Journal of Process Control 40 (2016) 119–133

Contents lists available at ScienceDirect

Journal of Process Control

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

Robust dynamic process monitoring based on sparse representation preserving embedding

Zhibo Xiao [a], Huangang Wang [a,*], Junwu Zhou [b]

[a] Institute of Control Theory and Technology, Department of Automation, Tsinghua University, Beijing 100084, China
[b] State Key Laboratory of Process Automation in Mining & Metallurgy, Beijing 100160, China

ARTICLE INFO

Article history:
Received 11 March 2015
Received in revised form 16 January 2016
Accepted 25 January 2016
Available online 1 March 2016

Keywords:
Dynamic process monitoring
Robust fault detection
Manifold learning
Neighborhood preserving embedding
Robust sparse representation

ABSTRACT

In this paper, a novel dimensionality reduction technique, named sparse representation preserving embedding (SRPE), is proposed by utilizing the sparse reconstruction weights and noise-removed data recovered from robust sparse representation. And a new dynamic process monitoring scheme is designed based on SRPE. Different from traditional manifold learning methods, which construct an adjacency graph from K-nearest neighbors or ε-ball method, the SRPE algorithm constructs the adjacency graph by solving a robust sparse representation problem through convex optimization. The delicate dynamic relationships between samples are well captured in the sparse reconstructive weights and the error-free data are recovered at the same time. By preserving the sparse weights through linear projection in the clean data space, SRPE is very efficient in detecting dynamic faults and very robust to outliers. Finally, through the case studies of a dynamic numerical example and the Tennessee Eastman (TE) benchmark problem, the superiority of SRPE is verified.

1. Introduction

As an important technique to enhance process safety and to ensure product quality, process monitoring has received tremendous attention in both academia and industry during the last two decades [1–3]. In modern industrial systems, owing to the wide use of sensors and implementation of advanced computer and information technology, process data, which can be efficiently collected and stored at low costs, usually have high dimensions and reflect rich information about the process characteristics [2,4]. As a result, these process data can be utilized for process modeling and monitoring. Multivariate statistical process monitoring (MSPM) is one of the most popular data-driven techniques and has been widely applied in real industrial processes for its simplicity. Principal component analysis (PCA) and partial least squares (PLS) are two of the most widely used models in MSPM [5–7], both of which project high dimensional, highly correlated process data onto a low dimensional latent subspace to retain the most data variation through the first few principle components. In the low dimensional subspace, the global Euclidean structure of the data is preserved. However, PCA assumes that the process data are Gaussian distributed, which is seldom the case in real industry. When the Gaussian assumption is not met, the local geometrical structure of the original data set can be lost in the low dimensional subspace, and thus the monitoring performance will be deteriorated.

Besides, MSPM methods assume that the process variables are sampled statistically independently over time. However this assumption is only valid over long sampling intervals. Because of the closed-loop control systems in industrial processes, the process samples are temporally correlated. When a fault only influences the dynamic characteristics of the process, the monitoring performance will be seriously hampered. To extend the PCA application to dynamic process monitoring, Ku et al. proposed a time lagged version of PCA called dynamic PCA (DPCA) [8]. In the DPCA model, time lagged measurements are added to the data matrix and traditional PCA is performed on the augmented data. Although DPCA can handle dynamic process better than PCA, within the DPCA model the cross-correlation among variables and auto-correlation over time are mixed, making the model parameters overly large and making it difficult to interpret the dynamic relationships. Besides, the score variables of the DPCA model are auto-correlated. To remove this autocorrelation, the univariate ARMA filters were proposed [9]. Besides the DPCA method, there are also some attempts based on the subspace modeling [10,11]. These attempts mainly focused on the subspace identification methods, e.g. numerical subspace state space system identification (N4SID), error in variable (EIV) identification, and canonical variate analysis (CVA) [12–14]. In the CVA

* Corresponding author. Tel.: +86 10 62781993; fax: +86 10 62786911.
E-mail addresses: xzb13@mails.tsinghua.edu.cn (Z. Xiao), hgwang@tsinghua.edu.cn (H. Wang).

http://dx.doi.org/10.1016/j.jprocont.2016.01.009
0959-1524/

model, both the past information vectors and the future information vectors are defined. Afterwards, the dynamics are modeled by capturing the relationships between the two vectors. The CVA model can be calculated based on the singular value decomposition of the covariance matrix of the two vectors.

Last but not the least, all PCA-based methods are based on the L2-norm objective function, which is prone to the presence of outliers, because the effect of the outliers with a large magnitude is exaggerated by the use of the L2-norm [15–17]. In modern industry, due to the failure of instrument and experiment errors, outliers are inevitable in historical database and costly to detect manually. When a PCA model is trained from this corrupted data set, the monitoring performance will be far from satisfactory. Recently, a number of nonlinear manifold-learning based dimension reduction (DR) techniques have shown promising results and proven to extract more meaningful information than PCA, such as IsoMap [18], Local Linear Embedding (LLE) [19,20] and Laplacian eigenmap [21]. All of these methods construct the DR model based on a weighted adjacency graph. In this graph, each vertex represents a training sample and each weighted-edge linking two vertices represents some proximity measure between samples. The objective of these manifold learning methods is to maximally preserve the local geometric structure of the data hidden in the underlying adjacency graph after projection onto a low dimensional subspace. As these nonlinear methods are only defined on the training data set and they cannot explicitly give low dimensional representation for a novel test sample, in order to solve the out-of-sample problem there has been extensive work on linear approximation algorithms of these manifold-learning methods, such as neighborhood preserving embedding (NPE) [22], locality preserving projection (LPP) [23–26], and isometric projection [27]. Among these linear projection methods, NPE [28], LPP [29] and various improvement methods based on them [30–33] have been successfully applied to process monitoring and achieved some promising results. These manifold based projection methods can handle the nonlinear and non-Gaussian characteristics of process data better than PCA as they can preserve the local geometric structure of the process data which is totally lost for PCA. In order to deal with the dynamic process monitoring problem, Miao et al. [30] proposed a method to construct the adjacency graph based on a time window, which shows better results than NPE and traditional PCA-based methods.

However, these manifold based projection algorithms still depend on an adjacency graph. This adjacency graph is usually constructed by the K-nearest neighbors or the ε-ball method, where two samples link with each other if and only if they reside among each others K nearest neighbors or within the ball of Euclidean distance ε. The graph construction procedure heavily depends on pair-wise sample Euclidean distance and can be easily affected by noise and outliers which are very common in process data. This means that the graph structure obtained above can be invalid and fail to express the true underlying manifold and relationships between samples. DR models derived based on this graph thus fail to characterize the real process or to give reliable monitoring results. Besides, the parameter selection of the adjacency graph (K or ε) is an open problem, which can only be set according to experience. Once the parameter has been set, all the samples in the adjacency graph will have a fixed size neighborhood. But in reality, the process data may have diverse probability density in different areas of the feature space. The adjacency graph thus needs to offer a datam-adaptive neighborhood. All these drawbacks somewhat limit the application of manifold-learning methods in process monitoring.

Sparse representation (SR) is a recently proposed statistical modeling tool and has shown to be very powerful in various application areas [34,35]. However, SR has not received enough attention in the field of process monitoring. To our best knowledge, there has been little work applying SR to model industrial processes. SR can select a subset of the training data to most compactly express a given data point, reconstructing this point by a linear combination of this subset plus an error term by solving an L1-norm minimization problem. After modeling the training data set through SR, a sparse weighted adjacency graph and the error-free reconstructed data can be obtained at the same time [36]. SR explicitly penalizes the dense Gaussian error through L2-norm and sparse large magnitude outliers through L1-norm [35]. As a result, the obtained adjacency graph is robust to outliers and noise, thus can better reflect the delicate relationships among training samples compared with traditional Euclidean distance based graph [37,38]. For process data, this relationship among samples not only represents the geometric topological structure of the data, but also reflects the dynamic characteristics of the data (auto-correlation). In other words, the graph constructed from SR can encode much more useful and meaningful information about the dynamic characteristics and geometric manifold structure of the process data. Besides, SR graph has a datam-adaptive neighborhood structure, which is automatically determined and needs not to specify a fixed neighborhood parameter beforehand. Lastly, the noise-removed data can be further utilized for robust process modeling and monitoring.

Inspired by the work of NPE which linearized the classic LLE algorithm, this paper proposes a novel robust DR technique, named sparse representation preserving embedding (SRPE), based on the sparse reconstructive weights and noise-removed data recovered from robust sparse representation. Compared with traditional PCA and manifold learning methods, SRPE has the following advantages. Firstly, SRPE performs DR in a clean data space, making it much more robust to noise and outliers. Secondly, SRPE tries to preserve the SR graph which encodes rich process dynamics and local geometric structure of the process data in the projected latent subspace, making it much more efficient in detecting faults associated with abnormal dynamic characteristics. Finally, SRPE is also a linear DR method, monitoring statistics T^2 and *SPE* can be easily extended from PCA.

The rest of this paper is organized as follows. First, some preliminary knowledge on NPE is briefly introduced. Then, the SRPE algorithm and the corresponding novel process monitoring scheme are detailed. To illustrate the effectiveness and superiority of the proposed SRPE process monitoring method, extensive comparative experiments are conducted on a dynamic numerical example and the Tennessee Eastman (TE) benchmark problem. Conclusions are drawn in the end.

2. Preliminary knowledge on neighborhood preserving embedding

NPE is a linear approximation algorithm to the classic LLE manifold learning method. In the NPE model, a training sample is first reconstructed by a linear combination of a few of its nearest neighbors. The objective of NPE is to preserve this reconstruction relationship in the projected low dimensional subspace. Because of its elegancy and effectiveness, NPE has attracted attention in both the computer vision and process monitoring communities. Suppose the training data set $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\} \subseteq R^m$ consists of n sample vectors in an m-dimensional real-valued feature space. NPE aims at learning a linear projection matrix $A \in R^{m\times p} (p < m)$, where p is the dimension of the latent subspace. The NPE algorithm procedure can be summarized as follows.

(1) Constructing the adjacency graph: The K nearest neighbors or the ε-ball method can be adopted for graph construction: Two samples are linked if one is among the other's K nearest neighbors or one is within the other's Euclidean distance ε-ball.