SENSOR FAULT DETECTION, DIAGNOSIS AND ACCOMMODATION FOR UNMANNED AERIAL VEHICLE (UAV)

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Abstract. *The paper presents a Sensor Fault Detection, Diagnosis and Accommodation Scheme for Unmanned Aerial Vehicle (UAV). This scheme involves the monitoring of Kalman Filter innovation process based on the hypothesis of normal system operation, i.e. under normal conditions, the innovation process is a Gaussian white noise with a zero mean and with a unit covariance matrix. Fault Detection and Diagnosis is accomplished by evaluating any change in the mean of the innovation process with respect to the normal operation. Thus, the faulty sensor is detected and diagnosed, and a new Kalman Filter is designed in order to allow the UAV continues its mission. In the simulation, the longitudinal model of an Aerosonde UAV is considered, and pitch rate gyro faults affecting the mean of the innovation process are considered.*
Keywords*: UAV, fault detection, fault diagnosis, sensor fault accommodation, Kalman Filter*

1. INTRODUCTION

An unmanned aerial vehicle (UAV) is an aircraft with no onboard pilot. UAVs can be classified according to different criteria such as mission types, mission sensors (type sensor), performance, endurance, and flight control system. UAVs can be remote controlled or fly autonomously based on pre-programmed flight plans. Also, UAVs may be used in many application in which involve high risk such as hazard environment (nuclear, chemical, or biological warfare), and location of difficult access due to the characteristic of the terrain and the presence of obstacle (Clade, 2000); (Pick, 2004); (Robison, 2004); (Heredia *et al.*, 2004); (Heredia *et al.*, 2005).

Inside this context, reliability plays an important role once the use of the same requires the improvement of safety condition in order to allow its routine airspace access. Also, UAV reliability study allow to identify potential means for improvement its mission availability and effectiveness as well as reduces acquisition cost (DoD, 2003). Besides, reliability evaluation can be used to how a system may fail, the consequences of failures and also to provide information to enable engineers, scientists, researches, managers, and project teams to relate the quality of their systems to economics and capital investment. In so doing it can lead to better and more economic design, and a much improved knowledge of the operation and behavior of a system (Billinton and Allan, 1983).

In this paper, we define UAV reliability as the probability that a UAV will operate without failure for the duration (t) of a specified mission profile, given that it was fully operation at time (t=0), as well as during in preflight tests.

Associated to reliability, are the concepts of Fault Detection and Diagnosis (FDD) in dynamic systems. FDD systems consist in to discover the existence of a failure and isolate the failed element responsible for the particular failure mode detected and consequently, operation's errors that could be remain unknown, thus creating, conditions necessary and enough to mitigate on problems related to eventual consequences which an unreliable behavior can cause in performance, stability, control, and integrity of this vehicles. Thus, a failure in any part of UAV can be catastrophic. If the failure is not detected and accounted for, the UAV may crash.

The most of the works reported in the last years about FDD methods for UAVs use observer-based FDD approach. The basic idea behind the observer or filter is to estimate the outputs of the system from the measurements by using either Luenberger Observer(s) in a deterministic setting or Kalman Filter(s) in a stochastic setting. FDD methods have been applied to autonomous vehicle as fixed-wing UAVs (Napolitano, 1998), tilt-rotor UAVs (Rago, 1999), autonomous Helicopters (Heredia *et al.*, 2004) and (Heredia *et al.*, 2005), small UAVs (Rupp, 2004) and (Drozeski, 2005), and others.

In this work, the detection, diagnosis, and accommodation procedure based on innovation process of Kalman Filter is presented, and applied to Aerosonde UAV model. The faults are assumed as change in the mean value of the sensor measurements of the UAVs. In Section 2, the main concepts of FDD are briefly presented. Section 3, the innovation approach to monitoring, detection, diagnosis, and accommodation of sensor fault are considered. The simulation results carried out of the Aerosonde UAV longitudinal model are presented. Section 4 and 5 are devoted to the conclusion and references.

2. FAULT DETECTION AND DIAGNOSIS

In literature on Fault Detection, Diagnosis and Accommodation System is not very old when compared to other areas of control engineering. The major studies and surveys have been written by Mehra and Peschon (1971), Beard (1971), Jones (1973) and Willsky (1976), followed by Anderson and Lee (1981), Isermann (1984), Gertler (1988), and, more recently by Patton *et al.* (2000) and, Hajiyev and Caliskan (2003). In general, main stages of FDD system which is widely accepted by the fault diagnosis community consist of the following tasks:

- Residual Generation: is a procedure for extracting fault symptoms from the system. Fault symptom is represented by the residual signal;
- Fault Detection: to make a binary decision (either that something has gone wrong or that everything is fine);
- Fault Isolation: to determine the exact location of the fault;
- Fault Identification: to estimate the size, type, or nature of the fault.
- Sensor Fault Accommodation: is system reconfiguration, where the estimative of the system state is corrected to minimize the effect of a fault.

In this paper, we will use the words failure and fault as synonyms although, the term failure suggests complete breakdown, while the term fault is to be understood as an unexpected change of system functions and is used to indicate that a malfunction may be tolerable at its present stage. A UAV failure may be occur in actuators, sensors, control system, software, structural, etc. Regarding to temporal evolution, failures can be classified in permanent faults, transient faults, and intermittent faults. Relatively to the type of failure signals, we can classify them in additive faults (measurement or process), or multiplicative faults.

Almost any classification of faults reflects, explicitly or implicitly, the framework in which the detection and diagnosis problem is posed. In this paper, the framework will be devoted to Analytical Redundancy (AR), which makes use of a mathematical model of the monitored plant and is often referred to as the “model-based approach” to FDD system. The AR is normally achieved through a comparison between a measured signal and its estimation, generated by the mathematical model of the system considered. The presence of faults is detected by means of the so-called residuals, i.e. quantities that are over-sensitive to the malfunctions.

Some of the criteria for assessing the performance of a detection and diagnosis scheme are promptness of detection, sensitivity to small faults, false alarm rate, and missed fault detection. The performance of a fault detection procedure is measured by its percentages of successful detections as well as its percentage of false alarms. A successful outcome is one which determines the correct health status. A false alarm is where a fault is declared when no fault exists whereas a missed alarm is where a fault is not detected when a failure occurs. Other terms that are often used to indicate FDD performance are detection delay, isolability, and robustness. In UAV application, the fault must be detected very quite otherwise it can destroy the UAV platform. Also, the compromises in detection system design among false alarm, sensitivity to incipient faults and promptness of detection depend on the understanding of the most important performance criteria of the monitored system.

3. INNOVATION-BASED FAULT DETECTION AND DIAGNOSIS SYTEM

FDD is the process of monitoring and detecting abnormal or out-of-tolerance behavior in a UAV, and isolating the source of the abnormality to subsystem or component. Once they are detected and diagnosed, corrective action could be taken in order to maintain the flight despite failure and its mission in an uninterruption operation. This is the purpose of the accommodation or reconfiguration task, which consist in increase to UAVs survavibility and safety.

Faults in UAVs can be detected and isolated with the aid of an innovation process of the Kalman Filter (Mehra and Peschon, 1971); (Willshy, 1976); (Basseville and Nikiforov, 1993); (Li and Goodall, 2003); (Hajiyev and Caliskan, 2003). The innovation process is defined as the different between the actual system output and the predicted output based on the predicted state. It is called as of innovation because it represents the new information brought in by the latest observation vector. It is well-known that, a system under normal conditions of operation, the innovation process is zero mean Gaussian with known covariance. However, under faulty conditions, this fault affects the mean of the innovation process and consequently, the error signal is large and contains systematic trends because the model no longer represents the physical system adequately.

Let the discussed linear dynamic system be specified by the system dynamics equation:

$$x(k+1) = \Phi x(k) + Bu(k) + Gw(k) \tag{1}$$

where $\Phi \ \varepsilon \ \Re^{nxn}$ is a system matrix; $x \ \varepsilon \ \Re^{nx1}$ is a system state vector; B $\varepsilon \ \Re^{nx1}$ is a control distribution matrix; u $\varepsilon \ \Re^{m}$ is control input vector; G $\varepsilon \ \Re^{nxn}$ represents the uncertain disturbance distribution matrix including unmodelled dynamics; and w is an n-dimensional system noise vector assumed to represent Gaussian white noise with w ~ N(0,Q).

Sensor equation:

$$z(k) = Hx(k) + v(k) \tag{2}$$

where z ε $\Re^{sx1}$ is a measurement vector; H ε $\Re^{sxn}$ is a system measurement; and v is an s-dimensional measurement noise vector assumed to represent Gaussian white noise with v ~ N(0,R) and independent from the system noise.

In this work, we use a single state estimation based on Kalman Filter, and for our interest only the output estimation is required. The use of a Kalman Filter driven by the full output vector can be found with the aid of the "Fig 1".

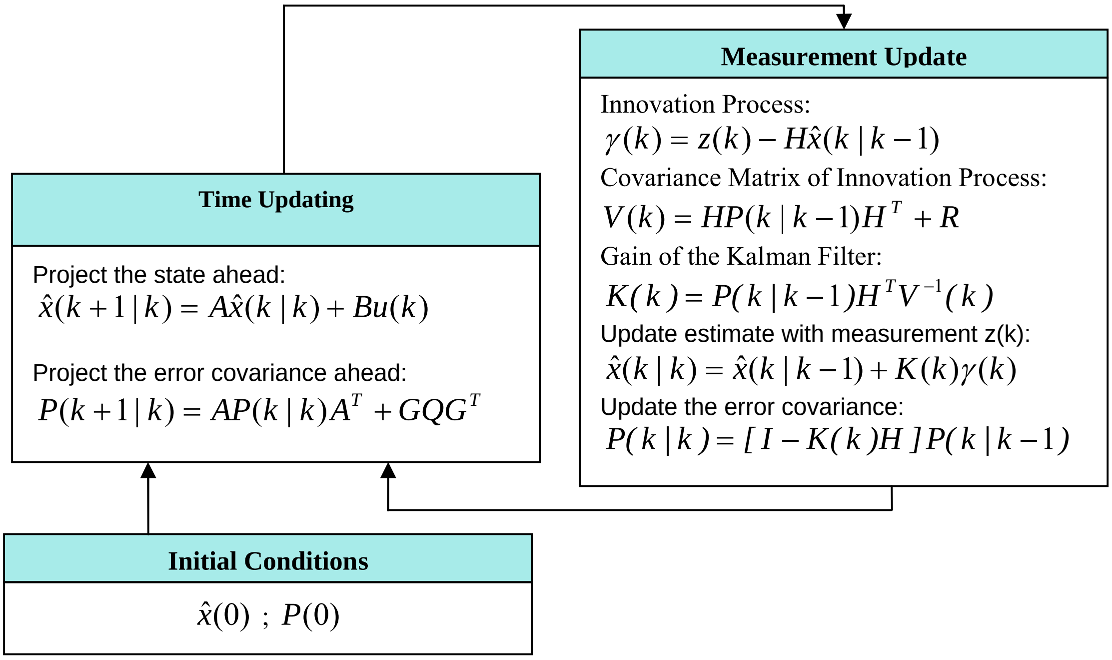

Figure 1. Kalman Filter Algorithm

3.1 Residual Generation

The innovation process of the Kalman Filter can be used to detect, diagnosis, and accommodation faults based on hypothesis of normal system operation, *i.e.* $\gamma(k) \sim N(0,V)$ when no fault occurs.

According to Himmelblau (1978), it is more appropriate to use the following normalized innovation process to detect and diagnosis the fault:

$$\tilde{\gamma}(k) = \frac{\gamma(k)}{\sqrt{V(k)}} \tag{3}$$

i.e. if the sensor is operating normally, the innovation process becomes a Gaussian white noise with zero-mean and unit covariance matrix.

Any faults in system dynamics can therefore be detected by a change in the weighted squared residual (WSR) measure

$$r(k) = \gamma^T(k).V^{-1}(k).\gamma(k) \tag{4}$$

Based on these properties, the following statistics can be used to test the mean value of normalized innovation process is equal to zero (Willsky, 1976); (Kadirkamanathan *et al.*, 2002); (Li and Goodall, 2003); (Hajiyev and Caliskan, 2003).

$$\rho(k) = \sum_{j=k-W+1}^{k} r(j) \tag{5}$$

where W is the length of the sliding window within which the residual measure is summed. The window length W should be chosen in accordance with the requirement for detection time and the fault alarm is set at time k when the condition. In the absence of a fault this quantity $\rho(k)$ is a chi-squared random variable χ^2 with Ws degrees of freedom and s is the dimension of measurement vector z.

3.2 Fault Detection

Based on the above, the following chi-squared hypothesis test can be achieved for Fault Detection:

$$\rho(k) \underset{H1}{\overset{H0}{\underset{>}{\overset{\leq}{\ }}}} \tau \tag{6}$$

where

- H0: free fault, *i.e.* $\tilde{\gamma}(k) \sim N(0,1)$
- H1: fault takes place in the sensors, *i.e.* $\tilde{\gamma}(k) \sim N(\mu(k-\theta),1)$

Here $\mu(k-\theta)$ represents an unknown bias that affects the mean of $\tilde{\gamma}(k)$ and may vary with respect to time. Threshold value τ that will be determined with the aid of χ^2 tables, depending on *Ws* and α - level of significance selected. τ is chosen according to the required false alarm probability, window length and χ^2 tables. For the given threshold, window length provides a trade-off between fast detection and false alarm rate.

Thus, the information for fault isolation can also be obtained by analyzing the components of the innovation vector $\tilde{\gamma}_i(k), i = 1,2,\ldots,s$ separately.

3.3 Fault Diagnosis

Once a fault to be detected, it is important to identify (locate) the faulty sensor responsible for the failure mode in order to isolate the same from the rest of the system. For this purpose, the innovation process is transformed into s one-dimensional sequences and, for each *k*, are calculated the mean and variance for each sensor up to the current state, as follows

$$\bar{\tilde{\gamma}}_i(k) = \frac{1}{M} \sum_{j=k-W+1}^{k} \tilde{\gamma}_i(j) \tag{7}$$

and

$$\hat{s}_i^2(k) = \frac{1}{M-1} \sum_{j=k-W+1}^{k} [\tilde{\gamma}_i(j) - \bar{\tilde{\gamma}}_i(k)]^2 \tag{8}$$

where $\bar{\tilde{\gamma}}_i(k)$ is sample mean and $\hat{s}_i^2(k)$ sample variance of the innovation process for each sensor, respectively. *W* is the amount of used realization.

The statistics of the faulty sensor is assumed to be affected much more than those of the other sensors. A possibility of checking the mean value of each innovation sequence (each one representing one sensor) in order to diagnose failed sensor, it is proposed to use the statistics below (Dodson, 2002); (Hajiyev and Caliskan, 2003).

$$\nu_i(k) = \frac{(W-1)\hat{s}_i^2(k)}{\sigma_i^2(k)}, \forall i,\ i = 1,2,\ldots,s \tag{9}$$

where $\nu_i(k)$ is subject to the χ^2 distribution with (W-1) degrees of freedom.

Taking into consideration that for each iteration *(k)* $\sigma_i^2 = 1$, we can write

$$\nu_i(k) = (W-1)\hat{s}_i^2 = \sum_{j=k-W+1}^{k} [\tilde{\gamma}_i(j) - \bar{\bar{\gamma}}_i(k)]^2, \quad \forall i, i = 1,2,\ldots,s \tag{10}$$

Considering two hypotheses presented previously, we can show that:

- In this case of the hypothesis H0 is true, the expected value $\nu_i(k)$ will be equal

$$\mathrm{E}[\nu_i(k)] = (W-1)\hat{s}_i^2 = W-1 \tag{11}$$

i.e. if the sensor is operating normally, $\nu_i(k)$ is a random variable with expected value *W-1* due to $\mathrm{E}[\hat{s}_i^2(k)] = \sigma_i^2 = 1$

- In this case of the hypothesis H1 is true, the expected value $\nu_i(k)$ behaviours

$$\mathrm{E}[\nu_i(k)] = \mathrm{E}\left\{ \sum_{j=k-W+1}^{k} [\tilde{\gamma}_i(j) - \bar{\bar{\gamma}}_i(k)]^2 \right\} + \mathrm{E}\left\{ \sum_{j=k-W+1}^{k} [\mu(k-\theta) - \frac{\sum_{j=k-W+1}^{k} \mu(k-\theta)}{W}]^2 \right\} \tag{12}$$

i.e. when a fault affects the mean value of the innovation process, the same will cause an asymptotic increase in the expected value of the $\nu_i(k)$ and $\nu_i(k)$ will exceed the threshold value $\chi^2_{\alpha,w-1}$ for fault diagnosis depending on confidence coefficient α , and *W-1* degrees of freedom.

Hereby, it may be proved that any chance in the mean of the innovation processes can be diagnosed. So, for the diagnosis of fault in instrument the next logic will be adopted:

If *H1 is true* ***AND*** *max* $\{\nu_i(k)\} > \chi^2_{\alpha,W-1}$

Then *Faulty Sensor is isolated.*

In this way, fault diagnosis can be carried out applying detection methods to each sensor of the system. Thus, the failed sensor is isolated, and a new Kalman Filter is designed in order to correct its estimate in order to minimize the effect of failure after the sensor fault occurred.

3.4 Fault Accommodation

To accommodate the fault in the system, the following adjustment or reconfiguration must be done (Hajiyev and Caliskan, 2003):

$$\hat{x}_{corr}(k \mid k) = \hat{x}(k \mid k-1) + K(k) IN_{corr}(k) \tag{13}$$

where

$$IN_{corr} = \left[z(k) - \bar{\nu}(k) - \hat{z}(k) \right] \tag{14}$$

and

$$\bar{\nu}(k) \approx \frac{1}{M} \sum_{j=k-W+1}^{k} \nu_i(j) \tag{15}$$

The purpose of the new Kalman Filter is provide to controller an accurate estimative of the system state so that the controller to achieve the new control signals, and consequently to accommodate the plant dynamics affected by the sensor fault.

4. SIMULATION

By the absence of a mathematical model of the real UAV dynamic, it used a linearised longitudinal dynamic of the Aerosonde UAV, obtained from simulation of the MATLAB/SIMULINK/AEROSIM BOCKSET (2005) through the aerosonde_trim.mdl file and trim_aerosonde.m file in following flight conditions V = 23 m/s, h = 1000 m, and mfuel = 3 kg.

States and sensors considered for this model are listed in "Tab.1",

Table 1. States and sensors used by the Aerosonde UAV.

State	Description	Sensor
u	Inertial velocity in x direction	GPS/INS
w	Inertial velocity in z direction	GPS/INS
q	Pitch rate	Rate Gyro
θ	Pitch angle	Attitute Gyro

and control input: $u(k) = \delta e$ (elevator deflection).

A UAV failure may be occur in actuators, sensors, control system, software, and structural. Here, it is assumed that the failure in actuators, structural, software, and control system or some combination of the four does not occur. In this paper dealt with the sensor fault detection, diagnosis, and accommodation. However, this scheme can be augmented for actuator and control surface faults.

Sensor faults dealt with here are so-called "soft failures". Soft failures are defined as inconsistencies between true and measured sensor values that are relatively small in magnitude and thus difficult to detect and diagnose by a simple range-checking approach. Soft faults can take different failure modes such as a fixed scalar, a fixed bias, a random bias, a drift, or intermittent spikes. For this purpose of checking in effectiveness of the algorithm, only fixed bias failure mode is considered and as example, this fault will be introduced in the pitch rate gyroscope.

In the simulation, *W=20, s=4,* and α *=0.95* are taken, and the thresholds of detection and diagnosis are found as *101.88* and *31.4* from the χ^2 table, respectively.

First, the behaviour of the system for the case free fault was considered in order to check effectiveness of the algorithms for detection, diagnosis, and accommodation via innovation process of Kalman Filter.

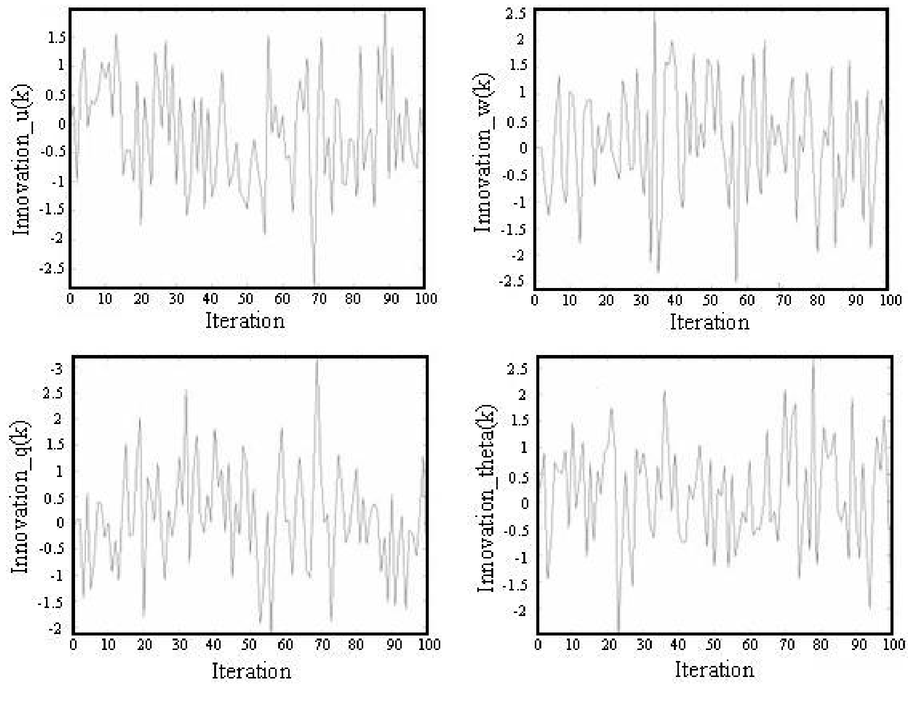

Figure 2. Kalman Filter innovation process in the case free fault

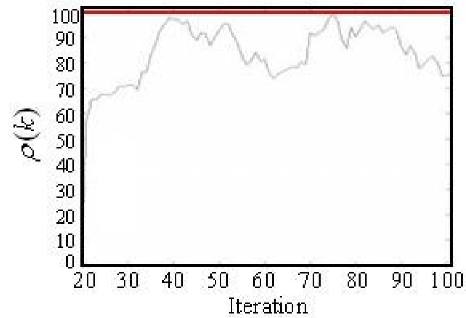

Figure 3. Fault Detection: behaviour of $\rho(k)$ when there is no sensor fault in the system.

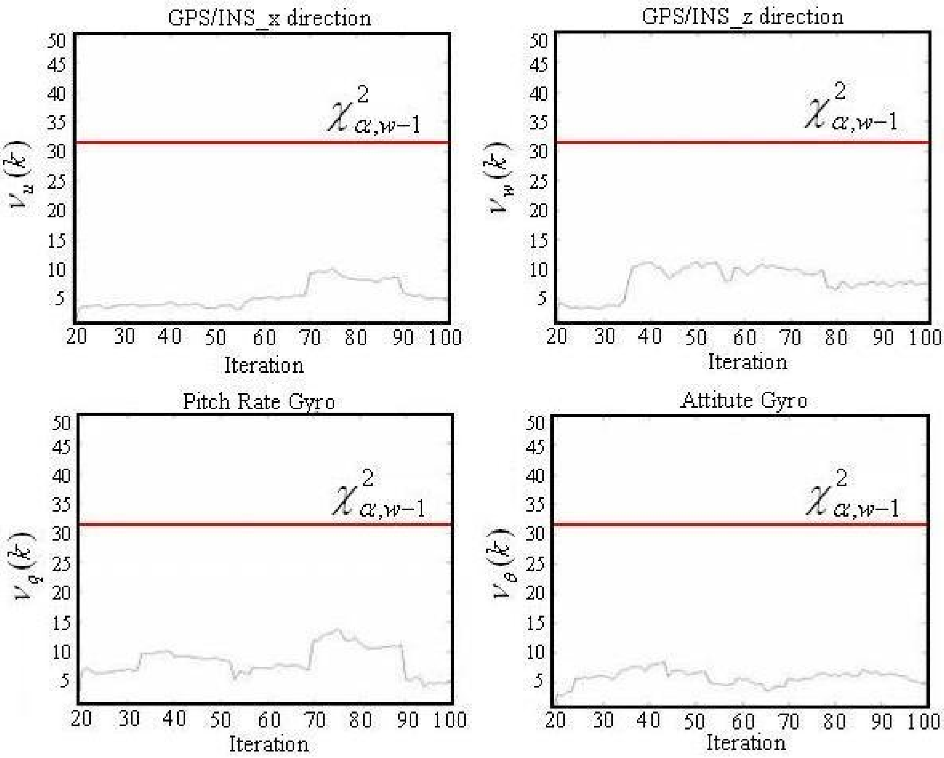

Figure 4. Fault Diagnosis: behaviour of $\nu_i(k)$ when there is no sensor fault in the system.

As shown in “Figure 2”, the system in the absence of fault holds as expected. “Figure 3” and “Figure 4” illustrate the statistic behaviour $\rho(k)$ and $\nu_i(k)$ for scenario where all the sensors remain fault free. The simulation results in this case show there is no sensor fault $\rho(k)$ is lower than the threshold of detection, and consequently $\nu_i(k)$ elements do not exceed the isolation thresholds. Hence H0 hypothesis is judged to be true.

Fixed Bias failure mode was introduced at iteration *k=30*. This fault affects the mean value of the innovation process in the pitch rate gyro channel, as seen in “Fig. 5”. The graph of $\rho(k)$ is shown in “Fig. 6”. When the failure mode considered occurs in the rate gyro, $\rho(k)$ grows rapidly exceeding the threshold of detection, and consequently the H1 hypothesis is judge to be true. Fault detection presented here is basically an alarm system, *i.e.* the system makes no attempt to diagnose (isolate) faults.

In “Figure 7” shows fault diagnosis is successfully achieved when the statistic $\nu_q(k)$ correspondent to pitch rate gyro sensor exceeds the threshold of diagnosis, isolating the respective failed sensor. Thus, a new Kalman Filter is designed in order to provide to controller an accurate estimative of the system state. The result of the correction of estimation via innovation process is show in “Fig.8”.

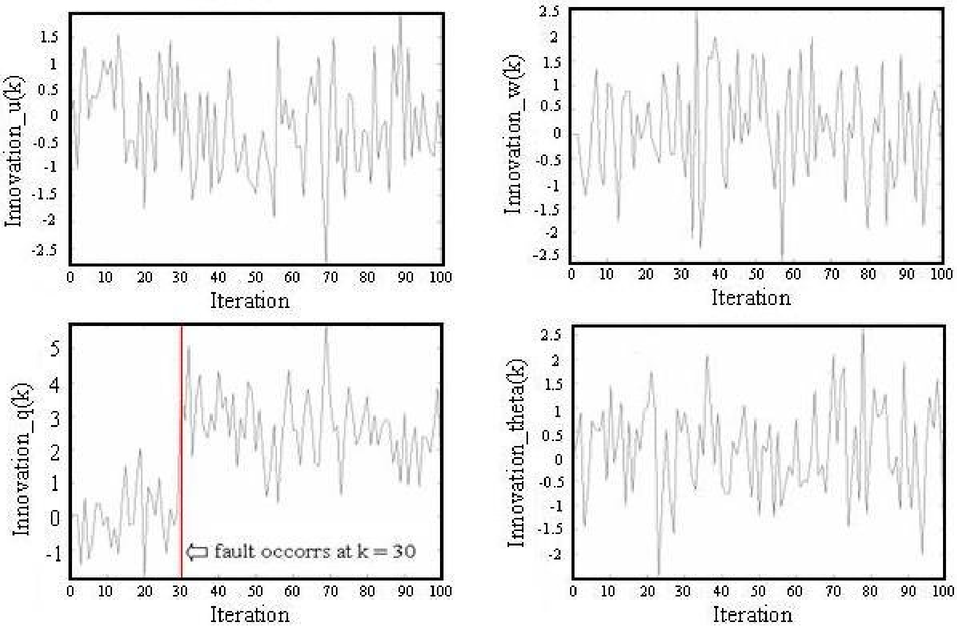

Figure 5. Kalman Filter innovation process in the case pitch rate gyro fault.

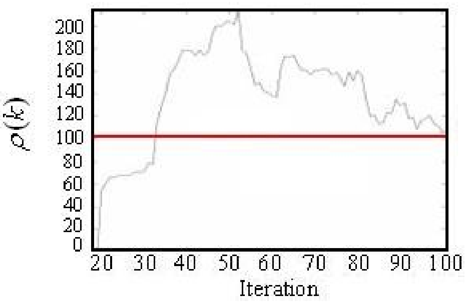

Figure 6. Fault Detection: behaviour of $\rho(k)$ in the case sensor fault.

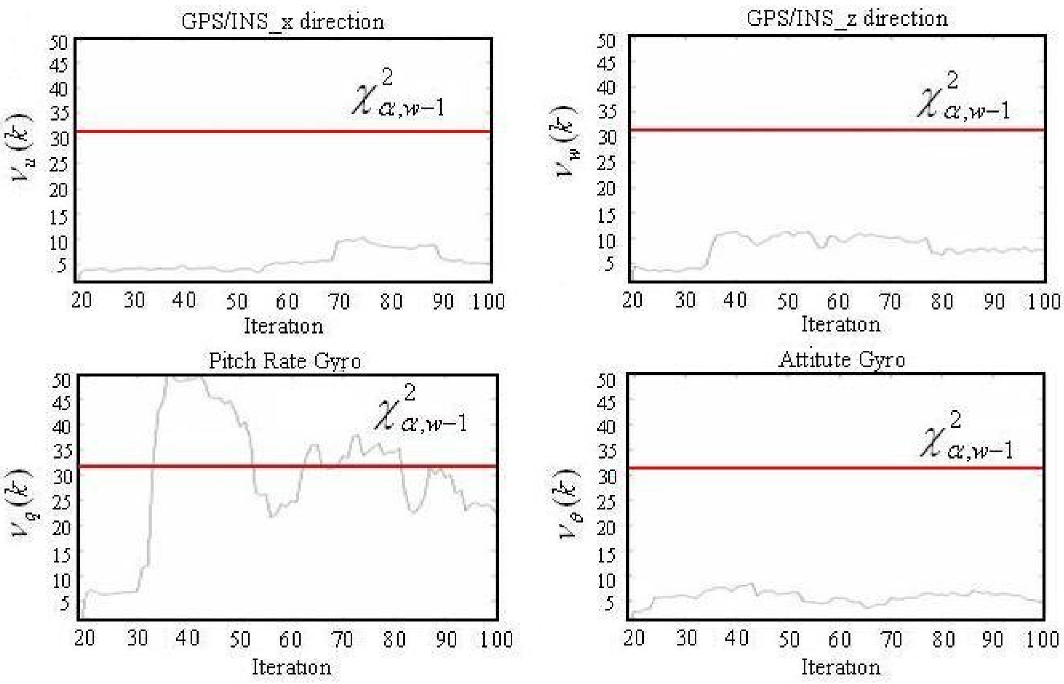

Figure 7. Behaviour of $v_i(k)$ in the case pitch rate gyro fault.

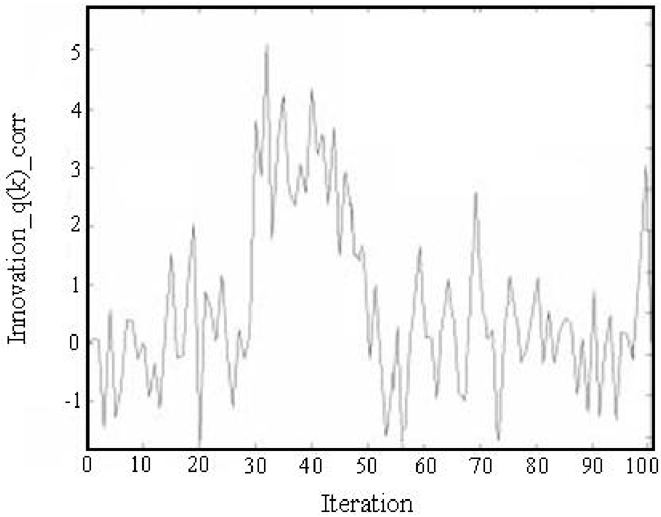

Figure 8: Reconfiguration of the (q) system state via innovation process

It is possible to conclude for this graph that the accomplishment of the correction of the estimate for sensor fault is necessary so that the system continues to operate satisfactorily.

5. CONCLUSION

The use of UAVs in many applications requires the improvement of safety conditions in order to allow an assessment of the risk posed by UAV to person and property in the development of airspace regulations with the purpose of avoiding potential accidents. In this paper has been presented a system for sensor fault detection, diagnosis, and accommodation and its application to the Aerosonde UAV. As an example, a sensor soft failure mode for pitch rate sensor has been considered. This failure mode affects the mean of the Kalman Filter innovation process. Once the fault is detected and assuming that the effects of the failed sensor on its channel is more significant than on the other channels, the diagnosis is presented and a new Kalman Filter is designed to reconfigurate the system states so that the system continues to operate satisfactorily. Thus, it provides to controller an accurate estimative of the system states and hence to accommodate the UAV dynamics affected by faulty sensor.

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