

Intelligent Attitude Control of Aircraft Based on LSTM

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Abstract. The flight attitude control is the core part of the maneuvering process in air combats. Traditional flight attitude control methods have high computational complexity, low flexibility and poor ability to learn sequential feature. This paper proposes a flight attitude control model based on long short term memory network, which utilizes its special gates structure to memorize historical information, and acquire the variation law of the attitude control variable from the time sequential data including the battlefield situation and flight parameters automatically. Moreover, the basic framework and training methods of the model are also introduced, and the influence caused by various LSTM network parameters is deeply discussed. The experiment results show that the proposed model has better prediction accuracy and convergence performance than the traditional recurrent neural network.

1. Introduction

It is extremely necessary to choose the appropriate flight attitude control model in air combat. At present, attitude intelligent control methods at home and abroad [1-4] are mostly based on the flight parameters of a single moment. Actually, the attitude change process of the aircraft has strong temporal dependence, so mining sequential feature of the aircraft attitude data is important to control the flight attitude reasonably. Deep Learning provides a new idea for aircraft flight attitude control with its excellent performance in network training, feature extraction and computational accuracy.

The common DL algorithms usually only consider the data characteristics of a single moment, while Recurrent Neural Network (RNN)[5] have good expression of dynamic behavior and sequential feature by introducing neurons with self-feedback[6], but the problem of gradient disappearance is easy to occur during training. The Long Short Term Memory (LSTM) network is one of the most effective RNN improvement models. Therefore, based on the LSTM network, an aircraft flight attitude control model is designed in this paper. By using the air combat data of multiple sequential points as the input signal, mining the sequential variation features, and predicting the value of attitude control variable at the next moment. This model is superior to other traditional algorithms in point of sequential features extraction. Finally, the effectiveness of the proposed model for flight attitude control is verified by experiments.

2. Flight attitude intelligent control framework based on sequential features

Controlling the flight attitude of the aircraft in the air combat needs to mine the flight control laws of both sides from the dynamically changing battlefield situation data, then calculate the estimated value of the attitude control variables at the next moment, and achieve the change of the flight attitude. Meanwhile, the changing of attitude is a dynamic process, which has a strong dependence on the posture of the historical moment and the situation of both sides, so considering the information of the multiple continuous historical points in the dataset is more reliable than considering only a single moment. Therefore, this paper adopts a flight attitude control model based on sequential features using LSTM network. By simulating the pilot's memory and judgment mechanism, using the information of multiple historical moments to predict the attitude control of the aircraft at the next moment, the model

can overcome the shortcomings of traditional models in the study of sequential features[7], the framework of LSTM-based attitude control model is given in Figure 1.

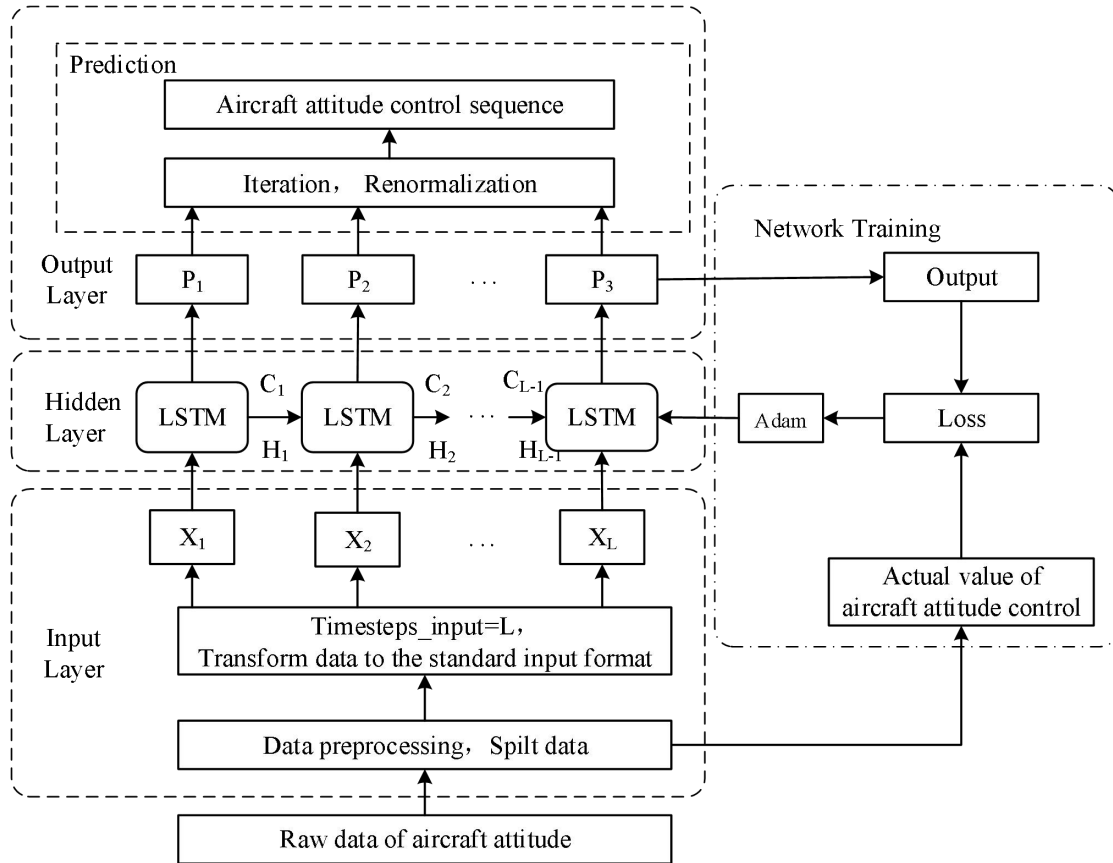


Figure 1 LSTM based fly m line attitude control model framework

3. Establishment of flight attitude intelligent control model based on LSTM

3.1. Related theory

As far as the network structure is concerned, RNN is same as the traditional neural network, but the hidden layer neurons in the RNN are interconnected, so RNN can memorize the previous information and use this information to influence the output of the following nodes. However, in practice, the problem of gradient disappearance or explosion will easily occur during training if the input sequence is too long.

LSTM network was originally proposed by Hochreiter & Schmidhuber as an improved model of RNN, its outstanding advantage is that it can learn the long-term dependence information of sequential data. LSTM replaces hidden layer neurons in RNN with gated memory cells, cells and three control gates —input gate, output gate, and forget gate can form a memory unit of LSTM, a LSTM network is composed of a group of such memory units. Figure 2 shows the structure of the LSTM memory unit with only a single cell, three gates in the figure let the information pass selectively by the Sigmoid activation function. The output of the function is a value between 0 and 1, which can describe every gate allows how much information to pass[8].

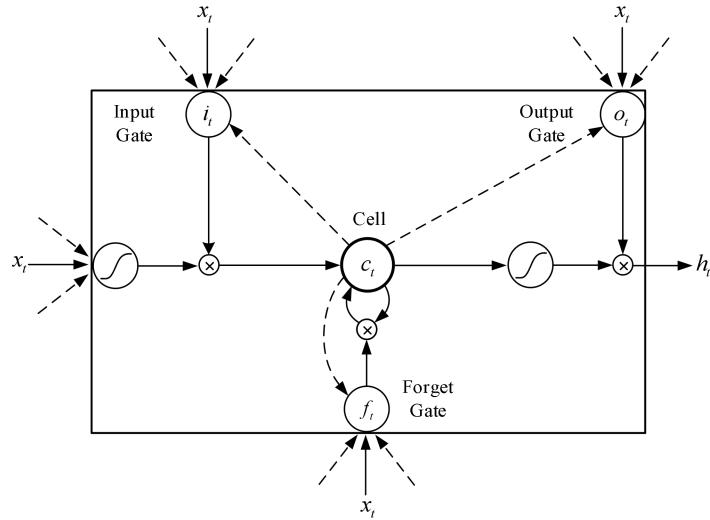


Figure 2. The structure of LSTM memory unit with single cell

3.2. Flight attitude intelligent control based LSTM

3.2.1 Time series data preparation and preprocessing. This paper sets against the backdrop of one-to-one air combat between red side and blue side, and gets data from an air combat simulation system that can simulate the pilot's real maneuver control process. The simulation time is set to 50s, the simulation step is 0.1s, and the simulation confrontation under different initial situation is carried out. Finally, data of 200 confrontations is randomly selected as the dataset of this paper. In order to ensure the comprehensiveness of the collected data, a total of 47 variables representing the state of the aircraft and battlefield situations were selected for collection. Supposing we are red side, these variables include the coordinate component and the velocity components of both sides, the acceleration components of the red aircraft, the heading angle, roll angle, pitch angle, the angle of attack, and the throttle coefficient and brake coefficient of the red aircraft, and 24 Boolean variables indicating the battlefield situation (e.g. whether the radar has target information, whether the pilot sees the target, etc.) are also included in the dataset. Therefore, every time of simulations generates 500 sample, each sample contains values of the above 47 features, 45 of which are characteristic of the state of the enemy aircraft, the other 2 features are attitude control variables of the red aircraft—the angle of attack changing rate and bank angle changing rate, they are the target features to be predicted by the model.

Moreover, to avoid the influence of the data dimension on the model's prediction accuracy, the data needs to be normalized firstly. In this paper, the data is normalized by the max-min normalization method, which can map the data values to [0,1].

3.2.2 Flight attitude control network based on LSTM. The core of the LSTM is the calculation of the input layer, hidden layer and output layer. The number of input layer nodes is equal to the number of features of the input vector, so the input layer in this paper has 46 nodes. The input layer also needs to convert the input time series data into a format of standard supervised-learning data of [Samples, Timesteps, Features], Samples represents the number of input samples; timesteps represents the time step length between the the input and the output of the model, timesteps is the key parameter of the LSTM model, the longer the timesteps, the more the number of loop layers in the model; features represents the dimension of the input sample.

The hidden layer contains several LSTM memory units. This paper selects the tanh function as the activation function for calculating the state value and output value of LSTM cells in the hidden layer.

The structure of the hidden layer is the key to affect the accuracy of the model. In this paper, the optimum structure of hidden layer is determined by several experiments with different numbers of hidden nodes and layers.

The number of output layer nodes is equal to the number of the output vector features. In this paper, the LSTM model is used to predict the two attitude control variables respectively, so the output layer has only 1 node. The output layer is also responsible for restoring the model's predictions to the original data format, ie, performing denormalization.

In the training process, this paper takes the Mean Squared Error (MSE) between the output value and the real value as the loss function L , and sets the loss minimization as the optimization target for the training process. At the same time, Xavier is used to initialize the weight of the flight attitude control network[9], and the adaptive moment estimation (Adam) algorithm[10], which can adaptively adjust the learning rate, is used as the optimization method of the loss function. The LSTM based attitude control algorithm flow is given in Table 1.

Table 1. The LSTM based attitude control algorithm flow

BEGIN
Initialize the net parameters $LSTM_{net}$;// Xavier
Set the max training time: steps;
Convert the format of input data;
Input the training data;
REPEAT
Calculate the output: $Y=LSTM_{forward}(X)$;
Calculate the loss function: $Loss = \frac{1}{T} \sum_{i=1}^T (y_i - y'_i)^2$;
Back updates the net parameters $LSTM_{net}$;//Adam
UNTIL (Satisfy termination condition) ;
Loss meets the termination condition or training times reach the maximum;
END

4. Simulation and analysis

4.1 Experimental design

4.1.1 Model property indexes. The core task of the flight attitude intelligent control model established in this paper is to predict the value of the attitude control variables at the next moment. This paper selects the MSE and the Mean Absolute Error(MAE) as a performance evaluation index for the model. The smaller the values of MSE and MAE, the better the predictive performance of the model. Meanwhile, this paper suggests that the data in the test dataset satisfying the formula(1) is considered to be predicted successfully, and it can be termed as small error points. Dividing the total number of small error points by the size of the test sample can obtain the small error Point ratio of the model.

$$\frac{|y_t - y'_t|}{|y_t|} < 5\% \quad (1)$$

The small error points ratio can directly reflect the ratio of the points predicted accurately. Therefore, the small error points ratio is used as the prediction accuracy of the model in this paper. The higher small error points ratio, the higher prediction accuracy of the model.

4.1.2 *Experimental design.* In order to verify the performance of LSTM algorithm in solving aircraft attitude control problem, this paper uses Python to design two sets of simulation experiments based on Tensorflow[11] and Keras.

- Experiment 1: Comparison of RNN and LSTM

Table 2. Initial parameters of RNN and LSTM

Values of parameters	RNN	LSTM
Hidden layer	1	1
Hidden layer nodes	100	100
Learning rate ⁷	0.01	0.01
Timesteps	80	80
Batch_size	300	300
Training times	10000	10000

Two attitude control models based on RNN and LSTM networks are constructed respectively. The specific network structure and parameters are shown in Table 2.

- Experiment 2: Comparison experiments of timesteps

The optimal network structure obtained from several experiments is used to construct multiple LSTM models with different sizes of input timesteps. The specific network structure settings are shown in Table 3.

Table 3. Parameter settings in the comparison experiments of timesteps

Hidden layer	Hidden layer nodes	Timesteps
1	100	30/50/80/100/150

4.2 Experimental results and analysis

4.2.1 *Comparison of RNN and LSTM model results.* Table 4 gives the prediction error statistics of two attitude control variables of the RNN and LSTM model. Figure 3 shows the variation of the training error with the iterations of the two models on the different attitude control variables.

Table 4. Statistical table of different models' prediction error

	Alpharate		Bankrate	
	RNN	LSTM	RNN	LSTM
MSE	0.05793	0.00923	0.07862	0.02097
MAE	0.09233	0.03513	0.12602	0.06462
Small Error Point Ratio	50.35%	86.94%	41.48%	72.48%

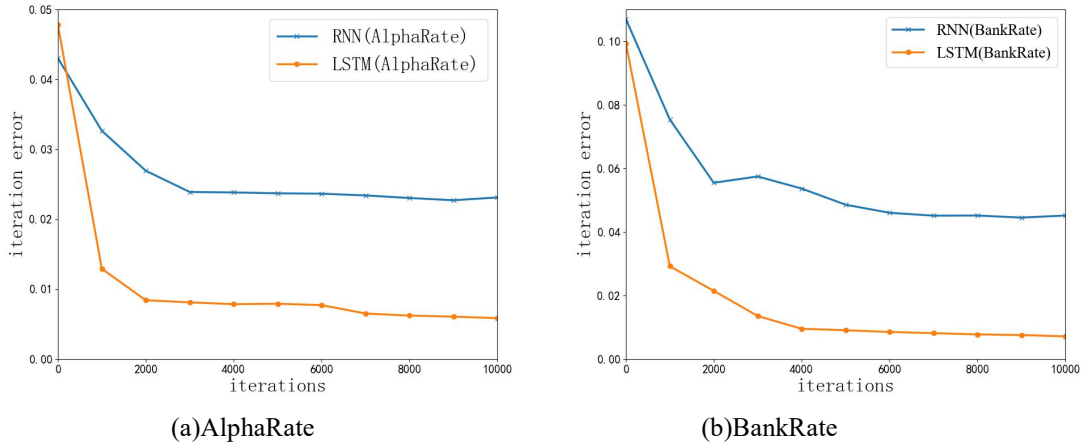


Figure 3. Training error variation chart

It can be seen that for two attitude control variables, with the same structure, the convergence speed of the LSTM model is significantly faster than the RNN model. As the training time increases, the error of the RNN model is not greatly improved. Combining the error comparison of the two models on the test dataset in table 4, it is observed that the LSTM attitude control model performs better than the RNN model, which verifies that LSTM can solve the gradient disappearance problem when RNN processes the long sequence data. Besides, it can be concluded that LSTM has higher prediction accuracy for both two attitude control variables from the small error point ratio in Table 4, which proves the feasibility of using LSTM model for attitude control.

4.2.2 The influence of timesteps on the result. Table 5,6 shows the prediction error for the LSTM models with different timesteps. It can be seen that as the input sequence length increases from 30, the prediction accuracy also increases greatly; the accuracy of the two attitude control variables reaches the highest when the timesteps is 80 and 100, respectively. It is visible that timesteps has a significant impact on the performance of the LSTM model. If the timesteps is too small, the data used for training is not enough for the model to learn the essential hidden laws in the sample, so that the accuracy is low. Increasing the timesteps reasonably can improve the prediction performance of the LSTM model, but continuously increasing timesteps can not improve the prediction accuracy sustainably, because the farther the data from the prediction period, the less influence on the prediction data. The cyclic structure of the LSTM network will be more complicated cause by the increase of the timesteps, which affects the training efficiency and accuracy of the model.

Table 5. Prediction error of AlphaRate

Timesteps	Alpharate		
	MSE	MAE	Small Error Point Ratio
30	0.02060	0.06215	68.43%
50	0.01227	0.05142	79.47%
80	0.00923	0.03513	86.94%
100	0.00969	0.03964	84.05%
150	0.00933	0.03525	86.61%

Table 6. Prediction error of BankRate

Timesteps	Bankrate		
	MSE	MAE	Small Error Point Ratio
30	0.04211	0.08154	56.28%
50	0.03451	0.07376	60.65%
80	0.02097	0.06462	72.48%
100	0.02003	0.06314	72.94%
150	0.02106	0.06627	70.10%

5. Conclusion

To the attitude control problem in one-to-one air combat, a LSTM flight attitude control model based on sequential features is established in this paper, the feasibility and accuracy of the model are verified by experiments, the influence of various factors in the LSTM model on the prediction accuracy is analyzed. The LSTM based aircraft attitude control model takes the dynamics and timing dependence of the flight attitude changing process into account, and uses the excellent feature extraction ability of the Deep Neural Network(DNN) to realize the autonomous learning of time series data and the intelligent prediction of the attitude control variables, improving the autonomy and flexibility of the flight attitude control model.

6. Acknowledgements

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7. References

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