environment. Subsequently, they formulated a formation geometric model elucidating the physical interconnections among ships and introduced a composite reward function to steer the training process. Xue, Z. (2023) enhanced the information pheromone update strategy, heuristic information, and state transition probability of the ant colony algorithm by integrating it with the artificial potential field method to accomplish both global and local path planning for ship avoidance during maritime navigation. Wang, Y. et al. (2024) integrated radial basis function (RBF) neural networks with Q-Learning algorithms to approximate the action value function Q. They optimized the action space and reward function considering heading angle, motion characteristics, and safety, redesigned the state space, and introduced a safety threshold. Ultimately, they refined the initial path using third-order Bezier curves to ensure heading stability during ship navigation. Yu, D., & Roh, M. I. (2024) introduced a hybrid approach to path planning that leverages the strengths of the Velocity Obstacle (VO) algorithm and the A* algorithm, significantly improving the safety and convenience of ship collision avoidance. Guo, S. et al. (2020) integrated the DDP algorithm with artificial potential fields, empowering the intelligent agent to learn the optimal operating strategy in unfamiliar environments through continuous interaction and historical experience data utilization. This facilitated unmanned ship path planning in unknown environments. Zhu, Z. et al. (2021) integrated the information pheromone concept from ant colony algorithms into the classical Dijkstra algorithm, thereby notably minimizing redundant points in the path planning process and lowering the mobility cost of ship navigation. Gao, P. (2023) et al. proposed combining ant colony algorithms with an improved artificial potential field method and introducing carbon emission constraints into the model to limit sudden speed changes of ships in various waterway sections, resulting in smoother planned paths and enabling real-time dynamic avoidance.

4. The Key Issues of Intelligent Ship Path Planning

4.1 Dynamic Obstacle Avoidance

The maritime navigation environment is characterized by high dynamism and uncertainty, encompassing intricate variations in natural elements like wind, waves, and currents. These factors exert a profound influence on vessel navigation, rendering path planning complex and challenging. Effective path planning entails the consideration of multiple factors, including the vessel's current position, destination, sailing speed, heading, and marine conditions, with the objective of identifying a route that is both safe and efficient. However, owing to the persistent fluctuations in factors such as wind, waves, and currents, the concept of an "optimal path" remains in a state of constant flux. Consequently, a path planning system must exhibit high real-time adaptability, swiftly adjusting navigation routes in response to environmental shifts to guarantee the safety and efficiency of vessel navigation. Scholars like Zhang Jinfen (2023) introduced time series and established a dynamic obstacle detection mechanism. They mapped the obstacle density to the RRT algorithm's search step length and corrected the optimal sampling step length based on the obstacle density around the sampling points, ultimately using the RRT algorithm to solve it. Sun Shuo (2023) addressed the limitations of traditional artificial potential fields regarding avoidance distance and collision avoidance timing. They enhanced the fixed obstacle repulsion range in the artificial potential field by incorporating a quaternion ship domain and developed a dynamically adjusted avoidance domain range based on ship speed to replace the fixed threshold obstacle repulsion field range, thus achieving dynamic avoidance distance. Lyu, H. (2024) devised a dynamic obstacle modeling approach grounded in the quaternion ship domain, amalgamating static and dynamic obstacle modeling. They crafted a virtual potential field for the target vessel constrained by COLREGs.

4.2 Path Rationalization

Due to the multitude of constraints encountered during ship navigation, including maneuvering performance limitations and compliance with navigational conditions, there are high expectations for the smoothness and rationality of path planning. This undoubtedly places greater demands on path planning algorithms. Scholar Cheng Xide (2024) introduced enhancements to the traditional artificial potential field method by integrating deviation torque and ship domain, creating a hybrid model of artificial potential field and maneuvering motion. These enhancements result in smoother turns when navigating through obstacles, ensuring that the turning angle at each point of the path meets the constraints of ship maneuvering motion. As a result, the path exhibits higher smoothness, better aligning with the demands of real navigation conditions.

When planning intelligent navigation paths for smart ships, minimizing navigation resistance and energy consumption is crucial. Energy-efficient path planning not only cuts operational costs but also mitigates carbon emissions, contributing to environmental protection and sustainable development. Thus, energy conservation should be a key objective in intelligent ship path planning. Employing advanced algorithms and techniques is essential to achieve efficient and economical navigation. Scholar Dong, L (2023), based on an adaptive ant system, proposed a ship energy consumption estimation model by analyzing the effects of wind, waves, and currents on energy consumption. They also devised two process evaluation metrics to bolster the ant system's performance. Scholar Huang Dengjun (2021) suggested incorporating factors like Allowable Course Range (ACR), Course Obstacle Region (COR), Safe Course Region (SCR), and the minimum feasible course angle F to constrain the ship's turning angle, thus mitigating the problem of large single-turning angles. They also introduced the notion of a predefined number of time steps through numerical analysis to effectively mitigate heading oscillation issues when employing the artificial potential field algorithm for path generation.

5. Conclusion and Outlook

Intelligent ship route planning algorithms have made remarkable advancements in recent years. These algorithms amalgamate ship dynamics, oceanography, and cutting-edge computing technologies, while also prioritizing navigation safety, efficiency, and environmental sustainability. Leveraging data fusion from various sensors like radar, AIS, and GPS, and integrating machine learning, deep learning, and other artificial intelligence techniques, intelligent ships can actively perceive their surroundings, accurately compute optimal routes, and execute dynamic obstacle avoidance maneuvers while optimizing energy consumption.

However, as the shipping industry continues to evolve and marine environments become increasingly complex, the demands on intelligent ship route planning algorithms are rising. Future algorithm development must prioritize real-time performance, robustness, and adaptability to handle various emergencies and extreme conditions effectively. Furthermore, with the emergence of autonomous navigation and unmanned driving technologies, route planning algorithms need to be seamlessly integrated with these advancements to achieve higher levels of intelligence and automation.

Looking ahead, we anticipate breakthroughs in intelligent ship route planning algorithms in the following areas:

(1) **Multi-agent collaborative path planning:** In intricate marine environments, multiple intelligent ships must collaborate on route planning to avoid collisions and enhance navigation efficiency. Researching multi-agent collaborative path planning algorithms to facilitate cooperation among ships is a pivotal focus of future intelligent ship route planning research.

(2) **Enhanced environmental perception and modeling accuracy:** Environmental perception and modeling are foundational to route planning. Future research will concentrate on enhancing the accuracy and real-time performance of environmental perception, along with the complexity and realism of environmental models. By integrating advanced sensor technologies, data fusion techniques, and machine learning methods, more comprehensive and precise perception and modeling of navigation environments can be achieved.

(3) **Consideration of multi-constraint path planning:** In practical applications, intelligent ship route planning often involves various constraint conditions such as navigation speed, energy consumption, and safety requirements. Future research will focus on efficiently and safely planning routes while satisfying these constraint conditions.

(4) **Robustness and adaptability of route planning:** In the face of complex and dynamic marine environments, intelligent ship route planning algorithms must exhibit strong robustness and adaptability. Future research will concentrate on enhancing the algorithm's capacity to address emergencies and environmental fluctuations, along with its capability for online learning and self-optimization.

(5) **Green navigation and energy-saving emissions reduction:** With growing environmental awareness, prioritizing green navigation and reducing energy consumption and emissions have become crucial aspects of intelligent ship route planning. Future research will emphasize optimizing route planning to minimize energy consumption and emissions while maintaining navigation efficiency and safety, thereby promoting green navigation.

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