International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Improvement Interpolation Method for Vessel Trajectory Prediction based on AIS Data

I Made Oka Widyantara
Department of Electrical Engineering
Udayana University
Bali, Indonesia
email: oka.widyantara@unud.ac.id

I Gede Sudiantara
Postgraduate Program of Electrical Engineering
Udayana University
Bali, Indonesia
e-mail: theysudi@gmail.com

I Putu Noven Hartawan
Postgraduate Program of Electrical Engineering
Udayana University
Bali, Indonesia
e-mail: novenhartawan@gmail.com

I Made Dwi Putra Asana
Department of Informatics Engineering
Institut Bisnis dan Teknologi Indonesia
Bali, Indonesia
e-mail: dwiputraasana@instiki.ac.id

Ngurah Indra Er
Department of Electrical Engineering
Udayana University
Bali, Indonesia
e-mail: indra@unud.ac.id

Ketut Buda Artana
Department of Marine Engineering
Faculty of Marine Technology, Sepuluh Nopember Institute of Technology
Surabaya, Indonesia
e-mail: ketutbuda@its.ac.id

Abstract—An acceptable shipping monitoring system should be able to provide early detection of vessel accidents. One of the keys to early detection is trajectory prediction. Even though the prediction results depend heavily on the historical data of the vessel trajectory, there are often missing values in the trajectory data due to disturbances in the Automatic Identification System (AIS) data transmission process. Therefore, this study proposes a preprocessing method that includes data cleaning, trajectory extraction, and a combination of Linear interpolation methods for straight-shaped trajectories and Cubic Spline interpolation for curved-shaped trajectories. Test results involving three different trajectories showed that the Gated Recurrent Units (GRU) method produces a smaller Root Mean Square Error (RMSE) value on linear interpolation. Visually, however, the GRU method with linear interpolation has a deficiency in the curved-shaped trajectories. Our studies involving the Bidirectional GRU (BiGRU), Long Short Term Memory (LSTM), and Bidirectional LSTM (BiLSTM) methods showed that the model built using the proposed interpolation method has a lower RMSE value. This study emphasizes that good predictions of vessel trajectories based on AIS data requires an additional process, namely the interpolation of vessel trajectories according to their shape.

Keywords- AIS; Trajectory; Interpolation; Prediction

I. INTRODUCTION

The construction of a vessel trajectory based on the vessel's position is commonly carried out using AIS data [1]. AIS is a tool for tracking vessel movements with onboard transceivers and terrestrial base stations [2]. The use of AIS devices has also been mandated by the International Convention for the Safety of Life at Sea (SOLAS) from the International Maritime Organization (IMO) as a monitoring tool for several types of shipping vessels [2], [3]. The exchange of information between AIS devices on ships and base stations on land is transmitted via VHF radio frequency in the format of the National Marine Electronics Association (NMEA). The data provided by AIS is dynamic data, in the form of vessel coordinates, vessel speed, turn rate, and so on and static data, in the form of vessel number data, vessel type, vessel length, and so on [4]. Therefore, the history of vessel movements can be monitored because the vessel position data is always recorded [5].

AIS data recording continues to generate large amounts of data about vessel position and is commercially accessible. With the large volume of AIS data, many things can be analyzed to find patterns of vessel behavior. AIS data analysis can be used to improve the management of sea transportation, one of which is the safety of navigation. The output of AIS data analysis is the discovery of trajectory vessel patterns, the detection of anomaly vessel activity, and the prediction of trajectory vessels [6], [7]. This capability makes AIS-based vessel navigation communication systems superior to other vessel monitoring systems such as radar, imagery, etc.[8].

To be considered as an acceptable monitoring system, the system should be able to provide early detection of vessel trajectories. Thus, incidents concerning navigational safety such as vessel collision cases can be prevented. Therefore, the ability to recognize and predict vessel trajectory is mandatory. Trajectory prediction is a critical AIS data analysis activity for early detection of vessel trajectory patterns [9]. Prediction results are one of the keys to avoiding the risk of vessel accidents and estimating vessel voyages.

Research trends regarding prediction of vessel trajectory using AIS data show that from the application of the probability method of vessel position data it is developing towards the application of neural network models. The neural network model that can be applied is a model that is able to handle a sequential time base. This is because the character of the AIS data is included in the spatio-temporal data where spatial represents the spatial dimension with coordinate values (latitude and longitude) and temporal which represents the time dimension, namely the time series data of receiving AIS messages. The movement of the coordinates of the vessel during the period of receiving AIS messages continuously forms a vessel trajectory. This sequential data is processed by the neural network model to predict the next trajectory. The neural network model, as used in several studies, namely RNN, LSTM and GRU, is a method with a sequential database. The accuracy of the prediction results is strongly influenced by the historical data of the vessel trajectory position. The quality of the AIS data received depends on the AIS equipment, the base station receiving the AIS message, and the navigation status of the vessel [4]. Interference often occurs in the AIS data transmission process, causing noise or errors in the data vessel trajectory. One technique to overcome this problem is the application of interpolation techniques to a vessel trajectory.

This research develops a framework for predicting trajectory with historical AIS data. The framework consists of cleaning the data, extracting trajectories from each vessel, and applying values of the missing position produced by the repair process with linear and cubic spline interpolation. Finally, the framework concludes with the training and testing on the trajectory predictions with a neural network model. This study aims to find a trajectory prediction model applicable to early warning systems for the security of maritime activities. Consequently, developing an acceptable predictive model from good AIS trajectory data is critical. Therefore, our main contribution is the application of linear and cubic spline interpolation at the preprocessing stage to improve AIS historical data.

II. Related Work

Previous studies predicting vessel's trajectories based on AIS data exist in the literature. However, stages in the process often commenced without preceded by the interpolation step. A research in [10] proposed the Single Point Neighbor Search (SPNS) method for trajectory prediction with AIS. The approach can estimate the next trajectory position with direct predictions from the vessel's historical data, but is limited to trajectory types with reversing behavior. Another study in [11] developed trajectory predictions with the Gaussian Mixture Model (GMM). In the study, several trajectory models were made and predicted using a prediction tree. The trajectory predictions in the tree were then paired with a GMM to provide a probabilistic model for obtaining future trajectories. A research in [12] follows a similar probabilistic approach by implementing the Gaussian Process Model to predict vessel trajectory. Both works showed that a good vessel position prediction can be extracted from regular trajectories. However, more complex vessel traffic dynamics were not discussed in each study which might show decreases in the prediction results.

The research trend on trajectory prediction is leaning towards applying the neural network method. Volkova et al. [1] developed a neural network model for trajectory prediction with AIS data. They deployed relatively simple AIS data processing by directly utilizing historical vessel trajectory data. The trajectory predictions in the study were inaccurate, especially when vessels moved into the interference zone and performed maneuvers. In research by Ma et al. [13], they performed trajectory predictions with multiple data processing. The study extracted the original trajectory point from the history of the vessel trajectory using a hierarchical grouping approach. Subsequently, the vessel trajectory was trained and predicted using the RNN and LSTM models. Both models showed high predictive performance, whereas the LSTM obtained higher performance with fine-tuning parameters. Another study by Bao et al. [14] described trajectory prediction using a combination of Multi-Head Attention (MHA) and Bidirectional Gate Recurrent Unit (BiGRU). MHA was applied to weight sequential data that became the input to the BiGRU input layer. Before entering the prediction process, the pre-processing stage commenced repairing the missing position value on the trajectory using linear interpolation. Interpolation was also utilized to complete the absent value of the vessel's position on the path 5 minutes away. The prediction results showed that MHA-BiGRU was better than other prediction methods. However, the prediction method only applies well to standard navigation data since linear interpolation only works well for straight trajectories. The linear interpolation does not work well on curved (maneuverable) trajectory shapes.

Results from the trajectory prediction models explained previously showed that the trajectory predictions are significantly influenced by the vessel's trajectory historical data quality. Therefore, it is necessary to additionally interpolate the vessel trajectory, where there are often missing position values in the AIS data. Apart from predictive research, there are several studies regarding additional interpolation techniques to handle various trajectory data. Du et al. [15] applied polynomial interpolation in vessel trajectory reconstruction based on AIS data. Their proposed method considers the dynamic information of the vessel in the interpolation process. The vessel's dynamic information included are the speed and direction of the vessel's motion. The inclusion of the vessel's dynamic information succeeded in filling in the missing values in the trajectory with linear and curvilinear motion. Zhang et al. [16] combined piecewise linear interpolation with cubic spline interpolation to achieve similar goals. The research divided the trajectory into two segments: the straight and the curved segment. The straight trajectory segments are determined by the position and the time-sparse sampling techniques. The remaining points not included in the straight trajectory segments are then considered as the curved trajectory segment. The straight trajectory segments were restored using the piecewise linear interpolation method, while the curved sections were gathered using the cubic spline interpolation method. Another study by Dong et al. [17] performed real-time trajectory interpolation using the Bezier Transition method on flying robot trajectory data. The results of their work showed the smoothing of the curved trajectory. The work by Guo et al. [18] applied kinematic interpolation to detect anomalies in vessel trajectories based on AIS data. The interpolation considered the position, speed, and the vessel's direction of motion. The interpolated points obtained are used as a comparison to detect anomalies in the vessel position. Follow-up research from Guo et al. [19] improvised on the kinematic interpolation by adding forward and backward track point to the interpolation process. The method performed well on a single trajectory vessel and vast AIS data.

Previous literature reviews confirm that application of added interpolation techniques has seldomly used to predict vessel's trajectory with AIS data, even though improved prediction results can only be achieved by the support of better historical data. This point towards the application of added interpolation techniques to predict trajectory due to the fact that the shape of the path varies in straight and curve. Therefore, our research focuses on how combined interpolation methods can improve the results of vessel trajectory predictions based on AIS data. We propose utilizing the linear interpolation method for straight trajectories and the cubic spline interpolation method for curved trajectories. The trajectory shapes are detected using the COG attribute if missing position values in the AIS data exist.

III. METHOD

This study aims to obtain optimal vessel trajectory data for improving the vessel's trajectories prediction. Based on some of the literature discussed in the previous section, the critical step of pre-processing to repair vessel trajectories has to be taken before the trajectory data fed into the neural network model. This study proposes improvement in the pre-processing stage of AIS data. The first step is removing outlier in the historical AIS data, followed by trajectory extraction that divides the vessel trajectories into a single trajectory. The next step is interpolating missing position to fix the trajectory data. The techniques used are linear and cubic spline interpolation based on identification of changes in the direction of the vessel's movement. The repaired trajectory then entered into the neural network model for predicting the vessel's trajectory. Fig. 1 shows the proposed framework in this study.

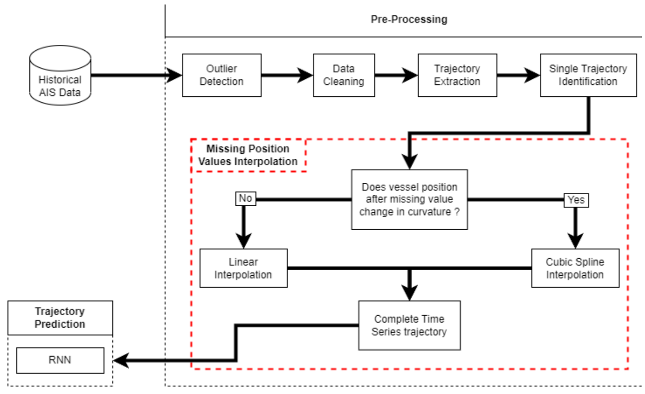


Figure 1. Proposed Framework

A. *Data Cleaning*

AIS raw data usually contains various errors due to interruptions in the data transmission process. For this reason, it is necessary to do data cleaning to improve the quality of AIS data. Data cleaning is also performed for several conditions in the data row. The data cleaning process is carried out by eliminating AIS data rows that contain the following conditions :

a) Does not have message types 1, 2, 3, 18, and 19 (because they do not contain vessel position data).

b) Abnormal vessel position, speed, and course over ground.

c) Status of the vessel that is moored or currently anchored.

d) Trajectory that doesn't last up to 8 hours.

B. *Trajectory Extraction*

Trajectory extraction aims to obtain vessel trajectory data in AIS data. Data extraction is done by grouping AIS data based on the vessel's unique identity or MMSI. Vessel position data is expressed as $p = \{t, lat, lon, SOG, COG\}$ grouped to represent trajectory data on a vessel. From a single trajectory vessel, it is possible to have more than one trajectory. Therefore, the trajectory cutting process needs to be done on each vessel trajectory. The trajectory trimming technique is carried out to divide the trajectory with the maximum span of time between vessel positions. First, a single trajectory vessel data is sorted by timestamp which is stated as $v = \{p1, p2, \ldots, pn\}$. The next step is to measure the timestamp difference per row sequentially. Vessel positions that exceed the specified time difference threshold will be marked as a new trajectory on a vessel. After the trajectory extraction process is complete, the vessel position feature is expressed as $p = \{t, lat, lon, SOG, COG, tr, diff\}$. The process of trajectory extraction is shown in Fig. 2.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

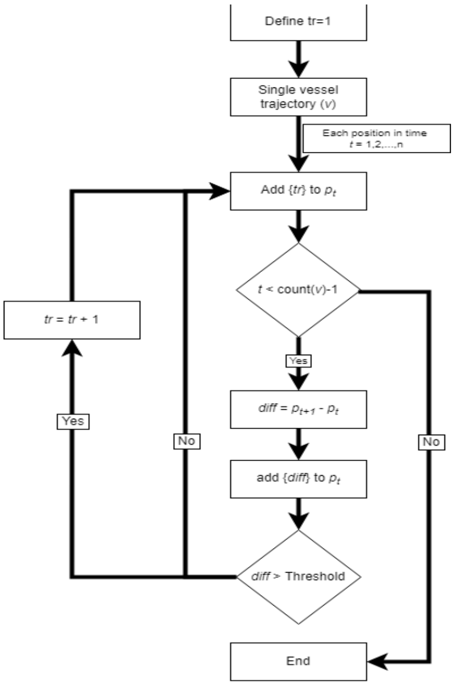


Figure 2. Trajectory trimming process

C. *Missing Position Interpolation*

The missing vessel position coordinate information has an impact on the prediction process of AIS data due to the inconsistent distribution of coordinate points in a trajectory. One technique that can be used to overcome missing position values in a trajectory is interpolation [15], [20]. Missing position values are identified by measuring the range of timestamp differences from the vessel's position at the time t and t+1. Based on the difference in timestamps, it can be defined how many vessel positions are missing on a vessel trajectory. To restore a lost position on a trajectory, a trajectory is repaired using an interpolation technique. According to the state of vessel navigation, vessel trajectories can be divided into straight trajectories and curved trajectories [16]. Identification of the type of straight trajectory and curved trajectory can be seen in the change in the direction of movement of the vessel in the vessel position data. The COG feature in AIS data can be used as a basis for determining the type of straight trajectory or curved trajectory for missing trajectories. Equation (1) is calculation of the COG value.

$$dcog_t = (|COG_t - COG_{t+1}|, 360 - |COG_t - COG_{t+1}|) \quad (1)$$

If there is a drastic difference in value dcogt, then the missing trajectory point will be defined as a turning trajectory type. For the straight trajectory type, a linear interpolation approach is applied to the missing vessel trajectory position. Every trajectory point lost at the time t and t+1 can be drawn as a straight line as in (2) [21]:

$$f(p) = \sum_{i=1}^{n} f_i(p) \quad (2)$$

Where n is the number of interpolated positions and *fi(p)* is the result of interpolation at one vessel trajectory position that is between *pt* dan *pt+1*. The function of *fi(p)* can be defined as in (3) :

$$f_i(p) = lat_t + (lon - lon_t)\frac{lat_{t+1} - lat_t}{lon_{t+1} - lon_t} \quad (3)$$

Meanwhile, for the curved trajectory type, the cubic spline interpolation approach is used. Besides being able to restore lost data, this approach is also able to provide smooth results on curved data types [22]. So this approach is suitable for curved trajectory types on vessel trajectories. Algorithm 1 shows the process of missing position interpolation.

Algorithm 1

Input: threshold of COG (c); **Output** : interpolated trajectory

```
for i=0;size(v) do //get all trajectory in (v)
  for t=0;size(p_i) do //get all feature in (p)
    if (p_t,diff > 1):
      Calculate dcog_t according to Eq.1
      if (dcog_t < c):
        Calculate linear interpolation
      end if
    end if
  end for
  Calculate cubic spline interpolation
  Combine all interpolation to (p)
end for
```

D. *Trajectory Prediction*

The neural network approach is used for the vessel trajectory prediction process. The application of this model is used because it is in accordance with the characteristics of the vessel trajectory which is based on time series data indexed in time sequence [23]. In addition, this model variant has also been tested to be able to provide the best accuracy in previous studies [14]. To predict the position of the vessel in the next time step, the sliding window method is applied to the data training process. The sliding window is adjusted to a certain time series length that shifts along the trajectory data [24].

The trajectory prediction process is carried out with several models of RNN variants. The model is suitable to be applied to AIS data having spatio-temporal data characteristics. To test all models, a comparison is made of the predicted trajectory (y̑) with the actual trajectory (y). This comparison is generated by applying the Root Mean Square Error (RMSE) method to find the error value in the trajectory prediction results [23], [25]. The lower the RMSE value obtained, the better the model is in producing vessel trajectory predictions. Equation (4) is RMSE value calculation.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n}} \quad (4)$$

IV. RESULT AND DISCUSSION

This study uses the AIS dataset captured by terrestrial antennas at Udayana University. The range of available AIS data covers the area in ALKI II (Lombok Strait) which consists of

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

2,402,820 data lines. The framework is implemented using the Python programming language.

A. Data Cleaning

Data cleaning is done to delete data rows based on the conditions described in the previous section. This process is executed by looping through the AIS data rows. As sample data on Table I shows examples of data that contain conditions in data cleaning. Rows one and two have a COG attribute that has a value of 360, where this value is included in the category of error values in AIS data. The third row has position values (latitude and longitude) that do not correspond to the world's geographic position ranges. The fourth line has an abnormal SOG value that exceeds 40 knots. Of the total 2402820 rows of AIS data, only 643500 met the predefined conditions. This amount has reduced 73% of the total dataset volume obtained.

TABLE I. RAW DATA CLEANING

MMSI	Timestamp	Latitude	Longitude	SOG	COG
525400427	04-06-22 16:00	-8.74025	115.20590	0	360
563041356	04-06-22 16:01	-8.72055	115.23440	0.1	360
525016683	04-06-22 22:03	91.00000	181.00000	102.3	360
525008043	05-06-22 08:44	-8.69865	115.34880	73.8	305.1

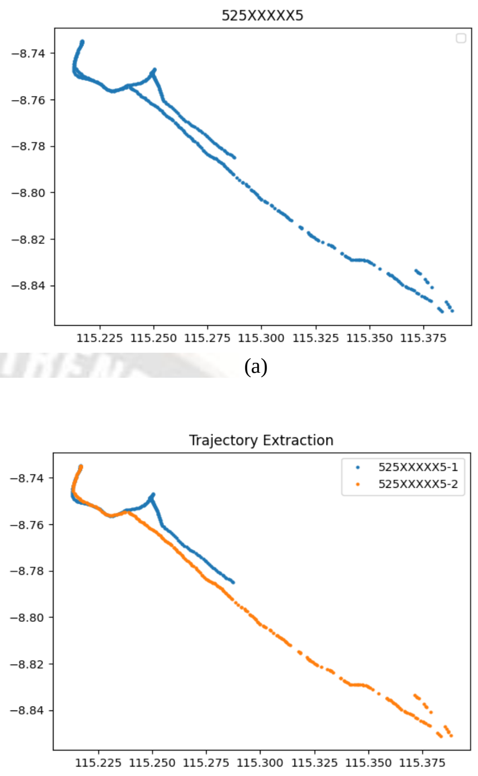
B. Trajectory Extraction

Trajectory extraction is carried out in two stages, namely grouping AIS data lines based on MMSI and trajectory trimming based on a predetermined threshold. Referring to the characteristics of the mooring vessel status [16], the threshold limit that can be used for dividing vessel trajectories is 60 minutes. One of the trajectory samples that has a time span that exceeds the threshold can be seen in Table II. Judging from the sample trajectory data, the timestamp values in row 3 and 4 have a difference of more than 60 minutes. So it is determined that there are 2 trajectories, namely trajectory 1 with data line coordinates no. 1,2,3 and trajectory 2 with data row coordinates no.4,5,6 in Table II.

TABLE II. TRAJECTORY TIMESPAN

No	Timestamp	Latitude	Longitude	SOG	COG
1	05-06-22 19:13	-8.73507	115.2169	1.4	230.7
2	05-06-22 19:14	-8.73488	115.2168	0.4	7.6
3	05-06-22 19:15	-8.73487	115.2168	0.3	241.8
4	05-06-22 23:22	-8.73543	115.2169	0.9	189.7
5	05-06-22 23:23	-8.73564	115.2169	1.6	195.6
6	05-06-22 23:24	-8.73603	115.2167	1.5	208.2

Visually the trajectory prediction stage is shown in Fig. 3(a) shows a visualization of coordinate grouping based on MMSI. Fig. 3(b) shows the visualization of trajectory trimming results based on a threshold value of 60 minutes. The trajectory trimming results are the output of the trajectory extraction process which is performed on each AIS data vessel based on the MMSI attributes.



(a)

(b)

Figure 3. Trajectory trimming (a) before and (b) after

C. Missing Position Interpolation

The missing position interpolation stage applies two interpolation methods, namely linear and cubic spline. The application of these two methods is adjusted to the results of the identification of vessel trajectory conditions, namely straight and curved. Linear interpolation is used to overcome missing values on straight trajectories, and cubic splines to overcome missing values on curved trajectories. The process of identifying straight and curved trajectory conditions in this study was carried out based on consideration of the time span and the course over ground (COG) value. Tracing the difference in the time span between points is used to determine the number of blank intervals in the trajectory. Tracing the difference in COG values between points is used to determine the condition of the vessel maneuvering so that it forms a curved trajectory [26]. The COG threshold value used to identify a curved trajectory is 10 degrees. In accordance with the rules of ITU-R, the time interval for AIS data transmission is between 2 and 180 seconds [16]. In this study, interpolation was carried out to obtain a trajectory with a consistent distance between coordinate points of 1 minute. Therefore the number of interpolation points is determined based on the time difference between 1 point and the next point in minutes. Table III shows the results of tracing data in a trajectory and determining the interpolation method applied. Data row one and row two on Table III has a 4-minute timestamp difference, so 3 interpolation points are needed. The difference in the COG value of the 2 data lines is 12.6, so the interpolation method used is Cubic Spline. The search is carried out from the starting point of a trajectory to the end point of the trajectory.

TABLE III. POINT TRACING RESULTS IN DETERMINING THE INTERPOLATION METHOD

No	Timestamp	Latitude / Longitude	COG	Interpolation Method	Interpolation Point Amount
1	06-06-22 04:06	-8.84668 / 115.3786	124.8	Cubic Spline	3
2	06-06-22 04:10	-8.84967 / 115.3820	137.4	Linear	1
3	06-06-22 04:12	-8.85134 / 115.3834	138.8	Cubic Spline	4
4	06-06-22 04:17	-8.85084 / 115.3884	357.2	Cubic Spline	2
5	06-06-22 04:20	-8.84798 / 115.3862	328.2	Linear	1
6	06-06-22 04:22	-8.84699 / 115.3856	325.5	Cubic Spline	7
7	06-06-22 04:30	-8.84080 / 115.3790	314.4	Linear	2
8	06-06-22 04:33	-8.83871 / 115.3769	321.5	Linear	5
9	06-06-22 04:39	-8.83488 / 115.3733	313.9	-	-

In Fig. 4 shows the interpolation process based on straight and curved vessel trajectories. The combined results of the linear and cubic spline interpolation methods are shown in Fig. 4, linear interpolation succeeds in adding points in a straight trajectory state, and cubic spline interpolation succeeds in adding points in a curved trajectory condition so that it shows smooth curvature of the vessel trajectory.

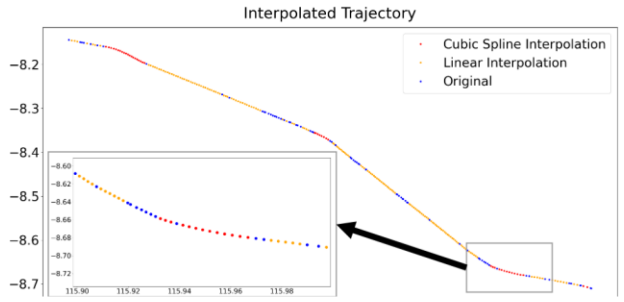


Figure 4. Interpolated trajectory

D. *Trajectory Prediction*

The trajectory prediction process in this study uses the vessel position features, namely latitude and longitude. The latitude and longitude vessel features are input data in the trajectory prediction modeling process using a neural network. To increase the precision and convergence of the model, the input data is normalized with a min-max scalar. The purpose of data normalization is to transform numeric values within a dataset into a standardized or common representation [27] range (0, 1) as in (5) [14]:

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (5)$$

Tabel IV shows some examples of data normalization results. The dataset is divided into training data and test data by dividing 80% training data and 20% test data. The training data is used in the model training process and the test data is used to evaluate the resulting trajectory prediction model.

TABLE IV. EXAMPLES OF NORMALIZED DATA

Timestamp	Raw Data		Normalized Data	
	Latitude	Longitude	Latitude	Latitude
05-06-22 23:33	-8.709953	116.038900	0.60406855	0.49214173
05-06-22 23:34	-8.709225	116.038100	0.60882325	0.48802668
05-06-22 23:35	-8.707005	116.034507	0.6133077	0.48386396
05-06-22 23:36	-8.704535	116.030335	0.61743464	0.47980106
05-06-22 23:37	-8.703058	116.027800	0.6211168	0.47598546

Dataset modeling uses the sliding window method to facilitate the neural network model in studying vessel trajectories. The trajectory prediction model development experiment in this study used recurrent neural network (RNN) variants, namely GRU, LSTM, BiGRU and BiLSTM. Parameter design in each model experiment is configured with the same value. The design parameters in the model are shown in Table V.

TABLE V. PARAMETER SETTING

Parameter Name	Value
Optimizer	Adam
Batch size	64
Loss function	Root Mean Square Error
Learning rate	0.00001

The results of the trajectory prediction experiment with the RNN model variant and the proposed interpolation method can be seen in Fig. 5 and Fig. 7. Fig. 5 shows the results of the vessel trajectory prediction with the condition that the vessel performs a small maneuver. Visually, the four RNN models show that the vessel trajectory prediction results are close to the actual trajectory position. Quantitatively the quality of predictions is measured based on the RMSE value. As shown in Table VI, the BiLSTM method produces the best RMSE values using the proposed interpolation method.

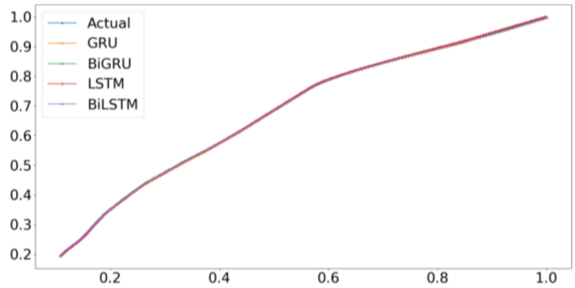


Figure 5. Prediction results of trajectory 1 using proposed method

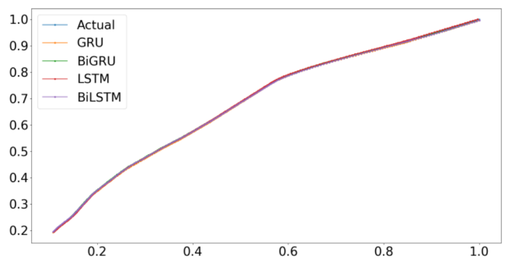
In this study, a comparative analysis of the proposed interpolation method was carried out with other interpolation methods, namely linear interpolation and cubic spline interpolation. The experimental results of the interpolation method comparison on the RNN model variants are shown in Table 6. The comparison results in Table 6 show that the BiGRU, LSTM, and BiLSTM models produce the best RMSE

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

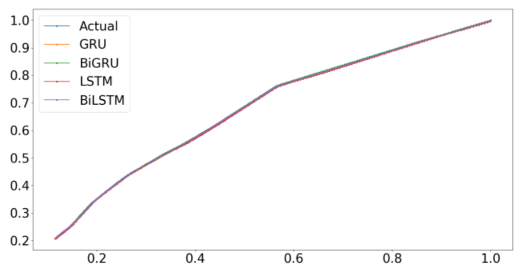
values when using the proposed interpolation method. Only the GRU model shows the best RMSE value in the linear interpolation method.

TABLE VI. COMPARISON OF RMSE SCORE OF RNN MODEL AND PROPOSED INTERPOLATION METHOD ON TRAJECTORY

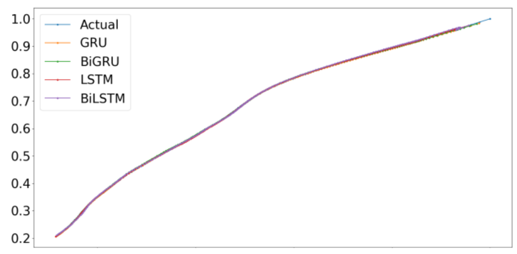
Interpolation Method	Model	RMSE
Linear and Cubic Spline (Proposed Method)	GRU	0.002639
	BiGRU	0.002009
	LSTM	0.001822
	BiLSTM	0.001723
Linear	GRU	0.002102
	BiGRU	0.002551
	LSTM	0.003020
	BiLSTM	0.002058
Cubic Spline	GRU	0.002922
	BiGRU	0.003702
	LSTM	0.004627
	BiLSTM	0.004859



(a)



(b)



(c)

Figure 6. Visual comparison of trajectory 1 prediction results (a) linear and cubic spline (b) linear (c) cubic spline

According to Fig. 6, visually the trajectory prediction by linear interpolation method does not show good smoothness under maneuvering ship conditions (Fig. 6(b)) compared to the proposed interpolation method (Fig. 6(a)).

The second experiment was carried out on a trajectory vessel with the condition that the vessel performs sharp maneuvers as shown in Fig. 7. The trajectory prediction visualization produced by the four RNN methods approaches the actual trajectory. In the curved trajectory type, the trajectory prediction results show good results by the four RNN methods with the proposed interpolation method.

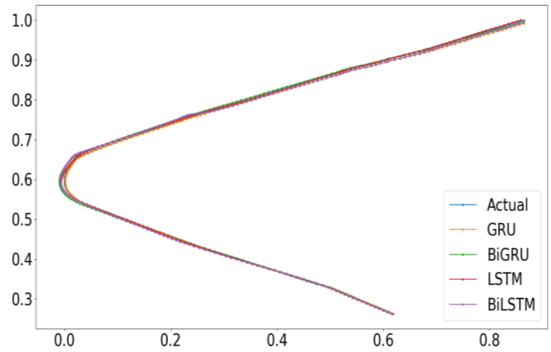


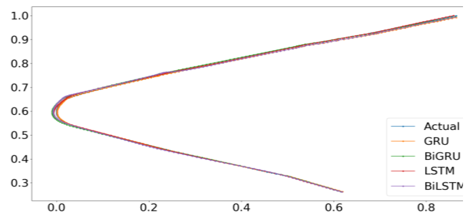
Figure 7. Prediction results of trajectory using proposed method

The comparison of the proposed interpolation method with other interpolation methods on curved trajectory types are shown in Table VII. Based on the comparison results, the BiGRU, LSTM, and BiLSTM models show the best predictive performance with the proposed interpolation method.

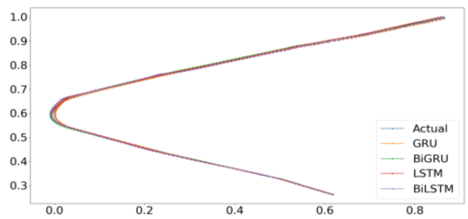
TABLE VII. COMPARISON OF RMSE SCORE OF RNN MODEL AND PROPOSED INTERPOLATION METHOD ON TRAJECTORY

Interpolation Method	Model	RMSE
Linear and Cubic Spline	GRU	0.004050
	BiGRU	0.004411
	LSTM	0.003707
	BiLSTM	0.004589
Linear	GRU	0.003851
	BiGRU	0.005969
	LSTM	0.005350
	BiLSTM	0.006636
Cubic Spline	GRU	0.005097
	BiGRU	0.006480
	LSTM	0.008259
	BiLSTM	0.008483

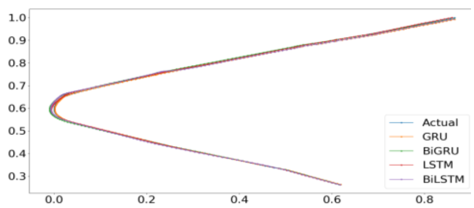
International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*



(a)



(b)

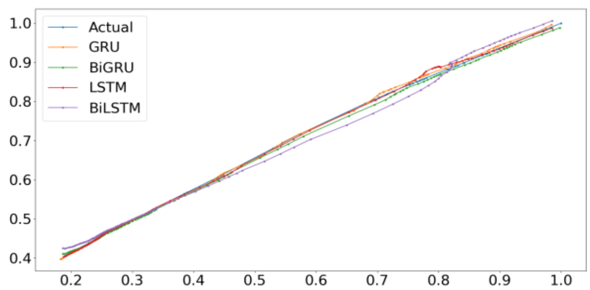


(c)

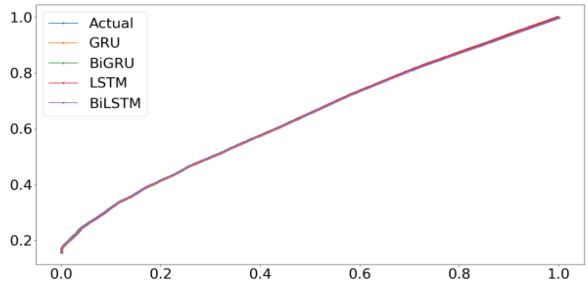
Figure 8. Visual comparison of trajectory 2 prediction results (a) linear and cubic spline (b) linear (c) cubic spline

According to the comparison of the RMSE values in Table VII, the GRU Model continues to show the lowest RMSE value in trajectory prediction when using the linear interpolation technique. However, visually as shown in Fig.8, the GRU trajectory prediction model with linear demonstrates a limitation in accurately predicting curved trajectories.

Fig. 9 shows a comparison of the trajectory prediction results without the interpolation method with the trajectory prediction using the proposed method. The results of the trajectory prediction without interpolation show more composition error than using the proposed interpolation method. This shows that the proposed interpolation has a significant effect on the results of the trajectory prediction.



(a)



(b)

Figure 9. Trajectory prediction results (a) without interpolation (b) using proposed interpolation method

As shown in Table 8, overall experimental results, the proposed interpolation method can produce the best RMSE values in the BiGRU, LSTM, and BiLSTM models. In the GRU model, the proposed method produces a better RMSE value than the cubic spline interpolation method. The linear interpolation method produces a better RMSE value than the proposed interpolation method. However, visually linear interpolation has a weakness in the curved trajectory type, shown in Fig. 6 and Fig. 8. A summary of the comparison of the RMSE trajectory prediction values with the RNN model between the proposed method and the linear interpolation method is presented in Fig. 10.

TABLE VIII. COMPARISON OF RMSE SCORE OF EACH MODEL AGAINST INTERPOLATION METHODS

Interpolation Method	**Model**	**Interpolation Method**		
		Proposed Method	**Linear Interpolation**	**Cubic Spline Interpolation**
Trajectory 1	GRU	0.002639	**0.002102**	0.002922
	BiGRU	**0.002009**	0.002551	0.003702
	LSTM	**0.001822**	0.003020	0.004627
	BiLSTM	**0.001723**	0.002058	0.004859
Trajectory 2	GRU	0.004050	**0.003851**	0.005097
	BiGRU	**0.004411**	0.005969	0.006480
	LSTM	**0.003707**	0.005350	0.008259
	BiLSTM	**0.004589**	0.006636	0.008483
Trajectory 3	GRU	0.002204	**0.001769**	0.002256
	BiGRU	**0.001930**	0.002086	0.002884
	LSTM	**0.001766**	0.002647	0.003670
	BiLSTM	**0.001616**	0.001885	0.003599

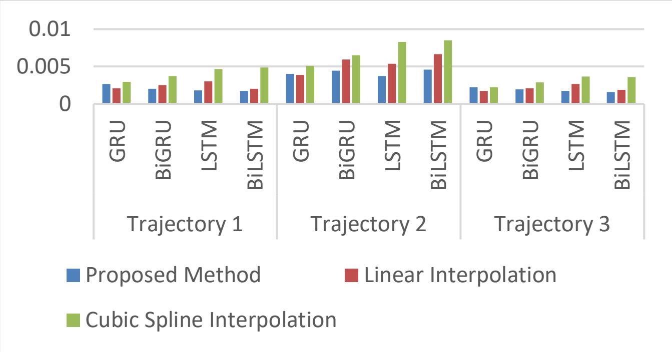


Figure 10. Comparison chart of RMSE for each model against interpolation methods

V. CONCLUSION

This paper has described a framework for improving the quality of vessel trajectory prediction results by applying Linear Interpolation and Cubic Spline techniques to the prediction pre-processing process. In the earliest stage, cleaning process initiated from 2402820 rows of AIS data where only 643500 rows met the conditions set. It was a 73% reduction from the total dataset volume. In the second stage, a trajectory extraction process is carried out with a time threshold of 60 minutes to produce a single trajectory from each vessel. Subsequently, combination of linear interpolation for the straight trajectories and cubic spline interpolation for the curved trajectories was executed after extraction of a single trajectory. The identification of turning trajectories then carried out utilizing COG information in AIS data. After good trajectory data was produced, trajectory prediction is carried out using a neural network approach. Vessel position features (Latitude, Longitude) were selected as the dataset for the prediction model.

Furthermore, this study compares the prediction results of three trajectories with the GRU, BiGRU, LSTM, and BiLSTM neural network models in the experiment section. Each prediction model then tested using three trajectory datasets: the dataset with the proposed interpolation method, the dataset with linear interpolation only, and the dataset with Cubic Spline interpolation only. From the test results, GRU method shows a smaller RMSE value on linear interpolation. However, visually the GRU method with linear interpolation has a deficiency in the curved trajectory shape. The BiGRU, LSTM, and BiLSTM results show that the model built with the proposed interpolation method has a lower RMSE value than data using one interpolation. We conclude that a combined procedure of vessel trajectory interpolation according to the type of trajectory is necessary to achieve a good prediction of vessel trajectory based on AIS data.

ACKNOWLEDGMENT

This research is supported and funded by the Ministry of Education, culture, research and technology of the Republic of Indonesia through the Higher Education Excellence Applied Research program with contract number B/110-22/UN14.4.A/PT.01.03/2022.

REFERENCES

[1] T. A. Volkova, Y. E. Balykina, and A. Bespalov, “Predicting ship trajectory based on neural networks using AIS data,” *J Mar Sci Eng*, vol. 9, no. 3, pp. 1–11, Mar. 2021, doi: 10.3390/jmse9030254.

[2] S. Mao, E. Tu, G. Zhang, L. Rachmawati, E. Rajabally, and G.-B. Huang, “An Automatic Identification System (AIS) Database for Maritime Trajectory Prediction and Data Mining,” 2018, pp. 241–257. doi: 10.1007/978-3-319-57421-9_20.

[3] H. Zhong, X. Song, and L. Yang, “Vessel Classification from Space-based AIS Data Using Random Forest,” in *2019 5th International Conference on Big Data and Information Analytics (BigDIA)*, IEEE, Jul. 2019, pp. 9–12. doi: 10.1109/BigDIA.2019.8802792.

[4] L. Zhang, Q. Meng, Z. Xiao, and X. Fu, “A novel ship trajectory reconstruction approach using AIS data,” *Ocean Engineering*, vol. 159, no. 12, pp. 165–174, 2018, doi: 10.1016/j.oceaneng.2018.03.085.

[5] E. M. Husni, M. R. Andanawari R. S, and R. H. Triharjanto, “Algoritma Peringatan Dini Pencurian Ikan Pada Data Automatic Identification System (AIS) Berbasis Terestrial Dan Satelit,” *Jurnal Teknologi Dirgantara*, vol. 14, no. 2, p. 81, Jul. 2017, doi: 10.30536/j.jtd.2016.v14.a2385.

[6] K. Wolsing, L. Roepert, J. Bauer, and K. Wehrle, “Anomaly Detection in Maritime AIS Tracks: A Review of Recent Approaches,” *J Mar Sci Eng*, vol. 10, no. 1, p. 112, Jan. 2022, doi: 10.3390/jmse10010112.

[7] A. Sidibé and G. Shu, “Study of Automatic Anomalous Behaviour Detection Techniques for Maritime Vessels,” *Journal of Navigation*, vol. 70, no. 4, pp. 847–858, Jul. 2017, doi: 10.1017/S0373463317000066.

[8] M. Fournier, R. Casey Hilliard, S. Rezaee, and R. Pelot, “Past, present, and future of the satellite-based automatic identification system: areas of applications (2004–2016),” *WMU Journal of Maritime Affairs*, vol. 17, no. 3, pp. 311–345, Sep. 2018, doi: 10.1007/s13437-018-0151-6.

[9] C. Wang, H. Ren, and H. Li, “Vessel trajectory prediction based on AIS data and bidirectional GRU,” in *2020 International Conference on Computer Vision, Image and Deep Learning (CVIDL)*, IEEE, Jul. 2020, pp. 260–264. doi: 10.1109/CVIDL51233.2020.00-89.

[10] S. Hexeberg, A. L. Flaten, B.-O. H. Eriksen, and E. F. Brekke, “AIS-based vessel trajectory prediction,” in *2017 20th International Conference on Information Fusion (Fusion)*, IEEE, Jul. 2017, pp. 1–8. doi: 10.23919/ICIF.2017.8009762.

[11] B. R. Dalsnes, S. Hexeberg, A. L. Flaten, B.-O. H. Eriksen, and E. F. Brekke, “The Neighbor Course Distribution Method with Gaussian Mixture Models for AIS-Based Vessel Trajectory Prediction,” in *2018 21st International Conference on Information Fusion (FUSION)*, IEEE, Jul. 2018, pp. 580–587. doi: 10.23919/ICIF.2018.8455607.

[12] H. Rong, A. P. Teixeira, and C. Guedes Soares, “Ship trajectory uncertainty prediction based on a Gaussian Process model,” *Ocean Engineering*, vol. 182, pp. 499–511, Jun. 2019, doi: 10.1016/j.oceaneng.2019.04.024.

[13] H. Ma, Y. Zuo, and T. Li, “Vessel Navigation Behavior Analysis and Multiple-Trajectory Prediction Model Based on AIS Data,” *J Adv Transp*, vol. 2022, pp. 1–10, Jan. 2022, doi: 10.1155/2022/6622862.

[14] K. Bao, J. Bi, M. Gao, Y. Sun, X. Zhang, and W. Zhang, “An Improved Ship Trajectory Prediction Based on AIS Data Using MHA-BiGRU,” *J Mar Sci Eng*, vol. 10, no. 6, Jun. 2022, doi: 10.3390/jmse10060804.

[15] H. Du, Y. Xiao, L. Duan, and S. Gao, “An algorithm for vessel’s missing trajectory restoration based on polynomial interpolation,” in *2017 4th International Conference on*

Transportation Information and Safety (ICTIS), IEEE, Aug. 2017, pp. 825–830. doi: 10.1109/ICTIS.2017.8047863.
[16] X. Zhang, Y. He, R. Tang, J. Mou, and S. Gong, "A Novel Method for Reconstruct Ship Trajectory Using Raw AIS Data," in *2018 3rd IEEE International Conference on Intelligent Transportation Engineering (ICITE)*, IEEE, Sep. 2018, pp. 192–198. doi: 10.1109/ICITE.2018.8492619.
[17] W. Dong, Y. Ding, J. Huang, L. Yang, and X. Zhu, "An optimal curvature smoothing method and the associated real-time interpolation for the trajectory generation of flying robots," *Rob Auton Syst*, vol. 115, pp. 73–82, May 2019, doi: 10.1016/j.robot.2019.02.004.
[18] S. Guo, J. Mou, L. Chen, and P. Chen, "An Anomaly Detection Method for AIS Trajectory Based on Kinematic Interpolation," *J Mar Sci Eng*, vol. 9, no. 6, p. 609, Jun. 2021, doi: 10.3390/jmse9060609.
[19] S. Guo, J. Mou, L. Chen, and P. Chen, "Improved kinematic interpolation for AIS trajectory reconstruction," *Ocean Engineering*, vol. 234, p. 109256, Aug. 2021, doi: 10.1016/j.oceaneng.2021.109256.
[20] P. Borkowski, Z. Pietrzykowski, and J. Magaj, "The Algorithm of Determining an Anti-Collision Manoeuvre Trajectory Based on the Interpolation of Ship's State Vector," *Sensors*, vol. 21, no. 16, p. 5332, Aug. 2021, doi: 10.3390/s21165332.
[21] V.-S. Nguyen, N. Im, and S. Lee, "The Interpolation Method for the missing AIS Data of Ship," *Journal of Navigation and Port Research*, vol. 39, no. 5, pp. 377–384, Oct. 2015, doi: 10.5394/kinpr.2015.39.5.377.
[22] J. Li, X. Li, and L. Yu, "Ship traffic flow prediction based on AIS data mining," in *2018 33rd Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, IEEE, May 2018, pp. 825–829. doi: 10.1109/YAC.2018.8406485.
[23] J. Park, J. Jeong, and Y. Park, "Ship Trajectory Prediction Based on Bi-LSTM Using Spectral-Clustered AIS Data," *J Mar Sci Eng*, vol. 9, no. 9, p. 1037, Sep. 2021, doi: 10.3390/jmse9091037.
[24] L. Zhang, J. Zhang, J. Niu, Q. M. J. Wu, and G. Li, "Track Prediction for HF Radar Vessels Submerged in Strong Clutter Based on MSCNN Fusion with GRU-AM and AR Model," *Remote Sens (Basel)*, vol. 13, no. 11, p. 2164, May 2021, doi: 10.3390/rs13112164.
[25] Z. Sidek, S. S. S. Ahmad, and N. H. I. Teo, "Associating deep learning and the news headlines sentiment for Bursa stock price prediction," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 31, no. 2, p. 1041, Aug. 2023, doi: 10.11591/ijeecs.v31.i2.pp1041-1049.
[26] L. Sang, A. Wall, Z. Mao, X. Yan, and J. Wang, "A novel method for restoring the trajectory of the inland waterway ship by using AIS data," *Ocean Engineering*, vol. 110, pp. 183–194, Dec. 2015, doi: 10.1016/j.oceaneng.2015.10.021.
[27] S. Subramanian, Y. K. Gounder, and S. Lingana, "Day-ahead solar irradiance forecast using sequence-to-sequence model with attention mechanism," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 2, p. 900, Feb. 2022, doi: 10.11591/ijeecs.v25.i2.pp900-909.