Fault Detection and Isolation of aircraft air data/inertial system

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Abstract

A method for failure detection and isolation for redundant aircraft sensors is presented. The outputs of the concerned sensors are involved in the computation of flight law controls, and the objective is to eliminate any perturbation before propagation in the control loop when selecting a unique flight parameter among a set (generally 3) of redundant measurements. The particular case of an oscillatory failure is investigated. The proposed method allows an accurate fault detection and isolation of erroneous sensor and computes a consolidated parameter based on the fusion of data from remaining valid sensors. The benefits of the presented method are to enhance the data fusion process with FDI techniques which improves the performance of the fusion when only few sources (less than three) are valid.

1. Introduction

The state-of-practice for aircraft manufacturers to diagnose guidance and control (G&C) faults and obtain full flight envelope protection at all times is to provide high level of hardware redundancy in order to perform consistency tests and to ensure sufficient available control action. In the frame of future environmentally-friendlier aircraft and structural design optimization, this paper deals with a method of integrity control based on the processing of anemometric and inertial data in the Flight Control Computer (FCC). The FCC provides data used to compute a command (position order) to servo-control each moving surface (see Figure 1). The data is acquired using an inertial acquisition system composed by several dedicated redundant units (usually three). The FCC generally receives three redundant values of each flight parameter from the sensors and computes unique flight parameter value required for the Flight Control laws computation. This specific data fusion processing, called "consolidation", classically consists of two simultaneous steps: from the three sources, selection of one unique and accurate parameter and in parallel, monitoring of each of the three independent sources to discard any failed source and to ensure that the selected value is correct. This overall "consolidation" processing selects the reliable flight parameters with the required accuracy by discarding any possible failed redundant source.

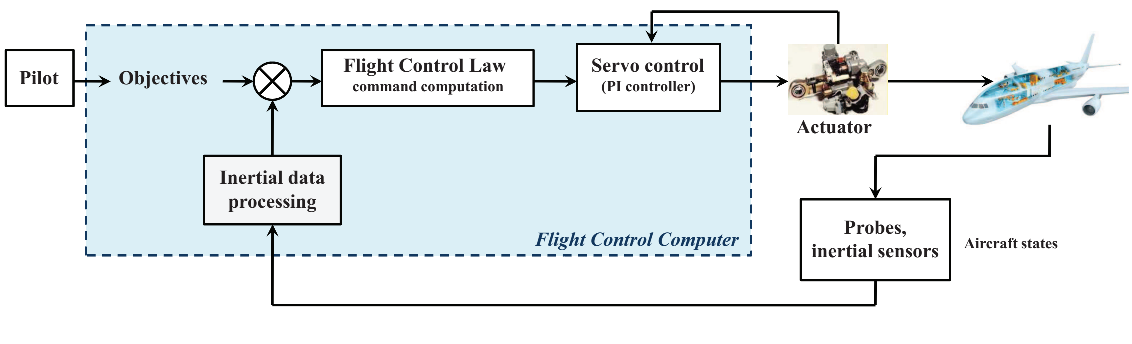

Figure 1: Flight Control Law computation

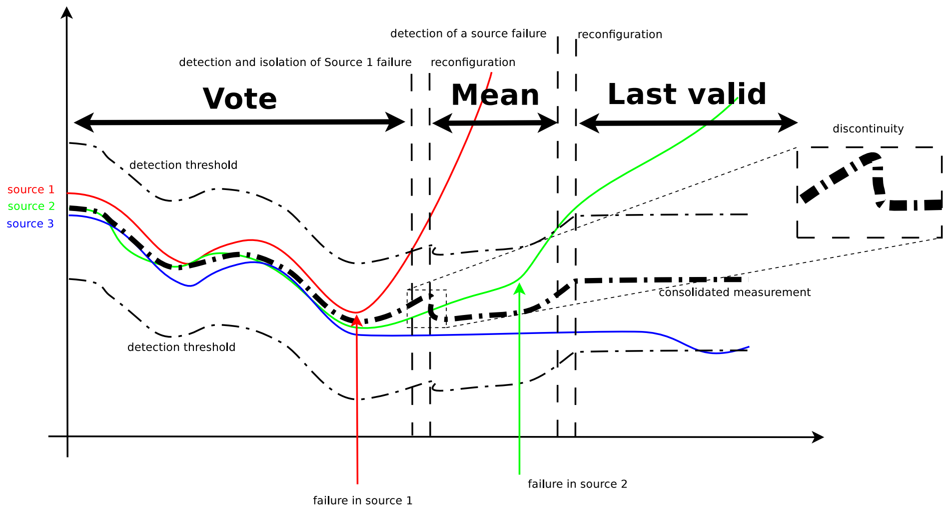

Figure 2: Triplex monitoring

Current consolidation state-of-practice allows to be compliant with stringent regulations. However, for future aircraft structural design optimization, it could be required to avoid the propagation of oscillations even of smaller amplitudes.

Fault-tolerant management system checks the consistency of all sensor outputs to detect a failed source, typically by using a majority-voting or a weighted mean method [2] or soft-computing approaches [3]. The main advantages of this architecture are that the design and integration simplicity [4]. Also, to provide safe operation, the architecture must have at least three valid sources, which means the fault tolerance couldn't be guaranteed after a single source failure : if a source fails, then it has to be removed from the fault tolerant architecture.

The sensor management system proposed in this paper aims to solve the inherent issue of losing a source in a three sensor acquisition system or triplex, and to be still capable of a sufficient fault tolerant data acquisition. The issue is investigated for very specific oscillatory failures that may occur in the flight parameter sensors. The presented approach is based on a hierarchical FDI structure which takes in consideration the number of healthy sensors in the system. When more than two sensors are available, soft computing techniques are used for data consolidation. Otherwise, filter-based FDI approach is used to detect the failure node by node. The novelty in the method is the use of a particular residual generator similar to the harmonic filter developed in [5] to transform the fault signature in the residual from sinusoid-like to step-like, greatly improving the detection rate for low amplitude oscillatory failures. The application is related to on-going research undertaken within the european ADDSAFE project [1] to assess the capability of efficient model-based FDD methods on realistic aircraft flight control systems.

This paper is organized as follows: The next section is devoted to problem formulation. Section three presents the proposed structure based on a mixed data fusion / fault detection and isolation method for consolidation. Section four presents the simulation results obtained from a high fidelity benchmark. Concluding remarks are discussed in the last section.

2. Problem Formulation

One class of flight parameter sensor failures is additive oscillations appearing on output signals. These failures are referred as Combined Oscillatory Failure Cases (COFC) in contrast of Oscillatory Failure Cases (OFC) which impact only one control surface [6, 7]. COFC can possibly impact several control surfaces. The measurements provided by the corrupted source could propagate through the control loop and may cause under some circumstances unwanted oscillations of the control surfaces. Thus, the corrupted sources need to be switched off as fast as possible.

Current industrial practices involve Triplex voting schemes as in [8, 9, 10]. The basic principle, shown in Figure 2, is to sort output signals and to give a 0.5 ponderation to the source providing the second (median) value of the parameter and a 0.25 ponderation to the two other source, then adding the results to obtain the value of the parameter. A threshold, centered around the obtained value, is used to detect the occurrence of a failure. When a COFC occurs, the corrupted source is detected when the provided measurement stays outside the threshold for a specific amount of time.

If only two sources are valid, the consolidation is performed by choosing the mean value of the two measurements. Notice the discontinuity when switching from vote-based consolidation to the mean-based one. If the difference between the two signals is superior to a specified threshold, then the two sources are discarded and the last correct value of the parameter is used. Fault isolation is possible only when the three sources are valid, and all measurement updates are lost when two sources are corrupted, since it cannot be decided which source can be trusted. Also, thresholds must be chosen offline for all the possible flight scenarii, involving long and costly experiments. Finally, as it can be seen in Figure 2, transients appear on the consolidated parameter. The main objective of this paper is to enhance the classical majority-vote triplex monitoring. Two failure cases are investigated: the first one starting with three valid sources initially (where the classical majority-based approach is appropriate) and the second one starting with two valid sources and a corrupted source initially (where the majority-based approach is impossible).

In order to improve the existing methodology on the first scenario and to extend failure isolation functionality on the second one, a mixed Data Fusion (DF) / Fault Detection and Isolation (FDI) method is proposed in the next section.

3. Detailed DF/FDI method

3.1 General Structure

The overall structure of the proposed method is shown in Figure 3. There are two major components: The first one is the fault detection and isolation module composed by residual generators and decision-making module, and the second component is the consolidation module. The role of the FDI module is to detect the corrupted source and to switch it off as soon as possible, while the consolidation module gives an accurate estimation of the parameter based on the measurement data provided by the valid sources. The knowledge of the flight control law is used to discriminate between the COFC and a possible (normal) sinusoidal control law of the pilot. The consolidation module provides also FDI functionality in the three valid sources scenario. In order to minimize the computation time, the FDI module is switched ON only when a sensor is declared corrupted, since when all the sources are valid, consolidation module provides sufficiently performant fault isolation.

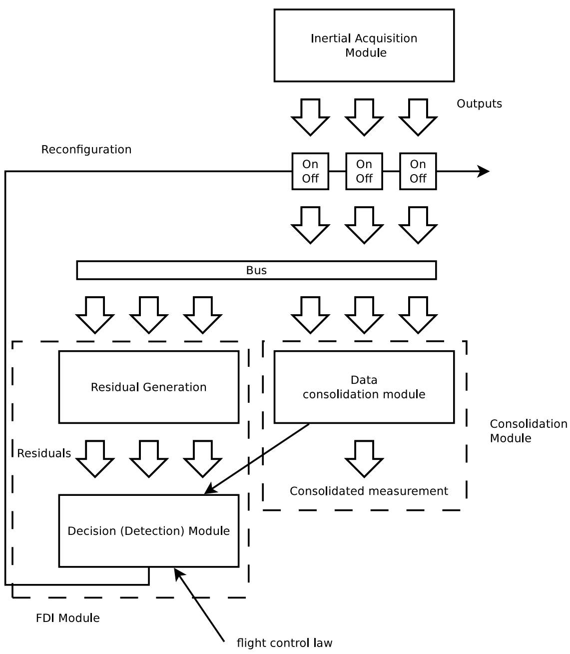

Figure 3: Overall structure of the proposed methodology

3.2 Consolidation module

The consolidation module is similar to the system proposed in [3]. The fusion between different sources is performed using a Fuzzy logic approach called *Soft-voting*. Each source is assigned a weight corresponding to the amount of trust it is credited, and the consolidated signal is the weighted average of all valid sources (equation 1).

$$S_{vote} = \sum_{i=1}^{n_{valid}} w_i S_i \tag{1}$$

with w_i representing the weight to the source S_i and n_{valid} corresponding to the number of valid sources. The weight w_i is computed from the membership degree $\mu_i \in [0, 1]$ assigned to each measurement (equation 2).

$$w_i = \frac{\mu_i}{\sum_{j=1}^{n_{valid}} \mu_j} \tag{2}$$

The computation of the different values of μ_i is given in [3, 11]. Each membership function is centered around the value provided by the corresponding source, and used to determine the membership degree of the source, which is given by the largest membership degree q_j of the remaining valid signals.

$$\mu_i = \max_{i \neq j}(\mu_i(q_j))$$

As it can be seen, the majority voting concept is used in soft voting as it is used in conventional consolidation. The difference is the contribution of the measurement signals: in conventional scheme, the contribution of the faulty signal is limited while in soft voting scheme it is reduced. The direct consequence of the “limitation” versus the “reduction” is the discontinuity of the consolidated measurement appearing when a failed source is switched off in the classical voting scheme. In the soft-voting based consolidation, the consolidated measurement remains smooth in all cases. The overall structure of the soft voting block is given in [11]. The monitoring component is based on a counter associated to each source and a maximum allowed threshold.

Table 1: Soft monitoring procedure

If $\mu_i = 1$ then $count_i = count_i - 1$
If $0 < \mu_i < 1$ then $count_i = count_i$
If $\mu_i = 0$ then $count_i = count_i + 2$

Another very important point is the periodic nature of the failure. Using this complementary information the detection can be performed by monitoring the periods between transitions from 1 to 0 of a membership degree μ_i as shown in Figure 4. When four successive 1 to 0 transitions of μ_i show periodicity, an OFC is detected. Notice that the counter also can provide a detection for a large amplitude OFC.

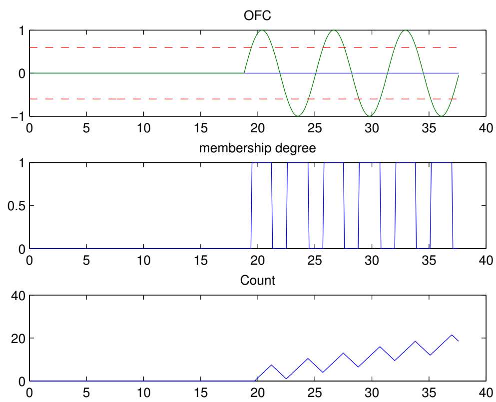

Figure 4: OFC behaviour

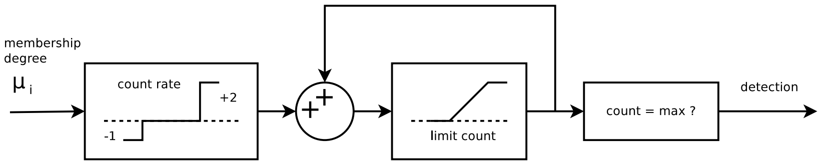

Figure 5: Soft Monitor

The overall scheme of the monitoring block is shown in Figure 5. Since the counter rate is not a function of the difference between the consolidated value and the i^{th} measurement as in the conventional scheme, but a function of the difference between the different measurements. Therefore, no transients occur when a source is switched off since its contribution to the consolidated parameter was already nil.

3.3 Fault detection and isolation module

Since the only knowledge on the system is the measured outputs and the characteristics of the expected failures, signal processing based FDI methods can be preferred. The proposed FDI module is based a particular characteristic of the harmonic filter proposed in [5]. For our problem, the parameter estimation functionality of this filter is useless, however the filter is very sensitive to new harmonics appearing in input signal spectrum. We shall use this functionality to design a selective residual generator.

The measured signals are noisy, so the direct residual generation is difficult. Additional filtering component is considered in the form of a near optimal steady state filter similar to the filter developed in [12, 13]. Finally, an abrupt change detection method is used to perform COFC detection. In this paper and because of harsh computer time constraints, we use a robust derivative estimator to amplify residual changes and threshold crossing detection. The thresholds are computed offline, in fault free conditions.

3.3.1 Kalman Filtering

Consider the following fault signal

$$f(t) = a\cos(\omega_0 t + \phi) \tag{3}$$

where a, ω_0 and ϕ are respectively the amplitude, frequency and phase of the sinusoidal signal $f(t)$. The corresponding state space model is

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 \\ -\omega_0^2 & 0 \end{bmatrix}}_{A} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{4}$$

$$f = \underbrace{\begin{bmatrix} a & 0 \end{bmatrix}}_{C} x + v$$

where v is Gaussian noise. The Kalman filter for this system is described as

$$\dot{\hat{x}} = A\hat{x} + H\left[y - C\hat{x}\right]$$

In [12], an appropriate value of H for this model is given by

$$H = 2\xi\omega_0 \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

It is a reasonable choice leading to a suboptimal steady state filter, with ξ being a small constant. The final state-space equation of this filter is given by

$$\dot{\hat{x}} = \begin{bmatrix} -2\xi\omega_0 & 1 \\ -\omega_0^2 & 0 \end{bmatrix} \hat{x} + 2\xi\omega_0 \begin{bmatrix} 1 \\ 0 \end{bmatrix} y \tag{5}$$

This corresponds to a stable second order between the output and $\hat{x}_1$

$$G(s) = \frac{Y}{\hat{X}_1} = \frac{2\xi\omega_0 s}{s^2 + 2\xi\omega_0 s + \omega_0^2}$$

This simple system provides near optimal performance when filtering sinusoidal signals around ω_0 frequency, $\pm 5Hz$, which fits rather well for the case of interest. However, should the OFC occur in a larger frequency band, the use of an extended Kalman filter must be considered, augmenting the state with the parameter $\Delta\omega_0$, representing the uncertainty on ω_0.

3.3.2 Residual generation

A classical decision making method in FDI is to check threshold crossing by the residual signal. An usual problem here is to determine appropriate threshold values in order to simultaneously maximize fault detection ratio and to minimize detection delay and false alarms rate. This problem has many possible solutions for fault signatures that induce abrupt changes in the system behavior, see for instance [14, 15]. But for oscillatory failures the problem is much more difficult, as classical abrupt change detection methods are ill-suited for detecting smooth changes in the system signals, especially in case of low amplitude oscillatory failures and noisy measurements.

A possible solution to this problem and the principal contribution of this paper is to transform the sinusoidal influence of the COFC in the system into a step-like influence. The determination of the detection threshold is simplified, and is solely based on the parameters of the measurement noise, usually available and depending on sensors performance. This transformation is obtained using an appropriate additional filter. From this perspective, the work reported in [5] will constitute the basis of the residual generator. In the original paper, an estimator is proposed to provide accurate estimation for a sinusoidal component in a noisy signal. It is shown that the outputs of the estimator converge asymptotically to the correct values. The core of the estimator is a third order nonlinear filter described by the relation:

$$\begin{cases} \dot{x}_1 = & Kx_3(-2\alpha[-2\alpha x_3 - \alpha^2 x_2 + u] - \alpha^2 x_3) - Kx_3^2 y - K[-2\alpha x_3 - \alpha^2 x_2 + u]u \\ \dot{x}_2 = & x_3 \\ \dot{x}_3 = & -2\alpha x_3 - \alpha^2 x_2 + u \\ y = & x_1 + Kx_3 u \end{cases} \tag{6}$$

The coefficients K and α are tuning parameters, with K acting like a gain and α acting like a damping ratio. When $t \to \infty$, the relation $\hat{\omega}_0 = \sqrt{|y|}$ is an accurate estimation of the pulsation of an input oscillatory signal from the form 3. The remaining parameters (amplitude and phase) are given by

$$a = \sqrt{\frac{-\hat{\dot{u}}^2}{y} + \beta^2} \text{ and } \phi = y - \beta$$

with $\beta = \frac{\hat{\ddot{u}}}{y}$, $\hat{\dot{u}} = yx_3 + 2\alpha[-2\alpha x_3 - \alpha^2 x_2 + u] + \alpha^2 x_3$ and $\hat{\ddot{u}} = y[-2\alpha x_3 - \alpha^2 x_2 + u] + 2\alpha y x_3 + \alpha^2[-2\alpha x_3 - \alpha^2 x_2 + u]$. $\hat{\dot{u}}, \hat{\ddot{u}}$ are input derivative estimates. The residual generator proposed in this paper is thus based on the nonlinear filter described in (6). The filter is sensitive to the input of an oscillatory signal and reacts by a slope change of the output y. The proof is ommited for the sake of brevity (see [5]).

3.3.3 Residual evaluation

The residual evaluation is a decision-making process which always comes down to a threshold logic of a decision function [17]. Due to measurement noises, modelling uncertainties, robust residual evaluation is the only way to keep the false alarm rate small with an acceptable sensitivity to faults. Classically, robust residual evaluation can be accomplished in many ways, for example by statistical data processing, data reconciliation, correlation, pattern recognition, fuzzy logic or adaptive thresholds. In our case, the harmonic filter provides a good discrimination for all nonperiodic outputs, and behaves in easily predictable way when a periodic signal is present in the processed data. Using the residual (or the energy of the residual) provided by the relations (6) and (5), the detection is possible using a discrete-time high gain observer proposed in [18]. The discrete transfer function is given below

$$T(z) = \frac{2\beta}{2\epsilon + \beta\Delta T} \times \frac{z - 1}{z + \frac{1 - \frac{2\epsilon}{\beta\Delta T}}{1 + \frac{2\epsilon}{\beta\Delta T}}} \tag{7}$$

where ΔT is the sampling time and β, ϵ are tuning parameters. The behaviour of this filter is fixed by the ratio $\frac{\Delta T}{\epsilon}$. High values (superior to 1) are taken when the noise is weak, and low values when the noise is strong.

frequencies [Hz]	0.2	0.7	5	10
amplitude [degrees]	0.5	1		

Table 2: COFC parameters

4. Simulation results

4.1 Protocol

In ADDSAFE project context [1], the simulations are performed using a high fidelity commercial aircraft benchmark under Matlab/Simulink environment. The measured parameter is the angle of attack. The measurement noise is a gaussian noise with a 10^{-4} variance. The sampling rate is $\Delta t = 0.01$ sec. Two cases are considered:

- a unique failure occurring at $t_{def} = 6$ sec on the first sensor with all units initially being healthy. The detection and the isolation of the COFC is performed using soft monitoring module.
- a second failure occurring at $t_{def} = 9$ sec on the second sensor with the first unit initially off-line. The detection and the isolation of the COFC is based on the analysis of the residuals corresponding to each source.

Note that the second case where only two valid sources are available is very similar to the case when only one valid source exist, since the FDI method proposed in this paper does not use data from other sources. For each case, simulations are performed with COFC of different frequencies and amplitudes (see Table 2).

The tuning parameters of the Kalman Filter are $\omega_0 = 4\pi = 2$ [Hz] and $\xi = 0.9$. The parameters of the harmonic filter are set to $K = 20$ and $\alpha = 10$. The parameter ω_0 is taken as the middle of the frequency band of the expected OFCs, i.e. $[0.1 - 10]$ Hz. The parameters ξ, K, α are chosen using a Pareto-optimum approach, maximizing fault detection ration and minimizing detection delay, missed detections and false alarms (see [11] to have an idea on the selection procedure). The values are given for a COFC of amplitude 0.5° and frequency of 0.7 Hz.

For the robust derivative estimator, β is set to 1. If the measurement noise is weak, one can take $\frac{\Delta T}{\epsilon} = 10$, but for our application the ratio is fixed to 0.3 to obtain the best detection/false alarm ratio. This value is obtained using the approach from the previous paragraph given in [11].

4.2 Unique failure scenario

Figure 6 shows the simulation results for the COFC case ($a = 0.5, f = 0.7$). Soft-computing based FDI scheme and classical voting approach are compared. It is easy to notice the discontinuity in the consolidated measurement obtained by the classical vote-based method, while the soft-computing based consolidated measurement remains smooth. The

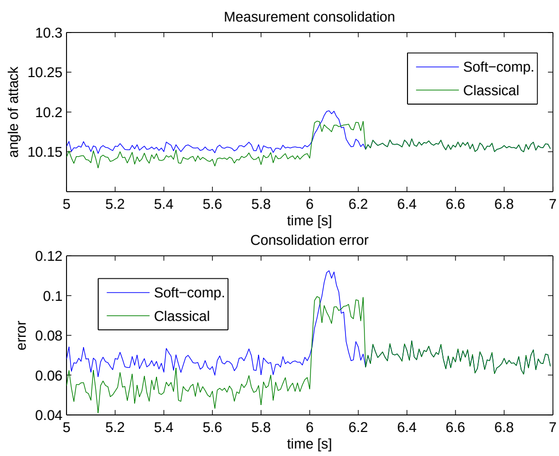

Figure 6: Soft monitoring simulation results

remaining COFC case results are processed likewise. The detection delays are given in the left part of Table 3. The

Soft-monitoring delays [s]					FDI delays [s]				
amp\freq	0.2	0.7	5	10	amp\freq	0.2	0.7	5	10
0.5	0.63	0.23	0.13	0.17	0.5	0.4	0.29	0.23	0.23
1	0.33	0.13	0.07	0.07	1	0.37	0.25	0.22	0.22

Table 3: Soft-monitoring and FDI detection delays (in seconds)

delays are given as the difference between COFC occurrence in the system and COFC detection by the implemented FDI method.

4.3 Double failure scenario

When two simultaneous OFC occur on the first and the second sensors, the consolidation module will perform detection but fails to switch off the faulty sources due to majority-vote principle (see section 2). However, the results given in the right part of table 3 can be notice that fault isolation is successfully carried by the implemented FDI approach for all fault frequencies. Hence, any possible wrong decisions could be corrected. Figure 7 shows the simulation results for the COFC case ($a = 0.5, f = 0.7$). The residual reacts as expected to the occurrence of the failure.

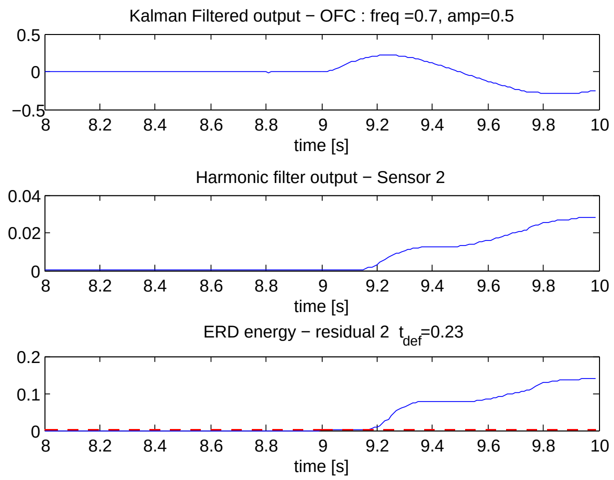

Figure 7: COFC detection and isolation based on residuals

4.4 Discussion

Simulation results show the complementarity of the two monitoring approaches. When all the flight parameter sensors are initially healthy, soft-monitoring successfully detection and switches off the corrupted source, with best performance achieved for frequencies superior to 0.2 Hz. When the soft-monitoring is not suitable, FDI based on residual generation successfully detects COFC failures for all frequencies compared to the work investigated in [11].

5. Conclusion

An approach to oscillatory failure detection and isolation in aircraft air data/inertial system is presented. Fuzzy logic approach for consolidation is combined with signal processing based FDI to extend the conventional scheme in order to manage a low number of healthy sensors. The proposed approach was successfully implemented on a high fidelity commercial aircraft benchmark, and the simulation results confirm efficiency of the combined FDI method versus the conventional scheme.

6. Acknowledgement

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