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Fault diagnosis of industrial process based on the optimal parametric t-distributed stochastic neighbor embedding

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Dear editor,

Fault diagnosis of industrial production processes are crucial for early detection of abnormal conditions and help operators to prevent accidents in a timely manner. Therefore, reasonably establishing a fault diagnosis model with better performance and reducing false alarm rate are vital for improving the efficiency of industrial operations and ensuring the safety and reliable operation of equipment.

Generally, process monitoring and fault diagnosis methods are mainly classified into three categories: analytical model-based, knowledge-based, and data-driven methods [1]. However, the industrial processes are complex so that it is difficult to obtain accurate mathematical models and sufficient process knowledge for large industrial production systems. A fault diagnosis method based on data-driven is more effective compared with the other two types of methods mentioned above [2]. It only relies on historical data and real-time data of process variables that are relatively easy to obtain. Qin et al. [3] used data-driven multivariate statistical methods such as principal component analysis (PCA), partial least squares (PLS), and fisher discriminant analysis (FDA) for industrial fault diagnosis. Roweis et al. [4] proposed nonlinear dimensionality reduction techniques based on manifold learning strategy. However, the actual industrial process data are strongly nonlinear, and the results obtained by the linear dimensionality reduction method may not reveal the nonlinear structure contained in the original data set. It will reduce the performance of the established fault diagnosis model. A nonlinear dimensionality reduction technique, called parametric t-distributed stochastic neighbor embedding (parametric t-SNE) [5], can solve these problems compared with the previously proposed methods and is used for fault classification of industrial processes in this study. The main characteristics of the parametric t-SNE are: (1) it can retain the nonlinear structure of high-dimensional fault data in the low-dimensional feature space; (2) it preserves the local and global structures of the original data in the feature space to achieve good classification results.

The model for online fault classification is constructed by integrating training data, parametric t-SNE algorithm and k-nearest neighbor (KNN) algorithm. The specific process is shown in Figure 1(a). Firstly, the detected real-time fault data are normalized. Secondly, a feature extraction model based on optimal parametric t-SNE is proposed to extract features of fault data. The high-dimensional industrial fault data are projected into the optimal classification low-dimensional space by parametric t-SNE. Finally, the KNN algorithm is used to calculate the extracted features to realize fault classification.

The major contributions of this study are: (1) the parameter optimization index is defined to select the optimal parameter for the parametric t-SNE algorithm; (2) an optimal fault classification model based on the parametric t-SNE is established to improve the fault classification performance. In addition, compared with traditional discriminant analysis methods such as FDA and local linear exponential discriminant analysis (LLEDA), the parametric t-SNE can better distinguish non-Gaussian nonlinear industrial fault data without too many features, and the accuracy is further improved. Meanwhile, the effectiveness and superiority of the proposed method are verified in the MNIST dataset, the Tennessee Eastman process, and the penicillin fermentation process.

Fault classification model and problem formulation. The fault classification model is shown in Figure 1(b), which consists of two stages. The first stage is to learn the nonlinear mapping between high-dimensional fault data space and low-dimensional feature space. The parametric mapping $f : X \longrightarrow Y$ from the data space X to the low-dimensional feature space Y is parameterized by means of a deep belief network (DBN) with weights W [6]. The second stage is to fine-tune the parameters of the map. The network weight is fine-tuned using t-SNE back-propagation as to minimize the cost function that attempts to retain the local and global structures of the data in the feature space.

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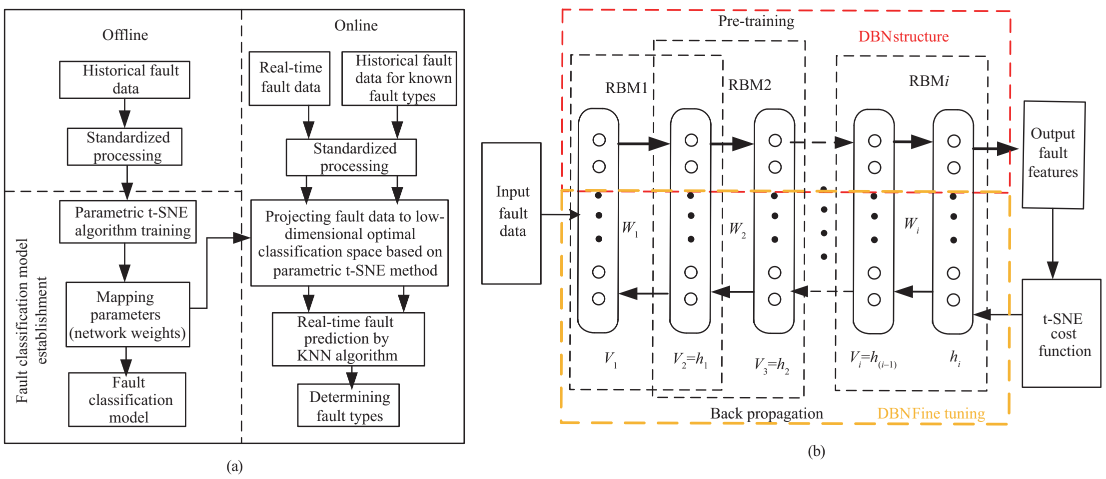

Figure 1 (Color online) (a) Industrial process fault classification diagnosis flow chart based on parametric t-SNE; (b) structure of fault classification model based on parametric t-SNE.

Finally, the offline fault classification model based on parametric t-SNE is obtained. When establishing a fault classification model based on the parametric t-SNE algorithm, the following three problems need to be solved.

Problem 1. Because the training data $x_1, x_2, \ldots, x_N$ are different types of indicators, they cannot be directly used as input to the model. According to the parametric t-SNE algorithm, the input data of the fault classification model is limited to the range of 0 to 1.

Problem 2. The t-SNE cannot learn the nonlinear mapping between the original high-dimensional data space and the low-dimensional feature space. However, the fault classification model must extract features of fault data by parameterizing the mapping function between high-dimensional data and low-dimensional features.

Problem 3. The parametric t-SNE algorithm has only one parameter "perplexity" (Perp) that must be prespecified by the user, but there is no guidance on how to choose it [7].

To solve the above three problems, the process of establishing a fault classification model based on the optimal parametric t-SNE can be summarized as follows.

Step 1. The training data $x_1, x_2, \ldots, x_N$ are normalized by

$$x_i = \frac{x_k - x_{\min}}{x_{\max} - x_{\min}}, \tag{1}$$

where x_i denotes normalized training data, x_k denotes the initial data, and $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of a single variable in the fault data, respectively.

Step 2. The DBN has enough hidden layers (with a nonlinear activation function) to be able to parameterize any complex nonlinear functions. DBN is composed of multiple layers of restricted Boltzmann machine (RBM), using the unsupervised greedy layer-by-layer method to obtain the weights of pre-training.

Step 3. Fine-tuning. The features obtained by inputting the historical fault data into the DBN are used as the sample initial solution $y^{(0)}$ in the t-SNE algorithm. Then, the network weights are fine-tuned using t-SNE back-propagation as to minimize the cost function. Finally, the optimal model parameters for the global deep belief network are obtained.

Step 4. The optimal value for Perp of parametric t-SNE algorithm, $\mathrm{Perp}_{\mathrm{opt}}$, can be obtained by

$$D = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{q_{ij}}, \tag{2}$$

$$\mathrm{Perp}_{\mathrm{opt}} = \arg \min_{\mathrm{Perp}} D, \tag{3}$$

where p_{ij} and q_{ij} are the probability distribution of data in X and Y, respectively. The lower the value of D is, the better high-dimensional data are represented in the embedded space. Therefore, a method to determine $\mathrm{Perp}_{\mathrm{opt}}$ is to run parametric t-SNE with every possible Prep ($\mathrm{Perp} \in [5, 50]$) and select $\mathrm{Perp}_{\mathrm{opt}}$ according to Eq. (3). Finally, the optimal fault classification model is obtained. For more details on fault classification model based on parametric t-SNE, please refer to Appendix A.

Experiments. The fault classification method based on optimal parametric t-SNE proposed in this study is used in the MNIST dataset, the Tennessee Eastman process, and the penicillin fermentation process to verify the effectiveness and superiority of this method. Compared with FDA and LLEDA [8], the parametric t-SNE can achieve better fault classification results with less features, and the accuracy is further improved. In addition, the parametric t-SNE can better distinguish non-Gaussian nonlinear industrial fault data. For more details on experimental verification and analysis, please refer to Appendix B.

Conclusion. This study aims to explore the performance optimization problem of fault classification models in industry. Based on the analysis of statistical-based, manifold learning and deep learning methods, an industrial fault classification method based on the optimal parametric t-SNE is proposed. This method first normalizes the initial data. Then, the model based on the optimal parametric t-SNE is used to extract the characteristics of industrial fault data. Finally, the KNN classification algorithm is used to calculate the extracted features to realize fault classification. The advantage of the optimal parametric t-SNE method is that it can better classify non-Gaussian nonlinear industrial data without more features. Through industrial data verification, this method is effective on improving the accuracy of industrial fault classification, and it has less uncertainty.

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Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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