ARTICLE IN PRESS

Information Sciences xxx (2014) xxx–xxx

Contents lists available at ScienceDirect

Information Sciences

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

Modeling and monitoring of multimode transition process based on reconstruction

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ARTICLE INFO

Article history:
Received 9 September 2012
Received in revised form 12 March 2014
Accepted 19 March 2014
Available online xxxx

Keywords:
Nonlinear reconstruction
Batch process
Fault direction

ABSTRACT

In this paper, a new nonlinear reconstruction algorithm is proposed for handling the multimode problem in the industrial processes. The contributions are as follows: (1) in different batch cycles, the transition patterns may follow different trajectories and reveal different characteristics. After the operation patterns change, the two neighboring modes still share some common correlations; (2) nonlinear reconstruction model is built based on traditional characteristics; and (3) a new fault direction matrix is designed to modify the reconstruction equation. The corresponding confidence regions are constructed according to their models respectively. The effectiveness of the proposed method has been demonstrated via simulated examples.

1. Introduction

Batch processes are widely used in various industries, such as chemical, pharmaceutical and food industry. The batch process monitoring has become a key issue. Many approaches have been proposed to ensure the safety of equipment operation and quality of product, [11,14,17,22]. Recently, multivariate statistical process control (MSPC) has been extensively studied [1,5,6,8,10,21,24].

The conventional fault diagnostic methods [2,4,10–13,16,18–23] usually focus on the single mode or several stable modes, ignoring the dynamic transition between different modes which represent the operation states of industrial process. The monitoring of transition process has become increasingly important. Recently, the transition process between two different modes has been investigated for improving identification accuracy. Based on the Gaussian model, GMM (Gaussian Mixture Models) was used to represent the transition process in a more accurate way [24]. But the GMM is sensitive to noise pollution and suffers high rate of false alarm when the clustering of multimode data gets over-lapped. By defining class radius and kernel radius, the ambiguous mode boundary was obtained [7]. The k-mean clustering algorithm was modified to solve this problem. However it is difficult to follow the irregular dynamics [15]. In fact, the models of transition processes are identified by the relationships between the transition processes and their two neighboring modes. When the batch processes are changed, the transition models are changed correspondingly. The GMM and clustering approaches are difficult to capture the dynamic behavior of the transition process effectively.

Alcala and Qin have proposed the linear reconstruction algorithm [3] which is an effective method for the dynamic process, though it only deals with linear dynamics. Zhang and Dudzic [25] designed an online monitoring system using multivariate statistical technologies for continuous steel casting process. The MPCA-based monitoring scheme was applied

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http://dx.doi.org/10.1016/j.ins.2014.03.111
0020-0255/

to monitor the transitional operation. Zhao and Yao proposed an online monitoring method for multimode processes with between-mode transitions for linear processes. Dunia and Qin [9] have proposed the reconstruction-based contribution (RBC) approach for process monitoring, which was proved to be an effective method fault, the rigorous diagnose analysis for the traditional contributions was presented to show the proposed reconstruction-based contribution method was better than the traditional contribution plot method. In this paper, the monitoring algorithm of nonlinear multimode transition process is proposed.

The rest of the paper is organized as follows: The original reconstructed method is introduced in Section 2. The modified reconstructed method is proposed to monitor the nonlinear transition processes in Section 3. A practical application is used to illustrate the effectiveness in Section 4. The conclusions are given in the final section.

2. Reconstructed method

In a multimode system, there usually is dynamic transition process between the switches of two different modes in addition to the stable modes. Hence the fault diagnosis algorithm must distinguish the transition process from the real faults. The reconstruction-based method which is an effective way to deal with dynamic problem has been proposed [2]. In the reconstruction algorithm, the fault direction is important because it affects the constitution of the dynamic factor. The fault detection depends on the understanding of the practical process but the general demand is that the fault direction should contain more fault information and can be used to identify the fault variables. In addition, the fault detection should also make the problem solvable.

In a system with n sensors, when a fault happens in sensor $\boldsymbol{x}_i$, the faulty measurement is $\boldsymbol{x} \in R^n$ and the assumptive direction of the fault is ξ_i, the linear reconstruction is

$$\boldsymbol{z}_i = \boldsymbol{x} - \xi_i f_i \tag{1}$$

where f_i is a coefficient vector, $\boldsymbol{z}_i$ is the reconstructed sample vector. The fault detection index is defined as follows

$$Index(\boldsymbol{z}_i) = \boldsymbol{z}_i^T M \boldsymbol{z}_i = \|\boldsymbol{z}_i\|_M^2 = \|\boldsymbol{x} - \xi_i f_i\|_M^2 \tag{2}$$

where $M = \widetilde{C}/\sigma^2 + D/\tau^2$. SPE is the squared prediction error. T^2 is the Hotelling statistic. σ^2 and τ^2 are the confidence limits of SPE and T^2, respectively. φ is a combining index. $P \in R^{n\times l}$ and $\widetilde{P} \in R^{n\times(n-l)}$ are the principle and residual loadings. l is the number of principle components. n is the number of samples. $\widetilde{C} = \widetilde{P}\widetilde{P}^T$ and $D = P\Lambda^{-1}P^T$. After consider the derivative of $Index(\boldsymbol{z}_i)$, we obtain

$$\frac{d(Index(\boldsymbol{z}_i))}{df_i} = -2(\boldsymbol{x} - \xi_i f_i)^T M \xi_i \tag{3}$$

From Eq. (3), we obtain

$$f_i = (\xi_i^T M \xi_i)^{-1} \xi_i^T M \boldsymbol{x} \tag{4}$$

The reconstruction-based contribution of variable $\boldsymbol{x}_i$ to the fault detection index, RBC_i^{Index}, is the amount of reconstruction along the direction ξ_i which can be expressed as

$$RBC_i^{Index} = \|\xi_i f_i\|_M^2 \tag{5}$$

From Eq. (5), we can obtain

$$RBC_i^{Index} = \left\|\xi_i(\xi_i^T M \xi_i)^{-1} \xi_i^T M \boldsymbol{x}\right\|_M^2 = \boldsymbol{x}^T M \xi_i (\xi_i^T M \xi_i)^{-1} \xi_i^T M \boldsymbol{x} \tag{6}$$

Eq. (6) represents the reconstruction-based contribution, RBC_i^{Index} represents the contribution of the variable $\boldsymbol{x}_i$ to the fault detection index of interest.

The reconstructed index, $Index(\boldsymbol{z}_i)$, is obtained by submitting the value of f_i into Eq. (2), which can be simplified as follows,

$$Index(\boldsymbol{z}_i) = \boldsymbol{x}^T M \left[I - \xi_i (\xi_i^T M \xi_i)^{-1} \xi_i^T M\right] \boldsymbol{x} = \boldsymbol{x}^T M \boldsymbol{x} - \boldsymbol{x}^T M \xi_i (\xi_i^T M \xi_I)^{-1} \xi_i^T M \boldsymbol{x} = Index(\boldsymbol{x}) - RBC_i^{Index} \tag{7}$$

Therefore,

$$Index(\boldsymbol{x}) = Index(\boldsymbol{z}_i) + RBC_i^{Index} \tag{8}$$

The reconstruction-based contribution method is a good way to deal with the dynamic problems. However, it cannot be applied to the nonlinear dynamic process.