FAULT DIAGNOSIS METHOD STUDY FOR COMPLEX SYSTEM BASED ON KALMAN FILTERS

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Abstract

Fault diagnosis is a challenging problem because data used in diagnosis contain random errors and often systematic errors as well. Furthermore, fault diagnosis plays a critical role in aircraft engines and the performance of their control systems. Using the robustness analysis of parametric uncertain systems, an improved algorithm based on Kalman filters is proposed. The algorithm takes the parametric uncertainties into consideration which can distinguish an actual fault from the model uncertainties. The residuals are errors between measured outputs and estimated outputs from a set of Kalman filters. Application to an aircraft engine clearly illustrates the improved performance of the proposed method, the results show that the proposed method helps the system accommodate parametric uncertainties in the model and reduce false alarms and missed detections.

1 Introduction

Although there was a decrease in world-wide jet operations 2001 and 2002 due to the 9/11 terrorist attacks and the outbreak of SARS (Severe Acute Respiratory Syndrome) [1], the reduced traffic has recovered, and jet operations have returned to an increasing trend as shown in Fig. 1. While air traffic has increased, the accident rate of the worldwide commercial jet fleet has decreased because of the advances in technology and the increase in reliability. Despite the low accident rate, the absolute number of accidents is expected to be large due to the large volume of operations.

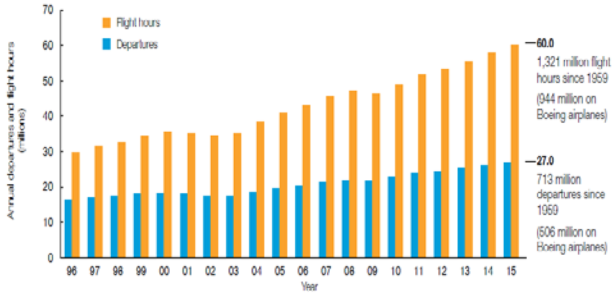

Fig. 1 Worldwide commercial jet operations

The demand for a safer and more reliable aircraft has stimulated considerable research on fault diagnosis approaches and technologies over decades [2]. With the development of the complex and large-scale systems, such as, aircrafts, automotive vehicles, high-speed railways, power systems and many other applications, the issues of reliability, affordability, safety and system integrity have become significantly important and been addressed in many research fields.

The approaches to fault diagnosis may be classified into three categories: model-based methods, knowledge-based methods and signal-processing-based methods. The literature review will focus on the model-based methods in this paper. Before addressing the model-based techniques, the knowledge-based techniques and signal-processing-based techniques will be briefly introduced below.

The knowled`ge-based methods are done within the artificial intelligence domain, using expert reasoning, fuzzy reasoning and neural networks, etc. These methods are appealing because they do not require explicit mathematical model of the monitored system. In order to develop the knowledge-based fault diagnosis system, the knowledge about the process structure and function of the monitored system s under different faulty conditions is required in advance. The basic knowledge to conduct this approach is training data which contains faults and the corresponding symptoms. The development of a knowledge-based fault diagnosis system usually takes considerable time and effort to make it effective. A large amount of work has been devoted to develop the knowledge based method in order to reduce the development time. The signal-processing-based techniques without model application are also used as FDI approaches, which include spectral analysis (time-frequency, time-scale analysis, etc) and statistical methods (signal classification, pattern recognition, etc).

With the development of digital computers and the availability of state variable and transfer function models of many practical systems, model-based fault diagnosis methods have received considerable attention. Model-based fault diagnosis methods use mathematical models of the monitored systems, the advantage of which is that no additional hardwares are required to realize a fault diagnosis system. The model-based fault detection based on analytical redundancy comprises two principal steps: residual generation and residual evaluation.

A great amount of research on model-based fault diagnosis of complex systems has been studied since the 1970s. Model-based fault detection and isolation methods rely on the accuracy of the model. Model or data uncertainty, disturbances and noise, etc., all have a great impact on the fault diagnosis design results. A challenge in the fault diagnosis applications is the design of a scheme which can distinguish between model uncertainties, disturbances and the occurrence of faults.

Model-based fault diagnosis methods use mathematical models of the monitored systems, the advantage of which is that no additional hardwares are required to realize a fault diagnosis system. The model-based fault detection based on analytical redundancy comprises two principal steps: residual generation and residual evaluation. Fig. 2 shows a general fault detection process scheme.

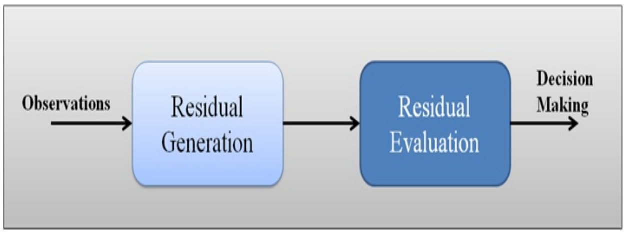

Fig. 2 Fault detection general process

The purpose of residual generation is to generate a fault indicating signal–residual, using the available input and output information from the monitored system. The residual signal is supposed to be nonzero in the occurrence of fault and zero when no fault is present. The residual is usually generated by comparing the measured system output with the mathematical model measured output estimates. There are two main properties in a model-based fault detection algorithm: robustness and sensitivity. Robustness means that the fault detection system does not produce false alarms due to unknown disturbances and modeling errors, while sensitivity means the fault detection scheme should be known as sensitive to faults and not cause missed detections.

In the absence of faults, a predetermined constant threshold would lead to more false alarms under modeling uncertainty, which is not tolerant under flight conditions [3-7]. In conclusion, this motivates the research of deriving a threshold method in the time domain, which is a function of time and control activity. The variable threshold will designed based on the time response analysis using Kalman filters. The variable threshold method derived gives the tube-shaped upper-and-lower bound for each system variable of the residual vector, which provides the insight of the residual variable. This knowledge can be used to analyze which sensor output is more sensitive to a fault.

2 Threshold Design Based on Kalman Filters

2.1 System Formulation

A depiction of the complex system is shown in Fig. 3. During flight, the sensors, actuators, and components are susceptible to failure.

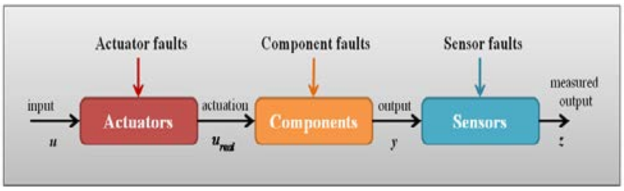

Fig. 3 Fault diagnosis system scheme

Consider a linear time-invariant discrete-time stochastic system with parametric uncertainty represented in Eq. (1).

$$\begin{cases} x_{e_{k+1}} = (\Phi + \Delta\Phi)x_{e_k} + (\Psi + \Delta\Psi)(u_k + f_{a_k}) \\ \qquad\qquad + d_k + \omega_k + f_{c_k} \\ z_{e_{k+1}} = Hx_{e_{k+1}} + v_{k+1} + f_{s_k} \end{cases} \tag{1}$$

where $k = 0, 1, \ldots, n$. Φ and Ψ are coefficient, $x_{e_k} \in R^n$ is a state vector, $u_k \in R^l$ is a control input vector, $d_k \in R^p$ is a disturbance vector (or unknown input vector), $z_{e_k} \in R^m$ is a measured output vector, $f_{a_k} \in R^l$, $f_{c_k} \in R^n$, $f_{s_k} \in R^m$ represent actuator fault vector, component fault vector and sensor fault vector, respectively. $\omega_k \in R^n$ and $v_k \in R^m$ are mutually uncorrelated jointly Gaussian white noise sequences.

Kalman filter is a recursive mean-squared state filter [8-11]. It is a time-varying digital filter that uses information from both the state and measurement equations. Consider a basic linear, time-varying, discrete-time, stochastic state variable model, and all faults and unknown inputs set to be zero, then the system is expressed as

$$\begin{cases} x_{k+1} = \Phi x_k + \Psi u_k + \omega_k \\ z_{k+1} = Hx_{k+1} + v_{k+1} \end{cases} \tag{2}$$

Then the Kalman filter for the system in Eq. (1) is shown as,

$$\hat{x}_{k+1|k} = \Phi\hat{x}_{k|k} + \Psi u_k \tag{3}$$

$$\hat{z}_{k+1|k} = H\hat{x}_{k+1|k} \tag{4}$$

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}(Hx_{e_{k+1}} + v_{k+1} - H\hat{x}_{k+1|k}) \tag{5}$$

2.2 The Threshold Design

The system with possible actuator and sensor faults can be described as:

$$\begin{cases} x_{e_{k+1}} = (\Phi + \Delta\Phi)x_{e_k} + (\Psi + \Delta\Psi)(u_k + f_{a_k}) \\ \qquad\qquad + \omega_k \\ z_{e_{k+1}} = Hx_{e_{k+1}} + v_{k+1} + f_{s_{k+1}} \end{cases} \tag{6}$$

where $f_{a_k} \in R^l$ is the actuator fault vector and $f_{s_k} \in R^m$ is the sensor fault vector. For this system, the state-prediction error variable and the residual are governed by the following equations:

$$e_{k+1|k} = \Phi(I_n - K_kH)e_{k|k-1} + \Delta\Psi u_k + \Delta\Phi x_{e_k} \\ + \omega\_k - \Phi K_k v_k + (\Psi + \Delta\Psi)f_{s_{k+1}} + (-\Phi K_k)f_{s_k} \tag{7}$$

$$r_{k+1} = He_{k+1|k} + v_{k+1} + f_{s_{k+1}} \tag{8}$$

Assume $\overline{\mathrm{K}}$ is the steady-state of Kalman filter gain K_{k+1}, Q and R are the covariance matrices for the process noise wk and v_k, respectively.

Given $(\Phi, \Psi, \mathrm{H}, \mathrm{Q}, \mathrm{R})$, we can first compute P_p, which is the positive definite solution of Eq. (9), then we can calculate $\overline{\mathrm{K}}$ as

$$\bar{K} = P_pH^T(HP_pH^T + R)^{-1} \tag{9}$$

Use Eq. (9) in the error variable Eq. (7), then

$$e_{k+1|k} = \bar{\Phi}e_{k+1|k} + \Delta\Psi u_k + \Delta\Phi x_{e_k} + \omega_{k_p} \\ + (-\Phi\bar{K})v_k \tag{10}$$

where

$$\bar{\Phi} = \Phi(I_n - \bar{K}H) \tag{11}$$

2.3 Optimization of the State-prediction Error

In the use of particle-swarm optimization algorithm to predict the time response of the q-th component of error variable state vector $e_{k+1|k}$, usually with a relatively simple form of fitting, so the amount of calculation of the algorithm will greatly reduce. In general, satisfactory forecasting results can be got by the depth of the spanning tree in the case of 4 to 5 layer.

Particle-swarm optimization algorithm is applied to select the suitable parameters of the state-prediction error, as shown in Fig. 4. The steps of determining the parameters by particle swarm optimization algorithm, which is given as followings:

Step 1. Randomly initialize a population of the particles.

Step 2. Compute the fitness values of each particle and compare the evaluated fitness value of each particle to its individual best.

Step 3. The global best and the individual best of each particle are introduced to evaluate the fitness of each particle.

Step 4. According to Eq. (12) and Eq. (13), Update the velocity and position of each particle.

$$v_{id}(t+1)=wv_{id}(t+1)+c_1r_1(p_{id}(t)-x_{id}(t)) +c_2r_2(g_i(t)-x_{id}(t)) \quad (12)$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \quad (13)$$

where $p_{id}(t)$ is the best previous position of particle i, c_1 and c_2 are the acceleration coefficients, w is the inertia weight, r_1 and r_2 are random variables in the range from 0 to 1.

Step 5. When maximum iteration is reached, the procedure ends, otherwise, go to step 2.

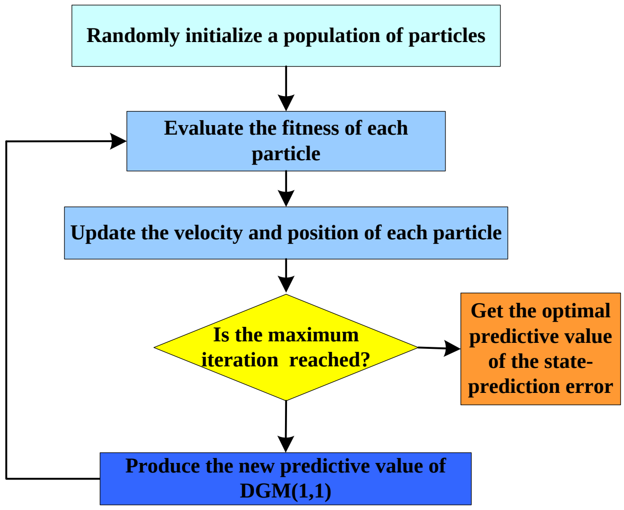

Fig. 4 The process of searching parameter of state-prediction error by PSO

3 Simulation Analysis

The aircraft engine model used in this paper is a nonlinear simulation model of an advanced high-bypass turbofan engine. A turbofan engine is composed of several main components: fan, low pressure compressor (LPC) or booster, high pressure compressor (HPC), combustion chamber, high pressure turbine (HPT), low pressure turbine (LPT) and nozzle. They are arranged in the direction along the gas path.

The engine state variables, control inputs and sensors in the model are listed in Tab. 1.

Tab. 1. State variables, control Inputs and sensors of the aircraft engine

State Variables(X)	Control Inputs	Sensors
low pressure rotor speed sensor (N1) high pressure rotor speed sensor (N2) LPC metal temperature (TLPC) HPC metal temperature (THPC) HPT nozzle metal temperature (THPT) LPT metal temperature (TLPT)	Fuel flow (FF) variable bleed valve (BV) variable stator vane angle (SVA)	N1 N2 HPC inlet temperature (T25) HPC inlet pressure (P25) combustor inlet temperature (T3) combustor inlet pressure (P3) LPT inlet temperature (T49)

Kalman filter is used in the observer design for sensor fault diagnosis. A full order Kalman filter is designed to check the output estimation results of the engine system under fault-free condition. A sinusoidal perturbation with the magnitude of 1% of the operating point value for the control SVA is injected. The measurements are simulated using remote data collection unit (RCU). The process of generating simulated data is depicted in Fig. 5.

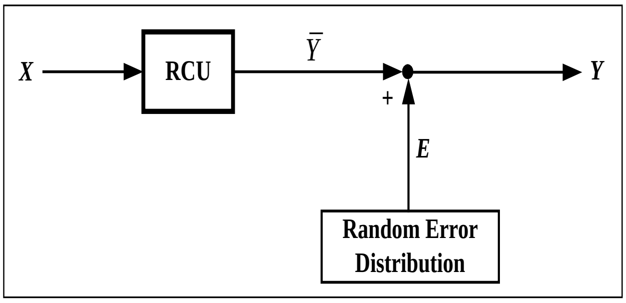

Fig. 5 Data generation process

Sensor fault diagnosis is determined by comparing the residual with the variable threshold. When the residuals cross the thresholds, it indicates the existence of a fault in the system.

The simulation results of sensor 6 fault is shown in Fig. 6. It is concluded that sensor 6 is faulty from the results of the residuals.

Based on the above simulation results, it is shown that the proposed dynamic threshold is capable of detecting incipient fault in the system sensor or actuator and does not cause false alarms or missed detections.

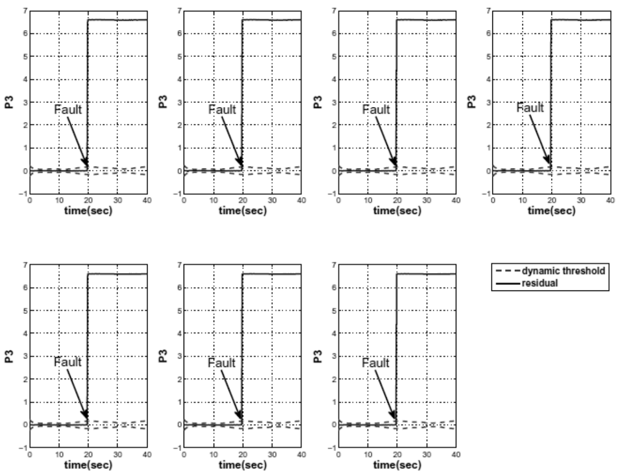

Fig. 6 Residual r_6 of the sensor z_6

4 Conclusions

We have applied the variable threshold method to a nonlinear high bypass turbofan aircraft engine simulation model. The simulation results have shown that the proposed method is capable of detecting incipient fault in the system sensor and does not cause false alarms or missed

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