MULTIPLE SENSORS SOFT-FAILURE DIAGNOSIS BASED ON KALMAN FILTER

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ABSTRACT

Sensor is the necessary components of the engine control system. Therefore, more and more work must do for improving sensors reliability. Soft failures are small bias errors or drift errors that accumulate relatively slowly with time in the sensed values that it must be detected because of it can be very easy to be mistaken for the results of noise. Simultaneous multiple sensors failures are rare events and must be considered. In order to solve this problem, a revised multiple-failure-hypothesis based testing is investigated. This approach uses multiple Kalman filters, and each of Kalman filter is designed based on a specific hypothesis for detecting specific sensors fault, and then uses Weighted Sum of Squared Residual (WSSR) to deal with Kalman filter residuals, and residual signals are compared with threshold in order to make fault detection decisions. The simulation results show that the proposed method can be used to detect multiple sensors soft failures fast and accurately.

KEYWORDS

soft-failure residual Kalman filter multiple-failure-hypothesis based testing fault detection and isolation

1. INTRODUCTION

Aircraft engine control system sensors are less reliable links in the event of failure will lead to control system failure, if timely and effective fault detection and identification, emergency measures can be taken to effectively prevent the engine control system performance degradation or even damage[1]. Practice shows that the sensor zero drift of soft failures, especially failures, because it changes slowly so difficult to detect. Therefore, accurate, timely and isolate sensor fault detection and identification can be seen important engineering significance. Great efforts have been done for improving the reliability of the Full-Authority Digital Electronic Control (FADEC) system[2],[3], especially engine control sensor. Engine sensor is the necessary components of the engine control system. Therefore, more and more work must do for improving sensors reliability[4]. Soft failures are small bias errors or drift errors that accumulate relatively slowly with time in the sensed values. Soft failures are generally due to component aging and other causes zero drift. When soft fault occurs, the sensor output is no longer reflect the true value that is difficult to ensure system performance. Therefore soft failure must be detected and isolation. Sensors in the event of a soft failure, the output of the sensor value is small deviation from the normal work, rather than the hard failure so obvious, and the change is slow that can be mistaken for the result of noise easily. So the hard failure detection algorithm to detect soft failure is not suitable.

Fault diagnosis is the key to generate residual information. The Kalman filter is the most effective way to produce a basic residual information. Some scholars have used the extended Kalman filter to solute the fault diagnosis, but due to model linearization error will seriously

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affect the precision, and even lead to filter divergence[5][6]. Some other scholars have proposed a kind of Unscented Kalman filter, which does not require linearization of nonlinear system that will lead to the larger estimation error[7][8]. Because filter model mismatch as the robustness of very poor, a weighted sum of squares residual method for fault detection. To solve the above problem, the paper describes an advanced sensor soft failure detection, isolation, and accommodation algorithm based the the maximum likelihood method. The implementation was achieved using parallel processing and a high level programming language. The algorithm is described and the hardware and software considerations necessary to achieve the real-time implementation are discussed along with some of the practical experience gained during the process.

2. ALGORITHM DESCRIPTION

2.1. Soft-failure Diagnosis Algorithm

The soft-failure detection and isolation logic consists of multiple-hypothesis-based testing. Each hypothesis is implemented by using a Kalman filter. Hard-failure diagnosis algorithm consists of only one Kalman filter. The soft detection and isolation logic structure consists of five hypothesis filters, one for normal mode operation(H_0)and four for the failure modes (one for each engine output sensor) that can be seen from Figure 1.

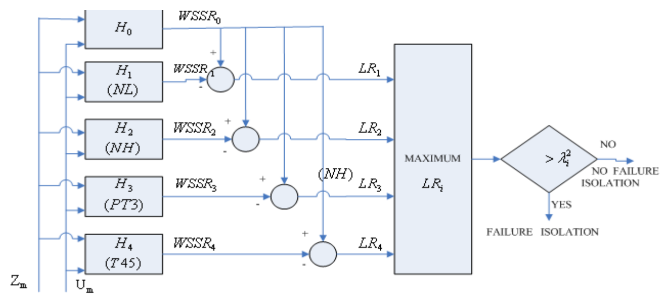

Figure 1. Soft failure isolation logic

The algorithm inputs are the measured engine inputs U_m and the measured engine outputs Z_m. These variables are defined as follows:

Controlled engine inputs U_m

WF -------------main combustor fuel flow

AJ ---------------exhaust nozzle area

Sensed engine outputs Z_m

NL --------------fan speed

NH --------------compressor speed

$PT3$ -------------combustor pressure

$T45$ --------------fan turbine inlet tempreture

For example, the first hypothesis filter H_1 uses all of the sensed engine outputs except the first, NL. The second uses all of the sensed outputs except the second, NH , and so on. Each hypothesis filter generates a statistic or likelihood called the weighted sum of squared residuals (WSSR) statistic, which is defined below. This statistic is subtracted from the normal-mode WSSR filter statistic. The maximum of the results is compared with the soft-failure detection and isolation threshold. If the threshold is exceeded, a failure is declared. If a sensor failure has occurred in NL , for example, all of the hypothesis filters except H_1 will be corrupted by the faulty information. Thus each of the corresponding likelihoods will be small except for H_1. Thus the H_1 likelihood will be the maximum, and it will be compared with the threshold to detect the failure.

Each hypothesis filter is identical in structure to the accommodation filter except for the switch matrix. Each hypothesis filter generates a unique residual vector γ_i.

Assuming Gaussian sensor noise, each sample of γ_i has a certain likelihood or probability.

$$L_i = p_i(\gamma_i) = ke^{-WSSR_i}$$

Where k is a constant and $WSSR_i = \gamma_i^T \Sigma^{-1} \gamma_i$ with $\Sigma = diag(\sigma_i^2)$ [9]. The σ_i are the adjusted standard deviations defined in standard normal distribution. These standard deviations values scale the residuals to unitless quantities that can be summed in the WSSR statistic. The WSSR statistic is smoothed to remove gross noise effects by a first-order lag with a time constant of 0.02sec. When the log of the ratio of likelihoods is taken.

$$LR_i = \log(L_i / L_0) = WSSR_0 - WSSR_i$$

If the maximum log likelihood ratio exceeds the threshold, a failure is detected and isolated and accommodation occurs. Three steps are taken for accommodation. First, all five of the filter (one accommodation and four hypothesis) switching matrices are reconfigured to account for the detected failure mode, Second, the states and estimates of all five filters are updated to the correct values of the hypothesis filter that corresponds to the failed sensor. Third, the interface switch matrix is reconfigured.

2.2. Accommadation Filter

From Figure 1, the conclusion can be seen that the sensor soft failure diagnosis algorithm is strongly dependent on accommodate filter, Kalman filter. Kalman filter is very powerful in estimations of past, present and even future states. It is greatly vital of the method designed in the paper. Kalman filter can generates residual vector γ, detect and isolate fault sensors used γ, finally can accommodate sensed outputs Z_m using the optimal estimates $\hat{Z}$ of fault sensors. Performance of the accommodation filter and the detection and isolation logic is strongly dependent on a model of the engine. The model used has a linear dispersed-space structure as follows.

$$\begin{cases} X(t+1) = \Phi X(t) + BU(t) + \Gamma W(t) \\ Z(t) = HX(t) + V(t) \end{cases} \tag{1}$$

The Kalman filter means that the model of noise can be obtained through statistical characteristic before filtering. A t the same time, the mean value and variance of noise matrix not only can be gotten, but also the gain matrix and error variance can be obtained. Considering of system noise W_k and observation noise V_k , engine control system can dispersed as equation (1).

$$X(k+1) = \Phi(k+1,k)X(k) + G(k+1,k)U(k) + \Gamma(k)W(k) \tag{2}$$

Supposed：

$$E[W_k]=0, Cov[W_k,W_j]=E[W_kW_j^T]=Q_k\delta_{kj} \tag{3}$$

$$E[V_k]=0, Cov[V_k,V_j]=E[V_kV_j^T]=R_k\delta_{kj} \tag{4}$$

$$Cov[W_k,V_j]=E[W_kV_j^T]=0 \tag{5}$$

From equation (3), (4), (5) supposed, kalman filter equations can be deduced.

$$\hat{X}_{k+1}=\hat{X}_{k+1/k}+K_kZ_{k+1/k}=\hat{X}_{k+1/k}+K_k(Z_k-H_k\hat{X}_{k+1/k})$$

$$\tilde{Z}_{k+1/k}=Z_{k+1}-\hat{Z}_{k+1/k}=H_{k+1}X_{k+1}+V_{k+1}-H_k\hat{X}_{k+1/k}=H_{k+1}\tilde{X}_{k+1/k}+V_{k+1}$$

$$\hat{X}_{k+1/k}=\Phi_{k+1,k}\hat{X}_k+G_{k+1,k}U_k$$

$$K_{k+1}=P_{k+1/k}H^T{}_{k+1}(H_{k+1}P_{k+1/k}H^T{}_{k+1}+R_{k+1})^{-1}$$

$$P_{k+1/k}=\Phi_{k+1,k}P_k\Phi^T{}_{k+1/k}+\Gamma_kQ_k\Gamma_k^T$$

$$(I-K_{k+1}H_{k+1})P_{k+1/k}(I-K_{k+1}H_{k+1})^T+K_{k+1}R_{k+1}K^T{}_{k+1}$$

Beginning term:

$$\hat{X}_0=E(X_0)=X(0)$$

$$P_0=E\{(X_0-\hat{X}_0)(X_0-\hat{X}_0)^T\}=E\{(X_0-X(0))(X_0-X(0))^T\}=P(0)$$

In the Kalman filter equations, the matrix Φ, G, H are typical state space system matrices where X is the 4×1 vector of estimates of the engine's state variables and γ is the 5×1 vector of residuals. The matrix K is Kalman filter gain matrix. All the system matrices as well as the Kalman gain matrix are scheduled as a function of operating point to model variations in engine dynamics. Almost all of the matrices' elements are nonzero, thus, almost all the elements must be multiplied through the filter equations.

2.3. Soft--failure Threshold

Since the $WSSR$ statistic the sum of Gaussian variables squared, it has a chi-squared distribution. Residual γ obey Gaussian distribution. The soft-failure detection and isolation threshold is determined by standard statistical analysis of this distribution to set the confidence level of false alarms and missed detections. When $LR_i \geq \lambda_i$ established, it can be said that no sensors soft-failure happened. On the contrary, sensor soft-failure happened.

3. MULTIPLE SENSORS HAPPENED SOFT-FAILURE EXPERIMENTS

Engine simulation is used to predict the engine response to the induced failures on ground and the proposed flight conditions. Each sample time is 0.02sec. For example, fan speed NL and combustor pressure $PT3$ have been happened soft-failure at the same time. The first hypothesis filter H_1 uses all of the sensed engine outputs except the first, NL. The second uses all of the sensed outputs except the second, NH , and so on. Now, multiple sensors soft-failure have occurred in NL and $PT3$. All of the hypothesis filters except hypothesis filter H_1 and hypothesis filter H_3 will be corrupted by the faulty information. Thus each of the corresponding likelihoods will be small except for hypothesis filter H_1 and hypothesis filter H_3. Thus the hypothesis filter H_1 and hypothesis filter H_3 likelihood will be the maximum, and they will be compared with the threshold to detect the failure. The output of all sensors curves include happening soft-failure sensors can be seen from Figure 2 to Figure 5.The output of each hypothesis filter can be seen from Figure 6 to Figure 9.

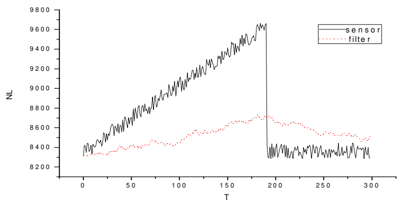

Figure 2. The Filter Curve of Fan Speed

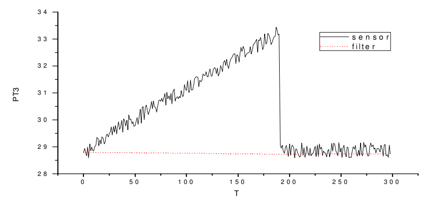

Figure 3. The Filter Curve of combustor pressure

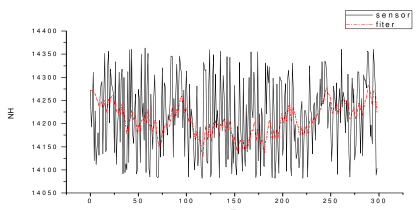

Figure 4. The Filter Curve of compressor speed

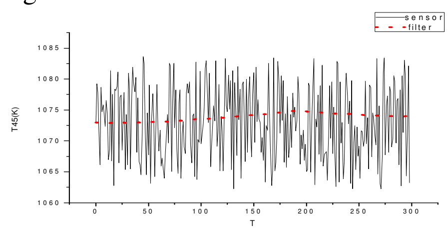

Figure 5. The Filter Curve of fan tempreture

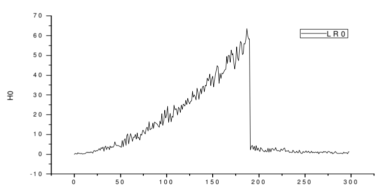

Figure 6. The Curve of Hypothesis H0

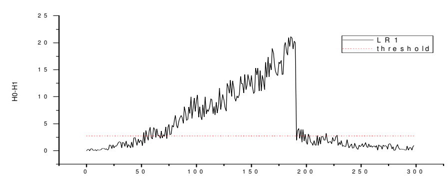

Figure 7. The Minus Curve of H0 and H1

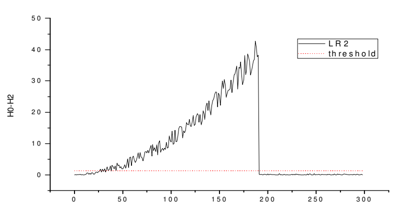

Figure 7. The Minus Curve of H0 and H2

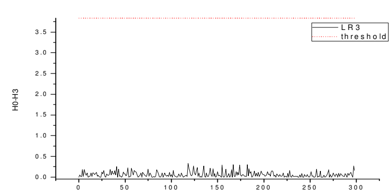

Figure 8. The Minus Curve of H0 and H3

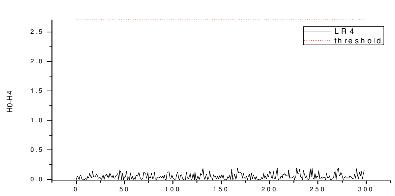

Figure 9 .The Minus Curve of H4

The drift signal of 8% slope has been given for sensor of fan speed NL on 10th sample while 180th sample on the sensor of combustor pressure $PT3$. The residuals of hypothesis Kalman filter can be seen to exceed threshold of sensor of fan speed NL and combustor pressure $PT3$, alarm yell will be given, then the faults can be isolated respectively. From the simulation curves, the conclusion can be drawn that the algorithm designed in the paper can detect and isolate fault immediately, then accommodate sensed signal in time and in effect.

4. CONCLUSION

In this paper, the multiple sensor soft-failure diagnosis algorithm based on hypothesis testing is successfully for improving sensors reliability. From the simulation curves, conclusion can be drawn that multiple sensor soft-failure not only can be detected and isolated timely, but also accommodated the sensed signal by the optional estimates reliably used Kalman filter. The multiple sensor soft-failure diagnosis algorithm based on hypothesis filter has low false alarm rate and detects faults quickly, which can be successfully applied to engineering fields.

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