Ship trajectory prediction using AIS data with TransFormer-based AI

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***Abstract*—Ship trajectory prediction is important to maintain maritime travel and logistics for both security and efficiency. Nowadays we can access public data from Automatic Identification System(AIS), however, there have remained challenges to predicting precise trajectories by using AIS data due to its complexity and diversity. Recent significant developments in AI technology including generative AI, such as TransFormer-based algorithms, have made us realise that those technologies have the potential to produce more accurate trajectory prediction. This study aims to develop a method of trajectory prediction using AI from AIS data. We used the data of fishing vessels tracked in Japanese territorial waters of the Pacific Ocean, which includes latitude, longitude, ship over ground, and course over ground, and converted them into four-hot vectors to analyse the complex trajectories. The accuracy of the prediction was evaluated by accumulating the distance between the predicted value and the actual measurement value for each time. Our results showed that the TransFormer-based method can predict the fishing vessels' trajectories which had been failed to predict by the LSTM-based method in previous studies. We conclude that the use of AI technology can contribute to the improvement of maritime traffic safety and sustainability, and could lead to more effective and versatile trajectory prediction algorithms.**

***Index Terms*—Trajectory prediction, AIS data, AI technology, TransFormer, Four-hot vectors, LSTM**

I. Introduction

Route prediction is vital for safe and efficient navigation, especially for ships. Conventional methods struggle with ship dynamics, but modern tech like AIS offers real-time data, though prediction remains complex. This research aims to develop AI-based route prediction from AIS data, enhancing vessel safety and traffic efficiency. Fishing vessels present unique challenges due to their short and complex movements. Previous methods like LSTM failed to accurately predict their trajectories. Statistical and machine learning models have been used for trajectory prediction, but none can handle AIS data's complexity. Our AI model successfully predicted fishing vessels' trajectories with a 5.4 km/hr error, comparable to cargoes or tankers. By understanding the necessity and difficulty of route prediction, this research proposes new solutions through AI technology to improve maritime traffic safety and sustainability.

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A. TrAISFormer

In this study, a TransFormer [1]-based AI algorithm is used for route prediction. Several AI-based route predictions have been carried out by previous studies, but they have not been sufficiently accurate. Recurrent neural networks (RNNs) have played a role in dealing with time series information processing and have been used for ship trajectory prediction, too. However, the new architecture, TransFormer, has the ability to deal with longer-term time series information and it is an algorithm that can perform possible parallel processing and has shown the potential to solve many remained problems. In our study, TrAIsFormer, which is modified for ship trajectory prediction with AIS data, was able to take into account multimodality in route prediction, which was a challenge, and performed well enough for route prediction by providing appropriate data cleansing and loss functions.

Fig.1 is the architecture of TrAISFormer. It has been build based on the Radford, et al. [2].

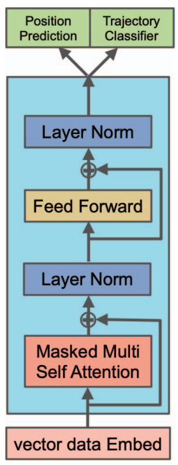

Fig. 1. Architecture of TrAISFormer.

B. Automatic Identification System

Automatic Identification System (AIS) is a system that automatically transmits and receives vessel information, such as call signals, vessel name, position, course, speed, and destination, using VHF radio waves, and exchanging information

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between vessel stations and shore stations. Currently, it is mandatory for vessels over a certain size to be equipped with this system, and furthermore, AIS radio wave collecting satellites have been launched, making it possible to acquire AIS from all over the world. Research is currently underway to utilise AIS for a variety of applications because there are several difficulties in using them due to the complexity and diversity of the data we explain in the next subsection, it makes difficult to utilize AIS.

C. Data cleansing

AIS data contain a large amount of irregular noise, so data cleansing is necessary to be carried out. The causes of the irregular noise are that they are changed by ship owners sometimes arbitrarily, also AIS transmission interval is not uniform, various intervals are set by each ship owner, also there exist many ships that do not transmit AIS.

In this study, [Latitude, Longitude, Ship over Ground(SOG), Course over Ground(COG)] are selected as input values for the TrAISformer [3]. We cleaned AIS with the following conditions for this study and sampled at five-minute intervals to fit the data for TrAISformer. Fig. 2 shows the cleansing scheme of AIS data for this study.

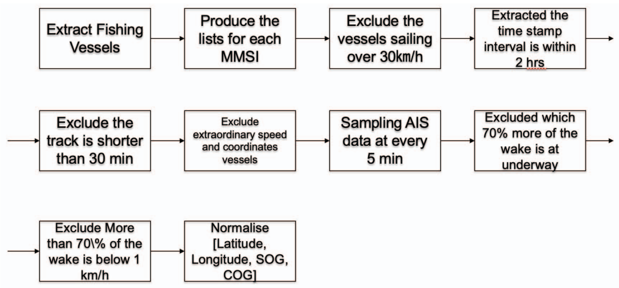

Fig. 2. Data cleansing scheme

II. Methods

A. Input data

The AIS data consists of real numbers originally, however, complex wakes failed to be learned by dealing with the data as real numbers. Based on the results, we converted the original records to a vector representation in this study, especially when we converted them into a four-hot vector. This data conversion worked well in our case to represent complex ship trajectories which included the multimodal probability. Fig. 3 shows the structure of four-hot vectors (Latitude, Longitude, SOG, COG) in the converted data. Fig. 4 shows the image of how TrAISformer solves the multimodal problem.

We used the AIS on Dec 1st to Dec 7th 2020, at 34°N $\sim$ 40°N, 138°E $\sim$ 150°E. The approximate area is shown in Fig. 5. We also limited the data which included more than 5 time points, recorded continuously longer than 30 hrs.

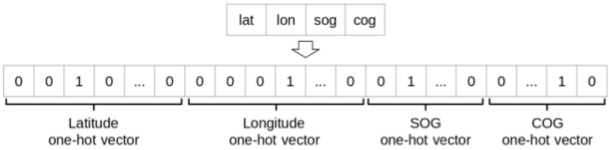

Fig. 3. Translation image of input real numbers into the four-hot vectors.

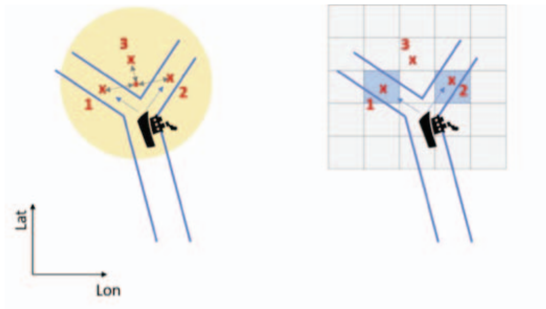

Fig. 4. Image of trajectory prediction by vector representation. The original data set consists of consecutive numbers. It can be the cause of difficulty in predicting bimodal probability. By using four-hot vectors which are discrete binary data, the difficulty is solvable.

B. Problem Statement

Trajectory prediction of AIS data is to predict the position of a ship at a certain time. The AIS trajectory x_t at time t consists of the following four elements as we mentioned: 1. Latitude, 2. Longitude, 3. SOG (speed), 4. COG (course). The prediction for L step ahead is T+1 observed values up to time T. Predicting $x_{T:L}$ = $\{x_{T+1}$, x_{T+2}, ..., $x_{T+L}\}$ from $x_{0:T}\{x_0$, x_1, ..., $x_t\}$ that is, consider the following conditional probability distribution.

$$p(x_{T+1:T+L}|x_{0:T}) \tag{1}$$

By factoring,

$$p(x_{T+1:T+L}|x_{0:T}) = \prod_{l=1}^{L} p(x_{T+L}|x_{0:T+l-1} \tag{2}$$

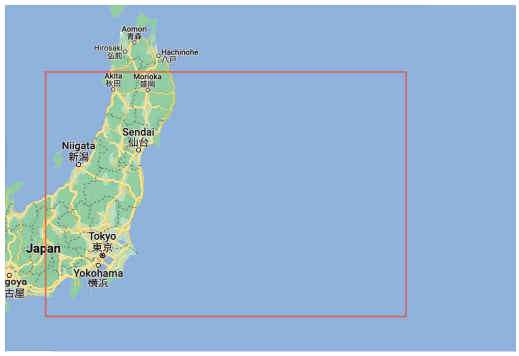

Fig. 5. The area 34 $\sim$ 40°N, 138 $\sim$ 150°E is indicated with the red line in this figure.

C. Trajectory extraction

We defined trajectories with the following definitions:

1) Indicating 20 or more AIS transmissions
2) Voyage time is longer than 4 hours
3) Timestamps, which are the intervals of the trajectories, keep less than 2 hours
4) SOG is less than 30 knots
5) The ship is sailing

D. Data presentation

A four-dimensional vector containing the position of vessels and velocity, such as:

$$x_t \triangleq [lat, lon, SOG, COG]^T \tag{3}$$

where lat = Latitude, lon = Longitude, SOG = SOG, COG = COG. Solving regression problems with continuous-value learning sources may be the cause of the low accuracy in predicting complex trajectories because there exists an infinite variation of the candidates theoretically, in contrast, the data amount for learning is not sufficiently big. Additionally, there exists another essential reason to prevent solving multimodal trajectories as a regression problem, that is the mean square error (MSE) defined as follows, which is used to represent the loss function between the predicted value and the true value;

$$L_{MSE} = \sum_{l=1}^{L} ||x_{T+1}^{pred} - x_{T+1}^{true}||_2^2 \tag{4}$$

Using MSE leads to an interpretation of conditional likelihood based on Gaussian assumption. However, the Gaussian assumption cannot handle multimodal data.

Now we chose to consider e_t to convert real numbers into a four-hot vector, which means using a vector representation of data as follows:

$$p(x_{T+1:T+L}|x_{0:T}) \rightarrow p(e_{T+1:T+L}|e_{0:T}). \tag{5}$$

We modeled e_t as a categorical distribution; which means, that by converting the data into a four-hot vector, we converted the trajectory prediction problem into a classification problem with 4 heads. If the probability of the existence of a ship at a certain time is

$$p_{T+1} = p(e_{T+1}|e_{0:T+l-1}), \tag{6}$$

then, the loss of function is expressed by CE (cross entropy error) and is as follows;

$$L_{CE} = \sum_{l-1}^{L} CE(p_{t+l}, h_{T+l}) \tag{7}$$

We show the example of a true probability distribution, Gaussian estimation distribution, and the case of our strategy(categorical estimation) in Fig.6.

1) Hyperparameter: The resolution of the four hot vectors is the Hyperparameter of this model. The resolutions are in Table I.

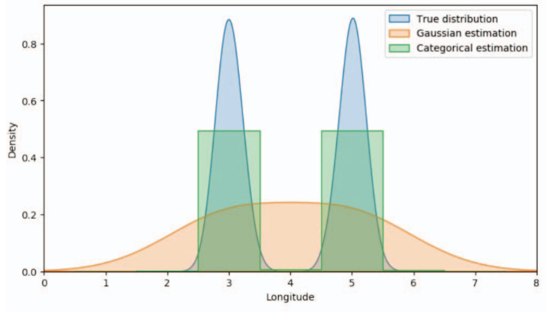

Fig. 6. Example of True probability distribution, Gaussian estimation distribution, and the case of our strategy(Categorical estimation). Gaussian estimation distributes between true probabilities and cannot solve multimodality.

TABLE I
HYPERPARAMETERS

Hyperparameters	resolution
Latitude	0.1°
Longitude	0.1°
SOG	1 knot
COG	5.0°
Predicting time	3 hrs
Epochs	50 epochs

E. Evaluation

By calculating the haversine distance d_k between the position of the predicted trajectory and the real position of the trajectory at each time point.

$$d_k = 2R_{sin}^{-1}\left(\sqrt{\sin^2(\bar{\Phi}) + \cos(\Phi_1)\cos(\Phi_2)\sin^2(\lambda)}\right) \tag{8}$$

where R is the earth radius, Φ_1 is the real latitude, Φ_2 is the predicted latitude, λ_1 is the real longitude, λ_2 is the predicted longitude, $\bar{\Phi} = \frac{\Phi_2 - \Phi_1}{2}$, $\lambda = \frac{\lambda_2 - \lambda_1}{2}$.

III. RESULTS

Fig. 8 shows the prediction error growth based on our analyses. Table II shows the exact values at 5 hrs and 10 hrs. Because the previous study which used LSTM could not predict the trajectories of fishing vessels and did not indicate error values [4], we could not compare the accuracy of our study and the previous study. In order to show how much our results for fishing vessels are accurate, we show the error growth which we applied to cargos and tankers with the previous study data in Table III. The error size of LSTM prediction at 1 hr is larger than the error size of our case at 5 hr with the same cargo and tanker data, and larger than 10 hr with the fishing vessels data.

We compared the other research with our results. Yan et al. [5] used Bi-LSTM, and the RMSE value of their algorithm was smaller than the RMSE of LSTM. Unfortunately, their results were indicated as RMSE between predicted and true trajectories at each time point. This result is difficult to compare directly with our result which compares the predicted future trajectory and the true trajectory from the last time point of training. Zhao et al. showed the results by the combination of GAT and LSTM. They indicated the results as the difference of degree between true and predicted latitude and longitude, after 10 s, 30 s, 1 min [6]. These values could translated into distance [m] and the distance after 10 s, 30 s, and 1 min were 1.93, 4.41, and 3.47 km, respectively. Here it is also difficult to compare directly but we can guess that their prediction for after 1 hr will not be a different order with their results, and it is the fact that our case at 1 hr was less than 2 km. These results suggest that our method is not worse than the GAT-LSTM combination.

These results suggest that our application using Transformer -based AI and a four-hot vector approach can predict complex trajectories of vessels better than RNN-based algorithms.

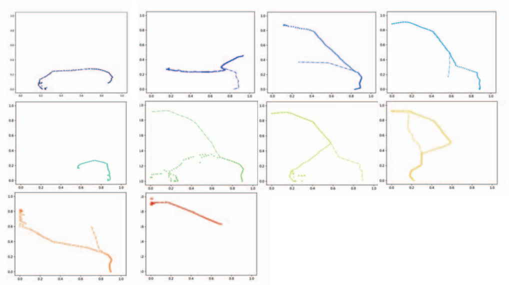

Fig. 7. Track Examples 10 examples trajectories are indicated. circle: learned trajectory; ×: predicted trajectory; dashed line: actual trajectory..

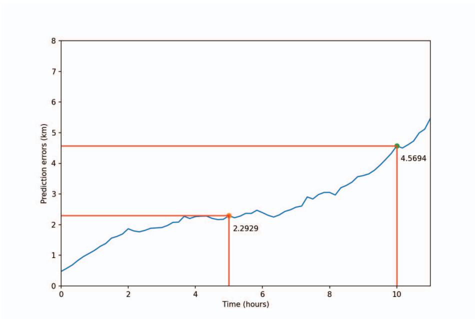

Fig. 8. The area 34 ∼ 40°N, 138 ∼ 150°E is indicated with the red line in this figure.

TABLE II
RESULTS OF FISHING VESSELS WITH TRAISFORMER(KM)

[hr]	5	10
TrAISFormer	2.29	4.57

IV. DISCUSSION AND CONCLUSION

The use of TransFormer-based deep learning algorithms has significantly improved the accuracy of vessel route prediction. This study dealt with fishing vessels, which are relatively more

TABLE III
RESULTS OF CARGOS AND TANKERS WITH TRAISFORMER(KM)

[hr]	1	2	3	5	10	15
TrAISFormer	0.890	1.67	2.90	5.93	11.37	20.84

difficult to predict than cargo and tankers because they move in more complex ways. Cargo and tankers are called regularly scheduled vessels and their routes do not change throughout the year, but fishing vessels are subject to seasonal changes.

For example, when route prediction is used for search and rescue operations, it needs to be more accurate than visual navigation, but in the case of visual navigation, the prediction error after three hours is 3 nautical miles, this is said to be about 5.556 km. That means the present study resulted in a higher accuracy than expected. Although the increase in error may be greater if the prediction time is further extended, the results show that within three hours of use, this approach can make a significant contribution to route prediction.

In the previous study [4], the direction of travel of the vessel was also taken into account in the assessment of route predictions, but the assessment method was not quantitative, and only scores for some of the wakes were written, making quantitative comparisons difficult. In conclusion, it appeared to be difficult to predict the route of fishing vessels in LSTM.

V. FUTURE CHALLENGES

The route predictions in TrAISformer overcome our expectations. One of the reasons is that the data period used was short (1/12/2020 - 7/12/2020) and included many similar vessels, in line with the reference paper. We are considering increasing the data period in the future.

We will also keep a close watch on trends in the AI field and consider more effective and versatile algorithms for route prediction by utilising new ideas.

ACKNOWLEDGMENT

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