Research on Ship Arrival Law Based on Route Matching and Deep Learning

Nian Pan *, Yan Ding, Jia Fu, Jiwei Wang, Hao Zheng
CSSC Marine Technology Co., Ltd. Beijing, China
*Corresponding author e-mail: xxcpb@cssc-cmc.com

Abstract. Maritime transportation has always been the most important mode of transportation in international trade. With the deepening development of economic globalization, the scale of international trade, which is the core content of economic globalization, is also expanding, and the shipping industry is also developing greatly. In this paper, aiming at improving the operation efficiency of container terminals, AIS data is used as the research basis to predict the arrival time of ships and reduce the uncertainty of arrival time of ships, so as to provide support for the construction of smart ports. The transitive closure method based on equivalence relation is used to fuzzy cluster the routes to be matched and the historical routes used for matching, and the optimal route matching is realized by cutting set selection. At the same time, the navigation trajectory features based on AIS data are constructed, and the RNN-LSTM (Recurrent Neural Networks-Long Short-Term Memory) model is proposed by using the characteristics of deep learning and time series. The results show that the RNN-LSTM ship trajectory prediction model based on deep learning can achieve excellent prediction results and provide technical support for intelligent transportation at sea.

Keywords: Route matching; Track prediction; Law of ship arrival; Deep learning.

1. Introduction
In recent years, with the implementation of IMO (International Maritime Organization)'s mandatory requirement for ships to be equipped with onboard automatic identification system (AIS), AIS base stations along the world coast have been built rapidly, and AIS has been widely used [1-2]. As far as the current development situation is concerned, a large amount of AIS data can be collected and stored through the network. Facing the rising AIS ship service information, new innovations can be found from the aspect of information processing. Therefore, it is an important content of shipping research to be able to mine practical and accurate potential information from the seemingly irrelevant data.

The rapid development of AIS system has been widely used in maritime field [3-4], which is a set of digital equipment and navigation equipment system using network, communication and electronic information display technology. It collects dynamic information such as navigation of various ships through its interface board GPS locator, depth sounder and gyrocompass, and provides real-time navigation information for ships through manipulation. The information sent by AIS includes ship number, ship position, draft, speed, bow direction, ship type, ship length and width, number of passengers, etc. AIS information contains a wealth of characteristic attributes of ship track at sea, which
provides an important data source for ship track prediction [5]. The existing ship trajectory prediction models mainly use the traditional machine learning technology, combined with the shallow model of complex kinematic equations. This prediction model is highly limited and can not achieve satisfactory results in practical application.

As a typical model of deep learning, cyclic neural network RNN can be used to process time series data [6]. Taking ship trajectory situation prediction as an example, the future situation depends on the situation value at the historical moment. In this paper, a deep learning model based on RNN-LSTM (Recurrent Neural Networks-Long Short-Term Memory) architecture is proposed. Combined with the information provided by AIS with strong real-time, large amount of data and rich data content, it can better solve the problem of ship trajectory prediction at sea.

2. Literature review

In sea areas or ports with high traffic density and complicated situations, it is an important technical support for early warning of maritime traffic accidents to track and predict the navigation trajectory of ships accurately and effectively by using VTS. At present, there have been many researches on ship trajectory prediction. In literature [7], Kalman filter algorithm is used to estimate the ship observation data by least square method, and the smooth ship trajectory is obtained, and then the prediction is made. The historical trajectory database is established based on the AIS data in document [8], and the historical similar trajectory is searched in the database according to the information of a specific ship, and the navigation state and arrival time of the ship are predicted according to the characteristics of the similar trajectory. Literature [9] combines AIS technology and four-element dynamic ship domain model, establishes a set of reasonable and effective decision-making model for ship collision avoidance, and constructs an auxiliary decision-making system for collision avoidance, which can realize the judgment of collision danger and situation, and give suggestions on avoidance direction and avoidance range; Literature [10] can analyze the location with high risk and high flow rate by establishing a real-time database management system based on AIS, and get better ship estimated time. In addition, it can be used to detect the arrival of ships and identify important traffic waters. In the literature [11-12], the relevant statistical data obtained by Tianjin Maritime Safety Administration, Tianjin Port Group and other departments are used to make statistical analysis on the arrival law of ships in the main channel of Tianjin Port.

With the continuous development of computer technology, more and more scholars use computer modeling and simulation methods to study ship traffic flow. At present, most scholars' simulation objects are single ports, locks and waterways. Literature [13] designed a port traffic flow simulation system based on multi-agent, which was applied to the demonstration research of different planning schemes in port area. Literature [14] establishes a cellular automata model to simulate the ship traffic flow when some waterways are closed. In reference [15], based on the grey system theory, the grey correlation scheme and grey dynamic modeling scheme of ship collision data mining are proposed. Literature [16] mainly studies the identification of maritime traffic flow characteristic information by using graphical attribute analysis and cluster analysis in data mining. In the literature [17], the mathematical statistics method is used and the test results show that the number of daily arrival ships in inland waterway obeys normal distribution, and the time interval between daily ships obeys Erlang distribution approximately. The track prediction model based on three-layer BP (Back Propagation) neural network designed in reference [18] has the characteristics of short time and strong universality, and is suitable for the real-time and efficient demand of VTS and other management systems for ship track prediction. However, the method used in literature [19] only predicts the spatial position of ships, and the dimension of trajectory is too narrow and shallow.
3. Research technique

3.1. AIS data preprocessing

The original ship information directly derived from AIS system is arranged according to the sequence of signal transmission time, and the data of different ships are mixed together. First, it is necessary to filter out the dynamic information of ships to be predicted from these information. The MMSI (maritime mobile service identity), IMO (international maritime organization number), ship name and call sign of a ship are all unique, so the data belonging to the same ship can be screened out according to any of the above four kinds of information.

The longitude and latitude of a ship change uniformly during navigation, and the longitude and latitude of the abrupt change point have changed dramatically. According to this feature, the latitude difference between two coordinate points can be calculated by using the program, and then the abrupt change point can be screened out. After such processing, the position, speed and track direction information corresponding to this point will be lost, and important feature points may be ignored. Because the speed and heading of the ship also change uniformly during navigation, a new point can be interpolated according to the coordinates, heading and speed information of the points on the left and right sides of this point to replace the abrupt point information, and clean and usable tracks can be obtained.

3.2. Route matching based on equivalence relation

In this paper, using the clustering method based on equivalence relation [20] and adopting transitive closure method, the course of route matching can be summarized into the following four steps, as shown in Figure 1:

![Diagram of clustering process based on equivalence relation]

Fig. 1 Clustering process based on equivalence relation
3.3. Establish the original data matrix:

Taking \( n \) historical routes extracted from the database as subclasses, the domain \( U = \{x_1, x_2, \ldots, x_n\} \) is obtained, which is the classified object; Each object has \( m \) indicators to express its traits:

\[
x_i = \{x_{i1}, x_{i2}, \ldots, x_{im}\}, (i=1, 2, \ldots, n)
\]

That is, the feature vector of each heading. Therefore, the original data matrix can be obtained as follows:

\[
\begin{bmatrix}
x_{11} & x_{12} & \cdots & x_{1m} \\
x_{21} & x_{22} & \cdots & x_{2m} \\
& & \ddots & \vdots \\
x_{n1} & x_{n2} & \cdots & x_{nm}
\end{bmatrix}
\]

3.4. Generate fuzzy similarity matrix:

Establishing fuzzy similarity matrix is also called calibration, that is, marking the statistical quantity \( r_{ij} (i=1, 2, \ldots, n, j=1, 2, \ldots, n) \) that measures the similarity between classified objects. The methods of determining \( r_{ij} = R(x_i, x_j) \) mainly borrow the similarity coefficient method, distance method and other methods of traditional cluster analysis. There are many ways to calculate \( r_{ij} \), which should be decided according to the nature of the problem.

Distance method: \( r_{ij} = 1 - c d(x_i, x_j) \), in which \( c \) is a properly selected parameter, so that \( 0 \leq r_{ij} \leq 1 \). Frequently used distances are:

3.4.1. Hamming distance:

\[
d(x_i, x_j) = \sum_{k=1}^{m} |x_{ik} - x_{jk}|
\]

3.4.2. Euclidean distance:

\[
d(x_i, x_j) = \sqrt{\sum_{k=1}^{m} (x_{ik} - x_{jk})^2}
\]

3.4.3. Chebyshev distance:

\[
d(x_i, x_j) = \max_{k=1}^{m} |x_{ik} - x_{jk}|
\]

In this paper, Hamming distance in the distance method is used to calculate the similarity statistic \( r_{ij} \), i.e. \( r_{ij} = 1 - c \sum_{k=1}^{m} |x_{ik} - x_{jk}| \), between the feature points of the ship's real-time route and the feature points of each historical route, which is also called absolute value reduction method.

3.5. Generate fuzzy equivalent matrix:

Because the fuzzy equivalent matrix can divide the universe equally, it can meet the needs of cluster analysis. However, under normal circumstances, the fuzzy relation constructed by the calibration process can only satisfy reflexivity and symmetry, but not transitivity, so only a fuzzy similarity matrix \( R \) is generated, not a fuzzy equivalent matrix. Therefore, in order to classify, a fuzzy equivalent matrix
should be generated on the basis of this fuzzy similar matrix. The most natural method is to obtain the transitive closure \( t(R) \) of this fuzzy similar matrix \( R \), so that a fuzzy equivalent matrix can be obtained.

When calculating transitive closure \( t(R) \), one of the most practical and effective methods is the flat method. Starting from the fuzzy similarity matrix \( R \), square it in turn: 
\[
R \rightarrow R^2 \rightarrow R^4 \rightarrow \Lambda \rightarrow R^2 \rightarrow \Lambda
\]
When \( R^k \circ R^k = R^k \) appears for the first time (indicating that \( R^k \) is transitive), \( R^k \) is the transitive closure \( t(R) \).

3.6. Division:
When the fuzzy equivalent matrix is generated, take a real number \( \lambda \in [0,1] \) and calculate \( t(R) = P \) (Boolean matrix), and get an equivalent division of the universe \( X \). When \( P_{ij} = 1 \), it means that \( x_i \) and \( x_j \) are in the same equivalent class. Otherwise, they are in different classes. If \( \lambda \) value is reduced from 1 to 0 in turn, a dynamic classification of \( X \) can be obtained, which gradually changes from thin to thick.

3.7. Ship trajectory prediction model based on RNN-LSTM

3.7.1. Recurrent Neural Network (RNN).
Recurrent Neural Networks (RNN), also known as recurrent neural networks, is a deep neural network model and one of the hot technologies in the field of deep learning in recent years. It has made remarkable achievements in the fields of natural language processing, speech recognition and image recognition [21]. Different from the traditional feedforward neural network, the cyclic neural network introduces directional loop, which can deal with the problem of the correlation between inputs.

![Hierarchical architecture diagram of RNNs](image)

Cyclic neural network seems to have memory, which memorizes the previous information and applies it to the calculation of current output, that is, the nodes between hidden layers are not connected but connected, and the input of hidden layers includes not only the output of input layer but also the output of hidden layer at the previous moment. Theoretically, RNN can process sequence data of any length. However, in practice, in order to reduce complexity, it is often assumed that the current state is only related to the previous states. Figure 2 shows the hierarchical structure of a standard cyclic neural network RNNs, which is input layer, hidden layer and output layer.

Fig. 3 is a neuron structure diagram of RNNs expanded into a complete network according to time sequence. In other words, based on the time series \( \{t = 1,2,\Lambda, T\} \), RNNs includes an input unit, and
the input set is marked as $\{x_0, x_1, \ldots, x_t, x_{t+1}, \ldots\}$, where $x_t$ represents the input at time $t$; $O$ is the output unit, marked $\{o_0, o_1, \ldots, o_t, o_{t+1}, \ldots\}$, where $o_t$ represents the output at time $t$.

![Fig. 3 RNNs expands the neuron structure diagram of the whole network according to the time sequence](image)

Different from others, each layer of the traditional neural network model uses different parameters, while each layer of RNN uses the same parameter $U, V, W$ at every moment, which ensures that RNN performs the same operation on all nodes, thus reducing the number of parameters to be learned.

3.8. LSTM model

Ordinary cyclic neural networks have the disadvantage of fast weakening of node memory, and LSTM (Long Short-Term Memory) long-short-term memory network model improves this disadvantage [22]. The LSTM model structure contains a group of interconnected recursive sub-networks, namely memory modules, which replace the memory units in ordinary RNN and are easier to train than ordinary RNN. Each module contains one or more autocorrelation core cells cell and three new cells-gates: input gate, output gate and forgetting gate, which are used to control the information flowing into the storage unit and from the unit to the network.

![Fig. 4 LSTM memory module with one neuron](image)
In this topic, they correspond to the writing, reading and resetting operations of the ship trajectory characteristic data sequence. Fig. 4 is an LSTM memory module including a memory cell. It can be seen from the figure that the input gate, the output gate and the forgetting gate are nonlinear aggregation units, which aggregate all the activations inside and outside the module, and control the activation of the core cell through the affiliated nodes (small black circles in the figure). In neural networks, the activation function can introduce nonlinear factors into the model and solve problems that linear models cannot solve.

3.9. Ship navigation trajectory prediction model

At present, AIS data is an important source for various maritime traffic management systems to obtain data representing ship navigation, which includes basic information such as ship identification MMSI, receiving time, longitude, latitude, speed and heading angle.

Ship trajectory prediction is essentially a regression problem using RNN-LSTM recurrent neural network. The ship's historical trajectory characteristics and current trajectory characteristics are taken as network input, and the ship's trajectory characteristic data at a certain time in the future is taken as network output. By training the network against the real value, the mapping relationship between the historical ship's trajectory and the future ship's trajectory characteristic data is established, and the future ship's trajectory characteristics can be estimated and predicted.

For a single ship, its trajectory characteristic $Y(t)$ at time $t$ can be expressed as [23]:

$$Y(t) = \{v, c, \ln g, lat, itv\}$$

In which $v, c, \ln g, lat, itv$ represents five characteristics of the ship at time $t$: speed, heading, longitude, latitude and time interval identification. Time interval identification is used to break through the bottleneck that the model can only select fixed time interval data for training and prediction, and can be extended to meet the needs of ship trajectory prediction at different time intervals.

In order to realize the prediction of ship trajectory, the characteristic data $Y(t-n+1), Y(t-1), Y(t)$ of ship trajectory at $n$ consecutive times is taken as the network input, and the characteristic data $Y(t+1)$ of ship trajectory at $t+1$ time is taken as the output, where $n$ corresponds to the size of the input layer step. Accordingly, the expression of the ship navigation trajectory prediction model is:

$$Y(t+1) = f([Y(t-n+1), Y(t-1), Y(t)])$$

4. Application case analysis

In this paper, taking L port in China as an example, firstly, taking the arrival information of ships in L port within one month as an experimental sample, the arrival time prediction model of container ships considering AIS information proposed in this paper is used to predict the arrival time of ships. In order to verify the practicability of the prediction results of the ship arrival time prediction model proposed in this paper, this paper takes the ship arrival time predicted by this model and the ship arrival time predicted by the schedule as the input parameters to carry out berth-shore-bridge joint optimization scheduling for these two container terminals, compares the two scheduling results, and then discusses the practicability and applicability of the prediction results of this model.

4.1. Prediction of arrival time of ships

Based on the historical AIS data of ships, the arrival time of ships that have started from the port of departure and destined for a port in the south is predicted, and finally the arrival time of container ships with a total of 277 voyages in one month is obtained.

Combined with a ship, this paper explains how to obtain the typical motion trajectory of the ship and predict the arrival time of the ship. According to the AIS data from the port of departure to the destination in the history of the ship, firstly, the average value $\bar{\mu}, \bar{v}$ of the ship's track direction and speed change rate and the ship $\bar{\mu} = 5.6$ and $\bar{v} = 0.7$ are calculated, and these two values are used as the threshold.
values of the track direction and speed change rate in the course of track division, and the divided track subsection 1631 is obtained.

Through many experiments, it is found that when the spatial distance threshold $\varepsilon$ is between 0.7-4.4 and the density $N_e$ is between 5-7, the core track sub-segment can be extracted and the noise track sub-segment visible to the naked eye can be avoided as the core track sub-segment. See table 1 for $\text{Sum}(O,TMT)$ obtained under different $\varepsilon-N_e$ combinations, and see fig. 5 for the changing trend of $\text{Sum}(O,TMT)$ with $\varepsilon-N_e$ combinations.

| $\varepsilon$ | 5   | 6   | 7   | 8   |
|--------------|-----|-----|-----|-----|
| 0.5          | 62.3| 60.2| 58.9| 56.9|
| 1            | 60.1| 58.3| 56.8| 55.3|
| 1.5          | 54.6| 52.1| 50.1| 48.2|
| 2            | 51  | 49.3| 47.6| 46.3|
| 2.5          | 42.6| 40.2| 38.3| 35.9|
| 3            | 62.6| 61.7| 60.2| 57.8|
| 3.5          | 64.7| 62.1| 61.6| 60.2|
| 4            | 77.9| 74.6| 73.1| 72.1|
| 4.5          | 94.7| 93.3| 92.1| 91.4|

**Fig. 5** LSTM memory module with one neuron Trend of $\text{Sum}(O,TMT)$ changing with $\varepsilon-N_e$ combination

It can be seen from fig. 5 that when $N_e$ is constant, when $\varepsilon$ increases from 0.5 to 2.5, $\text{Sum}(O,TMT)$ gradually decreases, and when $\varepsilon = 2.5$, $\text{Sum}(O,TMT)$ reaches the minimum value. After that, $\text{Sum}(O,TMT)$ became larger. The reason for this change is that when $\varepsilon$ is small, the screening conditions are strict, and the number of extracted core track sub-segments is small, which leads to a large error in the obtained typical motion track. When $\varepsilon$ is large, the screening conditions are loose, and the noise track sub-segment invisible to the naked eye is selected as the core track sub-segment, which also leads to a large error in the obtained typical motion track, which is also the reason for the high right side of the image.

Based on the typical motion trajectory, the sailing time of the ship from the departure port to the destination port is obtained, and the arrival time of the ship from the departure port to the destination port is calculated. By repeating the above process, the typical motion trajectories of ships from their
departure port to destination port in one month are obtained, and then the sailing time of ships is predicted. The prediction results are shown in Figure 6. It can be found from the figure that the blue line is closer to the straight line than the green line, which indicates that the ship sailing time predicted by this model is closer to the actual sailing time.

Fig. 6 Prediction results of ship sailing time

Table 2. Comparison and analysis table of arrival time error between model and shipping schedule in this paper

| Model               | Absolute value of error(min) | Error of late arrival ship(min) | Error of early arrival ship(min) |
|---------------------|------------------------------|--------------------------------|---------------------------------|
|                     | Maximum value | Minimum value | Average value | Standard deviation | Maximum value | Minimum value | Average value | Standard deviation | Maximum value | Minimum value | Average value | Standard deviation |
| This model          | 26            | 6             | 13            | 11               | 27            | 5             | 13            | 15               | -12           | -25           | -15          | 15                |
| Sailing schedule    | 117           | 9             | 44            | 23               | 125           | 11            | 47            | 28               | -18           | -97           | -63          | 36                |

According to table 2, through horizontal comparison, it can be seen that the indexes of ship late arrival and early arrival error obtained by this model are basically equal, which shows that the prediction effect of this model for ship late arrival and early arrival is the same; Through longitudinal comparison, it can be seen that the arrival time error predicted by this model is better than the arrival time error given by the shipping schedule.

4.2. Model performance analysis
277 sets of ship AIS data are still taken as the original data, and the data processing after AIS information analysis is as described in the previous two sections. Because the shallow-level track prediction model based on BP neural network and the deep-learning track prediction model based on LSTM are proposed in this subject, the experimental setup and steps are basically the same, and the 10-fold cross-validation strategy is also adopted.

RNN-LSTM model and GA-BP (Genetic Algorithm-BP) model, after their respective training, adopt the same data input and input the ship trajectory characteristics at five times ($t - 4, t - 3, t - 2, t - 1, t$) in the same format. After the training of the models, continuously predict the five times in a recursive way, and check the change of mean square error predicted by the two models. The results are shown in figure 7.
Fig. 7 Model mean square error graph

It can be seen from fig. 4-3 that the mean square error of GA-BP neural network prediction model test is larger than that of RNN-LSTM model at the first time of recursive test on the test set. With the continuous prediction of the output at multiple times, the mean square error curve of GA-BP neural network prediction model increases steeply, while the mean square error curve of LSTM model also increases positively due to the accumulation of time series, but its growth rate is far less than the former. It can be concluded that LSTM model has better prediction accuracy and lower mean square error than GA-BP neural network model. RNN-LSTM model adds a time dimension when considering the prediction of ship track, which makes RNN-LSTM model learn the movement trend of ship track in different time intervals, and is more suitable for ship prediction regression.

5. Conclusion

In this paper, the research of ship arrival rule based on AIS data and deep learning is studied. The fuzzy clustering of matched routes and historical routes is carried out by using the transitive closure method based on equivalence relation. The optimal route matching is realized through the selection of cut set. In this paper, the ship trajectories in the study area are divided into several clusters by using the established ship trajectories clustering model. From the results, it can be seen that the clusters obtained by the classification are more consistent with the actual situation of ship traffic flow; The main innovation of this paper is to propose a ship track prediction model trained by RNN-LSTM algorithm. This progressive improvement of neural network technology not only avoids the limitation of constructing complex kinematic equations by traditional methods, but also overcomes the inefficiency of manually describing the track characteristics of ships at sea. At the same time, it is also an in-depth exploration of ship track prediction methods.

In this paper, some research achievements have been obtained in obtaining the ship arrival rule model based on AIS data and deep learning. However, due to the limited time and level, there are still many areas to be improved, such as: In this paper, the influence of tidal and sea conditions is not considered in building the ship arrival model. In order to build a more realistic ship arrival model, considering these factors will be the next research content.

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