Prediction of Aircraft Aerodynamic Coefficient Based on Data-Driven Method

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Abstract. To identify the aerodynamic coefficient of aircraft that cannot be directly measured in actual flight, in this paper, the problem of aerodynamic coefficient identification has been solved with the rigid body three-degree-of-freedom model using aircraft dynamics model based approaches. And based on the data-driven method to predict the aerodynamic coefficients, based on radial basis function neural network (RBFNN) with particle swarm optimization (PSO) has been used to achieve the task. Taking the external disturbance and the noise of flight data into account, a section of flight data of the XXX aircraft is preprocessed. The aerodynamic coefficients are identified based on the pre-processed flight data, and the prediction results of the aerodynamic coefficients of the above methods are analyzed, which proves the effectiveness of using the data-driven method to predict the aerodynamic coefficients.

1. Introduction

Modern civil aviation airliners mostly use Fly-By-Wire System (FBWS)[1]. In digital fly-by-wire flight control systems, control law design is one of its key core technologies. Real-time identification of the aerodynamic coefficient of the damaged aircraft is essential for the correct update of the control law to ensure the normal operation of the aircraft under certain fault conditions[2]. At the same time, the identification of airplane aerodynamic coefficients is of great significance in establishing real-time simulation models of airplanes, especially in real-time simulation models based on airplane flight data. The aerodynamic coefficients obtained by the identification of flight data are more convincing than the aerodynamic coefficients obtained by calculating aerodynamics and wind tunnel experiments. At present, there are many estimation methods of aircraft aerodynamic coefficients. Common methods are based on physical models: maximum likelihood estimation method[3], least square method[4], genetic algorithm[5], etc. The model-based method is to estimate aerodynamic coefficients based on the physical model of the aircraft. The difficulty of this method is to establish an accurate aircraft model, which is more suitable for the steady flight phase. Another method is based on data driven, such as neural network [6]. Artificial Neural Network (ANN) recognizes the aerodynamic coefficients by using the characteristics of the neural network to approach the nonlinear function infinitely, based on the measurement of the input and output of the network without considering the internal physical mechanism of the system. SINGH[7]’s neural network identification of aerodynamic coefficients based on the stability or aerodynamic derivative's Delta method and Zeros method requires more accurate aerodynamic coefficient data to be known in advance.

Aiming at the identification problem of aerodynamic coefficients of an aircraft, this paper identifies
the aerodynamic coefficients of the aircraft during flight based on flight data and the aircraft dynamics model, and based on the PSO to optimize the RBFNN method to predict aerodynamic coefficients. The article obtains the aerodynamic coefficient of the aircraft in real time by establishing a model between the aerodynamic coefficient and the flight state, and finally establishes a real-time physical simulation model of the aircraft.

2. Flight data preprocessing

The airplane is a very complicated system, and the flight environment of the airplane is not actually the ideal stable atmosphere we set, and there is unavoidable disturbance. These disturbances make the actual flight status of the aircraft not absolutely certain even when it maintains a stable trim and level flight. The test flight data collected at this time often deviates from what we expect. When external disturbances cause the data collection sensor to jump, or the sensor itself has errors, it will cause random errors in the collected test flight data. If the wrong data is injected into the aerodynamic coefficient identification database, the flight mechanics model may be unrecognizable (the identification result diverges or converges to the wrong aerodynamic coefficient identification). Therefore, it is necessary to preprocess the flight test data in order to obtain reliable aerodynamic coefficient data.

2.1. Outlier recognition, elimination and correction

During the flight test of the aircraft, due to environmental interference or accidental jumps of equipment, the sensors often collect jump values that are unusual for the aircraft, that is, the outliers. Obviously, the existence of outliers will reduce the quality of aircraft test flight data, and then affect the accuracy of aircraft aerodynamic coefficient identification. Therefore, before identifying the system, the outliers in the aerodynamic coefficient data must be eliminated. This paper uses the seven-point second-order algorithm in the forward difference method proposed in the literature [8] to identify and eliminate outliers. And through Lagrangian interpolation method to correct the outliers to ensure the integrity of the data. The compensation value of the outlier point is calculated by bringing the three normal values before and after the outlier point into the Lagrangian interpolation formula.

2.2. Low-pass filtering

During the flight data measurement process, various interferences are encountered, which contain high-frequency components. Due to the motion characteristics of the dynamic system of the rigid body, the motion frequency of the aircraft is low, usually less than 10 Hz[8]. Therefore, it is necessary to perform low-pass filtering on the flight test data. Through the frequency spectrum analysis of the flight test data, the high-frequency components are determined, and a low-pass filter is designed to filter them. This paper uses the low-pass digital filtering technique given in the literature[8] to filter out the high frequency components in the data. Use a second-order low-pass filter to filter out noise.

2.3. Smoothing filter

The flight data of an aircraft generally contains useful signals and various interference signals. The purpose of data smoothing is to extract useful signals from the actual measured data of the aircraft. This paper uses the seven-point second-order center interpolation smoothing algorithm given in [8] to perform polynomial center smoothing.

The outlier identification, elimination and correction, low-pass filtering, and smooth filtering are performed on the angle of attack signal in a certain section of flight data of the XXX aircraft, and the results are shown in Figure 1.
3. Establish aerodynamic coefficient model

According to the literature [9], the ideal rigid body kinematics equation of the aircraft is established:

\[
\begin{align*}
    m \left( \frac{du}{dt} + qw - rv \right) &= A_x + G_x + T_x \\
    m \left( \frac{dv}{dt} + ru - pw \right) &= A_y + G_y \\
    m \left( \frac{dw}{dt} + pv - qu \right) &= A_z + G_z + T_z \\
    u &= V \cos \alpha \cos \beta \\
    v &= V \sin \beta \\
    w &= V \sin \alpha \cos \beta
\end{align*}
\]

In the formula: \( u, V, w, P, q, r \) represents the speed and angular velocity of each axis of the aircraft in the aircraft system. \( A_x, A_y, A_z, G_x, G_y, G_z, T_x, T_y \) represents the components of aerodynamic force, gravity, and engine thrust on each axis of the engine system. \( V, \alpha, \beta \) represents the true airspeed, angle of attack and sideslip angle of the aircraft in the airflow coordinate system. In the airflow coordinate system, the aerodynamic forces received by the aircraft during actual flight include lift, drag and lateral force, and the corresponding lift coefficient \( C_L \), drag coefficient \( C_D \) and lateral force coefficient \( C_Y \) [9].

According to the coordinate conversion matrix, the aerodynamic force and gravity in the machine system are obtained, as in formulas (3) and (4).

\[
\begin{align*}
    A_x &= -D \cos \alpha \cos \beta - C \cos \alpha \sin \beta + L \sin \alpha \\
    A_y &= -D \sin \beta + C \cos \beta \\
    A_z &= -D \sin \alpha \cos \beta - C \sin \alpha \sin \beta - L \cos \alpha
\end{align*}
\]
\[
\begin{align*}
G_x &= -mg \sin \theta \\
G_y &= mg \sin \phi \cos \theta \\
G_z &= mg \cos \phi \cos \theta
\end{align*}
\] (4)

Where: \( \phi, \theta \) is the Euler angle between the body coordinate system and the inertial coordinate system.

Establish the aerodynamic model of the aircraft according to the literature [9]:
\[
\begin{align*}
L &= f(Ma, \alpha, \bar{\alpha}, dEL, dER, iT) = q_e C_l \\
D &= g(Ma, \alpha, \bar{\alpha}, dEL, dER) = q_e C_d \\
C &= h(Ma, \beta, p, \tau, dAL, dAR, dR) = q_e C_e
\end{align*}
\] (5)

Where: \( p = \frac{qb}{2V}, \bar{\alpha} = \frac{qc}{2V}, \tau = \frac{rb}{2V}, \bar{\alpha} = \frac{\alpha c}{2V} \) (\( b \) : wingspan, \( c \) : average aerodynamic chord length, \( \bar{\alpha} \) : rate of change of angle of attack), \( q_e = 0.5 \rho V^2 \) (dynamic pressure) \( dEL, dER, dAL, dAR, dR, iT, Ma \) are the position of the left and right elevator, the position of the left and right aileron, the position of the rudder, the position of the horizontal stabilizer and the Mach.

Establish engine thrust model based on static test and flight correction. Obtain the nonlinear relationship between engine thrust and Mach, air pressure altitude, engine speed and total air temperature, as shown in equation (6).
\[
T = d(Ma, H, N, T_{er})
\] (6)

Where, \( H, N, T_{er} \) respectively represent the air pressure altitude, engine speed and total air temperature during the flight of the aircraft. The relationship between engine thrust and flight status data is fitted by neural network. According to the installation angle between the engine and the aircraft body axis, the components of the engine thrust on each axis of the aircraft system are calculated.

Based on the preprocessed flight test data, combined with equations (1)-(6), the aerodynamic coefficients of the XXX aircraft are identified, and a nonlinear model between the flight state of the aircraft and the aerodynamic coefficients is established. The aerodynamic coefficient identification results are shown in Figure 2. The drag coefficient increases with the increase of the angle of attack; the lateral force coefficient is related to the aircraft yaw angle rate, the yaw angle rate increases, and the lateral force coefficient increases; the lift coefficient increases with the angle of attack increases.

![Figure 2. Aerodynamic coefficient identification result](image)

4. PSO optimization RBFNN

RBFNN[10] can approximate the nonlinear function very well, but the selected network size is different and it is easy to cause the result to fall into the local optimal solution. Particle swarm algorithm
is a calculation method that optimizes the problem by iteratively improving candidate solutions for a given optimization range. Literature [11] proposed an estimation algorithm based on PSO and RBFNN. This method can effectively estimate the network output value, but changing the network size will make the output result unstable. Literature [12] proposed a high-dimensional particle swarm optimization algorithm (HDPSO) based on RBFNN and a "size-transfer" strategy to select and adjust the network size of RBFNN, named HDPSO-STRBF. When using PSO to optimize the center of the radial basis function in RBFNN, the number of parameters to be optimized is very large. It is difficult for traditional PSO to obtain satisfactory results. In HDPSO-STRBF, the velocity and position of particles will be partially updated. Help solve high-dimensional optimization problems. Through the proposed "size-transfer" strategy, the network scale of RBFNN can be adjusted and selected as needed. This paper is based on the HDPSO-STRBF prediction aerodynamic coefficients proposed in the literature [12].

5. Algorithm verification and result analysis

This paper uses HDPSO-STRBF algorithm to predict aerodynamic coefficients. Use Root Mean Squared Error (RMSE) to measure the estimation accuracy of the algorithm, namely

\[ E = \frac{1}{M} \sum_{j=1}^{M} (y_j - \hat{y}_j)^2 \]  

(7)

In addition, the Maximum Relative Deviation (MRD) and Maximum Absolute Deviation (MAD) are used as evaluation criteria, as shown in formulas (8)-(11):

\[ AD_j = \text{actual}_j - \text{estimated}_j \]  

(8)

\[ RD_j = \text{abs}(\frac{\text{actual}_j - \text{estimated}_j}{\text{actual}_j}) \]  

(9)

\[ MRD = \max(RD_j) \]  

(10)

MRD = \max(abs(AD_j))

In the formula: \( j = 1, 2, \cdots, M \) is the number of estimated samples, \( \text{actual}_j \) and \( \text{estimated}_j \) respectively represent the true value and estimated value of sample \( j \), \( AD_j \) and \( RD_j \) are the absolute error and relative error of the estimated sample, MRD and MAD represent the maximum relative error and maximum absolute error in the estimated sample. HDPSO-STRBF predicts aerodynamic coefficient, and the configured parameters are shown in Table 1.

| Table 1. HDPSO-STRBF Algorithm parameter configuration |
|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| Lift coefficient \( C_L \) | \( c_1 \) | \( c_2 \) | \( c_3 \) | \( w_{\text{max}} \) | \( w_{\text{min}} \) | \( x_{\text{max}} \) | \( x_{\text{min}} \) | \( T \) | \( \text{iter} \) | \( \beta \) |
| \( \alpha \) | 1.35 | 1.35 | 0.3 | 0.80 | 0.30 | 0.9 | 0.1 | 15 | 150 | -1.5 |
| \( \delta_{\text{max}} \) | 5e-4 | 18 | 30 | 1.2 | 0.6 | 0.25 | -0.2 | 30 | 60 |

| Drag coefficient \( C_D \) | \( c_1 \) | \( c_2 \) | \( c_3 \) | \( w_{\text{max}} \) | \( w_{\text{min}} \) | \( x_{\text{max}} \) | \( x_{\text{min}} \) | \( T \) | \( \text{iter} \) | \( \beta \) |
| \( \alpha \) | 1.40 | 1.40 | 0.3 | 0.85 | 0.35 | 1 | 0 | 15 | 150 | -1.5 |
| \( \delta_{\text{max}} \) | 5e-6 | 18 | 30 | 1.2 | 0.7 | 0.3 | -0.3 | 30 | 60 |

| Lateral force coefficient \( C_C \) | \( c_1 \) | \( c_2 \) | \( c_3 \) | \( w_{\text{max}} \) | \( w_{\text{min}} \) | \( x_{\text{max}} \) | \( x_{\text{min}} \) | \( T \) | \( \text{iter} \) | \( \beta \) |
| \( \alpha \) | 1.30 | 1.30 | 0.3 | 0.80 | 0.20 | 1 | 0.1 | 15 | 150 | -1.5 |
| \( \delta_{\text{max}} \) | 5e-3 | 18 | 30 | 1.2 | 0.6 | 0.25 | -0.2 | 30 | 60 |

In this test, two thousand five hundred test flight data samples of XXX aircraft are selected. Before using the HDPSO-STRBF algorithm to train the network, the test data is randomly divided into a training set and a test set, where the training set accounts for 85% of the total number of samples, and the test set accounts for 15% of the total number of samples. Use the parameter configuration in Table 1 to predict the aerodynamic coefficient, record the relative error in the prediction accuracy of the test set.
data, and the results obtained by performing 20 tests are shown in Table 2.

In Table 2, Min represents the minimum value of the relative error in the test data, Max represents the maximum value of the relative error in the test data, Mean represents the average value of the relative error of the 20 trials, and Std. represents the standard deviation of the relative error of the 20 trials. It can be seen from the table: 2) The standard deviation of the relative error in the aerodynamic coefficient prediction is small, indicating that the algorithm has good stability; 2) The maximum relative error and the maximum absolute error of the lift coefficient prediction are the smallest, indicating that the lift coefficient and there is a good non-linear relationship between the input variables; 3) The maximum relative error and the maximum absolute error of the lateral force coefficient prediction are the largest, indicating that the flight environment has a greater impact on the lateral force.

| MRD          |  |  |  |  |  |  |  |  |
|--------------|---|---|---|---|---|---|---|---|
| Lift coefficient | Min | Max | Mean | Std. | 2.6e-3 | 4.1e-3 | 3e-3 | 7e-4 |
| Drag coefficient | 0.009 | 0.045 | 0.023 | 0.018 | 4e-4 | 1.2e-3 | 9e-4 | 4e-4 |
| Lateral force coefficient | 0.019 | 0.050 | 0.025 | 0.019 | 3.6e-3 | 5.3e-3 | 4e-3 | 8e-4 |

During a certain experiment, set the neuron set $B=[40, 70]$ (L=40, U=70), and the prediction results of the resistance coefficient, lateral force coefficient and lift coefficient of the test set data are shown in Figure 3, Figure 4 and Figure 5.

In Figure 3, the maximum relative error is about 0.04, and the maximum absolute error is about ±0.001. The drag coefficient prediction accuracy is high. In this flight environment, HDPSO-STRBF can establish the aircraft drag coefficient model well.

In Figure 4, the maximum relative error is about 0.05, and the maximum absolute error is about ±0.005. The lateral force coefficient prediction accuracy is high. In this flight environment, HDPSO-STRBF can establish the aircraft lateral force coefficient model well.

In Figure 5, the maximum relative error is about 0.01, and the maximum absolute error is about
±0.004. The lift coefficient has high fitting accuracy. In this flight environment, HDPSO-STRBF can establish the lift coefficient model of the aircraft very well.

6. Conclusion
The article constructs the aircraft motion model based on the aircraft kinematics equations, and identifies the aircraft aerodynamic coefficients based on the flight test data. Among them, in order to obtain more accurate aerodynamic coefficients, the article preprocesses the flight data. A new algorithm based on PSO and RBFNN is adopted to estimate the aerodynamic coefficients. A strategy named “size-transferring” is developed to select and adjust the network size of the RBFNN. Besides, to solve the high-dimensional optimization problem during the estimation, a new approach based on the PSO algorithm is also adopted. Experimental results show that the algorithm can predict aerodynamic coefficients well and establish a real-time nonlinear model between flight status and aerodynamic coefficients.

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