Journal of Process Control 64 (2018) 112–122

Contents lists available at ScienceDirect

Journal of Process Control

journal homepage: www.elsevier.com/locate/jprocont

Isolating incipient sensor fault based on recursive transformed component statistical analysis

Jun Shang[a], Maoyin Chen[a,*], Hongquan Ji[b], Donghua Zhou[a,b,*]

[a] *Department of Automation, TNList, Tsinghua University, Beijing 100084, China*
[b] *College of Electrical Engineering and Automation, Shandong University of Science and Technology, Qingdao 266590, China*

A R T I C L E I N F O

Article history:
Received 20 February 2017
Received in revised form
14 December 2017
Accepted 7 January 2018

Keywords:
Fault isolation
Incipient sensor fault
Subspace reconstruction
Subblock detection
Recursive transformed component statistical analysis

A B S T R A C T

This paper considers the isolation problem of incipient sensor fault. Based on recursive transformed component statistical analysis (RTCSA), two different isolation methods are proposed. The first method is called subspace reconstruction, where elements in specific subspaces are eliminated, and then reconstructed by minimizing the reconstructed detection index. The faulty variable is determined by the least scaled reconstructed detection index. The second method is called subblock detection, which has less online computational complexity. The subblocks of the measurement matrix are sequentially selected in each sliding window to calculate the subblock detection indices, and the faulty variable is determined by the largest subblock detection margin. Compared with the existing isolation methods such as reconstruction-based contribution (RBC) and its variant termed as average residual-difference reconstruction contribution plot (ARdR-CP), the superior isolation performances of the proposed methods are illustrated by a numerical example as well as a simulation on a continuous stirred tank reactor.

1. Introduction

During the last two decades, data-driven process monitoring has attracted considerable attention due to increasing demand for safe and efficient operation of modern industrial processes [1–5]. As a main branch of data-driven process monitoring, multivariate statistical process monitoring (MSPM) utilizes data correlation information and multivariate statistical analysis techniques to implement fault detection and isolation tasks. Its representative methods, such as principal component analysis (PCA), partial least square (PLS), and independent component analysis (ICA), have been widely applied in various industrial processes [1,6].

In the framework for fault diagnosis, once a fault is detected, the next step is to isolate it. Fault isolation aims to identify the possible root cause of the fault, in preparation for further operations to correct the abnormal condition. For a sensor fault, the isolation is required to locate the faulty variable. Over the past decade, many isolation methods have been proposed [7–15]. Among numerous methods, contribution plot [9,10] and reconstruction-based contribution (RBC) [12,14,15] are two commonly used methods to isolate fault, both of which are based on PCA. One advantage of these approaches is that neither a priori fault knowledge nor historical fault data are required. However, contribution plot suffers from the smearing effect, which may lead to misdiagnosis [10,12]. Although the RBC method does not eliminate the smearing effect, it can guarantee correct isolation in the case of single sensor fault with a large magnitude [14].

In practical industrial processes, many abnormal conditions gradually evolve from incipient faults [16,17]. In general, diagnosing incipient faults can effectively avoid abnormal conditions. Since incipient faults usually have small magnitudes, it is more difficult to detect and isolate them without a priori fault knowledge. Recently, several approaches have been proposed to detect incipient faults such as recursive transformed component statistical analysis (RTCSA) [18]. With measurement vectors converted to orthogonal transformed components (TCs), the statistical information of the TCs in each sliding window is extracted for process monitoring. The RTCSA approach in [18] is only involved in fault detection but not isolation. In addition, several isolation approaches designed for incipient faults have been proposed, such as signed directed graph and qualitative trend analysis based framework [19], moving window reconstruction based contribution (MWRBC) [20], and average residual-difference reconstruction contribution plot (ARdR-CP) [21].

In this paper, we extend the RTCSA scheme to the problem of incipient sensor fault isolation. At present, only the single sensor

* Corresponding authors.
E-mail addresses: mychen@tsinghua.edu.cn (M. Chen), zdh@mail.tsinghua.edu.cn (D. Zhou).

https://doi.org/10.1016/j.jprocont.2018.01.002
0959-1524/

fault is involved in this work. Based on the RTCSA, two isolation methods, namely subspace reconstruction method and subblock detection method, are proposed. For the subspace reconstruction method, we sequentially construct the subspaces by selecting specific entries in each sliding window. The elements in subspaces are eliminated, and then reconstructed with the objective of minimizing the reconstructed detection index. We use the alternating direction method of multipliers (ADMM) to solve this nonconvex optimization problem, since the ADMM is suitable for distributed optimization and large-scale problems [22]. The faulty variable is determined by the least scaled reconstructed detection index.

However, when ℓ_∞-norm is selected as the scalarization for RTCSA-based detection, one update step of optimization algorithm in subspace reconstruction method has no closed-form solutions, leading to high computational complexity. Hence, in the case of ℓ_∞-norm, we implement the subblock detection method to isolate sensor fault. Specifically, we sequentially select the subblocks of the sample covariance matrix in each sliding window, and the subblock detection index is calculated using the eigenvalues of the sample covariance matrix. For each sampling instant when the detection index exceeds the control limit, the largest subblock detection margin is utilized to determine the faulty variable.

Compared to traditional reconstruction-based methods such as RBC, the reconstruction index in subspace reconstruction method is more complex and has higher computational cost. However, it may be more sensitive to incipient faults, which will be beneficial for correctly isolating them. Although the subblock detection method utilizes the detection index of the RTCSA, it implements fault isolation from the perspective of detecting a subblock of measurements. Simulation on a continuous stirred tank reactor (CSTR) as well as a numerical example both illustrate the superior performances of the proposed approaches, compared with the existing fault isolation methods.

The remainder of this paper is organized as follows. Preliminaries are given in Section 2. Section 2.1 gives an overview of the RTCSA for incipient fault detection and Section 2.2 discusses the properties of a sample covariance matrix. In Section 3, the proposed fault isolation method based on subspace reconstruction is elaborated. The subblock detection based fault isolation method is demonstrated in Section 4. In Section 5, a numerical example and a CSTR simulation are both used to examine the isolation performances of the proposed methods. Conclusions are given in Section 6.

2. Preliminaries

2.1. RTCSA revisited

Denote the original measurements as $\boldsymbol{X} \in \mathbb{R}^{n\times m}$, where n and m represent the numbers of samples and measured variables, respectively. The one-step w-width sliding window is used to stack process measurements:

$$\boldsymbol{X}_k = \begin{bmatrix} x_{k-w+1,1} & x_{k-w+1,2} & \cdots & x_{k-w+1,m} \\ x_{k-w+2,1} & x_{k-w+2,2} & \cdots & x_{k-w+2,m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{k,1} & x_{k,2} & \cdots & x_{k,m} \end{bmatrix}. \tag{1}$$

The original measurement data in each window are normalized as $\bar{\boldsymbol{X}}_k = (\boldsymbol{X}_k - \boldsymbol{1}\boldsymbol{\mu}_0^{\mathrm{T}})\boldsymbol{\Sigma}_0^{-1}$, where $\boldsymbol{\mu}_0 \in \mathbb{R}^m$ denotes the reference mean, and the diagonal matrix $\boldsymbol{\Sigma}_0 \in \mathbb{R}^{m\times m}$ represents the reference standard deviation. The covariance matrix of $\bar{\boldsymbol{X}}_k$ can be approximated as $\mathbf{cov}(\bar{\boldsymbol{X}}_k) \approx \boldsymbol{C}_k = \frac{1}{w}\bar{\boldsymbol{X}}_k^{\mathrm{T}}\bar{\boldsymbol{X}}_k$. $\boldsymbol{C}_k = \boldsymbol{P}_k\boldsymbol{\Lambda}_k\boldsymbol{P}_k^{\mathrm{T}}$, where the diagonal matrix $\boldsymbol{\Lambda}_k \in \mathbb{R}^{m\times m}$ and $\boldsymbol{P}_k \in \mathbb{R}^{m\times m}$ represent the eigenvalues of $\boldsymbol{C}_k$ and the corresponding eigenvectors, respectively. The eigenpairs can be recursively calculated by rank-one modification. Then $\bar{\boldsymbol{X}}_k$ can be transformed into $\boldsymbol{T}_k = \bar{\boldsymbol{X}}_k\boldsymbol{P}_k$. Each column of $\boldsymbol{T}_k$ represents a corresponding TC. In each sliding window, statistics of $\boldsymbol{T}$ can be represented by

$$\Theta^{\mathrm{T}} = \left[\boldsymbol{\mu}^{\mathrm{T}} \mid \boldsymbol{V}^{\mathrm{T}} \mid \boldsymbol{\Gamma}^{\mathrm{T}}\right] \tag{2}$$

where $\boldsymbol{\mu}$, $\boldsymbol{V}$, and $\boldsymbol{\Gamma}$ denote the first-order statistics, second-order statistics, and higher order statistics, respectively.

In brief, the detection index at the kth sampling instant can be computed by

$$D_k = \left\|\boldsymbol{\varsigma}^{-1}(\Theta_k - \Theta_0)\right\|_p \tag{3}$$

where $\Theta_k \in \mathbb{R}^{sm}$ denotes the statistics of the TCs in the kth sliding window, $\Theta_0 \in \mathbb{R}^{sm}$ represents the reference means of Θ trained from the historical dataset under normal conditions, s is the type number of selected statistics, $\|\cdot\|_p$ indicates the vector p-norm, and the diagonal matrix $\boldsymbol{\varsigma} = \mathrm{diag}\{\varsigma_1, \ldots, \varsigma_{sm}\}$ denotes the sample standard deviations of statistics of the TCs.

Specifically, if only the sample variances of the TCs are selected as monitored statistics, the calculation of Θ_k can be simplified as computing the eigenvalues of $\boldsymbol{C}_k$. For instance, if ℓ_∞-norm is selected as the scalarization, (3) reduces to

$$D_k = \max_{1\le j\le m}\left|\frac{\lambda_{j,k} - \mu_{\lambda_j^*}}{\varsigma_{\lambda_j^*}}\right| \tag{4}$$

where $\lambda_{j,k}$ denotes the jth largest eigenvalue of the sample covariance matrix $\boldsymbol{C}_k$, $\mu_{\lambda_j^*}$ and $\varsigma_{\lambda_j^*}$ denote the sample mean and sample standard deviation of λ_j under normal conditions, respectively.

2.2. Sample covariance properties

Assume that the detectable fault will have an impact on the measurement matrix, leading to deviations from normal conditions. However, the magnitude of the incipient fault is usually small, making it difficult to directly detect and isolate the fault even after employing some moving average techniques, especially when fault f has time-varying properties. In this subsection, we mainly analyze the effect of the sensor fault on the sample covariance matrix, which is the basis of the covariance subspace reconstruction method discussed in Section 3.1 and the subblock detection method discussed in Section 4.

Although the source of the fault is not necessarily known, the impact of the fault on the measurement matrix can be restricted in a subspace isolable from other faults [1]. Suppose the sample vector is represented by

$$\boldsymbol{x} = \boldsymbol{x}^* + \boldsymbol{\xi}f \tag{5}$$

where $\boldsymbol{x}^* \in \mathbb{R}^m$ denotes the fault-free portion of $\boldsymbol{x}$, and $\boldsymbol{\xi} \in \mathbb{R}^m$ is the coefficient vector representing the weight that f allocates to each variable. Note that f can change over time depending on its actual evolution. In the case of single sensor fault, $\boldsymbol{\xi}$ reduces to one column with nonzero values only on the faulty sensor.

Assume that f occurs at the lth variable x_l. From (5), the scaled data matrix $\bar{\boldsymbol{X}}$ in each sliding window can be calculated by

$$\bar{\boldsymbol{X}} = \left(\boldsymbol{X}^* + \boldsymbol{f}\boldsymbol{\xi}^{\mathrm{T}}\right)\boldsymbol{\Sigma}^{-1} \tag{6}$$

where $\boldsymbol{f} \in \mathbb{R}^w$ represents the fault vector in the w-width sliding window, and $\boldsymbol{\Sigma} = \mathrm{diag}\{\sigma_{x_1}, \ldots, \sigma_{x_m}\}$. Then the sample covariance matrix of $\bar{\boldsymbol{X}}$ in each sliding window can be represented by

$$\boldsymbol{C} = \frac{1}{w}\boldsymbol{\Sigma}^{-1}\left(\boldsymbol{X}^{*\mathrm{T}}\boldsymbol{X}^* + \boldsymbol{\xi}\boldsymbol{f}^{\mathrm{T}}\boldsymbol{X}^* + \boldsymbol{X}^{*\mathrm{T}}\boldsymbol{f}\boldsymbol{\xi}^{\mathrm{T}} + \boldsymbol{\xi}\boldsymbol{f}^{\mathrm{T}}\boldsymbol{f}\boldsymbol{\xi}^{\mathrm{T}}\right)\boldsymbol{\Sigma}^{-1}.$$