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A subspace learning-based feature fusion and open-set fault diagnosis approach for machinery components

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ABSTRACT

Open-set fault diagnosis is an important but often neglected issue in machinery components, as in practical industrial applications, the failure data are in most cases unavailable or incomplete at the training stage, leading to the failure of most closed-set methods based on fault classifiers. Thus, based on the subspace learning methods, this paper proposes an open-set fault diagnosis approach with self-adaptive ability. First, for feature fusion, without using traditional dimensionality reduction methods, a data visualization method based on t-distributed stochastic neighbor embedding is employed for its ability in mining and enhancing the fault feature separability, which is the key in fault recognition. Then, for open-set fault diagnosis, to detect unknown fault classes and recognize known health states in only one model, the kernel null Foley-Sammon transform is applied to build a null space. To reduce the misjudgment rate and increase the detection accuracy, a self-adaptive threshold is automatically set according to the testing data. Moreover, the final recognition results are described as distances, which helps the operators to make maintenance decision. Case studies based on vibration datasets of a plunger pump, a centrifugal pump and a gearbox demonstrate the effectiveness of the proposed approach.

1. Introduction

As machinery components play an important role in modern industrial applications, fault diagnosis for machinery component is of great significance in avoiding huge economic losses and catastrophic accidents. It is thus a hot research topic, and many methods have been proposed [1–4]. However, most of these methods focus on fault classification using supervised learning methods, based on a fundamental assumption that data of normal and all possible fault classes are available at the training stage, which deviates from most cases in practical applications [5–7]. With the increase in the complexity, sophistication, and quality of machinery components, it becomes increasingly difficult and extremely costly to consider all possible faults (e.g., various concurrent faults) in induced-failure tests, and it is a long process to collect failure data during equipment operation, which leads to the scarcity of complete failure data for a priori training [5,6,8]. Thus, instead of assuming a closed dataset comprising fixed and complete fault classes, modern fault recognition systems need to identify the data of entirely new (unknown) fault classes, which is viewed as an open set recognition problem [6,9,10]. Although open set fault diagnosis is imperative for the lifelong learning of diagnostic systems in real industrial applications, it has so far been poorly studied in machinery systems. Therefore, this paper seeks a systematic and automatic approach for the open set fault diagnosis of machinery components.

Novelty detection [11,12], also referred to in some studies as anomaly detection [13] or outlier detection [14], has been widely used in recent years in abnormal signal detection and gradually applied in open set recognition to identify unknown classes [15–17]. In 2014, Pimentel et al. reviewed the novelty detection methods and divided them into probabilistic, distance-based, reconstruction-based, domain-based, and information-theoretic categories [18], such as the Gaussian mixture model [19], the self-organizing map (SOM) [20,21], the one-class support vector machine (OC-SVM) [22,23], and the support vector data description (SVDD) [24,25]. Among these methods, SOM and SVDD are more widely used in the novelty detection of machinery components. Compared with most other neural networks, SOM is unsupervised and aims at domain description rather than probability density estimation [5,26]. SVDD, proposed based on the support vector machine theory, can build a flexible boundary to separate target data from novel or outlier data, with benefits in generalization and the use of kernels [5]. However, despite these benefits, it is hard to select an appropriate threshold for SOM, while the performance of SVDD relies heavily on the selection of parameters [27]. Moreover, not only SOM and SVDD but most of these novelty detection methods are essentially

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one-class classifiers, in which the training data belong to only one class, usually the normal state [18]. In contrast, under open set circumstances, the training data may belong to many classes, and the task is to decide whether the testing data belong to one of the known classes or to a new class outside the training set. To extend these one-class methods to multi-class cases, one can treat the training data of all available classes as one super-class [28] or combine the rejection results of all one-class models built for each available class separately [29]. However, the former strategy is unsuitable for training data belonging to faraway classes, while the latter strategy suffers from a more complex training process and higher time consumption.

Recently, a null space transformation method, called KNFST, is proposed to solve the high dimensional and small sample size problem in discriminant analysis. In view of the benefits of the null space method, this paper introduces KNFST to identify the unknown testing samples in the open set fault diagnosis of machinery components. Using KNFST, data of the same class are mapped into a single point, while data of different classes are mapped into different and separated points in a null space[10]. Then, the minimal Euclidean distance between the mapped testing sample and the mapped training data can be defined as the novelty score, which offers a good visualization for decision making [30]. To reduce the misjudgment rate and to increase the detection accuracy, a self-adapting threshold of the novelty score is automatically set according to the testing data.

As in engineering applications, the working conditions and loads of machinery components are complicated and variable, and the collected signals are nonlinear and non-stationary with noise interference; consequently, fault features extracted from a single perspective fail to reflect the complete fault information sufficiently. Thus, multi-perspective features extracted using multi-sensor signals and multiple methods are widely used [31–33], which conversely leads to high dimensionality, a complex data structure and information redundancy and leaves a greater burden for subsequent fault recognition algorithms [34]. To solve this dilemma, many feature fusion methods are proposed, which can be divided into three categories: feature selection, feature extraction, and feature combination [35]. As the prior class information of data is scarce in open set recognition, unsupervised and nonlinear feature extraction methods are more suitable in practical applications. However, most of these methods, such as Isomap and locally linear embedding (LLE), focus on retaining either the global or the local structure of the original features and neglect to retain or enhance the separability information; consequently, features of different faults are mixed in the mapped space, which leaves a significant challenge for fault recognition [36]. Hence, instead of using the traditional dimensionality reduction methods, a data visualization method named t-distributed stochastic neighbor embedding (t-SNE) [36],which focuses on enhancing the feature separability between different faults, is applied in this paper to fuse the multi-perspective features.

Thus, based on the above analysis, an open-set fault recognition approach is proposed for machinery components combing t-SNE with KNFST to improve fault detection accuracy and make fault diagnostic systems self-adaptive.

The rest of this paper is organized as follows. In Section 2, methods of t-SNE, KNFST, and local learning are introduced. In Section 3, the case studies performed to validate the methods of feature fusion and open set fault recognition are described. Lastly, the conclusion and future work are presented in Section 4.

2. Methodologies

2.1. t-SNE related methods

t-SNE was first proposed for visualizing data by Maaten & Hinton in 2008 [36]. As t-SNE is a variation of Stochastic Neighbor Embedding (SNE) [37], we first introduce SNE in the following.

2.1.1. Stochastic neighbor embedding

The core idea of SNE is to convert Euclidean distance-based similarities into conditional probability-based similarities between data points and to retain the similarity relations in the process of mapping the high-dimensional points into the low-dimensional space.

The similarity between data points $\mathbf{x}_i$ and $\mathbf{x}_j$ is measured by conditional probability $p_{j|i}$ that $\mathbf{x}_i$ would pick $\mathbf{x}_j$ as its neighbor if neighbors were picked in proportion to their probability density under a Gaussian centered at $\mathbf{x}_i$. Then, $p_{j|i}$ can be calculated by

$$p_{j|i} = \frac{\exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2/2\sigma_i^2)}{\sum_{k\neq i}\exp(-\|\mathbf{x}_i - \mathbf{x}_k\|^2/2\sigma_i^2)} \tag{1}$$

where $\mathbf{x}_k$ represents a neighborhood point around $\mathbf{x}_i$. For nearby data points, $p_{j|i}$ is relatively high; while for widely separated data points, $p_{j|i}$ will be nearly infinitesimal. The value of $p_{i|i}$ is set as zero.

In the low-dimensional space, let $\mathbf{y}_i$ and $\mathbf{y}_j$ represent the corresponding mapping points of $\mathbf{x}_i$ and $\mathbf{x}_j$. Then, the similarity between $\mathbf{y}_i$ and $\mathbf{y}_j$ can be measured by similar conditional probability $q_{j|i}$:

$$q_{j|i} = \frac{\exp(-\|\mathbf{y}_i - \mathbf{y}_j\|^2)}{\sum_{k\neq i}\exp(-\|\mathbf{y}_i - \mathbf{y}_k\|^2)} \tag{2}$$

where $\sigma_i = \frac{1}{\sqrt{2}}$ and $q_{i|i} = 0$, $\mathbf{y}_k$ represents a neighborhood point around $\mathbf{y}_i$.

Hence, to force mapping points $\mathbf{y}_i$ and $\mathbf{y}_j$ to model the similarity between data points $\mathbf{x}_i$ and $\mathbf{x}_j$ as well as possible, SNE tries to minimize the mismatch between $p_{j|i}$ and $q_{j|i}$ by minimizing a cost function, which is the sum of Kullback-Leibler divergences between the original (P_i) and mapping (Q_i) distributions over all other data points for each data point. Cost function C is given by

$$C = \sum_i KL(P_i \| Q_i) = \sum_i \sum_j p_{j|i}\log\frac{p_{j|i}}{q_{j|i}} \tag{3}$$

In SNE, a gradient descent method is applied to perform the minimization of cost function C, in which the gradient is given by a simple form:

$$\frac{\delta C}{\delta \mathbf{y}_i} = 2\sum_j (p_{j|i} - q_{j|i} + p_{i|j} - q_{i|j})(\mathbf{y}_i - \mathbf{y}_j) \tag{4}$$

In t-SNE, the perplexity is the only preset parameter, which can be interpreted as a smooth measure of the effective number of neighbors. The performance of SNE is fairly robust to the changes in the perplexity values, which makes SNE more easily applied in practical applications. The typical values of the perplexity are between 5 and 50. The detailed principle of SNE can be found in Ref. [37].

2.1.2. t-Distributed stochastic neighbor embedding

Although SNE provides reasonable good visualizations, it is hampered by two problems: The cost function is complex to optimize, and the widely separated data points tend to be crowded in the low-dimensional space. Thus, t-SNE is proposed to solve these problems.

First, t-SNE adopts a symmetrized version of SNE. Instead of minimizing the sum of the Kullback-Leibler divergences between conditional probabilities $p_{j|i}$ and $q_{j|i}$, the goal of t-SNE is to minimize a single Kullback-Leibler divergence between joint probability distributions P and Q in, respectively, high-dimensional and low-dimensional spaces:

$$C = KL(P\|Q) = \sum_i \sum_j p_{ij}\log\frac{p_{ij}}{q_{ij}} \tag{5}$$

Joint probability functions q_{ij} and p_{ij} are given by

$$q_{ij} = \frac{\exp(-\|\mathbf{y}_i - \mathbf{y}_j\|^2)}{\sum_{k\neq l}\exp(-\|\mathbf{y}_k - \mathbf{y}_l\|^2)} \tag{6}$$

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