To cite this article: DING Z G, ZHANG X Y, WANG C B, et al. Intelligent collision avoidance decision-making method for unmanned ships based on driving practice [J/OL]. Chinese Journal of Ship Research, 2020, 16(1). http://www.ship-research.com/EN/Y2020/V16/I1/96.

DOI: 10.19693/j.issn.1673-3185. 01781

Intelligent collision avoidance decision-making method for unmanned ships based on driving practice

DING Zhiguo[1], *ZHANG Xinyu*[*1], *WANG Chengbo*[1], *LI Quan*[2], *AN Lanxuan*[1]

1 Key Laboratory of Marine Simulation and Control for Ministry of Communications, Dalian Maritime University, Dalian 116026, China

2 Navigation College, Dalian Maritime University, Dalian 116026, China

Abstract: [**Objectives**] In order to realize the intelligent navigation and autonomous collision avoidance of unmanned ships in coastal areas, we propose an intelligent collision avoidance decision-making method based on driving practice. [**Methods**] First, the real-time rationality and uniqueness of the intelligent collision avoidance decision-making process for unmanned ships are analyzed. The ontological conceptual model of the navigation situation is then designed and combined with the International Regulations for Preventing Collisions at Sea (COLREGS) and good seamanship practices, and the ship encounter scenarios are quantitatively divided into 12 types. An improved composite assessment model of collision risk index is then proposed from the perspective of piloting practice to reflect collision risk more accurately. Finally, an intelligent collision avoidance decision-making model based on the operator's perspective (BOP) is built, and the optimal collision avoidance strategy is solved by taking the shortest total collision avoidance path as the objective function under the constraints of ship maneuverability and rudder angle amplitude limit. Simulation experiments are then conducted in different obstacle environments. [**Results**] The simulation results show that this method can accurately determine the piloting situation, provide a reasonable steering strategy and achieve effective collision avoidance in different obstacle environments. [**Conclusions**] This study provides a theoretical basis and method for realizing the intelligent collision avoidance decision-making and dynamic local collision avoidance path planning of ships.

Key words: unmanned ship; driving practice; intelligent collision avoidance decision-making; International Regulations for Preventing Collisions at Sea (COLREGS)

CLC number: U664.82; TP273.5

0 Introduction

With the rise of a new generation of artificial intelligence and unmanned driving technology in the field of navigation, marine transportation is developing rapidly to be intelligent. As carriers of marine intelligent transportation, unmanned ships have become the focus of shipping industries all over the world. In recent years, good results have been achieved in intelligent collision avoidance decision-making of unmanned vehicles. Thus, actively learning from the technology of unmanned vehicles, many experts and scholars try to solve intelligent collision avoidance decision-making of ships in the navigation context.

Autonomous navigation of unmanned ships includes four stages: perception, understanding, decision-making, and control. Specifically, decision-

Received: 2019 − 09 − 24 **Accepted**: 2020 − 12 − 08

Supported by: National Key R&D Program of China (2018YFB1601502)

Authors: DING Zhiguo, male, born in 1996, master degree candidate. Research interests: intelligent collision avoidance of unmanned ships, and traffic flow simulation. E-mail: dingzhiguo@dlmu.edu.cn

ZHANG Xinyu, male, born in 1978, Ph.D., professor, doctoral supervisor. Research interests: traffic information engineering, organizational optimal scheduling, traffic management systems, and unmanned ship technology. E-mail: zhang.xinyu@sohu.com

***Corresponding author**: ZHANG Xinyu

making is the key to safe navigation and obstacle avoidance of unmanned ships. Therefore, intelligent collision avoidance decision-making of unmanned ships has become the research focus of scholars. Its core lies in whether safe and effective decisions conforming to International Regulations for Preventing Collisions at Sea (COLREGS) and common practice of seamen can be quickly made in a complex and changeable marine environment. In fact, the practical problems to be solved in ships' intelligent collision avoidance decision-making are the same as those to be solved by ship operators in actual collision avoidance. The difference is whether to solve problems by operators or by computers. At present, intelligent collision avoidance decision-making of unmanned ships based on driving practice has rarely been studied. This paper intends to carry out research in this regard.

Based on driving practice, intelligent collision avoidance decision-making of unmanned ships includes perception and understanding of navigation situations, as well as decision-making about collision risk indexes, action timing and effectiveness of collision avoidance, and navigation resumption.

Perception of navigation situations refers to the active multi-modal perception of ship internal and external information, as well as navigation environmental information, by means of various shipborne sensors.

Understanding of navigation situations means structurally describing navigation situations of unmanned ships through classification and comprehension of perceived multi-source heterogeneous and multi-modal information. In addition, it refers to the quantitative classification of ship encounter scenarios according to COLREGS and common practice of seamen. At present, different criteria are available for the classification of encounter scenarios. Chen [1] analyzed and summarized target encounter characteristics (TEC), according to geometry laws of relative motion. On this basis, he concluded 15 TEC through relative courses of target ships, ship velocity ratios, and ranges of course difference between target ships and own ships, and proposed collision-avoidance schemes corresponding to different TEC. Perera et al. [2] divided the collision area of an own ship into eight zones and the relative course of a target ship into eight zones. Moreover, according to relative distances and velocity ratios of ships, they classified encounter scenarios into 144 kinds, of which 63 were effective. A higher quantification degree of encounter scenarios is more beneficial to collision avoidance decision-making. However, with the increase in influencing factors introduced, the system becomes more complex, requiring more traversal time. With reference to scenario modeling of unmanned vehicles, based on ontology, this paper built an ontological conceptual model of navigation situations. In addition, the paper realized online reasoning through knowledge representation of encounter scenarios according to COLREGS and driving practice. In this paper, encounter scenarios, as well as avoidance responsibilities and actions of the own ship, were given to provide a basis for intelligent collision avoidance decision-making to improve decision-making efficiency.

Collision risk indexes are the basis for taking actions of collision avoidance. Kearon et al. [3] proposed the method for determining collision risk indexes by weighting the distance to the closest point of approach *DCPA* and the time to the closest point of approach *TCPA* for the first time. Only considering the effects of two factors on collision risk indexes, this method may misjudge actual situations. In References [4-6], methods based on neural networks were used for determining collision risk indexes of ships. With *DCPA*, *TCPA*, relative bearing, course, and velocity as system inputs, these methods can yield good prediction effects. In References [7-9], collision risk indexes were studied through fuzzy theory. Based on the comprehensive consideration of *DCPA*, *TCPA*, azimuths of approaching ships, distance and velocity ratios, Liu et al. [7] built a fuzzy evaluation model of collision risk indexes. Moreover, they improved the membership function of *DCPA* through the quaternion ship domain (QSD), which can provide an accurate basis for collision avoidance decision-making. On the basis of considering the above five influencing factors in combination with ship maneuverability, visibility, and navigation water conditions, Xu et al. [8] modified fuzzy membership functions to improve the accuracy of collision risk indexes. On the basis of previous studies, this paper improved membership functions of collision risk indexes and redesigned a composite model of collision risk indexes according to navigational driving practice.

After the perception and understanding of navigation situations and the determination of collision risk indexes, unmanned ships need to make reasonable decisions on collision avoidance according to driving practice. Some scholars applied the potential field theory in collision-avoidance path planning of robots to collision avoidance of ships [10-12]. Although obstacles can be avoided theoretically in this way, requirements of navigation practice fail to be well met, as avoidance ranges and action modes are affected by gravitational and repulsive fields. Some scholars believed that timing for ship collision avoidance was directly related to the collision risk index *CRI* and thus used *CRI* as the evaluation index to make collision avoidance strategies [13-14]. However, *CRI* is affected by multiple factors including navigation environment, visibility, distance between two ships, azimuths of two ships, *DCPA*, *TCPA*, and ship velocity ratios. Moreover, the factors are mutually restricted. Therefore, the analysis of different influencing factors by different researchers will result in different *CRI.* Without complete consideration of all effects, the direct use of *CRI* as the decisive index of ship collision avoidance may cause great errors. Some scholars studied ship collision avoidance decision-making with a deep reinforcement learning (DRL) algorithm [15-16]. By constructing DRL models suitable for unmanned ships, they obtained basic collision-avoidance models through reinforcement training. However, this method requires a large amount of training data, and model structures are highly dependent on the data. As the algorithm takes a long time of training, real-time collision avoidance in unknown environment fails. Li et al. [17] put forward a method of personifying intelligent decision-making for vessel collision avoidance (PIDVCA). By imitating experienced operators (collision avoidance experts) in collision avoidance decision-making, based on dynamic collision-avoidance rule bases constructed through machine learning, vessels can make reasonable decisions conforming to COLREGS and common practice of seamen, with good collision avoidance effects being achieved. However, this method fails to fully consider all the encounter scenarios of a ship during its navigation. Moreover, with the increase in encounter scenarios, the rule base gradually expands, requiring a longer time to traverse.

It is important to reasonably determine avoidance timing, modes and ranges during ship collision avoidance. Rule 16 of COLREGS stipulates: "Every vessel which is directed to keep out of the way of another vessel shall, as far as possible, take early and substantial action to keep well clear." Experts and scholars have built collision avoidance decision-making models of ships by using geometric principles, velocity obstacles, potential field theory, fuzzy mathematics, neural networks, intelligent optimization, artificial intelligence, and expert systems. These methods are of certain theoretical guiding significance for the development of collision avoidance decision-making, but none of them can well match the reality of navigation.

At present, there are few studies on intelligent collision avoidance decision-making of unmanned ships from the perspective of driving practice. In view of this, this paper discussed ship collision avoidance decision-making in terms of driving practice. Firstly, the reasonableness, timeliness, and uniqueness of intelligent collision avoidance decision-making of unmanned ships were discussed. Then, three models required in intelligent collision avoidance decision-making were built: an ontological conceptual model of navigation situations, a multivariate composite assessment model of collision risk indexes, and an intelligent collision avoidance decision-making model based on the operator's perspective (BOP). Finally, simulation tests were designed to verify the effectiveness of the method in typical encounter scenarios.

1 Problem analysis

From the perspective of the driving practice of manned ships, the main problems that should be considered in the case of collision avoidance decision-making by unmanned ships are as follows.

1) Timeliness of decision-making.

A ship sailing at sea is restricted by winds, waves, currents, visibility, and water depth. Thus, it is necessary to comprehensively consider such factors in collision avoidance decision-making. A collision avoidance decision-making algorithm is required to respond quickly in a complex and changeable environment. The failure of the algorithm to guarantee its timeliness or make decisions within an acceptable time range will seriously threaten the navigation safety of the ship.

2) Reasonableness of decision-making.

A ship is required to be personified maximally in its autonomous collision avoidance decision-making. In the navigation of a manned ship, the operator will actively make comprehensive and experienced decisions with human-ship-environment integrated consideration based on the surrounding environment, navigation rules, and ship maneuverability. Similarly, an unmanned ship in autonomous decision-making also needs to comprehensively process and analyze multi-source heterogeneous information from its perception system to obtain an optimal collision-avoidance strategy, thus realizing personifying and optimal decision-making.

3) Uniqueness of decision-making.

In collision avoidance decision-making, an operator controls ship collision avoidance by judging collision risk indexes and then giving accurate decision information (rudder angles or velocity) according to the driving experience. This requires that an unmanned ship should not produce multiple solutions in implementing its decision-making algorithm, but output a unique, definite, and executable instruction.

In this paper, the above problems were fully considered during the research on intelligent collision avoidance decision-making of ships. On this basis, an ontological conceptual model of navigation situations of unmanned ships was built. In addition, in line with COLREGS and common practice of seamen, encounter scenarios of ships were quantified to establish a composite assessment model of collision risk indexes. Then, a BOP intelligent collision avoidance decision-making model was built from the perspective of driving practice. This model solves the optimal collision-avoidance strategy by taking the shortest total path of ship collision avoidance as the objective function. Thus, intelligent navigation and autonomous collision avoidance of ships can be realized.

2 Model establishment

An unmanned ship in autonomous navigation needs to interact with the environment in real time to obtain navigation states and then make behavior decisions through a learning algorithm. Fig. 1 shows the system architecture. Information on the current state of the ship and surrounding obstacles is input and passed to the behavior decision-making layer. After a series of calculations, decision-making information of the ship is output and passed to the control execution layer to control ship motion. In the figure, λ and ϕ are longitude and latitude of the ship, respectively; ψ is the course of the ship; u is the forward velocity of the ship; v is transverse movement velocity of the ship; r is the yawing angular velocity of the ship; $\Delta\psi$ is a course variation output by the decision-making; ΔV is a velocity variation output by the decision-making; δ is a rudder angle of the ship; V is navigation velocity of the ship.

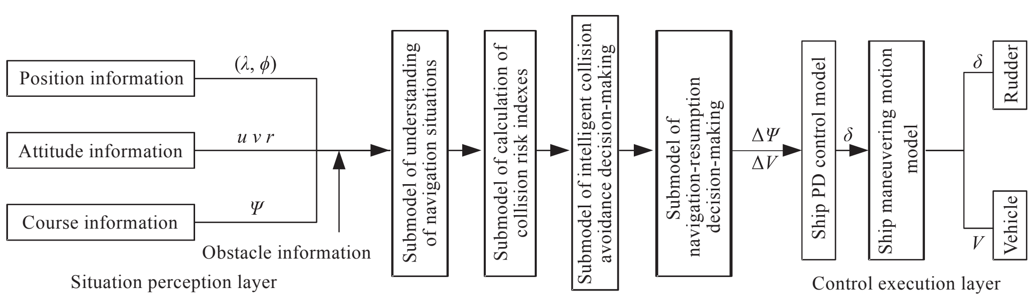

Fig. 1 Architecture diagram of the autonomous navigation system of an unmanned ship

2.1 Ontological conceptual model of navigation situations of unmanned ships

An accurate understanding of navigation situations of unmanned ships is a basis of behavior decision-making. The understanding of collision-avoidance scenarios is mainly to classify typical encounter scenarios based on the understanding of both COLREGS and common practice of seamen, providing a prerequisite for collision avoidance decision-making.

In COLREGS, three encounter scenarios are given: head-on, crossing, and overtaking situations, as shown in Fig. 2. However, during actual ship navigation, for different encounter situations, ships have different rights of way. Therefore, it is necessary to divide encounter scenarios in detail.

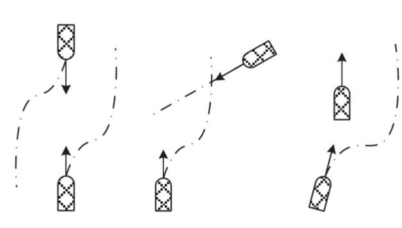

Fig. 2 Schematic diagram of three typical encounter scenarios

At present, understanding and modeling of navigation situations of unmanned ships are rarely studied, and no unified standard definition is available. A knowledge base of collision avoidance on the basis of simple "IF…THEN… " inference rules can hardly describe various encounter forms and collision-avoidance schemes. Based on the scenario modeling of unmanned vehicles [18], with the powerful information presentation capacity of the ontological conceptual model, this paper can logically express and quantify navigation situations. Moreover, it describes priori navigation knowledge according to driving practice to improve the efficiency of collision avoidance decision-making.

Understanding of navigation situations is to structurally describe navigation situations of unmanned ships by classifying and comprehending multi-source heterogeneous information from perception systems. First, navigation situations of unmanned ships are divided into entities and attributes according to the "ontology" theory. The entity class represents objective substances of different nature, and the attribute class describes object entities and relationship attributes between entities. In this paper, the attribute class is divided into entity and relationship attributes. Specifically, entity attributes include positions, courses, and velocity of entities, while relationship attributes include position, course, azimuth, and velocity relationships.

Information from a perception system contains static and dynamic information. Static information generally refers to static obstacle entities, including structured chart entities and other static obstacles. Specifically, chart entities include waterways and navigation aids of structured characteristics. Static obstacle entities refer to static unstructured entities, including anchored ships and reefs. Dynamic information generally refers to dynamic obstacles and environmental entities in the navigation environment.

An ontological conceptual model of navigation situations of unmanned ships was built through entity and attribute description of multi-source heterogeneous information from the perception system. On this basis, encounter scenarios were quantitatively classified according to COLREGS and good seamanship requirements and expressed with Prolog language.

According to COLREGS and driving practice, this paper divided an encounter area into six zones in terms of the azimuth relationship of a target ship: zones at the bow, at the stern, forward of the beam on the port side, abaft the beam on the port side, forward of the beam on the starboard side, and abaft the beam on the starboard side. In each encounter zone, encounter scenarios (ES) were divided into 12 kinds in terms of course and velocity relationships between the target ship and the own ship. Then, an understanding and division list of navigation situations was built based on the ontological conceptual model of ship navigation situations and the Prolog language, as shown in Table 1. In the table, HO refers to a head-on scenario; DHO refers to a dangerous head-on scenario; CR refers to a crossing scenario; OT refers to an overtaking scenario; q is the relative bearing of the target ship; ψ_t is the course of the target ship; ψ_0 is the course of the own ship; V_t is the velocity of the target ship; V_0 is the velocity of the own ship.

In view of the complex and changeable marine environment, according to driving practice, this paper put forward a scenario division method based on the ontological conceptual model of navigation

Table 1 Navigation situation understanding and division

No.	Azimuth of the target ship	Encounter scenario	Relative bearing/q	$\Psi_t-\Psi_0$	V_t, V_0	Avoidance action	Responsibility for collision avoidance
1	Bow	DHO	0~π/8	7π/8~9π/8	Arbitrary	Turn left	None
2		HO	15π/8~0	7π/8~9π/8	Arbitrary	Turn right	Equal
3		CR	15π/8~π/8	9π/8~13π/8	Arbitrary	Turn right	Give way
4		OT		13π/8~3π/8	$V_t<V_0$	Turn left or right	Give way
5		CR		3π/8~7π/8	Arbitrary	Keep course and speed	Stand on
6	Forward of the beam on the starboard side	OT	π/8~π/2	π~2π	$V_t<V_0$	Turn right	Give way
7		CR		π~2π	Arbitrary	Turn right	Give way
8	Abaft the beam on the starboard side	CR	π/2~5π/8	3π/2-2π	Arbitrary	Turn left	Give way
9	Stern	OT	5π/8~11π/8	3π/2~ /2π	$V_t>V_0$	Keep course and speed	Stand on
10	Abaft the beam on the port side	CR	11π/8~3π/2	0~π/2	Arbitrary	Keep course and speed	Stand on
11	Forward of the beam on the port side	OT	3π/2~15π/8	0~π	$V_t<V_0$	Turn right	Give way
12		CR		0~π	Arbitrary	Turn right	Give way

situations. With dimension reduction of navigation environment, the paper realized the understanding and division of navigation situations of unmanned ships. This provides a basis for intelligent collision avoidance decision-making and improves decision-making efficiency to a certain extent.

2.2 Multivariate composite assessment model of collision avoidance indexes

COLREGS gives no definition of collision risk, but many of its items are based on the premise of collision risk. Thus, it is necessary to build a quantification model of collision risk.

In navigation practice, while judging the existence of collision risk, an operator can intuitively perceive the urgency of risk, and then make qualitative and quantitative analyses. Usually, *DCPA*, inter-ship distance and its variation, and *TCPA* are used to judge the existence and degree of collision risk. Collision risk indexes of ships are affected by many factors, and such factors are mutually restricted. Therefore, based on previous studies, using fuzzy theory, this paper built membership functions of five influencing factors: *DCPA*, *TCPA*, inter-ship distance, relative azimuths, and ship velocity ratios. Moreover, the paper constructed a multivariate composite assessment model of collision risk indexes according to driving practice.

From Reference [8], a smaller inter-ship distance results in a higher risk of ship collision. From the difficulty of collision avoidance, a smaller distance yields a worse effect of collision avoidance. The membership function u_d of inter-ship distance at any time is as follows.

$$u_d = \begin{cases} 1; & d \leqslant d_1 \\ [(d_2 - d)/(d_2 - d_1)]^2; & d_1 < d \leqslant d_2 \\ 0; & d > d_2 \end{cases} \tag{1}$$

where d_1 is the last collision-avoidance distance, usually 12 times the ship length; d_2 is the coordinated collision-avoidance distance of a ship [19].

$$d_2 = 1.7\cos(q - 19°) + \sqrt{4.4 + 2.89\cos^2(q - 19°)} \tag{2}$$

Target ships in different azimuths affect collision risk indexes differently. Generally, a target ship on the starboard side has greater effects than that on the port side does, while the effects of a target ship forward of the beam are greater than those abaft the beam. The membership function u_q of relative bearing at any time is as follows.

$$u_q = \begin{cases} 1/[1 + (q/q_0)^2]; & 0 \leqslant q < 180° \\ 1/[(360° - q)/q_0]^2; & 180° \leqslant q < 360° \end{cases} \tag{3}$$

where q_0 is related to the ship's velocity ratio $K\left(K = \dfrac{v_t}{v_0}\right)$, $q_0 = \begin{cases} 40°, & K < 1 \\ 90°, & K = 1 \\ 180°, & K > 1 \end{cases}$

A greater ship velocity ratio results in a higher collision risk index. The membership function u_K of the ship velocity ratio at any time is as follows.

$$u_K = \frac{1}{1 + 2/K\sqrt{K2 + 1 + 2\sin\psi}} \tag{4}$$

DCPA greatly affects collision risk indexes, and a smaller *DCPA* can result in a higher degree of collision risk. The membership function u_{DCPA} of *DCPA* at any time is as follows.

$$u_{DCPA} = \begin{cases} 1; & |DCPA| < d_1 \\ [(d_2 - |DCPA|)/(d_2 - d_1)]^{3.0}; & d_1 \leqslant |DCPA| < d_2 \\ 0; & d_2 < |DCPA| \end{cases} \tag{5}$$

where d_2 is the minimum safe distance of approach. In order for simplified calculation, d_2 = 2 n mile. In view of the effects of ship size, collision is possible even in the case of a small *DCPA*. Therefore, the average length of the two ships is taken, generally about 0.1 n mile.

TCPA is an evaluation index for the degree of collision risk. A smaller *TCPA* means a higher degree of collision risk. The membership function u_{TCPA} of *TCPA* at any time is as follows.

$$u_{TCPA} = \begin{cases} 1; & TCPA < t_1 \\ [(t_2 - TCPA)/(t_2 - t_1)]^{3.03}; & t_1 \leqslant TCPA < t_2 \\ 0; & t_2 < TCPA \end{cases} \tag{6}$$

where t_1 is the time from the last steering point to the closest point of approach, $t_1 = \sqrt{{d_1}^2 - DCPA^2}/v_r$, and v_r is the velocity of a target ship relative to the own ship; t_2 is the start time of collision risk. In the practice of navigation, an operator has different perception degrees of risk from target ships at the same distance but with different azimuths and relative velocities. Therefore, it is difficult to use distance to determine the start of a collision. With reference to Reference [20], this paper took t_2 = 15 min as the start time of collision risk.

For combination rules of collision risk indexes, scholars have proposed different methods. According to Reference [8], this paper allocated fuzzy weight of target influencing factors as follows.

$$w_d = 0.14,\ w_q = 0.10,\ w_K = 0.08,$$
$$w_{DCPA} = 0.36,\ w_{TCPA} = 0.32 \tag{7}$$

For the original model, *CRI* is calculated as follows.

$$CRI = w_d u_d + w_q u_q + w_K u_K + w_{DCPA} u_{DCPA} + w_{TCPA} u_{TCPA}$$

According to driving practice, in the case of *DCPA* greater than the safe distance of approach, despite a small *TCPA*, there is no ship collision risk. Therefore, the improved *CRI* is as follows.

$$CRI = \begin{cases} 0; & u_{DCPA} = 0 \text{ or } u_{TCPA} = 0 \\ w_d u_d + w_q u_q + w_K u_K + w_{DCPA} u_{DCPA} + w_{TCPA} u_{TCPA}; & 0 < u_{DCPA} < 1,\ 0 < u_{TCPA} < 1 \\ 1; & u_{DCPA} = 1,\ u_{TCPA} = 1 \end{cases} \quad (8)$$

2.3 BOP intelligent collision avoidance decision-making model

On the basis of the previous models, intelligent collision avoidance decision-making of ships is mainly to solve the optimal timing and range of ship collision avoidance. As the timing and range of avoidance actions are restricted by COLREGS and affected by driving experience, operators take different actions in different encounter situations. Collision-avoidance measures taken at different timing will yield different effects, as shown in Fig. 3.

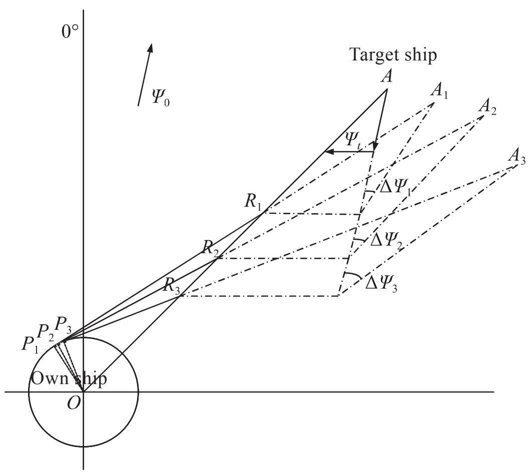

Fig. 3 Schematic diagram of ship steering and collision avoidance action mode

In Fig. 3, point O is the current position of the own ship; point A is the current position of the target ship; R_1, R_2, and R_3 are different timing for ship collision avoidance; P_1, P_2, and P_3 are different closest points of approach; $\Delta\psi_i$ (i = 1, 2, 3) is the range of a collision-avoidance action corresponding to different decision-making timing, i.e., a course variation; A_1, A_2 and A_3 are positions of the target ship with course variations of $\Delta\psi_1$, $\Delta\psi_2$, and $\Delta\psi_3$, respectively; *TC* is the true course of the unmanned ship; A_iO is the relative course of the two ships.

From the perspective of an operator's thinking and decision-making, by analyzing the geometric relationship of relative motion between the own ship and a target ship, this paper built a BOP intelligent collision avoidance decision-making model on the basis of ensuring ships can be passed and clear at a safe distance of approach. With the shortest total path of collision avoidance as the objective function, and ship maneuverability and COLREGS as constraints, the model solves an optimal collision-avoidance strategy by quantifying intervals of collision-avoidance steering. Fig. 4 shows the flow chart of the BOP intelligent collision avoidance decision-making model.

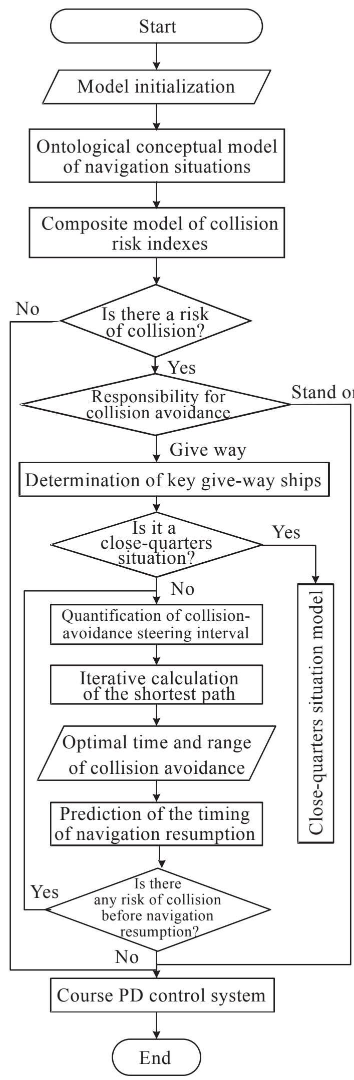

Fig. 4 Flow chart of BOP intelligent collision avoidance decision-making model

In the case of ship collision risk, it is necessary to geometrically calculate the range of collision avoidance according to the safe distance of approach. Taking collision-avoidance measures at different positions will lead to different lengths of ship collision-avoidance paths. In order to obtain an optimal collision-avoidance path in different steering ranges, we can construct an objective function as follows.

$$\min J = \sum_{k=1}^{n} \sqrt{(x_{k+1} - x_k)^2 + (y_{k+1} - y_k)^2} \tag{9}$$

where x_k and y_k refer to the current position of a ship; x_{k+1} and y_{k+1} refer to the next position of the ship.

It is difficult to analytically express the corresponding relationship between decision-making timing and paths of collision avoidance. Therefore, a quantification model of collision-avoidance distance is used to solve the steering range and collision-avoidance path at each collision-avoidance distance. According to driving practice, for an approaching ship forward of the beam, collision-avoidance actions are generally taken when the two ships are 4−6 n mile apart, while for an approaching ship abaft the beam, collision-avoidance actions are taken when the two ships are 3−4 n mile apart. In this paper, intervals of collision-avoidance steering were quantified. Avoidance decision-making timing (R_1, R_2, ..., R_n) was built according to a step of 0.1 n mile, and the one-dimensional vector of avoidance action ranges was ($\triangle\psi_1$, $\triangle\psi_2$, ..., $\triangle\psi_n$).

During the calculation of collision-avoidance paths, in view of COLREGS requirements and ship maneuverability restrictions, the following constraints should be met:

$$\text{s.t.} \begin{cases} 15° \leqslant \Delta\psi_i \leqslant 90° \\ -35° \leqslant \delta \leqslant 35° \\ d_0 \geqslant 4 \end{cases} \tag{10}$$

where d_0 is the initial distance between an unmanned ship and a dynamic target ship. According to both the steering diagram of radar-based collision avoidance and the requirements of "acting early, altering courses or velocity greatly, leaving broad sea room, and keeping well clear" in COLREGS, the range of ship collision-avoidance action was set to [15°, 90°]. For a general ship, steering torque can reach a maximum in the case of a rudder angle between 32° and 35°. Therefore, this paper took $|\delta|$ = 35° as the limit rudder angle of the ship. For an approaching ship forward of the beam, the last timing of steering is when the ship is at a distance of 4 n mile. In order to ensure a solution to the model, we set the initial distance between the own ship and the target ship to be greater than 4 n mile.

In driving practice, an operator is required to fully understand ship performance and consider ship steering time and turning characteristics in decision-making. In view of this, this paper adopted the three-degree-of-freedom integrated model proposed by Abkowitz [10]:

$$\begin{cases} X = m(\dot{u} - v\dot{\psi}) \\ Y = m(\dot{v} + u\dot{\psi}) \\ N = I_{zz}\ddot{\psi} \end{cases} \tag{11}$$

$$[X, Y, N]^{\mathrm{T}} = f(u, v, r, \dot{u}, \dot{v}, \dot{r}, \delta) \tag{12}$$

where X and Y are components of external force on the x-axis and y-axis, respectively; m is mass of a ship; I_{zz} is mass moment of inertia of the ship around the vertical axis passing through the center of gravity (rotational inertia); N is the moment of rotation of external force acting on the ship around the vertical axis passing through the center of gravity.

As estimation of hydrodynamic derivatives is not the focus of this paper, it is not described in detail here. The mathematical model of ship maneuvering in this paper was based on a typical standard Mariner ship of ITTC. Table 2 lists relevant ship data. The ship motion model can be obtained by using the table of dimensionless hydrodynamic data in Reference [21].

Table 2 Coefficients in the mathematical model of ship maneuvering motion of Mariner

Description	Value
Total length L_{oa}/m	171.80
Length between perpendiculars L_{bp}/m	160.93
Molded breadth B/m	23.17
Designed draught T/m	8.23
Displacement ∇/m³	18 541
Designed velocity U_0/kn	15
Rudder-angle limit δ/(°)	35

Reasonable steering, fast and smooth course variation, and short adjustment time should be taken into account in designing a ship steering controller to match with navigation reality. Therefore, a PD steering controller model was adopted in this paper. The control rate of δ is $C_\delta = -K_{\mathrm{p}}(\Psi - \Psi_{\mathrm{desired}}) + K_{\mathrm{d}}r$, where ψ is the current course of the ship, and Ψ_{desired} is the desired course in decision-making. Parameters of the ship PD control model were adjusted, with a proportional gain of K_{p} = 0.3 and a differential gain of K_{d} = 1.

After collision avoidance, the ship needs to resume navigation. During the research into the timing of ship resumption, there has always been a controversy about whether the ship returns to its initial motion state or its original route after collision avoidance. As far as collision avoidance is concerned, it is only necessary for the ship to return to its initial motion state, and returning to the original route is a function and task of the navigational automation system. Four common models for calculating the timing of course resumption were given in Reference [22].

1) Resume navigation when the target ship passes the abeam position of the own ship.

2) After navigation resumption of the give-way ship, make sure that *DCPA* between the ships is greater than the minimum safe distance of approach.

3) Resume navigation when the target ship passes the closest point of approach.

4) Resume navigation after the target ship passes the bow of the own ship.

No matter which way is taken to resume the navigation, it is necessary to ensure a safe distance of approach between two ships. According to the principle of geometric collision avoidance, this paper predicted the timing of ship navigation resumption. Fig. 5 shows a schematic diagram of calculating the timing of ship navigation resumption.

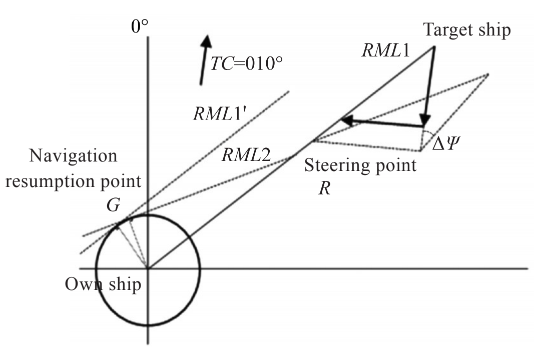

Fig. 5 Schematic diagram of solving the timing of re-sailing

Fig. 5 shows an encounter scenario of two ships. In the scenario, the own ship heads upwards and alters its course by $\Delta\Psi$ to avoid the target ship. Specifically, *R* is the determined timing for collision avoidance; *G* is the predicted navigation resumption point; *RML*1 is the relative motion path before collision-avoidance steering; *RML*2 is the relative motion path after ship course is altered; *RML*1' is a parallel path of *RML*1 and is tangent to the circle of minimum safe distance of approach of the own ship. *G* is the intersection between *RML*2 and *RML*1'. The time the ship takes to navigate from *R* to *G* is the timing for the ship to resume navigation. With calculated time and course of ship navigation resumption, the PD course controller can be used for navigation resumption steering.

3 Simulation test and analysis

In this section, a simulation test was conducted to verify the effectiveness of the intelligent collision avoidance decision-making method for unmanned ships based on driving practice. In the simulation test, the own ship adopted the parameters of a typical standard Mariner ship of ITTC. Based on Simulink of Matlab 2016a, the contrast simulation test was designed with python 3.6. The proposed method was compared with the traditional collision-avoidance algorithm which fails to consider the maneuvering motion model of a ship and determines avoidance timing through a detection circle (with a radius of 4 n mile). On this basis, the applicability and superiority of the proposed method were verified in typical encounter scenarios. Table 3 lists the initial navigation parameters of the unmanned ship and dynamic target ships, and the simulation step was set to 6 s.

Table 3 Ships' initial navigation state

Ship	Position (λ/ (°), φ/ (°))	Course Ψ / (°)	Velocity /kn
Unmanned ship	(161.10, 25.10)	45°	15
Dynamic target ship(TS1)	(161.21, 25.125)	315°	10
Dynamic target ship(TS2)	(161.32, 25.28)	225°	10
Dynamic target ship(TS3)	(161.24, 25.16)	45°	10

The goal of the simulation is that the unmanned ship can approach the target point and avoid dynamic target ships. In the case of no obstacle in the environment or obstacles not within the safe distance of approach, the unmanned ship maintains its course or resumes its navigation, adjusting its direction to move towards the target point. In the case of obstacles within the safe distance of approach, the unmanned ship avoids the obstacles in real time with the proposed algorithm and the traditional collision-avoidance algorithm. The simulation ends when the unmanned ship reaches the target point.

In the simulation of collision avoidance, three dynamic target ships navigate with unchanged courses and velocity, and encounter the unmanned ship successively, forming crossing, head-on, and overtaking situations. Fig. 6 shows the key moments of the ship collision-avoidance simulation. In the figure, the path intersections refer to historical paths of the unmanned ship passing through the rear parts of dynamic target ships after collision avoidance.

At T = 1 000 s, judging that the target ship 1 en-

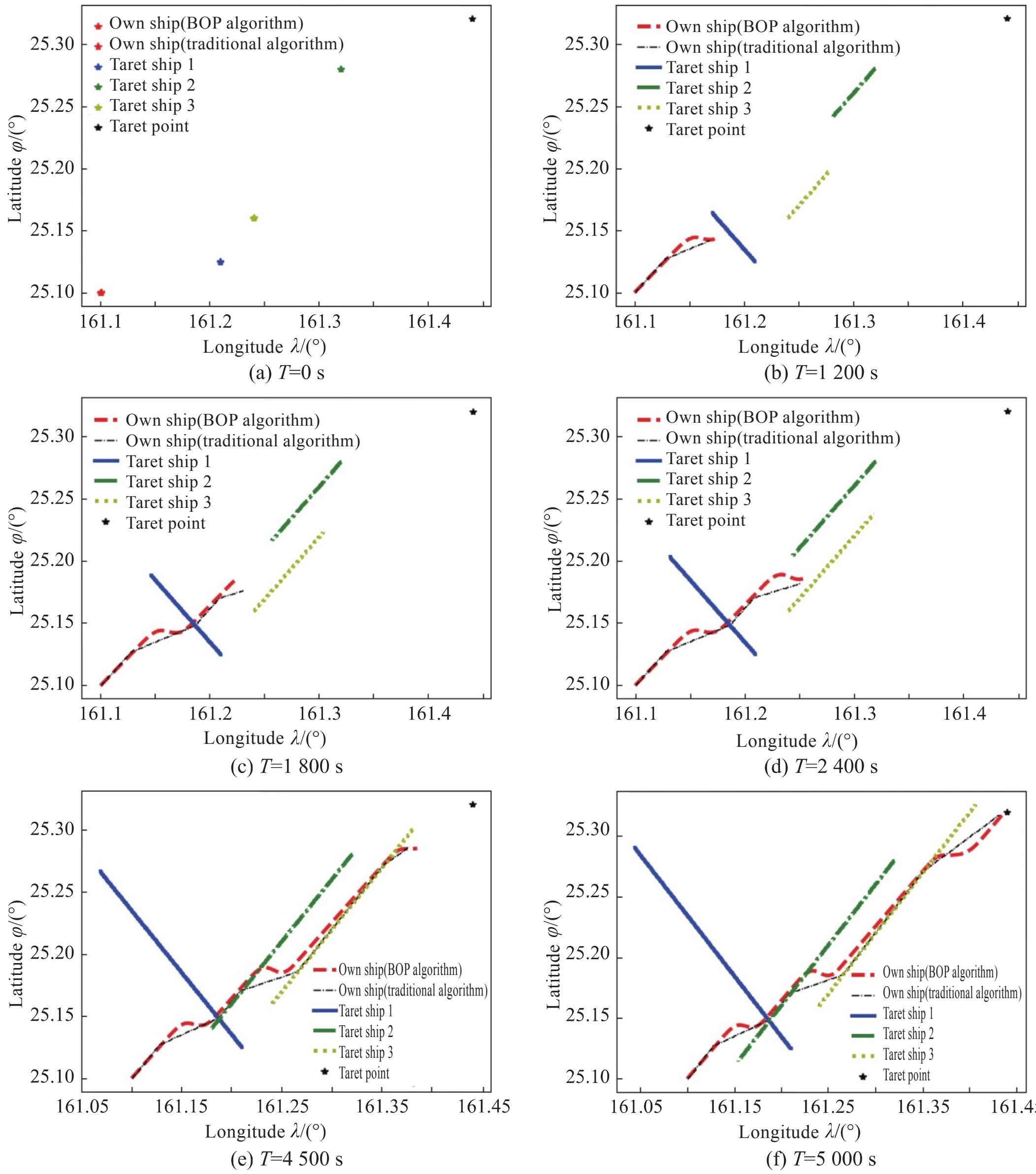

Fig. 6 Ships' collision avoidance simulation

ters its decision-making area, the unmanned ship analyzes the course and azimuth of the target ship and determines that there is a situation of crossing abaft the beam through course understanding. In this case, being a give-way ship, the own ship turns rightwards for avoidance, and its optimal collision-avoidance range is solved by the BOP intelligent collision avoidance decision-making method. At T = 2 000 s, the unmanned ship encounters the target ship 2, forming a head-on situation. In this case, being a give-way ship, the own ship turns rightwards for avoidance, and its optimal collision-avoidance range is calculated by the algorithms. At T = 4 500 s, the unmanned ship and the target ship are in an overtaking situation. In this case, the own ship is an overtaking ship, while the target ship is a give-way ship. As the target point is on the right side, the own ship overtakes from the starboard side. Compared with the proposed BOP method, the traditional collision-avoidance method yields fixed and earlier avoidance time, smaller steering ranges, and rougher paths. The total path of ship collision avoidance for the traditional method is 32.952 n mile, while that for the proposed BOP method is 25.022 n mile. Thus, the proposed method greatly shortens the navigation distance and improves the collision-avoidance performance.

From the simulation, when the unmanned ship has a risk of collision with target ships, it can make effective collision-avoidance decisions, and produce optimal collision-avoidance paths through the intelligent collision avoidance decision-making algorithm.

Fig. 7 shows the course and rudder-angle variations of the unmanned ship during collision avoidance. From the figure, the course varies rapidly and

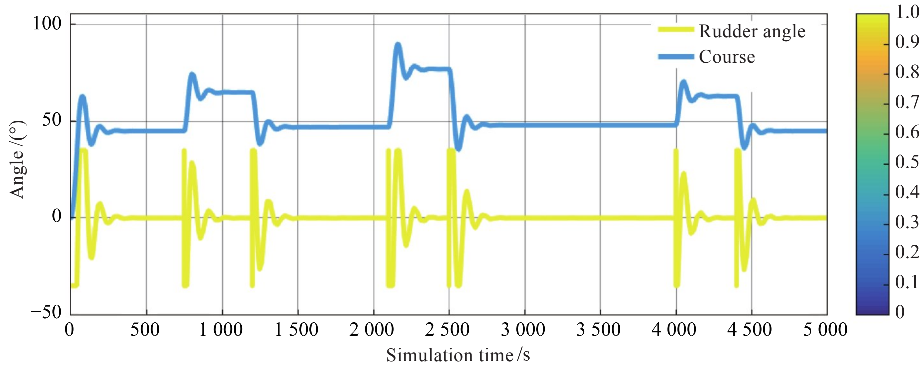

Fig. 7 Variation curves of course and rudder angle during collision avoidance

smoothly, with short adjustment time and small vibration. Moreover, the steering is smooth and reasonable, conforming to the navigation practice.

According to the simulation results, the unmanned ship can safely avoid target ships in different encounter situations, and produce optimal collision-avoidance strategies accordingly. This verifies the effectiveness of the proposed algorithm.

4 Conclusions

By analyzing the problems in collision avoidance decision-making of unmanned ships, this paper proposed an intelligent collision avoidance decision-making method based on driving practice. With this method, unmanned ships can interact with the environment in real time according to the information from their perception systems, so as to make collision-avoidance decisions and plan paths in line with COLREGS. Simulation tests in typical encounter scenarios show that the model can autonomously avoid collision in an unknown environment and calculate optimal paths, proving the effectiveness of the algorithm. In the following research, we need to constantly improve the models. In view of more complex environmental disturbances, we will add domain models of static and dynamic obstacles to better match the reality of navigation.

References

[1] CHEN G Q. Research on key technologies for ship collision avoidance automation [D]. Dalian: Dalian Maritime University, 2016 (in Chinese).

[2] PERERA L P, CARVALHO J P, SOARES C G. Fuzzy logic based decision making system for collision avoidance of ocean navigation under critical collision conditions [J]. Journal of Marine Science and Technology, 2011, 16 (1): 84−99.

[3] KEARON J. Computer programs for collision avoidance and traffic keeping [C]//Conference on Mathematical Aspects on Marine Traffic. London: Academic Press, 1977.

[4] WANG Z S, SHI C J. An improved neural network based model of collision risk index [J]. Navigation of China, 2007 (1): 65−67 (in Chinese).

[5] LI C Z, LI W, NING J. Calculation of ship collision risk index based on adaptive fuzzy neural network [C]// Proceedings of 2018 3rd International Conference on Modeling, Simulation and Applied Mathematics (MSAM). Shanghai: Science and Engineering Research Center, 2018: 223−227.

[6] TANG G R, XIE X L, PAN W. Design of intelligent collision avoidance expert system for ships in complex waters [J]. Ship & Ocean Engineering, 2019, 48 (3): 160−165 (in Chinese).

[7] LIU D D, SHI G Y, LI W F, et al. Decision support of collision avoidance based on shortest avoidance distance and collision risk [J]. Journal of Shanghai Maritime University, 2018, 39 (1): 13−18 (in Chinese).

[8] XU W, HU J Q, YIN J C, et al. Composite evaluation of ship collision risk index based on fuzzy theory [J]. Ship Science and Technology, 2017, 39 (7): 78 – 84 (in Chinese).

[9] SHI J X, ZHANG X Y. Collision avoidance decision model of ship collision risk [J]. Pearl River Water Transport, 2018 (18): 78−79 (in Chinese).

[10] LYU H G, YIN Y. Fast path planning for autonomous ships in restricted waters [J]. Applied Sciences, 2018, 8 (12): 2592.

[11] LYU H G, YIN Y. COLREGS-constrained real-time path planning for autonomous ships using modified artificial potential fields [J]. The Journal of Navigation, 2019, 72 (3): 588−608.

[12] LIN X J. Model research on automatic collision avoidance of ships in confined waterways based on improved potential field method [D]. Harbin: Harbin Engineering University, 2015 (in Chinese).

[13] YUAN Y Q. Intelligent collision avoidance of surface vehicles under multi-objective [D]. Harbin: Harbin Engineering University, 2019 (in Chinese).

[14] HE Y X, HUANG L W, XIONG Y, et al. The research of ship ACA actions at different stages on head-on situation based on Cri and COLREGS [J]. Journal of Coastal Research, 2015, 73 (Supp 1): 735−740.

[15] WANG C B, ZHANG X Y, ZHANG J W, et al. Meth-

od for intelligent obstacle avoidance decision-making of unmanned vessel in unknown waters [J]. Chinese Journal of Ship Research, 2018, 13 (6): 72−77 (in Chinese).
[16] SHEN H Q, HASHIMOTO H, MATSUDA A, et al. Automatic collision avoidance of multiple ships based on deep Q-learning [J]. Applied Ocean Research, 2019, 86: 268−288.
[17] LI L N, CHEN G Q, LI G D, et al. A review on PIDVCA system [J]. Navigation, 2014 (2): 42−49 (in Chinese).
[18] GENG X L. Research on behavior decision-making approaches for autonomous vehicle in urban uncertainty environments [D]. Hefei: University of Science and Technology of China, 2017 (in Chinese).
[19] DAVIS P V, DOVE M J, STOCKEL C T. A computer simulation of marine traffic using domains and arenas [J]. The Journal of Navigation, 1980, 33 (2): 215−222.
[20] SU K W. A study on the expert system for ship collision avoidance [D]. Dalian: Dalian Maritime University, 2007 (in Chinese).
[21] FOSSEN T I. Guidance and control of ocean vehicles [M]. Chichester, New York: Wiley, 1994.
[22] WANG P K, CHEN G Q, LI L N, et al. Integrity verification of calculation model for forecasting recovery limited time of ship [J]. Navigation of China, 2016, 39 (1): 55−59 (in Chinese).

基于驾驶实践的无人船智能避碰决策方法

丁志国[1], 张新宇[*1], 王程博[1], 黎泉[2], 安兰轩[1]
1 大连海事大学 航海动态仿真与控制交通行业重点实验室,辽宁 大连 116026
2 大连海事大学 航海学院,辽宁 大连 116026

摘　要:［目的］为实现沿海无人驾驶船舶自主航行,充分考虑无人驾驶船舶智能避碰决策的合理性和实时性后,提出并建立一种基于驾驶实践的无人船智能避碰决策方法。［方法］首先,以本体论为基础,设计无人驾驶船舶航行态势本体概念模型,并结合《国际海上避碰规则》及良好的船艺将船舶航行态势量化划分为12种会遇场景;然后,从驾驶实践的角度改进影响碰撞危险度因子的模糊隶属度函数,提出一种多元碰撞危险度评估模型,实现船舶碰撞危险度的精确计算;最后,以船舶避碰总路径最短为目标函数,提出一种基于驾驶员视角(BOP)的智能避碰决策模型,在船舶操纵性、舵角限幅等约束下求解最优避碰策略,并在典型的会遇场景下进行仿真实验。［结果］结果表明,该方法可以准确判断驾驶航行态势,给出合理的转向策略,实现典型会遇场景下的有效避碰。［结论］所做研究可为实现船舶自主航行提供理论基础和方法参考。

关键词: 无人驾驶船舶;驾驶实践;智能避碰决策;国际海上避碰规则