Aircraft Engine Sensor Fault Diagnostics Based on Estimation of Engine’s Health Degradation

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Abstract

A duty in development of an on-line fault detection algorithm is to make it associate with estimation of engine’s health degradation. For this purpose, an on-line diagnostic algorithm is put forward. Using a tracking filter to estimate the engine’s health condition over its lifetime, can be reconstructed an onboard model, which is then made to match a real aircraft gas turbine engine. Finally, a bank of Kalman filters is applied in fault detection and isolation (FDI) of sensors for the engine. Through the bank, the real faults that have occurred can be detected and isolated. The on-line fault detection algorithm has the ability of maintaining the effectiveness over the engine’s lifetime and is verified by simulation using a nonlinear engine model.

Keywords: aerospace propulsion system; Kalman filter; health degradation; sensor fault diagnostics

1. Introduction

Fault detection and isolation (FDI) logic plays a key role in enhancing the working safety and reliability and reducing the operating cost of aircraft propulsion systems. However, it is a challenging to ensure high reliability of the FDI task[1-3]. For this purpose, a variety of approaches were proposed[2-13].

W. C. Merrill, et al.[5] used a bank of Kalman filters for aircraft engine sensor FDI. That study successfully improved the control loop tolerance to sensor failures, which were considered as the engine failures most likely to happen under the harsh operating conditions. In that study, actuator failure was not taken into account. In the work by T. Kobayashi and D. L. Simon[6], an FDI system which used a bank of Kalman filters was developed for aircraft engine sensor and actuator FDI in conjunction with the detection of component faults. The results indicated that the proposed FDI system would be promising for reliable diagnostics of aircraft engine sensors and actuators. An analytical redundancy-based approach for detecting and isolating sensor, actuator, and component faults in complex dynamical systems, such as aircraft and spacecraft, was developed by E. C. Larson, et al.[7]. This method had limited applications in practices. A Kalman filter was applied to aircraft sensor and actuator fault diagnosis by C. Hajiyev and F. Caliskan[8]. This approach was based on the faults affecting the mean of the Kalman filter innovation sequence. A sensor fault that shifted the mean of the innovation sequence could be detected and isolated.

In general, in-flight diagnostic systems are designed under a nominal health, or a non-degrading condition, which constitutes a reference baseline for diagnostics. Any deviation observed in engine outputs from the reference values may indicate the presence of a fault. As an engine degrades overtime, in-flight diagnostic systems may lose their effectiveness. Engine health degradation is a normal aging process that occurs in all aircraft engines due to usage, and therefore can not be regarded as faults. However, similar to other faults, degradation causes the engine outputs to deviate from the normal. When an engine’s output deviation reaches a certain level, the diagnostic system may misinterpret it as a fault and generate a false alarm.

One approach to maintain the effectiveness of in-flight diagnostic algorithms, when it is applied to degrading engines, is to be periodically updated or redesigned based on the estimates of health degradation. Health degradation can be judged by trend monitoring systems. Through the updating based on the estimated health degradation, the health baseline of an in-flight diagnostic system can be adapted to the degraded engine, and thereby the system is able to diagnose a fault with effectiveness.

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In this article, the approach to diagnose sensor faults based on the engine's health degradation is discussed. Using the Kalman filter to estimate the deterioration of the engine, the onboard model can be reconstructed, and a bank of Kalman filters is applied in FDI of sensors for the aircraft gas turbine engine.

2. Engine Models

The engine model used in this study is for the nonlinear simulation of an advanced military twin-spool turbofan engine. The deterioration of engine performance is modeled by adjustments of 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 are low-pressure spool speed (XNL) and high-pressure spool speed (XNH); health parameters are FAN, BST, HPT, and LPT efficiencies; actuators are fuel flow (WFb) and nozzle area (A8), and sensors used in the study are XNL, XNH, booster exit pressure (P31), LPT exit pressure (P6) and LPT inlet temperature (T45).

The FDI logic uses the Kalman filter approach to estimate the state variables and health parameters, engine outputs from a set of sensors, and controlling commands. A linear model under consideration is represented by the following state-space equations:

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

where the vectors \(x\), \(h\), and \(u\) represent the state variables, health parameters, and controlling commands, respectively, \(y\) the sensor measurement vector, \(w\) and \(v\) the process and sensor noise, both assumed to represent Gaussian white noise. Their covariance matrices are:

\[
\begin{align*}
E[w(k)|j] &= 0 \\
E[v(k)] &= 0 \\
E[w(k + \tau)w^T(k)] &= Q(k \tau) \\
E[v(k + \tau)v^T(k)] &= R(k \tau)
\end{align*}
\]

3. Estimation of Health Degradation

As shown in Fig.1, as an important part in the model-based control and diagnostics logic, the onboard model and tracking filter use two sets of input signals, namely sensor measurements and actuator position. The engine’s degradation can be tracked by one Kalman filter based on the input signals. After the estimation of the Kalman filter, the onboard model can be shifted to the vicinity of the degraded engine.

In the Kalman filter problem setup, the engine state vector is augmented with health parameters as follows:

\[
\begin{align*}
\dot{x} &= \hat{A}x + \hat{Bu} + w \\
y &= \hat{C}x + Du + v
\end{align*}
\]

where

\[
\begin{align*}
\hat{x} &= \begin{bmatrix} x \\ h \end{bmatrix}, \hat{A} = \begin{bmatrix} A \ L \\ 0 \ 0 \end{bmatrix}, \hat{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}, \hat{C} = \begin{bmatrix} C \ M \end{bmatrix}
\end{align*}
\]

The estimated state vector \(\hat{x}_e\), the sensor measurements of \(y_e\), and the Kalman filter gain matrix can be found with the Kalman filter of the form:

\[
\begin{align*}
\dot{\hat{x}}_e &= \hat{Ax}_e + \hat{Bu} + K(y - y_e) \\
\hat{y}_e &= \hat{C}\hat{x}_e + Du \\
K &= P\hat{C}^T R^{-1}
\end{align*}
\]

where matrix \(P\) is the solution of the following steady-state Riccati equation:

\[
\begin{align*}
\hat{A}P + PA^T - P\hat{C}^T R^{-1}\hat{CP} + Q = 0
\end{align*}
\]

4. Fault Detection Algorithm for Sensors

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

1. To generate residual signals from the sensor measurements and their Kalman filter estimates.
2. To compare the residuals with thresholds to make fault detection.[9]

This article uses a model-based approach with a bank of Kalman filters for sensor FDI. The sensor and actuator faults are “soft fault”. A “soft fault” is defined as inconsistency between true and measured sensor values that are relatively small in magnitude and thus difficult to detect by a simple range-checking approach, whereas a “hard fault”—larger in magnitude and thus more readily to detect.

Each Kalman filter is designed for a specific sensor fault. In the case 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 faults that have occurred can be detected and isolated.[8,10] Fig.2 shows the structure of sensor FDI using a bank of Kalman filters. The bank of Kalman filters contains five Kalman filters where
five is the number of sensors to be monitored. The control input and a subset of the sensor measurements are fed to each of the five Kalman filters. The sensor which is not used by a particular filter is the one being mentioned by that filter for fault detection. For instance, Filter i uses the sensor subset that excludes Sensor i. Hence each Kalman filter estimates the augmented state vector using four sensors. Filter 1 uses all sensors except Sensor 1, Filter 2 does the same except Filter 2, and so on. Therefore, Filter 1 is able to estimate the augmented state vector from fault-free sensor measurements, whereas the estimates of the remaining filters are distorted by the fault in Sensor 1.

5. Simulation Results

The bank of Kalman filters function on the nonlinear dynamical model of an aircraft engine with faults in sensors. Fig.3 shows the estimation of a degrading engine. 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 that might be at fault: the sensor of XNH, XNL, P31, P6, and T45. The other engine states detected by sensors are fuel flow (WFM), afterburner flow (WFAs), altitude (ALT), Mach number (MA), variable stator vanes (A1), fan inlet guide vanes (A2), main burner exit temperature (T41), fuel/air ratio (WFAR), compressor surge margin (SMC), fan surge margin (SMF), net thrust (FN), and specific fuel consumption (sfc).

One Kalman filter, a trend tracking filter, is used to estimate the health degradation of the real engine. As shown in Fig.4, the values of \( W_1 - W_3 \) will turn zero given absence of degradation and fault. However, if the HPT efficiency decreases by 2% and the onboard model fails to shift to the vicinity of the degraded engine, the in-flight diagnostic systems may lose their effectiveness, as shown in Fig.5, making the values of the \( W_1 - W_3 \) grow rapidly and exceed the threshold, which results in a false alarm. This is because shifts in measured engine outputs are induced not only by faults but also by engine degradation. Consequently, the estimation of the degrading engine is critical to the FDI system.

As shown in Fig.6, after the Kalman filter accurately estimated the degradation of HPT, the onboard model shifts to the vicinity of the degraded engine, and the in-flight diagnostic system comes into effect. Over the engine’s lifetime, the engine health condition is estimated ceaselessly by the Kalman filter and on the basis of the estimates, the onboard model is updated. When the fault is added at 10 steps and stop at 200 steps in
the LPT inlet temperature measurement sensor and at the same time HPT efficiency decreases by 2%, the in-flight diagnostic system will detect and isolate the fault.

As shown in Fig.7, $W_1$-$W_4$ grow rapidly but $W_5$ remains nearly unchanged, which indicates that there being a fault in $T_{45}$ sensor.

6. Conclusions

This article investigates the aircraft engine sensor fault diagnostics based on the estimation of engine’s health degradation by a tracking filter. With this arrangement, the on-line fault detection algorithm is able to maintain its diagnostic effectiveness over the lifetime of the aircraft engine.

The proposed approach has been simulated using a nonlinear engine model. The results show that this approach is capable of retaining on-line fault detection ability in the process of an aircraft engine’s health degradation.

References