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Intelligent Obstacle Avoidance Algorithm Combined with Internet of Things Technology in Navigation

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With the prosperity and development of the Maritime Silk Road, China's maritime industry has reached a new stage. While the maritime transport industry has been vigorously developed, it has also brought great challenges to safe navigation. To realize intelligent navigation, effectively prevent maritime collision accidents, and improve navigation safety, an intelligent navigation obstacle avoidance platform based on Internet of Things technology is first proposed. Then, the research combines the analytical hierarchy process, artificial neural network and BP neural network algorithm, and introduces environmental factors to design an optimized intelligent navigation obstacle avoidance algorithm, so that the algorithm can make real-time intelligent adjustment strategies according to the changes of the actual environment. Finally, the collision risk at the location of the research ship is judged, and the priority list of obstacle avoidance is constructed by the risk value between different ships and the research ship, providing reference for the pilot. The research results showed that the prediction accuracy of I-IONA was 97.83%. In these two obstacle avoidance experiments, the decision-making efficiency of the four ships based on I-IONA was the highest, at 1. In practical applications, the priority list of obstacle avoidance was P, O and S2. In conclusion, I-IONA has better performance and practicability, enabling the research ship to respond more intelligently and quickly.

KEYWORDS: Internet of Things, Analytical hierarchy process, Intelligent obstacle avoidance algorithm, BP neural network, Intelligent navigation systems.

1. Introduction

With the development of the world economy and the transfer of the economic center, the international shipping center is moving towards East Asia. The Asia-Pacific ports, represented by China's coastal areas, have achieved unprecedented development relying on their superior geographical location. China has also shifted from a major producer of goods to a major consumer of goods through maritime transport [6, 22]. In addition, maritime transport is the main transport in international trade, accounting for more than 2/3 of the total international trade. More than 90% of China's total import and export cargo is transported by sea [14, 15]. Although the maritime transport industry has been greatly developed, it also brings great challenges to the safety of navigation. The challenges faced in the actual navigation process have two aspects. First, there are certain defects in the modern management and monitoring means of ships and the quality of pilots. The inertia of the ship is large, and the emergency response ability of the pilot is insufficient, so that the decision delay is very likely to cause serious accidents [19]. In addition, the digital information of relevant resources is relatively low and the timeliness of obtaining information is poor. Information construction is difficult to meet the development needs of modern maritime transport [7]. The rapid development of the maritime industry and artificial intelligence has made intelligent shipbuilding industry a popular trend. Intelligent obstacle avoidance technology, as one of the core technologies for intelligent navigation, is an important prerequisite for ensuring safe and efficient navigation of ships. At present, the relevant achievements on ship obstacle avoidance mainly rely on computers to complete intelligent ship obstacle avoidance simulation experiments. Considering the influence of complex factors such as ship parameters and surrounding environment on collisions between ships, the simulation process is more closely related to the actual situation [24]. However, most heuristic algorithms currently lack universality and have poor performance in the field of intelligent ship obstacle avoidance, and cannot consider the maneuverability of corresponding ships. Therefore, the actual application effect is questionable. The purpose of the research is to realize intelligent navigation, that is, the navigation field in intelligent transportation, and assist the driver to make correct decisions in time. Accurately predicting the position and collision risk level of a ship in the next stage can provide assistance for navigation safety. To achieve the above objectives, the research combines the actual needs of navigation, and uses IoT technology and artificial intelligence technology to build an Intelligent Obstacle Avoidance Algorithm Combined with IoT Technology (I-IONA) to predict the safety of ships navigating in complex environments. The innovation of the research mainly lies in proposing the I-IONA that combines IoT technology and artificial intelligence technology to assist relevant personnel in making correct schedules quickly and accurately, minimizing the occurrence of maritime accidents. The research structure is mainly divided into four parts. The first part reviews the achievements of intelligent ship obstacle avoidance technology and IoT technology applications in the field of navigation. The second part designs IoT-based navigation data collection and intelligent navigation obstacle avoidance algorithms. The third part validates the performance and application effectiveness of the proposed research methods. The last part summarizes the research. The main contributions of this study are as follows: (1) Utilizing IoT technology and artificial intelligence technology to construct the I-INOA algorithm can more effectively predict and avoid maritime collision accidents, thereby significantly improving maritime safety. (2) Professional personnel provide real-time obstacle avoidance priority lists to reduce human decision-making and assist relevant personnel in making correct navigation decisions quickly. (3) It is the application of artificial intelligence technology and IoT technology in navigation, promoting the development of the maritime industry towards intelligence and automation.

2. Related Work

The traditional obstacle avoidance method mainly relies on the lookout to timely detect danger through effective observation and quickly notify the on duty driver. The pilot shall judge the current situation and hazard types based on the navigation experience, and finally make a decision. However, with the rapid growth of maritime transport demand, the supply of professional maritime transport staff is obviously insufficient. Therefore, the demand for intelligent navigation obstacle avoidance system is increasing, and its core principle is intelligent navigation obstacle avoidance algorithm [17]. Li et al. introduced a risk index when measuring the collision risk between the research ship and the target ship. Then, an action flow chart in each case was established. This study took Yukun and Yupeng as simulation objects, and verified the usability of the intelligent collision avoidance system by simulating head-on, crossing, and overtaking situations [11]. Wang found that ship trajectory prediction was an important support for judging the path planning of intelligent ship collision avoidance. A generative confrontation network (GAN-AI) with attention and interaction module was designed to predict the trajectories of multiple ships. The research was tested on the historical track data of Zhoushan Port. Compared with seq2seq, GAN, and Kalman models, the prediction accuracy of GAN-AI model was improved by 20%, 24%, and 72%, respectively [20]. Li et al. proposed a lane keeping algorithm based on scene analysis to ensure the driver's comfort when driving state changes. The research verified that the algorithm made the vehicle intelligent and smooth along the planned path through various typical tests [10]. Wang et al. found that when two ships changed their course to avoid collision, the speed ratio was an important factor that must be considered. In the quasi-intelligent decision-making of ship collision avoidance, it was found that the collision effect was greatly affected by the speed ratio. The simulation experiment was carried out based on the ship intelligent collision avoidance simulation platform. According to the collision avoidance measures taken by the two ships, reasonable suggestions were put forward [21].

With the transfer of the world shipping center to China, China's shipping industry has ushered in unprecedented development opportunities. As the vigorous development of IoT industry, some scholars try to apply the IoT technology to the field of navigation [23]. Jaloudi introduced a cheap, scalable and interoperable SDR-IoT bridge. This method had good performance and could be used for Internet-based ship navigation monitoring [9]. Nuanmeesri designed a walking stick based on IoT equipment to help blind people realize intelligent navigation. The survey results showed that the accuracy of the walking route recommendation with walking stick was 98.81%, and there was a high consensus on the acceptance of the walking stick system [13]. To counter and defend distributed denial of mission attacks on modern IoT, Dwivedi et al. designed an integrated intrusion detection mechanism based on filter selection technology and machine learning algorithm. The result showed that the intrusion detection system with C4.5 achieved high detection rate and accuracy [5]. Chang et al. integrated IoT into intelligent iAIR system to provide real-time air pollution information map. The results showed that the system could send a warning message to the mobile application when the air quality dropped or the user's heart rate was abnormal, and activated the air purifier to improve the current air quality [2].

To sum up, there are very few research results on the application of intelligent navigation obstacle avoidance algorithm to the IoT technology of navigation. The research results of intelligent navigation obstacle avoidance algorithm based on IoT technology are not mature enough. To utilize IoT technology to provide intelligent decision-making for ships, as many factors as possible that affect navigation safety are added to the decision-making system, and an improved I-IONA is constructed by combining artificial intelligence algorithms.

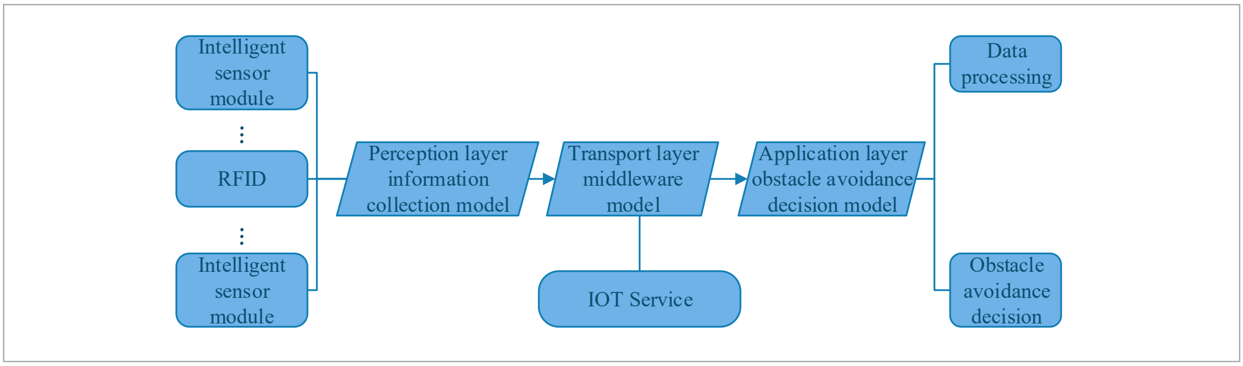
3. Design of Intelligent Obstacle Avoidance Algorithm Combined with Internet of Things Technology

3.1. Navigation Data Acquisition Based on IoT

The IoT technology is the third revolution in the information technology industry. According to the agreed protocol, the task object is connected with the network through information sensing equipment [4]. Objects can exchange information and communicate with each other through information media, thus realizing intelligent identification, supervision and other functions [8]. In the application of IoT technology, the most critical parts are the perception layer, the network transmission layer and the application layer [3]. The structural model of intelligent navigation obstacle avoidance decision-making platform combined with IoT technology is shown in Figure 1.

Figure 1

Structure Model of Intelligent Navigation Obstacle Avoidance Decision-Making Platform Combined with IoT Technology

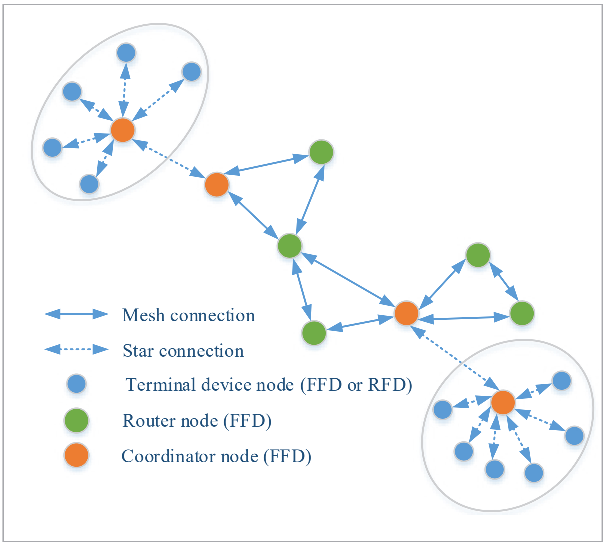


In Figure 1, the model includes information collection module at the perception layer, middleware transmission module at the transport layer, and intelligent obstacle avoidance decision-making module at the application layer. The information collection module includes collecting and storing the data information of each ship in the sea transportation. The middleware transmission module is a communication process based on Zigbee protocol, and then realizes real-time communication from the perception layer to the application layer. The transmission data are used for obstacle avoidance decision-making in the shipping process, and also uploaded to the server of the nearby base station to achieve information acquisition between ships. The sensing layer information acquisition module adopts the current mainstream Radio Frequency Identification (RFID) technology. Various intelligent sensor modules are comprehensively applied to the acquisition and processing of navigation information [1]. RFID is the key technology in IoT. The principle is to use wireless radio frequency to conduct non-contact two-way data communication, and sense the static data of ships by scanning the RFID tags of each ship. Each label is attached to the experimental ship. The ship status data information includes the length, width and height of the ship, the weight and type of the ship, etc. The RFID core module in the information collection module uses the YHY502TG module, which can be erased 100000 times using the ISO14443 protocol. The module can continuously read RFID tags. The collected data are intelligently processed by data mining software. After processing, it can provide the driver with intelligent obstacle avoidance decision of multi-ship encounter. The collection of ship dynamic attribute data includes actual data such as the distance between two ships, real-time speed of ships, and navigation direction of ships. The actual distance between two ships can be read by ultrasonic sensor, which measures the distance by receiving reflected waves. Formula (1) shows the measuring distance H.

$$H = \frac{Ton \cdot V_s}{2}. \tag{1}$$

In Formula (1), H represents the high level time. V_s represents the sound speed, usually at 340m/s. The speed sensor is used for data acquisition of the ship. Gyro sensor is used for collecting navigation direction data. The collection of comprehensive environmental data for ships includes various factors encountered by ships during actual navigation. All factors are divided into real-time collected data and human factor data. Real-time collected data include dynamic environmental factors such as weather conditions, air conditions and draft during the ship's navigation, which can be continuously sensed and acquired by corresponding sensors. The human factor data is controllable and knowable factors in the actual situation, which are recorded by the on-duty pilot before departure. After collecting the comprehensive environmental information data through various intelligent sensor modules, it can be connected to the middleware (IoT Service) through the data converter. Then, based on point-to-point communication of wireless sensor network, it is uploaded to the application layer for data processing. Finally, the environmental factor data of the ship during actual navigation are obtained. The information transmission communication module platform is based on Zigbee protocol wireless sensor network. Zigbee technology is a communication technology related to networking, security, and application software developed based on the IEEE802.15.4 wireless standard. The network structure is shown in Figure 2.

Figure 2
Zigbee Network Structure



In Figure 2, the terminal device node can receive and send information. The network coordination node is responsible for the network and assigns the appropriate network location. Router nodes are responsible for searching, establishing and repairing the path of message packets and transmitting message packets. The IoT Service is a service program that centralizes different applications on the same platform. During operation, firstly, each device is converted into a network interface through the serial port-network interface adapter to establish a connection with the IoT Service and complete the identification of the device type. Secondly, the communication parameters are initialized. Finally, the upper application is connected with the IoT Service to achieve application-level communication between each device and the upper application through middleware. Then the PC connects with the IoT Service. The upper application of intelligent navigation obstacle avoidance is simulated based on the MATLAB environment to predict the collision risk of the location after a certain time in the future. Meanwhile, the priority decision list for obstacle avoidance is recommended. The collected ship static attribute data is the tag information read by the RFID reader, while the dynamic attribute and comprehensive environmental information data are from different intelligent sensor modules. Therefore, the data types obtained are different, and the data needs to be processed. The details are shown in Table 1.

To sum up, a method for collecting and transmitting intelligent navigation information based on the IoT, as well as a structural model for an intelligent navigation obstacle avoidance decision-making platform, can be obtained.

3.2. Design of Intelligent Navigation Obstacle Avoidance Algorithm

According to the statistics of the Maritime Safety Administration, human factors account for 95% of the

Table 1
Collection and Processing of Various Types of Data

Data transmission terminal	RFID tag data transmission terminal	Intelligent sensor sensing data transmission terminal
Data reception	The RFID reader reads the RFID tag data information, and then transmits the data flow of the electronic tag through the RS232 serial interface	The intelligent sensor module senses different types of data and transmits the data information of the sensing module through RS232 serial interface and external LCD expansion device
Data processing	Verify serial data information, filter invalid data, and store it in data buffer	Verify the received data, filter different types of data, and store them in the data buffer
Data transmission	Read the relevant data transferred from the data, and use Zigbee protocol to send the data to the application layer through the network layer for decision-making	Read the data in the data buffer, and use Zigbee protocol to send the data to the application layer through the network layer for decision-making

ship collision accidents. Therefore, predicting potential collision risks in advance can greatly help offshore operators avoid risks. In view of different situations, a kind of intelligent sensor technology based on the IoT is proposed. Combined with BP neural network algorithm and actual situation, the I-IONA is constructed. The flowchart of the I-INOA is shown in Figure 3.

In Figure 3, the weights corresponding to environmental factors affecting navigation safety can be obtained based on Analytical Hierarchy Process (AHP). The environmental factors under the navigation conditions at that time are obtained from the environmental factor data collected by the perception layer module. Secondly, the prediction time T is comprehensively judged according to the environmental factors and the collected ship speed and course. Then, the trained BP neural network is used to predict the position S of the ship after the T time. Finally, the collision risk degree of the ship at S is evaluated through the nautical knowledge model. The environmental factors δ for safe navigation are determined according to the opinions of navigation experts, including six environmental factors, namely, the Aspect Ratio (AR), Weather Condition (WC), State of Visibility (SV), Draft Shallowness (DS), Driving Experience (DE), and Navigation Density (ND) of the two ships. The structural model of Safe Navigation (SN) is established by the AHP method, as shown in Figure 4.

For the weight of environmental factors, the judgment matrix SN of the target layer is first calculated, as shown in Formula (2).

$$SN = \begin{pmatrix} s_{11} \cdots s_{1n} \\ \vdots \quad \ddots \quad \vdots \\ s_{n1} \cdots s_{nn} \end{pmatrix}. \qquad (2)$$

In Formula (2), L_j and $C_j, j = 1, 2, \cdots 6$ represent the six environmental factors of SN, including SV, ND, WC, DE, DS, and AR. The element s_{nn} indicates that the environmental factors in row n and column n are

Figure 3

Flow diagram of I-INOA

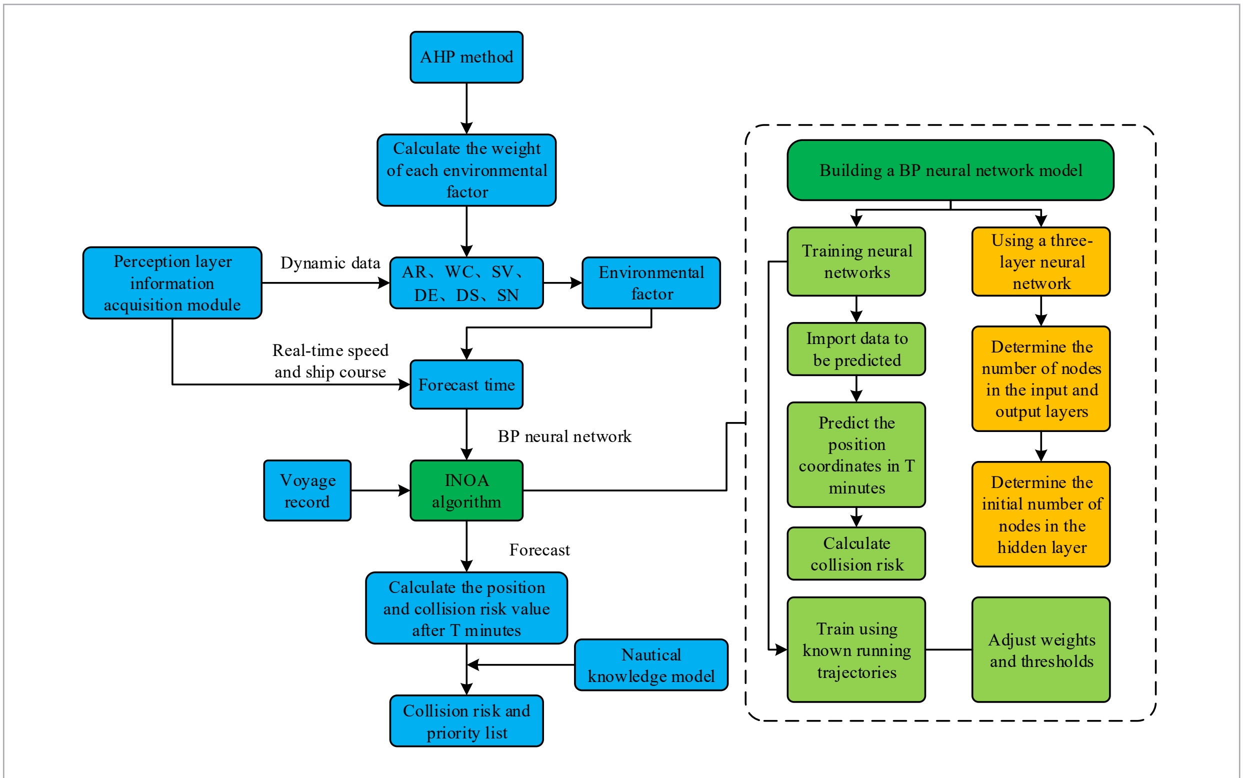
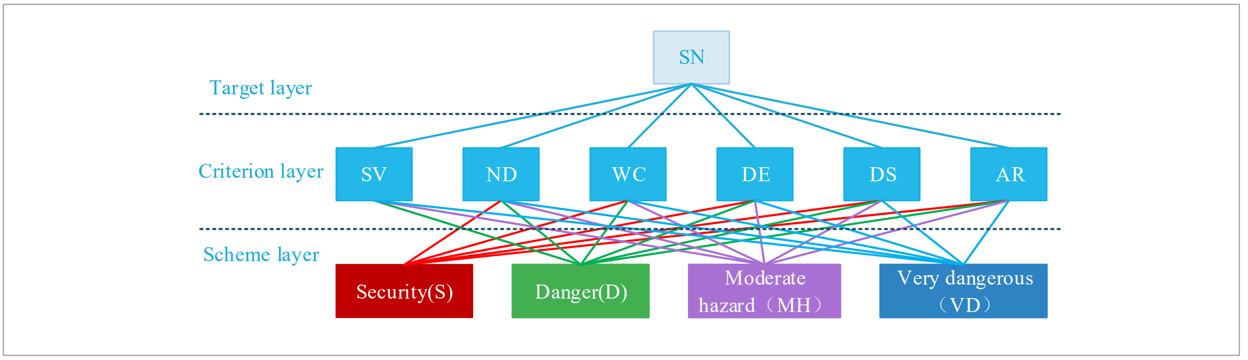


Figure 4
Structural Model of Safe Navigation Based on AHP



compared. The judgment matrix of SV is displayed in Formula (3).

$$SV=\begin{pmatrix}1 & 2 & 3 & 4\\ 1/2 & 1 & 2 & 3\\ 1/3 & 1/2 & 1 & 2\\ 1/4 & 1/3 & 1/2 & 1\end{pmatrix}. \tag{3}$$

In Formula (3), the row L_j and column $C_j, j=1,2,\cdots 4$ respectively represent the score of visibility. According to the evaluation factors of excellent, good, medium and poor, the evaluation sequence of SV is determined as $(4,3,2,1)$. The judgment matrix of ND is shown in Formula (4).

$$ND=\begin{pmatrix}1 & 2 & 3\\ 1/2 & 1 & 2\\ 1/3 & 1/2 & 1\end{pmatrix}. \tag{4}$$

In Formula (4), the row L_j and column $C_j, j=1,2,3$ represent the large, medium and small of ND. The evaluation sequence of ND is $(3,2,1)$. The judgment matrix of WC is shown in Formula (5).

$$WC=\begin{pmatrix}1 & 2 & 3 & 3 & 5 & 7\\ 1/2 & 1 & 2 & 3 & 3 & 5\\ 1/3 & 1/2 & 1 & 2 & 2 & 5\\ 1/5 & 1/3 & 1/3 & 1 & 1 & 3\\ 1/5 & 1/3 & 1/3 & 1 & 1 & 3\\ 1/7 & 1/5 & 1/5 & 1/3 & 1/3 & 1\end{pmatrix}. \tag{5}$$

In Formula (5), the row L_j and column $C_j, j=1,2,\cdots,6$ are sunny, cloudy, rainy, snowy, windy and foggy, respectively. The evaluation sequence of WC is $C_j, j=1,2,\cdots,6$. The judgment matrix of DE is shown in Formula (6).

$$DE=\begin{pmatrix}1 & 2 & 3\\ 1/2 & 1 & 2\\ 1/3 & 1/2 & 1\end{pmatrix}. \tag{6}$$

In Formula (6), the row L_j and column $C_j, j=1,2,3$ are DE greater than 20 years, 10-20 years and less than 10 years, respectively. The evaluation sequence of DE is $(3,2,1)$. The criterion matrix of DS is shown in Formula (7).

$$DS=\begin{pmatrix}1 & 2\\ 1/2 & 1\end{pmatrix}. \tag{7}$$

In Formula (7), the row L_j and column $C_j, j=1,2$ are the depth and depth of DS. The evaluation sequence of DS is $(2,1)$. The criterion matrix of AR is shown in Formula (8).

$$AR=\begin{pmatrix}1 & 2 & 3\\ 1/2 & 1 & 2\\ 1/3 & 1/2 & 1\end{pmatrix}. \tag{8}$$

In Formula (8), the row L_j and column $C_j, j=1,2$ are AR greater than 1, equal to 1 and less than 1, respectively. The evaluation sequence of AR is $(1,2,3)$. There is a $SN\zeta=n\zeta$ relationship between SN and the value sequence ζ of the environmental factors. n is the number of factors defined by SN. According to the theory of matrix algebra, ζ can be obtained by equation (9).

$$SN\zeta = \eta_{AMX}\zeta \ . \tag{9}$$

In Formula (9), η_{AMX} is the maximum characteristic value of SN. The consistency test of single level and total level is carried out in MATLAB, and the corresponding weights of environmental factors can be obtained, as shown in Formula (10).

$$\begin{aligned}\zeta &= \left(\zeta_{AR}, \zeta_{WC}, \zeta_{SV}, \zeta_{DS}, \zeta_{DE}, \zeta_{ND}\right) = \\ &= \left(0.073, 0.1399, 0.2965, 0.057, 0.2737, 0.1585\right),\end{aligned} \tag{10}$$

Formula (10) represents the judgment factors in the actual navigation environment. SV and DE have the largest weight, at 0.2965 and 0.2737, respectively. To predict the collision risk in a short time as soon as possible, environmental factors EF are introduced. The corresponding values T are calculated for the ships operating under different conditions, as shown in Formula (11) [22-23].

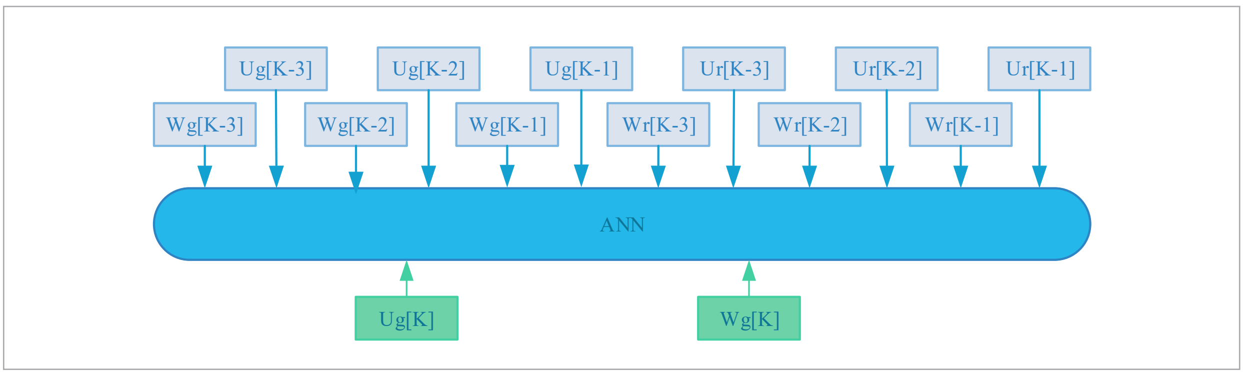
$$\begin{cases} EF = \sum_{j=1}^{n} \dfrac{Q_j \cdot \zeta_j}{LenN_j} \\ T = T_0 + \dfrac{v_X}{v_Y}\cos\left(\dfrac{d_X - d_Y}{360}\pi\right) + ef \end{cases} . \tag{11}$$

In Formula (11), X and Y refer to the ship and the meeting ship, respectively. $Q_j, j = 1, 2, \cdots, 6$ represents the evaluation of actual environmental factors. $\zeta_j, j = 1, 2, \cdots, 6$ represents the weight of each environmental factor. $LenN_j, j = 1, 2, \cdots, 6$ is the length of each environmental factor evaluation sequence, which is used for environmental factor normalization. $T_0 = 3$ is the reaction time given by expert opinions. v_X and v_Y, d_X and d_Y respectively represent the current speed and heading of the two ships. The intelligent navigation obstacle avoidance algorithm mainly uses BP neural network to predict the next navigation plan and trajectory after intelligent learning of the actual ship navigation. The research adopts the basic three-layer BP neural network structure to learn the ship navigation habits in a supervised learning mode. The learning process is mainly divided into forward transmission sub-process of working signal and reverse transmission sub-process of error signal. The three-minute prediction algorithm is that the intelligent navigation ship obstacle avoidance decision-making platform must make a decision within three minutes after obtaining the information of each ship [26]. The algorithm steps are to collect training data, establish BP neural network model, train the Artificial Neural Network (ANN), and finally estimate the position that each ship can reach in three minutes. The ANN structural model is shown in Figure 5.

In Figure 5, the input vector is the position vector of the first three minutes of data at the current time. The output vector is the position vector three minutes after the current time. Ug and Wg are the longitude and latitude of the ship's location. Ur and Wr are vector values of the horizontal and vertical directions of the ship's bow direction. K is the current value. However, in actual navigation, due to adverse weather conditions and other environmental impacts, the three-minute prediction algorithm cannot provide time support for people to take timely obstacle avoidance measures. Therefore, the three-minute

Figure 5

Schematic Diagram of ANN Structure Model



prediction algorithm is optimized. Aiming at the slow convergence speed and easy over-fitting of BP neural network, the study adopts the early termination iteration algorithm for learning optimization. To make the navigation obstacle avoidance algorithm more intelligent, EF is introduced to make the algorithm automatically adjust the best prediction time according to the changes of the actual navigation environment. BP neural network is used to predict the position coordinates S of the ship after T minutes. Finally, the collision risk value χ and risk degree of the ship at S are calculated, as shown in Formula (12).

$$\begin{cases} \chi_{Y|X} = \dfrac{H_{Y|X}}{MINH_{Y|X}} \\ H_{Y|X} = h_{XY} \sin\left(\dfrac{\psi_h - d_{Y|X}}{360}\pi\right) \end{cases} \tag{12}$$

In Formula (12), $\chi_{Y|X}$ is the collision risk value brought by Y to X. $H_{Y|X}$ represents the actual collision distance between two ships. $MINH_{Y|X}$ is the minimum collision distance input by the driver, which is 3 nautical miles. h_{XY} represents the distance between two ships. ψ_h is the heading of the relative motion vector of the two ships. $d_{Y|X}$ is the heading of Y. The classification of Security (S), Danger (D), Moderate Hazard (MH) and Very Dangerous (VD) in the scheme layer is shown in Formula (13).

$$\chi \in \begin{cases} [2,+\infty), S \\ [1.5,2), D \\ [1,1.5), MH \\ (0,1), VD \end{cases} \tag{13}$$

A smaller χ value indicates a higher risk factor for collision between two ships. The Formula (14) can be obtained by arranging χ values from small to large.

$$List(CRI) = (\chi_1, \chi_2, \cdots, \chi_n) \tag{14}$$

Formula (14) satisfies $\chi_j < \chi_k \, (j < k)$. If the ship is close, it indicates a greater risk of collision with X. Therefore, the obstacle avoidance should start from the most dangerous ship.

4. Result Analysis of Intelligent Obstacle Avoidance Algorithm Combined with Internet of Things Technology

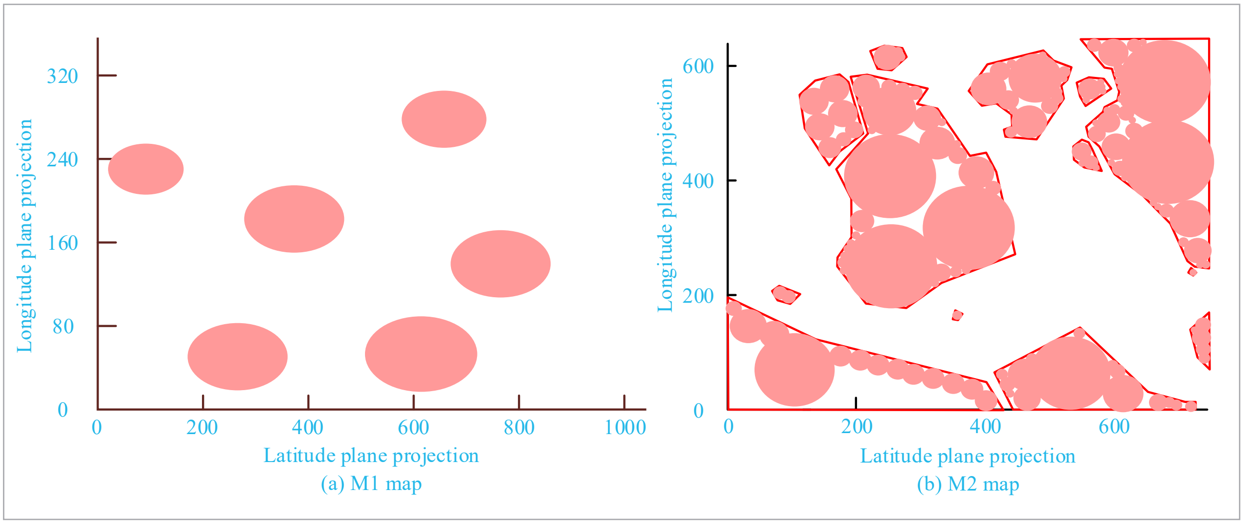
4.1. Preparation Before Simulation Experiment

To test the effectiveness and feasibility of the research method, the study first selects the navigation records of four ships with fixed routes within one week as simulation test data, with approximately 300 records for each ship. After the research method is stable, the historical navigation records of 30 other ships at one pole can be imported, totaling 25000 records. In addition, the data collected through sensors include temperature and humidity, lighting, speed, visibility, heading, and draft, as well as required dynamic data, static data, and environmental information data. After data collection, corresponding data discretization models based on maritime expert opinions can be constructed for processing. The processed data can be used as the input dataset. When conducting obstacle avoidance experiments, S1 ship is used as the research object, while S2-S4 is used as the dynamic other ship. Two types of random obstacle maps are constructed under complex water conditions, namely M1 and M2. M1 is used for performance analysis of different prediction algorithms, while M2 is a simulation map constructed based on actual sea areas and replaced obstacles in land and water areas with inflated circles. After processing, a simulation map of complex water areas in practical applications can be obtained.

The specific simulation map display diagram is shown in Figure 6. The experimental parameters are as follows. The corresponding weights for visibility, peer density, weather, driving experience, draft condition, and the length of the two ships encountered in the environmental factors are 0.2966, 0.1583, 0.1402, 0.2739, 0.054, and 0.077, respectively. In addition, to more scientifically verify the performance of the research method in control, the study selects the widely used methods for solving practical navigation problems, namely Multi-Layer Neural Control of High Order Uncertain Nonlinear System with Active Interference Suppression (MLNC-HUNSAIS), a new integrated robust scheme for Active Interference Suppression and Asymptomatic Tracking (ATNIRS), and a new type of integrated robust scheme for mis-

Figure 6

Specific Simulation Map Display Schematic Diagram



matched uncertain nonlinear systems, which are verified through M2 maps [16, 25]. To ensure the fairness and rationality of the comparative experiment, all comparison methods are tested under the same environmental conditions, including encountering ship parameters, etc. At the same time, to reduce the influence of randomness, multiple experiments are conducted and the average value of performance indicators is taken for evaluation.

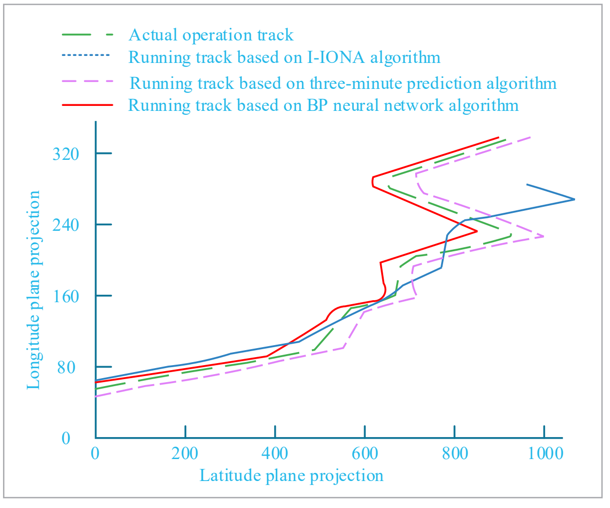
4.2. Performance Analysis of Intelligent Obstacle Avoidance Algorithm Combined With Internet of Things Technology

To verify the performance of the I-IONA proposed in the study, MATLAB is used as the simulation platform. The research data comes from two parts. The first part is the information acquisition module of the perception layer in the intelligent navigation obstacle avoidance platform, including the dynamic determination of environmental factors and the corresponding optimal prediction time. The other part comes from the navigation records of different types of ships in the global shipping service system to evaluate the effectiveness of I-IONA. During the test, the research selects the navigation records of four ships with fixed routes within one week as the simulation test data. Each ship records about 300 positions, and the ship number is S1-S4. In the simulation experiment, the same ship parameters and external environmental conditions are analyzed to ensure fairness when comparing different algorithms.

To evaluate the performance of I-IONA more scientifically, the proposed algorithm is compared with BP neural network algorithm and three-minute prediction algorithm. The prediction results of the two algorithms are shown in Figure 7. Compared with the other two algorithms, the I-IONA was closer to the actual operation trajectory of the ship. The prediction accuracy of I-IONA reached 97.83%. The three-minute prediction algo-

Figure 7

Prediction Effect of Two Algorithms



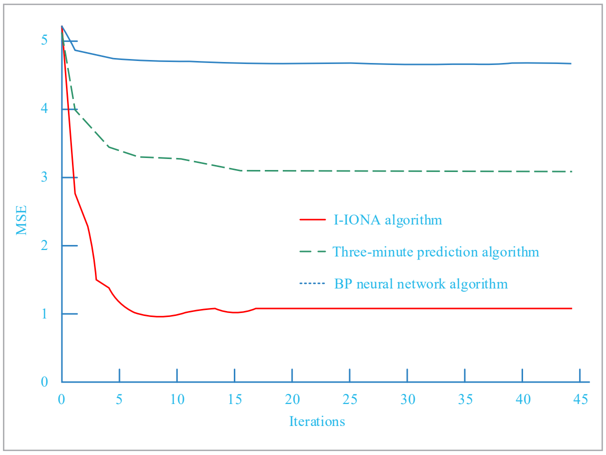
rithm was 89.65%, while the BP neural network was only 88.97%. The research results show that the proposed I-IONA has higher accuracy in the actual operation.

The neural network toolbox in MATLAB can also provide the Mean Square Error (MSE) function. This function is used to calculate the MSE between the output of the neural network and the target vector. A small MSE value indicates better fitting performance between the algorithm and the actual data, and more accurate data prediction. The MSE of predicted output and actual trajectory is obtained by calculating I-IONA and three-minute prediction algorithm. From Figure 8, the I-IONA reached the best state only after four iterations, and the error between the predicted ship route and the actual route was 1.1192. The three-minute prediction algorithm experienced 35 iterations to reach the best state. At this time, the error between the predicted ship route and the actual route was 4.1782. The BP neural network algorithm experienced 45 iterations to reach the optimal state. The error between the predicted ship route and the actual route was 5.3128. The research results show that the proposed I-IONA can provide more accurate ship navigation prediction in practical applications.

To further verify the feasibility of the proposed I-IONA in making obstacle avoidance decisions, the obstacle avoidance experiments are conducted on ships based on three different algorithms. The effectiveness result of obstacle avoidance decision is shown in Figure 9. The higher the decision efficiency score is, the better

Figure 8

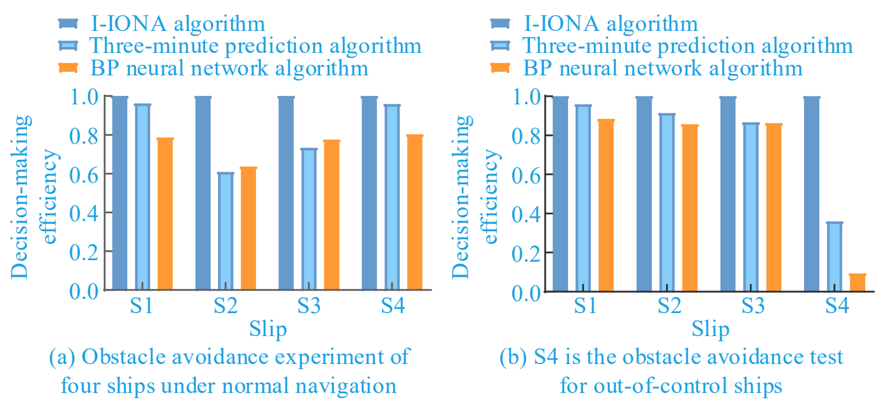
MSE Value Change Curve of Two Algorithms



the decision performance of the algorithm. When the decision-making efficiency was 1, the decision was ideal. Figure 9(a) shows the obstacle avoidance experiment of four ships under normal navigation. The decision-making efficiency of the four ships based on I-IONA was the highest, at 1. The decision-making efficiency of all ships based on BP neural network algorithm was the lowest in the obstacle avoidance experiment. The decision-making efficiency of S2 ship was the lowest, at 0.6359. Figure 9(b) is the obstacle avoidance test of S4 ship out of control. The decision-making efficiency of the four ships based on I-IONA was still the highest, at 1. The decision-making efficiency

Figure 9

Results of Effectiveness of Ship Obstacle Avoidance Decision Based on Different Algorithms in Two Types of Obstacle Avoidance Experiments

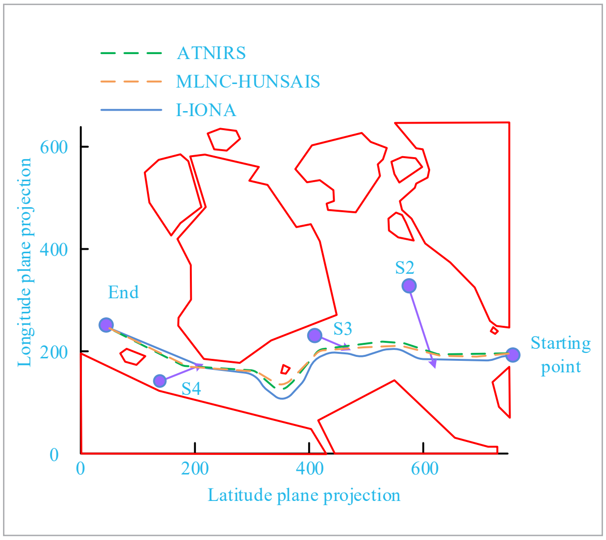


of S4 ship based on the three-minute prediction algorithm and BP neural network algorithm decreased significantly to 0.3588 and 0.09355, respectively. To sum up, I-IONA has better performance and accuracy. It has high feasibility and reliability in the practical application. The research results show that the proposed I-IONA can provide more accurate results.

To further analyze the control effect of the I-IONA in practical scenarios, comparative experiments are conducted on the M2 map. The results are shown in Figure 10. The research algorithm not only had good prediction performance, but also could provide four key points for the path during actual dynamic control. The S2-S4 ships corresponded to the first to third segments of the path. Among them, S2 was set to cross and encounter S1, and the algorithm could immediately make a decision to give way, which complied with navigation rules. S3 and S1 formed an overtaking situation. S1, as the overtaking ship, made a right turn to avoid it. S4 and S1 ships were in a head-on situation, and the research method could also make a decision to turn right and avoid. The above results indicate that the research method can accurately control the hull and make decisions that comply with navigation rules. The MLNC-HUNSAIS method and the ATNIRS method may experience certain heading oscillations when encountering multiple ships in complex waters, which may be due to the fact that the above two methods can only guide navigation direction through real-time collision risk assessment. Due to the uncoordinated dynamic changes of attraction and repulsion, there may be delays in obstacle avoidance control in certain scenarios, and it may even be impossible to ensure that incoming ships are outside the safe range. This indicates that although the automatic navigation system based on uncertain nonlinear systems has good robustness to uncertain factors, disturbance factors can cause damage to the system control, and the controller needs to continuously update its own parameters during application. This research method can achieve fast and stable heading changes, smooth obstacle avoidance paths, small fluctuations, and ensure a safe distance from dynamic other ships, providing safe and effective guidance for ship navigation. However, it only considers the obstacle avoidance decision-making of ships as single agents, and does not take into account real-time collaborative obstacle avoidance between ships.

Figure 10

Comparison of Control Effects of Different Algorithms on M2 map



4.3. Application of Intelligent Obstacle Avoidance Algorithm Combined with Internet of Things Technology in Navigation

To study the work of the I-IONA in the actual navigation, the research obtains the partial navigation records of the fishing vessel Z in the first ten days of May through the global shipping service system, including the operation time, the longitude and latitude corresponding to each time, the speed and the course.

There are 226 position data recorded in a single voyage, and the voyage is 77.15 nautical miles. After data

Figure 11

Fishing Ship Z Morning Navigation Track

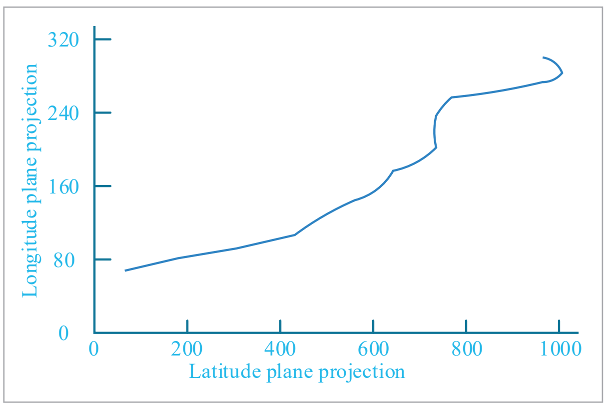


Table 2
Results of Prediction Time

Serial number	1	2	3	4	5	6
AR	1	2	3	2	2	2
WC	1	3	6	3	3	3
SV	1	2	4	2	2	2
DS	1	2	3	2	2	2
DE	1	2	3	2	2	2
ND	1	2	3	2	2	2
vX(nm/min)	8	8	8	25	14	14
Vy(nm/min)	6.3	6.3	6.3	20	15	15
dX(°)	60	60	60	60	60	60
dY(°)	300	300	300	300	300	300
T/(min)	2	3	5	3	3	4

processing, 190 effective positions are obtained. Longitude and latitude are converted into navigation path in Gauss projection rectangular coordinates, as shown in Figure 11. The navigation track of Z in the early stage was relatively flat. In the later stage, it changed greatly. The course changes greatly.

Combined with the real-time speed and heading information of the ship, the included angle between the heading direction and the true north can be determined to obtain the predicted time results, as shown in Table 2. From the results of columns 1 to 3 in the figure, the complex navigation environment indicated that T was shorter. The prediction accuracy of the ship's navigation position at the next moment was correspondingly higher. The results of columns 4 and 5 showed that when the environmental conditions were the same as the course of the two ships, both ships quickly indicated that the T value was shorter. The experimental records in columns 5 and 6 showed that under the same conditions, there were possible collision points on the extension line of the navigation direction of the two ships, and T was shorter.

The data used in the study is the navigation records of fishing ship Z (research ship), cargo ship S2, fishing ships P and O in the first ten days of May. Other fishing ships are target vessels. The actual situation is as follows. AR is 1, WC is sunny, SV is good, DE is medium, DE is 10-20 years, and ND is medium. The speed of ships encountered is 6.3nm/min, and T is 4 minutes. The χ between the three target ships and Z at the predicted position and the list results of obstacle avoidance risks are shown in Table 3. In Table 3, the collision risk of P and Z was the lowest, at 0.5526. It shows that the collision possibility between two ships is the greatest, and obstacle avoidance measures should be taken for P first. The χ values of O and S3 were 0.7651 and 1.6794, respectively. The priority list of obstacle avoidance was P, O and S2.

Table 3
Obstacle Avoidance Risk List Result

Ship	χ	Collision risk
S2	1.6794	D
P	0.5526	VD
O	0.7651	VD
List of collision risk values: $(0.5526, 0.7651, 1.6794)$		
Collision priority list: $(P, O, S2)$		

5. Conclusion

To avoid collision between ships during navigation and reduce the casualty rate of maritime accidents, the intelligent acquisition and transmission of ship data through IoT technology is explored. In the aspect of intelligent obstacle avoidance decision in IoT application layer, an I-IONA combining AHP and BP neural network algorithm is proposed. The experimental results showed that the prediction accuracy of I-IONA was 97.83%. It was 8.18% higher than the three-minute prediction algorithm and 8.86% higher than the BP neural network algorithm. In the obstacle avoidance experiment of four ships under normal navigation, the decision-making efficiency of four ships based on I-IONA algorithm was the highest, reaching 1. In the obstacle avoidance experiment of S4 ship out of control, the decision-making efficiency of the four ships based on I-IONA was still the highest, at 1. The decision-making efficiency of S4 ship based on the three-minute prediction algorithm and BP neural network algorithm decreased significantly to 0.3588 and 0.09355, respectively. In practical applications, the priority list of obstacle avoidance was P, O and S2 by calculating the risk degree values of three ships with the research ship. In conclusion, I-IONA has good performance. In practical applications, it can quickly obtain the obstacle avoidance priority list and make intelligent decisions. However, there are still shortcomings in the research, which focuses on the intelligent decision-making part, but lacks specific implementation plans. In future research, more advanced artificial intelligence technology can be introduced to assist ships in automatically executing obstacle avoidance commands based on the priority list.

Declarations

Ethical Approval

Not applicable.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Authors' contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Yu Guo and Wei Wang. The first draft of the manuscript was written by Yu Guo and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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