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# Novel robust fault diagnosis method for flight control systems*

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**Abstract:** A novel robust fault diagnosis scheme, which possesses fault estimate capability as well as fault diagnosis property, is proposed. The scheme is developed based on a suitable combination of the adaptive multiple model (AMM) and unknown input observer (UIO). The main idea of the proposed scheme stems from the fact that the actuator Lock-in-Place fault is unknown (when and where the actuator gets locked are unknown), and multiple models are used to describe different fault scenarios, then a bank of unknown input observers are designed to implement the disturbance de-coupling. According to Lyapunov theory, proof of the robustness of the newly developed scheme in the presence of faults and disturbances is derived. Numerical simulation results on an aircraft example show satisfactory performance of the proposed algorithm.

**Keywords:** fault diagnosis, adaptive multiple model, unknown input observer, flight control.

## 1. Introduction

Due to the growing demand for reliability, maintainability, and survivability in flight control system, the development of fast and accurate fault diagnosis algorithms is of paramount importance, and their applications have received considerable attention during the past two decades. Fruitful results can be found in some books[1−2] and references therein. The existing research work in the field of fault detection and diagnosis (FDD), for instance, among many others, are multiple model-based techniques under no disturbance conditions[3−7]. The method of using unknown input observers to diagnose faults was successfully applied in Refs. [1,8]. Residuals, decoupled from disturbances, can help to determine which fault has occurred. However, uncertainties in dynamic systems are an inevitable consequence and an accurate mathematical model of a physical process is not always available, so there is often a mismatch between the actual process and its mathematical model even under fault free conditions. This constitutes a source of false alarm which can corrupt the performance of the FDD system[9]. Furthermore, faults may cause the plant dynamics to switch abruptly from certain nominal point $P_0$ in the parametric space to the point $P_{\text{fault}}$ corresponding to the faulty plant; therefore, the original model is no longer valid. If none of the models coincides with the actual failed system, it can only assure that the residuals are bounded, but not that they tend to zero asymptotically, which will result in false alarm. From these points of view, firstly, there is a need for using multiple models representation to match different fault scenarios, secondly, the FDD system has to be made robust to such modeling errors and disturbances. Based on the above considerations, with respect to the control effector lock-in-place fault, a new robust FDD scheme, based on the combination of UIO with AMM, is presented. The proposed approach is evaluated using an aircraft example, and good results have been obtained.

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## 2. Problem description

### 2.1 Multiple model scheme

The proposed multiple model scheme is shown in Fig. 1. Faults may cause the plant dynamics to switch abruptly from one nominal point $P_0$ in the parametric space to the point $P_{\text{fault}}$, which represents one of assumed failure conditions in the system[10]. By representing each fault condition with one model in the parametric fault model set, fault diagnosis can be carried out when the "best-fit" model is found based on a performance cost index. Based on the multiple models representation, a bank of observers is designed to generate residuals for fault diagnosis. When the $i$th model matches the current failed system, the corresponding residual$r(i) = 0$, at the same time, for all other models (i.e.$j \neq i$), $r(j) \neq 0$ (definition of $r(i)$ will be given in subsection 3.3).

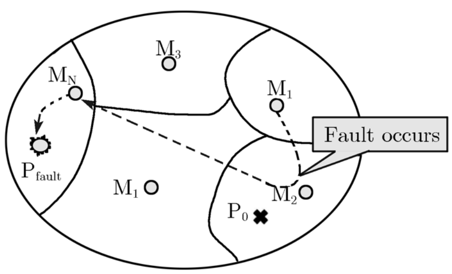


Fig. 1 Concept of multiple model based fault diagnosis scheme

### 2.2 System statement

Consider the dynamic equation described as follows

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + E\xi(t) \\ y(t) = Cx(t) \end{cases} \tag{1}$$

where $x(t) \in \mathbb{R}^n$is a state vector, $y(t) \in \mathbb{R}^m$ is an output vector, $u(t) \in \mathrm{R}^r$ is the control input vector, and $\xi(t) \in \mathbb{R}^q$ represents the unknown input vector. $A$,$B$,$C$ and $E$ are known matrices with appropriate dimensions. The pair $(A, B)$ is controllable, the pair $(A, C)$ is observable, and matrix $E$ should be full column rank. The term $E\xi(t)$ is used to describe additive disturbances and modeling uncertainties.

### 2.3 Methodology of UIO

The structure of UIO for system (1) is described as

$$\begin{aligned} \dot{z}(t) &= Fz(t) + TBu(t) + Ky(t) \\ \hat{x}(t) &= z(t) + Hy(t) \end{aligned} \tag{2}$$

where $\hat{x}(t) \in \mathbb{R}^n$ is the estimated state vector and $z(t) \in \mathbb{R}^n$ is the state of UIO, and $F$, $T$, $K$, $H$ are matrices to be designed.

**Definition 1** An observer for the system (1) is called an unknown input observer (UIO) if its state estimation error $e(t) = x(t) - x(t)$ asymptotically converge to zero despite of the unknown input$\xi(t)$, and the following relations hold

$$(HC - I)E = 0 \tag{3}$$

$$T = I - HC \tag{4}$$

$$F = A_1 - K_1C \tag{5}$$

$$K_2 = FH \tag{6}$$

$$K = K_1 + K_2 \tag{7}$$

**Theorem 1** Necessary and sufficient conditions for Eqs. (2) to be an UIO for the system (1) are

(1) rank($CE$)=rank($E$),

(2) ($C$, $A_1$) is detectable pair.

where

$$A_1 = A - E\left[(CE)^{\mathrm{T}} CE\right]^{-1} (CE)^{\mathrm{T}} CA \tag{8}$$

and Eq. (3) is solvable. A special solution is

$$H^* = E\left[(CE)^{\mathrm{T}} CE\right]^{-1} (CE)^{\mathrm{T}} \tag{9}$$

The proof is referred to Ref. [11] and hence, it is omitted here.

One of the most important steps in designing an UIO, when (2) holds true, is to stabilize $F$ by choosing the matrix $K_1$. In the case of rank$(C) = n$, all eigenvalues of the matrix $A_1 - K_1C$ are assigned to a single value $-\sigma < 0$, i.e.

$$A_1 - K_1C = -\sigma I \tag{10}$$

From Eq. (10), one can obtain

$$K_1 = (A_1 + \sigma I)C^+ \tag{11}$$

where $C^+$ is the pseudo-inverse of $C$.

According to the Definition 1, an UIO is designed by solving Eqs. (3)–(7).

## 3. Fault diagnosis scheme

### 3.1 Fault description

The lock-in-place fault of control effector is described as Ref. [12]

$$u_{pi}(t) = \begin{cases} u_{ai}(t), & t < t_{fi} \\ \bar{u}_i, & t \geqslant t_{fi} \end{cases} \quad i = 1, 2, \ldots, m \tag{12}$$

where $u_{pi}(t)$ and $u_{ai}(t)$ are the output and input of $i$th control effector, respectively. $t_{fi}$ denotes the fault instant of $i$th effector, $\bar{u}_i$ is the value at which the control effector locks, and $t_{fi}$ and $\bar{u}_i$ are unknown.

The system with control effector faults is described as

$$\dot{x}(t) = Ax(t) + B_i u(t) + b_i \bar{u}_i + E\xi(t) \tag{13}$$

where

$$B_i = [b_1, b_2, \ldots, b_{i-1}, 0, b_{i+1}, \ldots, b_m]$$

$$i = 1, 2, \ldots, m$$

where 0 is an $m$-vector with zero elements. Lock-in-place fault is modeled by removing the corresponding column of matrix $B_i$.

Consider all of lock-in-place fault scenarios, we have

$$\dot{x}(t) = Ax(t) + \bar{B}u(t) + \bar{b}\bar{u} + E\xi(t)$$
$$y(t) = Cx(t) \tag{14}$$

where $\bar{B}$, $\bar{b}$ and $\bar{u}$ denote all of lock-in-place fault scenarios of any one of $m$ control effectors.

### 3.2 Fault estimation design

Corresponding to multiple faulty models, a series of observers are constructed

$$\dot{z}_i(t) = Fz_i(t) + TB_i u(t) + Tb_i \hat{u}_i + Ky(t)$$
$$\hat{x}_i(t) = z_i(t) + Hy(t), \quad i = 1, 2, \cdots, m \tag{15}$$

where $\hat{u}_i$ is the estimate of $\bar{u}_i$ and given by

$$\dot{\hat{u}}_i = \mathrm{Proj}_{[u_{im}, u_{iM}]}\left\{-\gamma_i \hat{e}_i^{\mathrm{T}} P b_i\right\}$$
$$\hat{u}_i(0) \in [u_{im}, u_{iM}] \tag{16}$$

where $u_{im}$ and $u_{iM}$ denote the lower and upper limit of control effector, $P = P^{\mathrm{T}} > 0$ is a solution of $\Lambda_o^{\mathrm{T}} P + P\Lambda_o = -Q$, where $Q = Q^{\mathrm{T}} > 0$, $\gamma_i > 0$ is weighting coefficient, $e_i(t) = x(t) - \hat{x}_i(t)$ denotes the state estimate error, $i = 1, 2, \ldots, m$. $\mathrm{Proj}_{[u_{im}, u_{iM}]}\{\cdot\}$ is the projection operator whose role is to project the estimate $\hat{u}_i$ to the interval $[u_{im}, u_{iM}]$.

### 3.3 The fault diagnosis algorithm

From Eqs. (3)-(7) and at the same time, considering Eq. (1) and Eq. (15), one can obtain the state estimation error

$$\begin{gathered} \dot{e}_i(t) = (A - HCA - K_1 C) e_i(t) + \\ [(A - HCA - K_1 C) - F] z_i(t) + \\ [(A - HCA - K_1 C) H - K_2] y(t) + \\ \left[(I - HC)\bar{B} - TB_i\right] u(t) + \\ (I - HC)\bar{b}\bar{u} - Tb_i\hat{u}_i + \\ (I - HC) E\xi(t) = \\ Fe_i(t) + T\left(\bar{B} - B_i\right) u + T\left(\bar{b}\bar{u} - b_i\hat{u}_i\right) \end{gathered} \tag{17}$$

Then, in the case of a fault in the $i$th control effector, we have

$$\dot{r}_i(t) = Fe_i(t) + Tb_i(\bar{u}_i - \hat{u}_i) \tag{18}$$

where $r_i(t) = y(t) - \hat{y}_i(t) = C(x(t) - \hat{x}_i(t))$.

A natural way to decide when and to which model one should switch is to determine performance indexes $J_i(t)$ for each model and switch to the one with the minimum index at every instant. Switching among the models is based on the following performance indices

$$J_i(t) = c_1 \|r_i(t)\|^2 + \frac{c_2}{c_3 t + 1}\int_{t_0}^{t} \|r_i(\tau)\|^2 \mathrm{d}\tau,$$
$$i = 1, 2, \cdots, m \tag{19}$$

where $c_j > 0, j = 1, 2, 3$.

In residual vectors, some elements are more sensitive in model matching than others, they should be given a larger weight to enhance sensitivity, i.e.

$$r_i^*(t) = W_i r_i(t) \tag{20}$$

where $W_i$ is a diagonal weighting matrix, then Eq. (19) becomes

$$J_i(t) = c_1 \|r_i^*(t)\|^2 + \frac{c_2}{c_3 t + 1}\int_{t_0}^{t} \|r_i^*(\tau)\|^2 \mathrm{d}\tau \tag{21}$$

When the "best" model is found, $\lim_{t\to\infty} r_i(t)=0$, then $\lim_{t\to\infty} J_i(t)=0$. Thus, following decision logic can be used for declaring a fault occurrence

$$\begin{cases} r_i(t)\geqslant\lambda, \text{ fault has occured} \\ r_i(t_{fi})<\lambda, \text{ no fault occurs} \end{cases} \tag{22}$$

where $\lambda$ is a pre-specified threshold, and $t_{fi}$ is the time when a fault in $i$th control effector occurs.

### 3.4 Robustness analysis of the fault diagnosis scheme

In this section, we will address the robustness of the proposed scheme to the disturbances.

**Theorem 2** The switching index (21) assures that all signals in the system is bounded despite possible faults and the presence of nonzero disturbance $\xi(t)$, and in the case of $i$th control effector fault, $\lim_{t\to\infty}[\hat{u}_i-\bar{u}_i]=0$.

**Proof** Consider Lyapunov function

$$V_i(e_i,\phi_i)=\frac{1}{2}\left(e_i^{\mathrm{T}}Pe_i+\frac{\phi_i^2}{\gamma_i}\right) \tag{23}$$

Define input error $\phi_i=\hat{u}_i-\bar{u}_i$, when the $i$th effector locks, $\dot{\bar{u}}_i=0$, and hence $\dot{\phi}_i=\dot{\hat{u}}_i$, $i=1,2,\ldots,m$. The derivative of the Eq. (23) along the trajectories of the $i$th model is

$$\dot{V}_i(e_i,\phi_i)\leqslant -e_i^{\mathrm{T}}Qe_i+e_i\xi \tag{24}$$

Note that $\xi\in L^\infty$, there exists a constant $k_1>0$ such that $\|\xi(t)\|\leqslant k_1$ for all time. Substituting it into formula (24) yields

$$\dot{V}_i(e_i,\phi_i)\leqslant -\lambda_q\|e_i\|^2+k_1\|e_i\|= -\lambda_q\|e_i\|(\|e_i\|-k_1/\lambda_q) \tag{25}$$

where $\lambda_q$ denotes the minimum eigenvalue of $Q$. Since $\dot{V}_i(e_i,\phi_i)>0$ is possible only inside the set $\{e_i:\|e_i\|\leqslant k_1/\lambda_q\}$ that contains the point $e_i=0$, one can conclude that $e_i$ is bounded. Hence there exists a constant $k_2>0$ such that $\|e_i\|\leqslant k_2$ for all time. We further integrate $\dot{V}_i(e_i,\phi_i)$ to obtain

$$V_i(\infty)-V_i(0)\leqslant -\lambda_q\int_0^\infty \|e_i\|^2dt+k_2\int_0^\infty\|\xi\|\mathrm{d}t \tag{26}$$

Since both $V_i(\infty)$ and $V_i(0)$ are bounded, the above expression is also bounded; so, $e_i\in L^2$ and $\dot{e}_i\in L^\infty$, therefore $\lim_{t\to\infty}e_i=0$ and $\lim_{t\to\infty}J_i=0$. An unique equilibrium state is $e_i=0$, $\phi_i=0$ and $\xi(t)=0$. So $\lim_{t\to\infty}[\hat{u}_i-\bar{u}_i]=0$. This completes the proof.

**Remark** In a particular flight regime, aircraft dynamics immediately after the failure may be very far from its nominal (no-failure) dynamics. Furthermore, the system may never be free from large external disturbances and modeling errors. For these reasons, the paper has proposed a new method for fault diagnosis, and the problem is effectively solved using a combination of multiple model and unknown input observer.

## 4. An aircraft example

To validate the effectiveness of the proposed approach in this paper, a flight control system example is considered[13].

A six-state model of the linearized lateral dynamics is considered

$$\begin{cases} \dot{x}(t)=Ax(t)+Bu(t)+E\xi(t) \\ y(t)=Cx(t) \end{cases}$$

The states of the aircraft are represented by vector $x$ with $\alpha$ being the angle of attack, $q$ the pitch rate, $v$ the velocity, $\beta$ the sideslip, $p$ the roll rate, $r$ the yaw rate. $u$ denotes the control input with $\delta_{EL}$ being the left elevator command, $\delta_{ER}$ the right elevator command, $\delta_R$ the rudder command, $\delta_{AL}$ the left aileron command, and $\delta_{AR}$ the right aileron command. The control outputs are $y$. The system matrices are

$$A=\begin{bmatrix} -0.015\,6 & 0.048\,0 & -5.942\,0 & 0.002\,1 & 0 & 0 \\ -0.091\,0 & -0.958\,8 & 138.360\,6 & 0.016\,3 & 0 & 0 \\ 0.000\,2 & 0.004\,6 & -1.022\,0 & -0.000\,5 & 0 & -0.002\,9 \\ 0 & 0 & 0 & -0.280\,4 & 6.266\,7 & -150.143\,6 \\ 0 & 0 & 0.000\,3 & -0.182\,1 & -3.419\,3 & 0.640\,1 \\ 0 & 0 & 0.002\,5 & 0.045\,4 & -0.030\,4 & -0.453\,6 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.033\,9 & 0.033\,9 & 0.025\,1 & 0.025\,1 & 0 \\ -0.172\,2 & -0.172\,2 & -0.179\,8 & -0.179\,8 & 0 \\ -0.087\,3 & -0.087\,3 & -0.007\,5 & -0.007\,5 & 0 \\ -0.314\,9 & 0.314\,8 & 0.023\,3 & -0.023\,3 & 0.120\,5 \\ -0.189\,2 & 0.189\,0 & -0.346\,5 & 0.346\,5 & 0.123\,6 \\ -0.167\,8 & 0.167\,8 & -0.014\,7 & 0.014\,7 & -0.058\,8 \end{bmatrix}$$

$$C = \begin{bmatrix} 0 & 0 & 57.295\,8 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 57.256\,9 & 2.369\,6 \\ 0 & 0 & 0 & 0 & -2.369\,6 & 57.246\,8 \\ -0.015\,5 & 0.375\,6 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.376\,0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$E = [0.048\,6\ -0.956\,6\ 0.0046\ 0\ 0\ 0]^{\mathrm{T}}$$

In simulation, all of the filter eigenvalues are set to $\sigma = -3$, a step input vector is used as the system input $u(t)$, $\xi(t)$ denotes the disturbance to the system and is modeled as sine signal of amplitude 1, occurring at $t = 10\ s$. We assume that right elevator lock-in-place fault occurs at $t = 15\ s$ with $\bar{u}_1 = 1$.

Figure 2 shows the output response in the presence of fault, and the estimate of the lock-in-place fault is described in Fig. 3. Figure 4 illustrates the performance index $J_i(t)$ corresponding to the "best" model, $i = 1, 2, \ldots, m$. From these numerical results, it can be seen that the proposed method can detect and estimate Lock-in-Place fault with good accuracy.

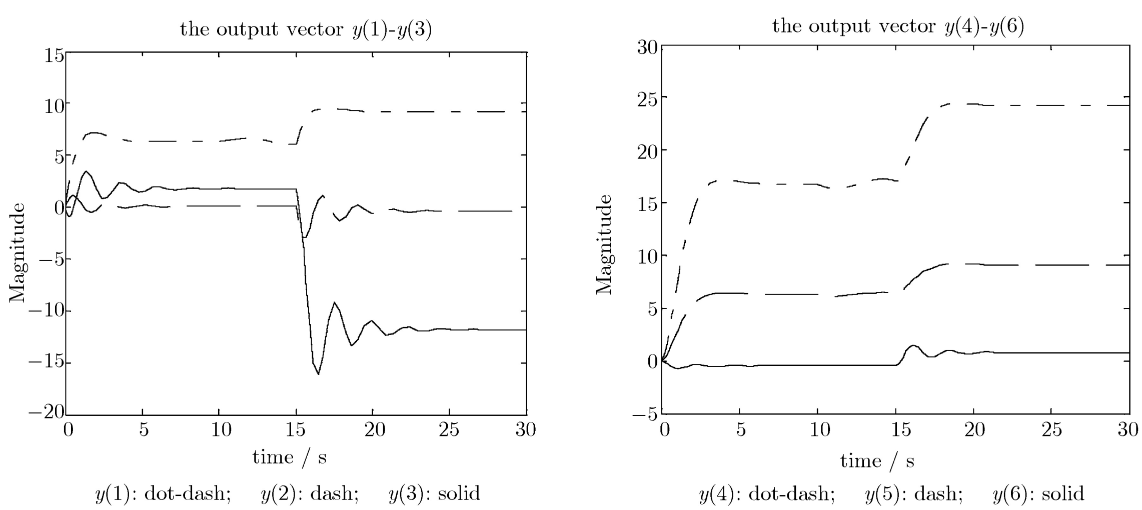


Fig. 2 The output response in the presence of fault and disturbance

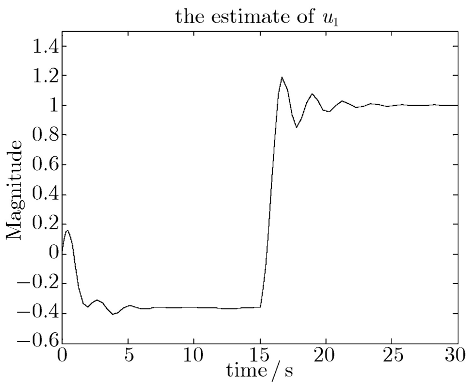


Fig. 3 The estimate of lock-in-place fault

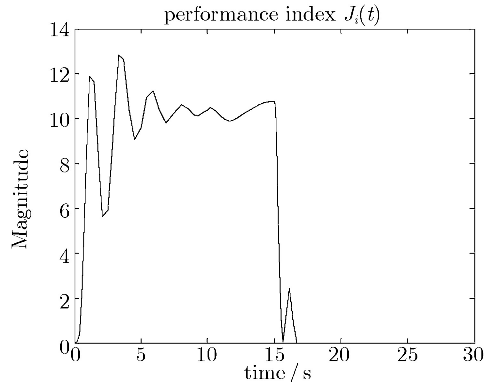


Fig. 4 The performance index $J_i\,(t)$

## 5. Conclusions

By combing multiple model and unknown input observer, a new fault diagnosis method is developed in this paper. The developed method can provide effective fault detection and magnitude estimation in the presence of Lock-in-Place faults and unknown disturbances. The design scheme of the proposed approach is straightforward and is easy to implement. Simulation results on an aircraft example showed the satisfactory performance. Future work will be focused on the new robust FDD method, which can relax the strict existence conditions of unknown input observer.

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