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A new fault detection method for non-Gaussian process based on robust independent component analysis

*Lianfang Cai, Xuemin Tian**

College of Information and Control Engineering, China University of Petroleum, Qingdao 266580, China

ABSTRACT

Conventional fault detection method based on fast independent component analysis (FastICA) is sensitive to outliers in the modeling data and thus may perform poorly under the adverse effects of outliers. To solve such problem, a new fault detection method for non-Gaussian process based on robust independent component analysis (RobustICA) is proposed in this paper. A RobustICA algorithm which can effectively reduce the effects of outliers is firstly developed to estimate the mixing matrix and extract non-Gaussian feature called independent components (ICs) by robust whitening and robust determination of the maximum non-Gaussian directions. Furthermore, a monitoring statistic for each extracted IC is constructed to detect process faults. Simulations on a simple example of the mixing matrix estimation and a fault detection example in the continuous stirred tank reactor system demonstrate that the RobustICA achieves much higher estimation accuracy for the mixing matrix and the ICs than the commonly used FastICA algorithm, and the RobustICA-based fault detection method outperforms the conventional FastICA-based fault detection method in terms of the fault detection time and fault detection rate.

Keywords: Fault detection; Non-Gaussian process; Independent component analysis; Mixing matrix; Robust whitening; Outliers

1. Introduction

As industrial processes become more and more complex, timely fault detection is extremely important for ensuring plant safety and improving product quality. With a large number of variables measured by sensors, multivariate statistical process monitoring (MSPM) approaches (BinShams et al., 2011; Ge and Song, 2013; Hu et al., 2013; Stubbs et al., 2012; Wang et al., 2012; Yu, 2011) have been developed rapidly in recent years to extract useful information from massive process data and to detect various process faults. Among them, principal component analysis (PCA) based MSPM methods are the most classic kind (Deng and Tian, 2013). PCA projects the correlated process variables into a smaller set of the uncorrelated latent variables called principal components (PCs) that retain most of the original variance, and many improved versions have been developed including local and global PCA (Yu, 2012b), multiscale kernel PCA (Zhang and Ma, 2011), dynamic kernel PCA (Jia et al., 2010), variable window adaptive kernel PCA (Khediri et al., 2011) and so on. Although PCA and its extended methods have been widely applied in the fault detection field, these methods can only consider up to the second-order variance-covariance statistic and cannot take advantage of the higher-order statistical information of process data (Lee et al., 2006), which may result in the inadequate feature extraction and degraded fault detection performance. Furthermore, these methods need to make the strict assumption that the extracted PCs follow a multivariate Gaussian distribution in order to determine the control limits of Hotelling's T^2 and the corresponding SPE monitoring statistics. In reality, the industrial process information is usually represented by fewer non-Gaussian latent variables (Yu, 2012a). The inconsistency between the assumption and the realistic industrial situations may make the estimated control limits improper and unreliable. As a result, the false alarm rate or missed alarm rate may be high and the fault indication may be misleading.

* *Corresponding author*. Tel.: +86 532 86983467.
E-mail addresses: tianxm_upc@hotmail.com, tianxm@upc.edu.cn (X. Tian).

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More recently, a newly emerging multivariate statistical method, known as independent component analysis (ICA), has drawn much attention from both the process engineers and academic researchers. ICA is originally derived for solving the blind source separation problem and has found wide-ranging applications in the field of telecommunications, audio signal separation, etc. Different from PCA, ICA can further make use of the higher-order statistic (Hyvärinen and Oja, 2000) or the second-order time-delayed covariance statistic (Cai et al., 2012b) to extract mutually independent non-Gaussian latent variables called independent components (ICs) from the original process variables, and can be looked upon as a useful extension of PCA. Therefore, ICA is especially suitable for fault detection on non-Gaussian processes which are more practical in the real-world manufacturing environment. Currently, some criterions have been put forward to develop various ICA algorithms and these criterions include the maximization of measures of non-Gaussianity such as kurtosis or negentropy, the minimization of mutual information and maximum likelihood estimation, etc. (Hyvärinen and Oja, 2000). Among the numerous ICA algorithms, the fast ICA (FastICA) algorithm (Hyvärinen and Oja, 2000) based on the maximum negentropy criterion is commonly adopted in the ICA-based fault detection methods for the reason that negentropy is a more direct and effective measure of non-Gaussianity, and the FastICA has a fast convergence rate and is computationally much less complex than a large part of the existing ICA algorithms (Tian et al., 2009). Kano et al. (2003) developed a univariate statistical process monitoring (USPM) method based on the FastICA which firstly utilized the FastICA to extract non-Gaussian ICs from process data and then monitored each extracted IC by using the average run length (ARL) index, and demonstrated its superior fault detection performance over the PCA-based MSPM method. On the basis of the ICs extracted by the FastICA, Lee et al. (2004) further developed an MSPM method by constructing three monitoring statistics I^2, I_e^2 and SPE, and employing the kernel density estimation (KDE) technique to determine the confidence limits. Hsu et al. (2010) argued that the use of the elliptical type monitoring statistics I^2, I_e^2 and SPE may not appropriately capture the characteristics of the extracted ICs because of the ICs' skewed distributions, and thus developed a rectangular type monitoring statistic named adjusted outlyingness (AO) to monitor non-Gaussian processes. Lee et al. (2011) analyzed the limitation of both the elliptical and rectangular monitoring statistics that these monitoring statistics may not accurately estimate the nonlinear feature space boundary of normal operating condition (NOC) and introduced a local outlier factor method to construct a monitoring statistic which can determine the nonlinear decision boundary along with NOC. In addition, taking different process characteristics into consideration, researchers have proposed various improved MSPM methods based on the FastICA. Stefatos and Hamza (2010) developed a dynamic independent component analysis (DICA) method for capturing dynamic pattern of non-Gaussian processes by augmenting original process data with previous observations and applying the FastICA to extract the ICs from the augmented data. Odiowei and Cao (2010) integrated canonical variate analysis (CVA) with ICA and developed a state-space ICA method for dynamic process fault detection. Tian et al. (2009) proposed a multiway kernel FastICA based on feature samples for monitoring nonlinear batch processes. Cai et al. (2012a) proposed a nonlinear process fault detection method by integrating kernel FastICA with a recently developed manifold learning method named locality preserving projections (LPP). To account for the multimodal characteristic of non-Gaussian processes, Zhang et al. (2013) developed a multimodal process fault detection method based on the Kronecker product and modified kernel FastICA. Rashid and Yu (2012) proposed a hidden Markov model based adaptive ICA approach for monitoring non-Gaussian processes with multimodality. In these studies, the FastICA has been used as a promising approach to extract non-Gaussian ICs feature for fault detection. However, the widely used FastICA cannot explicitly consider the influences of outliers and thus is vulnerable to outliers (Ollila, 2010). In fact, outliers always exist in industrial process data (Moller et al., 2005) because of the sensor faults, occasional fluctuations or other reasons. Under the adverse effects of outliers, the FastICA may not conduct non-Gaussian feature extraction effectively and reliably, and the performances of the FastICA-based fault detection methods may decline drastically. One usual practice for solving this problem is to remove outliers by preprocessing process data and then apply the FastICA to the preprocessed data (Hsu et al., 2010; Lee et al., 2011). But preprocessing of data is not always a good idea since it may destroy the correlation structure of multivariate data and may result in the loss of information (Wang and Romagnoli, 2005). Consequently, to develop a robust ICA algorithm which can eliminate or attenuate the effects of outliers without preprocessing of process data is extremely important for enhancing the performances of feature extraction and fault detection.

Motivated by the above analysis, a new fault detection method for non-Gaussian processes based on robust ICA (RobustICA) is proposed in this paper. The robust estimation of process data's covariance matrix is obtained by a minimum covariance determinant estimator and is then applied to conduct robust whitening of process data. A minimum entropy criterion is constructed based on the traditional maximum negentropy criterion and a robust entropy estimator is employed to estimate the entropy statistic. The particle swarm optimization algorithm (Trelea, 2003) is adopted to globally optimize the established criterion for determining the maximum non-Gaussian directions. A RobustICA algorithm is thus developed to estimate the mixing matrix and extract the non-Gaussian ICs feature. Subsequently, a monitoring statistic for each extracted IC is built to conduct fault detection. Two case studies including the mixing matrix estimation and the fault detection in the continuous stirred tank reactor system are used to demonstrate the effectiveness of the proposed method.

The remainder of this paper is organized as follows. In Section 2, the conventional FastICA-based fault detection method is briefly reviewed. Then, our proposed fault detection method based on RobustICA is formulated in detail in Section 3. The simulation results are shown in Section 4. Finally, our conclusions are drawn in section 5.

2. The conventional FastICA-based fault detection method

The conventional FastICA-based fault detection method contains two steps: the first step is using the FastICA to estimate the mixing matrix and the ICs feature; the second step is building monitoring statistics.

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