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Improved fault detection and diagnosis using sparse global-local preserving projections

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ABSTRACT

A new sparse dimensionality reduction method named sparse global-local preserving projections (SGLPP) is proposed. The SGLPP has two advantages. First, SGLPP can preserve both global and local structures of the data set. Second, SGLPP extracts sparse transformation vectors from the data set. The extracted sparse transformation vectors are able to reveal meaningful correlations between variables, which significantly improves the interpretability of SGLPP. These two advantages make SGLPP well suitable for fault detection and diagnosis in industrial processes. Therefore, a SGLPP-based process monitoring method is developed to improve the interpretability and the fault detection capability of monitoring models and to enhance the fault diagnosis capability. A full SGLPP model is combined with a set of partial SGLPP models to improve the fault sensitivity and to track the propagation of faults between process variables. In addition, three-level contribution plots, i.e., the variable-wise, group-wise, and group-variable-wise contribution plots, are constructed for fault evaluation and fault diagnosis. The effectiveness and advantages of proposed methods are illustrated with an industrial case study. The results indicate that the SGLPP models reveal real process mechanisms and control loops between process variables, and thus produces interpretable monitoring results. Moreover, the SGLPP-based method has better fault detection capability than conventional monitoring methods. Three-level contribution plots well show the effects of faults on process variables and produce reliable fault diagnosis results.

1. Introduction

Process monitoring is an effective way to improve the safety of industrial processes. It ensures safe operations, prevents equipment damages and maintains the normal production by detecting faults and diagnosing the root causes of faults. In the last several decades, owing to the wide applications of modern measurement techniques and the quick development of data analysis methods, data-driven process monitoring, also known as multivariate statistical process monitoring (MSPM), has become more and more popular [1–6]. Up to now, lots of MSPM methods have been proposed on the basis of some widely used dimensionality reduction techniques, such as principal component analysis (PCA) [7], partial least squares (PLS) [8], independent component analysis (ICA) [9], and locality preserving projections (LPP) [10]. These MSPM methods commonly extract a few latent variables from process data to capture main data features, and then build a monitoring model using extracted latent variables for fault detection and diagnosis.

A common drawback of above dimensionality reduction methods is the lack of sparsity in their solutions. Because of this drawback, each extracted latent variable is almost a linear combination of all input variables, hindering the physical interpretation of latent variables. In many cases, the sparse representation is required because it generates interpretable results and promotes better generalization [11]. The sparse representation of PCA has been widely investigated. For example, Zou et al. [12] proposed a sparse PCA (SPCA) algorithm, which formulates PCA as a regression-type optimization problem and imposes the elastic net (or lasso) penalization on regression coefficients. D'Aspremont et al. [13] used a semidefinite programming (SDP) relaxation to solve the sparse PCA problem and proposed the DSPCA algorithm. Moghaddam et al. [14] proposed the greedy SPCA (GSPCA) algorithm based on a greedy search technique. Journée et al. [15] developed a generalized power method named GPower for sparse PCA. Especially, Sriperumbudur et al. [16] proposed an efficient algorithm to solve the sparse generalized eigenvalue (GEV) problem using the d.c. (difference of convex functions) programming, which is applicable for

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sparse PCA, sparse canonical correlation analysis and sparse Fisher discriminant analysis simultaneously.

Although sparse PCA (SPCA) has better interpretability than PCA, it inherits a disadvantage from PCA. This disadvantage is that both SPCA and PCA only preserve the global Euclidean structure (i.e., data variance) of data but totally neglect the local data structure (i.e., local neighborhood relations among data points). Because the local neighborhood structure is also a very important aspect of data features, neglecting such important data information inevitably degrades the performance of PCA and SPCA. Consequently, PCA and SPCA cannot fully extract useful information from data. Moreover, PCA and SPCA are easier to be affected by outliers and noises. In recent years, to overcome the shortcoming of PCA, some new linear dimensionality reduction algorithms have been proposed by combining PCA with LPP, and they can simultaneously preserve global and local structures of the data set [17–20]. In particular, the global-local preserving projections (GLPP) proposed by Luo [18] builds a unified framework for preserving both global and local data structures. PCA and LPP are unified under the GLPP framework, and they are proved to be two special cases of GLPP [18]. However, similar to PCA and LPP, GLPP lacks sparsity, which may limit its applications in the cases where the result interpretation is very important.

A monitoring model without sparsity has three drawbacks in fault detection and fault diagnosis. First, it fails to reveal meaningful process mechanisms and control loops between process variables from process data. This drawback hinders the analysis and interpretation of monitoring results. Second, because of the lack of sparsity, a monitoring model may suffer from the redundant coupling and interferences between process variables, which reduces the fault sensitivity and the fault detection capability. Third, based on a monitoring model without sparsity, it is hard to accurately evaluate the effect of faults on each process variable, which may reduce the reliability and accuracy of fault diagnosis. In real industrial processes, there are complicated coupling between process variables, and thus faults may propagate between different process variables. In addition, a fault may do more harm to other process variables rather than the variables that cause the fault. All these bring large difficulty to fault diagnosis. Due to the lack of sparsity, the monitoring model cannot fully eliminate the meaningless coupling and interferences between process variables or reveal the propagation of faults between process variables, which degrades fault detection and diagnosis capabilities. Therefore, to improve the interpretability and the fault detection capability of monitoring models and to enhance the fault diagnosis capability, it is necessary to build sparse monitoring models and propose corresponding fault detection and diagnosis methods.

In this paper, the sparse global-local preserving projections (SGLPP) algorithm is proposed and used for process monitoring. To reveal meaningful correlations between variables, SGLPP extracts sparse transformation vectors, which contain fewer nonzero elements, from a data set. The optimization problem of SGLPP is solved by the sparse generalized eigenvalue (GEV) algorithm. A selection index is proposed for choosing a sparse solution with appropriate sparsity. A deflation procedure is developed for SGLPP to sequentially extract a set of sparse transformation vectors from the data set. A SGLPP-based process monitoring method is then developed. A full SGLPP model, which is build based on all sparse transformation vectors, is combined with a set of partial SGLPP models, which are separately build based on every sparse transformation vector, to improve the fault sensitivity and to track the propagation of faults between process variables. The T^2 and *SPE* statistics are used for fault detection. Based on the sparse monitoring model, three-level contribution plots, termed as variable-wise, group-wise and group-variable-wise contribution plots, are developed for fault evaluation and fault diagnosis. The effectiveness and advantages of the proposed methods are illustrated by a case study on the Tennessee Eastman (TE) process.

Notation: $\boldsymbol{X}$, $\vec{\boldsymbol{x}}$ and x denote matrix, vector and scalar, respectively. The ith element in vector $\vec{\boldsymbol{x}}$ is denoted as x_i. The $\|\vec{\boldsymbol{x}}\|_0$ denotes the cardinality of $\vec{\boldsymbol{x}}$ (i.e., the number of nonzero elements in $\vec{\boldsymbol{x}}$). The $\vec{\boldsymbol{x}} \le \vec{\boldsymbol{y}}(\vec{\boldsymbol{x}} \ge \vec{\boldsymbol{y}})$ indicates that $\forall i$: $x_i \le y_i (x_i \ge y_i)$. $\boldsymbol{I}_m$ is the identity matrix with the size of $m \times m$. $\mathbf{1}_n = (1, \ldots, 1)^T \in \Re^n$, and $[x]_+ = \max(0, x)$. The $\lambda_{\min}(\boldsymbol{X})$ denotes the smallest eigenvalue of $\boldsymbol{X}$. S^m, $S^m_+$and S^m_{++} denote the sets of symmetric, positive semidefinite and positive definite matrices with the size of $m \times m$, respectively. $\boldsymbol{X}^+$ denotes the Moore-Penrose pseudoinverse of $\boldsymbol{X}$. The $diag(\vec{\boldsymbol{x}})$ denotes a diagonal matrix with the principal diagonal being $\vec{\boldsymbol{x}}$.

2. A brief review of global-local preserving projections

Global-local preserving projections (GLPP) can preserve both global and local structures of data [18]. Given a data set $\boldsymbol{X} = [\vec{\boldsymbol{x}}_1, \vec{\boldsymbol{x}}_2, \cdots, \vec{\boldsymbol{x}}_n] \in \Re^{m \times n}$, GLPP seeks a transformation matrix $\boldsymbol{A} = [\vec{\boldsymbol{a}}_1, \vec{\boldsymbol{a}}_2, \cdots, \vec{\boldsymbol{a}}_l] \in \Re^{m \times l}$ to map $\boldsymbol{X}$ to $\boldsymbol{Y} = [\vec{\boldsymbol{y}}_1, \vec{\boldsymbol{y}}_2, \cdots, \vec{\boldsymbol{y}}_n] \in \Re^{l \times n} (l \le m)$ by$\vec{\boldsymbol{y}}_i = \boldsymbol{A}^T \vec{\boldsymbol{x}}_i$, such that $\boldsymbol{Y}$ well retains global and local structures of $\boldsymbol{X}$. The objective function of GLPP is [18]

$$J_{GLPP}(\vec{\boldsymbol{a}}) = \min_{\vec{\boldsymbol{a}}} \frac{1}{2} \left\{ \eta \sum\nolimits_{ij} (y_i - y_j)^2 W_{ij} - (1 - \eta) \sum\nolimits_{ij} (y_i - y_j)^2 \bar{W}_{ij} \right\} \tag{1}$$

where y_i=$\vec{\boldsymbol{a}}^T \vec{\boldsymbol{x}}_i$ is the projection of $\vec{\boldsymbol{x}}_i$, $\vec{\boldsymbol{a}} \in \Re^m$ is a transformation vector in $\boldsymbol{A}$, and $\eta \in [0, 1]$ is a weight coefficient to adjust the tradeoff between global structure preservation and local structure preservation. The term $\sum_{ij} (y_i - y_j)^2 W_{ij}$ in Eq. (1) is related to the local structure preservation, and the term $-\sum_{ij} (y_i - y_j)^2 \bar{W}_{ij}$ corresponds to the global structure preservation. W_{ij} and $\bar{W}_{ij}$ are weight coefficients representing adjacent and non-adjacent relationships between $\vec{\boldsymbol{x}}_i$ and $\vec{\boldsymbol{x}}_j$, respectively, which are defined as [18]

$$W_{ij} = \begin{cases} e^{-\frac{\|\vec{\boldsymbol{x}}_i - \vec{\boldsymbol{x}}_j\|^2}{\sigma_1}} & \text{if } \vec{\boldsymbol{x}}_j \in \Omega_k(\vec{\boldsymbol{x}}_i) \text{ or } \vec{\boldsymbol{x}}_i \in \Omega_k(\vec{\boldsymbol{x}}_j) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$\bar{W}_{ij} = \begin{cases} e^{-\frac{\|\vec{\boldsymbol{x}}_i - \vec{\boldsymbol{x}}_j\|^2}{\sigma_2}} & \text{if } \vec{\boldsymbol{x}}_j \notin \Omega_k(\vec{\boldsymbol{x}}_i) \text{ and } \vec{\boldsymbol{x}}_i \notin \Omega_k(\vec{\boldsymbol{x}}_j) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where σ_1 and σ_2 are constant parameters, and $\Omega_k(\vec{\boldsymbol{x}})$ denotes the neighborhood of $\vec{\boldsymbol{x}}$ that is defined by k nearest neighbors [18].

Eq. (1) can be rewritten as [18]

$$\begin{aligned} J_{GLPP}(\vec{\boldsymbol{a}}) &= \min_{\vec{\boldsymbol{a}}} \frac{1}{2} \left\{ \eta \sum\nolimits_{ij} (y_i - y_j)^2 W_{ij} - (1 - \eta) \sum\nolimits_{ij} (y_i - y_j)^2 \bar{W}_{ij} \right\} \\ &= \min_{\vec{\boldsymbol{a}}} \frac{1}{2} \sum\nolimits_{ij} (y_i - y_j)^2 R_{ij} \\ &= \min_{\vec{\boldsymbol{a}}} \left\{ \sum\nolimits_{i} y_i H_{ii} y_i^T - \sum\nolimits_{ij} y_i R_{ij} y_j^T \right\} \\ &= \min_{\vec{\boldsymbol{a}}} \left\{ \sum\nolimits_{i} \vec{\boldsymbol{a}}^T \vec{\boldsymbol{x}}_i H_{ii} \vec{\boldsymbol{x}}_i^T \vec{\boldsymbol{a}} - \sum\nolimits_{ij} \vec{\boldsymbol{a}}^T \vec{\boldsymbol{x}}_i R_{ij} \vec{\boldsymbol{x}}_j^T \vec{\boldsymbol{a}} \right\} \\ &= \min_{\vec{\boldsymbol{a}}} \vec{\boldsymbol{a}}^T \boldsymbol{X}(\boldsymbol{H} - \boldsymbol{R}) \boldsymbol{X}^T \vec{\boldsymbol{a}} \\ &= \min_{\vec{\boldsymbol{a}}} \vec{\boldsymbol{a}}^T \boldsymbol{X} \boldsymbol{M} \boldsymbol{X}^T \vec{\boldsymbol{a}} \end{aligned} \tag{4}$$

where $\boldsymbol{H}$ is a diagonal matrix with $H_{ii} = \sum_j R_{ij}$, $R_{ij} = \eta W_{ij} - (1 - \eta) \bar{W}_{ij}$, and $\boldsymbol{M} = \boldsymbol{H} - \boldsymbol{R}$ is the Laplacian matrix. To take into account the importance of y_i that is measured by H_{ii}, and further to avoid