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Automatic planning method of seawater navigation trajectory based on AIS big data

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ABSTRACT

In the context of economic globalization, shipping, as the main form of international trade, has developed rapidly. More and more intensive water ship traffic and navigation have a great burden on the channel. The frequent safety accidents in recent years have also sounded an alarm for people. In order to improve the safety of ship navigation and realize automatic and intelligent navigation trajectory planning, this study collects and processes ship navigation data based on Automatic Identification System (AIS), and introduces naive Bayesian algorithm to predict and analyze ship navigation data. In order to verify the effect of the algorithm in practical application, the ship navigation trajectory is predicted and simulated by selecting the data set. The simulation results show that the AIS system based on big data technology can realize the automatic and intelligent planning of navigation trajectory, which has higher accuracy than the traditional navigation trajectory planning method.

Keywords: Automatic Identification System; Big data; Navigation; Navigation track; Automatic planning

1. Introduction

With the development of modern international trade and the vigorous development of shipping industry, the number of ships is also growing at a very exaggerated rate. The safety problems in the shipping process are becoming increasingly prominent. It is required to have a system with prediction function to realize the automatic planning of ship navigation [1,2]. Automatic Identification System (AIS) is a comprehensive application system integrating ground network, satellite and radar. At present, the most important application is ship traffic service, which can realize the safe operation of ship [3,4]. When AIS signal is analyzed by traditional numerical analysis method, it is easy to cause instability of ship fitting trajectory, and it is difficult to deal with complex channel, especially in complex curve, and it is difficult to accurately estimate ship trajectory.

Liang and Zhang [5] proposed an adaptive particle swarm optimization algorithm combined with short-term memory network to build a ship trajectory prediction model, which can predict and analyze the abnormal behavior of ships and has high prediction accuracy [6–8]. The AIS system currently used is conducive to the risk assessment of maritime navigation, but the current system operation efficiency is low. Zhong et al. [9] proposed a deep learning method of recurrent neural network for optimization, which can significantly improve the processing efficiency of the system. Liu et al. [10] proposed a method based on segmented spatio-temporal constraints and combined with AIS system to find the abnormal behavior of the ship. When the ship driver manually closes the AIS system, the ship's trajectory cannot be recorded and found, which is not conducive to the development of supervision [11,12]. Huang et al. [13] proposed a roadway navigation safety evaluation method

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based on AIS system. In dB, the cross line method and Monte Carlo method are used to evaluate the grounding probability of ships. The final simulation results also show that the probabilities evaluated by these two methods are similar.

Han and Tian [14] introduced recurrent neural network to predict the ship's maneuvering behavior, and conducted a specific case simulation analysis with the ship's navigation trajectory of Xiamen port. The simulation results show that the ship's track law can be analyzed by using the ship's historical navigation trajectory, so as to predict the ship's future navigation position. Using the historical trajectory data of ships can better carry out the classification research of ships. Sheng et al. [15] extracted the characteristics of ship trajectory through logistic regression model, constructed a ship classifier, and gave three basic motion patterns, which can not only realize the type recognition of ships, but also mine the behavior patterns. Zhang et al. [16] proposed a three-step AIS system to build a ship's regional trajectory reconstruction model. The first step is to remove the outliers in the navigation trajectory data, the second-step is to estimate the ship's navigation state, and the third step is to fit the ship's trajectory. The prediction and fitting of the ship's trajectory using this model is significantly better than the linear regression model.

This research is based on the processing of ship navigation trajectory data by AIS system, and uses big data technology to deeply mine the navigation trajectory, so as to provide basic conditions for ship trajectory prediction. This research has the following two innovations: (1) A ship trajectory prediction method based on big data technology is proposed, and the automatic route planning and design is realized based on the predicted data. (2) It can make full use of a large amount of data in AIS system to simplify the processing of route trajectory data, which is helpful to realize the intelligence of ship trajectory.

2. Methods

2.1. AIS data acquisition system

2.1.1. Data acquisition and processing of AIS system

AIS is a ship borne digital navigation aid system integrating modern computer network technology and communication technology. Combined with GPS, the system can update the ship's information in real time. The ship can understand the navigation information of surrounding ships during navigation, and then avoid possible navigation safety risks through communication coordination [17–22]. From the main functions, AIS has four functions: the first function is to identify the information of ships; The second is to realize the communication between simple ships; The third is to track the ship's trajectory; The fourth is to provide the information of surrounding ships, so as to combine the information of their own ships to avoid possible collisions. The data collected by AIS system mainly include ship static, dynamic and voyage data. These three data can realize the four functions of AIS and be used for normal navigation of ships [23,24].

To plan the ship trajectory, its essence is to predict the ship trajectory, obtain the historical data of the ship, and analyze the ship trajectory data related to ship navigation. At present, AIS system is difficult to record the formal trajectory data of all ships, so the system can be used to identify and analyze the navigation state, speed and acquisition interval of ships.

The navigation state of a ship specifically includes the states of navigation, anchoring and grounding. Anchoring is defined as the key state of route segmentation, so a complete route should be the whole process of start → navigation → berthing. Set the AIS data sequence as $T = \{p_1, p_2, p_3, \ldots, p_n\}$, and the data extraction steps during ship navigation are as follows:

Step 1: Initialize S and S as the sequence set of ship route trajectories.

Step 2: After traversing AIS data sequence T, find the data point p_j with ship navigation status of "anchoring".

Step 3: Traverse from the "anchor" point to find the "sailing" state point p_k of the ship, obtain a new trajectory sequence $s = \{p_j, p_{j+1}, \ldots, p_{k-1}\}$ and add it to the S sequence set.

Step 4: Take point k as the new starting point and repeat Step 2 until all data are traversed until the end.

The key to successfully identify the route is to accurately obtain the starting point and end point of the route, and judge the navigation state of the ship through the collected interval, speed, longitude and latitude position and other data. When the ship stops, AIS system will stop data collection, and the system will collect data normally only when the ship is heading normally. In order to identify the starting point of the route, the data points collected for more than 12 h are set as the starting point of the route. The AIS data error caused by time anomaly or sensor may make the time of the front and rear track points of the ship in the running state longer. Therefore, it is necessary to set the time difference threshold and comprehensively determine the starting point of the ship's operation according to the changes of longitude, latitude and speed. When the ship starts and anchors, its instantaneous speed and relative position will change significantly, which can play a good role in ship state recognition. The data in step p_j can be traversed as the tangent point in step 12, and the data can be set as step 12. The data acquisition process of AIS system is shown in Fig. 1.

2.1.2. System data missing value processing

During navigation, the ship's trajectory data will be missing for various reasons, especially when the acquisition time span is too long. Now, a typical navigation data is used to demonstrate the data missing processing. The trajectory sequence of a route is T, the instantaneous speed of the ship is sog, indicating that the longitude and latitude of the ship's position are lng,lat, the instantaneous rotation angle of the ship is cog, and the state of the ship at time t_i can be expressed as $p_{t_i} = \{\mathrm{la}t, \ln g, \mathrm{sog}, \mathrm{cog}\}$. Solving the problem of missing data can be understood as the interpolation problem of missing data in the sequence. Set the original data sequence as $S = \{s_1, s_2, \ldots, s_n\}$ and the original data acquisition interval as 5–10 min. This time, select the missing values of adjacent data for more than 20 min for processing. If the interval between two data is longer, it means that there are more missing values.

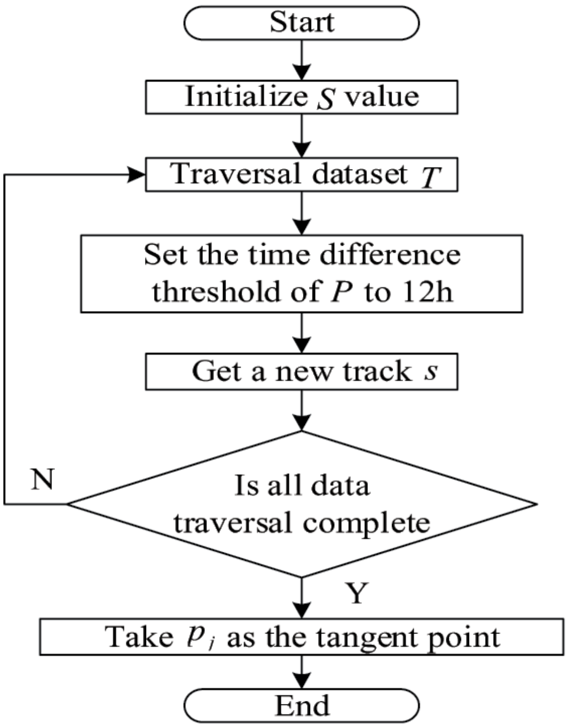

Fig. 1. AIS system ship trajectory data acquisition flow chart.

Let the time interval between t_i and t_{i-1} be Δt_i, the standard for judging whether missing value data processing is required is $\Delta t_i > 20$, and the calculation formula of the actual data quantity is:

$$\text{num} = \text{abs}\left(\frac{\Delta t_i}{10}\right) - 1 \tag{1}$$

The interval between the two points is planned to be 50 min, as shown in Fig. 2. There are 4 missing data values to be supplemented, and the interval of each is 10 min.

Because the ship trajectory data is a continuous data, the numerical interpolation method is selected to supplement the missing data, which can directly calculate the average value of the data set and take it as the missing data. Let the missing data in the original data sequence $T = \left\{p_{t_1}, p_{t_2}, p_{t_3}, \cdots, p_{t_n}\right\}$ be p_{t_i}, and take the k data closest to the data as the benchmark data, so the data sequence is:

$$T^* = \left\{p_{t_{i-\frac{k}{2}}}, p_{t_{i-\frac{k}{2}}+1}, p_{t_{i-\frac{k}{2}}+2}, \cdots, p_{t_{i+1}}, p_{t_{i+2}}, p_{t_{i+\frac{k}{2}}}\right\} \tag{2}$$

The weight of the w_j element in T^* is $p^*_{t_i}$, and the data to be filled is $p^*_{t_i}$, and its calculation formula is:

$$p^*_{t_i} = WT^* = w_1 p^*_1 + w_2 p^*_2 + w_3 p^*_3 + \cdots + w_k p^*_k \tag{3}$$

Lagrange interpolation is needed to fill in the missing value for the navigation track with large bending degree. Let the value point of $k + 1$ be $\left(t_0, p_{t_0}\right), \left(t_1, p_{t_1}\right), \cdots, \left(t_k, p_{t_k}\right)$, p_{t_i} represent the value of the corresponding time point of t_i series, and the Lagrange polynomial is:

$$L(t) = \sum_{i=0}^{k} p_{t_i} l_i\left(t_i\right) \tag{4}$$

$l_i(t)$ represents the difference basis function, and its calculation formula is:

$$l_i(t) = \prod_{j=0, i\neq j}^{k} \frac{t - t_j}{t_i - t_j} = \frac{\left(t - t_0\right)}{\left(t_i - t_0\right)} \cdots \frac{\left(t - t_{i-1}\right)}{\left(t_i - t_{i-1}\right)} \frac{\left(t - t_{i+1}\right)}{\left(t_i - t_{i+1}\right)} \cdots \frac{\left(t - t_k\right)}{\left(t_i - t_k\right)} \tag{5}$$

In Eq. (5), the relationship between t and t_i determines the value of $l_i(t)$: when $t = t_i$, $l_i(t) = 1$; when $t = t_j$, $l_i(t) = 0$. For the missing part of the navigation trajectory data, as long as the time period of missing data is known, the time point can be determined, and the missing value can be calculated by substituting it into Eq. (5).

2.2. AIS route prediction and planning analysis based on big data technology

2.2.1. Basic model of ship trajectory prediction and planning

The automatic planning of ship navigation trajectory is the prediction of navigation trajectory, and the trajectory planning is carried out according to the prediction results. The ship dynamics can be prefabricated in advance, the possible abnormal behaviors can be handled in advance, the navigation prediction and scheduling of other ships in

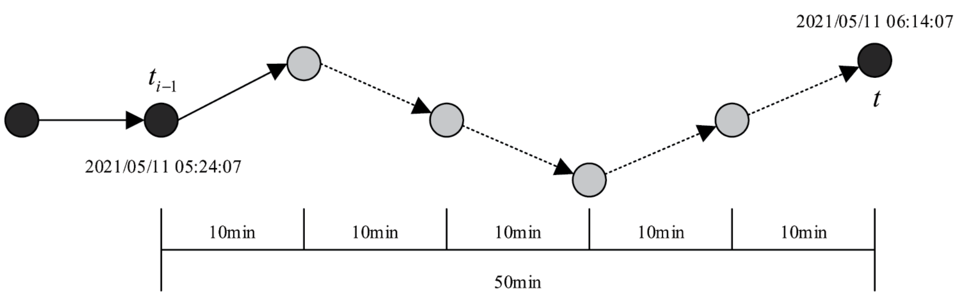

Fig. 2. Schematic diagram of missing data and interpolation.

different regions, and the automatic route planning, intelligent prediction and planning can be realized. Let the i trajectory point of the ship be t_i, the trajectory of the prediction planning analysis be S, and the i route be represented by S_i. The prediction of the future route trajectory is to realize the minimum difference between the actual route and the predicted route, which is represented by the difference degree $\left|Y-\hat{Y}\right|$. The smaller the value, the more accurate the prediction of the route trajectory. Therefore, it can be expressed by the mapping function $f(\cdot)$:

$$f(\cdot):\hat{Y}_i = f(T,S) \tag{6}$$

The typical schematic diagram of ship route trajectory prediction is shown in Fig. 3:

Each track can be understood as a collection of track segments. In order to predict the route, it is necessary to compare the current track with the route track. In order to achieve better route track prediction, better results can be obtained by segmentation. Each segmented segment contains three variable information: the starting point, the ending point and the number of routes. Set the number of routes as the number of routes and the number of ships as route_num, ship_num respectively, and the new route set after prediction and planning is expressed as:

$$L = \left\{\text{ship\_num}, \text{route\_num}, \text{start}, \text{end}, T\right\} \tag{7}$$

The segmented track segments can be regarded as a combination of small linear segments, which can retain all the information of the track segments to a great extent. For route trajectory prediction planning, it is necessary to predict and analyze the variables of each trajectory segment.

2.2.2. Route prediction and planning technology based on big data technology

This time, Bayesian network algorithm is selected for ship route prediction and planning. The algorithm model can calculate the conditional probabilities of different categories based on the given characteristic conditions. When it is applied to the prediction of ship route trajectory, different routes are regarded as categories and the existing trajectory data are regarded as characteristic conditions. According to the basic model of ship route, each route is divided into multiple route segments. The sequence of multiple route segments is $R = \{r_1, r_2, r_3, \ldots, r_n\}$ and the current navigation trajectory is $T = \{t_1, t_2, t_3, \ldots, t_m\}$. The current

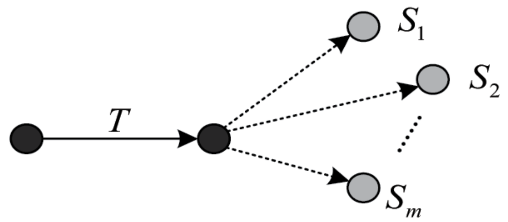

Fig. 3. Typical diagram of ship route trajectory prediction.

route trajectory of the ship is divided into segment sequence $T = \{s_1, s_2, s_3, \ldots, s_k\}$, the actual route segment sequence with ship trajectory T is $\bar{P} = \left\{\bar{P}_1, \bar{P}_2, \bar{P}_3, \cdots, \bar{P}_k\right\}$, and the new route obtained through ship trajectory prediction is R_c. The route prediction planning is carried out. Its essence is to obtain the new route $p\left(R_c \middle| T, \bar{P}\right)$ with the maximum probability, which can be obtained by using Bayesian formula:

$$p\left(R_c \middle| T, \bar{P}\right) \propto p\left(T, \bar{P} \middle| R_c\right) \cdot p\left(R_c\right) \tag{8}$$

Let the number of ships and the number of trips be M,L respectively, and the number of ships and trips on the new route be m,l respectively. The calculation formula of a priori probability is:

$$p\left(R_c\right) = \frac{m}{M} \tag{9}$$

Eq. (9) can also be expressed as:

$$p\left(R_c\right) = \frac{l}{L} \tag{10}$$

The calculation formula of joint probability $p\left(R_c \middle| T, \bar{P}\right)$ of new route track section and similar section is:

$$p\left(T, \bar{P} \middle| R_c\right) = p\left(T \middle| \bar{P}, R_c\right) \cdot p\left(\bar{P} \middle| R_c\right) \tag{11}$$

$\bar{P}$ and T are one-to-one correspondence, and the obtained real sequence is unique. Eq. (11) can be transformed into:

$$p\left(T \middle| \bar{P}, R_c\right) = \prod_{i=1}^{m} p\left(t_i \middle| \bar{p}_i, R_c\right) \tag{12}$$

Each route segment has a conditionally independent relationship, and there is no correlation between t_i and t_{i-1} from this, we can get:

$$p\left(t_i \middle| \bar{p}_i, R_c\right) = p\left(x_i, y_i, \text{cog}_i, \text{sog}_i \middle| \bar{p}_i, R_c\right) \tag{13}$$

Solve the correlation between route segment p_i and track segment t_i. The correlation determines the probability. The greater the correlation, the greater the probability. Further, the Markov hypothesis is used to solve the joint probability $p\left(R_c \middle| T, \bar{P}\right)$ between T and $\bar{P}$. Under the condition of given state sequence H, the sequence probability $p(H)$ is calculated:

$$p(H) = p\left(h_0, h_1, \cdots, h_m\right) = \prod_{i=1}^{m} p\left(h_i \middle| h_{i-1}\right) \tag{14}$$

Through further decomposition of Markov hypothesis, we can get:

$$p\left(\bar{P} \middle| \text{Rc}\right) = p\left(\bar{P}_0, \bar{P}_1, \bar{P}_2, \cdots, \bar{P}_m \middle| R_c\right) \propto \prod_{i=1}^{m} p\left(\bar{P}_i \middle| \bar{P}_{i-1}, R_c\right) \tag{15}$$

The result finding process of $p\left(\bar{P}_i \middle| \bar{P}_{i-1}, R_c\right)$ can be understood as the probability that the track segment in route R_c transfers from $\bar{P}_{i-1}$ to $\bar{P}_i$, that is:

$$p\left(\bar{P}_i \middle| \bar{P}_{i-1}, R_c\right) \approx p\left(\bar{P}_i \middle| P_{i-1}\right) \cdot p\left(R_c \middle| \bar{P}_i\right) \tag{16}$$

Finally, the probability formula of the new route can be calculated:

$$p\left(R_c \middle| T\right) = \prod_{i=1}^{m} p\left(t_i \middle| \bar{P}_i, R_c\right) \cdot \prod_{i=1}^{m} p\left(\bar{P}_i \middle| \bar{P}_{i-1}\right) \cdot p\left(r_c \middle| \bar{P}_i\right) \cdot p\left(R_c\right) \tag{17}$$

The navigation trajectory prediction and planning process based on Naive Bayes is shown in Fig. 4.

3. Results and discussion

3.1. Simulation analysis

3.1.1. Simulation setting and evaluation index

In order to verify the application effect of the proposed algorithm in ship route trajectory prediction and planning, two data sets *A* and *B* are selected for simulation analysis. Data set *A*, as the marked route in the route, contains various characteristic conditions in the route trajectory. Dataset *B* is a purely dimensionless dataset. Using the accuracy of ship trajectory prediction as the evaluation index, let the number of correct trajectories of ship trajectory prediction be *t*, the number of trajectories with wrong prediction planning in the predicted trajectories be *p*, and the calculation formula of accuracy is:

$$\text{precition} = \frac{t}{t+p} \tag{18}$$

The data in dataset *B* is randomly selected from the original database, and the average prediction accuracy can be calculated by multiple random experiments. Since the data of dataset *B* is unmarked, it is necessary to use the trajectory distance to measure the similarity between the actual heading and the predicted route, and judge by setting the threshold. When the distance between the two exceeds the threshold, it indicates that the prediction result is wrong, otherwise it indicates that the prediction result is correct. Suppose the predicted route is pi, the real route is oi, and the calculation formula of trajectory distance is:

$$\text{RMSE} = \text{dist}\left(o_i, p_i\right) \tag{19}$$

where dist() is the distance function.

3.1.2. Simulation results of ship trajectory prediction

The length of the ship's navigation trajectory has a great impact on the accuracy of the prediction and planning of the navigation trajectory. If only a short distance is navigated, the navigation trajectory may be extremely inaccurate. The route trajectory of the ship to be tested is shown in Fig. 5. T_1, T_2 and T_3 are three prediction points. When the ship reaches the corresponding prediction point position, the historical trajectory of the ship includes the sequence composed of all previous trajectories.

The trajectory prediction diagram of ship navigation is shown in Fig. 6. From Fig. 6a–d respectively correspond to the prediction results of ship reaching points T_1 to T_4.

3.2. Accuracy analysis of predictive simulation algorithm

The accuracy of the ship trajectory prediction method based on Naive Bayesian algorithm proposed in this study is compared with the traditional route trajectory prediction method, and five points T_1, T_2, T_3, T_4 and T_5 are selected for prediction. The prediction results are shown in Fig. 7.

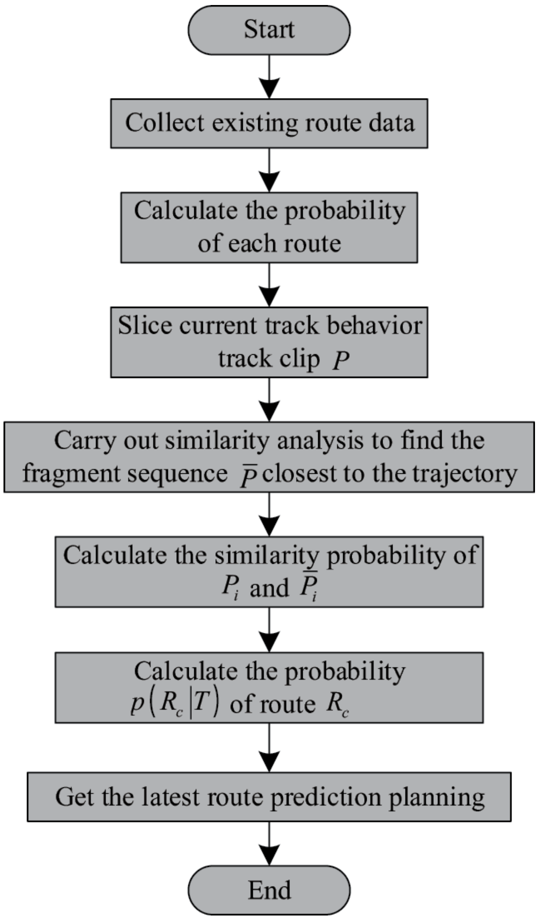

Fig. 4. Flow chart of ship route trajectory prediction and planning based on big data technology.

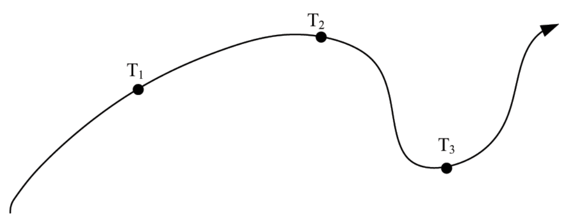

Fig. 5. Route trajectory diagram.

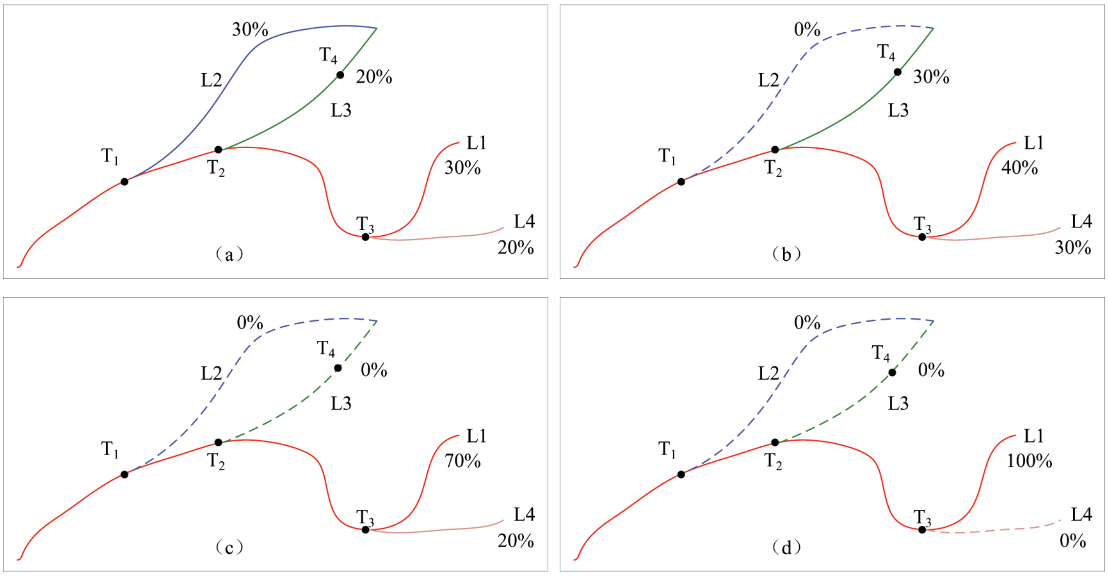

Fig. 6. Prediction diagram of ship navigation trajectory.

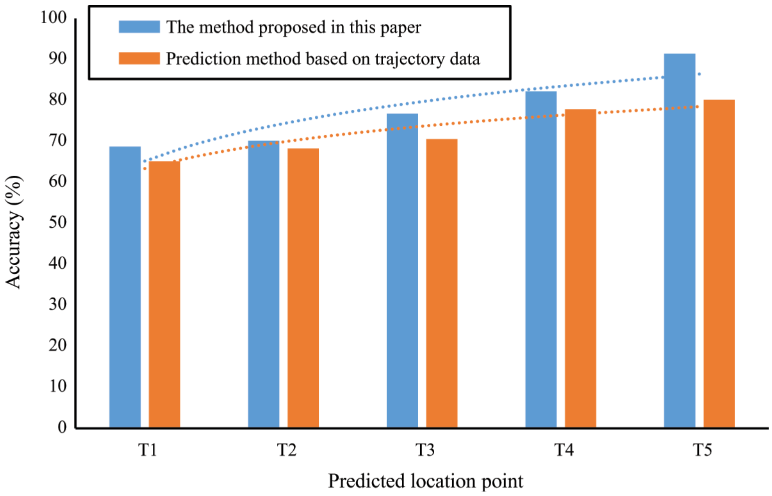

Fig. 7. Comparative analysis of prediction accuracy of ship trajectory.

As can be seen from Fig. 7, compared with the traditional ship trajectory prediction and planning method, the accuracy of ship trajectory prediction based on Naive Bayesian big data technology proposed this time is higher, and the accuracy increases from T_1 to T_5. This is because the description of ship trajectory increases with the increase of ship trajectory length, which makes the prediction more accurate. When the predicted location point reaches T_5, the accuracy reaches 91.41%.

4. Conclusion

As the most commonly used auxiliary equipment system for modern ship navigation, AIS system can realize information coordination, exchange and communication in the process of ship navigation, and avoid navigation safety risks to a certain extent. However, with the vigorous development of shipping industry, a simple AIS system has been difficult to meet the safe use needs of ship navigation. This time, based on the AIS system, the naive Bayesian algorithm is introduced to realize the prediction and planning of ship navigation trajectory by big data technology, cut the ship route trajectory into multiple route segments, and calculate the similarity probability between the predicted route and the actual route. In order to verify the application effect of the method proposed in this study, two data sets *A* and *B* are selected for simulation analysis. The simulation analysis results show that the ship trajectory prediction method based on Naive Bayesian algorithm has high accuracy. With the increase of navigation trajectory points, its accuracy will increase, and the accuracy can reach 91.41% when the predicted location point is T_5. In future research, we can predict the possible abnormal risks of ships based on the automatic planning and design of ship routes, and integrate image data to further improve the accuracy of prediction.

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