Abstract: Autonomous decision-making for ships to avoid collision is core to the autonomous navigation of intelligent ships. In recent years, related research has shown explosive growth. However, owing to the complex constraints of navigation environments, the Convention of the International Regulations for Preventing Collisions at Sea, 1972 (COLREGs), and the underactuated characteristics of ships, it is extremely challenging to design a decision-making algorithm for autonomous collision avoidance (CA) that is practically useful. Based on the investigation of many studies, current decision-making algorithms can be attributed to three strategies: alteration of course alone, alteration of speed alone, and alteration of both course and speed. This study discusses the implementation methods of each strategy in detail and compares the specific ways, applicable scenes, and limiting conditions of these methods to achieve alteration of course and/or speed to avoid collision, especially their advantages and disadvantages. Additionally, this study quantitatively analyzes the coupling mechanisms of alterations of course and speed for autonomous CA decision-making under different encounter situations, supplementing and optimizing the decision-making theory for ship autonomous CA. Finally, several feasible algorithms and improvement schemes for autonomous CA decision-making, combined with course and speed alterations, are discussed.

Keywords: collision-avoidance strategy; navigation; path planning; alteration of course and speed; autonomous ship; collision risk

1. Introduction

Owing to the advantages of large volume and low cost, waterway transportation accounts for approximately 90% of the global trade transportation volume. With the rapid development of the shipping industry and an increase in the number of ships, ships are being developed rapidly and intelligently. Compared with traditional manned ships, the decision-making and control technology of intelligent ships or Maritime Autonomous Surface Ships (MASS) has significant advantages in terms of economy, automation, and efficiency [1]. However, its decision-making mechanism is much more complicated than the former one since it needs to imitate a competent officer whose functionalities are experiential and intuitive [2] to perform CA decisions under all sorts of constraints [3,4], rather than to just provide instructions to the autopilot. These constraints include, but are not limited to, static obstacles, dynamic obstacles/ships [5], the COLREGs [6–8], limited ship’s maneuverability [2,9], accuracy of environment information [10], natural conditions, etc. [3,5,9,11,12]. Therefore, autonomous ship collision-avoidance (CA) decisions are challenging and worth studying in the field of marine navigation [9].
Autonomous ship CA decision is made from the perspective of safety, navigation practice, and regulations, using appropriate mathematical methods to determine CA measures, with the most dominant form being an optimal combination of altering course and changing speed simultaneously. In order to do this, as shown in Figure 1, the information of the navigation environment, the own ship, target ships, and other dynamic obstacles should firstly be collected, processed, and modeled to conduct a mathematical model of ship motion [5,13–15]. Additionally, according to the indicators of ship domain [16] and collision risk [17–21], and the identified complex ship encounter situations constrained by the COLREGs [22–25], sequential and proper CA actions are made to maintain a safe distance [26,27] between the own ship and target ships/obstacles to avoid collision.

Figure 1. Decision-making process of ship autonomous collision avoidance.

The CA strategies chosen by an officer varies with the person’s condition, the ship’s maneuverability, the navigation environment, and the application of the COLREGs. Due to the flexibility of the officer’s thinking, the underactuated characteristics of the ship, the complexity of the navigation environment, and the ambiguity of the COLREGs [28], a perfect CA decision is actually difficult to be completely simulated by mathematical or intelligent methods. Additionally, an autonomous CA decision-making mechanism and strategy selection principle followed by a machine should be framed and based on long-term accumulated human experience, maritime cases, and the requirements of the COLREGs [25,29–31].

At all times, ship collision avoidance at sea is typically achieved by altering the course, changing the speed, or a combination of both. In open waters, considering the response time of a vessel and the sailing habits of a crew, altering the course is the primary method of collision avoidance. In restricted waters, collision avoidance is often combined with speed changes [7]. Regardless of the type of CA action, according to the COLREGs, following the “early, large, wide, clear” principle is recommended. “Early” means taking large evasive action early and making such an action in ample time. “Large” means substantial action, that is, the action taken to avoid collision needs to be large enough to be easily observed visually by other vessels or by radar. If vessels are in sight of one another, it is common to alter by more than 30° at a time. In poor visibility, it is often necessary to alter by more than 30° and determine the timing of the turn. Regarding speed, it is usually advisable to slacken to half of the original speed or stop [25]. “Wide” means that a CA action should avoid the emergence of a close-quarters situation. Altering courses in open waters is the most effective way to avoid a close-quarters situation. In restricted waters, such as narrow waterways, ship CA actions should be conducted in a timely and substantial manner [7]. “Clear” means that a CA action should be effective and ensure that the other vessel is finally past and clear [30]. The original route should be resumed after complete collision avoidance is successful [32].

The COLREGs also require that vessels always sail at a safe speed at all times so that they can take proper and effective evasive actions to avoid collision and be stopped within a distance appropriate to the prevailing circumstances and conditions. Therefore, when the environment and the conditions of a ship change, it should be adjusted to sail at a safe speed [33].

For the above requirements on CA decisions of ships, there are still many uncertain choices and practices for a fully trained and experienced officer, which will directly affect the
safety of ships. There is a prominent difference between the decision-making mechanism of a computer and a human; consequently, it is an important subject to study the realization method and selection mechanism of autonomous CA decisions in a computer system. At present, many review articles focus on a variety of automatic CA decision-making methods based on mathematics and artificial intelligence [2,4,11,32,34–43], that is, the technologies themselves. However, the selection mechanisms and the methods of CA strategies in these technologies are not studied enough, which is an important reason limiting the application of these technologies [44,45]. Therefore, this study focuses on an autonomous CA strategy that combines course and speed alterations; compares and categorizes related research on autonomous ship CA strategies or algorithms locally and abroad; resolves their concerns and characteristics; analyzes the solved and existing problems; and suggests future research and development trends in this field.

The main contributions of this work are summarized as follows:

1. Based on the perspective of CA strategy selection, this paper divides current autonomous CA decision-making algorithms into three categories to cope with different navigation scenarios and needs.
2. This paper compares and discusses the specific measures adopted by current CA strategies in computer implementation and their advantages and disadvantages so as to provide a reference for designers of autonomous CA decision-making.
3. The influence of the coupling mechanisms of alteration of both course and speed on CA effect is quantitatively analyzed for the first time in this field from the perspective of autonomous CA decision-making effectiveness.

The remainder of this paper is organized as follows: Section 2 compares the development trends, publication sources, and keywords of the literature on ship CA decisions; Section 3 introduces and compares the methods of autonomous CA strategies based on altering course; Section 4 presents autonomous CA strategies based on altering speed; Section 5 presents and compares approaches to autonomous CA strategies based on alteration of both course and speed; Section 6 discusses the methods and constraints, and the effect of steering coupled with variable speeds on decisions; and Section 7 presents the conclusion and future research prospects.

2. Bibliometric Analysis and Thesis Research Factor

2.1. Development Trends and Source Analysis

The keyword used in the collection is “ship autonomous CA decisions”, which originates from the core collection of the Web of Science and is available exclusively in English. A brief bibliometric analysis of the literature was conducted to summarize the distribution and the scope of the literature from multiple perspectives. Figure 2 shows the publication dates of related papers over time. The number of papers published on autonomous CA decisions of ships is increasing annually, which is an important research issue in the current maritime field.

The sources of publications for the collection of the literature are shown in Figure 3: papers related to ship CA research are published in “Ocean Engineering”, “Journal of Navigation”, “Journal of Marine Science and Engineering”, and other nautical journals, and, in recent years, research on autonomous ship CA has rapidly increased. Research on autonomous CA is not limited to open waters, but includes more complex waters, such as narrow waterways. For illustrative purposes, a journal title’s size indicates the relative number of papers published in that particular journal.

According to navigation practices, there are four options for CA actions: (1) altering only the course; (2) altering only the speed; (3) altering the course and speed simultaneously; and (4) keeping the course and speed (the actions of stand-on vessels are not considered in this study) [46]. Most early autonomous CA algorithms alter the course to avoid collisions. Many studies plan the trajectory first and then control the ship to sail along the track, without including the control of speed; there are a small number of studies on autonomous CA based on speed alteration. As shown in Figure 4, a statistical analysis of the selected
papers cited in this study shows that 64.4% of studies alter course for collision avoidance, 11.5% change speed for collision avoidance, and 24.1% combine alterations of course and speed for collision avoidance.

Figure 2. Annual publication analysis of relevant papers.

Figure 3. Cloud map of publication sources.

Figure 4. Comparison of the number of CA papers.
2.2. Keywords

To better understand the development and the focus of automatic CA decision-making research in the literature, the abstracts of the selected papers were analyzed using the “VOSviewer” software, and the more popular research keywords are shown in Figure 5. The texts in assorted colors in the figure represent research hotspots in a chronological order. The size of the bubbles reflects the number of occurrences of the keywords in the literature, and the lines indicate their relevance to each other. These keywords indicate both the factors considered in the literature and the methodological or technical approach adopted, and they provide an overview of research on ship CA decisions in recent years.

Early research has mainly focused on “own ship”, “COLREGs”, and “path planning”. Over time, many new buzzwords have emerged in CA research, such as “simulation”, “navigational safety”, “autonomous ships”, and “risk assessment”.

This indicates that research on ship CA decision-making is deepening and developing gradually; more real constraints, such as the environment under study, that can reflect the actual situation and new methods, such as deep learning (DL), are being used to obtain better solutions. From the perspective of time, researchers have begun to focus on autonomous CA. From the perspective of environmental interference, restricted waters and environments combined with wind, waves [47,48], and current interference have become the focus of research. From an analysis of the complexity of ship encounter situations, research on multi-ship encounter situations has become a hot topic in recent years. In addition, with the improvement in the accuracy and reliability of CA, an increasing number of factors related to CA are considered, such as “ship maneuverability” and “real-time performance.”
2.3. Research Factors

The first two sections were used to analyze and collect the titles and abstracts from the selected papers and combine them with the hot-cloud vocabulary. To further analyze the characteristics of research on CA decision-making in different waters, based on the literature analysis of Vagale et al. [32], ten performance factors were chosen for a comparative study. The choice of these ten factors was based on the most commonly available and relevant information on algorithm descriptions.

We discuss each of the ten performance factors, P1–P10, in turn before making some general observations. Concerning Table 1:

<table>
<thead>
<tr>
<th>#</th>
<th>Factor/Content</th>
<th>Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>Classification of waters</td>
<td>Open waters (OW) and congested waters (CW)</td>
</tr>
<tr>
<td>P2</td>
<td>Encounter situation</td>
<td>Two-ship encounters (TE) and multi-ship encounters (ME)</td>
</tr>
<tr>
<td>P3</td>
<td>Types of obstacles</td>
<td>Static obstacles (SOs), dynamic obstacles (DOs), and mixed obstacles (MOs)</td>
</tr>
<tr>
<td>P4</td>
<td>Compliance with COLREGs</td>
<td>Yes (Y) and no (N)</td>
</tr>
<tr>
<td>P5</td>
<td>Environmental disturbance</td>
<td>Yes (Y) and no (N)</td>
</tr>
<tr>
<td>P6</td>
<td>Real-time performance</td>
<td>High (H), middle (M), and low (L)</td>
</tr>
<tr>
<td>P7</td>
<td>Ship maneuverability</td>
<td>Yes (Y) and no (N)</td>
</tr>
<tr>
<td>P8</td>
<td>Determination of collision risk</td>
<td>CPA, ship domain (SD), and collision risk index (CRI)</td>
</tr>
<tr>
<td>P9</td>
<td>Range or limit of altering course/speed</td>
<td>/</td>
</tr>
<tr>
<td>P10</td>
<td>Mechanism of altering course/speed</td>
<td>/</td>
</tr>
</tbody>
</table>

P1. Classification of research waters: open waters and congested waters. Generally, methods that can only avoid collision with dynamic target ships are suitable for open waters, and the others that can avoid collision with more than three dynamic ships and static obstacles simultaneously are suitable for congested waters.

P2. Depending on the complexity of the encounter situation, CA decision studies can be divided into two-ship and multi-ship encounters.

P3. Types of obstacles: static, dynamic, and mixed obstacles.

P4. Compliance with the COLREGs: consideration of compliance with the provisions of the COLREGs.

P5. Environmental disturbances: consideration of whether a ship is disturbed by wind, waves, and currents during a voyage.

P6. Real-time performance: the ability of an algorithm to react within a specified time. There are three levels: high (millisecond level, within 1 s), medium (second level, several seconds within 1 min), and low (more than 1 min).

P7. Ship maneuverability: this refers to the ability of a ship to maintain or change its motion state under control, that is, the ability of a ship to maintain or alter its course, speed, and position.

P8. The basis for judging the risk of collision is the consideration of the risk of collision, which is divided into distance to the closest point of approach (DCPA), time to the closest point of approach (TCPA), and ship domains (SDs).

P9. Altering the course/speed range: limited range of changing courses or speeds.

P10. Altering the course/speed laws: These are divided into objective function guide, heading/speed function, discrete variation, and gradual left/right-turn changes.

3. Automatic CA Strategy Based on Alteration of Course Alone

With the development of science and technology, the methods of these strategies have evolved from the earliest traditional mathematical methods to a stage where artificial
intelligence techniques and various algorithms are integrated to solve problems, while considering the COLREGs and actual navigation situations. By summarizing the literature on ship autonomous CA algorithms, these research methods can be mainly classified into algorithms based on mathematical models, artificial intelligence, and soft computing.

3.1. Algorithms Based on Mathematical Models

Mathematical model-based algorithms represent environmental disturbances and ship-motion models more accurately and use quantifiable methods to solve CA decision-making problems, including geometric analysis, velocity obstacles (VO), and model predictive control (MPC).

(1) Geometric analysis

Since the 1950s, the geometric analysis method has been used to solve the problem of automatic CA by establishing a geometric model of ship encounter to analyze the movement pattern in CA [49–51], including providing the DCPA, TCPA, and other CA parameters [21,52]. Lazarowska et al. [53] proposed a CA decision-making algorithm based on the path library method that considers the COLREGs, multi-ship encounters, and a few polygonal static obstacles. However, in this method, all target ships keep their course and speed so that the generated path is difficult to use in practice. Xu et al. [54] adopted a ship power-domain model based on the DCPA and TCPA to control ship course alteration and achieve ship CA. Tang et al. [55] proposed a CA algorithm by using a heading window, a set of unseaworthy heading angles as constraints, and a heading deviation angle as the optimization objective to determine the optimal navigation angle. This algorithm is less complex as only static obstacles are considered, and no dynamic obstacles are involved. As the earliest research method for CA [36], the geometric analysis method mainly aims at the encounter between two ships, usually assuming that the ships keep their course and speed without considering each ship’s scale or maneuvering performance, resulting in deviations between the calculation results and reality.

(2) VO

The velocity obstacle method is used to calculate the required heading or speed for CA by analyzing the spatial geometry between a ship and dynamic obstacles [17,22–24,27,56–61]. Tian et al. [58] proposed a method to avoid collisions by navigating a ship downstream to avoid static and dynamic obstacles based on the speed obstacle method. However, this method does not consider the requirements of the COLREGs. Zhang et al. [56] improved the speed obstacle method based on the dynamic vessel domain to avoid different obstacles according to an inland water environment, while considering the shallow-water effect. However, the resumption angle and the time were not calculated. Mou et al. [23] analyzed the relationship between the change in a ship’s velocity vector and the CA result after a nonlinear motion based on the ship’s domain and the speed-barrier method. They provided a collision-free-course-alteration range of the operating system, which can improve the efficiency of CA to a certain extent and is more in line with the requirements of the COLREGs and marine navigation habits. However, this method does not consider the maneuverability of a vessel and does not satisfy actual navigation conditions.

The VO method can avoid static and dynamic obstacles and can also consider the COLREGs, but it requires a good trajectory prediction of other vessels.

(3) MPC

MPC solves the finite-time, open-loop optimization problem online at each sampling time, based on the current measurement information obtained, and applies the first element of the resulting control sequence to the controlled object. The process is repeated at the next sampling time, and the optimization problem is refreshed and solved again using new measurements as the initial conditions for predicting the future trajectories of the system at that point. The MPC algorithm consists of three steps: first, predicting the future output of the system based on historical information and future inputs from the ship, acting as a
control via the course and speed; secondly, detecting the actual course and speed of the ship; and, thirdly, using this state to correct model-based prediction results before performing a new optimization. Abdelaal et al. [62] adopted a nonlinear MPC method combined with a ship-motion control model to achieve more accurate and fast ship CA decision-making and track control. However, their algorithm only considers CA between a single vessel and a point, such as a static obstacle, and only considers the alteration of the course to starboard. Based on the concept of optimal control, Chen et al. [63] established an optimal control model for multi-objective ship CA in open water, in which the ship’s heading is controlled by setting a rudder angle constraint. This can achieve multi-ship CA; however, the model takes a long time to compute, requires accurate initial conditions and constraints, and cannot handle environmental disturbances.

MPC has the advantages of a good control effect and strong robustness [8]. It can effectively overcome the uncertainty, nonlinearity, and correlation in the process, and it can easily deal with various constraints in the controlled and manipulated variables in the process. The influence of environmental factors on a ship can also be considered. However, the calculation time of the algorithm is affected by the complexity of the model. The more complex the model and the constraints, the calculation time of the algorithm will be longer.

(4) Game Theory (GT)

Game theory describes the interaction of multiple decision-makers’ strategies, where the behavior of each decision-maker has an impact on other decision-makers in the game process. Game theory focuses on how the behavior of a decision-maker affects the behavior of other decision-makers. Wang et al. [64] developed a probabilistic model to solve the ship CA problem and designed a greedy algorithm to search for possible movement paths using a cost function to determine the evasive strategy of an unmanned surface vessel. However, this method does not consider the effects of the COLREGs or environmental disturbances. Game theory can consider the requirements of the COLREGs and the parameters of vessel movement, and can avoid collisions with multiple vessels [10]; however, it cannot deal with static obstacles and has medium calculation time [65].

(5) Artificial Potential Field (APF)

The APF method establishes a virtual force field containing both gravitational and repulsive fields and controls the direction of ship movement under the combined effect of these two forces [66]. Liu et al. [67] improves the APF functions for dynamic ships considering the COLREGs. However, the algorithm fails to adopt the speed change strategy and cannot deal with static lake obstacles. Xue et al. [68,69] proposed automatic trajectory planning based on the APF method and velocity vector by applying the alteration of heading angle as the main method to avoid collisions and considering the method of deceleration for emergencies. In the simulation experiment, only the course was changed to avoid collisions, whereas the speed was not altered, and there was a lack of experiments during emergencies. Zhang et al. [70] designed an APF-based intelligent navigation approach for a USV in a complex environment with a randomly moving target and multiple static or moving obstacles, yet the COLREG rules were not considered. Huang et al. [71] introduced a ship-maneuvering motion control model by combining a synergistic ship domain model with the APF method, and considering the effect of ship length on ship CA. In addition, the method investigates the situation when two vessels cross paths and the give-way vessel does not comply with the COLREGs. Lee et al. [72] used the velocity-potential field as the field function in the APF method. The algorithm is divided into course-alteration and track-keeping modes. This algorithm is simple, easy to implement, and suitable for real-time distributed CA systems. However, this method is only suitable for CA operations in open water and requires appropriate action by the crew on board. Lyu et al. [6,14,73] proposed a path-guided hybrid APF (PGHAPF) approach and the improved versions for restricted waters even in a practical environment [5,13]. The approach assumes that course alteration is the only strategy to avoid collisions and integrates the potential field and gradient methods, including potential field-based path planning for arbitrary static obstacles,
gradient-based decision-making for dynamic obstacles, and optimization considering an a priori path and waypoint selection.

Although the APF method has fast calculation speed and strong adaptability, it has the disadvantage of a local minimum [43,74], which must be combined with other optimization algorithms to be solved [75].

3.2. Artificial Intelligence and Soft Computing-Based Algorithms

Neural networks, evolutionary algorithms, and swarm intelligence algorithms are the primary algorithms based on artificial intelligence and soft computing.

(1) Knowledge-based systems

Knowledge-based systems can generate and utilize knowledge from various sources, data, and information for problem-solving procedures and support human learning, decision-making, and action [76]. He et al. [29] proposed a method for timing and selecting options for steering CA actions under three postures, first time-point of collision risk (FTCR), first time-point of the close situation (FTCS), and first time-point of immediate danger (FTID), to determine the ship avoidance action based on the COLREGs and ship maneuvering information.

The problems of knowledge-based systems are that they are difficult to develop a complete, accurate, and concise knowledge base, and they cannot deal with issues outside the knowledge base.

(2) Neural Network (NN)

Neural networks, also known as artificial neural networks, are inspired by the human brain and mimic the way biological neurons transmit signals to each other [77]. Zhai et al. [78] used a multi-vessel automatic CA method based on deep neural networks using a double-depth Q-network and an empirical first-replay approach, which allows the model to converge faster, but the method cannot be used in actual navigation.

Neural networks can control ship movements without knowing the exact parameters of the ship; however, they must make full use of their methods and knowledge [79].

(3) Evolutionary algorithms

Evolutionary algorithms are based on the Darwinian evolutionary theory, which consist of genetic algorithms (GA), genetic programming (GP), evolution strategies (ES), and evolutionary programming (EP). In the CA process, an optimal path is determined by selection, crossover, variation, and population control [80,81]. Tsou et al. [82] used a GA in conjunction with the COLREGs and the field of ship safety to find the optimal path from an economic point of view and to provide the best steering angle, resumption timing, and resumption angle. However, this optimal route produces an avoidance route that is not in line with navigation experience, and it may obfuscate target ships.

Evolutionary algorithms can be adapted to a wide range of problems in various environments and achieve satisfactory results. Evolutionary algorithms are widely applicable, highly nonlinear, easily modifiable, and parallelizable. However, the crossover and variation rates in these algorithms are difficult to determine, and most of these parameters have been chosen empirically [83].

(4) Swarm intelligence algorithm (SIA)

An SIA is an optimization algorithm that imitates social biological groups, including bacterial foraging optimization (BFO), particle swarm optimization (PSO), and ant colony optimization (ACO). Liu et al. [84] used an optimization algorithm combining improved bacterial foraging and particle swarm algorithms, which has a strong global search capability and optimizes CA parameters, including CA angle and redirect angle, to generate CA routes for ships. Zheng et al. [85] proposed a hybrid path-planning algorithm that combines a simulated annealing algorithm and PSO, which can automatically give way and alter the course to avoid collisions. All of the above can only solve two-ship encounter situations or CA in a static environment [86] and cannot handle multi-ship encounter situations.
Lazarowska [87] used the ant colony algorithm to design an automatic CA decision algorithm considering the COLREGs, static obstacles, and multi-ship encounters. The algorithm assumes that all target ships keep their speed and course, and the calculation time of the algorithm is too long; therefore, real-time decision-making cannot be guaranteed. Zheng et al. [88] proposed an improved cultural particle swarm algorithm using the Kalman filter to smooth and predict a ship’s trajectory; this algorithm is based on the fuzzy distribution method, combined with the COLREGs, to determine the ship’s steering angle to achieve ship CA decisions. Zeng et al. [89] proposed a particle swarm genetic optimization CA decision algorithm that complies with the COLREGs, established a CA objective function based on the steering amplitude and sailing time, and obtained the optimal steering amplitude and required sailing time after steering. This method assumes that the evasive action information of the surrounding ships is obtained in real time between ships by using radar and AIS.

A swarm intelligence algorithm has the advantages of simple operation, fast convergence speed, and good global convergence, but the selection of parameters is important, and it is easy to fall into the local optimal solution.

(5) Fuzzy logic (FL)

Fuzzy logic describes a system in a fuzzy language and is used to describe both the quantitative and qualitative models of the system. Hu et al. [90] proposed an automatic CA algorithm considering steering system, which searched for a new course from a knowledge base containing basic experts and used T-S fuzzy logic to solve uncertainties in heading control systems.

Fuzzy logic can be used for the control of complex objects. However, in practice, it is easier to implement a simple application control. The greater the number of input and output variables, the more difficult the reasoning of the fuzzy logic is [91].

(6) Reinforcement learning (RL)

Reinforcement learning (RL) [92,93], deep reinforcement learning (DRL) [44,94,95], and other deep learning (DL) methods have been increasingly applied in the field of ship automatic CA [4,45]. For these methods, they consume significant time for training and their ability to deal with complex environments needs to be strengthened [96]. For example, target ships are set to keep their course and speed; otherwise, it is difficult to plan a feasible path [92]. Even the same input conditions may produce different CA decisions, and this uncertainty of the solution also limits their application in practice [97]. The reward function is mostly about the course and safety constraints. Even if multi-ship encounters can be handled, the interference of the environment still needs to be considered in the training of a CA decision-making model [93], and a cooperative multi-ship collision-avoidance scheme is also needed to be studied [95].

3.3. Summary and Comparison of Methods

Table 2 lists the considering factors in the automatic CA decision-making methods based on altering course. Because a CA action by changing course is easier to operate than a CA action by changing speed, and the former is easier to be found by target ships through vision, so ships often use steering avoidance in general navigation, especially in open waters. However, in restricted waters, it is difficult to ensure the safety of the ship only by steering avoidance due to the serious limitation of the steering range and operating space of the ship.
Table 2. Comparison of strategies based on altering course.

<table>
<thead>
<tr>
<th>Method</th>
<th>Refs.</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geometric analysis</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Discrete solution space</td>
<td>Trajectory base</td>
</tr>
<tr>
<td></td>
<td>[53]</td>
<td>CW</td>
<td>TE/ME</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>N</td>
<td>SD</td>
<td></td>
<td>Course alteration function</td>
<td>Only one target ship, without wind, waves, currents, and consideration of other disturbances.</td>
</tr>
<tr>
<td></td>
<td>[54]</td>
<td>OW</td>
<td>TE</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>Y</td>
<td>CPA</td>
<td></td>
<td>Course alteration function</td>
<td>Wind and current are not considered; only static obstacle avoidance.</td>
</tr>
<tr>
<td></td>
<td>[55]</td>
<td>CW</td>
<td>/</td>
<td>SO</td>
<td>N</td>
<td>N</td>
<td>H</td>
<td>Y</td>
<td>/</td>
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<tr>
<td>VO</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Goal-directed behavior</td>
<td>It does not consider the weather, sea conditions, and COLREGs constraints.</td>
</tr>
<tr>
<td></td>
<td>[58]</td>
<td>OW</td>
<td>ME</td>
<td>MO</td>
<td>N</td>
<td>N</td>
<td>/</td>
<td>Y</td>
<td>CPA</td>
<td></td>
<td>Goal-directed behavior</td>
<td>It does not consider the actual map, steering return angle, and time.</td>
</tr>
<tr>
<td></td>
<td>[56]</td>
<td>OW</td>
<td>TE/ME</td>
<td>MO</td>
<td>Y</td>
<td>Y</td>
<td>H</td>
<td>Y</td>
<td>CPA</td>
<td></td>
<td>Goal-directed behavior</td>
<td>It can only be used in open waters, and studies in restricted waters and more complex environments are required.</td>
</tr>
<tr>
<td></td>
<td>[23]</td>
<td>OW</td>
<td>ME</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>N</td>
<td>/</td>
<td></td>
<td>Goal-directed behavior</td>
<td></td>
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<tr>
<td>MPC</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Discrete variation</td>
<td>The algorithm only considers the CA between a single ship and point-like static obstacles.</td>
</tr>
<tr>
<td>Optimal control</td>
<td>[62]</td>
<td>OW</td>
<td>TE</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>Y</td>
<td>SD</td>
<td></td>
<td>Continuous change</td>
<td>The calculation time is long, and precise initial conditions and constraints are required.</td>
</tr>
<tr>
<td></td>
<td>[63]</td>
<td>OW</td>
<td>ME</td>
<td>DO</td>
<td>N</td>
<td>Y</td>
<td>L</td>
<td>Y</td>
<td>CPA and SD</td>
<td>Continuous change</td>
<td>It does not consider the impact of the COLREGs and environmental disturbances.</td>
<td></td>
</tr>
<tr>
<td>GT</td>
<td>[64]</td>
<td>OW</td>
<td>TE/ME</td>
<td>DO</td>
<td>N</td>
<td>N</td>
<td>H</td>
<td>Y</td>
<td>/</td>
<td></td>
<td>Discrete variation</td>
<td></td>
</tr>
<tr>
<td>APF</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Objective function guide</td>
<td>Natural conditions and static obstacles are not considered.</td>
</tr>
<tr>
<td></td>
<td>[67]</td>
<td>OW</td>
<td>TE/ME</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>Y</td>
<td>SD</td>
<td></td>
<td>Objective function guide</td>
<td>The impact of wind, waves, and currents on the ship is not considered.</td>
</tr>
<tr>
<td></td>
<td>[71]</td>
<td>OW</td>
<td>TE</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>M</td>
<td>Y</td>
<td>/</td>
<td></td>
<td>Objective function guide</td>
<td></td>
</tr>
<tr>
<td>APF</td>
<td>[72]</td>
<td>OW</td>
<td>TE/ME</td>
<td>MO</td>
<td>N</td>
<td>Y</td>
<td>/</td>
<td>Y</td>
<td>SD and CRI</td>
<td>Objective function guide</td>
<td>The influence of the shallow-water effect and shore-wall effect on ships is not considered.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[14]</td>
<td>CW</td>
<td>ME</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>Y</td>
<td>CPA</td>
<td>Objective function guide</td>
<td>It does not re-plan to the original route, and route optimization is not considered.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[68,69]</td>
<td>CW</td>
<td>TE/ME</td>
<td>MO</td>
<td>Y</td>
<td>Y</td>
<td>/</td>
<td>Y</td>
<td>CPA</td>
<td>Objective function guide</td>
<td>It does not consider weather conditions, extreme encounter cases, change of speed, or reversing in emergencies.</td>
<td></td>
</tr>
<tr>
<td>Knowledge-based system</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Cubic spline smoothing</td>
<td>Only the avoidance actions of stand-on ships are studied, and further research is needed on give-way ships.</td>
</tr>
<tr>
<td></td>
<td>[29]</td>
<td>OW</td>
<td>TE</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>Y</td>
<td>FSCR, FTCS, and FTID</td>
<td>Course alteration function</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NN</td>
<td>[78]</td>
<td>OW</td>
<td>ME</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>N</td>
<td>CPA</td>
<td></td>
<td>Discrete variation</td>
<td>It cannot be used for actual CA and does not consider restricted waters.</td>
</tr>
</tbody>
</table>
Table 2. Cont.

<table>
<thead>
<tr>
<th>Method</th>
<th>Refs.</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>[82]</td>
<td>CW</td>
<td>TE/ME</td>
<td>Y</td>
<td>N</td>
<td>M</td>
<td>N</td>
<td>CPA</td>
<td>−30° ~ 90°</td>
<td>Course alteration function</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[84]</td>
<td>OW</td>
<td>TE</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>N</td>
<td>CRI</td>
<td>30° ~ 80°</td>
<td>Objective function guide</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[85]</td>
<td>CW</td>
<td>TE</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>N</td>
<td>CRI</td>
<td>/</td>
<td>Right turn change</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[87]</td>
<td>CW</td>
<td>TE/ME</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>N</td>
<td>CRI</td>
<td>/</td>
<td>Objective function guide</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[88]</td>
<td>OW</td>
<td>TE</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>N</td>
<td>CRI</td>
<td>−35° ~ 35°</td>
<td>Objective function guide</td>
<td></td>
</tr>
<tr>
<td>SIA</td>
<td>[84]</td>
<td>OW</td>
<td>TE</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>N</td>
<td>CRI</td>
<td>30° ~ 60°</td>
<td>Right-turn change</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[87]</td>
<td>CW</td>
<td>TE/ME</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>N</td>
<td>CRI</td>
<td>/</td>
<td>Objective function guide</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[88]</td>
<td>OW</td>
<td>TE</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>N</td>
<td>CRI</td>
<td>/</td>
<td>Objective function guide</td>
<td></td>
</tr>
<tr>
<td>SIA and EA</td>
<td>[89]</td>
<td>OW</td>
<td>ME</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>N</td>
<td>CRI</td>
<td>/</td>
<td>Objective function guide</td>
<td></td>
</tr>
<tr>
<td>FL</td>
<td>[90]</td>
<td>OW</td>
<td>ME</td>
<td>DO</td>
<td>Y</td>
<td>Y</td>
<td>/</td>
<td>Y</td>
<td>CPA</td>
<td>−35° ~ 35°</td>
<td>Course alteration function</td>
<td></td>
</tr>
<tr>
<td>DRL</td>
<td>[45]</td>
<td>CW</td>
<td>ME</td>
<td>MO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>Y</td>
<td>SD</td>
<td>/</td>
<td>States, actions, and a reward function</td>
<td></td>
</tr>
</tbody>
</table>

“/” indicates that the index is not applicable to some papers.

It will create an avoidance route that is not in line with nautical experience.

The impact of wind, waves, and currents on the ship is not considered.

The shallow-water effect and the shore effect on ships are not considered.

The impact of wind, waves, and currents on the ship is not considered.

It assumes that all target ships (TSs) obey the COLREGs, and CA action information of TSs is obtained in real time.

It considers simple restricted waters with an isolated square obstacle and 3 TSs’ reactive collision avoidance, rather than a smart action in the far range.
Autonomous CA algorithms by ship steering can be applied to all types of water. Early steering maneuvers are required in restricted and complex waters. Many studies have focused on single or multiple dynamic obstacles and have considered three main scenarios: ship maneuverability is considered in most cases, including ship dynamics, maneuvering models, dynamic models, and target ship motion constraints and limitations. However, certain problems remain:

1. Most verification algorithms assume that target ships keep their speed and comply with the COLREGs and do not consider the violations of the COLREGs by target ships.
2. A part of these algorithms does not consider the maneuverability of the ship, which makes them unsuitable for actual ship navigation.
3. Environmental disturbances, such as wind, waves, and currents, are not considered.

4. Automatic CA Strategy Based on Alteration of Speed Alone

In addition to the strategy based on altering course, an avoidance strategy based on altering speed is also an important optional strategy for ships to autonomously avoid collisions, particularly in restricted waters. Considering the maneuvering characteristics of ships and the habits of sailors, there are few studies on autonomous CA strategies based only on the alteration of speed. However, research on the optimization and strategy selection for avoidance based on altering speed should not be ignored.

4.1. Optimization of Strategy Selection for Changing Speed

For the CA strategy based on changing speed, the timing, amplitude, and rate of the speed alteration, and the maneuvering characteristics of a ship have a significant impact on the final CA result. Bi et al. [98] proposed a method to determine the best avoidance timing and action for a ship. Ma et al. [99] used a bacterial foraging algorithm in combination with the COLREGs and the field of ship safety to find CA strategies for altering speed from an economical perspective, including optimal shifting time, amplitude, and navigation recovery time. This study assumed that a vessel’s speed can be immediately altered to a set value; however, in practice, speed alteration is gradual. Yu et al. [100] proposed a CA decision-making method for ship speed in narrow waters based on a mimic physics optimization algorithm. According to the requirements of the COLREGs on the speed-alteration action range and considering the influence of the deceleration stroke and the time required for deceleration on the CA effect, the collision risk and speed-alteration energy loss are used to evaluate the advantages and disadvantages of the CA decision, and the objective function of the ship’s speed-alteration CA is established.

According to different sailing situations, there are also some studies comparing the effects of different avoidance strategies through course and speed alterations and choosing the best one. Su et al. [101] studied a CA method for large ships in open waters. Considering the influence of difficult maneuvering ability and the large motion inertia of large ships, the slackening speed was prioritized, and geometric methods were used to calculate the speed. If the slackening speed cannot achieve the avoidance effect, collisions are avoided by ship steering.

Zhao et al. [57] improved the speed obstacle algorithm while considering ship maneuverability and the COLREGs and made decisions in two ways: altering course and altering speed. Hu et al. [102] established a multi-ship real-time collision risk analysis system with alteration course or speed based on the COLREGs and good ship skills, and they analyzed five factors affecting the collision risk of ships in real time. This study ignored the influence of ship maneuverability and could not avoid collisions with static obstacles. Nakamura et al. [103] designed an automatic CA system that selects the optimal solution by calculating the preference estimates of course and speed. This method can effectively solve the problem of navigation in congested waters.
4.2. Research on CA Law of Altering Speed

Altering speed avoidance includes increasing speed and slackening speed. In theory, increasing speed can also avoid collisions and conform to the safe speed requirement in the COLREGs. However, when sailing at sea, the feasibility of a ship to increase speed is weak. The acceleration of a ship causes the TCPA between two ships to decrease sharply, and the short reaction time for CA can easily appear as an illusion of target ships—altering speed only is difficult for target ships to visually see and not easily recognizable as course alteration—and increase the risk of collision [104]. However, there is sufficient reaction time for slackening speed [25]. When immediate danger occurs, it can also stop to avoid collision, which increases the safety of ship navigation [105]. In most cases, the CA strategy of a ship based on alteration of speed alone is slackening speed.

Automatic CA decision-making based on speed alteration also requires the right timing. An action that is too early does not conform to the CA psychology of a captain and officers, whereas too late an action will cause uncoordinated actions between ships and increase the risk of collision. In addition, under the influence of wind and waves [47,48], deceleration may lead to course changing of a ship. Therefore, to slacken speed or reverse it to avoid a collision, it is necessary to consider the ship’s course-keeping performance, the deflection effect of the bow when reversing, the forward stroke, the speed of the ship during the deceleration process, and the time required for the main engine to restart during an emergency. When a ship slackens speed, it should be noted that the speed cannot be less than the minimum value to maintain the rudder effect and avoid losing control of the ship. A CA action that only alters speed, whether for a conventional ship or an intelligent ship, is difficult for target ships to see visually and apparently, or it is not as easy to recognize as a course alteration. Therefore, it may appear as an obfuscate action to target ships, resulting in a collision.

5. Automatic CA Strategy Based on Altering Course and Speed

The autonomous CA strategy of a ship should be flexible and available at any time for course and speed alterations. Either one can be used alone or the two can be combined. However, the combination solution is technically difficult to implement because the CA effect of steering and the effect of speed alteration are not necessarily superimposed on each other, but may also be mutually offset [106].

5.1. Establishing Objective Function through Course and Speed

At present, research on a ship’s autonomous CA strategy combining altering course and speed is typically to construct the objective functions of speed and course, or their variation, to judge and select the optimal strategy [107].

According to the general requirements of the COLREGs, Zhang et al. [108] used a graphical method to analyze the CA performance of give-way and straight-way ships in typical encounter situations, calculated the collision probability, and used a linear expansion algorithm to alter the course and slacken speed. Szlapczynski [109] proposed a ship CA strategy based on an evolutionary algorithm by introducing a turning penalty mechanism and speed-reduction dynamic model that can minimize route detours while avoiding obstacles. Szlapczynski et al. [106,110] also used the ship domain to assess the collision risk of own ship using a ship dynamic model to estimate the moment and distance required to maneuver. A more applicable CA decision-making method is obtained by the improved modified Dijkstra’s algorithm to find the solution in a graph representing discrete solution space, which is tested in laboratory conditions and quasi-real conditions [9]. However, the CA maneuvers are limited to course alteration and those combing turns with speed reduction, and speed reduction is only conducted in the condition of keeping the course and natural deceleration owing to turns.

Huang et al. proposed a generalized velocity obstacle (GVO) algorithm, considering the COLREGs and ship dynamics in a certain extent. The feasible velocity is found by the UO set, i.e., a set collecting all the controls of the OS resulting in collisions to support the
OOWs in decision-making. It should be noted that when the error between the predicted trajectory and the actual trajectory of the OS is large, the solution may be a failure [111].

Based on the idea of MPC, Johansen et al. [112–114] considered a ship-motion model with wind and flow interference, used a limited control sequence to divide the course and speed, chose different CA actions to predict ship-motion trajectories during a defined period, and subsequently made selections from these trajectories for an optimal CA maneuvering strategy. However, in this method, the accuracy of the mathematical model of ship motion determines the effectiveness of CA decision-making, and the simulation of the experimental method based on scene generation cannot predict the abnormal maneuvering of target ships. Eriksen et al. [115,116] proposed a branching-course MPC (BC-MPC) algorithm, which is included in a three-level integrated COLAV (CA) system and used for path planning, regular CA of dynamic ships, and emergency situations according to different scenarios. A full-trajectory generation mechanism in this study consists of the numbers and duration of a series of course and speed maneuvers, at each level or trajectory of the system.

Hu et al. [117] proposed a multi-objective PSO algorithm that expresses the COLREGs as inequality constraints, integrates them into the algorithm, and sets an objective function that prioritizes the course/speed alteration preference over other objectives. Hirayama et al. [104] proposed a distributed stochastic search algorithm+ (DSSA+) to alter course and speed, considering the latest advances in ship maneuvering technology and the need to avoid collisions more effectively. However, there has been no analysis based on an actual situation for altering the course, speed, or a combination of course and speed alteration.

Tan et al. [118] proposed a fast-marching method (FMM) based on the path planning method for ship swarms, and a priority-based speed and heading-angle control algorithm considering the COLREGs, to design a CA strategy. This method fully considers the influence of environmental uncertainty, but it only considers the situation in which target ships keep their course and speed. Chen et al. [119] used a PSO algorithm to numerically optimize the CA criterion function and obtained the optimal path and corresponding operational decision for a ship to avoid collisions. However, the influence of ship motion characteristics has not been fully considered.

5.2. Safe-Speed and Limited-Speed Methods

Another method is to set a safe speed limit or to calculate the instant speed during steering and avoidance [75].

To solve the problem of ship CA in restricted waters, Zhang et al. [120] proposed a calculation method for ship CA time, distance, and position while considering multi-segment routes. This method considers the turning position, turning time, and safe speed of the ship. A safe speed can be used to avoid collisions near intersections in restricted waters. Zeng et al. [121] proposed a mathematical model for calculating DCPA and calculated the derivative of a ship’s course and speed. Thus, it is possible to quantitatively judge the effectiveness of changing course and speed to avoid collisions in different encounter situations.

It is difficult to achieve both safe speed and calculated speeds for ship maneuvering. In addition, these methods can only be used as auxiliary methods for CA, and they cannot deal with complex situations encountered by multiple ships in real time because these methods are not decision-making methods for the joint control of course and speed based on the risk of collision between ships.

5.3. Course and Speed Alteration Strategy Using Hybrid Algorithm

For steering avoidance, heading control can be achieved using only one algorithm. When combined with speed, it must be combined with methods such as speed vectors, collision cones, and deep reinforcement learning (DRL) [4].

Xu et al. [122] proposed a dynamic CA algorithm based on a layered artificial potential field with collision cone (LAPF-CC), using the relative distance and velocity as variables to determine the collision risk, and constructed a torque named “speed-torque”. The
speed-torque, attraction, and repulsion work together to alter the course and speed of a USV. Song et al. [123] introduced a new predictive APF (PAPF) method to plan a smoother path with turning angle limit and velocity adjustment. However, this method does not consider the influence of environmental disturbances, such as wind, waves, and currents on ships. Guo et al. [124] combined the APF with DRL to propose an automatic path-planning method for unmanned ships. This method divides the action control strategy into heading and speed change control. It has the advantages of high precision and small navigation errors; however, it does not consider the influence of a ship’s dynamic properties and environmental disturbances. Xu et al. [125] proposed an intelligent hybrid CA algorithm based on DRL combined with collision cones, which can determine CA timing and corresponding CA actions according to different obstacles. However, this method only deals with the circumscribed circle of a static obstacle and cannot deal with dynamic obstacles, such as ships.

Shen et al. proposed an autonomous intelligent CA algorithm for unmanned ships based on a deep competitive Q-learning algorithm and A* algorithm. Using the A* algorithm and combining the ship’s maneuvering characteristics, a parallel dynamic CA decision-making scheme was proposed, which could avoid collision with 2–4 dynamic target ships and 1 static obstacle by altering the course alone or simultaneously altering the course and speed, assuming that all target ships comply with the COLREGs [126]. However, in this study, the state of the surrounding obstacles was set as known, which was not the actual perceived environmental data, and the error of these data was not considered.

By comparing the methods and their various factors in Table 3, it is found that the CA strategies of combining course change and speed change can be mostly used in congested waters, but the environment is simplified a lot. For example, static obstacles are regarded as convex polygons or circles; dynamic data of other target ships are assumed to be known and accurate; and external hydrometeorological influences are ignored. However, there is still a big problem in these methods, which is that the CA strategies of steering and shifting behaviors are not integrated. In particular, the coupling mechanism between the two behaviors and its influence on the CA results, COLREGs compliance, operability of discrete decision space, and other difficult problems are not studied enough.
Table 3. Comparison of CA based on combined alteration of course and speed.

<table>
<thead>
<tr>
<th>Method</th>
<th>Refs.</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geometric analysis</td>
<td>[108]</td>
<td>OW</td>
<td>ME</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>Y</td>
<td>CPA</td>
<td>[30°~60°]</td>
<td>Turn right and gradually change</td>
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<td>Speed: −5%/step</td>
<td>Simulation results do not comply with the COLREGs.</td>
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<td></td>
<td>−30°~30°</td>
<td>Further research on more ship models is needed.</td>
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<tr>
<td>GVO</td>
<td>[111]</td>
<td>OW</td>
<td>ME</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>/</td>
<td>Y</td>
<td>CPA</td>
<td>[−90°~90°]</td>
<td>Utilize UO set to find the best solution</td>
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<td>[0~1] m/s</td>
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<td>Basic difference in predicted trajectory and actual nonlinear trajectory of</td>
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<td>the ship, leading to failure.</td>
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<tr>
<td>MPC</td>
<td>[112–114]</td>
<td>CW</td>
<td>TE/ME</td>
<td>MO</td>
<td>Y</td>
<td>Y</td>
<td>H</td>
<td>Y</td>
<td>CPA</td>
<td>[−90°~90°]</td>
<td>Discrete variation</td>
<td></td>
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<td>Speed: v, 0.5 v, 0</td>
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<td></td>
<td>The model accuracy needs to be high, and violation of the COLREGs by target</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>ships is not considered.</td>
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<td>BC-MPC</td>
<td>[115,116]</td>
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<td>Search space with a finite number of trajectories</td>
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<td>Discrete set of SOG and course accelerations</td>
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<td>Simple static obstacles, and the trajectory is not smooth.</td>
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<td>LAPF-CC</td>
<td>[122]</td>
<td>CW</td>
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<td>$\delta$: angle between OS speed and resultant force, with $\delta \leq \pi$</td>
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<td>Speed and heading are adjusted by driving force (maximum $F_{\text{max}}$)</td>
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<td>The coupling effect of speed change and heading change on CA is not</td>
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<td>DRL</td>
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<td>The influence of the ship motion model and environmental interference on</td>
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<td>the algorithm is not considered.</td>
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<td>DRL and APF</td>
<td>[124]</td>
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<td>TE/ME</td>
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<td>$\text{Speed change} [−15~15]$</td>
<td>Only static obstacles, without considering the COLREGs</td>
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<td>$\text{kn speed} [0~30]$</td>
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<td>Method</td>
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<td>Limitations</td>
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<td>GA</td>
<td>[109]</td>
<td>CW</td>
<td>TE</td>
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<td>Y</td>
<td>SD</td>
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<td>The amount of calculation is large, and the real-time performance is difficult to guarantee.</td>
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<tr>
<td>SIA</td>
<td>[117]</td>
<td>CW</td>
<td>ME</td>
<td>DO</td>
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<td>N</td>
<td>CPA</td>
<td>Speed: 0, v/2, 2 v</td>
<td>Gradual change</td>
<td>Lack of comparison with other multi-objective optimization algorithms, cannot be determined as optimal.</td>
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<td>DL and A*</td>
<td>[126]</td>
<td>CW</td>
<td>TE/ME</td>
<td>MO</td>
<td>Y</td>
<td>Y</td>
<td>H</td>
<td>Y</td>
<td>SD</td>
<td>Speed: Divide the speed of the ship into four sections and gradually reduce the speed</td>
<td>Discrete variation</td>
<td>Coordinated CA between ships and information on unknown obstacles are not considered.</td>
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<td>Random Searching</td>
<td>[104]</td>
<td>OW</td>
<td>ME</td>
<td>DO</td>
<td>Y</td>
<td>N</td>
<td>H</td>
<td>Y</td>
<td>CPA</td>
<td>[−45°−45°]</td>
<td>Discrete variation</td>
<td>It is necessary to set the steering and variable speed weight function.</td>
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6. Discussion

6.1. Comparison of Decision-Making Methods

Algorithms based on mathematical models need to establish models that are so accurate that it is difficult to deal with situations in restricted waters with environmental disturbances. The geometric analysis method usually assumes that a target ship keeps its course and speed, regardless of the size and maneuverability of the own ship, resulting in deviations between the calculation results and the actual situation. Game theory considers the requirements of the COLREGs and ship-motion parameters, but the calculation time is long, and this method cannot deal with static obstacles. MPC-based methods can consider the impact of environmental factors on ships, but the calculation time of the algorithm will be affected by the complexity of the mathematical model. The VO algorithm must establish a good prediction of the trajectory of target ships. The expert system has real-time decision-making ability; however, it has poor performance and does not have the ability to learn. The setting of parameters in swarm intelligence algorithms, such as ant colony algorithm, particle swarm algorithm, and bacterial foraging algorithm, determine the accuracy of the experimental results. Although the APF method exhibits fast calculation speed and strong adaptability, there is a shortcoming of the local minima, which must be solved in combination with other optimization algorithms. These algorithms are typically limited to obtaining good experimental results in specific environments or conditions. They also need to consider more complex environments that combine wind, waves, and current disturbances [16,48].

Among the algorithms based on artificial intelligence and soft computing, knowledge-based systems are the first to be established, and the key lies in establishing a complete and accurate knowledge base. Neural networks are generally not used alone for ship CA decision-making but are used to improve the “knowledge base.” Genetic algorithms are mostly used in evolutionary algorithms, and the key is the selection of algorithm parameters, and some constraints are imposed on these algorithms. Parameter selection in swarm intelligence algorithms is also very important, and it is easy to fall into the local optimal situation. Fuzzy logic can accurately reflect the methods of experts to solve complex problems and provides new ideas for solving the defects of traditional expert systems.

The literature distribution and applicability of the three CA strategies are shown in Figure 6. Through the literature comparison and analysis, it was found that the autonomous CA strategy by ship steering mainly solves the problem of two-vessel and multi-ship encounters in open waters, and it has the largest number of papers (more than 16 articles). The autonomous CA strategy through speed alteration mainly solves simple encounter situations and has a minimum number of papers. The autonomous CA strategy based on the combination of course and speed alterations solves the problem of multi-ship encounters in congested waters (about 13–14 articles). However, owing to the difficulty in researching this problem, advanced and effective research has not yet reached the required scale. The statistical law reflected in this figure is also in line with the general maritime avoidance behavior. First, most ships choose to alter course to avoid collision, owing to the obvious amplitude and straightforward operation, whereas a small percentage choose the combination of alteration of course and speed because the environment is complicated and the situation is urgent. Second, because a speed-change-based action is not as obvious as a course-change-based action from the visual perspective, and is restricted by the operation of a ship’s main engine, so it is not used much in navigation practice.

The size of a readily apparent maneuver in open waters is not explicitly defined in the COLREGs, while common practice often requires no less than 30° of heading change [25,127]. When altering course early, the required turning angle is smaller, and vice versa. As far as the alteration of speed is concerned, it is a gradual process, such that a vessel cannot stop or double her speed instantaneously. When the main engine is stopped, the thrust of the ship decreases. Initially, the speed of the ship is high, the resistance of the ship to water is large, and the speed of the ship decreases rapidly. When the speed of the ship decreases, the resistance of the ship also decreases, but it is exceedingly difficult
for the ship to stop completely and make a right judgment while in water. Therefore, the alteration of speed can be more refined, as in the literature [33], and the initial speed can be continuously reduced by 5%.

Figure 6. Analysis of three types of autonomous CA strategies and encounters.

In the CA strategy that combines altering course and changing speed, most studies only show the steering angle and speed-change amplitude; however, they do not study the coupling relationship between steering and speed-change strategies. In the process of turning at a large angle, a ship’s own rolling and yaw motions reduce the speed of the ship, and the steering operation alters the speed of the ship. In addition, environmental factors, such as the draft of the ship, current speed, wind direction, and wind speed, also affect the ship’s evasion action, and even the strategy of alteration of course alone cannot be separated from the impact on the ship’s speed.

Additionally, it is worth noting that a CA strategy with alteration of course and speed may strengthen or weaken the final CA effect compared to a single alteration of course or speed strategy. Therefore, in the process of autonomous avoidance, it is extremely important to study the coupling mechanism of course and speed alterations and their influence on the CA effect.

6.2. Influence of Alteration of Course and Speed Coupling Mechanisms on Collision Avoidance

This study discusses the influence of alteration of course and speed coupling mechanisms. During navigation, incoming ships can be divided into four quadrants: front right, front left, rear right, and rear left. For incoming ships in these quadrants, if alteration of course and speed are taken simultaneously, these actions can be divided into “alter course to starboard combined with slackening speed”, “alter course to starboard combined with increasing speed”, “alter course to port combined with slackening speed”, and “alter course to port combined with increasing speed”. By calculating the values of DCPA and TCPA, it can be determined whether the CA effects of compound actions cancel or superimpose each other. As shown in Figure 7, if own ship (initial heading 000°, initial speed 13 kn, and initial position (0,0)) and an incoming ship from the right front (heading: 240°, speed 15 kn, and position: (7,5,5)) are on a collision course, the initial DCPA and TCPA are −2.9689 nm and 0.3147 h, respectively.

Take one’s own ship to “turn right to avoid it” as an example, and perform 12 consecutive steps, with each step changing the course by 5° and the speed altering by 0.5 kn. The comparison chart shows that when there is no danger of collision, the two actions of acceleration and deceleration have little effect on the DCPA. However, after the DCPA gradually turns from a negative value to zero, that is, after the danger of collision is formed, compared with steering only, steering deceleration causes an increase in the DCPA to slow down, and the acceleration of steering leads to a rapid increase in the DCPA, which is
beneficial for the elimination of collision risk. Of course, it is impossible to judge the danger of collision by simply relying on the changes in the DCPA. Considering the change in the TCPA, the value of the TCPA is inversely proportional to the relative speeds of the two ships. If the speed of a ship increases, the relative speed of the two ships increases, and the value of the TCPA decreases. Therefore, the change curve of the TCPA decelerates to a gradual increase and accelerates to a gradual decrease. Therefore, it is comprehensively judged that the effects of altering course to starboard combined with slackening speed are superimposed, and the effects of a starboard turn combined with increased speed are mutually offset. The same can be proven for the other quadrants.

Figure 7. Change in DCPA and TCPA diagrams when an approaching ship from the right front turns to starboard to avoid collision: (a) own ship’s initial heading is 000°, and after 12 steps, she turns to starboard to 060°; and (b) own ship’s initial heading is 13 kn, and the blue solid line in the figure means that her speed is reduced from 13 to 7 kn over 12 steps; the red dotted line indicates that her speed gradually increases to 19 kn, and the yellow dotted-dashed line indicates that her speed remains unchanged. (c) The effects of unchanged speed, coupled acceleration, and deceleration on the DCPA. (d) The effects of unchanged speed, coupled acceleration, and deceleration on the TCPA.

As shown in Figure 8, the length of the curve represents the speed alteration: the long curve is the acceleration, the short curve is the deceleration, the orange straight line is the superposition of the CA effect, and the blue dotted line is the offset of the CA effect. If they cancel each other out, the avoidance maneuver becomes ineffective and can even lead to a collision.
The ship speed ratio refers to the ratio of the speeds of the two ships during the encounter, and it is a key factor for the ships to make decisions and analyze the avoidance effect. This has a direct effect on the avoidance effect. When the ship with a slow speed performs a CA action, the timing of the action should be earlier, and the range of action should be larger to obtain a better avoidance effect. According to Rules 8 and 13–17 of the COLREGs, collision situations can be divided into three types: head-on, crossing, and overtaking situations. CA situations related to the centered own ship are divided into six types, as shown in Figure 9 as A, B, C, D, E, and F [128].

![Figure 8. Steering and shifting effect diagram.](image)

![Figure 9. CA actions under the COLREGs.](image)
The ships in Area A originate from the front right. Regardless of the speed ratio between the own ship and target ships, the own ship is a give-way ship and performs the CA action of turning to starboard and slackening speed.

The ships in Area B cross from the right of the own ship, and the own ship is a give-way ship. When the own ship’s speed is higher than that of the target ships, she should turn to port combined with slackening speed to avoid a collision. When the own ship’s speed is lower than that of the target ships, she should turn to starboard combined with increasing speed to avoid a collision.

The ships in Areas C and D come up to the own ship from the right rear and the left rear, respectively. The own ship is overtaken, and she typically keeps her course and speed. Once it is necessary to avoid collisions caused by overtaken ships, she can take action to avoid collision by her maneuver alone. Such action includes altering course to port and slowing down to deal with the approaching ships in Area C, and it also includes altering course to starboard combined with deceleration to deal with the approaching ships in Area D.

The ships in Area E come from the left and front, and typically, the own ship should also keep her course and speed. If the own ship should take action to avoid a close-quarters situation, she may take a right turn combined with accelerated collision-avoidance action.

For ships in Area E, the two power-driven ships are involved in a head-on situation, and each should alter her course to starboard to avoid a collision.

The dashed arc in Figure 9 indicates the initial speed of the own ship. The inner and outer arcs of the dashed line represent the deceleration and acceleration of the own ship, respectively.

### 6.3. Decision-Making Constraints

The autonomous CA decision of a ship has complex multi-constraint attributes. These attributes include whether dynamic and static obstacles, the COLREGs, environmental interference, and ship maneuvering characteristics can be considered and whether they have real-time characteristics, determinism, and robustness, as shown in Figure 10. Determinism means that each instruction of the algorithm has an exact meaning, that is, only the same output can be obtained for the same input. Robustness means that the algorithm results are not affected by external environment and model interference. Through a literature analysis, it was found that most studies were based on simulation experiments when verifying the proposed CA strategy. An actual sailing experiment of a ship has the problems of excessive cost, lengthy test periods, consideration risks, and few test samples. There are also problems with the simulation experiments. Dynamic and static obstacles coexist in the environment of ship navigation; however, at present, there are not enough algorithms that can consider such a complex, mixed environment, which is accounted for by only 61.4% of studies. In addition, about 70% of the selected studies consider ship maneuverability, mainly by adding restrictions on the mathematical model of ship motion to the proposed algorithm, and more than 85% of the studies consider the COLREGs and real-time requirements, which is a good trend. However, about 40% of the studies have not considered the deterministic decision-making and robustness of the proposed algorithm. In particular, there are few algorithms considering environmental impact on decision-making, with only 31.8% of studies taking this into consideration. If automatic CA decision of ships is to be applied in practice, this aspect should be paid more attention to in subsequent CA strategy research.
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At present, smart ships must be able to perceive the navigation situation; analyze and judge the navigation danger; realize dynamic path planning and ship state control according to environmental changes; and accurately control the course, speed, and track. However, many research results still cannot be directly applied to smart ships, mainly because of the following problems:

1. Most research studies remain in the theoretical and simulation stages. Their methods of autonomous CA assume that the navigation environment is known, but the change in the navigation environment is a particularly important factor; whether these methods can be applied to the actual navigation environment remains to be considered and verified.

2. Most of the experiments assume that target ships maintain their speed or comply with the COLREGs. In actual sailing, target ships may violate the COLREGs. Only a small percentage considers the occurrence of this situation; however, the CA strategy of their experimental results does not conform to the COLREGs.

3. The navigation of intelligent ships is affected by very complex external environments, such as external wind, waves, currents, shallow-water effects, bank effects, and ship-to-ship effects, and it is difficult for current algorithms to fully simulate these complex environments and establish an accurate ship dynamic model and their environment model.

Based on the current state-of-the-art technologies available, the following solutions are proposed:

1. It is possible to conduct scene-dynamic modeling and risk analysis research on complex environments; simulate the effects of wind, waves, and currents; and evaluate an algorithm in combination with multi-ship encounters.

![Figure 10. Statistical analysis of decision constraint attributes in existing studies.](image-url)
(2) In an algorithm test, it is necessary to simulate the situation of target ships that do not comply with the rules, analyze the situation, and discuss the results. It is better to verify the autonomous CA algorithm and its strategy with a large number of automatically generated test samples to find out the performance boundary of the algorithm.

(3) The accuracy of a model significantly affects the results of the algorithm used. It is necessary to further study the ship-motion model under the influence of a complex external environment and combine deep learning and digital twin technologies to realize the autonomous control of a ship.

7. Conclusions

The proposed CA algorithms at present exhibit limitations in some cases, and it is necessary to use a variety of algorithm integration methods for different navigation scenarios:

(1) Deep learning can only obtain results based on a trained database, and it relies heavily on the accuracy of the database, which depends on the training model. Therefore, it can be combined with a CA model based on the APF, the A* algorithm, and other algorithms.

(2) Although MPC can control the course and speed simultaneously, it has significantly high requirements for the ship mathematical model, and the solution of the nonlinear objective function is also a significant problem. After adding constraints, the objective function can attempt to use a multi-objective optimization algorithm to derive the best decision.

(3) APF can effectively solve the path planning problem in a static environment. For real-time CA problems considering dynamic obstacles, only the relative distance between a ship and obstacles is typically considered, and it is easy to fall into local optimal problems. It can be combined with collision cones to identify risks, as well as with deep learning to train models to avoid local optimal problems.

In fact, the current literature does not lack methods of successful automatic CA under certain conditions, but there is a lack of research on how to achieve the same flexible CA decision-making and selection mechanism as human beings to cope with more complex environments in reality. This study collected and analyzed current methods and their internal policy selection and implementation mechanism related to ship CA decision-making. According to the autonomous CA action taken, it was divided into three strategies: alteration of course alone, alteration of speed alone, and alteration of both course and speed. Through the comparative research, the following conclusions are drawn:

(1) Steering avoidance can be used in any water area. For restricted waters, it is possible to take a large turn to avoid or to act early. In an emergency, combining turn and deceleration to avoid collision should be considered. The current study solves the problem through the simultaneous objective-function method and a hybrid algorithm of heading and speed changes. There are also other problems, such as CA actions that do not satisfy the requirements of the COLREGs, and the ship mathematical model is not sufficiently accurate.

(2) Regarding the autonomous CA strategy coupled with steering and variable speed avoidance, some scholars have made basic scenario assumptions and analyzed the effect of coupling avoidance. In fact, the scenarios encountered by ships are extremely complex, and the factors for judging danger should not only be the DCPA and TCPA, but the speed ratio of the ship and other factors should also be added. Research can be conducted on this aspect and provide a theoretical basis for the strategy selection of a ship’s autonomous CA.

(3) The selection of a CA strategy is closely related to the navigation environment, navigation rules, and ship maneuverability. It is necessary to combine these conditions to determine a selection mechanism for autonomous CA strategy with adaptive functions, which will significantly improve the autonomy level of smart ships.
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