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Attention-LSTM based Prediction Model for Aircraft 4-D Trajectory

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ABSTRACT

With the increase of aviation activities, airspace constraints and flight delays have become increasingly prominent in the process of air traffic management (ATM). How to increase airspace capacity within the limited airspace resources while ensuring smooth and safe aircraft operations is a challenge for civil aviation today. In order to accelerate the intelligent operation of air traffic control and promote the development of intelligent ATM systems, it becomes very important to improve the accuracy of trajectory prediction, which becomes very difficult due to the problems of sparse aircraft flight trajectory and different flight altitudes. In order to solve this problem, an Attention-LSTM trajectory prediction model is proposed in this paper. This model can extract the time series features of the trajectory using an long short-term memory (LSTM) network and improve the accuracy of trajectory prediction by extracting the important factors affecting the current point change using an attention mechanism. To verify the accuracy of our proposed model, this paper uses real trajectory data, and uses LSTM, support vector machine, and other models for comparison. The comparison results show that this model is better than the most advanced model, which further promotes the process of intelligent ATM systems.

Keywords: 4-D trajectory, attention mechanism, LSTM, neural network

Introduction

With the tremendous growth of civil aviation sector in recent years, air traffic flow has expanded dramatically, putting a strain on airspace resources. According to figures from the International Civil Aviation Organization, global air traffic flow doubles every 15 years, and the present air traffic and navigation system's operating capacity is reaching saturation. Countries around the world have proposed various coping strategies to coordinate airspace resources, such as Single European Sky ATM Research (SESAR)[1] in the United Kingdom and Next Generation (NextGen)[2] Transportation System in the United States, in response to increasingly serious problems such as limited airspace, flight delays[3], and intensified conflicts. These two missions have aided the development of Automatic Dependent Surveillance Broadcast (ADS-B)[4], a system that integrates modern technologies such as satellite navigation, communication technology, aerial equipment, and ground equipment. It is a significant technological breakthrough in the evolution of the aviation system. Solving air traffic route regulation and achieving optimum operational efficiency is also a significant technical achievement for the global civil aviation sector. ADS-B provides civil aviation with a safer and more efficient means of air traffic surveillance by collecting information and accurately positioning ground wireless sensor networks. This effectively improves the operational situational awareness of controllers and pilots, enhances the control capability of airlines, expands surveillance coverage, and improves air traffic safety, airspace capacity, and operational efficiency. As a result, determining how to employ ADS-B data analysis to enhance airspace efficiency, expand airspace capacity, improve flight safety, minimize flight delay time, and accomplish "low-carbon environment protection" is a critical component of the execution of the civil aviation policy.

One of the current effective tactics, based on restricted airspace resources, is to minimize the minimum spacing of airplanes, hence improving air flow[5] . The implementation of various countries' plans to relieve airspace tension has led to the proposal of an air traffic management model based on 4-D trajectory operations (TBO), which is based on accurate aircraft 4-D trajectory prediction, sharing trajectory dynamic information among air traffic control, airlines, and aircraft, and realizing collaborative decision-making between flight and control. On the other hand, using the 4-D trajectory, the precision of the anticipated arrival time of the aircraft is enhanced from the minute level to the ten second level, ensuring smooth and safe aircraft operation while boosting air flow. 4-D aircraft trajectory flight, which comprises longitude, latitude, altitude, and time, is a new trend in civil aviation and the major growth direction of civil aviation navigation technologies in China. The time series is added to the 3-D

aircraft trajectory, and the aircraft is needed to reach the defined waypoint at the stated time is more favorable to air traffic flow management.

For various flight itineraries, the aircraft's 4D trajectory information must be varied. The daily 4-D trajectory information for a scheduled trip, on the other hand, will fluctuate with changes in weather, payload, and cruising altitude. As a result, the 4-D trajectory's specificity and dynamics may be utilized to evaluate and mine past trajectory data, as well as pre-calculate the waypoint when the aircraft arrives at the next instant. Real-time synchronization and updates across departments to ensure the aircraft's safe and efficient operation based on collaborative decision-making.

The existing 4-D trajectory prediction accuracy is insufficient to fulfill the demands of civil aviation air traffic control. We need to figure out how to handle ADS-B data and use a more efficient temporal prediction model to increase aircraft trajectory prediction accuracy. As a result of the aforementioned issues, we apply the attention-LSTM model to predict aircraft trajectory data and pre-process the data to increase the efficacy of data training. The main contributions of this paper are as follows:

1) Attention-LSTM model is proposed for the prediction of aircraft trajectory. On the basis of time series prediction, it pays more attention to the influencing factors between the data, further extracts the characteristics of the data, and uses the attention mechanism to strengthen the influence of special data, and attenuate the influence of unnecessary factors, which improves the prediction accuracy of aircraft 4-D trajectory. Compared with the current aircraft 4-D trajectory prediction, the prediction accuracy of the model we proposed is higher than other advanced models.

2) Considering that different causes influence distinct phases of an aircraft's trajectory, which is represented in historical aircraft trajectory data. As a result, in this experiment, not only the data from the 4-D aircraft trajectory is taken into account, but also the speed and deflection heading angle to improve data diversity and predictability.

3) We use the sliding window data training approach, which helps to keep the anticipated trajectory regulated by the spatial span consistent. We pick the sliding window approach to choose the training data based on the properties of the aircraft trajectory data, which assures data continuity and is more favorable to model training.

The rest of this paper is organized as follows: the second part reviews the related research work on current trajectory prediction techniques; the third elaborates the principles and details of the prediction model proposed in this paper; the fourth part introduces the specific content of the experiment and shows that it outperforms other advanced models; in the last part summarizes and forecasts future directions.

Related Work

To accelerate the implementation of the aircraft 4-D trajectory based air traffic management(4-D-TBO) project, the primary goal is to improve the prediction accuracy of aircraft trajectory[6]. Currently, most researches on trajectory prediction are data-driven and rely on the data from ADS-B for analysis and processing. According to the structure and parameters of the algorithms, 4-D trajectory prediction methods are mainly classified into aircraft dynamic based models and flight state estimation methods and datadriven models based on machine learning. In recent years, machine learning methods have been continuously applied in various directions, such as natural language processing, machine vision, image processing etc., and have achieved very good results. Therefore, they have been gradually applied in the direction of aircraft trajectory prediction[3].

In the early air traffic control, the main consideration is the prediction accuracy. Traffic controllers use the predicted trajectory to make corresponding emergency measures. There are mainly two methods: aircraft-based dynamic model and state estimation method. The method based on the aircraft dynamics model is to establish the kinematic equation with the forces in process of the flight of aircraft to predict the future trajectory. The state estimation method is based on the transformation of flight parameters of the aircraft in each state to build a state transfer model. Using such models requires in-deep knowledge of aircraft states, parameters, and aircraft flight intentions. Qiao et.al.[7] proposed a trajectory prediction algorithm based on adaptive parameters selection hidden markov model (HMM), which adjusted parameters according to the dynamic changes in the movement process, and also introduced a density-based trajectory division algorithm to improve the prediction efficiency. Liu and Li[8] used aircraft intentions to guide the interactive multi-model algorithm for aircraft trajectory prediction, and improve the accuracy of trajectory prediction by establishing a dynamic model based on the heading angle at the previous moment. Richard and David[9] analyzed historical climb data around the world, and studied 11 common aircraft types to improve the aircraft trajectory prediction accuracy by predicting some unknown point mass model parameters. These methods can learn data features from specific aspects and improve the accuracy of prediction, but there is no way to learn the relationship between data adequately. On the other hand, the model has many parameters and the early research mainly considers the prediction accuracy of aircraft 3-D trajectory with real-time, and it cannot meet the needs of air traffic control in advance.

With the increasing of air traffic flow, the workload of controllers increases. How to make reasonable arrangements for air traffic in advance to ensure safe and orderly air traffic is a problem that needs to be solved at present. Air traffic management based on 4-D trajectory prediction adds time series to make prediction of various situations appearing in the airspace species and help controllers make decisions in advance. This method is considered as the main means to reduce the controller load intensity problem. Shi et.al.[10] proposed an LSTM neural network model to link the long-term relationship with the current

prediction task for aircraft trajectory prediction, which achieved good results in both 3-D and 4-D aircraft trajectory prediction. In order to further refine the model, Shi et.al.[11] also proposed a staged prediction model, which divided the aircraft flight process into three stages: climb, cruise and descent, and proposed three constraints respectively to construct an LSTM neural network with embedded constraints. Ma et.al.[12] used a hybrid model of CNN and LSTM to extract spatiotemporal features in data, which improved the ability to learn data features to a certain extent. Considering that the historical aircraft trajectory data contains various influences such as wind speed, resistance, meteorology etc., the influence weights of various factors need to be changed according to the transformation of the flight scenes. Therefore, we propose to use attention mechanism for feature weight learning.

Attention mechanism is favored by many researchers for its intuitiveness, versatility and interpretability, and is gradually used to solve unique problems in different fields such as natural language processing, machine vision, multi-task learning, recommender systems, and graph systems. remarkable results. Galassi et.al.[13] proposed a unified attention architecture model to process text data from 4-D: input representation, distribution function, compatibility function, and input-output, and classify a large number of current works in the natural domain. Wang et.al.[14] introduced a series of attention models and RNN neural network applications in the field of machine vision, and described in detail, the experimental results show the superiority of attention-based neural networks in this field. With the continuous application of attention mechanism, many researchers have started to use it in trajectory prediction tasks in recent years. Peng et.al.[15] proposed a SRA-LSTM model in which a social encoder uses the relative between pedestrians to obtain a representation of the social relationship between them, and later uses social interaction modeling to obtain the characteristics of social relationships between pedestrians. Tang et.al.[16] proposed an attention-based long short-term memory genetic algorithm (GA-LSTM), which combined spatiotemporal correlation analysis to predict urban road traffic flow. Messaoud et.al.[17] addressed a multi-head attention mechanism considering the joint representation of static scenes and agents to address multimodal future trajectory prediction. Lin et.al.[18] proposed a spatiotemporal attention long short-term memory neural network model (STA-LSTM) for vehicle trajectory prediction, which not only performs well in prediction performance but also has interpretability to explain the influence of historical trajectories and neighboring vehicles on the target vehicle. Based on this, we propose an attention-LSTM model for aircraft 4-D trajectory prediction, which not only has the advantages of LSTM in temporal prediction, but also incorporates an attention mechanism to focus on more important feature information and improve the prediction of the model.

Model

Attention-LSTM

The airplane trajectory points are sparser and the contributing elements are more complicated than ground traffic trajectories, resulting in low trajectory prediction accuracy. 4-D trajectory data is a typical time series, and the advantages of LSTM in processing time series may be leveraged to improve data interpretation and prediction. However, the flight path of the aircraft will change with changes in temperature, air pressure, and atmospheric density in different flight environments[19][20], making a single LSTM model unable to accurately analyze the important influencing factors in the current flight state, resulting in a greatly reduced utilization of information data rate. This difficulty was satisfactorily solved by introducing the Attention mechanism. It can assign different attention to the model and improve the important factors for the model to automatically handle different situations. As a result, this research introduces a novel trajectory prediction model, the Attention-LSTM model. It makes advantage of the attention mechanism's properties to pay greater attention to important influencing elements in prediction, increase the mining of tightly correlated influencing components, and improve prediction accuracy. The model architecture is shown in Figure 1.

The model architecture proposed in this paper is separated into four modules, as indicated in the figure: data processing, prediction, attention mechanism, and fully connected layer. The data processing module is in charge of converting the original trajectory data into a format that the model can read directly; the prediction module is in charge of processing various input factors in order to obtain feature information; and the attention mechanism is in charge of learning a set of attention coefficients as well as the feature information. The fully connected layer gets the filtered feature information and analyzes it to provide the final prediction result.

LSTM

A recurrent neural network (RNN) for processing extended sequences has been suggested as a result of the continual deployment of deep learning models. Because of its benefits in sequence prediction, RNN is frequently employed. RNN, on the other hand, exhibits gradient disappearance or explosion during long-term prediction. Researchers have proposed the LSTM neural network as a solution to this problem. The LSTM is a type of neural network made up of unit cells, each of which analyzes learning sequences using a specified gating mechanism, saves sequence features, and changes the current moment based on the input sequence's characteristics. LSTM has a significant position in temporal sequence prediction and is now commonly employed in the field of trajectory prediction addition to its potential to solve the long-term dependence problem.

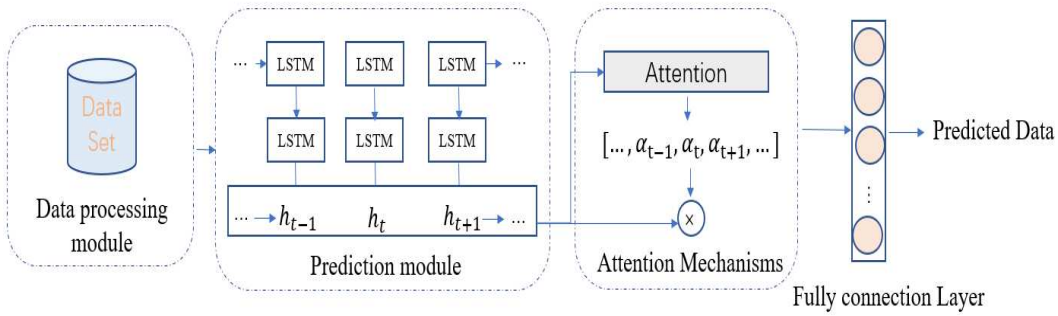

Figure 1. Attention-LSTM model

Unique to LSTM is the introduction of gating mechanisms: the input-gate, the output-gate, and the forget-gate. x_t is the input at time t, $h_(t-1)$ is the output of the hidden layer at time t-1, and h_t is the output at time t. The input-gate i_t is the input inside the cell at time t and W_i is the weight matrix. The data of i_t is the tanh of weighting and biasing the output of $h_(t-1)$ and input of x_t. After the activation function is calculated, the value of x_t is obtained.The specific calculation formula is as shown in equation (1).

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

W_o is the weight matrix of the output-gate, o_t is the output at time t, which is calculated by the tanh of weighting and biasing x_t and $h_(t-1)$,and finally update the input-gate by the activation function.The specific calculation formula is as shown in equation (2).

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o) \tag{2}$$

In the forget-gate, W_f is the weight matrix, the data of forget-gate f_t is the tanh of weighting and biasing x_t and $h_(t-1)$,and finally by the sigmoid activation function σ, the output value rangers between 0 and 1. The larger the value, the smaller the probability of being forgotten. When the value is 1, the input information x_t is completely reserved. The specific calculation formula is as shown in equation (3).

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

In the memory unit, C_t is the state of memory cell at time t. The f_t is multiplied by the $C_(t-1)$ and i_t is multiplied by $\hat{C}_t$,before the two are summed to calculate C_t. The specific calculation formula is shown in equation (4). W_C is weight matrix of the memory cell. The candidate cell state $\hat{C}_t$ is multiplied by the tanh of weighting and biasing x_t and $h_(t-1)$.And then through the activation function, the $\hat{C}_t$ is obtained. The specific calculation formula is shown in equation (5).

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \tag{4}$$

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

Finally, the output C_t of the LSTM at time t is the product of the state of the memory cell C_t after the tanh activation function and the output gate o_t at time t. The specific calculation formula is as shown in equation (6).

$$h_t = o_t * tanh(C_t) \tag{6}$$

Attention

The attention mechanism is a signal processing mechanism discovered by researchers in the study of human vision in the 1990s. It is a special structure embedded in the study of machine learning models. It is mainly used to automatically learn and calculate input data pairs. The magnitude of the impact of the output data. Adding the attention mechanism to the deep learning model is equivalent to adding the thinking process of the human brain to the model, so that more valuable information can be paid attention to when processing information, and the information that has no effect on the task will be ignored, so it can be Improve forecast accuracy. The main weight parameters in the attention mechanism are e_t, $_t$ and C_t. Where e_t is the weight score corresponding to different features at time t, the calculation formula is equation (7).

$$e_t = vtanh(W_e h_t + b_e) \tag{7}$$

Among them, v and W_e is the weight of the multilayer perceptron when calculating the attention weight, b_e is the bias of the multilayer perceptron when calculates the attention weight, and h_t is the output of the hidden layer at time t. α_t is the attention weight corresponding to different features at time t, and the calculation formula is equation (8).

$$\alpha_t = (expe_t)/(\Sigma_{j=1}^{n} e_j) \tag{8}$$

Among them, e_j is the weight scores corresponding to different features at time j. C_t is the output of the entire attention mechanism at time t, and the calculation formula is equation (9).

$$C_t = \Sigma_{j=1}^{n} \alpha_j h_j \tag{9}$$

The attention mechanism is used to adaptively calculate and adjust the hidden layer state value corresponding to the original output feature, focus on important information, and fully learn and absorb it, highlighting important factors, and further pay attention to the influence of the predicted track data, mining internal connections, Improve prediction accuracy.

Experiment

Experiments are used to illustrate the performance of the Attention-LSTM model described in this study. We applied a variety of relevant technologies before performing trajectory prediction, including data conversion, data preprocessing, and data spatiotemporal information analysis and mining. Figure 2 depicts the experimental procedure. First, we filter the experimental data and transform the original trajectory data into a model-readable format. Then, to manage the number of training sessions, input our training model and specify the loss value during the training process. The training will come to an end whenever the stated threshold has been attained. Finally, the projected and actual trajectory data are compared, the prediction error is determined, and the model performance is assessed based on the error value. The collecting of experimental data sets, assessment criteria, and the environment and characteristics employed in the studies are all part of the specific experimental task. Furthermore, by comparing the proposed model architecture to current state-of-the-art predictive models, this research was conducted to identify its superiority.

Support vector machine (SVM), back propagation (BP) neural network, and LSTM neural network were employed as comparative models in this paper to demonstrate the model's efficiency. The results of the experiments reveal that the attention-LSTM model offers clear advantages.

Data

The data for this experiment originates from Henan Air Traffic Management Bureau's ADS-B system data in Zhengzhou airspace, which was obtained in October 2020 and returned every 5 seconds. We selected 20 routes with a substantial amount of data as the experimental data after screening out more than 2 million aircraft trajectory data from 200 million pieces of data. This paper reads the airplane data from 16 radar sectors in a loop and stores this in a csv file according to various routes because the original data is json. Furthermore, the original data contains missing data, incorrect data, noisy data, and other items that cannot be directly entered into the model for training. As a result, before running the experiment, we interpolate, simplify, and look for anomalies in the data.

We utilize the sliding window approach to input data in the experiment; the window size is 10, and each time 1 timestamp is moved as the tensor of the input model. We use the longitude, latitude, altitude, speed, heading angle, and time series of the aircraft as the experimental data for the training model because of the hidden relationship between the experimental data. The specific data set acquisition process is shown in Figure 3.

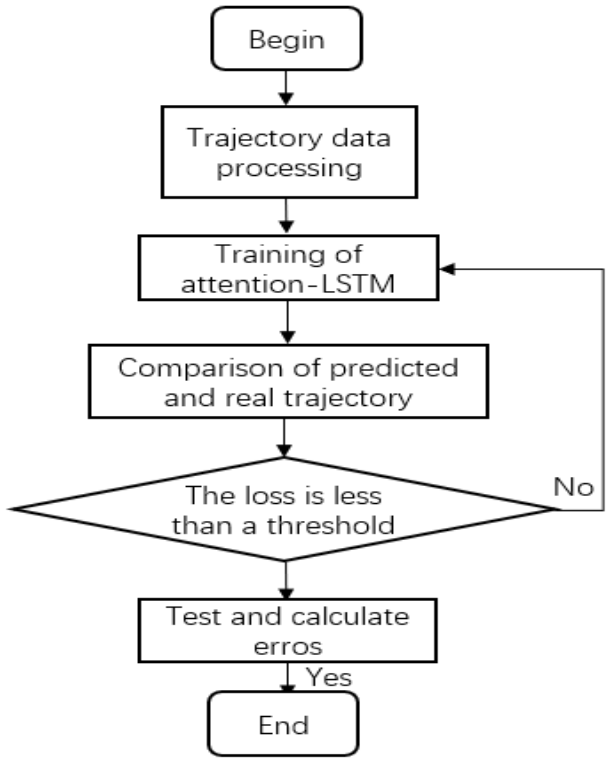

Figure 2. Flow chart of the experiment

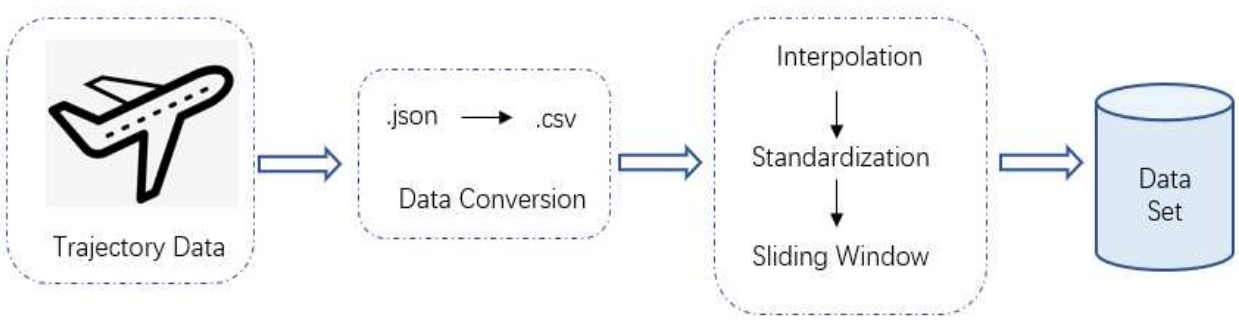

Figure 3. The acquisition of data set

Evaluation

The Euclidean distance is commonly employed to quantify the similarity between data while evaluating the performance of this approach. As a result, we employ the magnitude of three generally used error metrics in prediction, mean square error (MSE), mean absolute error (MAE), and root mean square error (RMSE), as the assessment criterion for model prediction accuracy. These three error numbers represent the differences between the anticipated aircraft trajectory point and the actual aircraft trajectory point during the actual flight. The formula for calculating error is presented below.

$$RMSE = \sqrt{((\Sigma_{d_i}^2)/n)} = \sqrt{(([(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2])/n))} \tag{10}$$

$$MAE = \Sigma_{i=1}^{n} \mid x_i - y_i \mid /n) \tag{11}$$

$$MAPE = [\Sigma_{i=1}^{n} \mid (x_i - y_i)/x_i \mid /n] \times 100\%) \tag{12}$$

where x_i is the predicted trajectory at time i, and y_i is the real trajectory at time i.

Optimizer

The experiments in this paper are all implemented in the same computer configuration (CPU: Intel(R) Core (TM) i9-9900K, memory:32GB, GPU: GeForce RTX 2080). All predictions are operated in the Python 3.7 environment, using the TensorFlow 2.1.0 GPU version as the framework.
The experimental model described in this paper is fed with the maximum and minimum standardized data. The optimizer is adam, and the learning rate lr is 0.0001. The number of training epoch is 1000. The model's parameters are described in Table 1.

	Layer	Size
1	LSTM	600
2	Dropout(rate=0.2)	-
3	LSTM	400
4	Dropout(rate=0.2)	-
5	LSTM	100
6	Dropout(rate=0.2)	-
7	LSTM	50
8	Dropout(rate=0.2)	-
9	Attention	-
10	Fully-connected	1

Table 1. Structure of LSTM.

Results

Since the original data is json, this paper reads the aircraft data of 16 radar sectors in a loop and saves it in a csv file according to different routes. In addition, there are missing data, wrong data, noise data, etc. in the original data, which cannot be directly input into the model for training. Therefore, we perform interpolation, simplification, and anomaly detection on the data before the experiment.
In this paper, we employ 70% of the experimental data as the training set and 30% as the test set under the aforementioned experimental conditions. Put the data into the attention-LSTM model after normalizing it to the maximum and minimum values. Longitude, latitude, and altitude prediction results are displayed in Figure 4(a)-(c).
The attention-LSTM model implemented in this paper has a good effect in the prediction of longitude, latitude, and altitude, and has several advantages over frequently used prediction methods, as shown by the experimental findings. However, due to the influence of multiple dimensions, there are some differences in the longitude and latitude prediction process, resulting in a poor fitting effect. On the other hand, while the predicted altitude value does not always match the actual airplane trajectory, the changing trend is consistent.
In order to more intuitively show the prediction results of the experimental model in this paper and the comparison experimental model, each model is compared the prediction data by 3-D. The results of the 3-D comparison experiment are shown in above Figure 4(d).
The proposed experimental model's error results are compared to the present state-of-the-art model, and the experimental results are provided in Table 2.

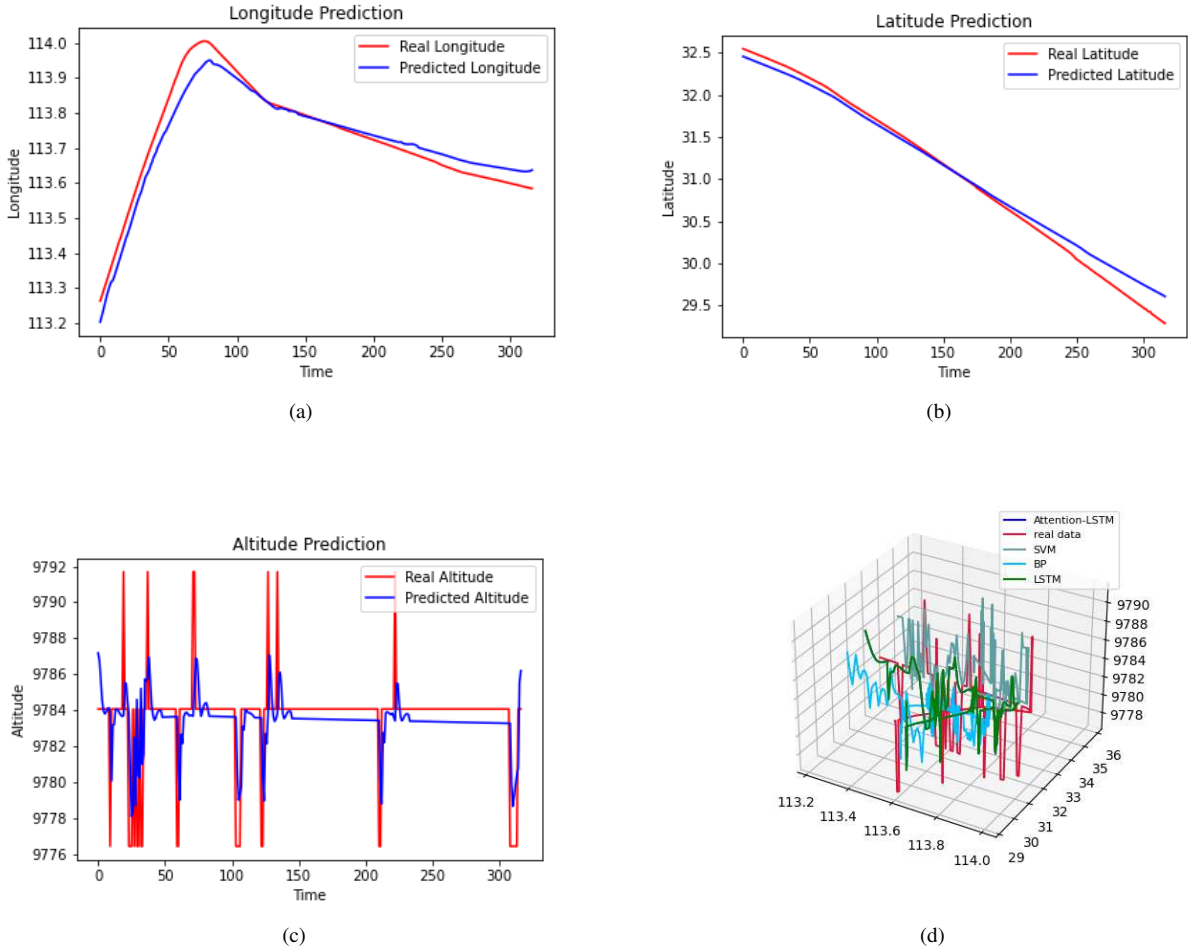

Figure 4. Prediction effect on the whole voyage with Attention-LSTM model

Models	Erro	Longitude	Latitude	Altitude
BP	RMSE	0.0663	0.9018	2.5502
	MSE	0.0044	0.8134	6.5035
	MAE	0.0607	0.7572	1.2365
SVM	RMSE	0.1355	4.021	3.4144
	MSE	0.0183	16.1752	11.6583
	MAE	0.1306	3.6250	3.0674
LSTM	RMSE	2.8443	0.7612	2.2687
	MSE	8.0904	0.5794	5.1473
	MAE	2.8440	0.7583	1.3924
Attention	RMSE	0.7709	0.9825	2.3721
	MSE	0.5943	0.9653	5.6271
	MAE	0.7574	0.8468	1.1653
Attention-LSTM	RMSE	0.0446	0.0818	2.1851
	MSE	0.0019	0.0067	4.7748
	MAE	0.0333	0.0691	1.2739

Table 2. The comparison of different models.

Table 2 shows that the attention-LSTM model developed in this paper outperforms currently popular prediction models in terms of prediction accuracy. Based on the experimental data, the BP neural network is more accurate than the LSTM neural network, but the BP neural network lags in latitude prediction during the experiment, therefore the model's prediction accuracy

has no reference value. Although overall performance is mediocre, the SVM algorithm outperforms the LSTM approach in several respects. However, in this paper, an ablation experiment was used to evaluate the model's performance, and the attention mechanism and the LSTM neural network were used to predict trajectory, respectively. This paper utilizes a combination of LSTM in time series data processing with the benefits of the attention mechanism in focusing on important influencing factors to provide more accurate 4-D trajectory prediction data.In conclusion, the prediction model proposed in this paper exceeds others.

Conclusion

In order to better analyze and process ADS-B data, improve the accuracy of 4-D aircraft trajectory prediction, and realize the operation of intelligent air traffic control as soon as possible, this paper proposes an attention-LSTM 4-D aircraft trajectory prediction model. By adding an attention mechanism, the model pays more attention to the interaction between data on the basis of LSTM prediction, integrates valuable influence information, and improves the accuracy of prediction. In addition, a series of preprocessing on the ADS-B data used in the experiment is also a necessary means to improve the prediction accuracy in this paper. The attention-LSTM model proposed in this paper is compared with LSTM neural network, SVM and BP neural network. Under the same experimental environment, the model architecture proposed in this paper outperforms the typical algorithms and most commonly used prediction models used in the track prediction field. In the next step of research, we plan to consider more factors that affect the flight process, such as meteorology, geographic features, and the interaction between aircraft, etc., and improve our prediction model to adapt to the needs of emergencies.

Data Availability

The data that support the findings of this study are available from the Civil Aviation Administration of China Central and Southern Regional Administration but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the Civil Aviation Administration of China Central and Southern Regional Administration.

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Author contributions statement

P.J., H.C., L.Z. designed and performed the experimental work. P.J., H.C.and D.H. analyzed the data, drafted and critically revised the manuscript. All authors discussed the results and commented on the manuscript.

Additional information

To include, in this order: **Accession codes** (where applicable); **Competing interests** (mandatory statement).

The corresponding author is responsible for submitting a competing interests statement on behalf of all authors of the paper. This statement must be included in the submitted article file.