An Automatic Identification System (AIS) Database for Maritime Trajectory Prediction and Data Mining

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Abstract—In recent years, maritime safety and efficiency become more and more important across the world. Automatic Identification System (AIS) tracks vessel movement by onboard transceiver and terrestrial and/or satellite base station. The data collected by AIS contains broadcast kinematic information and static information. Both of them are useful for anomaly detection and route prediction which are key techniques in intelligent maritime research area. This paper is devoted to construct a standard AIS database for maritime trajectory learning, prediction and data mining. A path prediction algorithm is tested on this AIS database and the testing results show this database can be used as a standardized training resource for different trajectory prediction algorithms and other AIS data mining algorithms.

I. INTRODUCTION

In the modern globalized economy, ocean shipping becomes the most efficient mode of transporting large numbers of commodities over long distance. The persistent growth of the world economy leads to increasing demand of maritime transportation with larger ship capacity and higher transporting speed [1]. Safety and security are key issues in maritime transportation. Intelligent maritime navigation system using AIS data improves the maritime safety with less cost compared with conventional maritime navigation system using human judgement. AIS messages contain broadcast kinematic information (including ship location, speed, heading, rate of turn, destination and estimated arrival time) and static information (including ship name, ship MMSI ID, ship type, ship size and current time), which can be transformed into useful information for intelligent maritime traffic manipulations, e.g. vessel path prediction and collision avoidance, and thus plays a central role in the future autonomous maritime traffic system. Over the last several years, receiving AIS messages from vessels and coastal stations has become increasingly ordinary.

Although sufficient AIS data can be obtained from many data providers, e.g. Marinecadastre (MarineC.) [3] and Sailwx [4], however, to the best of our knowledge, there is no existing standard AIS benchmark database in maritime research area, which make it quite inconvenient for researchers and practitioners in the field, since collecting a usable dataset may cost a lot of time. Furthermore, as the intelligent maritime system develop rapidly, there are many algorithms were developed that require a standard database to compare with each other and then make improvement. For example, in 2008, B. Ristic et al [9] proposed an anomaly detection and motion prediction algorithm based on statistical analysis of motion pattern in AIS data. In 2013, Premalatha Sampath generated vessel trajectory from raw AIS data and analysed the trajectory to identify the kinematic pattern of vessel in New Zealand waterways [10]. So in this paper, a standard AIS database, a meaningful tool for intelligent maritime research, is proposed. A standard AIS database can be used to verify efficiency of intelligent navigation system or if overfitting occurs.

The remaining parts of the paper are organized as follows: Section II describes the AIS data type and data source. Section III describes the detail process of constructing the AIS database. Then the structure and static information of our AIS database are summarized and described in Section IV. Finally, we conduct an experiment on the AIS database to show the usefulness of it in Section V.

II. PROPERTIES OF AIS DATABASE

This section describes the attributes of AIS data and introduces some popular AIS data providers.

A. AIS data attributes

AIS technology broadcast ship information and voyage information at regular time interval. The information can be received by onboard transceiver and terrestrial and/or satellite base station. There are some important attributes of AIS data: longitude, latitude, speed over ground (SOG), course over ground (COG), vessel’s maritime mobile service identity (MMSI), base date time, vessel type, vessel dimension, rate of turn (ROT), navigation status and heading. The detail descriptions of the important attributes can be found on the Wikipedia website [19]. In this paper, the standard AIS database contains longitude, latitude, SOG, COG, MMSI and base date time, which are the most useful attributes for maritime trajectory learning and prediction.

B. AIS data providers

There are many existing AIS data providers e.g. Marine Traffic (Marine T.) [12], VT explorer (VT E.) [13], FleetMon [16], Marinecadastre (MarineC.) [3] and Aprs [7]. In this paper, MarineC is selected to collect AIS data online. MarineC contains historical records from 2009 to 2014 in
America at a minute interval. We can choose and download AIS data files in specific month and specific interest area. We downloaded February 2009 AIS data in UTM zone ten. However, MarineCadastre is non-commercial, and thus it cannot guarantee the data quality which may lead to data missing and low time resolution. The solution to these problems is linear interpolation which will be introduced later in this paper.

III. AIS DATABASE CONSTRUCTION

This section describes the data processing tool and the detail process of constructing the standard AIS database we proposed. The whole process contains four parts: raw data pre-processing, raw data selecting, candidate data cleaning and missing data interpolating.

A. Raw Data Pre-Processing

The first step of constructing an AIS database is to download the raw database file with dbf format from http://www.marinecadastre.gov/ais/. Prior to download raw data online, the selection of interest area is necessary. In this paper, zone ten is chosen as interest area. The shaded part in the following figure is the chosen interest area.

![UTM Zone Map and data source location](image)

Fig. 1. UTM Zone Map and data source location

In order to pre-process the AIS data and pick out the useful data, an application which can transfer raw database file with dbf format to txt or csv format is required since txt/csv format file is much easier to process and analyze. Arcmap is the most frequent cited Geographic Information System (GIS) software and is mainly used to view, edit, and analyze geospatial data. As Arcmap is selected as our data transferring software, a tool of it named “export feature attribute to ASCII” was used for exporting feature class coordinates and attribute values to a space, comma, or semicolon-delimited ASCII text file. The exporting result is presented in Fig. 12 in Section IV.

B. Raw Data Selecting

After raw data pre-processing, it is necessary to select the candidate data from the raw data with csv/xlsx format. The Universal Transverse Mercator (UTM) zone. Among all UTM zones, zone ten is chosen as the candidate data selection contains two steps. First, the whole raw data are sorted by time and then sorted again by MMSI. In this way, the track of each single ship can be observed clearly. The second step is to calculate route complexity and longest duration of navigation since the candidate data selection is based on following two factors.

- Longest duration of navigation
- Route Complexity

If the SOG value of a vessel meets the following inequality, we call this vessel is in the navigation condition.

\[ \text{SOG} > 0 \] (1)

So the longest duration of navigation is defined as the longest duration in the navigation condition. The selected requirement of this property is that the trajectory data contains more than 500 AIS messages.

![Sample of route complexity](image)

Fig. 2. Sample of route complexity

For each single route, the \( \cos \theta \) of each ship position is calculated and the definition of route complexity is the mean value of \( \cos \theta \), which can be calculated by the following equation:

\[ \cos \theta = \frac{P_1 P_{i+1} \cdot P_{i+1} P_{i+2}}{|P_{i+1} P_{i+2}|^2} \] (2)

Where \( P_i(x_i, y_i) \) is vessel position at \( T_i \); \( x_i \) is the longitude of vessel at \( T_i \); \( y_i \) is the latitude of vessel at \( T_i \) and \( P_{i+1} P_{i+2} \) is the vector \((x_i - x_{i+1}, y_i - y_{i+1})\). The route complexity should be larger than 0.8 in our database.

C. Candidate Data Cleaning

After candidate data were obtained, further selection based on trajectories is required. All trajectories of candidate data are plotted by MATLAB. Based on observing all of trajectories, there are four noisy trajectory types as follows are removed (in the figures, the horizontal axis is longitude and the vertical axis is latitude):

- The trajectory contains too much missing data as we showed Fig. 3.
- The plotted trajectory is self-crossed as Fig.4.
• The immoderately high speed cause loose trajectory. Fig. 5 presents an example of loose trajectory.
• Tanglesome trajectory have too complex motion pattern as we presented in Fig.6.

![Discontinuous trajectory sample](image1)
![Crossed trajectory sample](image2)

Fig. 3. Discontinuous trajectory sample  Fig. 4. Crossed trajectory sample

Fig. 5. Loose Trajectory Sample  Fig. 6. Tanglesome trajectory sample

Once the noisy trajectory was detected, it should be removed. Finally, the 200 useful trajectories which contain 403599 AIS records are reserved and used to construct the standard AIS database. All trajectories plotted by our database contain little data missing and have explicit motion pattern. The plots in Fig. 7 show some typical trajectories in our database.

![Reserved trajectory sample](image3)

Fig. 7. Reserved trajectory sample. (The horizontal axis is longitude and the vertical axis is latitude)

D. Missing value interpolating

In our database, there are some missing data causing time discontinuousness which may affect the learning algorithm performances and data mining quality of the database. Besides to the missing value problem, the raw data also contains erroneous speed data. Before making the interpolation, we have to detect and remove the erroneous data in advance. Each AIS record represents a ship position. There are 403599 ship positions in our database. The detection of speed errors is based on SOG jump, which is the difference between current SOG and previous SOG. If the jump is larger than the threshold we set in advance, we calculate the distance between the two messages using the latest speed and test if this distance is consistent with the actual distance between the messages given by Haversine formula [18], i.e. the calculated distance should be close to the actual distance within a small threshold if the speed jump is correct. If not so, the latest speed is treated as erroneous and is set to previous speed. The second line data in Fig. 8 is an example of incorrect SOG jump. In order to interpolate the missing values efficiently, all of the AIS records with speed errors should be removed in advance.

![Example of SOG mutation](image4)

Fig. 8. Example of SOG mutation

For interpolation work, there are three steps: detecting data missing, judging if it needs interpolation and making linear interpolation. Data missing occurs when the time interval period between two consecutive messages is larger than one chosen interval. We choose one minute as the threshold interval in this paper. Once detected, these two message data are defined as the missing data pair. A sample of missing data pair is shown in Fig. 9, in which there is a five-minute interval between the two consecutive messages (the horizontal axis is longitude and the vertical axis is latitude). Then the missing time period is defined as the time range between the missing data pair and the great-circle distance between missing data pair calculated by Haversine formula [18]. Fig. 10 and Fig. 11 show a trajectory example before and after interpolation.

![Example of missing data pair](image5)

Fig. 9. Example of missing data pair

![Original Trajectory](image6)
![Interpolated Trajectory](image7)

Fig. 10. Original Trajectory  Fig. 11. Interpolated Trajectory
The computed distance divides the SOG (km/minute) of the earlier position. The division result, that is larger than two, requires linear interpolation. The principle of linear interpolation is that we presume that the ship is in uniform linear motion during the missing time period and the speed is considered as the SOG of the earlier position. The calculation and interpolation of the missing data are based on these two assumptions.

IV. DESCRIPTION OF AIS DATABASE

In this section, we introduce the standard AIS database we constructed in two parts: the structure and statistical information of the database.

A. Structure

The whole AIS database contains 200 clean trajectories stored in 200 csv/xlsx files. Each file is named by the MMSI and sorted by time. Each csv or xlsx file contains latitude, longitude, SOG, COG, ROT, time and MMSI of a single ship. Fig. 12 presents part of 235844000.xlsx as an example. In order to make it more convenient for us to use the database in MATLAB, we also store all of csv/xlsx files into 200ShipData.mat and add the ship type into it.

B. Statistical information

The raw data was chosen from limited area and time periods. The range of longitude is from -120 to -126 degree and the latitude is from 30 to 50 degree as we showed in Fig.1. The complexities of routes are larger than 0.87.

| Course over Ground (COG) Statuses | [337.5, 360]° | [0, 22.5) | [22.5, 67.5) | [67.5, 112.5) | [112.5, 157.5) | [157.5, 202.5) | [202.5, 247.5) | [247.5, 292.5) | [292.5, 337.5) |
|-----------------------------------|--------------|-----------|-------------|-------------|-------------|--------------|-------------|-------------|--------------|
| Statutes                          | North        | Northeast | East        | Southeast   | South       | Southwest    | West         | Northwest   |

| Speed over Ground (SOG) Statuses | [0, 3) | [3, 14) | [14, 23) | [23, 99) | Over 99 |
|---------------------------------|--------|--------|----------|---------|---------|
| Statutes                        | Slow   | Medium | High     | Very High | Exception |

| Data Quantity Range | Route Types |
|--------------------|--------------|
| [530, 1000)        | Short        |
| [1000, 2000)       | Medium       |
| (2000, 10000)      | Long         |
| Over 10000         | Exception    |

Fig. 16 shows the proportion of each route type with different trajectory length. After linear interpolation, the length of each trajectory has changed so we summarize the distribution of interpolated trajectories in Fig. 17, from which we can see that most of the trajectories in the processed database belong to medium and long categories.

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1 The files will be uploaded to UCI Machine Learning repository (http://archive.ics.uci.edu/ml/).
V. EXPERIMENTS

In this section, we summarize the experiment results and give an experimental demonstration of the usefulness of this database. The experiments are conducted for maritime trajectory learning and prediction that is to predict future motion of ship based on the current position and historic movement. We run Extreme Learning Machine (ELM) [20] [21] on our AIS database to predict the vessel trajectory.

AIS data is time series data and new data of each feature comes continuously with potentially uneven time interval. However, machine learning algorithms works on static vector data. It is a question how these machine learning algorithms could make the utmost use of historical data to predict different future vessel position with a dynamic prediction time. In this project, we introduce a new prediction modeling method, as illustrated in figure 18. Suppose the training set contains $s$ samples and each sample feature has length $l$. The prediction time is $t_p$. We start at current time $t_c$, indicated by red line. The first training sample is cut at time tick $t_c-t_p-l$ with time length $l$ and its target value is vessel position at time $t_c$. The second training sample is cut at time tick $t_c-t_p-l-1$ with time length $l$ and its target value is vessel position at time $t_c-1$ and so on for the rest of all training samples. The testing sample is cut backwards at $t_c$ with feature length $l$. This method makes sure that the latest data can be utilized for both training and testing, without any dependence to future information.

ELM is trained on training samples to extract features and then tested on the predicting samples to make the trajectory prediction and calculate the prediction error. We analyze the performance of the algorithm according to these testing results. In order to make a comprehensive evaluation of ELM, predicting the same trajectory in 20 minutes and 40 minutes is performed in this experiment.

The testing results contain two parts: prediction results and error distribution which are described and discussed in order in this section. The prediction results show the original and predicted trajectory and algorithm performance in intuitionistic way. The prediction results of 20 minutes and 40 minutes interval are presented in the Fig. 19 and Fig. 20. From these two figures, we can find the ELM performance of 20 minutes experiment is much better than 40 minutes one. Since the vessel motion is often affected by the dynamic and unpredictable sea weather, the task of predicting the route in 40 minutes is more challenging and complex.

VI. CONCLUSIONS

In conclusion, the testing results on our AIS database offer useful information for us to make further improvement to the ELM algorithms and provide us convincing evidence to demonstrate the efficiency and limits of ELM on trajectory

![Fig. 16. Length of Original Route Distribution](image1)

![Fig. 17. Length of Interpolated Route Distribution](image2)

![Fig. 18. Sample segmentation of trajectory prediction](image3)

![Fig. 19. Prediction Result: 20 min](image4)

![Fig. 20. Prediction Result: 40 min](image5)

![Fig. 21. Error Distribution: 20 min](image6)

![Fig. 22. Error Distribution: 40 min](image7)
The standard AIS database we collected is useful and efficient to evaluate the performance of ELM and other AIS data mining algorithms [22]. Our following work will be focus on conducting more experiments on the database using manifold clustering algorithm [23] and semi-supervised learning algorithms [24]. In the future, this database can also be used as a benchmark database to verify the efficiency of other novel AIS data mining algorithms and compare their performances.

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