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A process monitoring method based on noisy independent component analysis ☆

Lianfang Cai [a], Xuemin Tian [a], Sheng Chen [b,c,*]

[a] College of Information and Control Engineering, China University of Petroleum, Qingdao 266580, China
[b] Electronics and Computer Science, University of Southampton, Southampton SO17 1BJ, UK
[c] Faculty of Engineering, King Abdulaziz University, Jeddah 21589, Saudi Arabia

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ABSTRACT

Independent component analysis (ICA) is an effective feature extraction tool for process monitoring. However, the conventional ICA-based process monitoring methods usually adopt noise-free ICA models and thus may perform unsatisfactorily under the adverse effects of the measurement noise. In this paper, a process monitoring method using a new noisy independent component analysis, referred to as NoisyICAn, is proposed. Using the noisy ICA model which considers the measurement noise explicitly, a NoisyICAn algorithm is developed to estimate the mixing matrix by setting up a series of the fourth-order cumulant matrices of the measured data and performing the joint diagonalization of these matrices. The kurtosis relationships of the independent components and measured variables are subsequently obtained based on the estimated mixing matrix, for recursively estimating the kurtosis of independent components. Two monitoring statistics are then built to detect process faults using the obtained recursive estimate of the independent components' kurtosis. The simulation studies are carried out on a simple three-variable system and a continuous stirred tank reactor system, and the results obtained demonstrate that the proposed NoisyICAn-based monitoring method outperforms the conventional noise-free ICA-based monitoring methods as well as the benchmark monitoring methods based on the existing noisy ICA schemes adopted from blind source separation, in terms of the fault detection time and local fault detection rate.

1. Introduction

Efficient and reliable process monitoring plays an extremely important role in ensuring plant safety and product quality. As a large number of process variables are measured in industrial processes, multivariate statistical process monitoring (MSPM) approaches have attracted great attentions from both academic researchers and process engineers [1–3]. Among them, principal component analysis (PCA) is a classical method that has been widely studied in the process monitoring field [4–6]. Classical PCA can handle high-dimensional and highly correlated data by projecting them onto a low-dimensional subspace that contains the most variance of the measured data. However, PCA only considers up to the second-order statistics of the measured data to extract uncorrelated latent variables, and it lacks the ability to provide higher-order representations for the measured data [7]. Moreover, in PCA-based monitoring methods, the control limits of Hotelling's T-squared and the companion squared prediction error (SPE) statistics are determined based on the assumption that the extracted latent variables follow a multivariate Gaussian distribution. However, industrial data often obey non-Gaussian distributions, for which PCA-based monitoring methods are ill-suited [8]. More recently, a MSPM method, known as independent component analysis (ICA), has emerged as a powerful tool in process monitoring. It originates from the blind source separation problem and has found wide-ranging applications in many areas, including signal processing, telecommunications, and audio signal separation [9]. Different from PCA, ICA takes into account the higher-order statistics in recovering the mutually independent latent variables, called independent components (ICs), from the measured variables. The specified merits of ICA endow it with the ability to reveal more useful information from the measured data than PCA [10].

Because of its favorable performance in information extraction, many researchers have implemented ICA for monitoring process behaviours. Kano et al. [11] directly monitored the ICs obtained from an ICA algorithm and demonstrated the superiority of ICA

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* Corresponding author at: Electronics and Computer Science, University of Southampton, Southampton SO17 1BJ, UK.
E-mail addresses: cailianfang@163.com (L. Cai), tianxm@upc.edu.cn (X. Tian), sqc@ecs.soton.ac.uk (S. Chen).

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over PCA. However, in the method of [11], the number of monitoring charts increases with the number of ICs, which increases the computational burden on process monitoring. Lee et al. [12] proposed three Mahalanobis-type monitoring statistics based on the extracted ICs to alleviate the onerous monitoring task of ICs' charts. In the work [13], a local outlier factor method was adopted to build a density-based monitoring statistic based on the obtained ICs, and it was demonstrated that this approach achieves better monitoring performance than the Mahalanobis-type monitoring statistics. The authors of [14] proposed a particle swarm optimization assisted ICA method for process monitoring, which avoids the local minimum solution problem associated with the gradient based FastICA algorithm [15]. In the light of the important influence of the ICs' order on the monitoring performance, Wang et al. [16] sorted the ICs according to the minimum mean square prediction error criterion. The authors of [17] developed a state-space ICA algorithm for process monitoring to take into consideration both the auto-correlation and cross-correlation of the measured data. Based on the fact that the standard kernel density estimation method used for determining the control limit does not perform well with the calculated ICA based monitoring statistic which is usually correlated, Hsu et al. [18] adopted the support vector machine (SVM) to build a two-class classifier for fault detection with the ICA based monitoring statistic as the classifier's input. Since some of the latent variables may be Gaussian, Liu et al. [19] adopted PCA to obtain the Gaussian and non-Gaussian latent variables and then applied ICA to extract the non-Gaussian ICs from the retained principal components. To further account for the process's nonlinear behaviours, the author of [20] integrated the Kernel ICA with Kernel PCA to extract both the non-Gaussian feature information and Gaussian feature information for fault detection. Tian et al. [21] considered the nonlinear characteristics of batch processes and proposed a multiway kernel ICA monitoring method based on feature samples. Cai et al. [22] integrated the kernel ICA and local preserving projection (LPP) for nonlinear continuous process monitoring by taking into account both non-Gaussian information extraction and local neighborhood information preservation. In order to characterize the shifting modes and process uncertainty, Rashid and Yu [23] proposed a hidden Markov model based adaptive ICA approach for multimodal process monitoring. Taking both the multimodality and nonlinearity of processes into account, Zhang et al. [24] proposed a nonlinear multimode process monitoring method based on the Kronecker product and modified kernel ICA.

In all the above studies, ICA is utilized as an effective feature extraction tool. However, the commonly used ICA algorithms in the existing process monitoring methods, such as the FastICA based on the maximum negentropy criterion [15], are basically "noise-free" algorithms. Specifically, these algorithms use noise-free ICA models, and they are not very effective to take into account ubiquitous measurement noise. In the ideal case where there exists no measurement noise in the measured data, a noise-free ICA algorithm can effectively estimate the mixing matrix or de-mixing matrix. Once the mixing matrix or de-mixing matrix is obtained, the ICs can be easily calculated for process monitoring. As pointed out by Wang [25], however, the noise corruption always exists in industrial processes. When the measured data are corrupted by the measurement noise, the ICs may not be directly calculated because of the adverse effects of the measurement noise. Specifically, under the adverse disturbance of the measurement noise, the extracted ICs by a noise-free ICA algorithm may not represent the process operation information adequately and, consequently, they may result in unsatisfactory monitoring performance. Currently, in some other fields, such as the blind source separation, there exist some ICA algorithms which can explicitly consider the measurement noise. Specifically, Cichocki et al. [26] extended the existing adaptive algorithm with equivalent properties to reduce the bias in the de-mixing matrix caused by measurement noise and developed a recurrent dynamic neural network for estimating the unknown mixing matrix. The author of [27] proposed a contrast function based on Gaussian moments and developed a modified FastICA algorithm to estimate the mixing matrix. Cao et al. [28] proposed a robust prewhitening technique for reducing the effect of noise and a parametrized t-distribution density model which was combined with the light-tailed distribution model for estimating the mixing matrix. Liu et al. [29] explicitly considered the effect of noise by using the criterion of minimizing the normalized mean square prediction error to conduct the mixing matrix estimation. Yang and Guo [30] derived two new Gaussian moments algorithms for estimating the mixing matrix by combining Gaussian moments and likelihood estimation based on the assumption that independent components are the time signals. The authors of [31] combined the recursive least squares adaptive noise cancellation via QR decomposition and the FastICA to reduce the bias in the estimation of mixing matrix. Nevertheless, these "noisy" ICA algorithms were not introduced for the process monitoring purpose. The main reason lies in the fact that these "noisy" ICA algorithms usually require some strict assumptions, such as that the covariance matrix of the noise is a diagonal matrix with the identical diagonal elements or has been obtained by prior knowledge, which may not be satisfied in real industrial processes. Therefore, developing an appropriate "noisy" ICA algorithm which can effectively remove or alleviate the effects of the measurement noise is of great significance for improving the process monitoring performance. More specifically, how to obtain the ICs or ICs-related statistics that are resistant or robust to the measurement noise based on the estimated mixing matrix is an urgent problem to solve for process monitoring.

Motivated by the above analysis, in this contribution, a process monitoring method is proposed based on a new noisy independent component analysis, referred to as the NoisyICAn. First, we consider the measurement noise explicitly in the noisy ICA model, and develop the NoisyICAn algorithm, which does not need the knowledge of the noise's covariance matrix, to estimate the mixing matrix by building a series of the fourth-order cumulant matrices of the measured data and carrying out the joint diagonalization of these matrices with the least-squares based non-orthogonal joint diagonalization algorithm [32]. Furthermore, the estimated mixing matrix is adopted to establish the kurtosis relationships of the ICs and the measured variables, and an effective approach for recursively estimating the kurtosis of ICs is constructed. This further reduces the effect of the noise. Then, two monitoring statistics, the I^2 and SPE statistics, are built using the obtained recursive estimate of ICs' kurtosis to conduct process monitoring. Unlike the existing "noisy" ICA algorithms, such as the two algorithms given in [27,29], respectively, our proposed NoisyICAn algorithm does not require the information of the noise's covariance matrix and thus it can be applied more easily and conveniently to monitor actual industrial processes. In our extensive simulation study involving a simple three-variable system and a continuous stirred tank reactor system, we compare our proposed NoisyICAn-based monitoring method with the four benchmark schemes, the conventional noise-free FastICA-based monitoring method [12] and the kernel FastICA-based monitoring scheme [20,21] as well as the two monitoring methods based on the existing noisy ICA schemes of [27,29], referred to as the NoisyICA1 and NoisyICA2, respectively. The results obtained demonstrate that the proposed NoisyICAn-based monitoring method outperforms the other four benchmark methods in terms of the fault detection time and fault detection rate.

The remainder of the paper is organized as follows. In Section 2, the conventional ICA-based monitoring methods are briefly reviewed.