Intelligent Flight Control of Combat Aircraft Based on Autoencoder

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ABSTRACT

The intelligent flight control of the aircraft is the key process in the air combat maneuver process. The traditional flight control method has many steps, long time and low precision, which have great drawbacks in the air combat process. In this paper, based on the background of deep learning, a flight control model based on autoencoder is proposed. Using the characteristics of autoencoder dimension reduction and feature extraction, the low-dimensional attitude parameters of high-dimensional aircraft can be extracted from high-dimensional flight attitude parameters. The eigenvalues are then automatically obtained through the neural network to change the attitude control of the aircraft. In this paper, the basic framework and training methods of the model are designed, and the influence of various parameters of the autoencoder network on the performance of the model is deeply studied. The experimental results show that the proposed model has better prediction accuracy and convergence performance than the traditional BP neural network, and achieves the purpose of intelligently and quickly obtaining flight attitude control to intelligently control aircraft flight.

CCS Concepts

• Computing methodologies → Neural networks.

Keywords

Deep learning; Autoencoder; Artificial Intelligence; Flight Control

1. INTRODUCTION

Modern combat aircraft are developing in a highly automated, informatized, integrated, and intelligent manner, and the information provided to pilots is also exploding. It is difficult for pilots to make fast and accurate operations in a short period of time. Therefore, an efficient and accurate aircraft control method is sought and used in the pilot's auxiliary decision-making to improve the effectiveness of the system's mission, survivability in combat, and reduce the pilot's workload. It is especially important.

At present, most of the methods of flight control use a certain formula to calculate the attitude parameters, and then combine the pilot's judgment on the real-time space conditions to make corresponding operations on certain flight parameters of the aircraft[1-2]. For example, the generalized adaptive genetic algorithm (GSAGA) is used to optimize the proportional, differential and integral parameters of the fuzzy PID controller. A fuzzy PID controller and parallel dual redundant automatic throttle system for civil aircraft automatic throttle control system are designed. Flight control methods based on constant throttle control with constant angle of attack and automatic retarder control based on constant speed. The fixed calculation method is still used. Only the proportional, differential and integral parameters of the controller are optimized. Although the control effect of the system is improved, the steps required are long, time-consuming, and the accuracy is not high. To intelligently control the flight of the aircraft, it is still impossible to quickly and accurately estimate the control parameters of some major aircraft attitude parameters such as throttle and speed reducer in the changing operational environment.

In order to overcome the above problems in the prior art, this paper further develops the application of deep learning and artificial intelligence in the military field[3-5], and provides a flight control method based on an autoencoder, mainly for the throttle coefficient of an aircraft. The four main flight control quantities of throttle coefficient(TC), braking coefficient(BC), angle of attack changing rate(AOACR) and bank angle changing rate(BACR) are studied, predicted, adjusted and controlled, and the intelligent control of the aircraft is deeply studied.

2. AUTOENCODER THEORY BASIS

The autoencoder is an artificial neural network that can learn the efficient representation of input data through unsupervised learning in deep learning. Autoencoders can be used as powerful feature detectors for pre-training of deep neural networks. In addition, the autoencoder can also randomly generate data similar to the training data, which is called a generative model[6].

The principle of the autoencoder is to use the training samples as both the input and output of the network, that is, to represent a mapping relationship: \( h_{\phi}(x) = x \) the input signal is a collection of original samples: \( \{x^{(1)}, x^{(2)}, ..., x^{(n)}\} \), \( x^{(m)} \in \mathbb{R}^m \). Where \( m \) is the dimension of the input signal, these samples are input from the
input layer of the network, and are mapped to the hidden layer by nonlinear excitation. This process is called coding, and the hidden layer continues to be the input of the next layer, and is nonlinear. The excitation maps to the input layer to reconstruct the input data. This process is called decoding and is similar to the cost function of the BP neural network. Since the input from the encoder is equal to the output, its cost function is:

$$J_{AE}(W,b) = \frac{1}{n} \sum_{i=1}^{n} \left| \left| h_{W,b}(x^{(i)}) - x^{(i)} \right| \right|^2 + \frac{\lambda}{2} \| W \|^2$$

(1)

Where: the first term is the reconstruction error term, the second term is the regular term, which is used to prevent overfitting, $m$ is the number of input samples, $(x^{(i)}, y^{(i)})$ is a certain set of training samples, and $W$ is the matrix formed by the weight $w$ between the nodes of the encoder, $\|O\|$ is called the norm of $O$, and $\|X\|_2$ is the 2-norm of the matrix $X = [x_1, x_2, \ldots, x_n]^T$, which is defined as:

$$\|X\|_2 = \sqrt{x_1^2 + x_2^2 + \ldots + x_n^2}$$

(2)

The flight control network based on the autoencoder is constructed, and the relationship between the data can be extracted through layer feature extraction. As a representative network in deep learning, the autoencoder[7] can perform dimensionality reduction on flight state data, feature extraction and learning from high-dimensional data, and can express high with fewer dimensions. The characteristics of dimensional data. The combination of autoencoder and deep neural network greatly reduces the input dimension of the network, makes the whole network structure have fewer parameters, enhances the feature extraction ability of the whole network, and accelerates the convergence speed of the network. In the process of high-speed flight, the results can be obtained faster, and the network for extracting the connection between the various data of the aircraft is established in an intelligent and scientific way, which greatly reduces the calculation steps in the prior art and ensures that in a very short time. The results can be quickly obtained while greatly improving the accuracy.

3. FLIGHT NETWORK MODEL BASED ON AUTOENCODER

The flight control in the air combat process is to take the aircraft attitude data in real time during the flight process. Through the mining and learning of a large number of aircraft attitude data, find the law of controlling the flight of the aircraft, and predict the specific aircraft attitude data at the next moment, and provide it to the aircraft. The driver or the aircraft thus achieves the purpose of intelligently controlling the flight of the aircraft. Therefore, this paper proposes a flight control system based on autoencoder, through the flight control system to train and learn a large number of flight state data, learn the flight attitude parameters that meet the requirements, and feed the parameters back to the driver or aircraft to provide effective flight control. The program achieves the purpose of intelligently controlling flight. This greatly reduces the pilot's flight difficulty and further enhances the intelligence of the aircraft itself.

3.1. Data collection and preprocessing

The flight state parameters of the aircraft are collected from the flight simulation system. A total of 16628 sets of data were collected in this paper. Each set of data contains 47 flight state data for each simulation step, and includes four flight control parameters: TC, BC, AOACR and BACR. Among them, the training set uses 12000 sets of data, and the test set uses 4000 sets of data.

The 47 flight status data are: simulation duration, survival probability, heading angle of the machine, roll angle, pitch angle, etc. and 24 Boolean variables. Among them, 24 Boolean variables include whether the radar has target information, whether the pilot sees the target, whether the radar sensor system has target information, whether the radar sensor system can predict the target, whether the rate is greater than the stable flight rate, and whether the tangential throttle is greater than 0. Wait.

Among the collected flight state data, since the data dimension is not uniform, it will affect the prediction accuracy of the model. Therefore, the data should be normalized first, and then the data should be cleaned and filtered. In this paper, the normalization process uses the method of min-max normalization to map the data values between $[0, 1]$.

3.2. Network Construction

The flight control network is a deep neural network model based on the autoencoder. The flight control model based on the autoencoder is shown in Figure 1. The core of the neural network algorithm is the encoding and decoding process of the autoencoder and the calculation of the fully connected layer part.

![Figure 1. Flight control network based on autoencoder](image-url)

In the neural network model, the number of input layer nodes is equal to the feature number of the input vector, and combined with the characteristics of the autoencoder, so there are 43 neurons in the input layer and output layer of the autoencoder. In this paper, the Sigmoid function is chosen as the activation function for calculating the state value and output value of the neuron in the hidden layer. The hidden layer structure of the network is the key factor affecting the accuracy of the model. In this paper, through several experiments, the number of hidden layers and the number of hidden layer nodes are changed to determine the network hidden layer structure with the optimal predicted flight control. The number of output layer nodes is equal to the number of features of the model output vector. This paper needs to predict the four flight control quantities, so the number of output layer nodes is 4.

3.3. Network Training

In the training process, the normalized flight state data is first passed to the input layer of the autoencoder, and the abstract features of the aircraft state data are obtained by the autoencoder...
compression (encoding and decoding process) characteristics, from 43-dimensional. The aircraft data extracts 20-dimensional feature data that can express all the characteristics of the data, thereby reducing the dimension of the aircraft state data. Then the 20-dimensional data is transmitted to the fully connected layer network, and the Mean Squared Error (MSE) is selected as the loss function, and the minimum loss function is set to optimize the target for network training. At the same time, the Xavier method is used to initialize the weight of the flight control network[8], and the stochastic gradient descent algorithm[9] (SGD full name stochastic gradient descent) is used as the optimization method of the loss function in the training process. The network is trained and finally output. Four types of flight control are obtained: TC, BC, AOACR and BACR. Finally, the output layer will denormalize the prediction results of the model and restore them to the original data format.

![Figure 2. Flight control algorithm flow based on autoencoder]

4. SIMULATION ANALYSIS

4.1. Experimental design

4.1.1. Model performance evaluation indicators

The flight control system established in this paper mainly predicts the four flight control quantities at the next moment based on the current flight attitude parameters. In this paper, Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are selected as the performance evaluation indicators of the model. Their mathematical formulas are as follows:

\[ MSE = \frac{1}{n} \sum_{i=1}^{n} (y - \hat{y})^2 \]  \hspace{1cm} (3)

\[ MAE = \frac{1}{n} \sum_{i=1}^{n} |y - \hat{y}| \]  \hspace{1cm} (4)

\[ MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y - \hat{y}}{y} \right| \times 100 \hspace{1cm} (5)\]

Where \( n \) is the total sample size, which is the true value of the aircraft control parameters, which is the predicted value of the

4.1.2. Experimental design

The autoencoder-based flight control system designed in this paper will use the python language based on the tensorflow framework[10] to build an autoencoder-based neural network, and train the collected flight state data. Through continuous training and adjustment of parameters, the final determination of network structure parameters is as follows.

| Network structure and parameters | Autoencoder layer | Fully connected layer |
|----------------------------------|-------------------|-----------------------|
| Hidden layer number              | 1                 | 3                     |
| Number of hidden layer nodes     | 20                | 10-8-4                |
| Learning rate                    | 0.01              | 0.01                  |
| Number of training sets          | 12000             | 12000                 |
| Number of test sets              | 6000              | 6000                  |
| Batch_size                       | 800               | 800                   |

At the same time, the traditional neural network model is designed to train the same flight state data, and the performance evaluation index is compared with the results obtained by the autoencoder-based neural network.

4.1.3. Experimental results and analysis

Table 2 gives the prediction error statistics for the four flight control quantities based on the autoencoder neural network model.

| Flight control | MSE       | MAE       | MAPE     |
|----------------|-----------|-----------|----------|
| TC             | 0.0078743 | 0.043487  | 9.8793%  |
| BC             | 0.0034301 | 0.043275  | 9.783%   |
| AOACR          | 0.0049919 | 0.043376  | 9.824%   |
| BACR           | 0.0049242 | 0.043379  | 9.822%   |
| Average value  | 0.0500514 | 0.0481784 | 0.0488693 |

![Figure 3. Training error change chart]
It can be seen from Fig. 3 and Table 2 that the neural network model based on the autoencoder model has a fast convergence rate and good convergence effect for the training of four flight control quantities. The average MSE of the four flight control quantities is as low as 0.0053051, and the average MAE is 0.0433792. The MAPE averaged 9.827%. It is obvious from Fig. 4 that the neural network model based on the autoencoder converges much earlier than the traditional BP neural network model, and reaches the convergence state value earlier. Figure 5 shows the convergence process of the four flight control quantities. It can be seen that the convergence speeds of the four flight control quantities are slightly different. AOACR and BACR start earlier than BC and TC. Convergence, but the overall speed of the four is basically the same.

Combining the error comparison between the two models on the test set, the performance of the flight control model based on the autoencoder is better than the traditional neural network model. At the same time, from the performance evaluation index values in Table 3, it can be concluded that the flight control model based on the autoencoder has higher prediction accuracy for the four attitude control quantities, which proves the feasibility of using the autoencoder-based neural network model for flight control.

5. CONCLUSION
In this paper, the flight control problem is established by using the autoencoder-based neural network. The feasibility and accuracy of the model are verified by experiments on the model. The neural network flight control model based on autoencoder greatly changes the shortcomings of traditional flight control methods, such as many steps, long time and low precision, and overcomes the high dimensional, high consumption and long-term, traditional neural network model. The defect with low accuracy uses the autoencoder to extract the eigenvalues to reduce the characteristics of the dimension, reduces the parameters of the whole network, accelerates the convergence speed of the network, and realizes the autonomous learning of the flight attitude data and the intelligent prediction of the flight control volume. Improve the autonomy, flexibility and efficiency of the flight control model.

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