# A Bank of Kalman Filters and a Robust Kalman Filter Applied in Fault Diagnosis of Aircraft Engine Sensor/Actuator

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## Abstract

*In this paper, A Robust Kalman filter and a bank of Kalman filters are applied in fault detection and isolation (FDI) of sensor and actuator for aircraft gas turbine engine. A bank of Kalman filters are used to detect and isolate sensor fault, each Kalman filter is designed based on a specific hypothesis for detecting a specific sensor fault. In the event that a fault does occur, all filters except the one using the correct hypothesis will produce large estimation errors, from which a specific fault is isolated. When the Kalman filter is used, failures in the sensors and actuators affect the characteristics of the residual signals of the Kalman filter. While a Robust Kalman filter is used, the decision statistics changes regardless the faults in the sensors or in the actuators, because it is sensitive to sensor fault but insensitive to actuator fault. The proposed FDI approach above, is applied to a nonlinear engine simulation in this paper, and the evaluation results show that this approach to detect and isolate sensor and actuator faults is demonstrated.*

## 1. Introduction

Fault detection and isolation logic plays a crucial role in enhancing the safety and reliability, and reducing the operating cost of aircraft propulsion systems. However, achieving the FDI task with high reliability is a challenging problem [1]. For this purpose, various approaches have been proposed in the literature [2, 3, 4].

Firstly, two different fault detection algorithms, namely multiple hypotheses testing and neural networks that analyze the sensor residuals generated with an extended Kalman filter (EKF) based on an un-faulted engine model were developed and implemented by R. Randal et al. [5]. These two algorithms have complementary performance, which is exploited in a fusion algorithm to enhance the overall detection & classification performance. An observer-based robust sensor fault detection approach was applied to a jet engine simulation by R. J. Patton and J. Chen [6]. W. C. Merrill, J. C. Delaat, and W. M. Bruton used a bank of Kalman filters for aircraft engine sensor FDI [7]. This study successfully improved control loop tolerance to sensor failures, which were considered the most likely engine failures to happen under the harsh operating environment. In this study, actuator failure was not considered. An actuator failure may cause a false alarm or missed detection if not considered. In the study done by T. Kobayashi and D. Simon [8], a FDI system which utilizes a bank of Kalman filters is developed for aircraft engine sensor and actuator FDI in conjunction with the detection of component faults. In the meantime, a set of parameters that indicate engine component performance is estimated for the detection of abrupt degradation. The performance of the FDI system is evaluated against a nonlinear engine simulation for various engine faults at cruise operating conditions. The results indicate that the proposed FDI system is promising for reliable diagnostics of aircraft engines. An analytical redundancy-based approach for detecting and isolating sensor, actuator, and component faults in complex dynamical systems, such as aircraft and spacecraft is developed by E. C. Larson, E.B. Jr. Parker, and B. R. Clark [9]. This method has limited applications in practice. A Kalman filter was applied for aircraft sensor and actuator fault diagnosis by C. Hajiyev and F. Caliskan [10]. This approach was based on the faults affected the mean of the Kalman filter innovation sequence. A sensor fault that shifted the mean of the innovation sequence could be detected and isolated. A Roubst Kalman filter was used to distinguish the sensor and actuator faults. But, this method could not used to isolate which actuator is faulty.

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In this paper, we assume that only one of the sensors will fail at a time, and just only one actuator. Hence, detection and isolation between different actuators is not considered. The mean of the residual signals from sensor measurements and their estimated values are applied to detect and isolate sensor failures. An effective approach previously discussed is to distinguish the sensor and actuator fault during a nonlinear engine simulation.

## 2. Fault Detection and Isolation Logic

When a fault occurs, the first step is to detect it as soon as possible. The approach used for model-based fault detection is composed of two steps as follow.

1) Generate residual signals from the sensor measurements and their Kalman filter estimated values.

2) Compare the residuals with thresholds to make fault detection detections [11].

System noise, measurement noise and modeling uncertainty are key factors that affect detection performance. However, with the development of digital computational power, more sophisticated approaches have become possible.

A propulsion system with fault detection and isolation logic is shown in Fig.1. The Kalman filters use two sets of input signals; sensor measurements and control commands. Sensor measurements are corrupted by noise. Because actuator may be faulty, the true actuator position and control commands may be inconsistent. The difference between them is simply defined as a fault. In this paper, the sensor and actuator failures are "soft failures". Soft failure is defined as inconsistencies between true and measured sensor values that are relatively small in magnitude and thus difficult to detect by a simple range-checking approach, whereas "hard" failures are larger in magnitude and thus more readily detectable.

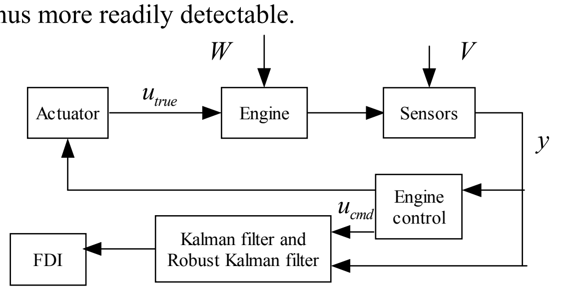


Fig.1 **Fault detection and isolation logic**

A linear model is represented by the following state-space equation:

$$\dot{x} = Ax + Bu + w$$
$$y = Cx + Du + v \quad (1)$$

Where the vectors $x$, $u$ represent the state variables, and control commands, respectively. $y$ is a sensor measurement vector, $w$ and $v$ are the process and sensor noise, respectively, they are both assumed to represent Gaussian white noise. Their covariance matrices:

$$\begin{aligned} &E\left[w(k)\right]=0; E\left[v(k)\right]=0 \\ &E\left[w(k+\tau)w^T(k)\right]=Q\delta(k\tau); \\ &E\left[v(k+\tau)v^T(k)\right]=R\delta(k\tau) \end{aligned} \quad (2)$$

where $\delta(k\tau)$ is the Kronecker symbol. The estimated state vector $\tilde{x}$, the sensor measurements of $y_e$ and the gain matrix $K$ can be gained by

$$\begin{aligned} &\tilde{x} = A\tilde{x} + Bu + K(y - y_e) \\ &y_e = C\tilde{x} + Du \\ &K = PC^T R^{-1} \end{aligned} \quad (3)$$

Where $P$ is given by the steady-state Riccati equation.

## 3. Fault Detection Algorithm for Sensor

In this paper, an approach based on a model with a bank of Kalman filters is used for sensor detection and isolation. Each Kalman filter is designed a specific sensor fault. In the event that a fault does occur, all filters except the one using the correct hypothesis will produce large estimation errors. By monitoring the residual of each filter, the specific fault that has occurred can be detected and isolated.

When the fault is detected as a sensor fault, then it is necessary to determine which sensor is faulty. For this propose, the structure for sensor FDI using a bank of Kalman filters is shown in Fig.2. The bank of Kalman filters contains 4 Kalman filters where 4 is the number of sensors being monitored. The control input and a subset of the sensor measurements are fed to each of the 4 Kalman filters. The sensor which is not used by a particular filter is the one being mentioned by that filter for fault detection.

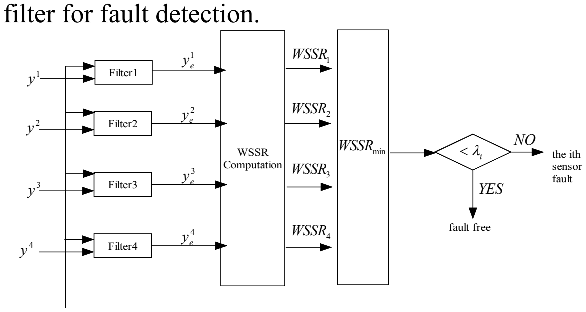


Fig.2 **Sensor fault detection isolation using bank of kalman filters.**

For each filter, the residual vector:

$$e^i = y_e^i - y \tag{4}$$

When we got the residual, the weighted sum of squares residuals for each of the Kalman filters were calculated as:

$$WSSR^i = V^i \left(e^i\right)^T \left(\Sigma\right)^{-1} e^i \tag{5}$$

Where $\Sigma = diag\left(\sigma^2\right)$ .The vector $\sigma$ is the noise standard deviation, and the additional weigh $V^i$ is the weighting factor.

The statistical function as in (5) has $\chi^2$ distribution consider the following two hypotheses:

$H_0$: system operates normally; $H_1$: fault occurs in the system.

If a confidence probability $a$ is given, the threshold can be found as in [13]. The following gives the detection theory:

$H_0$: $WSSR^i \le \lambda_i$ ; $H$: $WSSR^i \ge \lambda_i$

where $\lambda_i$ is the threshold.

## 4. Fault Detection Algorithm for Actuator

When a large discrepancy between commanded and true actuator positions does exist due to an actuator fault, it may cause significant errors. A Robust Kalman filter may be designed in order to isolate the sensor and actuator faults. A Kalman filter that satisfies the Dolye-Stein condition is referred to as Robust Kalman filter.

The Doly-Stein condition is expressed as follow [12].

$$K\left(I + H\phi K\right)^{-1} = B\left(H\phi B\right)^{-1} \tag{6}$$

Here $K$ is the Kalman filter gain, $\phi = \left(sI - A\right)^{-1}$, $A$ is the system matrix in continuous time, $B$ is the control distribution matrix in continuous time. $H$ is the system measurement matrix. If the Kalman filter process noise intensity matrix is defined as:

$$Q_q = Q_0 + q^2 BVB^T \tag{8}$$

Where $Q_0$ and $R_0$ are noise intensities matrix for the nominal plant, $V$ is any positive definite symmetric matrix. With these selections, then the RKF is obtained.

The value of the $q$ must be chosen carefully, if $q$ is chosen small, the RKF is a Kalman filter and becomes sensitive to actuator failures, on the other hand, if it is chosen large, noise effects increase and unexpected result occur in the RKF.

## 5. Simulation Results

The bank of Kalman filters and a Robust Kalman filter were implemented on the nonlinear dynamical model of an aircraft with faults in sensors and actuator. The use of the RKF is very useful in the isolation of sensor and actuator as it is insensitive to the latter failures.

The RKF was used to isolate whether the detected fault is a sensor fault or an actuator fault, when we add the fault at 20 steps and stop at 200 steps in the low-pressure spool speed measurement sensor, the plot for the RKF estimate is shown in Fig.4. Then, when the fault is in the actuator, the plot for the RKF estimate is similarly shown in Fig.3.

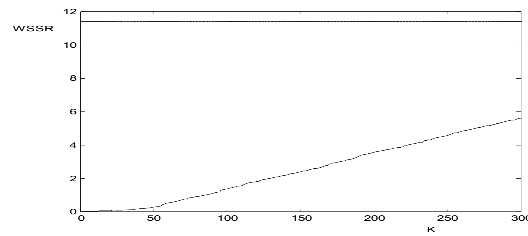


Fig.3 **Detection of actuator fault with RKF**

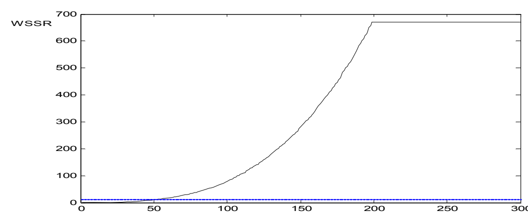


Fig.4 **Detection of sensor fault with RKF**

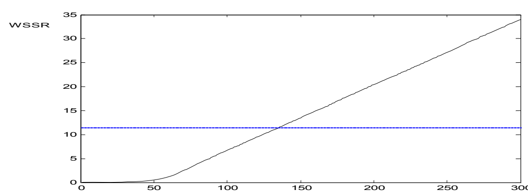


Fig.5 **Detection of actuator fault with KF**

As shown in Fig.3, detection of actuator fault is not possible when the RKF is used. But in Fig.4, when a fault occurs in the sensor, *WSSR* grows rapidly, and after 50 steps it exceeds the threshold. Hence, Fig.3 and Fig.4 illustrate that the RKF can detect the sensor faults, and cannot detect the actuator faults. On the other hand, if we use Kalman filter to isolate sensor or actuator fault, the plot for the KF estimate is shown in Fig. 5 and Fig. 6. These shown that use Klamna filter could not isolate sensor fault and actuator fault. As shown in Fig.3-6 only RKF can detect sensor failures, and cannot detect actuator failures.

In this paper, there are four sensors may be fault, i.e. low-pressure spool speed sensor, high-pressure spool speed sensor, high-pressure compressor exit pressure sensor, low-pressure turbine exit temperature sensor.

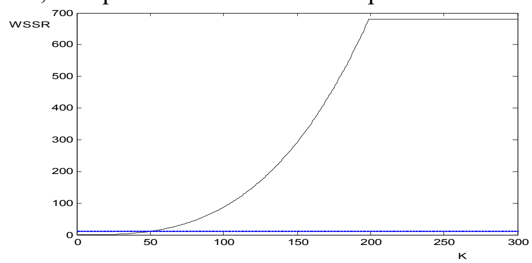


Fig.6 **Detection of sensor fault with KF**

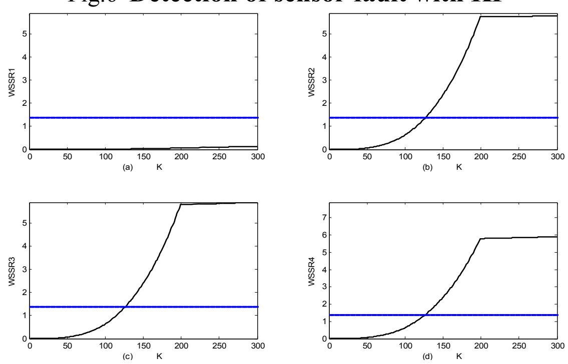


Fig. 7 **Fault detection of low-pressure spool speed measurement sensor when a bank of Kalman filters is used; ordinate: WSSR**.

When the low-pressure spool speed measurement sensor is faulty, as above mentioned, all filters except for filter 1 will use a corrupted measurement. Filter 1 will be able to estimate the engine outputs from fault-free sensor measurements, whereas the output estimates of the remaining filters (i.e., filters 2, 3 and 4) will be distorted by the fault in sensor 1. The *WSSR* and threshold for the 4 Kalman filters are shown in Fig. 7(a)-(d) respectively. *WSSR* plots for Kalman filter 2, 3 and 4 are also seen to be high whereas the *WSSR* for the Kalman filter 1 goes to zero. In this way we can successfully detect which sensor is faulty. The low-pressure spool speed measurement sensor is not used by filter 1. Hence, this sensor is faulty.

## 6. Conclusion

A novel approach has been proposed to detect and isolate the aircraft sensor and actuator failures occurred in the aircraft control system. A bank of Kalman filters were used to detect and isolate sensor failures, each of Kalman filter is designed based on a specific hypothesis for detecting a specific sensor fault. In the event that a fault does occur, all filters except the one using the correct hypothesis will produce large estimation errors, from which a specific fault is isolated. Failures in the sensors and actuators affect the characteristics of the residual signals of the Kalman filter. When the Kalman filter is used, the decision statistics changes regardless the faults in the sensors or in the actuators. While a Robust Kalman filter is used, it is easy to distinguish the sensor and actuator faults.

## 7. References


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