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1. Introduction

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

In an online engine fault diagnoses, two tasks may use Kalman filter to carry out: 1) evaluation of online engine state variables to renew the on-board model; 2) diagnoses of online aircraft engine sensor/actuator fault. How to solve the above problems through application of Kalman filter is discussed in this paper.

A challenge in developing an online fault detection algorithm is making it adaptive to engine health degradation. If the algorithm has no adaptation capability, it will eventually lose its diagnostic effectiveness. To address this problem, the integration of online diagnostic algorithms was investigated. The Kalman filter estimates engine health condition over the course of engine’s life. Then the on-board model could be reconstruct based on the estimated values of Kalman filter.

After all of the above, 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 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. 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 and insensitive to actuator fault.

W. C. Merrill, J. C. Delaat, and W. M. Bruton used a bank of Kalman filters for aircraft engine sensor FDI. 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. In the study done by T. Kobayashi and D. Simon, a fault detection and isolation (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. The results indicate that the proposed
the turbine engine for sensor fault diagnostics purpose. However this method can not or hardly distinguish the fault between sensor and actuator. A bank of Kalman filters and a robust Kalman filter are used to detect sensor and actuator faults. In addition, a bank of Kalman filters is used to detect which sensor is fault. Such technical are easy to implement in a real-time environment.

In the following sections of this paper, the problem setup for sensor fault diagnostics based on the engine health degradation. The deterioration can be estimated by one Kalman filter. Then the on-board model can be re-constructer based on the estimated values of Kalman filter. At last a bank of Kalman filters is applied in fault detection and isolation (FDI) of sensors for aircraft gas turbine engine. At the same time, we assumed 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 which from sensor measurements and their estimated values applied to detect and isolate sensor failures. An effective approach previously discussed in literature is to distinguish the sensor and actuator fault during a linear engine simulation.

2. Engine model

The engine model being used for this research is the nonlinear simulation of an advanced military twin-spool turbofan engine. Engine performance deterioration is modeled by adjustments to efficiency or flow coefficient scalars of the following four components: Fan (FAN), Booster (BST), High-Pressure Turbine (HPT), and Low-Pressure Turbine (LPT). These scalars representing the component performance deterioration are the health parameters. The engine state variables, health parameters, actuator, and sensor used in the current research are shown in Table 1.

<table>
<thead>
<tr>
<th>State variable</th>
<th>Health parameters</th>
<th>Actuators</th>
<th>Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>XNL</td>
<td>FAN efficiency</td>
<td>W_FB</td>
<td>XNL</td>
</tr>
<tr>
<td>XNH</td>
<td>BST efficiency</td>
<td>A_S</td>
<td>XNH</td>
</tr>
<tr>
<td>HPT</td>
<td>efficiency</td>
<td>P_31</td>
<td></td>
</tr>
<tr>
<td>LPT</td>
<td>efficiency</td>
<td>P_6</td>
<td>T_45c</td>
</tr>
</tbody>
</table>

Table 1. State Variables, Health Parameters, Actuators, and Sensors of the Engine Model

The FDI (Fault detection and isolation) logic uses the Kalman filter approach in order to estimate the state variables, health parameters, and engine output values from a given set of sensor measurements and control commands. A linear model under consideration is represented by the following state-space equations:

\[
\begin{align*}
\dot{x} &= Ax + Bu + Lh + w \\
y &= Cx + Du + Mh + v
\end{align*}
\]

(1)

where the vectors \(x\), \(h\), and \(u\) represent the state variables, health parameters and control commands, respectively. \(y\) is 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:
4.2 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 Dolye-Stein condition is expressed as follow.

\[ K \left( I + H \phi K \right)^{-1} = B (H \phi B)^{-1} \]  \hspace{1cm} (9)

Here \( K \) is Kalman filter gain, \( I \) is unit matrix, \( \phi = (sI - A)^{-1} \), \( A \) is the system matrix in continuous time, \( B \) is the control distribution matrix in continuous time. \( H \) is the system measurement matrix. The Kalman filter satisfies the Dolye-Stein condition called Robust Kalman filter.

For Kalman filters, \( K = P_q C^T R^{-1} \),

with \( P_q \) defined by the Riccati equation

\[ AP + PA^T - PC^T R^{-1} CP + Q_q = 0 \]

As usual we take \( Q = Q^T > 0 \) and \( R = R^T > 0 \) with \( \left( A, Q^{1/2} \right) \) and \( \left( C, A \right) \) stable and observable, respectively. For Kalman filters, they represent given process noise and measurement noise intensities. They are treated more freely as design parameters which we can select to suit broader purposes. In particular, let

\[
Q_q = Q_0 + q^2 BVB^T \\
R = R_q
\]  \hspace{1cm} (10)

Where \( Q_0 \) and \( R_0 \) are noise intensities matrix for the nominal plant, \( V \) is any positive definite symmetric matrix. With these selections, the observer gain for \( q = 0 \) corresponds to the nominal Kalman filter gain. However, as \( q \) approaches infinity, the gains are to satisfy as follow

\[
\frac{K R K^T}{q^2} \to BVB^T
\]  \hspace{1cm} (11)

Solutions of (11) must necessarily be of the form: \[ \frac{1}{q} K \to BV^{1/2} \left( R^{1/2} \right)^{-1} \]

Where \( V^{1/2} \) and \( R^{1/2} \) denote square root of \( V \) and \( R \), respectively, i.e.

\[
\left( V^{1/2} \right)^T V^{1/2} = V, \quad \left( R^{1/2} \right)^T R^{1/2} = R
\]

Then a Kalman filter satisfying with (9) will be a Robust Kalman filter. Because of the \( q \) factor, the Robust Kalman filter (RKF) is not an optimum filter. 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 1

The bank of Kalman filters was implemented on the nonlinear dynamical model of an aircraft engine with faults in sensors and the estimation of degraded engine as shown in Fig.4. The nonlinear dynamical model generates five sets of real signals at a given state. The sensor fault can be added on those signals directly. There are five sensors may be fault: High-pressure spool speed (XNH) sensor, Low-pressure spool speed (XNL) sensor, Booster exit pressure (P31) sensor, LPT exit pressure (P6) sensor, LPT inlet temperature (T45c) sensor.

Health degradation can be estimated by trend tracking filter. One Kalman filter was used to estimate the degradation of the real engine. If there were no degradation and no fault, the values of $WSSR_1 - 5$ go to zero, as shown in Fig.5. However, if the HPT efficiency degrades by 2% and the on-board model does not shift to the vicinity of the degraded engine then the in-flight diagnostic systems may lose their effectiveness, as shown in Fig.6.

The values of the $WSSR_1 - 5$ grow rapidly and all of them exceed the threshold. It causes a false alarm. This is because shifts in measured engine outputs are induced not only by faults but also by engine degradation. Estimation of the degraded engine is critical to the fault detection and isolation system.

Fig.7 shows that Kalman filter can estimate the degradation accurately. After this the on-board model can be shifted to the vicinity of the degraded engine, and the in-flight diagnostic system may be effective. The Kalman filter estimates engine health condition over the course of engine’s life. Based on the estimated health condition, the on-board model is updated. When we add the fault at 10 steps and stop at 200 steps in the LPT inlet temperature measurement sensor and at the same time HPT efficiency degrades by 2%, the in-flight diagnostic system can detect and isolate the fault. As shown in Fig.8, $WSSR_1 - WSSR_4$ grow rapidly but the $WSSR_5$ remains small. The results indicate that there is a fault in T45c sensor.

![Fig. 4. The simulation architecture of Sensor fault detection isolation using bank of kalman filters](www.intechopen.com)
Fig. 5. The value of $WSSR_1 - 5$ when no fault and no degradation exist.

Fig. 6. The value of $WSSR_1 - 5$ when the HPT efficiency degrades by 2% and no fault exist.

Fig. 7. The estimation of Kalman filter when the HPT efficiency degrades by 2%.
In this paper, there are four sensors that may be faulty, i.e., low-pressure spool speed sensor, high-pressure spool speed sensor, high-pressure compressor exit pressure sensor, low-pressure turbine exit temperature sensor.

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 value of WSSR and threshold for the 4 Kalman filters are shown in Fig. 13(a)-(d) respectively. The values of WSSR for Kalman filter 2, 3 and 4 are also seen to be high whereas the value of 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.

![Graphs showing WSSR for different Kalman filters](image)

Fig. 13. Fault detection of low-pressure spool speed measurement sensor when a bank of Kalman filters is used.