MASTER

A SYSTEM FOR UNATTENDED SURVEILLANCE OF NUCLEAR REACTOR BEHAVIOR*

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Abstract

A multivariate statistical pattern recognition system for reactor noise analysis is presented. The basis of the system is a transformation for decoupling correlated variables and algorithms for inferring probability density functions. The system is adaptable to a variety of statistical properties of the data, and it has learning, tracking, updating, and dimensionality reduction capabilities. System design emphasizes control of the false-alarm rate. Its abilities to learn normal patterns and to recognize deviations from these patterns were evaluated by experiments at the ORNL High-Flux Isotope Reactor. Power perturbations of less than 0.1% of the mean value in selected frequency ranges were readily detected by the pattern recognition system.

I. Introduction

Interest in the application of procedures capable of performing automatic monitoring functions in nuclear power plants stems from a need to provide assistance to plant operators in assimilating quickly the large number of interrelated signals that provide insight into the operational status of the plant.

Pattern recognition techniques appear to offer many of the features required for a solution of unattended monitoring problems. In the nuclear plant field, pattern recognition applications can be broadly divided into two categories: surveillance and diagnosis. The surveillance problem is one of classifying the status of the components being monitored into two classes: normal or abnormal. The diagnosis problem is concerned with identifying the source and degree of a detected abnormality. At the present time, much of the work on automated monitoring is being focused on the surveillance problem.

Unlike many pattern recognition applications where representative patterns from each class of interest are available, it is difficult to obtain patterns characterizing abnormal behavior in components of a nuclear plant. Simulation of abnormal behavior by planned failure of components in a plant is usually not a feasible alternative for generating the desired abnormal patterns because of governmental

regulations and implementation costs. The design of a pattern recognition system for nuclear reactor surveillance is thus reduced to characterizing normal behavior and establishing limits above which the operation of a component is classified as abnormal. This approach is based on the assumption that data which are labeled as normal are derived from plant components whose operation is within design specifications.

II. Elements of an Autonomous Surveillance System

A system designed to operate autonomously (or with as little operator assistance as possible) must be capable of performing two essential tasks: (1) learning, and (2) decision making. The learning function deals with the problem of establishing the limits of normal behavior via what may be termed a "training phase," during which the components under observation are assumed to be operating in their intended state. The decision making process deals with the problem of determining when a signal is outside the normal operating regions established during the training phase.

The basic components of an autonomous monitoring system are shown in Fig. 1. Measurements performed on the plant components of interest are conditioned and preprocessed in order to compress the raw data and extract features which are suitable for classifying the behavior of the input signals. Typical measurements used in monitoring the status of a nuclear plant are: neutron noise, pressure, temperature, flow, and sonic signals. The features extracted from these signals are typically based on either a probabilistic or frequency-domain type of analysis. Examples of the first category are moments and amplitude level-crossing statistics. Frequency-domain features are the result of Fourier transform considerations.

In situations where several features are extracted from the measurements, it is convenient to organize this information in the form of a feature (or pattern) vector:

$$\underline{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad (1)$$

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where x_i is the i th feature and n is the total number of features extracted. Pattern vectors of the form shown in Eq. (1) are the principal representation used in recognition systems designed to operate on the types of data described above. During training, these vectors are used by the pattern recognition state shown in Fig. 1 to estimate the boundaries of normal operation. After training is completed, each input vector is used by this stage as the basis for autonomously determining the status of the plant from the information learned during the training phase.

III. A Recognition Strategy

As indicated in Section I, the typical nuclear reactor surveillance problem is characterized by a lack of abnormal data, thus reducing many recognition strategies to that of learning the limits of normal behavior (as defined during training).

Let $S_{\underline{x}}$ be a training set of n -dimensional pattern vectors. By definition, these vectors are assumed to have been derived from plant components which were operating within design specifications. Although $S_{\underline{x}}$ consists of normal vectors, a certain amount of variability between these vectors is to be expected. If interpreted in n -dimensional space, the population of vectors in $S_{\underline{x}}$ describes a region of normal operation. In view of the above comments, a logical approach to the problem of recognizing deviations from normal conditions is to enclose the training region by an $(n-1)$ -dimensional surface.

If n is equal to 2 or 3 the elements of $S_{\underline{x}}$ can be plotted and an enclosing surface can usually be found by inspection. When n is greater than 3, the problem can no longer be visualized. A more serious difficulty, however, is establishing an enclosing boundary of arbitrary complexity. This is true not only because the number of coefficients required to define the surface increase sharply as a function of increasing n [1], but also because the problem of specifying a meaningful fit is in general not a trivial task. An approach that has been widely accepted in the statistical analysis of multivariate data is to use a hyperellipsoidal enclosure whose location and shape are determined, respectively, by the mean vector and covariance matrix of the data. This type of enclosure has the advantage that its principal axes are oriented in the directions of maximum data variance.

The equation of a hyperellipsoid is given by

$$(\underline{x} - \underline{m}_{\underline{x}})' \underline{C}_{\underline{x}}^{-1} (\underline{x} - \underline{m}_{\underline{x}}) = T \quad (2)$$

where $\underline{m}_{\underline{x}}$ and $\underline{C}_{\underline{x}}$ are the mean vector and covariance matrix of the vector samples in $S_{\underline{x}}$, T is a nonnegative threshold, and the prime (') indicates transposition.

In order to classify a given observation $\underline{x}$ as being either normal or abnormal, we define the Mahalanobis distance between $\underline{x}$ and $\underline{m}_{\underline{x}}$, which is given by

$$D(\underline{x}) = (\underline{x} - \underline{m}_{\underline{x}})' \underline{C}_{\underline{x}}^{-1} (\underline{x} - \underline{m}_{\underline{x}}) \quad (3)$$

If $D(\underline{x}) \leq T$ we say that $\underline{x}$ is normal; otherwise we say that it is abnormal. Geometrically, this corresponds to $\underline{x}$ being treated as a normal vector if it is either on the surface or inside the ellipsoidal enclosure, and abnormal if it is outside the boundary.

The Mahalanobis distance is a single multivariate measure which is inversely weighted by the covariance characteristics of the training data. It is often of interest for analysis purposes to have available one-dimensional measures for system performance. If the original sensed data is expressed in the form of Eq. (1), one approach is to use a linear transformation of the form

$$\underline{y} = \underline{A} \underline{x} \quad (4)$$

where $\underline{A}$ is an $n \times n$ matrix. It can be shown that the transformed vectors, $\underline{y}$, have mean

$$\underline{m}_{\underline{y}} = \underline{A} \underline{m}_{\underline{x}} \quad (5)$$

and covariance matrix

$$\underline{C}_{\underline{y}} = \underline{A} \underline{C}_{\underline{x}} \underline{A}' \quad (6)$$

Since $\underline{C}_{\underline{x}}$ is a symmetric matrix, a complete set of orthonormal eigenvectors can always be found [2]. If the rows of $\underline{A}$ are chosen as the normalized eigenvectors of $\underline{C}_{\underline{x}}$, Eq. (6) becomes the Hotelling (or discrete Karhunen-Loève) transformation, and the resulting vectors $\underline{y}$ will have components that are uncorrelated, with their variances being given by the eigenvalues of $\underline{C}_{\underline{x}}$ [3]. This implies that the covariance matrix $\underline{C}_{\underline{y}}$ has the following properties: (1) the off-diagonal elements c_{ij} ($i \neq j$) are zero, and (2) the element c_{ii} is equal to the variance of the i th component of the transformed vectors.

The Hotelling transform can be used as the basis for reducing pattern dimensionality. The procedure is to centralize the original observations about their mean $\underline{m}_{\underline{x}}$ so that Eq. (4) becomes

$$\underline{y} = \underline{A} (\underline{x} - \underline{m}_{\underline{x}}) \quad (7)$$

Since $\underline{A}$ is an orthonormal matrix, we have that $\underline{A}^{-1} = \underline{A}'$ and $\underline{x}$ can be recovered from $\underline{y}$ by using the relation

$$\underline{x} = \underline{A}' \underline{y} + \underline{m}_{\underline{x}} \quad (8)$$

Suppose, however, that instead of forming $\underline{A}$ from the n eigenvectors of $\underline{C}_{\underline{x}}$, only m eigenvectors ($m < n$) are used. In this case the $\underline{y}$ vectors will be m -dimensional and Eq. (8) yields only an approximation to $\underline{x}$. It can be shown [4, 5] that the approximation will be optimal in the least-square-error sense if the m eigenvectors selected correspond to the largest eigenvalues of $\underline{C}_{\underline{x}}$. If the eigenvectors of this matrix are arranged so that $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$, then the error incurred in the approximation can be expressed in the form

$$R = \sum_{i=1}^n \lambda_i - \sum_{i=1}^m \lambda_i \\ = \sum_{i=m+1}^n \lambda_i \quad (9)$$

It is noted that the error is zero when $m = n$.

After the data have been decoupled by using Eq. (4) [or Eq. (7) if dimensionality reduction is also desired], the uncorrelated components of the $\underline{y}$ vectors are treated separately, as if they were statistically independent, thus reducing the problem to that of formulating detection procedures for one-dimensional variables. This approximation, becomes exact only if the data are Gaussian.

One simple approach for establishing a one-dimensional statistical detection scheme is as follows. If the i th component y_i of the vector $\underline{y}$ has the probability density function $p_i(y_i)$, the probability that any y_i is less than or equal to a value a_i is

$$P(y_i \leq a_i) = \int_{-\infty}^{a_i} p_i(y_i) dy_i \quad (10)$$

Similarly, the probability of y_i being equal to or exceeding a value b_i is

$$P(y_i \geq b_i) = \int_{b_i}^{\infty} p_i(y_i) dy_i \quad (11)$$

Any observation y_i that is outside the interval $[a_i, b_i]$ is, by definition, abnormal. The thresholds a_i and b_i are obtained by specifying values for $P(y_i \leq a_i)$ and $P(y_i \geq b_i)$ and then by solving Eqs. (10) and (11) for a_i and b_i by numerical integration methods. Thus, the probability of an alarm (i.e., the probability of y_i outside $[a_i, b_i]$) can be controlled at will by the operator by specifying $P(y_i \leq a_i)$ and $P(y_i \geq b_i)$.

By substituting Eq. (4) into Eq. (3) and using Eqs. (5) and (6), it can be shown that $D(\underline{y}) = D(\underline{x})$. The importance of this result is that one can work in the uncorrelated space and still obtain a multivariate measure of performance in the original

space. Also, since $\underline{C}_{\underline{y}}$ is a diagonal matrix, the matrix inversion required to implement the Mahalanobis distance is a trivial computational task, thus providing this additional detection tool with little additional cost.

IV. Training

The training approach used in any pattern recognition system is directly influenced by the type of data classification algorithms used in the last stage of Fig. 1. For the classification approach discussed in the previous section, the first stage of training consists of estimating the mean vector and covariance matrix by using the vector samples in $\underline{S}_{\underline{x}}$. In order to obtain uncorrelated variables, it is also necessary to compute the eigenvectors of $\underline{C}_{\underline{x}}$. Algorithms for obtaining these quantities are discussed in [6].

When Eqs. (10) and (11) are used as a basis for detection, the estimation of the probability density functions needs to be incorporated as part of the training process. We investigated three approaches for obtaining these estimates: (1) histogram approximations; (2) a statistical inference approach where an assumption is made concerning the form of $p_i(y_i)$ and the hypothesis evaluated using the Kolmogorov-Smirnov test [7, 8, 9]; and (3) direct estimation of each density by potential functions [1, 10]. The algorithms used to implement these approaches are discussed in [6]. Their performance is discussed in the following section.

V. Experimental Results

The performance of the pattern recognition system was evaluated with noise data from the ORNL High-Flux Isotope Reactor (HFIR). The extraction and use of information from noise signals originating within a nuclear power plant for assessing the operational status of the plant has been advocated for a number of years [11-15]. Reactor incidents that resulted in a partial loss of core mechanical integrity or of fuel element cooling has been reported where a conspicuous change in the nature of a randomly fluctuating variable preceded the incidents [16-18].

The data used for testing recognition performance were recorded at the HFIR during rod-perturbation experiments in which a 4 ± 0.5 -Hz noise signal was injected into the control rod servo demand system [19]. The control rods moved in response to the fluctuating demand, causing perturbations of less than 0.1% about a 98-MW mean level in the signal from the neutron detector. This signal was amplified and recorded, and its power spectral density (PSD) was computed with and without the 4-Hz perturbation. The PSDs without the perturbation constituted the training set; those with the perturbation were used as "abnormal" observations to test the recognition sensitivity of the system after the training phase was completed. The training set contained 357 PSDs from a 12-hour continuous learning period. The abnormal set had 51 PSDs.

Pattern Classification Experiments

Each pattern x was formed as the $\log_{10}$ of a 30-dimensional vector: components 2-19 contained PSDs from 0.5 to 5 Hz at 0.25-Hz intervals, components 20-30 contained PSDs from 5.5 to 10 Hz at 0.5-Hz intervals, and component 1 was the square root of the average of the other 20 components.

The training set was used to determine the covariance matrix of the normal process, and the decoupling transformation matrix was formed from the eigenvectors of this 30 x 30 matrix. Application of Eq. (4) to the original vectors yielded a decoupled training set. Figure 2 shows in pictorial form the covariance matrix of the original and transformed vectors. In this representation, the brightness of the small squares is proportional to the amplitude of the covariance matrix. Thus, the black (zero) off-diagonal terms in Fig. 2(b) indicate that the elements of the y vectors were indeed decorrelated by the decoupling transformation.

The system was first trained using histograms with probabilities of 0.005 to establish thresholds a and b for each of the 30 components of the pattern vectors. After training was completed, each of the 51 abnormal patterns was input for classification, and all were flagged as falling outside the bounds of normal operation.

After detection of an abnormality, the system displays a set of data analysis options (Fig. 3) to aid the operator in interpreting the abnormality. The following descriptions of these options are based on the first pattern in the abnormal set.

Option 1 ("code 1" of Fig. 3) displays graphs on the same coordinate system of the average PSD (as determined from the training set) and the abnormal PSD input pattern. Option 1(A) plots the patterns before their transformation, and flags abnormal individual components (Fig. 4). Option 1(B) plots the mean and abnormal pattern after their transformation (Fig. 5). Option 1(C) plots the abnormal components of the transformed pattern, such that their distances from the corresponding component of the average plot are relative to the number of standard deviations that each component lies outside the thresholds of abnormality (Fig. 6).

Option 2(A) lists the limits (a_1, b_1) for each abnormal component, the value of each abnormal component, and the relative distance outside the normal limits in units of standard deviations (Fig. 7). Although data classification is carried out in the transformed space, interpretation is made easier by knowledge of which components in the untransformed space contributed most to a given abnormality. One way to obtain this information is as follows. After training is completed, a variable vector x is set equal to the mean of the training patterns. Then, a single component x_1 is incremented by some Δx_1 , transformed, and tested for abnormality by using the limits in the transformed space. When the pattern is sufficiently distorted to be classified as abnormal, that value of x_1 becomes the upper limit of normality for the component in the untransformed space. The lower limit is determined in the same manner by decrementing x_1 from its mean value. This procedure can be used to

determine the limits of normality for every component similar to the limits (a_1, b_1) calculated in the transformed space. However, since the limits in the untransformed space do not account for correlation effects they are not used for classification. The results of this procedure constitute Option 2(B) (Fig. 8). Components 13-16, corresponding to the frequency range from 3.25 to 4.0 Hz, are labeled as abnormal, which corresponds approximately to the 4-Hz noise perturbation. Option 2(C) is analogous to Option 2(B), except that the technique for determining abnormal components in the original space is based on the Mahalanobis distance (Fig. 9).

Option 3 displays both the Mahalanobis distance of the observed pattern and the base Mahalanobis distance $D_{\max}(y)$ (Fig. 10). The Mahalanobis distance of the observed, abnormal pattern is much greater than the maximum Mahalanobis distance for any of the training patterns, indicating that, in this case, the Mahalanobis distance and the histogram approaches agree that the observation is abnormal. This agreement held for all patterns in the abnormal set.

Option 4 displays a histogram of any component of the training set in the transformed space, along with the corresponding limits (a_1, b_1). The histogram of component 30 (Fig. 11), for example, shows that this component is well outside the upper limit.

Options 5 through 7 give the user latitude in obtaining other observations. Option 5, which allows the user to recall a pattern that has been processed, might be desirable for checking the conditions just prior to the occurrence of an abnormality. With Option 6, the user can observe the next pattern without losing control of the surveillance program, and Option 7 returns control to the surveillance program to continue monitoring. Finally, Option 8 terminates the monitoring process.

As a second experiment, the system was trained by statistical inference. The K-S test was applied to the training data, assuming that each transformed component was characterized by a log-normal probability density function. Since the training data were formed from the logarithms of PSD values, the problem was to test these data against a Gaussian assumption. It was found that only component 30 failed the test. This overall agreement with the log-normal assumption explains the similarity of classification results obtained with the histogram and Mahalanobis distance approaches.

The limits for each component were determined by integrating the corresponding log-normal densities [Eqs. (10) and (11)], and the classification experiment was repeated. Although the limits were generally different than those in the histogram experiment, each of the abnormal patterns was also flagged by the system when log-normal densities were used.

Data Reduction Experiments

Since all the necessary elements for data reduction using the above approach are available in the pattern recognition system, experiments were conducted to evaluate signature degradation and recognition performance in the reduced space. To show

the effect of reduction on the shape of the PSDs, a typical data vector from the normal set was reduced in dimensionality, reconstructed using Eq. (8), and then plotted, along with the original, for several values of m ranging between 28 and 1. Some of the results are shown in Fig. 12. These plots indicate that individual component amplitudes start becoming significantly distorted at approximately 20% reduction in dimensionality. The general profile of the signal as a whole, however, was retained even as the dimensionality was reduced to one. A smoothing effect is to be expected since the reduction transformation is based on minimizing the square-error and should, therefore, be representative of a least-square-fit approximation to the mean of the sample set used to estimate the covariance matrix.

To show the effect of data reduction on an observation not representative of the training set, an abnormal data vector was reduced in dimensionality, reconstructed, and plotted along with the original (Fig. 13) in the manner previously described for a normal observation. For this pattern, distortion of individual components developed more rapidly than for the training sample. The general shape, however, was retained until approximately 50% reduction. As the degree of reduction was increased further, the approximation became distorted with an overall left shift. This tendency to shift the overall profile of the pattern might be explained as an attempt of the transformation to make the abnormal pattern conform to the general profile of the training data. This is a plausible conclusion when one considers that the transformation matrix contains information concerning the training set as a whole, while individual observation vectors are required to provide amplitude weights for each component. Thus, as the dimensionality of these weighting vectors is reduced, specific amplitude information is lost and the general information contained in the transformation matrix becomes predominant.

From the previous observations concerning reconstruction error, data reduction is seen to perform significantly better on observation vectors which are representative of the training data set. This restriction is acceptable within the context of the proposed use of dimensionality reduction in routine logging of normal observations. The occurrence of an abnormal observation would preclude enabling the dimensionality reduction process because it is desirable to preserve non-routine observations in full detail for further diagnostic processing.

In order to test the effects of dimensionality reduction on classification performance, each normal and abnormal vector was reduced from 30 dimensions to 1 in steps of one. After each reduction step, all samples were submitted to the pattern recognition system for classification. Identical classification results to those already described were obtained for values of reduction down to $m = 2$, thus indicating that more information than was strictly necessary for proper classification was available in the original observations.

IX. Concluding Remarks

The foregoing experimental results show that it is feasible to implement a recognition system that will (1) learn the characteristics of normal

operation in a reactor, (2) detect small variations from the normal pattern, and (3) reduce the dimensionality of input vectors.

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Figure 1.

Figure 2.

Figure 3.

Figure 4.

Figure 5.

Figure 6.

Figure 7.

TEST #	LIMITS FOR NORMAL PSD	OBSERVED PSD	STDEV OFF	
	LOWER	UPPER		
20	-0.5555E-01	-0.6307E-01	-0.1752E-01	7.34
2	-0.2310E-01	-0.1490E-01	-0.4545E-01	5.13
4	-0.1470E-01	-0.7572E-01	-0.1153E-01	4.55
16	-0.5900E-01	-0.6070E-01	-0.2552E-01	1.77
25	-0.7820E-01	-0.6950E-01	-0.3523E-01	1.62
7	-0.1320E-01	-0.6840E-01	-0.5846E-01	1.57
14	-0.1302E-01	-0.9411E-01	-0.2190E-01	1.40
29	-0.2210E-01	-0.4850E-01	0.9470E-01	1.00

Figure 8.

FIG 6. LIMITS FOR NORMAL PSD				
	LOWER	UPPER	STDEV OFF	
20	-0.2400E-01	-0.1900E-01	-0.5772E-01	4.73
10	-0.1400E-01	-0.7400E-01	0.2000E-01	2.91
13	-0.3950E-01	-0.1000E-01	0.1100E-01	2.12
18	-0.1660E-01	-0.1000E-01	0.6600E-01	1.83
19	-0.3600E-01	-0.8700E-01	0.3700E-01	1.27

Figure 9.

FIG 9. DISTANCE OFF	
1	120.02
12	16.33
14	53.48
15	11.23
16	29.16
17	6.54

Figure 10.

MANALANDIS DISTANCE	
BASE	= 0.62195E-02
OBSERVED	= 0.38546E-03

Figure 11.

Figure 12.

Figure 13.