Neurocomputing 200 (2016) 70–79

Contents lists available at ScienceDirect

Neurocomputing

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

Fault detection of multimode non-Gaussian dynamic process using dynamic Bayesian independent component analysis

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ARTICLE INFO

Article history:
Received 25 May 2015
Received in revised form
12 March 2016
Accepted 15 March 2016
Available online 29 March 2016

Keywords:
Multimode process
Dynamic data
Independent component analysis
Bayesian inference
Probability mixture model

ABSTRACT

Independent component analysis (ICA) has been widely used in non-Gaussian multivariate process monitoring. However, it assumes only one normal operation mode and omits the dynamic characteristic of process data. In order to overcome the shortcomings of traditional ICA based fault detection method, an improved ICA method, referred to as dynamic Bayesian independent component analysis (DBICA), is proposed to monitor the multimode non-Gaussian dynamic process. In this method, matrix dynamic augmentation is applied to extract dynamic information from original data. Then for analyzing multimode non-Gaussian data, Bayesian inference and ICA are combined to establish a probability mixture model. The ICA model parameters are obtained by the iterative optimization algorithm and the mode of each observation is determined by Bayesian inference simultaneously. Lastly case studies on one continuous stirring tank reactor (CSTR) simulation system and the Tennessee Eastman (TE) benchmark process are used to demonstrate the effectiveness of the proposed method.

1. Introduction

With rapid development of modern industries, fault diagnosis technology shows its great importance in ensuring process safety and improving production quality [1–3]. In recent decades, data-driven fault diagnosis technology has attracted the increasing attention from researchers and engineers because abundant data is collected and stored in industrial process database. Data-driven fault diagnosis method is often referred to as multivariate statistical process monitoring (MSPM) method, which monitors process status by extracting the intrinsic features from the high-dimension dataset. The most common feature extraction tools in MSPM include principal component analysis (PCA), partial least square (PLS) and independent component analysis (ICA) [4–7].

For PCA and PLS based fault detection and diagnosis methods, process data is assumed to be with the Gaussian distribution. However, the non-Gaussian characteristic is usually found in real industrial data. To deal with this problem, researchers have developed ICA based process monitoring methods, which are able to compute the statistically independent components from non-Gaussian data. Li et al. [8] applied ICA to reduce the dimension of monitored dynamic signals by obtaining some independent latent variables and Kano et al. [9] proposed to monitor the independent components for fault detection. For comprehensive monitoring of multivariable process, Lee et al. [10] built three monitoring statistics to judge process status. In order to mine the features from nonlinear system data, kernel ICA was proposed to compute nonlinear independent components for fault diagnosis [11,12]. For coping with dynamic characteristic of process variables, dynamic ICA method was presented to analyze the variable auto-correlation by augmenting the observed data matrix [13,14]. Aiming at batch process monitoring, Guo and Li [15] and Tian et al. [16] developed different multi-way independent component analysis methods. To distinguish the importance of each independent component, weighted independent component analysis (WICA) was proposed by examining the changings of all independent components [17]. In order to reduce the influence of measurement noise, noise-resistant joint diagonalization ICA was built by Tian et al. [18].

All the aforementioned ICA methods assume only one normal operation mode for process monitoring. However, due to the factors such as season alternant, equipment aging and raw materials changing, multiple operation modes have been usually implemented in real industrial operations. The conventional single mode MSPM methods may not provide the best monitoring performance for multimode processes. The early work of multimode process fault detection was performed by improving PCA and PLS methods. Multi-PCA and multi-PLS based monitoring approaches were developed by Zhao et al. [19,20], which firstly implement data clustering and then construct multiple models for different operating conditions. Tong et al. [21] proposed a mode unfolding strategy to update models online adaptively. Ma et al. [22] presented a novel local neighborhood standardization (LNS) strategy

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http://dx.doi.org/10.1016/j.neucom.2016.03.015
0925-2312/

to make multimode data obey similar distribution. By using Gaussian mixture model for multimode data analysis, researchers proposed the mixture PCA [23] and mixture PLS [24] methods. In recent years, some multimode ICA methods have been developed. Ge et al. [25] applied a fuzzy C-mean method for mode clustering and built an ICA-PCA model for each mode. Zhu et al. [26] built a k-ICA-PCA modeling method by combing an ensemble clustering strategy. Rashid et al. [27] used the hidden Markov model to describe the multiple modes and then built local ICA models.

To sum up, some of the present methods [19–24] can deal with multimode data but do not consider the non-Gaussian and dynamic characteristics. Other methods [25–27] utilized ICA for handling multimode non-Gaussian data, but data clustering and statistical modeling are treated as two separated stages, which may degrade the monitoring performance. Therefore, it is necessary to build a compact fault detection method, which is able to deal with dynamic, multimode and non-Gaussian characteristics simultaneously and integrate data clustering and statistical modeling together. In recent studies, a new ICA model, called as ICA mixture model has been proposed [28,29] to execute data clustering and statistical modeling simultaneously, which provides a new means for multimode non-Gaussian data analysis.

Motivated by the above analysis, a new method called dynamic Bayesian independent component analysis (DBICA) is proposed for monitoring multimode dynamic industrial process with non-Gaussian distribution. The main contributions of the proposed method include the following two points: (1) Bayesian ICA model is built to describe multimode non-Gaussian data. It is capable of executing data clustering and statistical modeling simultaneously while many other methods need to implement preliminary clustering step. (2) Considering the auto-correlation between measurements, dynamic matrix augmentation is applied to build a dynamic multimode monitoring method.

The remainder of this paper is organized as follows. ICA based fault detection method is reviewed in Section 2. Dynamic ICA method is explained in Section 3. Then, Section 4 gives a detailed description about DBICA method. Section 5 lists the DBICA based process monitoring procedure. Two case studies on one continuous stirring tank reactor (CSTR) process and the Tennessee Eastman (TE) chemical process are given to verify the proposed method in Section 6. Finally, the conclusions of this work are drawn in Section 7.

2. ICA method

ICA is a well-known tool for non-Gaussian data analysis, which is able to extract the intrinsic features hidden in high-dimensional data. For one given training dataset $\boldsymbol{X} \in \boldsymbol{R}^{m \times n}$ with n samples of m variables, ICA assumes that it is the linear combinations of m unknown independent components $\boldsymbol{S} \in \boldsymbol{R}^{m \times n}$, which can be expressed as

$$\boldsymbol{X} = \boldsymbol{A}\boldsymbol{S} \tag{1}$$

where $\boldsymbol{A} \in \boldsymbol{R}^{m \times m}$ is the mixing matrix.

The objective of ICA is to estimate the mixing matrix $\boldsymbol{A}$ and the independent components $\boldsymbol{S}$ from the training matrix $\boldsymbol{X}$, simultaneously. Usually, ICA algorithm finds a demixing matrix $\boldsymbol{W}$ to reconstruct the independent components $\hat{\boldsymbol{S}}$ given by

$$\hat{\boldsymbol{S}} = \boldsymbol{W}\boldsymbol{X} \tag{2}$$

such that $\hat{\boldsymbol{S}}$ becomes as independent as possible.

There are many optimization algorithms to solve the above problem. In this paper, we use the FastICA algorithm proposed by Hyvärinen [30], which is a simple and efficient fixed-point ICA algorithm. In FastICA algorithm, whitening transformation is firstly performed to eliminate the correlation among variables, which is formulated as

$$\boldsymbol{Z} = \boldsymbol{Q}\boldsymbol{X} \tag{3}$$

where the sphering matrix $\boldsymbol{Q} = \boldsymbol{\Lambda}^{-1/2}\boldsymbol{U}^{\mathrm{T}}$ could be obtained by the eigen-decomposition of the covariance matrix

$$\frac{1}{n-1}\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}} = \boldsymbol{U}\boldsymbol{\Lambda}\boldsymbol{U}^{\mathrm{T}} \tag{4}$$

where $\boldsymbol{\Lambda}$ is the diagonal matrix of eigenvalues and $\boldsymbol{U}$ is the eigenvector matrix.

Then based on the whitened matrix $\boldsymbol{Z}$, the independent components are computed as

$$\hat{\boldsymbol{S}} = \boldsymbol{B}^{\mathrm{T}}\boldsymbol{Z} \tag{5}$$

where $\boldsymbol{B}$ is an orthogonal matrix solved by FastICA algorithm. More details about FastICA can be seen in the related papers [30,31].

By combining Eqs. (2), (3) and (5), the independent components are expressed as

$$\hat{\boldsymbol{S}} = \boldsymbol{B}^{\mathrm{T}}\boldsymbol{Q}\boldsymbol{X} = \boldsymbol{W}\boldsymbol{X} \tag{6}$$

where the relation between $\boldsymbol{B}$ and $\boldsymbol{W}$ can be easily obtained as

$$\boldsymbol{W} = \boldsymbol{B}^{\mathrm{T}}\boldsymbol{Q} \tag{7}$$

For a test vector $\boldsymbol{x}$, the dominant independent components are computed by

$$\hat{\boldsymbol{s}}_d = \boldsymbol{W}_d\boldsymbol{x} \tag{8}$$

where $\boldsymbol{W}_d$ is a reduced matrix including the first d rows of $\boldsymbol{W}$ which are sorted by the Euclidean norm of each row.

Furthermore, a reconstructed vector $\hat{\boldsymbol{x}}$ is calculated by [14]

$$\hat{\boldsymbol{x}} = \boldsymbol{Q}^{-1}\boldsymbol{B}_d\hat{\boldsymbol{s}}_d = \boldsymbol{Q}^{-1}\boldsymbol{B}_d\boldsymbol{W}_d\boldsymbol{x} \tag{9}$$

where the reduced matrix $\boldsymbol{B}_d$ can be established by $\boldsymbol{B}_d = (\boldsymbol{W}_d\boldsymbol{Q}^{-1})^{\mathrm{T}}$.

For fault detection and process monitoring, two types of monitoring statistics I^2 and SPE are constructed, which are given by

$$I^2 = \hat{\boldsymbol{s}}_d^{\mathrm{T}}\hat{\boldsymbol{s}}_d \tag{10}$$

$$SPE = \boldsymbol{e}^{\mathrm{T}}\boldsymbol{e} = (\boldsymbol{x} - \hat{\boldsymbol{x}})^{\mathrm{T}}(\boldsymbol{x} - \hat{\boldsymbol{x}}) \tag{11}$$

To determine the control limits of monitoring statistics I^2 and SPE, the kernel density estimation method [10,32] is applied in this article. Firstly the monitoring statistics I^2 and SPE in normal operating condition are calculated by Eqs. (10) and (11). Then the univariate kernel density estimation is used to obtain the density functions of the normal statistics I^2 and SPE. Finally, the 95% confidence limit of each statistic can be obtained by finding the value which occupies the 95% area of its density function. If one of two statistics exceeds the confidence limit, a fault signal is triggered.

3. Dynamic ICA method

The basic ICA method supposes that the observed variables are time-independent. That is to say, ICA omits the auto-correlation feature of observed variables. However, as the measured values of real process variables describe the process dynamic behavior, there are often auto-correlation characteristic in the time series of observed variables.

To deal with the process dynamic property, data matrix augmentation technique was proposed by Ku et al. [33]. By this technique, each observed vector is augmented with the previous τ measurements. The original observed matrix $\boldsymbol{X} = [\boldsymbol{x}(1)\boldsymbol{x}(2)\cdots\boldsymbol{x}(n)]$