Hybrid Fault Detection and Isolation Techniques for Aircraft Inertial Measurement Sensors

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Abstract

In this paper, a redundancy management system for aircraft is studied, and fault detection and isolation algorithms of inertial sensor system are proposed. Contrary to the conventional aircraft systems, UAV system cannot allow triple or quadruple hardware redundancy due to the limitations on space and weight. In the UAV system with dual sensors, it is very difficult to identify the faulty sensor. Also, conventional fault detection and isolation (FDI) method cannot isolate multiple faults in a triple redundancy system. In this paper, two FDI techniques are proposed. First, hardware based FDI technique is proposed, which combines a parity equation approach with a wavelet based technique. Second, analytic FDI technique based on the Kalman filter is proposed, which is a model-based FDI method utilizing the threshold value and the confirmation time. To provide the reference value for detecting the fault, residuals are calculated using the extended Kalman filter. To verify the effectiveness of the proposed FDI methods, numerical simulations are performed.

Key Word : Redundancy Management, Fault detection and Isolation, Wavelet Transform

Introduction

Many FDI (Fault Detection and Isolation) techniques, the key process of redundancy management system, have been studied since 1960. Generally, FDI techniques are classified into two categories: hardware redundancy management and analytic redundancy management. In the hardware redundancy management system, multiple sensors are used for cross monitoring, and therefore, it is usually complicated and very expensive. Analytic redundancy management system uses the mathematical model of the system. Recently, analytic redundancy methods have been developed using the observer approach, parity space approach, and robust parameter estimation approach. Note that the analytic redundancy based FDI techniques cannot sometimes diagnose the sensor fault properly due to modeling uncertainties[1-3].

FDI techniques can also be divided into two classes according to the system levels: system level FDI and local sub-system level FDI. The system level FDI, usually depending on the outputs of different sensors, has several drawbacks. This technique may not guarantee safety and robustness because different sensors have their own distinct characteristics. Recently, local sub-system level FDI techniques, for example signal based ILM (In-Line Monitoring) techniques, have been studied for FDI. These techniques use the direct sensor outputs without any preprocessing or external support[4-9].

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This paper proposes two hybrid FDI techniques: 1.) the first method is a model-free FDI technique that combines Parity Equation Approach (PEA) and the ILM technique utilizing Discrete Wavelet Transform (DWT). The PEA uses geometrical relationship of skewed sensors, and the DWT technique is based on sensor signal processing. Because the proposed method does not use aircraft mathematical model, it can be applied to a UAV system or low cost aircraft, which have dual sensor redundancy. 2.) the second method hybridizes Cross Channel Monitoring (CCM) and observer based analytic redundancy technique. Because the analytic redundancy is usually dependent on the accuracy of model, a nonlinear aircraft model is used to construct analytic redundancy. The proposed method can detect and isolate multiple sensor faults by utilizing the analytic model. Numerical simulations using high performance aircraft system are performed to show the performance of the proposed FDI techniques.

Model-Free Hybrid Method for Skewed Redundant Sensors

Parity Equation Approach

Parity equations used in FDI techniques should be independent of sensor inputs. In this paper, geometrical arrangements are used to construct the parity equations. The measurement equation of inertial sensors including fault signal and measurement noise can be represented as follows.

$$m(t) = Hx(t) + e + f \tag{1}$$

where $m(t)$, $x(t)$, e, f, and H denote the measurement of n sensors, signal with respect to the body fixed axis, noise signal, fault signal vector, and direction cosine matrix from the body fixed axis to the sensor axis, respectively.

If three or more sensors are not installed on the same plane, that is, they are mutually independent, then ${}_nC_4$ parity equations can be composed by a linear combination of four sensors. The null space vector of four columns' partial matrix of H constitutes the coefficients of the parity equations. For example, if four redundant sensors are set up with tilted angles with respect to a body axis as shown in Fig. 1, only one parity equation can be obtained. One parity equation can only detect the fault, but cannot isolate the faulty sensor. If a fault occurs at a certain sensor, the parity equations related to the faulty sensor will have a nonzero value.

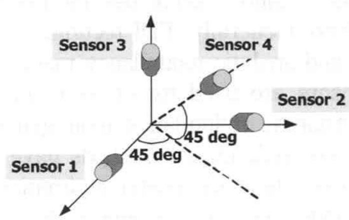

Fig. 1. Geometric configuration of tilted redundant sensors

Basic Concept of Discrete Wavelet Transform

Wavelet transform can be used for analyzing the non-stationary signal, and therefore, it can be used for fault detection.[10-12] Wavelet transform provides similar time-frequency localization with important differences. The Continuous Wavelet Transform (CWT) formula is represented as follows.

$$(T^{CWT} f)(a,b) = \int f(t)\psi^{a,b}(t)dt \tag{2}$$

where the continuous mother wavelet is denoted as

$$\psi^{a,b}(t) = |a|^{-1/2}\,\psi\left(\frac{t-b}{a}\right) \tag{3}$$

In Eq. (3), a and b vary continuously on the set of real number, $\boldsymbol{R}$, under the constraint $a \neq 0$. $\psi^{a,b}(t)$ has a time-width adapted to the frequency. As a in Eq. (3) changes, different frequency contents can be considered. As b in Eq. (3) changes, the time localization center is moved. As a result, wavelet transform has better performance to 'zoom in' on the short lived high frequency or to 'zoom out' to detect slow oscillations.[1, 13]

Similarly, the mother wavelet can be dilated and translated discretely by selecting $a = a_0^{\ m}$ and $b = nb_0 a_0^{\ m}$ where a_0 and b_0 are constants with $a_0 > 1$ and $b_0 > 0$, $m, n \in Z$. The discrete wavelet transform (DWT) is defined as follows.[13-18]

$$(T^{DWT} f)(m,n) = \int f(t)\psi^{m,n}(t)dt \tag{4}$$

where the discretized mother wavelet is

$$\psi^{m,n}(t) = a_0^{\ -m/2}\,\psi\left(\frac{t - nb_0 a_0^{\ m}}{a_0^{\ m}}\right) \tag{5}$$

The simple choice of $a_0 = 2$ and $b_0 = 1$ provides a dyadic-orthonormal wavelet transform. Orthonormal properties enable the multi-resolution signal decomposition technique to decompose a signal into scales with different time and frequency resolution.[14-17]

Multi-resolution Signal Decomposition using DWT

Let us discuss the ILM technique based on discrete wavelet transform. Given a signal s of length N, the DWT requires $\log_2 N$ computation steps, whereas the FFT requires $N\log_2 N$ steps. It implies that the DWT is much faster and has smaller computation loads than the FFT. Therefore, the DWT is suitable for real-time fault detection based on the ILM.

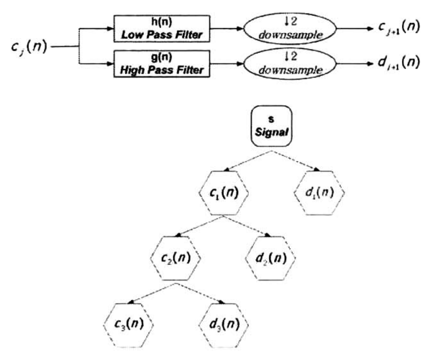

Fig. 2. Multiresolution Signal Decomposition Step

Starting from a signal s, the first step produces two sets of coefficients: approximation coefficients $c_1(n)$, and detail coefficients $d_1(n)$. These vectors are obtained by convolving s with the low-pass filter $h(n)$ for 'the approximations', and with the high pass filter $g(n)$ for 'the details'. The general higher scale decompositions are performed in the same way as described above.[17-19] The sequence of the MSD (Multi-resolution Signal Decomposition) technique is represented by Fig.

2. By using this MSD technique, the sensor signal is decomposed into two other signals; one is the approximated or smoothed version of the sensor signal, and the other is the detailed version of the sensor signal that contains the noise and fault components containing sharp edges, transitions, and jumps at the bias, drift, spike faults, and so on. In this paper, the key idea of the MSD theory is briefly presented. A precise treatment of the MSD theory can be found in Ref. 18. In brief, the MSD technique localizes and discriminates a disturbance signal from the original signal. Thus, the MSD technique using the DWT can be applied to the fault detection of the sensor.

The choice of wavelets plays an important role in detecting various types of faults. If our interest lies in detecting short and fast transient faults, Daubechies' 4 wavelet('Db4') is one of the possible consideration. On the other hand, for slow transient faults such as the drift, Db8 or Db10 is comparably suitable.[17] Here Db4 wavelet is used, and to detect the slow transient faults, the higher scale decomposition signal of MSD is used for compensation. As the wavelet goes to the higher scales, the analyzing wavelets become less localized due to the dilation nature of the wavelet.

If the sensor noise $n(t)$ is a Gaussian white noise with variance σ^2, then the discrete wavelet transform of $n(t)$, $T^{DWT}n(t)$, also has the Gaussian process with a variance $E[\|T^{DWT}n(t)\|^2]$. $E[X]$ denotes the expected value of a random variable X, and $\|\cdot\|^2$ represents a 2-norm in $L^2(R)$. If the sensor has relatively accurate noise characteristics, the threshold of the fault alarm can be set to be three times as much as the standard deviation as follows.

$$Th_{fault} = 3\,E[\|T^{DWT}n(t)\|^2] \tag{6}$$

Model-free Hybrid Fault Detection and Isolation

It has been said that FDI technique based on hardware redundancy is a traditional, simple, and reliable. It has also been applied to real aircraft safety systems, though high-level redundancies make the system complicated and expensive. Especially, contrary to the conventional aircraft systems, FDI using the triple or quadruple hardware redundancy cannot be suitable for UAV due to many constraints such as space and cost. Using PEA technique based on hardware redundancy, the fault can be clearly detected even for the limited multiple sensor system; however, the fault isolation is not easy due to the lack of parity equations. On the other hand, the ILM technique using the DWT has the capability of detecting each sensor fault due to the local sharp variation property of the wavelet transform. Nevertheless, wavelet transform based FDI has some drawbacks. Aircraft is a high-level dynamic system and may perform various abrupt maneuvers. If an aircraft is maneuvering abruptly, the wavelet transformed signals of sensor outputs vary sharply. Such variations may generate false alarms. In addition, DWT is a fast algorithm, but deals with the finite length of signals. Thus, it has difficulties in processing the real-time sensor signals of the aircraft.

Since hardware redundancy based FDI techniques and wavelet transform based ILM methods have their own weak points, a more efficient FDI algorithm can be made by combining these two methods. When the number of redundant sensors is limited, the lack of parity equations can be compensated by DWT based ILM technique. Similarly, the false alarm of DWT due to aircraft maneuvers can be prevented by PEA. Note that other parity methods such as Parity Space Approach (PSA), Least Square Residual Approach (LSRA), and Generalized Likelihood Ratio Test (GLT) can be used as a hardware redundancy based FDI technique. Also, other signal processing techniques such as Windowed Fourier Transform, Autoregressive Time Series Model, and Power Spectral Analysis can be used instead of DWT technique.[1-3]

In this study, the hybrid FDI technique is proposed for the limited redundant sensor system of an aircraft. The limited redundant sensor system mounted with tilted angles is apt for low cost, small size, or disposable UAV. It is mentioned why the concept of hybridizing PEA and DWT can be effective for FDI. However, two things should be carefully considered in the implementation

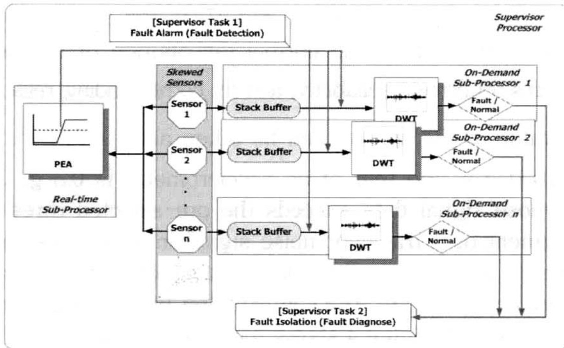

Fig. 3. The implementation concept of Model-free Hybrid FDI scheme

of the model-free hybrid FDI scheme. The first consideration is the priority of the fault detection and alarm. DWT has false alarm problems with abrupt maneuvers, while PEA is independent of signal conditions. Therefore, PEA should have the priority to judge the fault situation. The second consideration is the computation load of DWT. PEA has a low computation load, but DWT intrinsically has a higher computation load due to the convolution sequences with a finite length of sensor data in store. In addition, DWT computation is worthless in the normal situations. Consequently, PEA has to be computed real-time and DWT should be performed by the on-demand computation.

Figure 3 shows the implementation concept of the proposed model-free hybrid FDI scheme. Real-time subprocessor computes the value of the parity equation with sensor data. Supervisor processor keeps an eye on the threshold excess of parity equation value. Meanwhile, the stack buffer of each on-demand subprocessor accumulates a specific length of time series of the sensor data in flight. Once the fault situations occur, the parity equation value exceeds the threshold. In the same time, the supervisor processor declares the emergent sensor fault situation (Fault Detection) and sends the fault alarm to each on-demand subprocessor. Within a specific short period, each on-demand subprocessor operates DWT calculation with the stored sensor signal and the supervisor processor judges which sensor is faulty (Fault Isolation). A critical design parameter is the stack size of the on-demand subprocessor, i.e. the sensor data length of DWT. As a stack size is shorter, DWT is computed faster. The computation time is also dependent on the performance of the embedded processor. Therefore, the sensor data length of DWT should be decided considering the hardware computation capacity and the safety margin of the aircraft control scheme.

Model-based Hybrid Method for Parallel Redundant Sensors

Hardware Redundancy Management

Hardware redundancy methodologies require multiple sensors and therefore, are inefficient with respect to space and cost. Using a mathematical model, the number of redundant components can be reduced. CCM is widely used in hardware redundancy management, and threshold and confirmation times are used in the fault detection process. In CCM, the voting method is used to determine the reference value by comparing several signals. A triple system chooses the mean value of the sensor outputs in case all sensors are healthy. Once one sensor fails, the mean value of the remaining two sensors becomes the reference value[20].

The threshold value is determined by considering a range of standard signals[21-22]. Sensor output signal usually consists of a true value and error. Error consists of noise and fault. Due to the noise, sensor signal is dispersed from the true value. There are many ways to obtain the threshold value. In this paper, we assume the sensor signal has a normal distribution expressed as

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2} \right] \tag{7}$$

where x is discrete data, μ is the mean of x, and σ is the standard deviation of x.

A Fault signal is distinguished by the normal distribution of the healthy signal. Generally, a fault tolerant system requires 99 percent reliability, and its corresponding reliability range is $|x| \le 2.575\sigma$. Therefore, the threshold value of the system can be taken as $C_v = 2.575\sigma$. Generally, the threshold value of a gyroscope is 10 deg/s, and that of an accelerometer is 0.3 g. Confirmation time is the time to alarm the fault whose signal data exceeds the pre-selected threshold value. Confirmation time prevents the misjudgment of a transient noise signal in a short period being considered as a fault. Repetitive experiments are one way to decide the confirmation time. Assuming that the representative standard deviation is 1.5σ, the confirmation time of a gyroscope is 0.35 second, and that of an accelerometer is 0.2 second. Figure 4 shows the schematic diagram of the hardware redundancy management system.

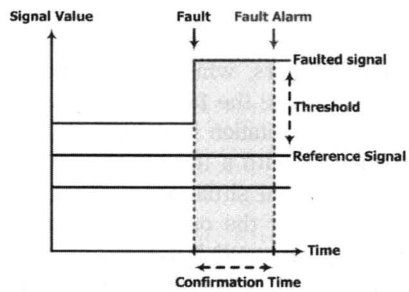

Fig. 4. Fault Detection in Hardware Redundancy Management

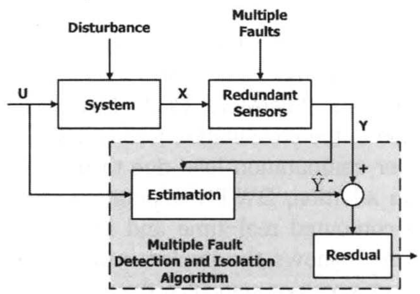

Fig. 5. Sensor Multiple Fault Detection Block Diagram

Multiple Fault Detection Method

An airliner and high-performance aircraft should have high reliability against every possible fault. However, when multiple faults occur in a triple redundancy system, the conventional FDI methods cannot detect these multiple faults. In this paper, we propose a multiple fault detection method that can detect the multiple sensor faults by using the observer-based analytic method[23-24]. Figure 5 shows the block diagram of a multiple fault detection method.

The process of multiple fault detection method is as follows. Assume that the multiple faults of two sensors occur at time t_1, as shown in Fig. 6. Sensor fault is detected at $t_1 + kT$ by the conventional CCM algorithm. Note that T is the sampling time, and kT is the confirmation time. After a fault is detected, the multiple fault detection method is activated to find which sensors are faulty. State estimation values after the fault cannot be used because they are contaminated by the faulty sensor signal. The fault detection method proposed in this paper only uses the estimated state values before the fault as well as the input signal after the fault to estimate the state values at the time of $t_1 + (k+1)T$. These values can be used as reference values for the fault diagnosis. In this paper, a nonlinear aircraft model is used.

Consider a discrete nonlinear state-space equation of sampling time T.

$$x(t+T) = g(x(t), u(t)) + w(t) + f(t) \tag{8}$$

$$y(t+T) = h(x(t+T)) + v(t)$$

where $x \in R^n$, $u \in R^p$, $y \in R^m$ are state, input, and output, respectively. And $w(t)$, $f(t)$, $v(t)$ are disturbance noise, fault, and measurement noise, respectively.

An observer for fault detection can be represented as follows.

$$\hat{x}(t+T) = g(x(t), u(t)) \tag{9}$$
$$\hat{y}(t+T) = h(\hat{x}(t+T))$$

Assuming that a fault occurs at time t_1. The state estimation at time $t_1 + 2T$ can be described as

$$\hat{x}(t_1+2T) = g(\hat{x}(t_1+T), u(t_1+T)) = g[g[(x(t_1), u(t_1))], u(t_1+T)] \tag{10}$$
$$\hat{y}(t_1+2T) = h(\hat{x}(t_1+2T))$$

Similarly, a state estimation value at $t_1+(k+1)T$ can be represented as follows.

$$\hat{x}(t_1+(k+1)T) = g[g[\cdots[g(x(t_1), u(t_1)), u(t_1+T)], \cdots u(t_1+(k-1)T)], u(t_1+kT)] \tag{11}$$
$$\hat{y}(t_1+(k+1)T) = h(\hat{x}(t_1+(k+1)T))$$

Let y_{fault1}, y_{fault2}, $y_{nofault}$ be the signals of faulty sensors 1, 2, and non-faulty sensor. Residuals at time $t_1+(k+1)T$ are defined as

$$r_1 = \hat{y}(t_1+(k+1)T) - y_{fault1}(t_1+(k+1)T)$$
$$r_2 = \hat{y}(t_1+(k+1)T) - y_{fault2}(t_1+(k+1)T) \tag{12}$$
$$r_3 = \hat{y}(t_1+(k+1)T) - y_{nofault}(t_1+(k+1)T)$$

The residuals are used to judge which sensors are failed. Residuals of faulty sensors will exceed the threshold value, and the residual of healthy sensor will remain within the threshold.

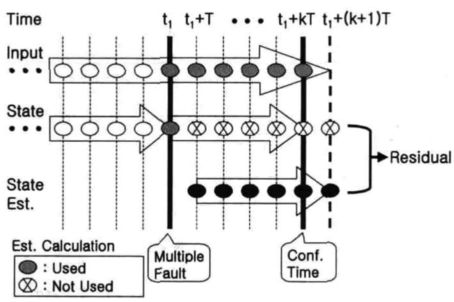

Fig. 6. Principle of Sensor Multiple Fault Detection Method

Numerical Simulations

Model-free method for skewed redundant sensors

Figure 1 shows the geometric configuration of the four skewed sensors considered in this study. Three sensors are coincident with three orthogonal axes and the other one is skewed. This configuration has the minimum number of sensors for fault detection. Since three or more sensors are not on the same plane, one parity equation can be obtained.

In case 1, it is assumed that the angular velocity of aircraft is perturbed and oscillating, and a sudden bias fault occurs in sensor 3 at 53 seconds. Figure 7 shows that the parity equation detects the fault at 53 seconds but cannot isolate the faulty sensor. Figure 8 shows that DWT of each sensor can isolate the faulty sensors; sensor 3. The first level detail decomposition (D1) of sensor 3 shows the best detection of the fast change or discontinuity at 53 seconds.

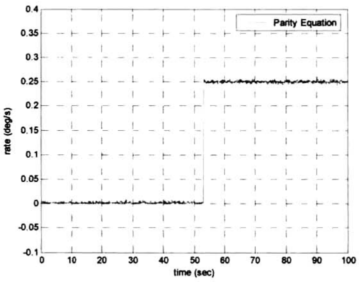

Fig. 7. Parity equation history (Case 1. sudden bias)

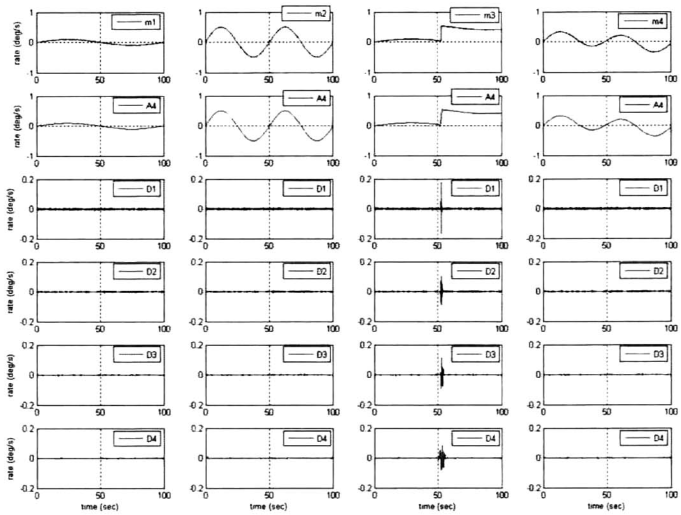

Fig. 8. Each sensor's DWT history (Case 1. sudden bias)

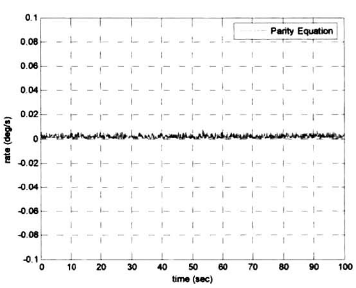

Fig. 9. Parity equation history (Case 2. abrupt maneuver : no fault)

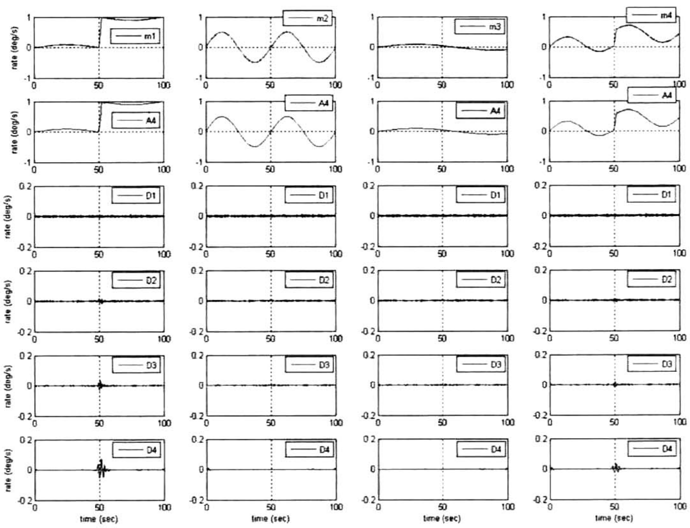

Fig 10. Each sensor's DWT history (Case 2. abrupt maneuver : no fault)

In case 2, it is assumed that the aircraft maneuvers abruptly and a fault does not occur in any sensor. Figure 9 shows that the parity equation does not show any fault. Figure 10 shows that DWT of each sensor seems to indicate faults; sensor 1 and 4, even though all sensors are healthy. This results propose that the parity equation should have the priority over DWT to detect the fault and generate the fault alarm.

In conclusion, Cases 1-2 verified the effectiveness of the model-free hybrid FDI technique to show that PEA compensates the weakness of DWT technique.

Model-based method for parallel redundant sensors

An F-16 nonlinear aircraft model with speed of 300 ft/sec at the altitude of 30,000 ft is used, and the measurement noise is considered.[25] The magnitude of the measurement noise is about the same level as that of the real sensor noise. The standard deviation is set up to 0.01. The sensor noise can affect the FDI scheme seriously. Because the fault signal and the sensor noise have similar property, it is not easy to distinguish those signals.[26] Therefore, the sensor noise should be removed before the fault detection process. In this paper, the extended Kalman filter is used.[27-28]

Table 1. Fault Scenarios

Scenario	Fault Component	Remark
1	12 deg/s bias (Roll, pitch, yaw gyro, IMU II) 12 deg/s bias (Roll, pitch, yaw gyro, IMU III)	
2	30 deg/s bias (Roll rate gyro, IMU II) - 30 deg/s bias (Yaw rate gyro, IMU III)	5 deg aileron input before fault - 10 deg elevator input after fault
3	30 deg/s bias (pitch rate gyro, IMU II) - 30 deg/s bias (pitch rate gyro, IMU III)	Side wind effect considered

Several scenarios were considered to verify the performance of the multiple fault detection algorithm. Two gyroscopes in three IMU (Inertial Measurement Unit) system fail at 10 seconds. The threshold value was taken as 10 deg/s, and the confirmation time was 0.34 second. Considered scenarios are summarized in Table 1. The results of numerical simulation are shown in Figs. 11-13.

Figure 11 shows the residuals of Scenario 1. The residual of the faulty sensor exceeds the threshold after the confirmation time, but the residual of healthy sensor stays within the threshold. As shown in Fig. 12 (Scenario 2), the effects of the input can be negligible. Figure 13 shows the

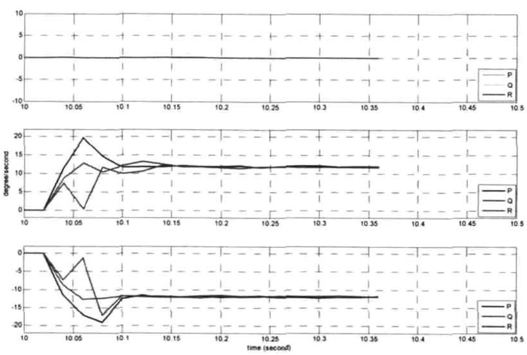

Fig. 11. Residual of the First Sensor Multiple Fault Scenario

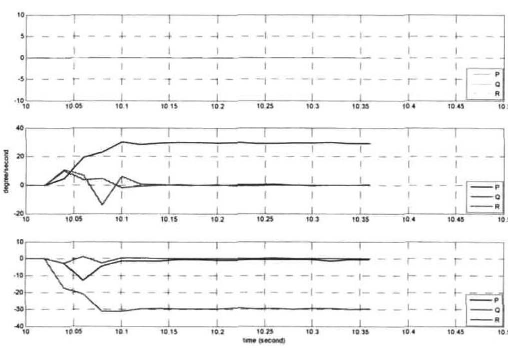

Fig. 12. Residual of the Second Sensor Multiple Fault Scenario

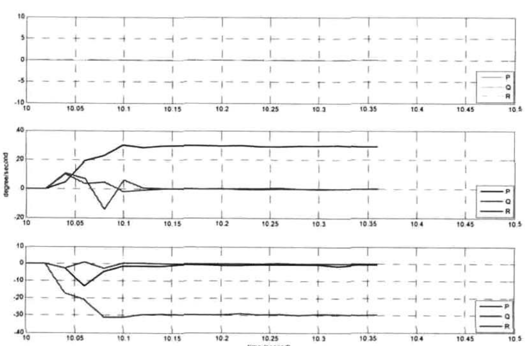

Fig. 13. Residual of the Third Sensor Multiple Fault Scenario

result of Scenario 3. Even though the residual of the healthy sensor is larger than those of other scenarios due to external disturbance, fault detection can be correctly performed. Simulation results show that the proposed multiple fault detection method can detect and isolate the multiple faults correctly in the environment of aircraft maneuver and external disturbance.

Conclusion

In this paper, two hybrid fault detection and isolation techniques are proposed. First, model-free hybrid FDI scheme is proposed to compensate the drawbacks of the hardware redundancy based FDI method and the signal processing based ILM method. Simulation results showed that multiple faults of the limited redundancy system can be detected and isolated. Model-free hybrid FDI can be applied to the case where an accurate mathematical model of aircraft is unavailable. Second, the model-based hybrid fault detection method is proposed to enhance the conventional CCM methods that cannot detect the multiple faults. Residuals were calculated using the observer of the nonlinear aircraft mathematical model. Model-based hybrid FDI scheme combined the analytic redundancy management technique to the hardware redundancy management technique. Nonlinear aircraft model and the extended Kalman filter were used to verify the performance of proposed FDI method.

Acknowledgments

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