for higher Mach numbers, aerodynamic nonlinear effects are observed.

At Mach 0.92, the most unstable flutter condition predicted by nonlinear TSD equation is observed on the $[30_2/0_2]_s$ laminate, but linear flutter analysis indicates the $[105_2/0_2]_s$ laminate. The flutter frequencies for both linear and nonlinear analyses are similar for this case, and all flutter frequencies are located between mode 1 and 2. Physically, this means that the flutter phenomena for this Mach number is dominantly coupled by the first bending and torsion modes (Fig. 1). At Mach 0.95, the linear and nonlinear results are quite different because of the effect of a strong rearward shock wave. The $[60_2/0_2]_s$ laminate has the lowest flutter velocity and is approximately 58% of the reference value. In general, for an isotropic wing model, the nonlinear flutter analysis that includes shock effects gives a lower (conservative) flutter velocity than those of the linear flutter analysis. It is noted that LCO are observed for several fiber orientations at Mach 0.92 and 0.95; thus, some of the presented flutter velocities are, in reality, the lowest values in which LCO response is present. The computed flutter frequencies are quite different for the fiber angle range of 45–105 deg because the flutter mode is significantly changed by the effect of nonlinear unsteady aerodynamics. At Mach 1.2, the more unstable cases predicted by the nonlinear analysis are shown at about $\theta = 15$, 30, and 120 deg. However, the linear analysis shows much lower flutter velocities than those of the nonlinear analysis on the $[45_2/0_2]_s$, $[60_2/0_2]_s$, and $[75_2/0_2]_s$ laminates, whereas the others show similar results compared to the nonlinear analysis. Comparisons of the flutter frequencies found from linear and nonlinear analyses are very similar except for the $[75_2/0_2]_s$ laminate. Finally, note from the linear and nonlinear analyses that the $[150_2/0_2]_s$ laminate commonly shows good flutter performance in both transonic and supersonic flows.

Conclusions

The authors examined the flutter characteristics of a sweptback composite missile wing in transonic and supersonic flows. Detailed comparisons of the effect of fiber orientation were presented to show the dynamic response and flutter stability characteristics of a laminated composite wing model. Comparisons were conducted within the transonic regime at Mach 0.92, 0.95, and 1.2. It was observed that the effect of fiber angle on the flutter stability is related to an inherent aerodynamic nonlinearity related to strong shock motions in transonic and low-supersonic flows. It was also observed that flutter frequencies change substantially due to the change of the flutter mode, which is related to the shock motions. It has been shown that there may be at least one lamination configuration for the missile wing that satisfies good flutter performance in both transonic and supersonic flows.

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Parameter Estimation from Flight Data of an Unstable Aircraft Using Neural Networks

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Introduction

THE maximum likelihood (ML) estimator in its several forms has been the most widely and successfully used for estimating aircraft stability and control derivatives (parameters) of a stable aircraft. However, for an unstable aircraft, difficulties can be expected because of 1) integration of equations of motion of the open-loop model generally resulting in diverging solutions, 2) the potential for correlation between input and output variables, 3) controllers suppressing the transients and thereby reducing information content in measured signals.[1] Although equation error methods do not face the preceding difficulties, they are not preferred mainly because of the need for accurate state reconstruction and biased estimates in the presence of measurement noise. Thus a need exists to find new approaches for estimating parameters of an unstable aircraft, and it is in this context that the present work explores the suitability of recently proposed Delta method[2,3] by applying it on simulated flight data as well as on flight data obtained via discretization of analog plots of real-flight data of an unstable aircraft.

Delta Method

The Delta method[2,3] is based on the understanding of what a stability/control derivative stands for; the stability/control derivatives represent the variation of the aerodynamic force or moment coefficients caused by a small variation in one of the motion/control variables about the nominal value, whereas all of the other variables are held constant. For example, to estimate $C_{m\alpha}$ the feed forward neural network (FFNN) is first trained to map the input file variables, say, α, q, and δ to the output variable C_m. Next, a modified network input file, wherein α values at each time point are perturbed by $\pm\Delta\alpha$ while all of the other variables retain their original values, is presented to the trained network, and the corresponding predicted values of the perturbed C_m (C_m^+ for $\alpha + \Delta\alpha$ and C_m^- for $\alpha - \Delta\alpha$) for each of the input-output samples are obtained at the output node. Now, the stability derivative $C_{m\alpha}$ is given by $C_{m\alpha} = (C_m^+ - C_m^-)/2\Delta\alpha$. If N is the number of input-output samples used by the network, then the estimated parameter is given by the average over N samples, and the sample standard deviation is an indicator of the accuracy of the estimates.[2,3]

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Table 1 Parameter estimates from flight data of an unstable aircraft

Parameter	True Value	Estimated Parameters	
		Noise = 0.0	Noise = 5%
$C_{L\alpha}$	2.920	2.852 (0.065)[a]	2.852 (0.073)
$-C_{Lq}$	14.740	11.154 (1.723)	13.021 (0.467)
$C_{L\delta}$	0.435	0.451 (0.038)	0.489 (0.065)
$C_{m\alpha}$	0.150	0.142 (0.007)	0.132 (0.004)
$-C_{mq}$	34.740	34.521 (0.683)	33.291 (0.274)
$-C_{m\delta}$	2.500	2.513 (0.010)	2.440 (0.048)

[a]Sample standard deviation.

Generation of Simulated Flight Data and FFNN Training

For generating longitudinal simulated data of an unstable aircraft, the example aircraft chosen is the stable aircraft used in Ref. 4, except that the stability derivative $C_{m\alpha}$ is assigned a positive value of 0.15 instead of the original negative value of -1.66. An unstable aircraft would generally have feedback control system. We assume that feedback, if any, is turned off and only the open-loop response is considered. The following equations of motion were used to generate flight data:

$$\dot{\alpha} - q = -(\rho u s/2m)[C_L], \qquad C_L = C_{L\alpha}\alpha + C_{\mathrm{Lq}}(qc/2u) + C_{L\delta}\delta \tag{1a,b}$$

$$\dot{q} = \left(\rho u^2 sc/2I_y\right)[C_m], \qquad C_m = C_{m\alpha}\alpha + C_{\mathrm{mq}}(qc/2u) + C_{m\delta}\delta \tag{1c,d}$$

where air density $\rho = 1.076$ kg/m^3, aircraft velocity $u = 203$ m/s, wing area $s = 180.79$ m^2, mean aerodynamic chord $c = 4.663$ m, aircraft mass $m = 130620$ kg, moment of inertia about y axis $I_y = 867{,}500$ kg/m^2. The stability and control derivatives $C_{L\alpha} \ldots C_{m\delta}$ were assigned the true values as given in Table 1.

If real-flight data of an unstable aircraft were to be generated by separate surface excitation with feedback off,[1] then control inputs employed for data generation have to be of both limited duration and small amplitude. Conforming to it, simulated flight data for a multistep 3-2-1-1 type elevator input were generated for duration of 7 s at an interval of 0.1 s, and the elevator amplitude was fixed to a low value of 0.025 rad. The fourth-order Runge–Kutta method was employed to integrate Eq. (1) to compute time histories of α and q. The corresponding values of C_L and C_m were calculated via the true values of parameters as shown in Table 1. The true values of parameters are required and used for the sole purpose of generating simulated flight data; the delta method does not require even an order of magnitude information about the parameters. This is in contrast to the conventional methods like the ML estimator, where such information is required in the form of initial values. For the case of real-flight data, the C_L and C_m would be computed using the measured values of accelerations a_z and $\dot{q}$:

$$C_L = (2mg/\rho u^2 s)a_z, \qquad C_m = \left(2I_y\big/\rho u^2 sc\right)\dot{q} \tag{2a,b}$$

The set of (α, q, δ) and (C_L or C_m) form, respectively, the input and output files for the training of FFNN. A total of 70 input-output samples was used. The FFNNs for the present study was simulated by using the neural network toolbox of MATLAB® 5.3. The activation function used was the sigmoidal function, and the backpropagation algorithm was used for training the network.

Parameter Estimation from Simulated Flight Data

The parameters to be estimated are the longitudinal derivatives $C_{L\alpha}$, C_{Lq}, $C_{L\delta}$, $C_{m\alpha}$, C_{mq}, and $C_{m\delta}$. It was also of interest to see how the accuracy of estimates is affected by the presence of measurement noise in the input and the output variables of the network. To this purpose, pseudonoise was added to α, q, C_L, and C_m. The noise was simulated by generating successively uncorrelated pseudorandom numbers having a normal distribution with zero mean and assigned standard deviation, the standard deviation corresponding approximately to the designated percentage (1 and 5%) of the maximum amplitude of the corresponding variables. Parameter estimates via the delta method from flight data with no noise and 5% noise are presented in Table 1.

From Table 1 it is observed that for no noise case most of the parameters are well estimated; only the weak derivative C_{Lq} is relatively poorly estimated. Even for noise level of as high as 5%, the estimates are reasonable and show only a marginal deterioration. These observations indicate the potential of the delta method for estimating parameters from flight data of an unstable aircraft and show the robustness of the method with respect to measurement noise in the flight data.

Parameter Estimation from Discretized Analog Plots of Real-Flight Data

The ultimate test of ability of a method for estimating parameters of an unstable aircraft would come from its validation on real-flight data. However, real-flight data of an unstable aircraft could not be procured, and, therefore, the following next-best substitute of real-flight data was considered for analysis and validation. The analog plots of real-flight data of the X-31A aircraft in unstable flight regime, given in Ref. 1, were discretized and interpolated to yield data at an interval of 0.1 s for α, q, $\dot{q}$, and δ. Because no information about the geometric, moment of inertia, and reference flight condition is given,[1] we could not compute C_m using Eq. (2b). This difficulty is circumvented by choosing to estimate derivatives $\partial\dot{q}/\partial\alpha$, $\partial\dot{q}/\partial q$, and $\partial\dot{q}/\partial\delta$ instead of $C_{m\alpha}$, C_{mq}, and $C_{m\delta}$. These derivatives will differ from the corresponding nondimensional derivatives $C_{m\alpha}$, C_{mq}, and $C_{m\delta}$ by a constant factor only. Furthermore, it is realized that the ratio $C_{m\alpha}/C_{m\delta}$ is the same as the ratio $(\partial\dot{q}/\partial\alpha)/(\partial\dot{q}/\partial\delta)$. This is easily verified as follows:

$$\dot{q} = \left(\rho u^2 sc\big/2I_y\right)C_m = \left(\rho u^2 sc\big/2I_y\right)[C_{m\alpha}\alpha + C_{\mathrm{mq}}(qc/2V) + C_{m\delta}\delta] \tag{3}$$

On differentiation with respect to α and δ, Eq. (3) yields, respectively, Eqs. (4a) and (4b):

$$\frac{\partial\dot{q}}{\partial\alpha} = \left(\frac{\rho u^2 sc}{2I_y}\right)C_{m\alpha}, \qquad \left(\frac{\partial\dot{q}}{\partial\delta}\right) = \left(\frac{\rho u^2 sc}{2I_y}\right)C_{m\delta} \tag{4a,b}$$

Now, dividing Eq. (4a) by Eq. (4b) gives

$$\left(\frac{\partial\dot{q}/\partial\alpha}{\partial\dot{q}/\partial\delta}\right) = \frac{C_{m\alpha}}{C_{m\delta}} \tag{5}$$

Because our estimates of $\partial\dot{q}/\partial\alpha$, $\partial\dot{q}/\partial q$, and $\partial\dot{q}/\partial\delta$ could not be compared directly with $C_{m\alpha}$, C_{mq}, and $C_{m\delta}$ given in Ref. 1, we instead check the equivalence of it as given by Eq. (5). It can be pointed out that the comparison is valid only if Eq. (3) were a good approximation to the following equation given in Ref. 1:

$$\dot{q} = \left(\rho u^2 sc\big/2I_y\right)C_m^{c.g.} + (1/I_y)M_{\mathrm{engine}}^{\mathrm{c.g.}} \tag{6}$$

The assumption of equivalence between Eqs. (3) and (6) implies that the contributions to the pitching moment as a result of engine thrust do not vary significantly with the motion variables α and q (for example, $\partial M_{\mathrm{engine}}^{\mathrm{c.g.}}/\partial\alpha = 0$). Furthermore, the steady-state contributions to the pitching moment about c.g. from the aerodynamic forces and engine would be equal and opposite of each other and cancel out. In other words, perturbations in motion variables about the steady state are assumed to be governed solely by the perturbations in the aerodynamic pitching moment $(\rho u^2 sc/2I_y)C_m^{\mathrm{c.g.}}$ as given by Eq. (3), implying no contribution from the second term on the right-hand side of Eq. (6). It is within such approximations that the equality of ratios $(\partial\dot{q}/\partial\alpha)/(\partial\dot{q}/\partial\delta) = C_{m\alpha}/C_{m\delta}$ is used to compare our estimates with those reported in Ref. 1 for the X-31A aircraft.

It is worth a mention that the network inputs used for training the network were $(\alpha - \alpha^*)$, $(q - q^*)$, and $(\delta - \delta^*)$, where the asterisks

Table 2 Parameter estimates from discretized flight data of X-31A unstable aircraft

Parameters	$\partial\dot{q}/\partial\alpha$	$\partial\dot{q}/\partial q$	$\partial\dot{q}/\partial\delta$	$C_{m\alpha}$	C_{mq}	$C_{m\delta}$
Delta	2.539 (0.396)[a]	−1.269 (0.351)	−10.150 (0.851)	——	——	——
Ref. 1	——	——	——	0.119	−1.650	−0.57

[a]Sample standard deviation.

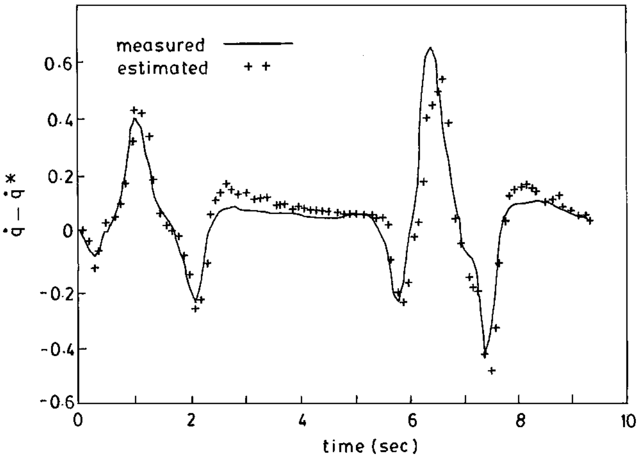

Fig. 1 Comparison of measured and computed accelerations ($\dot{q} - \dot{q}^*$) via the delta method.

denote the trim value of the corresponding variables. This is done to conform results with those reported in Ref. 1. Similarly the output variable is defined as ($\dot{q} - \dot{q}^*$). The use of ($\dot{q} - \dot{q}^*$) would also ensure that the assumption made earlier for representing Eq. (3) by Eq. (6) is reasonable, because it implies cancellation of steady-state contributions to pitching moment from the aerodynamic forces and propulsive unit forces.

Once the network is trained, the delta method is used to estimate derivatives $\partial\dot{q}/\partial\alpha$, $\partial\dot{q}/\partial q$, and $\partial\dot{q}/\partial\delta$, and the results are shown in Table 2. The parameter estimates of $C_{m\alpha}$, C_{mq}, and $C_{m\delta}$ from Ref. 1 are also given for ready reference.

Using Table 2, it is readily seen that the ratio $(\partial\dot{q}/\partial\alpha)/(\partial\dot{q}/\partial\delta) = -0.250$ compares reasonably with the ratio $C_{m\alpha}/C_{m\delta} = -0.208$ despite the uncertainties caused by discretization of analog plots of real-flight data and omission of contributions to C_m from the propulsive forces. Next, the estimated derivatives $\partial\dot{q}/\partial\alpha$, $\partial\dot{q}/\partial q$, and $\partial\dot{q}/\partial\delta$ are used to compute the estimated $(\dot{q} - \dot{q}^*) = (\partial\dot{q}/\partial\alpha)\alpha + (\partial\dot{q}/\partial q)q + (\partial\dot{q}/\partial\delta)\delta$. The so-estimated ($\dot{q} - \dot{q}^*$) shows reasonable match with the actual (discretized) ($\dot{q} - \dot{q}^*$) as shown in Fig. 1. The discrepancy between the actual and estimated values of ($\dot{q} - \dot{q}^*$) can be largely assigned to an insufficient number of input variables in the network input file, which, in turn, was caused by a lack of information (for example, about thrust contributions) made available in Ref. 1.

Conclusions

The neural-network-based delta method is shown to be a good alternative to the existing methods for estimating parameters of an unstable aircraft. It does not require postulation of aircraft model, initial guess values of parameters, or estimation of initial conditions. It is a noniterative method and uses the measured flight data directly to train the neural network and subsequently estimate parameters in one go. The applicability of the delta method is shown on simulated as well as discretized analog plots of real-flight data. The results suggest that the delta method can be used advantageously to estimate parameters of an unstable aircraft.

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Flight Testing Radar Detection of the Saab 105 in Level Flight

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Nomenclature

G	=	antenna gain
k	=	wave number
P_{min}	=	minimum power level of the received signal necessary for detection
P_t	=	transmitted power
R_d	=	detection range
α	=	angle of attack
γ	=	flight-path angle
λ	=	wavelength
ν_0	=	radar-dependent detection distance
σ	=	radar cross section

Introduction

THE Department of Aeronautics at the Royal Institute of Technology (KTH) has for some time been involved in developing methods for aircraft trajectory optimization. When the developed methods are used, it is possible to compute a flight path taking the aircraft from one state to another in minimum time or using minimum fuel.[1−3] The optimized trajectories have been flight tested by the Swedish Air Force using the supersonic Saab J35 Draken[2] and the jet trainer Saab 105 (Ref. 4).

It is unlikely, in modern combat scenarios, that the optimal flight path with respect to the aircraft performance only is very useful. The main threat against aircraft is radar, which stands for radio detection and ranging. The effectiveness of the radar is determined by range and the geometry of the aircraft. The detection time is defined as the time interval between the instant at which the aircraft is first detected and the instant at which the aircraft reaches the specified target. The detection distance is the distance from the target to the position at which the aircraft is first detected by radar. Given an initial position and a target position, the offset distance is defined as the perpendicular distance to an alternative flight path parallel to the original flight path. Hence, a flight path pointing directly at, or above, the target is defined to have zero offset.

The purpose of the present study is to perform a preliminary investigation of the possibility to reduce the distance to the location where an aircraft is first detected by hostile radar by considering the radar cross section (RCS) properties of the aircraft. To gain understanding of the potential decrease in detection time, a numerical example is considered.

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