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Optimizing Ship Pilotage with Intelligent Information Services: Integrating GIS-Based Big Data Positioning and Neural Network Approaches

Yunye Ren
Associate professor, School of Nautical Technology, Jiangsu Shipping College, Nantong 226010, China, Email: renyunye123@163.com

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Abstract: The development of the shipping industry has put forward new requirements and challenges for its pilotage and services. To promote navigation development and ensure safe and efficient ship navigation, experiments have been conducted to combine geographical information systems (GIS) big data with neural systems, resulting in a proposed intelligent ship pilotage service method. This paper presents a novel approach to building a ship pilot system using GIS technology. The system is enhanced with the introduction of the Faster-RCNN model to improve its positioning function, and Gaussian distribution is employed to optimize the loss function. Finally, the system's ship pilot service set time parameters are solved based on ship entry and exit scheduling to achieve intelligent navigation and services for ship piloting. The data showed that on the MarineT dataset, the research method (GIS big data positioning-neural network) achieved its maximum fitness value at 36 iterations of the system, with a value of 99.78. At the same time, when the system ran 66 times, the average absolute percentage error obtained by the research method infinitely approached 0. In addition, based on the AIS dataset, when the recall rate of the four algorithms was 0.800, the accuracy of the research method was 0.873, with the highest numerical value. Practical applications have shown that when the system iterated 51 times, the total waiting time for ship piloting in and out of the port quickly decreased to 177.92 hours, which is significantly better than manual scheduling time. The aforementioned findings suggest that the implemented system has the capability to considerably decrease piloting time, deliver cutting-edge technical aid for the current expansion of the shipping sector, and establish a stable basis for future intelligent shipping technology.

Keywords: GIS positioning, big data, neural network, ships, pilot, intelligent services, information service.

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1. Introduction

In today's globalized world, ship transportation has become the main mode of cargo transportation. With the continuous growth of global trade volume, the demand for accurate and efficient navigation information services for ships has also increased. Traditional ship navigation methods rely on the expertise and professional knowledge of the captain or crew. However, advancements in technology have led to the emergence of more precise and efficient methods that are now widely implemented. Geographic Information System (GIS), as a computer-based tool, can perform graphical analysis of things that exist and events that occur on the Earth (Zhang and Zheng, 2020). GIS provides researchers with a geographically centric approach to viewing and analyzing data. Through GIS, humans can capture, store, inspect, and present location related data (Lou et al., 2021). In addition, in terms of ship navigation, GIS can provide detailed geographic, hydrological, and meteorological data to help ships make better navigation decisions. At the same time, big data and neural network technology have added more intelligence and flexibility to modern navigation systems. Big data analysis can predict future routes and potential obstacles based on past navigation data and ship behavior patterns, thereby providing more accurate navigation recommendations (Liu et al., 2022). Neural networks, especially deep learning methods, can perform pattern recognition on a large amount of navigation data, providing more personalized and accurate navigation services (Jahanbakht et al., 2021; Islam et al., 2023). The study aims to objectively determine the structure and parameters of the ship pilotage service (SPS) set model. The plan is to develop a more advanced, efficient, and intelligent ship pilotage system by utilizing GIS technology along with neural networks. It is expected to provide novel technical support for ship piloting while also establishing a standardized set of pilot services for ports and ships, enhancing the development of intelligent maritime transportation.

The paper is divided into four parts. The second part is about the current development status of artificial intelligence, GIS technology and ship piloting systems at home and abroad. The third part extensively outlines the research methodology, wherein the novel integration of GIS big data and Faster-RCNN is executed to develop a ship pilotage intelligent service system (SPISS). Among them, Faster-RCNN is an efficient object detection network that combines a Region Proposal Network (RPN) and a fast Convolutional Neural Network (CNN) to achieve fast and accurate object detection. Part 4 is the performance test and application effect of the designed system. Part 5 is a summary statement of the entire research.

The main contributions of the paper can be divided into three points. First, this study combines GIS big data positioning technology with advanced neural network algorithms to provide an innovative intelligent information service platform for ship piloting. This integrated method opens up a new research direction in the field of maritime navigation and provides a new theoretical and practical basis for subsequent research. Second, this paper presents a system capable of real-time processing of a vast quantity of marine environment and navigation data, providing substantial benefits in managing intricate and dynamic maritime scenarios, and enhancing navigation safety and efficiency. Third, through performance testing and application analysis, this study proves the effectiveness of using neural networks to provide navigation intelligent services, which has rarely been covered in previous research.

2. Related Works

In ship piloting, the introduction of GIS can effectively help navigators carry out their work more efficiently, and in recent years, this technology has received widespread attention from scholars from all walks of life. Chen et al. (2020) proposed to apply GIS technology to the development of urban planning intelligent management information systems to design spatial data models for urban construction. The system's overall performance was inherently stable and could provide effective support for urban planning. Mustafa et al. (2020) used GIS technology to construct a model framework that could meet the needs of tourists. This model created a platform by integrating travel demands and various technologies such as remote sensing maps. This system has the ability to efficiently search and navigate tourist destinations, leading to a substantial increase in traffic allocation coverage. To effectively plan cities, Zhu and Zhou (2020) proposed the effective application of GIS technology and machine learning algorithms in virtual city construction models. This model captured multiple features of a city and had excellent performance, meeting the expected goals. Chen and Wu (2022) deployed more 5G network artificial intelligence (AI) in monitoring systems to avoid maritime accidents caused by monitoring failures during maritime navigation. The performance of this system was significantly superior to other studies and could reduce the incidence of maritime accidents. Wang et al. (2021) proposed to apply the BeiDou Satellite Navigation System (BDS) to the maritime remote sensing positioning and detection system to ensure safety during navigation and avoid accidents. This model could be widely applied in ships and maritime engineering, providing intelligent services for the navigation of maritime ships.

At the same time, many scholars have also explored other different technologies and methods in the field of related navigation. Li et al. (2020) proposed applying improved CNN to view generation service boxes to meet the needs of multi view video surveillance. The obtained system framework could effectively improve the accuracy of monitoring horizontal images from 83.2% to 89.8%, effectively eliminating blind spots in the view. Liu et al. (2022) proposed a satellite joint land based automatic recognition system to apply intelligent service systems to the maritime joint network. It integrated effective loss functions to make the prediction results of the obtained data more robust and reliable in different navigation environments and had excellent prediction performance. Lou et al. (2021) proposed a new type of autonomous driving method to improve the safety of ships during navigation. Its fusion of LSTM models enabled real-time adjustment of the ship's heading to ensure the safe operation of the system during low sea waves. This model had high prediction accuracy and could effectively meet the requirements of safe navigation of ships. Zhang and Zheng (2020) proposed the application of the Internet of Things and Cloud Computing Technology (C-CT) in marine logistics information platforms to achieve intelligent logistics information. The resulting platform could effectively achieve real-time positioning and monitoring of land and sea cargo, significantly improving the positive efficiency of maritime logistics management. Cui and Zhang (2020) introduced various technologies, such as C-CT and GPS navigation in the software system to improve the comprehensive performance of the hybrid positioning system. It could optimize parameters based on the actual needs of users and reduce system maintenance costs.

In summary, GIS technology has been widely applied in various geographical explorations and has achieved good results. At the same time, various AI methods and technologies have also been applied to offshore management systems, but there are currently few studies that combine GIS technology with neural network algorithms and apply them to the SPISS. And ship pilotage is the key to reducing ship accidents and safety hazards. To this end, this paper adopts an innovative method to develop a new SPISS by integrating GIS big data and neural networks. The system first uses GIS technology to build a basic framework for ship piloting, then integrates the Faster-RCNN model to enhance the system's positioning capabilities and applies the Gaussian distribution method to optimize the loss function. In addition, the paper also focuses on analyzing the ship's entry and exit scheduling process. By calculating the time parameters of the ship's pilot service, it is expected to realize intelligent management and service optimization of the ship's pilot process.

3. SPISS Integrating GIS Technology and AI Methods

Ship pilotage and transportation are an important part of the navigation industry in all countries around the world. To make ship pilotage technology and systems serve humans more intelligently, the experiment plans to combine GIS and AI technology to build a SPISS. Among them, GIS big data provides precise geographical location information, which is crucial for path planning, collision avoidance, environmental monitoring, etc. Neural networks, on the other hand, have advantages in processing complex data, learning ship behavior patterns and predicting potential navigation problems. The experiment combines the two and applies them to the navigation industry, hoping to improve detection accuracy and make ship positioning more accurate.

3.1. Design of SPS Based on GIS Positioning and Faster-RCNN

To better carry out the service functions of the SPISS, a SPS is prioritized and constructed using GIS technology. The system mainly consists of five parts, namely GPS satellite positioning system, platform client, system server, database, and Google Map server. The system is designed using a modular structure and can be mainly divided into three modules: the application program on the platform client, the data service on the server side, and the mobile positioning module. Fig. 1 shows the overall architecture of the system.

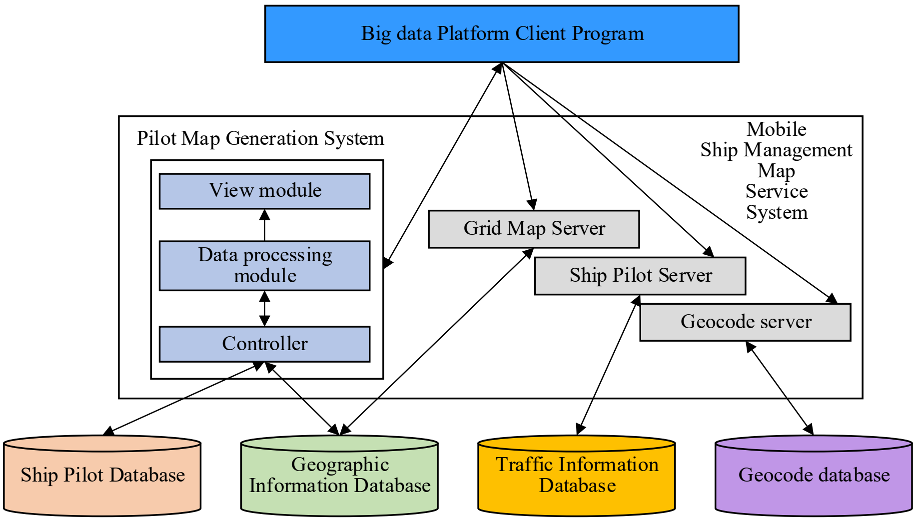

Fig. 1. Overall framework of the system

The SPS based on the constructed system is redesigned. Ship piloting target positioning is actually a multi target detection task. To achieve more comprehensive ship piloting and positioning, Faster-RCNN was selected as the model in the experiment. In the ship piloting systems, real-time and accuracy are crucial to ensuring navigation safety, and Faster-RCNN can effectively provide excellent performance in these two aspects. The Faster-RCNN model integrates classification and regression operations into a network. The loss function for this model is composed of two parts: the classification loss and the regression loss (Amin et al., 2023; Chen and Wu, 2022). The specific calculation is Eq. (1).

$$L(p,u,t^u,v) = L_{cls}\left(p,u\right) + \lambda\left[u \geq 1\right] L_{loc}\left(t^u,v\right) \tag{1}$$

In Eq. (1), $L_{cls}\left(p,u\right)$ represents the loss of classification error. However, when performing ship pilotage classification tasks, the logarithmic function is used to calculate the classification loss. The experiment calculates the probability values for each individual category. The classification loss function is Eq. (2).

$$L(Y,P(Y|X)) = -\log P(Y|X) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log\left(p_{ij}\right) \tag{2}$$

In Eq. (2), X represents the input unit. Y represents the output unit. $L(Y,P(Y|X))$ represents the loss between the predicted value and the true value. N represents the number of samples. M represents the number of categories. y_{ij} represents whether category j belongs to the real category in instance x_i. p_{ij} represents the binary probability value of the category. The regression stage of ship pilotage prediction box can be divided into RPN training stage prediction loss and offset loss relative to the target box. The specific calculation is Eq. (3).

$$L_{loc}\left(t^u,c\right) = \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}\left(t_i,t_i^*\right) \tag{3}$$

In Eq. (3), t_i represents the position information $\left\{t_x,t_y,t_w,t_h\right\}$ of the anchor box. t_i^* represents the actual offset from the target box. N_{reg} represents the size of the feature map. λ represents the weight coefficient. When the model performs regression operations for target localization, the experiment uses the $SmoothL_1$ loss function with better robustness as the main function to perform regression training on the regions between categories, as shown in Eq. (4).

$$\begin{cases} L_{loc}(t^u, v) = \sum_{i \in \{x,y,w,h\}} SmoothL_1\left(t_i - t_i^*\right) \\ SmoothL_1\left(x\right) = \begin{cases} 0.5x^2, if\ |x| < 1 \\ |x| - 0.5, otherwose \end{cases} \end{cases} \tag{4}$$

In Eq. (4), x represents the deviation between the predicted result and the actual target. The $SmoothL_1\left(x\right)$ function is used to determine the anchor point. When using the Faster-RCNN model for ship pilotage detection research in the experiment, the positioning loss calculation of the system is based on the gradient backpropagation of the target box and boundary box. It does not take into account the uncertainty of the positioning of the prediction box, so it is not possible to make corrections to the predicted pilot plan. Here, Intersection over Union (IoU) is introduced to evaluate the regression effect of pilot bounding boxes. Furthermore, to address the challenge of inconsistent alignment between the two bounding boxes, an experiment introduces a penalty term factor to comprehensively evaluate various situations. Additionally, the experiment models the distance between the center of the prediction box and the target box with the minimum matrix containing both elements (Song et al., 2020). This function is defined as DIoU, as shown in Eq. (5).

$$L_{DIoU} = 1 - IoU + \frac{\rho^2\left(b, b^{gt}\right)}{c^2} \tag{5}$$

In Eq. (5), $\frac{\rho^2\left(b, b^{gt}\right)}{c^2}$ represents the penalty factor. b, b^{gt} represents the center points of the candidate region and the target region, respectively. $\rho(\cdot)$ represents a function that can calculate Euclidean distance. c represents the diagonal distance of the minimum matrix containing the two; d represents the distance between the center neighborhoods of the two boxes. In the process of regression design for the bounding box of SPS, it is necessary to redesign the encoding form of the prediction box to independently optimize it. Introducing the Gaussian distribution method again to improve the loss function twice, and learning the degree of dispersion of the position information between the prediction box and the target box. Simultaneously using a combination of variance voting and NMS to effectively screen redundant candidate boxes In traditional Faster-RCNN network position prediction, the position of the target box is represented by a four-dimensional vector $\left(x, y, w, h\right)$. The experiment uses probability distribution to represent the reliability of the predicted box's position, with each coordinate of the candidate box being relatively independent. A univariate Gaussian distribution is used to model the candidate box. To facilitate the description process, the coordinate information of the bounding box is unified and set to x. The coefficient is set as shown in Eq. (6).

$$P_e\left(x\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x - x_e)^2}{2\sigma^2}} \tag{6}$$

In Eq. (6), x_e represents the candidate box position in the prediction stage. σ represents the standard deviation, which is the degree of uncertainty in the prediction. When σ infinity approaches 0, it means that the position of the prediction box is more closely aligned with the position of the target box. For the true target box position in the dataset, probability distribution is also used to represent it. When the standard deviation approaches zero infinitely, it can be converted into a Dirac function, as shown in Eq. (7).

$$P_D(x) = \sigma\left(x - x_g\right) \tag{7}$$

In Eq. (7), x_g represents the position of the real target box. The ship and the pilot target point form a two-point target box together, which is helpful for planning the ship's pilot route.

3.2. Design of Time Parameter Solution Method for SPS Set Based on Entry and Exit Dispatch

During the navigation of ships entering and leaving the port, the depth of the waterway limits the ship's draft. Deep draft vessels almost navigate at critical positions, so they are unable to conduct 24-hour pilot operations in and out of the port, resulting in limited pilotage time for vessels entering and leaving the port. This limitation is called the tidal time window. At the same time, for the entire ship port scheduling, there may be situations of waiting for multiple days, such as bulk cargo ships and oil tankers. Therefore, the port dispatch center will face continuous scheduling for multiple days. For this situation, the experiment adopts a strategy of overall scheduling, daily optimization, and constrained adjustment. Fig. 2 shows the scheduling plan for ships entering and exiting the port for multiple consecutive days.

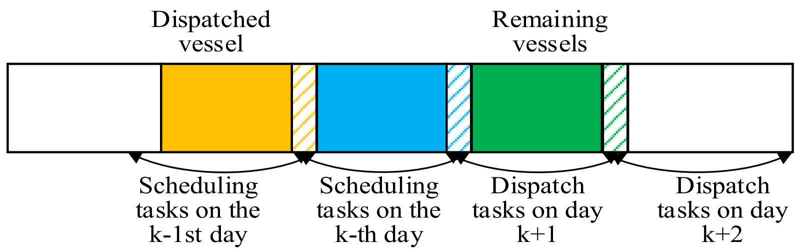

Fig. 2. Scheduling plan for ships entering and exiting ports for multiple consecutive days

In Fig. 2, when the scheduling time is Day k, the scheduling tasks for that day include the remaining ships on Day $k-1$, the scheduled ships on Day k, and the remaining ships on Day k. If the scheduling task of the ship on Day k cannot be completed on time, it is necessary to transfer the scheduling task of that day to the scheduling task of day $k+1$. To effectively prevent ships from waiting for a long time and repeatedly appearing in the subsequent scheduling, the experiment adjusts the waiting time of the ships according to their rental fees. The purpose is to reduce the high rent caused by long-term waiting and increase the proportion of remaining ship rent. Related research has found that different ships have different requirements for piloting. From the perspective of total waiting time, the objective function is defined to obtain Eq. (8).

$$\min F_1 = \sum_{i=1}^{m}\left(TI_i + \Delta TI_i - ETAI_i\right) + \sum_{j=1}^{n}\left(TO_j + \Delta TO_j - ETAO_j\right) \tag{8}$$

In Eq. (8), $\min F_1$ represents the objective function. $TI_i(\forall i \in I)$ represents the starting time for the dispatch of the i-th ship entering the port. ΔTI_i represents the sailing time spent by the i-th ship entering the port, ($\forall i \in I$). $ETAI_i(\forall i \in I)$ represents the lower limit of the scheduling time for the i-th incoming vessel, which is the time when the vessel is fully ready. $TO_j(\forall j \in J)$ represents the starting time of the departure of the j-th vessel. $ETAO_j(\forall j \in J)$ represents the lower limit of the dispatch time for the j-th vessel to depart, which is the time when the vessel fully passes through the tunnel. $\Delta TO_j(\forall j \in J)$ represents the sailing duration of the j-th vessel leaving the port. The delay in time during the pilotage of ships can affect the interval between sailing times, which poses certain safety hazards. To effectively solve safety issues, it is necessary to set the operating speed and safety distance of the ship. The expression of the ship safety distance model is Eq. (9).

$$S_{total} = A \cdot \exp\left\{ -\left[\frac{(Sp-a)\cos\theta + (V-b)\sin\theta}{\sigma_{Sp}}\right]^2 - \left[\frac{-(Sp-a)\cos\theta + (V-b)\sin\theta}{\sigma_V}\right] \right\} + c \tag{9}$$

In Eq. (9), A represents the amplitude of the model. (a,b) represents the offset coordinates of the model. σ_{Sp},σ_V represents the horizontal and vertical axes of the model and corresponds to Sp,V respectively. θ represents the rotation angle of the model (clockwise is the positive direction). c represents the offset constant of the independent variable S_{total} of the model. S_{total} represents the total intersection area. When the value of S_{total} is 0, the safety distance between ships will be updated, as shown in Eq. (10).

$$\ln\left(-\frac{A}{c}\right) = \left[\frac{(Sp-a)\cos\theta + (V-b)\sin\theta}{\sigma_{Sp}}\right]^2 + \left[\frac{-(Sp-a)\cos\theta + (V-b)\sin\theta}{\sigma_V}\right]^2 \tag{10}$$

In Eq. (10), assuming $\varepsilon = (Sp-a)\cos\theta, \zeta = (V-b)\sin\theta$ and setting the speed V_0 of ships entering and exiting the port while sailing in the channel. The speed will be adjusted in case of encountering situations, which meet the relevant requirements for ship navigation. Assuming that the speed V_0 is changed to V by parking, and the adjustment time is τ. The definition of τ is Eq. (11).

$$\tau = 0.00105\frac{\Delta V_0^2}{R_0}\left(\frac{1}{V} - \frac{1}{V_0}\right) \tag{11}$$

In Eq. (11), R_0 represents the corresponding ship resistance when the ship begins to decelerate, in units of 9.81KN. The time delay encountered by inbound and outbound vessels in the waterway is τ_{ij}, which together forms matrix T. The number of columns and rows in the matrix is equal to the total number of ships entering and exiting the port. Because $\tau_{ij} = \tau_{ji}$ in the matrix, $T_{12} = (T_{21})'$ exists. The calculation of the matrix is Eq. (12).

$$T = \begin{bmatrix} 0 & T_{12} \\ T_{21} & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & \tau_{1m+1} & \cdots & \tau_{1m+n} \\ 0 & \cdots & 0 & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & \tau_{mm+1} & \cdots & \tau_{mm+n} \\ \tau_{m+11} & \cdots & \tau_{m+1m} & 0 & 0 & 0 \\ \cdots & \cdots & \cdots & 0 & 0 & 0 \\ \tau_{m+n1} & \cdots & \tau_{m+nm} & 0 & 0 & 0 \end{bmatrix} \quad (12)$$

In Eq. (12), matrix T belongs to $R^{(m+n)\times(m+n)}$. In response to the delay and increase in sailing time caused by problems encountered by ships, it is necessary to update the sailing termination time $TI+\Delta TI, TO+\Delta TO$ of ships entering and leaving the port. On the basis of the analytical formula for the delay encountered, a comprehensive consideration is given to the impact of the total longitudinal distance between ships, and ultimately a linear constraint condition for scheduling time is obtained. Due to the fact that incoming ships will use the same channel, it is necessary to maintain a certain longitudinal spacing and duration between two ships entering the port continuously. Assuming that the entry times of the i-th vessel and the $i+1$-th vessel correspond to TI_i and TI_{i+1}, and the time intervals between the two vessels are τI_{ii+1}, respectively. Based on the above theory, departing ships also need to meet the spacing requirements, so the calculation of the time interval required for entering the port is Eq. (13).

$$\begin{bmatrix} M & 0 \\ 0 & N \end{bmatrix} \begin{bmatrix} TI_i \\ \cdots \\ TI_{\mathrm{m}} \\ TO_I \\ \cdots \\ TO_n \end{bmatrix} - \begin{bmatrix} \tau I_{12} \\ \cdots \\ \tau I_{\mathrm{m}-1m} \\ \tau O_{12} \\ \cdots \\ \tau O_{n-1n} \end{bmatrix} \le 0 \quad (13)$$

In Eq. (13), M, N represents the matrix. $\tau I_{12}, \cdots, \tau I_{\mathrm{m}-1m}, \tau O_{12}, \cdots, \tau O_{n-1n}$ represent the entry and exit time of the ship. The experiment employs a nonlinear fitting method to address the nonlinear challenge of time-varying tidal heights and position changes. Additionally, it establishes nonlinear constraints on the timing of tidal travel to ensure that the tidal heights meet the ship's excess water depth requirements throughout the entire voyage. The logical relationship between the final SPS, inbound and outbound scheduling plan, and the parameterization of the pilotage service set is Fig. 3.

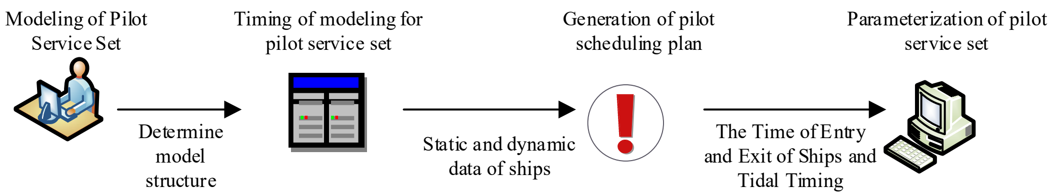

Fig. 3. Logic of System Collection

4. Performance Testing and Application Effectiveness of Intelligent Information Service System for Ship Pilotage

Before conducting the experiment, the relevant parameters of the simulation experiment operation system are established, with reference to pertinent research on navigation and pilotage intelligent service systems, to mitigate any experimental variability introduced by divergent system parameters.

Table 1. The experimental basic environmental parameters

Parameter variables	Parameter selection
Operating system	Windows 10
Operating environment	MATLAB
System Memory	48GB
CPU main frequency	2.62Hz
Graphics card	RTX-2070
Data storage system	SQL Server
Data analysis platform	SPSS 22.0
Central Processing Unit	Intel Corei7-4590

To ensure the fairness and rationality of the experiment, AIS trajectory clustering algorithm (AIS-DBSCAN), E-Navigation based ship intelligent route service system (E-Navigation), and 3D GIS-big Earth data based Arctic Northeast Channel ship navigation information service system (3D GIS-big Earth data), which can also be applied in SPISS, were selected for performance comparison with research method (Wu et al., 2022). The three methods are all aimed at achieving the ultimate goal of the ship pilotage intelligent information service system - improving the safety and efficiency of maritime navigation. GIS technology, SPS technology, AIS-DBSCAN technology, and 3D GIS-big Earth data System can all plan routes and provide customized planning for navigation routes. At the same time, the selection of these methods and technologies is based on an in-depth understanding of navigation needs and feasibility analysis of advanced technologies. Therefore, these three methods were selected for comprehensive comparison with the research construction method. All parameters were kept constant throughout the experiment except for specific experimental conditions. The number of iterations of all algorithms was set to 200, and the Automatic Identification System (AIS) dataset and MarineT dataset were selected as the basis to compare the performance of different models. The AIS dataset contains the ship's position, speed, heading, identification information (such as MMSI number, call sign, and ship name), ship type, size, navigation status, etc. AIS data is collected through AIS transmitters installed on ships, which regularly transmit the ship's position and other relevant information. Since AIS is an automatic identification system used for information exchange between ships and maritime monitoring centers, the experiment named it AIS dataset. The sources of MarineT data sets include ocean buoys, weather stations, remote sensing satellites, oceanographic research institutes, etc. Data in this dataset are usually collected and organized by government agencies, scientific research institutions, or international ocean research organizations. The information resources of both data sets are open to the public and come from official official channels. The experiment first analyzes the convergence changes of four different algorithms on two data sets. The specific results are shown in Fig. 4.

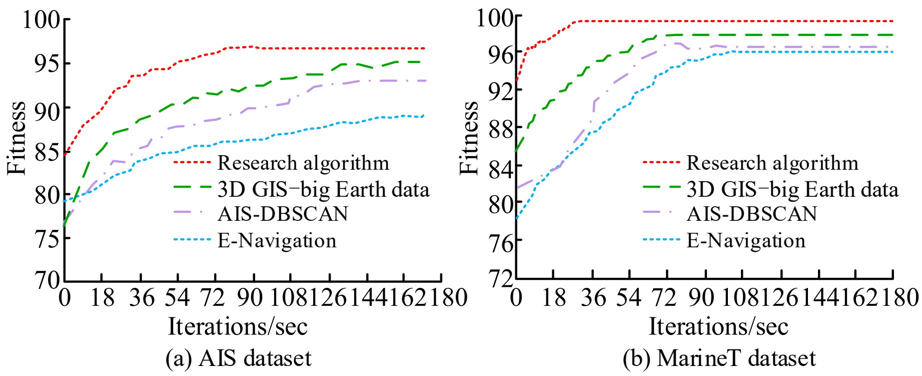

Fig. 4. Comparison of convergence changes

Figs. 4(a) and 7(b) show the changes in fitness values on the AIS and MarineT datasets. In 7(a), when the system iterates to 78 times, the research method has a maximum fitness value of 96.23. At this point, the fitness values of the other three methods are constantly changing, and there is no stable fitness value. In Fig. 4(b), when the system runs continuously for about 36 times, the research method has a maximum fitness value of 99.78. The other three methods all slowly show stable fitness values after 90 iterations, and the values are all smaller than the research method. The above results indicate that the fitness value of the research method has always been the highest, and when conducting experiments in the same experimental environment, it has a faster convergence speed and a faster operational efficiency of the system. Next, based on the AIS dataset, the changes in recall and accuracy of the four algorithms are compared. Fig. 5 shows the changes in the PR curve.

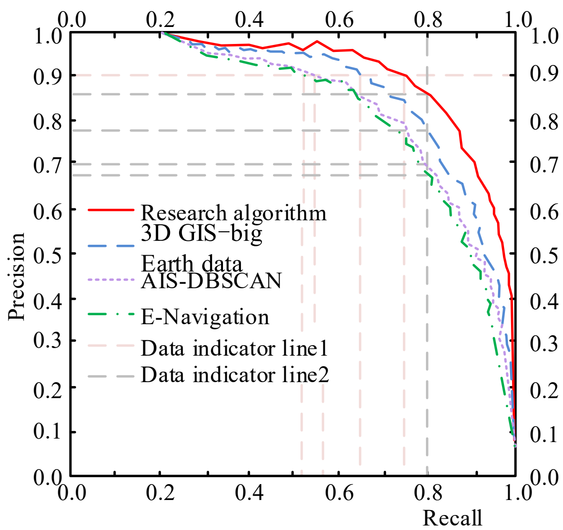

Fig. 5. Changes in PR curves corresponding to four algorithms

In Fig. 5, when the accuracy of the four algorithms is 0.900, the recall rate of the research method is relatively high, with a value of 0.741. At this point, the recall rates for 3D GIS-big Earth data, AIS-DBSCAN, and E-Navigation are 0.644, 0.587

and 0.513, respectively. On the contrary, when the recall rates of all four algorithms are 0.800, the accuracy of the research method is better, with a value of 0.873. At this point, the accuracy rates of 3D GIS-big Earth data, AIS-DBSCAN, and E-Navigation are 0.785, 0.699, and 0.681, respectively. The above data indicates that the application of research methods in SPISS has a high accuracy and recall rate, which can provide reliable services for ship pilotage and ensure the market position of the pilotage service system in the field of shipbuilding. Then, based on this, the Mean-absolute percentage-error (MAPE) of different algorithms running on two datasets is compared, as shown in Fig. 6.

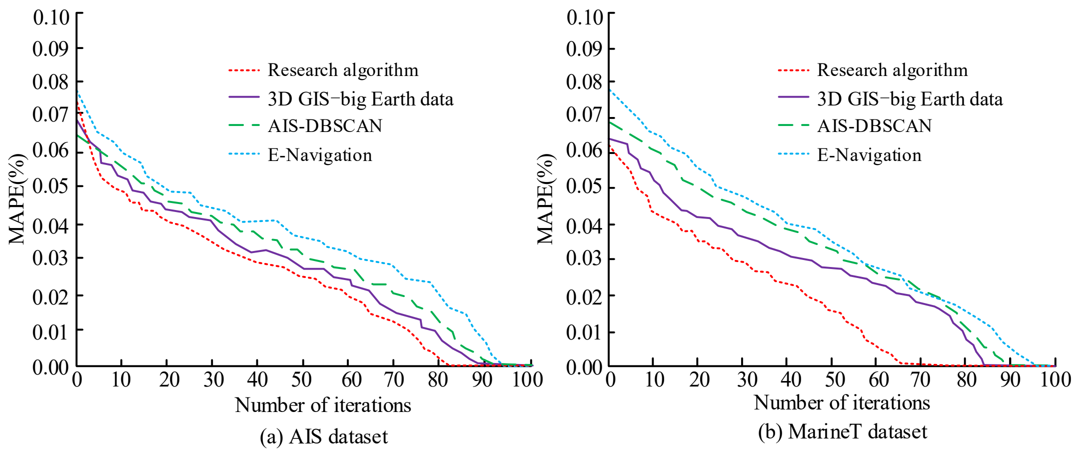

Fig. 6. Percentage of Different Average Absolute Errors

Figs. 6(a) and 6(b) show the changes in MAPE on the AIS and MarineT datasets. In Fig. 6(a), when the MAPE value of the research method approaches 0 infinitely, the number of iterations of the system is 82. The MAPE values of 3D GIS-big Earth data, AIS-DBSCAN, and E-Navigation are 0.00853, 0.01233 and 0.02012, respectively, which are significantly higher than those of the research method. In Fig. 6(b), when the number of system iterations is 66, the comprehensive MAPE value of the research method begins to change to 0. At this point, the MAPE values for 3D GIS-big Earth data, AIS-DBSCAN, and E-Navigation are 0.02033, 0.02542 and 0.02648, respectively. When the MAPE values of the other three methods start to approach 0, the corresponding system iterations are all greater than 80 times. The above data show that there are significant differences between the research method and other methods. This could be due to the utilization of the Faster-RCNN in the research approach, which is coupled with the regional proposal network to achieve precise detection results for ship entities. This enables the constructed system to have higher piloting accuracy. This further proves that the research method has smaller errors and better overall performance when running in the SPISS. Next, taking 34 ships as examples, statistical analysis is conducted on the iterative process of solving the ship's inbound and outbound scheduling scheme, as well as the error between the optimal solution and the mean solution of the total waiting time during the process. The results are shown in Fig. 7.

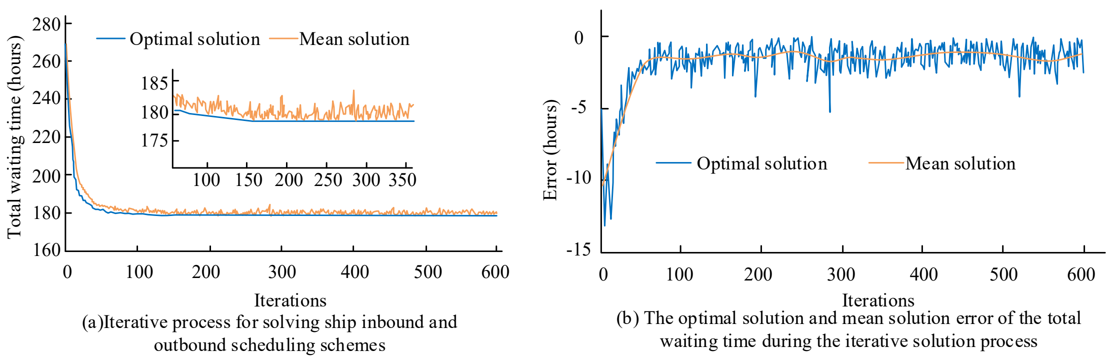

Fig. 7. Solution and waiting time of entry and exit plan

Fig. 7(a) shows the iterative process for solving the ship's inbound and outbound scheduling plan. After 51 iterations, the optimal solution for the total waiting time of ships entering and leaving the port gradually decreases from 263.21 hours at the beginning and eventually converges to 177.92 hours. The filtering values in Fig. 7(b) show that at the beginning of the system iteration, the initial error between the optimal solution and the mean solution is 10.33 hours. When the system runs continuously until 518 times, the corresponding error is only 1.4 hours. There are a total of 34 ships in the experiment, so the initial error of the system's waiting time during the pilot search for each ship is 18.5 minutes, and the final error is about 2.5 minutes. This indicates that under the operation of the built system, the search time for ship piloting services is shorter and the piloting error is smaller. This may be because under the operation of the research method, the system can achieve the reduction of ship pilot service set time through inbound and outbound port scheduling, which confirms the actual superior performance of the research method. Finally, a comparison is made between the research method and the time consumption of manual scheduling pilotage to obtain Fig. 8.

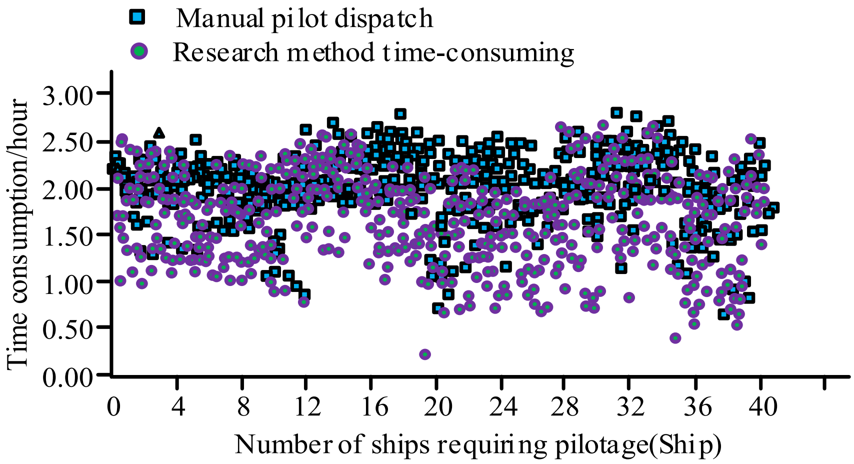

Fig. 8. Comparison of pilotage scheduling time consumption

In Fig. 8, the time consumption of the two ship piloting methods is generally consistent. However, there is a significant gap in some data, which may be due to subjective factors in manually piloting and scheduling ships. The research method is more time-consuming for ship piloting, and the overall time is below the graph, indicating that the research method takes less time to complete the piloting and can enter and exit the port more quickly.

All the above data are selected through experiments. The values of different performance indicators are constantly changing as the number of system iterations changes. The performance indicators for the research method consistently show optimal numerical values. The selection of experimental parameters accounted for the feasibility of the design and the needs of the actual application scenarios.

5. Discussion

The ship pilotage intelligent information service system developed in this study combines GIS big data positioning and neural network technology to optimize channel planning and improve the safety and efficiency of maritime navigation. Performance test results demonstrated that the system efficiently and accurately processes large-scale marine environment data and real-time navigation data, providing reliable ship piloting services and ensuring the system's market position in ship-related fields. Especially under complex sea conditions, the system can effectively identify potential risks and provide effective suggestions. The system's practical application effects were demonstrated through the example of 34 ships, where it utilized the deep learning capabilities of neural networks to analyze extensive navigation data for optimal route planning. Secondly, a statistical analysis was conducted on the iterative process of solving the entry and exit scheduling plan for the ship, examining both the optimal solution and the mean solution error for the total waiting time involved in the process. Under the operation of the research system, the ship pilot service experiences reduced search times and fewer pilot errors.

Taken together, the intelligent ship pilotage information service system, based on GIS big data positioning and neural network, has significant potential to enhance the safety and efficiency of maritime navigation. Through continuous improvement and optimization, this system may become a key auxiliary tool for future maritime navigation, providing more accurate and reliable support for ship piloting.

6. Conclusion

With the rapid growth of the global economy and the increasing prosperity of the shipping industry, the importance of SPS is gradually becoming apparent. To better serve humanity, this study proposed a SPISS that integrated GIS technology and neural network algorithms. Firstly, it utilized GIS technology to construct an intelligent positioning system and introduced Gaussian distribution and Faster CNN algorithm to improve the system. Finally, the piloting time for ships entering and leaving the port was solved. The results verified that when running on the AIS dataset, the fitness value of the research method was the highest at 96.23 when the system iterated 78 times. In the PR curve variation, when the accuracy of all algorithms was 0.900, the recall rate of the design method was as high as 0.741, while the recall rates of 3D GIS-big Earth data, AIS-DBSCAN, and E-Navigation were 0.644, 0.587 and 0.513, respectively. On the MarineT dataset, when the number of system iterations was 66, the comprehensive MAPE value of the designed method began to change to 0. At this point, the MAPE values for 3D GIS-big Earth data, AIS-DBSCAN, and E-Navigation were 0.02033, 0.02542 and 0.02648, respectively. In practical applications, the total waiting time for ship piloting in and out of ports under the designed method had been significantly reduced to 177.92 hours, and the error was relatively small. The above results all proved that the designed system can be effectively applied to SPS, reduce ship pilotage time, and promote the development of ship pilotage and transportation. However, the port environment in actual port operations exhibits complicated maritime geography, posing new opportunities and challenges for the maritime service system, as well as unsolved issues. These problems can be divided into two points. First, the ship target images are of different sizes and unevenly distributed, and the color of the ship target is similar to the background, which makes feature extraction difficult. The key is to increase the difference between the ship and the background and design a feature extraction network that is consistent with the ship image. The accuracy of ship detection can be further improved. Second, in terms of dispatch models, the economic benefits of ship operations can be fully considered. The timing of a ship's arrival at a port has a close correlation with fuel consumption and berth availability. These factors influence the ship's speed control, which can ultimately result in drifting.

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Institutional Review Board Statement

Not applicable.

References

Amin, S. N., Shivakumara, P., Jun, T. X., Chong, K. Y., Zan, D. L. L., and Rahavendra, R. (2023). An augmented reality-based approach for designing interactive food menu of restaurant using android. *Artificial Intelligence and Applications, 1(*1), 26-34.

Chen, M. Y., and Wu, H. T. (2022). An automatic-identification-system-based vessel security system. *IEEE Transactions on Industrial Informatics, 19(*1), 870-879.

Chen, Z., Chen, R., and Chen, S. (2020). Intelligent management information system of urban planning based on GIS. *Journal of Intelligent and Fuzzy Systems, 40(*4), 6007-6016.

Cui, J., and Zhang, F. (2020). Design and development of GPS navigation and positioning system based on AutoCAD platform. *Computer-Aided Design and Applications, 18(*S3), 46-57.

Islam, A., Othman, F., Sakib, N., and Babu, H. M. H. (2023). Prevention of shoulder-surfing attack using shifting condition with the digraph substitution rules. *Artificial Intelligence and Applications, 1(*1), 58-68.

Jahanbakht, M., Wang, W., Hanzo, L., and Azghadi, M. R. (2021). Internet of underwater things and big marine data analytics—a comprehensive survey. *IEEE Communications Surveys & Tutorials, 23(*2), 904-956.

Li, Y., Sarvi, M., Khoshelham, K., and Haghani, M. (2020). Multi-view crowd congestion monitoring system based on an ensemble of convolutional neural network classifiers. *Journal of Intelligent Transportation Systems, 24*(1-6), 437-448.

Liu, R. W., Liang, M., Nie, J., Lim, W. Y. B., Zhang, Y., and Guizani, M. (2022). Deep learning-powered vessel trajectory prediction for improving smart traffic services in maritime Internet of Things. *IEEE Transactions on Network Science and Engineering, 9*(5), 3080-3094.

Lou, R., Wang, W., Li, X., Zheng, Y., and Lv, Z. (2021). Prediction of ocean wave height suitable for ship autopilot. *IEEE Transactions on Intelligent Transportation Systems, 23(*12), 25557-25566.

Mustafa, R. A. M., Christie, J. S., and Hildebrand, E. (2020). Developing an "intelligent" high-fidelity GIS-based travel demand model framework for improved network-wide traffic estimation. *Canadian Journal of Civil Engineering, 47*(8), 885-897.

Song, X., Zhang, H., Akerkar, R., Huang, H., Guo, S., Zhong, L., and Culotta, A. (2020). Big data and emergency management: concepts, methodologies, and applications. *IEEE Transactions on Big Data, 8(*2), 397-419.

Wang, X., Liu, J., Khalaf, O. I., and Liu, Z. (2021). Remote sensing monitoring method based on BDS-based maritime joint positioning model. *Computer Modeling in Engineering & Sciences, 127(*2), 801-818.

Wu, A., Che, T., Li, X., and Zhu, X. (2022). A ship navigation information service system for the Arctic Northeast Passage using 3D GIS based on big Earth data. *Earth's Big Data, 6*(4), 453-479.

Zhang, N., and Zheng, K. (2020). Research and design of the architecture of the marine logistics information platform based on big data. *Journal of Coastal Research, 106(*SI), 628-632.

Zhu, B., and Zhou, J. (2020). Virtual design of urban planning based on GIS big data and machine learning. *Journal of Intelligent and Fuzzy Systems, 40(*14), 6263-6273.

Yunye Ren is an associate professor at the School of Nautical Technology at Jiangsu Shipping College. He engaged in navigation technology research with the Maritime Safety Administration of the People's Republic of China. Dr. Ren is issued with a GMDSS REC certificate and a magnetic compass surveyor's certificate.