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Aeroengine Multi-Fault Diagnosis Based on Hierarchical Multi-mode Filtering

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ABSTRACT

Carry out model-based online fault diagnosis for aero-engine sensors, actuators and components. Traditional methods use a set of filters to estimate the current state of the engine, and then process the estimated residuals of each filter to obtain the diagnosis result. For single engine faults, this method has a good diagnostic effect, but when double engine faults are considered, the amount of calculation will greatly increase, and the accuracy and real-time performance of fault diagnosis cannot meet the requirements. In this regard, this paper proposes a fault diagnosis algorithm based on hierarchical multi-mode filtering, which combines the advantages of hybrid Kalman filtering and multi-mode adaptive filtering algorithms, and uses a hierarchical diagnosis architecture for fault diagnosis. First, establish a hybrid Kalman filter bank of sensors, actuators and components, and then layer them. The first layer diagnoses the normal state of the engine and single fault conditions, and the second layer diagnoses the double fault conditions on the basis of the first layer fault diagnosis, and finally outputs the diagnosis results comprehensively. This method can meet the real-time and accuracy requirements for single and double fault diagnosis of the engine.

Keywords: Multi-Fault diagnosis; Hybrid kalman filter; hierarchical multi-mode filtering

INTRODUCTION

In recent years, there have been many researches on the application of multi-mode adaptive filtering methods for fault diagnosis[1-5]. The standard multi-mode adaptive filtering algorithm is composed of a set of parallel Kalman filter banks, each filter corresponds to a different model, including normal working model and failure model. The conditional probability of each model is calculated by hypothesis testing, which can determine the state of the system (whether there is a failure and the type of failure). But when it is used to detect double or multiple faults in the system, this algorithm needs to establish all possible fault models, and each model must correspond to a Kalman filter, which requires a large number of filter parallel operations and increases the diagnosis time. In order to simplify the algorithm, this paper proposes a hierarchical multi-model filtering technology for multiple fault diagnosis of complex systems. After a single fault is determined to occur, a set of new filters based on the previous single fault can be activated to detect the second fault of the system, which reduces the number of filters in parallel operation, and therefore can effectively reduce the calculation time and the amount of calculation.

MULTI-MODE ADAPTIVE ALGORITHM

The principle of the multi-mode adaptive filter is shown in Figure 1. A corresponding Kalman filter is designed for each fault, thereby obtaining a set of filter banks containing N parallel independent filters. The filter bank takes the control input vector $u(k)$ and the observation vector $y(k)$ as inputs, and obtains the corresponding residual $r_i(k)$ and the state estimation value $\hat{x}_i(k)$ of each model at the time after filtering. Since the model of each filter is different, the residuals and state estimation values obtained are also different. The size of the residuals can reflect the degree of conformity between each filter model and the actual state of the system. Then, the conditional probability $p_i(k)$ of each filter can be calculated through the hypothesis testing algorithm, and finally the estimated value of each model state is calculated by probability weighting to obtain the comprehensive state estimate of the system.

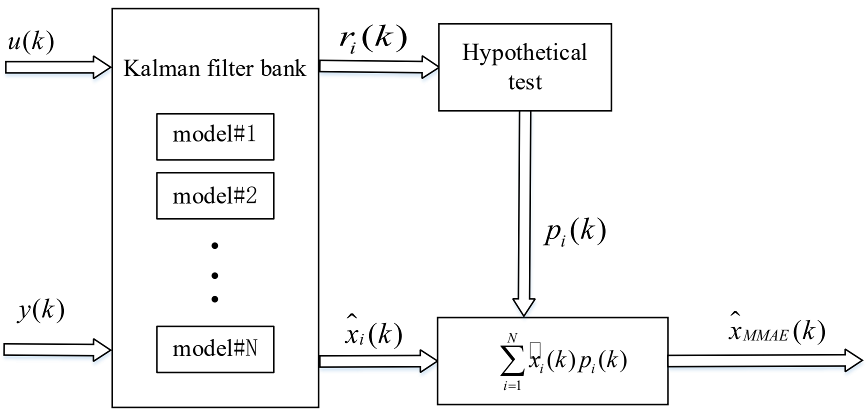


Figure 1 Principle of multi-mode adaptive filter

Kalman Filter

(1) State prediction

One-step prediction equation

$$\hat{x}(k \mid k-1) = A\hat{x}(k-1) + Bu(k-1) \tag{1}$$

One-step prediction equation of mean square error

$$P(k \mid k-1) = AP(k-1)A^T + Q(k-1) \tag{2}$$

(2) State correction

Filter gain equation (weight)

$$K(k) = P(k \mid k-1)C^T + \left[CP(k \mid k-1)C^T + R(k)\right]^{-1} \tag{3}$$

Filtering estimation equation (the optimal value at time k)

$$\hat{y}(k \mid k-1) = C\hat{x}(k \mid k-1) + Du(k) \tag{4}$$

$$\hat{x}(k) = \hat{x}(k \mid k-1) + K(k)\left[y(k) - \hat{y}(k \mid k-1)\right] \tag{5}$$

Filtering mean square error update matrix (optimal mean square error at time k)

$$P(k) = \left[I - K(k)C\right]P(k \mid k-1) \tag{6}$$

In the iterative process of the Kalman filter algorithm, after the system parameters are determined, generally only the initial state value $\hat{x}(0)$ and the initial value of the mean square error $P(0)$ need to be given, and the five core equations of the Kalman filter can be used for iterative calculations, so the calculation process is very convenient to use a computer for programming and has a strong practicability.

AEROENGINE MULTI-FAULT DIAGNOSIS BASED ON HIERARCHICAL MULTI-MODE FILTERING

System Model

The sensor fault model can be expressed as:

$$y_{out}(t) = y(t) + Tf_s(t) \tag{7}$$

Among them, $y_{out}(t)$ represents the actual output of the sensor; $y(t)$ represents the normal state output of the sensor; $T \in R^{m \times m}$ represents the fault distribution matrix of the sensor; $f_s(t) \in R^m$ represents the fault function of the sensor.

The failure model of gas part components can be established as follows:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Lh(t) \\ y(t) = Cx(t) + Du(t) + Mh(t) \end{cases} \tag{8}$$

Among them, A, B, C, D is the state space matrix of the system; L, M are the system degradation matrices. $h = [\Delta f_{af}, \Delta e_{af}, \Delta f_{ac}, \Delta e_{ac}, \Delta f_{th}, \Delta e_{th}, \Delta f_{tl}, \Delta e_{tl}, \Delta e_b]^T$ is the performance degradation parameter of the gas part component.

The actuator failure is generally expressed as:

$$u_{out}(t) = u(t) + Gf_u(t) \tag{9}$$

where, $G \in R^{n \times q}$ represents the fault distribution matrix of the actuator, and $f_u(t) \in R^q$ represents the fault function of the actuator. When the actuator is normal, the output is denoted as u , and the actual output of the actuator is denoted as u_{out} . In actual work, due to physical limitations, the control capability of the actuator cannot be adjusted infinitely. The output of the actuator is generally within a certain range (with upper and lower limits), which is:

$$u_{min} \le u_{out}(t) \le u_{max} \tag{10}$$

Hybrid Kalman Filter

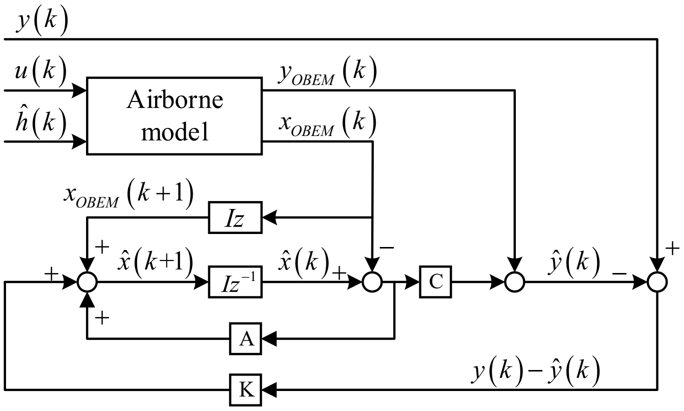


Figure 2 Hybrid Kalman filter structure

The structure of the hybrid Kalman filter is shown in Figure 2, and its calculation formula is as follows:

$$\hat{x}(k+1) - x_{OBEM}(k+1) = A\left[\hat{x}(k) - x_{OBEM}(k)\right] + K\left[y(k) - \hat{y}(k)\right] \tag{11}$$

$$\hat{y}(k) = C\left[\hat{x}(k) - x_{OBEM}(k)\right] + y_{OBEM}(k) \tag{12}$$

In the formula, x_{OBEM} and y_{OBEM} are the state variables and output of the airborne model, respectively. After the engine's health degradation occurs, there is no need to change the matrix parameter (A, C, K) of the hybrid Kalman filter, only the degradation parameters of the airborne model in the structure need to be updated to maintain the effectiveness of the algorithm.

Aeroengine Multi-Fault Diagnosis Based on Hierarchical Multi-mode Filtering

In order to solve the problem that a large number of filters need to be operated in parallel in the above algorithm, this paper uses a fault diagnosis algorithm based on layered multi-mode filtering to deal with single fault and multiple faults in layers. The architecture of the fault diagnosis algorithm is shown in Figure 3.

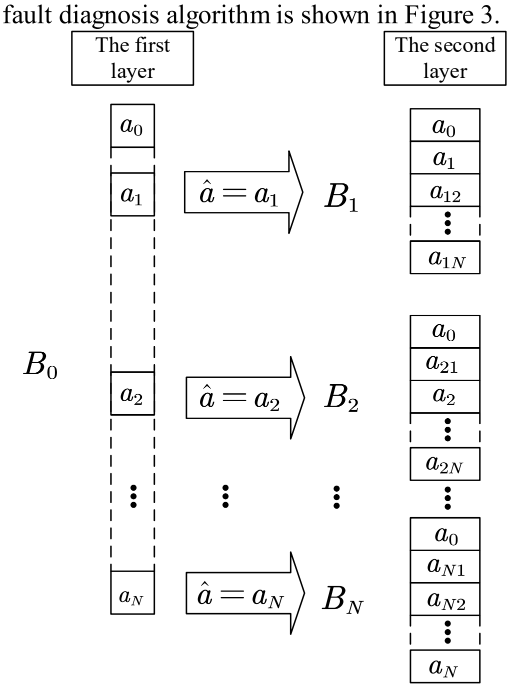


Figure 3 Diagnosis algorithm architecture based on hierarchical multi-mode filtering

First, the model set A is divided into $N+1$ sub-model sets:

$$A = \{B_0, B_1, \ \ldots, B_N\} \tag{13}$$

The definition of each sub-model set is as follows:

$$
\begin{aligned}
B_0 &= \{a_0, a_1, a_2, \ \dots, a_N\} \\
B_1 &= \{a_0, a_1, a_{12}, \ \dots, a_{1N}\} \\
B_2 &= \{a_0, a_{21}, a_2, \ \dots, a_{2N}\} \\
&\vdots \\
B_N &= \{a_0, a_{N1}, a_{N2}, \ \dots, a_{N(N-1)}, a_N\}
\end{aligned} \tag{14}
$$

where, B_0 is the first layer of the fault diagnosis system, which contains the normal state model and the single fault model, $B_1 \sim B_N$ is the second layer of the fault diagnosis system, which contains all the double fault models, and each sub-model set B_i contains the normal state model a_0 , A single failure model a_i and a double failure model related to a_i. Through this design, it can be ensured that the system can still return to the normal mode after detecting a single fault, or maintain its single fault mode unchanged.

First, use the filter bank contained in the first layer sub-model set B_0 to perform online fault diagnosis on the engine. Since it contains a normal state model and a single fault model, determine whether the system fails and identify a single type of failure. Once a single fault is successfully identified, the filter bank contained in the second layer of the corresponding dual fault model will be activated. Based on the diagnosis results of the first layer of filter bank, the engine's double faults will be diagnosed. Although the filter bank of the second layer model contains N sets of filters from B_1 to B_N, it only needs to run one set of filters according to the results of the first fault diagnosis each time during the fault diagnosis process, that is, only $N+1$ filters are needed in parallel. Calculation can greatly reduce the amount of calculation. In addition, the filter bank of the second-level model contains filters in a normal state, so even if a false alarm occurs in the first-level diagnosis, the fault diagnosis result can return to the normal state.

When using hierarchical multi-mode filtering algorithm to diagnose aero-engine faults, in order to adapt to engine degradation and improve filtering accuracy, hybrid Kalman filter is used to replace general Kalman filter to estimate engine state. The structure of the fault diagnosis is shown in Figure 4, which is mainly composed of an aero engine, a two-layer hybrid Kalman filter bank and a fault probability calculation module.

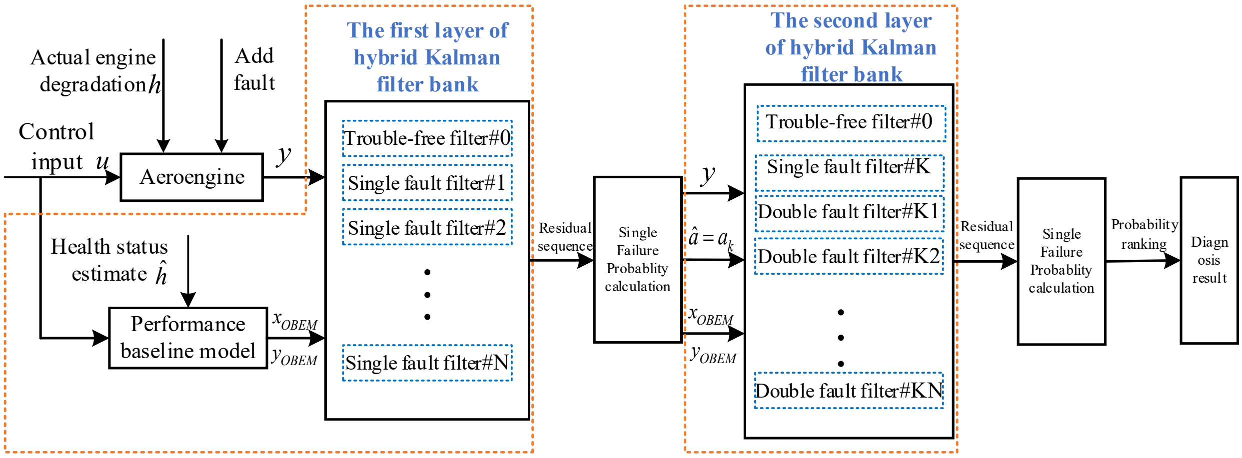


Figure 4 Structure diagram of fault diagnosis

(1)In the fault diagnosis algorithm, the airborne adaptive model is used to replace the real aero engine. By adding performance degradation parameters and different fault types to it, the performance degradation and failure occurrence of the real engine during service can be simulated.

(2) The filters contained in the two-layer hybrid Kalman filter bank correspond to the normal state of the engine and all fault models. All hybrid Kalman filters share the same performance baseline model, which receives the input signal u and periodically updates the health parameters $\hat{h}$, provide steady-state reference values x_{OBEM} and y_{OBEM} for the Kalman filter. The Kalman filter receives the steady-state reference value and the actual measurement parameters, performs online estimation of the current state of the engine, and obtains the output estimation value and the residual error sequence of the measurement value.

(3) The failure probability calculation module adopts the standard multiple hypothesis testing method, calculates the failure probability according to the residual sequence estimated by each filter, and sorts and outputs the failure probability.

The working process of the fault diagnosis algorithm is as follows: First, use the first-layer hybrid Kalman filter bank to estimate the current state of the engine, and obtain the residual sequence of the system output measurement value and the estimated value, and then use the hypothesis test sum the Gaussian probability density function calculates and ranks the probability of each fault model, and selects the single fault a_k with the highest occurrence probability as the basis of the second-level fault diagnosis. The second layer of the hybrid Kalman filter bank selects a fault-free filter, the single fault a_k filter and the single fault a_k combined with other faults are combined with the double fault filter to estimate the engine state and calculate the residual error. The double failure probability calculation method is the same as the single failure, and finally the probability is sorted and the failure diagnosis result is output.

Hypothesis Testing

The hypothesis testing algorithm can recursively calculate the conditional probability $p_i(k)$ that each fault parameter is "correct" based on the residual characteristics observed by the N filters and the probability $p_1(k-1),\ldots,p_N(k-1)$ at the previous moment:

$$p_i(k)=\frac{f_{y(k)|a,Y(k-1)}(y_k \mid a_i,Y_{k-1})\,p_i(k-1)}{\sum_{j=1}^{N} f_{y(k)|a,Y(k-1)}(y_k \mid a_j,Y_{k-1})\,p_j(k-1)} \tag{15}$$

where $f_{y(k)|a,Y(k-1)}(y_k \mid a_i,Y_{k-1})$ is the conditional probability density of the current observation vector $y(k)$, i.e.

$$f_{y(k)|a,Y(k-1)}(y_k \mid a_i,Y_{k-1})=\zeta_i(k)\,e^{-(1/2)r_i^T(k)S_i^{-1}(k)r_i(k)} \tag{16}$$

$$\zeta_i(k)=(1)\Big/\left((2\pi)^{n/2}\left|S_i(k)\right|^{1/2}\right) \tag{17}$$

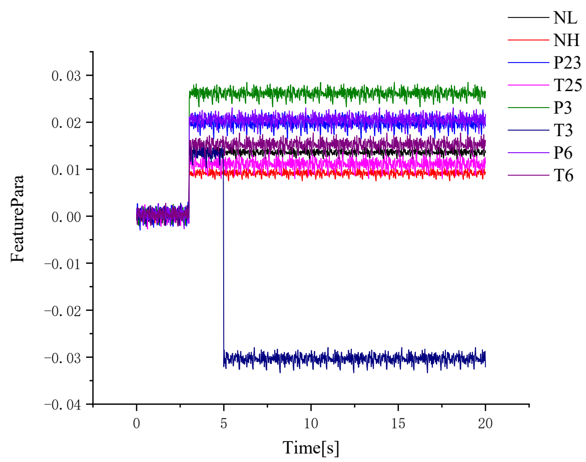
Where n is the dimension of the observation vector $y(k)$. $S_i(k)$ is the covariance, which is a constant Gaussian white noise sequence;

Finally, the comprehensive state estimate $\hat{x}_{MMAE}(k)$ calculated with $p_i(k)$ as the weight:

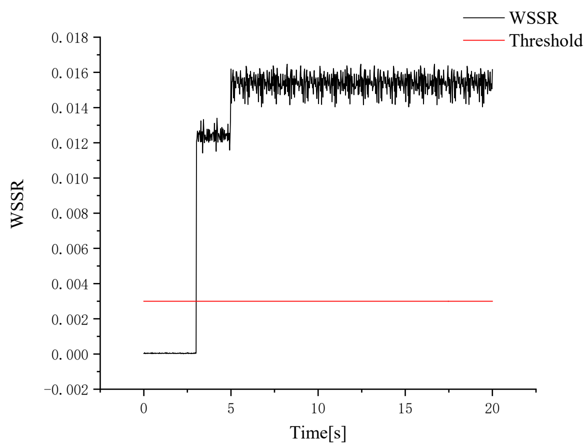
$$\hat{x}_{MMAE}(k)=\sum_{i=1}^{N}\hat{x}_i(k)\,p_i(k) \tag{18}$$

FAULT DIAGNOSIS SIMULATION

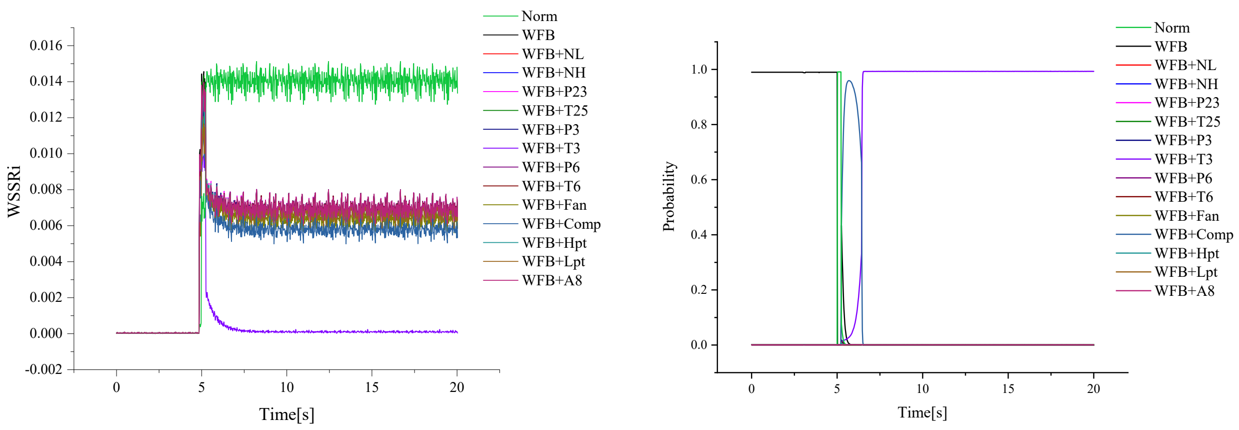
There are 16 types of combined faults of sensors and actuators. This paper takes $W_{fB}+T_3$ fault as an example to simulate and verify the designed fault diagnosis algorithm. In the 3s, a constant deviation fault is added to the fuel metering unit to increase the fuel flow by 5%. In the 5s, the T_3 sensor fault is simulated and a step fault with -5% deviations is set for it. The simulation result is shown in Figure 5. Figure (a) is the response curve of each Feature Para. It can be seen that due to the increase of fuel oil volume, the deviation of each sensor increases after 3s. After the 5s, the value of T_3 sensor is reduced by -5% deviation faults. Figure (b) is the characteristic parameter weighted sum of squares and the threshold response curve. It can be seen from the figure that $WSSR$ starts to exceed the threshold at 3s, indicating that the engine is malfunctioning. At 5s, the value of $WSSR$ continues to rise, indicating that double malfunction. Figure (c) is the residual weighted square sum curve of each filter. After the single filter bank initially diagnoses the W_{fB} fault, the dual filter bank starts to start around 5s. It can be seen that the $W_{fB}+T_3$ curve has the largest decrease and remains at near zero value. Figure (d) is the conditional probability curve of each filter. It can be seen that as the probabilities continue to accumulate, the probability of occurrence of $W_{fB}+T_3$ double fault at 7.23s will eventually approach 1, and the conditional probability of other filters will approach 0. It indicates that the fuel metering unit and sensor T_3 are malfunctioning. In summary, the designed fault diagnosis algorithm can effectively detect and isolate the double faults of sensors and actuators.



(a) Response of each characteristic parameter



(b) Comparison of weighted sum of squares of feature parameters and threshold



（c）Weighted sum of squares of the Residuals of each filter

（d）Conditional probability of each filter

Figure 5 Simulation results of dual faults of m sensor and fuel metering unit

CONCLUSIONS

Aiming at the problem of double fault diagnosis, this paper proposes a fault diagnosis algorithm based on hierarchical multi-mode filtering, which combines the advantages of hybrid Kalman filter and multi-mode adaptive filtering, and uses a hierarchical diagnosis architecture to diagnose faults. This method can greatly reduce the amount of calculation in fault diagnosis, can effectively adapt to engine performance degradation, improve filtering accuracy, and solve the key issues of threshold selection and evaluation, making the decision-making process of fault detection more stable.

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