A Survey of Fault Detection, Isolation, and Reconfiguration Methods

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***Abstract*—Fault detection, isolation, and reconfiguration (FDIR) is an important and challenging problem in many engineering applications and continues to be an active area of research in the control community. This paper presents a survey of the various model-based FDIR methods developed in the last decade. In the paper, the FDIR problem is divided into the fault detection and isolation (FDI) step, and the controller reconfiguration step. For FDI, we discuss various model-based techniques to generate residuals that are robust to noise, unknown disturbance, and model uncertainties, as well as various statistical techniques of testing the residuals for abrupt changes (or faults). We then discuss various techniques of implementing reconfigurable control strategy in response to faults.**

***Index Terms*—Analytic redundancy, fault detection, fault isolation, fault reconfiguration, survey.**

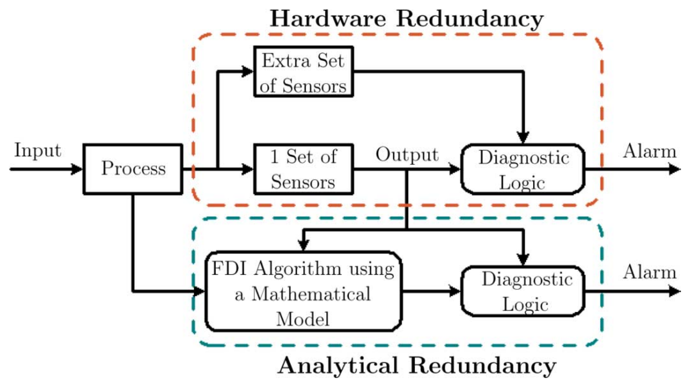

Fig. 1. Illustration of the concepts of hardware redundancy and analytical redundancy for FDI.

I. Introduction

FAULT detection, isolation, and reconfiguration (FDIR) is an important and challenging problem in many disciplines such as chemical engineering [1]–[4], nuclear engineering [5], [6], aerospace engineering [7], [8], and automotive systems [9]. In aerospace engineering, for example, although aircraft systems are built with high level of redundancy to tolerate hardware and software faults, robust fault diagnosis is also used to monitor and assess the aircraft's safety. In some cases, if a fault can be quickly detected and identified, appropriate reconfiguration control actions may be taken. A notable example is a fly-by-wire flight control system which reduces the complexity, fragility and weight of a hydromechanical flight control system, but also presents more reliability problems. A high-level redundancy design coupled with a robust fault diagnosis scheme would be required to ensure that such systems can meet the stringent safety requirements of aircraft operations.

The International Federation of Automatic Control (IFAC) SAFEPROCESS Technical Committee defines a fault as an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable/usual/standard condition [10], [11]. Such malfunctions may occur in the individual unit of the plants, sensors, actuators or the switching logic components. FDIR is a control methodology which ensures continual safe or acceptable operation of a system when a fault occurs through fault detection and isolation (FDI), and controller reconfiguration in response to the specific fault. The FDI problem consists of making a binary decision—either that something has gone wrong or that everything is fine, and of determining the location as well as nature of the fault [12]. In general, FDI methods utilize the concept of redundancy, which can be either a hardware redundancy or analytical redundancy as illustrated in Fig. 1. The basic concept of hardware redundancy is to compare duplicative signals generated by various hardware, such as measurements of the same signal given by two or more sensors. The common techniques used in the hardware redundancy approach are the cross channel monitoring (CCM) method, residual generation using parity generation (for example, based on sensor geometry or signal pattern), and signal processing methods such as wavelet transformation, etc. On the other hand, analytical redundancy uses a mathematical model of the system together with some estimation techniques for FDI. As the analytical redundancy approach generally does not require additional hardware, it is usually a more cost effective approach compared to the hardware redundancy approach. However, the analytical redundancy approach is more challenging due to the need to ensure its robustness in the presence of model uncertainties, noise, and unknown disturbances. Generally, the analytical redundancy approach can be divided into quantitative model-based methods and qualitative model-based methods. The quantitative model-based methods, such as the observer-based methods, use explicit mathematical models and control theories to generate residuals for FDI. On the other

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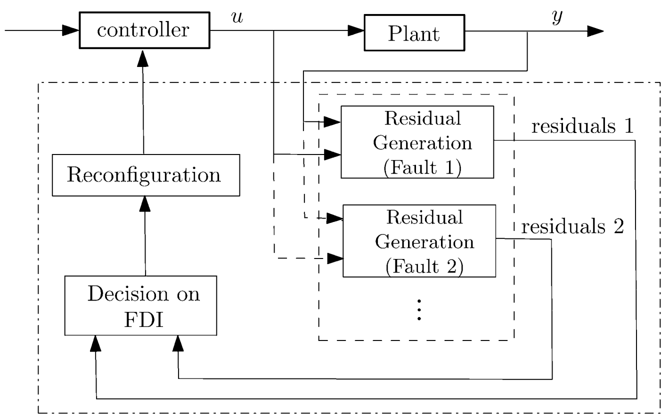

Fig. 2. Fault detection, isolation, and reconfiguration scheme.

hand, the qualitative model-based methods use artificial intelligence (AI) techniques, such as pattern recognition, to capture discrepancies between observed behavior and that predicted by a model. This paper focuses mainly on the quantitative model-based approach to FDIR. We would only briefly discuss the AI techniques to point out some recent works that aim to combine the AI methods with the quantitative model-based approach. The qualitative model-based methods belong to an important area in FDI and we hope to give a more detailed coverage of these methods in future work.

A general structure of an analytical redundancy-based (or model-based) FDIR system is illustrated in Fig. 2. The FDIR problem can be divided into three steps. The first step is to generate a set of variables known as residuals by using one or more residual generation filters. These residuals should ideally be zero (or zero mean) under no-fault conditions. In order to be useful in practical applications, they should be insensitive to noise, disturbances, and model uncertainties while maximally sensitive to faults. Some FDIR schemes use two or more residual generation filters in parallel for fault isolation. In such schemes, each of the residual generation filters is designed to be sensitive only to a selective set of faults. The second step is to make decisions on whether a fault has occurred (fault detection) and on the type of faults that have occurred (fault isolation) based on the residuals. This step is usually done using statistical tools to test if the residuals have significantly deviated from zero. Finally, the controller is reconfigured online in response to any faults detected.

In the analytical redundancy approach, the residuals are generated based on a mathematical model of the system. The mathematical model may be developed from first principles such as that of a mechanical system derived based on Newton's law of motion, or it may be determined based on past experience or past observations, such as those derived based on system identification techniques. In practice, the mathematical model usually cannot describe the behavior of the actual system exactly due to modeling errors and uncertainties in model parameters. Furthermore, practical systems are usually subjected to noise and unknown disturbances. This results in residuals that are nonzero under no-fault conditions. There are generally two approaches to overcome this problem, shown as follows.

1) *Robust Residual Generation:* One approach is to design a robust filter or estimator that generates residuals which are insensitive to noise and uncertainties, and at the same time sensitive to faults. Examples of this approach are the fault detection filters [13]–[17], the observer-based methods [18], [19], the parity relation methods [20], [21], the parameter estimation methods [22], [23], and Kalman filter-based methods [24].
2) *Robust Residual Evaluation:* Another FDI strategy is to develop robust hypothesis testing algorithms to evaluate the residuals which are considered as random variables. The strategy focuses on robust methods of detecting a change in signals or system parameters which correspond to faults. The simplest decision rule is to declare that a fault occurs when the instantaneous value of a residual exceeds a constant threshold. More sophisticated decision rules may consist of adaptive thresholds, or may be based on statistical decision theories such as generalized likelihood ratio (GLR) test or sequential probability ratio test (SPRT) [12], [25], [26].

The FDIR problem is a well-established subject on which various books and papers have been written. Willsky has presented key concepts of analytical redundancy in model-based FDI in an early survey paper [12]. Frank [19] has written a comprehensive survey of observer-based FDI methods. Isermann has presented some basic fault detection methods, and illustrated fault detections by parameter monitoring and special correlation methods in his survey paper [23]. Various surveys of parity relation methods in FDI can be found in [21], [27] and [28]. Various books have also given comprehensive review of the concepts and applications of model-based FDIR methods [26], [29]–[32]. More recent survey papers include a three-part review paper by Venkatasubramanian *et al.* [2]–[4] which focused on FDI methods and applications in process chemical engineering, and a survey paper by Angeli *et al.* [33] which focused on numerical and artificial intelligence FDI methods. In [34], Isermann presented an introduction to various model-based FDIR techniques. A tutorial introduction to FDIR techniques and applications in drive-by-wire systems has been given by Isermann in [9]. Over the last decade, the FDIR problem has gained increasing considerations in various engineering applications. The objective of this paper is to give a comprehensive survey of recent development in FDI over the last ten years with a limited coverage on reconfiguration techniques. Furthermore, a survey paper could either cover a limited number of papers with a detailed comparison or cover as many papers as possible with a brief comparison. In this paper, we aim to cover as many published materials as possible with a brief comparison that is addressed in Section VI. More detailed comparisons with simulation results for some specific FDIR methods are being planned as our follow-on research.

The rest of this paper is organized as follows. An overview of model-based fault detection, isolation, and reconfiguration methods is presented in Section II. In Section III, we survey some recent developments in robust residual generation techniques. The statistical decision techniques and the reconfiguration control techniques are discussed in Sections IV and V, respectively. In Section VI, we give a comparison of the various

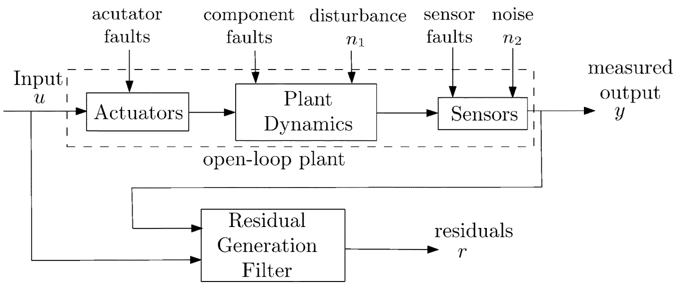

Fig. 3. Fault model used for designing the residual generation filter.

FDI techniques in terms of their performance, residual characteristics, complexity, and robustness. Conclusions are given in Section VII.

II. Overview of Fault Detection, Isolation, and Reconfiguration Techniques

In this section, we briefly describe the basic concept of FDI. We assume a linear system model since many fundamental FDI methods, such as detection filter and unknown input observers, are based on such a model.

A. System and Fault Modeling

Fig. 3 illustrates a general fault model for fault detection and isolation. The plant dynamics are modeled as

$$x(t+1) = (A+\Delta A)x(t) + (B+\Delta B)u(t) + E_1 n_1(t) \quad (1)$$
$$y(t) = (C+\Delta C)x(t) + (D+\Delta D)u(t) + E_2 n_2(t) \quad (2)$$

where $x \in \mathcal{R}^n$ is the state vector, $u \in \mathcal{R}^q$ is the plant's input vector, $y \in \mathcal{R}^m$ is the output vector measured by the sensors, and n_1 and n_2 are noise or unknown disturbance vectors. It is assumed that the plant's input vector u is known, but the system model may contain model uncertainties $\Delta A, \Delta B$, etc.

The faults in the system can generally be classified into three types: actuator faults, sensor faults, and component faults. The actuator faults and sensor faults typically represent faults in the actuators and sensors of the system respectively. They are commonly modeled as *additive faults* in the system (1)–(2). The component faults typically represent faults which lead to changes in the parameters of the system dynamics. They are commonly modeled as *multiplicative faults*, i.e., they are modeled as changes in the parameters of the system matrices. For example, an aircraft aileron or elevator stuck at a deflection results in an actuator fault, while a control surface damage or a fuselage damage results in a component fault. Hence, a general fault model for the system (1)–(2) is

$$\begin{aligned} x(t+1) &= (A+\Delta A+\Delta A_c)x(t) + (B+\Delta B+\Delta B_c)u(t) \\ &\quad + E_1 n_1(t) + B f_a(t) \end{aligned} \quad (3)$$
$$\begin{aligned} y(t) &= (C+\Delta C+\Delta C_c)x(t) + (D+\Delta D+\Delta D_c)u(t) \\ &\quad + E_2 n_2(t) + f_s(t) \end{aligned} \quad (4)$$

where $f_a(t)$ represents the actuator faults, $f_s(t)$ represents the sensor faults, $\Delta A, \Delta B$, etc., represent the model uncertainties, and $\Delta A_c, \Delta B_c$, etc., represent the component faults.

One of the main objectives of FDI methods is to generate residuals which are insensitive to noise, disturbances, and model uncertainties. However, this is a difficult task in general. Some FDI algorithms, such as the classical unknown input observers and the parity relations method, could be designed to be robust to additive noise and disturbances, provided that the matrices E_1 and E_2 are known. It is usually difficult to consider the components faults and model uncertainties in the multiplicative form as given in (3) and (4). One way to overcome this problem is to model the model uncertainties $\Delta A, \Delta B$, etc. as additive disturbances with time-varying disturbance-to-state system matrices. Similarly, for fault isolation, it is also advantageous to replace the component faults $\Delta A_c, \Delta B_c$, etc., with an additive fault vector $f_c(t)$. The corresponding fault model is

$$x(t+1) = Ax(t) + Bu(t) + E_1(t)n_1(t) + Bf_a(t) + F_1(t)f_c(t) \quad (5)$$
$$y(t) = Cx(t) + Du(t) + E_2(t)n_2(t) + f_s(t) + F_2(t)f_c(t). \quad (6)$$

In the above model, the vectors $n_1(t)$ and $n_2(t)$ may include model uncertainties and the corresponding matrices E_1 and E_2 may be time-varying.

Let $n(t) = [n_1(t)\ n_2(t)]^T$ be the noise vector and $f(t) = [f_a(t)\ f_s(t)\ f_c(t)]^T$ be the fault vector. The state-space model (5)–(6) can be transformed into the input-output framework as

$$y(t) = G(z)u(t) + F(z)f(t) + E(z)n(t) \quad (7)$$

where

$$\begin{aligned} G(z) &= C(zI-A)^{-1}B + D \\ F(z) &= [(zI-A)^{-1}E_1\ E_2] \\ E(z) &= [(zI-A)^{-1}B\ I\ (zI-A)^{-1}F_1 + F_2]. \end{aligned}$$

B. Residual Generation

As illustrated in Fig. 3, the residual is a signal generated based on the input vector $u(t)$ and the output vector $y(t)$, or

$$r(t) = g(u(t), y(t)). \quad (8)$$

Commonly, the residual $r(t)$ is the difference between the measured output $y(t)$ and an estimated output $\hat{y}(t)$ computed based on the plant's model, i.e.,

$$r(t) = y(t) - \hat{y}(t). \quad (9)$$

For fault detection, the residual should satisfy the following properties.

- *Invariance Relation:* When no fault occurs, the mean of the residual $E[r(t)]$ should be zero.
- *Fault Detectability:* When any of the faults in (5)–(6) occurs, $E[r(t)]$ should deviate from zero.

In practical applications, the residuals are corrupted by the presence of noise, unknown disturbances, and uncertainties in the system model. Hence, many FDI methods aim to generate robust residuals that are insensitive to these noise and uncertainties, while sensitive to faults. These methods can be grouped in a few basic approaches, namely:

a) full-state observer-based methods;
b) unknown input observers;
c) parity relations approach;
d) optimization-based approach;
e) Kalman filter-based approach;

f) stochastic approach;
g) system identification approach;
h) nonlinear systems approach;
i) discrete event systems/hybrid systems approaches;
j) artificial intelligence (AI) techniques.

The above residual generation methods will be discussed in Section III.

C. Fault Isolation

For fault isolation, the residuals generated should not only be sensitive to faults, they also need to be able to distinguish between different types of faults. There are two approaches to generate such residuals which facilitate fault isolation. One method, known as the directional residual approach, is to generate residual vectors that lie in a specified direction in the residual subspace corresponding to each type of fault. The fault isolation problem is then transformed into one of determining the direction of the residual vector. The other method is the structured residual approach, in which each residual vector is designed to be sensitive to a single or selective set of faults, and insensitive to the rest. Structured residuals are usually characterized by an incidence matrix in which the rows correspond to residuals and columns correspond to faults. A "1" in the incidence matrix represents coupling between a residual and a fault, and a "0" represents no coupling. For isolation, all columns must be different. A special case in which each residual is designed to respond to a single fault is known as a diagonal structure.

D. Decision Making

Once the residuals are generated, the next step is to determine whether any fault has occurred and to determine the location or type of each fault based on statistical tests of the residuals. The simplest approach is to decide that a fault has occurred when the instantaneous value of a residual vector exceeds a constant threshold. In some applications, stochastic system models are considered and the residuals generated are known or assumed to be described by some probability distributions. It is then possible to design decision tests based on adaptive thresholds. More robust decision logics use the history and trend of the residuals, and utilize powerful or optimal statistical test techniques. The well-known examples of these statistical test techniques are as follows:

a) sequential probability ratio test (SPRT);
b) cumulative sum (CUSUM) algorithm;
c) generalized likelihood ratio test;
d) local approach.

These statistical tests will be discussed in detail in Section IV.

E. Reconfiguration

The reconfiguration step involves changing the controller in response to the faults detected to ensure safe or satisfactory operation of the system. There are various methods of reconfiguration control, such as those based on online learning or system identification. In this paper, we focus on reconfiguration control methods based on FDI techniques. These methods, which are classified as the multiple-model approach and the adaptive control approach, will be discussed in Section V.

Fig. 4 presents a summary of the various classifications of FDIR techniques which we will discuss in the rest of this paper.

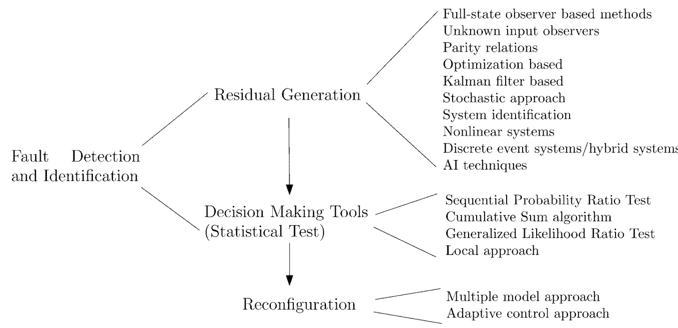

Fig. 4. Classifications of FDIR techniques.

III. Residual Generation Methods

In this section, we survey some robust residual generation methods for FDI. We would first discuss the basic residual generation techniques classified in Section II, namely: the full-state observer-based methods, unknown input observers, parity relations approach, optimization-based approach, Kalman filter-based approach, stochastic approach, robust estimation techniques, system identification techniques, and AI techniques. In addition, we also survey some FDI methods designed specifically for nonlinear systems, discrete-event systems, and hybrid systems. Finally, we briefly discuss some recent methods of generating residuals with special structures that facilitate fault isolation.

A. Full-State Observer-Based Methods

We consider a simple version of the fault model in (5)–(6)

$$x(t+1) = Ax(t) + Bu(t) + E_1 n_1(t) + Bf_a(t) \quad (10)$$
$$y(t) = Cx(t). \quad (11)$$

A full-state-observer of the system is given by

$$\hat{x}(t+1) = A\hat{x}(t) + Bu(t) + L(y(t) - \hat{y}(t)) \quad (12)$$
$$\hat{y}(t) = C\hat{x}(t) \quad (13)$$

where $\hat{x}$ is the estimated state and L is the gain matrix. The residual is given by

$$r(t) := W(y(t) - \hat{y}(t)) = WC\xi(t) \quad (14)$$

where W is a weighting matrix and $\xi := x - \hat{x}$ is the state estimation error. The error dynamics are given by

$$\xi(t+1) = (A - LC)\xi(t) + E_1 n_1(t) + Bf_a(t). \quad (15)$$

The gain L is then chosen such that $A - LC$ is asymptotically stable, and the residual $r(t)$ has some desired properties. Two common design approaches are the eigenstructure assignment methods and the fault detection filter.

In the eigenstructure assignment approach [27], [35], the residual $r(t)$ is made insensitive to the disturbance $n_1(t)$ by nulling the transfer function matrix of $n_1 \to r$. From (14) and (15), the transfer function is given by

$$WC[zI - (A - LC)^{-1}]E_1 = 0. \quad (16)$$

The objective is to choose W and L such that (16) is satisfied. This can be achieved by one of the following methods [27].

1) *Left Eigenvector Assignment:* Choose W and L such that $WCE_1 = 0$ and all rows of WC are the left eigenvectors of $A - LC$.

2) Right Eigenvector Assignment: Choose W and L such that $WCE_1 = 0$ and all columns of E_1 are the right eigenvectors of $A - LC$.

The design procedures for the eigenstructure assignments can be found in [35]. This approach can also be used to generate structural residuals. For example, let $f_i(t)$ be a specific fault component. The residual $r(t)$ can be made insensitive to the fault $f_i(t)$ by considering it as a disturbance $n_1(t)$.

The fault detection filter was first proposed by Beard [13] and subsequently refined with a geometric interpretation of the filter by Jones and Massoumnia [14], [36]. Considering the error dynamics in (15). Let $f_i(t)$ be a specific fault component (i.e., $f_i(t)$ is an element of $f_a(t)$). The effect of the fault $f_i(t)$ on the estimation error is given by

$$\xi(t+1) = (A - LC)\xi(t) + B_i f_i(t). \tag{17}$$

In a fault detection filter, the gain L is chosen such that $A - LC$ is stable and the error $\xi(t)$ corresponds to fault f_i remains in a constant subspace (or direction) $\mathcal{U}_i$. Hence, the corresponding direction of the residual is $WC\mathcal{U}_i$. Furthermore, if all the subspaces of the residuals correspond to the various faults are independent, fault isolability can be achieved. Note that the fault detection filters generally do not consider the effects of disturbance or noise.

Design algorithms of the fault detection filter have been developed by White and Speyer [15], and Park *et al.* [16], [17]. The design procedures are too complicated to be described here. Wilbers and Speyer [37] have used a fault detection filter for detecting aircraft sensor and actuator faults. It has been found that this fault detection filter could be sensitive to small parameter variations when the eigenvectors of the observer are ill conditioned. The robustness issue of the fault detection filter has been addressed by Douglas and Speyer in [38] and [39]. Chung and Speyer [40] have considered a robust fault detection filter design based on a game-theoretic approach.

B. Unknown Input Observers

The basic idea of the unknown input observer approach is to generate state estimation errors which are decoupled from the unknown input disturbance (or noise) vector $n_1(t)$ in (1). This approach was introduced by Watanabe and Himmelblau [41], and has subsequently been refined by Frank and Wünnenberg [19], [42]. The unknown input observer approach remains an active area of research, and has been considered by many investigators in recent years. To illustrate the basic idea of the unknown input observer, we consider the fault model

$$x(t+1) = Ax(t) + Bu(t) + Gn_1(t) + Bf_a(t) \tag{18}$$
$$y(t) = Cx(t) \tag{19}$$

where $x(t) \in \mathcal{R}^n$ and $y(t) \in \mathcal{R}^m$. An pth order unknown input observer is given by

$$\eta(t) := Tx(t) \tag{20}$$
$$\hat{\eta}(t+1) = L_1\hat{\eta}(t) + L_2u(t) + L_3y(t) \tag{21}$$

where $\eta(t) \in \mathcal{R}^p, n - m \leq p \leq n$, and the matrices T, L_1, L_2, and L_3 are chosen such that the estimation error of the observer $e(t) = \hat{\eta}(t) - \eta(t)$ is independent of the unknown vector $n_1(t)$, and that $e(t)$ converges to zero asymptotically in the absence of faults. Specifically, from (18), (19) and (21), we have

$$\begin{aligned} e(t+1) = L_1e(t) &+ (L_2 - TB)u(t) \\ &+ (L_3C - TA)x(t) - TGn_1(t) - TBf_a(t). \end{aligned} \tag{22}$$

Choosing the matrices T, L_1, L_2, and L_3 such that

$$TG = 0 \tag{23}$$
$$L_2 - TB = 0 \tag{24}$$
$$L_3C - TA = -L_1T \tag{25}$$

and L_1 has stable eigenvalues, we have

$$e(t+1) = L_1e(t) - TBf_a(t). \tag{26}$$

Chen *et al.* [43] have proposed a systematic procedure of choosing the matrices T, L_1, L_2, and L_3 for a full-order unknown input observer. The necessary and sufficient conditions for the existence of this observer are also given. The advantage of the full-order observer is that it gives freedom to the designer to make directional residuals for fault isolation. Furthermore, a full-order observer gives more freedom in meeting other design objectives, such as rate of convergence or variance of estimation errors.

As shown in [43], the existence of an unknown input observer depends on certain rank conditions. In some applications, the rank conditions are not satisfied and hence it is not possible to achieve a complete decoupling between the residual and the unknown input. However, it is possible to minimize the effects of the unknown input which cannot be decoupled with the residual. Amato and Mattei [44] proposed an unknown input observer which decouples the unknown input from the estimation error where possible, and minimize the effect of the remaining disturbances in an H_∞ sense.

In classical unknown input observers, possible dynamic uncertainties in the system model are grouped in an additive unknown input, such as $f_c(t)$ in (5). In some practical situations, this method may not be suitable as certain rank conditions in the system input matrices have to be satisfied. In [45], an unknown input observer-based fault detection scheme which considers the system dynamic uncertainties directly and explicitly, as in (3), is proposed. The fault detection scheme is illustrated with an application in an industrial rolling mill.

While most works in model-based fault detection techniques dealt with systems modeled as a first-order state-space form, Demetriou [46] proposed an unknown input observer for vector second-order systems. A vector second-order system is one whose dynamics are described by a set of second-order differential equations which consist of both state velocities and accelerations. These vector second-order systems are widely encountered in mechanical systems (whose models are derived from first principles based on Newton's law of motion, or Lagrange equations of motion). While second-order differential equations can be expressed in the first order form, it is argued that the first order form does not carry over information about the physical state of the system [47]. Demetriou presented the necessary stability and convergence properties along with the existence conditions. The proposed unknown input observer is utilized in fault detection for detecting actuator and sensor faults. A control reconfiguration scheme is implemented based on an adaptive estimate of the actuator fault.

Park and Lee [48] investigated a systematic and straightforward fault estimation scheme for robust process FDI. The authors proposed the use of a special type of coordinate transformation, which is an extension of the coordinate transformations given by Hou [49] in the observer design for a linear system with both faults and unknown inputs. The use of the proposed transformation significantly reduces the order of the resultant observer and simplifies the design procedures. The information from the observer is used to reconstruct the shape and magnitude of the fault, and to estimate the unknown input for FDIR purposes. Specifically, these estimates are further used to construct additional control inputs for fault tolerant control. The proposed strategy has been validated through simulation studies performed on the control of a vertical takeoff and landing (VTOL) aircraft in the vertical plane.

C. Parity Relations Approach

Several survey papers have been written on parity relation (or parity equation)-based fault detection methods in the 1990's [21], [27], [28]. The concept of the parity relation-based fault detection approach is to form residuals as the difference between the system and model outputs. These residuals are then subject to a linear transformation. These two steps together constitute the residual generator that provides the desired FDI properties. There are various schemes to find such residual generation filters (expressed in parity equations or parity relations) that satisfy the required response properties. In general, the residual generation filters should be designed to enhance fault isolation so that they each exhibit directional or structural properties in response to a particular fault and they also need to possess certain properties such as robustness to noise, disturbances, or model errors. In [21], Gertler surveyed the basic concepts of residual generation for both additive and multiplicative faults. The implementation of the residual generation filters was also discussed.

Consider the fault model in (7). The primary residual vector is computed as

$$\nu(t) = y(t) - G(z)u(t). \tag{27}$$

From (7) and (27), we have

$$\nu(t) = F(z)f(t) + E(z)n(t) \tag{28}$$

which indicates the effects of faults and noise (or disturbances) on the primary residuals. We generate the enhanced residuals by the transformation

$$r(t) = W(s)\nu(t) \tag{29}$$

where $W(z)$ is chosen such that the enhanced residuals has some specified response, $N(z)$, to the fault vector and is not sensitive to the noise vector. Hence, we choose $W(z)$ such that

$$r(t) = N(z)f(t)$$

or, from (28) and (29)

$$W(z)[F(z)\ E(z)] = [N(z)\ 0]. \tag{30}$$

Equation (30) has one or more solutions, for arbitrary $N(z)$, if and only if

$$\mathrm{Rank}(F(z)) + \mathrm{Rank}(E(z)) \leq m$$

where m is the dimension of the output vector y.

There are typically two approaches of specifying the fault response $N(z)$. In the directional residual approach, we choose the residuals to have specific and independent directional responses corresponding to the respective faults, or

$$\begin{aligned} N(z) &= \gamma(z)\left[\beta_1\ \beta_2\ \ldots \beta_{N_f}\right] \\ r(t) &= N(z)f(t) = \gamma(z)\left[\beta_1 f_1(t) + \beta_2 f_2(t) + \ldots \right. \\ &\quad \left. + \beta_{N_f} f_{N_f}(t)\right] \end{aligned}$$

where $f_i(t)$ is the ith component of $f(t)$ and N_f is the number of faults.

In the structural residual approach, we choose each residual to respond only to a subset of faults. For example, if the ith residual is to respond only to fault 1, then we choose the ith row of $N(z)$ as

$$N_i(z) = \gamma_i(z)[1\ 0 \ldots 0].$$

The design of parity relations can also be carried with the state-space model. This is known as the Chow–Willsky scheme [50], or the parity space approach. As an example, we consider the state-space model (5)–(6) with the input, noise, and component faults ignored, or

$$\begin{aligned} x(t+1) &= Ax(t) + Bf_a(t) \\ y(t) &= Cx(t) + f_s(t). \end{aligned}$$

We define a parity vector $p(t)$ as

$$p(t) := Vy(t) = VCx(t) + Vf_s(t). \tag{31}$$

By choosing the matrix V such that $VC = 0$, we have

$$p(t) = Vf_s(t). \tag{32}$$

It can be seen that the ith column of V determines the direction of the parity vector $p(t)$ due to the ith sensor fault. Chow and Willsky extend this parity relation approach by consider the output equations

$$\begin{aligned} y(t-k) &= Cx(t-k) + f_s(t-k) \\ y(t-k+1) &= CAx(t-k) + CBf_a(t-k) + f_s(t-k+1) \\ &\vdots \\ y(t) &= CA^k x(t-k) + CA^{k-1}Bf_a(t-k) + \ldots \\ &\quad + CBf_a(t-1) + f_s(t). \end{aligned}$$

These equations can be written into a compact form

$$\tilde{y}(t) = Px(t-k) + Q\tilde{f}_a(t) + R\tilde{f}_s(t)$$

where $\tilde{y}(t) = [y^T(t-k)\ldots y^T(t)]^T, \tilde{f}_a(t) = [f_a^T(t-k)\ldots f_a^T(t-1)]^T$ and $\tilde{f}_s(t) = [f_s^T(t-k)\ldots f_s^T(t)]^T$. Let the parity vector be $p(t) = V\tilde{y}(t)$. The ith component of the parity vector is independent of the state vector if

$$V_i P = 0 \tag{33}$$

where V_i is the ith row of V. Note that V_i is of dimension $(k+1) \times m$ and the number of homogeneous equations in (33) is n (the dimension of the state vector). The remaining freedom of V_i can be used to decouple the response from some faults or disturbances.

It is known that there is a tradeoff in the design of a parity relation-based residual generation: a parity space of lower order means easier online implementation but poorer performance, while a parity space of higher order yields better performance but leads to higher computational cost. Ye *et al.* [51] attempted to overcome this design tradeoff by introducing a stationary wavelet transform into the traditional parity relation-based residual generation filters. The authors have shown that when using parity vectors of the same order, the stationary wavelet transform approach can provide at least one optimal performance index which is at least equal to or better than that delivered by the traditional approaches. As a result, the designed fault detector could achieve a better performance with the same computation cost.

In [52], Ding *et al.* considered the parity relation-based fault detection approach using temporal redundancy. It has been shown that increasing the order of the parity relation leads to an increase of the dimension of the parity space (i.e., the dimension of the parity vector $p(t)$), which means more freedom for the residual generation filter design and thus improvement of the performance of the parity relation-based fault detector. These results were applied to investigate the robustness problem in fault detection, and it has been shown that increasing the order of the parity equations may improve the system robustness. In [53] and [54], the authors have designed parity relation-based fault detectors for multiple sensors. The residual is generated from a fully decoupled parity equation and it is shown that it is sensitive to a special sensor fault only. From the residuals generated from the fully decoupled parity equations, the faults are then estimated using a recursive least-squares method.

D. Optimization-Based Approach

The robust residual generation problem can also be formulated as an optimization problem, such as that of minimizing the sensitivity of the residuals with respect to noise or unknown disturbance, and maximizing their sensitivity with respect to faults. A survey paper of this approach based on the perspective of control theory has been given by Stoustrup and Niemann [55]. The paper focused on formulating a very general class of FDI problems (with model uncertainty, parameter uncertainty, and a class of nonlinear systems) into standard robust control problems. The paper discussed both feedback controller and fault detection observer/filter design. It showed that there is a tradeoff between good fault detection and good performance of the closed-loop system for uncertain systems. This paper also briefly discussed design issues associated with nonlinear FDI methods.

Song and Collins [56] considered fault detection for linear systems with modeling uncertainties using an H_2 estimation method. The H_2 estimator is designed based on the parameter-dependent bounding approach and multiplier theory [57]. It is claimed that this approach is less conservative than methods based on the small gain theorem and fixed Lyapunov function theory. The robust H_2 estimation problem is then formulated as a parameter optimization problem in which the upper bound is minimized subject to a Riccati equation constraint. A continuation algorithm that uses the Broyden, Fletcher, Goldfab, and Shanno (BFGS) corrections is developed to solve the minimization problem. The FDI technique is illustrated with an application in a longitudinal flight control system.

Stoorvogel *et al.* [58] considered fault detection and isolation as an optimal estimation problem. The objective is to design an optimal estimator that is insensitive to disturbances, while the estimate is the best-possible estimate of the fault signal measured by either an H_2 or an H_1 norm. The paper has also studied the problem of fault signal estimation, i.e., that of determining the extent of failure.

Wang and Lam [59] considered a linear time-invariant system with uncertainty in system matrices and additive uncertainties in the outputs. The problem is formulated as a multi-objective optimization problem, whose objectives are to minimize a linear combination of: 1) the sensitivities of the residuals to the uncertainties and faults; 2) the size of the observer gain; 3) the numerical conditioning of the observer. The problem is converted into a gradient-based optimization and explicit gradient formulae are provided. The FDI technique has been illustrated with an application in a robotic manipulator, and an application in a vertical takeoff and landing aircraft.

In [60], Chen and Speyer designed a fault detection filter which detect one fault (known as the target fault) and reject other faults (known as nuisance faults) and sensor noise using an optimization technique. The target faults, nuisance faults, and sensor noise are modeled as uncorrelated white Gaussian noise. A residual generation filter is designed such that the residual is sensitive to only the target fault, and insensitive to the nuisance faults and sensor noise. This is formulated as a disturbance attenuation problem, which is then solved as an optimization problem. It had been shown that in the limit when the disturbance attenuation bound and the sensor noise go to zero, the filter is equivalent to an unknown input observer. In [61], the fault detection filter has been generalized to linear time-varying systems using a least-squares technique. The paper considers fault detection of linear time-varying systems with nuisance faults (unknown inputs) and random sensor noise (or output noise). The fault detection problem is formulated as a min-max problem by generalizing the least-square derivation of the Kalman filter. For a linear time-invariant system, the filter is equivalent to an unknown input observer. Hence, the filter could be seen as an extension of the unknown input observer to the time-varying case. In [62], Chen *et al.* similarly designed a detection filter by maximizing the transmission from the target fault (to be detected) to the projected output error while minimizing the transmission from the nuisance faults (to be blocked). The transmission from the process and sensor noise to the residuals is also minimized for robustness.

Darkhovski and Staroswiecki [63] considered fault detection of dynamic system containing nuisance parameters (unknown or uncertain parameters) that cannot be decoupled from the residual. A hypothesis testing problem which involves both the fault parameters and the nuisance parameters is set up. Since the nuisance parameters are unknown, the decision problem is set in a game-theoretical framework such that the decision maker guesses the nuisance parameters while "Nature" chooses the actual ones. The loss function expresses the penalty endured by the decision maker for not being able to guess the correct parameter values.

E. Kalman Filter-based Approach

The Kalman filter approach can be considered as a special case of stochastic optimization using linear quadratic optimization techniques. Mehra and Peschon [64] first introduced a general procedure for FDI using residuals (or innovations) generated by the Kalman filter. The faults are diagnosed by statistical testing on whiteness, mean and covariance of the residuals. Common statistical tools for testing the Kalman filter residuals are the Maximum Likelihood method, or the generalized likelihood ratio (GLR) test, which will be discussed in detail in Section IV.

A well-known Kalman filter-based approach is the multiple model adaptive estimation (MMAE) approach [65]–[67]. In the MMAE approach, the system dynamics are described by a stochastic linear system model with uncertain parameters (which represent the faults) in the state matrices. It is assumed that the uncertain parameters can take on only discrete values from a finite set. A Kalman filter is then designed for the system dynamics corresponding to each parameter value, resulting in a bank of Kalman filters for the FDI scheme. The MMAE has been applied to many FDI problems in aerospace systems, including the aircraft flight control systems [68], [69] and inertial navigation systems [70]. A characterization of Kalman filter residuals for the MMAE has been presented in [71], and the result has been utilized in actuator and sensor failure detections in an aircraft flight control system. One notable feature of this approach is that since the number of failure modes is finite, it is possible to employ a control algorithm that has been specifically designed for each failure mode. On the other hand, some applications may require a large number of modes to represent all possible failures, which could thereby result in high computational costs. The relation of the multiple model FDI approach with reconfiguration control will be further discussed in Section V.

In the MMAE approach, a bank of Kalman filters runs in parallel independently. Such an approach is effective in handling problems with unknown, but constant, structures or parameters [72]. However, the problem of fault diagnosis and reconfigurable control may not fit well into such a framework because, in general, the system structure or parameter does change as a component or a subsystem fails. The exact solution to this problem requires a bank of Kalman filters whose number increases exponentially in time. An effective suboptimal solution to this problem is the Interacting multiple-model (IMM) approach to FDI proposed by Zhang and Li [73]. In the IMM approach, the occurrence or recovery of a failure in a dynamic system has been explicitly modeled as a finite-state Markov chain with known transition probabilities. The IMM algorithm considers the structural changes of the system explicitly by Gaussian approximations and a hypothesis merging technique known as "mixing". The performance of the IMM algorithm for FDI has been illustrated in [72]. In [74], Kim *et al.* have also proposed a FDI technique using a fuzzy-tuned IMM filter for aircraft flight control systems.

F. Stochastic Approach

The Kalman filter-based approach assumes a stochastic system model with Gaussian noise and residuals. Several authors have considered FDI for stochastic systems with more general probability distributions. In [75]–[77], fault detection algorithms have been considered for stochastic systems whose output is described as probability density functions (PDFs) instead of the classical input-output transfer function or state-space model. The authors used a B-spline expansion technique to approximate the output PDFs.

Several authors have considered robust residual generation using robust control techniques, such as L_1 estimation or H_∞ estimation techniques. Curry and Collins [78] considered robust fault detection for linear systems with both unknown disturbances and modeling uncertainties. The fault detection scheme consists of a bank of robust L_1 state estimators, which are designed using the mixed structured singular value technique [79]. This technique is less conservative in modeling the uncertainties than other techniques such as the small-gain theorem or fixed quadratic Lyapunov functions. The reduced conservatism allows the estimators to be used for more accurate fault detection. Specifically, the fixed thresholds are smaller, allowing the detection of smaller faults. The mixed structured singular value and L_1 theories are used to determine the appropriate threshold for fault detection.

Yaesh and Shaked [80] considered a state-space model of systems with uncertain parameters. Using a H_∞ approach, the state estimator is able to achieve a prescribed estimation error level when the state matrices of the model lie in a prescribed uncertainty polytope. It is claimed that this robustness property with respect to system uncertainties can be very useful when dealing with fault detection problems in flight control systems. In the paper, this property is used to detect possible faults occurring in a low-cost servo actuator without position feedback.

G. System Identification Methods

FDI could be done by using parameter estimation or system identification techniques. In this approach, a model of the physical system under normal operating conditions is estimated or identified either offline or online. It is then assumed that faults in the system would be reflected in a change of the parameters in the system model. The FDI problem then involves detecting any change in the system parameters. In an early survey paper [23], Isermann illustrated that process fault diagnosis can be achieved via estimation of unmeasurable process parameters and/or state variables. Simani *et al.* [81] have written a book on FDI methods with focus on system identification techniques. The survey paper by Isermann [82] also discusses system identification techniques in FDI.

Kim *et al.* [83] proposed a systematic statistical approach for detecting incipient faults in power distribution feeders. A parameter evaluation and isolation process runs in parallel with the fault detection process. The parameter evaluation and isolation process monitors observation data as well as a fault log of a feeder to identify the parameters that best correlate with a particular fault. The authors used a Laplace trend analysis technique to decide which parameters have a positive trend with the actual fault.

Recently, Basseville *et al.* [84], [85] have investigated the use of a subspace-based technique for system identification and fault detection. The subspace-based methods [86] are linear system identification algorithms based on either time domain measurements or output covariance matrices in which different subspaces of Gaussian random vectors play a key role. In [84], a system identification-based FDI technique is proposed for monitoring of structures which are subject to both fast unmeasured variations in their environment and small slow variations in their modal (vibrating) properties. Various applications, such as an online monitoring system for aero-elastic flutter of an aircraft, are discussed.

H. Nonlinear Systems

Several researchers have investigated extensions of classical robust residual generation techniques, such as unknown input observers, to nonlinear systems.

Chen and Saif [87] presented a fault detection and isolation design for Lipschitz nonlinear systems based on the unknown input observer approach. Faults are grouped into various distinct combinations, and an unknown input observer is designed for each combination for fault isolation. Using a Lyapunov approach, a sufficient condition for the existence of the unknown input observer design, which ensures that the estimation error converges to zero in the presence of unknown inputs, is derived. Another sufficient condition, which can be used to design an unknown input observer, is also derived based on a LMI. By using unknown input observers for various distinct combinations of the inputs, the FDI scheme is able to isolate both single and multiple actuator faults. An extension of this method to isolate sensor faults by using an output filter is also presented. In [88], Pertew *et al.* also considered the problem of unknown input observer design for Lipschitz nonlinear systems. In [88], the observer design problem is converted into a classical H_∞ optimal control problem.

Persis and Isidori [89] have designed a nonlinear filter for a class of affine nonlinear systems for FDI using a differential geometry approach. The proposed method is applicable to nonlinear systems that have *conditioned invariant distributions*, which is an extension of the concept of *unobservability subspace* in linear systems [90]. They also presented a necessary condition for the fault isolation problem to be solvable in these nonlinear systems. The design methodology of the nonlinear filter is analogous to that of the fault detection filters investigated in [13]–[15] and [36] for linear systems.

Zhang *et al.* [91] have designed an online fault detection and isolation scheme for nonlinear uncertain systems. The paper considers general nonlinear systems with full-state measurements, and with the assumption that the state vectors and control inputs remain bounded before and after the occurrence of a fault. The proposed architecture consists of a bank of nonlinear adaptive estimators, one of which is used for detection and approximation of faults, whereas the rest are used for online fault isolation based on the adaptive threshold functions. The presented fault isolation analysis consists of three parts: 1) derivation of adaptive thresholds to avoid false alarm; 2) investigation of fault isolation conditions that characterize the class of faults which can be isolated by an isolation scheme using fault mismatch functions; and 3) computation of a fault isolation time that is defined as the length of a time interval between the detection of a fault and the determination of its type. A similar FDI scheme is studied in [92] for a sensor bias type of faults.

I. Discrete Event Systems and Hybrid Systems

While most FDI techniques deal with systems with continuous states, some researchers have investigated the FDI problem for systems that contains discrete states only, or systems that contain both discrete states and continuous states (or hybrid systems).

Baroni *et al.* [93] considered the model-based diagnosis of a class of distributed discrete-event systems known as active systems. An active system is modeled as a network of communicating automata where each automaton describes the behavior of a system component by reacting to possibly harmful external events. This diagnostic technique deals with the asynchronous events that do not need a global diagnoser to be incorporated, but it features an online progressive reconstruction of the behavior of the active system guided by available observations. This technique is effective for a large scale active system. The diagnostic method encompasses reconstruction planning, behavior reconstruction, and diagnosis generation.

Lunze and Schröder [94] investigated the fault detection and isolation problem in sensors and actuators of dynamical systems with discrete-valued inputs and outputs. A generalized observer scheme [95] which has been proposed for systems with continuous-variable inputs and outputs, is developed in [94] for discrete systems. The proposed method modeled the system as a stochastic automaton rather than a set of differential equations. The generalized observer scheme is used for a fault detection module to cope with plant faults that are different from actuators or sensor faults.

Zhong *et al.* [96] considered the robust fault detection problem for a category of discrete-time linear Markovian jump systems with an unknown input. The fault detection filter is an observer-based residual generation filter, whose matrices are dependent on the system mode. In [97], Zhang *et al.* investigated the problem of fault detection in periodic systems by solving a difference periodic Riccati system. The proposed method provides an optimized compromise between robustness to unknown disturbances and sensitivity to faults. The authors then proposed the design of an optimal fault detection system for a linear discrete-time periodic system.

One approach to FDI, similar to the multiple model approach, is to consider it as a problem of hybrid state estimation. In this approach, the faulty modes of a plant or process are modeled as the discrete states of a hybrid system. The FDI problem then consists of estimating the hybrid state (i.e., continuous state and discrete state) of the system. When the continuous state dynamics in each discrete state (or mode) is linear, this hybrid estimation problem could be solved using the MMAE or IMM algorithms. When the continuous state dynamics in each mode is nonlinear, a commonly used hybrid estimation technique is known as the particle filter method [98], [99]. The particle filter method performs state estimation by utilizing samples (known as particles) to represent the PDFs of the state estimate. However, a problem, known as particle deficiency (or sample impoverishment), could occur due to a lack of enough particles to represent the mode transition probabilities of a rare-occurring mode, which corresponds to a fault. In [100], Tafazoli and Sun proposed a method to overcome the problem of particle deficiency by adding a step in the conventional particle filter procedure to estimate the most likely mode using both the observation information and the prior mode transition information.

In [101], Narasimhan and Biswas presented a methodology for online tracking and diagnosis of hybrid systems. The authors developed parameterized plant models where faults are represented by abrupt changes in system parameters. They applied the model-based diagnosis methodologies, which exploit the analytical redundancy between the model and the system measurements [29], to the hybrid systems. The effectiveness of the approach is demonstrated with experiments conducted on the fuel-transfer system of a fighter aircraft.

In [102], Wang and Gao considered FDI for uncertain continuous-time state delayed systems with Markovian Jump parameters. The designed fault detection filter is a Markovian jump system. The designed fault detection filter is robust to modeling errors, unknown inputs and control inputs. The existence of the above filters is established in terms of linear matrix inequalities.

Zhao *et al.* [103] addressed key modeling and computational problems at the interface between model-based diagnosis techniques and signature analysis to enable the efficient detection and isolation of incipient and abrupt faults in hybrid systems. A hybrid automata model that parameterizes abrupt and incipient faults is introduced. An approach for FDI design is then presented based on this model.

J. AI Techniques

So far, we have discussed fault detection methods, based on control and statistical theories, which are researched mainly by the FDI community. A notable class of model-based techniques using computer science and AI theories have also been actively researched in the diagnostic (DX) community. We do not discuss the AI model-based methods in detail due to space constraints. However, we wish to point out some of the recent developments in this field. We hope to give a detailed review of this topic in future work.

Both the control model-based methods and AI model-based methods rest on detecting discrepancies in the observations and the behavior predicted by the model for fault detections. However, the DX community uses qualitative models and logical approaches, such as causal models and pattern recognitions. As pointed out by one of the reviewers, there are recent efforts to bridge the works in both fields. Cordier *et al.* [104], [105] have proposed a formal framework of linking the analytical redundancy relations (ARRs) of the control model-based methods with the consistency-based logical approach of the DX approach. Several recent works have focused on developing FDI methods by combining the concept of ARR of the FDI community with the logical reasoning tools of the DX community [106]–[108].

IV. Decision Making Tools

Following the residual generation, the next step in the FDI problem is to detect any significant changes in the residuals which indicate faults. The problem can be formulated as a process of testing for a change in a parameter θ of the system. Given a set of measurements or observations, a decision is made at each time step to test the following hypotheses:

$$H_0 : \theta = \theta_0 \tag{34}$$
$$H_1 : \theta = \theta_1 \neq \theta_0. \tag{35}$$

As long as the decision is taken in favor of the hypothesis H_0 (no fault), the sampling and test continue. Sampling is stopped (or a fault is declared[1]) after the first sample of observations for which the decision is taken in favor of H_1. This hypothesis testing could be expanded for multiple faults (such as Fault 1, Fault2, ..., Fault N) by Multiple Hypothesis Testing such as

$$\begin{aligned} H_0 &: \theta = \theta_0 \\ H_1 &: \theta = \theta_1 \\ &\vdots \\ H_N &: \theta = \theta_N. \end{aligned}$$

The development of the change detection problem was stimulated by Wald in 1947 when "Sequential Analysis" was published and a Sequential Probability Ratio Test (SPRT) was introduced. Subsequently, the cumulative sum (CUSUM) algorithm (also known as the Page–Hinkley Stopping Rule) [109] was proposed by Page to detect a change in the mean by testing a weighted sum of the last few observations, i.e., a moving average. Page also pointed out that this rule is equivalent to performing a SPRT. The theoretical properties of this rule have been investigated for a long time from both online and offline points of view. The most significant early works in that direction are those by Shiryayev [110] and Lorden [111]. They formulated an "Optimal Stopping (or Detection)" problem and proposed simple rules which are optimal (or asymptotically optimal) in an appropriate sense. The general problem of optimality of random processes in discrete time was considered and developed by Chow *et al.* [112]. The problem of change detection has remained an area of strong interest in recent years. Various survey papers on the change detection methods can be found in [12], [23], [25], and [113]. In [26], Basseville and Nikiforov discussed the basic concepts of various statistical change detection tools, with emphasis on parametric statistical tools for detecting abrupt changes in discrete time signals and dynamic systems. The book by Gustafsson [31] discusses both the theories of model-based filtering and change detection. It covers various fault detection problems in aircraft application, automatic control, signal processing, etc.

In the rest of this section, we describe the details of the following hypothesis test techniques: the SPRT, the CUMSUM algorithm, the generalized likelihood ratio test, and the local approach.

[1]In most applications, the statistical test continues in real-time after a fault has been detected.

A. Sequential Probability Ratio Test

Given a sequence of observations $z_0, z_1, \ldots, z_k$, the Sequential Probability Ratio Test (SPRT) computes the cumulative sum of the log-likelihood ratio recursively as follows:

$$S_k = S_{k-1} + \Lambda_k \tag{36}$$

where

$$\Lambda_k = \log \frac{p_{\theta_1}(z_k|z_{k-1}, \ldots, z_0)}{p_{\theta_0}(z_k|z_{k-1}, \ldots, z_0)}. \tag{37}$$

Note that $p_\theta(z_k|z_{k-1}, \ldots, z_0)$ denote the conditional PDF of the observation z_k, which depends on the parameter θ. The stopping rule is then as follows:

- if $S_k \geq b$, accept H_1;
- if $S_k \leq a$, accept H_0;
- else continue the test.

The constants a and b, where $a < b$, are design parameters.

Malladi and Speyer [114] have derived an online multiple hypothesis Shiryayev SPRT [115] by adopting a dynamic programming approach. It has been shown that for a certain criterion of optimality, this generalized Shiryayev SPRT detects and isolates a change in hypothesis in the conditionally independent measurement sequence in minimum time.

The SPRT has been used to develop a dynamics sensor validation system for a reusable launch vehicle [116]. The SPRT is used with a multivariate state estimation technique as core elements of a commercial dynamics sensor validation system, which is designed to improve launch vehicle mission safety and system dependability by enabling rapid development and cost effective maintenance of embeddable real-time software to reliably detect process-critical sensor failures.

An application of the SPRT to the health monitoring of a satellite system has been reported in [87] and [117]. A fault detection filter is used to generate the residuals. Due to disturbances and uncertainty, the residual fails to go to zero even in the absence of a fault. To overcome this, a multiple-hypothesis test based on the Shiryayev SPRT is used to enhance the robustness of the FDI scheme.

A measure of the performance of a FDIR scheme is the speed of detection, i.e., how quickly the system determines that a change has occurred. In [118], [119], Kim proposed a performance index for the speed of adaptation, and developed a minimal time-change detection algorithm (MT-CDA) which minimizes the time delay in detecting a change for a fixed false alarm probability. The MT-CDA is based on Shiryayev's optimal stopping rule [110]. Specifically, let t_0 be the time when a fault occurred and t_d be the time when the fault is detected. The MT-CDA algorithm minimizes the average delay $E[\sup(t_d - t_0, 0)]$, subject to a given false alarm rate, i.e.,

$$Pr[t_d < t_0] \leq \alpha \tag{38}$$

where α is given.

B. CUSUM Algorithm

The CUSUM algorithm is equivalent to a repeated SPRT in which the test is restarted as long as the decision is taken in favor of H_0. The stopping rule for the CUSUM algorithm can be written recursively as [26]

$$S_k = \begin{cases} S_{k-1} + \Lambda_k, & \text{if } S_{k-1} + \Lambda_k > 0 \\ 0, & \text{if } S_{k-1} + \Lambda_k \leq 0 \end{cases} \tag{39}$$

and the decision is taken in favor in H_1 when $S_k \geq b$.

The asymptotic minimax ("worst case") optimality of the CUSUM has been proven in [111], where Lorden has given a lower bound for the worst mean delay for detection and has proven that the CUSUM algorithm reaches this lower bound. Nikiforov has extended the CUSUM algorithm to solve both the change detection and isolation problem in [120]. This is done by extending CUSUM to multiple hypotheses testing, and the statistical properties of this algorithm are investigated. The paper provides a lower bound for the criterion in a class of sequential change detection/isolation algorithms. It has been shown that the proposed algorithm is asymptotically optimal in this class.

Pradhan *et al.* [121] proposed a fault detector for digital relaying based on a moving sum index. The algorithm computes the sum of one cycle of data of power system current samples continuously. With the availability of a new sample of data in an online scheme, the oldest sample is discarded and the sum is recalculated for the new window. The method was tested under a variety of fault and disturbance conditions in a typical power system. A comparative assessment with existing techniques was carried out to establish its effectiveness.

In [122], a fault detection algorithm for a power relay system based on a two-sided cumulative sum (CUSUM) test is proposed. The performance of the algorithm has been tested extensively under various operating conditions. The effectiveness of the algorithm has been found to be better than the traditional methods in the presence of noise, system frequency deviation, and other uncertainties. It has been verified that the algorithm is not affected by a load change in the system.

C. Generalized Likelihood Ratio Test

One method of testing the hypotheses in (34)–(35) when the parameter θ_1 is unknown is to use the maximum likelihood estimate of θ_1. This method results in the generalized likelihood ratio (GLR) algorithm which computes

$$S_k = \max_{0 \leq j \leq k} \max_{\theta_1} S_j^k(\theta_1) \tag{40}$$

where

$$S_j^k(\theta_1) = \sum_{i=j}^{k} \log \frac{p_{\theta_1}(z_i|z_{i-1}, \ldots, z_0)}{p_{\theta_0}(z_i|z_{i-1}, \ldots, z_0)}. \tag{41}$$

In general, the test statistic S_k of the GLR algorithm cannot be computed recursively. Willsky and Jones [123] derived a recursive algorithm for the GLR test on the residual (or innovation) generated by a Kalman filter by exploiting the linear system property, the Gaussian noise property, and additive effect of the fault on the system. A modified algorithm, which uses the maximum likelihood estimate (MLE) of the innovation, instead of the likelihood ratio, has been proposed by Basseville and Benveniste [124].

In [125], Kellar *et al.* extended the GLR test to stochastic dynamic systems with unknown inputs. Necessary and sufficient conditions for designing a stable modified Kalman filter are given. Moreover, a fault detection and isolation procedure based on the GLR test and a geometrical detectability condition of faults are developed.

Li and Kadirkamanathan [126] reported the use of the GLR test and a particle filter method to solve the FDI problem in general nonlinear and non-Gaussian systems.

Wilson and Sutter [127] have used a GLR test in an automatic thruster FDI system for a thruster-controlled spacecraft. The FDI scheme is capable of detecting and isolating hard, abrupt, and multiple faults using only existing navigation sensors such as gyros or accelerometers.

Trapier *et al.* [128] have tested two change detection algorithms, namely the CUSUM algorithm and the GLR algorithm, in the detection of precursors that could indicate inlet buzz in a supersonic air inlet. A supersonic air inlet buzz is a shock wave oscillation which can lead to thrust loss, engine surge, or even structural damage in aircraft engines. Trapier conducted experiments which showed the existence of precursor phenomena that can appear several tenths of seconds before the onset of buzz. The two change detection algorithms were tested on experimental pressure signals and have been shown to be capable of detecting these precursors.

The GLR has been employed in target tracking applications to detect abrupt changes in target maneuvers [129], [130]. Recently, Dionne and Michalska [131] proposed a new GLR algorithm, known as the adaptive-H_0 GLR detector, for detection of abrupt target maneuvers. The new algorithm is designed to improve the robustness (of the conventional GLR) with respect to uncertainties in the system input, which frequently arise in the context of target tracking applications. Specifically, the new algorithm is able to adapt its reference realization of the unknown inputs online based on the measurements received. This alleviates the need for an *a priori* knowledge or assumption on the input realization, as is required in the conventional GLR algorithm.

D. Local Approach

The local approach to change detection problem was first introduced by Nikiforov [132]. In the local approach, instead of testing the log likelihood function (or log likelihood ratio) based on measurements, a Taylor's series expansion of the log likelihood function is considered. As a result, the first-order derivative term in the Taylor's series expansion, known as the efficient score, is used for the test. The efficient score is given by

$$s_k = \frac{d}{d\theta}\log(p_\theta(z_k|z_{k-1},\ldots,z_0))|_{\theta=\theta_0}. \qquad (42)$$

It can be shown by the Central Limit Theorem that the efficient score is asymptotically Gaussian distributed. Furthermore, any change in the parameter θ is reflected in a change in the mean of the efficient score. As a result, a general class of change detection problems can be transformed into the basic problem of testing for a change in the mean value of a Gaussian vector. Furthermore, as the local approach consider small changes in system parameters, it is useful for detecting small or incipient faults.

The local approach has been further investigated in [133], in which Benveniste *et al.* presented a systematic approach for the design of change detection and model validation algorithms for dynamical systems based on the local approach. It has been shown that the local approach provides a general methodology to associate to any adaptive algorithm an optimal testing procedure for both change detection and model validation problems.

Basseville has presented a tutorial introduction to the local approach in [134]. The paper describes both the key components of this theory and real industrial examples, which are: damage monitoring and predictive maintenance of a complex mechanical structure, fault detection of a gas turbine, and fault detection in the catalytic converter and oxygen sensor of an automotive system.

The local approach has been applied to change detection problems in nonlinear dynamic systems by Zhang *et al.* [73]. The authors considered nonlinear systems modeled by differential algebraic equations, which are then transformed into an input-output representation by eliminating the unknown state variables. The local approach is then used to detect any changes in the parameter θ of the system model.

In [135], the fault detection problem is formulated as a problem of detecting changes in the parameters of a linear model of the system. The model parameters are estimated using a generalized least square method, and changes in the model parameters are detected using the local approach. It has been shown that the local detection algorithm is robust to measurement noise.

In [136], Li *et al.* proposed a fault technique for nonlinear systems based on the predictive filter [137] and the local approach. A fault in the nonlinear system is interpreted as a change in the modeling uncertainties. The asymptotic local approach is used as a statistical decision tool to detect small changes in the modeling errors. The proposed FDI technique is used to detect component and sensor faults in a satellite attitude measurement system.

V. Reconfiguration

In many applications, such as in a flight control system, it is important to determine the best appropriate control actions following a failure in order to ensure continuous safe operation of the system. This could be achieved by reconfiguration control, i.e., reconfiguring the controllers online in response to the faults. In this paper, we focus on reconfiguration control methods based on FDI. We would like to note that there are also other approaches to reconfiguration control, such as reconfiguration methods based on online learning, which would be beyond the scope of this paper.

In the following, we classify the FDI-based reconfiguration control methods into the multiple-model approach and the adaptive control approach.

A. Multiple-Model Approach

In the multiple-model approach, a bank of parallel models is used to describe the system under normal operating mode and under various fault conditions, such as actuator failures. A corresponding controller is designed for each of these models. A suitably chosen switching mechanism is designed to determine the mode of the system at each time step, and to select the corresponding controller that is designed for that mode. This results in robust and improved performance under various operating conditions.

The multiple-model control schemes are closely related to the multiple-model fault detection scheme discussed in Section III. The MMAE has been used in an adaptive reconfigurable control scheme, such as the reconfigurable flight control schemes in [138] and [139]. The IMM approach has also been used to design an integrated fault detection and fault tolerant aircraft flight control system by Zhang and Jiang in [72] and [140]. Working independently, the IMM approach to FDIR has also been reported by Efe and Atherton [141], and Mehra *et al.* [142]. Kumar has also proposed an IMM-based FDIR algorithm for flight control system in [143]. Many authors have also designed reconfigurable flight control laws based on the multiple-model-based approach, as can be seen in [144]–[146] and [147].

B. Adaptive Control Approach

Another common approach in reconfigurable control is to utilize an adaptive controller to ensure robust or acceptable level of performance under abrupt changes in system parameters. This is known as the adaptive control approach and it is generally classified into two methods: the indirect adaptive control method which employs a parameter isolation process and the direct adaptive control method which does not require an explicit parameter isolation process.

Various authors have considered adaptive controllers for systems with actuator failures [148]–[152]. Boskovic *et al.* [148] described the design of an automatic control reconfiguration scheme for accommodation of multiple actuator failures in a class of plants where the number of control inputs is larger than the number of controlled outputs. The authors developed a "multiple model" adaptive control law using the Lyapunov theory to guarantee the asymptotic convergence of output tracking errors. Chen *et al.* [149] designed a direct adaptive control scheme for actuator failures characterized by unknown input signals stuck at some unknown fixed values at unknown time instants. They derived sufficient conditions for actuator failure compensation and designed an adaptive controller based on the conditions. In [150], Tao *et al.* developed a direct adaptive state-feedback controller for the linear time-invariant system in the presence of both actuator failures and unknown system parameters using Lyapunov theory. A similar scheme which uses an output-feedback controller has been designed in [151], and an extension of the control scheme to nonlinear systems has been investigated in [152].

Many applications of adaptive flight control laws have been discussed in the literature. In [153], adaptive flight control laws are designed to compensate for actuator failures or surface damage. Oppenheimer and Doman [154] investigated a few adaptive guidance, control, and trajectory shaping methods based on various techniques, such as dynamic inversion and system identification, for autonomous air vehicles. Ganguli *et al.* [155] reported a Control Upset Prevention and Recovery System, developed jointly by Honeywell Labs and NASA Langley Research Center, that provides control law reconfiguration, fault detection, fault isolation and pilot cueing. The performance of the system on a civil transport aircraft has been tested via a piloted simulation. The performance of this system has been further investigated in [156] with additional sensor models and performance evaluation in the presence of measurement errors. In [157], Kim *et al.* designed an indirect adaptive control algorithm for aircraft flight control systems in the presence of unknown system parameters and actuator failures. The system parameters are estimated online using Fourier transformation and are used to design the control gain.

VI. Discussions and Comparisons

In this section, we present a comparison of the various FDI methods discussed in the paper, in terms of their performance, residual characteristics, complexity, and robustness. The performance of a fault detection algorithm is usually measured in terms of the tradeoffs between the false alarm rate and the mean detection delay. For fault isolation, we are interested in the characteristics (structural or directional) of the residuals. For the issue of robustness, we are concerned about the sensitivity of the algorithm's performance to noise, disturbances, and model uncertainties.

In terms of the residual characteristics, Gertler [158] has shown that the various observer-based methods, such as eigenstructure assignment, fault detection filters, and unknown input observers give identical residuals with that of an equivalent parity relation method. The basic idea of the observer-based methods is to generate residuals from an observer. In the absence of fault, the observer tracks the actual plant and the residual will have a zero mean. Further, the observers are designed to yield residuals that facilitates fault isolation. On the other hand, the parity relations approach transforms either the input-output transfer function or the state-space models of the plant to yield directional or structural residual vectors directly. Hence, fault isolability can be determined prior to the design process. Both the unknown input observers and the full-state observer-based methods could be designed to be robust to unknown disturbances (provided the matrices E_1 and E_2 in (5) and (6) are known). However, from (20), the unknown input observer uses a generalized (possibly reduced-order) observer instead of a full-state observer. Thus, the unknown input observer may be a preferred approach (for reduced complexity) if a full-state estimation is not required. Secondly, instead of nulling directly the response of the residual to unknown disturbances, the unknown input observer nulls the response of the observed state estimation error, and consequently the residual, to the unknown disturbances. If a full-state-observer is used, a direct approach of decoupling the residual from the disturbances could be more advantageous. Note that the observer-based methods and the parity relations approach generally do not consider multiplicative faults or model uncertainties. In most cases, they are also limited to linear time-invariant systems. Note that in the presence of unmodeled disturbances or model uncertainties, the fault detection algorithm would fail to yield zero-mean residual in the absence of faults. This error could be compensated by choosing a higher detection threshold in the statistical decision test for the residual, at the expense of higher detection delays. The issue regarding the robustness of these methods to model uncertainties is an important but difficult question. In most applications, one could expect that the more complex the system model is, the more sensitive the FDI scheme would be to model errors and uncertainties.

The optimization methods have been proposed for various kinds of systems, including nonlinear and time-varying systems. Most optimization methods could also be formulated such that the sensitivities of the residuals with respect to noise, disturbance, and/or model uncertainties are minimized. The optimization technique has been used in the generalization of the fault detection filter or unknown input observer to nonlinear or time-varying systems. However, one may need to exercise care and reservations in the implementation of these methods in applications. These methods generally provide solutions to the FDI problems based on the optimization of some mathematical objective functions. There is no guarantee about the usefulness and performance of these solutions in the underlying applications. In some cases, the design of the optimization method, such as the choice of design parameters in the objective functions, could be complex.

The multiple model Kalman filter-based methods is much more complex in implementation compared to the observer based or parity relations methods, particularly when the number of failure modes is high. An advantage of the Kalman filter-based approach is that it provide "optimal" filtering under the normal (no-fault) operating condition. The parallel structure of the Kalman filters also allow the system to adapt quickly and hence provide accurate state estimation after a fault occurs. The multiple model approach could be extended to nonlinear or time-varying systems by techniques, such as the extended Kalman filters. The approach could be used for detecting multiplicative (or component) faults as well as additive faults. The main drawback of this approach, besides complexity, is that it has to assume that the fault parameters takes on discrete values from a finite set. For some faults in which the fault parameters take on continuous values, a few fault models may be used to describe a single fault. However, this results in higher complexity and may lead to higher false alarm rates.

The presence of both continuous state dynamics and discrete state dynamics in hybrid systems introduces additional difficulty and complexity to the FDI problem. Most FDI methods consider robust residual generation in the presence of unknown disturbance or system uncertainties. For hybrid systems, we need to consider also uncertainties associated with the discrete state transitions. An example of how this issue affects the performance of a fault detection scheme can be found in an aircraft conformance monitoring application [159]. In this application, the fault detection scheme produces residual that has a zero mean in the absence of discrete state transitions, but nonzero means in the presence of nondeterministic discrete state transitions. So far, it appears that no researcher has explicitly consider a FDI method that can generate zero mean residuals in the presence of such uncertainties.

The system identification methods could be applicable to linear or nonlinear systems. These methods are also useful for detecting small or incipient faults. However, the performance of the system identification method is closely related to the statistical decision techniques used to detect the change in parameters.

The well-known statistical decision techniques, the SPRT and the CUSUM algorithms, are the most easy to implement. Their statistical properties have also been thoroughly investigated. The GLR test is also easy to implement and has generally very good performance for detecting additive faults and component faults. The local approach, while being more complex, has been shown to have good performance for detecting small or incipient faults.

Finally, we would like to remark that FDI performance, i.e., the minimization of the mean detection delay for a low false alarm or miss detection rate, is closely related to the ability of diagnosis and computational complexity of the methods. The explicit discussions and comparisons of various methods on the diagnosability and computational complexity issues will be informative. More detailed discussions on these issues are left as future work.

VII. Conclusion

The ability to ensure the desired performance of a dynamic system both in the absence and presence of faults is an important task in many applications of control engineering. FDIR is one control methodology of accomplishing this task. In this paper, we have discussed various FDIR techniques, broadly classified based on robust residual generation techniques, statistical decision techniques, and reconfiguration control techniques.

The robust residual generation techniques generate residuals which are insensitive to noise and uncertainties, and at the same time sensitive to faults. Some of these techniques could also generate residuals with special structures that facilitate fault isolation. We have discussed various robust residual generation techniques which include the full-state observer-based methods, the unknown input observers, the parity relations approach, the optimization-based approach, the Kalman filter-based approach, the stochastic approach, the system identification approach, and the artificial intelligence techniques. We have also surveyed some of the techniques which are designed specifically for nonlinear systems, discrete-event systems, and hybrid systems.

The statistical decision techniques focus on developing robust hypothesis testing algorithms to detect any change in signals or system parameters which correspond to faults based on the residuals. We have discussed various hypothesis test algorithms which include the cumulative sum algorithm, the SPRT, the generalized likelihood ratio test, and the local approach.

The reconfiguration step involves changing the controller in response to the faults detected and identified to ensure safe or satisfactory operation of the system. We have classified the reconfiguration techniques into the multiple-model approach which uses a finite set of switching controllers, and the adaptive control approach which changes the parameters of a controller in response to faults detected.

In this paper, we have attempted to comprehensively cover the various model-based FDIR methods in many control applications. While it is not possible to discuss every method in detail, we hope that our presentations have provided the readers a good introduction to the various quantitative model-based FDI methods and their applications developed in the last decade. We hope to review other FDI techniques, such as those based on artificial intelligence methods, in future research.

REFERENCES

[1] I. Nimmo, "Adequately address abnormal situation operations," *Chem. Eng. Progr.*, vol. 91, no. 9, pp. 36–45, 1995.

[2] V. Venkatasubramanian, R. Rengaswamy, K. Yin, and S. N. Kavuri, "A review of process fault detection and diagnosis part I: Quantitative model-based methods," *Comput. Chem. Eng.*, vol. 27, pp. 293–311, 2003.

[3] V. Venkatasubramanian, R. Rengaswamy, K. Yin, and S. N. Kavuri, "A review of process fault detection and diagnosis part II: Qualitative models and search strategies," *Comput. Chem. Eng.*, vol. 27, pp. 313–326, 2003.

[4] V. Venkatasubramanian, R. Rengaswamy, K. Yin, and S. N. Kavuri, "A review of process fault detection and diagnosis part III: Process history based methods," *Comput. Chem. Eng.*, vol. 27, pp. 327–346, 2003.

[5] X. An, J. Gu, B. Zhao, D. Xu, and S. Xi, "Application of FBOLES-a prototype expert system for fault diagnosis in nuclear power plants," *Reliab. Eng. Syst. Safety*, vol. 44, no. 3, pp. 225–235, 1994.

[6] K. Kim and E. B. Bartlett, "Nuclear power plant fault diagnosis using neural networks with error estimation by series association," *IEEE Trans. Nucl. Sci.*, vol. 43, no. 4, pp. 2373–2388, Aug. 1996.

[7] C. Favre, "Fly-by-wire for commercial aircraft: The Airbus experience," *Int. J. Control*, vol. 59, no. 1, pp. 139–157, 1994.

[8] D. Briere and P. Traverse, "Airbus A320/A330/A340 electrical flight controls—A family of fault-tolerant systems," in *Proc. 23rd Int. Symp. Fault-Tolerant Comput.*, 1993, pp. 616–623.

[9] R. Isermann, R. Schwartz, and S. Stolzl, "Fault-tolerant drive-by-wire systems," *IEEE Control Syst. Mag.*, vol. 27, no. 5, pp. 64–81, Oct. 2002.

[10] R. Isermann, "Trends in the application of model-based fault detection and diagnosis of technical processes," *Control Eng. Practice*, vol. 5, no. 5, pp. 709–719, 1997.

[11] D. V. Schrick, "Remarks on terminology in the field of supervision, fault detection and diagnosis," in *Proc. IFAC Symp. Fault Detection, Supervision Safety for Techn. Process. (SAFEPROCESS)*, 1997, pp. 959–964.

[12] A. S. Willsky, "A survey of design methods for failure detection in dynamic systems," *Automatica*, vol. 12, pp. 601–611, 1976.

[13] R. V. Beard, "Failure accommodation in linear systems through self-reorganization," Ph.D. dissertation, Dept. Aeronautics Astronautics, Massachusetts Inst. Technol., Cambridge, Feb. 1971.

[14] L. H. Jones and H. L. Jones, "Failure detection in linear systems," Ph.D. dissertation, Dept. Aeronautics Astronautics, Massachusetts Inst. Technol., Cambridge, MA, Feb. 1973.

[15] J. E. White and J. L. Speyer, "Detection filter design: Spectral theory and algorithm," *IEEE Trans. Autom. Control*, vol. 32, no. 7, pp. 593–603, Jul. 1987.

[16] J. H. Park, Y. Halevi, and G. Rizzoni, "A new interpretation of the fault-detection filter 1: Closed-form algorithm," *Int. J. Control*, vol. 60, no. 5, pp. 767–787, 1994.

[17] J. H. Park, Y. Halevi, and G. Rizzoni, "A new interpretation of the fault-detection filter 2: The optimal detection filter," *Int. J. Control*, vol. 60, no. 5, pp. 767–787, 1994.

[18] R. N. Clark, D. C. Fosth, and V. M. Walton, "Detecting instrument malfunctions in contol systems," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 11, pp. 465–473, Nov. 1975.

[19] P. M. Frank and J. Wünnenberg, S. G. Tzafestas, M. G. Singh, and G. Schmidt, Eds., "Sensor fault detection via robust observers," in *Proc. System Fault Diagnostics, Reliab. Related Knowledge-Based Approaches*, 1987, vol. 1, pp. 147–160.

[20] J. C. Deckert, M. N. Desai, J. J. Deyst, and A. S. Willsky, "F-8 DFBW sensor failure identification using analytic redundancy," *IEEE Trans. Autom. Control*, vol. 22, no. 5, pp. 795–809, Oct. 1977.

[21] J. Gertler, "Fault detection and isolation using parity relations," *Control Eng. Practice*, vol. 5, no. 5, pp. 653–661, 1997.

[22] C. Bakiotis, J. Raymond, and A. Rault, "Parameter and discriminant analysis for jet engine mechanical state diagnosis," presented at the IEEE Conf. Decision Control, Fort Lauderdale, FL, 1979.

[23] R. Isermann, "Process fault detection based on modeling and estimation methods: A survey," *Automatica*, vol. 20, no. 4, pp. 387–304, 1984.

[24] R. K. Mehra and I. Peshon, "An innovations approach to fault detection and diagnosis in dynamic systems," *Automatica*, vol. 7, pp. 637–640, 1984.

[25] M. Basseville, "Detecting changes in signals and systems—A survey," *Automatica*, vol. 24, no. 3, pp. 309–326, 1988.

[26] M. Basseville and I. V. Nikiforov, *Detection of Abrupt Changes: Theory and Application*. Englewood Cliffs, NJ: Prentice Hall, 1993.

[27] R. J. Patton and J. Chen, "Robust fault detection using eigenstructure assignment: A tutorial consideration and some new results," in *Proc. 39th Conf. Dec. Control*, Brighton, U.K., Dec. 1991, pp. 2242–2247.

[28] R. J. Patton and J. Chen, "A review of parity space approaches to fault diagnosis for aerospace systems," *J. Guid., Control, Dyn.*, vol. 17, no. 2, pp. 278–285, 1994.

[29] J. Gertler, *Fault Detection and Diagnosis in Engineering Systems*. New York: Marcel Dekker, 1998.

[30] J. Chen and R. J. Patton, *Robust Model-Based Fault Diagnosis for Dynamic Systems*. Norwell, MA: Kluwer, 1999.

[31] F. Gustafsson, *Adaptive Filtering and Change Detection*. New York: Wiley, 2000.

[32] J. Korbicz, J. M. Koscielny, Z. Kowlaczuk, and W. Cholewa, *Fault Diagnosis*. Berlin, Germany: Springer-Verlag, 2004.

[33] C. Angeli and A. Chatzinikolaou, "On-line fault detection techniques for technical systems: A survey," *Int. J. Comput. Sci. and Appl.*, vol. 1, no. 1, pp. 12–30, 2004.

[34] R. Isermann, "Model-based fault-detection and diagnosis status and applications," *Annu. Rev. Control*, vol. 29, no. 1, pp. 71–85, 2005.

[35] R. J. Patton and J. Chen, "On eigenstructure assignment for robust fault diagnosis," *Int. J. Robust Nonlinear Control*, vol. 10, pp. 1193–1208, 2000.

[36] M. A. Massoumnia, "A geometric approach to the synthesis of failure detection filters," *IEEE Trans. Autom. Control*, vol. 31, no. 9, pp. 839–846, Sep. 1986.

[37] D. M. Wilbers and J. L. Speyer, "Detection filters for aircraft sensor and actuator faults," in *Proc. IEEE Int. Conf. Control Appl.*, Jerusalem, Israel, 2002, pp. TA.4.3.1–TA.4.3.6.

[38] R. K. Douglas and J. L. Speyer, "Robust fault detection filter design," *J. Guid., Control, Dyn.*, vol. 19, no. 1, pp. 214–218, 1996.

[39] R. K. Douglas and J. L. Speyer, "H_∞ bounded fault detection filter," *J. Guid., Control, Dyn.*, vol. 22, no. 1, pp. 129–138, 1999.

[40] W. H. Chung and J. L. Speyer, "A game-theoretic fault detection filter," *IEEE Trans. Autom. Control*, vol. 43, no. 2, pp. 143–161, Feb. 1998.

[41] K. Watanabe and D. M. Himmelblau, "Instrument fault detection in system with uncertainties," *Int. J. Syst. Sci.*, vol. 13, no. 2, pp. 137–158, 1982.

[42] P. M. Frank and J. Wünnenberg, "Robust fault diagnosis using unknown input schemes," in *Fault Diagnosis in Dynamic Systems: Theory and Application*, R. J. Patton, P. M. Frank, and R. N. Clark, Eds. Englewood Cliffs, NJ: Prentice-Hall, 1989, pp. 47–98.

[43] J. Chen, R. J. Patton, and H. Y. Zhang, "Design of unknown input observers and robust fault-detection filters," *Int. J. Control*, vol. 63, no. 1, pp. 85–105, 1996.

[44] F. Amato and M. Mattei, "Design of full order unknown input observers with H_∞ performance," presented at the IEEE Int. Conf. Control Appl., Glasgow, Scotland, U.K., Sep. 2002.

[45] D. W. Gu and F. W. Poon, "A robust fault-detection approach with application in a rolling-mill process," *IEEE Trans. Control Syst. Technol.*, vol. 11, no. 3, pp. 408–414, Mar. 2003.

[46] M. A. Demetriou, "Using unknown input observers for robust adaptive fault detection in vector second-order systems," *Mechan. Syst. Signal Process.*, vol. 19, pp. 291–309, 2005.

[47] M. J. Balas, "Do all linear flexible structures have convergent second-order observers?," *AIAA J. Guid., Control, Dyn.*, vol. 22, no. 6, pp. 905–908, 1999.

[48] T. G. Park and K. S. Lee, "Process fault isolation for linear systems with unknown inputs," *IEE Proc.—Control Theory Appl.*, vol. 151, no. 6, pp. 720–726, 2004.

[49] M. Hou and P. C. Müller, "Design of observers for linear systems with unknown inputs," *IEEE Trans. Autom. Control*, vol. 37, no. 6, pp. 871–875, Jun. 1992.

[50] E. Y. Chow and A. S. Willsky, "Analytical redundancy and the design of robust failure detection systems," *IEEE Trans. Autom. Control*, vol. 29, no. 7, pp. 603–614, Jul. 1984.

[51] H. Ye, G. Wang, and S. X. Ding, "A new parity space approach for fault detection based on stationary wavelet transform," *IEEE Trans. Autom. Control*, vol. 49, no. 2, pp. 281–287, Feb. 2004.

[52] X. Ding, L. Guo, and T. Jeinsch, "A characterization of parity space and its application to robust fault detection," *IEEE Trans. Autom. Control*, vol. 44, no. 2, pp. 337–343, Feb. 1999.

[53] H. Song and H. Y. Zhang, "An approach to sensor fault diagnosis based on fully-decoupled parity equation and parameter estimate," in *Proc. 4th World Congr. Intell. Control Autom.*, Shanghai, China, Jun. 2002, pp. 2750–2754.
[54] C. W. Chan, S. Hua, and Z. Hong-Yue, "Application of fully decoupled parity equation in fault detection and identification of dc motors," *IEEE Trans. Ind. Electron.*, vol. 53, no. 4, pp. 1277–1284, Jul./Aug. 2006.
[55] Stoustrup and Niemann, "Fault estimation—A standard problem approach," *Int. J. Robust Nonlinear Control*, vol. 12, pp. 649–673, 2002.
[56] T. Song and E. G. Collins Jr., "Robust H_2 estimation with application to robust fault detection," *J. Guid., Control Dyn.*, vol. 23, no. 6, pp. 1067–1071, 2000.
[57] E. G. Collins, H. W. M. Chellaboina, and T. Song, "Robustness analysis in the delta-domain using fixed-structured multipliers," in *Proc. IEEE Conf. Dec. Control*, Piscataway, NJ, 1997, pp. 3286–3291.
[58] A. Stoorvogel, H. H. Niemann, A. Saberi, and P. Sannuti, "Optimal fault signal estimation," *Int. J. Robust Nonlinear Control*, vol. 12, pp. 697–727, 2002.
[59] H. Wang and J. Lam, "Robust fault detection for uncertain discrete-time systems," *J. Guid., Control Dyn.*, vol. 25, no. 2, pp. 291–301, 2002.
[60] R. H. Chen and J. L. Speyer, "Optimal stochastic fault detection filter," presented at the Amer. Control Conf., San Diego, CA, Jun. 1997.
[61] R. H. Chen and J. L. Speyer, "A generalized least-squares fault detection filter," *Int. J. Adapt. Control Signal Process.*, vol. 14, pp. 747–757, 2000.
[62] R. H. Chen, D. L. Mingori, and J. L. Speyer, "Optimal stochastic fault detection filter," *Automatica*, vol. 39, pp. 377–390, 2003.
[63] B. Darkhovski and M. Staroswiecki, "A game-theoretic approach to decision in FDI," *IEEE Trans. Autom. Control*, vol. 48, no. 5, pp. 853–858, May 2003.
[64] R. K. Mehra and J. Peschon, "An innovations approach to fault detection and disgnosis in dynamic systems," *Automatica*, vol. 7, pp. 637–640, 1971.
[65] D. T. Maqill, "Optimal adaptive estimation of sampled stochastic processes," *IEEE Trans. Autom. Control*, vol. 10, no. 4, pp. 434–439, Oct. 1965.
[66] P. S. Maybeck, *Stochastic Models, Estimation and Control*. Arlington, VA: Navtech Press, 1994, vol. 1.
[67] P. S. Maybeck, *Stochastic Models, Estimation and Control*. Arlington, VA: Navtech Press, 1994, vol. 2.
[68] T. E. Menke and P. S. Maybeck, "Multiple model adaptive estimation applied to the VISTA F-16 flight control system with actuator and sensor failures," in *Proc. IEEE Nat. Aerosp. Electron. Conf.*, Dayton, OH, May 1992, pp. 441–448.
[69] T. E. Menke and P. S. Maybeck, "Sensor/actuator failure detection in the VISTA F-16 by multiple model adaptive estimation," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 31, no. 4, pp. 1218–1229, Oct. 1995.
[70] N. A. White, P. S. Maybeck, and S. L. DeVilbiss, "MMAE detection of interference/jamming and spoofing in a DGPS-aided inertial system," in *Proc. ION GPS-98 Conf.*, Nashville, TN, Sep. 1998, pp. 905–914.
[71] P. D. Hanlon and P. S. Maybeck, "Characterization of Kalman filter residuals in the presence of mismodeling," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 36, no. 1, pp. 114–131, Jan. 2000.
[72] Y. M. Zhang and J. Jiang, "An interacting multiple-model based fault detection, diagnosis and fault tolerant control approach," in *Proc. 38th Conf. Dec. Control*, Phoenix, AZ, Dec. 1999, pp. 3593–3598.
[73] Y. M. Zhang and X. R. Li, "Detection and diagnosis of sensor and actuator failures using IMM estimator," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 34, no. 4, pp. 1293–1313, Oct. 1998.
[74] S. Kim, J. Choi, and Y. Kim, "Fault detection and diagnosis of aircraft actuators using fuzzy-tuning IMM filter," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 44, no. 3, pp. 940–952, 2008.
[75] H. Wang and W. Lin, "Applying observer based FDI techniques to detect faults in dynamic and bounded stochastic distributions," *Int. J. Control*, vol. 73, pp. 1424–1436, 2000.
[76] H. Wang, "Detecting faults in dynamic and bounded stochastic distributions: An observer based technique," in *Proc. Amer. Control Conf.*, Arlington, VA, 2001, pp. 482–487.
[77] L. Guo and H. Wang, "Fault detection and diagnosis for general stochastic systems using B-spline expansions and nonlinear filters," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 52, no. 8, pp. 1424–1436, Aug. 2005.
[78] T. D. Curry and E. G. Collins Jr., "Robust fault detection and isolation using robust L_1 estimation," *AIAA J. Guid., Control, Dyn.*, vol. 28, no. 6, pp. 905–908, 2005.
[79] M. K. H. Fan and J. C. Doyle, "Robustness in the presence of mixed parametric uncertainty and unmodeled dynamics," *IEEE Trans. Autom. Control*, vol. 36, no. 1, pp. 25–38, Jan. 1991.
[80] I. Yaesh and U. Shaked, "Robust H_∞ deconvolution and its application to fault detection," *J. Guid., Control Dyn.*, vol. 23, no. 6, pp. 1001–1012, 2000.
[81] S. Simani, C. Fantuzzi, and R. J. Patton, "Model-based fault diagnosis in dynamic systems using identification techniques," in *Volume Information and System Science*. London, U.K.: Springer, 2003.
[82] R. Isermann, "Supervision, fault-detection and fault-diagnosis methods—An introduction," *Control Eng. Practice*, vol. 5, no. 5, pp. 639–652, 1997.
[83] C. J. Kim, S. J. Lee, and S.-H. Kang, "Evaluation of feeder monitoring parameters for incipient fault detection using laplace trend statistic," *IEEE Trans. Ind. Appl.*, vol. 40, no. 6, pp. 1718–1724, Nov./Dec. 2004.
[84] M. Basseville, A. Benveniste, M. Goursat, and L. Mevel, "Subspace-based algorithms for structural identification, damage detection, and sensor data fusion," *EURASIP J. Adv. Signal Process.*, 2007.
[85] M. Basseville, A. Benveniste, M. Goursat, L. Hermans, L. Mevel, and H. van der Auweraer, "Output-only subspacebased structural identification: From theory to industrial testing practice," *J. Dyn. Syst., Meas. Control, Trans. ASME*, vol. 123, no. 4, p. 668676, 2001.
[86] P. Van Overschee and B. De Moor, *Subspace Identification for Linear Systems*. Boston, MA: Kluwer, 1996.
[87] R. H. Chen, H. K. Ng, J. L. Speyer, L. S. Guntur, and R. Carpenter, "Health monitoring of a satellite system," *J. Guid., Control, Dyn.*, vol. 29, no. 3, pp. 593–605, 2006.
[88] M. Pertew, H. J. Marquez, and Q. Zhao, "Design of unknown input observers for Lipschitz nonlinear systems," in *Proc. Amer. Control Conf.*, Portland, OR, Jun. 2005.
[89] C. De Persis and A. Isidori, "A geometric approach to nonlinear fault detection and isolation," *IEEE Trans. Autom. Control*, vol. 46, no. 6, pp. 853–865, Jun. 2001.
[90] C. De Persis and A. Isidori, "On the observability codistributions of a nonlinear system," *Syst. Control Lett.*, vol. 40, p. 297304, 2000.
[91] X. Zhang, M. Polycarpou, and T. Parisini, "A robust detection and isolation scheme for abrupt and incipient faults in nonlinear systems," *IEEE Trans. Autom. Control*, vol. 47, no. 4, pp. 576–593, Apr. 2002.
[92] X. Zhang, T. Parisini, and M. M. Polycarpou, "Sensor bias fault isolation in a class of nonlinear systems," *IEEE Trans. Autom. Control*, vol. 50, no. 3, pp. 370–376, Mar. 2005.
[93] P. Baroni, G. Lamperti, P. Pogliano, and M. Zanella, "Diagnosis of a class of distributed discrete-event systems," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 30, no. 6, pp. 731–752, Nov. 2000.
[94] J. Lunze and J. Schröder, "Sensor and actuator fault diagnosis of systems with discrete inputs and outputs," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 34, no. 2, pp. 1096–1107, Apr. 2004.
[95] Y. S. Chow, H. Robbins, and D. Siegmund, *Diagnosis in Dynamical Systems via State Estimation A Survey*. Amsterdam, The Netherlands: Reidel, 1987.
[96] M. Zhong, H. Ye, P. Shi, and G. Wang, "Fault detection for Markovian jump systems," *IEE Proc.—Control Theory Appl.*, vol. 152, no. 4, pp. 397–402, 2005.
[97] P. Zhang, S. X. Ding, G. Z. Wang, and D. H. Zhou, "Fault detection of linear discrete-time periodic systems," *IEEE Trans. Autom. Control*, vol. 50, no. 2, pp. 239–244, Feb. 2005.
[98] A. Doucet, N. Gordon, and V. Krishnamurthy, "Particle filters for state estimation of jump Markov linear systems," *IEEE Trans. Signal Process.*, vol. 49, no. 3, pp. 613–624, Mar. 2001.
[99] H. A. P. Blom and E. A. Bloem, "Exact Bayesian and particle filtering of stochastic hybrid systems," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 43, no. 1, pp. 55–70, Jan. 2007.
[100] S. Tafazoli and X. Sun, "Hybrid system state tracking and fault detection using particle filters," *IEEE Trans. Control Syst. Technol.*, vol. 14, no. 6, pp. 1078–1087, Nov. 2006.
[101] S. Narasimhan and G. Biswas, "Model-based diagnosis of hybrid systems," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 37, no. 3, pp. 348–361, May 2007.
[102] H. R. Wang and H. J. Gao, "Robust fault detection for uncertain time-delay systems with Markovian jump parameters," in *Proc. 6th Int. Conf. Mach. Learn. Cybern.*, Hong Kong, Aug. 2007, pp. 19–22.
[103] F. Zhao, X. Koutsoukos, H. Haussecker, J. Reich, and P. Cheung, "Monitoring and fault diagnosis of hybrid systems," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 35, no. 6, pp. 1225–1240, Dec. 2005.

[104] M.-O. Cordier, P. Dugue, M. Dumas, F. Lévy, J. Montmain, M. Staroswiecki, and L. Travé-Massuyès, "AI and automatic control approahces of model-based diagnosis: Links and underlying hypotheses," in *Proc. IFAC 4th Symp. Fault Detection, Supervision, Safety Techn. Process.*, Budapest, Hungary, 2000, pp. 25–32.

[105] M.-O. Cordier, P. Dague, F. Lévy, J. Mountmain, M. Staroswiecki, and L. Travé-Massuyès, "Conflicts versus analytical redundancy relations: A comparative analysis of the model based diagnosis approach from the artificial intelligence and automatic control perspectives," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 34, no. 5, pp. 2163–2177, Oct. 2004.

[106] S. Gentil, J. Montmain, and C. Combastel, "Combining FDI and AI approahces within causal-model-based diagnosis," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 34, no. 5, pp. 2207–2221, Oct. 2004.

[107] B. Pulido and C. A. González, "Possible conflicts: A compilation technique for consistency-based diagnosis," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 34, no. 5, pp. 2192–2206, Oct. 2004.

[108] L. Travé-Massuyès, T. Escobet, and X. Olive, "Diagnosability analysis based on component-supported analytical redundancy relations," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 36, no. 6, pp. 1146–1160, 2006.

[109] E. S. Page, "Continuous inspection schemes," *Biometrika*, vol. 41, pp. 100–115, 1954.

[110] A. N. Shiryayev, *Optimal Stopping Rules*. New York: Springer-Verlag, 1978.

[111] G. Lorden, "Procedures for reacting to a change in distribution," *Annals Math. Stat.*, vol. 42, no. 6, pp. 1897–1908, 1971.

[112] Y. S. Chow, H. Robbins, and D. Siegmund, *Great Expectations: The Theory of Optimal Stopping*. Boston, MA: Houghton Mifflin, 1971.

[113] S. G. Tzafestas and K. Watanabe, "Modern approaches to system/sensor fault detection and diagnosis," *Journal A*, vol. 31, no. 4, pp. 42–57, 2000.

[114] D. P. Malladi and J. L. Speyer, "A generalized Shiryayev sequential probability ratio test for change detection and isolation," *IEEE Trans. Autom. Control*, vol. 44, no. 8, pp. 1522–1534, Aug. 1999.

[115] J. L. Speyer and J. E. White, "Shiryayev sequential probability ratio test for redundancy management," *J. Guid., Control, Dyn.*, vol. 7, no. 5, pp. 588–595, 1984.

[116] J. P. Herzog, Y. Y. Yue, and R. L. Bickford, "Dynamics sensor validation for reusable launch vehicle propulsion," in *Proc. AIAA/ASME/SAE/ASEE Joint Propulsion Conf.*, Jul. 1998, AIAA-1998-3604.

[117] R. H. Chen, H. K. Ng, J. L. Speyer, L. S. Guntur, and R. Carpenter, "Health monitoring of a satellite system," in *Proc. AIAA Guid., Nav., Control Conf.*, Aug. 2004, AIAA-2004-5121.

[118] S. Kim, "A development of minimal time-change detection algorithm (MT-CDA) in system parameters and its application to flight systems," Ph.D. dissertation, Dept. Elect. Eng., UCLA, Los Angeles, 1993.

[119] S. Kim, "The minimal time detection algorithm of changes in control parameters and its application to flight systems," in *Proc. 33rd IEEE Conf. Dec. Control*, Lake Buena Vista, FL, 1994.

[120] I. V. Nikiforov, "A generalized change detection problem," *IEEE Transactions on Information Theory*, vol. 41, no. 1, 1995.

[121] K. Pradhan, A. Routray, and S. Mohanty, "A moving sum approach for fault detection of power systems," *Electrical Power Components Syst.*, vol. 34, pp. 385–399, 2006.

[122] A. K. Pradhan, S. R. Mohanty, and A. Routray, "A cumulative sum-based fault detector for power system relaying application," *IEEE Trans. Power Delivery*, vol. 23, no. 1, pp. 79–86, Jan. 2008.

[123] A. S. Willsky and H. L. Jones, "A generalized likelihood ratio approach to the detection and estimation of jumps in linear systems," *IEEE Trans. Autom. Control*, vol. 21, no. 1, pp. 108–112, Feb. 1976.

[124] M. Basseville and A. Benveniste, "Design and comparative study of some sequential jump detection algorithms for digital signals," *IEEE Trans. Acoust., Speech Signal Process.*, vol. 31, no. 3, pp. 521–535, Jun. 1983.

[125] J. Y. Keller, L. Summerer, M. Boutayeb, and M. Darouach, "Generalized likelihood ratio approach for fault detection in linear dynamic stochastic systems with unknown inputs," *Int. J. Syst. Sci.*, vol. 27, no. 12, pp. 1231–1241, 1996.

[126] P. Li and V. Kadirkamanathan, "Particle filtering based likelihood ratio approach to fault diagnosis in nonlinear stochastic systems," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 31, no. 3, pp. 337–343, Aug. 2001.

[127] E. Wilson and D. Sutter, "Motion-based thruster fault detection and isolation," presented at the Infotech@Aerosp., Arlington, VA, Sep. 2005.

[128] S. Trapier, S. Deck, and P. Duveau, "Timefrequency analysis and detection of supersonic inlet buzz," *AIAA J.*, vol. 45, no. 9, pp. 2273–2284, 2007.

[129] J. R. Dodle, A. S. Willsky, and S. W. Gully, "Nonlinear generalized likelihood ratio algorithms for maneuver detection and estimation," in *Proc. Amer. Control Conf.*, Piscataway, NJ, 1982, p. 985987.

[130] J. Korn, S. W. Gully, and A. S. Willsky, "Application of the generalized likelihood ratio algorithm to maneuver detection and estimation," in *Proc. Amer. Control Conf.*, Piscataway, NJ, 1982, p. 792798.

[131] D. Dionne and H. Michalska, "Novel adaptive generalized likelihood ratio detector with application to maneuvering target tracking," *J. Guid., Control, Dyn.*, vol. 29, no. 2, pp. 465–474, 2006.

[132] I. V. Nikiforov, "Sequential detection of abrupt changes in stochastic systems," in *Detection of Abrupt Changes in Signals and Dynamical Systems, Volume 77 of Lecture Notes in Control and Information Sciences*. Berlin/Heidelberg, Germany: Springer, 1985, pp. 216–258.

[133] A. Benveniste ad, M. Basseville, and G. V. Moustakides, "The asymptotic local approach to change detection and model validation," *IEEE Trans. Autom. Control*, vol. 32, no. 7, pp. 583–592, Jul. 1987.

[134] M. Basseville, "On-board component fault detection and isolation using the statistical local approach," *Automatica*, vol. 34, no. 11, pp. 1391–1415, 1998.

[135] B. Huang, "Detection of abrupt changes of total least squares models and application in fault detection," *IEEE Trans. Control Syst. Technol.*, vol. 9, no. 2, pp. 357–367, Mar. 2001.

[136] J. Li, C. W. Chan, and H. Y. Zhang, "Asymptotic local approach in fault detection based on predictive filters," *J. Guid., Control, Dyn.*, vol. 28, no. 6, pp. 1112–1122, 2005.

[137] P. Lu, "Nonlinear predictive controllers for continuous systems," *J. Guid., Control, Dyn.*, vol. 17, no. 3, pp. 553–560, 1994.

[138] P. S. Maybeck and D. L. Pogoda, "Multiple model adaptive controller for the STOL F-15 with sensor/actuator failures," in *Adv. Robust Adaptive Control*, K. S. Narendra, R. Ortega, and P. Dorato, Eds. Piscataway, NJ: IEEE Press, 1992.

[139] P. S. Maybeck and R. D. Stevens, "Reconfigurable flight control via multiple model adaptive control methods," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 27, no. 3, pp. 470–480, May 1991.

[140] Y. Zhang and J. Jiang, "Integrated active fault-tolerant control using IMM approach," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 37, no. 4, pp. 1221–1235, Oct. 2001.

[141] M. Efe and D. P. Atherton, "The IMM approach to the fault detection," presented at the 11th IFAC Symp. Syst. Identification, Fukuoka, Japan, Jul. 1997.

[142] R. K. Mehra, C. Rago, and S. Seereeram, "Failure detection and identification using a nonlinear interactive multiple model (IMM) filtering approach with aerospace applications," presented at the 11th IFAC Symp. Syst. Identification, Fukuoka, Japan, Jul. 1997.

[143] M. Kumar, "Fault detection identification and reconfiguration of flight control system using IMM estimator," in *Proc. Digit. Avionics Syst. Conf.*, Oct. 2007.

[144] J. D. Boskovic and R. K. Mehra, "Stable multiple model adaptive flight control for accommodation of a large class of control effector failures," in *Proc. Amer. Control Conf.*, 1999, pp. 1920–1924.

[145] M. Gopinathan, J. D. Boskovic, R. K. Mehra, and C. Rago, "A multiple model predictive scheme for fault-tolerant flight control design," in *Proc. 37th IEEE Conf. Dec. Control*, 1998, pp. 1376–1381.

[146] B. Jung, S. K. Jeong, D. H. Lee, and Y. Kim, "Adaptive reconfigurable flight control system using multiple model mode switching," presented at the 16th IFAC World Congr., Prague, Czech Republic, Jul. 2005.

[147] B. Jung, Y. Kim, C. Ha, and M. J. Tahk, "Nonlinear reconfigurable flight control system using multiple model adaptive control," presented at the 17th IFAC Symp. Autom. Control Aerosp., Toulouse, France, Jun. 2007.

[148] J. D. Boskovic, S. H. Yu, and R. K. Mehra, "A stable scheme for automatic control reconfiguration in the presence of actuator failures," in *Proc. Amer. Control Conf.*, 1998, pp. 2455–2459.

[149] S. Chen, G. Tao, and S. M. Joshi, "On matching conditions for adaptive state tracking control of systems with actuator failures," *IEEE Trans. Autom. Control*, vol. 47, no. 3, pp. 473–478, Mar. 2002a.

[150] G. Tao, S. M. Joshi, and X. L. Ma, "Adaptive state feedback and tracking control of systems with actuator failures," *IEEE Trans. Autom. Control*, vol. 46, no. 1, pp. 78–95, Jan. 2001.

[151] G. Tao, S. Chen, and S. M. Joshi, "An adaptive actuator failure compensation controller using output feedback," *IEEE Trans. Autom. Control*, vol. 47, no. 3, pp. 506–511, Mar. 2002.

[152] X. D. Tang, G. Tao, and S. M. Joshi, "Adaptive actuator failure compensation for parametric strict feedback systems and an aircraft application," *Automatica*, vol. 39, no. 11, pp. 1975–1982, 2003.

[153] M. Bodson and J. Groszkiewicz, "Multivariable adaptive algorithms for reconfigurable flight control," *IEEE Trans. Control Syst. Technol.*, vol. 39, no. 11, pp. 217–229, Nov. 1997.

[154] M. W. Oppenheimer and D. B. Doman, “Efficient reconfiguration and recovery from damage for air vehicles,” presented at the AIAA Guid., Nav., Control Conf., Keystone, CO, Aug. 2006.

[155] S. Ganguli, G. Papageorgiou, S. Glavaski, and M. Elgersma, “Piloted simulation of fault detection, isolation and recofiguration algorithms for a civil transport aircraft,” presented at the AIAA Guid., Nav., Control Conf., San Francisco, CA, Aug. 2005.

[156] S. Ganguli, G. Papageorgiou, and S. Glavaski, “Aircraft fault detection, isolation and reconguration in the presence of measurement errors,” presented at the AIAA Guid., Nav., Control Conf., Keystone, CO, Aug. 2006.

[157] K. S. Kim, K. J. Lee, and Y. Kim, “Reconfigurable flight control system using direct adaptive method,” *J. Guid., Control, Dyn.*, vol. 26, no. 4, pp. 543–550, 2003.

[158] J. Gertler, “All linear methods are equal-and extendible to (some) nonlinearities,” *Int. J. Robust Nonlinear Control*, vol. 12, pp. 629–648, 2002.

[159] T. G. Reynolds and R. J. Hansman, “Investigating conformance monitoring issues in air traffic control using fault detection techniqes,” *J. Aircraft*, vol. 44, no. 2, pp. 1307–1317, Sep.–Oct. 2005.

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