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Fault Diagnosis With Process Uncertainty

A nonparametric pattern classification method is introduced for fault diagnosis of complex systems. This method represents the fault signatures by the columns of a multi-valued influence matrix *(MVIM), and uses adaptation to cope with fault signature variability. In this method, the measurements are monitored on-line and flagged upon the detection of an abnormality. Fault diagnosis is performed by matching this vector of flagged measurements against the columns of the influence matrix. The MVIM method has the capability to assess the diagnosability of the system, and use that as the basis for sensor selection and optimization. It also uses diagnostic error feedback for adaptation, which enables it to estimate its diagnostic model based upon a small number of measurement-fault data.*

1 Introduction

Fault diagnostic systems can prevent the unnecessary shutdown of machinery when on-line cure of the identified irregularity is possible, or reduce maintenance costs by avoiding disassembly to inspect components. These systems can also save considerable time during the experimental evaluation of new designs when machinery is more prone to failure.

Diagnostic systems generally use a multitude of observations for diagnosis and use diagnostic models to define the relationship of the measured signals to individual faults (Pau, 1975). Diagnostic models are either *mechanistic* or *empirical*. *Mechanistic* models which are derived from the physics of the process are dynamic state models that assume complete knowledge of the measurement noise characteristics, and represent the process faults as their state variables (Willsky, 1976; Isermann, 1984). These models have an analytical foundation, therefore, they can take advantage of various parametric identification techniques for diagnosis (e.g., see Stein and Park, 1988; Ono et al., 1987), and since these models can be analyzed in the framework of the control systems theory, they can be used to assess the diagnosability (observability) of the system and use that for sensor selection. Unfortunately, most mechanical systems are too complex for mechanistic modeling, so this approach has limited application (Willsky, 1976).

Empirical models, on the other hand, are developed from heuristically defined and/or experimentally established fault signatures. Since these models do not need a detailed understanding of the process, they have been widely adopted for performance monitoring of complex systems (Collacott, 1976; Cempel, 1988; Lyon and DeJong, 1984). One group of these models is developed in the Artificial Intelligence domain and is the basis for *expert diagnostic systems* (Gilmore and Gingher, 1986). Typically, the expert's knowledge is represented by the "if-then" rules, and the observations/measurements are contained in a fact base. An inference engine selects the rules to apply by matching the conditional side of the rules to the observations. These expert systems generally require a long processing time and are not suitable for on-line applications. Other models, in order to reduce processing time, use a much simpler format. Some of these models consider scalar fault signatures and require measurements which are affected by only one fault (e.g., see Lyon and DeJong, 1984). Since finding such measurements is not practical in many real situations where the obtained fault signatures may overlap, these models have inherent difficulty in producing reliable results. Some other models, in order to cope with the overlap of scalar fault signatures, use vectors of fault signatures (e.g., see Ledley, 1973; Reisig and Decarlo, 1986; Ishida et al., 1987). Although these models are effective in tolerating the overlap between the fault signatures, they cannot cope with the variability of fault signatures commonly caused by process variations (process noise), or introduced through signal processing (measurement noise).

In an attempt to cope with the variability of fault signatures, the use of statistical pattern classification techniques has been proposed for fault diagnosis (e.g., see Kulikowski, 1970; Gallant, 1987). In this approach, the array of measurements are classified into "decision regions" associated with individual faults, and diagnosis is performed by attributing the obtained measurements to specific decision regions (Duda and Hart, 1973). Although this approach is effective when the probabilistic structure of the system is known, due to high costs associated with the experimental acquisition of fault signatures necessary for the formation of reliable decision regions, it is limited in utility.

This paper introduces a nonparametric pattern classification method for fault diagnosis which does not require any knowledge of the probabilistic structure of the system. This method uses a linear discriminant function for pattern classification that allows the use of feedback in estimating/updating its diagnostic model. The use of feedback provides the method with a fast learning algorithm which can estimate the diagnostic model despite inadequate statistics about the fault signatures.

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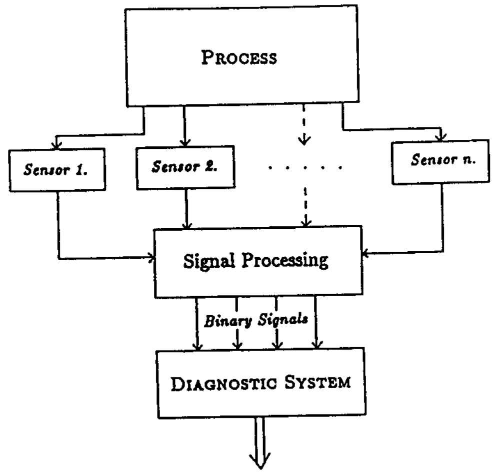

Fig. 1 Schematic diagram of the proposed sensor-based diagnostic system

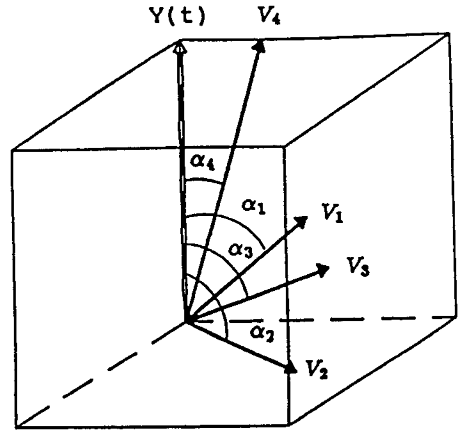

Fig. 2 Geometric representation of diagnostic reasoning in the MVIM method

Based on its linear discriminant function, this method also has the capability to assess the diagnosability of the system. Diagnosability analysis can be used to determine redundancy between measurement which can be used as the basis for sensor selection and optimization.

2 The MVIM Method

The MVIM method is based on a *multi-valued influence matrix* (MVIM) which represents the uncertain relationship between the process faults and measurements. Measurements are monitored in-process and *flagged* upon the detection of abnormalities, as illustrated in Fig. 1. For *flagging*, parametric and/or nonparametric signal processing techniques commonly used for fault detection can be employed (e.g., see Isermann, 1984; Pau, 1975). The flagged measurements are then posted in a flagged measurement vector which is matched against the individual columns of the influence matrix (influence vectors) for diagnostic reasoning. Influence vectors which represent the signature of individual faults are continuously updated by a learning algorithm to improve diagnosis.

2.1 Diagnostic Model. The multi-valued influence matrix representing the relationship between the measurements and faults is defined as

$$\mathbf{Y}(t)=\mathbf{A}\{\mathbf{X}(t)\} \tag{1}$$

where

$$\mathbf{Y}(t)=[y_1(t),\,y_2(t),\,\ldots,\,y_m(t)]^T \tag{2}$$

represents the *flagged measurement vector*,

$$\mathbf{X}(t)=[x_1(t),\,x_2(t),\,\ldots,\,x_n(t)]^T \tag{3}$$

represents the vector of faults, t denotes time, and $\mathbf{A}$ is the influence matrix which relates the inherently variable flagged measurement vectors to process faults. The vectors $\mathbf{Y}$ and $\mathbf{X}$ are binary vectors; i.e., the magnitudes of y_i (individual flagged measurements) and x_i (individual faults) can only be equal to 0 or 1, representing the status of the particular measurement and fault at the time, respectively. Since faults usually occur one at a time, only one of the x_i is assumed to be equal to 1 at any time. The influence matrix $\mathbf{A}$ is an $(m\times n)$ matrix whose components are numbers between 0 and 1 and define the degree of certainty associated with the casual relationship between pairs of faults and measurements. (For example, $a_{ij}=0.8$ implies that the possibility of the ith measurement being affected by the jth fault is 0.8.) According to this definition, in order to avoid the occurrence of undetected faults, the measurements must be selected such that at least one a_{ij} per column be equal to 1.

2.2 Diagnostic Reasoning. Diagnostic reasoning in the MVIM method is based on matching the vector of flagged measurements against individual influence vectors. The particular influence vector closest to the vector of flagged measurements is considered to correspond to the occurred fault. The closeness of vectors in the MVIM method is based on their orientation. Accordingly, the possibility of occurrence (*diagnostic certainty measure*) of each fault is defined as the cosine of the angle between its influence vector and the vector of processed measurements. The geometric representation of this reasoning is illustrated in Fig. 2 for a three dimensional measurement vector. Vectors V_1, V_2, V_3, and V_4 in this figure represent the influence vectors, and vector Y is the vector of flagged measurements.

Based on the above analogy, the vector of *diagnostic certainty measures* which ranks the faults for their possibility of occurrence can be defined as

$$\hat{\mathbf{X}}=\cos\{\alpha_1,\,\alpha_2,\,\ldots,\,\alpha_j,\,\ldots,\,\alpha_n\}^T \tag{4}$$

where α_j denotes the angle between the jth influence vector $\mathbf{V}_j$ and the flagged measurement vector $\mathbf{Y}$. The angle α_j can be defined by its direction cosines to give

$$\hat{x}_j=\cos\alpha_j=\bar{\mathbf{V}}_j^T\bar{\mathbf{Y}} \tag{5}$$

where $\bar{\mathbf{V}}_j$ and $\bar{\mathbf{Y}}$ are the normalized vectors of vectors $\mathbf{V}_j$ and $\mathbf{Y}$, respectively, defined as

$$\bar{\mathbf{V}}_j=\frac{\mathbf{V}_j}{\|\mathbf{V}_j\|}=\left\{\frac{a_{ij}}{\sqrt{\Sigma_{i=1}^m a_{ij}^2}}\right\} \tag{6}$$

and

$$\bar{\mathbf{Y}}=\frac{\mathbf{Y}}{\|\mathbf{Y}\|}=\left\{\frac{y_i}{\sqrt{\Sigma_{i=1}^m y_i^2}}\right\} \tag{7}$$

Using the formulation of equation (5) the vector of diagnostic certainty measures $\hat{\mathbf{X}}$ can be defined as

$$\hat{\mathbf{X}}=\{\hat{x}_j\}=\bar{\mathbf{A}}^T\bar{\mathbf{Y}} \tag{8}$$

where $\bar{\mathbf{A}}$ is the influence matrix in normalized form. Diagnostic reasoning in the MVIM method is based on obtaining the vector of diagnostic certainty measures $\hat{\mathbf{X}}$. To obtain $\hat{\mathbf{X}}$, however, the normalized form of the influence matrix, $\bar{\mathbf{A}}$, is required. Since this matrix is generally not known a priori, it will have to be estimated.

2.3 Learning. One of the main features of the MVIM method is its capability to use the diagnostic error as feedback in estimating/updating $\bar{\mathbf{A}}$. Based on this learning strategy, individual columns of the influence matrix are adjusted recursively after the occurrence of each fault to minimize a criterion function. One possible choice for this criterion function is the squared sum of the diagnostic error

$$J=\sum_{k=1}^{N}e_k(t)^2=\sum_{k=1}^{N}[x(t)-\hat{x}(t)]^2, \tag{9}$$

and the use of recursive least-squares (RLS) estimation for learning, provided that the diagnostic errors are zero-mean independent random variables and the measurements are "persistently excited" (Ljung, 1987). The RLS algorithm as applied to the MVIM method has the form

$$\hat{\bar{\mathbf{V}}}_j(k_j)=\hat{\bar{\mathbf{V}}}_j(k_j-1)+\frac{\mathbf{P}(k-1)\bar{\mathbf{Y}}(k)}{\lambda+\bar{\mathbf{Y}}(k)^T\mathbf{P}(k-1)\bar{\mathbf{Y}}(k)}[x_j(k_j)-\hat{x}_j(k_j-1)] \tag{10}$$

$$\mathbf{P}(k)=\frac{1}{\lambda}\left[\mathbf{P}(k-1)-\frac{\mathbf{P}(k-1)\bar{\mathbf{Y}}(k)\bar{\mathbf{Y}}(k)^T\mathbf{P}(k-1)}{\lambda+\bar{\mathbf{Y}}(k)^T\mathbf{P}(k-1)\bar{\mathbf{Y}}(k)}\right] \tag{11}$$

where $x_j(k_j)$ is always equal to 1 denoting the "ideal" value of the diagnostic certainty measure for the jth fault, $\hat{x}_j(k_j-1)$ represents the estimated value of the diagnostic certainty measure based on the current value of the influence vector $\hat{\bar{\mathbf{V}}}_j(k_j-1)$, $k_j=1, 2, \ldots, N_j$ represents the number of occurrences of the jth fault, $k=\Sigma_{j=1}^{n} k_j$ denotes the total number of fault occurrences, $\mathbf{P}(k)$ is the matrix of estimation gains, λ is the "forgetting factor" (Goodwin and Sin, 1984) used to give more weight to the new data for time-varying systems, and $\bar{\mathbf{Y}}(k)$ is the vector of flagged measurements. The performance of the above learning algorithm is demonstrated in simulation in the next section.

2.4 Diagnosability Assessment. A system is considered to be diagnosable if every fault can be uniquely identified. This, in turn implies that each fault must generate a unique fault signature to satisfy the diagnosability condition, and that the *degree of diagnosability* of the system be defined in terms of the closeness of the fault signatures (influence vectors in the MVIM method). The uniqueness requirement in the MVIM method is defined in terms of the orientation of the influence vectors by a diagnosability matrix of the form

$$\mathfrak{D}=f[\beta_{ij}] \tag{12}$$

where f is a monotonic increasing function and β_{ij} are the angles between pairs of influence vectors defined as

$$[\beta_{ij}]=\cos^{-1}(\bar{\mathbf{A}}^T\bar{\mathbf{A}}). \tag{13}$$

According to this diagnosability matrix, the degree of diagnosability of the system is represented by $f(\beta'_{ij})$ $(i\neq j)$, where β'_{ij} is the smallest off-diagonal component among the β_{ij}. One possible choice for the function f in equation (12) is the sine function which produces the diagnosability matrix

$$\mathfrak{D}=\sin[\cos^{-1}(\bar{\mathbf{A}}^T\bar{\mathbf{A}})]. \tag{14}$$

The above diagnosability matrix is an n dimensional symmetric matrix with 0's on its diagonal, which represents the degree of diagnosability of the system by its smallest off-diagonal component. The diagnosability results can be used to determine the redundancy between the measurements, which can be used as the basis for sensor selection and optimization. The application of diagnosability analysis for sensor selection is discussed in the next section.

3 Example

The MVIM method is concerned with on-line diagnostics. It has several important features: it does not require any knowledge of the probabilistic structure of the system, it uses feedback in estimating its diagnostic model, and it can assess the diagnosability of the system. In this section, we discuss the application of the MVIM method and demonstrate its performance by comparing it with a Bayes classifier in simulation. For this purpose, a turning process is considered as the application domain. The turning process exemplifies a system which cannot be adequately represented by a mechanistic model, and due to the variability of its fault signatures cannot be diagnosed by the existing empirical diagnostic methods.

Four irregularities are considered in this turning example: (1) tool breakage, (2) hard spots in the workpiece, (3) chip entanglement, and (4) chatter. A brief description of the above irregularities and the common signatures used for their detection follows.

- *Tool Breakage.* Tool breakage can cause serious damage to the tool holder, the workpiece, or the machine, so it must be detected immediately for the viable operation of an automated process. Several signals have been used for tool breakage detection in turning (Tlusty and Andrews, 1983). The cutting force shows a distinct pattern consisting of a sudden jump followed by an immediate drop in magnitude for a few milliseconds (Koenig et al., 1978). Acoustic emission (AE), which is a low amplitude high frequency stress wave caused by the rapid release of strain energy, shows an increase in its amplitude (Kakino, 1980; Moriwaki, 1980). The spindle motor current has been reported to show a sudden drop after tool breakage, due to idle cutting, followed by an increase in its magnitude (Matsushima et al., 1982; Mohri et al., 1982).
- *Hard Spots.* Hard spots are inhomogeneities in the workpiece which can be tolerated. However, since they cause spikes in signals such as the cutting force and spindle motor current which may be confused with tool breakage, they must be detected to prevent unnecessary shutdowns of the machine. Hard spots are expected to have little effect on the AE signal, due to the absence of fracture.
- *Chip Entanglement.* Chip entanglement is usually caused by long continuous chips wrapping around the tooling and workpiece, causing damage to the surface finish of the part and interfering with workpiece and tool changes. A good indicator of chip form has been reported to be bursts in the AE signal (Lan and Dornfeld, 1984; Yee, et al., 1986). Chip entanglement can also load the spindle and feed motor drives, which may be detected through the drive currents.
- *Chatter.* Regenerative chatter is self-excited vibration between the tool and the workpiece, which adversely affects the surface finish, dimensional accuracy, tool life, and machine life, and must be diagnosed and cured by reducing the cutting speed (Tobias, 1965). Since chatter is believed to be caused by a phase lag between the cutting force and the uncut chip thickness, cutting force oscillations are often used for chatter detection (e.g., see Marui et al., 1983).

Based on the above survey, individual signals which must be monitored to diagnose the above irregularities can be determined. One of the main features of the MVIM method is its ability to determine whether a system is diagnosable based on the influence matrix estimated from the selected set of measurements. Once the diagnosability of the system has been verified, an optimal subset of measurements can be selected for diagnostic purposes. The candidate measurements which can be used for diagnosability assessment are: (1) the magnitudes of the three components of the cutting force signal, to detect spikes caused by tool breakage or hard spots; (2) the amplitude of the frequency spectrum of the cutting force signal, to detect chatter vibrations; (3) the RMS amplitude of the AE signal at high frequencies (0.1 to 1 MHz), to detect tool breakage; (4) bursts in the AE signal, to detect chip entanglement; (5) the amplitude of the spindle motor current, to detect tool breakage; (6) the feed motor current, to detect chip entanglement; and (7) vibration of the machine, for general condition monitoring. Among the above signals, the spindle motor current may contain the same information as the cutting force signal, however, it may not be as strongly affected by hard spots, and its inclusion may improve the diagnosability of the

Table 1 Values of estimated matrices $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$, and the diagnostic results of the MVIM method and Bayes after 80 fault occurrences

Estimated Matrices	
$\hat{\mathbf{A}}$	$\hat{\mathbf{B}}$
$\begin{bmatrix} 0.50 & 0.84 & 0.21 & 0 \\ 0.22 & 0 & 0.17 & 0.93 \\ 0.50 & 0 & 0.18 & 0 \\ 0.16 & 0 & 0.84 & 0 \\ 0.50 & 0.43 & 0.30 & 0.34 \\ 0.42 & 0.32 & 0.32 & 0.15 \end{bmatrix}$	$\begin{bmatrix} 1 & 1 & 0.15 & 0 \\ 0.55 & 0 & 0.15 & 1 \\ 1 & 0 & 0.20 & 0 \\ 0.30 & 0 & 1 & 0 \\ 1 & 0.80 & 0.4 & 0.35 \\ 0.95 & 0.50 & 0.45 & 0.05 \end{bmatrix}$
Diagnosed faults	
74	66

Table 2 Values of estimated matrices $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$, and the diagnostic results of the MVIM method and Bayes after 80 iterations for the time varying matrix B

Estimated Matrices	
$\hat{\mathbf{A}}$	$\hat{\mathbf{B}}$
$\begin{bmatrix} 0.55 & 0.84 & 0.21 & 0 \\ 0.24 & 0 & 0.17 & 0.90 \\ 0.32 & 0 & 0.22 & 0 \\ 0.18 & 0 & 0.84 & 0.27 \\ 0.55 & 0.44 & 0.29 & 0.33 \\ 0.46 & 0.32 & 0.31 & 0.11 \end{bmatrix}$	$\begin{bmatrix} 1 & 1 & 0.15 & 0 \\ 0.55 & 0 & 0.15 & 1 \\ 0.75 & 0 & 0.25 & 0 \\ 0.30 & 0 & 1 & 0.2 \\ 1 & 0.80 & 0.4 & 0.35 \\ 0.95 & 0.45 & 0.45 & 0.05 \end{bmatrix}$
Diagnosed faults	
72	62

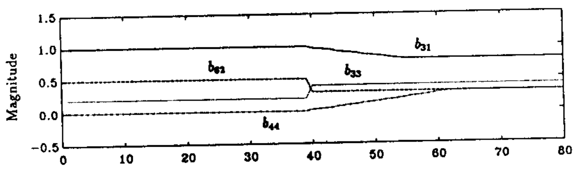

Fig. 3 Variations of parameters b_{31}, b_{33}, b_{44}, and b_{62} with time

system. In monitoring the above signals, care must also be taken to account for variations caused by changes in the cutting variables (i.e., feed, depth of cut, and cutting speed). State and parameter estimation techniques can be used for this purpose (e.g., see Danai and Ulsoy, 1987). Other measurements which may also need to be considered to improve diagnosability are the spectra of the spindle and feed motor currents, tool and workpiece displacements, and power.

For the purpose of simulation, an arbitrary matrix

$$\mathbf{B}=[b_{ij}]=\begin{bmatrix} 1 & 1 & 0.1 & 0 \\ 0.5 & 0 & 0.1 & 1 \\ 1 & 0 & 0.2 & 0 \\ 0.2 & 0 & 1 & 0 \\ 1 & 0.8 & 0.5 & 0.5 \\ 0.9 & 0.5 & 0.5 & 0.1 \end{bmatrix} \tag{15}$$

was assumed to contain the state-conditional probability densities of the *flagged* measurements y_i given that the fault x_j has occurred, such that

$$b_{ij}=P(y_i=1\,|\,x_j). \tag{16}$$

This matrix was used to simulate the measurement flags as faults were posted at random (i.e., x_j were set equal to 1, one at a time).

Both the Bayes classifier and the MVIM method need to estimate their diagnostic models (the probability density matrix **B** and the normalized form of the influence matrix $\hat{\mathbf{A}}$), as these models are generally not known a priori. Matrix $\hat{\mathbf{A}}$ was estimated according to the least-squares algorithm of Section 2.3 ($\lambda=1$), and Matrix $\hat{\mathbf{B}}$ was estimated using the formula (Duda and Hart, 1973)

$$\hat{b}_{ij}=\frac{1}{N_j}\sum_{k_j=1}^{N_j} y_i(k_j) \tag{17}$$

where N_j denotes the total number of occurrences of the jth fault.

According to Bayes classification theory, the set of discriminant functions which minimize the average probability of error for statistically independent y_i are defined as (Duda and Hart, 1973)

$$g_j(\mathbf{x})=P(x_j\,|\,Y)=\prod_{i=1}^{n} b_{ij}^{y_i}(1-b_{ij})^{1-y_i} \tag{18}$$

where $g_j(\mathbf{x})$ represents the discriminat function associated with the jth fault and Y is the vector of processed measurements. According to Bayes decision theory, the largest discriminant function in the above set is attributed to the occurred fault.

Several simulation runs were conducted, during which matrices $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ were estimated after the occurrence of each fault and fault diagnosis was performed based on the current values of $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$. The estimated matrices $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$, along with the diagnostic results of a simulation run with 80 fault occurrences (i.e., $N=\Sigma_{j=1}^{4} N_j=80$) are shown in Table 1. (The initial values of $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ were null matrices.)

The diagnostic results in Table 1 indicate that the MVIM method is considerably more effective in fault diagnosis (74 correct diagnoses compared to 66 by Bayes). This better performance is due to the more efficient learning algorithm of the MVIM method based on the utilization of feedback, which is particularly significant in the early stages of learning. Otherwise, for an "accurate" $\hat{\mathbf{B}}$, the Bayes classifier is as effective as the MVIM method, as it is expected to produce the minimum average probability of error (Duda and Hart, 1973). The faster convergence of the MVIM method is particularly important in practical applications, where the lack of adequate statistics hinders the accurate estimation of matrix $\hat{\mathbf{B}}$, which is essential for the reliable utilization of the Bayes classifier. The use of feedback for learning is also significant when the statistical structure of the system may change with time due to factors such as time-variability of the process, changes in the operating conditions, and/or variation in sensor sensitivity. To study the performance of the MVIM method in such cases, a time-varying matrix **B** such as

$$\mathbf{B}(t)=\begin{bmatrix} 1 & 1 & 0.1 & 0 \\ 0.5 & 0 & 0.1 & 1 \\ b_{31}(t) & 0 & b_{33}(t) & 0 \\ 0.2 & 0 & 1 & b_{44}(t) \\ 1 & 0.8 & 0.5 & 0.5 \\ 0.9 & b_{62}(t) & 0.5 & 0.1 \end{bmatrix}$$

was considered. The parameters b_{31}, b_{33}, b_{44}, and b_{62} vary as shown in Fig. 3. The estimated matrices $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ after 80 fault occurrences, along with the diagnostic results of the two methods for this time-varying case are shown in Table 2. (For this case, the value of the forgetting factor λ in the RLS algorithm was set equal to 0.95 to account for the time variability of the process.) As observed from Table 2, the more efficient learning algorithm of the MVIM method clearly enhances the performance of the MVIM method (72 correct diagnoses compared to 62 by Bayes).

In addition to its more efficient learning algorithm which improves its diagnostic capability in the early stages of learning, the MVIM method also produces a better resolution in ranking the faults for possibility of occurrence. For example, using the estimated matrices $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ in Table 1 and a posted flagged measurement vector

$$Y=\{1 \quad 1 \quad 1 \quad 0 \quad 1 \quad 1\}^T,$$

the Bayes discriminant functions give the likelihood of each fault as

$$g(\mathbf{x})=\{0.36 \quad 0 \quad 0 \quad 0\}^T,$$

whereas, the diagnostic certainty measures produced by the MVIM method rank the faults for possibility of occurrence as

$$\hat{\mathbf{X}}=\{0.96 \quad 0.71 \quad 0.53 \quad 0.63\}^T,$$

which is a more detailed ranking for diagnosis. This more detailed ranking can save inspection time in cases where misdiagnosis occurs and the next fault candidate needs to be identified.

Based on the estimated matrix $\hat{\mathbf{A}}$, the diagnosability of the system can also be determined. For this purpose, the diagnosability matrix $\mathfrak{D}$ in equation (14) is computed using $\hat{\mathbf{A}}$ in Table 1

$$\mathfrak{D}=\begin{bmatrix} 0 & 0.64 & 0.75 & 0.90 \\ 0.64 & 0 & 0.91 & 0.98 \\ 0.75 & 0.91 & 0 & 0.95 \\ 0.90 & 0.98 & 0.95 & 0 \end{bmatrix} \tag{19}$$

which shows that vectors $\mathbf{V}_1$ and $\mathbf{V}_2$ are the closest influence vectors in the above matrix ($d_{12}=0.64$ is the smallest off-diagonal component in matrix $\mathfrak{D}$), and that the degree of diagnosability of the system is 0.64.

To use the diagnosability results for sensor selection, the influence of individual measurements on the diagnosability of the system needs to be studied. For this purpose, individual measurements can be eliminated one at a time and the diagnosability of the system can be computed to reflect the effect of the eliminated measurement on the relative orientation of influence vectors. For example, the elimination of y_3 (the amplitude of the AE signal) will change the diagnosability matrix to

$$\mathfrak{D}'=\begin{bmatrix} 0 & 0.43 & 0.80 & 0.86 \\ 0.43 & 0 & 0.92 & 0.98 \\ 0.80 & 0.92 & 0 & 0.93 \\ 0.86 & 0.98 & 0.93 & 0 \end{bmatrix} \tag{20}$$

which has a diagnosability measure of 0.43. This shows that this measurement has a relatively large influence on the diagnosability of the system and should not be eliminated.

4 Conclusion

A new fault diagnostic method is introduced to cope with the fault signature variability of complex systems. It utilizes a *multi-valued influence matrix* (MVIM) as its diagnostic model, which is estimated/updated using diagnostic error feedback. As such, the MVIM method can be classified as a nonparametric pattern classifier which does not require any knowledge of the probabilistic structure of the system. This makes the method a good candidate for fault diagnosis when inadequate statistics precludes the use of statistical pattern classification techniques. In addition to the above features, the MVIM method can assess the diagnosability of the system which can be used as the basis for sensor selection and optimization. The application of the MVIM method to a turning process is explained, and its performance is demonstrated and compared with a Bayes pattern classifier in simulation. The use of feedback in learning is shown to enhance the performance of the MVIM method considerably in the early stages of diagnosis.

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