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Fault detection of multimode process based on local neighbor normalized matrix

Jinyu Guo, Tangming Yuan, Yuan Li *

College of Information Engineering, Shenyang University of Chemical Technology, Shenyang, Liaoning Province 110142, China

A R T I C L E I N F O

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A B S T R A C T

In recent years, a variety of fault diagnosis methods of multimode process have been developed. However, these multimode fault diagnosis methods need to assume that the data of batch production process is even-length, and there is no pollution in the data. To obtain better monitoring performance in a batch process with uneven-length data, a fault detection algorithm of multi-mode process based on local neighbor normalized matrix (LNNM) is proposed in this paper. The method highlights the contour features of various modes, accurately captures the nonlinear position relationship between modes and within modes. The local weighted algorithm (LWA) is first used to preprocess the uneven-length batch data. Then the main local neighbor normalized matrix is constructed for the training set of equal length. The K-means algorithm is used to mode clustering. In each mode, the local outlier factor (LOF) method is used to determine the first control limits for removing outliers. The MPCA model is established and the second control limits are determined for each mode. Furthermore, the matching coefficients of the control limits of each mode are calculated, and the unified statistics and control limits are determined. The fault detection of multimode process is carried out under the unified control limits. The algorithm is applied to the actual industrial semiconductor process. Simulation results show that the proposed algorithm improves the fault detection rate relative to the traditional fault detection algorithms. The effectiveness of the method is verified.

1. Introduction

In the pharmaceutical, chemical, food, and semiconductor industry, it is a need to continuously improve the automation degree of the system to meet the smooth and safety requirements of the production operation. At the same time, it also makes the complexity of industrial process more and more highly. The security of the system faces severe challenges. In this case, if a fault occurs, it often causes a series of chain reaction of production devices, even causes serious consequences such as interruption of production, and production equipment fault, leading to huge economic losses. So how to monitor the production process, and discover the fault in time is a research hotspot in the field of process control in recent years. In this research field, a multivariate statistical process monitoring (MSPM) method based on a large amount of historical data has been widely getting attention, and has made a number of research achievements [1–9].

The traditional MSPM methods such as principal component analysis (PCA) [10] and partial least squares (PLS) [11] are mainly used in the fault diagnosis of continuous process. According to the data characteristics of batch process, the following relevant fault diagnosis methods are proposed. Multiway principal component analysis (MPCA) [12] solves three dimensional data structure problem, and carries out the detection and diagnosis of the batch process. However, MPCA assumes that the process data follow the normal distribution and have a linear relationship. As a result, the monitoring performance of MPCA is often unsatisfactory for the nonlinear process of multimode. Multiway kernel principal component analysis (MKPCA) [13–14] by mapping nonlinear data into kernel space, only needs to define the inner product in the feature space. However, there is not an effective method to select the width of the kernel, which limits the application of the algorithm. Based on multiway independent component analysis (MICA), Yu [15] proposed a hybrid and interactive information model, which solves the problem that the fault detection methods of batch process can not deal with the problem of intrinsically multi-directional operation. Guo [16] proposed an on-line fault detection method of batch process based on DMOLPP. It combined sliding window technology with orthogonal locality preserving projections (OLPP) for on-line detection of batch process, improving the performance of batch process.

However, in order to meet the needs of the market and raw material changes, the multimode process is more common which produces high value and diversity of products. Compared with traditional batch process, multimode batch process is more complicated, with serious nonlinear, time-varying and multiple operation conditions, which makes the fault diagnosis of multimode batch process more challenging. In recent years, many scholars have analyzed the industrial process of

* Corresponding author.
E-mail address: li-yuan@mail.tsinghua.edu.cn (Y. Li).

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multimode from different perspectives, and proposed a variety of fault diagnosis methods [17–25]. The fault detection methods of multimode process are mostly from the multi-model integration and single model based on local information store in two directions. Multi-model integration needs to consider how to build multiple sub-models and how to integrate the results of each sub-model. This process often requires certain priori knowledge. In order to solve the fault detection problem of multimode batch process with nonlinear and non-Gaussian characteristics, Q. Peter He [26–27] proposed the fault detection algorithm based on k-nearest neighbor (KNN). In order to build a single model to realize the multimode process monitoring, Ma et al. [28] proposed a fault detection method using Mahalanobis distance-based local outlier factor (MDLOF). Liu et al. [29] proposed a multimode process monitoring strategy based on the local density estimation. These methods don't assume that the data follow single distribution, have a better monitoring effect for chemical process with complex data distribution, and open a new route for fault detection and diagnosis of multimode process. However, these multimode fault diagnosis methods need to assume that the data of batch production process is even-length, and there is no pollution in the data.

Due to the production characteristics of batch process, the production cycle of different batch is different. The problem of uneven-length batch will inevitably appear. The shortest length method is usually used to solve the problem of uneven-length of batch process. The shortest length method is used to intercept the rest of batch in the length of the shortest batch. The method is simple, fast, and so on. This method has a certain effect on the multimode batch process, which has little difference in data characteristics for the late reaction stage and tends to be stable. However, the difference of batch data for some of the reaction processes is large. The shortest length method will lose some important information, which will affect the accuracy of the fault diagnosis. Therefore, this method has some limitations. Another method dealing with uneven-length data is based on multi-block statistics (MBS) [30]. The method divided the unequal batch process into sub blocks of the same number, and calculated the mean and variance of each sub block. These statistics are combined into an equal length feature vectors. Principal component analysis (PCA) is used to monitor the uneven-length batch process. But the number of blocks has certain influence on the effect of process monitoring. How to determine the number of blocks is a challenge to the present. On the other hand, the field data inevitably contain errors of different degrees, measurement noise, system noise, and so on. These problems will swear the data, which make the data of multimode production process generate local outliers [31–32]. The outliers can cause the direction of the principal component to offset. If the analysis and preprocessing of the outliers is not performed before the fault detection, the accuracy of the fault diagnosis will be affected. For the fault detection of uneven-length and multimode batch process, a fault detection algorithm of multi-mode process based on local neighbor normalized matrix (LNNM) is proposed in this paper. This method can avoid the loss of information that influence the clustering effect of multimode process [33], remove of outliers, and make the fault diagnosis results of multimode batch process more accurate by constructing the main and secondary local neighbor normalized matrices.

The rest of this paper is organized as follows. A fault detection method of multimode process based on LNNM is proposed in Section 2. The simulation results are given to show the effectiveness of the proposed method in Section 3. Finally, conclusions are summarized in Section 4.

2. Fault detection of multimode process based on local neighbor normalized matrix

2.1. Preprocessing based on local weighted algorithm

In the batch process, due to different production requirements, there will produce uneven-length batch data. Three-dimensional description

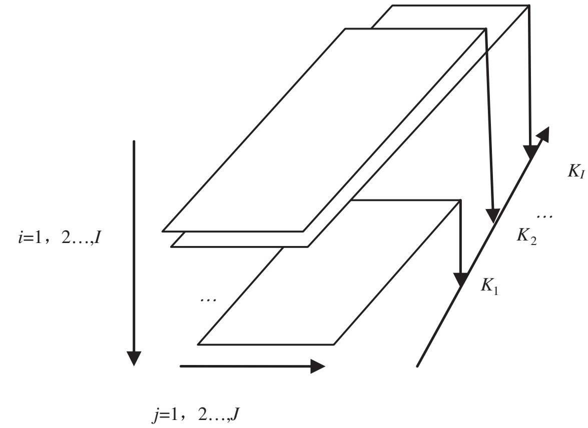

Fig. 1. Three-dimensional description of uneven-length batch data.

of uneven-length batch data is shown in Fig. 1. At present, most of the fault detection methods are implemented on the equal length data, so how to deal with the uneven-length data is a hotspot of research in recent years.

From the data characteristics, it can be seen that the uneven-length data is the special case of missing data. Missing data points can occur in any part of the sample data, but the missing data of uneven-length sample is concentrated in the latter part of the sample, so that it can restore the missing part of uneven-length data according to the method for dealing with missing data. In order to solve the uneven-length problem of batch process, a preprocessing algorithm based on local weighted algorithm (LWA) is proposed in this paper. LWA is an effective algorithm for data restoration. It makes full use of local information to choose the k nearest neighbors according to certain rules, and determines the corresponding weights. The missing data points are reconstructed by the k nearest neighbors and weights.

In each batch (batch index $i = 1, 2,\ldots, I$), assume that J process variables are measured online at $K(K = K_1, K_2,\ldots, K_i)$ time instances throughout the operation cycle which is not uncertain, forming each irregular batch data set, denoted as $\mathbf{X}$. $\mathbf{X}$ can be expressed as:

$$\mathbf{X} = [\mathbf{X}_1, \mathbf{X}_2, \cdots \mathbf{X}_i, \cdots, \mathbf{X}_I] \tag{1}$$

where $\mathbf{X}_i \in R^{K_i \times J}$ denotes the i-th batch matrix. Each batch matrix is unfolded respectively to vectors along the direction of time, and the set of all batches is called $\mathbf{B}$. $\mathbf{B}$ can be expressed as:

$$\mathbf{B} = [\mathbf{B}_1 \;\; \mathbf{B}_2 \cdots \mathbf{B}_i \cdots \mathbf{B}_I] \tag{2}$$

where $\mathbf{B}_i \in R^{1 \times C_i}$, and $C_i = K_i \times J, i = 1, 2, \cdots I$ is the length of $\mathbf{B}_i$.

Because there are different time length K_i for each batch $\mathbf{X}_i$, the trajectories length is not the same after the three dimensional data set $\mathbf{X}$ is unfolded. In order to fully retain the length of the longer batch, a longer batch is regarded as a benchmark, and the missing parts of shorter batches are reconstructed by the neighbors and weights.

The length of all batches is arranged into vector $\mathbf{L}$ in descending order, and the two dimensional data matrix $\mathbf{B}$ is rearranged according to the order of vector $\mathbf{L}$, denoted as $\mathbf{B}^*$.

$$\mathbf{L} = [l_1 \;\; l_2 \;\; \cdots l_i \;\; \cdots \;\; l_I] \tag{3}$$

where $l_1 \geq l_2 \geq \cdots \geq l_i \cdots \geq l_I$.

In order to effectively use the information of longer batches, matrix $\mathbf{B}^*$ is divided into complete data matrix $\mathbf{F}$ and incomplete data matrix $\mathbf{M}$, and the dimensions D of the matrix $\mathbf{F}$ is determined. We choose the length of the longest batch as the dimensions of the matrix in general, that is, $D = l_1$. In general cases, when the number of batch meeting the conditions is small, we reduce the size of D accordingly, and choose