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LSTM-Based Temporal Modeling for ADS-B Trajectory Prediction: A Comparative Review of Approaches

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Abstract: ***Recent advances in artificial intelligence and big data, particularly deep learning architectures such as convolutional neural networks, have enabled new capabilities for processing complex spatiotemporal data. Automatic Dependent Surveillance–Broadcast (ADS-B) trajectory data, characterized by high-dimensional spatiotemporal features and inherent uncertainty, present significant challenges for accurate prediction. This study focuses on temporal feature modeling for trajectory prediction, systematically examining various Long Short-Term Memory (LSTM) network-based approaches. By comparing different LSTM variants and their effectiveness in capturing temporal dependencies, the paper offers insights into model selection and identifies future research directions for enhancing prediction accuracy in air traffic surveillance and management systems.***

Keywords: ADS-B trajectory; LSTM; trajectory prediction; spatiotemporal data; deep learning.

1. INTRODUCTION

Recently, China's aviation industry has entered a stage of rapid development, and convenient and fast travel has become the first choice for many passengers. Looking to the future, the number of civil flights and drones will grow rapidly, and it is expected that the total number of aircraft may double in the next decade, which will undoubtedly bring greater pressure to air traffic flow management. The next-generation air traffic control system TBO (Trajectory-Based Operations) under experiment is designed based on initial plan information, with 4D trajectory management as the core, focusing on the accurate calculation and prediction of aircraft 4D trajectories. This concept has been incorporated into the Global Air Navigation Plan (GANP) by the International Civil Aviation Organization (ICAO) and is regarded as a key element in improving air traffic management efficiency [1]. Research on 4D trajectory prediction has gradually gained popularity, with numerous studies both domestically and internationally. Literature [2] proposes a 4DT trajectory prediction model based on the BADA database, which reconstructs constraints from aspects such as flight altitude, speed, and heading angle, and optimizes the 4DT algorithm by proposing RTA.

In 2019, Ma Lan and Gao Yongsheng proposed a trajectory prediction method based on ADS-B data mining in document [3], which uses CURE clustering analysis after denoising and other processing of the original data. Dong Xinfang proposed terminal area 4D trajectory modeling and prediction based on the Gaussian mixture model in document [4]. Daeke proposed and proved in document [5] that trajectory data from Mode S radar and ADS-B can dynamically predict (DAP) aircraft downlink parameters. Yu Liu found in document [6] that the heading angle direction of the flight trajectory can be updated through real-time ADS-B trajectory data, and proposed the IMM interactive algorithm to predict the aircraft trajectory. For the prediction of time series data, deep learning methods, especially focusing on Long Short-Term Memory (LSTM) networks, are widely used because they perform well in related tasks, so current research mainly focuses on the application of LSTM networks.

With the application of emerging technologies such as ADS-B (Automatic Dependent Surveillance-Broadcast) and TBO (Trajectory-Based Operations), the air traffic management system generates massive amounts of data. Extracting the key value of this information has become an important foundation and challenge for the high-quality development of civil aviation. Currently, deep learning has shown good performance in multiple fields such as computer vision processing, natural language processing, and speech recognition. Many researchers use deep learning technology to analyze ADS-B datasets and model them to achieve trajectory prediction, which has gradually attracted attention in recent years. This paper conducts a series of in-depth discussions and analyses on trajectory prediction using the ADS-B dataset from the ADS-B data center, aiming to provide new perspectives and ideas for trajectory traffic prediction.

2. CONSTRUCTION OF ADS-B DATASET

2.1 Collection of ADS-B Data

The ADS-B data center system is an all-weather operating system with high stability and reliability, designed to provide real-time ADS-B data processing to ensure air traffic safety. The system architecture adopts a distributed design and is implemented based on the client/server model. Currently, the data that the ADS-B data center can receive mainly includes information about aircraft, which mainly involves features such as flight number, 24-bit address code, longitude and latitude, altitude, speed, and heading. These data characteristics can all be used for subsequent data prediction model calculations. In this process, the ADS-B decoding device is responsible for processing the received messages, and successfully parsed messages will be retained in the local data center in CAT021 format. The center will organize the original information multiple times and extract the data into .txt format, named with the corresponding date and saved on the server, preparing for subsequent analysis and mining of real ADS-B data. This information is stored on a dedicated server called FDP (Flight Data Processor), which records a log file every hour. The data in this log file mainly comes from aircraft information sent by ground stations in various locations, and these ADS-B related data cannot be used directly because the sent content is in .txt file format.



2.2 Data Preprocessing

As the core of data preprocessing, data cleaning is mainly used to solve data quality defects caused by factors such as system failures, human errors, or transmission errors during data collection. Its core goal is to process missing records, redundant records, and useless data through systematic technical means while maintaining the authenticity and structural integrity of the collected dataset, thereby eliminating the interference of data noise on the analysis process. To obtain comprehensive flight trajectory data for a specific flight, the initial step is to use the pandas library to convert the .txt file into CSV format, extract flight information for each date from it, then group based on the flight number, and generate a CSV file named after the flight number.

Researchers compared multiple flight paths and ultimately selected a flight trajectory with the most detailed data records. The flight data includes the complete navigation route, all important waypoints, and covers the takeoff and landing airports. This selection will provide sufficient support for subsequent neural network training and minimize performance evaluation errors caused by insufficient data. After analyzing the key data in the files, we obtained the flight path information of a certain flight. Next, we need to continue processing this dataset. First, redundant fields are deleted. Then, the two indices of date and time are integrated into a unified time index, which

can reduce redundant time data and facilitate subsequent analysis and processing. If there are a small number of missing values in the dataset, the average of the values at the previous and next moments can be used for replacement to reduce measurement errors. Next, the normalization method of linear functions is used to process the values of each column to ensure that the data is on the same scale. Finally, the flight trajectory data is divided into a training set and a test set. The first 75% of the flight data is selected as the training data for the model; the remaining 25% is used as the test set, aiming to make predictions and thereby calculate errors between different algorithms. Converting time series data into a supervised learning format, by defining the duration of the historical window, the predicted time steps, and the output dimensions, time series features can be effectively engineered. Taking an original N ×6 -dimensional dataset as an example, which includes timestamps and five features such as longitude, latitude, altitude, heading angle, and vertical speed, if the data from the first two time steps are used to predict the next time step, a sample construction method will be formed. This method uses continuous two frames of 6-dimensional data as input and the next frame of 6-dimensional data as output, thereby establishing the correlation between time series and the coupling relationship between features through the design of a rolling window. In a dataset containing multiple time series, we try to set only two observations per time step, such as considering only longitude and latitude, as shown in the figure below.

Table 1: Latitude and Longitude Dataset

Time	Latitude	Longitude
58:56.1	39.54052	116.3919
58:57.1	39.54052	116.3919
59:00.0	39.54125	116.3918
59:01.0	39.54125	116.3918
59:29.0	39.54125	116.3918
59:30.1	39.54166	116.3917
59:33.0	39.54166	116.3917
59:34.0	39.54263	116.3915
59:39.0	39.54263	116.3915
59:40.0	39.54263	116.3915
59:43.0	39.54308	116.3914
59:44.0	39.54308	116.3914

3. TRAJECTORY PREDICTION METHODS BASED ON DIFFERENT LSTMS

The experiments in this section conduct a comparative analysis of three time series prediction models, including the basic single-layer Long Short-Term Memory network (LSTM), Bidirectional Long Short-Term Memory network (Bi-LSTM), and Long Short-Term Memory network with multiple stacked hidden layers (Stacked LSTM). By evaluating the performance of different model architectures, the differences in their predictive capabilities are analyzed.

The classic LSTM successfully mitigates the challenges faced by recurrent neural networks in handling long-distance dependencies by introducing memory cells and gating mechanisms. However, it has limitations, as it only processes time series in a unidirectional manner. Therefore, when deriving the current state, it relies solely on past information without considering the influence of future information. Hence, the Bidirectional Long Short-Term Memory network (Bi-LSTM) emerged, which integrates the relational information between the past and the future through bidirectional time series modeling, thereby enhancing the model's contextual understanding ability. The core of Bi-LSTM consists of two symmetric LSTM networks with non-interfering parameters. The forward LSTM processes the input sequence in chronological order, accumulating dependent features from history to the present, while the backward LSTM scans the sequence in reverse order to capture potential connections from the future to the present. Bi-LSTM is similar to traditional LSTM in parameter adjustment, and during backpropagation, the weights of the bidirectional networks need to be optimized synchronously.

3.1 Prediction Models Based on LSTM, Bi-LSTM, and Stacked LSTM

The single-layer LSTM model consists of four main parts, where the time step of the input layer is set to 16. Under this configuration, each sample is composed of 16 consecutive time steps, and each time step contains 6 different feature variables, forming an input data dimension of 16×6 . Secondly, an LSTM layer with 50 hidden units is used to mine dynamic features in the time series. Thirdly, a regularization layer, following the LSTM layer, adopts the

Dropout method to randomly discard 20% of neurons to prevent the model from overfitting. Fourthly, a fully connected layer, whose function is to convert the high-dimensional features output by the LSTM into a single predicted value, with the dimension set to 1 to adapt to subsequent univariate time prediction tasks. To improve the generalization ability of the model, the outputs of all hidden layers are processed by Dropout. It is worth mentioning that the LSTM layer can generate complete sequence results in the time dimension, but the final prediction only relies on the output of the last time step, which can better emphasize the close relationship between the features at the end of the sequence and the prediction target.

The Bi-directional LSTM model is a single-structure design, whose core lies in replacing traditional LSTM units with Bi-directional LSTM. This model includes an input layer, a bidirectional LSTM layer, a dropout layer, and a fully connected layer.

A stacked Long Short-Term Memory network is a composite model composed of multiple LSTM units, which we refer to as a stacked LSTM model. This model constructs its structure by alternately stacking LSTM units and fully connected layers. The structural design includes an input layer, two LSTM hidden layers, two dropout layers, and a final fully connected layer.

3.2 Design of the Prediction Task

This study will employ three types of models: LSTM, Bi-directional LSTM, and Stacked LSTM, focusing on trajectory prediction using the dataset of flight 71bf55 and conducting performance evaluation. In the data processing stage, the first three-quarters of the total data volume of the flight is allocated as the training set, and the remaining quarter is used as the test set. In the process of converting time series into a supervised learning task, a specific conversion method is adopted. The model takes data from the first 16 time steps across five dimensions—longitude, latitude, altitude, heading angle, and vertical velocity—as input, with the longitude at the 17th time step as the output target. Subsequently, the input consists of six-dimensional data from step 2 to step 17, and the corresponding output is the longitude at step 18, and so on. Through this series of cyclic operations, the entire training data is effectively converted into a clear input-output format, greatly facilitating the model's learning of underlying data patterns. Based on the above method, trajectory prediction can be regarded as a step-by-step prediction of a single variable over a short period, aiming to effectively estimate longitude. The prediction of other variables follows the same basic principle as the longitude prediction method and thus will not be elaborated on in detail here.

Here, we define (Pi) as the predicted trajectory at time (i), and (Ri) as the actual flight path at that time. Regarding the relevant metrics for evaluating model prediction performance, if the three values we focus on (RMSE, MAE, MAPE) are closer to zero, it indicates that the difference between the predicted values and the actual trajectory data is smaller. This fully demonstrates that the model used exhibits higher accuracy in predicting flight trajectories.

4. EXPERIMENTAL RESULTS AND PERFORMANCE TESTING

4.1 To clearly demonstrate the prediction ability of each model for flight paths

It is planned to simulate the first 2500 data points (approximately 500 seconds) in the test set. Each simulation graph will simultaneously display the real trajectory data and the prediction results from the three models to facilitate direct comparison of their prediction effects. In summary, by summarizing the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) of different models, the prediction effects of each model can be evaluated in depth from the perspective of errors. The predictions of different feature values are shown in the following figures:

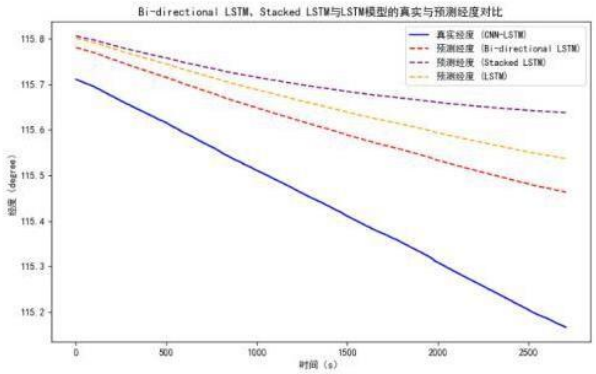


Figure 1: Longitude Prediction Result

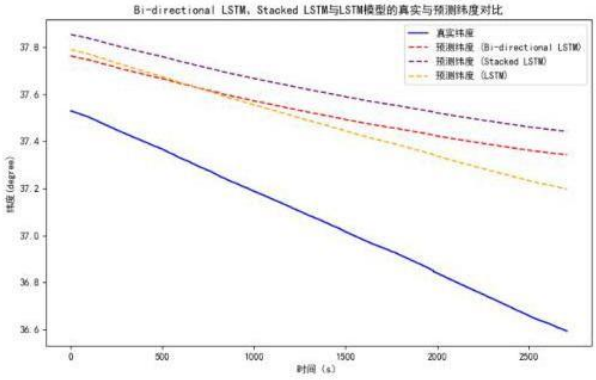


Figure 2: Latitude Prediction Result

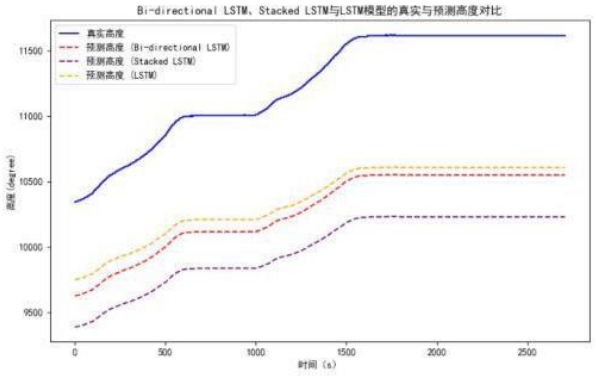


Figure 3: Altitude Prediction Result

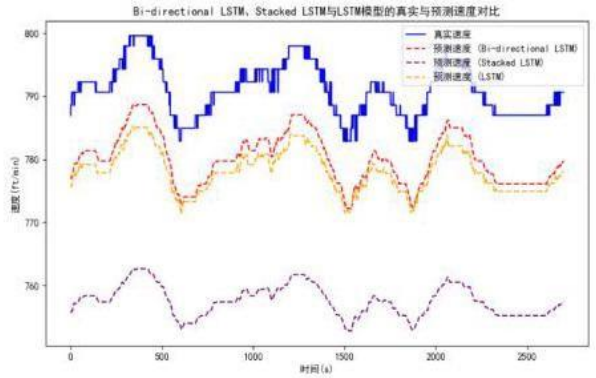


Figure 4: Speed Prediction Results

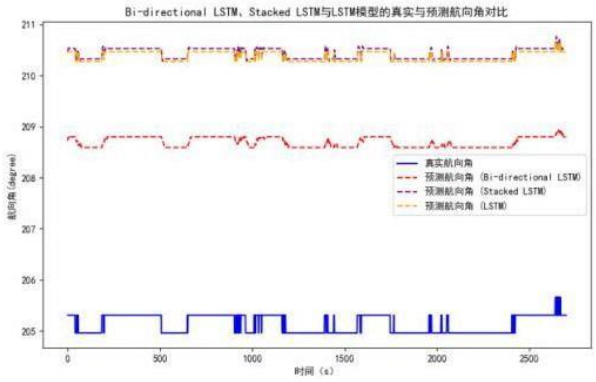


Figure 5: Heading Angle Prediction Results

4.2 Experimental Performance Analysis

Through simulation analysis of the above experimental results, the involved parameters indicate that when Long Short-Term Memory (LSTM), Bi-directional LSTM, and Stacked LSTM are applied to predict five characteristic variables, only the prediction results of the two characteristic variables (longitude and speed) have curves relatively close to the shape of the actual trajectory; while in the prediction of the three characteristic variables (latitude, altitude, and heading angle), there is a significant gap with the actual values. Although the above three models can achieve prediction functions to some extent, the overall effect is still insufficient. Subsequently, three performance indicators, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), will be calculated to further verify the results. RMSE represents the standard error, and MAE refers to the mean absolute error; both are methods to measure errors, with smaller values indicating better performance.

According to the calculation results, the three models perform best in longitude prediction and worst in heading angle prediction. In addition, the prediction capabilities of these three models for heading angle and speed are significantly inferior to their performance in predicting the other three characteristic variables. After summing and averaging the Root Mean Square Errors (RMSE) of the predictions for the five characteristic variables, it can be concluded that the average prediction error of LSTM is 144.70, that of Bi-directional LSTM is 171.25, and that of Stacked LSTM is 306.69. It can be seen that the prediction ability of LSTM is significantly better than that of Bi-directional LSTM and also better than that of Stacked LSTM. As shown in the following table:

Table 2: Prediction Errors of Three Models

Data	Bi-directional LSTM			Stacked LSTM			LSTM		
Feature	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Longitude	0.1253	0.1192	0.1033	0.2251	0.2097	0.1818	0.2508	0.2301	0.1995
Latitude	0.4699	0.4539	0.8271	0.5321	0.5209	1.4076	0.5047	0.4871	0.6169
Altitude	837.71	834.78	7.4155	1501.41	1485.43	13.1647	698.5	693.05	6.147
Speed	14.7499	14.7159	1.8601	27.0243	26.9683	3.4085	16.1974	16.1654	2.0433
Heading angle	3.2029	3.2014	1.5607	4.2657	4.2647	2.079	8.0556	8.055	3.9268

Mean Absolute Percentage Error is commonly referred to as MAPE. When the calculation result is 0%, the corresponding model can be considered perfect; conversely, if the result exceeds 100%, it indicates that the model performs poorly and may have a large deviation from the true value. Through relevant analysis, it was found that for the calculation of MAPE values for longitude and latitude, the results obtained by the LSTM and bidirectional models are both below 1. This indicates that the predictions made by these two models on these three variables are worthy of reference. However, when predicting longitude features, the results of the Stacked LSTM model appear to be more meaningful.

Overall, the three models mentioned above have a certain degree of predictive ability to some extent, but their performance still needs to be enhanced. In the prediction tasks of different features, the three models perform relatively well in predicting longitude, but there is still significant room for improvement in predicting other features.

5. CONCLUSION

Among the three LSTM prediction models compared, the LSTM model performs relatively well. Verified by specific experiments, the Stacked LSTM model constructed by simply stacking LSTMs does not improve performance; instead, it shows a decline in performance. It can be seen from this that the key to improving prediction effectiveness lies in the ingenious and detailed design of the network model. When predicting speed, among the three models, the Bidirectional LSTM demonstrates more prominent performance, and the overall prediction effect does not differ significantly from that of the LSTM model. In summary, when analyzing the prediction results of the LSTM, Bidirectional LSTM, and Stacked LSTM models, each shows its own advantages and disadvantages in terms of different feature values.

The trajectory prediction method based on ADS-B historical data mining is suitable for airspace management systems with high real-time requirements, and its predicted trajectory can provide a reference for 4D calculation. The results show that this method can predict the 4D trajectory relatively accurately and has a certain reference effect on actual flights.

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