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*Review*

# Review of Ship Behavior Characteristics in Mixed Waterborne Traffic

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**Abstract:** Through the continuous development of intellectualization, considering the lifecycle of ships, the future of a waterborne traffic system is bound to be a mixed scenario where intelligent ships of different autonomy levels co-exist, i.e., mixed waterborne traffic. According to the three modules of ships' perception, decision-making, and execution, the roles of humans and machines under different autonomy levels are analyzed. This paper analyzes and summarizes the intelligent algorithms related to the three modules proposed in the last five years. Starting from the characteristics of the algorithms, the behavior characteristics of ships with different autonomous levels are analyzed. The results show that in terms of information perception, relying on the information perception techniques and risk analysis methods, the ship situation can be judged, and the collision risk is evaluated. The risk can be expressed in two forms, being graphical and numerical. The graphical images intuitively present the risk level, while the numerical results are easier to apply into the control link of ships. In the future, it could be considered to establish a risk perception system with digital and visual integration, which will be more efficient and accurate in risk identification. With respect to intelligent decision-making, currently, unmanned ships mostly use intelligent algorithms to make decisions and tend to achieve both safe and efficient collision avoidance goals in a high-complexity manner. Finally, regarding execution, the advanced power control devices could improve the ship's maneuverability, and the motion control algorithms help to achieve the real-time control of the ship's motion state, so as to further improve the speed and accuracy of ship motion control. With the upgrading of the autonomy level, the ship's behavior develops in a safer, more efficient, and more environment-friendly manner.

**Keywords:** mixed waterborne traffic; ship behavior; ship autonomy; information perception; intelligent decision-making; execution

## 1. Introduction

With the continuous development and breakthrough of modern technologies in information, communication, sensors, and artificial intelligence, intellectualization has become an important development direction for waterborne transportation systems. Intelligent shipping is an emerging modern shipping industry state led by the deep integration of traditional shipping elements with modern technologies. From a global perspective, various countries are actively promoting research on intelligent vessels, with plans to have unmanned autonomous vessels in operation within the next decade. In June 2017, the International Maritime Organization (IMO) clarified that the Maritime Autonomous Surface Ships (MASS) is defined as a ship which, to a varying degree, can operate independently of human interaction [1]. In 2018, the fully autonomous ferry Falco, developed by Rolls-Royce and Finnish FinFerries, realized an automated voyage with 80 passengers on board. In September 2019, Nippon Yusen Kaisha (NYK) completed the world's first sea trial of a "manned autonomous ship", performing various tests under the latest IMO

Interim Guidelines for MASS trials. In December 2019, the maiden voyage of "Tendon 0" was taken in Zhuhai Dong'ao Island, which was China's first self-developed cargo ship with an independent navigation function [2]. Horizon 2020 [3], the biggest EU Research and Innovation program, has supported a range of intelligent shipping and intelligent ship-related projects, including the AUTOSHIP project [4], the NOVIMAR project [5], the MOSES project [6], and the AEGIS project [7]. The autonomous ships are also considered for the Arctic development of the Northern Sea Route [8].

However, the intellectualization of the waterborne traffic system cannot be quickly achieved. In 2020, the global commercial shipping fleet reached 99,800 ships of 100 gross tonnage and above [9]. The intellectualization of existing vessels is unlikely to be completed in a short amount of time—it requires a rather long process. According to the prediction by the World Maritime University, the proportion of remotely monitored autonomous ships would reach 15% by around 2040. In addition, IMO has divided the autonomy level of MASS into four classes, and ships can switch among different levels as required [1].

Level one: Ships with automated processes and decision support. The crew on board operates and controls the ship, while some operations can be automated and at times be unsupervised, but with crew on board ready to take control.

Level two: Remotely controlled ships with crew on board. The ship is controlled and operated from another location. The crew is available on board to take control of the shipboard system and functions.

Level three: Remotely controlled ships without crew on board. The ship is controlled and operated from another location, without crew on board.

Level four: Fully autonomous ships. The operating system of the ship is capable of making decisions and determining actions by itself.

Therefore, regardless of the current development stage of the intelligence of a waterborne traffic system, its future is bound to be a mixed system where intelligent ships of different autonomy levels co-exist, i.e., a mixed traffic scenario.

In the field of road traffic, mixed traffic is usually defined as the phenomenon of mixing different types of transport, which mostly involves motor vehicles, bicycles, and pedestrians interfering with each other [10]. With the development of autonomous driving technology, the hybrid traffic of manned and unmanned vehicles has gradually attracted research interest, such as the analysis of macroscopic hybrid traffic flow characteristics and the development of microscopic driving behavior models [11]. This paper focuses on microscopic ship behavior in mixed waterborne traffic scenarios, where ship behavior is usually defined as the mode and pattern of action of a particular class of ships. In existing studies, ship behavior generally refers to behavior such as path, speed, and course, etc. A solution framework to support situation awareness in a mixed environment is considered by Perera et al. [12]. The review on ship behavior established a generic behavior identification model, but which did not consider the behavioral differences of different ship types under specific external environmental constraints [13]. A behavioral clustering-based classification for harbor ships using Automatic Identification System (AIS) data is proposed in a subsequent study [14]. In the further research, the impacts of external factors on ship behavior considering changes in ship size is investigated [15].

So far, few researchers have investigated the ship behavior under mixed traffic scenarios. It is significant to extract the behavioral characteristics of various types of autonomous ships in mixed waterborne traffic scenarios and master the methods and rules of ship navigation and collision avoidance, which would enhance the navigation safety, reduce the navigation conflicts, improve the waterway capacity, and upgrade the level of waterborne traffic supervision.

This paper analyzes the roles of man and machine on different autonomy levels based on the three modules of "perception–decision–execution" and proposes a classification method for the ship autonomy level. The relevant intelligent algorithms on the three main modules in the last five years are analyzed and summarized. Starting from the algorithm

features, the behavioral characteristics of ships with different autonomy levels adopting the corresponding algorithms are further analyzed.

## 2. Research Method

In this section, the research method is introduced. A framework of intelligent ships illustrating the three modules is presented, based on which a classification of the ship autonomy level is proposed.

### 2.1. Basic Framework of Intelligent Ships

The intelligent ship is a huge and complex system, which involves theories and technologies in multiple fields, such as ship design and manufacturing, sensor techniques, intelligent decision-making, maritime communication, information fusion, etc. Generally, an intelligent ship system consists of three subsystems, namely an information perception system, decision-making system, and execution system, respectively. These three modules interact with each other, and the stability and reliability of any module will affect the final task execution efficiency and the ship safety. The inner relationship among subsystems of an intelligent ship system is shown in Figure 1.
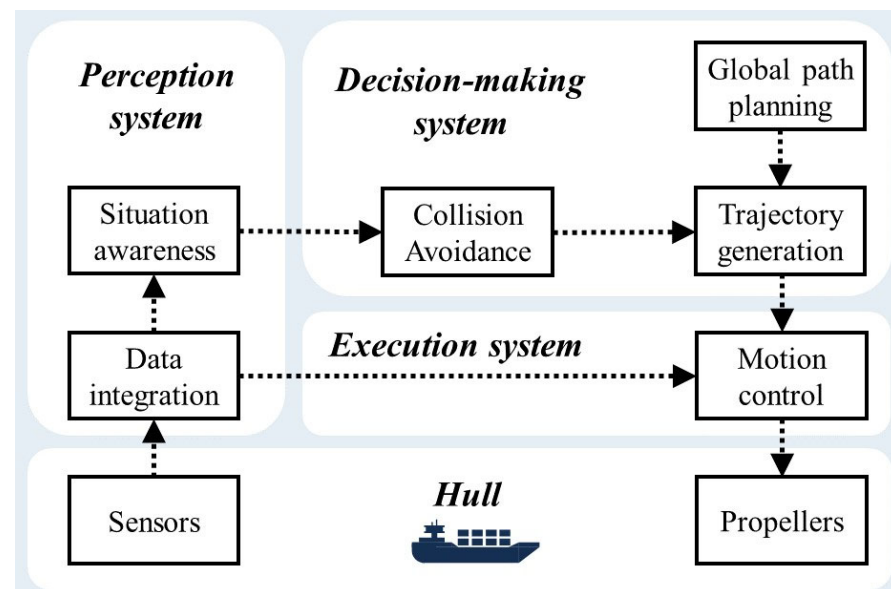


**Figure 1.** Illustration of subsystems within an intelligent ship system.

The perception system collects the information provided by various sensors and obtains the ship's situation awareness through information fusion techniques. Based on the ship's perceived situation, considering the requirements of global path planning and collision avoidance operation, the decision-making system generates the planned trajectory and transmits its instructions to the execution system. Finally, according to the instructions received and the fusion of sensor information, the execution system drives the main engine, propeller, rudder, and other devices. Afterwards, the execution results are fed back to the perception system through sensors to update the ship situation awareness information for next-step decision-making.

### 2.2. Autonomy Hierarchy

So far, several international authorities have announced their approaches of autonomous ship classification, which includes Lloyd's register of shipping (LR). On 8 July 2016, LR declared to divide the autonomy level of ships into seven levels, from AL0 to AL6. It was the first time classifying the ship autonomy level, and this classification method has also been widely adopted by the academic community. The classification standard for

autonomous ships issued by LR is presented in Table 1 [16]. This classification standard ranges from the ordinary ship without any independent function (AL0), to the human–machine joint decision-making system (AL1 and AL2), then to the autonomously navigated ship with onshore operator monitoring (AL3–AL5), and finally to the fully autonomous ship without manual operation (AL6).

**Table 1.** The ship autonomy classification standard by LR.

| Level | Description |
|---|---|
| AL0 | No automation function, manual navigation of a ship. |
| AL1 | On-ship decision support system, data available to crew. |
| AL2 | Off-ship decision support system, shore monitoring. |
| AL3 | Semi-autonomous ship with active human-in-the-loop where crew can intervene. |
| AL4 | Human-in-the-loop, the ship operates autonomously with human supervision. |
| AL5 | Fully autonomous ship with means of human control. |
| AL6 | Fully autonomous ship without the need for any human intervention. |

Afterwards, the Norwegian Forum for Autonomous Ships (NFAS), Danish Maritime Authority (DMA), Marine Autonomous Systems Regulatory Working Group (MASRWG), IMO, and other institutions successively proposed their classification standards of ship autonomy.

Based on the classification criteria of ship autonomy by the institutions, this paper proposes an autonomy classification method on the basis of the three modules of intelligent ships, "perception–decision–execution". The level of ship autonomy is determined by analyzing and comparing the involvement of humans and machines in each module. This paper classifies the ship autonomy into five levels: manual operation level, machine-aided level, remote-control level, onshore supervision level, and fully autonomous level, which are listed in Table 2 in detail.

**Table 2.** Classification of ship autonomy.

| | Perception | Decision | Execution |
|---|---|---|---|
| Manual operation | Manual | Manual | Manual |
| Machine-aided | Human-in-the-loop (On- and off-board data) | Human-in-the-loop (On- and off-board data) | Manual |
| Remote-control | Human supervision (Broad level) | Human supervision (Broad level) | Human supervision (Broad level) |
| Onshore supervision | Rarely supervised | Rarely supervised | Rarely supervised |
| Fully autonomous | Unsupervised | Unsupervised | Unsupervised |

The correspondence between the proposed classification method and the methods used by other institutions is presented in Table 3. Manual operation level refers to the ordinary ships whose perception, decision-making, and execution are completed manually, corresponding to AL0 by LR, AAB by NFAS, and AL0 by MASRWG. Compared to the manually operated ships, machine-aided ships have improved the participation of machines in the perception system to realize the automatic acquisition of information at both ends of the ship and shore. This way, the crew can make navigation decisions using such information. From remote-control ships to fully autonomous ships, there are no crew on board. As the autonomy level increases, the human intervention on the ship control gradually diminishes. The machines would gradually replace the role of humans to control the ship operation. Eventually, the full autonomy of the ship is achieved, corresponding to the highest level defined by other institutions.

**Table 3.** Correspondence table for ship autonomy criteria.

|                     | LR        | NFAS | IMO/DNA | MASRWG   |
|---------------------|-----------|------|---------|----------|
| Manual operation    | AL0       | AAB  |         | AL0      |
| Machine-aided       | AL1, AL2  |      | M       |          |
| Remote-control      | AL4       |      | RU      | AL2, AL3 |
| Onshore supervision | AL5       | PUS  |         | AL4      |
| Fully autonomous    | AL6       | CUS  | A       | AL5      |

The manual operation level refers to the ships not equipped with any navigational aids, which have been gradually phased out from the market. Currently, the majority of operating ships are at the machine-aided stage, which aims at safer navigation via the assistance of machines. The research and development of unmanned ships are mostly at the remote-control stage, yet limited to the small-size ships. In November 2020, the British company SEA-KIT remotely commanded the Unmanned Surface Vessel (USV) "Maxlimer" through three satellites to complete a 22-day exploration mission [17]. The Yara Birkeland, the world's first zero-emission, fully automated container ship developed by the Yara Group in cooperation with the Kongsberg Group, started its maiden voyage in November 2021 [18]. This ship is expected to come into commercial operation carrying humans from 2022. Starting with a two-year technical test period, the ultimate goal of the ship is to achieve fully autonomous navigation.

## 3. Characteristics of Intelligent Algorithms

To research the behavior of autonomous ships, this section describes the three modules of perception, decision-making, and execution of a ship in detail. Besides the explanation of the module-related intelligent algorithms, a set of evaluation criteria are introduced for each type of algorithm to compare the characteristics. The possible limitations are discussed at the end of the introduction of each part.

### 3.1. The Perception System

3.1.1. Information Perception Technology

The information perception system includes perception sensors and information fusion techniques. It obtains the information about the ship's own state and the environment that the ship is in. By identifying the ship's situation, the perception system provides a data basis for collision avoidance and path planning, which is expected to lead to safer and more reliable navigation. The information on the ship's own state includes the position, speed, course, and other navigational information, as well as the information on the operational state of the equipment systems and the state of the carried cargo. The environmental information refers to the meteorological and hydrological conditions, and the status of surrounding vessels and obstacles. Depending on the type of equipped sensors, the intelligent ship information perception technologies can be distinguished in the following four categories.

1. Radar-based information perception technology

Radar is an essential sensor in the maritime field. The perception is mostly in the form of processing of radar images and signals. This category of equipment includes the ultrasonic radar, millimeter-wave radar, continuous-wave radar, etc. Radar has high resolution and accuracy, and can be used in all-weather and wide-area detection. However, there are also certain limitations: the detection of radar is susceptible to weather conditions, and the radar images often suffer from problems such as noise interference, uneven brightness, target loss, etc. [19].

2. Lidar-based information perception technology

Light Detection and Ranging (Lidar) works in a similar way to radar. It is mainly used for purposes of target detection and obstacle avoidance. Achtert et al. combined Doppler

radar with a steady-motion platform to measure the atmospheric wind profiles [20]. The results show that the data coverage of this method is comparable to that of land-based measurements. However, this method provides a more detailed and higher temporal resolution view of atmospheric boundary variability, compared to the radiosonde measurements. Compared to radar, Lidar has a higher range accuracy and stronger anti-interference capability, but the detection range is smaller.

3. AIS-based information perception technology

AIS, as an important tool for the perception of waterborne traffic information, provides a complementary source of data to radar, since it has no dead zone. However, this method only applies to vessels equipped with AIS transponders. Thus, AIS cannot be taken as the only form of information perception for intelligent ships. Prasad et al. utilized AIS data and multi-sensor information to augment the data from weather sensors, which can be applicable for the control and navigation of ships in foggy weather or other restricted-visibility conditions [21]. Zhou et al. developed a regression model using AIS data to quantify the impacts of wind and current on ship behavior without the input of specific ship maneuvering details [15]. Regarding the data quality, the current AIS data mostly contain errors and data loss, which may lead to wrong or at least incomplete information acquisition.

4. Vision-based information perception technology

Vision sensors acquire the image information of the surrounding environment by machine vision and process the captured images to achieve environmental perception. Wang et al. proposed a framework for automatic detection and localization of USV real-time targets based on binocular vision [22]. It extracts and matches the features within a target area determined by a deep convolution network. Then, the target is localized using the calibrated binocular camera parameters in the triangulation measurement principle. The experimental results proved the delivery of both accurate detection and high-precision positioning results in real-time applications. Currently, vision sensors would be the cutting-edge method to perceive the surrounding information. However, to achieve a full overview of the surroundings, a sophisticated sensor system is needed, which possibly implies a high risk of machine failure.

3.1.2. Risk Perception Method

Intelligent ships rely on sensors to obtain basic information, apply information fusion techniques to judge the ship's situation, and estimate the collision risk. There have been a number of studies on the risk analysis or assessment of ship collision. Some researchers tend to indicate the risk as a numerical index, such as the Minimum Safety Passing Distance (MSPD) [23,24] and the Collision Risk Index (CRI) [25–29], which is deemed as a numerical form of risk. Whereas, the other way to reflect risk is in two-dimensional graphics, such as Ship Domain (SD) [30–33], dangerous region (DR) [34–36], and action lines (AL) [37,38].

The MSPD method usually provides a deterministic result of a collision event in the given scenario, i.e., occurrence or non-occurrence. The premise is that when both the own ship (OS) and the target ship (TS) keep their course and speed, if the Distance at the Closest Point of Approach (DCPA) is smaller than the MSPD, a collision occurs. On the contrary, OS can safely pass TS. This method has been widely adopted for manned and unmanned ships [23,24]. In addition, the MSPD is also an essential risk indicator in CRI calculation [39].

The assessment of ship collision is influenced by multiple factors, such as ship speed, course, distance to TS, speed ratio, and meteorological and hydrological conditions, etc. Besides, the presence of sensor errors also leads to the uncertainty of the collision process. The CRI measurement provides an exact value of the threat level, which is an intuitive indicator of the collision risk. The current main CRI measurement methods include the DCPA and the Time to the Closest Point of Approach (TCPA) weighting methods [25,26], fuzzy logic algorithms [27], and neural networks [28]. When using the weighting method to measure CRI, the different dimensions of DCPA and TCPA are usually ignored, which

makes the calculation result inaccurate. In addition, in the multi-ship situation, it is impossible to objectively reflect the threat level of each ship. Fuzzy logic methods are quite subjective when calculating CRI, and can only be applied in certain specific scenarios. Neural network algorithms require a substantial storage of expert experience and knowledge in advance and plenty of sample learning. Thus, this algorithm cannot satisfactorily fulfill the instantaneity requirement of CRI.

SD is a graphic depiction of the ship collision risk, which is usually a group of areas around OS to visualize the risk. When TS enters or is about to enter the area, a collision alert is triggered. Szlapczynski et al. defined two SD-based safety parameters: Degree of Domain Violation (DDV) and Time to Domain Violation (TDV) [30]. The results show that the accuracy of DDV/TDV is higher than that of the DCPA/TCPA. Qiao et al. developed a quadratic ship domain model considering the uncertainty of ship position and proposed a method to calculate the spatial collision risk, which had been improved in further applications [31]. Some researchers assess the collision risk by developing new SD models. Bakdi et al. developed an adaptive SD model for risk identification through a spatial risk function based on the type of encounter situation and collision hazard [32]. The results showed competitive advantages in terms of intuitiveness and computational efficiency. Aiming at the shortage of including single factors in SD in previous studies, Guan et al. established an SD model based on fuzzy logic considering multiple variables [33]. The obtained results support the decision-making of collision avoidance and early prediction of collision risk. However, the calculation of this method is complex, and not suitable for risk identification in the case of multi-ship encounters.

The DR is designed to collect a set of OS's speed or course that leads to a conflict with TS and display this set of speed or course to the Officer on Watch (OOW) in a graphical form. Velocity Obstacle (VO) is a typical algorithm in this category. It is capable of seeking out the optimal collision-free solution in two-ship and multi-ship encounter scenarios [34], considering ship dynamics [35] and maneuverability [36].

The method of AL focuses on identifying a line of action around OS in geographic space, which indicates the final timing of OS to complete collision avoidance through a series of actions. AL is usually obtained by simulations. Szlapczynski et al. determined AL by a series of simulations of various types of ship encounters under different conditions using a hydrodynamic model of ship movement [37]. Namgung et al. established an adaptive neuro fuzzy inference system to judge the CRI of the optimal position and timing [38]. The system ensures that the OOW has sufficient time to make decisions and take the necessary actions of collision avoidance.

Based on the manifestations of the risk perception methods presented above, the models referred by literature research are summarized in Table 4.

**Table 4.** Overview of ship risk perception methods and the application of corresponding models.

| Category | Abbreviation of Method | Description | Model Applications in the Literature |
|---|---|---|---|
| Numerical | MSPD | Provide deterministic results of collisions by comparing the distance between ships and the size of MSPD. | [23,24] |
| | CRI | Assign weights to influencing factors to calculate the probability of a collision occurring. | [25–29] |
| Graphical | SD | Deemed to be a risk of collision when TS enters or will enter SD. | [30–33] |
| | DR | Collect the set of speeds or courses that cause the OS to conflict with the TS, then displays the set in the image to the OOW. | [34–36] |
| | AL | The final time for OS to take evasive action to avoid a collision | [37,38] |

Among the risk perception methods, the number of models adopting CRI and SD is the highest. Only a few models apply the method of MSPD, DR, and AL. MSPD can be deemed as a basis for the calculation of CRI, while DR and AL can provide decision-making support for ship collision avoidance on the basis of SD display. In the future, more models adopting DR and AL can be developed for collision risk perception purposes.

When the collision risk is indicated in a numerical form, it can be intuitively compared. A higher value indicates higher risk, and vice versa. For intelligent ships, risks in the numerical form are easier to involve in the system control link, and provide an informative basis for intelligent decision-making. In the multi-ship encounter situation, the graphic expression of risk allows to intuitively divide TSs into several groups defined by graphical indicator, SD, DR, or AL. However, in such a form, the risks of TSs in each group still cannot be further compared. The graphic form is indeed more intuitive for the operator, which can be integrated into the map to support the OOW in obtaining an overview of the surrounding situation. To make full use of the advantages of both methods, a risk perception platform with integrated collision risk digitalization and visualization can be considered in the future. It is expected to more efficiently and accurately perceive the risks.

In current navigation practice, the collision risk can be assessed with the assistance of some techniques and systems on board. However, for manned ships, the OOW mostly tends to judge the risk by good seamanship and situational awareness, considering the perceived information from the assistance system, instead of directly adopting the indicated risk result. Thus, the risk perception result still largely depends on the experience, knowledge, and skills of the crew. However, it is difficult for OOWs to maintain good situational awareness and precautions when simultaneously monitoring multiple ships. For intelligent ships, the collision risk can be monitored in real-time via reliable and timely identification of obstacles by sensors and information fusion techniques.

Most of the risk perception models are based on AIS data. Generally, the uncertainty of trajectory data is not considered. Besides, there could be some special circumstances when the AIS equipment is off, or the signal transmission fails. In such a situation, AIS data are no longer available, let alone the data accuracy. These facts lead to the error between the theoretical research and the reality. In the future, it is necessary to introduce parameters of uncertainty when developing risk perception models to consider the corresponding impacts and integrate alternative methods without AIS data as mandatory input.

### 3.2. The Decision-Making System

An intelligent decision-making system involves various techniques, such as path planning, risk conflict detection, intelligent collision avoidance, energy efficiency management, etc. It can continuously generate smooth and feasible optimal paths based on the perception system information, mission requirements, and environmental status. Afterwards, the system sends the decision command to the execution system. In the system, path planning and intelligent collision avoidance are the core techniques in the field of unmanned ships. Path planning aims to find out the collision-free paths on the map considering static obstacles, while intelligent collision avoidance focuses on avoiding collisions with dynamic or unknown obstacles. Six groups of ship collision avoidance techniques for decision-making are identified, which are introduced as follows [40].

Rule-based (RB) methods use a set of pre-defined rules to guide collision avoidance. One approach is to incorporate the International Regulations for Collision Avoidance at Sea (COLREGs) and good seamanship into the rule system. The system is able to propose rule-compatible operations for OS in various scenarios, which are usually based on fuzzy logic [41–43] and neural network algorithms [42]. Since it is impossible to enumerate all rules for all scenarios, the method can only provide collision avoidance guidance for specific scenarios.

Virtual vector (VV) methods obtain the ship's motion by generating a virtual vector field, in which the Artificial Potential Field (APF) method is the specific algorithm. Lazarowska introduced a method to solve the planning of a safe path, using a discrete APF

and path optimization algorithm to calculate an optimized collision-free trajectory. The solution is conflict-free, but may not be optimal [44].

The methods of discretization of solutions with collision check (DSCC) discretize the solution space of collision avoidance and eliminate the dangerous solution via collision detection. Then, the collision-free solution is selected from the rest. The typical algorithms include the Dynamic-Window (DW) algorithm, the discrete input optimization (DIO) algorithm, etc. Serigstad et al. proposed a Hybrid Dynamic-Window (HDW) algorithm as a reactive collision avoidance method to improve the trajectory planning when approaching an obstacle [45].

Continuous solutions with collision constraints (CSCC) methods formulate collisions as constraints and find collision-free solutions in a continuous solution space. The approach uses polygons or circles to represent obstacles for collision detection and then applies certain algorithms to calculate a set of control inputs that lead to collisions, such as the VO algorithm [34,46], Vision Cone (VC) [47], etc. Accordingly, the optimal collision avoidance solution can be acquired. Another approach is to use collision detection as a constraint in the optimization to obtain a collision-free solution. A typical algorithm is the Model Predictive Control (MPC)-based collision avoidance [48], which provides a solution at minimum cost.

Re-planning (RP) methods transform the collision avoidance problem to a path planning problem by searching for the collision-free paths in the free configuration space. Two groups of algorithms are found. One group relies on graph searching methods, such as the Fast Marching Method (FMM) [49] and Particle Swarm Optimization (PSO) [50]. The other directly uses evolutionary algorithms to find paths, such as Ant Colony Optimization (ACO) [51], etc. The obtained path does not directly depend on the graphical map.

The presented algorithms found in the literature are usually adopted in a combined way in maritime practice to perform collision avoidance, which is a hybrid of algorithms (HA). Chen et al. proposed a Time-varying Collision Risk-based Fast Marching Square (TCR-FM2) algorithm that combines FM and VO for path planning of autonomous vessels [52].

Table 5 lists the classification of the collision avoidance methods together with brief descriptions.

**Table 5.** Classification of intelligent collision avoidance methods during decision-making.

| Abbreviation of Methods | Description |
| --- | --- |
| RB | Adopt pre-defined rules to guide collision avoidance. |
| VV | Determine the ship's motion by generating a virtual vector field. |
| DSCC | Search the discrete solution space and find a collision-free solution or an optimal solution. |
| CSCC | Formulate collisions as constraints and find the optimal solution in continuous space. |
| RP | Transform the collision avoidance problem to a path planning one and search for a collision-free path in the free configuration space. |
| HA | Combine some of the above-mentioned methods. |

Looking into the collision avoidance decision models in the literature, two types of behavioral features are extracted: decision-making category and decision-making preference. The decision-making is classified into three categories by a decrease of the randomness: large operation, small operation, and trajectory. Large operation refers to the operation of only steering to portside or starboard as the decision, which involves much randomness and probably leads to low accuracy and efficiency of ship collision avoidance. Small operation changes the specific rudder angle or other operations with less randomness as the decision, which improves the accuracy and efficiency compared to the large operation. The trajectory is a series of operations including course alteration and speed change in the form of a path to realize the optimal collision avoidance result. The decision preference is divided into three types: course alteration, speed change, and a combination of both, which reflects the collision avoidance operations by an increase of complexity. The combination mode refers to the operation of continuous course alterations and speed changes within a period

of time. According to the intelligent decision algorithm categorization, the decision-making category, and the type of decision-making preference, the behavioral characteristics of the intelligent decision-making process of the referred models in the literature are summarized in Table 6.

**Table 6.** Overview of the behavioral characteristics of the intelligent decision-making process in the models in the literature.

| Model | Decision-Making Algorithm | Decision-Making Category | | | Decision-Making Preference | | |
|---|---|---|---|---|---|---|---|
| | | Large Operation | Small Operation | Trajectory | Course Alteration | Speed Change | Combination |
| [27] | RB | | √ | | | | √ |
| [40] | CSCC | | √ | | | | √ |
| [41] | RB | √ | | | √ | | |
| [42] | RB | √ | | | √ | | |
| [43] | RB | | √ | | √ | | |
| [44] | VV | √ | | | √ | | |
| [45] | DSCC | | | √ | | | √ |
| [46] | CSCC | | √ | | | | √ |
| [47] | CSCC | | | √ | | | √ |
| [48] | CSCC | | | √ | | | √ |
| [49] | RP | | | √ | | | √ |
| [50] | RP | | √ | | | | √ |
| [51] | RP | | | √ | | | √ |
| [52] | HA | | | √ | | | √ |
| [53] | DSCC | | √ | | | | √ |
| [54] | DSCC | | √ | | | | √ |
| [55] | DSCC | √ | | | √ | | |
| [56] | HA | √ | | | | | √ |
| [57] | DSCC | | √ | | √ | | |
| [58] | RP | | | √ | | | √ |
| [59] | HA | | | √ | | | √ |
| [60] | HA | | | √ | | | √ |
| [61] | RP | | | √ | | | √ |

Abbreviations: RB: rule-based; VV: virtual vector; DSCC: discretization of solutions with collision check; CSCC: continuous solutions with collision constraints; RP: re-planning methods; HA: hybrid of algorithms.

The behavioral characteristics of the decision-making methods are summarized as follows. The RB method mainly adopts the operation of course alteration to fulfill collision avoidance, and seldom concerns trajectory planning. It is probably due to a lack of quantitative analysis of the predefined rules in the RB method. The VV method performs the collision avoidance operation mainly by determining the magnitude of altering course. The CSCC method adopts the operations with less randomness as the decision and always combines the operation of course alteration and speed change to realize the precise execution of the collision avoidance action. However, the DSCC method has a wider range of decision types and preferences. The RP method always guides the collision avoidance operation via planned trajectories. The HA method also tends to take a reasonable collision avoidance trajectory as the decision.

Most intelligent decision-making algorithms adopt operations with small randomness, such as a specific course change or planned trajectory, as collision avoidance decisions. In terms of decision-making preference, the operations with high complexity are preferred for collision avoidance, being the combined manner. As can be seen from Table 6, no model solely relies on speed change to accomplish collision avoidance, which is probably because of the large inertia of the ship. However, it does not mean that the option with only speed change can never work. In special circumstances when course alteration is restricted, speed change can be an alternative.

Currently, the decision-making of collision avoidance for the manned ships mostly relies on the empirical knowledge. From the perspective of navigation practice, the obtained decision scheme should satisfy the four principles of "early, large, wide, clear" required by COLREGs, but with the efficiency often ignored. There is a lack of standardized machine-language-based framework rule interpretation. Thus, for specific encounter situations, COLREGs and other navigational guidance cannot provide quantitative support for the judgment. However, the application of decision-making algorithms could be a solution to these problems. Improving the existing algorithms and considering more constraints to reach more efficient and reasonable decision-making capabilities would be an important research and development direction in the future.

### 3.3. The Execution System

The core objective of the execution system is to generate the appropriate control variables at the proper timing in cooperation with the information perception system and the decision-making system to achieve the expected execution result within the capability of the ship actuator. The main function of this system is to perform the operational motion control of the intelligent ship. The main task is to ensure that, during the sailing along the optimal planned path, two subgoals can be achieved. On the one hand, the intelligent ship can avoid collision with the surrounding static and dynamic obstacles. On the other hand, the instances of course alteration and speed change can be as few as possible.

The execution system includes two parts: the power control unit and the motion control algorithm.

### 3.3.1. Power Control Unit

The power control unit consists of a propulsion unit and a course control unit. The common ship propulsion modes include diesel propulsion, water jet propulsion, electric propulsion, etc. The course control is usually fulfilled by rudder and steering engine equipment.

The marine diesel engine has been widely used in the field of ship propulsion, since it is economical, easy to start, and has high thermal efficiency. The ship propulsion system is composed of the main engine, transmission device, shaft system, propeller, etc. The operating principle is to transmit the power from the main engine to the propeller via the transmission device and shaft system, which completes the mission of propelling the ship. However, this system still has some shortcomings, e.g., complex structure, large space occupation by the shaft system, low transmission efficiency, loud noise, frequent equipment failure, etc. These disadvantages drive the attention toward more advanced water jet propulsion systems and electric propulsion systems.

Water jet propulsion uses the water pump as the ship propeller, which propels the ship via the reactive force of the water jet from the pump. This method has good maneuverability and flexibility, strong adaptability to different working conditions, and low resistance. Thus, it has been more widely applied in high-speed and high-performance ships. However, there still exists some disadvantages, such as low propulsion efficiency at low speed, easy inhalation of debris at the water inlet, complicated maintenance, etc.

The electric propulsion system consists of the prime motor, electric generator, electromotor, control equipment, and propeller. The prime motor converts mechanical energy to electric energy, which is transmitted to the propeller via the electromotor. The electric energy is converted to thrust energy to propel the ship. Pod propulsion and shaftless rim-driven thruster are the two cutting-edge propulsion methods, both of which have the advantages of flexible arrangement, rapid response, convenient maneuvering, adaptive flexibility, and high reliability. They will be optimal alternatives for future intelligent ocean ships.

The currently operating ships generally adopt a combination of follow-up and automatic rudder as the steering engine, which can be freely switched between themselves. The follow-up rudder controls the ship via the helmsman's steering, while the automatic rudder realizes the purpose of keeping stable or altering course according to the instructions from

the automatic navigation system. In this way, the workload of manual steering can be reduced, and the accuracy of the path control can be guaranteed.

### 3.3.2. Motion Control Algorithm

The ship motion control algorithm is the core technique of the execution system. By integrating factors such as navigation, weather, route information, and ship maneuverability, the algorithm can derive the course or rudder angle command as required. Accordingly, the ship can be controlled to sail along the planned path. In this way, it is expected to reduce the workload of the crew, save energy consumption, and improve navigation safety. PID control is widely used in engineering practices because of its simple structure and few adjustment parameters. However, the traditional PID algorithm cannot handle the uncertainty problem well. To compensate for the disturbances caused by environmental factors, control algorithms, such as adaptive PID [62], adaptive MPC [63–66], and adaptive dynamic surface control [67,68], have been gradually applied to ship control. With the development of modern control theory, intelligent algorithms, such as sliding mode control (SMC) [69], backstepping [70–75], fuzzy control [76], and neural network [77–80], are also widely adopted in the field of ship control.

This section analyzes the characteristics of ship behavior in the scenarios with the control algorithm applied, including the error convergence rate and path control accuracy. The error convergence rate refers to the time when the ship's tracking error converges to zero or an acceptable range, and can be further categorized into straight-line tracking and curve tracking depending on the tracking trajectory. The path control accuracy refers to the error between the ship's trajectory and the planned path. It is used to quantitatively evaluate the performance of path tracking, including tracking error, yaw error, and Integral Absolute Error (IAE). Table 7 summarizes the characteristics of the ship behavior using the control algorithm.

**Table 7.** Classification of intelligent collision avoidance methods during decision-making.

| Model | Error Convergence Rate | Path Control Accuracy | | |
|---|---|---|---|---|
| | | Tracking Error | IAE | Yaw Error |
| [62] | 15 s | T: 0.032 m | | |
| [63] | 35.5 s | T: 0.495 m | | |
| [64] | L: 29.52 s; C: 167.25 s | | | |
| [65] | L: 9 s; C: 50 s | | | |
| [66] | | T: 0.7603 m | | |
| [67] | 163 s | | T: 81.7 | |
| [69] | | | T: $1.1 \times 10^3$ | |
| [70] | 200 s | 0 | | |
| [71] | 48 s | 0 | | |
| [72] | 20 s | 0 | | |
| [73] | | H: 0.4805 m; V: 0.4784 m | | |
| [74] | 20 s | arbitrarily small error | | |
| [75] | 10 s | | | |
| [76] | | | | 2.27° |
| [77] | | T: <1 m | | |
| [78] | | | H: $1.11 \times 10^3$; V: $0.93 \times 10^3$ | |
| [80] | | | | 0.39° |

Abbreviation: L: line; C: curve; H: horizontal direction; V: vertical direction; T: total value without direction specification.

In the simulation experiments, most control models can keep the tracking error within 1 m or even zero, which achieves good path control results. However, the quantification criteria of control accuracy are different. A unified quantitative indicator of the path control accuracy can be defined to further evaluate the model performance.

The problem of the error convergence time of control algorithms is not addressed in some studies, while instantaneity is the essential requirement of the control algorithm.

Thus, it is necessary to develop the ship motion control model under the premise of real-time control.

The present manned ships mostly rely on manual operation of the engine and rudder to realize ship motion control. There is always a time delay from the order by OOW to the execution of equipment. For intelligent ships, certain improvements are expected in execution time and execution accuracy due to the improvement of execution equipment and the application of control algorithms.

## 4. Ship Behavior on Different Autonomy Levels

In this section, the behaviors of autonomous ships at the different autonomy levels described in Section 2 will be individually evaluated using the algorithm characteristics introduced in Section 3. The ship behaviors at different autonomy levels during collision avoidance have been qualitatively illustrated for an intuitive comparison.

### 4.1. Manual Operation Level

In the process of information perception, decision-making, and execution, the quality of navigation of ships at the manual operation level completely depend on the crew's expertise and skills, which makes it difficult to be guaranteed.

In terms of information perception, the crew mainly obtains environmental information via their visual and auditory senses, which has low reliability due to the limited observation range and the high possibility of interference by external factors. As for collision avoidance decisions, the crew refers to COLREGs and local rules and applies their experience and expertise for collision avoidance operation. However, COLREGs only define basic behavior principles in specific encounter scenarios without detailed quantitative instructions to support situational assessment, which can hardly be directly applied in decision-making. Moreover, the pursuit of efficiency and economy is neglected as well. Regarding the execution, the huge intrinsic inertia and the random interference by the environmental factors make the ship motion control difficult. For ships at the manual operational level, the execution is usually poorly performed in terms of accuracy and stability control.

Figure 2 illustrates the operation of a manual operation level ship in a collision avoidance scenario. When approaching an obstacle or an oncoming ship and starting the actions, there is a time delay mainly composed of the reaction and decision time of the OOW and the response time of the execution equipment. To reach the purpose of safe navigation, the ship usually follows the safety principle in such a scenario, adopting a large turning angle. To use as little steering effort as possible, the ship normally sails in a straight line and resumes to the original course after being "past and clear", as suggested by COLREGs.
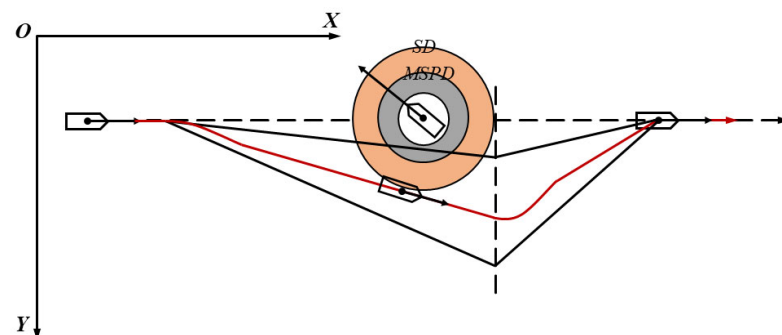


**Figure 2.** Illustration of the collision avoidance process of a ship at the manual operation level. The red line represents the collision avoidance path decided by the OOW, while the area between the two black lines shows the distribution range of the positions of ships.
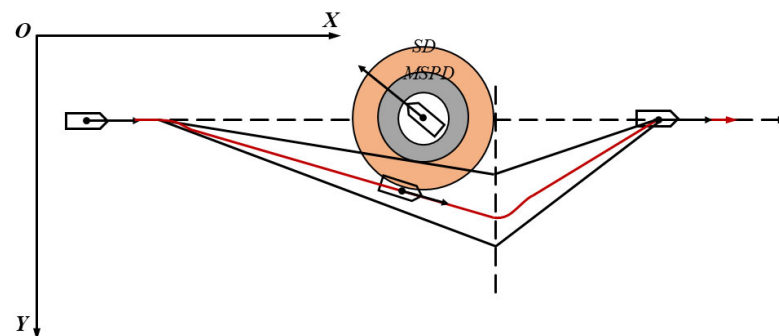
### 4.2. Machine-Aided Level

Ships at the machine-aided level realize the automation of some specific functions with the assistance of machines, such as automatic course tracking. However, crews are still needed on board to complete the full sailing operations. The vast majority of ships currently in operation are at this autonomy level.

Based on the perception systems of the previous level, the machine aids such as AIS and Radar are added to have a broader monitoring range and higher information perception efficiency. For example, the application of maritime radar and AIS can acquire information about the surrounding environment nearly in real time. The ships at the machine-aided level complement the manual operation level in decision-making by providing other applicable alternatives of operations. On the aspect of execution, some navigation operations are also automated. For instance, the automatic rudder is used to keep the course stable, which reduces the workload of manual steering.

Despite the machine assistance, ships at this level are essentially manually operated and unable to respond to changes of environment and situation as quickly as high-autonomy ships. Time delays due to human factors still exist, as well as for the equipment execution. Secondly, there are also deficiencies in the trajectory control accuracy and energy efficiency management. The real-time control of speed and course is difficult to be realized, too. However, in comparison with ships of manual operation, the ships at the machine-aided level have improvements in time delay (shorter time delay) and track control accuracy (smaller distribution range), which enhances the navigation safety, as shown in Figure 3.



**Figure 3.** Illustration of the collision avoidance process of a ship at the machine-aided level.
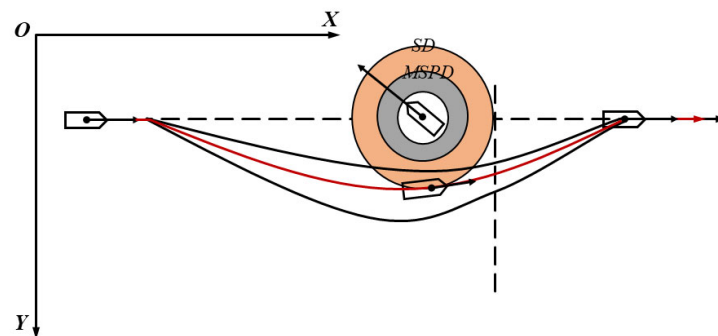
### 4.3. Remote-Control Level

Before the maturity of fully autonomous navigation technology, the autonomous ships cannot meet the maneuvering requirements of navigation safety under the circumstances of complicated waters, bad weather, or equipment damage. Thus, a remote-control center is necessary to ensure the operation safety by remotely switching to manual control. In normal circumstances, the ships at this level can operate autonomously under the monitoring of the control center. Currently, the research on unmanned ships is mainly at this stage.

The remote-control ship returns the perceived environmental information and ship status to the control center. By applying the information fusion techniques using multi-source sensor data and the display technique of Mixed Reality (MR), the visualized remote interaction with intelligent ships can be realized.

The remote intelligent decision-making system applies the intelligent decision-making algorithms to realize the intelligent design and real-time optimization for the ship's navigation, which makes the optimal decision of the next-step action for the autonomous ship. Such a decision mostly considers the requirements of both safety and efficiency. The decision-making process is carried out under the monitoring of the control center, which requires the validity and completeness of information transmission between the remote-control center and the ship. In most waters, the ship–shore communication relies on satellite communication, which has the defects of vulnerability to interference by

weather conditions, small communication bandwidth, and a long communication time delay. Besides, the decision-making time and quality of the person in charge in the control center is negatively affected due to the quality of the received information. Thus, when the autonomous ship sails in the above-mentioned extreme situations, the uncertainty of navigation will increase. Considering all influencing factors of humans and machines, higher uncertainty would lead to higher risks of navigation safety.

Ships at this level are usually equipped with a multi-directional power propulsion system, applying a motion control algorithm in cooperation with the dynamic positioning technique. It effectively improves the accuracy of ship motion control and maneuverability, which also enables the intelligent control of course and trajectory in open waters. Compared with the current operating ships, it shows obvious advantages in control accuracy and collision avoidance efficiency. A similar case for a ship at this level is illustrated in Figure 4.
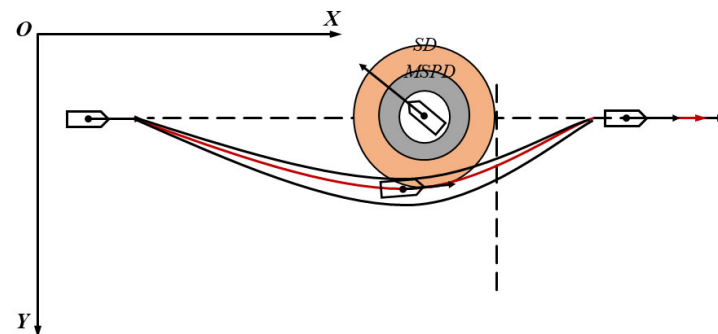


**Figure 4.** Illustration of the collision avoidance process of a ship at the remote-control level.

### 4.4. Onshore Supervision Level

In comparison with the ships at the previous level, the ships under onshore supervision have stronger autonomous control and scenario adaptability. It allows effective collision avoidance control in waters with complex traffic conditions and during berthing and unberthing phases, which means all-water collision avoidance and autonomous berthing and unberthing. The main function of the control center is transformed to supervise the operation of the ship, but still with the right to intervene in the high-impact decisions.

The ship at this level sails autonomously under the supervision of the onshore control center. Under the premise of energy efficiency management, it is capable of autonomously making decisions in scenarios such as dense traffic, bad weather, berthing and unberthing, navigation optimization, etc. It uses the power control unit and motion control algorithms to effectively release the manual workload and improve the working environment, which fundamentally reduces the influence of human factors on the navigation safety of ships. The illustrated path for the onshore supervision ship is presented in Figure 5.



**Figure 5.** Illustration of the collision avoidance process of a ship at the onshore supervision or fully autonomous level.

*4.5. Fully Autonomous Level*

The fully autonomous ship no longer requires the continual supervision of the control center. The intervention only occurs in cases of emergency or at the request of the system. Its behavior performance is almost the same as the ship at the onshore supervision level, as shown in Figure 5.

*4.6. Discussion*

With the continuous development of the ship's intellectualization, intelligent ships at different autonomy levels will be put into operation in succession. However, in the current research on ship behavior, the differences among ships are only distinguished by manned and unmanned ships. The autonomy differences among intelligent ships are seldom considered. Research on ship behavior at different autonomy levels can be conducted in the future.

The research on ship behavior usually adopts simulation results based on collected or given data, generally irrespective of the possible existence of external data sources. This leads to errors when applying intelligent algorithms. In the future, it is necessary to consider the uncertainty of parameters in the study of ship behavior under the undefined influences.

**5. Conclusions**

With the continuous development and breakthrough of modern technologies in information, communication, sensors, and artificial intelligence, various countries have been actively promoting the research of intelligent ships. The ships are continuously developing towards intellectualization, to eventually become unmanned. However, the intellectualization of the whole waterborne traffic system cannot be quickly achieved, and is bound to be a hybrid system with intelligent ships at different autonomy levels co-existing. Therefore, it is important to investigate the ship's behavior under the mixed traffic scenario and master the methods and principles of ship navigation and collision avoidance to improve the navigation safety, reduce the navigation conflicts, improve the waterway capacity, and upgrade the maritime traffic supervision level.

This paper identified the three modules of the intelligent ship system, i.e., information perception, decision-making, and execution control. For each module, the currently adopted methods were analyzed. Based on the proposed classification of ship autonomy level, the behavioral characteristics of various types of autonomous ships were compared and discussed. For information perception, risk can be judged in a combined form of numerical indicators and visual graphics by applying data fusion techniques using multi-source ship sensor data. It enables the ships to evaluate their own situations in complex surroundings. In terms of decision-making, the researchers proposed intelligent algorithms to provide the optimal collision avoidance decision considering the ship's motion characteristics under the premise of energy efficiency management. Regarding execution, the studies adopted new power control unit and motion control algorithms to optimize the results of ship behavior control. It can be seen that as the level of ship autonomy upgrades, human functions in the three modules of perception, decision-making, and execution are gradually replaced by machines. The interaction between humans and intelligent systems is becoming more and more frequent.

Promoting autonomous shipping is not just a matter of continuing the existing research on manned and unmanned ships (machine-aided and full autonomy) but filling the blanks (remote-control and onshore supervision) between them. Specifically, rendering unmanned ships more operator-friendly and exploring more functions of existing manned ships. The future research could focus on: (1) studying the transition phase from manned to unmanned ships, (2) considering the effects of uncertainty on the models, (3) integrating realistic environment simulations, and (4) adding safety verification. Achieving safe and efficient navigation of ships in future mixed waterborne traffic scenarios would be the ultimate goal.

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