A Neuro-Control Design Based on Fuzzy Reinforcement Learning

Katebi, S.D.; Blanke, M.

Comparative Study of Parametric and Non-parametric Approaches in Fault Detection and Isolation

Report

by

S. D. Katebi, M. Blanke,
M. R. Katebi

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Department of Control Engineering
Aalborg University
Fredrik Bajers Vej 7, DK-9220 Aalborg Ø, Denmark.

Abstract

This report describes a comparative study between two approaches to fault detection and isolation in dynamic systems. The first approach uses a parametric model of the system. The main components of such techniques are residual and signature generation for processing and analyzing. The second approach is non-parametric in the sense that the signature analysis is only dependent on the frequency or time domain information extracted directly from the input-output signals. Based on these approaches, two different fault monitoring schemes are developed where the feature extraction and fault decision algorithms employed are adopted from the template matching in pattern recognition.

Extensive simulation studies are performed to demonstrate satisfactory performance of the proposed techniques. The advantages and disadvantages of each approach are discussed and analyzed.

Contents

Chapter 1

Introduction

Fault detection and isolation have increasingly become an important issue in modern and complex automated manufacturing and process plants. Any malfunctioning and performance degradation of equipment and instrumentation can lead to a substantial increase in the plant operation and maintenance cost. As the complexity of the new process plant increases, the traditional approach of hardware redundancy in fault monitoring techniques becomes uneconomical and inefficient. This trend is particularly evident in safety critical systems where hardly any fault can be tolerated.

The above considerations have lead to significant growth of research in the area of Fault Detection and Isolation (FDI) in recent years. Through the concerted efforts of many researchers a number of promising FDI techniques have emerged[1-4]. In contrast to the traditional techniques that rely upon hardware redundancy, these modern approaches are based on the analytical and/or heuristical redundancy. To achieve analytical redundancy, these schemes employ various signal processing techniques, such as, state estimation, systems identification, adaptive filtering and statistical decision theory. Comprehensive surveys of all these methods can be found in [1, 3]. The heuristic redundancy methods are based on the qualitative information extracted from human expert operator. These information are usually represented by linguistic variables and fuzzy based techniques are employed for approximate reasoning and further processing. The latter technique is not discussed in the present report.

In general the current research effort has concentrated on two main approaches. One is based on a mathematical model of the process under study. The main components of such techniques are residual and signature generation to be further processed and analyzed by suitable fault decision algorithms [4]. The advantage of this approach is that information related to the structure of the plant can be easily obtained and analyzed. The drawback is that the performance of these techniques depends highly on an accurate mathematical model and the underlying identification method utilized to collect and collate information. Furthermore for high order complex systems, added problems of parameter convergence and heavy computation burden are also significant. On the other hand the non-parametric based techniques are usually simpler and easily implementable in practice. A major disadvantage is that the extracted information is only restricted to the input and output of the plant and internal plant information can not be easily obtained.

Two techniques are developed in this report in order to compare the above two approaches. The Parametric Technique (PT) is based on the AutoRegressive eXogeneous (ARX) modeling technique which has been found to be very useful in many applications such as spectral analysis [5], coding of speech and images [6, 7], modeling and classification of two-dimensional shapes [8] and adaptive signal processing [9]. Also, because of its conceptual simplicity and easy implementability, use of (AR) modeling techniques for FDI has been advocated in [1, 3]. Parametric modeling techniques form a powerful approach to signature analysis. Usually such techniques consist of autoregressive (AR) or AutoRegressive Moving Average (ARMA) modeling of the input-output data sequence. The estimated input-output model may then be used to check the healthiness of the device or process under study. Alternatively, the model coefficients may be used as a template that characterizes a particular signature of the process. Subsequently, for the purpose of classification, an unknown signature may be compared with the set of stored templates, and the most similar one chosen as the destination class.

The Non-Parametric Technique (NPT) is based on Fourier analysis. This technique is developed by forming Fourier descriptors of the discrete input-output sequence to represent a template which characterize a particular signature of the process. Subsequently for the purpose of classification, this signature is compared with a set of prestored signatures, associated with no fault and various faulty conditions. A difference function expressed as an Euclidean metric norm between the normalized test signature and those of the input-output signature is formulated as a basis for this comparison. The matching process is carried out by finding a prestored template which gives minimum distance to the test template.

In both approaches, it is proved that the information utilized by fault classification and fault decision algorithm is invariant under input scaling.

In order to investigate the performance of the proposed techniques, simulation studies are performed on a closed loop system comprises an armature DC motor connected in unity feedback, series compensation configuration.Non-additive faults are considered and lumped parameter model of the system is used, thus, parameter variations are treated as faulty conditions. A comparison is then made between the two approaches using the theoretical and simulation results presented in this report.

The organization of this report is as follows. In Section 2 the ARX of fault signatures is presented. Model order selection and parameter estimation are developed and discussed in Section 3. Section 4 describes the FDI scheme based upon ARX model, and pattern classification technique. The spectral representation of fault signature is given in Section 5. The formulation of the difference function and the normalization of the fault signature are given in Section 6 and 7, respectively. Experimental results and simulation studies are presented in Section 8. A comparison of the two techniques is given in Section 9 and the conclusion is drawn in Section 10.Finally, recommendations are outlined for further investigation in section 11.

Chapter 2

Parametric Method

2.1 Autoregressive Modeling of Fault Signature

Consider a system represented by a linear transfer operator H, which transforms the input signal $u(k)$ into an output signal $y(k)$. The usual methods of signature analysis involve spectral analysis of the signals, $u(k)$ and $y(k)$, for detection and identification of faults .

The input-output data sequence collected from a device or a process is usually non-stationary (in the statistical sense). One of the commonly used technique for handling such signals involves block (or batch) processing [6, 7]. Supposing N denotes the length of each data block, the problem of concern here consists of modeling $u(k), y(k)$, $1 \leq k \leq N$ by a stochastic black-box type model. A possible model, known as AutoRegressive with external input (ARX), has the following form:

$$a(q^{-1})y(k) = b(q^{-1})u(k) + \sqrt{\beta}w(k) + \alpha \tag{2.1}$$

where $a(q^{-1})$ and $b(q^{-1})$ are polynomials of order m and p, α is a bias term and $w(k)$ denotes a zero-mean white noise sequence with variance equal to β. We assume that both no-fault as well as all the fault signatures admit such representation.

Suppose the estimates of the parameters are available and denoted by $\hat{a}_i, \hat{b}_j$, $\hat{\alpha}$ and $\hat{\beta}$, respectively. For FDI application, we are interested in constructing a feature set from these estimates, which is invariant under input scaling. Such a feature set is established in the following Lemma:

<u>Lemma 1</u>

Consider an input-output data sequence $\{u(k), y(k), k = 1, 2, ..., N\}$ that corresponds to either no-fault or a fault signature. If the sequence is modeled by the ARX model 2.1, then the following feature set is invariant under any scaling of the input sequence, $u(k)$:

$$[a_1, a_2, ..., a_m, b_1, b_2, ..., b_p, \frac{\alpha}{\sqrt{\beta}}] \tag{2.2}$$

<u>Proof:</u>

Let $\{u(k), y(k), k = 1, 2, ..., N\}$ denote the input-output data sequence corresponding to the original signature, and $\{\bar{u}(k), \bar{y}(k), k = 1, 2, ..., N\}$ denote the same for a modified signature obtained by scaling the input i.e., setting: $\bar{u}(k) = Su(k)$ where S is the scaling factor. Since the system under consideration is linear, this also implies that:$\bar{y}(k) = Sy(k)$.

Suppose the modified signature obeys the following ARX model:

$$\bar{a}(q^{-1})\bar{y}(k) = \bar{b}(q^{-1})\bar{u}(k) + \sqrt{\bar{\beta}}w(k) + \bar{\alpha}. \tag{2.3}$$

Substituting for $\bar{y}(k)$ and $\bar{u}(k)$ yields:

$$\bar{a}(q^{-1})y(k) = \frac{\bar{\alpha}}{S} + \bar{b}(q^{-1})u(k) + \frac{\sqrt{\bar{\beta}}}{S}w(k) \tag{2.4}$$

Comparing equations 2.1 and 2.4 gives:

$$\bar{a}(q^{-1}) = a(q^{-1}) \quad \bar{b}(q^{-1}) = b(q^{-1}) \quad \frac{\bar{\alpha}}{S} = \alpha \quad \frac{\sqrt{\bar{\beta}}}{S} = \sqrt{\beta}.$$

2.1.1 Model Order Selection and Parameter Estimation

The parameter estimation problem may be formulated by minimizing the variance of the ARX model prediction error. The predictor of $y(k)$, given the past input-output samples, can be expressed as $\hat{y}(k) = \hat{\theta}^T\Phi(k)$ where Φ is the regression vector and $\hat{\theta}$ is the vector of parameters.

Therefore, the prediction error may be written as:

$$e(k) = y(k) - \hat{\theta}^T\Phi(k) \tag{2.5}$$

The estimate $\hat{\theta}$ that minimizes the least squares criterion is given by:

$$\hat{\theta} = [\Sigma_{k=1}^N \Phi(k)\Phi(k)^T]^{-1}[\Sigma_{k=1}^N \Phi(k)y(k)] \tag{2.6}$$

An estimate of the bias term is obtained from the sample mean estimate:

$$\hat{\alpha} = \frac{1}{N}\Sigma_{k=1}^N[y(k) - \hat{\theta}^T\Phi(k)]. \tag{2.7}$$

The model residual error variance can then be found with the sample covariance estimate as: $\hat{\beta} = \frac{1}{N}\Sigma_{k=1}^N[y(k) - \hat{\theta}^T\Phi(k) - \hat{\alpha}]^2$.

The least square technique is adopted here for several reasons. First of all, it is very simple to implement and has been found very reliable and useful in many applications [10, 11]. Furthermore, the least squares Levinson algorithm, being recursive in order, is particularly suitable for model order selection. Such a selection can be based upon Akaike Information Criterion (AIC).

The parameter estimated vector is also invariant under input scaling. The proof is similar to Lemma 1.

2.2 FDI Scheme Based Upon ARX Model

In any FDI scheme, two tasks are involved; namely, Detection and Isolation of faults. The main goal of the ARX modeling scheme is to perform Isolation and classification of faults. However, as shown below, a slight modification of the technique allows detection of the faults as well.

2.2.1 Fault Detection Scheme

In principle, the fault detection scheme consists of continuous monitoring of a residual error sequence for detection of any jump in its mean value. For generating the residual error sequence, the input-output data sequence is continuously modeled by an ARX model of the form (1). With the availability of a new pair of input-output data sample, the model parameter estimates are updated using the recursive least squares technique. At each instant the residual error sequence is computed from (5). For detecting a jump in the mean value of the residual error sequence any of the standard algorithms, such as, filter derivative, Shiryaev's, or Hinkley's can be used [2, 12]. Any jumps in the mean of the residual error sequence signifies onset of a fault. Upon detection of such a fault, the following procedure is used for its classification.

2.2.2 Pattern Classification Techniques

Although there are a wide variety of possible approaches to the development of classifiers for fault Isolation problems, the first line of approach is generally to consider discriminant analysis, and in particular, the linear case. The reasons for this choice are many, but most pervasive ones are the freedom from the need for specific class statistics, and the simplicity of automated classifier implementation. Specifically, discriminant based classification assumes that the functional form of the decision boundary is selected a priori. This differs from the traditional Bayesian methods which describe detection boundaries based on the shapes of the respective sample probability distribution. Detail discussions of linear discriminant classifiers can be found in [13, 14]. For purpose of brevity only the main ideas are summarized here.

A linear discriminant classifier, also known as a linear machine, is characterized by n linear discriminant functions corresponding to n classes, $C_i, \quad 1 \leq i \leq n$. These discriminant functions have the following form:

$$g_i(X) = w_0 + \Sigma_{j=1}^q, w_{ij}x_j \quad 1 \leq i \leq n \tag{2.8}$$

where $X = [x_1, x_2, ..., x_q]^T$ denotes the feature vector and $W_i = [w_{i1}, w_{i2}, ..., w_{iq}]^T$ is known as the i^{th} weight vector. The term w_0 serves as a threshold. The decision rule assigns X to class C_i if $g_i(X) > g_j(X)$ for all $j \neq i$. By this method the feature space is partitioned into n decision regions:

$$D_i = \{X \mid g_i(X) > g_j(X), \quad 1 \leq j \leq n, \quad j \neq i\}, \quad 1 \leq i \leq n \tag{2.9}$$

An important special class of linear machine which is proposed to be used here, is the minimum distance classifier. If two prototypes reference signatures, X_1 and X_2, are given for the classes C_1 and C_2, a minimum distance classifier assigns a test sample X to the class which corresponds to the nearest of the two prototypes. The simplest distance measure is the squared Euclidean distance from the sample X to X_i. The discriminant functions can now be represented as:

$$g_i(X) = X^T X_i - \frac{1}{2} X_i^T X_i, \quad 1 \leq i \leq n \tag{2.10}$$

Other, more sophisticated minimum distance classifiers are formed by weighting the features or subjecting them to linear transformation so as to improve the clustering and separation of the various classes. One such method, known as the Feature Weighting (FW) method, is employed in the simulation study.

The feature weighting method [8, 14] attempts to minimize the mean squared distance between members of the same class by applying a metric which emphasizes those features that are closely clustered, and de-emphasizes the features which vary widely. Given a feature vector of unknown class, a similarity measure which is a weighted sum of the Euclidean distances between the unlabeled vector and all the training vectors in a particular class is calculated. This cumulative distance function is calculated for each class of interest, and the most similar class is chosen. Sebestyen [14] has shown that the optimal feature weights for a particular class are inversely proportional to the standard deviation of each of their associated feature vector elements. The weighted cumulative distance measure between an unlabeled feature vector V and the training vectors $\{X\}$ of class C can be written as:

$$\alpha(V, \{X\}) = [\Pi_{j=1}^{q} \sigma_j]^{\frac{2}{q}} [(Z^H Z) + q] \tag{2.11}$$

where $Z = [\frac{v_1 - \bar{x}_1}{\sigma_1}, \frac{v_2 - \bar{x}_2}{\sigma_2}, ..., \frac{v_q - \bar{x}_q}{\sigma_q}]^T$. Here $\bar{X}$ denotes the class sample mean vector, σ_j is the standard deviation of the j^{th} feature elements, q is the dimension of the feature vector, and $[.]^H$ denotes the conjugate transpose of [.].

One of the drawbacks of FW method concerns the implicit assumption that the feature elements are mutually uncorrelated. More accurate, albeit computationally complex, minimum distance classifiers may be used if necessary. In particular, mention may be made of the Rotated Coordinate System (RCS) method. Neural Networks paradigms have also been used for fault clssification.

The fault classification scheme presented is based upon two implicit assumptions that each fault signature admits a unique ARX-model representation and the faults belonging to the same class but differing in severity or magnitude, form a cluster in the feature space.

The two main steps of the fault pattern classification scheme may then be summarized as follows.

Step 1: Off-line training scheme.

This involves simulation of known faults of varying degrees, collection of input-output training data sequences, ARX model fitting, and construction of training feature sets.

Step 2: On-line classification scheme.

Following detection of either an incipient or an abrupt fault, this step involves collection of fault signature samples, ARX model fitting, and finally, classification using a pattern recognition scheme previously described. If the training features are de-correlated and clustered, use simple Euclidean distance classifier(9). Otherwise, if the features are de-correlated but require clustering, use FW method (10). If, in addition to clustering, de-correlation is also necessary, use RCS method.

Chapter 3

Non Parametric method

3.1 Spectral Representation of Fault Signature

Consider the function: $z(k) = u(k) + jy(k)$ which can be exactly represented as the convergent sum of a complex Fourier series [15]: $z(k) = \Sigma_{i=0}^{n} Z(n)e^{j2\pi nT}$ where

$$Z(n) = \frac{1}{T}\int_0^T z(t)e^{-j2\pi nT}dt. \tag{3.1}$$

For a known input-output sequence $u(k)$ and $y(k)$, $z(k)$ may be used in either time or the frequency domain to represent a template that characterizes a particular signature of the process. Subsequently, for the purpose of classification, an unknown signature may be compared with the set of stored templates and the most similar one selected as the destination class [16]. The proposed criteria as a basis of comparison is a difference function expressed as an Euclidean metric norm between the normalized test signature and those of the discrete input-output signature prior to comparison. It is shown that the normalization of the process signatures provides a difference function which is invariant under any input scaling.

3.1.1 Formulation of the Difference Function

Consider the difference function between a test signature z_1 and a template z_2 to be defined as:

$$D^2 = \frac{1}{2T}\int_0^T |z_1(t) - z_2(t)|^2 dt \quad or \quad D^2 = \frac{1}{2}\Sigma_0^{\infty}|z_1(n) - z_2(n)|^2 \tag{3.2}$$

where z_1 and z_2 are corresponding Fourier coefficients. If these Fourier coefficient are band-limited, that is for some M, $z_1(n) = 0$ and $z_2(n) = 0$ for all $|n| > \frac{M}{2}$ then the sampling theorem guarantees that all the information can be retrieved from a sequence of M distinct samples.

Assuming that the exact co-ordinate of the signal is determined at a sequence of N points where $N \geq M$. Defining the following sequence for integer i, $u[i] = u(k), \quad k = i\frac{T}{N}$, the Discrete Fourier Transform (DFT) can then be written as;

$$Z[n] = \frac{1}{N}\Sigma_{i=0}^{N-1} z[i]e^{-j2\pi niN} \tag{3.3}$$

with the corresponding inverse transform as:

$$z[i] = \Sigma_{n=0}^{N-1} Z[n]e^{j2\pi niN} \tag{3.4}$$

The coefficients given by equation(14) exists for all values of n and are cyclic with period N. It is not difficult to modify these expressions to be able to use any consecutive N terms, particularly the N terms symmetrically disposed about zero that is;

$$z[i] = \Sigma_{-(N-1)/2}^{(N-1)/2} Z[n]e^{j2\pi niN} \tag{3.5}$$

for odd N (modification for even N is straight forward). These values can be specified in terms of continuous Fourier coefficients given in equation(12).

$$z[i] = \Sigma_{n=}^{N} Z(n) e^{j2\pi iN} \tag{3.6}$$

Since $Z(n) = 0$ for $|n| > \frac{(N-1)}{2}$ it follows that:

$$z[i] = \Sigma_{-(N-1)/2}^{(N-1)/2} Z(n) e^{j2\pi niN} \tag{3.7}$$

Subtracting equation (16) from (18) gives:

$$\Sigma_{-(N-1)/2}^{(N-1)/2} (Z(n) - Z[n] e^{j2\pi niN)} = 0 \tag{3.8}$$

Therefore

$$\Sigma_{i=0}^{N-1} |\Sigma_{-(N-1)/2}^{(N-1)/2} |Z(n) - Z[n] e^{j2\pi niN}|^2 = 0 \tag{3.9}$$

expanding equation (20) and interchanging the order of summations leads to the result that $Z(n) = Z[n]$ for all n in the range $|n| \leq \frac{(N-1)}{2}$. Outside this range the values of $Z(n)$ are zero and those of $Z[n]$ are a cyclic continuation.

The difference function can now be expressed in terms of DFT;

$$D^2 = \frac{1}{2} \Sigma_{n=0}^{N-1} |Z_1[n] - Z_2[n]|^2 \tag{3.10}$$

or by Parseval's identity for the DFT we have

$$D^2 = \frac{1}{2N} \Sigma_{i=0}^{(N-1)} |z_1[i] - z_2[i]|^2 \tag{3.11}$$

Where $Z_1[n], Z_2[n], z_1[i], z_2[i]$ are the corresponding discrete forms of terms used in equation(14). Using only a finite set of samples equations(21) can be employed to calculate the difference function between two given sequences without errors. If the tow sequences are not sampled at identical number of points then prior to calculation of the difference function, the shorter sequence may be padded by zeros.

3.1.2 Normalization of Fault Signatures

It is required that the signatures be normalized such that the difference function remain invariant with respect to a given transformation [15,16,17]. For the FDI application of time-invariant and deterministic systems it is sufficient to establish that the derived difference function is invariant with respect to scaling. This property is established by the following lemma.

Lemma 2.
Consider input-output sequence $u(k), y(k), K = 1, 2, ...N$ that corresponds to either no fault or a fault signature. If the sequences are represented by the complex DFT as in equation(14) and the difference function is derived as in equation(22), then D^2 is invariant to any scaling.

Proof.

Consider the effect of introducing scale factors S_1 and S_2

$$D^2 = \frac{1}{2N} \Sigma_{i=0}^{(N-1)} |S_1 z_1[i] - S_2 z_2[i]|^2 \tag{3.12}$$

Minimizing equation **??** with respect to S_1 and S_2 respectively and combining leads to:

$$S_1^2 \Sigma_{i=0}^{N-1} |z_1[i]|^2 = S_2^2 \Sigma_{i=0}^{N-1} |z_2[i]|^2 \tag{3.13}$$

If the scaling factors are to be the chosen independently both sides of equation(24) must be equal to an arbitrary constant. A value of N can be chosen to give:

$$S_1 = \sqrt{\frac{N}{\Sigma_{i=0}^{N-1}|z_1[i] - \bar{z}_1|}} = \frac{1}{\sigma_1} \tag{3.14}$$

Where σ_1 is the standard deviation and $\bar{z}_1 = \frac{1}{N}\Sigma_{i=0}^{N-1} z_1[i]$ is the mean of the signature coordinates. Representation of these results in the frequency domain is;

$$\bar{z}_1 = Z_1[0] \tag{3.15}$$

$$\sigma_1^2 = \Sigma_{n=1}^{N-1}|Z_1[n]|^2 \tag{3.16}$$

Note that the difference function that have been normalized for scaling has a maximum value of unity.

Chapter 4

Experimental Results

The plant chosen for simulation study is a closed-loop feedback control example taken from [18]. As illustrated in Figure 4.1, it consists of an armature controlled DC motor, connected in unity feedback, series compensator configuration. The transfer function, of the closed-loop system is given by:

$$\frac{Y(s)}{U(s)} = \frac{G(s)}{1+G(s)} \tag{4.1}$$

$$G(s) = \frac{K(s+A_1)}{s(s+A_2)(s+A_3)} \tag{4.2}$$

The nominal values of K, A_1, A_2 and A_3 are given as: $K = 1, \quad A_1 = 2.0, \quad A_2 = 0.8, \quad A_3 = 1.0$ First the parametric modeling approach in conjunction with pattern recognition technique is used and the following results are obtained. In order to ensure an accurate and efficient parameter convergence in the least square estimation, the external excitation, $u(t)$, was chosen to be:

$$u(t) = 2. \times [sin(T) + cos(2T) + sin(3T)] \tag{4.3}$$

It is apparent that overall closed-loop system is of order 3. Thus, it should be represented by a third order ARX model. However, in order to illustrate the power of the proposed FDI scheme, we deliberately chose the following second order ARX model to represent the input-output behavior of the closed-loop system:

$$y(k) + a_1 y(k-1) + a_2 y(k-2) = \alpha + b_1 u(k-1) + b_2 u(k-2) \tag{4.4}$$

Four different kinds of faults were simulated; namely, changes in A_1, A_2, A_3 and K respectively. A rough spectral analysis of the no-fault as well as the fault signatures indicated presence of dominant frequency components below $25Hz$. Thus, providing for an adequate safety margin, we chose the sampling frequency to be $100Hz$.

The task of the pattern classification involved categorization of the input-output signatures into five different classes; namely, no fault, fault in A_1, fault in A_2, fault in A_3, and fault in K respectively. Five training samples pertaining to each class, that is, a total of twenty five training samples, were used to train the classifier. In case of the no-fault class, the training samples were generated by introducing minor (less than 0.5%) variations in the system parameters and collecting the resulting input-output signatures. In case of fault in A_1, the training samples were generated by introducing $+5\%, -8\%, +10\%, -12\%, +15\%$ changes around the nominal value of A_1, and collecting the resulting input-output signatures. This procedure was repeated for the remaining three fault classes as well. Next for each class, five sets of ARX model parameters were estimated from the five training samples. Five feature vectors were generated; their mean was computed and stored. The mean feature vectors pertaining to the five different classes were found to be as given in Tabel 4.1.

In order to test the performance of the overall scheme, four different faults were simulated; namely,
F_1 : $+10\%$ change in A_1 (from its nominal value)
F_2 : $+4\%$ change in A_2 (from its nominal value)
F_3 : -7% change in A_3 (from its nominal value)
F_4 : -20% change in K (from its nominal value).

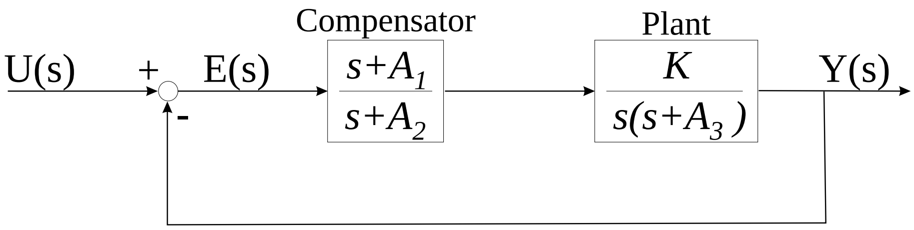

Figure 4.1: Configuration of the Armature Controlled DC motor.

Feature Elements	No Fault X_1	Fault in A_1 X_2	Fault in A_2 X_3	Fault in A_3 X_4	Fault in K X_5
a_1	1.98	1.86	1.97	1.45	1.84
a_2	-0.99	-0.85	-0.97	-0.99	-0.86
b_1	1.2×10^{-2}	6.13×10^{-2}	4.98×10^{-4}	6.2×10^{-2}	1.12×10^{-2}
b_2	1.38×10^{-2}	-6.20×10^{-2}	-6.20×10^{-3}	-6.50×10^{-2}	-9.50×10^{-2}
$\frac{\alpha}{\sqrt{\beta}}$	1.26	136.50	123.41	131.07	143.37

Table 4.1: Mean feature vectors pertaining to five classes of signature

All faults were detected successfully using the technique described in Section 4. Both Shiryaev's and Hinkley's methods were tested. The performance of Hinkley's was found to be slightly superior to that of Shiryaev's. Following successful detection, the performance of the classifier was tested. Although we could have used feature weighting method for more accurate classification, we deliberately chose the simple Euclidean minimum distance classifier. Even this simple scheme allowed all the fault signatures to be correctly classified. This attests to the usefulness of the proposed FDI scheme. Tabel 4.2 shows the computed distances of the test sample features from the stored training features pertaining to the five different classes. The asterisks in each row point out the minimum distance.

The same example was used for the non-parametric approach and similar simulation studies have been performed. In this case two different test inputs was used namely a unit step and a summation of sinusoids, i.e. $u(t) = 2.[sin(3T) + cos(3T) + sin(T)]$. A sampling time of 0.01 seconds and blocks of 400 samples were examined.

Four different kinds of fault were simulated as in the parametric method. The task of pattern recognition is to categorize the input-output signatures into five different classes. Similarly five different training samples pertaining to each class were used. In case of no-fault class, the training samples were generated by introducing minor(less than 0.5%) variation in system parameters and storing the mean input-output signatures. The training samples were generated for each input signal separately by introducing the same

	Distance From				
Test Feature	X_1 No Fault	X_2 Fault in A_1	X_3 Fault in A_2	X_4 Fault in A_3	X_5 Fault in K
F_1 10 % change in A_1	18912.0	1.50×10^{-2} *	105.0	12.70	44.71
F_2 4 % change in A_2	16338.0	91.56	0.304 *	37.50	268.4
F_3 -7 % change in A_3	17511.0	25.59	25.60	2.52 *	141.03
F_4 -20 % change in A_4	22650	171.86	539.60	273.74	39.60 *

Table 4.2: Distance of the test feature vectors from prestored templates $X_i, \quad 1 \leq i \leq 5$

changes around the nominal values of each parameters and storing the mean in each case.

Similar experiments to the parametric technique were carried out. For a particular input the fault signature was compared with all of the corresponding stored signatures by calculating the Euclidean distances (D^2). The most similar one corresponding to maximum D^2 was then selected. The results for unit step input is shown in Tabel 4.3. and those for the sinusoidal summation in Tabel 4.4, where the asterisks in each row indicates the maximum value of D^2 , that is the minimum distance. In all cases the faults were detected and isolated successfully using the proposed scheme.

Stored Signature

Test Signature	No Fault	Fault in A_1	Fault in A_2	Fault in A_3	Fault in K
F_1 10 % change in A_1	2.05	0.48 *	5.65	113.30	1.35
F_2 4 % change in A_2	0.99	6.88	0.11 *	126.70	8.30
F_3 -7 % change in A_3	256.10	253.20	254.98	184.00 *	256.10
F_4 -20 % change in A_4	2.20	1.10	4.50	112.40	0.82 *

Table 4.3: The distance of the simulated fault signatures from the trained templates ($D^2 \times 1000$) for unit step input signal $u(t) = 1$

Stored Signature

Test Signature	No Fault	Fault in A_1	Fault in A_2	Fault in A_3	Fault in K
F_1 10 % change in A_1	11.39	1.31 *	27.43	35.24	4.34
F_2 4 % change in A_2	3.82	28.42	0.53 *	2.31	29.62
F_3 -7 % change in A_3	134.86	131.79	15.10	3.96 *	294.00
F_4 -20 % change in A_4	10.10	2.47	19.04	23.40	1.03 *

Table 4.4: The asterisk in each row indicates the minimum distance

Chapter 5

Comparison

The performance of the two fault monitoring schemes is compared for a number of commonly observed problems encountered in practice. In the simulation study, the classification technique is deliberately kept similar in order to make the comparison more realistic. The following issues are discussed:

Model Complexity The PT requires an accurate mathematical model of the system. The complexity of the model is proportional to the square of the plant order. Therefore, this approach is not suitable for high order systems unless decentralized or parallel algorithms are used. In contrast, the NPT approach requires very little modeling effort.

Parameter Convergence One major problem with the PT is the control of the rate of convergence of the parameter estimation algorithm. It is well known that these algorithms should be periodically made active by resetting the initial parameters and techniques such as forgetting factor should be used to monitor the convergence problem.

Structural Information One of the main advantage of the PT is the possibility of extracting information about the structure of the plant. This information is very useful to locate and isolate faults in the system. This characteristics make the technique appropriate for closed loop feedback systems where the control structure comprises actuator, plant and sensor. By relating the parameters to each of these components, the faults may be easily localized and isolated.

Detection Algorithm An advantage of the PT is that it automatically provides a detection scheme through monitoring the residual error. While for the NPT, a detection scheme independent of the classification algorithm should be used.

Decision Algorithm The complexity and problems of fault decision algorithm are very similar in both approaches. In principle the reliability of these decision depends on the accuracy and validity of the information extracted and the parameter supplied. These are the parameter estimates in the PT and the Fourier coefficients in the NPT.

Computational Requirements The computation requirement is in general higher for PT. This is mainly due to parameter estimation algorithm.

False Faults Both techniques require extensive testing and simulation in order to identify the no fault and faulty templates. Based on the assumption that the stored information is sufficient to cover all possible faults, the false fault rate for each technique will then depend on accuracy of parameter estimates for PT and Fourier descriptor for NPT. Although no firm conclusion can be drawn, simulation studies shows that this rate is higher for PT.

Robustness Defining robustness as the insensitivity of the fault monitoring scheme to unpredicted internal or external disturbance, the NPT is more robust since it only depends on the input and output signals. A major change in the dynamics of the plant does necessitates the change of model order and structure for the PT.

Multi-Input Multi-Output Systems A major problem with the fault monitoring system for MIMO system is the identification and isolation of the interaction dynamics between each pair of inputs and outputs. Although no attempt is made to extend the present techniques to MIMO systems, but it intuitively obvious that the interaction can be handled much easier in PT.

Application Areas In general PT is more appropriate for systems where it is necessary to localize the faults. It is usually difficult to model high frequency dynamics because of its random nature. Therefore, the PT is better suited to systems where faults occurring in low frequency range. The NPT can handle faults of high frequency nature but the problem of high frequency sampling and limited word length should be resolved. The NPT is therefore recommended for systems where the location and nature of likely faults are known.

Chapter 6

Conclusion

Two FDI schemes based on the parametric and non-parametric approach have been presented. Both techniques are invariant under input scaling and use template matching for fault classification. The parametric technique uses the estimate of an ARX model while the non-parametric uses the Fourier descriptors to construct feature sets.

The PT is not suitable for high order systems unless decentralized or parallel algorithms are used. This is due to the high computation requirement and convergence problems with the parameter estimation algorithm. The main advantage of the PT is its flexibility to extract information about the internal structure of the plant including the interactions between different subsystems. This is very useful to locate any isolate faults in the system. It is therefore more appropriate for dynamic systems with closed loop feedback configuration.

On the other hand the computation requirement is much smaller for NPT. Simulation studies shows that the false fault rate is also lower and the algorithm is more robust to random disturbances. Finally, this technique can detect and identify faults in any frequency range provided the problem of high sampling rate and limited word length can be resolved.

6.1 Further Investigations

(i) Comparison with observer based techniques.

(ii) Modeling the fault as additive signals.

(iii) Extension to disturbuted parameter systems.

(iv) Extension to nonlinear systems, continuous differentiable as well as hard nonlinearities.

(v) Application of Neural Networks for faults classification.

(vi) Use of heuristic information and fuzzy systems.

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