Aircraft Surface Trajectory Prediction Method Based on LSTM with Attenuated Memory Window

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Abstract. With the rapid development of the global air transport industry, airport surface traffic is increasingly busy. The safety hazards of taxiing conflict still exist during the airport operation for the initially planned taxiing path about aircraft, which directly affects the operational safety and efficiency of the airport surface. Using the correlation and dependence between the position sequences of aircraft glide motion, a method based on Long Short Term Memory networks (LSTM) is used. Combining the change of the motion state of the surface aircraft, the attenuation memory window is introduced to improve the hidden layer structure to further enhance the prediction accuracy in the LSTM model, and it is compared and verified under different parameters. The method realizes the target of surface position prediction for the aircraft in future period, lays the foundation for aircraft surface taxiing conflict detecting, and avoids taxiing conflict.

1. Introduction
The calculation of the surface trajectory for a certain period of time becomes a key factor affecting the rationality and safety of path planning [1]. Common approaches to trajectory prediction are point mass models, probability models and machine learning models. In terms of the point mass models, reference [2] established the dynamic model of aircraft sliding by multi dimension stress analysis of the aircraft to realize the prediction of aircraft runway slide trajectory. Reference [3] introduced a nominal velocity profile on the basis of reference [2], combined with the BADA data, and established the aircraft surface taxiing trajectory prediction model. In terms of the probability models, using Monte Carlo method, track prediction is realized indirectly by estimating wind speed and airspeed [4]. Reference [5] achieved trajectory prediction by using extended Kalman Filter method to estimate UAV motion status. In terms of the machine learning models, neural networks was applied to predict an aircraft trajectory in the vertical plane, which is trained by a set of real historical trajectory [6], reference [7] train model to realize trajectory prediction by historic data and GLM (Generalized Linear Models) with a stepwise regression.

Because of the strong correlation and dependence of the position sequence of the aircraft's gliding motion, the time series method can be used to analyze and interpret the implicit relationship between the sequence values. The circulatory neural network is an important method in the field of artificial intelligence in dealing with time series problems [8]. Because of this, based on historical data, this paper uses a method of recurrent neural networks, combined with changes in the movement state of aircraft scenes, introduces attenuation memory mechanisms to improve the hidden layer structure in LSTM(Long Short Term Memory networks), and further improve the accuracy of trajectory prediction models.
2. Trajectory data preprocessing

According to the aircraft historical data set provided by Chongqing Jiangbei Airport, select historical trajectory data on a straight taxiway. Use the following formula:

\[ T'_k = k \cdot T, \quad k \in \mathbb{N}^* \]  

(1)

Where \( k \) is the sampling factor and is a positive integer. \( T \) is the period of the scene tracking radar acquisition trajectory data. The equidistant sampling obtains \( n \) track point sequences expressed as:

\[
\left[ (x_1, y_1, v_1), (x_2, y_2, v_2), \ldots, (x_n, y_n, v_n) \right]
\]  

(2)

\((x_t, y_t, v_t)\) respectively indicate the latitude, longitude and speed of the track point at time \( t \). Differences between \( t \) and \( t+1 \) entries in the trajectory sequence, ie, first-order differential processing:

\[
x'_t = x_{t+1} - x_t, \quad y'_t = y_{t+1} - y_t, \quad v'_t = v_{t+1} - v_t
\]  

(3)

Among them, \( x_t, y_t \) and \( v_t \) respectively correspond to the basic items of the difference processing. Get a new \( n-1 \) track point sequence represented by:

\[
\left[ (x'_1, y'_1, v'_1), (x'_2, y'_2, v'_2), \ldots, (x'_{n-1}, y'_{n-1}, v'_{n-1}) \right]
\]  

(4)

Use the sklearn tool in the machine learning library to scale the first-order difference track point sequence to the range \([-1,1]\) with the MinMaxScaler function and save the output parameter scaler of the function, then use the normalized data with the machine. The pandas tool in the learning library is converted to a supervised learning sequence. The operation flow is shown in Figure 1.

![Track sequence data conversion operation flow chart](image)

**Figure 1.** Track sequence data conversion operation flow chart.

\( n_{\text{vars}} \) indicates the number of input data variables, \( n_{\text{in}} \) indicates the number of input sequences, and \( n_{\text{out}} \) indicates the number of predicted sequences. It is constructed using the DataFrame() function. The data object, Shift() function, respectively constructs the input sequence data and the predictable sequence tag data, and concatenates them with the Concat() function to form the final supervised learning track point sequence data. The processed data sample format is as shown in Table 1.

**Table 1.** Supervised learning sequence data format.

| \( x_{t-2} \) | \( y_{t-3} \) | \( v_{t-3} \) | \( x_{t-2} \) | \( y_{t-2} \) | \( v_{t-2} \) | \( x_{t-1} \) | \( y_{t-1} \) | \( v_{t-1} \) | \( x_t \) | \( y_t \) | \( v_t \) | \( x_{t+1} \) | \( y_{t+1} \) | \( v_{t+1} \) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| \( x_1 \) | \( y_1 \) | \( v_1 \) | \( x_2 \) | \( y_2 \) | \( v_2 \) | \( x_3 \) | \( y_3 \) | \( v_3 \) | \( x_4 \) | \( y_4 \) | \( v_4 \) | \( x_5 \) | \( y_5 \) | \( v_5 \) |
| \( x_2 \) | \( y_2 \) | \( v_2 \) | \( x_3 \) | \( y_3 \) | \( v_3 \) | \( x_4 \) | \( y_4 \) | \( v_4 \) | \( x_5 \) | \( y_5 \) | \( v_5 \) | \( x_6 \) | \( y_6 \) | \( v_6 \) |
| \( x_3 \) | \( y_3 \) | \( v_3 \) | \( x_4 \) | \( y_4 \) | \( v_4 \) | \( x_5 \) | \( y_5 \) | \( v_5 \) | \( x_6 \) | \( y_6 \) | \( v_6 \) | \( x_7 \) | \( y_7 \) | \( v_7 \) |
| \( x_4 \) | \( y_4 \) | \( v_4 \) | \( x_5 \) | \( y_5 \) | \( v_5 \) | \( x_6 \) | \( y_6 \) | \( v_6 \) | \( x_7 \) | \( y_7 \) | \( v_7 \) | \( x_8 \) | \( y_8 \) | \( v_8 \) |
3. Construction of trajectory prediction model based on LSTM with attenuated memory window

According to the characteristics of the time series problem, the trajectory prediction at the current moment is related to the scene aircraft movement situation at the past moment. Analyze the scene movement state of the aircraft over a long period of time, according to the change of speed, can roughly be reduced to three types of movement: acceleration, deceleration and uniform movement, as shown in Figure 2. During the time period $t_1 \sim t_2$, the aircraft did speed up; during the time period $t_2 \sim t_3$, the aircraft did a uniform movement; during the time period $t_3 \sim t_4$, the aircraft did a deceleration movement. According to the memory property of the LSTM unit, when the position prediction is performed within the time period $t_2 \sim t_3$, the data stream generated during the time period $t_1 \sim t_2$ will cause an illusion of acceleration motion state disturbance at the current moment of the movement, resulting in an increase in the prediction error.

Aiming at the problem of historical memory perturbation of the current state of movement, a mechanism is needed to downplay the correlation between different state-of-motion data over time. To this end, attenuation memory mechanisms are introduced to weaken the influence of this long-period subtle influence, which helps build more accurate trajectory prediction models. Therefore, based on the construction of the LSTM-based trajectory prediction model, combined with the fluidity of the data in the model training process, the data flow in the hidden layer is weakened by the exponential decay of the memory window sliding with the training set to the current moment. The effect of movement status. Specifically, the attenuation coefficient is introduced into the hidden layer, which can be adjusted according to the characteristics of the change in the trajectory data. The value in this paper is 0.9, which is applied to the cell state element. The LSTM framework with improved hidden layer is established as shown in the Figure 3.

![Figure 2. Scene movement status changes.](image)

![Figure 3. LSTM framework with improved hidden layer.](image)
The input layer data of the predictive model framework is derived from the original trajectory sequence under different sampling periods, and is processed by first-order difference, maximum value standardization, and supervised learning sequence conversion. The dimension of the input data is M*3, including latitude, longitude, and speed. In the hidden layer, the flow of information delivered to the next moment by each LSTM unit includes two states, cell state and hidden state. In the output layer, the tag data is the position sequence and velocity normalized at the next time. Network training, and reverse propagation update weights until the loss value converges. The expression of mathematical relations is as follows:

\[ c_t = \lambda^w \prod_{i=1}^{w} c_{t-i} \]  

(5)

Where t represents the most recent data moment within the sliding window and W represents the sliding window size.

4. Model validation and result analysis

4.1. Comparison of prediction results under different activation function

Figure 4, Figure 5, and Figure 6 show the prediction models constructed using LSTM for the three activation functions, respectively, and perform better trajectory predictions for 10 trainings.

Figure 4. trajectory prediction effect with sigmoid activation function.

Figure 5. trajectory prediction effect with tanh activation function.
Figure 6. trajectory prediction effect with relu activation function.

In the three figures, the line with a star indicates the degree of deviation of the trajectory prediction. From the comparison of the three graphs, the prediction deviation under the Relu activation function is the smallest and the prediction performance is the best.

4.2. Comparison of prediction results with attenuated memory window

In order to illustrate the impact of the introduction of the fading memory window on the prediction effect, the paper sets the attenuation memory window to 0, 20, and 40 under the condition of selecting the Relu activation function. The configuration of other model parameters is consistent with Table 2.

Table 2. Verification environment configuration used by the LSTM framework

| Parameter item                  | Experimental parameters |
|---------------------------------|-------------------------|
| GPU                             | GTX1080                 |
| Deep Learning Framework         | Keras/TensorFlow        |
| Activation function             | Sigmoid/Tanh/Relu       |
| loss function                   | MSE                     |
| Optimization method             | Adam                    |
| Number of neurons               | 10/ 20/ 30/ 50/ 80/ 100 |
| Epochs                          | 50                      |
| Training Set/ Test Set          | 400/ 6                  |

Among them, Fig 6 can represent the prediction result that the attenuation memory window is 0, Fig 7 and Fig 8 show the prediction result that the attenuation memory window is 20 and 40 respectively.
Figure 7. Window size of 20.

Figure 8. Window size of 40.

From the comparison of the three graphs, it can be seen that the accuracy of the trajectory prediction model with improved attenuation memory window has been further improved, and with the expansion of the attenuation memory window, the prediction effect of the model is relatively better. In order to more clearly compare the degree of optimization of the model, the paper separately calculates the root mean square error (RMSE) and training time of the three, as shown in Table 3.

Table 3. Comparison of prediction errors with fading memory window.

| Model          | Windows number | Prediction error (RMSE) | Training time(min) |
|----------------|----------------|-------------------------|--------------------|
| LSTM           | 0              | 0.001589                | 6min               |
| Improved LSTM  | 20             | 0.000934                | 10min              |
|                | 40             | 0.000317                | 13min              |

It can be seen from the table that with the increase of the number of windows, the improved LSTM prediction model with an attenuation memory window can further enhance the accuracy of the prediction model, thus verifying the improved performance of the improved model. At the same time,
however, the computational complexity of the predictive model also increases in multiples, and the training duration increases significantly.

5. Conclusion

In the paper, firstly, the historical gliding data are sampled, first-order differential, standardized, and other preprocessing. Secondly, the surface movement state of aircraft is analyzed, and the attenuation memory window is introduced to improve the hidden layer structure, so that the trajectory prediction model based on LSTM is constructed. Finally, the model is compared and verified under different parameters. The results show that the introduction of the attenuated memory window can greatly improve the prediction effect of the prediction model and reduce the prediction error.

6. References

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