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Progressive identification of lateral nonlinear unsteady aerodynamics from wind tunnel test data

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Dear editor,
Modern aircrafts have been increasingly demanded to extend the flight envelop to high incidences. The super maneuverability at post-stall angles of attack has become the dominated design goal for advanced combat aircrafts. In this case, the aerodynamic response will present strong nonlinearity and unsteadiness. The conventional aerodynamic derivative model could not be applicable any more. The modeling and identification of nonlinear unsteady aerodynamics has become a realistic challenge and the accurate modeling is of great value for aircraft control law design and flight simulation. There are mainly four models for unsteady aerodynamics: indicial response [1, 2], state-space [3], differential equation [4, 5], and artificial intelligence [6, 7].

In this study, a small-scale model of advanced combat aircraft is investigated on its modeling and identification of lateral nonlinear unsteady aerodynamics. We first apply Harmonic analysis [1] to recognize the degree of nonlinearity and unsteadiness of aerodynamic responses. Then, a simpler model is modified from [5] to describe lateral nonlinear unsteady aerodynamics by using a first-order differential equation with characteristic time constant and high order polynomials. Finally, we propose an improved optimization algorithm to identify unknown model parameters, which combines the Gauss-Newton (GN) and Quasi-Newton methods for the maximum likelihood estimator.

Wind tunnel tests and harmonic analysis. Static tests and large amplitude yawing harmonic oscillation tests were conducted in a 3.5 m × 2.5 m, low speed wind tunnel called FL-8 at AVIC Aerodynamics Research Institute. Static tests were designed at a wide range of nominal pitching angles θ from 0° to 80°. In every fixed θ, a set of static tests were conducted every four degrees of the varying nominal yawing angle ψ from −40° to 40°. In the same θ, yawing harmonic forced oscillation tests were performed with an initial yawing angle $\psi_0 = 0°$, large amplitude $\psi_A = 30°$ and four different oscillation frequencies $f = \{0.2\ \text{Hz}, 0.4\ \text{Hz}, 0.6\ \text{Hz}, 1.0\ \text{Hz}\}$. The nominal yawing angle has the form $\psi = \psi_A \sin(wt)$ where $w = 2\pi f$.

Before aerodynamic modeling, harmonic analysis is used to help understand the characteristics of aerodynamic responses. Compared with [1], the static response here is removed from the aerodynamics in advance to simplify the analysis. The result shows that the aerodynamic response can be divided into four regions, which are the linear steady case ($0° < \theta < 20°$), the nonlinear unsteady case ($25° < \theta < 45°$), the linear unsteady case ($50° < \theta < 60°$) and the linear steady case ($70° < \theta < 80°$). This study focuses on the nonlinear unsteady case which is the most complicated.

Lateral nonlinear unsteady modeling. Considering a fixed pitching angle and all zero control surface deflections in wind tunnel tests, a simplified

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model can be constructed according to the differential equation model for longitudinal motion in [5] and modified for lateral aerodynamics. The model can be formulated as

$$C_a = C_{a_{\rm att}}(\beta) + \tilde{C}_{a_r}(\beta)\frac{rb}{2V} + C_{a_{\rm dyn}}(t), \quad (1)$$

where $C_{a_{\rm att}}(\beta)$ is the term associated with the attached flow, $\tilde{C}_{a_r}(\beta)$ represents the term combining the dependencies on yawing angular velocity r and derivative of sideslip angle $\dot{\beta}$, and $C_{a_{\rm dyn}}(t)$ describes the unsteady response which is related to the time history. In this study, a first-order differential equation with a characteristic time constant is used to represent this dynamic process in time lag and it can be expressed as

$$\tau\frac{{\rm d}C_{a_{\rm dyn}}}{{\rm d}t} + C_{a_{\rm dyn}} = \tilde{C}_{a_{\rm dyn}}, \quad (2)$$

where τ is the characteristic time constant varied according to different pitching angles. $\tilde{C}_{a_{\rm dyn}}$ stands for the steady value of $C_{a_{\rm dyn}}$ when the unsteady adjustment is finished. Considering a static case where $\frac{{\rm d}C_{a_{\rm dyn}}}{{\rm d}t} = 0$ and $r = 0$, we can obtain the expression of static aerodynamic response by substituting them into (1) and (2) as follows:

$$C_{a_{\rm st}} = C_{a_{\rm att}}(\beta) + \tilde{C}_{a_{\rm dyn}}. \quad (3)$$

As $C_{a_{\rm st}}$ can be solved from static tests directly, the right side of (2) can be replaced by $C_{a_{\rm st}} - C_{a_{\rm att}}(\beta)$, which can avoid the identification of $\tilde{C}_{a_{\rm dyn}}$.

To capture the nonlinearities in aerodynamic responses, the terms $C_{a_{\rm att}}(\beta)$ and $\tilde{C}_{a_r}(\beta)$ in (1) can be assumed to have nonlinear dependencies on the sideslip angle. High order polynomials are appropriate to characterize these two terms and third-order is adequate as follows:

$$C_{a_{\rm att}}(\beta) = a_0 + a_1\beta + a_2\beta^2 + a_3\beta^3, \quad (4)$$

$$\tilde{C}_{a_r}(\beta) = b_0 + b_1\beta + b_2\beta^2 + b_3\beta^3, \quad (5)$$

where a_j, b_j $(j = 0, 1, 2, 3)$ are the unknown parameters along with the characteristic time constant τ to be estimated.

Only three terms $C_{a_{\rm att}}(\beta)$, $\tilde{C}_{a_r}(\beta)$ and τ need to be identified with just nine unknown parameters, which has a considerable small amount of calculation. Besides, a clear physical explanation can be given by the characteristic time constant in this model to measure the unsteady flow adjustment process in time lag. For yawing forced oscillation tests in wind tunnel, the characteristic time constant only depends on the pitching angle.

Model parameters estimation. The maximum likelihood method [4] is applicable to estimate the unknown parameters of the proposed model. The negative log-likelihood function can be expressed as follows:

$$\begin{aligned} &-\ln l(\mathcal{C}_{\rm seq};\Theta) \\ &= \frac{N}{2} + \frac{N}{2}\ln\frac{1}{N}\sum_{i=1}^{N} v^2(i) + \frac{N}{2}\ln 2\pi, \end{aligned} \quad (6)$$

where $\mathcal{C}_{\rm seq}$ is the observation sequence of N aerodynamic measurements and Θ is the vector of unknown parameters. $v(i) = C_{a_{\rm mea}}(i) - C_a(i)$ is the observation noise which has a normal distribution with zero mean value. $C_{a_{\rm mea}}(i)$ denotes the measurement from wind tunnel tests. Therefore, the likelihood function $l(\mathcal{C}_{\rm seq};\Theta)$ is only correlated with the second term in the right side of (6). We can formulate the cost function as follows:

$$J(\Theta) = \frac{1}{N}\sum_{i=1}^{N}\left[C_{a_{\rm mea}}(i) - C_a(i)\right]^2. \quad (7)$$

To maximize the likelihood function, the cost function should get to the minimum. It is obviously a nonlinear optimizing problem. The GN is generally used to solve this problem in aerodynamic modeling. It has a quick descent in the cost function. However, it is easy to get a local convergent or even divergent result which strongly depends on the initial vector of unknown parameters Θ_0. Only when Θ_0 is close to the optimal solution, the GN is likely to reach a satisfying convergent result. Unfortunately, it is impractical to have an ideal initial vector of unknown parameters in advance. To overcome this problem, an improved nonlinear optimization algorithm is proposed here, which combines the GN and Quasi-Newton with Davidon-Fletcher-Powell (DFP) equation method (QN-DFP). The QN-DFP is proposed by Davidon at first and improved by Fletcher and Powell later. It has the property of quadratic convergence which means it can always keep a descent in cost function. But the descent can be slow and it is likely to get trapped into a local convergence. Thus, it is reasonable to combine the GN and QN-DFP not only to avoid divergence, but also to have a fast convergence speed.

Figure 1(a) depicts the block diagram of the proposed optimization algorithm procedure. Firstly, the initial values of a_j, b_j $(j = 0, 1, 2, 3)$ can be estimated by the least square method (LS) from wind tunnel test data, assuming the unsteady term $C_{a_{\rm dyn}}(t)$ is zero. The remaining parameter τ is given a random positive number which is less than

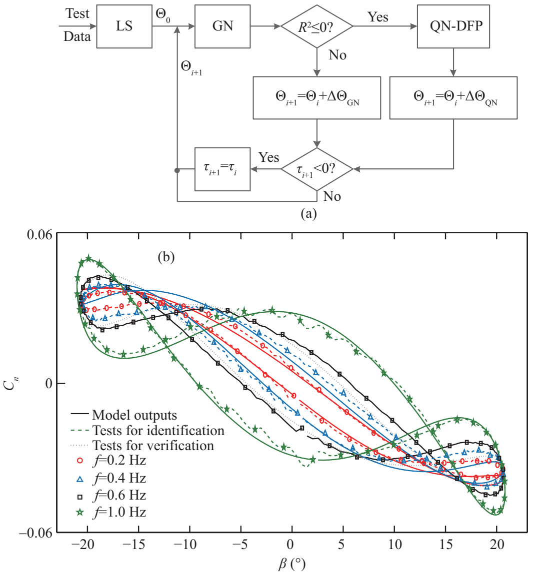

Figure 1 (Color online) (a) Block diagram of the proposed optimization algorithm process; (b) comparisons between wind tunnel tests and identified model outputs when $\theta = 45°$.

1 as its initial value. In every step of optimization iterations, the GN is first used to obtain the parameter variation $\Delta\Theta_{\rm GN}$. The multiple correlation coefficient R^2 is chosen as a measure to decide whether the optimization result is divergent. If it is not more than zero, a divergent result can be expected and the QN-DFP is then used to get a new parameter variation $\Delta\Theta_{\rm QN}$. We can get the updated parameters Θ_{i+1} by adding $\Delta\Theta_{\rm GN}$ or $\Delta\Theta_{\rm QN}$ to the current parameters Θ_i. Note that the characteristic time constant τ should be kept positive during the optimization iteration process on account of its physical meaning. If the updated τ_{i+1} is not more than zero, it will be replaced by the current τ_i. The next iteration step continues by updating the unknown parameters Θ_{i+1} as a new input. The optimization algorithm stops iterating when R^2 no longer changes.

Modeling and identification results. The large amplitude yawing oscillation tests at a fixed pitching angle $\theta = 45°$ with four different oscillation frequencies $f = \{0.2\ \text{Hz}, 0.4\ \text{Hz}, 0.6\ \text{Hz}, 1.0\ \text{Hz}\}$ are applied to the modeling of yawing moment coefficient. The iteration process of the proposed optimization algorithm compared with the GN and QN-DFP can be found in Appendix A. The GN starts to diverge at the fifth iteration step. The QN-DFP reaches a convergent result $R^2 = 0.9700$ at the seventh step. The proposed algorithm also approaches convergence at the seventh step, but it has a higher value of $R^2 = 0.9895$ which is more closer to 1. Obviously, the proposed optimization algorithm can get a more satisfying convergent result in few iteration steps. In Figure 1(b), the dash lines represent the tests which are used to identify the proposed aerodynamic model and the dot lines stand for the test applied to the verification of identified model. Model outputs are portrayed by the solid lines which are in remarkable accordance with all corresponding test data. The similar results for other pitching angles $\theta = 25°, 30°, 35°, 40°$ which are also nonlinear unsteady cases can be found in Appendix A.

Conclusion. The results strongly indicate the validity of the proposed aerodynamic model and optimization algorithm, which not only has an excellent capacity of model fitting but also provides accurate model predictions. In the future, the dependence on pitching angles will be explored.

Supporting information Appendix A. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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