JOURNAL OF GUIDANCE, CONTROL, AND DYNAMICS
Vol. 18, No. 6, November–December 1995

Identification of a Nonlinear Aerodynamic Model of the F-14 Aircraft

Thomas L. Trankle*
Systems Control Technology, Inc., Palo Alto, California 94304
and
Stephen D. Bachner†
U.S. Naval Air Warfare Center, Patuxent River, Maryland 20670

This effort identified a full subsonic flight envelope model of the aerodynamics of the F-14 aircraft. The data set consisted of 8.9 h of flight data stored as 983 separate maneuver files. The analysis used a unified system identification computer code implementing kinematic consistency, model structure determination, and parameter estimation functions. The code implements generalized filter error, encompassing both equation error and output error types of performance measures. The code can operate in a nearly automated manner, completely processing about 1 h of flight data in about 40 h of Unix workstation time. The resulting aerodynamic model represents nonlinear angle of attack, Mach number, and static flexibility effects. This model has 521 independent aerodynamic terms and 97 independent instrumentation terms. The identified model is an incremental model that adds to an existing nonlinear simulation. One and two dimensional spline functions represent the aerodynamic coefficients.

Nomenclature

C_D^I = incremental drag coefficient
C_L^I = incremental lift coefficient
$C_{l_{\text{stab}}}^I$ = incremental stability axis roll moment coefficient
C_m^I = incremental pitch moment coefficient
$C_{n_{\text{stab}}}^I$ = incremental stability axis yaw moment coefficient
C_y^I = incremental side force coefficient
$\boldsymbol{f}$ = system dynamics vector function
$f_{a_x}^C$ = CASTLE x body axis aerodynamic force
$f_{e_x}^C$ = CASTLE x body axis engine force
f_i^I = incremental x body axis force, $i = x$, y, or z axis
f_x = total body axis force, $i = x$, y, or z axis
$\boldsymbol{h}$ = measurement vector function
K_e = engine scale factor
$\mathcal{L}$ = parameter estimation cost function
M = Mach number
m_x = total x body axis roll moment
m_x^C = CASTLE x body axis roll moment
m_x^I = incremental x body axis roll moment
$\boldsymbol{n}$ = measurement noise vector
p' = dimensionless stability axis roll rate
$\bar{q}$ = dynamic pressure
q' = dimensionless stability axis pitch rate
r' = dimensionless stability axis yaw rate
$\boldsymbol{u}$ = control vector
$\boldsymbol{w}$ = process noise vector
$\boldsymbol{x}$ = system state vector
$\boldsymbol{y}$ = system measurements vector
α = angle of attack
β = angle of sideslip
Δt = sample period
δa = differential tail deflection
δf = flap deflection
δr = rudder deflection
δs = symmetric tail deflection
δsb = speed brake deflection
δsp = spoiler deflection
$\delta \Lambda$ = wing sweep change from nominal program
$\boldsymbol{\theta}$ = unknown parameters
ν = innovation
κ = filter weight ratio vector
τ = filter time constant
$\hat{()}$ = estimated quantity

Introduction

THE U.S. Naval Air Warfare Center Aircraft Division's manned flight simulator maintains the Navy's high-fidelity F-14 engineering simulator. Because this simulation is used for flight test support, accident investigations, control law design and analysis, and engineering development, an accurate model of the aircraft is a necessity. Specifically, simulation of flying qualities that accurately represent the F-14 requires a high-fidelity, nonlinear, six degree-of-freedom aerodynamic model.

The F-14 aerodynamic model uses force and moment data from several wind-tunnel sources. Although representing both subsonic and supersonic flight, the model is aerodynamically challenged in some specific areas. Table 1 shows the effects that are not modeled or are incompletely modeled in the current simulation. Because of these limitations, the manned flight simulator wanted to improve the fidelity of the subsonic portion of the flight envelope using flight test data and aerodynamic parameter estimation techniques.

Table 1 Existing model limitations

	PATO	Low speed	High speed
Landing gear	x[a]	x	
Flap/slat combined	x	x	x
Ground effects	x		
Symmetric tail	x		
Sideslip	x		
Direct lift control	x		
Basic pitch moment, lift, drag forces	x		
Angle of attack rate		x	x
Low angle of attack		x	x
Off schedule sweep		x	x
Glove vane			x
Static flexibility		x	x

[a]x indicates a problem area.

Presented as Paper 93-3634 at the AIAA Atmospheric Flight Mechanics Conference, Monterey, CA, Aug. 9–11, 1993; received Feb. 8, 1994; revision received Feb. 7, 1995; accepted for publication March 20, 1995.

*Senior Engineer, Aeronautical and Marine Systems Sector; currently Senior Staff Engineer, Dynamics and Control Laboratory, Lockheed Martin Palo Alto Research Laboratory, Palo Alto, CA 94301. Member AIAA.

†Aerospace Engineer, Aeromechanics Division.

Table 2 Data channels used in analysis

Channel	Use: Kinematic mode	Use: Aerodynamic mode
Differential tail		u[b]
Rudder		u
Symmetric tail		u
Speed brake		u
Wing sweep		u
Maneuvering flap		u
Temperature	u	u
Power level angle		u
Airspeed	y[a]	y
Pitch rate	u	y
Angle of attack	y	y
Longitudinal accel.	u	y
Normal accel.	u	y
Pitch angle	y	y
Altitude	y	y
Angle of sideslip	y	y
Roll rate	u	y
Yaw rate	u	y
Lateral accel.	u	y
Roll angle	y	y
Yaw angle	y	y

[a]y indicates system measurement. [b]u indicates system input.

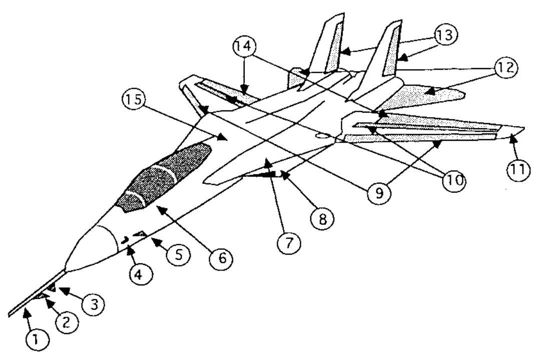


Fig. 1 F-14 aircraft with flight test instrumentation: 1) flight test noseboom and pitot probe, 2) noseboom AOA vane, 3) noseboom AOS vane, 4) production pitot probe, 5) production AOA vane, 6) pilot location accelerometer package, 7) glove vane (not shown), 8) engine performance sensors, 9) leading-edge slats, 10) spoilers (4 per wing), 11) variable-sweep wing, 12) symmetric tails, 13) rudders, 14) flaps (maneuver and auxiliary), and 15) fuel state sensors, CG accelerometers, rate, and attitude packages.

We used system identification methods to determine an improved model of the F-14 aircraft. Data processing employed the important but distinct functions of instrumentation consistency calibration, model structure determination, and parameter estimation. A computer code called GUPIE (Grand Unified Program for Identification and Estimation) implemented these functions. (A computer code today is sometimes called a toolbox or a solution.) GUPIE uses some of the methods employed by an earlier system identification code[1] called SCIDNT (Systems Control IDeNTification).

Instrumentation System

The instrumentation system provided complete measurement of engine state, all control surface deflections and all velocity, angular rate, translational acceleration, and attitude components (Fig. 1, Table 2). The sampling rate was 20 samples per second for a total of 102 channels. The system identification processing used 39 of these.

Flight Test Program

The data collected were obtained during 15 flight tests performed between March and September 1988. In all, approximately 30 flight hours were flown for the collection of the parameter identification test data. This resulted in the collection of nearly 500,000 samples of data for analysis. Each flight resulted in the collection of about 2500 seconds of data suitable for analysis using parameter estimation methods.

Table 3 Integrated test block

Title and maneuver duration	Description
Bank to bank roll (30 s)	Use lateral stick to roll left from 45 to 90 deg. Then use lateral stick to roll right by the same amount.
Sinusoidal longitudinal (30 s)	Swept sine in longitudinal stick. Use about ±5 deg of symmetric tail.
Sinusoidal lateral (30 s)	Swept sine in lateral stick. Use about ±5 deg of differential tail.
Sinusoidal directional (30 s)	Swept sine in pedals. Use about ±10-deg ruder.
Steady heading sideslips (60 s)	Use rudder and differential tail to trim for about 5-deg left sideslip. Hold for 30 s. Then release, trim for right sideslip, hold for 30 s. Release. Requires about 20-deg rudder 10-deg differential tail.
Military power acceleration (30 s)	Increase thrust to maximum non afterburner, about 60 throttle units. Accelerate about 140 kn.
Idle power deceleration (90 s)	Decrease thrust to flight idle, about 7 throttle units. Decelerate about 140 kn.
Maximum power acceleration (20 s)	Increase thrust to maximum with afterburner, about 120 throttle units. Accelerate about 150 kn.
Idle power deceleration with brake (60 s)	Decrease thrust to flight idle, about 7 throttle units. Extend aerodynamic brake. Decelerate about 140 kn.
Large amplitude longitudinal (60 s)	Use two or three cycles of symmetric tail motion of ±5 deg. Duration of each cycle is about 20 s. Leads to about ±20-deg pitch angle changes.
Wind up turns (50 s)	Roll aircraft approximately 90 deg. Slowly increase angle of attack until reach maximum normal acceleration allowed.

Table 4 High angle-of-attack test block

Title	Description
Three-axis control doublets	Apply doublet in longitudinal and lateral stick, pedal.
Pull to max Nz	Roll into turn. Apply symmetric tail to increase angle of attack to obtain maximum allowable normal acceleration.
Bank to bank roll	Perform with lateral stick and with rudder pedal.
Steady sideslip	Trim for about 5-deg left sideslip. Then release and trim for right sideslip.

The flight envelope covered during the tests ranged from a Mach number of 0.15 to 0.95 and an altitude of 5 to 30,000 ft (Fig. 2). Angle of attack ranged from −4 to +40 deg. At each flight condition, the aircraft executed 11 types of maneuvers from an integrated test block (Table 3) and four types from a high angle of attack test block (Table 4).

Aerodynamic Model

Sources of the CASTLE (Baseline) Model

The F-14 baseline aerodynamics model appears in the Controls and Simulation Test Loop Environment (CASTLE) used at the Naval Air Warfare Center. The aerodynamic data are from six distinct wind-tunnel databases. Each database covers a different portion of the flight envelope defined by Mach number and angle of attack. All databases have landing gear and landing flaps retracted, i.e., cruise configuration, except the power approach (PA) data base. The model configuration for the PA wind-tunnel tests was landing gear extended, full landing flaps, and F-14 DLC off. Incremental effects for direct lift control (DLC) engaged and speed brake deflections are available. For the cruise configuration, the maneuver flaps and slats are extended for all angles of attack (AOA). All databases

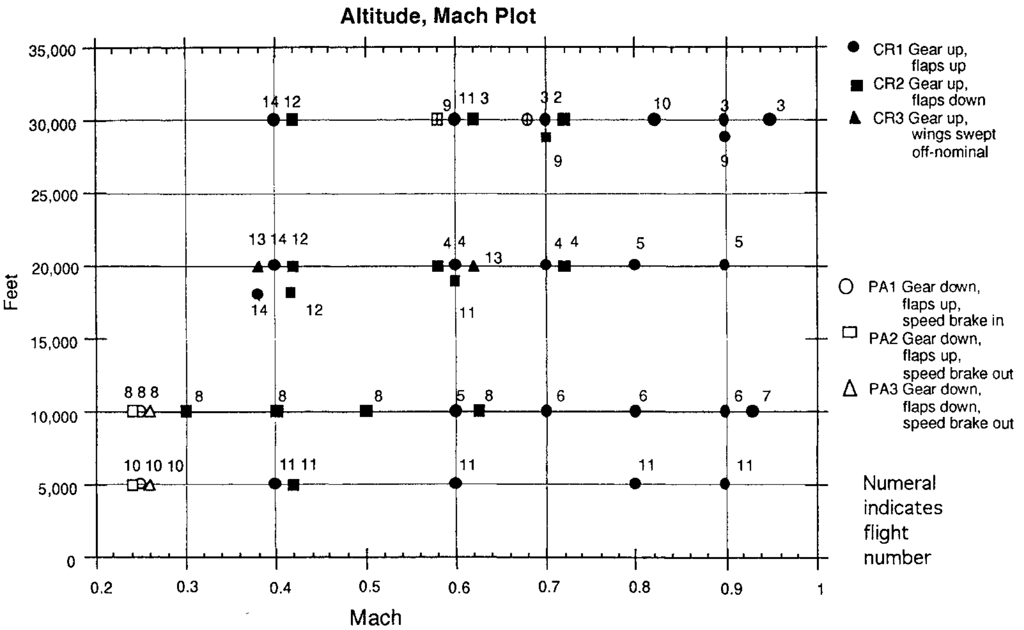


Fig. 2 Mach, altitude test envelope.

have wing sweep at the wing's programmed Mach-α schedule. Two store configurations for subsonic, cruise configuration are modeled, representing two common missile and external tank configurations.

The aerodynamic data were obtained by NASA Langley,[2,3] Bihrle Applied Research (BAR),[4,5] NASA Dryden, David Taylor Naval Ship Research and Development Center, and Grumman Aircraft Corporation (GAC).[6] Not all of the data are formally published as of this writing.

Incremental Model Concept

To simplify integration of the identified model with the existing simulation, we used an incremental model to represent the identified aerodynamic effects. The identified model adds to the existing model. It does not replace the existing model. We could then easily integrate the identified model with the baseline CASTLE simulation by adding a single subroutine call.

The expressions for the total x axis forces and moments have the form

$$f_x = f_{a_x}^C + K_e \cdot f_{e_x}^C + f_x^I \tag{1}$$

$$m_x = m_{a_x}^C + K_e \cdot m_{e_x}^C + m_x^I \tag{2}$$

There are analogous expressions for the y and z axis forces and moments. The C superscript indicates a CASTLE model term, and the I superscript indicates an incremental model term. The CASTLE model computes both aerodynamic (a subscript) and engine (e subscript) effects. K_e is a scale factor on the engine effects. We estimated a value for this scale factor along with instrumentation and aerodynamic terms. Engineering judgment of experienced flight test personnel suggested that including a scale factor having a value between 0 and 1 would be an adequate representation of actual engine performance. The a priori CASTLE simulation assumes that the engine is in nearly perfect operating condition.

Form of Incremental (Identified) Model

We based the form of the incremental model on our experience with previous high-performance aircraft operating in the subsonic and transonic regime.[7] The incremental model uses one specific form for $0.3 \le M < 0.99$ (high Mach number) and a somewhat modified form for $0 < M \le 0.3$ (low Mach number). The three force and three moment dimensionless coefficients are functions of one- and two-dimensional cubic spline functions[8] (Table 5). Spline functions have become a popular method for representing nonlinear aerodynamic functions.[9] Spline functions can represent highly nonlinear functions with a minimum of independent parameters.

Table 5 High Mach number model form

$$C_L^I = C_L^{\langle 5,5\rangle}(\alpha, M) + C_L^{\Lambda\langle 5,5\rangle}(\alpha, \delta\Lambda) + C_{L_{\delta f}}^{\langle 5\rangle}(M)\delta f$$
$$+ C_{L_{\delta s}}^{\langle 5\rangle}(M)\delta s + C^{\bar{q}}{}_{L\bar{q}}^{\langle 5,5\rangle}(\alpha, M)\bar{q}$$
$$C_D^I = C_D^{\langle 5,5\rangle}(\alpha M) + C_D^{\Lambda\langle 5,5\rangle}(\alpha, \delta\Lambda) + C_{D_{\delta f}}^{\langle 5\rangle}(M)\delta f$$
$$+ C_{D_{\delta sb}}^{\langle 5\rangle}(M)\delta sb + C_{D_{\bar{q}}}^{\bar{q}\langle 5,5\rangle}(\alpha, M)\bar{q} + C_{D_{\beta\beta}}\beta\beta$$
$$C_{l_{\text{stab}}}^I = C_{l_0}^{\langle 5\rangle}(M) + C_{l_p}^{\langle 5\rangle}(M)p' + C_{l_r}^{\langle 5\rangle}(M)r' + C_{l_\beta}^{\langle 5\rangle}(M)\beta$$
$$+ C_{l_{\delta a}}^{\langle 5\rangle}(M)\delta a + C_{l_{\delta r}}^{\langle 5\rangle}(M)\delta r + (C_{l_{\delta a\bar{q}}}\delta a + C_{l_{\beta\bar{q}}}\beta)\bar{q}$$
$$C_m^I = C_m^{\langle 5,5\rangle}(\alpha, M) + C_m^{\Lambda\langle 5,5\rangle}(\alpha, \delta\Lambda) + C_{m_{\delta f}}^{\langle 5\rangle}(M)\delta f$$
$$+ C_{m_q}^{\langle 5,5\rangle}(\alpha, M)q' + \left[C^{\bar{q}}{}_{m\bar{q}}^{\langle 5,5\rangle}(\alpha, M) + C_{m_{\delta s\bar{q}}}\delta s\right]\bar{q} + C_{m_{\delta s}}^{\langle 5\rangle}(M)\delta s$$
$$C_{n_{\text{stab}}}^I = C_{n_0}^{\langle 5\rangle}(M) + C_{n_p}^{\langle 5\rangle}(M)p' + C_{n_r}^{\langle 5\rangle}(M)r' + C_{n_\beta}^{\langle 5\rangle}(M)\beta$$
$$+ C_{n_{\delta a}}^{\langle 5\rangle}(M)\delta a + C_{n_{\delta r}}^{\langle 5\rangle}(M)\delta r + C_{n_{\delta r\bar{q}}}\delta r\bar{q}$$
$$C_y^I = C_{y_0}^{\langle 5\rangle}(M) + C_{y_\beta}^{\langle 5\rangle}(M)\beta + C_{y_{\delta r}}^{\langle 5\rangle}(M)\delta r + C_{y_{\delta r\bar{q}}}\delta r\bar{q}$$

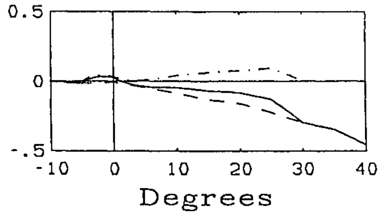
The aerodynamic coefficients having the form $C^{\langle n\rangle}(x)$ are one-dimensional spline functions in the variable x having n knots. The terms having the form $C^{\langle n,m\rangle}(x, y)$ are two-dimensional spline functions having n knots for the first variable x and m knots for the second variable y. Terms with a subscript such as α or $\beta\beta$ are factors multiplying the aircraft state function α or β^2. The independent parameters used in the spline representation are the values of the coefficient C at the knot locations. A $C^{\langle n,m\rangle}(x, y)$ spline has n^*m independent parameters.

Figure 1 shows the static pitch moment term as a function of angle of attack and Mach number. This figure shows the basic CASTLE term, the identified spline function increment, $C_m^{\langle 5,5\rangle}(\alpha, M)$, and the total coefficient.

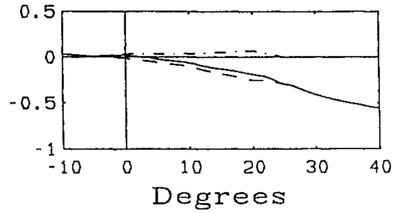
For $M \le 0.3$, the incremental model freezes Mach number effects at their value for $M = 0.3$. This ensures continuity when switching between low and high Mach regimes. Also, the model has additional spline terms to represent flap deflection and landing gear effects.

System Identification Method

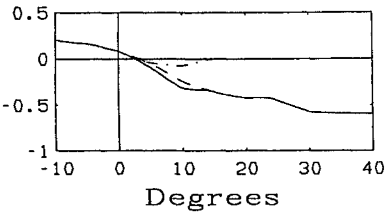
To estimate the parameters of the aerodynamic model, we applied nonlinear filter error system identification. Previous work in aircraft aerodynamic systems identification has used equation error applied to nonlinear models[9–11] output error applied to nonlinear models,[8] filter error (usually applied to linear models[12] but sometimes to nonlinear models[13]), and model structure determination by subset regression applied to nonlinear models with an equation



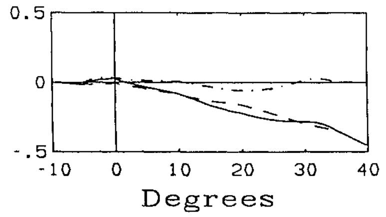
a) $C_m(\alpha, M)|_{M=0.2}$



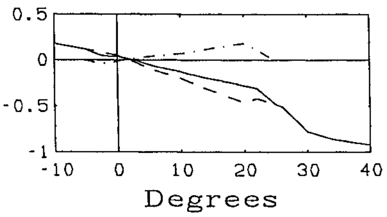
b) $C_m(\alpha, M)|_{M=0.7}$



c) $C_m(\alpha, M)|_{M=0.98}$



d) $C_m(\alpha, M)|_{M=0.5}$



e) $C_m(\alpha, M)|_{M=0.9}$

Fig. 3 Example identified coefficient (pitch moment): ——, total coefficient; - - - -, a priori (CASTLE) coefficient; -·-·-·-, identified incremental coefficient.

error criterion.[11] Our method used equation, filter, and output error parameter estimation and model structure determination methods in an integrated manner. In particular, we applied subset regression methods directly to the nonlinear filter error criterion.

The filtering algorithm used to form the filter error criterion is a simple but innovative one that greatly enhances the reliability and speed of convergence of parameter estimation. Proper choice of the time constants of the filter can force the filter error algorithm to mimic either equation error or output error in addition to filter error. The program can process multiple flight maneuvers simultaneously. We have been able to estimate parameters in a nearly automated manner. Particularly, all of the data used in the processing (about 1.25 h, or 90,000 samples) can be loaded into the program. Estimation of as many as 90 parameters in one run using all of these data is quite feasible using a desktop Unix workstation. Such a run requires about 40 h of time on a SPARCstation 2 computer. Initial parameter estimation, using equation error, final parameter estimation, using filter error, and validation, using output error, are possible using the same code. Changing a single input parameter (defining filter time constants) changes the output/filter/equation error mode of operation of the code.

The general form of the model used by the system identification is

$$\dot{x} = f[x, u, w, t, \theta] \tag{3}$$

$$y = h[x, u, t, \theta] + n \tag{4}$$

where $\boldsymbol{x}$ represents the Nx system states, $\boldsymbol{y}$ represents the Ny measurements, and $\boldsymbol{u}$ represents the Nu inputs; $\boldsymbol{n}$ and $\boldsymbol{w}$ are unmeasurable stochastic terms; $\boldsymbol{w}$ represents process noise whereas $\boldsymbol{n}$ represents measurement noise; and $\boldsymbol{\theta}$ is a set of unknown parameters.

Kinematic Mode

The data consistency calibration mode of operation, called the kinematic mode (Table 2, column 1), treats the inertial channels (translational acceleration and angular rate) as the input vector $\boldsymbol{u}$.[14] The kinematic mode then integrates $\boldsymbol{u}$ to provide estimates $\hat{y}$ of the other aircraft motion channels, such as attitude, altitude, and airspeed. The kinematic mode of operation can estimate instrument scale and bias terms to make the $\boldsymbol{u}$ and $\boldsymbol{y}$ channels consistent.[15]

Aerodynamic Mode

In the aerodynamic parameter estimation mode of operation, called aerodynamic mode (Table 2, column 2), our method uses the control surface deflections such as δs, δa, and δf, as the input vector $\boldsymbol{u}$. We then use the aerodynamic equations of motion to integrate these inputs to provide estimates of the inertial channels and of the same channels used in the kinematic mode.

Performance Measure

In both kinematic and aerodynamic mode, we estimate parameters by minimizing a fit error cost function $\mathcal{L}(\theta)$. The minimization uses a Levenberg–Marquardt[16,17] (LM) procedure. The algorithm estimates the partial derivatives needed by LM using a finite difference approximation.[18] The cost function has the form

$$\mathcal{L}(\theta) = \frac{1}{2}\sum_{k=1}^{Nm}\left\{\sum_{j=1}^{j=Ny}\left[\sum_{i=1}^{i=Nt(k)}\frac{\nu_{jk}^2(\theta, t_i)}{W_j^2}\right]\right\} \tag{5}$$

where

$$\nu_{j,k}(\theta, t_i) = \hat{y}_{j,k}(\theta, t_i) - y_{j,k}(t_i) \tag{6}$$

where Nm is the number of multiple flight maneuvers being processed; $Nt(k)$ is the number of time points in maneuver k; $\hat{y}_{jk}(\theta, t_i)$ is the estimated value of channel j at time t_i for maneuver k and W_j is a weighting factor on channel j. Usually, we set W_j to the approximate rms noise level on that channel. The algorithm estimates $\hat{y}_{j,k}(\theta, t_i)$ by propagating the equations of motion with the aid of the filter.

Filter Overview

Both kinematic and aerodynamic modes use a filter to propagate the equations of motion and to produce estimates $\hat{y}_{j,k}(\theta, t_i)$. The filter operates on a predict-update cycle. The filter first propagates the state estimate ahead one time step from t_i to t_{i+1} using a first-order Euler method applied to the equations of motion. After this prediction step, the program computes estimated measurements $\hat{y}_{j,k}(\theta, t_{i+1})$. At this time, the program computes the innovations vector $\nu_{k,m}(\theta, t_{i+1})$ at t_{i+1}. Next the program updates the state estimate using the measurement available at t_{i+1}.

If the filter gains are low, the propagation of the equations of motion leads to an output error formulation of the performance measure, Eq. (5). This low-gain formulation compensates for measurement noise but not for process noise. If the filter gains are high and the sampling period is small relative to the system time constants, the performance measure approximates equation error. This high-gain formulation compensates for process noise but not for measurement noise. Intermediate values of the gains give a filter error performance measure. An intermediate level of gains, implementing filter error, compensates for both process and measurement noise in an effective compromise.

We have found that we can have the best of all worlds by variation of the filter gains during the search for the optimal compromise of the filter error formulation. The equation error performance measure leads to rapid convergence of the iterative parameter search. However, the parameter estimates from equation error are sensitive to measurement noise. Nonlinear filter error is relatively insensitive to measurement noise. However, the convergence of the iterative methods used to minimize this cost function is prohibitively slow. Our procedure has been to initially run an estimation case in equation error mode. That is, we run it with very high filter gains. After convergence (usually only requiring two iterations) we reduce the filter gains and rerun the estimation problem. We continue these steps until we reach gain levels corresponding to an optimum balance between measurement and process noise. Our experience with the F-14 data set is that this only takes three to four cycles.

Kalman Filter for Kinematic Mode

In the kinematic mode, we use a classical Kalman filter formulation. We have found that we can estimate calibration terms, such as bias and scale factor, by minimizing a cost function of the form of Eq. (5). Additionally, we can estimate noise levels by minimizing a likelihood cost function.[14]

Simple Filter Used by the Aerodynamic Mode

Design of a Kalman filter using the aerodynamic equations would be difficult. Such a design would require repeated linearization of the aerodynamic equations as angle of attack and Mach number change. Instead of using the complete Kalman formulation or a constant gain measurement feedback,[13] we use a very simple filter rule. The state update uses the simple rule

$$(x_{\text{updated}})_i = (\kappa_{\text{filter}})_i (x_{\text{propagated}})_i + [1 - (\kappa_{\text{filter}})_i](x_{\text{measured}})_i \tag{7}$$

where the elements of the filter weight vector κ_{filter} are chosen as

$$(\kappa_{\text{filter}})_i = \frac{1}{e^{\tau_i/\Delta t}} \tag{8}$$

The state x_{measured} is the value of the state vector determined directly from the measurements available at the update time:

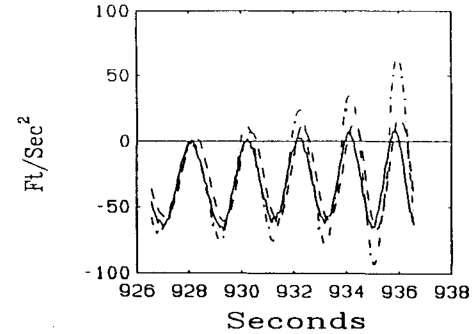
$$x_{\text{measured}} = \boldsymbol{h}^{-1}[\boldsymbol{y}, \boldsymbol{u}, t, \boldsymbol{\theta}] \tag{9}$$

Even in pure output error mode, propagation of the equations of motion requires the $\boldsymbol{h}^{-1}$ function to set the initial conditions for each maneuver.

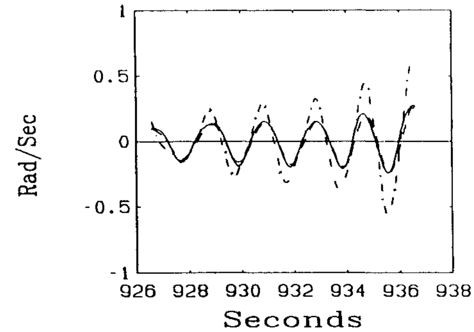
Experience with the F-14 data set indicates that choosing $\tau = 0.05$ s gives rapid convergence (i.e., equation error performance). Choosing $\tau = 3$ s gives good filter error performance. To estimate a set of parameters, we typically run an initial case with $\tau = 0.05$, a second case with $\tau = 0.5$, a third case with $\tau = 1.0$, and finally a case with $\tau = 3.0$. At the start of each case, we set the parameter values to those estimated by the end of the previous case.

Model Structure Determination

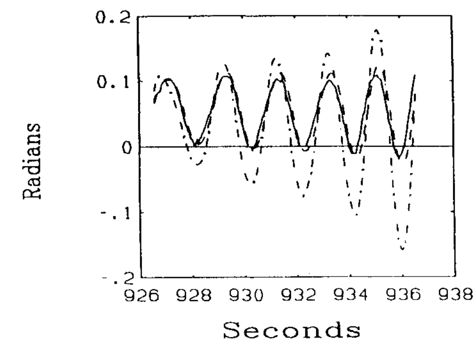
We have applied a subset regression approach to the determination of the structure for the aerodynamic model. The use of subset regression in structure determination for aerodynamics models was proposed as early as 1974.[19] In using subset regression to attack the model structure problem, the analyst first hypothesizes a very complex structure that includes all possible terms that might be present in the true model. This model will inevitably be overparameterized. The analyst then determines a subset of the complete set of hypothesized terms that best represents the observed data. The subset regression must solve two problems. First, it must find the subset of each size (i.e., number of parameters) that best fits the observed data. For example, if there are 100 candidate terms, the method must find the one parameter model that best fits the data, the two parameter model that best fits the data, . . . , the 99 parameter model that best fits the data, and it must evaluate the single 100 parameter model. Second, the method must determine which of these 100 models, each having a different number of parameters, is the best overall. We have found that branch and bound tree search methods



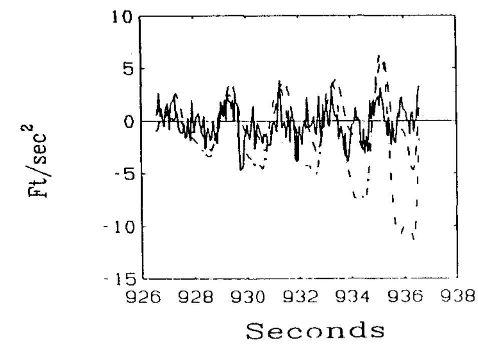
a) Normal acceleration a_z



b) Pitch rate Q



c) Angle of attack α



d) Longitudinal acceleration a_x

Fig. 4 Model fit comparison for sinusoidal longitudinal input at Mach 0.9: ——, data; - - - -, identified model; ········, a priori (CASTLE) model.

(originally developed, appropriately enough, by researchers at the U.S. Forest Service) completely solve problem one.[20] An automatic approach to problem two remains to be found, however. We have used engineering insight to compare subsets of various sizes. A major tool here is a plot of residual fit error vs number of parameters. This is always monotonic decreasing with increasing number of parameters. The best subset will usually be near the point where this curve begins to level off.

Our model structure determination started with all of the possible independent spline parameters appearing in Table 5 as given candidate parameters. The C_L equation, for example, has 85 candidate independent parameters. This is because there are 25 independent parameters in $C_L^{(5,5)}(\alpha, M)$, 25 in $C_L^{\Lambda(5,5)}(\alpha, \delta\Lambda)$, etc. The model structure analysis then selected a subset of these candidates for identification. Another term for our model structure determination might be parameter selection.

Subset regression was first developed for the analysis of linear least square problems. We apply it to the nonlinear problem by using it on the linearized least square problem that arises in the application of the Levenberg–Marquardt method to the nonlinear least square problem. This approach is effective in either the kinematic or aerodynamic modes.

Identification Results

The identified model is valid over a Mach number range from 0.2 to about 0.9. The model represents all six degrees of freedom of the aircraft with flaps up or down and corrects several problems with the a priori model. The model has 521 independent parameters. The system identification analysis identified values for 285 of these. Model structure determination investigated the identifiability of the other parameters but did not find that the values differed significantly from zero. The identified model represents three aerodynamic effects not included in the a priori model, namely wing sweep off nominal, dynamic pressure (static flexibility effects), and landing gear deployment. Figure 4 shows a sample data set for one maneuver (longitudinal sinusoid at Mach = 0.9) with the time history match of the a priori model and the identified model.

Summary and Conclusions

This system identification data analysis procedure developed a very detailed, six DOF full subsonic envelope model of a complex aircraft. Identified aerodynamic effects include wing sweep, dynamic pressure, and landing gear as well as basic static longitudinal effects and angular rate damping effects. Identifying an increment to an existing simulation allows easy integration with the baseline simulation.

A nonlinear filter error algorithm provides initial parameter estimation, final parameter refinement, and validation. Adjusting the filter gains during the parameter search achieves rapid convergence of the LM estimation algorithm. It is most effective to begin with a high-gain filter and finish with a low-gain filter.

Using three key aerodynamic system identification concepts (kinematic consistency, model structure determination, and filter error parameter estimation) in an integrated fashion is a very effective procedure for attacking aerodynamic modeling problems having realistic complexity.

Acknowledgments

The U.S. Naval Air Warfare Center, Aircraft Division, under Contract N00421-88-D-0227 funded this work, and Systems Control Technology, Inc., internal research and development supported this work.

References

[1]Hall, W. E., and Gupta, N. K., "System Indentification for Nonlinear Aerodynamic Flight Regimes," *Journal of Spacecraft and Rockets*, Vol. 14, No. 2, 1977, pp. 73–80.

[2]Huffman, J., Fox, C., and Grafton, S., "Subsonic Longitudinal and Lateral Directional Static Stability Characteristics of a Variable Sweep Fighter Configuration Employing Various Control Surface Deflections at Angles of Attack of 0 to 50 deg and Large Sideslip Angles," NASA TM 74050, Nov. 1977.

[3]Grafton, S., and Anglin, E., "Dynamic Stability Derivatives at Angles of Attack from −5 to 90 deg for a Variable-Sweep Fighter Configuration with Twin Vertical Tails, NASA TN D-6909, Oct. 1972.

[4]Barnhart, B., "Incremental Rotational Aerodynamic Model for the F-14 Airplane," Bihrle Applied Research, Rept. 83-6, 1983.

[5]Barnhart, B., "Incremental Rotational Aerodynamic Math Model for the F-14 Airplane," Bihrle Applied Research, Rept. 86-4, 1986.

[6]Anon., "F-14A Stability and Control and Flying Qualities Report, Status III, Part II: Aerodynamic Characteristics and Dimensional Data," GAC Rept. A51-335-R-70-2.

[7]Vincent, J. H., Franklin, S. N., Rabin, U. H., and Trankle, T. L., "Nonlinear System Indentification Methodology Development Based on F-4S Flight Test Data Analysis," Final Report to Naval Air Test Center under Contract N00421-81-C-0289, Dec. 1983.

[8]Trankle, T. L., Vincent, J. H., and Franklin, S. N., "System Identification of Nonlinear Aerodynamic Models," *Advances in the Techniques and Technology of the Application of Nonlinear Filters and Kalman Filters*, AGARDograph No. 256, March 1982.

[9]Batterson, J. G., and Klein, V., "Partitioning of Flight Data for Aerodynamic Modeling of Aircraft at High Angles of Attack," *Journal of Aircraft*, Vol. 26, No. 4, 1989, pp. 334–339.

[10]Sri-Janyantha, M., and Stengel, R. F., "Determination of Nonlinear Aerodynamic Coefficients Using the Estimation-Before-Modeling Method," *Journal of Aircraft*, Vol. 25, No. 9, 1988, pp. 796–804.

[11]Stalford, H. L., "High-Alpha Aerodynamic Model Identification of T-2C Aircraft Using the EBM Method," *Journal of Aircraft*, Vol. 18, No. 10, 1981, pp. 801–809.

[12]Maine, R. E., and Iliff, K. W., "Formulation and Implementation of a Practical Algorithm for Parameter Estimation with Process and Measurement Noise," *SIAM Journal of Applied Mathematics*, Vol. 41, No. 3, 1981, pp. 558, 579.

[13]Jategaonkar, R. V., and Plaetschke, E., "Algorithms for Aircraft Parameter Estimation Accounting for Process and Measurement Noise," *Journal of Aircraft*, Vol. 26, No. 4, 1989, pp. 360–372.

[14]Trankle, T. L., and Rabin, U. H., "Maximum Likelihood Tuning of a Vehicle Motion Filter," *Journal of Guidance, Control, and Dynamics*, Vol. 13, No. 5, 1990, pp. 842–849.

[15]Keskar, D. A., and Klein, V., "Determination of Instrumentation Errors from Measured Data Using Maximum Likelihood," AIAA Paper 80-1602, 1980.

[16]Levenberg, K., "A Method for the Solution of Certain Nonlinear Problems in Least Squares," *Quarterly Applied Mathematics*, Vol. 2, 1944, pp. 164–168.

[17]Marquardt, D. W., "An Algorithm for Least Squares Estimation of Nonlinear Parameters," *Journal of the Society of Industrial and Applied Mathematics*, Vol. 11, No. 2, 1963, pp. 431–441.

[18]Brown, K. M., and Dennis, J. E., "Derivative Free Analogues for the Levenberg–Marquardt and Gauss Algorithms for Nonlinear Least Squares Approximation," *Numerische Mathematik*, Vol. 18, 1971, pp. 289–297.

[19]Hall, W. E., Jr., Gupta, N. K., and Smith, R. G., "Identification of Aircraft Stability and Control Coefficients for the High Angle-of-Attack Regime," Technical Rept. 2 to Office of Naval Research under Contract N00014-72-C-0328, March 1974.

[20]Furnival, G. M., and Wilson, R. W., Jr., "Regressions by Leaps and Bounds," *Technometrics*, Vol. 16, No. 4, 1974, pp. 499–511.