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Review

A Review of Artificial Intelligence-Based Optimization Applications in Traditional Active Maritime Collision Avoidance

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Abstract: The probability of collisions at sea has increased in recent years. Furthermore, passive collision avoidance has some disadvantages, such as low economic efficiency, while active collision avoidance techniques have some limitations. As a result of the advancement of computer technology, active collision avoidance techniques have also been optimized by using artificial intelligence-based methods. The purpose of this paper is to further the development of the field. After reviewing some passive collision avoidance schemes, the paper discusses the potential of active obstacle avoidance techniques. A time-tracing approach is used to review the evolution of active obstacle avoidance techniques, followed by a review of the main traditional active obstacle avoidance techniques. In this paper, different artificial intelligence algorithms are reviewed and analyzed. As a result of the analysis and discussion in this paper, some limitations in this field are identified. In addition, there are some suggestions and outlooks for addressing those limitations. In a way, the paper can serve as a guide for the development of the field.

Keywords: active collision avoidance techniques; artificial intelligence algorithms; collisions at sea; traditional active obstacle avoidance; time-tracing approach

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1. Introduction

During the last few years, the rapid development of science and technology has accelerated the process of ocean exploration, which has led to the continuous development and utilization of marine resources. Important marine structures, marine equipment, and sea bridges have contributed to economic development as well as scientific and technological advancement [1–5]. As part of these efforts, marine equipment assists people in exploring the ocean's resources, including both physical and chemical resources [6–9]; sea bridges facilitate coastal transportation and promote regional development, etc. Due to the increasing number of navigable ships and various complex environmental factors, there has been an increase in the risk of ship-bridge collisions and ship-marine equipment collisions. Maritime collisions can cause serious damage to marine structures [10–14], further threatening the safety of people and the economy. As shown in Figure 1, such issues are receiving increasing attention.

A major contribution to the economic efficiency of marine equipment and the safety of personnel is the research conducted on collision risk reduction methods. The majority of current collision risk reduction strategies are passive collision avoidance strategies. Passive collision avoidance methods, however, have disadvantages, such as low economic efficiency and limited flexibility. As a result, people gradually began to explore active collision avoidance methods. However, traditional active collision avoidance methods mainly rely on sensors, radar, and other devices, resulting in the following limitations: route planning accuracy cannot be adapted to complex sea conditions and bad weather, high reliance on seafarers' manual judgment, high data processing complexity, and limited detection ranges.

The field of information and computer technology has undergone rapid development in recent years. Computing and processing information has become much more efficient thanks to advances in technologies, such as cloud computing, high-performance processors, big data analytics, and Artificial Intelligence. Active collision avoidance methods have been optimized through the use of artificial intelligence techniques. Figure 2 illustrates the relevance of using Artificial Intelligence to optimize the development of active collision avoidance techniques.

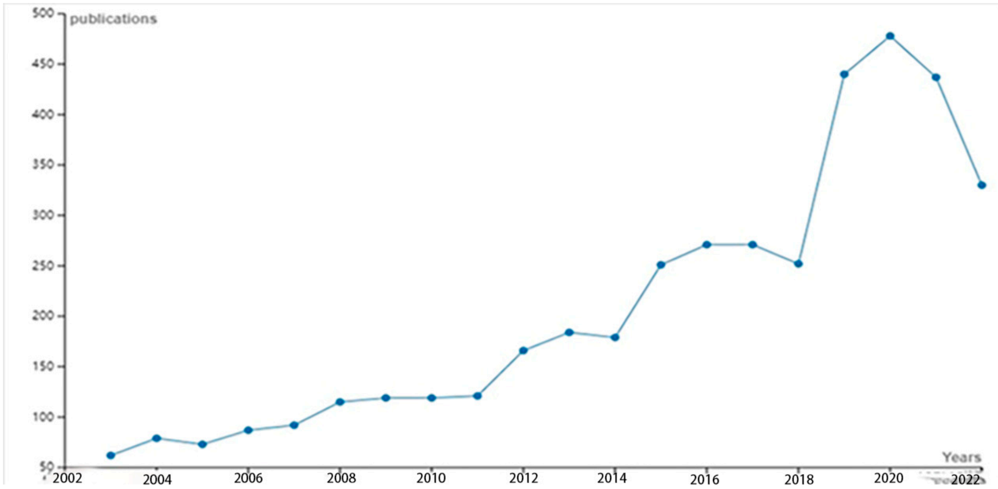

Figure 1. The number of published results about marine*collision in the Web of Science.

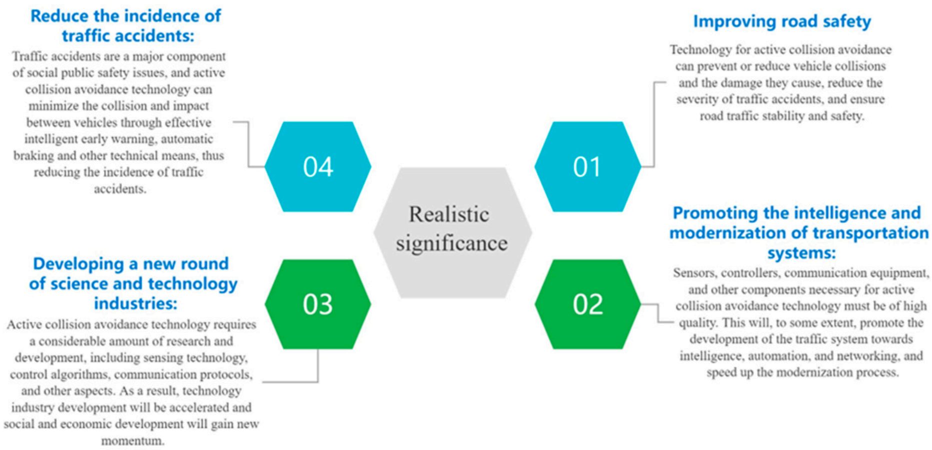

Figure 2. Relevance of developing AI-based active collision avoidance technology.

The purpose of this paper is to contribute to the advancement of the field and to provide a guide for its future development. After conducting keyword searches in the Web of Science, Arxiv, and other repositories, layer-by-layer screening was conducted to identify the literature that met the requirements of this paper. The paper begins by reviewing some cases of passive collision avoidance and discussing its shortcomings, followed by a chronological review of active collision avoidance techniques. The purpose of this paper is to review the application of different algorithms of Artificial Intelligence in order to optimize traditional active collision avoidance and path planning, as well as to conduct a discussion and analysis to identify some challenges and shortcomings. To address these difficulties, we also provide some constructive suggestions and development perspectives. Some aspects of this paper can serve as a guide for the development of the field.

2. Passive Collision Avoidance Case

By reviewing some classic cases of passive collision avoidance and analyzing them through discussion, the article indirectly discovers the potential of passive collision avoidance.

The Flexible Floating Collision Prevention System (FFCPS) prevents collisions between uncontrolled vessels and non-navigational bridges. Figure 3 illustrates this: (A) Schematic diagram of Flexible Floating Collision-Prevention System; (B) Floating structure; (C) Mooring system. The system is composed of a cable chain, a floating structure, and a mooring system. By sliding the anchor, the mooring system serves to position the system and absorb the impact energy of the system. In order to prevent damage to the mooring chains and the connecting cable chains, movable anchors are used. However, this device is less flexible, more difficult to install, and requires a high level of maintenance due to the complexity of the sea state [15].

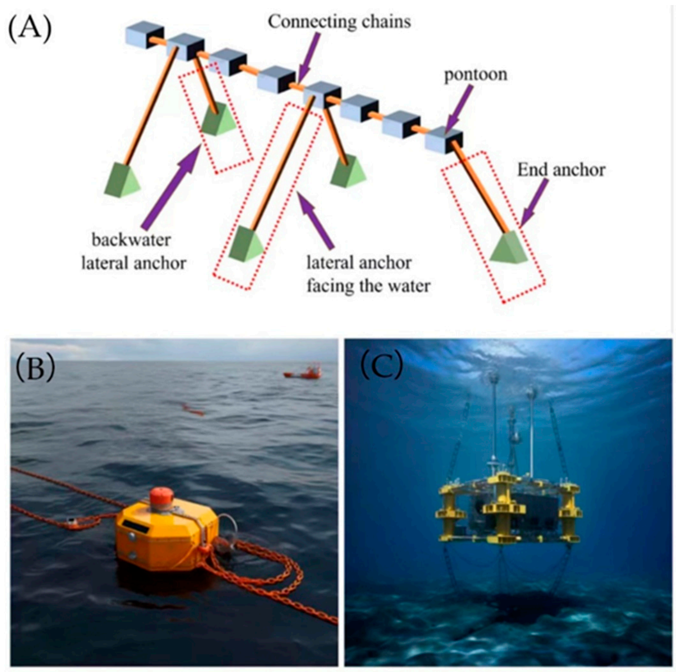

Figure 3. (**A**) Schematic diagram of Flexible Floating Collision-Prevention System; (**B**) Floating structure; (**C**) Mooring system.

In Figure 4, a protective jacket structure of offshore steel jackets is used to protect bridges from collisions. As a result of this structure, the bridge is able to maintain good stability when it is struck [16].

Figure 5 illustrates a passive collision avoidance device for a tethered anchor floating suspension bridge proposed by Moe et al. Each floater is attached to a floating structure by a tether. By increasing the amount of diving, drag, and hydrodynamic mass added during a collision, the barrier dissipates energy [17].

To protect bridges against ship impacts, there is an energy dissipation device with a low-cost steel frame structure. There is a vertically supported crash cap attached to the pier by a series of steel girders arranged in a frame. It is designed to dissipate energy while limiting the force transmitted to the protected pier by forming a plastic hinge [18].

Bridge pier impact loads can be reduced by using a floating two-stage buffer collision-prevention system (FTBCPS). Anti-collision stages consist of two main components. The first step in reducing the velocity of the ship and changing the ship's initial direction of movement is to stretch and fracture the polyester ropes. Secondly, it consumes the ship's kinetic energy due to the damage and deformation caused by the FTBCPS and the ship [19].

Figure 4. Concept Sketch of a Steel Jacket.

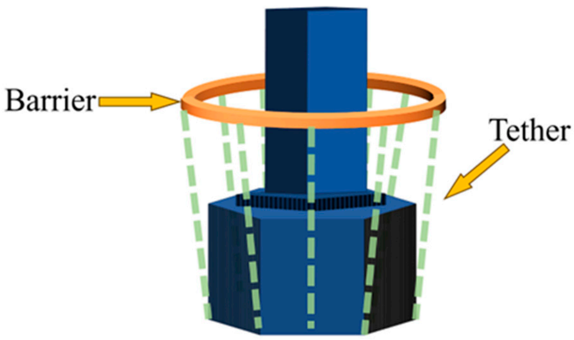

Figure 5. Model of the barrier system.

The adaptive arresting vessel device (AAVD) is used for the protection of bridges in non-navigable waters from ship collisions. They discussed and determined the key parameters that affect the arresting effect of AAVD through a scale model experiment and preliminarily evaluated the feasibility of AAVD. The AAVD full-scale test section has been constructed, and the stopping ship collision test has been conducted. According to the experimental results, the system is capable of stopping a yawing ship effectively, demonstrating the feasibility and reliability of both the technology principle and the engineering design, as shown in Figure 6 [20].

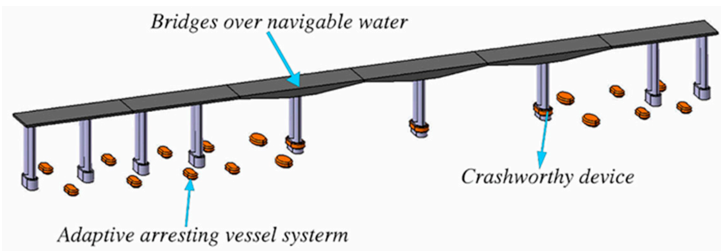

Figure 6. Anti-collision device for bridges over navigable and non-navigable water.

All the above-mentioned passive collision avoidance cases share a number of common characteristics. The design of marine equipment or the design of protection devices achieves energy absorption in order to achieve cushioning impact resistance through the design of the structural design. There are, however, a number of shortcomings associated with these collision avoidance methods:

- Passive collision avoidance technology can only play a protective role in the event of a collision but cannot prevent a collision from occurring in the first place;
- Increasing the structural strength and impact resistance of offshore facilities requires the use of more materials and more complex designs, which increases the cost of passive collision avoidance technologies and puts some pressure on companies' financials;
- In order to ensure their effectiveness and reliability, passive collision avoidance technologies need to be regularly inspected and maintained. As a result, these maintenance tasks are expensive in terms of human resources, materials, and financial resources;
- As offshore facilities vary in size and shape and specific design and testing are required for each offshore facility, which increases the cost and difficulty of designing and building offshore facilities.

3. Active Collision Avoidance Methods

Offshore active collision avoidance methods are capable of preventing collisions to a certain extent. Active collision avoidance methods have great potential for optimizing the disadvantages of passive collision avoidance methods due to their ability to reduce the probability of collision events to a large extent.

3.1. Development Process

Active collision prevention at sea has been developed in four stages. Figure 7 illustrates this. The first phase of the development occurred between the early 1900s and the 1940s. Active collision avoidance at sea was primarily achieved through manual observation and the most basic radar system during this period. The second phase of development occurred between the 1950s and the 1980s. During this time period, automated navigation systems were introduced, which utilized sensors and computer technology to monitor a vessel's location, speed, and heading. The third stage, between the 1990s and early 2000s, witnessed the gradual development of maritime active collision avoidance technology, which combined ship and shore-based communications with advances in information technology. During the fourth stage, from the early 21st century to the present, laser radar, sonar, and camera technology have made maritime active obstacle avoidance technology more accurate and reliable. At the same time, methods such as machine learning for running path planning and algorithms for image processing and pattern recognition are also being explored. As a result of these technologies, collision avoidance can be enhanced by analyzing and identifying different obstacles in real-time.

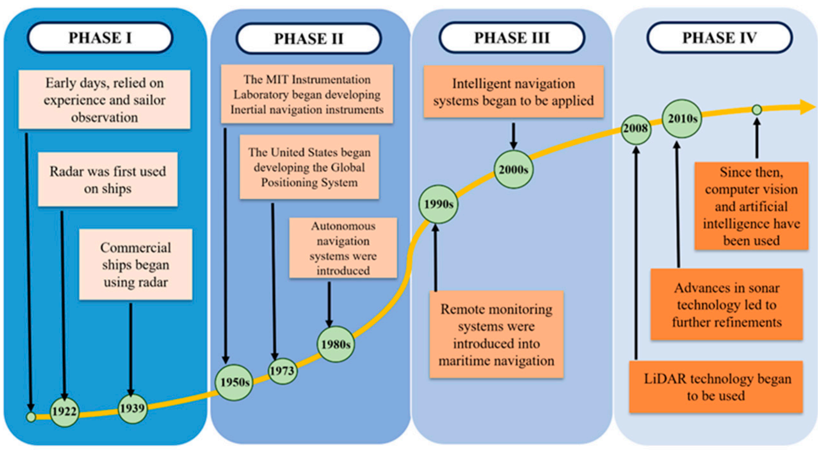

Figure 7. The evolution of active obstacle avoidance technology at sea.

3.1.1. Phase I

The development of technology was at a low point at the beginning of this period. Sailors' experience and visual observation were the primary means of avoiding collisions at sea [21]. Radar was first introduced to ships in 1922. Researchers from the US Navy placed transmitters and receivers across the Atlantic and observed that ships passing through the beam's path caused the received signal to fluctuate [22]. In addition, in 1928, L. S. Alder obtained a provisional patent for Naval radar in the UK [23]. While useful for navigation and obstacle avoidance, these radar systems are more limited and cannot provide detailed information about obstacles. Commercial ships began using radar in 1939 [24].

3.1.2. Phase II

Under the auspices of the Air Force, the MIT Instrumentation Laboratory began developing Inertial navigation instruments in the 1950s [25]. The development of Inertial navigation instruments for ships has also been gradual since then [26]. Using accelerometers and gyroscopes, inertial navigation systems calculate a vessel's position, speed, and heading by measuring its acceleration and angular velocity. Due to the problem of error accumulation, such systems can provide a relatively high degree of accuracy but must be used in conjunction with other navigational systems [27–29]. In 1973, the United States began developing the Global Positioning System (GPS), which provides more accurate positional information for automated navigation systems [30]. In the 1980s, autonomous navigation systems were introduced to the world of navigation. Computer technology and sensors are used in autonomous navigation systems in order to achieve autonomous vessel control and collision avoidance. A vessel's course, speed, and maneuver can be automatically adjusted based on preset rules and goals in order to avoid collisions and optimize navigational efficiency [31,32]. The technology, however, requires further improvement in terms of precision and accuracy.

3.1.3. Phase III

In the 1990s, remote monitoring systems were introduced into maritime navigation [33]. Remote monitoring systems transmit real-time information about a ship's position, speed, and heading to shore-based control centers using satellite communications and terrestrial transmission equipment. By analyzing this data and providing timely navigation advice and navigational warnings, shore-based control centers can assist ships in avoiding potentially dangerous areas. It was in the 2000s that intelligent navigation systems began to be applied to ships. In an intelligent navigation system, radar, satellite navigation, communications, and computer technology are utilized to provide highly automated monitoring of the surroundings of a ship in real-time, as well as collision avoidance decisions based on that information [34,35].

3.1.4. Phase IV

In 2008, LiDAR technology began to be used in the field of active obstacle avoidance at sea. In LiDAR, a laser beam is emitted, and its reflected signal is measured to determine the distance between a target object and a sensor [36]. Advances in sonar technology led to further refinements in maritime obstacle avoidance systems in the early 2010s [37]. Since then, computer vision [38] and artificial intelligence [39] have been used in the development of marine obstacle avoidance systems.

3.2. Traditional Methods

There are several active collision avoidance methods at sea, including Automatic Identification Systems (AIS), Automatic Radar Plotting Aids (ARPA), Electronic Chart Display and Information Systems (ECDIS), Vessel Traffic Management Systems (VTMIS), and observation methods that rely heavily on manual labor, including navigational watch and sailor observation. Because the last category of methods can be viewed as a purely manual method based on the crew's experience, some systems have developed, such as collision avoidance rules [40]. This section does not provide a detailed description of them.

3.2.1. Autonomous Identification System

The Autonomous Identification System (AIS) is a system that uses sensors, such as radar, Automatic Identification System (AIS), and satellite imagery to monitor and identify ships in the maritime industry [41]. In Autonomous Identification Systems, AIS is one of the most widely used technologies. The AIS is based on the Global Automatic Ship Identification System (GMDSS).

An AIS transmits and receives information about a ship's position, speed, course, and name using VHF radio waves. A good mastery of position and speed enables AIS to perform a number of functions, including autonomous collision avoidance and operation supervision [42,43]

A study has been conducted on the potential impact of Automatic Identification Systems (AIS) on ship bridges on the safety of maritime navigation. According to the study, 8% of the AIS transmissions in the sample contained at least one piece of inaccurate data, and the reliability of the data provided by AIS often failed to meet requirements [44].

A proposed Automatic Identification System (AIS) was proposed by Saravanan et al. in order to prevent fishermen from crossing international maritime borders and to assist them in avoiding collisions [45].

3.2.2. Automatic Radar Plotting Aid

Through the use of radar technology, the ARPA system detects ships and other obstacles around them and calculates their position, speed, and direction. ARPA uses this data to automatically plot the movements of other vessels and predict their future locations. Captains and crews can utilize this predictive data to identify potential hazards and take appropriate action to avoid them [46].

According to one study, Automated Radar Plotting Aid (ARPA) systems are often mistaken for inland waterway structures and land objects in inland rivers and harbors [47].

3.2.3. Electronic Chart Display and Information System

The ECDIS system is a collision warning system that is based on electronic charts and navigation systems. The system integrates information about a ship's position and navigation with data from nautical charts in order to provide warnings and recommendations regarding ship maneuvers [48].

It is possible to adjust the scale of an electronic nautical chart by using the zoom function. However, excessive zooming in or out may cause a false sense of security, as it may lead to misinterpretations of the accuracy of routes and hazards. As a result of zooming in and out, certain specific features and information may be automatically hidden or displayed, which may interfere with a mariner's overall understanding of the navigational environment. Therefore, mariners should exercise caution when using the zoom function and always maintain a thorough understanding and visual observation of the entire course at all times [49].

3.2.4. Vessel Traffic Management System

The purpose of vessel traffic management systems is to monitor maritime traffic and provide real-time traffic intelligence and risk assessments to assist captains and crews in making informed decisions [50]. Thus, the method produces a final avoidance result that is highly dependent on the operations of the crew.

3.3. Associated AI-Algorithms

According to the review above, active collision avoidance offers greater potential in terms of economic benefits and other factors than passive collision avoidance. Traditional active collision avoidance techniques, however, have some disadvantages. With the application of artificial intelligence methods to maritime active collision technology, some of these drawbacks have been overcome [51]. The majority of collision problems at sea occur during complex sea states, including adverse weather conditions, busy shipping lanes, ocean currents, and coastlines. Active obstacle avoidance methods cannot cope well with complex sea conditions, but artificial intelligence provides a better solution to avoid collisions in complex sea conditions. In addition, sophisticated algorithms and the use of big data technology can ensure compliance with COLREGs in the event of an accident or an emergency situation. Various AI algorithms are discussed in this section.

3.3.1. Ant Colony Optimization Algorithm

It is a meta-heuristic algorithm based on the path taken by ant colonies in search of food. The ACO algorithm solves the optimization problem by simulating the release of pheromones by ants in their environment [52,53]. Figure 8 illustrates a simple model of the ACO algorithm. Similarly, ships are capable of simulating their intentions by releasing pheromones and planning collision avoidance paths based on the pheromones left by their surroundings. Using an iterative optimization process, the ACO algorithm considers the interactions between ships and the environment in order to find the best collision avoidance paths, thereby improving safety and efficiency. The best collision avoidance scheme can be determined by taking into account several factors, such as course distance, speed, ship type, etc.

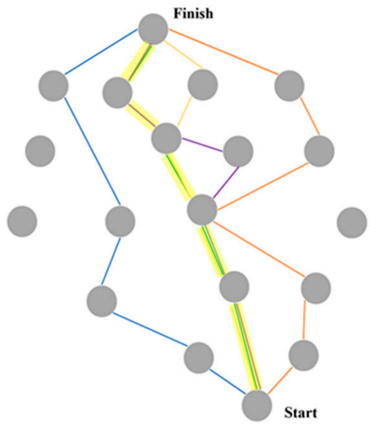

Figure 8. A simple model of the ACO algorithm. The gray dots represent nodes, the thin lines of different colors represent different ant travel paths, and the fluorescent yellow thick lines represent the best paths iterated.

An analysis of the path planning problem for autonomous surface ships found that the "Ant Colony Optimization" algorithm yielded superior results. By using the algorithm, the model is able to determine the best trajectory for maneuvering [54].

Based on ant colony optimization (ACO), Lazarowska presents a new approach to path planning in dynamic environments. An unmanned surface vehicle (USV)'s navigation, guidance, and control system incorporates an intelligent obstacle detection and avoidance system, which can be used as part of the decision support system on board [55].

An incoming ant colony optimization algorithm (ACO) can be used to avoid collisions between unmanned surface vehicles (USVs). Using this algorithm, we are able to solve the problems of insufficient search capability, slow convergence, and falling into local optima [56].

A path-planning algorithm proposed by Fu et al. makes it possible for submarines to navigate safely in complex underwater environments. The algorithm consists of a global path-planning component and a local dynamic obstacle avoidance component. Global path planning is accomplished using an improved Artificial Potential Field Ant Colony Optimization (APF-ACO) algorithm, which yields shorter paths, fewer inflection points, and greater stability than other similar algorithms [57].

Underwater vehicles in high-energy environments can be avoided by using the ant colony optimization (ACO) algorithm [58].

Using an improved ant colony clustering algorithm, Liu et al. automatically select an appropriate search range by a clustering algorithm that matches the complexity of different environments. As a result, USV can fully utilize its limited computational resources and improve the performance of path planning [59].

3.3.2. Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is a group intelligence-based optimization algorithm. As shown in Figure 9, based on the behavior of a flock of birds or a school of fish, the PSO algorithm solves complex problems by simulating the behavior of individual birds as they search for food in the search space. In the PSO algorithm, the position and velocity of the particles are updated based on the experiences of each particle and the collective experience of the whole flock by viewing the search space as the position of the particle population. By comparing its own optimal position with the optimal position of the whole population (global optimal solution), each particle adjusts its position and velocity to better explore the search space [60–62].

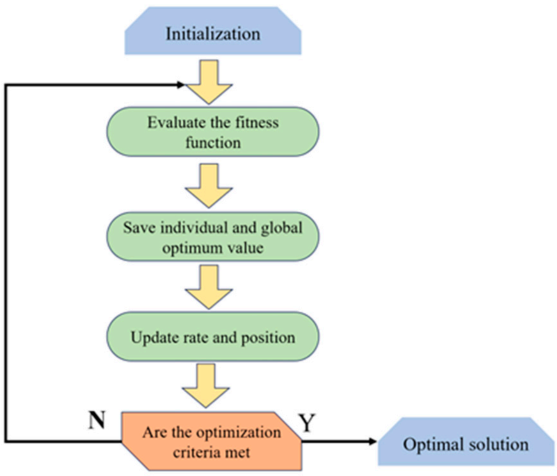

Figure 9. Basic structure of the particle swarm optimization (PSO) algorithm.

An improved Tent mapping is introduced to address the problem of premature convergence of PSO in a study on the effectiveness of the Chaotic Particle Swarm Optimization (CPSO) algorithm in ship collision avoidance based on the analysis of existing collision avoidance strategies [63].

The PSO algorithm was used by Wang et al. to find safe and smooth sailing routes as well as efficient sailing speeds. According to the results, the proposed method can effectively achieve a safe and smooth sailing route and a fast speed for a ship experiencing an accident [64].

Based on standard encounter types, Kang et al. simulated several maritime traffic scenarios. These scenarios are used to test the proposed PSO algorithm [65].

In complex ocean environments, an autonomous underwater vehicle (AUV) path planning strategy has been developed. Using particle swarm optimization (PSO) algorithms and local path modification (LPM)-based replanning schemes, the strategy continuously optimizes the optimal trajectory and avoids collisions with static and dynamic obstacles [66].

3.3.3. Genetic Algorithm

As an optimization algorithm, Genetic Algorithm (GA) simulates the process of biological evolution. By simulating natural selection, genetic variation, and gene crossover, it seeks to determine the best solution. Figure 10 shows the basic process of the Genetic Algorithm. A Genetic Algorithm encodes the solution to the problem as an individual (chromosome) consisting of a string of genes. Each gene represents a variable in the problem, and each individual represents a possible solution. To form a population, an initial set of individuals is randomly selected. An individual's fitness is evaluated by a fitness function; the higher the fitness, the greater the likelihood of the individual's selection. To generate new individuals, a selection operation is performed based on the selection probability, followed by crossover and mutation operations. A solution that satisfies the stopping condition is iterated until an optimal solution is found [67,68]. It is possible to apply genetic algorithms to the problem of ship active collision avoidance in order to determine the most effective collision avoidance strategy. Every individual can represent a possible navigation strategy, including parameters such as heading and speed. Through continuous iteration and evolution, the genetic algorithm searches for the globally optimal collision avoidance strategy. Each individual's fitness is evaluated by a fitness function, which considers factors such as distance, speed, and heading to other ships. Selection, crossover, and mutation operations are performed based on the fitness to produce new individuals.

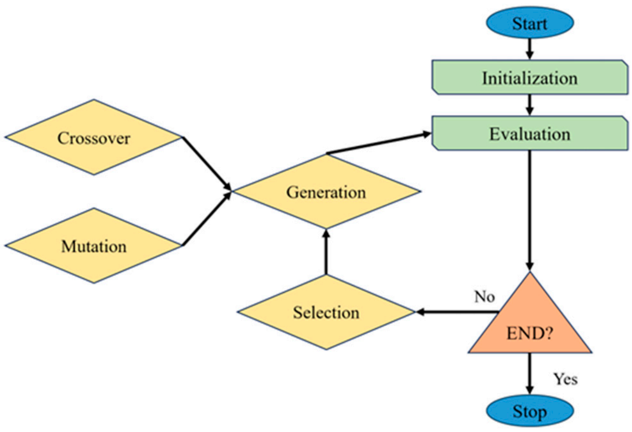

Figure 10. The basic process of the Genetic Algorithm.

Genetic Algorithms and artificial intelligence are being used to develop a decision support tool for ship collision avoidance route planning and alerting. By considering the international regulations for the prevention of collisions at sea (COLREGS) and the safety domain of ships, it provides theoretically crucial recommendations for the shortest collision avoidance routes from an economic perspective [69].

To study how to assist the crew in determining and controlling the ship's course, Ito, Zhnng, and Yoshida used a genetic algorithm [70].

A quadratic optimization genetic algorithm combining the ship motion characteristics was proposed by Wang et al. in order to achieve automatic route planning under complex navigation environments [71].

An effective collision avoidance system depends on the ability to determine the best trajectory. The mathematical model of ship maneuvering motion is described by Cheng, Liu, and Zhang as the basis for the ship collision avoidance system. To determine the ship trajectory in inland waterways, taking into account different navigational constraints, an optimization method based on genetic algorithms is applied [72].

In a marine environment with strong currents and enhanced spatiotemporal variability, A. Alvarez, Caiti, and Onken proposed a genetic algorithm for autonomous submersible path planning. Finding a safe path is the objective [73].

3.3.4. Reinforcement Learning Algorithms

By interacting with the environment, Reinforcement Learning (RL) learns optimal behavioral strategies in a dynamic environment. By observing feedback and reward signals from the environment, it optimizes the decision-making process through trial and error. Figure 11 illustrates a typical framework for a reinforcement learning (RL) scenario. There are three main components of Reinforcement Learning: The Agent, the Environment, and the Reward. As a result of observing the state of the environment, the Agent chooses to perform an action. In response to the Agent's action, the Environment provides a new State and a corresponding Reward. Based on the observed feedback, the intelligent body updates its strategy in order to maximize the cumulative reward by learning to choose the best course of action from the current situation [74–76].

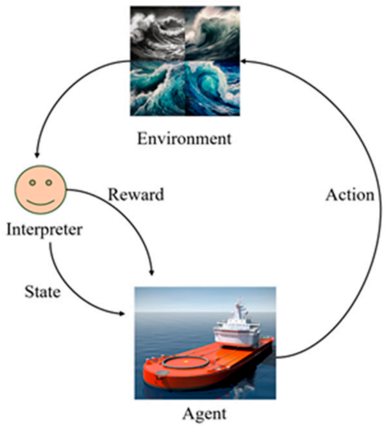

Figure 11. A typical framework for a reinforcement learning (RL) scenario.

In order to improve the path planning capability of AUVs in unknown environments, Chu et al. proposed a deep reinforcement learning (DRL) method based on dual deep Q networks (DDQN) [77].

Rongcai, Hongwei, and Kexin developed an autonomous collision avoidance system based on deep reinforcement learning in open water to address the challenge of planning local paths for multiple vessels in complex, dynamic environments [78].

An obstacle avoidance autonomous surface ship (ASV) strategy was developed by Zhou et al. based on reinforcement learning [79].

Xu et al. proposed an intelligent hybrid collision avoidance algorithm based on deep reinforcement learning to achieve autonomous collision avoidance for unmanned surface vehicles (USVs) [80].

Deep reinforcement learning and rolling wave planning are used to improve the performance of an unmanned surface vehicle (USV). A path planner is used to generate a potential path for the entire trip without specifying motion details, and a decision module is used to avoid dynamically generated obstacles and navigate through the agent in the near future [81].

A deep reinforcement learning (DRL) algorithm-based autonomous navigation decision algorithm for maritime autonomous surface ships (MASS) was proposed by Zhang et al. It consists of two layers: a scene segmentation layer and an autonomous navigation decision layer. According to the International Code for Collision Avoidance at Sea (COLREG), the scenario segmentation layer quantifies the sub-scenarios [82].

In a continuous state space environment, Wang et al. proposed a new algorithm for avoiding impact potholes called Approximate Representation Strong Chemical Learning (AR-RL) (2023) [83].

For unmanned surface vehicles (USVs), Fan et al. propose a collision avoidance algorithm that complies with international regulations (COLREGs) in order to prevent collisions at sea. USVs are trained to navigate safely and efficiently using reinforcement learning and a finite Markov decision process [84].

An autonomous ship path tracking and collision avoidance system can be improved by using a deep reinforcement learning algorithm. By ensuring that a vessel follows a predefined path, the proposed algorithm avoids collisions when encountering a moving vessel [85].

3.3.5. Artificial Neural Network

An artificial neural network (ANN) mimics the structure and function of a neural network in the human brain. Figure 12 shows the simple structure of an artificial neural network. By simulating the connections between neurons and the transmission of electrical signals, it realizes information processing and learning. By learning and training, artificial neural networks are capable of extracting features from input data and performing tasks such as pattern recognition, classification, and prediction [86–93].

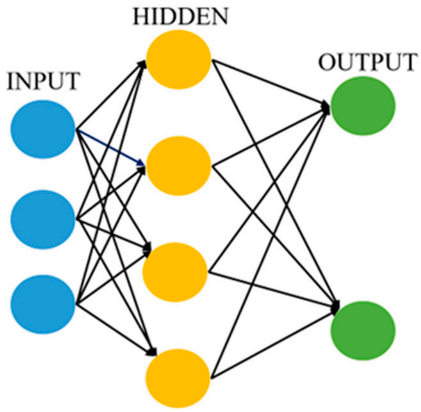

Figure 12. The simple structure of an artificial neural network, which is a set of interconnected nodes, is inspired by the simplification of neurons in the brain. Here, each circular node represents an artificial neuron, and arrows represent connections from the output of one artificial neuron to the input of another.

It is possible to apply artificial neural network algorithms to the problem of ship active collision avoidance. Firstly, it is necessary to collect and prepare relevant navigational data, such as ship position, speed, heading, and radar data. As a result of these data, an artificial neural network model is trained to learn the ship's behavior patterns and laws. By inputting real-time ship navigation data into the trained neural network model, predicted ship behaviors or decision-making suggestions can be obtained after the training has been completed. The ship can actively take collision avoidance measures based on these predictions, such as adjusting course and speed or communicating with other vessels in the area.

To predict the future position of manually controlled vessels, Simsir et al. proposed an artificial neural network (ANN) that utilizes data from manually controlled vessels [93,94].

To prevent collisions between vessels on the high seas, Kim and Park developed an artificial neural network (ANN). In the study, it was found that the ANN is capable of providing timely and appropriate collision avoidance actions based on information from navigational equipment, such as radars and automatic identification systems (AIS). For training, ANNs may require large quantities of data, which can be time-consuming and expensive [95].

3.4. Other Technologies

Yilmaz et al. investigated the problem of path planning for autonomous underwater vehicles (AUVs) in the context of adaptive sampling. They developed a mathematical formulation called MILP, which is capable of handling multiple AUVs and multi-day sampling. MILP can model all constraints required by various problem scenarios. As a result, the problem formulation can be extended and modified in the future [96].

Based on historical successful collision avoidance cases, Gao et al. propose to employ an encoder-decoder neural network based on a sequence-to-sequence (Seq2Seq) model [97].

A multi-trajectory planning algorithm has been proposed for automated underwater vehicles (AUVs) in complex underwater environments by Gong et al. [98].

A dynamic predictive guidance technique has been proposed by Kozynchenko et al. for the purpose of preventing collisions at sea. This technique is based on an optimal control problem formulation and a nonlinear model of a three-dimensional ship. The simulation results demonstrate the feasibility and effectiveness of the proposed technique and software. Further research and development of ship collision avoidance systems can be conducted using the simulation framework developed [99].

MahmoudZadeh et al. investigated the underwater rendezvous problem, which involves a single automated underwater vehicle (AUV) meeting a leading underwater rescue vessel in a chaotic and variable operating environment. A nonlinear optimal control problem (NOCP) was formulated and solved using an evolutionary algorithm. To adapt to the changing environment, a new online path-planning mechanism was developed and implemented on a follower AUV [100].

Liu et al. proposed a hybrid clustering model to analyze maritime traffic patterns and detect anomalies in ports. Combining K-Means and DBSCAN algorithms, the model clusters ship trajectories based on their departure and destination characteristics as well as their dynamic and spatial characteristics [101].

A model for real-time multi-vessel collision risk analysis and collision avoidance decision-making was proposed by Hu et al. Using fuzzy logic, the model calculates collision risk and determines whether to change course or speed in order to avoid a collision. To reduce the number of maritime accidents caused by human error and failure, the model provides early warning and decision support to the officer of the watch (OOW) [102].

To enhance the autonomy of an unmanned surface vehicle (USV), Guardeño et al. propose a new algorithm called Robust Reactive Static Obstacle Avoidance System (RRSOAS). A prior knowledge of the USV's mathematical model and controller is not required in order to use the algorithm. Rather, it uses an estimated closed-loop model (ECLM) to estimate the likely future trajectory of the USV and accounts for prediction errors caused by uncertainty by modeling the shape of the USV as a time-varying ellipse. Using an occupancy probability grid as the environment model updated by the LiDAR sensor model, the algorithm utilizes a variable prediction horizon and exponential resolution to discretize the decision space [103].

Guardeño et al. proposed a new static automatic adjustment environment for obstacle avoidance (ATESOA) method for unmanned surface vehicles (USVs). By using a simplified model of the LiDAR sensor, this environment allows the adaptation of different SOA methods. The proposed ATESOA can be adapted to different SOA methods and used to evaluate the performance of these methods in different scenarios with varying obstacle distributions [104].

Using a sequential conditional generation adversarial network (seq-cGan), Gao et al. proposed a new method for avoiding ship collisions. To make appropriate anthropomorphic collision avoidance decisions, the proposed method does not require a risk assessment procedure [105].

4. Discussion and Result

4.1. Difficulties and Limitations

In this paper, we review the use of artificial intelligence-related techniques to achieve active collision avoidance. To build a model using AI-related techniques, a large amount of data is required. According to the above review, artificial intelligence has four major limitations and difficulties when it comes to implementing active collision avoidance technology, including difficulties obtaining data, the complexity of algorithms that meet the needs, hardware limitations, and robustness and security issues.

4.1.1. Difficulty in Accessing Data

For active collision avoidance to be realized, there is a great deal of data support, but obtaining these data is not easy, and it is also necessary to label and process these data, which is also a time-consuming and laborious process. In addition, this problem is a particular challenge associated with the application of deep learning methods in the field of active collision prevention. Here are some of the current limitations in this area:

(1) A large amount of data is required to realize active collision avoidance, including vehicle trajectory, traffic light status, road conditions, etc. It is, however, not an easy task to obtain these data since it requires a considerable amount of time and resources, both human and material;
(2) A problem with data annotation is that the collected raw data must be annotated and processed, such as annotating the vehicle trajectory, annotating the status of traffic signals, etc., which is also time-consuming and labor-intensive;
(3) There are a number of issues related to data quality. For example, there may be uncollected data or noise in the data as a result of weather, light, and other factors. This will also impact the accuracy and stability of an algorithm;
(4) Privacy issues: Data collected involve sensitive information such as personal privacy, which must be protected and processed, increasing the difficulty of acquiring and processing the data.

4.1.2. Algorithmic Complexity

Active collision avoidance techniques require the use of complex algorithms for decision-making and prediction, which require high levels of accuracy and stability while simultaneously taking into account a wide range of different situations and factors, making the algorithms more complex and difficult to perform.

(1) Active collision avoidance technologies require complex computer vision and image processing algorithms to perceive and understand the environment around the vehicle, including the trajectory of the vehicle, the status of traffic lights, and road conditions;
(2) Active collision avoidance technology must make decisions based on the results of environment sensing, such as whether to brake, whether to avoid obstacles, etc., which requires the use of complex algorithms;
(3) As part of active collision avoidance technology, the technology must be able to predict and plan for future traffic conditions, such as predicting the trajectory of other vehicles, planning their own routes, etc., which requires the application of complex algorithms for prediction and planning;
(4) In order to determine whether it is necessary to brake or avoid obstacles within a few hundred milliseconds, active collision avoidance technology must respond in real-time, for instance, within a few hundred milliseconds. Real-time response algorithms are, therefore, necessary for efficient collision avoidance technology.

4.1.3. Hardware Limitations

In order to implement active collision avoidance technology, hardware devices, such as high-precision sensors and computer processors, must be used, which adds cost and complexity and impacts aspects such as vehicle weight and energy consumption.

(1) In order to achieve active collision avoidance technology, high-precision sensors are required, such as LIDAR, cameras, millimeter wave radar, etc. For accurate environmental perception, these sensors should be capable of high accuracy, high resolution, high frame rate, etc;
(2) A high-performance computer processor is required to realize active collision avoidance technology, such as GPUs, FPGAs, etc. In order to enable quick data processing and decision-making, these processors must have high speeds, low latency, and high concurrency;
(3) In order to implement active collision avoidance technology, a large number of hardware devices will be used, resulting in an increase in the weight and energy consumption of the marine vehicle, which will have an adverse effect on its performance and endurance;

(4) Hardware devices, such as high-precision sensors and computer processors, are expensive and add complexity and difficulty to the system, which increases the cost and difficulty of developing an active collision avoidance system.

4.1.4. Robustness and Security

Algorithms based on artificial intelligence are susceptible to adversarial attacks and interference. A number of factors can affect the accuracy and reliability of algorithms, including deceptive sensor inputs and malicious interference. Therefore, it is important to ensure the robustness and security of algorithms.

(1) It is possible for attackers to spoof an active collision avoidance system by modifying sensor data in order to generate incorrect decisions. To improve the robustness of the system, it is necessary to detect and filter sensor inputs that appear anomalous, as well as to use multiple sensors for redundant detection;
(2) Attackers may attempt to interfere with the normal operation of the AI active collision avoidance system by jamming its communications or control systems. In order to prevent malicious interference and intrusion, it is necessary to strengthen the system's cybersecurity measures, such as the use of encrypted communication, authentication, and access control techniques.

4.2. Suggestions and Future Prospects

Following the above discussion and analysis, the following suggestions and outlooks are offered.

4.2.1. Recommendations on Data Issues

(1) Incorporating advanced sensor technologies, such as LIDAR, cameras, millimeter wave radar, etc., can improve the accuracy and quality of data collection, thereby reducing the difficulty of processing and labeling the data;
(2) By developing smarter data labeling and processing algorithms using machine learning and other technologies, the efficiency and accuracy of data labeling and processing can be improved, thereby reducing the difficulty associated with obtaining data;
(3) Simulators can be utilized for data acquisition in order to reduce the cost and time of the acquisition process as well as improve the quality of the data acquired;
(4) In order to facilitate the circulation and utilization of data, we should promote data sharing and openness. By doing so, the difficulty of acquiring data will be reduced, and the development and application of artificial intelligence will be facilitated.

4.2.2. Recommendations on Algorithmic Issues

(1) Improve the accuracy and stability of algorithms by using deep learning technologies: Deep learning technologies are capable of learning features and laws from data automatically, therefore improving the accuracy and stability of algorithms and reducing their complexity;
(2) An introduction to multimodal information: Multimodal information can provide richer data sources, including data collected with multiple sensors, such as LIDAR, cameras, millimeter wave radar, etc., enhancing the accuracy and reliability of environment perception.
(3) Improve algorithm architecture: Optimizing algorithm architecture can enhance the efficiency and speed of algorithms, for example, by utilizing parallel computing, distributed computing, and other technologies so as to improve their ability to respond in real time.

4.2.3. Recommendations on Hardware Issues

(1) New sensor technologies: The development of new sensor technologies, such as microwave radar and infrared sensors, will improve the accuracy and performance of the sensors as well as reduce the cost and energy consumption;

(2) Optimization of hardware design: By optimizing hardware design, for example, by using lightweight materials, optimizing circuit design, etc., it is possible to reduce the weight and energy consumption of hardware equipment as well as other aspects of the impact, thus improving the vehicle's performance and range;
(3) Developing computer processors with higher performance and lower power consumption to meet the demand for real-time processing of large amounts of data and execution of complex algorithms. In addition, it may be possible to improve computational efficiency and speed by using techniques based on distributed computing and parallel processing.

4.2.4. Recommendations on Robustness and Security Issues

(1) Evaluation and testing of models: It is essential to conduct a comprehensive evaluation and testing of models. There is a need to develop specialized evaluation and testing methods to detect and fix potential vulnerabilities and bugs, as well as to validate the robustness and security of algorithms under different adversarial attacks and interference scenarios;
(2) Improve the interpretability and trustworthiness of AI algorithms so that their decision-making processes can be understood and verified. Improve the reliability and acceptability of AI systems through the development of explanation mechanisms, transparency frameworks, and model visualization methods;
(3) Development of database technology: Database techniques are used to create training datasets containing data on the marine environment of various types, sizes, and situations. The data may include information regarding the position and speed of the ship, the currents, waves, water depths, weather conditions, as well as many other factors. AI systems can make accurate predictions and decisions by synthesizing these diverse data sets;
(4) Using artificial intelligence and machine learning, decision-support systems can analyze data on the marine environment and make recommendations for action based on the specific circumstances of a ship. A system such as this can assist ships in making collective decisions to avoid collisions and provide an additional level of safety;
(5) Developing a data-sharing and collaboration platform will allow ships to share and access real-time marine environmental data, as well as promote information sharing and collaboration. The ships will be able to better understand the dynamics of the surrounding ships and make corresponding decisions, thereby improving overall navigational safety.

5. Limitations of the Article

Using a time-tracing approach, this paper examines the development of active collision avoidance at sea as well as some cases of passive and active collision avoidance. The main AI algorithms applied to active collision avoidance techniques are reviewed on this basis in order to provide an overview of the potential of AI approaches to the maritime collision problem. During the review and discussion, some limitations of the development of this field are highlighted, as well as some directions for research, but the review of this paper is biased toward current research status in artificial intelligence algorithms, with a limited focus on real-world application cases. As a result, there are some limitations to the scope of the article.

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