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Industrial process fault detection based on locally linear embedded latent mapping

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Dear editor,

Industrial processes have become bigger and more complex with the rapid development of computer, network, and automation technology. However, these advances have increased the potential for faults. Minor faults in the chemical process stream may result in wasting resources or poor product quality; the most serious faults may lead to life-threatening incidents, such as explosions and fires. Therefore, fault detection has become a critically important step in chemical processing [1]. Data-driven fault detection methods, such as latent mapping (LM), partial least squares regression (PLS), and Fisher linear discriminant analysis, have attracted widespread attention from academia [2]. Among them, LM is the most widely used method. Although LM can extract the global characteristics of data, it cannot select the local information. In recent years, the manifold learning algorithm has been widely used to map data to a low-dimensional space. This has allowed the data to maintain the local nearest neighbor structure, similar to the original data space, so the algorithm can extract the local features of the data effectively. As a classical manifold learning algorithm, local linear embedding (LLE) is widely used in face recognition, machine learning, data mining, and many other fields. Wang et al. [3] used the local linear embedding algorithm to diagnose the faults of a spindle in topological space.

Most chemical processes are complex nonlinear processes, so it is very important to retain the nonlinear characteristics of data in dimensional reduction processes. To improve the process monitoring, a novel performance indicator-oriented concurrent subspace process monitoring method, containing three subspaces with different degrees of importance, is proposed by Song et al. [4]. As a nonlinear algorithm, LLE can factor in the internal structure and geometric characteristics of data in the process of dimensional reduction [5]. It can retain the local neighborhood structure similar to the original data space, and retain the nonlinear characteristics of data.

The aim of this study is fault detection in industrial processing with nonlinear or high dimensions. We attempt to integrate the LM algorithm into the local linear embedding algorithm, and propose a novel local linear embedding latent mapping algorithm (LLELM) for fault detection. The LLELM is designed to improve the performance of process monitoring. Our objective is to preserve the global characteristics of the original sample space in the projected low-dimensional space, while preserving the local neighborhood structure of the sample. This research comprises three aspects. First, LLELM overcomes the shortcomings of LM and can effectively deal with the nonlinear problem. Second, LLELM makes up for the shortcomings of LLE, and can retain the main information from the data after dimensional reduction. Third, LLELM can improve the fault detection rate and can reduce the false alarm rate compared with LM, which is proven by simulation of the Tenessee Eastman (TE) process.

The LLELM algorithm incorporates the idea of LLE algorithm into the objective function of the LM algorithm, so that mapping to a low-dimensional space using LLELM can retain both the global and local characteristics of data. This is convenient for comprehensive extraction of data features. The global objective function of LLELM is defined as follows:

$$J(\boldsymbol{W})_{\text{global}} = \max_{\boldsymbol{W}} \sum_{i=1}^{n} \boldsymbol{W}^{\mathrm{T}} \boldsymbol{C} \boldsymbol{W}, \tag{1}$$

where $\boldsymbol{C}$ is the covariance matrix of the original sample $\boldsymbol{X}$ and $\boldsymbol{W}$ is the weight matrix. Use $\boldsymbol{y}_i$ $(i = 1, 2, 3, \ldots, D)$ to bulid the low-dimensional embedded space. The local objective function of LLELM is defined as follows:

$$J(\boldsymbol{W})_{\text{local}} = \min_{\boldsymbol{W}} \sum_{i=1}^{n} \|\boldsymbol{y}_i - \boldsymbol{W}_{ij}\boldsymbol{y}_j\|_2^2, \tag{2}$$

where the weight $\boldsymbol{W}_{ij}$ represents the reconstructed contribution of the j-th sample point to the i-th sample point. Eq. (2) can be obtained from

$$J(\boldsymbol{W})_{\text{local}} = -\max_{\boldsymbol{W}} \sum_{i=1}^{n} \|\boldsymbol{y}_i - \boldsymbol{W}_{ij}\boldsymbol{y}_j\|_2^2. \tag{3}$$

Considering the global objective function and the local objective function, the objective function of LLELM can be

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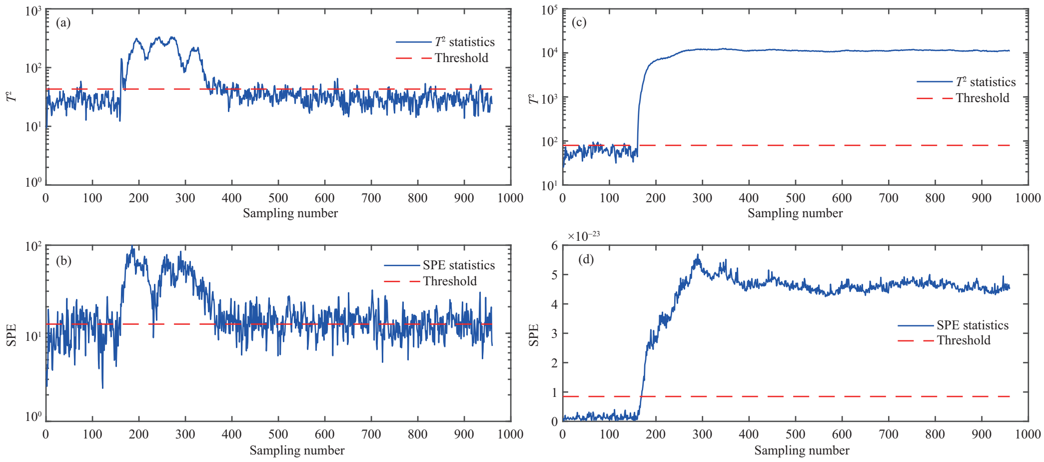

Figure 1 (Color online) Detection results of Fault 5. (a), (b) LM statistics changing maps; (c), (d) LLELM statistics changing maps.

defined as

$$\begin{aligned} J(\boldsymbol{W})_{\text{LLELM}} &= \max_{\boldsymbol{W}}\left(\boldsymbol{W}^{\text{T}}\boldsymbol{C}\boldsymbol{W}+\lambda\left(\max_{\boldsymbol{W}}\sum_{i=1}^{n}\|\boldsymbol{y}_i-\boldsymbol{W}_{ij}\boldsymbol{y}_j\|_2^2\right)\right) \\ &= \max_{\boldsymbol{W}}\boldsymbol{W}^{\text{T}}\boldsymbol{S}\boldsymbol{W}, \end{aligned} \tag{4}$$

$$\boldsymbol{S}=\boldsymbol{C}-\lambda\boldsymbol{X}(\boldsymbol{I}-\boldsymbol{W})^{\text{T}}(\boldsymbol{I}-\boldsymbol{W})\boldsymbol{X}^{\text{T}}, \tag{5}$$

where λ is a smoothing factor. When λ takes a negative value, global and local features can be extracted more comprehensively. By solving the eigenvectors corresponding to the largest D eigenvalues of $\boldsymbol{S}$, we can get the projection matrix $\boldsymbol{W}$. The projection from high-dimension to low-dimension can be accomplished using

$$\boldsymbol{Y}=\boldsymbol{W}^{\text{T}}\boldsymbol{X}. \tag{6}$$

After characteristic decomposition of the covariance matrix $\boldsymbol{S}$, we obtain eigenvalues λ_i $(i=1,2,\ldots,p)$ and arrange them in descending order, to determine the number of principal components according to cumulative percent variance (CPV) criterion. The characteristic matrix corresponding to the selected eigenvalue is the main element load matrix. The LLELM model of the process matrix $\boldsymbol{X}$ is established as

$$\boldsymbol{X}=\boldsymbol{T}\boldsymbol{P}^{\text{T}}=\sum_{i=1}^{k}t_ip_i^{\text{T}}+\boldsymbol{E}, \tag{7}$$

where $\boldsymbol{T}$ is the score matrix, $\boldsymbol{P}$ is the load matrix, $\boldsymbol{E}$ is the residual matrix, and k is the number of principal elements obtained by CPV criterion. To monitor the process, T^2 and Q statistics are constructed in principal component subspace and residual subspace, respectively [6].

$$T^2=\sum_{i=1}^{k}\frac{t_i^2}{\lambda_i}, \tag{8}$$

$$Q=\boldsymbol{e}\cdot\boldsymbol{e}^{\text{T}}=\boldsymbol{e}(\boldsymbol{I}-\boldsymbol{P}\boldsymbol{P}^{\text{T}})\boldsymbol{e}^{\text{T}}. \tag{9}$$

In Eq. (8), λ_i represents the eigenvalue. $\boldsymbol{e}$ is the residual matrix and $\boldsymbol{I}$ represents the corresponding unit matrix in Eq. (9). The calculation of the control limits TL and QL based on the statistics T^2 and Q are expressed as

$$TL=\frac{k(n-1)}{n-k}F(k,n-k,\alpha), \tag{10}$$

$$QL=\theta_1\left[\frac{c_\alpha\sqrt{2\theta_2h_0^2}}{\theta_1}+1+\frac{\theta_2h_0(h_0-1)}{\theta_1^2}\right]^{1/h_0}, \tag{11}$$

where k represents the number of principal elements. T^2 approximately obeys the F distribution with degrees of freedom k and $n-k$. c_α is the critical value of normal distribution at test level. $h_0=1-2\theta_1\theta_3/(3\theta_2)^2$ and $\theta_i=\sum_{j=k+1}^{p}\lambda_i^j$, $i=1,2,3$. The number of principal components is selected according to the 0.85 variance cumulative contribution rate.

LLELM is applied to TE process data to analyze its performance. TE data contains a training data set and a test data set. The data used for modeling is normal data with 500 samples. The number of samples used for testing is 960: the first 160 samples are normal samples, and the last 800 samples are fault samples. There are 12 operation variables and 41 measurement variables. Fifty-two process variables are selected for this simulation. According to [7], the number of adjacent points for LLE algorithm $K=33$ is selected. LM uses the variance contribution method to select the number of principal components. The variance contribution rate is 0.85 and the confidence for the statistics is 0.95. From experience, the smoothing factor λ is 0.5.

Twenty-one kinds of faults in TE process are detected by using the LLELM model and LM model. Fault 5 is the step change in the inlet temperature of condenser cooling water in TE process. Figure 1(a) shows that LM detected the fault accurately at 161 sampling points. After 350 sampling points, both T^2 and Q statistics failed to detect the fault, but the fault is not eliminated at this time. The compensation of the control circuit makes the T^2 and Q statistics return to normal values. Figure 1(b) shows that using T^2 and Q statistics, LLELM can detect the fault quickly after it occurs, and the alarm status is maintained after the compensation effect of the control loop occurs. This indicates that the fault has not been eliminated, so the fault can be detected accurately and continuously. The fault detection rate of LLELM is higher than that of LM; therefore, the LLELM can effectively reduce the false alarm rate.

Conclusion. A novel method of fault detection, named the LLELM algorithm, is proposed. The advantage of LLELM is that it can integrate the manifold learning of LLE into the objective function of LM, and combine the advantages of LM and LLE. Firstly, LLELM can deal with nonlinear data successfully, by projecting data into low-dimensional space, and keeping the data characteristics of the original space. In addition, LLELM can retain most of the main information from the data after dimensional reduction through LM. After mapping the data to low-dimensional space, T^2 and Q statistical models are constructed to monitor process faults. Through TE process simulation, the results of LLELM and LM are compared and analyzed. LLELM is found to have a higher detection rate and a lower false alarm rate than LM, which verifies the effectiveness and superiority of the LLELM algorithm in industrial process fault detection.

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