A Method of Fault Signature Extraction for Improved Diagnosis

Hsinyung Chin
Graduate Research Assistant.

Kourosh Danai
Assistant Professor.
Mem. ASME

Department of Mechanical Engineering,
University of Massachusetts,
Amherst, MA 01003

Efficient extraction of fault signatures from sensory data is a major concern in fault diagnosis. This paper introduces a self-tuning method of fault signature extraction that enhances fault detection, minimizes false alarms, improves diagnosability, and reduces fault signature variability. The proposed method uses a Flagging Unit to convert the processed measurements to binary vectors, and utilizes nonparametric pattern classification techniques to estimate the fault signatures. The performance of the Flagging Unit, which relies on its adaptation algorithms to optimize its performance based upon a sample batch of measurement-fault vectors, is demonstrated in simulation.

Introduction

Identifying the cause of process abnormalities is important for process automation. Diagnostic systems can prevent the unnecessary shutdown of machinery when irregularities can be cured by manipulating the operating parameters, and can save inspection time by pinpointing the failed component. The latter is particularly important during development and evaluation of new designs when components are more prone to failure.

Diagnostic systems detect process abnormalities through processing the sensory data and flagging the processed measurements, and perform diagnostic reasoning by comparing the flagged measurements against the fault signatures represented in a diagnostic model (see Fig. 1). In cases where the process can be represented by a model, model-based signal processing can be applied to account for variations in the measurements caused by changes in the operating conditions and to enhance detection through the use of parametric identification techniques (Isermann, 1984). In the absence of suitable process models, nonparametric identification techniques are usually used for signal processing (Cempel, 1987). In either case, the processed measurements represent the difference between various functions of the measurements and the expected values of these functions in the normal (no-fail) mode plus "noise" (Willsky, 1976). The main challenge in fault diagnosis is to extract reliable fault signatures from the noise contaminated processed measurements, so as to establish a reliable diagnostic model.

Two general approaches are commonly used to establish the diagnostic model: *deterministic* and *statistical*. In the *deterministic* approach the main effort is concentrated on obtaining stationary fault signatures by accurate modeling of the process and its noise characteristics (e.g., see Basseville and Benveniste, 1986; Chow and Willsky, 1984). This approach offers a simple and logical framework for diagnostic reasoning when a complete model of the process and its noise characteristics is available. However, since our knowledge of the interaction between faults and measurements in the presence of process nonlinearities and changing process conditions is limited for most real systems, the repeatability of fault signatures cannot be generally ensured and the use of such a deterministic diagnostic model would result in false alarms, undetected faults, and/or misdiagnosis. By contrast, the *statistical* approach does not assume repeatability of the fault signatures, but instead relies on methods of statistical pattern classification to estimate the fault signatures (e.g., see Hankley and Merrill, 1971; Pau, 1981). For this purpose, fault signatures are represented by "decision regions" (Duda and Hart, 1973) and diagnosis is performed by attributing the obtained processed (or flagged) measurements to these decision regions. Although this approach is effective in coping with fault signature variability, it requires knowledge of the probabilistic structure of the system. Due to high costs associated with the experimental acquisition of measurement-fault data necessary for the attainment of such a knowledge, this approach is usually limited in applicability.

A preferred approach to the statistical development of diagnostic models is the use of nonparametric pattern classification techniques, so as not to require knowledge of the probabilistic structure of the system (Duda and Hart, 1973). Recently, the authors introduced a nonparametric pattern classification method with a fast learning algorithm based on diagnostic error feedback that enables it to estimate its diagnostic model based on a small number of measurement-fault data (Danai and Chin, 1991). This method utilizes a *multi-valued influence matrix* (MVIM) as its diagnostic model and relies on a simple diagnostic strategy ideally suited to on-line diagnosis. The MVIM method can also assess the diagnosability of the system and variability of fault signatures which can be used as the basis for sensor selection and optimization.

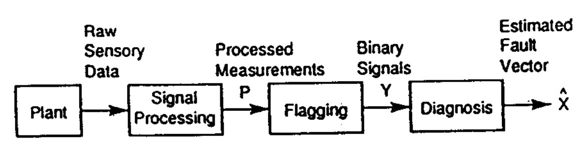

Fig. 1 Illustration of the various stages of fault diagnosis

Contributed by the Dynamic Systems and Control Division for publication in the JOURNAL OF DYNAMIC SYSTEMS, MEASUREMENT, AND CONTROL. Manuscript received by the Dynamic Systems and Control Division September 1990; revised manuscript received March 1991. Associate Editor: R. Shoureshi.

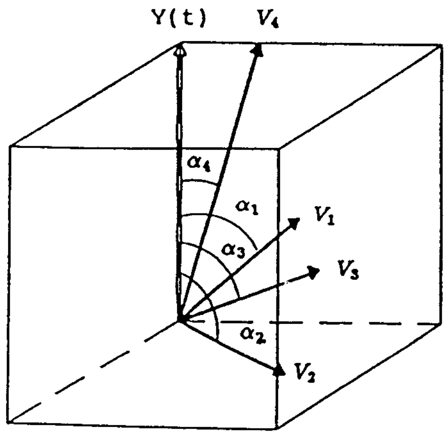

Fig. 2 Geometric representation of diagnostic reasoning in the MVIM method

In this paper, we introduce a *Flagging Unit* which can take advantage of the information provided by the MVIM to enhance the uniqueness of fault signatures (diagnosability) and minimize their variability, as well as to ensure detectability and minimize the number of false alarms. In this Flagging Unit, the processed measurements are first flagged by thresholds and then filtered by a single-layer network. A sample batch of measurement-fault vectors is used to tune the Flagging Unit. Once all the measurement vectors in the sample batch are flagged, the MVIM is estimated to provide the indices for fault signature variability and system diagnosability. These indices along with the number of false alarms and undetected faults are then fed back to the Unit's adaptation algorithm to tune the Unit's parameters in its next adaptation iteration. The parameters of the Flagging Unit are tuned iteratively until its performance indices are extremized.

2 Diagnosability and Fault Signature Variability

Diagnosability and fault signature variability are two of the criteria used to optimize the flagging operation. Diagnosability is the measure of uniqueness of fault signatures. Fault signature variability quantifies their consistency in the presence of process and measurement noise. Both diagnosability and fault signature variability are defined by the MVIM method as described below.

If the normalized version of individual flagged measurements $\mathbf{Y}(t) \in \mathcal{B}^m$ (Fig. 1) are represented by the vector $\overline{\mathbf{Y}}(t)$

$$\overline{\mathbf{Y}}(t) = \frac{\mathbf{Y}}{\|\mathbf{Y}\|} = \left\{ \frac{y_i}{\sqrt{\sum_{i=1}^{m} y_i^2}} \right\}, \tag{1}$$

and the normalized versions of individual fault signatures are represented by the columns $\overline{\mathbf{V}}_j$ of an $m \times n$ influence matrix $\overline{\mathbf{A}}$, such as

$$\overline{\mathbf{A}} = [\overline{\mathbf{V}}_1\ \overline{\mathbf{V}}_2 \ldots \overline{\mathbf{V}}_j \ldots \overline{\mathbf{V}}_n] \tag{2}$$

then the vector of diagnostic certainty measures $\hat{\mathbf{X}}$ can be defined as

$$\hat{\mathbf{X}} = \{\hat{x}_j\} = \cos\{\alpha_1, \alpha_2, \ldots, \alpha_j, \ldots, \alpha_n\}^T = \overline{\mathbf{A}}^T \overline{\mathbf{Y}} \tag{3}$$

to represent the closeness of the orientation of individual fault signatures to the orientation of the flagged measurement vector. Parameter n in Eq. (2) represents the number of process faults and α_j in Eq. (3) represents the angle between the jth influence vector $\mathbf{V}_j$ and the processed measurements vector $\mathbf{Y}$, as illustrated in Fig. 2.

The matrix $\overline{\mathbf{A}}$ is not available a priori and must be estimated. The estimation of individual columns of matrix $\overline{\mathbf{A}}$ is based upon the minimization of a criterion function of the form

$$J_j = \sum_{k_j=1}^{N_j} e_j(k_j)^2 = \sum_{k_j=1}^{N_j} [x_j(k_j) - \hat{x}_j(k_j)]^2 \tag{4}$$

in terms of the diagnostic error e_j associated with individual faults. In the above equation, x_j is always equal to 1 denoting the "ideal" value of the diagnostic certainty measure for the jth fault, $\hat{x}_j$ represents the estimated value of the diagnostic certainty measure based upon the current value of $\overline{V}_j$, and N_j denotes the total number of fault occurrences for the jth fault. The above estimation strategy, due to its utilization of feedback, has been shown to provide good estimates of matrix $\overline{\mathbf{A}}$ with relatively small numbers of measurement-fault vectors (Danai and Chin, 1991).

The matrix $\overline{\mathbf{A}}$ is estimated based upon the available set of flagged measurement vectors. Therefore, it is directly affected by the flagging operation and can be used as the basis to evaluate the performance of the Flagging Unit. We define system diagnosability and fault signature variability as the criteria to judge the performance of this unit in providing unique and consistent fault signatures for the estimation of matrix $\overline{\mathbf{A}}$.

The 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 can be defined in terms of the closeness of the fault signatures (influence vectors in the MVIM) by a diagnosability matrix of the form

$$\mathfrak{D} = f[\beta_{ij}] \tag{5}$$

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

$$[\beta_{ij}] = \cos^{-1}(\overline{\mathbf{A}}^T \overline{\mathbf{A}}). \tag{6}$$

According to this diagnosability matrix, the degree of diagnosability of the system is represented by $f(\beta_{ij}')$ $(i \neq j)$, where β_{ij}' denotes the smallest off-diagonal component among the β_{ij}. One possible choice for the function f in Eq. (5) is the sine function which gives the diagnosability matrix

$$\mathfrak{D} = \sin[\cos^{-1}(\overline{\mathbf{A}}^T \overline{\mathbf{A}})] \tag{7}$$

which is an n dimensional symmetric matrix with 0's on its diagonal. According to the definition of diagnosability, the index of diagnosability (d) can be defined to be the smallest off-diagonal component of matrix $\mathfrak{D}$.

The variability of the flagged measurement vectors is another important factor which affects the quality of diagnosis by the MVIM method, as it affects the rate of convergence of matrix $\overline{\mathbf{A}}$. Since individual columns of the matrix $\overline{\mathbf{A}}$ are adapted recursively to represent the orientation of fault signatures, their variances can be used to represent the variability of fault signatures. For this purpose, the variance matrix of the matrix $\overline{\mathbf{A}}$ can be estimated as (Duda and Hart, 1973)

$$\hat{\Sigma} = [\hat{\sigma}_{ij}] = \left[1/N_j \sum_{k_j=1}^{N_j} (\overline{y}_i(k_j) - \hat{\overline{a}}_{ij}(k_j))^2 \right] \tag{8}$$

where N_j represents the total number of fault occurrences for the jth fault and $\overline{a}_{ij}$ denote the estimated components of the matrix $\overline{\mathbf{A}}$. We define the index of fault signature variability (v) to be the largest component of this matrix, while the trace of this matrix would also be a good candidate.

3 Flagging Unit

The Flagging Unit uses a sample set of measurement-fault vectors to tune its parameters iteratively. At the end of each iteration, the total number of false alarms and undetected faults are counted, and the diagnosability of the system and variances of the fault signatures are estimated from the MVIM.

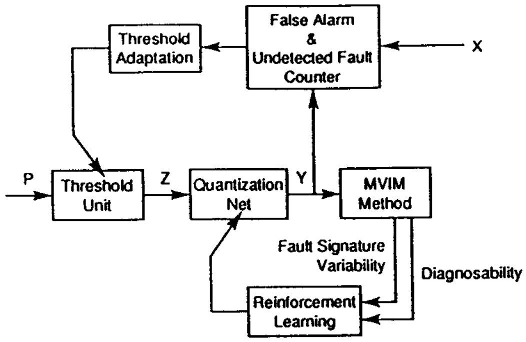

Fig. 3 Schematic of the Flagging Unit

These indices are then used as feedback in the next adaptation round of the Flagging Unit. Adaptation stops when the total number of false alarms and undetected faults are minimized, and the diagnosability and fault signature variability indices satisfy the performance criteria.

The Flagging Unit is structured such that it can take full advantage of its feedback information. False alarms and undetected faults can be directly related to individual threshold levels. Therefore, a Threshold Unit is incorporated in the Flagging Unit (see Fig. 3) so that its weights (threshold levels) can be adjusted to minimize the number of false alarms and undetected faults in the training set. Diagnosability and fault signature variability, on the other hand, cannot be related directly to the threshold levels or the direction these thresholds should be changed. To incorporate a learning method which can benefit from this feedback information, a Quantization Net is cascaded to the Threshold Unit to be adapted by reinforcement learning.

The processing of measurements in the Flagging Unit is as follows (see Fig. 3). Each processed measurement vector $\mathbf{P} \in \mathcal{R}^m$ is first passed through the Threshold Unit (consisted of a vector of m threshold levels) to produce a binary vector $\mathbf{Z} \in \mathcal{B}^m$. This vector is then multiplied by the weights of the Quantization Net

$$\mathbf{Q} = [\mathbf{W}_1 \ldots \mathbf{W}_i \ldots \mathbf{W}_m] \tag{9}$$

and hard-limited as

$$y_i = \begin{cases} 1 & \text{when } \mathbf{Z}^T\mathbf{W}_i \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

to produce a binary vector $Y \in \mathcal{B}^m$, that is used by the MVIM method to estimate the fault signatures. The vectors $\mathbf{W}_i$ in Eq. (9) represent the columns of the Net associated with individual measurements.

The adaptation algorithm used for the Threshold Unit has the form

$$T_i(l+1) = T_i(l) + \alpha f_i/N - \beta u/N \tag{11}$$

where T_i denotes the threshold level corresponding to the ith measurement, f_i represents the total number of false alarms corresponding to the ith measurement, u denotes the total number of undetected faults in the batch, l denotes the iteration step, N represents the size of the training set (number of measurement vectors used for adaptation), and α and β denote positive adaptation gains. The negative sign used in front of β indicates that fault undetectability is corrected by lowering all the threshold levels. Of course, it should be noted that the above algorithm alone does not necessarily guarantee the minimization of false alarms or undetected faults, as its convergence stops when an equilibrium point such as $\alpha f_i/N = \beta u/N$ for all measurements is reached. However, since the measurements are subsequently passed through a Quantization Net whose parameters are constantly changed for adaptation purposes, there is always a high probability that this equilibrium point will be disturbed and the thresholds will be adjusted

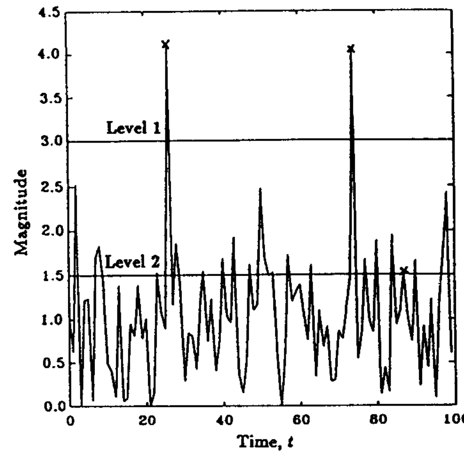

Fig. 4 Typical measurement signal produced through simulation (× denotes fault occurrences)

further to reduce the number of false alarms and undetected faults.

The adaptation method utilized for the Quantization Net, unlike the method adopted for the Threshold Unit, cannot directly benefit from its feedback information. The feedback information to this net (system diagnosability and fault signature variability) is provided by a separate unit (the MVIM), whose output cannot be related directly to a desired output of the Quantization Net. Therefore, adaptation based upon supervised learning is not possible and an alternative learning method must be used (Hinton, 1987). The adaptation strategy adopted for the Quantization Net is based upon the principle of reinforcement learning (Widrow et al., 1973), which uses a performance index J in terms of the network output to assess the relative success of the adaptation algorithm according to some pre-specified criteria. If J indicates success, then the trend of adaptation is continued (reward), otherwise the trend is changed (punishment).

The learning algorithm designed for the Quantization Net has the form

$$w_{ij}(k+1) = w_{ij}(k) + \text{sgn}(J) q_j(k) [y_i(k) - \mathbf{Z}^T(k)\mathbf{W}_i(k)]/N \tag{12}$$

where the w_{ij} denote the components of the net, W_i represents its columns, k corresponds to the data set in the training batch being processed, N represents the total number of training data sets (batch size), and q_j denote the components of the adaptation gain vector $\mathbf{Q} \in \mathcal{R}^m$, which are updated according to the relationship (Ljung, 1987)

$$\mathbf{Q}(k) = \frac{\mathbf{R}(k-1)\mathbf{Z}^T(k)}{1 + \mathbf{Z}(k)\mathbf{R}(k-1)\mathbf{Z}^T(k)} \tag{13}$$

where the matrix $\mathbf{R}$ denotes the covariance matrix computed as

$$\mathbf{R}(k) = \mathbf{R}(k-1) - \mathbf{Q}(k)\mathbf{Z}(k)\mathbf{R}(k-1). \tag{14}$$

Reward and punishment in this algorithm are defined as

$$\text{sgn}(J) = \begin{cases} + & d(l) > d(l-1), \\ & \text{or } v(l) < v(l-1) \\ - & \text{otherwise} \end{cases} \tag{15}$$

where $d(l)$ and $v(l)$ are the diagnosability and fault signature variability indices after the lth iteration, respectively. It should be noted that the above algorithm (Eqs. (12)–(14)) is basically a recursive least-squares algorithm (Ljung, 1987), except for the inclusion of sgn(J) which incorporates "reward" and "punishment" in the adaptation process.

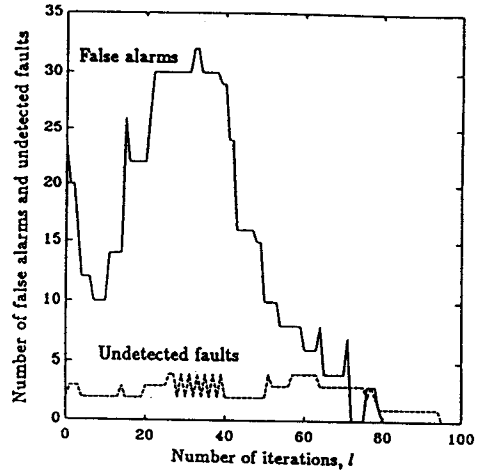

Fig. 5 Total number of false alarms and undetected faults during adaptation of the Flagging Unit (initial threshold levels set arbitrarily)

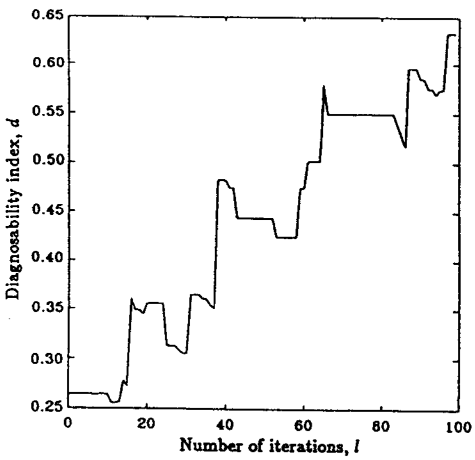

Fig. 6 Diagnosability index (*d*) during adaptation of the Flagging Unit (initial threshold levels set arbitrarily)

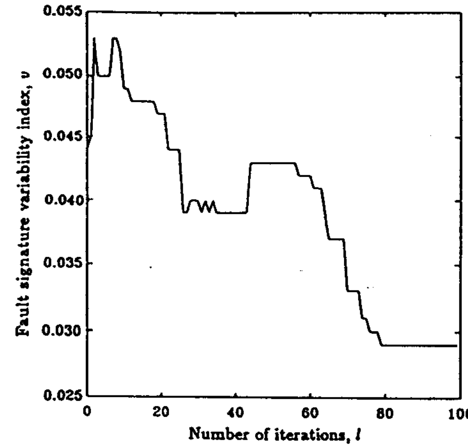

Fig. 7 Fault signature variability (*ν*) during adaptation of the Flagging Unit (initial threshold levels set arbitrarily)

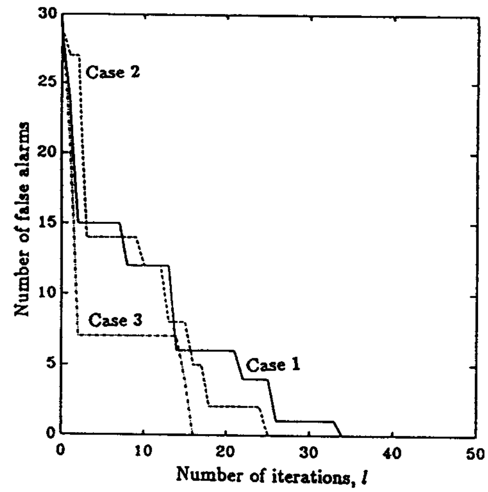

Fig. 8 Total number of false alarms during adaptation of the Flagging Unit. Case 1: all four criteria are used, Case 2: fault signature variability is not considered, Case 3: diagnosability is not considered

4 Simulation Results

The effectiveness of the Flagging Unit was investigated in simulation. For this purpose, four faults ($\mathbf{X} \in \mathcal{B}^4$) were generated at random and their effects on the six processed measurements ($\mathbf{P} \in \mathcal{R}^6$) were simulated according to arbitrary probability densities defined in the matrix

$$\mathbf{B} = \begin{bmatrix} 1.0 & 1.0 & 0.1 & 0.0 \\ 0.5 & 0.0 & 0.1 & 1.0 \\ 1.0 & 0.0 & 0.2 & 0.0 \\ 0.2 & 0.0 & 1.0 & 0.0 \\ 1.0 & 0.8 & 0.5 & 0.5 \\ 0.9 & 0.5 & 0.5 & 0.1 \end{bmatrix} \tag{16}$$

Noise was also added to these measurements through pseudo-random number generators, such that flagging by simple thresholds would not eliminate false alarms or guarantee complete fault detection. A typical sample of measurements produced through simulation is presented in Fig. 4, which indicates that no suitable threshold level can result in the effective identification of fault signatures. For example, a threshold set at Level 1 would not guarantee fault detection completely, whereas the threshold set at Level 2 would produce false alarms. The batch used to tune the Flagging Unit consisted of 100 measurement vectors **P**. After each iteration, which consisted of flagging all the measurement vectors, the total number of false alarms and undetected faults were counted and the indices for system diagnosability (d) and fault signature variability (v) were computed from the MVIM to be used as feedback for the next training iteration of the Flagging Unit.

As a first attempt to test the adaptation algorithms, the initial weights of the Threshold Unit were set arbitrarily. Figures 5–7 show the performance indices after several learning iterations, which indicate that the Flagging Unit was quite effective in reducing the number of false alarms and undetected faults (see Fig. 5), as well as improving the diagnosability of the system and reducing the variability of fault signatures (see Figs. 6 and 7).

Perhaps a better strategy for the initial selection of the threshold levels, is to set them at the mean values of their corresponding processed measurements (Chow and Willsky, 1984). Figures 8–10 (Case 1) show the performance of the learning algorithm with this new choice of threshold levels. It is interesting to note that this more careful selection of threshold levels improved fault detection (the number of undetected faults has been reduced to zero) and enables the adaptation algorithm to eliminate false alarms much more rapidly (33 iterations, compared to 95 in Fig. 5). In order to investigate the competing effects of the diagnosability and fault signature variability criteria on the adaptation algorithms, two other tests were also performed where these two criteria were separately considered. Figures 8–10 (Case 2 and Case 3) show the adaptation results in cases were fault signature variability and diagnosability were respectively eliminated as performance indices. It is quite clear that with the elimination of any of the

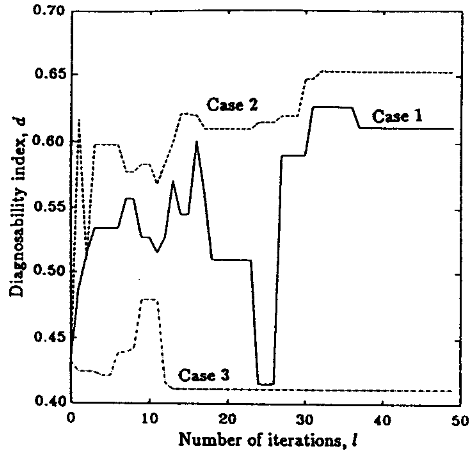

Fig. 9 Diagnosability index (d) during adaptation of the Flagging Unit. Case 1: all four criteria are used, Case 2: fault signature variability is not considered, Case 3: diagnosability is not considered

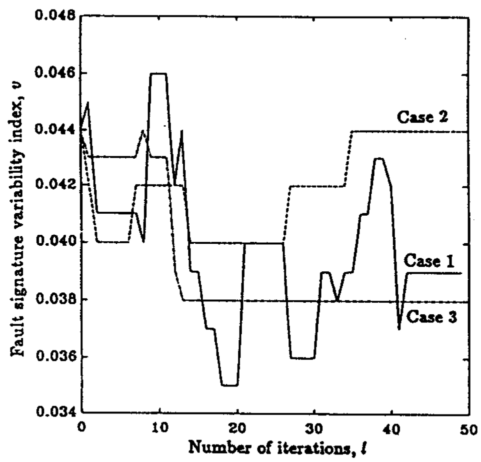

Fig. 10 Fault signature variability (v) during adaptation of the Flagging Unit. Case 1: all four criteria are used, Case 2: fault signature variability is not considered, Case 3: diagnosability is not considered

above two criteria higher levels of performance can be achieved for the remaining indices, and that the adaptation algorithms are quite effective in finding a compromise when all criteria are considered simultaneously. The values of α and β in Eq. (11) were set at 0.7 for all the above cases.

5 Conclusion

A Flagging Unit is introduced to minimize false alarms, ensure fault detectability, enhance diagnosability, and reduce fault signature variability. This unit uses a sample set of measurement-fault vectors to tune its parameters through iterative learning, and utilizes a nonparametric pattern classification method to estimate diagnosability of the system and variability of the fault signatures after each flagging iteration. The adaptation strategy, which is based upon both supervised and reinforcement learning principles, has been demonstrated in simulation. The results indicate that the Flagging Unit is quite successful in ensuring detectability and eliminating false alarms, as well as creating a balance between diagnosability and fault signature variability. The effectiveness of the introduced Flagging Unit is currently under investigation by application to a helicopter power transmission and for tool breakage detection in machining.

Acknowledgments

This research was supported in part by the National Science Foundation (grant No. DDM-9015644).

References

Basseville, M., and Benveniste, A., eds., 1986, *Detection of Abrupt Changes in Signals and Dynamical Systems*, Springer-Verlag, New York, NY.

Cempel, C., 1987, "Simple Condition Forcasting Technique in Vibroacoustical Diagnostics," *Mechanical Systems and Signal Processing*, Vol. 1, No. 1, pp. 75–82.

Chow, E. Y., and Willsky, A. S., 1984, "Analytical Redundancy and the Design of Robust Failure Detection Systems," *IEEE Trans. on Automatic Control*, Vol. AC-29, No. 7, July, pp. 603–614.

Danai, K., and Chin, H., 1991, "Fault Diagnosis With Process Uncertainty," ASME JOURNAL OF DYNAMIC SYSTEMS, MEASUREMENT AND CONTROL, Vol. 113, No. 3, pp. 339–343.

Duda, R. O., and Hart, P. E., 1973, *Pattern Classification and Scence Analysis*, Wiley, New York, NY.

Hankley, W. J., and Merrill, H. M., 1971, "A Pattern Recognition Technique for System Error Analysis," *IEEE Trans. on Reliability*, Vol. R-20, No. 3, Aug., pp. 148–153.

Hinton, G. E., 1987, *Connectionist Learning Procedures*, Technical Report CMU-CS-87-115, Department of Computer Science, Carnegie-Mellon University, Pittsburgh, PA 15213.

Isermann, R., 1984, "Process Fault Detection Based on Modeling and Estimation Methods—A Survey," *Automatica*, Vol. 20, No. 4, pp. 387–404.

Ljung, L., 1987, *System Identification—Theory for the User*, Prentice-Hall, Englewood Cliffs, N.J.

Pau, L. F., 1981, *Failure Diagnosis and Performance Monitoring*, Marcel Dekker, New York, NY.

Widrow, B., Gupta, N. K., and Maitra, S., 1973, "Punish/Reward: Learning with a Critic in Adaptive Threshold Systems," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. SMC-3, No. 5, Sept., pp. 455–465.

Willsky, A. S., 1976, "A Survey of Design Methods for Failure Detection in Dynamic Systems," *Automatica*, Vol. 12, pp. 601–611.