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OF A FAULT INFERRING NONLINEAR DETECTION
SYSTEM ALGORITHM FOR AVIONICS SENSORS

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DESIGN CONSIDERATIONS FOR FLIGHT TEST OF A FAULT INFERRING NONLINEAR DETECTION SYSTEM ALGORITHM FOR AVIONICS SENSORS

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Abstract

This paper summarizes the modifications made to the design of a fault inferring nonlinear detection system (FINDS) algorithm to accommodate flight computer constraints and the resulting impact on the algorithm performance. An overview of the flight data-driven FINDS algorithm is presented. This is followed by a brief analysis of the effects of modifications to the algorithm on program size and execution speed. Significant improvements in estimation performance for the aircraft states and normal operating sensor biases, which have resulted from improved noise design parameters and a new steady-state wind model, are documented. The aircraft state and sensor bias estimation performances of the algorithm's extended Kalman filter are presented as a function of update frequency of the piecewise constant filter gains. The results of the failure detection performance of a new detection system strategy, as a function of gain update frequency, are also presented.

Introduction

Integrated avionics concepts are being implemented in aircraft which feature maximum efficiency through relaxed static stability and which require flight crucial information from the avionics sensors. Safety, reliability, and performance requirements for these aircraft dictate automatic selection of valid sensor data and quick rejection of invalid data. An effort at NASA Langley Research Center has been directed toward fault tolerant concepts for redundant avionics sensors. A fault inferring nonlinear detection system (FINDS) has been developed to provide detection, isolation, and compensation for hardware failures in flight control sensors and ground-based navigation aids (Refs. 1,2).

As opposed to earlier work, FINDS can operate without any hardware redundancy. The F-8 failure detection and isolation (FDI) method requires dual redundancy for each sensor type to detect a sensor failure (Ref. 3). Both the F-8 and DIGITAC A-7 studies consider only flight control sensors (Refs. 3,4). The structure of the FINDS algorithm is an extension of the technique used in Ref. 5 and is applicable to nonlinear dynamic systems. Hence, it requires the implementation of a single high-order filter and several first-order filters, as opposed to the multiple hypothesis testing approach, which requires several high-order filters (Refs. 6,7).

The FINDS algorithm is designed to provide reliable estimates for aircraft position, velocity, attitude, and horizontal winds to be used for guidance and control laws in the presence of possible failures in the avionics sensors. Failures are identified with the use of analytic relationships between the various sensor outputs arising from the aircraft point mass equations of motion. This feature of the FINDS algorithm increases the reliability of a given avionics sensor configuration, since a failure can be detected and isolated even if there is only one sensor of a given type in the configuration.

The fault tolerant system methodology is formulated in the context of simultaneous state estimation and failure identification in discrete time nonlinear stochastic systems. The FINDS algorithm consists of 1) a no-fail filter (NFF), which is an extended Kalman filter (EKF) based on the assumption of no sensor failures and which provides estimates for aircraft states and normal operating sensor biases; 2) a bank of detectors which are first-order filters used to estimate bias jump failure levels in sensor outputs; 3) likelihood ratio computers; and 4) a decision function which isolates the failed sensor by selecting the most likely failure mode depending on the likelihood ratios. When a sensor failure is detected and isolated, the algorithm is restructured to eliminate the failed sensor from further processing and to remove the accumulated effects of the sensor failure on the NFF. Failure identification decisions are monitored with the use of a healer algorithm; sensors falsely identified as failed or recovered from failures are restored to the system.

The FINDS algorithm was developed with the use of a digital simulation of a commercial transport aircraft (B-737). Flight recorded data for this aircraft were used to address the issues of sensor modeling inaccuracies, time varying sensor biases, time correlation in the sensor errors, etc. (Refs. 8,9). The object of the current effort has been to modify FINDS to "fit" the size constraints of a flight computer and to meet real-time execution requirements without compromising sensor FDI and state estimation performance (Ref. 10). The thrust of this effort, therefore, has been directed toward 1) converting the program code to single-precision; 2) replacing general-purpose matrix

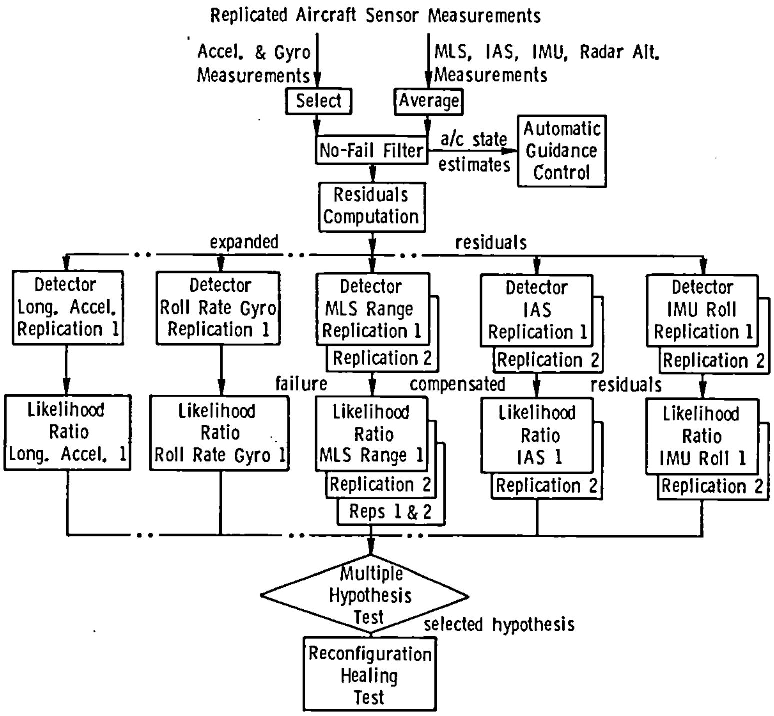

Fig. 1 Fault inferring nonlinear detection system structure.

computations with specialized routines; 3) using a constant state-transition matrix in the system model instead of a time-varying one; 4) implementing piecewise constant gains in the NFF; and 5) redesigning the multiple hypothesis test to replace the simultaneous detection and isolation test with a sequential detection and isolation test.

FINDS Algorithm Overview

Given redundant measurements of the on-board sensors and navigation aids, which comprise the avionics sensor suite on an aircraft, the FINDS algorithm generates fault tolerant estimates for the vehicle states required by the guidance and control laws in the presence of possible sensor failures. The desired qualities of the system include utilization of available analytical redundancy, timely detection of sensor failures, acceptable false alarm performance, ability to recover from false alarms, and minimal complexity.

The baseline configuration developed for the FINDS algorithm to meet these requirements is shown in Fig. 1. This filter-detector-isolator structure consists of: 1) a NFF, which is implemented as an EKF to provide estimates for the aircraft state variables and normal operating sensor biases; 2) a bank of detectors, which are first-order Kalman filters to estimate bias jump failure levels in sensor outputs; 3) likelihood ratio computers; and 4) a decision function which selects the most likely failure mode in the Bayesian sense based on the likelihood ratios.

The FINDS algorithm was developed with the use of aircraft point mass equations of motion mechanized in a runway-based, flat-earth Cartesian coordinate system (see Fig. 2). The sensor suite consists of body mounted gyros and accelerometers; indicated airspeed (IAS); a platform INS, which supplies attitude measurements; and a ground based navaid (MLS), which transmits range, azimuth, and elevation measurements to the aircraft.

The gyro and accelerometer sensor measurements form the input to the aircraft dynamics equation, while the MLS, IAS, and INS attitudes provide measurements for the system dynamics. The aircraft state estimates provided by the NFF include position, velocity, and attitude of the vehicle relative to the runway axes, and horizontal winds.

Fig. 1 indicates that only one set of the replicated input sensors and the average of the replicated measurement sensors enter the NFF. This serves to reduce the overall complexity of the NFF. The NFF also functions as a navigator by estimating the aircraft states; it also filters the measurements in order to constantly correct the propagated state estimates. Since the NFF is formed as an EKF, it is independent of flight path. The NFF also generates a residual sequence for the averaged measurements, as seen in Fig. 1.

The failure detection and isolation part of the FINDS algorithm uses the NFF residuals, which are formed from the averaged measurement sensors. The purpose of the residuals computation block is to form this sequence for the individual measurement sensors. This expanded residual sequence drives the bank of detectors.

The bank of detectors is a set of first-order Kalman filters, each of which estimates the level

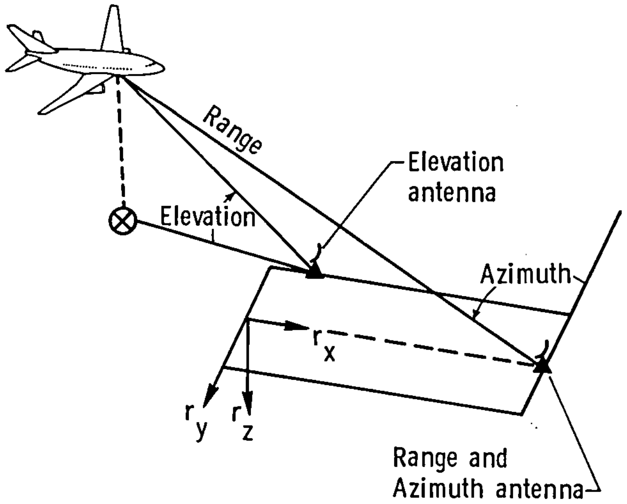

Fig. 2 Runway coordinate system and MLS geometry.

of an hypothesized sensor failure. Each detector outputs a compensated residual sequence in which the effects of the hypothesized failure are removed from the expanded residuals by processing the estimated failure level. Each compensated residual sequence is used in the computation of a likelihood ratio for a hypothesis corresponding to a sensor failure. The likelihood ratio reflects the a posteriori probability of its residual sequence corresponding to the true hypothesis. All the likelihood ratio computers drive a decision module.

The decision rule selects the most likely sensor failure based on an M-ary hypothesis test. This test minimizes the Bayes risk, which is a weighted average of making incorrect decisions. The decision output of the M-ary hypothesis test indicates which sensor has failed.

When a failure is detected and isolated, the reconfiguration block is used to restructure the FINDS algorithm. When a gyro or accelerometer (input sensor) fails, the faulty sensor is replaced. If there are no more valid sensors of that type, the NFF is restructured, provided it is able to function, with the remaining set of sensors. When a measurement sensor fails, the isolated sensor is flagged to be inactive, and appropriate changes are made in the NFF statistics; also, the NFF is collapsed to accommodate the loss of all the sensors of a given type. The reconfiguration block also functions to reinitialize the NFF, detectors, and likelihood ratios following identification of a failure.

To recover from false alarms, each failed sensor is given a healing test. Input sensors are tested by comparison with sensors of the same type used by the NFF. A failed measurement sensor is tested with the NFF estimate of that sensor. These are binary hypothesis tests conditioned on the decision rule that the sensor currently in use is healthy.

FINDS Algorithm Modifications

As stated earlier, the current effort has been directed toward reducing the FINDS algorithm program size and increasing its execution speed from the baseline configuration without compromising FDI and estimation performance. The goal is to "fit" the algorithm on a flight computer for testing in a commercial transport environment. The development computer under consideration has 128 Kb of memory and 294 K Whetstone performance (Ref. 11).

As illustrated in Table 1, significant reductions in program size have resulted from 1) conversion from double to single precision; 2) reduction from triple to dual redundancy; 3) incorporation of failure simulation routines in an external processor program; and 4) elimination of interactive input/output routines. The increase in execution speed was accomplished by 1) converting to single precision; 2) using specialized matrix computation routines; 3) using a constant state-transition matrix in the system model; 4) implementing piecewise constant gains in the NFF; and 5) replacing the simultaneous detection and isolation capability of the FINDS multiple hypothesis test with a sequential detection and isolation test.

Table 1 FINDS program size and execution speed modifications summary

FINDS Modifications	Program Size Kb	Execution Speed (x real-time) Detectors off	on
Double Precision	340	30	120
Single Precision	240	20	60
Reduced Array sizes			
Failure Preprocessor	170	15	50
Delete Interactive I/O	126	15	50
Special Matrix Routines			
Constant State-Transition Matrix	115	10	30
New Detection Strategy (without isolation test)			
Gain Update 20 Hz	115	10	11
Gain Update 4 Hz	115	3	3.5
Gain Update 2 Hz	115	2	2.3
Gain Update 1 Hz	115	1.3	1.4

The FINDS algorithm's execution speed has been improved by using a constant state-transition matrix, since a time varying, state-dependent one must be updated by the partials of an input transition matrix at every iteration. This change effectively decouples the NFF's translational and rotational dynamics. Furthermore, to take advantage of the system inherent matrix properties, specialized matrix routines were substituted for general purpose matrix computations. For example, a special positive definite symmetric matrix inverse routine was used in place of a generalized inverse one.

Performance Analysis With Flight Data

Sensor data recorded over 266 seconds of flight, while the aircraft is within MLS coverage, is used to verify design modifications and performance of the FINDS algorithm. The sampling frequency of the data is 20 Hz. The flight profile can be summarized with the following mapping:

1) Descent — Aircraft descends in flight path oblique to the runway at a constant sink rate (0-100 seconds)

2) Alignment maneuver — Aircraft aligns with runway at constant altitude (100-140 seconds)

3) Landing maneuver — Aircraft aligned and descending to touchdown (140-266 seconds)

The design considerations for FINDS requires a tradeoff between best estimation performance and best failure detection performance (Ref. 8). Based on the flight data, therefore, the design values for the NFF noise parameters were chosen to reflect not only the sensor error statistics, but also to ensure that the filter makes adequate use of all the sensors in generating the aircraft state estimates.

Another change made in the filter design has been the introduction of a new steady-state wind model. Ref. 8 assumed a zero process noise and a time constant of 1000 seconds for the horizontal wind model. These estimates showed a marked dependence on aircraft maneuvers. For this effort, a process noise of 0.1 m/s on both the x and y direction winds and a time constant of 100 seconds have been introduced. These values have been chosen to model a slowly varying wind component in addition to the steady-state winds.

Table 2 presents the design values used for the NFF process noises associated with input sensors, horizontal winds, and the noise parameters for the measurement sensors. All the results presented in this paper have been obtained using these values.

Table 2 Design values for no-fail filter noise parameters

Variable	Noise S.D. Per Repl	Replications Used	Units
Process Noises			
Acc. Long.	0.05	1	m/s/s
Acc. Lat.	0.05	1	m/s/s
Acc. Vert.	0.05	1	m/s/s
Gyro Roll	0.05	1	deg/s
Gyro Pitch	0.05	1	deg/s
Gyro Yaw	0.05	1	deg/s
x-Wind-rw	0.10	N/A	m/s
y-Wind-rw	0.10	N/A	m/s
Measurement Noises			
MLS Azim.	0.06	1	deg
MLS Elev.	0.06	1	deg
MLS Range	6.00	1	m
IAS	3.00	2	m/s
INS Roll	0.25	2	deg
INS Pitch	0.50	2	deg
INS Yaw	0.30	2	deg

The NFF uses only one replication of the MLS sensor measurements, since the second channel for these measurements has to be simulated to have a complete dual-redundant sensor suite. The second channel is kept in standby status to be used in the event of a failure (similar to the set-up for input sensors). Based on the sensor analysis of Ref. 8, the MLS noise is assumed to be white.

The state estimate time history of ground track and altitude profile as the aircraft goes through the flight segments from runway approach to constant altitude, and runway alignment to final descent is given in Fig. 3. The run begins at time zero and ends at 266 seconds. The aircraft vertical velocity profile and roll attitude estimate time histories are given in Fig. 4. These figures show that the altitude is held constant while performing the bank maneuver to align with the runway. The horizontal wind estimates are given in Fig. 5. The wind estimates portray a gradually diminishing crosswind starting at 10 m/s and reducing to 2 m/s at the end of the run.

The NFF's measurement residual time histories for MLS range and IAS are given in Fig. 6. In comparison with earlier analyses (Refs. 8,9), these sequences show a smaller mean and uncorrelated behavior. The high level MLS range residuals at approximately 47 and 105 seconds are caused by increased MLS range noise at these two instants. The presence of wind gusts at the lower altitudes is evidenced by the increased IAS residuals near the end of the run.

The estimation performance of the NFF has been improved with the use of the modified steady-state wind model and noise design parameters. These changes have resulted in a better sensor bias and aircraft state estimation performance, as evidenced

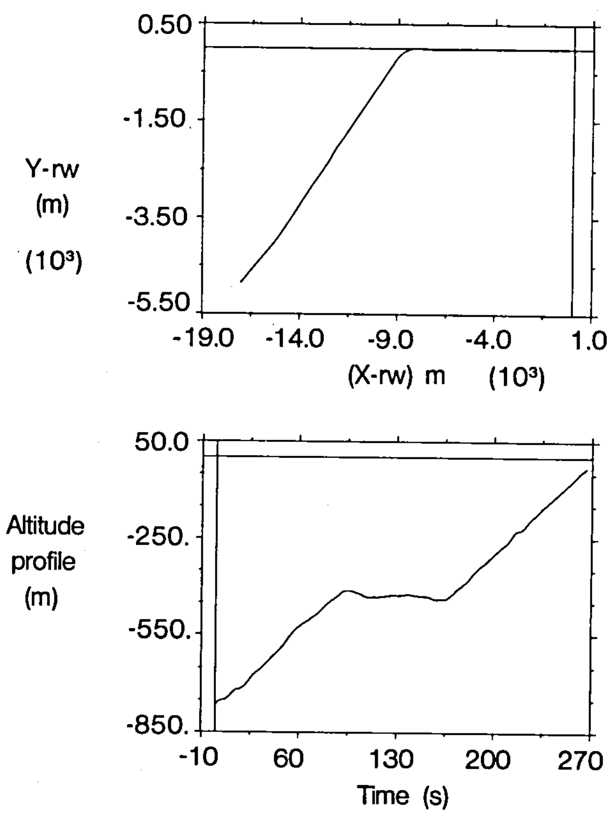

Fig. 3 Estimated aircraft ground track and altitude profile.

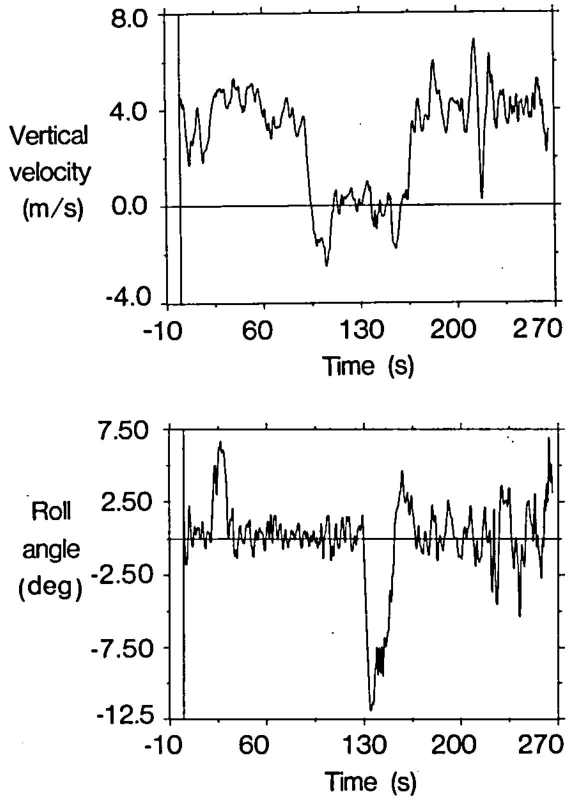

Fig. 4 Vertical velocity profile and roll attitude estimate.

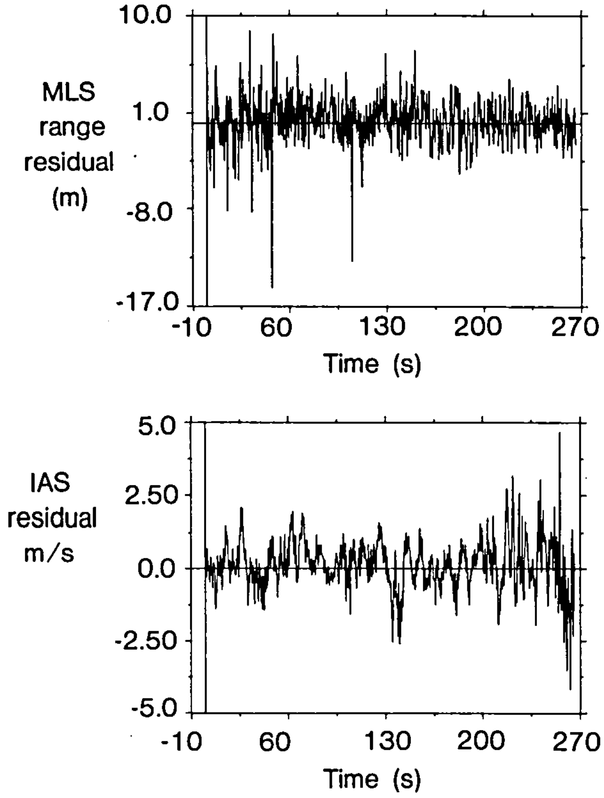

Fig. 6 No-fail filter residual for MLS range and IAS.

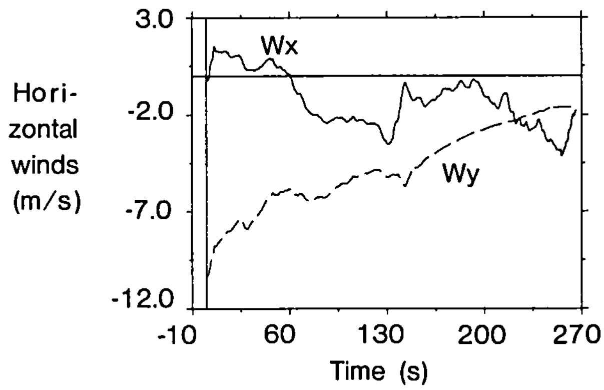

Fig. 5 Horizontal wind estimates.

by a less time-correlated and closer to zero mean NFF residuals sequence than previously reported (Refs. 8,9). Furthermore, the improved state estimation has resulted in significantly better failure detection and false alarm performance. The failure detection performance was improved by replacing the multiple hypothesis test over a fixed window of expanded residuals with a set of mean detection tests over various moving windows of the averaged NFF residuals. Low-level MLS, IAS, and attitude sensor failures are detected instantaneously with the new detection strategy, while input sensor failures are detected in the minimum time allowed by the incremental information generated in the sensor residuals (Ref. 10).

Estimation Performance with Piecewise Constant Gains

A major consideration for improving the execution time of the FINDS algorithm is to use piecewise constant gains in the NFF computations. A study of the NFF gain time histories reveals that these gains, along with their associated covariance matrices, have a slowly time varying behavior after initial transients. Hence, an investigation was undertaken to update the gains at multiples of the sampling period. This change has a favorable impact on the execution time since two seventh order matrix inversions as well as system observation and covariance matrix updates are eliminated in the intermediate sampling instants.

An analysis of the state estimate time histories at gain update frequencies of 20, 4, 2, and 1 Hz shows increased initial transients as the frequency decreases, but little difference in the same state estimates in the latter part of the flight. The bias estimation performance for the vertical accelerometer for all the update frequencies examined is given in Fig. 7. The accelerometer bias in the baseline case of 20 Hz takes approximately 40 seconds to converge, whereas it takes about 100, 150, and 250 seconds, respectively, to converge for the 4, 2, and 1 Hz cases. Clearly, the vertical accelerometer bias estimates take longer to converge as the gain update frequency decreases; however, the NFF

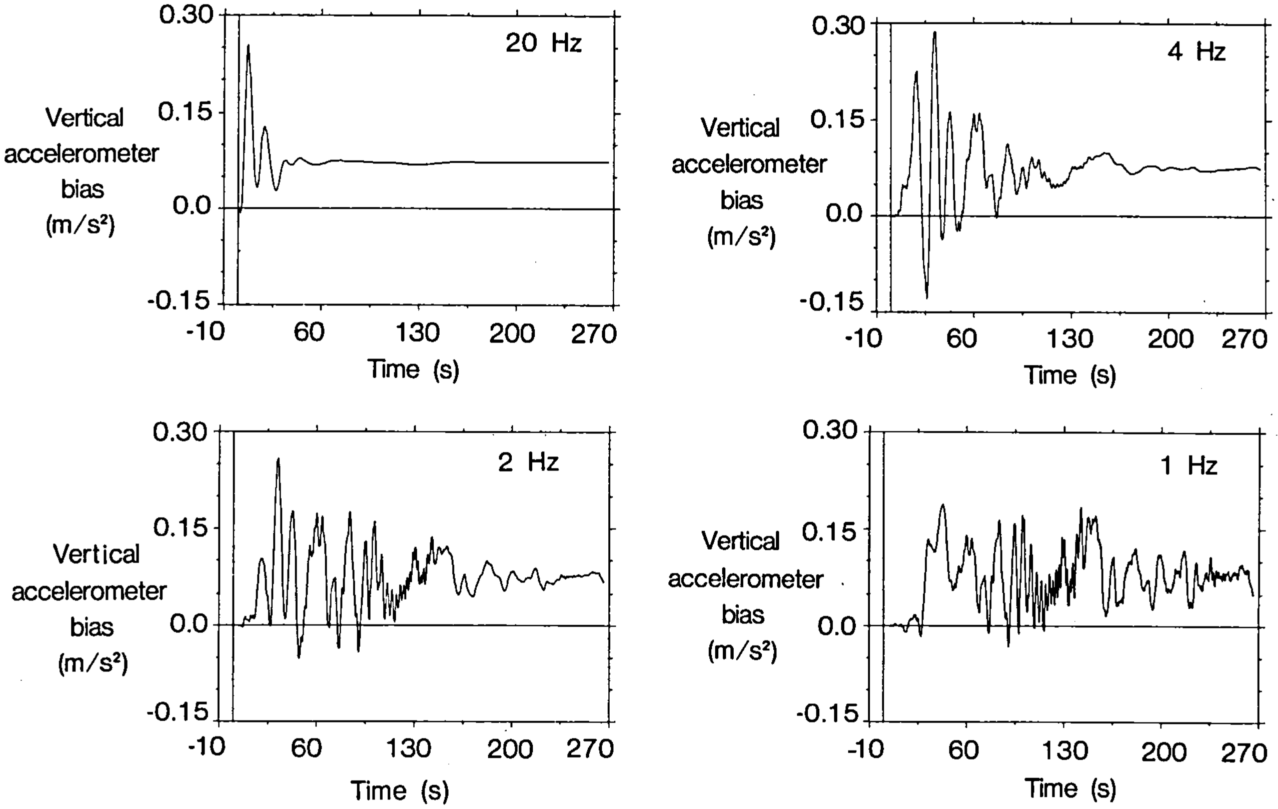

Fig. 7 Vertical accelerometer bias estimates as a function of gain update frequency.

residual sequences continue to verify an acceptable filter performance as indicated in Table 3. The low sample means and standard deviations of the residuals verify the extremely good estimation performance of the NFF.

Failure Detection/Isolation Design Considerations

Since the NFF residual sequence forms the input to the detectors, the failure signature on any residual, and hence its detectability, is determined by the amount of use that the NFF makes of any sensor in the estimation process. As discussed earlier, the design values for the NFF noise parameters were chosen to ensure the adequate use of all sensors in generating the aircraft state estimates. The result was improved estimation performance; also, the statistics of the NFF residuals improved. Table 4 shows the values selected for the measurement sensor noise parameters employed in the computation of the filter measurement residual covariance used by the detectors.

The inherent limitations to the baseline implementation of the FINDS algorithm include 1) a total of seventeen detectors (first-order Kalman filters) have to be executed at every iteration with the current replicated suite of avionics sensors, and this adversely affects the execution

Table 3 No-fail filter residuals statistics

Sensor	MLS Azim. deg	MLS Elev. deg	MLS Range m	IAS m/s	INS Roll deg	INS Pitch deg	INS Yaw deg
Mean							
20 Hz	1.37E-3	4.22E-4	1.67E-1	1.44E-1	-1.73E-3	3.19E-3	1.05E-2
4	1.78E-3	2.83E-4	1.12E-1	1.05E-1	-1.56E-4	4.74E-4	-2.05E-5
2	1.18E-3	3.38E-4	1.01E-1	5.13E-2	-1.11E-4	5.33E-4	3.55E-4
1	3.32E-4	5.96E-4	8.72E-2	2.29E-2	-2.73E-5	1.01E-3	4.17E-4
Std. Dev.							
20 Hz	7.35E-3	8.26E-3	2.03E-0	8.36E-1	3.70E-2	2.50E-2	1.16E-1
4	8.28E-3	7.44E-3	2.02E-0	7.92E-1	3.66E-2	2.46E-2	1.11E-1
2	8.34E-3	7.02E-3	1.97E-0	7.57E-1	3.63E-2	2.48E-2	1.10E-1
1	8.52E-3	6.76e-3	1.97E-0	6.95E-1	3.58E-2	2.52E-2	1.08E-1

Table 4 Design values for measurement sensor noise parameters used by the detectors

Variable	Noise S.D. per Repl.	Replications Used	Units
MLS Azim	3.00E-02	1	deg
MLS Elev	3.50E-02	1	deg
MLS Range	5.50E-00	1	m
IAS	2.00E-00	2	m/s
INS-Roll	1.30E-01	2	deg
INS-Pitch	1.50E-01	2	deg
INS-Yaw	5.00E-01	2	deg

speed of the algorithm; 2) a fixed-length detection window is used, and the sensor failures injected randomly occur within this detector decision window; this renders the detection time and failure level estimates dependent on the time of failure onset within a particular detection window; and 3) the expanded NFF residual sequence used by the detectors does not portray the same low mean value and uncorrelated behavior as the NFF averaged measurement residuals. To improve on both execution speed and detection performance, therefore, a new strategy for the detectors has been implemented as described below.

From Table 3 and Fig. 6 it is evident that the NFF residuals have a small mean value. It is possible to perform a detection test on the NFF residuals over a moving window without performing an isolation test. First, the residual sequence of the NFF is defined by,

$$r(k) = \bar{y}(k) - h(\hat{x}(k/k-1)) - D\hat{b}(k-1)$$

where, $\bar{y}(k)$ is the average of the replicated measurement sensors used by the NFF, $h(\hat{x})$ is the nonlinear transformation relating the aircraft states to the measurements, D is the measurement sensor bias matrix, and $\hat{b}$ is the composite bias vector containing the input sensor biases. Second, it is possible to compute the sample mean of the residual sequence over a moving window from,

$$\bar{r}(k) = 1/N \sum_{j=k-N+1}^{k} r(j)$$

Third, perform the test of mean by computing the likelihood ratio,

$$\Lambda = N\,(\bar{r}^T(k)\; R^{-1}\; \bar{r}(k))$$

and compare to a predetermined threshold to decide on a sensor failure. This test can be performed for different moving windows. In the event of a failure decision, a failure isolation test is made by running the detection test over the last N_i NFF expanded residuals.

The input sensor failures take longer to detect than the measurement sensor failures since these failures must propagate through the NFF dynamics. Thus, two different moving window lengths of the NFF residuals have been implemented: a length of one sample for the measurement sensors, and a length of 10 samples for the input sensors. The computed means and standard deviations of the NFF residuals are the same for both moving windows, and the likelihood ratios were calculated as 13.5 and 63.5 for the 1 and 10 sample windows, respectively. Hence, a Chi-square test with type 1 error size of 0.01, which implies a threshold of 18.5 given seven degrees of freedom, would yield no false alarms for a decision window length of one sample, and a test threshold of 65-70 would yield no false alarms for a moving window of length 10 samples.

Table 5 presents the results of the new detection strategy for sensor failures injected into the flight data with the NFF gain update frequency at 20 Hz. The first set of runs include a failure occurring at 82.1 seconds into the flight when all bias estimates have converged and the bank maneuver is yet to be executed. The input sensor failures take a significant amount of time to get detected and isolated, while the MLS and INS attitude failures are detected without any delay. The IAS failure, which corresponds to a 4.5 σ bias jump, is detected on the ninth sample of the detection window after its occurrence.

In the second series of runs, failures were inserted in each sensor at 145.4 seconds in the middle of the aircraft maneuver for runway alignment. The sensor failures are detected in approximately the same time as the first series of runs.

The third set of failures was inserted at 238.7 seconds during the final approach path about 4000 m from the runway. The lateral and vertical accelerometers show significant decrease in detection time. The increase in detection time in the IAS sensor is caused by the presence of wind gusts, ground effect, and larger IAS residuals as seen in Fig. 7.

Table 5 Bias failure detection summary for revised detector strategy

Sensor Type	Failure Level Injected	20Hz. Detection Time For Failure Injected at 82.1 s	145.4 s	238.7 s
Acc. Long.	0.15 g	4.05 s	3.95 s	3.75 s
Acc. Lat.	0.13 g	5.20 s	4.75 s	2.70 s
Acc. Vert.	0.15 g	4.95 s	3.85 s	2.10 s
Gyro Roll	0.90 deg/s	0.45 s	0.35 s	0.40 s
Gyro Pitch	1.0 deg/s	0.45 s	0.50 s	0.50 s
Gyro Yaw	1.0 deg/s	1.65 s	1.45 s	1.50 s
MLS Azim	0.18 deg	0.0 s	0.0 s	0.0 s
MLS Elev	0.18 deg	0.0 s	0.0 s	0.0 s
MLS Range	40.0 m	0.0 s	0.0 s	0.0 s
IAS	9.0 m/s	0.45 s	0.40 s	1.20 s
INS Roll	2.0 deg	0.0 s	0.0 s	0.0 s
INS Pitch	1.5 deg	0.0 s	0.0 s	0.0 s
INS Yaw	4.0 deg	0.0 s	0.0 s	0.0 s

Detection Performance with Piecewise Constant Gains

The statistics for the NFF residual sequences with gain update frequencies of 4, 2, and 1 Hz exhibit a small mean and essentially uncorrelated behavior; also, the minimum and maximum values of the residuals are approximately the same at all the frequencies examined (Ref. 10). Hence, the same likelihood ratio failure thresholds have been used with the new detection test for all the gain update

Table 6 Effect of piecewise constant gains on detection times for injected failures

Sensor Type	Failure Level Injected	Failure Level Injection Time 82.1 seconds				Failure Level Injection Time 145.4 seconds				Failure Level Injection Time 238.7 seconds			
		Detection and Isolation Times seconds											
		20 Hz	4 Hz	2 Hz	1 Hz.	20 Hz	4 Hz	2 Hz	1 Hz	20 Hz	4 Hz	2 Hz	1 Hz
Acc. Long.	0.15 g	4.05	5.25	n.d.	n.d.	3.95	4.50	6.00	7.90	3.75	3.85	5.90	n.d.
Acc. Lat.	0.14 g	5.20	n.d.	n.d.	n.d.	4.75	5.90	n.d.	n.d.	2.70	2.80	2.95	n.d.
Acc. Vert.	0.15 g	4.95	11.0	n.d.	n.d.	3.85	4.50	n.d.	n.d.	2.10	2.25	2.55	n.d.
Gyro Roll	0.9 deg/s	0.45	0.45	0.50	0.55	0.35	0.35	0.35	0.35	0.40	0.40	0.40	0.40
Gyro Pitch	1.0 deg/s	0.45	0.50	0.50	0.55	0.50	0.50	0.45	0.45	0.50	0.50	0.50	0.50
Gyro yaw	1.0 deg/s	1.65	1.60	2.35	n.d.	1.45	2.00	2.05	2.30	1.50	1.50	1.50	1.55
MLS Azim.	0.18 deg	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Elev.	0.18 deg	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Range	40.0 m	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
IAS	9.0 m/s	0.45	0.45	n.d.	n.d.	0.40	0.40	0.40	0.40	1.20	1.20	1.20	1.45
INS Roll	2.0 deg	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pitch	1.5 deg	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Yaw	4.0 deg	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

frequencies.

Table 6 shows the results for all the gain update frequencies for failures injected under the same conditions as described above. With the 20 Hz frequency as the baseline and considering the failures injected in the flight data at 82.1 seconds, the accelerometer failure detection performance is affected the most as the update frequency is lowered. This is caused by the relatively slow convergence of the accelerometer biases. With gain update frequencies lower than 4 Hz, these biases have not yet converged to steady-state when the increased bias failure is injected into the flight data. Thus, with the bias filter covariances still high, the corresponding bias estimates begin to converge to a new steady-state value to compensate for the undetected failure level. This results in a lower failure signature in the NFF residuals, thereby reducing the information available to the detectors. Investigation of the incremental information into the accelerometer detectors tends to verify this slow detection time (Ref. 10).

The inability to detect the failure of the yaw rate gyro at the 1 Hz update frequency is caused by the high noise characteristics of the INS yaw sensor and the level of failure injected. Although the MLS and INS measurement sensor failures are detected instantaneously for all the update frequencies, the IAS sensor failure is not detected at the lower update frequencies because of the low level of injected failure.

When the failures are injected at 145.4 seconds, there is considerable improvement in the detection times of the accelerometers and the IAS sensor. Roll and pitch rate gyro failure detection performance does not get affected; however, yaw rate gyro failure detection shows an improvement at the lower update rates. All the measurement sensors now show excellent detectability at every gain update frequency.

Finally, when the failures are injected at 238.7 seconds during the final flight segment, the accelerometer failure detection performance shows added improvement. In this case, the bias estimates have had a longer time to converge to steady-state before the bias failures are injected. Rate gyro and measurement sensor failures are detected with the same consistency as before.

In summary, low gain update frequencies have no effect on MLS and INS attitude failure detection performance, but IAS and input sensor failure detection performance become degraded at gain update frequencies below 4 Hz. False alarms have not been observed at any gain update frequency.

Concluding Remarks

This paper has presented some preliminary design considerations for flight testing the FINDS algorithm. The efforts to reduce the program size and execution speed have resulted in improvements in state estimation, failure detection, and false alarm performance over previously reported results. The failure detection performance as a function of piecewise gain update frequency indicates that 4 Hz is the lowest frequency useable for the IAS, rate gyros, and accelerometers for the flight data considered. The reduced program size and execution speed set specifications for required computational capability to flight test the FINDS algorithm.

A current effort is directed toward implementing the decoupled rotational and translational dynamics in a dual flight computer configuration. This would allow real-time operation of FINDS at a gain update frequency of 4 Hz or higher as dictated by the bias estimation performance.

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16. Abstract

This paper summarizes the modifications made to the design of a fault inferring nonlinear detection system (FINDS) algorithm to accommodate flight computer constraints and the resulting impact on the algorithm performance. An overview of the flight data-driven FINDS algorithm is presented. This is followed by a brief analysis of the effects of modifications to the algorithm on program size and execution speed. Significant improvements in estimation performance for the aircraft states and normal operating sensor biases, which have resulted from improved noise design parameters and a new steady-state wind model, are documented. The aircraft state and sensor bias estimation performances of the algorithm's extended Kalman filter are presented as a function of update frequency of the piecewise constant filter gains. The results of a new detection system strategy and failure detection performance, as a function of gain update frequency, are also presented.

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