CATT Technical Report 01-11-01

Fault-Tolerant Control and Reconfiguration for High Performance Aircraft: Review

Ying Huo[*] Petros A. Ioannou[#] and Majdedin Mirmirani[£]

[*#] University of Southern California

Dept. of Electrical Engineering-Systems

Los Angeles, CA 90089

[£] California State University, Los Angeles

Dept. of Mechanical Engineering

Los Angeles, CA 90032

[*] email: yhuo@usc.edu, (tel) : 1-213-740-6257

[#] email : ioannou@usc.edu, (tel) : 1-213-740-4452, (fax) : 1-213-740-4418

[£] email : mmirmir@calstatela.edu, (tel) : 1-323-343-4492, (fax) : 1-323-343-5004

This work has been supported by the Air Force Office of Scientific Research Grant # F4920-01-0489.

Abstract

This report reviews fault-tolerant control schemes for high performance aircrafts that emphasize combining fault diagnosis and control reconfiguration. The paper outlines the principles and relevant techniques of model-based fault diagnosis, as well as robustness and solutions. A discussion of advantages and drawbacks of each approach is presented. The basic schemes of model-free fault diagnosis are introduced and control reconfiguration methods based on the fault diagnosis are presented.

1. Introduction

Fault-tolerant control aims at making the system stable and retain acceptable performance under the system faults. Fault Tolerant Flight Control System (FTFCS) has become a critical issue in the operation of high-performance airplanes, space vehicles, and structures, where safety, mission satisfaction, and significant material value are among the main concerns. With a FTFCS system the flying aircraft can maintain high performance even with impairments to the actuators, sensors or control surfaces, and thus increase the aircraft survivability, and probability of mission success.

With FTFCS systems controlled flight is achievable even with the presence of failures, however, it is necessary to modify the commands to the actuators and reconfigure the control law. Fault-tolerant control methods can be classified into two categories: the first group is based on fault detection and isolation and the second group is independent of fault diagnosis (zhou and Frank, 1998). The first uses the on-line fault detection and isolation to monitor the system and when any fault occurs the control laws are redesigned to make the faulty systems maintain the performance. The second is to design fixed controllers without consideration of whether the fault has occurred or not. It is obvious that to design fixed controllers that are robust to failures are very difficult and only time-invariant linear systems have been considered (Joshi, 1987; Marrison and stengel, 1998). Here our emphasis is on the first category and the main methods of fault diagnosis and controller reconfiguration techniques for aircrafts are overviewed.

Fault Detection and Isolation (FDI) is an important part in fault-tolerant control systems and it is desirable to provide warnings and diagnostic information as soon as the failure develops, so that the controllers are reconfigured and the further deterioration is prevented. According to generally accepted terminology, the task of FDI consists of the following steps: (Gertler, 1988; Patton, 1991)

- Fault detection, i.e., the indication that something is going wrong in the system.
- Fault isolation, i.e., the determination of the exact location of the failure.
- Failure identification, i.e., the determination of the size of the failure. According to the depth of the information used of the physical process, the approaches to the problem of failure detection and isolation fall into two major groups:
- methods that do not make use of the mathematical model of plant dynamics, or, model-free FDI;
- methods that do make use of the quantitative plant model, or, model-based FDI.

In this review paper Section 2 is devoted to methods used in model-based FDI, and Section 3 discusses the robustness problems in model-based FDI. In Section 4 the other category of fault detection and isolation — model-free FDI approaches - are organized. Section 5 illustrates the methods used for controller reconfiguration. Section 6 gives some conclusions.

2. Model-based Fault Detection and Isolation (FDI)

A broad class of fault detection and isolation methods makes explicit use of a mathematical model of the plant, which we referred to as model-based FDI. This approach is motivated by the conviction that utilizing deeper knowledge of the system results in more reliable diagnostic decisions. In the last 20 years different approaches for fault detection using mathematical models have been developed, see, e.g., (Willskey, 1976; Isermann, 1984; Gertler, 1988; Frank, 1990). Since the dynamics of aircrafts is well studied, it is readily possible to implement it into the fault diagnosis process, and such work can be found in Deckert, et al, 1977; Chandler, 1989; Ioannou, et al, 1989; Patton, 1991; Rauch, et al, 1993; Polycarpou, 1994; etc.
The main idea behind the model-based FDI is " analytical redundancy", the comparison of measurement data with *prior* known mathematical model of the physical process (Chow and Willsky, 1984). Model-based FDI is superior to " hardware redundancy " generated by installing multiple sensors for the same measured variable in that analytical redundancy has more simple, flexible structure; while less equipment, weight, and cost (Beard, 1971).
In this section we will elaborate the concepts of model-based FDI. Section 2.1 will give the mathematical models of systems in faulty and fault-free stages. Section 2.2 is a general description of steps required in model-based FDI, and the rest of the two sections will give an outline of different methods used in model-based FDI.

2.1 Mathematical Model of the System

Most model-based failure detection and isolation methods rely on linear dynamic models. In the case of a non-linear system, this implies a model linearization around an operating point. Although aircraft dynamics are inherently nonlinear, aerodynamic nonlinearities and inertial coupling effects generally are smooth enough in the operating regions so that linear design techniques are applicable (Stengel, 1993).
In this section we use the open-loop system model in model-based FDI. For modeling purposes, an open-loop system can be separated into three parts: actuators, system dynamics and sensors as illustrated in Fig 1.

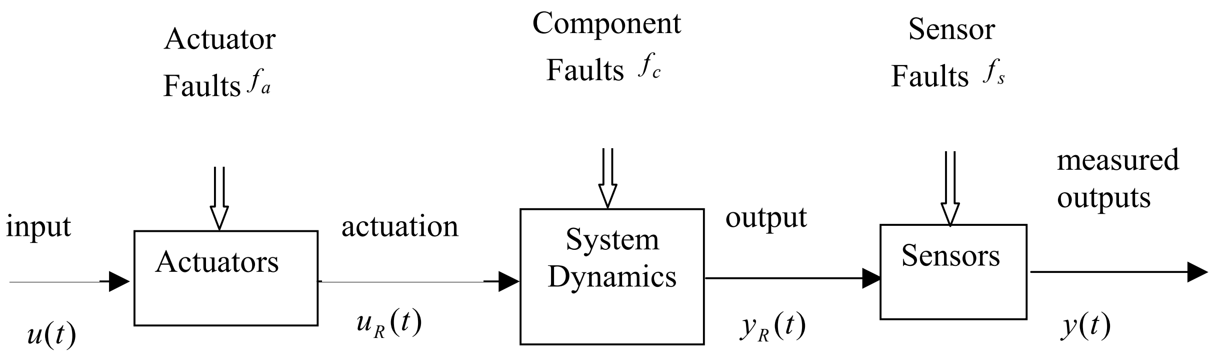

Fig. 1 Open-loop System with Faults

Here, $u(t)$ is the known input vector, $y(t)$ the vector of measured output signals, $u_R(t)$ and $y_R(t)$ are signals corrupted by actuator and sensor faults. In the fault-free case, the system dynamics shown in Fig 1 can be described by the state-space model as

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu_R(t) \\ y_R(t) = Cx(t) + Du_R(t) \end{cases} \tag{1}$$

where $x(t)$ is the state vector, and A, B, C, D are matrices of proper dimensions. Substituting in (1)

$$u_R(t) = u(t) + f_a(t), \quad f_a(t) - \text{actuator fault}$$
$$y(t) = y_R(t) + f_s(t), \quad f_s(t) - \text{sensor fault}$$

and including the component faults, $f_c(t)$, which represents the case when some condition changes in the system that make the quantitative model invalid, the model of the dynamic system becomes

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Bf_a(t) + f_c(t) \\ y(t) = Cx(t) + Du(t) + Df_a(t) + f_s(t) \end{cases} \tag{2}$$

In general cases, the state-space model of a system with all possible faults takes the form

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + R_1 f(t) \\ y(t) = Cx(t) + Du(t) + R_2 f(t) \end{cases} \tag{3}$$

where $f(t)$ is a $q \times 1$ fault vector, with each element corresponding to a specific fault.
An input-output transfer matrix representation for the system with possible faults is then described as

$$y(s) = G_u(s)u(s) + G_f(s)f(s) \tag{4}$$

where

$$\begin{cases} G_u(s) = C(sI - A)^{-1}B + D \\ G_f(s) = C(sI - A)^{-1}R_1 + R_2 \end{cases}$$

From a practical point of view it is reasonable to make no further assumptions about the fault modes but consider them as unknown time functions. The corresponding distribution matrices R_1 and R_2 of faults are usually assumed to be known (Frank, 1994; Chen and Patton, 1999).
It is worth noting that the system model required in model-based FDI is the open-loop although we consider that the system is in the control loop. This is because the input and output information required in model-based FDI is related to the open-loop system. Hence, it is not necessary to consider the controller in the design of a fault diagnosis scheme. However, in the case that the input to the actuator, $u(t)$, is not available, one has to use the reference command $r(t)$ in FDI. Hence, the model involved is the closed-loop model of the relationship between $r(t)$ and $y(t)$. For these cases, the controller plays an important role in the design of diagnostic schemes (Wu, 1992; Jacobson and Nett, 1991) and the interconnection between fault diagnosis and robust control is a topic calling for future research.

2.2 Model-based FDI Concepts

In model-based FDI, faults are detected by setting a threshold (fixed or variable) on a "residual" generated from the difference between real measurements and estimates of these measurements using the mathematical model. A number of residuals can be designed with each having special sensitivity to individual faults.
Fig.2 illustrates the general and conceptual structure of a model-based fault diagnosis system comprising two stages of residual generation and decision-making (Chow and Willsky, 1984; Isermann, 1997).

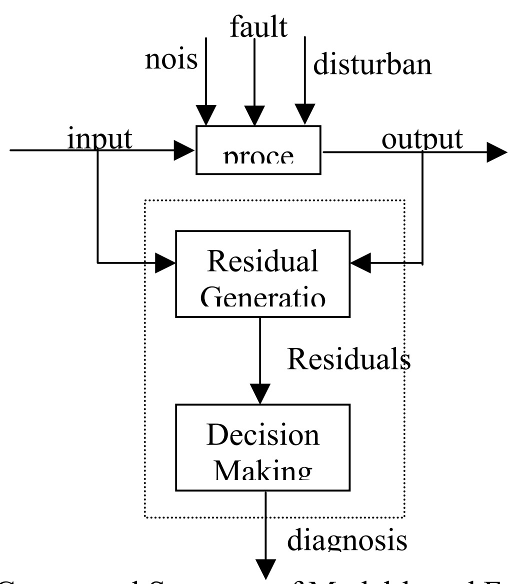

Fig. 2 Conceptual Structure of Model-based Fault Diagnosis

The *residual* is a signal, $r(t)$, that carries information on the time and location of the faults. It should be near zero in fault-free case and deviate from zero when a fault has occurred. The decision process evaluates the residuals and monitors if and where a fault has occurred. Denote by $J(r(t))$ and $T(t)$ the decision function and the threshold, a fault can be detected by the following test

$$\begin{cases} J(r(t)) \leq T(t) & for \quad f(t)=0 \\ J(r(t)) > T(t) & for \quad f(t)\neq 0 \end{cases} \tag{5}$$

The isolation of a specific fault, say, the i th out of q possible faults, requires

$$\begin{cases} J(r_i) \leq T_i & for \quad f_i(t)=0 \\ J(r_i) > T_i & for \quad f_i(t)\neq 0 \end{cases}, \quad i=1,2,\cdots,q \tag{6}$$

2.2.1 Residuals Generation Methods

A traditional method of detecting faults is to use limit checking, i.e., to compare process variables with preset limits; the exceeding of a limit indicates a fault situation. Although simple, this method has a serious drawback in that the process variables may be varying

with different operating states, thus the check limit is dependent on the operating state of the process. On the contrary, residual signals are quantities that represent the inconsistency between the actual system variables and the mathematical model. They are independent of the system operating state and respond only to faults, which makes it a direct development of the limit checking method (Chen and Patton, 1999).
A typical structure of a residual generator is shown in Fig. 3, which involves processing of the input and output data of the system (Basseville, 1988; Gertler, 1988).

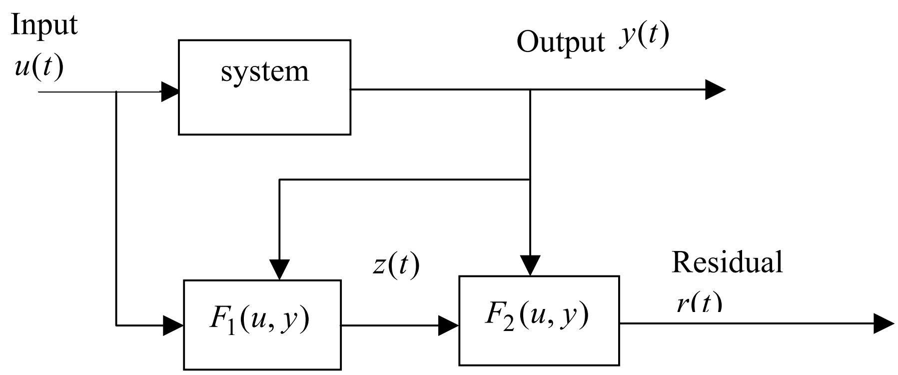

Fig 3 Redundancy Signal Structure of a residual generator

The simplest approach to residual generation is the use of system duplication. That is, the system F_1 is made identical to the original system model and the signal z is the simulated output of the system, thus the residual r is the difference between z and y. The disadvantage of this method is that the stability of the simulator cannot be guaranteed when the system being monitored is unstable. A direct extension to the simulator-based residual generation is to replace the simulator by an output estimator, as shown in Fig. 4 (Patton, 1991).

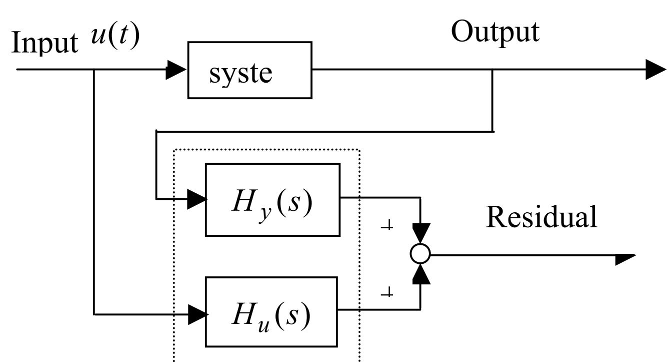

Fig. 4 The General Structure of a residual generator

This structure is expressed mathematically as

$$r(s) = \begin{bmatrix} H_u(s) & H_y(s) \end{bmatrix} \begin{bmatrix} u(s) \\ y(s) \end{bmatrix} = H_u(s)u(s) + H_y(s)y(s) \quad (7)$$

Here $H_u(s)$ and $H_y(s)$ are transfer matrices which are realizable using stable linear systems. In order to make the residual become zero for the fault-free case the following condition must hold.

$$H_u(s) + H_y(s)G_u(s) = 0 \tag{8}$$

Eq. (7) is a *generalized representation* of all residual generators. Design of the residual generator means the choice of the transfer matrices $H_u(s)$ and $H_y(s)$. Usually residuals are generated using analytical approaches, such as observers, parameter estimation or parity equations based on analytical redundancy. It is important to note that the aim of the residual generator is not to estimate the state of the plant but rather to respond promptly to the occurrence of a fault (Patton and Lopez-Toribio, 1999).

To accomplish requirements (5), (6), the residual generator must posses the following properties of fault detectability and isolability (Gobbo and Mapolitano, 2000; Frank, 1994)

Fault detectability—A fault $f_i(t)$ is said to be *detectable* if $g_{fi}(s) \neq 0$ where $g_{fi}(s)$ is the ith element of the transfer matrix $G_f(s)$ defined in Eq.(4). The detectability condition $g_{fi}(0) \neq 0$ is evident because otherwise the fault effect on the residual will disappear although the fault effect still exists in the system.

Fault isolability— A fault is isolable if it is distinguishable from other faults using one residual set (or a residual vector) and such residual set is said to have the isolability property.

2.2.1.1 Observer-based Residual Generation

The basic idea of the observer or filter-based approaches is to estimate the states or outputs of the system from the measurements by using either Luenberger observers in a deterministic setting (Beard, 1971; Frank 1990) or Kalman filters in a stochastic case (Willsky, 1976; Basseville, 1988). The flexibility in selecting observer gains has been studied (Frank and Ding, 1997).

In practice, it is desired to estimate a linear function of the state, i.e. $Lx(t)$, using a generalized Luenberger observer with the following structure

$$\begin{cases} \dot{z}(t) = Fz(t) + Ky(t) + Ju(t) \\ w(t) = Gz(t) + Ry(t) + Su(t) \end{cases} \tag{9}$$

where $z(t)$ is the state vector of the observer, F, K, J, R, G and S are matrices of appropriate dimensions. The output $w(t)$ of this observer is an estimate of $Lx(t)$ which converges to $Lx(t)$ in an asymptotic sense if

$$\lim_{t\to\infty}[w(t) - Lx(t)] = 0$$

If the matrix L is taken to be $L = C$, the residual vector is defined as

$$r(t) = Q[y(t) - \hat{y}(t)] = L_1 z(t) + L_2 y(t) + L_3 u(t) \tag{10}$$

where $\hat{y}(t) = w(t) + Du(t)$.

$$\begin{cases} L_1 = -QG \\ L_2 = Q - QR \\ L_3 = -Q(S+D) \end{cases}$$

When the matrices satisfy the conditions

$$\begin{cases} F \text{ has stable eigenvalues} \\ TA\text{-}FT = KC \\ J = TB - KD \\ L_1 T + L_2 C = 0 \\ L_3 + L_2 D = 0 \end{cases}$$

The residual generator is thus

$$r(s) = [L_1(sI - F)^{-1}K + L_2]y(s) + [L_1(sI - F)^{-1}J + L_3]u(s) \tag{11}$$

Applying the residual generator to system (3), the residual will be

$$\begin{cases} \dot{e}(t) = Fe(t) - TR_1 f(t) + KR_2 f(t) \\ r(t) = L_1 e(t) + L_2 R_2 f(t) \end{cases} \tag{12}$$

where $e(t) = z(t) - Tx(t)$, and it is seen that the residual depends only on faults. The observer-based residual generator always exists because any input-output transfer function matrix has the observable realization (Chen and Patton, 1999).

Fault detection filters (Beard, 1971; White and Speyer, 1987; Park and Rizzoni, 1994; Park, J.H., Halevi, Y. and Rizzoni, G., 1994) are a particular class of the full-order Luenberger observer with a specially designed feedback gain matrix such that the output estimation error (residual vector) is fixed along with a predetermined direction for an actuator fault, or lies in a specific plane for a sensor fault, as will be discussed later.

2.2.1.2 Parity Space Approach

The parity equation method is first proposed by (Chow and Willsky, 1984) using the redundancy relations of the dynamic system. The basic idea is to provide a proper check of the parity (consistency) of the measurements for the monitored system. Consider the discrete-time system

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + R_1 f(k) \\ y(k) = Cx(k) + Du(k) + R_2 f(k) \end{cases} \tag{13}$$

The redundancy relations are specified mathematically as

$$\underbrace{\begin{bmatrix} y(k-s) \\ y(k-s+1) \\ \vdots \\ y(k) \end{bmatrix}}_{Y(k)} - H \underbrace{\begin{bmatrix} u(k-s) \\ u(k-s+1) \\ \vdots \\ u(k) \end{bmatrix}}_{U(k)} = Wx(k-s) + M \underbrace{\begin{bmatrix} f(k-s) \\ f(k-s+1) \\ \vdots \\ f(k) \end{bmatrix}}_{F(k)} \tag{14}$$

where

$$H = \begin{bmatrix} D & 0 & \cdots & 0 \\ CB & D & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{s-1}B & CA^{s-2}B & \cdots & D \end{bmatrix}; \quad M = \begin{bmatrix} R_2 & 0 & \cdots & 0 \\ CR_1 & R_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{s-1}R_1 & CA^{s-2}R_1 & \cdots & R_2 \end{bmatrix}; \quad W = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix}$$

A residual signal can be defined as

$$\begin{aligned} r(k) &= V[Y(k) - HU(k)] \\ &= VWx(k-s) + VMF(k) \end{aligned} \tag{15}$$

To satisfy the fault detectability criterion, the matrix should also satisfy the condition

$$VW = 0 \tag{16}$$

$$VM \neq 0 \tag{17}$$

Once the matrix V is derived, the residual signal can be generated. For an appropriately large s, solution of Eq. (16) always exists. This means that a parity relation-based residual generator for fault detection always exists (Chen and Patton, 1999).

2.2.1.3 Parameter estimation method

Model-based FDI can also be achieved by the use of system identification techniques if the basic structure of the model is known (Isermann, 1984; Isermann 1997). This approach is based on the assumption that faults are reflected in the physical system parameters such as friction, mass, resistance, etc. The basic idea is that the parameters of the actual process are estimated on-line using well known parameter estimation methods and the results are compared with the parameters obtained initially under the fault-free case. Any discrepancy indicates a fault. Consider the system model

$$y(t) = f(\theta, u(t)) \tag{18}$$

where θ is the model coefficient vector of the system. By an on-line parameter identification, one can abtain the estimation of the model coefficient at time step $k-1$ as $\hat{\theta}_{k-1}$. Assuming the coefficient estimation at time step k is $\hat{\theta}_k$, the residual can then be defined as either of the followings:

$$\begin{aligned} r(k) &= \hat{\theta}_k - \theta_0 \quad or \\ r(k) &= y(k) - f(\hat{\theta}_{k-1}, u(k)) \end{aligned} \tag{19}$$

It is not easy to achieve fault isolation using parameter estimation method because the parameters identified cannot always be converted back to the system physical parameters (Isermann, 1984).

2.2.2 Residual Evaluation Techniques

After a residual signal is derived, the evaluation of the residual to distinguish a particular fault from others follows. In model-based FDI one can establish the structured residual set which is sensitive to specific faults and insensitive to other faults (Gertler, 1993). The other way is to design a directional residual vector that lies in a fixed direction corresponding to a particular fault in the residual space.

2.2.2.1 Dedicated Observer Scheme (DOS)

The main idea of dedicated observer scheme (DOS) in fault isolation is to use a bank of residual signals. Each of the residuals is sensitive to a specific fault while insensitive to the rest of possible faults (Fig. 5) (Wunnenberg, 1990). The task of isolating faults can be achieved by comparing each residual signal with the initially set threshold and the resulting Boolean decision table. The fault isolation logic can be expressed as

$$\begin{cases} r_i(t) > T_i & \Rightarrow \quad f_i(t) \neq 0; \\ r_i(t) \leq T_i & \Rightarrow \quad f_i(t) = 0; \end{cases} \quad i = 1,2,\cdots,q \tag{20}$$

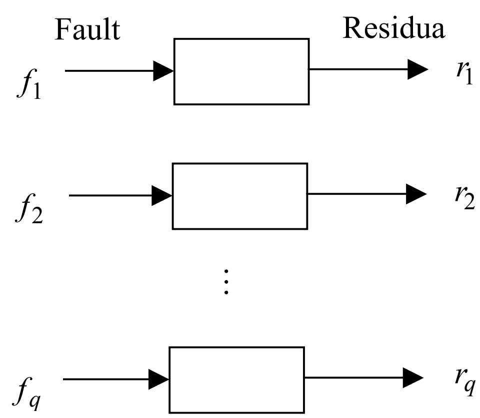

Fig. 5 Structured Residual Set (Dedicated Scheme)

The DOS scheme is good enough for the sensor faults. However, it has no robustness to unknown inputs like disturbance, uncertainty and noise (Wuennengerg, 1990; Frank, 1990).

2.2.2.2 Generalized Observer Scheme (GOS)

The generalized observer scheme in fault isolation also uses a set of structured residual signals, but the difference with DOS lies in the fact that all residuals of the generalized residual set are generated to be sensitive to all but one fault, i.e.

$$\left.\begin{array}{c} r_i(t) \leq T_i \\ r_j(t) > T_j, \forall j \in \{1,\cdots,i-1,i+1,\cdots,q\} \end{array}\right\} \Rightarrow f_i(t) \neq 0 \tag{21}$$

The logic of GOS is shown in Fig.6 for the case of totally 3 possible faults.

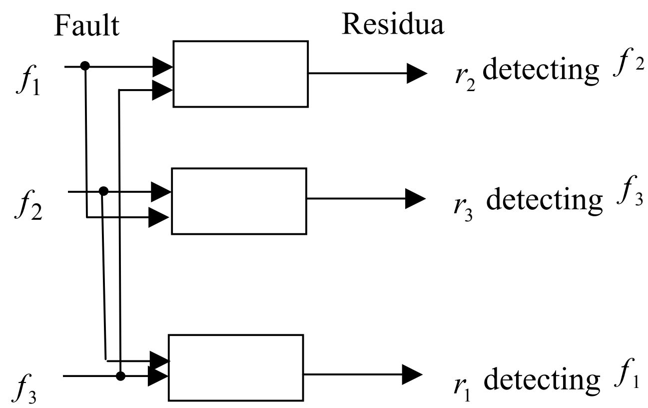

Fig. 6 Structured Residual Set (Generalized Observer Scheme)

2.2.2.3 Directional Residual Set Evaluation

The third way to accomplish fault isolation is to use the directional residual vector. The idea is to design the residual signal so that each of them is close to the signature direction, $\vec{l}(f)$, of the fault f. The signature of fault is a Boolean vector (binary code) in the residual space that represents the specific fault. The fault isolation is achieved by comparing the residual vector and the signatures of different faults. The fault with the signature direction that is closest to the residual signal will be the most likely fault occurred. Fig.7 illustrates the scheme of fault isolation using directional residual vector. In this example fault f_2 is determined as the result of fault isolation.

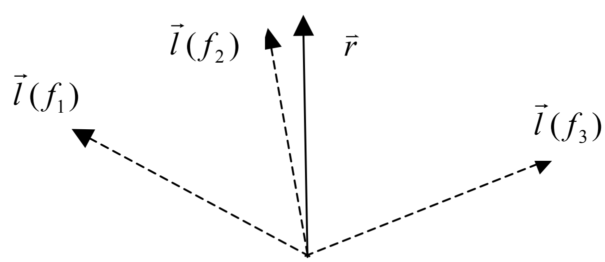

Fig. 7 Fault Isolation with Directional Residual Set

3. Robustness Problems in Model-based FDI

Model-based FDI techniques have the advantages of taking full use of the prior quantitive information of the dynamics and the success of on-line FDI. The price to pay is that they are potentially sensitive to modeling errors and the need for a quantitative model. However to obtain an accurate model is almost impossible. In real life the model errors such as disturbance and noise on the working system as well as uncertainties of the parameters of the dynamics are inevitable, giving rise to the problem of robustness in fault detection and isolation. *Robustness* is defined as the ability of a procedure to isolate faults in the presence of modeling errors (Gertler, 1988; Frank and Ding, 1997). Robustness is an important problem since disturbances and uncertainties could interfere

with fault isolation and make fault detection unachievable when the effect of model errors in the residual override that of the faults.
A number of methods have been proposed to address this problem in applications to aircrafts and flight control (Patton and Kangethe, 1988; Stengel, 1991). In this section we discuss the methods in robust residual generation and evaluation.

3.1 Robust Residual Generation Problem

The task of robust residual generation is to design a residual signal that is highly sensitive to faults but decoupled from disturbance and inaccuracies of the model. Taking model errors into consideration the dynamics of the system described in (3) becomes

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + E_1 d(t) + R_1 f(t) \\ y(t) = Cx(t) + Du(t) + E_2 d(t) + R_2 f(t) \end{cases} \tag{22}$$

Here $d(t)$ is the time function of unknown inputs such as disturbance, noise and uncertainty of the model, and E_1, E_2 are assumed to be known matrices of proper dimensions, i.e., the disturbances, *etc.* are *structured*. A number of methods to determine matrices E_1, E_2 have been presented in the last decade (Patton and Chen, 1992; Gertler and Kunwer, 1995; Frank and Ding, 1994).
With the state-space model the output of system in frequency domain with possible faults and model errors is:

$$y(s) = (G_u(s) + \Delta G_u(s))u(s) + G_f(s)f(s) + G_d(s)d(s) \tag{23}$$

where

$$\begin{cases} G_u(s) = C(sI - A)^{-1}B + D \\ G_f(s) = C(sI - A)^{-1}R_1 + R_2 \\ G_d(s) = C(sI - A)^{-1}E_1 + E_2 \end{cases}$$

and $\Delta G_u(s)$ describes modeling errors in matrices $A, B, C,$ and D.
Replacing $y(s)$ in (7) with the above output the residual signal will be

$$r(s) = H_y(s)\Delta G_u(s)u(s) + H_y(s)G_d(s)d(s) + H_y(s)G_f(s)f(s) \tag{24}$$

with the condition that $H_u(s) + H_y(s)G_u(s) = 0$ as in Eq.(8).
To accomplish the task of fault detection and isolation with the presence of unknown inputs and other possible faults in the residual signal, the effect of a specific fault has to be decoupled from that of the other faults and the unknown inputs. The decoupling can be achieved if

$$H_y(s)G_d(s) = 0 \tag{25}$$

If the above condition does not hold, perfect decoupling from the unknown input is not achievable. An alternative approach is to solve the optimal or the approximate decoupling by minimizing the following performance index (Ding and Frank, 1991):

$$J = \frac{\|H_y(jw)G_d(jw)\|}{\|H_y(jw)G_f(jw)\|} \tag{26}$$

over a specific frequency range. The extreme case $J=0$ means that the effect of unknown inputs on the residual signal is completely decoupled.

3.2 Robust Residual Designs

Many methods have been developed to enhance the robustness of the residual generation methods discussed in the previous section. Other methods such as H_∞ Optimization and nonlinear designs have also been exploited to generate robust residual signals.

3.2.1 Unknown Input Observer Scheme

The main idea of unknown-input observer is to estimate the state without coupling among faults and from unknown inputs (Watanabe and Himmelblau, 1982; Wunnenberg, 1990). Since the control signal $u(t)$ is always known, the system model described in (22) can be simplified as

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + E_1 d(t) + R_1 f(t) \\ \bar{y}(t) = Cx(t) + E_2 d(t) + R_2 f(t) \end{cases} \tag{27}$$

where $\bar{y}(t) = y(t) - Du(t)$.

The unknown input observer is given by

$$\begin{cases} \dot{z}(t) = Fz(t) + K\bar{y}(t) + Ju(t) \\ r(t) = L_1 z(t) + L_2 \bar{y} \end{cases} \tag{28}$$

The estimation error defined as $e(t) = z(t) - Tx(t)$ and the residual signal are governed by

$$\begin{cases} \dot{e}(t) = Fe(t) + Ju(t) + KCx(t) + KE_2 d(t) + KR_2 f(t) - TAx(t) - TBu(t) - TE_1 d(t) - TR_1 f(t) \\ r(t) = L_1(e(t) + Tx(t)) + L_2 Cx(t) + L_2 E_2 d(t) + L_2 R_2 f(t) \end{cases} \tag{29}$$

Suppose the initial system is a fault-free case, i.e. $f_i(t_0) = 0$, the conditions to make the fault detectable, say,

$$\begin{cases} f_i(t) = 0, i = 1,2,\cdots,q \Rightarrow r(t \to \infty) = 0 \\ \text{any } f_i(t) \neq 0, i = 1,2,\cdots,q \Rightarrow r(t) \neq 0 \end{cases} \quad t \geq t_0 \tag{30}$$

are satisfied if the following equations hold

$$\begin{cases} F \text{ has stable eigenvalues} \\ TA\text{-}FT = KC \\ TE_1 = 0 \\ KE_2 = 0 \\ L_2 E_2 = 0 \\ J = TB \\ L_1 T + L_2 C = 0 \end{cases} \tag{31}$$

When all these conditions are satisfied, the estimation error and the residual signals obeying (29) will become

$$\begin{cases} \dot{e}(t) = Fe(t) + KR_2 f(t) - TR_1 f(t) \\ r(t) = L_1 e(t) + L_2 R_2 f(t) \end{cases} \tag{32}$$

It reveals that the residual is independent of disturbances and will only rely on the fault information since the estimation error is asymptotically converges to zero.

An illustrative example is given below (Chen and Patton, 1999). Consider the linearized longitudinal flight control system with white noise sequences

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + \zeta(k) + Ed(k) \\ y(k) = Cx(k) + \eta(k) \end{cases}$$

where $x = \begin{bmatrix} v_y & \omega_z & \delta_Z \end{bmatrix}^T$ is the state vector with pitch angle δ_z, pitch rate ω_Z and normal velocity v_y. $\zeta(k)$ and $\eta(k)$ are the input and output zero mean white noise sequences with covariance matrices Q and R. The matrices are

$$A = \begin{bmatrix} 0.9944 & -0.1203 & -0.4302 \\ 0.0017 & 0.9902 & -0.0747 \\ 0 & 0.8187 & 0 \end{bmatrix}, B = \begin{bmatrix} 0.4252 \\ -0.0082 \\ 0.1813 \end{bmatrix}, C = I_{3\times3}$$

$$Q = diag\{0.01, 0.01, 1\times10^{-4}\}, R = 0.01I_{3\times3}$$

The term $Ed(k)$ represents the parameter perturbation in matrix A and B:

$$\begin{aligned} Ed(k) &= \Delta Ax(k) + \Delta Bu(k) \\ &= E\left\{\begin{bmatrix} \Delta a_{11} & \Delta a_{12} & \Delta a_{13} \\ \Delta a_{21} & \Delta a_{22} & \Delta a_{23} \end{bmatrix} x(k) + \begin{bmatrix} \Delta b_1 \\ \Delta b_2 \end{bmatrix} u(k)\right\} \quad \text{with } E = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \end{aligned}$$

The simulation assumes the aerodynamic coefficients are perturbed by $\pm 50\%$, i.e. $\Delta a_{ij} = -0.5a_{ij}$ and $\Delta b_j = 0.5b_j$. Fig.8 shows the absolute values of the state estimation errors and Fig.9 gives the detection function when an incipient fault occurs in the sensor at time instant $k = 50$ and the actuator at $k = 100$, individually.

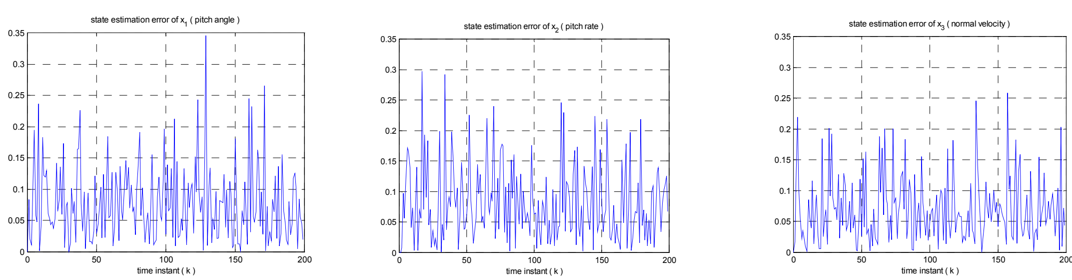

Fig.8 The State Estimation Error for State Variables

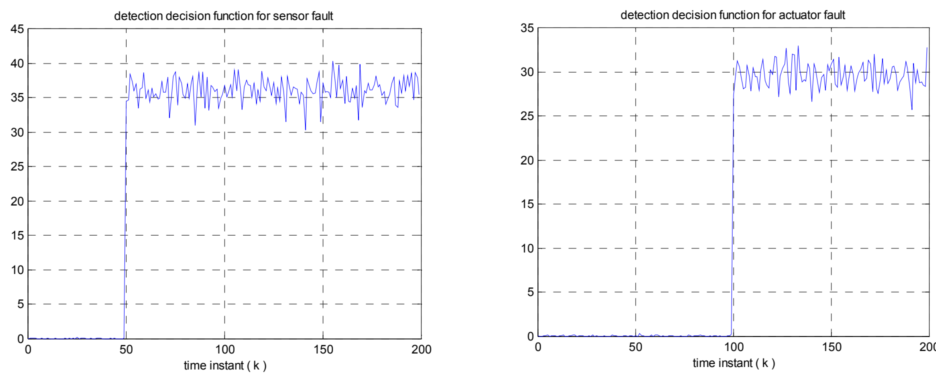

Fig.9 The Fault Detection Function when a fault occurs

Hou and Muller (1994) presented a unified viewpoint in designing Unknown Input Observers (UIOs). The main methods in their study are designing reduced order UIOs using algebraic approaches and so on. In fact, the reduced order and full order UIOs are the same in the sense of disturbance decoupling if the conditions of disturbance decoupling are satisfied. Thus it is possible to design full-order UIOs to achieve other required performances using the extra design freedom. Now consider the Beard Fault Detection Filter (BFDF) introduced in section 2.2.1.2. The main drawback of that scheme was the lack of robustness. To improve its robustness Chen, Patton and Zhang (1996) presented a method combining UIO and BFDF theories to use the freedom of reduced order UIOs to make the residual vector "directional" as introduced in section 2.2.2.3.

3.2.2 Eigenstructure Assignment for Robust FDI

In the design of UIOs the state estimation error is independent of the disturbances, and the residual is defined as the weighted linear transformation of the state estimation error. Therefore, the residual is independent of the disturbances. An alternative way to accomplish robust residual generation is to make the residual de-coupled from disturbances directly, while the state estimation error may be dependent on the unknown inputs. Eigenstructure assignment approach is such a method presented in (Patton, et. al, 1986) and applied to robust FDI of flight control in (Shen et al, 1998).
The main idea of eigenstructure assignment method is to assign the left or right eigenvectors of the observer to be orthogonal to the disturbance distribution directions. Consider the system state equations

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + E_1(d) + R_1 f(t) \\ y(t) = Cx(t) + D(t) + R_2 f(t) \end{cases} \qquad (33)$$

Comparing with the state model in (22) the term $E_2 d(t)$ disappears after a transformation of the output $y(t)$ and the matrix C (Chen and Patton, 1999). The full order observer is used as

$$\begin{cases} \hat{x}(t) = (A - KC)\hat{x}(t) + (B - KD)u(t) + Ky(t) \\ \hat{y}(t) = C\hat{x}(t) + Du(t) \\ r(t) = Q[y(t) - \hat{y}(t)] \end{cases} \tag{34}$$

Define the state estimation error as $e(t) = x(t) - \hat{x}(t)$, the residual are governed by

$$\begin{cases} \dot{e}(t) = (A - KC)e(t) + E_1 d(t) + R_1 f(t) - KR_2 f(t) \\ r(t) = He(t) + QR_2 f(t) \end{cases} \tag{35}$$

To make the residual independent of the disturbances, the following condition must hold

$$G_{rd}(s) = QC(sI - A + KC)^{-1} E_1 d(s) = 0 \tag{36}$$

The sufficient conditions for satisfying the disturbance de-coupling requirement (32) are

$$\begin{cases} QCE_1 = 0 \\ \text{All rows of } H = QC \text{ are left eigenvectors of (A - KC) correponding to any eigenvalues} \end{cases} \tag{37}$$

There are methods to assign the left observer eigenvectors, for instance, parametric approach (Duan, et al, 1997). It is also feasible to achieve disturbance decoupling by assigning right eigenvectors of the observer (Patton and Kangethe, 1988; Choi et al, 1995; Choi, 1998). The restriction of eigenstructure assignment is that the number of independent disturbances to be decoupled is smaller than the number of independent available measurements.

3.2.3 Robust FDI using Optimal Parity Relations

Consider the discrete model of the system dynamics with disturbances and possible faults as follows

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + E_1 d(k) + R_1 f(k) \\ y(k) = Cx(k) + Du(k) + E_2 d(k) + R_2 f(k) \end{cases} \tag{38}$$

Similar to Eq. (14), the output equations with unknown inputs $d(.)$ and $f(.)$ become

$$\underbrace{\begin{bmatrix} y(k-s) \\ y(k-s+1) \\ \vdots \\ y(k) \end{bmatrix}}_{Y(k)} = H_0 x(k-s) + H_1 \underbrace{\begin{bmatrix} u(k-s) \\ u(k-s+1) \\ \vdots \\ u(k) \end{bmatrix}}_{U(k)} + + H_2 \underbrace{\begin{bmatrix} d(k-s) \\ d(k-s+1) \\ \vdots \\ d(k) \end{bmatrix}}_{DD(k)} + H_3 \underbrace{\begin{bmatrix} f(k-s) \\ f(k-s+1) \\ \vdots \\ f(k) \end{bmatrix}}_{F(k)} \tag{39}$$

where

$$H_0 = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix} \tag{40}$$

$$H_1 = \begin{bmatrix} D & 0 & \cdots & 0 \\ CB & D & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{s-1}B & CA^{s-2}B & \cdots & D \end{bmatrix} \tag{41}$$

$$H_2 = \begin{bmatrix} E_2 & 0 & \cdots & 0 \\ CE_1 & E_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{s-1}E_1 & CA^{s-2}E_1 & \cdots & E_2 \end{bmatrix} \tag{42}$$

$$H_3 = \begin{bmatrix} R_2 & 0 & \cdots & 0 \\ CR_1 & R_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{s-1}R_1 & CA^{s-2}R_1 & \cdots & R_2 \end{bmatrix} \tag{43}$$

The residual signal is generated with the actual measurements $u(.)$ and $y(.)$ as follows

$$r(k) = V[Y(k) - H_1 U(k)] \tag{44}$$

As discussed in Eq.(16) and Eq.(17), the conditions for fault detectability are

$$VH_0 = 0 \tag{45}$$

$$VH_3 \neq 0 \tag{46}$$

To satisfy the disturbance decoupling condition another requirement is needed, i.e.

$$VH_2 = 0 \tag{47}$$

Equation (47), the requirement for perfect disturbance decoupling, is rather restrictive and there is no analytic solution in some cases. The solution in these cases is to solve the approximate unknown input decoupling rather than achieving perfect disturbance decoupling. The idea is to minimize the performance index

$$J = \frac{\left\| \partial r / \partial d \right\|}{\left\| \partial r / \partial f \right\|} \tag{48}$$

in order to strike a compromise between the effect of faults and unknown inputs. Such work can be found in (Wuennenberg, 1990; Lou, et al., 1986; Frank, 1990) and a review of parity space approaches to fault diagnosis for aerospace systems is given in (Patton and Chen, 1994).

3.2.4 Frequency Domain Design and H-infinity Optimization

It is from the fact that unknown inputs and faults have different frequency characteristics that the frequency domain designs for fault detection are available (Viswanadham and Minto, 1988; Kinnaert and Peng, 1995). For the system and output equation described in (22) and (23), the residual generator via factorization is given by (Ding and Frank, 1991)

$$r(s) = Q(s)(\widetilde{M}(s)y(s) - \widetilde{N}(s)u(s)) \tag{49}$$

Here $G_u(s) = \widetilde{M}^{-1}(s)\widetilde{N}(s)$ is the left coprime factorization of the transfer matrix $G_u(s)$

$$\begin{aligned} \widetilde{M}(s) &= -C(sI - A + KC)^{-1}K + I \\ \widetilde{N}(s) &= C(sI - A + KC)^{-1}(B - KD) + D \end{aligned} \tag{50}$$

K is the feedback matrix chosen to make $(A - KC)$ stable; and the matrix $Q(s)$ is a stable and proper transfer function matrix defined as a weighting matrix which can be static or dynamic. Substituting the model in Eq. (22) into (49) the residual signal is obtained as follows:

$$r(s) = Q(s)(N_f(s)f(s) + N_d(s)d(s)) \tag{51}$$

with

$$\begin{cases} N_f(s) = C(sI - A + KC)^{-1}(R_1 - KR_2) + R_2 \\ N_d(s) = C(sI - A + KC)^{-1}(E_1 - KE_2) + E_2 \end{cases} \tag{52}$$

The perfect disturbances decoupling requires (Frank and Ding, 1994)

$$\begin{cases} Q(s)N_f(s) = diag(t_1(s), \cdots, t_q(s)) \in RH_\infty \\ Q(s)N_d(s) = 0 \end{cases} \tag{53}$$

where RH_∞ is the set of all stable and proper transfer matrices.

In the term of the transfer matrices $G_f(s)$ and $G_d(s)$ the perfect decoupling condition is given by (Frank and Ding, 1994)

$$\begin{cases} rank\{[G_f(s) \quad G_d(s)]\} = rank\{G_f(s)\} + rank\{G_d(s)\} \\ rank\{G_f(s)\} = g \quad (\text{the number of independent faults}) \end{cases} \tag{54}$$

When such conditions do not hold, perfect disturbances decoupling is not achievable. In this case, the best approach is to obtain an optimal approximation that minimize the following performance index

$$J = \min_{Q(s)} \frac{\|Q(s)N_d(d)\|}{\|Q(s)N_f(s)\|} \tag{55}$$

This optimization problem and the H_∞ approach are studied by Ding and Frank (1991). Other methods using singular value decomposition techniques are presented by Lou, et al. (1986); Mangoubi, et.al. (1992), *etc*.

3.2.5 Nonlinear Residual Generation

The methods discussed above are all for linear models of the system dynamics, which rarely represent the real case practically. The first method to deal with nonlinearity is to obtain the linear approximation at an operating point and utilize robust techniques to make the residual signals insensitive to model errors, as studied above. The problem of these methods is that the strategy works only within a small range near the operating point. If the system operates in a wide dynamic range, the linearized model may fail to describe the dynamics and the linear techniques are not applicable. The preferred way to address the nonlinearity is to deal with it directly and develop nonlinear fault detection and isolation techniques. Some existing methods such as nonlinear and adaptive observer designs have been exploited to address the nonlinear fault detection and isolation (Ding and Frank, 1992). To find a "universal" model for nonlinear systems neural networks are introduced (Narendra and Parthasarthy, 1990). Similarly, to overcome the problem of precision and accuracy of the models used in FDI, fuzzy logic is integrated in model-based FDI (Dexter and Benouarets, 1997; Takagi and Sugeno, 1985).

3.3 Methods of Robust Residual Evaluation

As discussed before, the residual evaluation is to compare the decision function of the residual signal $J(r(t))$ and the threshold T initially set in fault free case. A fault can be detected by (5) and different faults are isolated by (6). Besides a number of robust residual generation methods, there are also some approaches that increase the robustness in residual evaluation. The main idea of these approaches is to pick up different thresholds that are modified with residuals or control activity of the system as oppose to the use of one fixed threshold applicable only to a specific operation point and sensitive to unknown inputs like disturbances.

3.3.1 Adaptive Threshold Method

An intuitive approach is to use adaptive thresholds, i.e. variable threshold. Since the residual and the decision function may change with the changing control inputs in the presence of system parameter uncertainties, the false alarms may be generated when the changes are large enough to exceed the fixed value of the threshold. In order to increase robustness in such cases, an adaptive threshold was proposed (Clark, 1989; Frank, 1995) which varies dependently on the control input. Fig.10 gives a graphic illustration of this scheme.

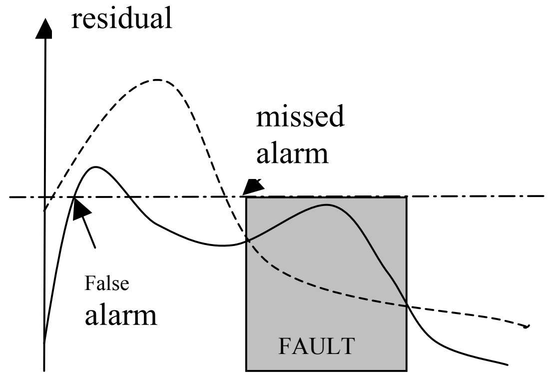

Fig.10 Application of an Adaptive Threshold in Robust FDI

—— residu ---- adaptiv e _._ fixed threshol

Consider the residual signal in Eq.(24), and assume that unknown inputs are decoupled, the residual signal in fault free case is

$$r(s) = H_y(s)\Delta G_u(s)u(s) \tag{55}$$

Assume that the model error is bounded by

$$\|\Delta G_u(jw)\| \leq \delta \tag{56}$$

thus

$$\begin{aligned}\|r(jw)\| &= \|H_h(jw)\Delta G_u(jw)u(jw)\| \\ &\leq \|H_h(jw)u(jw)\|\|\Delta G_u(jw)\| \\ &\leq \delta\|H_h(jw)u(jw)\|\end{aligned} \tag{57}$$

The adaptive threshold $T(t)$ for Eq.(20) and (21) can be selected as

$$T(s) = \delta H_y(s)u(s) \tag{58}$$

Clearly this threshold will change with the input and therefore become adaptive to the system operation.

3.3.2 Robust Threshold Selector

A similar way to increase the robustness in residual evaluation is to use the robust threshold selector presented by Emani-Naeini, et al. (1988) represented in the block diagram shown below in Fig.11.

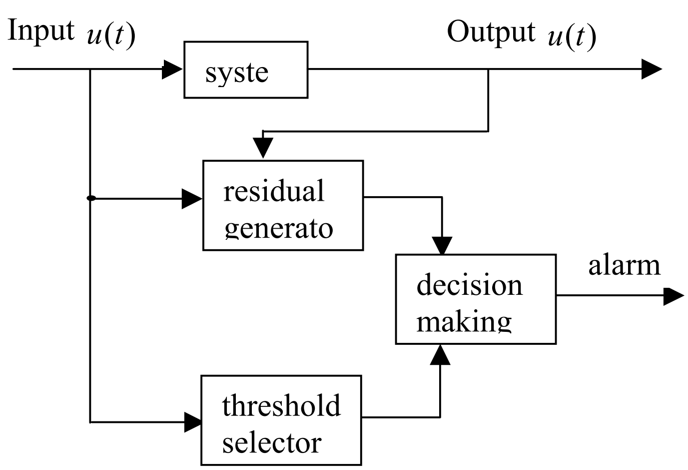

Fig.11 Robust FDI With Use of Threshold Selector

With properly chosen threshold the residual is no longer compared with a fixed threshold. The control activity and the system operation states influence the variable threshold and hence improve the fault detection and isolation.

4. Model-free FDI Techniques

The methods mentioned so far were all based on quantitative models of the system dynamics, which are not applicable when the models of the system are not available. As a complement, there is a branch of fault detection and isolation that deals with cases when only the qualitative model of the dynamics or no model at all is available. In this section we will introduce some of these methods that are applicable to aircraft dynamic and control.

4.1 Fault Diagnosis Using Qualitative Models

It is often difficult to develop an accurate mathematical model of the system dynamics, whereas cruder description of the system is easier to achieve. Fault diagnosis of dynamic systems can also be accomplished based on declarative knowledge called "qualitative models". The qualitative models require only declarative (heuristic) information of the variables - the tendencies and the magnitudes of the signals - so that robustness to uncertainty is achieved (Chen and Patton, 1999). Qualitative-based FDI methods can be used when no analytical mode is available, the on-line information is not given in quantitative measurements, or the parameters of the system structure are not precisely known.

Qualitative model-based FDI does not use quantitative residual generation to generate the symptoms of faults but turns to qualitative knowledge usage (Isermann, 1994). The qualitative knowledge includes fault-tree, i.e. the connection of symptoms and faults, the process history and fault statistics. Through human observation and inspection heuristic characteristic values in the form of noise, color, smell, etc. are generated. The heuristic information can also be expressed in linguistic terms like "little", "medium" or "full". Based on the available heuristic knowledge the diagnostic reasoning (forward and backward reasoning) strategies can be adopted (Isermann, 1994) and on-line expert systems are also applicable (Frank, 1990). An alternative way is to use qualitative observers based on Markov chain models which, like quantitative observers used in model-based FDI, generate and evaluate residuals for stochastic systems (Zhuang et al, 1998). Chessa and Santi (2001) presented a graph-based diagnosis with multiple faults in which the error propagation between system components is modeled as a direct graph. Pecht, et al. (2001) suggested an on-board hardware-software diagnostic means referred to as built-in test when failure occurrences were uniquely associated with the operating environment and the usage of this method into Boeing 767 and 777 proved its usefulness.

4.2 Diagnosis Using Classification Method

The task of fault diagnosis is to identify the most possible fault causing the appeared symptom in system operation. Denote by $S^T = \begin{bmatrix} S_1 & S_2 & \cdots & S_n \end{bmatrix}$ the features of the system in operation and ${S_0}^T = \begin{bmatrix} S_{1,0} & S_{2,0} & \cdots & S_{n,0} \end{bmatrix}$ the reference vector determined for the normal behavior in fault free case, $\Delta S^T = S^T - S_0^T$ is the symptom vector that indicates the occurrence of one or more fault(s). The binary vector

$$F^T = \begin{bmatrix} F_1 & F_2 & \cdots & F_q \end{bmatrix}$$

expresses the fault f_i as either "happened" with $F_i = 1$ or "not happened" with $F_i = 0$. If no further information is available for the relations between features and faults, classification or pattern recognition methods can be used (Isermann, 1997). The block diagram of classification methods is shown in Fig. 12.

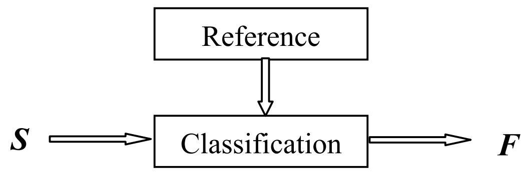

Fig. 12 Fault Diagnosis Using Classification Methods

In Fig.12, the relationship between S and F is learned or trained experimentally and stored, forming the explicit database. By comparison of the observed S with the normal reference S_0, the fault indication vector F can be concluded.

Bayesian classification is a main kind of probability-based statistical classification method that works on the premise that classified faulty and fault-free data exist. The nearest neighbor scheme is a geometrical classification similar with Bayesian classifier while it makes no statistical assumptions (Molnar, 1997). A more generalized classification method is to use neural-networks because of their ability to approximate nonlinear relations and determine flexible decision regions in continuous or discrete form (Molnar, 1997; Hoffman, et al, 2001). Also fuzzy classification is possible which is at the edge of probability theory and the expert system (Isermann, 1997).

4.3 Application of Computational Artificial Intelligence in FDI

Artificial intelligence (AI) has been exploited for FDI for a period of time (Frank, et al, 1997). Integrating the symbolic and quantitative knowledge by a neuro-fuzzy system is a new trend in this area (AI-Jarrah and AI-Rousan, 2001; Benkhedda and Patton 1996; Frey and Kuntze, 2001). The advantage is the neuro-fuzzy system feasibly combines the learning ability of neural networks with the explicit knowledge representation of fuzzy logic, and thus can model and design nonlinear systems efficiently. Patton and Lopez-Toribio (1999) integrated B-Spline neural network and fuzzy logic dealing with the qualitative information to diagnose faults. The general parameter adaptation fuzzy neural network is presented by Akhmetov, et al. (2001).

Another trend in FDI using AI is to use fuzzy residual evaluation (Kiupel, et al., 1995). The purpose is to release only weighted alarms instead of yes-no decisions. The final decision is made by both a decision maker with fuzzy logic and the human operator. The method contains no defuzzification but it has to be understandable for the operating persons.

5. Controller Reconfiguration

Based on the fault detection and isolation techniques, the dynamic system is under monitoring during the operation for any possible fault. To make the aircraft dynamic tolerant to failures controller reconfiguration need to be adopted, which modifies the controller in either structure or parameters in order to control the flight and mission in an uninterrupted operation.

5.1 Control Reconfigurability Analysis

The task of the reconfigurable controller reconfiguration is to retain nominal stability and performance characteristics. This requires that the on-design controllability and observability be preserved (Stengel, 1991). At the same time the reconfiguration should, at least, provide sufficient stability long enough for the FDI process to take place and new controllers switch in (Chandler, 1989). In order to implement a reconfiguration strategy the following control surfaces and mechanisms are needed (Napolitano and Swaim, 1989)

- control surfaces like speed brakes, wing flaps, rudder below fuselage, etc;
- thrust control mechanisms.

and the quantities to be available for reconfiguration purposes include

- actuator position for each actuator;
- aircraft body angular and linear velocities in three body axes;
- aircraft attitude and angle of attack.

5.2 Reconfiguration Law Design

The block diagram in Fig.13 illustrates the fault detection, isolation and controller reconfiguration for control surfaces using multiple model for the F/A -18 aircrafts (Rauch, 1995).

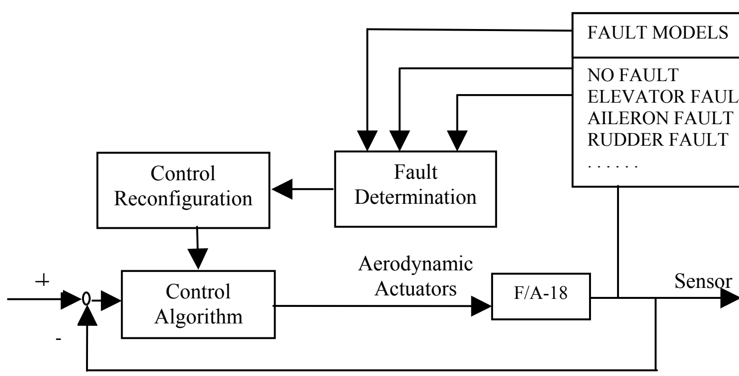

Fig. 13 Fault Detection, Isolation and Reconfiguration for Aircraft Control Surfaces

Here the decision function monitors the sensors and compares measured system response with the estimate response from the system models built in fault-free case. Once a potential fault is detected, fault isolation fulfills the task of isolation an position of the fault, and controller reconfiguration, based on stored control laws designed for each anticipated fault. However, there is a trade-off between speed of reconfiguration and computer storage requirements since the structures and parameters for all failed states can be generated off-line and stored for future use requiring an enormous memory (Stengel, 1991). Alternatively, the reconfigured control can use a pseudo-inverse approach to implement a feedback control law similar to that of the primary controls used in nominal operation without fault. In other words, the new feedback control is calculated to achieve equal product of the new control matrix (K_{new}) and the new control (u_{new}) with the product of the previous control matrix K times the control u, i.e.

$$K_{new}u_{new} = Ku \tag{59}$$

If a fault occurs, the control influence matrix K_{new} is derived from K by eliminating the column corresponding to the failed control input. If the redundancy in the actuators is available the new control signal u_{new} can be calculated using the pseudo-inverse as follows

$$u_{new} = (K_{new}{}^{T} K_{new})^{-1} K_{new} Ku \tag{60}$$

A more general approach is to develop a new LQR control law based on the model of the system that corresponds to the faults (Rauch, 1994; Moerder,et al, 1989). In the work of Moerder, et al, (1989) the reconfiguration control law was presented for AFTI F16 aircraft at Mach 0.8 and 5000 ft altitude. The stabilization is achieved by a proportional-integral-filter (PIF) output feedback regulator given by

$$\begin{cases} u(k+1) = u(k) + \Delta T[\eta(k) - \eta(k-1)] \\ \qquad \eta(k) = -Gy(k) \end{cases} \tag{61}$$

where $u(.)$ is the control command vector, $y(.)$ the plant output vector, and ΔT the controller sampling interval. The PIF feedback gain matrix is scheduled as

$$G(\theta) = G_0 + \sum_{j=1}^{n} \theta_j G_j \tag{62}$$

Here $\theta = [\theta_1 \cdots \theta_j \cdots \theta_n]^T$ is the vector representing the surface effectiveness loss of n control surfaces. $\theta_j = 0$ implies fully effectiveness while $\theta_j = 1$ indicates faulty or missing effectiveness of the j th control surface. The gain matrix G_j is obtained using LQG output feedback stabilization design. The objective is to minimize a cost function

$$J_j = \lim_{N\to\infty} \frac{1}{2(N+1)} E\left\{ \sum_{k=0}^{N} x_j^T(k+1) Q_j x_j(k+1) + u_j^T(k) R_j u(k) \right\}, \quad Q_j, R_j \geq 0 \tag{63}$$

where x_j is the state vector and u_j the control vector of a collection of linear discrete-time plant models with respect to different faults.

Rattan (1985); Ioannou, et al, (1989) presented the evaluation of control mixer concept for reconfiguration of flight control system. The reconfiguration algorithm computes a new control mixer gain matrix to distribute the forces and moments of the failed control surface to the remaining healthy surfaces. The difference is that Patton "lock" the failed control surface to the center position, i.e., the input to the failed surface is zero, while in the latter paper the surface is allowed to be stucked at any position although this non-zero stuck needs accommodation by a compensating input signal. Assume the unimpaired, healthy aircraft is modeled as

$$\dot{x}_0 = A_0 x_0 + B_0 \delta \tag{64}$$

The subscript "0" implies the system is working in the normal fault-free case; $x_{n\times1}$ denotes the state vector of the aircraft and $\delta_{s\times1}$ the aircraft control surface deflection vector which is governed by the control vector u as

$$\delta = K_0 u \tag{65}$$

Assume the fault detection and isolation unit diagnosed that the j th control surface failed, i.e. the surface got stuck at $\delta_j = \overline{\delta}_j$, the system dynamic becomes

$$\dot{x} = A_0 x + B_0{}^j [Ku + d] + b_{0j}\bar{\delta}_j \tag{66}$$

where $B_0^j = B_0 - \begin{bmatrix} 0_{1,1} & \cdots & 0_{1,s} \\ & \vdots & \\ 0_{j-1,1} & \cdots & 0_{j-1,s} \\ 1_{j,1} & \cdots & 1_{j,s} \\ 0_{j+1,1} & \cdots & 0_{j+1,s} \\ & \vdots & \\ 0_{n,1} & \cdots & 0_{n,s} \end{bmatrix} B_0$; and b_{0j} is the j th column of B_0.

K and d are control mixer and compensating signal to be designed in order that x is as close to x_0 as possible, i.e.

$$B_0 K_0 u = B_0{}^j [Ku + d] + b_{0j}\bar{\delta}_j \tag{67}$$

Consider the condition that Eq.(67) must hold for fault-free case as $\bar{\delta}_j = 0$, the solution to (67) is given by

$$\begin{cases} K = (B_0^j)^+ B_0 K_0 \\ d = -(B_0^j)^+ b_{0j}\bar{\delta}_j \end{cases} \tag{68}$$

where $(B_0^j)^+$ denotes the pseudoinverse of matrix B_0^j.

To achieve controller reconfiguration there was also some work on the variable structure model following control (Zinober, et al, 1988; Mudge and Patton, 1988) in which the design objective is to develop a controller which forces the aircraft dynamics to follow the dynamics of an ideal model. In Martins, et al (2001) the language techniques are introduced to model the controlled dynamical systems and a learning algorithm for controller reconfiguration is proposed. Ahmed-Zaid, Ioannou, et al (1991) proposed a fault accommodation method based on adaptive control theory (Ioannou and Sun, 1996) in the sense that with the presence of failures the control law was reconfigured using on-line estimates of the faulty aircraft dynamics. This method requires no explicit information of types of faults and hence it simplifies the design and is resistant to false alarms. Polycarpou(1994) presented a systematic procedure for constructing nonlinear estimation using neural networks and a stable learning scheme is used for accommodating failures. Recently Zhou and Frank (2001) proposed a PID state feedback control for nonlinear stochastic systems in closed loops combined with fault detection and accommodation.

6. Conclusion

In this paper we reviewed the methods applicable for fault-tolerant control of aircrafts with the emphasis on approaches combining fault diagnosis and controller reconfiguration. Main principles and most relevant techniques of model-based and model-free fault diagnosis were reviewed. The robustness problem was also discussed. It was seen that the methods of analytical redundancy is to some degree more mature but the demand is an accurate analytical model of the system dynamics. In the application of aircrafts, knowledge-based methods are often used since they do not require prior quantitative models but the learning algorithms of neural networks or rules and reasoning of expert system together with restored control laws in fault status may require an enormous computer memory.

The basic schemes of controller reconfiguration based on fault diagnosis decision were also summarized. There are a number of results related to using FDI to mechanical systems and control surfaces of an aircraft, while techniques for on-line identification of fault models with time-varying nonlinearities and robust FDI using closed loop models are still of research interest. Other future research topics include severe single and multiple failures accommodation and disturbance compensation through controller restructuring and approaches enhancing sensitivity of fault-tolerant control systems to failures while maintaining robustness properties.

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