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Ship Track Prediction Based on AIS Data and PSO Optimized LSTM Network

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Abstract

Predicting the dynamic information of ship navigation is the basic work of ship abnormal behavior analysis, so improving the performance of prediction models is of great significance for advancing intelligent monitoring at sea.Aiming at the problem of insufficient accuracy of existing ship trajectory prediction models, a long-term and short-term memory network (LSTM) ship track prediction model based on adaptive particle swarm optimization (PSO) optimization is proposed in this paper.The particle swarm algorithm was used to optimize and improve the number of hidden layer nodes, learning rate, maximum number of iterations, and the number of input layer steps in the LSTM network, so as to obtain a better ship track prediction model.A PSO-LSTM model was constructed using AIS data, and experiments were performed using ship AIS data in the VTS waters Wusong Traffic Management Center . Comparing the experimental results with several other models, it was found that the PSO-LSTM prediction model has higher accuracy.

Keywords

Particle Swarm Optimization (PSO), Long Short-Term Memory Network (LSTM), Ship Track Forecast.

1. Introduction

With the rapid development of the economy and the rapid development of maritime trade, the volume of maritime traffic continues to increase. Especially important channels and ports. Vessel traffic is extremely congested. Use the Vessel Traffic Service System (VTS) to accurately and effectively carry out the voyage of ships Timely tracking and forecasting are important technical supports for early warning of marine traffic accidents.There have been many studies on ship trajectory prediction. Reference [1] used Kalman filter algorithm to estimate the ship's observation data by least squares method to obtain the smooth ship trajectory, and then predicted.Reference [2] improved the Kalman filter algorithm, and applied it to the ship's trajectory processing to predict the ship's trajectory.Reference [3] used competitive neural network to detect and track the ship's navigation status, and extended the Kalman filter algorithm to estimate the ship's navigation status.Literature [4] used the support vector machine model to predict the track of a ship out of control in the target waters.Reference [5] introduced the ship's sailing position based on time series, and used the gray prediction model to predict the ship's sailing position.Reference [6] introduced a new type of machine learning algorithm based on Bayesian network—Gaussian regression process and applied it to ship trajectory prediction in mobile communication environment with high anti-interference requirements.In [7], a grey model combined with a Markov chain was used to predict the ship's trajectory. The above-mentioned traditional machine learning prediction methods are all linear prediction methods, and the expert knowledge is required to construct the kinematics equations of the

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ship. In addition, external environmental factors have a greater impact on the ship's movement, resulting in the complexity of the ship's motion trajectory, and mathematical equations are established in real time Difficult to implement, most of them only apply to the ideal state.Reference [8] designed a simple three-layer BP neural network prediction model for track, which has the characteristics of short time and strong versatility, which is suitable for real-time and efficient requirements of ship trajectory prediction by management systems such as VTS.However, the literature [8] only predicted the space position of the ship, and lacked the prediction of the ship's dynamic information.Literature [9] based on this, taking advantage of the large amount of information in AIS data, proposed the combination of ship AIS information and BP neural network to predict the ship's navigation behavior, and realized multi-dimensional ship navigation feature prediction. However, for complex ship navigation trajectory prediction problems, the BP neural network has limited mapping and representation capabilities, and BP parameters are difficult to adjust. However, the generalization ability of the BP neural network algorithm is limited, which can easily cause training to fall into a local optimal problem, and it is impossible to time Changes in the sequence are modeled.Reference [10] uses AIS data combined with deep learning algorithms to establish RNN-LSTM deep learning prediction models, which can randomly process sequence data with various time differences, and also solves the problem of BP neural network being too simple, rough, and low precision, but short and long term The structure of the memory network is complex, and the model parameters of the network are difficult to set, such as step size, batch size, learning rate, number of hidden layer units, and so on.These parameters can directly control the topology of the network model. Different parameters can train different prediction models and the prediction performance is very different. Therefore, it is particularly important to choose the appropriate model parameters.At present, the choice of hyperparameters of network models often depends on the researcher's experience and the results of multiple experiments, which consumes a lot of manpower and computing resources. Therefore, this paper proposes a LSTM ship track prediction model based on particle swarm optimization algorithm, using PSO The optimization algorithm can tightly combine the ship's navigation characteristics with the topology of the LSTM neural network to obtain better prediction performance.

2. Algorithm introduction

2.1 RNN-LSTM Recurrent neural network

A neural network is a highly complex non-linear, adaptive information processing system composed of a large number of processing units interconnected.It consists of a group of neurons with directed connections. Data is exchanged with the outside through input and output interfaces. By adjusting the strength of the connections between internal neurons, the input-to-output mapping is established, and a certain amount of data is formed by learning from sample data. The accuracy of the mapping rules and its outstanding learning ability omit the step of system modeling, which is especially suitable for situations where the rules are unknown or uncertain, and the distribution and parallelism make the neural network highly fault-tolerant and robust. Multi-layer neural networks can approximate continuous maps with arbitrary accuracy.

Recurrent neural network (RNN) introduces the concept of time series data in the design, making it more adaptable in the processing of time series data.(1) RNN has gradient disappearance and gradient explosion problems, and cannot effectively process time series data with long time dimension; (2) RNN model needs to delay the length of the window in advance, but the optimal value of this parameter is difficult to obtain .A standard recurrent neural network RNNs is composed of an input layer, a hidden layer, and an output layer,Where x_t is the input at time t, o_t is the output at time t, U, V, and W represent the three-layer weight matrix coefficients. These three coefficients are shared in the entire RNN network, ensuring that each nerve in the network The operations performed by the meta are the same, and the number of parameters in the RNNs is also reduced.

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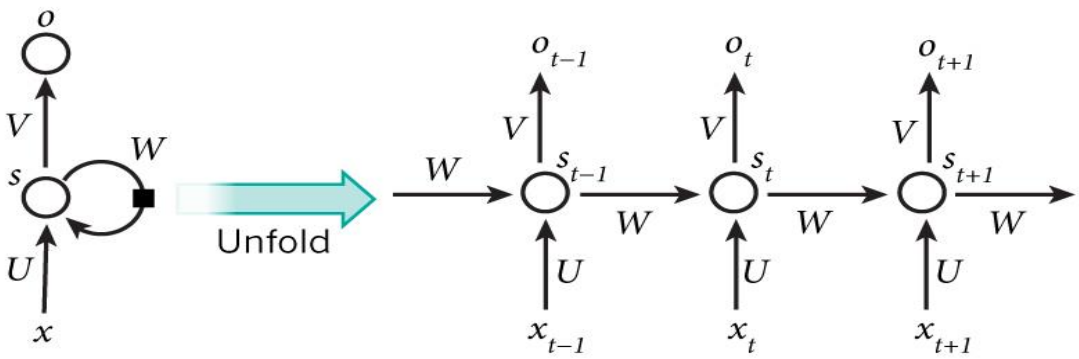

Fig. 1

RNNs are a chain structure, the internal structure of each neuron is the same, and they are all a neural network, but when the learning step is too long, the learning performance of the entire network will be significantly reduced:

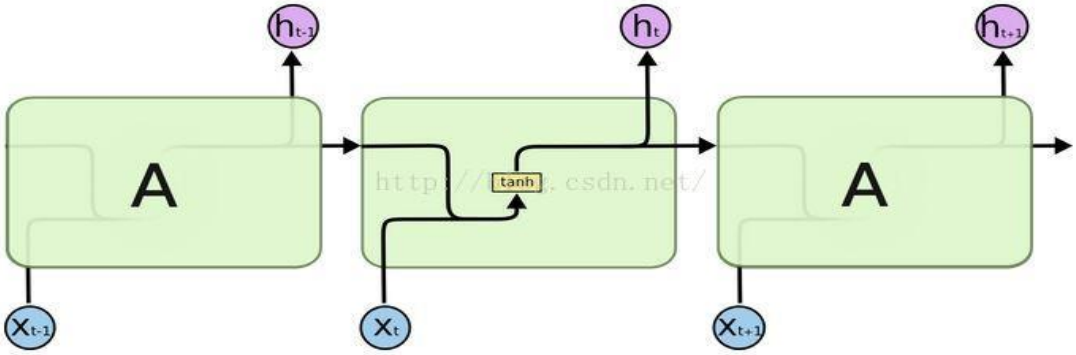

Fig. 2

Aiming at the problem of memory decay in RNNs, a long short-term memory network (LSTM)[11] was proposed. Long short-term memory network (LSTM) is a special RNN network. LSTM is also a chain structure, but the internal structure of the repeating unit is different. It is not a separate neural network layer, but four neural networks. These 4 Influence each other. It is a deformation based on RNN, which is to add memory cell and gate structure to neurons in its hidden layer. These include forgetting gates, input gates, and output gates, so that the weight of the self-loop is changed, thereby avoiding the problem of gradient disappearance or gradient explosion, and it can learn long-term dependencies well.

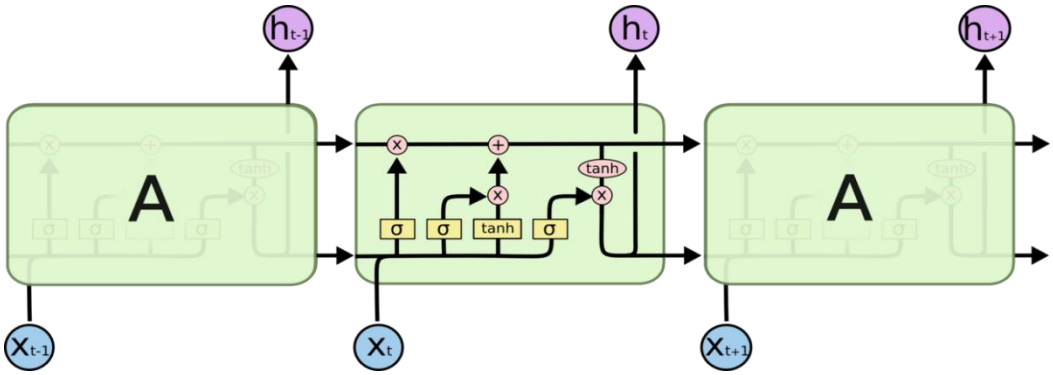

Fig. 3

The LSTM uses two gates to control the content of the unit state c. One is the forget gate, which determines how much the unit state at the previous moment is retained to the current moment, and the other is the input gate, which determines The key to how much the network's input is saved to the unit state at the current moment is the unit state, which runs through the horizontal line in Figure 4. The unit state is similar to a conveyor belt, which runs through the entire chain, with only small linear

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interactions, making it easy to make information Constant flow down;The LSTM uses an output gate to control how much the unit state is output to the current output value of the LSTM. The gate activation function uses the sigmoid function, which is defined as:

$$f(x)=\frac{1}{1+e^{-x}} \tag{1}$$

The input and output activation functions use the tanh function, which is defined as:

$$g(x)=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{2}$$

Forgotten Gate:

$$f_t=\sigma(W_f\cdot[h_{t-1},x_t]+b_f) \tag{3}$$

Input gate:

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i) \tag{4}$$

Input status of the current cell:

$$\tilde{C}_t=\tanh(W_C\cdot[h_{t-1},x_t]+b_C) \tag{5}$$

Cell status at the current moment:

$$C_t=f_t\circ C_{t-1}+i_t\circ\tanh(W_C\cdot[h_{t-1},x_t]+b_C) \tag{6}$$

Output gate:

$$o_t=\sigma(W_o\cdot[h_{t-1},x_t]+b_o) \tag{7}$$

The final output of the LSTM is determined by the output gate and the unit state:

$$h_t=o_t\circ\tanh(C_t) \tag{8}$$

Where x_t: the input vector of the LSTM neuron

f_t: Activation vector for oblivion gate

i_t: Activation vector of input gate

o_t: Activation vector for output gate

h_t: Output vector of LSTM neuron

C_t: Neuron cell state vector

W: Weight vector

b: Bias term

2.2 Particle swarm optimization

The idea of particle swarm algorithm originates from the research on the social behavior of birds. The simplest and most effective method for bird predation is to search for the area of the bird closest to the food, and to achieve group evolution through assistance and information sharing between individuals.The algorithm treats the individuals in the group as a particle in a multi-dimensional search space. Each particle represents a possible solution to the problem. Its characteristic information is described by three indicators: position, speed, and fitness value. The fitness value is calculated by the fitness function. It is obtained that the size of the fitness value represents the pros and cons of the particles.Particles "fly" at a certain speed, and change the direction and distance of movement according to their own and other particles' moving experience, that is, the optimal fitness value of themselves and the group. Constantly iteratively search for better regions to complete the optimization process in the global search space.

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Particle swarm optimization[12] It is an optimization algorithm established by simulating swarm intelligence. It is mainly used to solve optimization problems. It can optimize the whole world and has a strong ability of global parameter search. The specific principle is that in a D-dimensional search space, a population is composed of particles, which is $X=(X_1,X_2,...,X_n)$, and it is assumed that the characteristic information of the first particle at time is:

The location is: $X_i^t=[X_{i1}^t,X_{i2}^t,...,X_{iD}^t]^T$

The speed is: $V_i=[V_{i1}^t,V_{i2}^t,...,V_{iD}^t]^T$

Individual optimal position: $p_i^t=[p_{i1}^t,p_{i2}^t,...,p_{iD}^t]^T$

Globally optimal position: $p_g^t=[p_{g1}^t,p_{g2}^t,...,p_{gD}^t]^T$

Particles iteratively change the position and velocity of particles to achieve the optimal state. The main control conditions for changing the position and velocity of particles are the historical best position P_i^t and the optimal position P_g^t of the population. The particle updates the position and velocity of the next-generation particle according to the following formula, then the velocity and position information of the particle at time $t+1$ is:

$$V_{id}^{t+1}=\omega V_{id}^t+c_1r_1^t(P_{id}^t-X_{id}^t)+c_2r_2^t(P_{gd}^t-X_{id}^t) \tag{8}$$

$$X_{id}^{t+1}=X_{id}^t+V_{id}^t \tag{9}$$

In the formula: ω is the inertia weight, which controls the effective balance of particles between global detection and local mining; D is the dimension of the particles, and c_1 and c_2 are acceleration factors, respectively, to adjust the step size to fly to itself and the best position globally; r_1 And r_2 are random numbers distributed between $[0,1]$. In order to prevent blind search of particles, their position and velocity are limited to the interval $[-X_{\max},X_{\max}]$、$[-V_{\max},V_{\max}]$.

2.3 PSO optimization LSTM algorithm steps:

Step 1: Divide the experimental data into training data, verification data, and test data.

Step 2: Initialize the parameters. Determine the population size, number of iterations, learning factors, and other initial values of the parameters.

Step 3 : Initialize particle position and velocity, where each particle consists of:

$X_i^0=(k_i^0,\alpha_i^0,N_i^0,l_i^0)$,Among them, k represents the number of hidden layer neurons, α represents the learning rate of the LSTM prediction model, N represents the maximum number of iterations of the LSTM network, and l represents the number of steps in the input layer.

Step 4: Determine n LSTM prediction models from the population particles, and train the error function corresponding to the model as the fitness function of each particle, that is:

$$fit=0.5*\sqrt{\frac{1}{J}\sum_{j=1}^{J}(\hat{y}_j^t-y_j^t)^2}+0.5*\sqrt{\frac{1}{K}\sum_{k=1}^{K}(\hat{y}_k^t-y_k^t)^2} \tag{10}$$

In order to get the fitness value of all particles. In the formula: y_j^t and y_k^t are the expected output value of the training sample and the expected output value of the verification sample at time t, respectively. Most previous studies only used the fitting error of the training samples as the fitness value. If the neural network is over-fitted, the model prediction effect obtained is not optimal. The error of the verification sample directly reflects the prediction effect of the model. Therefore, the fitness function includes both the fitting error of the training sample and the verification error of the verification sample.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202005_6(5).0005

Step 5: Calculate the fitness value corresponding to each particle position X_i by formula (10), so as to obtain the initial individual extreme value P_i^t of all particles, traverse the fitness value P_g^t of all particles, and obtain the optimal value of the particle swarm. Then in In each iteration, the corresponding particle velocity is updated by formulas (8) and (9), and then the particle position is updated.

Step 6: Then according to the judgment condition of the end of the iteration, if the iteration ends, go to step 7; otherwise return to step 5.

Step 7: The optimal particle is output, the LSTM prediction model is obtained, and then it is trained and substituted into test data to obtain the final prediction result.

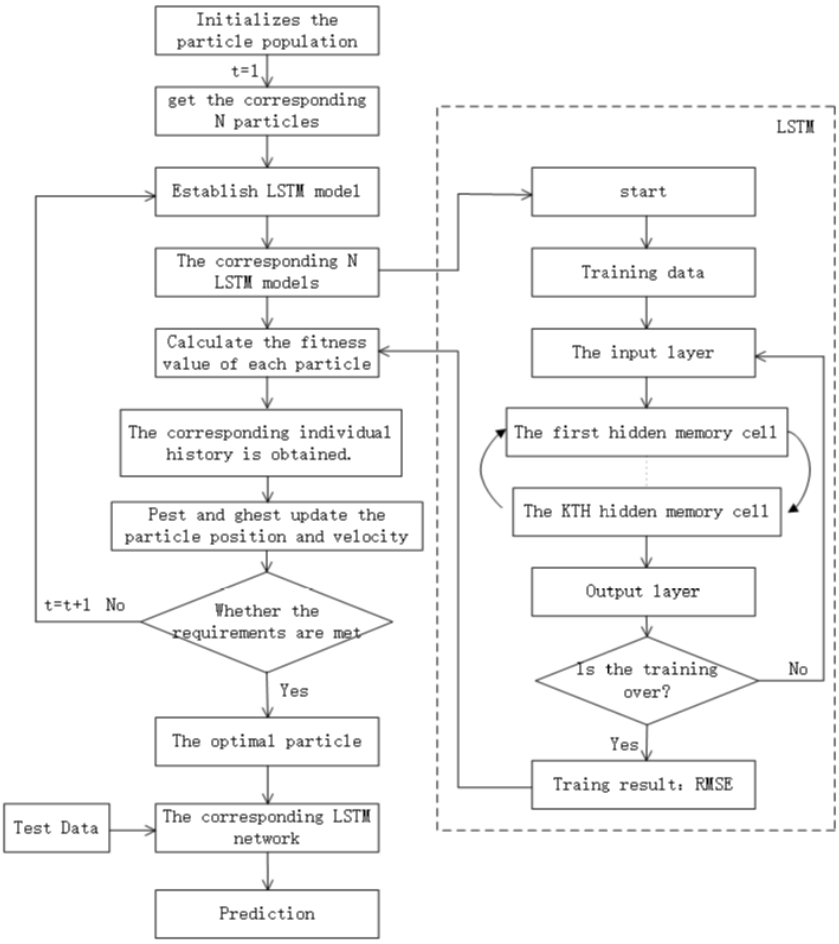

Fig. 4 PSO optimized LSTM algorithm flowchart

3. Ship track prediction model based on PSO-LSTM

3.1 Data preprocessing

Before constructing the training and test sets, some preprocessing operations need to be performed on the original water quality data. Because the Taihu data used in this article is provided by the National Science and Technology Basic Condition Platform, outliers have been processed many times before the data is released. Therefore, this article does not perform outlier processing on the data, and only fills in the vacant values. Considering that many indicators of water quality monitoring data have different dimensions and dimensional units, in order to eliminate the dimensional impact between the indicators, this paper normalizes the original data on the basis of filling the gaps.

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3.1.1 Vacancy and Outlier Processing

Due to various artificial and external factors, there may be some erroneous data in the collected AIS data. Therefore, the original data needs to be properly processed. Deleting the wrong AIS data reduces the large data errors that may occur in the post-processing, thereby improving the follow-up. Efficiency of work. Obviously incorrect records in AIS data include the following 4 categories:

(1) A record of the maritime mobile communication service identification code (MMSI) of the ship is not a 9-digit or unreasonable record;

(2) The latitude and longitude of the ship exceeds a reasonable range;

(3) The speed and course of the ship exceeds a reasonable range;

(4) The collection time of ship information is beyond a reasonable range.

This paper focuses on the prediction of the ship's track of a single ship. The main data includes time, latitude and longitude, heading to ground, and ship speed,Preprocess the data to fill in the missing data, and use linear interpolation [13] to fill in the missing data:

$$S_{t_i} = S_{t_k} + \frac{S_{t_m} - S_{t_k}}{t_m - t_k}(t_i - t_k) \tag{11}$$

3.1.2 Data Normalization

In order to improve the model's convergence speed and model accuracy, and reduce network prediction errors caused by large order differences between input data, the data is first normalized. Since all data is deterministic, a standardization method of dispersion is used. (Min-Max) Process the data. Min-Max is a linear transformation of the original data, so that the result falls in the [0,1] interval. The formula is:

$$X^* = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{12}$$

3.2 Ship track prediction model

First, the main source of ship data is AIS, which includes dynamic and static data. Dynamic data: longitude, latitude, speed, heading, and heading angle. Static data: captain, width, MMSI, reception time, etc.

The application of the PSO-LSTM prediction model to the prediction of ship trajectory is essentially a regression problem. The ship's historical trajectory characteristics and current trajectory characteristics are used as network inputs, and the ship's trajectory characteristic data at a certain time in the future is used as the network output. By comparing the predicted value with the true value, then the historical ship's track characteristic data and the expected ship's track characteristics are established A special mapping relationship of the data, and then the prediction of future ship track data is realized. The LSTM model is established by the network parameters obtained from the optimal particles output from the PSO group. For a certain ship, the ship characteristic data at time t is:

$$Y(t) = \{\alpha, \lambda, c, v\} \tag{13}$$

Among them, α、λ、c、v represents the four characteristics of the ship at time: latitude, longitude, heading, and speed. In order to predict the ship trajectory, the ship's trajectory characteristic data $Y(t-l+1),...,Y(t-1)$ and $Y(t)$ at successive times are used as network inputs, and the ship at time $t+1$ The trajectory characterization data $Y(t+1)$ is used as the output, where l represents the number of steps in the input layer. According to this, the expression of the ship trajectory prediction model is:

$$Y(t+1) = g(\{Y(t-l+1), Y(t-l),..., Y(t-1), Y(t)\}) \tag{14}$$

Where g is the LSTM prediction model.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202005_6(5).0005

3.3 Model parameter settings

The PSO-LSTM model structure consists of an input layer, a hidden layer, and an output layer. The loss function uses root mean square error. The model training process is optimized using the Adam algorithm. The network model is built in the Keras framework.This model sets the number of hidden layer neurons, learning rate, maximum number of iterations, and time window size as LSTM model parameters.n order to reduce the influence of human factors on the model, the experiment set the parameter value range according to the specific conditions of the ship's AIS data: Specify the value range of the number of hidden layer units [10, 30], and the learning rate range [0.000, 1, 0.005], The range of the number of iterations [500, 2000], and the value range of the time window [1, 20].At the same time, the number of particles in the particle swarm is set to 30, the maximum number of iterations is 500, the speed inertia weight ω is 0.8, and the acceleration factor $c_1 = c_2 = 2$. The number of PSO-LSTM training times is directly determined by the model error loss. When the model is iterated to 400 times, the error loss function reaches a convergence state. Therefore, the number of trainings of the PSO-LSTM model is 400.

4. Experimental analysis

4.1 Experimental environment and data

The experimental platform is based on the deep learning framework Tensorflow's upper framework Kreas, the experimental programming language uses python3.5, and the integrated development tool is pycharm.

The original experimental data are derived from the AIS information of ships in the waters of the Yangtze River Estuary, and they are stored in the MySQL database after decoding. Design the field information of MMSI, TIME, LONGITUDE, LATITUDE, SOG and COG according to the input requirements of the model.

4.2 Experimental protocol and evaluation criteria

In order to verify the effectiveness of the proposed method, 1,000 sets of ship AIS data were selected as experimental data, and the selected data were all on-the-fly and a certain speed as experimental data, of which 600 were used as training data and 200 were used as verification data. 200 groups were used as test data. First process the AIS data. As described in 3.1 above, the processed ship data is input as a two-dimensional array.

The root mean square error (RMSE) is used as the evaluation index of the ship's trajectory prediction model. The root mean square error is the arithmetic square root of the expected value of the difference between the observed value and the predicted value of the ship. The RMSE expression is as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_{observed}^{n} - Y_{pridicted}^{n})^2} \tag{15}$$

The smaller the value of RMSE, the better the performance of the ship prediction model and the number of samples.

4.3 Analysis of experimental results

The prediction result is mainly through the trained LSTM ship trajectory prediction model, The optimal parameters of the PSO model are: the number of hidden layer units is 9, the learning rate is 0.025, the maximum number of iterations is 1200, and the time window size is 8.The test data is input to obtain the prediction data and its corresponding RMSE value. The experimental results are shown in the figure below, including the comparison of the latitude and longitude of the two prediction models, the comparison of the ship speed and the course to ground， by comparing the prediction of the ship's trajectory with the real trajectory by the two prediction models in Figure 5 (a), the blue represents the real trajectory, the green dotted line represents the LSTM model predicted trajectory, and the red represents the PSO-LSTM model predicted trajectory. It is found that the prediction effect

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of the PSO-LSTM prediction model is better, basically coincides with the original trajectory, and the stability is better; by comparing the prediction of the ship speed with the real speed in the two prediction models in Figure 5 (b), the continuous Comparison of data at 40 moments, blue represents the actual speed, green dotted line represents the predicted speed of the LSTM model, and red represents the predicted speed of the PSO-LSTM model. It is found that the prediction effect of the PSO-LSTM prediction model is better, which is the same as the original speed point at the same time. The error is extremely low, and the stability is better; compare the prediction of the ship's course with the real direction through the two prediction models in Figure 5 (c), and randomly select 40 consecutive time data for comparison. The blue represents the real track, The green dotted line represents the LSTM model predicting the track, and the red represents the PSO-LSTM model predicting the course. It is found that the PSO-LSTM forecasting model has a better prediction effect, which is basically the same as the original course. coincide;

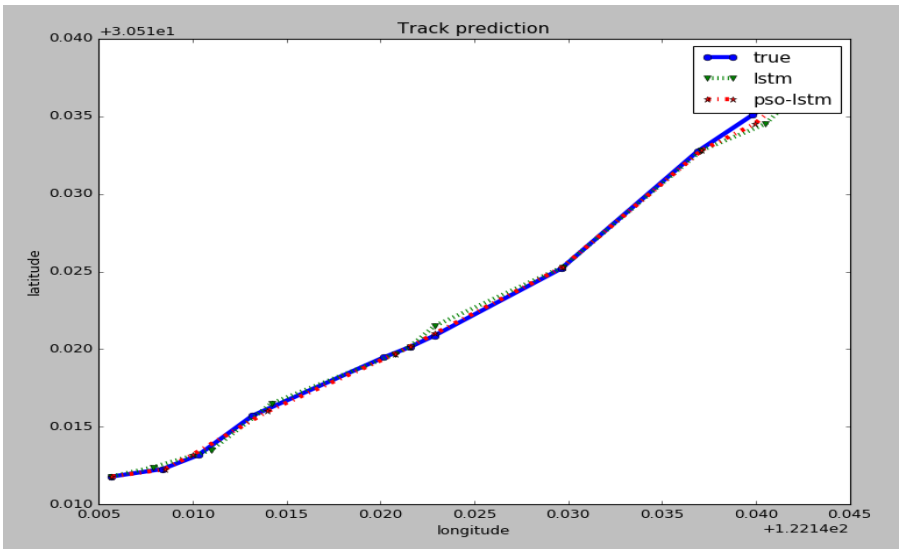

Fig. 5(a) Analysis of Track Forecast Results

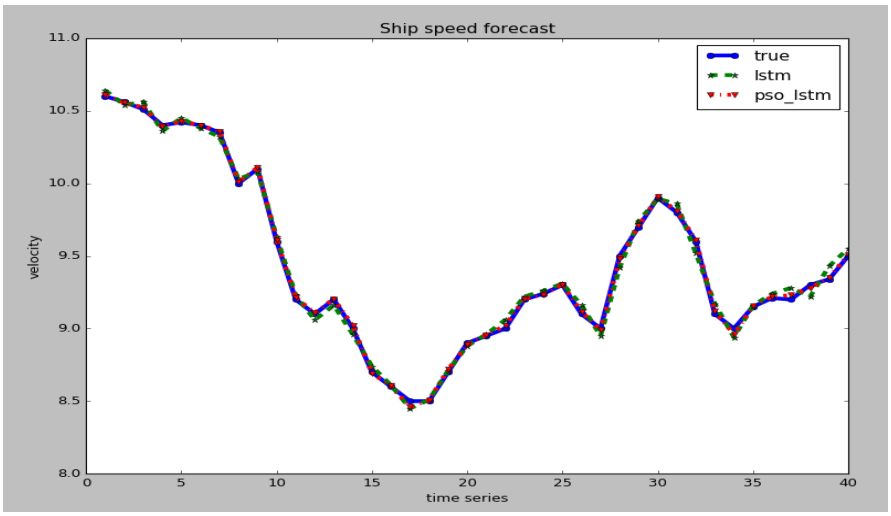

Fig. 5(b) Analysis of speed prediction results

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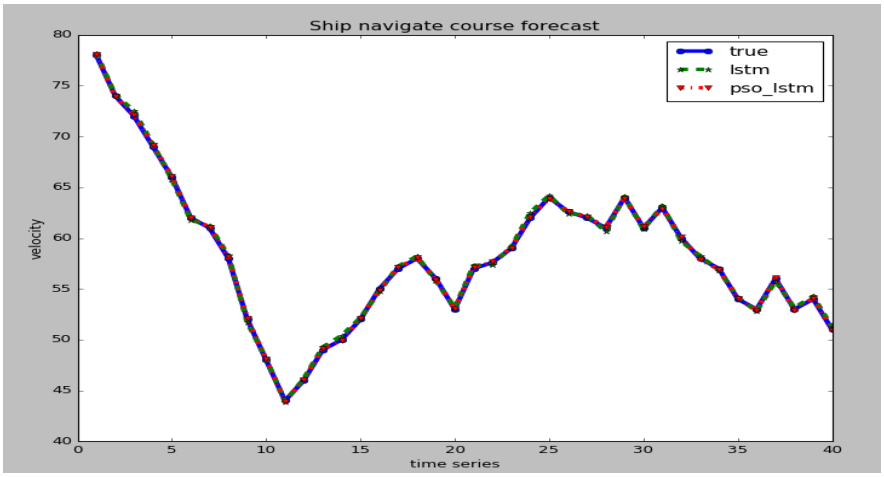

Fig. 5(c) Analysis of course prediction results

Combined with the AIS ship data, the two prediction models were used for testing. By comparing the error results of the two prediction models of PSO-LSTM and LSTM, the RMSE of the prediction results of the two prediction models for latitude prediction were 5.714e-003 and 2.137, respectively. e -003, the RMSE of the longitude prediction results are 6.246e -003 and 2.623e -003, the RMSE of the heading prediction results are 7.925e -003 and 2.674e -003, and the RMSE of the speed prediction results are 4.327e -003 and 1.579e-003, it can be found that the prediction accuracy of the LSTM prediction model optimized by particle swarm optimization has been significantly improved.

Table 1

prediction model	characteristic	RMSE
LSTM	longitude	6.246e -003
	Latitude	5.714e -003
	course	7.925e -003
	navigational speed	4.327e -003
PSO-LSTM	longitude	2.623e -003
	Latitude	2.137e -003
	course	2.674e -003
	navigational speed	1.579e -003

5. Conclusion

Based on the research of ship track prediction, this paper proposes a PSO-LSTM prediction model. The particle swarm algorithm is used to optimize the LSTM network structure to obtain a more optimized prediction performance model. The AIS data is used to predict the ship dynamic information. The results show that The optimized LSTM prediction model improves the accuracy of ship track prediction. The existing model uses the data from the previous l time to predict the $l+1$, but then uses the data from time $T-l$ to $T+1$ to predict the next data and iterative prediction based on the predicted data. There are still real-time calculation problems in ship early warning. In the next stage of research, we plan to introduce a distributed real-time computing system into the ship's track prediction to meet the problem of high real-time prediction delay.

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