FRA-LSTM: A Vessel Trajectory Prediction Method Based on Fusion of the Forward and Reverse Sub-Network

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Abstract—In order to improve the vessel’s capacity and ensure maritime traffic safety, vessel intelligent trajectory prediction plays an essential role in the vessel’s smart navigation and intelligent collision avoidance system. However, current researchers only focus on short-term or long-term vessel trajectory prediction, which leads to insufficient accuracy of trajectory prediction and lack of in-depth mining of comprehensive historical trajectory data. This paper proposes an Automatic Identification System (AIS) data-driven long short-term memory (LSTM) method based on the fusion of the forward sub-network and the reverse sub-network (termed as FRA-LSTM) to predict the vessel trajectory. The forward sub-network in our method combines LSTM and attention mechanism to mine features of forward historical trajectory data. Simultaneously, the reverse sub-network combines bi-directional LSTM (BiLSTM) and attention mechanism to mine features of backward historical trajectory data. Finally, the final predicted trajectory is generated by fusing output features of the forward and reverse sub-network. Based on plenty of experiments, we prove that the accuracy of our proposed method in predicting short-term and mid-term trajectories has increased by 96.8% and 86.5% on average compared with the BiLSTM and Seq2seq. Furthermore, the average accuracy of our method is 90.1% higher than that of compared the BiLSTM and Seq2seq in predicting long-term trajectories.

Index Terms—Automatic Identification System (AIS) data, intelligent trajectory prediction, long short-term memory (LSTM), attention mechanism, intelligent maritime transportation.

I. INTRODUCTION

The rapid development of the global trading economy is increasingly dependent on transcontinental maritime transportation. Vessel transportation optimization technologies have also developed rapidly, such as unmanned intelligent vessel [1]–[3], vessel collision avoidance [4], vessel trajectory prediction [5], [6], vessel trajectory tracking control [7], and so on [8]–[10]. As shown in Fig.1, the Oresund Strait connects Sweden and Denmark, and the Baltic Sea connects many countries in Eastern Europe with the Atlantic Ocean. Therefore, there are many transportation lines in these maritime areas, and maritime economic activities are vibrant. Also, a large number of vessels have a fixed route for long-sea transportation and trade. To maintain regular maritime economic activities, the safety and security of maritime transport have always been a topic of great concern to all countries. However, due to a series of factors such as the volatile marine climate, the complex distribution of submarine reefs, and the variability of ocean currents, the certain safety risks to the standard navigation of maritime transportation could not be ignored. With the development of artificial intelligence, the rapid growth of autonomous marine transport models has promoted global trading economics, and the demand for naval transportation has increased sharply. Maritime traffic monitoring is crucial for ensuring naval transportation safety and activity. An Automatic Identification System (AIS) is an automated tracking system installed on a vessel. The maritime mobile service identity (MMSI) in AIS is applied to connect with longitude, latitude, speed, heading, and other contextual information [11].

Vessel trajectory prediction is one of the necessary means to ensure the safety of maritime transportation. The sea traffic map shown in Fig. 1 is drawn by the AIS vessel trajectory data collected in the Danish Maritime Authority (DMA) [12]. As shown in Fig. 1, the Baltic Sea and the Oresund Strait are adjacent to many eastern European countries. There are numerous vessels, various trade activities, and obvious maritime transportation routes. In particular, as for freighters and cruise liners, they all prefer the seasoned route and fixed trajectories. Also, some vessels are berthed in ports and conducting marine environmental monitoring. However, ensuring maritime traffic safety in the complicated marine transportation environment is significant. Therefore, realizing effective monitoring of traffic flow and early warning of vessel collision avoidance have always been the focus of current research. Vessel trajectory prediction is one of the hot issues, and it plays a decisive role in maritime risk early warning and route planning. Trajectory prediction is divided into short-term (a few minutes) and long-term (up to a few hours) trajectory predictions [6]. Trajectory prediction calculates the future trajectory, mathematically expressed as a trajectory line with time stamps and useful information forward.

The current popular vessel trajectory prediction methods are divided into the linear models such as the Constant Velocity Model [13], [14], Ornstein-Uhlenbeck model [15], [16], and the non-linear models. Linear models such as machine learning models [17], [18], neural networks [5], [19]–[21] and knowledge-based methods [22], [23]. However, both the linear model and non-linear model did not apply comprehensive historical trajectory data for trajectory prediction. As shown in Fig. 2, current research often deploys the previous historical trajectory data to predict the target trajectory segment. Still, they did not consider the effect of the historical trajectory data behind the target trajectory segment on the target trajectory. At the same time, as shown in Table III, we have proved...
through experiments that the accuracy of the current work is significantly reduced when predicting the long-term trajectory segment.

To solve the above problems, we consider integrating historical trajectory data, using deep learning methods to dig out more information features from history trajectory data. Our approach can effectively improve the prediction accuracy of long-term trajectories and provide better maritime traffic early warning and route planning services.

A. Motivation and Contributions

The main idea of the current vessel trajectory prediction research is to analyze and mine the AIS data. You et al. [24] in 2020 introduced an extended sequence-to-sequence model based on AIS data, which implemented a recurring grid unit (GRU) network to encode historical vessel spatiotemporal sequences into context vectors. The model preserved the order relationship between trajectory positions and solved the problem of gradient descent. The GRU network was adopted as a decoder to output the target trajectory positioning sequence. However, the literature [24] only considered the sequence relationship between the positions, which did not consider the influence of the vessel’s motion behaviors such as acceleration and steering on the trajectory prediction during the traveling process [24]. In 2020, to improve the accuracy of vessel trajectory prediction, Liu et al. developed a two-stage data-driven machine learning hull trajectory reconstruction framework [5]. In the first stage, they introduced a density-based clustering method to identify unwanted outliers automatically. In the second stage, they proposed a supervised learning technique based on bidirectional long-short-term memory (BLSTM), that recovered the time stamp points degraded by random outliers in the vessel's trajectory. However, the literature [5] applied the BLSTM network to retrieve the abnormal value devalued trajectory points, not consider the influence of the backward existing trajectory data on the target recovery trajectory data. We reproduced the vessel trajectory prediction work of BLSTM [5] and Seq2seq [24], and their results proved that they were only effective for short-term prediction, but the accuracy of long-term trajectory prediction was significantly reduced. Hence, how to eliminate the above shortcomings, consider the influence of navigation behavior on trajectory prediction, and improve the accuracy of vessel trajectory prediction, which is the motivation of this paper.

The above considerations provide a strong motivation for improving short-term and long-term trajectory prediction accuracy by considering integrated historical vessel trajectory data. As shown in Fig. 3, we propose an Automatic Identification System (AIS) data-driven long short-term memory (LSTM) method based on the fusion of the forward sub-network and the reverse sub-network (termed as FRA-LSTM) to predict the vessel trajectory. The main contributions of this paper are as follows:

i) Considering the comprehensive historical trajectory data, a new forward and reverse network fusion predict model based on AIS data, instead of traditional one-way trajectory
prediction methods in [5], [19]–[21] using neural network, is proposed.

ii) By introducing the attention mechanism, a novel dynamically capture the weights of the influence of motion behavior attention network is designed, and the new result can improve to the existing one in [5] where behavioral action is neglected.

iii) Different from the existing vessel trajectory prediction [5], [24], we are the first time to consider the influence of comprehensive historical trajectory data on trajectory prediction. Thus, the accuracy and the performance of FRA-LSTM can be better guaranteed.

B. Organization

The rest of the paper is organized as follows. Section II briefly describes the state of the art in terms of two aspects: the linear model, the non-linear model. Section III mainly defines the vessel trajectory prediction problem and a detailed explanation of the overall system architecture. The AIS-based forward and reverse network fusion trajectory prediction method is presented in Section IV. Extensive experiments and analyses are carried out in Section V. Section VI concludes this paper.

II. RELATED WORKS

A. The Linear Models

The linear model is a typical trajectory prediction method, which is also called the constant velocity model. For example, Posada et al. [14] in 2011 analyzed the historical patterns of normality and risk based on the open-source web-GIS function. Greidanus et al. in 2013 employed vessel trajectory data synthesis maritime situation map [13], real-time tracking of interested vessels in the entire designated sea area. Pallotta et al. [15] in 2014 presented a vessel prediction method, based on the popular Ornstein-Uhlenbeck stochastic processes, whose parameters are estimated from historical patterns of life. In 2016, a long-term target state prediction method based on Ornstein-Uhlenbeck’s (OU) stochastic process with real-world data was proposed in [16].

Although linear models were simple and highly reliable, some commercial systems often applied linear models for vessels trajectory prediction. However, the linear vessel trajectory predict model lacked sensitivity to vessel motion behaviors (such as changing course or speed), resulting in a decrease in the accuracy of trajectory prediction. Therefore, some researchers preferred implementing machine learning methods for trajectory prediction.

B. The Non-linear Models

The non-linear models can solve the shortcomings of linear models, which are mainly divided into machine learning, knowledge-based, and control theory-based methods. In 2012, the extended Kalman filter (EKF) algorithm was implemented in [25] for vessel prediction in maritime surveillance systems. In 2015, a vessel trajectory prediction method that combined the gray-scale projection and Markov chain technology was proposed in [26]. Qi et al. [17] in 2016 proposed a model based on trajectory clustering and classification to support vessel trajectory prediction. Young et al. [27] in 2017 proposed a vessel position prediction method based on random forest [28], [29], and neural networks. Xiao et al. [30] in 2020 applied a particle filter algorithm [31] to predict the channel.

Compared with machine learning methods, prediction models based on neural networks could achieve better prediction accuracy because the neural network method could learn the current state and capture the changing trend of the sailing state. Xu et al. [32] in 2012 employed a three-layer back propagation (BP) neural network to predict the future trajectory of vessels. Borkowski et al. [11] in 2017 merged trajectory data with timestamped information into neural network input and proposed a method based on general regression neural network (GRNN) to predict vessel trajectory. In 2019, a long-term trajectory motion prediction method based on a combined trajectory classification and LSTM network framework was proposed in [21]. Jie et al. [33] in 2020 implemented a bi-directional long-short-term memory (BiLSTM) method to obtain the temporal and spatial dependence of behavior and its influence on future risks.

III. PRELIMINARIES

This section defines the FRA-LSTM model with the quantified trajectory position and the historical trajectory segment expression. Moreover, the working principle of our predictive method is explained through the input and output of the model.
AIS data → AIS data preprocessing → Get valid AIS data → Forward sub-network → Fusion → Reverse sub-network → Generate vessel prediction trajectory

Fig. 5. Frame diagram of the FRA-LSTM trajectory prediction method.

architecture. Finally, the preprocessing method of original AIS data is given.

A. Problem Definition

Based on the data collected by the AIS system, the vessel’s trajectory position data can be quantified. As shown in Fig. 2, existing studies have used the previous \( L \) historical trajectory data points to predict the future \( k \) position trajectory points. By analyzing maritime traffic and transportation laws in the Oresund Strait and the Baltic Sea, we find that freighters and cruise liners like mature routes and have fixed trajectories. The AIS system can receive the trajectory data of the vessel’s entire route. Therefore, we propose to apply the comprehensive historical trajectory data of vessels as model samples. As shown in Fig. 4, both forward and reverse historical vessel trajectory data can be adopted to act on the intermediate target trajectory segment. Each trajectory position information tuple of the vessel comprises \( MMSI \), longitude, latitude, the speed over ground (sog), the course over ground (cog), and time. We define a single trajectory point tuple information as \( P(\text{time}, \text{MMSI}, \text{lon}, \text{lat}, \text{sog}, \text{cog}) \).

As shown in Fig. 4, by contrast with existing studies [5], [24], [30], we apply \( L \) historical trajectories in the previous period and \( L \) historical trajectories in a later period. Location points are employed to predict the middle \( k \) location trajectory points. \( T_{L+1:tL+k} \) represents the intermediate prediction target trajectory point, the front \( t1:tL \) represents the forward \( L \) historical trajectory points, and \( tL+k+1:t2L+k \) represents the backward \( L \) historical trajectory points. We employ forward and reverse historical trajectory data as the input of the FRA-LSTM model to fuse the information feature extraction of the vessel’s comprehensive historical trajectory data.

B. Framework Overview

Based on the above definition of the ship trajectory prediction problem, we will introduce the FRA-LSTM model in detail. As shown in Fig. 5, the FRA-LSTM model proposed in this paper is mainly divided into three parts: forward sub-network, reverse sub-network and features fusion. Firstly, we explain the input of the forward sub-network and the backward sub-network: 1) The input of the forward sub-network is the trajectory point of \( L \) steps before the target prediction trajectory segment. 2) The input of the reverse sub-network structure is the target predicting the trajectory points of \( L \) steps behind the trajectory segment. Secondly, the forward sub-network achieves the LSTM network and the attention mechanism to mine the characteristics of the forward historical trajectory data. The backward sub-network implements the BiLSTM network and the attention mechanism to mine the reverse historical trajectory data attributes. In detail, we apply LSTM and BiLSTM network mainly to capture the features of the vessel’s time series sequence. Moreover, the attention mechanism is implemented to extract the influence of the vessel’s historical motion behavior (such as acceleration, turning, etc.) on the target trajectory segment. Finally, forward and reverse output characteristics are merged through the fully connected layer network to realize the prediction of the target trajectory segment.

As shown in Fig. 6, we give a detailed architecture diagram of the model proposed in this article. For the FRA-LSTM model, we extract multiple historical vessel trajectory data as input. We mark the historical trajectory data input into the forward sub-network at time \( t \) as \( Input_{\text{forward}} = \{p_{t+\Delta t_1}, p_{t+\Delta t_2}, \ldots, p_{t+\Delta L}\} \). Correspondingly, we mark the historical trajectory data of the input reverse sub-network as \( Input_{\text{reverse}} = \{p_{t+\Delta L_1}, p_{t+\Delta L_2}, \ldots, p_{t+2\Delta L+k}\} \). At the same time, we mark the output of the forward sub-network as \( Output_{\text{forward}} = \{p_{t+\Delta L_1}, p_{t+\Delta L_2}, \ldots, p_{t+\Delta L+k}\} \) and the output of the reverse sub-network as \( Output_{\text{reverse}} = \{p_{t+\Delta L_1}, p_{t+\Delta L_2}, \ldots, p_{t+\Delta L+k}\} \). Output_{\text{forward}} and Output_{\text{reverse}} of the forward and reverse sub-network structures are designed for fusion learning using a fully connected network. Finally, our method outputs the value of the predicted trajectory segment of the target vessel. Special attention is paid to the forward sub-network sample input length, and the reverse sub-network in the architecture diagram are all \( \Delta L \). Significantly, we can change the input sequence length \( \Delta L \) value of the model according to the actual task requirements.

Compared with existing research, the advantage of our method is that the information characteristics of comprehensive historical trajectory data can be deeply mined. Moreover, using the attention mechanism can help us obtain the influence of the motion behavior in the historical trajectory on the predicted trajectory segment.

C. AIS Data Preprocessing

Unlike some existing research work that adopts simulation generate data, our job is verified by actual AIS vessel data. Firstly, we remove the missing values in the AIS sample data set and filter out historical trajectory data with apparent trajectories. To realize the mining of more dimensions in AIS data, we select six parameters related to each vessel as

![Frame diagram of the FRA-LSTM trajectory prediction method.](image-url)
training samples: maritime mobile service identity (MMSI), latitude (lat), longitude (lon), speed over the ground (sog), course over ground (cog), and time. Meanwhile, we select the vessel data whose historical trajectory data must be greater than a certain number within the training time range to filter out long-term trajectory vessel data. Therefore, the trajectory data on a specific maritime transportation line can be expressed as \( T_{\text{raj}} = \{p_1, p_2, \ldots, p_n\} \), where \( n \) represents the total number of sampled trajectory points of the vessel. We mark the trajectory position of the boat at time \( t \) as \( p_t = \{\text{lat}_t, \text{lon}_t, \text{sog}_t, \text{cog}_t, \text{time}_t\} \), where \( \text{lat}_t, \text{lon}_t, \text{sog}_t, \text{cog}_t, \text{time}_t \) respectively indicate the longitude, latitude, the speed over ground, the course over ground, and sampling time of the sampling point at the time \( t \).

Secondly, to obtain ordered vessel spatio-temporal data, the sample data be sorted according to MMSI and time. The segmented data are recorded as \( T^r_{\text{raj}} = \{p^1_t, p^2_t, \ldots, p^n_t\} \), and each segmented track point is recorded as \( p^i_t = \{\text{lat}_t^i, \text{lon}_t^i, \text{sog}_t^i, \text{cog}_t^i, \text{time}_t^i\} \). The Min-Max normalization method is applied to normalize the segmented data. The vessel trajectory data calculated by the formula \( x^* = \frac{x^* - \min x^*}{\max x^* - \min x^*} \), is expressed as \( T^r_{\text{raj}} = \{p^1_t, p^2_t, \ldots, p^n_t\} \). Where \( \max x^* \) represents the maximum value in a particular field in the sample data, \( \min x^* \) means the minimum value in a specific area in the sample data, \( x^* \) is the divided data, and \( x^* \) is the normalized data. We substitute the data of each dimension \( p^i_t \) into the maximum and minimum formula to calculate that \( p^i_t = \{\text{lat}_t^i, \text{lon}_t^i, \text{sog}_t^i, \text{cog}_t^i, \text{time}_t^i\} \) represents the normalized longitude, latitude, ground speed, ground heading, and time.

Finally, the trajectory sequence data are divided at time \( t \) into \( E_t = \{p^1_{t+k-1}, p^1_{t+k}, \ldots, p^2_{t+k-1}\} \). We make the window moves forward to a new unit for the forward prediction input sample data until it reaches an orbital point that is \( L \) length from the last moment. The window is employed to slide from back to front for reverse sub-network input sample data until the distance from the first point is \( L \) length. Among them, \( E^p_{\text{raj}} = \{E^p_{t-L}, E^p_{t-L+1}, \ldots, E^p_t\} \) represents the forward and backward sliding window trajectory sequence data of the sample and \( E^p_{\text{raj}} = \{E^p_{t-L}, E^p_{t-L+1}, \ldots, E^p_t\} \) means the back sliding window of the input sample. After the trajectory data sliding process, the data preprocessing is completed.

IV. FRA-LSTM PREDICTION MODEL

After finishing the data preprocessing, the historical trajectory data is mined to realize the prediction of the ship trajectory. In this section, the network structure will be elaborated that composes the FRA-LSTM model.

A. LSTM Memory Block

The vessel trajectory AIS data contains many timestamped trajectory space points composed of sequential timestamped trajectory points, which are essentially time series data. Although recurrent neural networks (RNNs) can predict time series data, RNNs have the problem of gradient exploding or gradient vanishing. To solve these problems, the LSTM network originally proposed by Hochreiter and Schmidhuber [34] can be applied successfully to learn the necessary long-term dependencies with the help of recurrent networks. The detailed architecture of the LSTM network [35] is shown in Fig. 7.
LSTM can save important, relevant information obtained from historical input. LSTM performs memory and forgetting functions by controlling three gates, remembering relevant information obtained in previous steps, and ignoring irrelevant data. The preprocessed vessel trajectory $T_{raw} = \{p_1^n, p_2^n, \ldots, p_n^n\}$ is chosen as the input sequence (i.e., a time series) of the LSTM network structure. LSTM can calculate the hidden vector $H = \{h_1, h_2, \ldots, h_n\}$ and the output vector $\bar{T} = \{\bar{p}_1, \bar{p}_2, \ldots, \bar{p}_N\}$ and update the following two equations recursively:

$$h_n = \text{LSTM} (p_n, h_{n-1}; W)$$  \hspace{1cm} (1)

$$\bar{p}_n = W_{hp} h_n + b_\bar{p}$$  \hspace{1cm} (2)

where $W$ represents the weighting matrix in the $n$th time-stamped trajectory point degraded by random anomalies, and $b$ represents the bias vector.

1) The forget gate $f_t$ is responsible for filtering past information about the vessel’s trajectory and behavior. We found that the existing time-series location points and operational actions (such as continuous acceleration, steering, etc.) of the boat during the movement will affect the prediction accuracy. Therefore, the purpose of the forget gate is filtering out information that is useless for vessel trajectory prediction under the supervision of the government, to reduce training time and storage requirements.

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

among them, $h_t$ is the vector encoding the vessel trajectory and motion state from $t = 0$ to $t-1$, which represents the vessel motion behaviors during this period. $x_t$ is the vessel trajectory and motion behavior feature, which is input as time $t$. $W_f$ and $b_f$ are the weights and biases in the forget gate, respectively. The $\sigma$ is the tanh function.

2) The input gate determines which vessel motion behavior information needs to be updated at time $t$ and temporarily record the current input information. The updatable exercise state $C_t$ includes historical information before time $t$ and current input information. In this process, $C_t - 1$ is applied to calculate $C_t$. By deploying this recursive method, information about the order of trajectories is stored:

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

$$\bar{C}_t = \tanh (W_c * [h_{t-1}, x_t] + b_c)$$  \hspace{1cm} (5)

$$C_t = f_t * C_{t-1} + i_t * \bar{C}_t$$  \hspace{1cm} (6)

3) The output gate $o_t$ selects the vessel motion state information that significantly impacts the trajectory prediction and outputs the final vessel motion state $h_t$ at time $t$.

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

$$h_t = o_t * \tanh (C_t)$$  \hspace{1cm} (8)

### B. Bidirectional LSTM Recurrent Structure

We closely relate to the degraded spatial points and the adjacent points from two opposite directions in-vessel trajectory prediction. Therefore, the one-way LSTM mentioned in the previous section only conducts training and inference in a single order, which can easily limit the improvement of vessel trajectory accuracy. In contrast, as shown in Fig. 8, BiLSTM [36], [37] can perform forward and backward training and inference. Theoretically, BiLSTM can produce more robust trajectory improvement results compared with traditional LSTM. In particular, BiLSTM can be regarded as composed of two unidirectional LSTMs executed in different directions, that simultaneously consider forward and backward information in the input trajectory through two opposite layers. For the bi-directional LSTM recurrent structure, the recurrent networks can be performed by the following equations:

$$\vec{h}_n = \text{LSTM} (p_n, \vec{h}_{n-1}; \vec{W})$$  \hspace{1cm} (9)

$$\hat{h}_n = \text{LSTM} (p_n, \hat{h}_{n-1}; \hat{W})$$  \hspace{1cm} (10)

$$\bar{p}_n = W_{\bar{h}_p} \vec{h}_n + W_{\bar{h}_{\bar{p}}} \hat{h}_n + b_{\bar{p}}$$  \hspace{1cm} (11)
where $W$ represents the weight matrix and $\overrightarrow{h}_t$, $\overleftarrow{h}_t$ represents the forward and backward layers’ hidden state and weight matrix. The superior performance of BiLSTM is due to the natural combination of two-way network and one-way LSTM under a unified learning framework, and the output of each direction (related to the forward and backward) is connected and transmitted to the next hidden layer. Thus, tapping the time dependence of the input trajectory points can accurately predict the vessel trajectory in the reverse historical trajectory segment.

C. Attention Mechanism

During the vessel, the vessel’s navigation trajectory and behavior characteristics are not the same. For example, the vessel’s navigation route and the action of accelerating, decelerating, turning, and avoiding during a particular time will affect the vessel’s trajectory at a specific time. Thus, the vessel’s existing route and motion behavior in different periods will affect the accuracy of the predicted trajectory model. In the time window, a specific time step contributes to predicting the target trajectory segment. However, suppose there is only the output of the LSTM or BiLSTM network at the time step $t+k$. In that case, it represents the position and behavior information of the vessel at $t+k$ (that is, trajectory prediction $k$ points), which is deployed to predict the future trajectory (see Eq. 12 - Eq. 13) lose the influence of sports behavior in different periods. Therefore, attention mechanisms can be employed to quantify the impact of other behavior on each vessel’s trajectory prediction.

The attention mechanism was first proposed for machine translation tasks by Bahdanau et al [38]. The central concept of this mechanism is that words and sentences can make different contributions to the meaning of the text. The different attention can be assigned weights to other words to improve the understanding of text semantics applying the attention mechanism. The instantaneous motion behaviors (such as acceleration, deceleration, and turning behaviors) during the vessel’s navigation can be analogous to the words in the text translation task. The trajectory points of the boat in the future time step corresponding to the trajectory and semantics of the text. By deploying this analogy, the attention mechanism is adopted to quantify the different effects of vessel motion behavior on trajectory prediction in different time frames:

$$p \left( traj_{t+k} \mid x_1, x_2, \ldots, x_T \right) = p \left( traj \mid \overrightarrow{h}_t, \overleftarrow{h}_t \right) \quad (12)$$

$$\begin{cases} \left[ h_t^f \right] = \text{LSTM} \left( x_1, x_2, \ldots, x_T \right) \\ \left[ h_t^r, h_t^r \right] = \text{BiLSTM} \left( x_1, x_2, \ldots, x_T \right) \end{cases} \quad (13)$$

$$p^f \left( traj_{t+k} \mid x_1, x_2, \ldots, x_T \right) =$$

$$p^f \left( traj_{t+k} \mid x_1, x_2, \ldots, x_T \right) =$$

$$p^r \left( traj_{t+k} \mid x_{\Delta L+1}, x_{\Delta L+2}, \ldots, x_T \right) =$$

$$p^r \left( traj_{t+k} \mid x_{\Delta L+1}, x_{\Delta L+2}, \ldots, x_T \right) =$$

The most significant difference between this method and the basic LSTM and BiLSTM methods is that it does not only try to apply the output state $h_t$ at the last moment to reflect the trajectory of the entire period. On the contrary, it focuses on the vessel’s critical trajectory and movement behavior at a specific point in time to produce trajectory changes. As shown in the following Eq. 14 - Eq. 15, the existing track and motion state at each moment $[h_1, h_2, \ldots, h_t]$ are the input to the attention layer. The contribution of each frame is calculated by $[\alpha_1, \alpha_2, \ldots, \alpha_t]$, which is calculated using the Eq. 19. Based on Bahdanau’s attention calculation method [38], the widespread attention is calculated as follows:

$$\left( h_t^f, h_t^r, \ldots, h_t^f \right) = \text{LSTM} \left( x_1, x_2, \ldots, x_T \right) \quad (16)$$

$$\left( h_t^r, \overrightarrow{h}_t^r, \overleftarrow{h}_t^r, h_t^r, \ldots, h_t^r, \overrightarrow{h}_t^r \right) =$$

BiLSTM $\left( x_{\Delta L+1}, x_{\Delta L+2}, \ldots, x_T \right)$

$$\begin{cases} \mu_t^f = \tanh \left( W_h h_t^f + b_w \right) \\ \mu_t^r = \tanh \left( W_h h_t^r + b_w \right) \end{cases} \quad (18)$$

$$\alpha_t^f = \frac{ \exp ( W_h \mu_t^f \cdot W_r \bullet \alpha^f ) }{ \sum_t \exp ( W_h \mu_t^f \cdot W_r \bullet \alpha^f ) }$$

$$\alpha_t^r = \frac{ \exp ( W_h \mu_t^r \cdot W_r \bullet \alpha^r ) }{ \sum_t \exp ( W_h \mu_t^r \cdot W_r \bullet \alpha^r ) } \quad (19)$$

$$s^f = \sum_t \alpha_t^f h_t^f \quad s^r = \sum_t \alpha_t^r h_t^r \quad (20)$$

where $h_t^f = \left[ h_t^f, h_t^r, \ldots, h_t^f \right]$, $h_t^r = \left[ h_t^r, h_t^r \right]$. $W_w$ and $W_\mu$ are the weights of the fully connected layer, respectively, and $s$ is all time steps $[h_1, h_2, \ldots, h_t]$ representing the movement state of the entire navigation process. $\alpha$ is the normalized weight of each movement behavior state of the vessel, namely, the attention learning score. In traditional natural language processing, the attention score is employed to describe the contribution of each word to the semantics or emotions of the text. However, in our trajectory prediction task, the attention score quantifies the impact of vessel motion characteristics on the target predicted trajectory degree. Thus, the future trajectory is obtained as $traj = f_{fe} (s)$, where $f_{fe}$ is the fully connected layer. On the one hand, the cross-entropy is compared between the predicted and actual sailing trajectory. On the other hand, we apply the backpropagation algorithm, the corresponding parameters in the model can be trained.

Finally, the pseudo code of the FRA-LSTM model training process is given as Algorithm 1.

V. EXPERIMENTAL RESULTS AND DISCUSSION

To verify the accuracy of our proposed vessel trajectory prediction method at different time periods, extensive experiments will be conducted on the actual open-source data set [12] of the DMA.
Algorithm 1 FRA-LSTM Trajectory Predict Algorithm

Input: Comprehensive AIS data collection $C(n)$.
Output: Target trajectory prediction data.

1: Compute forward trajectory behavioral features $X_{\text{forward}}(k)$ of vessel from $C(n)$;
2: Compute reverse trajectory behavioral features $X_{\text{reverse}}(k)$ of vessel from $C(n)$;
3: Generate the positive and reverse training data set $M_{\text{train}}$ and $M'_{\text{train}}$ from $X_{\text{forward}}(k), X_{\text{reverse}}(k)$;
4: for mini batch $M, M'$ in $M_{\text{train}}, M'_{\text{train}}$ do
5: for $T$ time window data $M_T, M_T'$ in $M, M'$ do
6: for $t = 1$ to $T$ do
7: Using forward LSTM, reverse BiLSTM to encoder $h_t, h'_t$;
8: end for
9: Compute Attention score $\alpha$ and $s_p$
10: Compute $\text{traj}_p$ from $s_p$
11: end for
12: Training the model FRA-LSTM with back propagation algorithm
13: end for
14: return the FRA-LSTM model

A. Experimental Setup

(1) Experimental data settings
The Maritime Mobile Service Identifier (MMSI) is employed to identify the information of each boat and the timestamp field is to obtain the vessel’s trajectory. Our method select more than 2.86 million AIS data collected by the DMA 1 from 7:30-14:30 on January 1, 2018, as the experimental raw data.1 As mentioned in Section III-C, because the original AIS data is in a large amount, the data preprocessing method mentioned above is developed to extract the data, and the screening results are as shown in Table I.

To verify the effectiveness of the FRA-LSTM model in predicting the trajectory of the short-term, medium-term, and long-term periods, the forecast target period is set as 1 minute, 5 minutes, 20 minutes, and 60 minutes respectively. As shown in Table II, to quantify the model’s forecast period for the vessel’s trajectory, different forecasting durations are set to be converted into forecast fixed trajectory points. Thus, the FRA-LSTM model can assess the prediction duration and the number of trajectory points according to task requirements in actual business applications.

B. Experiment Result Analysis

(1) Our Method Compare with BiLSTM and Seq2seq
By comparing the AIS channel data set collected by the DMA, the effectiveness of the proposed method is verified compare with the vessel trajectory prediction method presented in existing works [5], [24].
- **BiLSTM**: a vessel AIS trajectory prediction model based on the combination of forwarding LSTM and backward LSTM [5] considers both previous and future information through two relatives (i.e., forward and backward) layers, suitable for Sequence labeling tasks that are related up and down.
- **ST-Seq2Seq**: a vessel AIS trajectory prediction model based on Seq2Seq [24]. The model achieved an RNN composed of a single-layer GRU unit to memorize the historical trajectory point sequence and then employed the RNN composed of a single-layer GRU unit to decode the recorded information to predict the future trajectory point sequence.
- **FRA-LSTM**: this paper proposes a vessel trajectory prediction model based on AIS data forward and reverses network fusion.

These models are validated on a data set collected by the DMA. The historical AIS trajectory sequence of the specified period (as shown in Table II for details) is input to predict the trajectory sequence of the future period. The FRA-LSTM model and comparison work have done five sets of experiments, and the experimental results will be analyzed as follows. As shown in Fig. 9, the LOSS convergence of the training process is firstly compared in different periods of prediction.

From Fig. 9, the FRA-LSTM model proposed in this paper can be seen fully converges after training for a certain number of Eps. After the three models are trained to combine thoroughly, compared to the comparison work [5], [24], the LOSS of our method is entirely at a low level. However, from forecasting short-term and long-term results, the longer the forecast period, the value of LOSS gradually increases. At the same time, the root means square error (RMSE) value is

| Input duration (minutes) | Forecast duration (minutes) | Input track points | Predict track points |
|-------------------------|-----------------------------|-------------------|---------------------|
| 5                       | 1                           | 5                 | 1                   |
| 10                      | 5                           | 10                | 5                   |
| 20                      | 20                          | 10                | 10                  |
| 60                      | 60                          | 20                | 20                  |

TABLE II

STRATEGIES FOR TAKING POINTS UNDER DIFFERENT FORECAST DURATIONS

To verify the effectiveness of our proposed FRA-LSTM model, it will be compared with the trajectory prediction work of BLSTM-based [5] and Seq2seq [24].

1The dataset is publicly available on https://www.dma.dk/SikkerhedTilSoes/Sejladsinformation/AIS/Sider/default.aspx.

The python library, Keras, was applied to build our models. In this paper, a random objective function optimization algorithm (Adam) is implemented to update the parameters in the training process. The batch size is set as 64 and the training epoch value is 300 for model training. This article sets the sample as 80% of the training set and 20% as the test set.
From the evaluation results in Fig. 10, the effect of predicting short-term, such as 1 minute, 5 minutes, can be seen to be more evident than the existing work advantage. In particular, FRA-LSTM effectively predicts long-term periods such as 40 minutes and 60 minute long periods. Although, when indicating the mid-to-long-term trajectory segment, all models are slightly inferior to the previous time when predicting the last moment. Our proposed method is still better than the existing works. This situation occurs because after the time series samples are input to the LSTM network, the characteristic error of each layer will be passed to the last network layer along with the recurrent neural network, resulting in an increase in the prediction error at the last moment. Meanwhile, our method still maintains a precise superiority level in the mid-and long-term trajectory prediction.

(2) Our Method Compare with ForwardNet and ReverseNet

The forward and backward sub-network fusion is implemented in our work, and these two sub-networks can also be used to predict the target trajectory segment. To verify that our fusion model is better than the single sub-network structure, five sets of experiments are still done on these works to illustrate the effect of our work. The RMSE is employed to evaluate the trajectory points of the forward sub-network and the reverse sub-network in different, as shown in Fig. 11.

Fig. 11. Comparison of RMSE evaluation indicators with forward and reverse sub-networks.

From Fig. 11, if only the forward or reverse sub-networks in the fusion model are deployed alone to predict the target trajectory segment, the effect of the FRA-LSTM model we proposed is significantly better than theirs.

At the same time, five sets of experiments have been done for comparison. The forward and reverse sub-networks predict the average trajectory points in different periods for comparison, as shown in TABLE III.

![Fig. 9. Compare LOSS evaluation indicators with existing work.](image)

![Fig. 10. Compare RMSE evaluation indicators with existing work.](image)

![Fig. 11. Comparison of RMSE evaluation indicators with forward and reverse sub-networks.](image)

| Model         | Index | 1min | 5min | 20min | 60min |
|---------------|-------|------|------|-------|-------|
| BiLSTM [5]    | rmse  | 0.002114 | 0.214252 | 0.585156 | 0.297357 |
| Seq2seq [24]  | rmse  | 0.002072 | 0.214352 | 0.586365 | 0.313298 |
| ForwardNet    | rmse  | 0.012011 | 0.256550 | 2.807849 | 0.287239 |
| ReverseNet    | rmse  | 0.203958 | 0.324801 | 2.769723 | 0.449026 |
| FRA-LSTM      | rmse  | 0.001826 | 0.015974 | 0.094385 | 0.048464 |
In TABLE III, the RMSE values of each point in 1 minute, 5 minutes, 20 minutes, and 60 minutes are shown respectively. And the average of these point’s RMSE is taken to value the experimental results of different periods. From the experimental results of TABLE III, it can be seen that the FRA-LSTM model achieves significantly excellent short-term to long-term trajectory sequence prediction on the AIS data sample set of the DMA.

(3) Evaluations on Variants of Our Method

Both the forward and reverse sub-networks in the FRA-LSTM model are composed of cyclic neural LSTM networks. Therefore, when predicting the trajectory of a vessel, the different cyclic neural networks in other forward and reverse directions may affect the trajectory prediction effect. The prediction effects of vessel trajectory are compared under different network structure fusion models through experiments, that settings are the same as the values set in TABLE II. The other network structures are compared mainly from the following aspects:

- The forward sub-network is composed of a single-layer GRU recurrent neural network unit and attention mechanism, and the reverse sub-network is composed of a single-layer BiGRU recurrent neural network unit and attention mechanism;
- The forward sub-network is composed of a single-layer GRU recurrent neural network unit and attention mechanism, and the reverse sub-network is composed of a single-layer BiLSTM recurrent neural network unit and attention mechanism;
- The forward sub-network is composed of a single-layer LSTM recurrent neural network unit and attention mechanism, and the reverse sub-network is composed of a single-layer BiGRU recurrent neural network unit and attention mechanism;
- The forward sub-network comprises a single-layer LSTM recurrent neural network unit and attention mechanism. The reverse sub-network is composed of a single-layer BiLSTM recurrent neural network unit and attention mechanism.

As shown in TABLE IV, the experimental results are following:

| TABLE IV | PERFORMANCE COMPARISON OF DIFFERENT STRUCTURES OF FRA-LSTM |
|----------|------------------------------------------------------------|
| Forward + Reverse | 1min | 5min | 20min | 60min |
| GRU + BiGRU | 0.003187 | 0.058189 | 0.050829 | 0.037900 |
| GRU + BiLSTM | 0.002723 | 0.080065 | 0.046762 | 0.042907 |
| LSTM + BiGRU | 0.003976 | 0.018851 | 0.047852 | 0.085086 |
| LSTM + BiLSTM | 0.001234 | 0.015533 | 0.047526 | 0.041668 |

According to the experimental results shown in TABLE IV, when the cyclic neurons of the forward network and the reverse network are both LSTM, the trajectory has more significant effects.

Therefore, the prediction model based on FRA-LSTM can be to effectively predict short-term to long-term navigation trajectories. From TABLE IV, when the forward self-network and backward sub-network structures in the fusion model are LSTM, the convergence speed is faster, and the prediction effect is better. Moreover, when the FRA-LSTM model predicts the sequence of trajectory points, as the number of predicted trajectory points increases, the error changes smaller.

VI. CONCLUSION

In this paper, an AIS data-driven LSTM method based on the fusion of the forward sub-network and the reverse sub-network to predict the vessel trajectory has been designed for vessel trajectory prediction. The main idea of the method is to implement the fusion of forward and reverse sub-networks for comprehensive historical vessel trajectory data. After enough experiments, the proposed vessel trajectory prediction method has been proven to have an average of 96.8% and 86.5% higher accuracy than BiLSTM and Seq2Seq in predicting short-term and medium-term trajectories, and the average accuracy has 90.1% higher than BiLSTM and Seq2Seq in predicting long-term trajectories. The future work will focus on the trajectory prediction of ocean-going vessels based on satellite AIS data.

ACKNOWLEDGMENT

The authors would like to thank Jiangjin Yin, Hamning Jiang, and Chen Zhang for discussing experiments for the research. Meanwhile, they like to express their gratitude to Wei Peng, Jianming Guo, and Shulei Liu for revising the paper. Last, the authors would like to thank Xu Liu, Jiaxiang Luo, and Xianqi Chen for guiding on paper format.

REFERENCES

[1] S. Thombre, Z. Zhao, H. Ramm-Schmidt, J. M. V. Garcia, T. Malkamaki, S. Nikolskiy, T. Hammarberg, H. Nuortie, M. Z. H. Buihuyi, S. Sarkka, and V. V. Lehtola, “Sensors and AI Techniques for Situational Awareness in Autonomous Ships: A Review,” IEEE Transactions on Intelligent Transportation Systems, pp. 1–20, 2020.
[2] H. Yu, A. T. Murray, Z. Fang, J. Liu, G. Peng, M. Solgi, and W. Zhang, “Ship Path Optimization That Accounts for Geographical Traffic Characteristics to Increase Maritime Port Safety,” IEEE Transactions on Intelligent Transportation Systems, pp. 1–12, 2021.
[3] L. Y. Hao, H. Zhang, T. S. Li, B. Lin, and C. L. Chen, “Fault tolerant control for dynamic positioning of unmanned marine vehicles based on T-S fuzzy model with unknown membership functions,” IEEE Transactions on Vehicular Technology, vol. 70, no. 1, pp. 146–157, 2021.
[4] L. P. Perera, J. P. Carvalho, and C. G. Soares, “Sensors and AI Techniques for Situational Awareness to Increase Maritime Port Safety,” IEEE Transactions on Vehicular Technology, vol. 63, no. 4, pp. 1539–1554, 2014.
[5] R. W. Liu, J. Nie, S. Garg, Z. Xiong, Y. Zhang, and M. S. Hossain, “Data-driven trajectory quality improvement for promoting intelligent vessel traffic services in 5G-enabled maritime iot systems,” IEEE Internet of Things Journal, vol. 8, no. 7, pp. 3574–3585, 2021.
[6] Z. Xiao, X. Fu, L. Zhang, and R. S. M. Goh, “Traffic Pattern Mining and Forecasting Technologies in Maritime Traffic Service Networks: A Comprehensive Survey,” IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 5, pp. 1796–1825, 2020.
[7] C. Shen, Y. Shi, and B. Buckham, “Path-Following Control of an AUV: A Multiobjective Model Predictive Control Approach,” IEEE Transactions on Control Systems Technology, vol. 27, no. 3, pp. 1334–1342, 2019.
[8] Y. Huang, Y. Li, Z. Zhang, and R. W. Liu, “GPU-Accelerated Compression and Visualization of Large-Scale Vessel Trajectories in Maritime IoT Industries,” IEEE Internet of Things Journal, vol. 7, no. 11, pp. 10794–10812, 2020.
[9] E. Tu, G. Zhang, L. Rachmawati, E. Rajabally, and G. B. Huang, “Exploiting AIS Data for Intelligent Maritime Navigation: A Comprehensive Survey from Data to Methodology,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 5, pp. 1559–1582, 2018.

[10] S. Fang, Y. Wang, B. Gou, and Y. Xu, “Toward Future Green Maritime Transportation: An Overview of Seaport Microgrids and All-Electric Ships,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 207–219, 2020.

[11] P. Borkowski, “The ship movement trajectory prediction algorithm using navigational data fusion,” *Sensors (Switzerland)*, vol. 17, no. 6, 2017.

[12] Danish Maritime Authority, “Danish AIS Data.” https://www.dma.dk/Sider/default.asp, 2021.

[13] H. Greidanus, M. Alvarez, T. Erikson, P. Argentiert, T. Cokacar, A. Pavesesi, S. Falchetti, D. Nappo, F. Mazzarella, and A. Alessandrini, “Basin-Wide Maritime Awareness From Multi-Source Ship Reporting Data,” *TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation*, vol. 7, no. 2, pp. 185–192, 2013.

[14] M. Posada, H. Greidanus, M. Alvarez, M. Vespe, T. Cokacar, and S. Falchetti, “Maritime awareness for counter-piracy in the Gulf of Aden,” *International Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 249–252, 2011.

[15] G. Pallotta, S. Horn, P. Braca, and K. Bryan, “Context-enhanced vessel prediction based on Ornstein-Uhlenbeck processes using historical AIS traffic patterns: Real-world experimental results,” *FUSION 2014 - 17th International Conference on Information Fusion*, 2014.

[16] L. M. Milleniori, P. Braca, and P. Willett, “Consistent Estimation of Randomly Sampled Ornstein-Uhlenbeck Process Long-Run Mean for Long-Term Target State Prediction,” *IEEE Signal Processing Letters*, vol. 23, no. 11, pp. 1562–1566, 2016.

[17] L. Qi and Z. Zheng, “Trajectory prediction of vessels based on data mining and machine learning,” *Journal of Digital Information Management*, vol. 14, no. 1, pp. 33–40, 2016.

[18] S. Liu and Y. Lin, “Introduction to grey systems theory,” *Understanding Complex Systems*, vol. 68, pp. 1–399, 2010.

[19] A. S. W. Erik Wiener Jan O. Pedersen, “A Neural Network Approach to Topic Spotting,” *Proceedings of 4th Annual Symposium on Document Analysis and Information Retrieval*, pp. 317–332, 1995. [Online]. Available: citeeseer.ifi.unizh.ch/wiener95neural.html

[20] A. Khan, C. Bil, and K. E. Marion, “Theory and application of artificial neural networks for the real time prediction of ship motion,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 3681 LNII, no. June 2014, pp. 1064–1069, 2005.

[21] W. Li, C. Zhang, J. Ma, and C. Jia, “Long-term vessel motion prediction by modeling trajectory patterns with AIS data,” *ICTIS 2019 - 5th International Conference on Transportation Information and Safety*, pp. 1389–1394, 2019.

[22] B. Ristic, B. La Scala, M. Morelande, and N. Gordon, “Statistical analysis of motion patterns in AIS data: Anomaly detection and motion prediction,” *Proceedings of the 11th International Conference on Information Fusion*, FUSION 2008, 2008.

[23] F. Mazzarella, V. F. Arguedas, and M. Vespe, “Knowledge-based vessel position prediction using historical AIS data,” *2015 Workshop on Sensor Data Fusion: Trends, Solutions, Applications*, SDF 2015, pp. 1–6, 2015.

[24] L. You, S. Xiao, Q. Peng, C. Clarabunt, X. Han, Z. Guan, and J. Zhang, “ST-Seq2Seq: A Spatio-Temporal Feature-Optimized Seq2Seq Model for Short-Term Vessel Trajectory Prediction,” *IEEE Access*, vol. 8, pp. 218 565–218 574, 2020.

[25] L. P. Perera, P. Oliveira, and C. G. Soares, “Maritime traffic monitoring based on vessel detection, tracking, state estimation, and trajectory prediction,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 3, pp. 1188–1200, 2012.

[26] T. Xiaopeng, M. Zhe, and C. Xu, “Inland River,” pp. 706–714, 2015.

[27] J. M. Johnson, “Predicting Vessel Trajectories From Ais Data Using R,” *Security*, no. June, pp. 1–55, 2017.

[28] Y. L. Pavlov, “Random forests,” *Random Forests*, pp. 1–122, 2019.

[29] T. K. Ho, “The random subspace method for constructing decision forests,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 832–844, 1998.

[30] Z. Xiao, X. Fu, L. Zhang, W. Zhang, R. W. Liu, Z. Liu, and R. S. M. Goh, “Big Data Driven Vessel Trajectory and Navigating State Prediction With Adaptive Learning, Motion Modeling and Particle Filtering Techniques,” *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–14, 2020.

[31] P. Del Moral, “Nonlinear filtering: Interacting particle resolution,” *Comptes Rendus de l’Académie des Sciences - Series I - Mathematics*, vol. 325, no. 6, pp. 653–658, 1997.