DETECTION AND ISOLATION OF CONTROL SURFACE EFFECTIVENESS LOSS IN AIRCRAFT BY USING FILTER BANK APPROACH

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Abstract

This paper addresses the fault detection and isolation (FDI) problem for control surface effectiveness loss (PEL) in self-repairing flight control systems. The proposed FDI algorithm can deal with the case when the control surface damage changes both control matrix B and system matrix A. It is proved that the algorithm is robust to modeling error and disturbance. The real time hardware in the loop simulation also shows that the algorithm possesses the aforementioned advantages.

1 Introduction

The self-repairing flight control systems have shown its significant importance on improving the reliability, maintainability, survivability and life cycle cost of aircraft flight control systems.[1]. The self-repairing flight control system actually is a kind of fault tolerant control systems that can be classified into two categories: passive fault tolerant and active fault tolerant. The former uses robust control techniques to ensure that the closed loop system remain insensitive to certain faults [2], and the later reconfigures or restructures the control system based on either a priori knowledge of expected fault types or the information provided by a fault detection and isolation mechanism [3,4]. This paper will study the self-repairing flight control systems with active fault tolerant strategy based on fault detection and isolation .

FDI is an essential ingredient property of the self-repairing flight control system. The tasks of FDI is to identify the fault type and its severity with prompt response, accurate diagnosis and robust to modeling error, disturbance and measurement noise. Basically, we have two kinds of FDI approaches, model based approaches and knowledge based approaches. Model based FDI approaches [5,6] can be defined as the detection, isolation and characterization of faults components of a system from the comparison of the system's available measurements with a priori information represented by the system's mathematical model. Knowledge based FDI approaches [7,8] use the artificial intelligent techniques to emulate the human thought process to find a system malfunction by a computer based on a knowledge base, rule base and inference engine. The combination of these two approaches also attracts interests in this research field.

The essential requirement for a model based FDI algorithm to be prompt, accurate and robust is to generate a residual that is simple to produce, sensitive to faults and insensitive to modeling error, disturbances and noise. There are several ways to generate the residual for a system with faults. The state observer approach [9,10] has become a popular approach due to the flexibility of design, the relative ease in achieving robustness in fault detection and isolation, the algorithm and software simplicity, and speed of response in detecting and isolating faults.

This paper proposes a new FDI algorithm that uses a specially designed bank of filters to detect and isolate the percent effectiveness loss of aircraft control surfaces which changes the control matrix and the system matrix. It is proved that the proposed algorithm is robust to modeling error and disturbance.

2 Problem formulation

Consider a normal aircraft described by the following model:

$$\dot{x} = Ax + Bu \qquad y = Cx \tag{2.1}$$

where, $x \in R^n$, $u \in R^p$, $y \in R^l$, x, u, and y are the aircraft state vector, control vector and output vector respectively. A damaged aircraft with effectiveness losses at certain control surfaces could be represented by the model of the form:

$$\dot{x} = (A + k_i \Delta A_{fi})x + (B + k_i \Delta B_{fi})u \qquad y = Cx \tag{2.2}$$

where, k_i is the percent effectiveness loss of ith control surface, $\Delta A_{fi}, \Delta B_{fi}$ denote the changes caused by effectiveness loss of ith control surface. $\Delta A_{fi}, \Delta B_{fi}$ are defined as

$$\Delta A_{fi} = A_{fi} - A \qquad \Delta B_{fi} = B_{fi} - B \tag{2.3}$$

where, A_{fi}, B_{fi} denote the corresponding system matrix and control matrix when the ith control surface has 100 % effectiveness loss. f_i denotes the failure mode which could be the failure on one of the ailerons, elevators , canards and rudders. In this paper, only brutal and large faults and single failure mode are considered. It should be pointed out that in most FDI algorithms ΔA_{fi} is not considered. But in reality the wind tunnel data shows that the damage at a control surface not only changes the control matrix B but also changes the system matrix A. Those FDI algorithms which don't take ΔA_{fi} in consideration can detect the fault but can not diagnose the fault with required precision. When the modeling error and disturbance are considered, dynamics of the damaged aircraft is defined as:

$$\begin{aligned} \dot{x} &= (A + \Delta A + k_i \Delta A_{fi})x + \\ &\quad (B + \Delta B + k_i \Delta B_{fi})u + d \\ y &= Cx \end{aligned} \tag{2.4}$$

where, $\Delta A, \Delta B$ denote the modeling error and d denotes a disturbance. For m control surfaces, design m+1 filters as follows:

$$F_0 : \dot{\hat{x}} = A\hat{x} + Bu + LC(x - \hat{x}) \qquad \hat{y} = C\hat{x} \tag{2.5}$$

$$F_j : \dot{\hat{x}}_{fj} = A_{fj}\hat{x}_{fj} + B_{fj}u + L_{fj}C(x - \hat{x}_{fj}) \qquad \hat{y}_j = C\hat{x}_{fj} \qquad \forall j = 1,2,\ldots m \tag{2.6}$$

It is noticed that filter F_0 is based on the model of normal aircraft and filter F_j is based on the model of f_j failure mode with 100% effectiveness loss. It should be pointed out that the amount of the filters can be reduced by using the knowledge of symmetrical structure of aircraft. Assume that (A, C) and (A_{fi} C), $\forall i = 1,2,\ldots m$ are completely observable pairs. Then the filters can be designed by using eigenvalue assignment method such that:

$$A - LC = A_{fi} - L_{fi}C = -\Lambda, \qquad \forall i = 1,2,\ldots m$$

where, $\Lambda = diag\{\lambda_i\}$, $\lambda_i >> 0$, $\forall i = 1,2,\ldots n$, λ_i is chosen large enough to ensure the fast convergence of the estimation errors.

Define the residuals of the filters as:

$$\xi_0 = x - \hat{x}$$

$$\xi_i = x - \hat{x}_{fi} \qquad i = 1,2,\ldots m$$

Then, a set of residual equations can be driven from equations (2.4), (2.5) and (2.6).

$$
\begin{aligned}
\dot{\xi}_o &= -\Lambda\xi_o + (\Delta A + k_i \Delta A_{fi})x + \\
&\quad (\Delta B + k_i \Delta B_{fi})u + d \\
\eta_o &= C\xi_o
\end{aligned}
\tag{2.7}
$$

$$
\begin{aligned}
\dot{\xi}_j &= -\Lambda\xi_j + (\Delta A + A - A_{fj} + k_i \Delta A_{fi})x + \\
&\quad (\Delta B + B - B_{fj} + k_i \Delta B_{fi})u + d \\
\eta_j &= C\xi_j \\
\forall i &= 1,2,\dots m, \qquad \forall j = 1,2,\dots m
\end{aligned}
\tag{2.8}
$$

where, η_o and η_j are the outputs of the residuals generators.

In order to simplify the proofs, an integral operator is defined as

$$
I_0^t[f(x,u,\tau)] = \int_0^t e^{-\Lambda(t-\tau)} f(x,u,\tau)\,d\tau
$$

Obviously, the integral operator has the following properties:

- $I_0^t(f_1 + f_2 + \dots + f_m) = I_0^t(f_1) + I_0^t(f_2) + \dots + I_0^t(f_m)$
- $I_0^t(kf) = kI_0^t(f), \qquad \forall \; k = const.$
- $I_0^t(f\ ) = I_0^{t_1}(f\ ) + I_{t_1}^t(f\ )$

3 Main result

Detection and isolation are different in their nature and requirements. Detection only needs to answer whether there is a fault occurring in the aircraft with lower false alarm rate and lower missed fault detection rate, but isolation should answer what, where and how is the fault with fast and accurate identification. In order to optimally use the system resource, to increase the precision of detection and isolation, proposed FDI algorithm separates detection and isolation operations and to provide different residuals, algorithms and thresholds for detection and isolation.

3.1 Detection algorithm

Definition 3.1: Define differential residual at fault occurring time t_f as

$$
\Delta\dot{\eta}_o(t_f) = \dot{\eta}_o(t_f^+) - \dot{\eta}_o(t_f^-)
$$

Theorem 3.2: Consider the damaged aircraft (2.4), filter (2.5) and residual equation (2.7), the differential residual $\Delta\dot{\eta}_o$ is not related to modeling error and disturbance, but only related to the fault.

Proof: Define residual systems ξ_o^- and ξ_o^+ as follows:

System ξ_o^-:

$$
\begin{cases}
\dot{\xi}_o^- = -\Lambda\xi_o^- + \Delta Ax + \Delta Bu + d & \forall t \le t_f^- \\
\dot{\xi}_o^- = -\Lambda\xi_o^- + \Delta Ax + \Delta Bu + d \,\Big|_{t=t_f} & \forall t \ge t_f^+
\end{cases}
$$

System ξ_o^+:

$$
\begin{cases}
\dot{\xi}_o^+ = -\Lambda\xi_o^+ + \Delta Ax + \Delta Bu + d & \forall t \le t_f^- \\
\dot{\xi}_o^+ = -\Lambda\xi_o^+ + (\Delta A + k_i \Delta A_{fi})x + \\
\quad (\Delta B + k_i \Delta B_{fi})u + d & \forall t \ge t_f^+
\end{cases}
$$

Considering the continuity of modeling error, disturbance, aircraft states, aircraft controls and the residuals, we have :

$$
\begin{aligned}
\Delta\dot{\eta}_o(t_f) &= C(\dot{\xi}_o^+ - \dot{\xi}_o^-)\Big|_{t=t_f} \\
&= C(k_i \Delta A_{fi} x + k_i \Delta B_{fi} u)\Big|_{t=t_f}
\end{aligned}
$$

Therefore the detection algorithm is robust to modeling error and disturbance. In the application, the differential residual is replaced by the first order difference signal of the residuals. In the case of existing serious measurement noise, a certain filtering process is needed and the residual which is sensitive to control surface failures but not sensitive to noise should be chosen such as the residuals of pitch and roll rate signals.

3.2 Isolation algorithm

Theorem 3.3 Consider the damaged aircraft (2.2) and residual equation (2.7) and equation (2.8) without modeling error and disturbance, if x and u are linearly independent then, for ith control surface failure, iff j=i the following equation holds:

$$(1-k_i)\bar{\eta}_o - k_i\bar{\eta}_i = 0, \qquad \forall i = 1,2,\ldots m$$

where, $\bar{\eta}_o$ and $\bar{\eta}_i$ are the steady values of the residual outputs.

Proof:

1), j=i, by equation (2.7) and equation (2.8) without modeling error and disturbance, we have:

$$\eta_o(t) = Ce^{-\Lambda t}\xi_o(0) + CI_o^t(k_i\Delta A_{fi}x + k_i\Delta B_{fi}u)$$
$$\eta_i(t) = Ce^{-\Lambda t}\xi_i(0) + CI_o^t[(k_i-1)\Delta A_{fi}x + (k_i-1)\Delta B_{fi}u]$$

For steady values of $\eta_o(t)$ and $\eta_i(t)$, we have:

$$(1-k_i)\bar{\eta}_o - k_i\bar{\eta}_i = (1-k_i)k_iCI_o^t(\Delta A_{fi}x + \Delta B_{fi}u) + k_i(k_i-1)CI_o^t(\Delta A_{fi}x + \Delta B_{fi}u) = 0$$

2), $j \neq i$,

$$(1-k_i)\bar{\eta}_o - k_i\bar{\eta}_j = k_iCI_o^t[(\Delta A_{fi} - \Delta A_{fj})x + (\Delta B_{fi} - \Delta B_{fj})u] \neq 0$$

since, $\Delta A_{fi} - \Delta A_{fj} \neq 0$, $\Delta B_{fi} - \Delta B_{fj} \neq 0$, $k_i \neq 0$, and x and u are linearly independent.

Remark 3.4 According to theorem 3.3, we can drive the percent effectiveness loss estimation equation as follows:

For j=i, we have:

$$k_i = \frac{\bar{\eta}_{os}}{\bar{\eta}_{os} - \bar{\eta}_{is}}, \quad \forall s = 1,2,\ldots n, \forall i = 1,2,\ldots m$$

The control surface percent effectiveness loss calculated by using different elements of the vectors $\bar{\eta}_o$ and $\bar{\eta}_i$ are equal and constant.

Let $t_1 = t_f + \Delta t$, and Δt is carefully chosen such that within Δt, $Ce^{-\Lambda t}\xi_o(0)$ and $Ce^{-\Lambda t}\xi_i(0)$ die away, but the modeling error and disturbance remain unchanged. This is feasible since Λ is properly designed and the modeling error and disturbance vary slower comparing to brutal fault and the dynamics of filters. Usually Δ t is chosen as 7-10 sampling periods to prevent from the false alarm and incorrect fault identification.

Theorem 3.5 Consider the damaged aircraft (2.4), and the residual equations (2.7) and (2.8), the control surface percent effectiveness loss estimation equation:

$$k_i = \frac{\Delta\bar{\eta}_{os}}{\bar{\eta}_{os} - \bar{\eta}_{is}}, \quad \forall s = 1,2,\ldots n, \forall i = 1,2,\ldots m$$

is robust to modeling error and disturbance, , where, $\Delta\bar{\eta}_o$ is the steady state of $\Delta\eta_o$ with

$$\Delta\eta_o = \eta_o^+ - \eta_o^- = C\left(\int_0^{t_1} \dot{\xi}_o^+ d\tau - \int_0^{t_1} \dot{\xi}_o^- d\tau\right)$$

Proof:

$$\bar{\eta}_o - \bar{\eta}_i = CI_o^{t_1}[(\Delta A + k_i\Delta A_{fi})x + (\Delta B + k_i\Delta B_{fi})u + d] - CI_o^{t_1}\{[\Delta A + (k_i-1)\Delta A_{fi}]x + [\Delta B + (k_i-1)\Delta B_{fi}]u + d\} = CI_o^{t_1}(\Delta A_{fi}x + \Delta B_{fi}u)$$

and

$$\bar{\eta}_o^- = CI^{t_1}_o(\dot{\bar{\xi}}_o^-)$$

$$\bar{\eta}_o^+ = CI^{t_1}_o(\dot{\bar{\xi}}_o^+)$$

$$\Delta\bar{\eta}_o = \bar{\eta}_o^+ - \bar{\eta}_o^- = k_i CI^{t_1}_o(\Delta A_{fi} x + \Delta B_{fi} u)$$

Then it leads to

$$k_i(\bar{\eta}_o - \bar{\eta}_i) = \Delta\bar{\eta}_o$$

Since t_f can be accurately estimated by the detection algorithm, $\Delta\bar{\eta}_o$ can be calculated from the difference between the residual outputs before and after the failure.

4. Design and simulation

At a flight state of M=0.6 and H=3km, an aircraft is modeled as

$$\dot{x} = Ax + Bu$$
$$y = Cx$$

where, $x = [\alpha\ \omega_z\ \beta\ \omega_x\ \omega_y]^T$, α represents the angle of attack, ω_z represents the pitch rate, β represents the slide angle, ω_x represents the roll rate and ω_y represents the yaw rate. $u = [\delta_{zr}\ \delta_{zl}\ \delta_{xr}\ \delta_{xl}\ \delta_y]^T$, δ_{zr}, δ_{zl} are the changes in right and left elevator settings, δ_{xr}, δ_{xl} are the changes in right and left aileron settings and δ_y is the change in rudder setting. The measurement matrix C=I. According to the normal aircraft model, and 5 damaged aircraft models, (each model for 100% effectiveness loss of a particular control surface), 6 filters should be designed. By using the symmetrical knowledge of the aircraft, only 4 filters are actually needed. They are: F_0 is related to normal model, F_1, F_2, F_3 are related to the models of 100% effectiveness loss in right elevator, right aileron and rudder respectively. Filters are designed such that Λ is a diagonal matrix with the diagonal elements equal to 200.

The differential residual related to roll rate is used for fault detection and the residuals related to pitch rate and roll rate are used for fault diagnosis, because of their higher signal to noise ratio and higher sensitivity to failure.

The simulation is carried out in a real time hardware in the loop simulation environment. The simulation results are shown in figures 4.1--4.4.The simulation runs with 10% modeling error, 5% maximum pitch rate white noise, 50% effectiveness loss occurring at $t_f = 1$ sec. Fig. 4.1 shows that when a fault occurs the differential residual related to roll rate has a brutal change which initiates the detection logic. Fig. 4.2, shows that in F_1 the estimated k_1 by using pitch rate and roll rate related residuals are the same and equal to 50%. Fig. 4.3 and fig. 4.4 show that in F_2 and F_3 the estimated k_2 and k_3 by using pitch rate and roll rate related residuals are different and time varying. The simulation results verify that the right elevator damages with 50 % effectiveness loss.

5 Conclusions

This paper proposes a scheme for detection and isolation of control surface effectiveness loss in aircraft by using the filter bank approach. The individual filter is designed based on the pole assignment method, according to models of the normal aircraft and the damaged aircraft in different failure modes with 100% effectiveness loss. Based on the specially designed filter bank a fault detection and isolation algorithm are driven. This scheme can deal with the case when the fault changes both control matrix B and system matrix A. It is proved that the detection of the fault and the isolation of the fault location and the percent effectiveness loss are robust to modeling error and disturbance.

References

1 Eslinger R A & Chandler P R (1988), Self-repairing flight control system program overview, Proc. Of the IEEE National Aerospace and Electronics Conference, Dayton, OH, May, 504-511.

2. D D et al, (1989), Application of precomputed control Eterno J S et al, (1985), Design issues for fault-tolerant restructurable aircraft control, Proc. 24th IEEE CDC, Fort Lauderdale, 900-905.
3. Moerder laws in a reconfigurable aircraft flight control systems, J. Guidance, Dynamics & Control, 12,(3),May/June,325-333.
4. Gao Z & Antsaklis P J (1991), Stability of the pseudo-inverse method for reconfigurable control systems, Int. J Control, 53,(3),717-729.
5. Patton R J & Kangethe S M (1989),Robust fault diagnosis using eigenstructure assignment of observers, Fault diagnosis in dynamic systems: theory and application, Prentice Hall

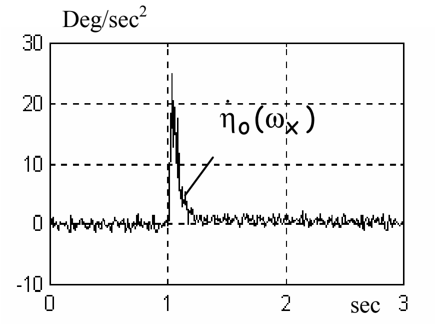

Fig. 4.1 fault detection

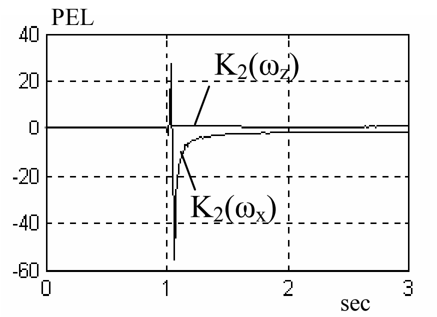

Fig.4.3 PEL estimated from F_2

6. Gertler J J (1988), Survey of model -based failure detection and isolation in complex planes, IEEE control systems magazine,8,(6),December, 3-11.
7. Handelman D A & Strengel R F (1989), Combining expert system and analytical redundancy concepts for fault tolerant flight control, J. Guidance, Control and Dynamics, 12,(1), 39-45.
8. Frank P M (1990), Fault diagnosis in dynamic system using analytical and knowledge based redundancy-a survey and some new results, Automatica, 26,(3),459-474.
9. Frank P M (1991), Enhancement of robustness in observer-based fault detection, Proc. Of IFAC symposium SAFEPROCESS'91, Baden-Baden, Sept. 10-13,459-474.
10. Frank P M (1993), Advances in observer-based fault diagnosis, Proc. Of the conference TOOLDIAG'93' Toulouse, April

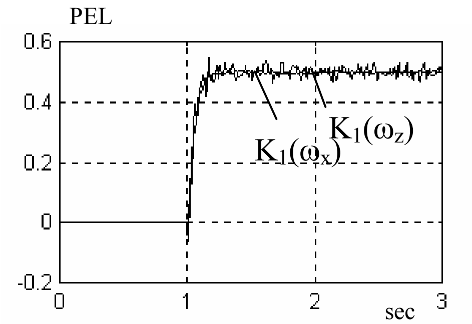

Fig. 4.2 PEL estimated from F_1

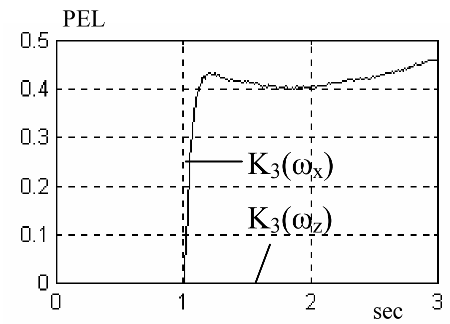

Fig. 4.4 PEL estimated from F_3

5-8, 1993, CERT, France.