JOURNAL OF GUIDANCE, CONTROL, AND DYNAMICS
Vol. 18, No. 2, March–April 1995

Air Data Prediction from Surface Pressure Measurements on Guided Munitions

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The control of guided munitions over wide ranges of flight conditions has posed new requirements for estimating air data parameters. A common approach to meet the control stability margins and time response requirements is varying autopilot gains as a function of estimated air data parameters. A feasibility study to estimate air data parameters using flush-orifice pressure sensors has been completed. Wind-tunnel measurements of static pressure on sensors mounted on a representative missile nose were used. The primary objective of this study was to explore options for in-flight estimation of air data parameters using only the static pressure data base. The air data parameters of interest include Mach number, angle of attack, aerodynamic roll angle, and freestream pressure. An iterative process based on the differential corrections method was used to determine the air data parameters and expected error in the final estimates. Examples are given that provide sensitivity to pressure measurement noise and different sensor configurations. The air data estimates obtained with this method are suitable for autopilot gain scheduling over a wide range of flight conditions.

Nomenclature

C_p = pressure coefficient
M = Mach number
P = pressure
Re = Reynolds number
α = angle of attack
γ = ratio of specific heats
ϕ = aerodynamic roll angle
Δ = incremental change

Subscripts

i = generalized pressure sensor number
e = estimate
T = total
∞ = freestream
0 = initial estimate or previous value

Introduction

THE estimation of air data parameters for guided munitions over a wide range of Mach number, altitude, and angle-of-attack conditions is required to improve guidance and meet control requirements. High angle-of-attack flight has complicated the design of autopilots. This is especially true at some combinations of high angles of attack and wind angle orientation where aerodynamic coupling is significant. Successful implementation of aerodynamic cross-coupling compensation requires accurate estimates of angles of attack and sideslip. A typical solution to meet the stability margins and response requirements is to schedule autopilot gains with flight conditions such as Mach number, altitude, and angle of attack.

At high angles of attack it is difficult to measure air data accurately with traditional sensing devices. Different approaches to angle-of-attack estimation have been developed that rely on inertial instrumentation. Freeman's[1] method, using only accelerometers, requires extensive modeling of aerodynamic stability derivatives. In addition, this type of estimator system requires that other air data parameters, such as dynamic pressure, be provided by other on-board estimators. Other approaches (Olhausen[2]) use inertial navigation systems (INSs) with accelerometers, gyros, and velocity estimates along with the Euler angle transformation matrix. Angle of attack and sideslip are computed from the velocity components after transforming the velocity vector from the inertial to the vehicle body system. This type of approach, in addition to requiring an INS and initialization from the launch platform, is susceptible to errors induced by winds.

Flush-orifice pressure sensors have been shown to avoid some of these difficulties. These sensors are mounted in the vicinity of the missile nose and measure the static pressure at the orifice location. The flush-orifice air data system concept was originally developed at NASA Langley Research Center for high-speed re-entry vehicles. These sensors do not induce additional drag and leave the flow undisturbed.

Objectives

The objective of this study is threefold. First, this study evaluates the quality and features of the measured surface pressure data. Second, the feasibility and performance of an air data estimation algorithm using the differential corrections method[3] are investigated. Third, algorithm accuracy is examined in the presence of noise and different sensor configurations. Robustness of the recommended algorithm is desired for missile launch angles of attack up to 60 deg at an arbitrary aerodynamic roll angle.

Air data parameters required to be estimated from static pressure measurements in both captive-carry and free-flight modes include flight Mach number, total angle of attack, windward meridian orientation with respect to the vertical reference (the aerodynamic roll angle), and freestream static pressure (from which altitude can be estimated). Application to an axisymmetric missile nose geometry with arbitrary windward meridian orientation is assumed.

Typical accuracy requirements for the air data parameters are as follows: Mach number, ± 0.1; angle of attack, ± 5 deg; freestream pressure, ± 0.1 atm; and aero roll angle, ± 10 deg.

Algorithm development is based on a wind-tunnel data base of surface static pressure measurements for a representative missile nose geometry. The wind-tunnel data were obtained at freestream Mach numbers from 0.65 to 1.4, angles of attack of zero to 67 deg, and missile body increments of 3 deg to 5 deg up to one-half the angular spacing between sensors.

Previous Work

Whitmore et al.[4] report results of subsonic flight tests of a static pressure air data system developed for a high-angle-of-attack research aircraft. The flight test program used the NASA F-18 High Alpha Research Vehicle (HARV)[5] aircraft and required accurate air

Received May 24, 1993; revision received Jan. 4 1994; accepted for publication Feb. 27, 1994.

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data parameters to be available for flight control system operation. A nonintrusive high-angle-of-attack flush air data sensing (HI-FADS) system was developed.

The HI-FADS design employs a set of twenty-five 0.06-in.-diameter pressure orifices, arranged in four annular rings, drilled in a small fiberglass-reinforced plastic cap mounted on the nose of the F-18 HARV. Performance was demonstrated with all 25 ports and with a subset of 9 orifices. A flow model was developed to relate HI-FADS pressure measurements to the freestream air data parameters.

Deshpande et al.[6] has presented the results of a study to optimize the location of static pressure orifices for a flush-orifice air data system designed for hypersonic flight application on the Aeroassist Flight Experiment. The expected pressure distribution was developed from modified Newtonian theory that was corrected for the flight vehicle application. No experimental data were used in the study. Random errors were added to pressures given by the theoretical model to simulate flight measurements of pressure for selected air data parameter conditions.

Similar to the approach of Whitmore et al.,[4] the system of equations of Deshpande et al.[6] is linearized about the estimated state consisting of the angle of attack, sideslip angle, and total pressure. (Total pressure includes freestream pressure and Mach number effects.) The linearized system is solved by an iterative scheme.

The A-12 aircraft[7] approach was also reviewed. The production air data system for the A-12 aircraft is referred to as the flush air data system. It uses 10 flush pressure sensors distributed over the aircraft. The 10 pressure sensors were located on the A-12 at locations providing the greatest sensitivity to the four air data parameters of interest: angle of attack, angle of sideslip, Mach number, and freestream static pressure. The approach uses results from extensive scale model wind-tunnel tests of the A-12 configuration. The wind-tunnel tests provided pressure coefficients for each pressure sensor location in a data base as nonlinear functions of angle of attack, angle of sideslip, and Mach number. Reynolds number effects were apparently not accounted for in the data base.

Current Approach

The wind-tunnel data available for this investigation included pressure coefficients for 32 static pressure sensors spaced uniformly around the model nose geometry in 2 rings having 16 pressure sensors each. Figure 1 illustrates the model nose geometry and sensor locations. Only the 16 sensors in the forward ring were used in this analysis. In a tactical configuration a seeker sensor will be located in the vehicle nose. Due to this physical constraint, a stagnation pressure sensor was not included in the test apparatus. In an iterative algorithm, estimation accuracy is typically improved with increased number of sensors, including one of the sensors located near the stagnation point. Given packaging constraints, it is desirable to use a minimum number of sensors that meet accuracy requirements.

The approach was to extract and format the data into a suitable data base for an iterative solution algorithm. The solution algorithm is based on the differential corrections method[3] and results in a system of four equations in four unknowns, the corrections to the air data parameters. Corrections to estimates of the air data parameters require the inversion of a 4×4 matrix for each iteration. Convergence is attained when the expected pressure distribution matches the measured pressures in a least-squares sense. Sensor fault detection was incorporated into the software using the 3-sigma error bound of Whitmore et al.[4]

Wind-Tunnel Data Analysis

A data reduction program was developed to extract pertinent data from the forward ring of sensors. Once data from the sensors are extracted by the data reduction program, the data are converted to surface pressures and stored in matrix format as functions of angle of attack and orientation from the windward meridian. The stated accuracy of the pressure system is $\pm 0.584 + 0.012\%$ measured value in pounds per square foot (psf), which is typically below 1.0 psf for the conditions tested. The data sample rate is 50 samples/s, and the data from each sensor are averaged over time to provide stable data.

Pressure Distributions

Figure 2 shows representative subsonic pressure distributions around the missile nose. According to Fig. 2, the pressure data vary predictably on the entire windward side and over a portion of the leeward side of the missile. For increasingly higher angles of attack, the windward pressures continue to increase (as expected) and the leeward pressures continue to decrease in reasonable steps until the angle of attack reaches 30 deg–35 deg. Beyond 30 deg–35 deg the leeside sensors begin to show a significant pressure variation. This variation is probably due to the onset of unsteady separated flow/asymmetric vortical shedding. The wind-tunnel data show that significant separated flow regions began to develop at an angle of attack of 30 deg–35 deg. Given the Reynolds number of 2.5×10^6 per foot for this Mach number, laminar separation probably occurred unless the boundary layer was tripped into turbulence.

Another significant observation from Fig. 2 is the noticeable leeside asymmetric nature of the pressures beyond an angle of attack of 20 deg. Above 20 deg the right and left halves of the missile clearly experience different pressures on the leeside. As with the sensor-to-sensor variation in the leeside pressures previously mentioned, this asymmetric pressure behavior is probably due to the asymmetric subsonic flow separation.

The final observation from Fig. 2 is the location of the point of pressure invariance with angle of attack. Notice that the measured pressures for each angle of attack are within approximately 50 psf for the sensors located at 135 deg and 225 deg. It is interesting to note that this pressure is very close to the freestream pressure of 1,130 psf. By comparing data from several identical test conditions, the pressure data are very repeatable on most of the leeside sensors. Variation in measured pressures for the leeside sensors was typically less than 20 psf, even for the highest angles of attack.

Figure 3 illustrates the typical pressure distribution for the supersonic Mach number data. The supersonic pressure distributions

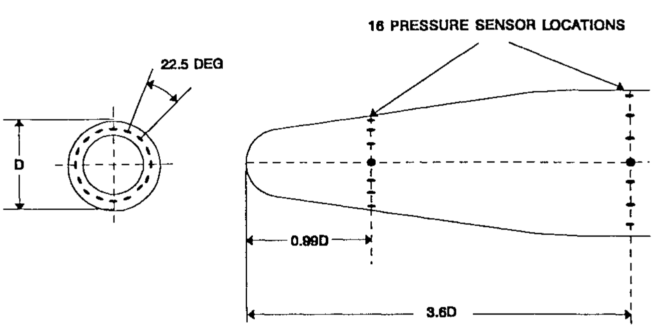

Fig. 1 Test configuration.

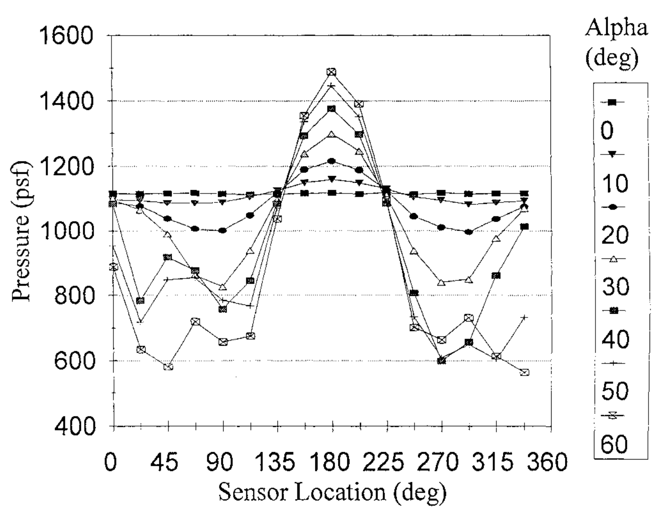

Fig. 2 Typical subsonic pressure distribution.

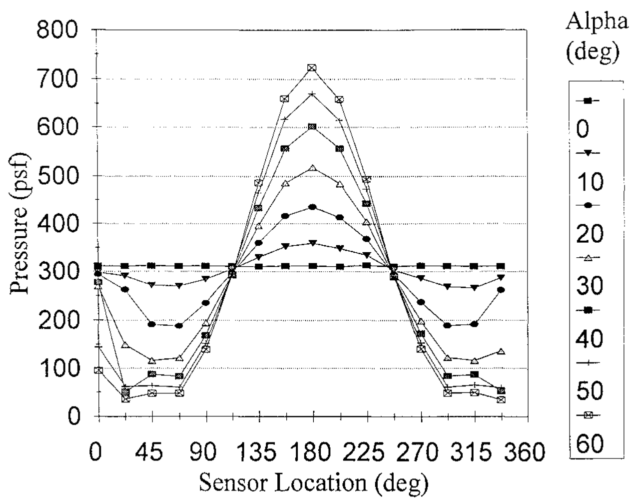

Fig. 3 Typical supersonic pressure distribution.

were found to be highly repeatable for every sensor around the body, even on the leeside. In comparison with the subsonic data, the points of pressure invariance have moved further from the windward direction.

Algorithm Initialization Implications

As expected, the pressure sensor closest to the windward meridian exhibits the largest surface pressure; therefore, the pressure sensor location returning the largest pressure can be used as the initial estimate of wind plane orientation. If uniformly spaced sensor locations are used, the likely error in wind plane orientation will not exceed one-half of the circumferential spacing (about 11 deg for the 16-pressure-sensor configuration).

The wind-tunnel data also indicate that, for the test conditions and configuration of this study, near invariance of the pressure distribution occurs at a point on either side of the peak, windward pressure. This pressure invariance point occurs almost uniformly at about 45 deg from the wind plane at subsonic conditions and at about 67 deg from the wind plane at transonic and supersonic conditions. Further, this invariance occurs at a pressure level close to the freestream pressure. Therefore, the pressure measurements at the two defined locations on either side of the peak pressure sensor (±45 deg for subsonic conditions or 67 deg for transonic/supersonic conditions) can be averaged to provide an initial estimate of the freestream pressure.

Obtaining Mach number and angle-of-attack initial estimates requires additional processing. Examination of the wind-tunnel pressure distributions indicates that both increasing Mach number and increasing angle of attack result in greater differences between the maximum pressure and the minimum pressure around the nose. Since Mach number and angle of attack cannot be isolated by simple circumferential pressure difference, another discriminant is required before algorithms can be developed to provide initial Mach number and angle-of-attack estimates.

Differential Corrections Method: Algorithm Development

An iterative least-squares search technique based on the standard differential corrections method was used to provide estimates of air data parameters (i.e., Mach number, angle of attack, aerodynamic roll orientation, and freestream pressure). Convergence of the iterative method is required to be fast relative to the time interval over which significant changes in individual air data parameters can occur. For this feasibility study, time-invariant pressure measurements were used for convergence verification and algorithm evaluation. However, the iterative schemes used can provide continuous estimates of air data parameters for time-varying surface pressure measurements.

The differential corrections method uses a linear least-squares solution technique for an otherwise nonlinear descriptive model of a physical process. The approach uses linearization of the nonlinear model about a reference condition consisting of the current estimates of the system state variables (e.g., air data parameters for the present application.

The static pressure at a sensor i on the nose of the missile is assumed to be a function of the Mach number, freestream pressure, freestream temperature, total angle of attack α_T, and circumferential angle between the total angle-of-attack plane and sensor i on the surface, ϕ_i.

An iterative estimation process was developed to improve estimates of air data parameters. The best estimate of air data parameters is expected to occur when the differences between the expected and measured pressures at all sensors i are a minimum in a least-squares sense. The expected pressures at sensors i are derived from the available data base for the current estimates of the air data parameters.

The iterative procedure is constructed to use 1) the residuals (i.e., the differences between expected and measured pressures) at sensors i and 2) the sensitivity of the pressure at sensors i to variations in air data parameters to provide corrections to correct current estimates of those parameters until convergence in a least-squares sense occurs. Linearization of the model about a reference condition (i.e., the current estimates of air data parameters) provides the sensitivities as the first-derivative terms in a Taylor series expansion of the pressure about the reference condition.

Increments to the estimated air data parameters are defined as follows:

$$\begin{aligned} M_\infty &= M_{\infty,0} + \Delta M_\infty \\ P_\infty &= P_{\infty,0} + \Delta P_\infty \\ \alpha_T &= \alpha_{T,0} + \Delta\alpha_T \\ \phi_i &= \phi_{i,0} + \Delta\phi_i \end{aligned} \tag{1}$$

Define the residual at port i as the difference between the most recent pressure measurement and the estimated pressure at that point as obtained from the data base. The residual at point i for the original estimates is therefore

$$R_{i,0} = P_i - P_{i,e}(M_{\infty,0},\ P_\infty,\ \alpha_{T,0},\ \phi_{i,0}) \tag{2}$$

and for the improved parameter estimates it is

$$R_i = P_i - P_{i,e}(M_\infty,\ P_\infty,\ \alpha_T,\ \phi_i) \tag{3}$$

where $P_{i,e}$ is the estimate of P_i as obtained from the data base for the estimates of air data parameters. A first-order Taylor series expansion about the current parameter set can be written as

$$R_i = R_{i,0} + \frac{\partial P_{i,e}}{\partial M_\infty}\Delta M_\infty + \frac{\partial P_{i,e}}{\partial P_\infty}\Delta P_\infty + \frac{\partial P_{i,e}}{\partial \alpha_T}\Delta\alpha_T + \frac{\partial P_{i,e}}{\partial \phi_i}\Delta\phi_i \tag{4}$$

For the new parameter estimates to be optimum requires that the sum of squares of the new residuals, R_i, be a minimum. This in turn requires that the partial derivative of the summation term be zero relative to each air data parameter.

Defining the terms

$$\begin{aligned} A_i &= \frac{\partial P_{i,e}}{\partial M_\infty} & B_i &= \frac{\partial P_{i,e}}{\partial P_\infty} \\ C_i &= \frac{\partial P_{i,e}}{\partial \alpha_T} & D_i &= \frac{\partial P_{i,e}}{\partial \phi_i} \end{aligned} \tag{5}$$

the derivative equations can be written as

$$\begin{aligned} \sum A_i R_i &= 0 & \sum B_i R_i &= 0 \\ \sum C_i R_i &= 0 & \sum D_i R_i &= 0 \end{aligned} \tag{6}$$

Writing these equations in terms of the residuals based on the previous estimates $R_{i,0}$ results in the normal or generalized equations, which in matrix form can be defined as

$$\begin{bmatrix} \sum A_i^2 & \sum A_i B_i & \sum A_i C_i & \sum A_i D_i \\ \sum B_i A_i & \sum B_i^2 & \sum B_i C_i & \sum B_i D_i \\ \sum C_i A_i & \sum C_i B_i & \sum C_i^2 & \sum C_i D_i \\ \sum D_i A_i & \sum D_i B_i & \sum D_i C_i & \sum D_i^2 \end{bmatrix} \begin{bmatrix} \Delta M_\infty \\ \Delta P_\infty \\ \Delta \alpha_T \\ \Delta \phi_i \end{bmatrix} = \begin{bmatrix} \sum A_i R_{i,0} \\ \sum B_i R_{i,0} \\ \sum C_i R_{i,0} \\ \sum D_i R_{i,0} \end{bmatrix} \tag{7}$$

This system of equations represents four equations in four unknowns, the corrections to the air data parameters. Given the residuals based on the prior parameter estimates, $R_{i,0}$, and the sensitivities represented by the derivative terms A_i, B_i, C_i, and D_i as obtained from the data base, the corrections to the air data parameters can be obtained from the normal equations. The process can be continued until the sum of squares of the residuals is less than a prescribed value.

For this study, the derivative terms needed in the normal equations were first developed from 1) the wind-tunnel data base for derivatives with respect to angle of attack and roll orientation and 2) appropriate interpolation relationships between Mach number and freestream pressure levels. The wind-tunnel data base contained data at only one freestream pressure for each Mach number, so derivatives with respect to freestream pressure at constant Mach number could not be developed from the data base. Also, the wind-tunnel data were available at relatively sparse Mach number intervals. Derivatives with respect to Mach number are believed to be better represented by an analytical formulation rather than by a finite difference approximation relative to Mach number using the available data base. However, for mission application, additional wind-tunnel data at varying pressure levels and additional Mach numbers will allow derivatives with respect to both of these variables to be developed from the data base itself.

The pressure coefficient is defined as

$$C_p = \frac{P_i - P_\infty}{(\gamma/2)P_\infty M_\infty^2} \tag{8}$$

so that the local pressure is

$$P_i = P_\infty + \tfrac{1}{2}\gamma C_p P_\infty M_\infty^2 \tag{9}$$

The pressure coefficient can be presumed to be a function of freestream Mach number and freestream Reynolds number, so the derivatives of P_i with respect to M_∞ and P_∞ can be written if $C_p(M_\infty, R_e)$ is given. The functional behavior C_p is dependent on the flight regime interest (i.e., subsonic, transonic, supersonic, or hypersonic Mach number and laminar, transitional, or turbulent boundary-layer conditions). Scaling within these regimes can be based on computational results, analytical expressions (e.g., modified Newtonian expressions for high Mach numbers), or typical similarity results (e.g., Gothert's rule for three-dimensional, small-perturbation flow). For this feasibility analysis, C_p was assumed constant over the small-Mach-number interval of the iterative search process, so local pressure varied linearly with freestream pressure and quadratically with freestream Mach number.

Initialization of the iterative search algorithm is required, and the algorithm can use externally supplied state estimates, if available, or the pressure sensor data itself if no other air data estimates are accessible to the on-board processor. Use of the sensor data for freestream pressure and aerodynamic roll-angle initialization was discussed earlier. For this feasibility study, autonomous initialization of the algorithm using pressure sensor data was selected for freestream pressure and aerodynamic roll angle. Initialization of angle of attack and Mach number was selected from a random distribution. Better startup algorithms have been developed allowing for faster convergence of the initial estimates.[8]

Application of Differential Corrections Methodology

Development of Aerodynamic Derivative Tables

Since the approach requires aerodynamic derivatives with respect to the air data parameters, a software package was developed to take all the wind-tunnel measured pressures for a particular run number and numerically estimate the derivatives in both angle of attack and roll angle. Central differencing is used except for the first and last derivatives in a particular direction where forward and backward differences are used, respectively.

FORTRAN Program Description

Given the differential corrections methodology, a FORTRAN-based software program was developed to accept pressure sensor data and estimate the flight conditions required to yield these data. Simulated pressure data were generated from the available wind-tunnel data, with and without additive pressure noise, to use as representative measurements. The computer program was designed to read a set of these pressure data (i.e., measured pressures) from an external file and then use the wind-tunnel data base to estimate flight conditions yielding these pressures.

Enhancements Over Basic Algorithm

The program monitors the iteration progress and provides a perturbation in the estimated flight conditions if the root-mean-square (rms) value of the residual is not diminishing toward an expected level. A steady-state residual level well above the pressure measurement accuracy is characteristic of convergence toward a local minimum. After examination of the wind-tunnel aerodynamic derivatives and the theoretical pressure/Mach derivatives, it appears that a similarity exists between the derivatives with respect to angle of attack and Mach number. For a fixed Mach number a slight change in the angle of attack yields a similar body pressure variation as the case for which the angle of attack is fixed and the Mach number is varied. This type of relationship between Mach number and angle of attack makes it possible to reach a local minimum rms residual value instead of the global minimum, where the rms residual is an absolute minimum consistent with the pressure measurement uncertainty. The program can detect a local minimum and step the solution beyond this point, for example, by decreasing the estimated angle of attack by 5 deg and increasing the estimated Mach number by 0.1.

During execution, the differential corrections method continues to diminish the residuals by refining the estimated flight conditions until the rms residual value falls below the specified value. Experimentation has shown that very good convergence can be reached in a minimum number of iteration cycles by using an rms value of 2.0 psf.

The program can also run automatically through as many pressure data sets as are contained in the external pressure file. This option was employed to run through 1,000 or more pressure data sets to monitor the performance of the method in a near continual operation (i.e., flight) mode. In order to run in the automatic mode, the program was modified to provide initial estimates of the flight conditions. To provide these estimates, a random, normally distributed noise model was superimposed on the true angle of attack, Mach number, and roll angle. The errors in the initial estimates of these three parameters were bounded between 10 and 50% of the actual parameter values. The roll-angle error was implemented to account for the fact that a sensor will not always be directly aligned with the relative wind direction. The initial freestream pressure estimate comes from the empirical observation that the pressure is relatively invariant and near the freestream pressure roughly 45 deg (subsonic conditions) or 67 deg (transonic/supersonic conditions) from the windward direction for the tested nose configuration. Once the highest pressure sensor is found, the program simply averages the pressures from the sensors approximately 45 deg or 67 deg (depending on the initial Mach number estimate) on either side of the windward sensor and assumes this value as the initial estimate of the freestream pressure.

Based on both subsonic and supersonic analyses without sensor noise, the method often yields faster, more accurate flight condition estimates when pressure data from the most leeside sensors are discarded. The program allows the user to specify the number of sensors used on both sides of the most windward sensor. If too few sensors are used, steady-state errors can become a problem for certain flight conditions. Since the windward side pressure data are very similar for increasing angles of attack, the method needs data from a few well-behaved leeside sensors to provide uniqueness for a particular set of flight conditions.

Solution Scheme

The generalized matrix equations outlined in the algorithm development section are formed by linearly interpolating/extrapolating the aerodynamic pressure and derivative data at the current estimation of the flight conditions. Once the generalized matrix equations are generated, the program solves these equations for the flight condition increments (Mach number, angle of attack, aerodynamic roll angle, and freestream pressure) by Gaussian elimination with partial pivoting. The estimated flight conditions are then updated by these increments. This solution process is repeated until the rms residual value falls below the specified value or until the maximum number of iterations is reached.

Results

Results of sensitivity analysis to different sensor configurations and pressure measurement noise are described in this section. All statistical information presented in Figs. 4–7 includes subsonic and supersonic flow conditions and is based on 10,000 individual runs per sensor configuration. There were 28 angles of attack available from the wind-tunnel data, and each angle of attack was executed roughly 350 times with different initial estimates of the air data parameters. All test cases were executed first without noise to isolate the obtainable system accuracy as a function of the number of sensors used. The baseline 16-sensor configuration uses all available sensor data to determine the air data parameters. The other two sensor configurations (13 and 11 sensors) were formed by discarding data from the three and five most leeside pressure sensors when the estimated angle of attack exceeded 30 deg.

The test cases that include pressure noise were executed for the same three sensor configurations. Existing flight test data[4,6] indicate that the random noise level that can be expected in the measured pressures is less than 1% of the full scale of the pressure transducer. For this feasibility study, the random measurement noise was modeled by a normal distribution with a one-sigma variance of 1% of the freestream static pressure.

Given the unusual behavior of the Mach 0.65 data (i.e., slightly unrepeatable, asymmetric) compared to the supersonic data, evaluating the performance of the method with the Mach 0.65 data is

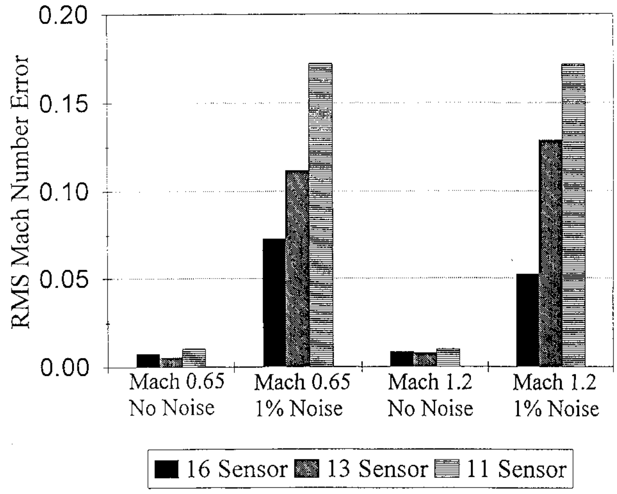

Fig. 4 Mach accuracy.

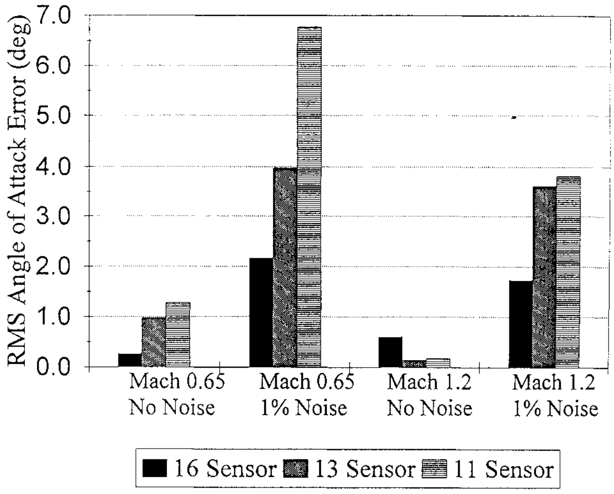

Fig. 5 Angle-of-attack accuracy.

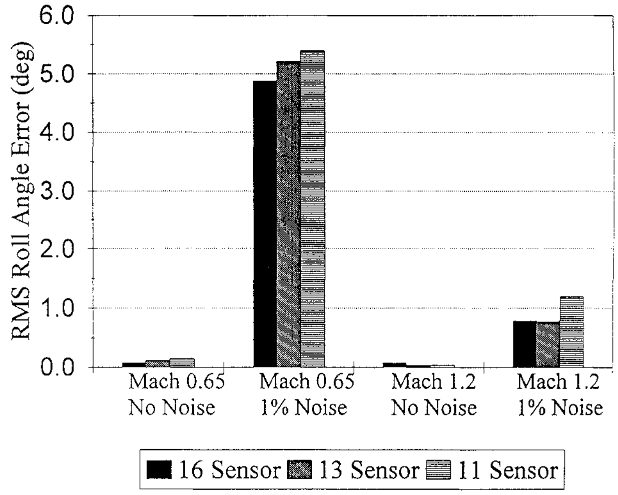

Fig. 6 Aerodynamic roll-angle accuracy.

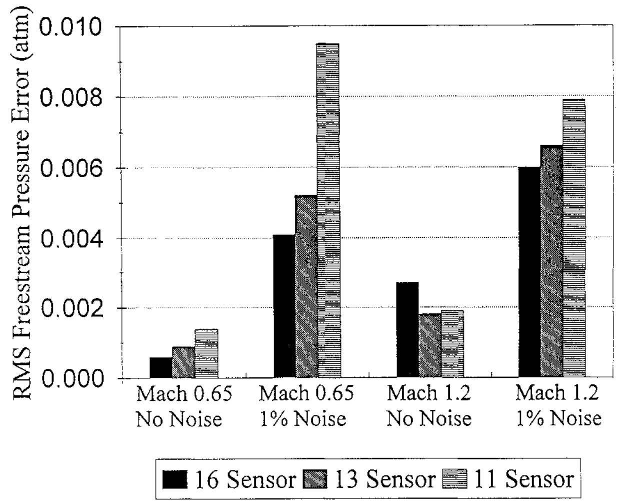

Fig. 7 Freestream pressure accuracy.

the most rigorous test of the differential corrections methodology. Since the supersonic pressure data (Mach 1.2) were symmetrical and repeatable, with discrete variations in the sensor pressure for increasing angles of attack, the method was expected to perform better on the supersonic data than on the subsonic data.

As shown in Fig. 4, the accuracy of the solution algorithm is degraded significantly by noise. This trend is the expected result since the presence of pressure noise diminishes the ability of the algorithm to distinguish definite trends in the difference between the measured and estimated pressure distributions. Another expected result shown in Fig. 4 is that, as the number of sensors is decreased, the achieved Mach number accuracy decreases rapidly, but only when noise is included in the pressure data. Without noise, system performance is only slightly degraded when only 11 sensors are used. It is reasonable to conclude that when noise perturbs the sensor data, greater accuracy is achieved when more sensors are used. In fact, all 16 sensors are required to meet the Mach number estimation accuracy of 0.1.

Figure 5 shows essentially the same trends shown in Fig. 4, except that the effect of noise is more pronounced for the subsonic Mach number than for the supersonic Mach number. Considering the pressure differences (difference in maximum windward pressure and minimum leeside pressure) across the forebody for both subsonic and supersonic flight conditions (Figs. 2 and 3), a 1% noise level should degrade the subsonic performance of the algorithm more than the supersonic performance. As the angle of attack increases from zero to 20 deg, Figs. 2 and 3 indicate that the pressure difference across the forebody is significantly greater for the Mach 1.2 data than for the Mach 0.65 data. For Mach 1.2 the pressure difference at 20 deg angle of attack is 80% of the freestream pressure, whereas the Mach 0.65 data indicate that the pressure difference is only 22% of the freestream pressure. With this significant disparity in the pressure difference magnitude for the two Mach numbers, it is expected that a 1% noise level will more seriously affect algorithm performance for subsonic Mach numbers.

Figure 6 shows that the subsonic roll-angle accuracy is most affected by the addition of noise. Once again, the smaller pressure difference for the subsonic data decreases the ability of the algorithm to find the correct aerodynamic roll angle. At subsonic conditions and low angles of attack, the noise level essentially becomes the same order of magnitude as the pressure difference across the missile, thereby masking the true aerodynamic roll angle.

Figure 7 indicates that, although noise decreases the ability of the algorithm to find the correct freestream pressure, the achieved accuracy is within 0.010 atm of the true pressure. When all 16 sensors are used, the freestream pressure accuracy is within 0.006 atm.

Conclusions

A review of the wind-tunnel data shows that there are certain flight conditions where it may be beneficial to retain all the pressure data, and there are conditions where data from some of the leeside sensors should be discarded. Depending upon the true noise level found in flight, discarding some leeside data may improve air data estimates. However, for high noise levels, results indicate that all 16 sensors should be retained to meet typical autopilot accuracy requirements. Since evidence exists on benefits to both retaining and discarding certain leeside pressure data, additional algorithms can probably be developed to determine when to retain and discard certain data.

The differential corrections method provides reasonable flight condition estimates at Mach 0.65 and Mach 1.2 for every available angle of attack between 5 deg and 67 deg even with high sensor noise. The method typically provides flight condition estimates that are suited for autopilot gain scheduling at both subsonic and supersonic Mach numbers.

Aerodynamic lag and other transient effects in the flow field during missile maneuvering may cause degradation in estimation accuracy. These issues can be better addressed by flight tests. Until some flight test results are available, high body angular rates can be expected to affect the system in the same way that noise affects the system, that is, through decreased accuracy. Time lag effects due to body motion and real-time algorithm solution could be investigated using a missile flight simulation. Preliminary algorithm timing analyses indicate that the algorithm can provide adequate data rate for autopilot implementation.

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