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Fault diagnosis of time-varying processes using modified reconstruction-based contributions

Lamiaa M. Elshenawy [a,*], Tarek A. Mahmoud [b]

[a] Department of Industrial Electronics and Control Engineering, Faculty of Electronic Engineering, Menoufia University, 32952 Menouf, Egypt
[b] Department of Industrial Electronics and Control Engineering, Faculty of Electronic Engineering, Menoufia University, 32952 Menouf, Egypt

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ABSTRACT

This paper presents a modified reconstruction-based contributions for sensor fault diagnosis in continuous time-varying processes. The proposed fault diagnosis method is based on recursive updating of the loading subspaces of principal component analysis (PCA) with a low computational cost. The diagnosability of the proposed diagnosis method is proved mathematically for single sensor faults with large magnitudes. The control limits of the reconstruction contributions indices are computed and updated recursively to adapt the time-varying characteristics. Moreover, a complete adaptive algorithm for fault detection and diagnosis phases is provided for adaptive process monitoring. The efficiency of the proposed approach is demonstrated using a simulated time-varying example and a continuous stirred tank reactor (CSTR) process. The results show the ability of the proposed approach to adapt with the time-varying characteristics and still correctly diagnose the sensor faults even in the case of relatively moderate and small faults.

1. Introduction

Many engineering systems are critical-safety systems. Therefore, there is an increasing claim on safety and reliability to process malfunctions. Data driven methods-based process monitoring have received significant attention both in application and research fields. Multivariate statistical process monitoring (MSPMs) are examples of data driven methods. Classical MSPMs, such as principal component analysis (PCA), partial least squares (PLS), fisher discriminant analysis (FDA), independent component analysis (ICA) and canonical variate analysis (CVA) have been widely applied to process monitoring. A good review of these methods are found in [7,20,33,21,9,32]. Yin et al. [43] introduced a valuable comparative study of the basic data driven methods based process monitoring. The Conventional MSPM methods can acquire satisfactory results for the time-invariant processes. However, most industrial processes have time-varying characteristics such as deactivation of a catalyst, aging and change in operating point. So, there is a need to adaptive process monitoring schemes [41].

The process monitoring model includes two steps, fault detection and fault diagnosis. Several adaptive approaches for fault detection have been reported in the literature. They include recursive, moving window and exponential weighted moving average strategies [23,8,28,12,36]. Recently, Haimi et al. [17] employed moving window PCA approach to detect abnormal behavior of wastewater treatment plant (WWTP). Shang et al. [38] proposed a recursive canonical variate analysis approach for fault detection of time-varying chemical processes. Bakdi and Kouadri [4] introduced an adaptive thresholding scheme based on an exponentially weighted moving average (EWMA) control chart statistic to detect small changes and abrupt shifts in the industrial processes. Jiang and Braatz [19] proposed a canonical variate analysis (CVA) approach to detect faults that change in the process correlations.

The second step is to identify the main source of the fault. Several fault diagnosis methods have been developed for statistical process monitoring. The most fault diagnosis common method is the traditional contribution plots [31]. The idea is that the faulty variables have high contributions to the monitoring indices. Other diagnosis methods have been developed such as reconstruction methods [10,45,33,24–27,22,18], structured residuals based on multivariate statistical methods [15,34,29], angle-based methods [35,44,46], statistical signatures of PCA [30]. Alcala and Qin [2] proposed a new technique named reconstruction-based contribution (RBC) based on the PCA model. They proved that under the case of simple sensor faults, the RBC guarantees correct fault diagnosis, whereas,

* Corresponding author.
E-mail addresses: lamiaa.elshenawy@el-eng.menofia.edu.eg (L.M. Elshenawy), Tarek.Mohamed@el-eng.menofia.edu.eg (T.A. Mahmoud).

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the traditional contribution plots cannot. Sun and Zhan [39] proposed a fault diagnosis method based on between mode similarity analysis (BMSA) reconstruction for multi-mode processes. Good surveys have been written in the topic of fault diagnosis [3,14]. The aforementioned fault diagnosis methods are designed for time-invariant processes. Because most fault diagnosis methods depend on the loading vectors, which need to be updated for time-varying processes, these methods should be developed to be suitable for adaptive process monitoring schemes [11,37].

In this paper, the reconstruction-based contributions fault diagnosis method will be modified to be recursive to handle the normal process changes and still sensitive to modest faults. One of the most important problem associated with the recursive adaptive methods is the high computational costs, due to repeated eigenvalue decomposition (EVD) or singular value decomposition (SVD). Champagne [6] proposed the FOP technique to derive the eigenpairs of the data covariance matrix from perturbation expansions of the eigenvalue decomposition (EVD) and Willink [42] proposed the same technique for the singular value decomposition (SVD). Elshenawy et al. [12] proposed a recursive PCA model based on the FOP technique (RPCA-FOP), which significantly reduced the on-line computational cost of the recursive PCA model for fault detection. The cost of the RPCA-FOP technique was $O(m^2)$ whilst the cost of other known adaptive techniques such as standard SVD and inverse iteration approaches was $O(m^3)$ [16], Lanczos approach was $O(m^2 l_k)$ [23], fast MWPCA was $O(m^3)$ [40] and MWPCA using incremental method was $O(m^2 l_k)$ [28], where m and l_k are the number of process variables and the retained principal components (PCs), respectively. The main purpose of this paper is to build a low computational cost adaptive fault detection and diagnosis approach for continuous time-varying processes. The proposed approach uses the first order perturbation (FOP) theory to adapt the monitoring model on-line. The main contributions of this paper are concluded as:

1. Proposing a numerically efficient recursive reconstruction-based contribution method for sensor fault diagnosis of continuous time-varying processes. The proposed method includes updating the reconstruction-based contributions indices and their control limits.
2. Analyzing the diagnosability of the proposed recursive fault diagnosis method.
3. Incorporating the RPCA-FOP model and the proposed recursive reconstruction based contributions fault diagnosis method in an integrated framework for adaptive fault detection and diagnosis.

The rest of the paper is organized as follows: Section 2 gives a brief review of RPCA-FOP approach for fault detection. Section 3 then explains the proposed adaptive reconstruction-based contributions for fault diagnosis. This is followed by a description of a complete scheme for adaptive process monitoring in Section 4. Section 5 shows the simulation results by application to two simulation studies. The conclusions and the future research directions appear in Section 6.

2. Preliminaries

2.1. Notation

PCA is a MSPM method that is widely applied in engineering and science fields [32]. Let a data matrix $X = [x_1, x_2, \ldots, x_n]^T \in \Re^{n\times m}$ with n samples and m sensors. Normalization of the data matrix X is an important step to represent the common-cause of the process variability. The matrix X is scaled to zero mean for a covariance-based PCA model and to unit variance for a correlation-based PCA model. The PCA model is expressed as two parts, $\hat{X}$ and $\tilde{X}$, the predicted and the residual matrices, respectively.

$$X = \hat{X} + \tilde{X} = \hat{T}\hat{P}^T + \tilde{T}\tilde{P}^T \tag{1}$$

where $\hat{P}$ and $\tilde{P}$ are the principal and the residual loading vectors that can be obtained by performing an eigen decomposition on the sample covariance matrix S as

$$S = \frac{1}{n-1}X^T X = \left[\hat{P}\tilde{P}\right]\begin{bmatrix}\hat{\Lambda} & O \\ O & \tilde{\Lambda}\end{bmatrix}\left[\hat{P}\tilde{P}\right]^T \tag{2}$$

$\hat{\Lambda} = diag\{\lambda_1\, \lambda_2, \ldots, \lambda_\ell\}$, $\tilde{\Lambda} = diag\{\lambda_{\ell+1} \ldots, \lambda_m\}$ and ℓ is the number of the leading eigenvectors of S or the number of the retained principal components (PCs). Each of $\hat{P}$ and $\tilde{P}$ is considered as a linear transformation of any sample measurement into principal component subspace (PCS) and residual subspace (RS), respectively. For a measurement vector $x \in \Re^m$, its projection to PCS and RS, respectively, are

$$\hat{x} = \hat{P}\hat{P}^T x \tag{3}$$

$$\tilde{x} = \tilde{P}\tilde{P}^T x \tag{4}$$

2.2. Recursive PCA

The key idea of the recursive PCA model is to update its construction, that means eigendecomposition of the sample covariance matrix S recursively, which may be prohibitive. Many algorithms have been proposed to overcome this problem. One of them is FOP method with a computational complexity cost of $O(m^2)$ [6,42,12]. Because the covariance matrix is interpreted as a product of eigenvalues (λ_i) and eigenvectors (v_i), the eigenstructure can be updated at time sample k instead of the covariance matrix itself.

$$\lambda_{k,i} = (1-\mu)\lambda_{k-1,i} + y_i^2 \tag{5}$$

$$v_{k,i} = v_{k-1,i} + \sum_{j=1}^{m} b_{ji} v_{k-1,j} \tag{6}$$

$$b_{ji} = \begin{cases} -b_{ij} = y_j y_i/\lambda_{k-1,i} & ,j \neq i \\ 0 & ,j = i \end{cases} \tag{7}$$

where $y_i = v_{k-1,i}^T \sqrt{\mu} x_k$, μ is a small positive number and $(i, j = 1, \ldots, m)$.

2.3. Recursive fault detection indices

The most common indices of PCA model-based fault detection are Hotelling's T^2, $Q-statistic$ and a combined index φ [33]. Updating these indices is an important for process monitoring based on RPCA model [23].

2.3.1. Hotelling's T^2

Hotelling's T^2 index measures the variations in the PCS

$$T_k^2 = x_k^T \hat{P}_k \hat{\Lambda}_k^{-1} \hat{P}_k^T x_k = x_k^T A_k x_k \tag{8}$$

where $A_k = \hat{P}_k \hat{\Lambda}_k^{-1} \hat{P}_k^T$. The Hotelling's T^2 index is approximated with χ^2 distribution, ℓ_k degrees of freedom and a significance level α

$$\sigma_k^2 = \chi^2_{\alpha,\ell_k} \tag{9}$$

2.3.2. Q-statistic

The $Q-statistic$ measures the variations in the RS

$$Q_k = \left\|\tilde{x}_k\right\|^2 = x_k^T \tilde{P}_k \tilde{P}_k^T x_k = x_k^T B_k x_k \tag{10}$$