



## A Deep Learning-based VSAT+BDS Fishing Vessel Intelligent Monitoring and Position Prediction

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**SUMMARY:** *With the rapid development of marine fishery informatization, how to achieve accurate monitoring through fishing vessel data is an important research direction to improve the intelligent level of marine traffic supervision. In this study, VSAT and BDS technologies are used to build an intelligent monitoring system for fishing vessels to effectively supervise them. In order to realize accurate fishing vessel position prediction, the improved joint probabilistic data association algorithm is used to realize the fusion of information VSAT and BDS, and then the LSTM-based fishing vessel position prediction method is designed. Comparison experiments show that the average accuracy of this paper's algorithm for fishing vessel position fishing vessels are above 80%, which is improved by 8.6%~14.8% and 5.3%~13.4% in the training set and test set, respectively, and the standard deviation of prediction accuracy is 3.07, which is significantly smaller than the comparison method. The JPDA-LSTM algorithm has a superior prediction performance compared with other comparison algorithms, and can meet the fishing vessel needs of intelligent monitoring.*

**KEYWORDS:** VSAT; BDS; JPDA algorithm; LSTM algorithm; position prediction; intelligent monitoring of fishing vessels

## 1 Introduction

In recent years, the marine economy has become a favorable engine for pulling the national economy. Fisheries, as an important part of the marine economy, is one of the high-risk industries, vulnerable to the natural environment and man-made factors. The rapid development of water transportation and the sharp increase in the demand for aquatic products have led to the emergence of many "three-no fishing vessels" (i.e., those without names or numbers, without certificates, and without home ports), which evade supervision and engage in illegal operations during the fishing moratorium period and in foreign waters. This has encroached upon the legitimate and law-abiding fishing rights and interests of vessels and fishermen, resulting in overfishing and seriously damaging the sustainable development of the ecological environment in fishery waters [1-5]. The "three-less fishing vessels" are mixed in the legal fishing vessels, with strong concealment and various operation modes, usually choosing the crisscrossing and complicated channel waters, the blind area of maritime law enforcement and even the high sea area for operation, which seriously breaks the order of fishery management and increases the difficulty of management by the supervisory departments [6-8]. Most of the "three-less fishing vessels" have outdated

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equipment, backward technology, lack of driving, navigation-related training, there are fishery safety hazards, resulting in fishing accidents, which seriously jeopardize the safety of fishermen's personal and property [9, 10]. The existing technology is difficult to effectively regulate three-less fishing vessels, and it is necessary to design a system to regulate three-less fishing vessels to ensure the safety of fishery production and legality.

The existing information-based regulatory system uses BeiDou Satellite Navigation System (BDS), VSAT (Very Small Aperture Terminal), video surveillance and other technologies to obtain fishery production data on people, vessels and ports, and to realize navigation and communication. Xiufang et al. constructed a fishing vessel monitoring system based on BDS and Linux platform, which monitors the position and navigation status of the fishing vessel in real time by integrating electronic map, effectively utilizes BeiDou's wide-coverage and high-reliability characteristics, solves the problem of far-sea network coverage, and realizes the timely response of distress search and rescue [11]. However, the fishing vessel BDS information is relayed and reported to the command center via satellite with low reporting frequency, at least once in fifteen minutes, which cannot be effectively monitored in real time. Ma et al. applied the VSAT technology to the maritime satellite system, which adopts the star topology with Ku-band to support tasks such as facsimile, voice, and data, and the transmission quality of its satellite link meets the reliability requirements [12]. Pavur et al. study highlighted VSAT as a critical data link for offshore operations and the leakage of sensitive information of several large shipping companies through VSAT and confirmed the existence of real threats such as man-in-the-middle attacks [13]. Wawrzyniak et al. utilized the existing surveillance video streams in harbors and rivers for ship detection and tracking, which is usable under certain conditions, but still has limitations in wake currents and bad weather [14]. And ports arrange video surveillance systems, video information back to the command center, relying on manual detection, mainly used for after-the-fact traceability, lack of real-time analysis and processing of data.

Deep Learning (DL) technology is an application of artificial intelligence with the ability to learn, to train itself with data and extract features from it, and to apply it to areas such as recognition and classification, accomplishing tasks such as risk prediction, voyage monitoring, path prediction, and position prediction for ships. Zhou and Wang created a ship risk prediction framework that fuses DL of long and short-term memory with Bayesian inference, which predicts the ship state by processing the trajectory time series and combines the environmental and obstacle data for Bayesian risk assessment, realizing real-time and accurate prediction of collision and grounding risk and providing intelligent early warning and decision-making support for maritime safety [15]. Yoo et al. proposed an attention mechanism and sequence-to-sequence DL prediction model based on the attention mechanism and fusion of diurnal and nocturnal operational features for sudden large-angle steering of offshore fishing vessel trajectories, which improves the ship path prediction accuracy and is expected to be used for collision avoidance and traffic decision support [16]. Focusing on long-time ship position prediction required for maritime safety, Ibadurrahman et al. innovatively applied DL to ship position prediction at 24-hour intervals, which is capable of accurately predicting a vessel's position on a 24-hour cycle [17]. Li et al. developed a computer vision enhancement algorithm based on the YOLO (You Only Look Once) model and constructed a dataset of fishing vessel dynamics over the past ten years, which provides an effective solution for near real-time, reusable monitoring of industrial light fishing dynamics [18]. Liu et al. used a two-stage missing packet complementation strategy combined with a two-way recurrent neural network to learn temporal correlation and a self-encoder with linear aggregation to capture multivariate mutations, which was able to efficiently extract the complex navigational dynamic conditions of the ship and improve the

information sensing ability of BDS ship monitoring [19]. This study shows that DL-based self-encoder multivariate capture for BDS vessel monitoring can be beneficial for coping with VSAT leakage in offshore operations by capturing navigational environment features. In addition, Wang et al. fused the BDS vessel monitoring system data with the DL framework for vessel monitoring during the fishing moratorium in the East China Sea and the Yellow Sea, and proposed a preprocessing protocol and used a convolutional neural network-bidirectional long and short-term memory hybrid model to achieve a fishing behavior classification accuracy of 89.98% [20]. Du et al. proposed a multimodal adaptive DL recognition model, which effectively distinguishes homogeneous non-fishing and heterogeneous fishing behaviors in the data of automatic vessel identification system by fusing the time-frequency features of vessel trajectories with the trajectory images, providing a new solution for intelligent monitoring of fishing vessel operations [21]. Therefore, with the help of DL, it can improve the accuracy and real-time performance of BDS and VSAT in monitoring fishing vessels, and facilitate the prediction of fishing vessel position.

In this paper, a fishing vessel intelligent monitoring system based on VSAT+BDS is constructed, which can intelligently monitor the state information of the fishing vessel, and utilize the position reporting function of VSAT and BDS to realize the management of the fishing vessel's position monitoring, position prediction, and abnormal alarm. Based on the communication data of VSAT and BDS, the multi-source information fusion is realized by using the improved JPDA-based algorithm, and then a 4-layer LSTM neural network structure oriented to the position prediction of the fishing vessel is designed to train the neural network based on the data structure of 5 time-steps and the historical motion data for the rapid learning of the fishing vessel's motion pattern, and a deep learning-based fishing vessel position prediction method is proposed. The trajectory data of fishing vessels are collected as experimental samples to train the JPDA-LSTM model, and multiple prediction algorithms are selected to conduct comparative experiments on the training set and the test set, respectively, to evaluate the position prediction performance of the model.

## 2 Intelligent monitoring system for fishing vessels based on VSAT+BDS

At present, the marine economy, especially the marine fishery sector, is facing many serious challenges, such as overfishing of fishery resources, frequent accidents on fishing vessels, and repeated smuggling at sea, etc. These problems not only lead to the deterioration of the marine ecological environment, but also have a huge impact on the operating environment of the marine fishery industry. The most powerful solution to these problems is to realize comprehensive and intelligent monitoring of marine fisheries. In order to realize the accurate monitoring of the state of marine fishing vessels, this paper realizes a fishing vessel intelligent monitoring system based on VSAT+BDS.

### 2.1 System architecture

Remote Intelligent Surveillance System is a remote application system based on digital video surveillance equipment, which enables users to realize video surveillance and video recording through IP network. Choosing a suitable IP network transmission method is the first issue in designing intelligent monitoring system, and the main transmission methods available at present are fiber optic, wireless transmission, digital private line, Internet, VSAT communication. Compared with the terrestrial transmission method, VSAT communication using satellite transmission has certain advantages, and can overcome the various

shortcomings of the terrestrial transmission method to expand the application range of the remote monitoring system.

BeiDou system is a regional satellite navigation and positioning communication system developed and established by China itself, BeiDou short message (BDS) equipment uses five geosynchronous satellites in the BeiDou system to realize two-way message communication. The equipment has the function of all-weather positioning in the BeiDou service area, has the function of receiving and sending short messages, and is interconnected with the broadcasting system on board to realize the function of receiving code sound prompts and voice broadcasting of message information.

Therefore, in order to effectively supervise the state of fishing vessels, this paper realizes an intelligent monitoring system for fishing vessels based on VSAT+BDS communication, and the architecture of this system is shown in Fig. 1. When receiving satellite data, the shipborne sensor acquires the current state information of the fishing vessel and then sends the data to the monitoring center through VSAT and BDS. After the VSAT and BDS commanders receive the information of the fishing vessel, the monitoring center parses the information of the fishing vessel and stores it, and then displays the state of the fishing vessel on the electronic nautical chart.

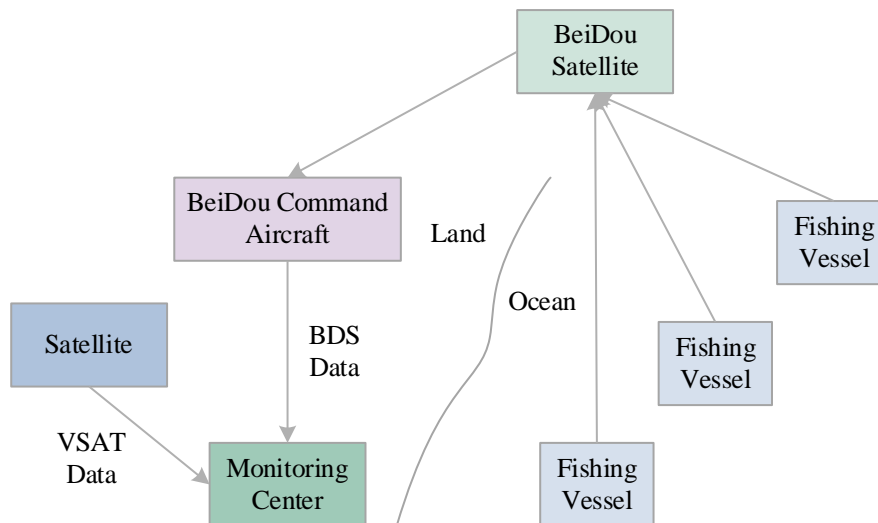


Figure 1: Intelligent monitoring system for fishing boats based on VSAT+ BDS

## 2.2 System functions

The fishing vessel monitoring system based on VSAT+BDS will update the current status of the fishing vessel in the Oracle database after receiving the data, and at the same time store the track data into the MongoDB database. This paper carries out relevant research on fishing vessel position prediction, so that when the system encounters problems such as data packet loss, it can make a more accurate assessment of the state of the fishing vessel through position prediction, and it can take the initiative to detect anomalies in the state of the fishing vessel when it receives the position data of the fishing vessel, which can help the monitoring personnel to discover the abnormal information of the fishing vessel in time and take measures to deal with it.

The main function modules of BeiDou and AIS-based fishing vessel monitoring system include chart management, vessel management and abnormal alarm.

The chart management module includes functions such as chart ranging, chart surface

measurement, and chart photography, which mainly provide some system tools for the monitoring personnel to monitor the status of fishing vessels.

Vessel management module includes functions such as vessel query, track playback, area playback and so on. Vessel query function can query fishing vessel information accurately or vaguely according to the query conditions, including vessel name, Beidou equipment number, MMSI, vessel status update time and so on. The track playback function can display the historical track of the fishing vessel with specified data source (VSAT or BDS) and start/end time on the chart for the system monitor to view. The area playback function can select an area in the chart to query all the fishing vessels passing through the area within 24 hours and play back their trajectories to the chart.

Abnormal alarm module includes abnormal alarm, alarm query and alert area functions. The shipborne Beidou sensor will add the abnormal status information of the fishing vessel when sending the vessel status information, including dismantling alarm, manual alarm, wreck alarm, etc. At the same time, the system will also actively detect the abnormality for the position of the fishing vessel's trajectory and motion status after receiving the vessel status information, and the abnormal alarm function will be triggered if the fishing vessel is judged as abnormal status. The alarm query function can query the abnormal status of the fishing vessel according to the vessel name, Beidou equipment number, MMSI and start/stop time. Meanwhile, the system can also set up a maritime alert area and send a warning to the monitoring personnel when the fishing vessel enters the alert area.

### 3 Deep learning-based location prediction methods

In the field of sea state monitoring, it is of great significance in ship state monitoring and anomaly detection to predict the ship's state at the next moment and get the ship position prediction result by using the ship's historical trajectory data. Therefore, this chapter combines JPDA algorithm and LSTM neural network to realize the information fusion and position prediction of VSAT and BDS, respectively, and proposes the position prediction algorithm of fishing vessel (JPDA-LSTM).

#### 3.1 JPDA-based multi-source information fusion

The Joint Probabilistic Data Association (JPDA) algorithm is more effective for single-sensor and multi-target tracking, and the intelligent monitoring system of the fishing vessel in this paper is configured with a variety of sensors, including VSAT and BDS, each of which may get multiple target information. In the environment of multi-sensor and multi-target tracking of intelligent ships in this paper, the traditional JPDA algorithm is mainly used to have the problem of too much computation. Therefore, the JPDA algorithm is improved in this paper.

##### 3.1.1 Improved JPDA algorithm

The Joint Probabilistic Data Association Algorithm (JPDA) is specifically designed as follows:

The algorithm assumes the existence of  $M$  objectives and its algorithmic equations and variables are described as:

$$A^t(i+1) = M^t(t)A^t(i) + X^t(t), t \leq T \quad (1)$$

$$C^t(i) = \begin{cases} N(i)A^t(i) + Y(i) \\ B(i) \end{cases} \quad (2)$$

where  $A$  is a target variable,  $C$  is a measurement variable,  $M, N$  are known matrix quantities,  $X$  and  $Y$  are relatively independent variables, where  $X$  is a zero-mean state noise variable,  $Y$  is a zero-mean detection noise vector, and  $t$  is a detected target at moment  $i$ .

The correlation region of the target  $t$  at moment  $i$  is defined as:

$$r_i^t = C \left\{ C \left| \left( C - \hat{C}_{ii-1}^t \right) S_i^t \left( C - \hat{C}_{ii-1}^t \right)^T \leq g_t^2 \right. \right\} \quad (3)$$

where:  $\hat{C}_{ii-1}^t$  is the detection value of target  $t$  at  $i$  moment,  $S_i^t$  is the covariance of the data received by the target  $t$  at  $i$  moment, and  $g_t^2$  is the tracking threshold value that falls into the detection region of the sensor.

Let there be  $n(i)$  valid messages at moment  $i$ , denoted as  $C_{i,1}, C_{i,2}, \dots, C_{i,m(i)}$ , and the set of valid messages at moment  $i$  is  $C_i = \{C_{i,j}\}_{j=1}^{n(i)}$ , and when the value of the detection target falls within the tracking threshold, multiple detection targets may appear in the intersecting region, and the JPDA algorithm calculates the probability that each detection target information is associated with the first detection value. Let  $\theta(i) = \{\theta_i(i)\}_{i=1}^h$  be the set of all joint event values at moment  $i$ , and  $h$  denote the number of elements in  $\theta(i)$ , and after setting  $\theta_{jt}(i) = U_{i=1} \theta_{jt}^i(i)$ , and  $j = 1, 2, \dots, m(i)$ , denote the events in which measurements  $j$  are associated with targets  $t$ .

Based on the full probability formula and JPDA related formula, the filtered value of the target at  $i$  moment can be obtained as:

$$\hat{A}^t(i|i) = \sum_{j=0}^{m(i)} \beta_{jt}(i) \hat{A}_j^t(i|i) \quad (4)$$

where  $\hat{A}_j^t(i|i)$  is the estimated value obtained by filtering the target  $t$  with the  $j$ th measurement value at the  $i$ th moment.

The JPDA algorithm in this paper adopts the dual tracking gate design idea of tracking gate 1 based on position information and tracking gate 2 based on operation characteristics, and in the process of tracking gate design, in addition to the consideration of the target position characteristics, it also takes into account the operation characteristics such as the direction of motion, which combines the position characteristics of the target and the motion characteristics, so as to effectively limit the redundancy information appearing in the correlation gate, reduce the target and the detection data between the association probability events, and reduces the purpose of JPDA computation.

The volume of the tracking gate 1 based on the position information, which is built by predicting the data center with the position of the target  $t$  at the  $i$  moment, is  $V^t(i) = \phi_M \gamma^{M/2} |W^t(i)|^{1/2}$ , where the degree of freedom is  $M$ , and then:

$$\varphi_M = \frac{\pi^{M/2}}{\eta(M/2+1)} = \begin{cases} \frac{\pi^{M/2}}{(M/2)!}, & M \text{ is even} \\ \frac{2^{M+1}((M+1)/2)!\pi^{M-1}}{(M+1)!}, & M \text{ is odd} \end{cases} \quad (5)$$

The sensors in this paper are VSAT and BDS, which can provide data related to the operating state such as the direction of target motion or speed, so the speed characteristics can be introduced on the basis of tracking gate 1. Assuming that the predicted motion direction of the target  $t$  at  $i$  moment is  $\theta$  and  $\beta$ , and it is a valid echo-detecting target falling into the area of tracking gate 1, the formula is as follows:

$$\begin{aligned} \theta &= \arctan\left(\frac{\hat{y}(i|i-1)}{\hat{x}(i|i-1)}\right) \\ \beta &= \arctan\left(\frac{\hat{z}(i|i-1)}{v_{xy}}\right) \\ v_{xy} &= \sqrt{(\hat{y}(i|i-1))^2 + (\hat{x}(i|i-1))^2} \end{aligned} \quad (6)$$

Based on the idea of dual tracking gate design, to reduce the correlation events between the target information falling into the intersection region of the tracking threshold and the sensor sources, this paper performs the homologation of the great likelihood method according to the set of sensors.

At  $i$  time, in the set of  $Z^N$  detections of  $N$  sensors on  $Q$  targets, each sensor has  $m_n$  ( $n=1,2,\dots,N$ ) detection results. Remember that the set of detections at  $i$  is:

$$Z^n = \{Z_n\}_{n=1}^N \quad (7)$$

The set of detection information for a target is:

$\Gamma^i = \{Z_{1i}, Z_{2i}, \dots, Z_{N_i}\}$  where  $i=1,\dots,Q$ , denoting a  $Q$  target set, which constitutes  $Z^N$  divisions, with a total of  $L$  sets of possible divisions,  $i=0$ , and  $l=0$  for the set of false goals.

### 3.1.2 VSAT+BDS Information Flow

The intelligent monitoring system in this paper receives the navigation data and equipment information sent by the VSAT and BDS of this ship, as well as accesses the external information of the shore-based center, and provides real-time decision-making and control information for the intelligent ship shipping by automatically sensing and obtaining the ship's own position, speed, heading, and other parameters of the ship's movement, so as to make the navigation process of the intelligent ship safer and more reliable. The design of the information flow of the VSAT and BDS is as shown in Fig. 2 shown. Intelligent monitoring system acquires real-time data such as VSAT and BDS to realize real-time monitoring of the dynamic information of the target, solves the redundant information in the spatial coverage area of the sensors through the JPDA multi-source information fusion technology in this paper, and predicts the position of the fishing vessel through the deep learning algorithm.

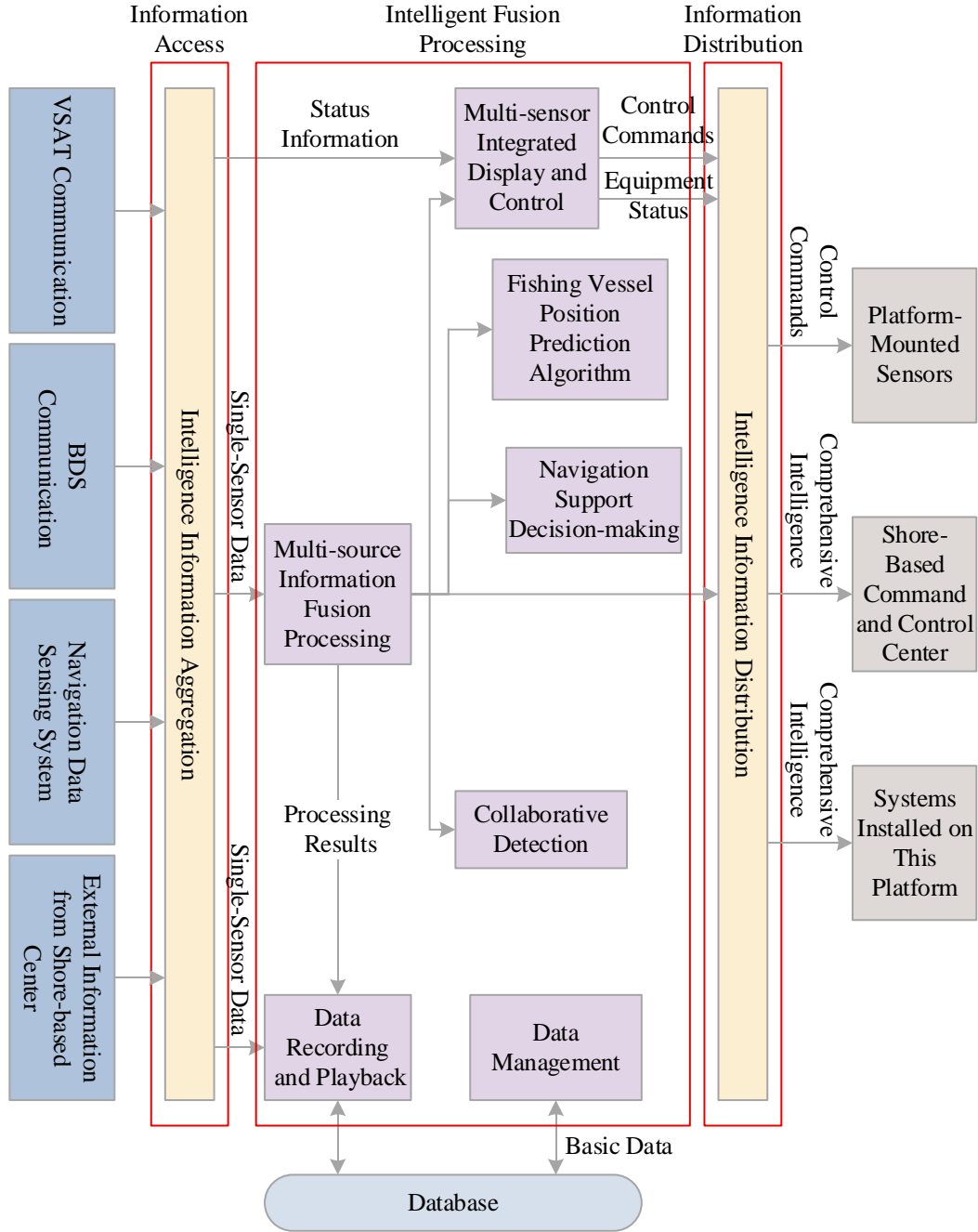


Figure 2: VSAT+BDS information flow design block of the fishing boat

## 3.2 LSTM-based location prediction

In this section, LSTM recurrent neural networks are used to quickly learn the historical voyage data of fishing vessels and realize the fast prediction of future vessel positions.

### 3.2.1 RNN and LSTM networks

Recurrent neural networks, also known as recurrent neural networks (RNN), are widely used in speech recognition, text analysis, etc. Compared with traditional fully connected neural networks, RNNs fully consider the temporal characteristics of the data and solve the back-and-forth correlation problem between the input data, which is widely used in speech

recognition, text analysis, etc. VSAT and BDS data are typical data with temporal characteristics, and VSAT and BDS messages sent by ships are with precise time stamp. Compared with the traditional neural network structure (i.e., feed-forward neural network), recurrent neural networks are more efficiently trained to handle time-series data. When processing time-series data, a feed-forward neural network, given a time window  $n$ , connects the information of each time point into a long information vector  $X$  as the input of the neural network, and outputs the result  $H$  after passing through the hidden layer:

$$h = \tanh(W_{xh} \cdot \text{concat}(x_1, x_2, \dots, x_n) + b) \quad (8)$$

Recurrent neural networks greatly improve the training efficiency compared to feed-forward neural networks.  $h_t$  in RNN is the output of the hidden layer of the neural network at time  $t$ , and in the location prediction task considered in this paper, it is also the output of the neural network at the current moment. The input of the dynamic neural network at a certain time node not only comes from the current data information  $x_t$ , but also considers the output of the hidden layer of the neural network at the previous time step, and  $h_{t-1}$  is calculated as shown in equation (9):

$$h_t = \tanh(W_{xh} \cdot x_t + W_{hh} \cdot h_{t-1} + b) \quad (9)$$

Traditional recurrent neural networks suffer from the problem of gradient vanishing during training, which leads to the rapid decay of the influence of historical information on the current node, which is improved by the emergence of the Long Short Memory Network network model (LSTM).

The traditional nodes in the recurrent neural network are replaced by LSTM cells, and the input received by the neural network from the previous time step at the moment of  $t$  in LSTM includes, in addition to the traditional hidden layer output  $h_{t-1}$ , another state information  $c_{t-1}$ , which is generally referred to as the cell state. In addition, LSTM also adds some “gate” structures to control the inflow of information and thus affect the cell state: forgetting gate, input gate and output gate, the outputs of which are denoted as  $f_t, i_t$  and  $o_t$  in the figure, where the forgetting gate controls whether to forget the hidden cell state of the previous layer or not, and the input gate is responsible for processing the input of the current moment and thus used for the cell state. The input gate is responsible for processing the current input and thus used for cell state update while the output gate is used to process the last hidden layer output and the current input  $x_t$  to update the new hidden layer state  $h_t$ . Each gate passes through a nonlinear function  $\sigma$  to control the output of the gate between 0-1 before output, in this paper, we use the sigmoid function, the expression is shown in Eq. (10), and the function curve is shown in Fig. (11), with 0 indicating that the gate is completely closed and 1 indicating that the gate is completely open. The mathematical representations of the three gates are shown in equations (11) to (13):

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad (10)$$

$$f_t = \text{sigmoid}(W_{xf} x_t + W_{hf} h_{t-1} + b_f) \quad (11)$$

$$i_t = \text{sigmoid}(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (12)$$

$$o_t = \text{sigmoid}(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (13)$$

Finally, during this time step, based on the output state of each gate, the cell state and the hidden layer state are updated as shown in Eq:

$$c_t = f_t * c_{t-1} + i_t * \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (14)$$

$$h_t = o_t * \tanh(c_t) \quad (15)$$

### 3.2.2 Adam weights update

A neural network system consists of three main elements: training data, test data and network structure. Training data through the training algorithm to update the weight parameters in the network structure so that the network in the test dataset to show good performance, neural network weights update mainly rely on the training process of back propagation of the chain derivation method for iterative gradient descent so as to achieve the optimization of the objective function, the formula (16) represents the general principle of the gradient descent algorithm:

$$\begin{cases} \theta_t = \theta_{t-1} - \eta \cdot g_t \\ g_t = \nabla_{(\theta_{t-1})} J(\theta_{t-1}) \end{cases} \quad (16)$$

where  $\theta_t$  is the current iteration after the update of the weights, better weights should make the neural network in the test data to achieve higher accuracy,  $\eta$  is the learning rate, used to control the step size of the gradient update in each iteration, the selection of the learning rate is particularly critical in the training process, a larger learning rate will lead to the weights of the optimal result of the oscillation of the neighborhood, too small will make the convergence rate too slow,  $J(\theta)$  is the loss function,  $g_t$  is the gradient of the loss function relative to the weights.  $J(\theta)$  is the loss function, and  $g_t$  is the gradient of the loss function relative to the weights.

In order to achieve a more efficient update of the weights, this paper uses the most widely used and efficient stochastic optimization method - Adam algorithm, which can give the adaptive learning rate of each gradient descent, reducing the memory requirements in the computation process. Its computational process:

$$\begin{aligned} \hat{m}_t &= \frac{m_t}{1 - \beta_1^t} \\ \hat{v}_t &= \frac{v_t}{1 - \beta_2^t} \end{aligned} \quad (17)$$

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\hat{v}_t} + \varepsilon} \hat{m}_t \quad (18)$$

where  $m_t$  and  $v_t$  can be viewed as first-order moment estimates  $E|g_t|$  and second-order moment estimates  $E|g_t^2|$  for the gradient  $g_t$ . The  $\varepsilon$  is the step size, which takes the default value of 0.001, and the  $\beta_1^t$  and  $\beta_2^t$  are the default decay indices for the moment estimates, again taking the default values of 0.9 and 0.999.

### 3.2.3 LSTM network structure design

In this paper, a 4-layer LSTM neural network is designed for fishing vessel position prediction. Position prediction is different from macro-level data mining such as route mining, and each fishing vessel has its unique movement pattern. Unlike the previous practice of using all the data of a certain sea area to train the model, this section adopts the method of using the historical data of a single fishing vessel to train the LSTM network and predict the latitude/longitude position of the next moment, in order to realize the rapid training of the network and the near real-time prediction.

The vessel motion feature data  $x(t), x(t+1), x(t+2), x(t+3), x(t+4)$  from five consecutive moments are used as inputs to the LSTM network, and the next moment's position telegrams  $y(t+5)$  are used as outputs for the training of the network, and the specific expressions for the inputs and outputs:

$$x(t) = \{\Delta t, COG_t, SOG_t, Lon_t, Lat_t, \Delta t_y\} \quad (19)$$

$$y(t) = \{Lon_t, Lat_t\} \quad (20)$$

where  $\Delta t$  is the time gradient of the five input moments of data relative to the previous data,  $\Delta t$  of the first input data is set to 0, and  $\Delta t_y$  is the time difference of the output data relative to the fifth moment of input. The range of values of inputs such as latitude, longitude, speed, heading, time, etc. varies greatly, and the data preprocessing also adopts the maximum-minimum normalization method. After using the neural network to predict the sailing position characteristics of the fishing vessel, it is also necessary to carry out the inverse normalization of the predicted results, so that the predicted data conforms to the actual range and significance.

## 4 Experimental results and analysis

### 4.1 Data sets

The trajectory data used in the experiments in this section are selected from a set of fishing vessel intelligent monitoring system running in X city, with the time range from May 1, 2025 to May 7, 2025, and the 60 selected fishing vessel trajectories all have two types of data sources, VSAT and BDS. Since the sampling interval of the BDS trajectory data is 600 seconds and the data sampling time interval is large, this section interpolates the BDS fishing vessel trajectories to obtain the trajectory data with a sampling time interval of 120 seconds, and then time-aligns the VSAT trajectory data with the interpolated BDS trajectory data. The selected fishing vessel trajectory data are divided into training set and test set according to the ratio of 5:1.

## 4.2 Experimental setup

The length of the current trajectory of the fishing vessel has an important effect on the position prediction, the fishing vessel may predict different results at different stages, if the fishing vessel has only sailed a short distance, the result of the position prediction may be very inaccurate because the fishing vessel has only just departed and it is difficult to make a prediction by the current position, however, if the fishing vessel has sailed a relatively long distance, the prediction result is more accurate. Based on this fact, this paper carries out the following simulation in the experiment: for each fishing vessel trajectory in the prediction data set, set 5 position prediction points, i.e., the fishing vessel trajectory from the departure of the fishing vessel to the trajectory point is known to carry out the position prediction. 5 position prediction points are set up as follows (P1, P2, P3, P4, P5): 15%, 25%, 35%, 55%, and 75% (x% indicates the number of trajectory lengths x from the sequence of trajectories) (counting the points at x% of the trajectory length from front to back).

## 4.3 Model Training Analysis

In the process of model training, you can save the training log as a .log format file, and then do visual analysis. Visual analysis is to be able to show the resultant parameter changes in the training process in the form of graphs, and by analyzing the graphs, it can guide how to train the model. The RNN algorithm is selected for comparison, the loss curve of the number of iterations of the RNN algorithm is shown in Figure 3, and the loss curve of the number of iterations of the JPDA-LSTM algorithm in this paper is shown in Figure 4. The Loss fluctuation of the RNN algorithm is more obvious, and it is generally a decreasing trend, but the Loss decreases faster in the first 800 times, and then decreases slower straight afterwards, and the Loss fluctuates around 7.0 in the end. In the Loss curve of the algorithm in this paper, the Loss decreases sharply around 50 iterations, and the convergence speed of the network training process is significantly improved. Then as the number of iterations increases, the Loss gradually decreases. It decreases to about 0.25 at about 200 iterations, and then it stabilizes at about 0.25, and with the increase in the number of iterations, the loss basically does not decrease, and the Loss finally stabilizes at about 0.25. From the Loss curve comparison, it can be found that the localization loss of the RNN algorithm is larger than the algorithm in this paper. And the loss of the RNN algorithm decreases slowly, and the JPDA-LSTM algorithm in this paper converges faster than the RNN algorithm.

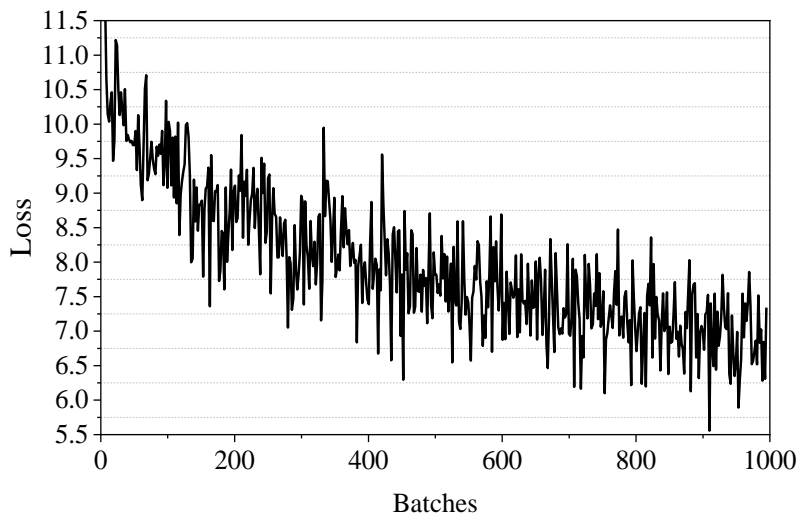


Figure 3: RNN algorithm's iteration frequency loss curve

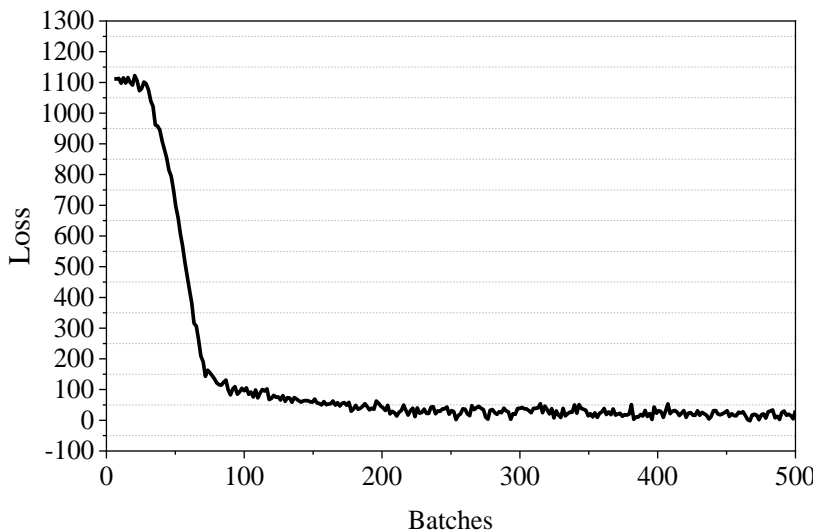


Figure 4: JPDA-LSTM algorithm's iteration frequency loss curve

Fig. 5 shows the iterative IOU curve of the RNN algorithm, indicating the change of the average intersection and merger ratio (IOU) of the location prediction as the number of iterations increases. Before 4000 iterations, the IOU constantly fluctuates up and down around 0.2, and after the number of iterations exceeds 4000, the IOU rapidly increases. Finally, it can be basically stabilized at about 0.88. And the fluctuation is getting smaller and smaller, and the IOU tends to stabilize after 10,000 iterations of the RNN network, and the accuracy of the model is higher at this time, and the prediction results are also more stable.

Figure 6 shows the iterative IOU curve of JPDA-LSTM algorithm. In the first 4000 trainings, the IOU improves rapidly and fluctuates between 0.3 and 0.9. In 5000 iterations of training, the IOU gradually stabilizes, stabilizing at about 0.95.

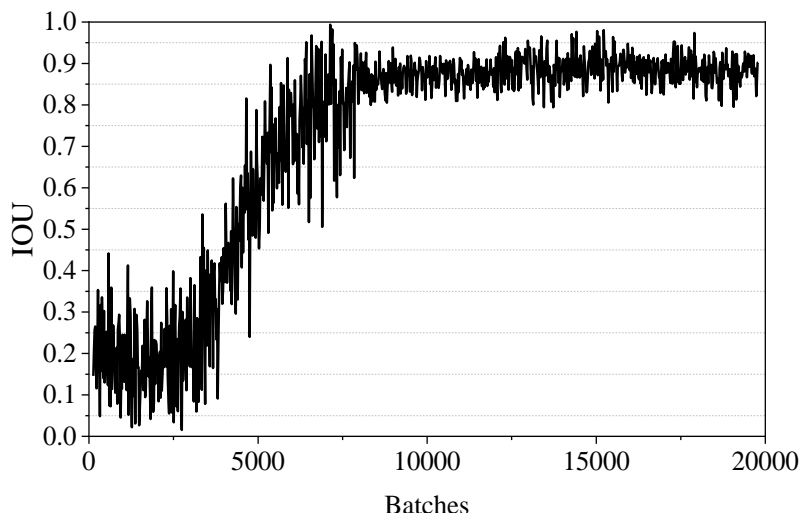


Figure 5: RNN algorithm's iteration IOU curve

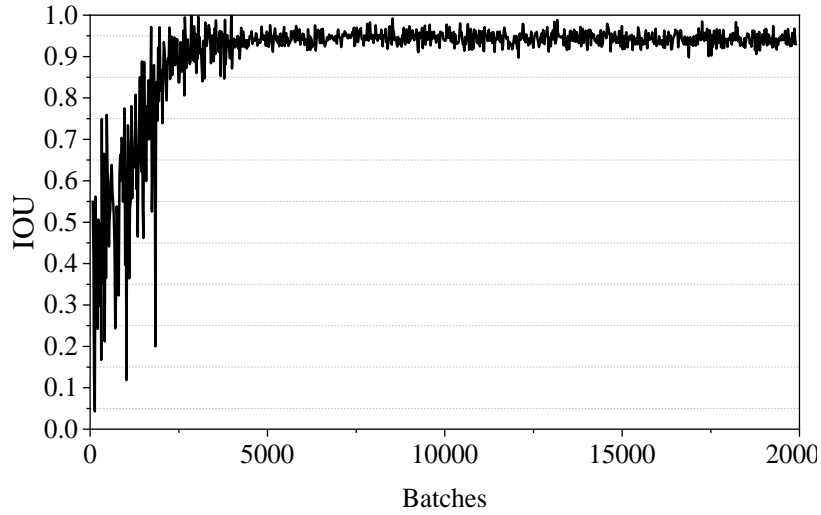


Figure 6: JPDA-LSTM algorithm's iteration IOU curve

#### 4.4 Location forecast analysis

##### (1) Training set

Experiments are conducted on the training set using a variety of prediction methods, including the KNN algorithm, the plain Bayes (NB) algorithm, the FNN algorithm, the RNN algorithm, the GRU algorithm, the Transformer algorithm, and the JPDA-LSTM algorithm in this paper, and the results of the accuracy of the prediction of each prediction algorithm are shown in Fig. 7, in which the horizontal axis indicates a variety of individual prediction points, and the vertical axis indicates the prediction accuracy rate.

From the overall trend, the trend of each curve is gradually increasing, indicating that the accuracy of the prediction from P1 to P5 is constantly increasing, which is due to the fact that the trajectory of the known fishing vessels from P1 to P5 is getting longer and longer, and there are more and more descriptions of the positions of the fishing vessels, and therefore the prediction is getting more and more accurate. From the algorithm of prediction, the highest prediction accuracy is the JPDA-LSTM based prediction algorithm in this paper, no matter from the various prediction points to see the position prediction results are obviously better than other algorithms, and the prediction accuracy in the two position points of P4 and P5 is more than 90%, respectively 92.1% and 93.8%. And the prediction accuracy of Transformer-based prediction algorithm also exceeds 90% at location point P5. However, the three algorithms based on KNN, based on FNN and based on RNN are less effective, especially the KNN-based prediction algorithm has the worst overall prediction effect, with a mean prediction accuracy of only 71.5% for the five fishing vessel positions. The mean values of the position prediction accuracy of the plain Bayesian algorithm, the FNN algorithm, the RNN algorithm, the GRU algorithm, the Transformer algorithm, and the JPDA-LSTM algorithm in this paper are 74.6%, 73.5%, 73.6%, 76.3%, 77.7%, and 86.3%, respectively, and the algorithm of this paper improves the accuracy of predicting the prediction of the position prediction compared to the other algorithms by 8.6% ~14.8%.

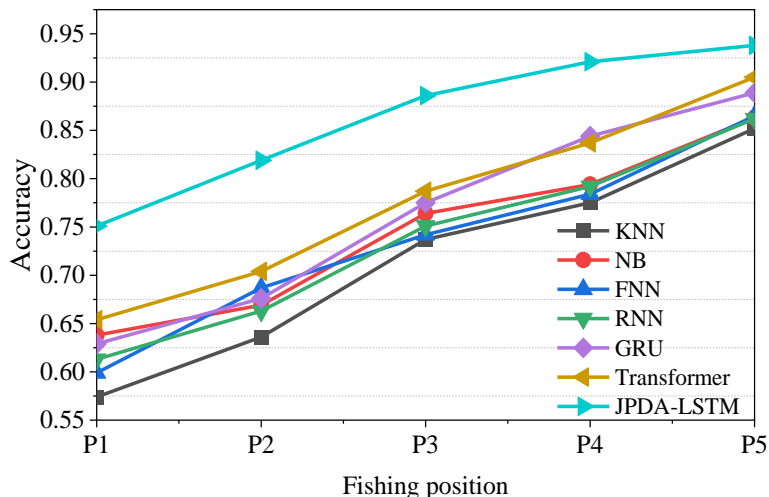


Figure 7: Prediction accuracy of each prediction algorithm

(2) Test set

Experiments were conducted on the test set using a variety of prediction methods, and the accuracy results of each prediction algorithm in the test set are shown in Fig. 8, where the horizontal axis represents a variety of individual prediction points and the vertical axis represents the prediction accuracy. From the overall trend, same as the training set, the accuracy of the prediction from P1 to P5 position gradually increases. In terms of the overall prediction results, the average prediction accuracy of the test set is relatively lower. In terms of prediction algorithms, JPDA-LSTM algorithm is still significantly due to the other algorithms, from P1 to P5 the accuracy of this algorithm in predicting the position of the fishing vessel is higher than the rest of the individual algorithms, more than 87% in T4 and T5, and more than 81% in T3. The average prediction accuracy of JPDA-LSTM algorithm is 80.5%, which is higher than the accuracy of the KNN algorithm, the plain Bayes algorithm, the FNN algorithm, the R3 algorithm, the R4 algorithm, the R4 algorithm and the R4 algorithm. algorithm, FNN algorithm, RNN algorithm, GRU algorithm, and Transformer algorithm's 67.1%, 69.3%, 70.4%, 73.6%, 73.6%, and 75.2%, which is an improvement of 5.3% to 13.4%.

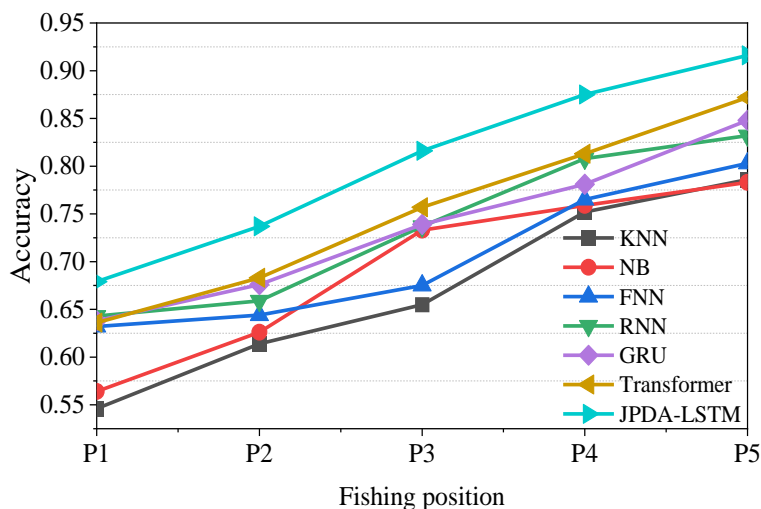


Figure 8: The accuracy of each prediction algorithm of the test set

The position prediction standard deviation of different algorithms is shown in Figure 9. The standard deviation of position prediction of this paper's algorithms are smaller than other algorithms, and the average value of the standard deviation of position prediction is 3.07, while the average value of the standard deviation of position prediction of other algorithms are larger than 4. Therefore, this paper's JPDA-LSTM algorithm is more effective for the prediction of fishing vessel position.

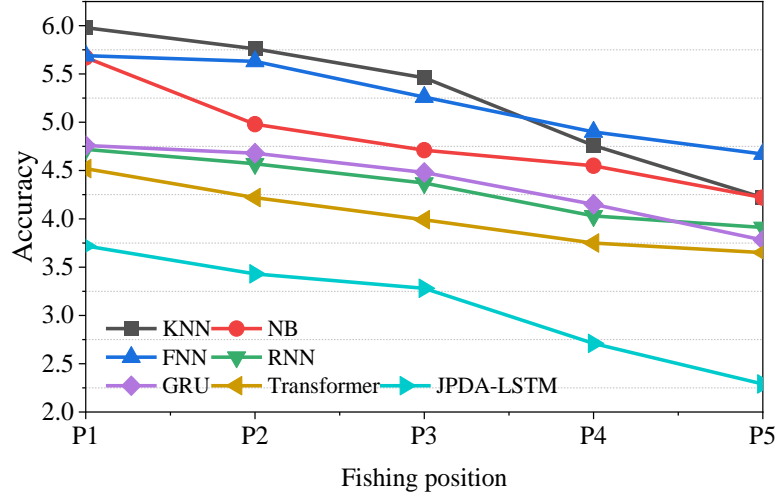


Figure 9: The standard deviation of the location prediction of different algorithms

## 5 Conclusion

Fishing vessels lack navigation and instant communication means when operating at sea, so this paper realizes an intelligent monitoring system for fishing vessels based on VSAT communication and BDS technology. Fishing vessel position prediction can not only estimate the state of the fishing vessel when the data of the fishing vessel is lost, but also can sense the possible abnormal behavior of the fishing vessel in advance and focus on monitoring the fishing vessel, so the deep learning algorithm is utilized to study the fishing vessel position prediction algorithm with multi-source information fusion. The main research results are as follows:

(1) A fishing vessel intelligent monitoring system based on VSAT and BDS is built, and the main functions include chart display, vessel query, trajectory playback, position prediction, and abnormal alarm, etc., among which position prediction is an important part of the fishing vessel intelligent monitoring system.

(2) The proposed position prediction algorithm has faster convergence speed, with smaller positioning loss and larger average intersection and merger ratio results, and the Loss value and IOU value in the model training are stable at about 0.25 and 0.95. With the growth of the fishing vessel trajectory, the position prediction accuracy of the model continues to improve. The position prediction accuracy of this paper's algorithm performs best in both training set and test set experiments, with mean values of 86.3% and 80.5%, respectively, which are improved by 8.6%~14.8% and 5.3%~13.4%, respectively, compared with other comparison methods. And the mean value of the standard deviation of the position prediction of this paper's algorithm is the smallest, 3.07, which is lower than the other comparison methods. The experiments show that the JPDA-LSTM algorithm in this paper has higher fishing vessel position prediction accuracy.

In the context of the increasingly developed shipping industry, it is of great significance to

study the intelligent monitoring of fishing vessels. This paper builds an intelligent monitoring system for fishing vessels, which can realize the dynamic monitoring of fishing vessels, predict the sailing position of fishing vessels, and provide a basis for the analysis of traffic flow and the avoidance of shipping accidents. The research content of this paper is limited to the prediction of the position of the fishing vessel, and in the future, further research can be conducted on the fault avoidance and abnormal alarm based on the prediction of the position of the fishing vessel.

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