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PCA Based Fault Diagnosis for the Actuator Process

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Abstract : This paper deals with the problem of fault diagnosis for identifying a single fault when the number of assumed faults is larger than that of predictive variables. Principal component analysis (PCA) is employed to isolate and identify a single fault. PCA is a method to extract important information as reducing the number of large dimension in a process. The patterns of all assumed faults can be recognized by PCA and these can be employed whether a new fault is one of predefined faults or not. Through PCA, empirical models for analyzing patterns can be trained. When a single fault occurs, the pattern generated by PCA can be obtained and this is used to identify a fault. The performance of the proposed approach is illustrated in the actuator benchmark problem.

Key words : fault diagnosis, DAMADICS, fault identification, principal component analysis

1. Introdution

Fault detection and isolation (FDI) are of considerable importance for the safe operation of chemical processes. When faults occur in a chemical process, operators must quickly detect the faults, diagnose their root causes, and then bring the process back to a normal operating condition. However, there are many difficulties and ambiguities in manual detection and diagnosis due to the complex structures and dynamics of integrated chemical plants. Therefore, automated fault diagnosis system has become a requisite for the safe operation of complex chemical processes [1,2].

According to a series of review articles by Venkatasubramanian et al. [3,4], FDI methodologies can be categorized as quantitative model-based, qualitative model-based, and process history based methods. While the first two FDI approaches need accurate mathematical equations representing process phenomena (either quantitative or qualitative model structure) on the process, process history based methods require only process historical data [4]. Model-based monitoring makes use of mathematical models of the supervised system. However, perfectly accurate and complete models of a physical system are almost never available [4].

Contrary to the model-based approach, process history based methods do not need an explicit system model. They are capable of handling high dimensional and correlated process variables and they are powerful tools of revealing the presence of the abnormalities [4]. In this class of FDI approaches, one examines the data to find any pattern of process variables that indicate the occurrence of a fault [1]. Since faults generate different patterns from the normal operating condition area, various pattern recognition and clustering algorithms based on the online such as PCA, the fisher discriminant Analysis, k-means, fuzzy c-means clustering, etc. have been widely used.

In this paper, PCA, which is one of widely used process history based methods, is employed to identify a fault in the benchmark problem with the aid of available data. The aim of this paper is to propose an effective FDI approach without detailed process information or first principle equations.

This paper is organized as follows. In Section 2, the basic theoretical concepts used herein are explained. Section 3 shows the strategy of proposed model including off-line and on-line analysis. In Sections 4 and 5, the results of the proposed algorithms for a case study are discussed. The final section gives concluding remarks.

2. PCA

Analysis of chemical data using principal component analysis (PCA), especially for detecting faults in chemical processes, has been intensively studied for the past

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decade [2]. This study used PCA to extract information using data measured during normal operating conditions. PCA produces a new set of projected variables known as principal components (PCs) in a least square sense. PCA is based on an orthogonal decomposition of the covariance values of the data and decomposes the data into the score vector, T, and loading vector, P. The equation of PCA is given as;

$$X = \sum_{i=1}^{a} t_i p_i^T + E = TP^T + E_i \quad (1)$$

where E is the residual term. In above equation, the dimension of X is reduced to a lower number, a, and score vectors or latent variables, T, contain important information of an original data set. In this study, PCA is used to extract information and patterns of assumed faults using data loading vector, P, from normal operating condition. In this paper, PCA is used to extract important information of a process. In next section, the way to use PAC is illustrated.

3. The Proposed Fault Diagnosis Strattegy

3.1 Off-line Analysis: Empirical Model Construction based on PCA

In order to isolate a true fault among assumed faults, the empirical model based on PCA and normal operating condition data is developed throughout off-line analysis. If the projection area of the latent variables from PCA is located within that of one among assumed faults, this fault can be identified.

The loading vector, P, can be obtained from the data of normal operating conditions and two main latent variables or Principal Components (PCs) of the data, which is available from a process, can be extracted using P. Two latent variables of faulty data produced from P are shown in Fig. 1.

In Fig. 1, there is large difference between the projection area of the normal operating condition and an assumed fault. After calculating all projection areas for predefined faults, these areas can be employed to identify a fault.

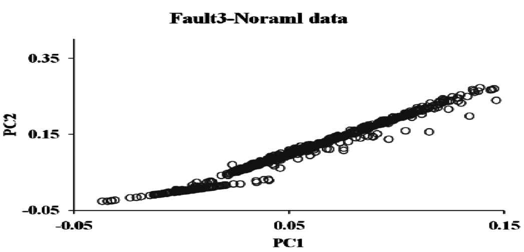

Fig. 1. The two latent variables of process data obtained from loading vector of normal operating condition data when Fault 3 of the actuator process occurs. This figure indicates that a process fault leads to change the area of latent variables from normal operating conditions.

3.2 On-line diagnosis

When a fault occurs, the latent variables of the data are calculated by PCA. To identify a fault, the location of latent variables has to be recognized. If two latent variables of faulty data are located in the projection area of only one existing fault, the identification of a single fault can be finally achieved. If two latent variables are located out of the projection area of existing assumed faults, this is considered as a novel fault.

4. A Case Study

4.1 Benchmark actuator process

In this paper the actuator benchmark process is used due to its popularity in the field of FDI systems. Because the number of assumed faults is larger than variables in this problem, it is very hard to isolate a single fault so that this problem is very suitable to be verified by the proposed approach. The actuator benchmark process was constructed by the Development and Application of Methods for Actuator Diagnosis in industrial Control Systems (DAMADICS) research training network to compare the properties of fault detection and isolation methods based on a real sugar factory.

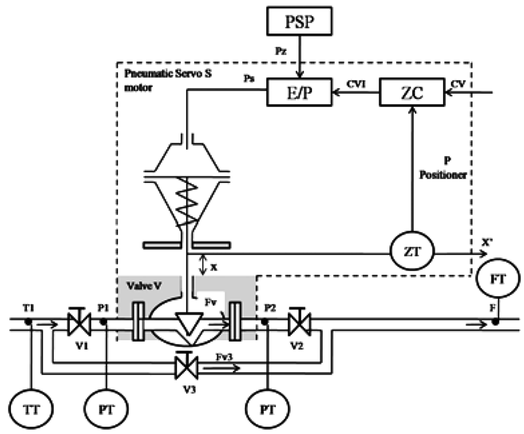

Fig. 2. The diagnostic procedure for all faults based on PCA.

Fig. 2 and Table 1 show the actuator scheme [5] and process variables. The actuator process consists of three main components: control valve, spring-and-diaphragm pneumatic servo-motor and positioner. The control valve is a device used to prevent and/or limit the flow of fluids. The control valve is changed by a servomotor. The

Table 1. Measured and unmeasured variables of DAMADICS taken from [5].

Measured variables
- External controller output (CV)
- Flow sensor measurement (F)
- Valve input pressure (P1)
- Valve output pressure (P2)
- Liquid temperature (T1)
- Rod displacement (X)
- Positioner supply pressure (Pz)
- Pneumatic servo-motor chamber pressure (Ps)
- Position P controller output (CVI)

positioner is a device used to eliminate the control-valve-stem miss-positions produced by external or internal sources, such as friction, pressure unbalance, hydrodynamic forces etc. It is comprised of an inner loop with a P controller of a cascade control structure, including the output signal of the outer loop of the flow or level controller and the inner loop of the position controller.

Table 2 shows the simulated faults. Fault 7 directly affects the exogenous variables, T. Therefore, this fault can be directly identified as monitoring these variables. Excluding this fault, 9 faults are studied based on PCA.

4.2 Case study of Fault 3

Mechanical wear (friction, cavity, aging, fatigue) or chemical treatment (corrosion) of a valve seat and plug is slowly developing in Fault 3. This fault increases the plug travel or valve seat diameter. Fig. 1 shows the pattern difference of latent variables generated by PCA between Fault 3 and a normal operating condition. This difference can be used to identify a fault.

Table 2. The set of simulated faults

Fault	Description
F1	Valve clogging
F2	Valve plug or valve seat sedimentation
F3	Valve plug or valve seat erosion
F4	Increase of valve or bushing friction
F5	External leakage (leaky bushing, covers, terminals)
F6	Internal leakage (valve tightness)
F7	Medium evaporation or critical flow
F8	Twisted servo-motor’s piston rod
F9	Servo-motor’s housing or terminals tightness
F10	Servo-motor’s diaphragm perforation

5. Diagnosis Results

Fig. 3 summarizes the diagnostic procedure of all faults calculated by PCA. As monitoring the difference between latent variables generated by PCA, it is possible to detect a fault. Among 10 faults, it is possible to perfectly discriminate Faults 2, 4, 5, 6, and 7. In case of other faults (Fault 1, 3, 8, 9, and 10), PCA is not able to isolate these. However, these can be divided into two groups. The one is Fault 1 and 10 and the second is Fault 3, 8, and 9. To isolate these faults included in two groups, further research should be performed.

The efficiency of our proposed approach was evaluated in terms of accuracy and resolution. The accuracy indicates whether the results of fault diagnosis are including a true fault. The accuracy would be 1 if the fault candidates include a true fault at each step. Otherwise the accuracy would be 0. Resolution is the average number of fault candidates considered as a true fault from the initial fault detection to the last. If our proposed approach suggests only a single true fault, the resolution would be 1.

In Table 3, the average resolution and accuracy are obtained when the measurements are taken every 1 minute from the initial detection time to the last.

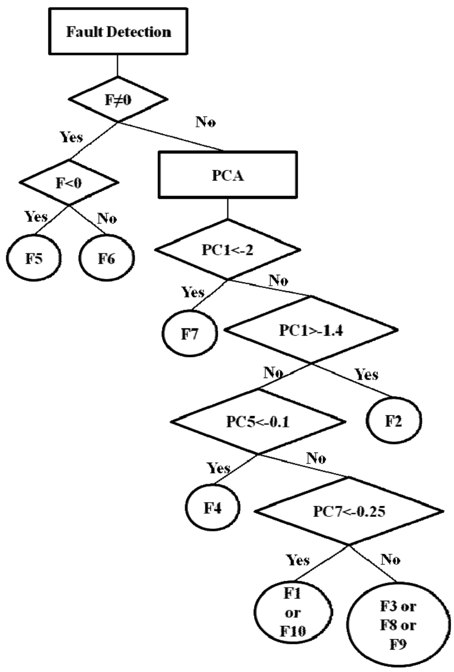

Fig. 3. The diagnostic procedure for all faults based on PCA.

6. Conclusion

This paper proposed an effective approach for process

Table 3. The results of the proposed model for DAMADICS

	Accuracy	Resolution
Fault 1	1	2
Fault 2	1	1.19
Fault 3	1	3
Fault 4	1	1.00
Fault 5	1	1.23
Fault 6	1	1.00
Fault 7	1	1.08
Fault 8	1	3
Fault 9	1	3
Fault 10	1	2

fault diagnosis based on PCA. The PCA is used to build empirical models using the available data from the process. The proposed model is quite practical in that data readily available from the process could be used without time-consuming and expensive efforts to find out accurate model equations in complex processes.

A PCA based analysis is performed for diagnosing a true fault when a single fault occurs. The proposed model between patterns and latent variables from PCA provides a tool to isolate a true fault and predict its strength.

The proposed approach can isolate a fault correctly and inform which fault occurs in a process. The proposed models can help operators find out the deviation of a fault comparing with existing faults in a chemical plant. The results of a case study show that our proposed algorithm provides satisfactory accuracy and resolution and detection delay.

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