A Data Based Approach To On-line Process Fault Diagnosis

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Abstract: This paper describes a data based technique for on-line process fault detection and diagnosis. The only knowledge required in this approach is process measurement data covering the events of various faults. The data can be obtained from the recorded operating history of a process or from simulation studies. They are usually the easiest available knowledge about a process since various process variables are measured during operations and those measurements can be easily collected and stored by a computer. Through multi-variable statistical data analysis, the features of various faults can be discovered and used in fault detection and diagnosis. In the technique presented here, principal component analysis is performed for the data corresponding to each fault and the loading vector of the first principal component is taken as the direction of the associated fault in the measurement space. During process supervision, principal component analysis is performed for the current on-line measurements whose direction is taken as the loading vector of the first principal component. Fault diagnosis is performed by comparing the direction of the current on-line measurements with that of various faults. The fault whose direction is very aligned with the current data direction is a plausible fault and is taken as the diagnosis result. The technique is very easy to implement and can be used to complement current fault diagnosis techniques. Applications of the proposed technique to the on-line fault diagnosis of a CSTR (continuous stirred tank reactor) system demonstrate that the technique is robust to measurement noise and effective in diagnosing faults.

Keywords: Fault diagnosis, process supervision, statistical data analysis, principal component analysis.

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1. Introduction

Process equipments are subject to failures during operation. Failures could reduce production efficiency, damage equipment, lead to plant shut downs, or even result in hazards. Prompt detection and diagnosis of faults is becoming more and more important due to the increasing economic and environmental demands. As a result, fault detection and diagnosis is becoming a vast research subject attracting a huge number of researchers from different areas. Various approaches have been proposed, tackling this issue from different angles. These can be broadly divided into model based approaches and knowledge based approaches (Patton et al, 1989). Model based approaches generally utilise results from the field of control theory. Isermann (1984) describes a fault diagnosis approach based on parameter estimation. The approach is based on the fact that a fault will cause changes in certain physical parameters which in turn will lead to changes in some model parameters. It is then possible to detect and diagnose faults by monitoring the estimated model parameters. When using this approach, it is essential to have the knowledge about the relations between faults and model parameters. Frank (1990) gives a survey of fault diagnosis approaches based on state estimation. Estimated states provide redundant information about the system and fault diagnosis can be performed by analysing this redundant information. When using this approach, a fairly accurate state space model of the system should be developed.

Knowledge based approaches generally utilise results from the field of Artificial Intelligence. The early knowledge based diagnosis systems usually use expert system techniques and the knowledge employed is often the experience of process operators (Nelson, 1982). Such knowledge is often referred to as "shallow knowledge" since it does not contain any first principles about the system under consideration. Shallow knowledge based diagnosis systems could face problems when dealing with infrequent occurring faults since knowledge about such incidents is generally lacking. Furthermore, the knowledge acquisition procedure is generally tedious and time consuming though some researchers have attempted to develop diagnostic rules through machine learning techniques (Gupta and Ali, 1988; Zhang and Roberts, 1992b).

Many of the recent knowledge based diagnosis systems are based on deep knowledge. The most common deep knowledge based diagnosis approaches include causal search and hypothesis testing (Moor and Kramer, 1986). In the causal search approach, faults are diagnosed by causally tracing symptoms backward along their propagation paths. The knowledge used includes functions of individual components and their connections. A method for formulating diagnostic rules from such knowledge is described in Zhang and Roberts (1991). In the hypothesis testing approach, the knowledge employed contains models of the process under normal operating conditions and under various faulty conditions. These models are used to predict the behaviour of the process under the normal operating condition and various faulty conditions. Fault detection and diagnosis is then performed by comparing the predicted behaviour with the actual observations. Usually the models used are qualitative models of the process. Several researchers have successfully attempted this approach (Zhang et al, 1990a; 1990b; 1991; Montmain and Gentil, 1991a; 1991b). Deep knowledge based diagnosis systems can provide reliable diagnosis since the reasoning is based on the first principles governing the process under consideration. However, considerable effort is usually required for building these diagnosis systems.

To reduce the development efforts in building knowledge based diagnosis systems, neural networks based diagnosis systems have been developed (Venkatasubramanian and Chan, 1989; Watanabe et al, 1989; Zhang and Roberts, 1992a). In this approach, the only knowledge required is training data which contain faults and their symptoms. Through training, the relations between faults and their symptoms can be discovered and stored as network weights. The trained network can then be used to diagnose faults in that it can associate the observed abnormalities with their corresponding faults.

For industrial processes, the most easily obtainable knowledge is usually the process measurement data. During operations, a large number of process variables are measured and these measurement data could be easily collected and stored by a computer. For some processes where the first principles governing these processes are not clear or too complicated, then measurement data could be the prime knowledge about the processes. In this paper, we propose a data based approach, which utilises the most easily available knowledge about a process, for on-line process fault detection and diagnosis.

The proposed approach is similar to neural network based approaches but is easier to implement. The only knowledge required is the measurement data covering the normal operating condition and various faulty conditions. The data could be obtained from the operating history of a process and/or from simulation studies. The data can be analysed using multivariable statistical data analysis techniques and features associated with various faults can be discovered. The proposed approach can also diagnose and learn diagnostic knowledge about novel faults.

The paper is structured as follows. The next section details the data based diagnosis approach. Discovering fault features from principal component analysis (PCA) is then described. Section 3 presents an application to the fault diagnosis of a CSTR system. The last section contains some concluding remarks.

2. Fault Diagnosis by the Principal Component Analysis of Data

2.1. Principal Component Analysis

Principal component analysis (PCA) is one of the widely used multivariable statistical techniques which considers all the noisy and highly correlated measurements on a process, but projects the information down onto low dimensional subspaces which contain all the relevant information about the process. PCA is a procedure used to explain the variance in a single data matrix, X. The principal component decomposition of X can be represented as follows

$$X=t_1p_1^T+t_2p_2^T+\ldots+t_kp_k^T+E \qquad (1)$$

In the above equation, t_i and p_i are the *ith* score vector and the *ith* loading vector, $t_ip_i^T$ is the *ith* principal component, and E is a matrix of residuals. Score vectors are orthogonal and so are loading vectors which are of unit length. Principal components are arranged in a decreasing order of importance. A rank *n* matrix X can be decomposed as the sum of *n* rank 1 principal components. However, if there exist correlations and noise in the data, then the first a few principal components are usually sufficient to describe the major variances in the data. The remaining principal components usually describe the variances of the noise and, by discarding them, noise filtering effects are achieved. For example, in principal component regression, the first few principal components, instead of the raw data, are used in modelling the relations between input and output data to reduce the effects of correlations and noise in data.

PCA is generally used to reduce the dimension of correlated multivariable data. In process supervision, a small number of principal components, instead of a large number of measurements, can be monitored. Wise and Ricker (1989) describe such applications in a liquid fed ceramic melter process. Here, we are interested in using PCA to find fault directions, which are represented by the first loading vectors of sets of process data to the considered faults.

2.2. Fault Diagnosis Through PCA

A set of process data covering a fault event is collected. The nominal means of measurements are then subtracted from the corresponding variables. Next, the data are scaled such that different measurements should have similar significances. Suppose that there are *n* measured variables and *m* samples of measurements are collected. The measurement data can then be represented as

$$X=\left[x_1x_2\ldots x_n\right] \qquad (2)$$

where $x_1, x_2, \ldots, x_n \in R^{m\times 1}$. Let the means and standard deviations of measurements be

$$M=\left[m_1m_2\ldots m_n\right] \in R^{1\times n} \qquad (3)$$

$$S=\left[s_1s_2\ldots s_n\right] \in R^{1\times n} \qquad (4)$$

then the measurement data can be mean centred and scaled as follows.

$$X_n=\left(X-(1\;1\;\ldots\;1)^TM\right)\operatorname{diag}\left\{1/s_1\;1/s_2\;\ldots\;1/s_n\right\} \qquad (5)$$

The data covering the incidence of a fault are generally polarised such that variances in the data are mainly represented by the first principal component. Through PCA, the first loading vector of the data can be calculated and it can be used to represent the direction of a fault in the measurement space. Here, it should be realised that score vectors and loading vectors are not unique. For example, the first score vector and the first loading vector can be either t_1 and p_1, respectively, or $-t_1$ and $-p_1$, respectively. When using the first loading vector to represent the direction of a fault, it is therefore necessary to compare it with the actual data. If the directions of process variables oppose those suggested by the first loading vector, then a negative sign should be multiplied to the first loading vector. By putting the directions of various faults together, a fault direction library can be formed and represented by a matrix

$$F=\left[D_1D_2\ldots D_n\right] \qquad (6)$$

where D_i is the fault direction of the *ith* fault.

The currently monitored process measurements can also be analysed through PCA. The first loading vector can be taken as the direction of the current data. Denote it by M_D, then the alignment between M_D and the direction of the *ith* fault, D_i, can be measured by $M_D^TD_i$, which is the cosine of the angle between M_D and D_i. When $M_D^T D_i$ is very close to one, then M_D and D_i are very close in their directions. If $M_D^T D_i$ is zero, then M_D and D_i are orthogonal.

If M_D and D_i are very closely aligned, then it is very likely that the *ith* fault has occurred. Fault diagnosis can then be performed by comparing the alignment between the current data direction and the library of fault directions. The fault whose direction is very close to the current data direction is a plausible fault that occurred and can be taken as the diagnosis result.

A diagnostic threshold, τ, is defined such that when

$$M_D^T D_i \geq \tau \tag{7}$$

it is indicative that the *ith* fault has occurred. Generally, τ is quite close to 1, for example, 0.98.

In process fault diagnosis, there is a problem of fault diagnosibility, i.e. whether a fault can be distinguished from other faults based on the available on-line measurements. To distinguish the *ith* fault from others, angles between the direction of the *ith* fault and those of other faults should be greater than twice the threshold angle, $\cos^{-1}\tau$. Equivalently, cosines of these angles should be less than the cosine of twice the threshold angle. That is

$$D_i^T D_j < \cos\left(2\cos^{-1}\tau\right) = 2\tau^2 - 1 \qquad \forall j, j \neq i \tag{8}$$

Eq (8) ensures that any data directions classified as representing the *ith* fault will not be classified as representing any other faults and, hence, it can be used as a criterion to test fault diagnosibility. If a fault cannot be distinguished from other faults, then certain additional process variables should be measured to increase the dimension of the data space, so that the angles among fault directions in this new data space could be wide enough to distinguish between the various faults.

Given the directions of a set of considered faults, the diagnostic threshold, τ, can be selected as follows to ensure diagnosibility among the considered faults.

$$\tau > \cos\left(\frac{1}{2}\cos^{-1}\left(\max_{i,j} D_i^T D_j\right)\right) = \sqrt{\left(1 + \max_{i,j} D_i^T D_j\right)/2} \qquad j \neq i \tag{9}$$

A diagnostic threshold selected according to Eq (9) will ensure that angles among fault directions are greater than twice the threshold angle and, hence, it will guarantee diagnosibility among these faults. It should be realised that a diagnostic threshold satisfying the above condition can ensure fault diagnosibility among the considered faults, but it cannot guarantee fault diagnosibility when novel faults present. In the latter case, τ should generally be quite close to one to maintain diagnosibility.

2.3 Learning New Diagnostic Knowledge

The approach presented here can also deal with novel faults which are not included in the fault library. During diagnosis, knowledge about novel faults can be learnt and stored in the fault library.

When abnormalities in on-line measurements have been detected but the current data direction is not very well aligned with any fault directions in the fault library, it is very likely that a novel fault occurred. Once the occurrence of a novel fault is confirmed, the current data direction can be stored in the fault library as the direction of the novel fault. Using this technique, diagnostic knowledge about novel faults is learnt. When adding this newly learnt diagnostic knowledge to the fault library, existing diagnostic knowledge is not affected.

2.4 The NIPALS Algorithm

There are several ways to calculate principal components and one of them is the nonlinear iterative partial least squares (NIPALS) method (Geladi and Kowalski, 1986). The NIPALS algorithm calculates principal components individually. It calculates t_1 and p_1 from the X matrix. Then the outer product, $t_1p_1^T$, is subtracted from X and the residual E_1 is calculated. This residual can be used to calculate t_2 and p_2:

$$E_1 = X - t_1p_1^T$$

$$E_2 = E_1 - t_2p_2^T$$

...

Since we are only interested in the first principal component, NIPALS will be a very efficient algorithm to employ and computation can be terminated once the first principal component is calculated.

The NIPALS algorithm can be summarised as follows:

(1) take a vector x_j from X and call it t_1:$t_1 = x_j$;

(2) calculate p_1:$p_1^T = t_1^TX/t_1^Tt_1$;

(3) normalise p_1^T length to 1:$p_1^T = p_1^T/||p_1||$;

(4) calculate t_1:$t_1 = Xp_1/p_1^Tp_1$;

(5) compare the t_1 used in step 2 with that obtained in step 4. If they are the same, stop (the iteration has converged). If they still differ, go to step 2.

3. Fault Diagnosis of a CSTR System

3.1 The CSTR System

The proposed fault diagnosis method has been applied to a simulated CSTR system. The CSTR system is presented in Figure 1, where an irreversible heterogeneous catalytic exothermic reaction from reactant A to product B takes place in the reactor vessel. The process objective is to indirectly maintain the product concentration at a desired level by controlling temperature, residence time and mixing conditions in the

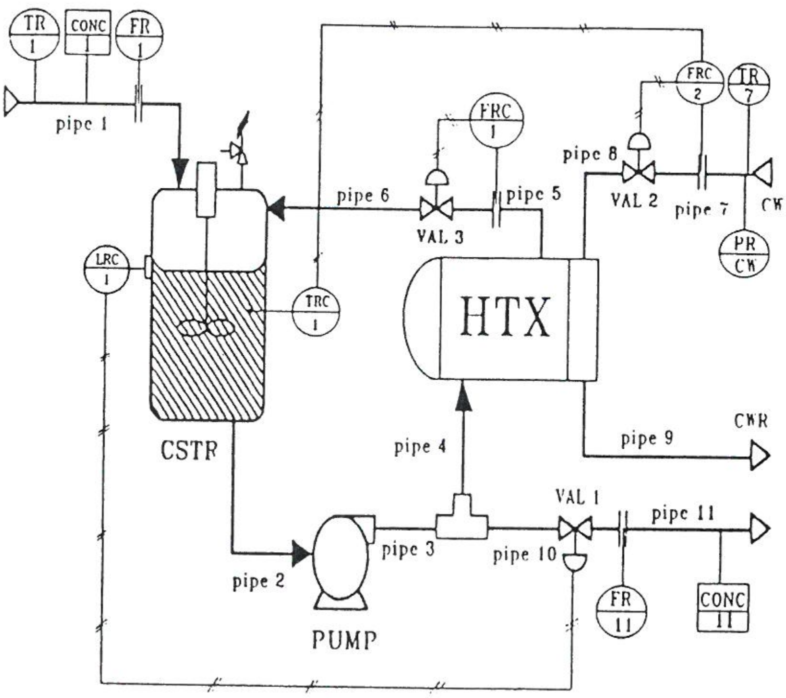

Figure 1. The CSTR System

CSTR. To provide temperature control, part of the reactor outlet stream is recycled to the reactor through a heat exchanger (HTX). The temperature in the reactor is controlled by manipulating the flow rate of the cold water fed to the heat exchanger via a cascade control system. The residence time is controlled by maintaining the level in the reactor, and the mixing condition is controlled by maintaining the recycle flow rate. Constant physical properties and constant boundary pressures of all input and output streams are assumed. A dynamic model of the system has been developed and it is capable of investigating the operations of the process under normal conditions as well as under various faulty conditions (Zhang, 1991).

3.2 Fault Diagnosis

There are 11 measurements and three controller outputs (to the manipulated valves) in the CSTR system. When developing a fault diagnosis system, 11 possible faults are considered and they are listed in Table 1. The effects of these faults are analysed through simulation studies. During simulation, random noises are added to measurements and controller outputs. When adding a fault to the process, the resulting measurements and controller outputs are collected. The data are then mean centred by subtracting the normal means of process variables and they are scaled such that the process variables will have similar significances.

Table 1. Fault List

Fault No.	Faults
1	Pipe 1 blockage
2	External feed-reactant flow rate too high
3	Pipe 2 or 3 is blocked or pump fails
4	Pipe 10 or 11 is blocked or control valve 1 fails low
5	External feed-reactant temperature abnormal
6	Control valve 2 fails high
7	Pipe 7, 8, or 9 is blocked or control valve 2 fails low
8	Control valve 1 fails high
9	Pipe 4, 5 or 6 is blocked or control valve 3 fails low
10	Control valve 3 fails high
11	External feed-reactant concentration too low

Principal component analysis is then performed for each set of data to determine the corresponding fault directions. By putting fault directions together, a library of fault directions is formulated. In this case, the library of fault directions is a 14x11 matrix where each column is the direction of a particular fault.

For the 11 considered faults,

$$\max_{\substack{i,j \\ j \neq i}} D_i^T D_j = 0.85$$

and, according to Eq(9), τ should be selected greater than 0.9618 to ensure diagnosibility. Here, the diagnostic threshold, τ, is selected as 0.97.

During operations, measurements and controller outputs are collected. Limits for the measured variables and their rates of changes are set to detect abnormalities in the process. If any variables or their rates of changes exit the corresponding limits, then it is detected that abnormalities present in the process and the fault diagnosis system begins to diagnose the associated faults. The direction of the current data is calculated and compared with the library of fault directions. If the current data direction is very aligned with the direction of a particular fault, then it is very likely that fault has occurred and a diagnosis result is issued.

When abnormalities are detected but the direction of the current data is not very well aligned with any fault directions, it is then indicative that a novel fault has occurred. The direction of the current data is stored as the direction of the novel fault and will be used in future diagnosis.

3.3 Performance of the Fault Diagnosis System

All the 11 possible faults are tested during simulation studies. They were initiated at various levels of severity and they were all diagnosed successfully. Several case studies are presented below.

3.3.1 Case Study 1

In this case, the fault tested is Fault No.1: "Pipe 1 blockage". This fault is simulated by reducing the feed reactant flow rate to 90% of its nominal value. This fault is quite a slight fault in that the pipe is only partially blocked (10% blockage). The data length considered here is only 1 and the current data direction is simply obtained by mean centring and scaling the currently sampled data. Alignments of the current data direction and the library of fault directions are plotted in Figure 2 and it is clearly indicated that the current data directions is very aligned with the direction of Fault No.1, "Pipe 1 blockage". In Figures 2 to 5, y axes represent the inner products of the current data direction and various fault directions, i.e. the cosines of angles between these directions. The fault is initiated at 0 seconds and Figure 2 indicates that it could be diagnosed after only 20 seconds (5 samples). Therefore, even for a very slight fault, the diagnosis method presented here can diagnose it very quickly.

3.3.2 Case Study 2

Fault No.8, "Control valve 1 fails and gives high outputs", is simulated. Alignments between the current data direction and the library of fault directions are shown in Figure 3 where the fault is initiated at 0 seconds. Figure 3 shows that 20 seconds after the initiation of the fault, the current data direction becomes closely aligned with the direction of Fault No.8. Again, the correct diagnosis is obtained soon after the fault occurred.

3.3.3 Case Study 3

Novel faults are considered in this case. Fault No.11 is deleted from the library of fault directions so that it becomes a novel fault. Fault No.11 is then simulated and alignments between the current data direction and the library of fault directions are compared. It can be seen from Figure 4 that the current data direction is not very well aligned with any of the ten fault directions. A novel fault is then indicated and other techniques should be used to diagnose this fault. Suppose that, later, it is found that this fault is "Feed reactant concentration low". The current data covering this event is then analysed through PCA and the loading vector of the first principal component is then taken as the direction of this fault and the library of fault directions is augmented.

After the library of fault directions has been augmented, the same fault is initiated again with different severities. Alignments between the current data direction and the library of fault directions are shown in Figure 5. The fault is initiated at 0 seconds and Figure 5 indicates that it can be diagnosed after 16 seconds.

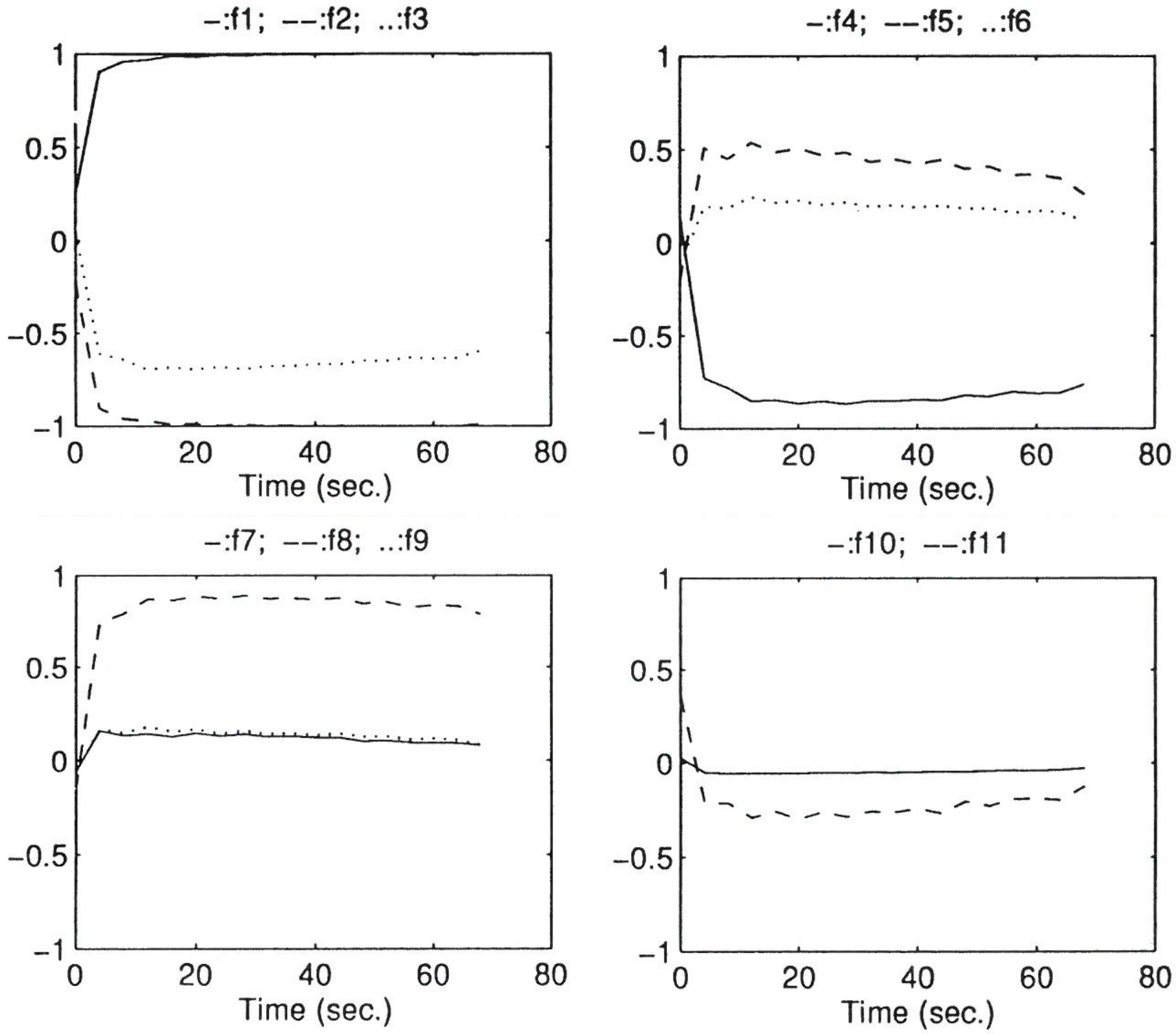

Figure 2. Alignments of the Current Data Direction with Fault Directions (Case Study 1)

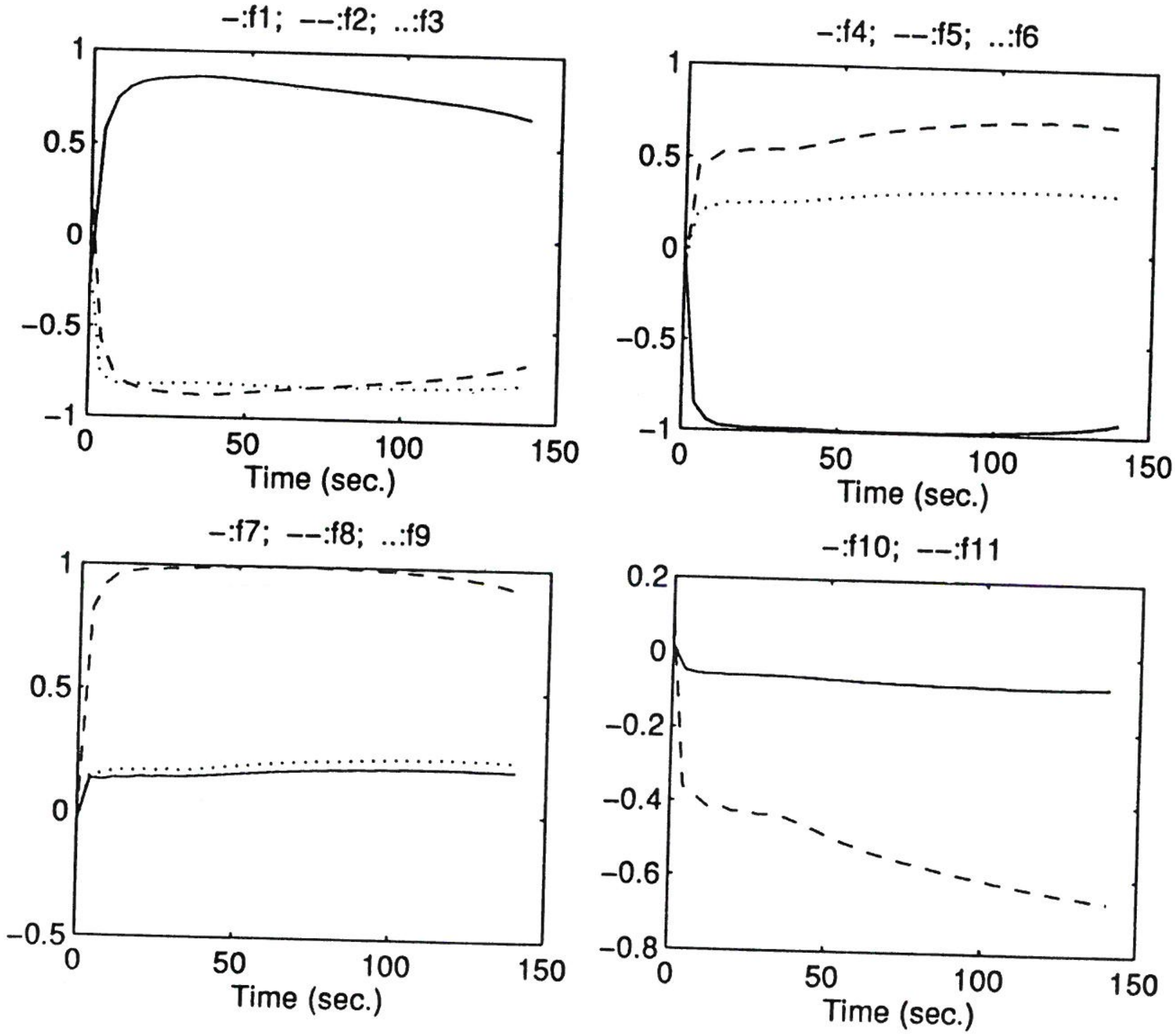

Figure 3. Alignments of the Current Data Direction with Fault Directions (Case Study 2)

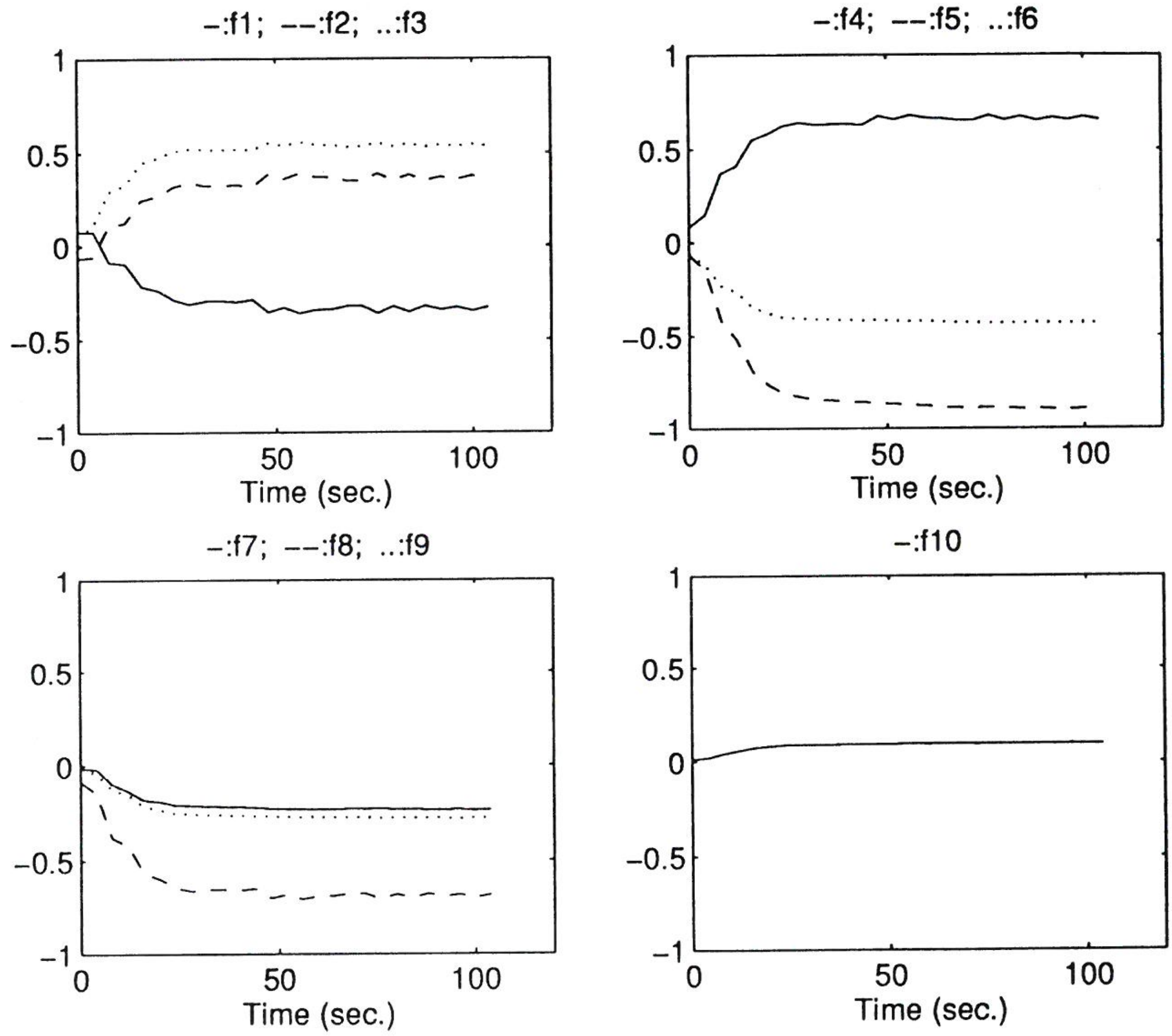

Figure 4. Alignments of the Current Data Direction with Fault Directions (Case Study 3, without Fault No. 11)

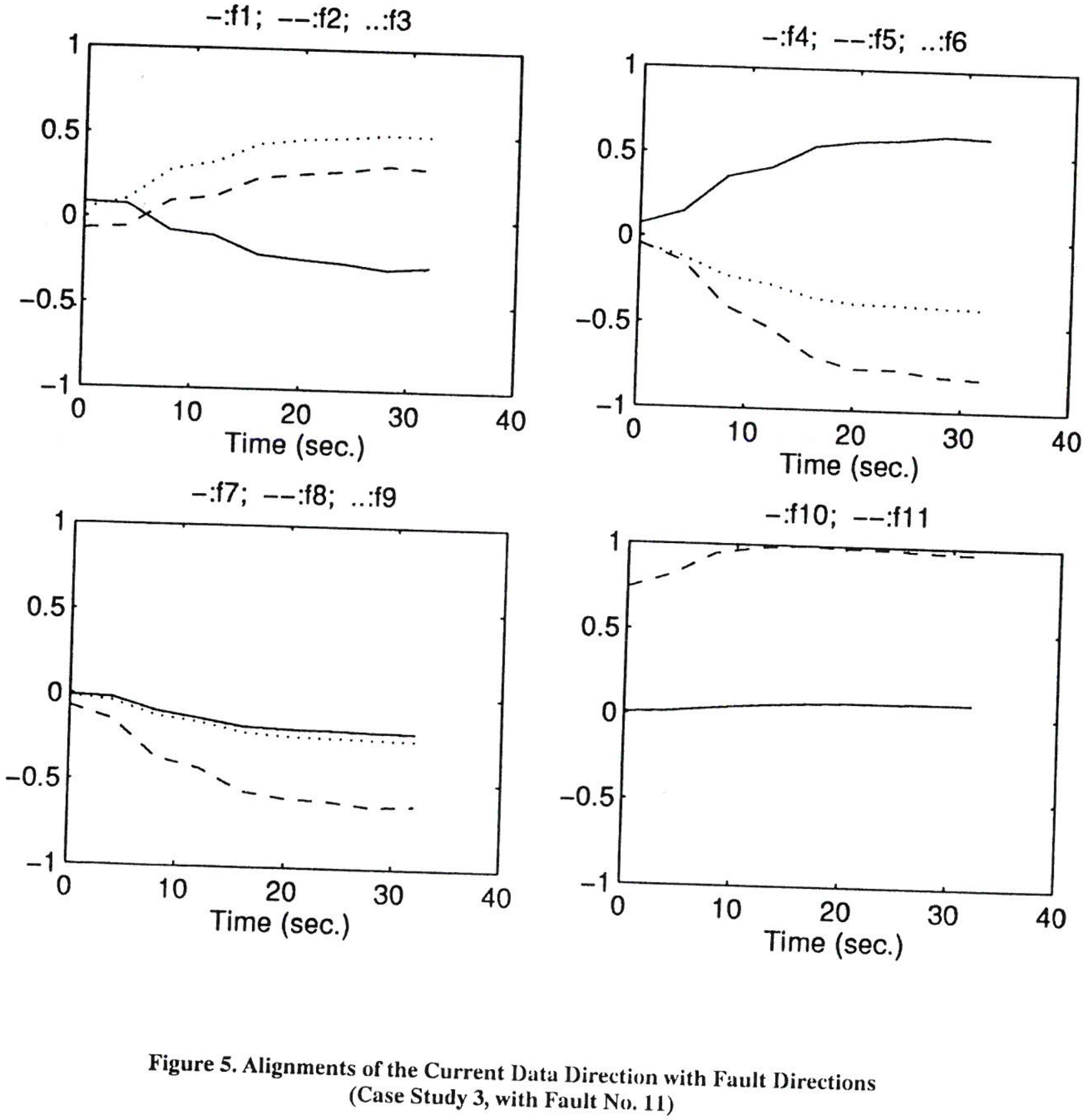

Figure 5. Alignments of the Current Data Direction with Fault Directions (Case Study 3, with Fault No. 11)

4. Conclusions

Measurement data are usually the most easily available form of knowledge about a process. Fault diagnosis systems based on such knowledge could be easy to develop and maintain. Through multivariable statistical data analysis, features associated with different faults can be discovered and used in fault diagnosis. In the technique presented here, the features are fault directions in the measurement space and those directions are taken as the loading vector of the first principal component of the corresponding measurement data. Fault diagnosis can then be performed by comparing the alignments of the current measurement data direction and various fault directions.

The proposed method can also deal with novel faults and learn diagnostic knowledge about novel faults. Learnt knowledge about novel faults can be simply added to the fault library without affecting previously obtained knowledge. Thus, diagnostic knowledge can be accumulated gradually.

The proposed technique is very easy to develop and utilizes the most easily available information about a process. It can be used to supplement other fault diagnosis methods.

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