Study on Aerodynamic Parameter Estimation Method Based on Wavelet Neural Network and Modified PSO Algorithm

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Abstract. This paper puts forward an aerodynamic parameter estimation method which combines the Wavelet Neural Network(WNN) with Modified Particle Swarm Optimization(MPSO) technique. This method directly and accurately constructs the relationship among flight parameters and aircraft aerodynamic parameters. Preliminary aerodynamic parameters and derivatives are derived from wind tunnel data. With strong nonlinear mapping ability, WNN is used to construct the relationship among Mach number, angle of attack, and rudder with longitudinal aerodynamic parameters. Then, the MPSO is used to estimate aerodynamic parameters based on the test-flight data. And WNN is retrained to amend the relationship among Mach number, angle of attack, and rudder with longitudinal aerodynamic parameters. Simulation verification indicates that MPSO has better estimation accuracy than Maximum Likelihood(ML) method. Comparison results of simulation experiments and flight-test data of a tactical missile show that simulated data based on estimated parameters matches with the flight-test data, which prove the effectiveness and validity of the trained WNN.

1. Introduction
A valid aerodynamic model and an accurate estimation of aircraft parameters are crucial for designing high performance control systems. Several conventional methods such as Maximum Likelihood method have been applied on parameters estimation, which are prone to being effective. Even though, these methods also have their disadvantages and limitations. For example, a given model postulation is required in the methods.

In recent years, Artificial neural networks(ANNs) have been used in variety of applications. Some scientists identify aerodynamic parameters based on ANNs. There are three main kinds of methods as follows: Delta and Zero Method[1], Neural Partial Differential (NPD) method[3,4], conventional estimation algorithm combined with neural network [2,5]. Moreover, the Feed-Forward Neural Networks[2,3,4,5] has been used the most widely, such as Back Propagation NN[6], Radical Basis Function NN[7].

Despite so many studies, obtaining time-varying aircraft parameters is still a problem. This paper aims to overcome the difficulties with WNN and MPSO. With strong nonlinear mapping ability, WNN is used to construct the relationship among Mach number, angle of attack, and rudder with longitudinal aerodynamic parameters. Then, the MPSO is used to estimate aerodynamic parameters based on the test-flight data. And WNN is retrained to amend the relationship among Mach number, angle of attack, and rudder with longitudinal aerodynamic parameters.
This paper is organized as follows: Section 1 is an introduction to the development of aircraft parameter estimation. Section 2 describes the process of aerodynamic parameter modelling. Section 3 and section 4 introduce the Wavelet Neural Network and modified Particle Swarm Optimization algorithm, respectively. In section 5, simulation results are presented, including training of WNN and estimation of aerodynamic parameters. Finally, section 6 concludes the paper.

2. Aerodynamic Mathematical Modeling and Parameter Identification Process
The aerodynamic model used to describe the aerodynamic characteristics of the axisymmetric aircraft is as follows:

\[
\begin{align*}
C_x &= C_{x0} + C_{x\alpha} \alpha + C_{x\delta} \delta_z \\
C_y &= C_{y\alpha} \alpha + C_{y\delta} \delta_z \\
C_M &= M_{\alpha\alpha} \alpha + M_{\alpha\delta} \delta_z \\
\end{align*}
\]

The aim of the paper is to estimate unknown parameter vector consisting of aerodynamic parameters namely, \([C_{x0}, C_{x\alpha}, C_{x\delta}, C_{y\alpha}, C_{y\delta}, M_{\alpha\alpha}, M_{\alpha\delta}]\) as given in equation (1).

The process of the aircraft parameter estimation contains three steps:
1. Aerodynamic parameters are obtained from wind tunnel data, and the relationship is built among Mach number, angle of attack, rudder and longitudinal aerodynamic parameters using NN;
2. Aerodynamic parameters are modified with MPSO technique using the test-flight data;
3. The relationship is rebuilt among Mach number, angle of attack, rudder and modified aerodynamic parameters by retraining NN.

3. Wavelet Neural Network
For the excellent capability of wavelet transform, wavelet neural networks have been applied widely in nonlinear signal representation and modelling. There are mainly two types of WNN structures. One is the combination of wavelet transform and NN, the other is the combination of wavelet function and NN. The latter is employed in most studies, which has the same structure with basic feed forward NN.

In the design of WNN, a main problem is determination of hidden layer node number and node excitation function. The model of the network is as follows:

\[
y_k(x) = \sum_{j=1}^{J} w_{kj} \varphi(\frac{X_j - b_j}{a_j}), k = 1, 2...m, j = 1, 2,...J
\]

\[
X_j = \sum_{i=1}^{J} w_{ji} x_i
\]

Where \(b_j\) denotes the translation coefficient, \(a_j\) denotes the dilation coefficient. \(y_k, x_i\) are the output and input of the WNN, respectively. \(\varphi(\cdots)\) denotes the wavelet base function of WNN.

In this paper, Morlet wavelet function will be used, the expression of which is as follows [8]:

\[
\varphi(t) = e^{-r^2/4} e^{i\omega_0 t}, w_0 = 1.75, k = 2
\]

Where \(w_0\) is the central frequency.

To train the WNN, conjugate gradient algorithm is used to obtain weights \(a_j, b_j, w_{ji}, w_{kj}\).

4. Modified Particle Swarm Optimization Algorithm
PSO algorithm is a biology-based evolutionary algorithm, which is derived from the predation behavior of birds. Similar to genetic algorithm, PSO algorithm searches the optimal solution from a
group of points based on group iterations. PSO algorithm is easy to implement, and therefore particularly suitable for engineering applications.

When solving an optimization problem, each particle remembers and follows the current optimal particle, while searching for optimal solutions in the solution space. If a better solution is found, it will be used as a basis to find the next solution. At each iteration, once individual extreme point and global extreme point, represented as \( P_i \) and \( P_g \), are found, particles update their velocity and position. The updating formulas are as follows:

\[
\begin{align*}
    v_{id}^{k+1} &= v_{id}^k + C_1 r_1 (p_{id} - x_{id}^k) + C_2 r_2 (p_{gd} - x_{id}^k) \\
    v_{id}^{k+1} &= \begin{cases} 
    v_{id}^{\text{max}}, & v_{id}^{k+1} \geq v_{id}^{\text{max}} \\
    -v_{id}^{\text{max}}, & v_{id}^{k+1} < v_{id}^{\text{max}} 
    \end{cases} \\
    x_{id}^{k+1} &= x_{id}^k + v_{id}^{k+1}
\end{align*}
\]

(4)

Where \( v_{id}^k \) and \( x_{id}^k \) are the current velocity and position of the \( d \)-th dimension for particle \( i \) in the \( k \)-th iteration. \( C_1 \) and \( C_2 \) represents learning factor.

For the aerodynamic parameter estimation with strong nonlinearity, this paper employs a modified particle swarm optimization algorithm by dynamically changing inertia weights, which has better global search capabilities. The following are the improvement formulas[9]:

\[
\begin{align*}
    w^k &= e^{-\alpha^k t^k} \\
    \alpha^k &= \frac{1}{n} \sum_{j=1}^{n} \left[ f(X_j^k) - f(X_{\text{min}}^k) \right] \\
    f(X_j^k) &= f(x_{1j}, x_{2j}, \ldots, x_{nj}) \\
    f(X_{\text{min}}^k) &= \min_{i=1, \ldots, n} f(X_i^k)
\end{align*}
\]

(5)

Where \( f(X_j^k) \) and \( f(X_{\text{min}}^k) \) is the corresponding function value of the \( i \)-th particle and the optimal particle at the \( k \)-th iteration, respectively.

5. Numerical Experiments and Examples

5.1 Initial training of Neural network based on wind tunnel data

The process aims to establish the relationship between Mach number, angle of attack, rudder and aerodynamic derivatives. Force and moment coefficients under different Mach numbers, angles of attack, and the rudder are obtained from wind tunnel data. The aerodynamic derivative is then determined by a numerical differentiation method, which would be the output of WNN. Then, all the data is normalized.

The input variables are \([M, \alpha, \delta_z]\), and \([C_x, C_y, C_{\alpha}, C_{\delta_z}, M_x, M_y]\) are output variables. The node number in the hidden layer of WNN is set to 20. The training performance index is Mean Square Error.

5.2 The longitudinal-directional aerodynamic parameter estimation based on flight data

The flight data with process noise comes from longitudinal maneuvers of an aircraft. A node represents a Mach number, an angle of attack, and a rudder. And the longitudinal maneuvers are carried out under different nodes within 0.6 seconds, in which the angle of attack and the rudder undulate to excite the motion mode of the aircraft. To achieve this goal, the input of the rudders is all
designed to satisfy the above requirements. Then the MPSO algorithm is employed to estimate the aerodynamic parameters, where the parameters of the algorithm are set as follows:

Particle swarm size: \( n = 50 \), search space dimension: \( D = 7 \), learning factor: \( C_1 = C_2 = 2.75 \), the maximum number of iterations is set to \( N = 1000 \). The iteration ends when reaching the maximum number of iterations.

Identification results of two sets of different flight parameters are shown in the table 1. Compared with the maximum likelihood algorithm, the identification result of the MPSO algorithm is closer to the true value.

Table 1. Comparison results of aerodynamic parameters estimation between ML and MPSO method

|       | ML       | MPSO     | True value | ML       | MPSO     | True value |
|-------|----------|----------|------------|----------|----------|------------|
|       | \( Ma = 0.8, \alpha = 4, \delta = -5 \)     |          |            | \( Ma = 0.5, \alpha = 10, \delta = -5 \) |
| \( x_0 \) | 0.8114   | 0.8228   | 0.8231     | -0.3134  | -0.3886  | -0.4157    |
| \( x_\alpha \) | -0.0105  | -0.0115  | -0.0123    | -0.0782  | -0.0770  | -0.0756    |
| \( x_\delta \) | 0.0204   | 0.0132   | 0.0163     | 0.0056   | -0.0035  | -0.0092    |
| \( y_\alpha \) | 0.3293   | 0.3291   | 0.3290     | 0.3628   | 0.3643   | 0.3644     |
| \( y_\delta \) | 0.0832   | 0.0831   | 0.0831     | 0.0938   | 0.0940   | 0.0940     |
| \( M_\alpha \) | -0.0209  | -0.0240  | -0.0241    | -0.0341  | -0.0326  | -0.0338    |
| \( M_\delta \) | -0.0369  | -0.0376  | -0.0399    | -0.0427  | -0.0421  | -0.0423    |

5.3 Training of WNN for modified aerodynamic parameters

In section 4.1, the relationship among Mach number, angle of attack, rudder and longitudinal aerodynamic parameters is established. However, aerodynamic parameters from the wind tunnel data cannot accurately reflect the aerodynamic characteristics of the aircraft. Then, in section 4.2, the corresponding aerodynamic parameters are modified by test flight data. Hence, in this part, the parameters of WNN will be modified.

As is known to all, the aerodynamic parameters of the aircraft during the actual flight are continuously varied. A well-trained neural network has such ability: without complex numerical operations, the corresponding aerodynamic derivatives obtained when the value of any set of Mach number, angle of attack, and rudder is entered.

To validate the effectiveness of the trained WNN, a simulation experiment with a duration of 3.6 seconds is carried out, where aerodynamic parameters change once every 0.1 seconds. And the comparison results with the corresponding real flight test trajectory are shown in figure 1 and figure 2. The results show that the trained NN can effectively and accurately estimate aerodynamic parameters.
6. Conclusion

An aerodynamic parameter estimation method combining WNN with MPSO technique is raised in this paper. The proposed method is verified by the aerodynamic modelling examples based on wind tunnel data and test-flight data. Simulation results manifest that the parameter estimation accuracy of MPSO method exceeds that of the ML method. From the results of simulation experiments and flight-test data, the simulated data based on estimated parameters matches well with the flight-test data. It is proved that the proposed method is effective for aerodynamic parameters estimation and the trained WNN is useful to obtain the time-varying aerodynamic parameters.

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