MULTIPLE MODEL ADAPTIVE ESTIMATION APPLIED TO
THE VISTA F-16 FLIGHT CONTROL SYSTEM WITH
ACTUATOR AND SENSOR FAILURES

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ABSTRACT

Multiple model adaptive estimation (MMAE) is applied to the Variable In-flight Stability
Test Aircraft (VISTA) F-16 flight control system. Single actuator and hard sensor
failures are introduced and system performance is evaluated. Performance is enhanced by the
application of a modified Bayesian form of MMAE, scalar residual monitoring to reduce ambiguities, dithering where advantageous, and purposeful commands.

1. Introduction

For many applications, it is highly desirable to develop an aircraft flight control
system with reconfigurable capabilities: able to detect and isolate failures of sensors
and/or actuators and then to employ a control algorithm that has been specifically designed
for the current failure mode status. One means of accomplishing this, in a manner that is
ideally suited to distributed computation, is multiple model adaptive estimation (MMAE) [1-4]
and control (MMAC) [5-7].

Assume that the aircraft system is adequately represented by a linear perturbation
stochastic state model, with a (failure status) uncertain parameter vector affecting the
matrices defining the structure of the model or depicting the statistics of the noises entering
it. Further assume that the parameters can take on only discrete values: either this is
reasonable physically (as for many failure detection formulations), or representative
discrete values are chosen throughout the continuous range of possible values. Then a
Kalman filter is designed for each choice of parameter value, resulting in a bank of K
separate "elemental" filters. Based upon the observed characteristics of the residuals in
these K filters, the conditional probabilities of each discrete parameter value being
"correct", given the measurement history to that time, are evaluated iteratively. In MMAC,
a separate set of controller gains is associated with each elemental filter in the
bank. The control value of each elemental controller is weighted by its corresponding
probability, and the adaptive control is produced as the weighted average of the
elemental controller outputs. As one alternative (using maximum a posteriori, or
MAP, rather than minimum mean square error, or MMSE, criteria for optimality), the control
value from the single elemental controller associated with the highest conditional
probability can be selected as the output of the adaptive controller.

Previous efforts investigated the application of a multiple model adaptive control
to the short takeoff and landing (STOL) F-15 [8,9]. The system was modeled with four
elemental controllers designed for a healthy aircraft, failed pitch rate sensor, failed
stabilator, or failed "pseudo-surface" - a combination of canards, ailerons, and trailing
edge flaps. Conclusions from this study indicated that the elemental filters must be
carefully tuned to avoid masking of "good" versus "bad" models. This observation is not
compatible with Loop Transmission Recovery (LTR) tuning techniques. Other research efforts
demonstrated the effectiveness of the MMAC algorithm using seven elemental controllers
designed for a healthy aircraft, one of three actuator failures, or one of three sensor
failures [10,11]. The study included effects of single and double failures, and partial
failures as well as hard failures. It also demonstrated the effectiveness of alternate
techniques to resolve ambiguities using modified computational techniques and scalar residual
monitoring.

2. MMAC and MMSE-Based Control

Let a denote the vector of uncertain parameters in a given linear stochastic state
model for a dynamic system, in this case depicting the failure status of sensors and
actuators of the aircraft. These parameters can affect the matrices defining the structure of
the model or depicting the statistics of the noises entering it. In order to make
simultaneous estimation of states and parameters tractable, it is assumed that a can take on
only one of K discrete representative values. If we define the hypothesis conditional
probability $p_k(t_i)$ as the probability that a assumes the value $a_k$ (for $k = 1,2,\ldots,K$),
conditioned on the observed measurement history to time $t_i$:

$$p_k(t_i) = \text{Prob}[a = a_k | Z(t_i) = \mathbf{z}_i]$$  \hspace{1cm} (1)

then it can be shown [1-4] that $p_k(t_i)$ can be evaluated recursively for all $k$ via the
iteration:

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in terms of the previous values of $p_j(t_{i-1}), \ldots, p_k(t_{i-1})$, and conditional probability densities for the current measurement $z(t_i)$ to be defined explicitly in Equation (12). Notationally, the measurement history random vector $Z(t_i)$ is made up of partitions $z(t_1), z(t_2), \ldots, z(t_i)$ that are the measurements available at the sample times $t_1, \ldots, t_i$; similarly, the realization $Z_i$ of the measurement history vector has partitions $z_1, \ldots, z_i$. Furthermore, the Bayesian multiple model adaptive controller output is the probability weighted average [5-7]:

$$u_{MMAC}(t_i) = \sum_{k=1}^{K} u_k[S_k(t_i), t_i] \cdot P_k(t_i) \tag{3}$$

Here $u_k[S(t_i), t_i]$ is a deterministic optimal full-state feedback control law based on the assumption that the parameter vector equals $a_k$, and $S_k(t_i)$ is the state estimate generated by a Kalman filter similarly based on the assumption that $a = a_k$. If the parameter were in fact equal to $a_k$ then certainty equivalence [5] would allow the LQG (Linear system, Quadratic cost, Gaussian noise) optimal stochastic control to be generated as one of the $u_k[S_k(t_i), t_i]$ terms in the summation of Eq. (3).

More explicitly, let the model corresponding to $a_k$ be described by an "equivalent discrete-time model" for a continuous-time system with sampled data measurements:

$$x_{k}(t_{i+1}) = A_k(t_{i+1}, t_i)x_k(t_i) + B_k(t_i)u(t_i) + G_k(t_i)w_k(t_i) \tag{4}$$

$$z(t_i) = H_k(t_i)x_k(t_i) + v_k(t_i) \tag{5}$$

where $x_k$ is the state, $u$ is a control input, $w_k$ is discrete-time zero-mean white Gaussian dynamics noise of covariance $Q_k(t_i)$ at each $t_i$, $z$ is the measurement vector, and $v_k$ is discrete-time zero-mean white Gaussian measurement noise of covariance $R_k(t_i)$ at $t_i$, assumed independent of $w_k$; the initial state $x(t_0)$ is modeled as Gaussian, with mean $x_{0_k}$ and covariance $P_{0_k}$ and is assumed independent of $w_k$ and $v_k$. Based on this model, the Kalman filter [11] is specified by the model update:

$$A_k(t_i) = H_k(t_i)P_k(t_i)H_k^T(t_i) + R_k(t_i) \tag{6}$$

$$K_k(t_i) = P_k(t_i)H_k^T(t_i)A_k^{-1}(t_i) \tag{7}$$

$$S_k(t_{i+1}) = S_k(t_i) + K_k(t_i)[z_i - H_k(t_i)x_k(t_i)] \tag{8}$$

and the propagation relation:

$$S_k(t_{i+1}) = \Phi_k(t_{i+1}, t_i)S_k(t_i) + B_k(t_i)u(t_i) \tag{9}$$

$$P_k(t_{i+1}) = \Phi_k(t_{i+1}, t_i)P_k(t_i)\Phi_k^T(t_{i+1}, t_i) + G_k(t_i)G_k(t_i)S_k(t_i) \tag{10}$$

$$P_k(t_{i+1}) = \Phi_k(t_{i+1}, t_i)P_k(t_i)\Phi_k^T(t_{i+1}, t_i) + G_k(t_i)G_k(t_i)S_k(t_i) \tag{11}$$

The multiple model adaptive estimation (MMAE) algorithm is composed of a bank of $K$ separate Kalman filters, each based on a particular value $a_k, \ldots, a_K$ of the parameter vector, as depicted in Figure 1. Instead of generating a control vector $u_k$, the MMAE generates a probabilistically weighted state estimate vector $x_{MMAC}(t_i)$. These state estimates are used by the flight control system to generate the control vector $u_k$. Such MMAE-based control filters in this research rather than a MMAC because the incorporation of the full VISTA F-16 flight control system illustrates another step toward the maturation of the MMAC/MMAE algorithms. When the measurement $z_i$ becomes available at time $t_i$, the residual vector $r_k$ is generated in each of the $K$ filters according to the bracketed term in Eq. (a), and used to compute $p_i(t_i), \ldots, p_k(t_i)$ via Eq. (2). Each numerator density function in (2) is given by the Gaussian form:

$$p_i(t_i) = \frac{1}{(2\pi)^{m/2}|A_k(t_i)|^{1/2}} \exp\left[-\frac{1}{2} r_k^T A_k^{-1}(t_i) r_k \right] \tag{12}$$

where $m$ is the measurement dimension and $A_k(t_i)$ is calculated in the $k$-th Kalman filter as in Eq. (6). The denominator in Eq. (2) is simply the sum of all the computed numerator terms and thus is the scale factor required to ensure that the $p_k(t_i)$'s sum to one. One expects the residuals of the Kalman filter based upon the "best" model to have mean squared value most in consonance with its own computed $A_k(t_i)$, while "mismatched" filters will have larger residuals than anticipated through $A_k(t_i)$. Therefore, Eqs. (2), (3), and (6) - (12) will most heavily weight the filter based upon the most correct assumed parameter value. However, the performance of the algorithm depends on there being significant differences in the characteristics of residuals in "correct" vs. "mismatched" filters. Each filter should be tuned for best performance when the "true" values of the uncertain parameters are identical to its assumed value for these parameters. One should specifically avoid the "conservative" philosophy of adding considerable dynamics pseudonoise, often used to guard against
detection and isolation algorithm, this is not a restrictive constraint.

The flight control system depicts the true system by including control effects given by left and right stabilators, left and right flaperons, rudder and leading edge flaps. The model is developed with constant thrust.

Flight Control System. The flight control system (FCS) model is a Fortran representation of the VISTA F-16 FCS. The model accurately represents the true system by including longitudinal, lateral, and directional channels. Each channel provides command force gradients, command limiting, signal magnitude and rate limiting accomplished within the controller software, gain scheduling, biases, filtering characteristics, and true surface position and rate limiting. Sensor measurements are corrected for position error where applicable. The flight control system requires seven sensor inputs for proper performance including: velocity, angle of attack, pitch rate, normal acceleration, roll rate, yaw rate, and lateral acceleration.

The development of a detailed model allows for a realistic evaluation of the MMAE algorithm. The flight control system and linearized aerodynamic models were validated separately and as a system using a six-degree-of-freedom nonlinear simulation. Results indicated excellent correlation provided that the constraints of the linear aerodynamic perturbation model were not violated. Given the short convergence times typical for a fault detection and isolation algorithm, this is not a restrictive constraint.

4. Algorithm Implementation

Hypothesized Failures. The parameter space, denoted by the vector quantity \( a \), was discretized into twelve hypothesized hard failures: left stabilator, right stabilator, left flaperon, right flaperon, rudder, velocity sensor, angle of attack sensor, pitch rate sensor, normal acceleration sensor, roll rate sensor, yaw rate sensor and the lateral acceleration sensor. Additionally, the no-failure aircraft condition was included to provide an initial system configuration prior to failure transition. Total or "hard" actuator failures are modeled by zeroing out the appropriate columns of the control input matrix \( B \) of Eq. (4) and hard sensor failures are modeled by zeroing out the corresponding rows of the measurement matrix \( H \) of Eq. (5).

Bayesian Form. The final probability-weighted average of the state estimates, computed as shown in Figure 1, is produced by a Bayesian form of the MMN algorithm. A Bayesian form of the MMAE algorithm allows for a blending of filters designed for hard failures and those designed for no-failures to address partial or soft failures. Practical implementation requires a lower bound when computing the probabilities according to Eq. (2). The addition of a lower bound prevents the algorithm from assigning any single \( p_k(t) \) a value of zero, which would prevent it from being considered in future probability computations. From the iterative nature of Eq. (2), if \( p_k(t) \) were assigned a value of zero (i.e. \( p_k(t) = 0 \)), which would prevent it from being considered in future probability computations. From the iterative nature of Eq. (2), if \( p_k(t) \) were assigned a value of zero (i.e. \( p_k(t) = 0 \)), the addition of a lower bound provides another favorable characteristic. The number of iterations required to increase a very small, but nonzero, \( p_k \) is directly proportional to the magnitude of the \( p_k \). By providing a lower bound we allow \( p_k \) values, previously not important to the combined state estimate, to increase in a timely manner if the system state changes.

"Beta Dominance". As discussed earlier in Section 2, the hypothesis probabilities \( p_k(t) \) are calculated according to Eq. (2). Earlier efforts [2,4,6,10] noted that the leading coefficient preceding the exponential term in Eq. (12) does not provide any useful information in the identification of the failure. As discussed in Section 2, the likelihood quotient,

\[
L_k(t_j) = r_k(t_j)A_k^{-1}r_k(t_j) \tag{14}
\]

compares the residual with the hypothesized filter’s internally computed residual covariance. Filters with residuals that have mean square values most in consonance with their internally computed covariance are assigned the higher probabilities by the MMAE algorithm. However, if the likelihood quotients were nearly identical in magnitude for all \( k \), the probability computations would be based upon the magnitude of the determinants of the \( A_k(t) \) matrices, resulting in an incorrect assignment of the probabilities. This effect is known as "Beta Dominance". Because sensor failures, as simulated by zeroing out a row of \( H \), yield
demonstrate the relationship of the probability of the probabilities does not alter the fact that the computed probabilities sum to one.

Scalar Residual Monitoring. Incorrect or ambiguous failure identification may be resolved through the use of scalar residual monitoring. Eqs. (2), (12), and (13) demonstrate the relationship of the probability calculations, the probability density function, and the likelihood quotient. These three equations demonstrate the dependency of the probability calculations on the magnitude of the likelihood quotient, Eq. (13). The likelihood quotient is merely the sum of scalar terms relating the product of any two scalar components of the residual vector and the filter’s internally computed covariance for those two components. If a sensor failure occurs, the single scalar term associated solely with that sensor should have a residual value whose magnitude is much larger than the associated variance in all of the elemental filters except for the filter designed to "look" for that sensor failure. Scalar residual monitoring can be used as an additional vote when attempting to reduce or eliminate failure identification ambiguities.

Purposeful Commands. Failure detection and isolation using the MMAE algorithm requires a stimulus to disturb the system from a quiescent state. The MMAE algorithm's performance depends upon the magnitude of the residuals within incorrect filters having large residual values. Residuals are the difference between measurements and filter predictions of those measurements. Incorrect filters will provide poor estimates relative to the filter based on the "true" system status. Small deviations from a quiescent state will be virtually indistinguishable from system noise, providing poor failure detection and identification. Having justified the need for stimuli to "shake up" the system, rationale was developed to select stimuli, control deflections, and improve performance. Previous efforts selected a pitch down maneuver to aid in the identification on the longitudinal axis of an aircraft with generally favorable results [14]. However, fundamental differences exist between earlier research and this effort. Earlier efforts concentrated on applying the MMAC algorithm, evaluating its performance, and designing algorithms to maintain stability and control in the longitudinal axis. A longitudinal pitch down maneuver was sufficient to provide enough system excitation for good performance. A three-axis sophisticated control system requires excitation in multiple axes to provide adequate residual growth in filters whose hypothesis does not reflect the true system failure status. The purposeful commands used in this effort were longitudinal stick pulses, lateral stick pulses, and varying amounts of rudder application. Ordinary aircraft maneuvering would probably be more than sufficient to provide adequate excitation and good performance; straight-and-level flight would be more challenging (though less flight critical) for a failure detection system.

Autonomous Dithering. Autonomous dithering enhances failure detection and identification by providing sufficient excitation in benign non-maneuvering flight conditions or as a pilot-selectable option. A number of dither signals were evaluated, including square waves, triangle waves, combinations of these forms, and sine waves. Pulse trains using a square wave form produced good performance with one drawback: failures are not detected until the application of the pulse. Additionally, pilots may find the application of a dither signal of sufficient strength to provide good failure detection and isolation objectionable, unless he were able to turn such dithering on and off himself. Sufficient data was not available to relate pilot comments and normal and lateral accelerations in this application, so dithers were designed to be as subliminal as possible while yielding desired identifiability of failures.

5. Performance

The application of the multiple model adaptive estimation algorithms to the VISTA F-16 aircraft in a low dynamic pressure case provided an interesting test for this technique. The flight condition, 0.4 Mach at an altitude of 20000 ft., demonstrated algorithm performance in a low dynamic pressure scenario. Earlier efforts studied the VISTA F-16 at a higher dynamic pressure and emphasized different failure scenarios and characteristics [15]; the case of low dynamic pressure yields a more difficult identification problem. The original goal was to evaluate the MMAE algorithm's ability to detect and isolate failures within the flight control system and not to evaluate the ability of the controller to maintain control of the vehicle after the identification of the failure. An added benefit of using the VISTA F-16 flight control system was the absence of any single-failure-induced loss of control. The figures presented in this section are single data runs as opposed to Monte Carlo runs averaged over a number of runs, in order to exhibit real-time signal characteristics (Monte Carlo runs were used to corroborate performance attributes over multiple experimental trials).

Purposeful Commands. Figure 2 demonstrates a left stabilator failure induced at 3.0 seconds. A square wave dither signal occurs in all three channels every 3.0 seconds beginning at 0 seconds. The pulse widths and magnitudes were different for each channel and were determined by trial and error. Typical pulse cycles, the application of a pulse of positive amplitude followed by the application of a pulse of negative amplitude, were usually approximately 0.25 seconds. Figure 2 presents performance data after a failure at 3.0 seconds and the application of a longitudinal stick pull for a duration of 3.0 seconds, starting at 3.0 seconds. It displays only the no-failure and failed actuator elemental filter probabilities; the failed-sensor elemental filters never
attained any appreciable portion of the total probability. The FF, A1, A2, A3, A4, and A5 designations are the fully functional (no failure), left stabilator, right stabilator, left flaperon, right flaperon, and rudder elemental filters, respectively. For the left stabilator failure with a simultaneous purposeful command of 10 lbs aft stick, the algorithm exhibits a lag time of approximately 0.2 seconds prior to positive failure identification. A small spike is evident in the right stabilator elemental filter during the detection and decision period. Occasionally, ambiguities arise between the left and right stabilators for small periods of time during a stabilator failure (purposeful roll rates could be used to isolate which stabilator failed, once the algorithm detects that one of the stabilators has failed). Since the left and right stabilators provide pitch control and augment the roll channel, the identification task is significantly more difficult than that of an actuator dedicated to a single channel task. If the aircraft has a roll angle, the surface positions of the left and right actuator may not be the same. If one of the surface positions is smaller than the other, failing one surface may produce a different system response from failing the other. The result may provide different probability convergence phenomena. The solution is usually to increase the purposeful command or dither signal to a level sufficient to produce proper system excitation. However, if the dither command is too large, a pilot may object to normal or lateral accelerations that result from commands which he did not initiate. A large purposeful or dither command may reduce the algorithm performance by inducing large transients. The Kalman filter gains within each of the elemental filters are designed for steady state performance. The system state variables will require a longer settling time as larger amplitude transients are produced. Increased stick activity can produce the same effect.

Figure 3 illustrates a left flaperon failure induced at 3.0 seconds. In this failure scenario, a rudder application of 45 lbs for a duration of 3.0 seconds combined with a longitudinal and lateral stick pulse demonstrates algorithm performance. The flaperons are control surfaces which do not produce significant changes in state parameters in a short period of time. In this case, the failure detection is identified in approximately 0.2 seconds. Thereafter, the algorithm attempts to declare a fully functional aircraft, and finally 0.6 seconds later, positively identifies that failure as a failed left flaperon. During the 0.6 second interval when the left flaperon is not selected, four filters share the total probability, including: fully functional, left flaperon, right flaperon, and the pitch rate sensor (not shown). If a lateral stick command is introduced from 3 sec to 6 sec of the simulation, the probability remains at the fully functional filter until 3.8 seconds. At that time, the probability is transferred directly and entirely to the left flaperon and remains there for the duration of the run.

Figure 4 shows the performance of the algorithm for a rudder failure induced at 3.0 seconds. Control applications are given by a 45 lb rudder kick and hold for a duration of 3.0 seconds, and a longitudinal and lateral stick pulse. Results demonstrate a 0.2 second lag between the induction of the failure and positive identification by the proper elemental filter. The "drop out" of the probability during 3.6 to 3.8 second interval is gained by the yaw rate sensor elemental filter (not shown).

Figure 5 depicts the elemental filter probabilities for the seven elemental filters that assume failed sensors. A pitch rate failure is induced at 3.0 seconds while simultaneously applying a longitudinal command of 10 lbs aft stick. The labels S1, S2, S3, S4, S5, S6, and S7 are the sensor designations for the velocity, angle of attack, pitch rate, normal acceleration, roll rate, yaw rate, and lateral acceleration elemental filters, respectively. In this scenario, the probability is transferred directly from the fully functional filter (not shown) to the pitch rate sensor filter, S3, at the time of the failure. The lag to failure detection and identification in this case is less than 0.2 seconds. Sensor failures are usually identified quickly due to the direct relationship between the variable the sensor measures and the residual calculation upon which the probabilities are based.

In general, purposeful commands aid in the
identification process and often enhance performance. However, periods of large amplitude or high frequency stick activity can cause ambiguities and delay the identification process. Each axis must be stimulated by a control input to achieve good performance. Typical flight control maneuvers should be more than sufficient to provide the level of excitation necessary to achieve acceptable algorithm performance. Dither signals optimized to provide good failure detection and identification characteristics can provide the best algorithm performance, when used to augment typical maneuver inputs (i.e., dither is added to a particular channel if the input commands do not excite that channel).

Identification of Failure in Benign Flight Conditions. For flight conditions where little control activity is present, flight safety can be maintained through the use of autonomous dithering signals, or pulses. As previously described in this section, a dither signal is applied to each axis every 3.0 seconds. Dither signal amplitudes and frequencies were artificially limited to produce no more than ±0.05 g's normal acceleration and ±0.1 g's lateral acceleration. These restrictions were developed to allow a dither system to run in the "background" during the flight phase, providing failure detection capability in benign flight conditions. The dither was temporarily disabled when a pilot command was induced in that channel. Dither commands in channels without a pilot command were executed.

Figure 6 illustrates a left flaperon failure induced at 3.0 seconds. In this case, the failure is detected initially but not locked until approximately 4.9 seconds. The "missing" probability was picked up by the yaw rate filter and the lateral acceleration filter (not shown). In this scenario, performance could be enhanced by increasing the pulse amplitude of the dither signal. Figure 7 doubled the rudder pulse amplitude. The correct failure was identified in approximately 0.16 seconds. The lateral acceleration was approximately 0.2 g's, probably too large to be undetected by a pilot. While this dither may be unacceptable as a "background" dither, it is perfectly acceptable as a failure identification test. If a pilot believed a failure existed but could not identify the failure, he would select this option.

Figure 8 displays a rudder failure induced at 3.0 seconds. The dither signal was not large enough to affect immediate identification. The correct failure is identified after a delay of approximately 2.2 seconds. The angle of attack, pitch rate, normal acceleration, roll rate, and yaw rate sensor all contain some portion of the probability throughout the 8-second run. This suggests insufficient excitation to provide good algorithm performance. Figure 9 increases the amplitude of the rudder dither pulse. In this case, the failure is identified after a delay of approximately 0.1 second. The notch in the probability at approximately 6.0 seconds is due to the application of another dither pulse. This pulse shakes up the system to enhance
identifiability. However, the Kalman filters were designed using steady state gains. After the application of the dither pulses, the system returns to a steady state condition and again the rudder is identified as the correct failure.

**Residual Characteristics.** Figure 10 illustrates residual characteristics for a left stabilator failure. Figure 10 is the velocity residual for the elemental filter assuming a left stabilator has failed. The velocity residual was selected for display since it provides clear indications that a failure has occurred. In this scenario, a constantly applied sine wave dither signal was developed using the normal and lateral acceleration criteria discussed earlier. The frequency of the dither was approximately 2.38 Hz. Prior to the induction of the failure, the residual violated the 2 sigma bound (+/- 0.0058 ft/sec), appeared time correlated rather than white, and the residual frequency matched the dither frequency. The 2 sigma bound is based on the left stabilator elemental filter’s internally computed variance for the velocity residual. This behavior clearly indicates that the hypothesis of a failed left stabilator is incorrect for the first 3 sec. of the simulation. After the declaration of a left stabilator failure at 3.0 seconds, the velocity residual appears more white and moves within the 2 sigma bounds; note, however, that it takes about a second for the apparent residual bias to reduce to a negligible value. Scalar residual monitoring provides positive evidence of a failure. This additional voter is useful in the reduction of ambiguities in actuator failures. For actuator failures, initial results indicate that the velocity, normal acceleration, yaw rate, and lateral acceleration residuals provide the best indications of a failure.

6. **Summary**

A multiple model adaptive estimation algorithm with one fully functional, five failed-actuator and seven failed-sensor elemental filters illustrates the algorithm’s performance when applied to a VISTA F-16 flight control system using a linearized aerodynamic model. A modified Bayesian approach allows for a blending of state estimates and provides lower bounds to enhance algorithm convergence properties. Compensation for "Beta Dominance" enhances algorithm performance by not allowing the term preceding the exponentiation in Eq. (12) to enter into the calculations. This term biases the calculation of the probabilities toward the filter whose $A_k(t)$ matrices have the smallest determinants. Scalar residual monitoring aids in resolving ambiguities by demonstrating residual characteristics consistent with a true failure.

The algorithm demonstrates good convergence characteristics during purposeful commands and dither signals. Optimizing the dither to improve algorithm performance is effective. However, large dither signals cannot be considered subliminal and may be considered objectionable by a pilot; allowing him to turn the dither on and off may be more useful practically.
References