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Review of Parity Space Approaches to Fault Diagnosis for Aerospace Systems

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This paper provides a tutorial review of the state of the art in parity space fault diagnosis approaches with particular emphasis on aerospace systems. The basic concepts and definitions are given and a consistent framework is presented to draw together the important links amongst the known methods for fault diagnosis. Residual generation in the parity space has been recognized as a core element in this framework. The robustness and isolation problems are the main focus of the paper. Recent research topics on robust fault diagnosis are outlined, and new ideas as to how the parity space approach can be used to deal with robustness are discussed.

I. Introduction

MODERN aerospace systems are often subject to unexpected changes, such as component faults and variations in operating conditions, that tend to degrade the overall system performance. To design a reliable, fault-tolerant control system, or to maintain a high level of performance for complex vehicles, e.g., spacecraft and aircraft, etc., it is crucial that such changes are detected promptly and diagnosed so that corrective action can be taken to reconfigure the control system and accommodate the change.[1-9] A "fault" is to be understood as an unexpected change in the system that tends to degrade the overall system performance (e.g., component malfunction), although it may not represent the "failure" of physical components. We use the term fault rather than failure to denote a malfunction rather than a catastrophe.[3,8] The term failure suggests complete breakdown of a system component or function, whereas the term fault may be used to indicate that a malfunction is present and it may be serious or tolerable. A monitoring subsystem used to detect faults and diagnose their location and significance in a system is called a fault diagnosis system. Such a system must consist of two main tasks—fault detection and fault isolation (FDI) (see Fig. 1).[3,8] The fault detection consists of making a binary decision—either that something has gone wrong or that everything is fine. The fault isolation task is to determine the source of the fault, e.g., which sensor or actuator has become faulty. To achieve the system reconfiguration to response faults, the fault identification (to identify the magnitude and occurring time of faults) is also a necessary task of fault diagnosis.

FDI can be achieved using a replication of hardware (e.g., computers, sensors, actuators, and other components) in what is known as hardware redundancy in which outputs from identical components are compared for consistency.[3,8] Alternatively, FDI can be carried out using analytical or functional information about the system being monitored, i.e., based on a mathematical model of the system.[3,8] The latter approach is known as analytical redundancy, which is also known invariably as model-based or quantitative FDI. Model-based FDI is currently the subject of extensive research and is being used in highly reliable control systems.[1-9] However, research is still under way into the development of more reliable diagnosis methods.[8,9]

Research attention in recent years has been on robust methods for FDI,[9,10] which are able to detect incipient (soft or small) faults in a system before they are manifested as problems requiring either human operator or automatic system intervention (accommodation or control reconfiguration). In the safety-critical process control field, incidents such as the Three Mile Island accident and the Chernobyl disaster, have demonstrated both the need for meaningful and reliable practical diagnosis and the need to provide the human operator with this information speedily and in a suitable format. These lessons can also be useful in the aerospace domain. When understood correctly and designed properly, model-based parity space methods can provide the required levels of robustness for such high integrity systems.

Within the framework of model-based methods, there are two main groups of FDI methods (see Fig. 1). The first group is the parameter space method, which uses parameter estimation and identification techniques. Methods in the second group make use of the signal space, the idea being to analyze the characteristic properties of the output and input signals. The traditional way of FDI is the use of limit checking, i.e., to compare system variables with preset limits, for which the exceedance of a limit can indicate a fault situation. Although

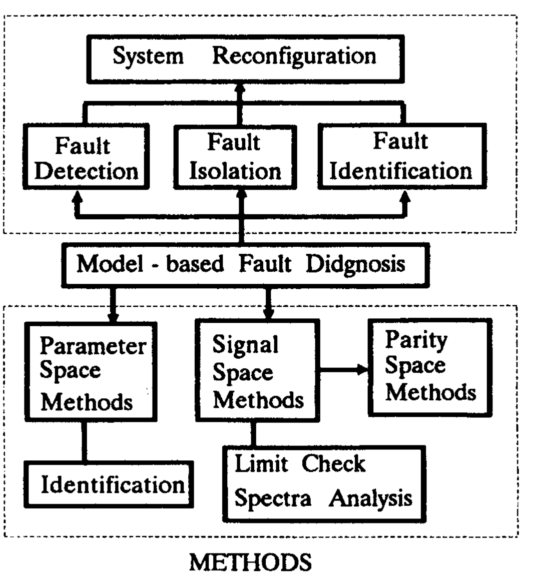

Fig. 1 Tasks and methods of fault diagnosis.

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very simple, this method has a serious drawback, namely that the system signals may vary in accordance with different operating conditions and inputs of the monitored system, and the limit check has thus to be dependent on operating conditions and inputs. The so-called parity space methods have been proposed to overcome this difficulty. The idea here is to generate auxiliary signals (residuals or parity vectors) that are independent of system operating conditions and system inputs under nominal operating conditions while carrying fault "information." Residuals are indicators of faults; they are only affected by faults (ideally). Hence, it is possible to use a fixed threshold to detect faults.

The parity space is defined as a space in which all elements are residuals (or parity vectors). Residuals and parity vectors are synonymous in this context. The parity space can also be called a residual space. The relation (or equation) that generates the residual (parity vector) is called a parity relation (or equation). The task of FDI is then to construct a parity space and analyze its elements. This is what we mean by the parity space approach to FDI. The term parity was first used in connection with digital logic systems and computer software reliability to enable parity checks to be performed for error checking. In the FDI field, it has a similar meaning in the context of providing an indicator for the presence of a fault (or error) in system components.

The model-based parity space FDI process consists of two stages (Fig. 2): 1) residual generation: the system's inputs and outputs are processed by an appropriate algorithm (a processor) to generate residual signals that are nominally near zero and deviate from zero in characteristic ways when particular faults occur and 2) decision making: the residuals are examined for the likelihood of faults using proper decision functions and decision rules. A decision process may consist of a simple threshold test on the instantaneous values or moving averages of residuals, or it may be used directly on methods of statistical decision theory, e.g., sequential probability ratio testing.

This paper is concerned mainly with the residual generation stage of FDI, with emphasis on isolation and robustness problems. Residual signals are obtained by exploiting the dynamic relationships among the sensor outputs and actuator inputs. The general design requirements and methods for constructing residual generators are outlined in the paper. Parity space approaches to FDI are applicable to sensor, actuator, and component fault diagnosis for aerospace systems and do not require knowledge of fault behaviors.

The aim of this paper is to review the parity space approaches, however, a new unifying restatement of the FDI techniques is also included. Although there have been a number of surveys on the FDI subject, these have been limited in their scope, and there has been a growing need for a unifying restatement of the connections between the various methods developed. It has become clear that publications on this topic have often discussed the same issues repeatedly using different notation and alternative definitions of the same concepts. There has also been little apparent recourse to defining goals and links with other publications. To typify this problem the

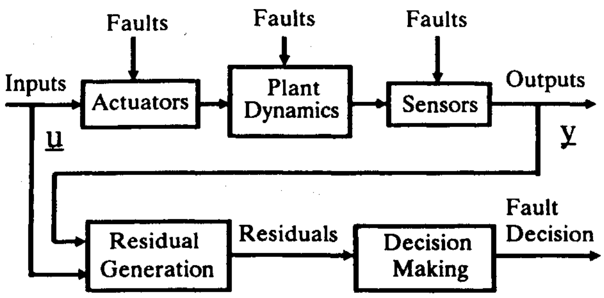

Fig. 2 Two-stage structure of an FDI process.

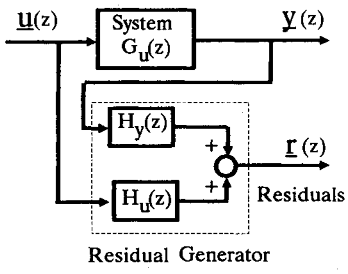

Fig. 3 Transfer function structure of residual generators.

terms parity vector, residual vector, etc., have been used rather loosely, and standard definitions have been lacking in the literature.

II. Basic Concepts of Residual Generation

Though the systems are usually continuous, the diagnostic computations are normally performed on sampled data. Here, we consider the discrete state-space linear model of the monitored system as

$$x(k+1) = Ax(k) + Bu(k) + R_1 f(k) \tag{1}$$

$$y(k) = Cx(k) + Du(k) + R_2 f(k) \tag{2}$$

where $x(k) \in R^n$ state vector, $y(k) \in R^m$ output vector, and $u(k) \in R^r$ input vector, and A, B, C, and D are known matrices with appropriate dimensions. $f(k) \in R^q$ is a fault vector, and each element $f_i(k)$ $(i = 1, 2, \ldots, q)$ corresponds to a specific fault. From a practical point of view it is unreasonable to make further assumptions about the fault characteristics, but consider these as unknown time functions. The matrices R_1 and R_2 are known as fault entry matrices, which represent the effect of faults on the system. The input-output description of the system

$$y(z) = G_u(z)u(z) + G_f(z)f(z) \tag{3}$$

where

$$G_u(z) = C(zI - A)^{-1}B + D \tag{4}$$

$$G_f(z) = C(zI - A)^{-1}R_1 + R_2 \tag{5}$$

Residual generation plays an important role in FDI. To be useful indicators of faults, the residuals should be small in the absence of faults, and one or more of them should become large in the presence of a fault. The residuals are usually based on (weighted) comparisons between actual and estimated outputs (generated from the mathematical model). Hence, model-based FDI can be defined as the determination of faults of a system from the comparison of the measurements of the system with a priori information represented by the model of the system through generation of residual quantities and their analysis. A transfer function structure of the residual generator is shown in Fig. 3.

A general form of the residual generator can then be expressed as

$$r(z) = H_u(z)u(z) + H_y(z)y(z) \tag{6}$$

Here, $H_u(z)$ and $H_y(z)$ are transfer function matrices that are realizable using stable linear systems. The residual should be made zero for the fault-free and no uncertainty case, i.e.,

$$r(z) = 0 \quad \text{and} \quad y(z) = G_u(z)u(z) \tag{7}$$

To satisfy this requirement, $H_u(z)$ and $H_y(z)$ must satisfy

$$H_u(z) = -H_y(z)G_u(z) \tag{8}$$

Equation (6) is a unified and generalized representation of all residual generators. The design of the residual generator results simply in the choice of the transfer matrices $H_u(z)$ and $H_y(z)$, which must satisfy Eq. (8). Different residual generation methods correspond to different parameterizations of $H_u(z)$ and $H_y(z)$. The observer residual structure is an example of the parameterization of $H_u(z)$ and $H_y(z)$. One can obtain any residual generators using different forms for $H_u(z)$ and $H_y(z)$ designed to meet any performance specification.

When faults occur in the monitored system, the response of the residual vector is

$$r(z) = H_u(z)G_f(z)f(z) \tag{9}$$

To detect the ith fault in the residual $r(z)$, the ith column $[H_y(z)G_f(z)]_i$ of the transfer matrix $[H_y(z)G_f(z)]$ should be nonzero, especially for steady values, i.e.,

$$[H_y(z)G_f(z)]_i \neq 0 \qquad \text{and} \qquad [H_y(0)G_f(0)]_i \neq 0$$

If those conditions are satisfied, the ith fault can be said to be detectable using the residual. This is the detectability problem.

The isolability of faults is also an important issue. In precise terms, isolability is the ability of a procedure to distinguish (isolate) certain specific faults. Although a single residual signal is sufficient to detect faults, a set of residuals (or a residual vector) is required for fault isolation. To facilitate the isolation problem, residual sets are usually generated in one of the following ways: 1) structured residual set: To generate a set of residuals, each residual is designed to be sensitive to a subset of faults while remaining insensitive to other faults,[3,9,11] and 2) directional residual vectors: To make the residual vector lie in fixed and fault-specific directions (or subspaces) in the parity (residual) space in response to a specific fault.[3,9,11-13] The basis for the isolation of a fault is the fault signature, i.e., a feature obtained from a diagnostic model defining the effects associated with a fault.[12,13] Each signature must be uniquely related to one fault to accomplish fault isolation. Consider the sensor and actuator fault isolation problems

$$x(k+1) = Ax(k) + Bu(k) + B_1 f_a(k) \tag{10}$$

$$y(k) = Cx(k) + Du(k) + f_s(k) \tag{11}$$

or

$$y(z) = G_u(z)u(z) + G_a(z)f_a(z) + f_s(z) \tag{12}$$

where $f_s(z)$ is the sensor fault vector and $f_a(z)$ the actuator fault vector. When sensor faults occur, the residual vector will be

$$r(z) = H_y(z)f_s(z) \tag{13}$$

Here the fault transfer matrix $H_y(z)$ will be chosen according to specific requirements. For the isolation purpose, we can make $r(z)$ independent to the ith sensor fault by simply making the ith column of $H_y(z)$ equal to zero. If $H_y(z)$ is a diagonal matrix, each element of the residual is only affected by a specified sensor fault; this is very useful for fault isolation. The only constraint on $H_y(z)$ is that it be stable and implementable. Once it has been chosen, $H_u(z)$ can be determined by Eq. (8). As the transfer matrix $H_y(z)$ can be chosen freely to meet any required isolation property, sensor fault isolation is always possible.

When actuator faults occur in the system, the residual is

$$r(z) = H_y(z)G_a(z)f_a(z) \tag{14}$$

In this case, the fault transfer function matrix is $H_y(z)G_a(z)$. To make $r(z)$ independent of the ith actuator fault, the choice of $H_y(z)$ must ensure that the ith column of matrix $H_y(z)G_a(z)$ is equal to zero. For any given fault transfer matrix $H_y(z)G_a(z)$, the stable and implementable $H_y(z)$ does not always exist. That is to say, we do not have full freedom to achieve required actuator fault isolation performance. Hence, actuator fault isolation is not always possible. This problem is also discussed in Ref. 14. Unknown input observers,[15,16] the eigenstructure assignment technique,[17-19] and the fault (failure) detection filter theory[12,13] can all be used to deal with the actuator fault isolation problem.

III. Residual Generator Synthesis

The generation of residual signals is a central issue in parity space FDI schemes. This section reviews a rich variety of approaches for residual generation. Section II has described a residual generator structure in terms of transfer functions. In this section, the residual generator is interpreted in terms of redundant signals as shown in Fig. 4. The system F_1 generates an auxiliary (redundant) signal y_1 which, together with y, generates the residual r which satisfy the relation

$$r = F_2(y, y_1) = 0 \tag{15}$$

for the fault-free case. The simplest approach to FDI is the use of system duplication (parallel redundancy), i.e., the system F_1 is made identical to the original system and has the same input signal. The residual is the difference between the original and duplicated (parallel) system outputs. To reduce the cost and complexity due to parallel redundancy, the role of the parallel hardware duplication of plant in block F_1 can be replaced by a mathematical model of plant. To achieve the required FDI performances, the residual can be processed further by a (dynamic or static) weighting.

A. Residual Generators Synthesis in the State Space

1. *Observer-Based Methods*

The basic idea behind the observer- or filter-based approaches is to estimate the outputs of the system from the measurements (or a subset of measurements) by using either Luenberger observer(s) in a deterministic setting[7,11] or Kalman filter(s) in a stochastic setting.[1,11,19] Then, the (weighted) output estimation error (or innovations in the stochastic case) is used as a residual. The flexibility in selecting observer gains has been fully exploited in the literature yielding a rich variety of FDI schemes. A popular approach, for instance, is to use a bank of estimators (Kalman filters or observers) where each estimator is designed for a different fault hypothesis.[8,11] Such schemes provide a good framework for multiple hypothesis testing for FDI. Another approach is to choose the observer gain so that the residual has a fixed direction or is kept in a fixed subspace in the parity space to correspond to each fault. If the fault directions are separable in the output space, then fault isolation is possible in this framework. This so-called failure (fault) detection filter approach was proposed first by Beard.[12]

2. *Parity Vector (Relation) Methods*

Initially, the parity vector (parity relation) method was applied to the hardware redundancy problem.[23] This concept was then generalized by Chow and Willsky[21] and Lou et al.[22] for the case of using the temporal redundancy relations of the dynamic system. It is important, however, to note that essentially the same scheme has been suggested by Mironovski[23] (see also Ref. 2). Although Mironovski does not use the term parity vector, the essential ideas are the same as those of the

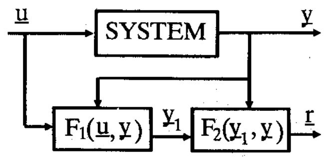

Fig. 4 Signal structure of residual generators.

remaining authors. The parity relation approach is based on checking the consistency of the mathematical relations between the outputs (or a subset of outputs) and inputs. These relations may lead to direct redundancy, which gives the static algebraic relations amongst the sensor outputs, or they may lead to temporal redundancy, which gives the dynamic relations between inputs and outputs.

Combining Eqs. (1) and (2) from time $k-s$ to time k yields the following redundancy relations (for no fault case):

$$\begin{bmatrix} y(k-s) \\ y(k-s+1) \\ \vdots \\ y(k) \end{bmatrix} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix} x(k-s) + H \begin{bmatrix} u(k-s) \\ u(k-s+1) \\ \vdots \\ u(k) \end{bmatrix} \tag{16}$$

where

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

The parity vector (residual) $r(k)$ is given as follows:

$$r(k) = V\left\{ \begin{bmatrix} y(k-s) \\ y(k-s+1) \\ \vdots \\ y(k) \end{bmatrix} - H \begin{bmatrix} u(k-s) \\ u(k-s+1) \\ \vdots \\ u(k) \end{bmatrix} \right\} \tag{17}$$

where the matrix V (called the residual generator) is chosen such that the residual $r(k)$ is to satisfy Eq. (15), thus

$$V \begin{bmatrix} C \\ CA \\ \vdots \\ CA^s \end{bmatrix} = 0 \tag{18}$$

Note that, for an appropriately large s, it follows from the Cayley-Hamilton theorem that such a matrix V always exists. An appropriate value for s can be found by the designer by systematically increasing this index. Mironovski[23] has shown that the minimum order of s is always between the smallest and the largest Kronecker invariant index. Now, using the definition of V, it is clear that $r(k)$ is zero when the system is functioning correctly, but in the presence of a fault in the system this residual may become nonzero. Assuming that $V = [\alpha_s, \alpha_{s-1}, \ldots, \alpha_1, \alpha_0]$ and $VH = -[\beta_s, \beta_{s-1}, \ldots, \beta_1, \beta_0]$, Eq. (17) can be rewritten as

$$r(k) = \sum_{i=0}^{s} [\alpha_i y(k-i) + \beta_i u(k-i)] \tag{19}$$

or

$$r(k) = \sum_{i=0}^{s} [\alpha_i z^{-i} y(z) + \beta_i z^{-i} u(z)] \tag{20}$$

This is clearly a moving average process with no recursive operations between the inputs $\{u(z), y(z)\}$ and the residual $r(z)$. This expression can be used to implement the residual generation process, which is illustrated in Fig. 5.

Chow and Willsky[21] and Lou et al.[22] studied this method in detail and discussed implementation problems and robustness issues. The faults isolation problem can be solved by designing a structured residual set.[11,21,22] However, it is not very easy to design a directional residual vector using this method. It has been shown by Massoumnia,[24] Frank and Wünnenberg,[16] and more fully by Patton and Chen,[25] that the parity vector approach is equivalent to the use of a deadbeat observer. An observer having a deadbeat structure gives rise to a nonrecursive or finite-impulse response algorithm format. This result implies that the parity vector method provides less design flexibility when compared with methods that are based on observers without any restriction.

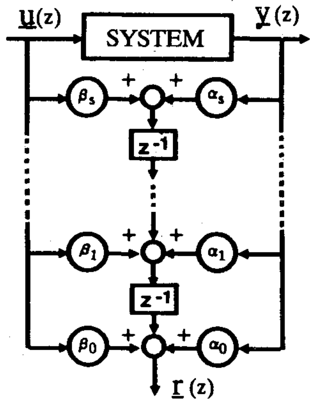

Fig. 5 Block diagram of the *s*th-order parity vector.

B. Residual Generator Synthesis Using Input-Output Relation

The residual generator can be synthesized using the transfer function matrix of the monitored system. Gertler et al.[9,26,27] first introduced this approach, preferring to call it the parity equation method. With reference to Fig. 4, we can simply substitute the system transfer function $G_u(z)$ for F_1, i.e., to simulate the monitored system. In this case, the redundant signal is the simulated output and the residual is the difference between the actual and simulated output

$$r_1(z) = y(z) - G_u(z)u(z) \tag{21}$$

Assume that the transfer function matrix $G_u(z)$ is

$$G_u(z) = \frac{1}{\phi(z)} T(z) \tag{22}$$

where $T(z)$ is a polynomial matrix in z^{-1}, and $\phi(z)$ is a polynomial in z^{-1}. Then the residual can be defined as

$$r_2(z) = \phi(z)r_1(z) = \phi(z)y(z) - T(z)u(z) \tag{23}$$

Although very simple, one of the difficulties in the use of Eqs. (21) and (23) to generate residual is that fault isolation is not easy to achieve due to insufficient design freedom. Another drawback in the use of Eq. (21) is that it will result in an unstable residual generator when the monitored system is unstable. To increase the design freedom and to meet the required isolation and robust performance, a dynamic (or static) weighting $W(z)$ matrix is used to weight the previous residuals (Gertler et al.[9,27]), i.e.,

$$r(z) = W(z)r_i(z) \qquad i = 1, 2 \tag{24}$$

By suitable design of $W(z)$, the robust and isolation problems can be solved. Gertler et al.[9,27] have proposed a number of approaches (including orthogonal parity equation) to design the transfer matrix $W(z)$ for solving the isolation and robustness problem. Both the directional residual vector and the structured residual set can be designed using their method.

Within the input-output relation framework, Viswanadham et al.[28,29] and Ding and Frank[30] proposed the factorization method to design stable residual generators. The basis of this method is that any transfer function has the stable left-coprime factorization

$$G_u(z) = M^{-1}(z)N(z) \tag{25}$$

where $M(z)$ and $N(z)$ are transfer matrices that are realizable using stable linear systems. The residual generator is then defined as

$$r(z) = W(z)r_3(z) = W(z)[M(z)r_1(z)]$$
$$= W(z)[M(z)y(z) - N(z)u(z)] \tag{26}$$

The implementation of the observer-free approach to residual generation is very simple as it requires only the input and output information. However, this approach can be a disadvantage if internal information (e.g., states) of the system is required.

IV. Robustness in Model-Based Fault Diagnosis

Clearly, the reliability of an FDI scheme must be higher than the monitored system. The main problem to obstruct the progress and improvement in reliability of model-based FDI is the robustness with respect to modeling uncertainty. By this we mean the degree to which the FDI performance is unaffected by modeling errors and unknown (unmeasured) disturbances. Model-based FDI uses models of the monitored system so that, if the model is accurate and the characteristics of all the disturbances are known, FDI can be very straightforward and the robust problem is trivial. However, for a practical system, the modeling uncertainty is inevitable. Both faults and uncertainties affect the residual, and discrimination between their effects is difficult. The task in the design of a robust FDI system is thus to generate residuals that are insensitive to uncertainties, but at the same time sensitive to faults, and therefore robust.

Currently, the most powerful and successful way to achieve robustness in FDI is to make use of disturbance decoupling ideas.[10,17,18,31-34] In these approaches, all uncertainties are summarized as disturbance terms acting on the dynamic model, which can be illustrated as follows:

$$x(k+1) = Ax(k) + Bu(k) + E_1 d(k) + R_1 f(k) \tag{27}$$

$$y(k) = Cx(k) + Du(k) + E_2 d(k) + R_2 f(k) \tag{28}$$

Alternatively, the input-output form is

$$y(z) = G_u(z)u(z) + G_d(z)d(z) + G_f(z)f(z) \tag{29}$$

and

$$G_d(z) = C(zI - A)^{-1}E_1 + E_2 \tag{30}$$

The terms $E_1 d(k)$ and $E_2 d(k)$ are used to represent uncertainties acting on the system. The disturbances $d(k)$ are unknown, but the distribution matrices E_1 and E_2 are assumed to be known (i.e., the directions represented by the columns of these matrices are known). This is an example of structured uncertainty. Note that in some cases the matrix E_2 is null. If we substitute $y(z)$ of Eq. (29) into the residual generator of Eq. (6), the residual is

$$r(z) = H_y(z)G_f(z)f(z) + H_y(z)G_d(z)d(z) \tag{31}$$

If the residual generator has been designed to satisfy

$$H_y(z)G_d(z) = 0 \tag{32}$$

the disturbance is totally decoupled from the residual. That is to say, the residual can be made independent of all disturbances to enable robust FDI. This is the principle of disturbance decoupling. This is a special case of the output-zeroing problem.

Disturbance decoupling designs can be achieved by using the unknown input observer[16,31,34] or, alternatively, eigenstructure assignment.[10,17,18,32,33] The latter is a direct way to design disturbance decoupled residual generators. By suitable assignment of the eigenstructure of the observer, the residual can be designed to provide disturbance decoupling. Disturbance decoupling design can also be achieved using frequency domain approaches.[9,27,34]

If condition (32) does not hold, perfect (accurate) decoupling cannot be obtained. One can consider the approximate decoupling, i.e., to find an optimal solution by minimizing a performance index containing a measure of the effects of both disturbance and the faults. An appropriate performance index can be defined as

$$J = \frac{\|H_y(e^{j\omega T})G_d(e^{j\omega T})\|}{\|H_y(e^{j\omega T})G_f(e^{j\omega T})\|} \tag{33}$$

By minimizing the performance index J over a certain frequency range, approximate decoupling is achievable.[7,34]

Clearly, a necessary assumption for disturbance decoupling is that the disturbance distribution matrix must be known a priori. In more general problems, the uncertainty structure is unknown (i.e., the uncertainty is unstructured) and for such cases, the robustness problems are more difficult to solve. In this case, the system can be described as

$$y(z) = \{G_u(z) + \Delta G_u(z)\}u(z) + \{G_f(z) + \Delta G_f(z)\}f(z) \tag{34}$$

and the residual is

$$r(z) = H_y(z)\{G_f(z) + \Delta G_f(z)\}f(z) + H_y(z)\Delta G_u(z)u(z) \tag{35}$$

For unstructured uncertainties as defined by $\Delta G_u(z)$ and $\Delta G_f(z)$, it is very difficult to achieve robust residual generation. One way of achieving it is to obtain an approximate structure for the uncertainties. When this approximate structure is used to design disturbance decoupling residual generators, approximately robust FDI is achievable. Patton and Chen[32,33] have shown that, even for a system as complex as the jet engine, the uncertainty distribution can be estimated either for one operating point or over a wide dynamic range of operation of the engine. The results have shown that, for a complex and very nonlinear three-spool thermodynamic engine, a simple estimation procedure can be used to estimate the uncertainty distribution at some operating points. Once the E_1 and E_2 matrices corresponding to individual operating points are known, an optimization procedure can then yield the optimum uncertainty distribution to enable a robust FDI design. This approximate structured description is considered an optimal description of the uncertainty in the jet engine system and can even be updated online. Patton and Chen[32,33] have demonstrated that this powerful approach works well over a wide range of operation of a simulated nonlinear engine system, and the results are shown in Sec. V.

Robust FDI by robust residual design is defined as the class of active methods.[10] By this, we mean that the effect of uncertainties on residuals has been minimized, or on the other hand, the effect of faults on residuals has been maximized. Efforts to enhance the robustness of FDI can also be made at the decision making stage, and we have termed this the passive approach.[10] As the consequence of parameter uncertainties, disturbances, and noise encountered in a practical application, one will rarely find a situation where the conditions for perfect robust residual generation are fully met. This is especially true for unstructured uncertainty. It is therefore necessary to provide sufficient robustness not only in the residual generation stage but also in residual evaluation stage (a step in decision making). The goal of robust residual evaluation is to enable reliable decision making in the sense that the false alarm and missed alarm rates due to uncertainties of residuals become satisfactorily small. This goal can be achieved in several ways, e.g., by statistical data processing, averaging, correction, or careful selection of the threshold.

The common approach to decision making concerning faults is to define a nonzero threshold at which the decision

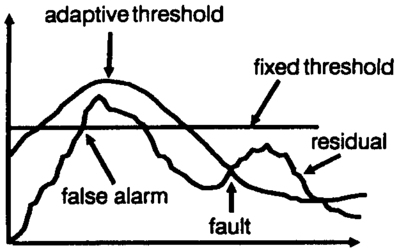

Fig. 6 Adaptive threshold and residual.

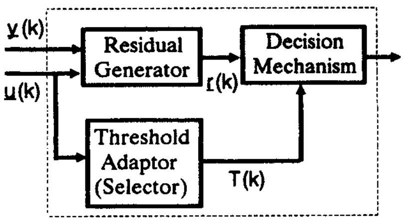

Fig. 7 FDI scheme with threshold adaptor or threshold selector.

functions are compared. Usually, fixed thresholds are used. If a decision signal exceeds the threshold, the occurrence of a fault is assumed. If, on the other hand, the decision function remains below the threshold, the monitored process is considered free of faults. The problem with the fixed threshold approach is that the sensitivity to faults will be intolerably reduced if the threshold is chosen too high, whereas the rate of false alarms will be too large when the threshold is chosen too low. The proper choice of the threshold is a delicate problem. The idea is based on the perception that in the case of system uncertainties, the residual fluctuates with the changing system inputs even if no fault occurs. Walker[35] has proposed to determine the optimal threshold via Markov theory. In the case of large maneuvers these changes might be large enough so that there is no fixed threshold that allows a satisfactory FDI at a tolerable false alarm rate. To increase the robustness in such a situation it is possible to use adaptive thresholds,[36-38] where thresholds are varied according to the control activity of the plant.

Figure 6 shows the typical shape of an adaptive threshold for direct residual evaluation. The question is how to determine the adaptive threshold law. Clark[36] used an empirical adaptive law. More recently, Emami-Naeini et al.[37] proposed the threshold selector method. In this method, the adaptive threshold can be obtained in a systematic way. This approach was then generalized by Ding and Frank,[38] and this is shown in Fig. 7.

The use of adaptive thresholds is a passive approach to robust FDI. By this we mean that no effort is made to design a robust residual. The robust problem is tackled by reliable decision making under the situation of uncertain residuals. A combination of active and passive approaches can offer potential for real robustness, especially when considering practical applications. It is believed that the success of an FDI scheme depends on the accuracy and choice of modeling of the monitored process. Hence, some attention in the field of robustness study must be paid to ensure that sufficient modeling of the monitored process is achieved.

V. Example: Jet Engine System

The correct operation of a gas turbine is very critical for an aircraft and, if faults occur, the consequences can be extremely serious.[5] There is therefore a great need for simple and yet highly reliable methods for detecting and isolating faults in the engine. Here, we consider an example of the detection of engine sensor faults. The jet engine has the measurement variables N_L, N_H, T_7, P_6, and T_{29}. N denotes a compressor shaft speed, P denotes a pressure, and T represents a measured temperature. A fully nonlinear thermodynamic simulation model of a jet engine is used as a test rig to illustrate the robustness of a model-based FDI scheme. This model has 17 state variables including pressures, air and gas mass flow rates, shaft speeds, absolute temperatures, and static pressure. The jet engine is a highly nonlinear dynamic structure that has grossly different steady-state operation over the entire range of spool speeds, flow rates, and nozzle areas. The linearized 17th-order model is used here to simulate the system. The nominal operating point is set at 70% of the demand high spool speed (N_H). For practical reasons and convenience of design, we choose to employ a fifth-order model to approximate the 17th-order model. The model reduction errors and other errors are summarized as disturbances. The details of the estimation of the approximate uncertainty structure and the design of robust observer-based residual generators can be found in the papers of Patton and Chen.[32,33] Here, FDI performance is assessed using simulation. A particular emphasis of this application study is the power of the method to detect soft or incipient faults that are otherwise unnoticeable in the measurement signals. These attributes are well illustrated in the following graphical time responses. As the FDI scheme was made robust against modeling errors, the scheme is able to detect incipient faults under conditions of modeling uncertainty.

Figure 8 shows the faulty output T_7 and the corresponding residual when a fault occurs on the temperature sensor T_7. The fault signal is very small compared with the output signal, and consequently, the fault cannot be detected directly in the output. It can be seen that the residual has a very significant increase when a fault has occurred on the system. A threshold can easily be placed on the residual signal to declare the occurrence of faults.

This research has also made use of real data recorded from an engine test rig as a step towards evaluating the requirements of a real-time fault monitor. The results of this aspect of the work cannot be presented at this time.

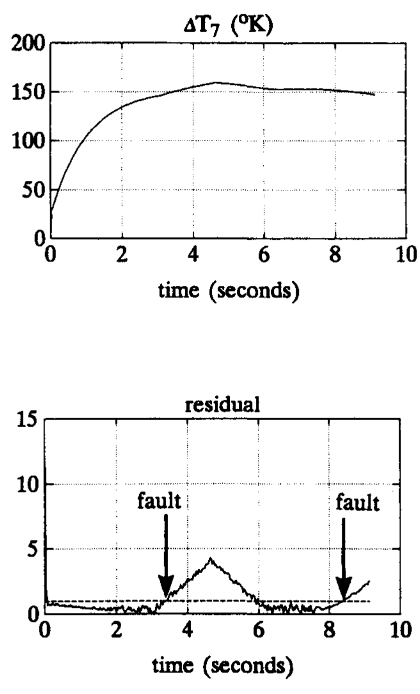

Fig. 8 Faulty output of sensor T_7 and corresponding residual.

VI. Concluding Remarks

In this paper the parity space approaches to fault diagnosis have been surveyed with particular interest in robustness issues. It has been pointed out that the major issues of fault diagnosis are isolability of specific faults and robustness with respect to uncertainties. Isolability is related primarily to the structure of the residual generating model and can be achieved by appropriate design of the residual generator. Particular emphasis has been placed on residual generator synthesis methods by comparing a number of residual generator design methods. The majority of studies in robustness for model-based fault diagnosis have focused on robust residual-generation problems. Observer-based strategies to residual generation have stimulated a significant interest in the development of methods related to the robust control problem; this is possible as the observer is the dual of the controller design problem. These active approaches tackle the robustness problem in a more direct way, by considering the real mechanisms of uncertainty (structured or unstructured). Decoupling ideas are used whenever the uncertainty can be considered as structured, and this can be achieved, for example, by using either eigenstructure design or the unknown input observer. Research into unifying ideas associated with the parity space has provided insight into ways in which the robustness issues can be developed. An important aspect of the model-based approach to fault diagnosis is the simplicity of structure of the algorithm used to generate the residual signal for detection and isolation. Although the method outlined focuses to some extent on state-space concepts, the actual algorithm uses only input-output processing of all measurable signals. This algorithm simplicity is very important when considering the need for system verification and validation, for example for air worthiness certification. This aspect of the work, together with the fact that the decoupling of modeling uncertainty has been well tackled, serve to highlight the potential of using parity space approaches in real applications.

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