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An automatic and robust features learning method for rotating machinery fault diagnosis based on contractive autoencoder

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ABSTRACT

Fault diagnosis of rotating machinery is vital to improve the security and reliability as well as avoid serious accidents. For instance, robust fault features are crucial to achieve a high diagnosis precision. However, traditional feature extraction methods rely on an abundant amount of expertise and human interference. As a breakthrough in fault diagnosis, deep learning holds the potential to automatically extract discriminative features without much prior knowledge and human interference. However, only a few deep learning models are designed to deal with noise and extract robust features. Contractive autoencoder (CAE) is a potential tool to grasp the internal factors and directly obtain the hidden robust features by penalizing the Frobenius norm of the Jacobian matrix of the hidden features with respect to the inputs. Thus, this paper proposes a method based on stacked CAE for automatic robust features extraction and fault diagnosis of rotating machinery. Gearbox and bearing fault diagnosis experiments are conducted, and the testing accuracy of the proposed method is approximately 100% for both two cases and higher than that of other methods, which fully validates the effectiveness and superiority of the proposed method. In addition, experiments and correlation analysis under different signal-to-noise ratios (SNRs) are conducted. Results show that the diagnosis accuracies of the proposed method are higher than those of the stacked autoencoder (AE) network under each SNR, especially when under 0 dB, the testing accuracies of the proposed method are 4.14% and 5.88% higher than those of the stacked AE network in two case studies, and the correlation coefficients of the CAE are higher than those of the AE, which demonstrate the capability of CAE in mining more robust features compared to the regular AE automatically and the superiority of the proposed method in fault diagnosis.

1. Introduction

Rotating machinery is widely used in the industrial field and is considerably important to the economic development of the society. With the development of science and technology, rotating machinery is developing toward automation, complication, intelligence and high speed. Such development indicates that the working environment is worse than before, that is, this environment suffers from high temperature and pressure and large load. Consequently, faults are inevitable. Unexpected faults in the rotating machinery may cause failure of the entire mechanical system to operate normally, thereby resulting in enormous economic losses and calamitous casualties. Thus, security and reliability have become the crucial concern in modern society (Cui et al., 2017). Effective fault diagnosis is crucial and considerably significant to monitor the operation condition and improve the security and reliability of the rotating machinery to reduce equipment maintenance cost and avoid unexpected casualties.

Many researchers have devoted efforts in rotating machinery fault diagnosis, and many methods have achieved successful applications. Feature extraction is the basis of fault diagnosis (He and Ding, 2016). The quality of the extracted features determines the diagnosis accuracy directly. Wavelet transform (WT), empirical mode decomposition (EMD), as well as EMD variations, statistical parameter analysis, and envelope analysis, are the commonly used feature extraction methods. For instance, feature extraction using WT had been applied in the fault diagnosis of roller bearing (Huo et al., 2017), aero engine (Wang et al., 2017), and induction machinery (Bouzida et al., 2011). WT also had been combined with support vector machine (SVM) for feature extraction and fault diagnosis of bearing and gearbox (Shen et al., 2013). A study had provided a detailed review of WT in feature extraction and fault diagnosis (Yan et al., 2014). Meanwhile, EMD method had been

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implemented in feature extraction and fault diagnosis of helicopter main gearbox bearing (Duan et al., 2016). EMD also had been combined with radial basis function neural network for feature extraction and fault diagnosis of gearbox (Liu et al., 2016a, b). A study had provided a detailed description and application of methods based on EMD and its variations in feature extraction and fault diagnosis of rotating machinery (Lei et al., 2013). In addition, statistical parameter such as spectral kurtosis had been applied for feature extraction and fault diagnosis of motor bearing (Tian et al., 2016). Although these feature extraction methods were successful in fault diagnosis, they rely on a considerable amount of human interference to extract and analyze discriminative features for accurate fault diagnosis. This process is time-consuming and unsuitable for dealing with big data. Meanwhile, these feature extraction methods are based on signal processing and analysis, which require abundant expertise about signal processing and analysis as well as fault diagnosis. In addition, determining the most suitable features for extraction is difficult, and different features may directly lead to different diagnosis results, which is unstable (Lu et al., 2017a, b).

Deep learning creates a significant breakthrough in machine learning, and is able to take advantage of deep architectures to automatically extract essential high-level features without any human interference (LeCun et al., 2015). Thus, deep learning is time-saving and does not require artificial selection of the most suitable features. In general, deep learning is superior in automatically extracting representative features and able to deal with big data compared to traditional feature extraction methods. To date, methods based on deep learning have been successfully applied in speech recognition (Hannun et al., 2014; Van den Oord et al., 2013), computer vision (Ronao and Cho, 2016; Ji et al., 2013; Zhang et al., 2016; Toshev and Szegedy, 2014; Girshick et al., 2014), natural language process (Johnson and Zhang, 2014), and medical application (Koziol et al., 2014). Recurrent neural network had been applied for feature extraction and speech recognition (Hannun et al., 2014), while convolution neural network (CNN) and 3 Dimension CNN had been applied for feature extraction and human activity recognition (Ronao and Cho, 2016; Ji et al., 2013). CNN also had been implemented in text categorization (Johnson and Zhang, 2014). Stacked sparse autoencoder (SAE) had been successfully applied for feature extraction of halftone images with an average classification accuracy of over 99.44% (Zhang et al., 2016). Then, restricted Boltzmann machines had been applied for automatic hepatocellular carcinoma recognition (Koziol et al., 2014). These achievements fully illustrate the automatic feature learning capability of deep learning methods. Motivated by the achievements of deep learning methods in these recognition fields, an increasing number of researchers are devoted to applying deep learning methods to automatically extract discriminative fault features and diagnose faults. Deep belief network (DBN) had been applied successfully for automatic feature extraction and fault diagnosis of reciprocating compressor valves (AlThobiani and Ball, 2014), aircraft, and electric power transformer (Tamilselvan and Wang, 2013). CNN also had been applied for automatic feature extraction and fault diagnosis of bearing and gearbox (Xia et al., 2017; Chen et al., 2015). Meanwhile, stacked AE and its variation stacked SAE had been utilized successfully for automatic feature extraction and fault diagnosis of bearing and gearbox (Jia et al., 2016, 2017). In addition, a study also had combined stacked AE with softmax regression for feature extraction and fault diagnosis of bearing (Tao et al., 2015).

In practical fault diagnosis cases, collected signals are often influenced by various forms of noise or even overwhelmed completely, thereby increasing the difficulty of fault diagnosis. Thus, an increasing number of studies focus on automatically denoising and extracting robust features with deep learning methods. For instance, digital wavelet frame had been applied for denoising, then stacked SAE and back propagation neural network had been combined for fault feature extraction and fault diagnosis of bearing (Tan et al., 2015). However, it still requires human interference and cannot extract robust features from the original signals automatically. Then, denoise autoencoder (DAE) had been widely applied to denoise and extract robust features from corrupted inputs automatically, and then diagnose bearing and gearbox faults (Guo et al., 2016; Lu et al., 2017a, b). Although DAE can extract robust features and achieve satisfying applications in fault diagnosis, it takes some time to select the most suitable corruption level and then corrupt the collected signals into corrupted inputs of the DAE. A low corruption level is less effective for robustness, whereas a high corruption level leads to much important information lost. Studies showed that CAE is able to automatically extract more robust features, which are invariant to small changes of the inputs due to its penalty term without any prior knowledge and human interference (Rifai et al., 2011; Poole et al., 2014). Then, stacked CAE had been applied successfully for robust features extraction and multimodal video classification (Liu et al., 2016a, b). Besides, stacked CAE and DAE also had been combined to extract robust features for recognition of hand-written numerals (Chen et al., 2014) and fault diagnosis of rotor and bearing (Shao et al., 2017). Compared with the DAE, the selection of the most suitable corruption level and the corruption of the collected signals can be avoided using CAE, which is more time saving and convenient. Thus, this paper proposes a stacked CAE-based method for automatic robust feature learning and fault diagnosis of rotating machinery. Because bearings and gearboxes are important elements of rotating machinery, which directly influence the operation condition of the rotating machinery, bearing and gearbox fault diagnosis are conducted to validate the effectiveness and superiority of the proposed feature learning and fault diagnosis method. In addition, comparative experiments and correlation analysis under different SNRs are conducted to further demonstrate and explain the superiority of the CAE in mining more robust features than the AE for fault diagnosis. The contributions of this paper can be summarized as follows:

(1) In order to reduce human interference and the interference of noise on features extraction, a fault diagnosis method based on contractive autoencoder is proposed to extract robust features automatically, which achieves higher diagnosis accuracy than other existing methods.
(2) Fault diagnosis experiments under different SNRs are conducted to further demonstrate the superiority and ability of the proposed method in automatic and robust features learning.
(3) Correlation analysis is carried out to validate and explain the capability of the proposed method in mining robust features automatically.

The rest of the paper is organized as follows. Section 2 briefly introduces the background of the stacked CAE network, including the structure of the CAE, the stacked CAE network, and the training process of the stacked CAE network. The detailed diagnosis flow chart of the proposed method is shown in Section 3. Two fault diagnosis cases are investigated in Section 4 to validate the effectiveness and superiority of the proposed method. Important conclusions are presented in Section 5.

2. Brief introduction to the stacked CAE network

2.1. CAE

AE is an unsupervised feature learning neural network with three layers, as depicted in Fig. 1, where the hidden layer represents the learned features. The input and hidden layers form the encoder network, which is responsible for transforming the original inputs into hidden features, whereas the hidden and output layers form the decoder network, which is responsible for reconstructing the original inputs from the learned hidden features.

For each input vector $\boldsymbol{x}^d$ from datasets $\left\{\boldsymbol{x}^d\right\}_{d=1}^{M}$, the hidden vector $\boldsymbol{h}^d$ and the reconstruction vector $\hat{\boldsymbol{x}}^d$ are defined as

$$\boldsymbol{h}^d = f(\boldsymbol{W}^{(1)}\boldsymbol{x}^d + \boldsymbol{b}^{(1)}) \tag{1}$$