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Air Data Sensor Fault Detection using Kinematic Relations

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Abstract This paper presents a Fault Detection and Isolation (FDI) method for Air Data Sensors (ADS) of aircraft. In the most general case, fault detection of these sensors on modern aircraft is performed by a logic that selects one of, or combines three redundant measurements. Such a method is compliant with current airworthiness regulations. However, in the framework of the global aircraft optimization for future and upcoming aircraft, it could be required, e.g. to extend the availability of sensor measurements. So, an improvement of the state of practice could be useful. Introducing a form of analytical redundancy of these measurements can increase the fault detection performance and result in a weight saving of the aircraft because there is no necessity anymore to increase the number of sensors. Furthermore, the analytical redundancy can contribute to the structural design optimization. The analytical redundancy in this method is introduced using an adaptive form of the Extended Kalman Filter (EKF). This EKF uses the kinematic relations of the aircraft and makes a state reconstruction from the available measurements possible. From this estimated state, an estimated output is calculated and compared to the measurements. Through observing a metric derived from the innovation of the Extended Kalman Filter (EKF), the performance of each of the redundant sensors is monitored. This metric is then used to automatically isolate the failing sensors.

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1 Introduction

In this paper a newly developed architecture for Air Data Sensors (ADS) monitoring is proposed. The method deals with the Fault Detection and Isolation (FDI) of measurements required for the Electronic Flight Control System (EFCS) of aircraft and is part of the work performed for the Advanced Fault Diagnosis for Sustainable Flight Guidance and Control (ADDSAFE) project. The goal of the ADDSAFE project is to research and develop model-based Fault Detection and Diagnosis (FDD) methods for aircraft flight control systems, mainly sensor and actuator malfunctions [12]. Furthermore, the ADDSAFE project aims at closing the gap between the academic field of research of FDD and the practical application of these methods in industry.

1.1 Motivation

In Fig. 1 an overview is given of the typical architecture of EFCS of an aircraft. As can be noticed, one way of how faults can be introduced in the control loop is by sensor faults, indicated as Air Data and Inertial Reference System (ADIRS) faults in the figure. Faulty measurements which are fed back to the flight control

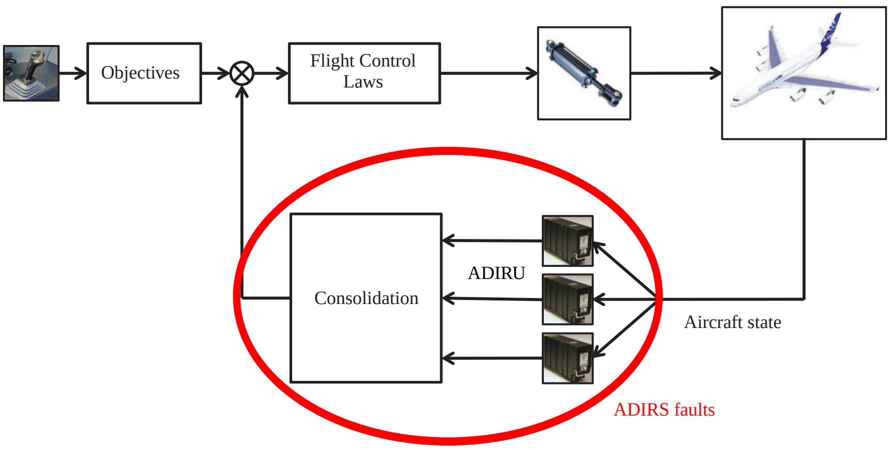

Fig. 1 Flight control architecture of an aircraft

laws can create unwanted control signals, leading e.g. to higher loads on the aircraft structure. For that reason, the aircraft structures are designed to withstand these unwanted loads up to a level at which it is guaranteed that the faults can be detected and appropriate actions can be taken.

However, for upcoming and future aircraft one important aspect is the structural design optimization. This can lead to a substantial decrease in the weight of the aircraft, which again leads to an increase in the aircraft's performance, including a decrease in fuel consumption, a decrease of produced noise and an increased range. Furthermore, these advantages also satisfy the newer societal imperatives toward an environmentally friendlier aircraft.

Sensor fault detection for flight parameter measurements, like e.g. air data and inertial measurements in modern aircraft is generally achieved through the use of typically three redundant measurement units (e.g. Air Data and Inertial Reference Units (ADIRUs) [22]). Through a decision logic, also called consolidation process, the correct measurement is selected and used by the EFCS [10],[22].

Improving the FDD performance of the aircraft's EFCS allows to optimize the aircraft structural design and performance, resulting in a lower operating cost and decreased environmental impact [13], as explained above.

Another motivation for the development of analytical redundancy for aircraft parameter measurements is to extend the availability of the sensor measurements. Instead of adding one or several new sensors, the option of adding a "virtual" sensor, i.e. analytical redundancy, gives the advantage no additional weight is required. This results again in the same advantages as described in the previous paragraph.

These two main reasons indicate the need to create new advanced FDD methods and to close the gap between academic research and industrial application.

1.2 Antecedents and main contribution

In this work a model-based FDD approach is presented for the fault detection of Air Data Sensors (ADS), in particular applied to the angle-of-attack measurements. Different methods have been investigated for mitigating the effects of failing ADS, such as: signal based diagnosis [16],[9], alternative sensing methods which are fault tolerant [4], robust fault detection approaches [11], finding ways to operate without traditional ADS[6]. Other solutions for the problem of ADIRS monitoring dealing with oscillatory faults are presented in [3],[2].

In this paper a method is introduced based on the general kinematic relations of aircraft. By relating different available measurements in the ADIRU, it becomes possible to perform FDD of the ADS. For this purpose, an adaptive modification of the EKF is applied to the kinematic equations. The Kalman Filter (KF) and its numerous modifications have been used in the field of aerospace engineering since it was developed in the 1960s [14]. In this way, the EKF has also been used for sensor fault detection [7].

The EKF was originally formulated for state estimation of dynamic systems when the dynamics and measurement equations are nonlinear, but linearizable [17] and has been widely used for sensor monitoring and fusion techniques [1]. The method that will be proposed here directly builds on this principle, i.e., using the redundant measurements available form the multiple ADIRUs the state of the aircraft is reconstructed by means of a adaptive version of an EKF which was first introduced by [19]. [15] proposes sensor fault detection by evaluating the innovation sequence of the filter. This information can furthermore be used to fuse the measurements in such a way that failing sensors are detected and isolated.

1.3 Structure of the paper

In the next section the FDD problem to solve is introduced, giving the system description and the fault scenarios. In Section 3 the proposed FDD method is described and in Section 4 the simulation results are presented. The paper ends with a conclusion in Section 5.

2 Problem Definition

2.1 System Definition

One of the key elements of this method is the use of the kinematic equations that describe the aircraft's behavior, i.e., the state reconstruction is achieved using the measurements of the Inertial Reference Unit (IRU). When the load factors and the rotational rates are used as inputs to the EKF, the state of the aircraft can be reconstructed ([5]). The big advantage of this approach lies in the following three points:

1. The method developed is valid over the whole flight envelope of the aircraft. This means that no special measures need to be taken such as gain scheduling, etc.
2. Secondly, the method can be applied to any aircraft, without large modifications (except for the location of the sensors). So the developed method is general for aircraft.
3. The method is insensitive to other types of faults, e.g. actuator faults, control surface jamming, etc.

The aircraft kinematics can be represented by the following nonlinear system:

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{f}(\mathbf{x}(t)) + \mathbf{G}(\mathbf{x}(t))\left(\mathbf{u}(t) + \mathbf{w}(t)\right) \\ \mathbf{z}(t) &= \mathbf{C}\mathbf{x}(t) \\ \mathbf{z}_m(t) &= \mathbf{C}\mathbf{x}(t) + \mathbf{v}(t) \end{aligned} \tag{1}$$

Where $\mathbf{x}$ represents the state of the system, $\mathbf{u}$ the input and $\mathbf{z}$ the measurable output of the system. $\mathbf{w}(t)$ and $\mathbf{v}(t)$ represent Gaussian white noise sequences and are the measurement noise of respectively the measured input and output. In this particular case, the state description can be reduced to a five state system, and these states are measurable:

$$\mathbf{x} = \left[V_{TAS}\ \alpha\ \beta\ \phi\ \theta\right]^{\top} \tag{2}$$

$$\mathbf{u} = \left[A_x\ A_y\ A_z\ p\ q\ r\right]^{\top} \tag{3}$$

$$\mathbf{z} = \left[V_{TAS}\ \alpha\ \beta\ \phi\ \theta\right]^{\top} \tag{4}$$

Where V_{TAS} is the true airspeed, α the angle-of-attack, β the side-slip angle, ϕ the roll angle and θ the pitch angle. A_x, A_y, and A_z are the accelerations at the center of gravity, p, q, and r the rotational rates. Note that a transformation is necessary to convert the measured load factors at the IRU to accelerations at the center of gravity. Furthermore, note that $\mathbf{C} = \mathbf{I}$. In fact, both the inputs to this system and the outputs are measured from the aircraft and can be assumed available in the EFCS for each modern aircraft. Although the position of an aircraft can be considered a part of the state, it is not required for the purpose of fault detection of the ADS. Having only these five states, will decreases the computational load of the proposed method. Furthermore, no wind influences are accounted for in this work. However, according to [20] it is possible to estimate the wind, giving a more precise estimate of the state of the aircraft if necessary, at the cost of a larger state vector and so increased computational load.

According to [8], the kinematic state update equations can be described by:

$$\begin{aligned} \dot{V} &= g\left(-\sin\theta\cos\alpha\cos\beta + \sin\phi\cos\theta\sin\beta + \cos\phi\cos\theta\sin\alpha\cos\beta\right) \\ &\quad + A_x\cos\alpha\cos\beta + A_y\sin\beta + A_z\sin\alpha\cos\beta \end{aligned} \tag{5}$$

$$\begin{aligned} \dot{\alpha} &= \frac{g}{V\cos\beta}\left(\cos\phi\cos\theta\cos\alpha + \sin\theta\sin\alpha\right) \\ &\quad + \frac{1}{V\cos\beta}\left(A_z\cos\alpha - A_x\sin\alpha\right) + q - \tan\beta\left(p\cos\alpha + r\sin\alpha\right) \end{aligned} \tag{6}$$

$$\begin{aligned} \dot{\beta} &= \frac{g}{V}\left(\sin\theta\cos\alpha\sin\beta + \sin\phi\cos\theta\cos\beta - \cos\phi\cos\theta\sin\alpha\sin\beta\right) \\ &\quad + \frac{1}{V}\left(-A_x\cos\alpha\sin\beta + A_y\cos\beta - A_z\sin\alpha\sin\beta\right) + p\sin\alpha - r\cos\alpha \end{aligned} \tag{7}$$

$$\dot{\phi} = p + q\sin\phi\tan\theta + r\cos\phi\tan\theta \tag{8}$$

$$\dot{\theta} = q\cos\phi - r\sin\phi \tag{9}$$

which defines $\mathbf{f}(\mathbf{x})$ and $\mathbf{G}(\mathbf{x})$ in Eq. (1).

2.2 Fault Scenario

The definition for the fault scenario follows from the ADDSAFE project [12]. All faults investigated in this paper are related to the measurement of the angle-of-attack α, however the method developed can be extended to the monitoring of the measurements of the true airspeed V_{TAS} and the side-slip angle β, without losing generality. Different types of faults are considered, such as oscillating faults, runaway faults and increased noise faults, of which examples are shown in Fig. 2. Note that in this graph, and all other graphs in this paper, all values are normalized to the operational range of the measurements. Furthermore, also the time axis will be normalized for each simulation.

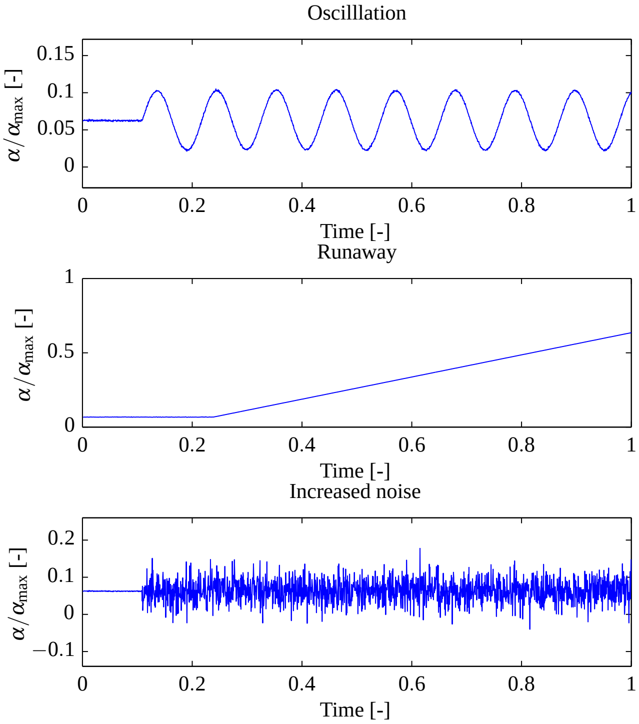

Fig. 2 Different types of faults

Each of the different type of faults can occur on one or simultaneously on two sensors. Whereas the fault detection of the case of only one failing sensor is a trivial task, the fault detection when two sensors fail at the same time is less obvious without incorporating any kind of analytical redundancy. An overview of the different faults investigated and there amplitudes is shown in Table 1.

Table 1 Fault Amplitudes (for the runaway, the rate is expressed as a percentage of $\alpha_{\max}$, for the extra noise the standard deviation of the noise as a percentage of $\alpha_{\max}$)

Scenario	Fault type	Amplitude (% of $\alpha_{\max}$)
1	Oscillation 1 sensor	4
2	Oscillation 2 sensors	11
3	Runaway slow 2 sensors	9
4	Runaway fast 2 sensors	33
5	Extra noise 1 sensor	2
6	Extra noise 2 sensors	14

3 FDD Approach

The general idea of the approach taken here is to fuse the redundant measurements based on the quality of the measurement. This is achieved by filtering the available measurements using an EKF and comparing the state estimates with the redundant measurements based on a so-called "*R*-adaptation" [21], which will be explained in Section 3.2.

For this purpose, first the basic principles of the EKF are briefly explained, which is essential in understanding the method. Then the sensor monitoring algorithm is addressed, which is used to perform the FDD.

3.1 Extended Kalman Filter

The standard EKF exists of two main steps. The first step can be called the prediction of the estimated mean of the state of the system, and uses the system dynamic equations. Also the covariance of the estimate is predicted. This step can be represented by:

$$\hat{\mathbf{x}}_{k|k-1} = \hat{\mathbf{x}}_{k-1|k-1} + \int_{t_{k-1}}^{t_k} \left[\mathbf{f}(\hat{\mathbf{x}}(\tau)) + \mathbf{G}(\hat{\mathbf{x}}(\tau))\mathbf{u}_m(\tau)\right] \mathrm{d}\tau \tag{10}$$

$$\mathbf{P}_{k|k-1} = \Phi_k \mathbf{P}_{k-1|k-1} \Phi_k^\top + \mathbf{Q}_d \tag{11}$$

Where $\hat{\mathbf{x}}_{k|k-1}$ is the estimated state at time $t = t_k$, knowing the measurement at time $t = t_{k-1}$. $\mathbf{u}_m(t)$ represents the measured input to the system. The matrix $\mathbf{P}_{k-1|k-1}$ represents the covariance matrix of the estimated state at time $t = t_{k-1}$. The matrix Φ_k is the discretized version of the Jacobian matrix $\mathbf{F}_k$, both defined as follows:

$$\Phi_k = e^{\mathbf{F}_k \Delta t} = \sum_{n}^{\infty} \frac{\mathbf{F}_k^n (\Delta t)^n}{n!} \tag{12}$$

$$\text{with: } \mathbf{F}_k = \left. \frac{\partial \left(\mathbf{f}(\mathbf{x}) + \mathbf{G}(\mathbf{x})\mathbf{u}\right)}{\partial \mathbf{x}} \right|_{\mathbf{x}=\hat{\mathbf{x}}_{k|k}} \tag{13}$$

and from [18] we can approximate $\mathbf{Q}_d$ as:

$$\mathbf{Q}_d(k) = \Gamma_k \mathbf{Q} \Gamma_k^\top \tag{14}$$

$$\text{with: } \Gamma_k = \left(\int_{k-1}^{k} \Phi_k \Delta t \right) \mathbf{G}(\hat{\mathbf{x}}_{k|k}) \tag{15}$$

where $\mathbf{Q} = E\left[\mathbf{w}(t)\mathbf{w}^\top(t)\right]$ represents the input noise covariance matrix.

The second step is the measurement update. It is represented by:

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}^\top \left(\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top + \mathbf{R} \right)^{-1} \tag{16}$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \left(\mathbf{z}_m - \mathbf{h}(\hat{\mathbf{x}}_{k|k-1}) \right) \tag{17}$$

$$\mathbf{P}_{k|k} = \left[\mathbf{I} - \mathbf{K}_k\mathbf{H}\right] \mathbf{P}_{k|k-1} \left[\mathbf{I} - \mathbf{K}_k\mathbf{H}\right]^\top + \mathbf{K}_k\mathbf{R}\mathbf{K}_k^\top \tag{18}$$

Where $\mathbf{K}$ is the Kalman gain, $\mathbf{H} = \frac{\partial \mathbf{h}}{\partial \mathbf{x}} = \mathbf{I}$, and $\mathbf{R} = E\left[\mathbf{v}(t)\mathbf{v}^\top(t)\right]$ the measurement noise covariance matrix. Furthermore, from these equations we can define the innovation as $\mathbf{z}_{m_k} - \hat{\mathbf{z}}_k$ and the innovation covariance matrix as:

$$\mathbf{V}_{e_k} = \mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top + \mathbf{R} \tag{19}$$

This standard EKF can be applied to the system described in Section 2.1 with the triple measurement of the angle-of-attack α augmented in the measurement vector. Note that is was chosen for this approach in favor of a dedicated filter for each ADIRU, as to reduce the computational load. In this case, a simulation was chosen with a double runaway fault, i.e., sensor 1 and 2 experienced the same runaway fault at $t = 0.03$. In Fig. 3 the result of the estimated angle-of-attack ($\hat{\alpha}$) can be seen compared to the three different measurements. As can be noticed, the estimated value of the angle-of-attack is in between the measured values. This is logical, as the assigned variances to the different sensors, through the matrix $\mathbf{R}$, are equal. Therefore, each measurement of the same variable is equally weighted by the filter. From the figure it is clear that it cannot be decided on this information which sensor is failing, and which sensor is providing a correct value. In this we find a motivation to modify the algorithm such that FDI becomes possible by monitoring the performance of the sensors.

3.2 Adaptive Fusion

Instead of using all redundant measurements as separate observations in an adaptive EKF [23], here is chosen to fuse the redundant measurements based on their performance. For this, a certain metric is introduced which represents the performance (fault-free/fault) of the sensor.

The theoretical innovation covariance of the EKF is represented by (19). This value can also be estimated online:

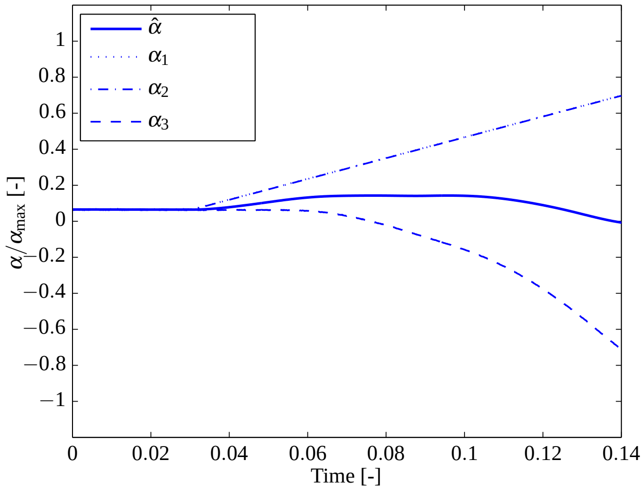

Fig. 3 $\hat{\alpha}$ compared with measurements for runaway fault of sensor 1 and 2 (equal fault value), regular EKF

$$\hat{\mathbf{V}}_{e_k} = \frac{1}{N} \sum_{i=k-N+1}^{k} (\mathbf{z}_{m_i} - \hat{\mathbf{z}}_i)(\mathbf{z}_{m_i} - \hat{\mathbf{z}}_i)^\top \tag{20}$$

where N represents the moving window width. In the case a sensor fails, for each diagonal value, the estimated value will exceed the theoretical value, i.e.:

$$\hat{V}_{e_{k_{(i,i)}}} \geq \left[\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top\right]_{(i,i)} + R_{(i,i)} \tag{21}$$

where the subscript $\ldots_{(i,i)}$ means the value on the ith diagonal. Now one can introduce the diagonal scale factor matrix $\mathbf{S}(k)$ ([21]) such that:

$$\hat{V}_{e_{k_{(i,i)}}} = \left[\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top\right]_{(i,i)} + S_{k_{(i,i)}} R_{(i,i)} \tag{22}$$

And therefore the values of $\mathbf{S}(k)$ can be calculated as:

$$S_{k_{(i,i)}} = \left(\hat{V}_{e_{k_{(i,i)}}} - \left[\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top\right]_{(i,i)}\right) R^{-1}_{(i,i)} \tag{23}$$

In the fault free case, the matrix $\mathbf{S}(k)$ will approximate the unity matrix $\mathbf{I}$, in a faulty case, the diagonal value related to the failing sensor will increase and become bigger than 1. To perform the fusion of the redundant measurements, the scale factors are calculated for the different sensors. Then a weighted average of the three measurements is taken using the reciprocals of $S(k)$ as weights:

$$\alpha_c = \frac{1}{\sum_{i=1}^{3} \frac{1}{S^*_{\alpha_i}}} \sum_{i=1}^{3} \frac{1}{S^*_{\alpha_i}} \alpha_i \tag{24}$$

As can be noticed, in the case one or two sensors give a bad measurement, the related value of $S(k)$ will increase and the faulty measurement will be given a lower weight. As will be shown in the results, the scale factor of the faulty measurement is much larger than 1, so $S(k) \gg 1$, and as such the faulty measurements will have almost no influence on α_c. The detection and isolation signal will then be based on whether the value of $S(k)$ will exceed a preset threshold. Another approach would be to set a threshold, and disregard any measurement with a scale factor above this threshold.

Note that the method as presented here is limited to the detection of measurement faults related to the signals in $\mathbf{z}$, as defined in Eq. (4). It is assumed that the input measurements $\mathbf{u}$ are fault-free.

4 Simulation Results

The method described above is applied to the system described in Section 2.1. Simulations were run on the ADDSAFE benchmark. Two main tuning parameters are required to be determined for the application of the filter. First of all, there is the time window N, over which the estimate of the innovation covariance is calculated. This parameter depends on the system dynamics and the required detection performance. However, setting this parameter is trivial, and is done by trial and error. The second tuning parameter is the threshold T introduced in the previous paragraph. This parameter can be set based on the amplitude of the residuals in fault-free cases. Although the matrices $\mathbf{Q}$ and $\mathbf{R}$ can be considered as tuning variables, they are related to the performance of the sensors measuring the input and output vectors $\mathbf{u}$ and $\mathbf{z}$. Therefore, both matrices should be based on the real sensor performances which are considered to be known.

First, the method was applied to the same simulation as shown in Fig. 3. The result is shown in Fig. 4. As can be noticed, the estimated $\hat{\alpha}$ now follows the correct measurement α_3 and α_1 and α_2 are discarded. Fig. 5 shows the values of S_{α_i}, $i = 1,2,3$. The scale factors related to sensor 1 and 2 clearly show an increase in value after the fault occurred. Other typical results for the different scenarios described in Table 1 are shown in Figs. 6, 7, 8 and 9.

A simulation campaign was set-up to test the proposed FDI method. This campaign existed of fault-free simulations in which different maneuvers were performed to test the false alarm rate. These simulations included sudden pitch up maneuvers with high angle-of-attack attitudes and lateral maneuvers including substantial side slipping of the aircraft. The introduction of faults occurred during simulations of the cruise condition of the aircraft, for the faults presented in Table 1.

The simulation campaign involved changing the following parameters of the simulations: the flight parameters (altitude, velocity), geometric parameters (mass, position of center of gravity), uncertainties in the measurements (mass, velocity, center

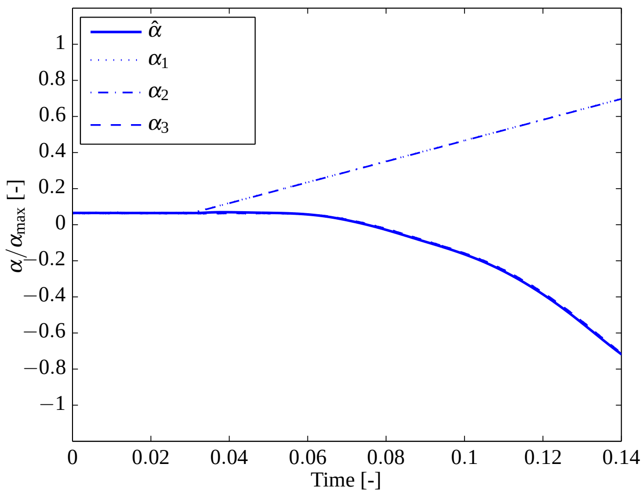

Fig. 4 $\hat{\alpha}$ compared with measurements for runaway fault of sensor 1 and 2 (equal fault value), EKF with adaptive fusion

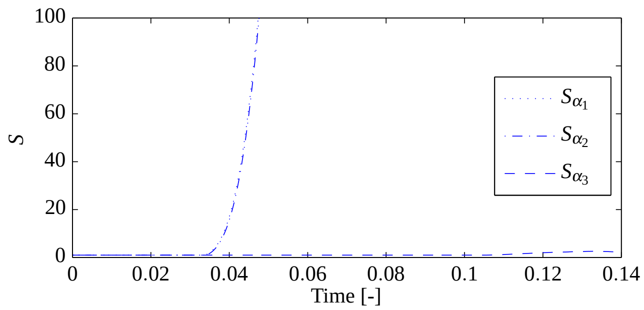

Fig. 5 S_α for the different sensors for runaway fault of sensor 1 and 2 (equal fault value), EKF with adaptive fusion

of gravity, altitude) and the aerodynamic coefficients. All these parameters were adjusted in two different ways: using the extreme values (all uncertainties on the minimum or maximum value at the same time) and using Monte Carlo simulations. In this way, a large part of the flight envelope of the aircraft was covered.

In Table 2 an overview is given of the detection performance of these simulations, consisting of 252 simulations (152 parametric variations and 100 Monte Carlo variations) for each scenario. In this table, "DTP" stands for "Detection Time Performance" and is expressed in function of the maximal allowed detection time for that type of fault. As can be noticed, for the different fault scenarios considered, a 100% fault detection performance was achieved, i.e., no missed detections and

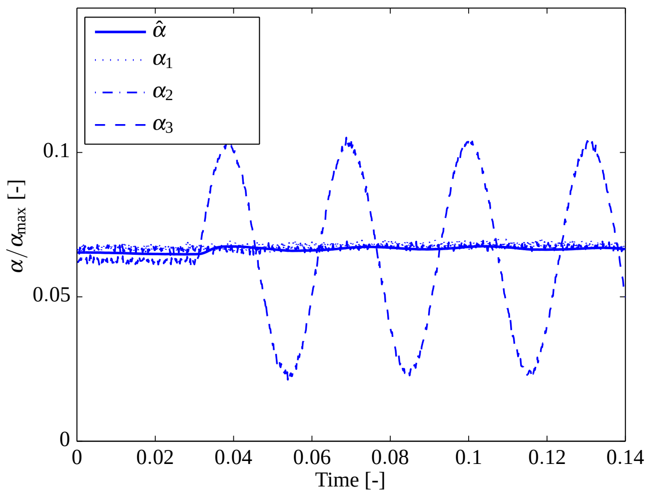

Fig. 6 $\hat{\alpha}$ compared with measurements for oscillatory fault of sensor 3, EKF with adaptive fusion

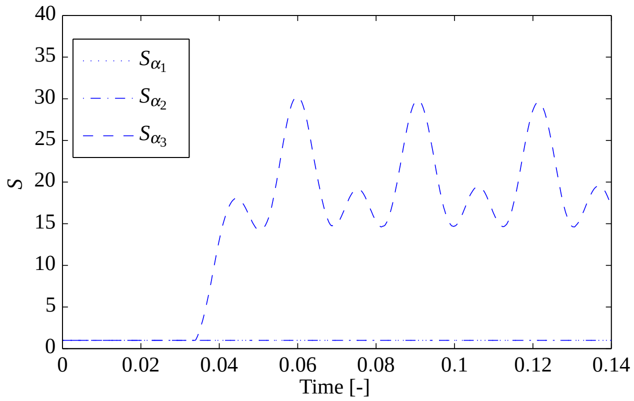

Fig. 7 S_α for the different sensors for oscillatory fault of sensor 3, EKF with adaptive fusion

no late detections. The low values for scenario 1 and 5 are due to different maximum allowed detection times. It can be noted that the absolute detection times for both one or two sensors failing were in the same magnitude order, i.e., the absolute detection time is not influenced by the amount of sensors (one or two) that are failing. Furthermore, no false alarms were obtained during the simulation of fault-free maneuvers. Here only results are presented for the detection of faults in the angle-of-attack sensors. However, it should be noted that this FDI method can be extended to the other variables in the measurement vector $\mathbf{z}$ without losing any functionality.

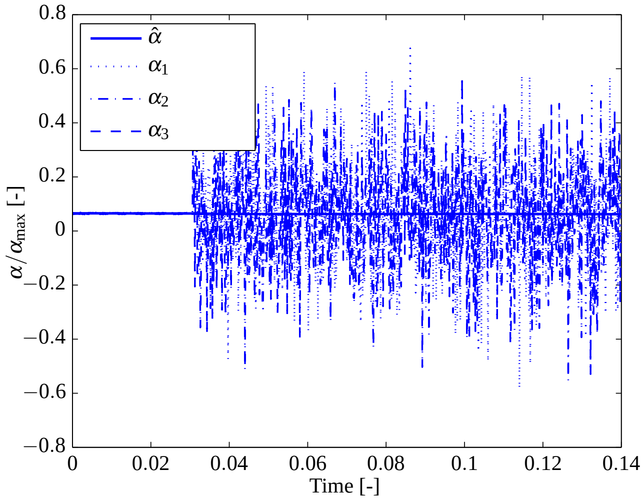

Fig. 8 $\hat{\alpha}$ compared with measurements for “noise” fault of sensor 1 and 2, EKF with adaptive fusion

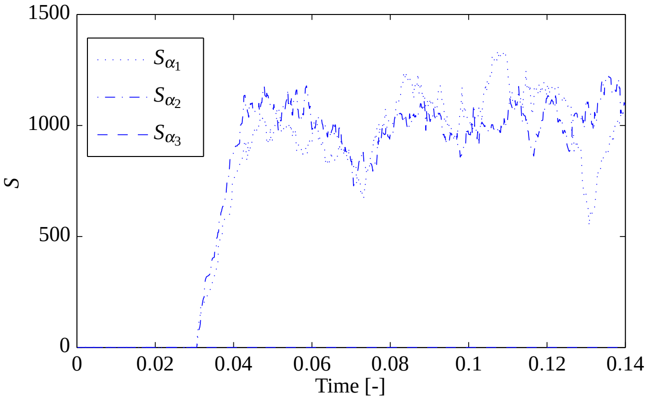

Fig. 9 S_α for the different sensors for “noise” fault of sensor 1 and 2, EKF with adaptive fusion

As these types of faults can be detected and accounted for by the same methodology, it can be stated that the fault detection of one specific variable is insensitive to other faults. The detection of measurement faults of the variables in the input vector **u**, being the accelerations and rotational rates, is not considered in this work, and so these measurements are assumed to be fault-free, i.e., FDI for these measurements is covered by a different methodology.

Table 2 Summary of obtained simulation results

#	Detection (%)	DTP mean	DTP max	DTP min
1	100	0.0063	0.0068	0.0062
2	100	0.16	0.18	0.14
3	100	0.41	0.95	0.32
4	100	0.16	0.20	0.13
5	100	0.0035	0.0042	0.0030
8	100	0.06	0.06	0.06

5 Conclusion

This paper presented an algorithm based on an adaptive modification to the EKF that is capable of providing mathematical redundancy for the purpose of sensor fault detection. The main advantages of this method are the independence from the dynamics of the aircraft and it's low tuning complexity. In fact, the only aircraft specific knowledge required is the exact location of the IRU and the sensor performance characteristics. Because only kinematic and no dynamic (forces and moments) relations are used, no special measures need to be taken to make to method valid over the whole flight envelope of the aircraft. This results in a very low tuning complexity, limited to setting a time window and one threshold. Furthermore, it should be noted that this method can be extended to other air data measurements, which will be investigated in future work.

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