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Rolling bearing fault feature learning using improved convolutional deep belief network with compressed sensing

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A B S T R A C T

The vibration signals collected from rolling bearing are usually complex and non-stationary with heavy background noise. Therefore, it is a great challenge to efficiently learn the representative fault features of the collected vibration signals. In this paper, a novel method called improved convolutional deep belief network (CDBN) with compressed sensing (CS) is developed for feature learning and fault diagnosis of rolling bearing. Firstly, CS is adopted for reducing the vibration data amount to improve analysis efficiency. Secondly, a new CDBN model is constructed with Gaussian visible units to enhance the feature learning ability for the compressed data. Finally, exponential moving average (EMA) technique is employed to improve the generalization performance of the constructed deep model. The developed method is applied to analyze the experimental rolling bearing vibration signals. The results confirm that the developed method is more effective than the traditional methods.

1. Introduction

Rotating machinery plays an important role in modern industry, and the condition monitoring of rotating machinery has attracted more and more attentions [1]. Rolling bearing is one of the most significant components in rotating machinery, which greatly affects its overall performance [2]. Due to the harsh working conditions, rolling bearing will get various faults which may result in unexpected downtime and huge economic losses. Therefore, automatic and reliable diagnosis of bearing faults is practical and meaningful.

Vibration analysis is a widely used technique for the condition monitoring of key parts in rotating machinery [3]. At present, two main types of methods have been proven effective to rotating machinery fault diagnosis: signal processing [4–7] and intelligent diagnosis [8–11]. Intelligent diagnosis is the new development of machinery fault detection technology, in which artificial neural network (ANN) and support vector machine (SVM) are the two most popular methods. Generally, two important steps are necessary for rotating machinery fault diagnosis based on ANN or SVM: feature extraction using signal processing techniques and fault classification using pattern recognition techniques. Chine et al. [12] calculated several feature parameters and used ANN for photovoltaic systems fault diagnosis. Volterra series was proposed by Xia et al. [13] to reveal the working conditions of rotor-bearing system, and back propagation (BP) neural network was used as the fault classifier. Jamadar et al. [14] extracted 24 dimensionless parameters to describe bearing working conditions, and adopted BP neural network to classify various faults. Two new features and seventeen statistical parameters were developed by Ali

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et al. [15] to characterize the bearing health conditions, and ANN was constructed for fault identification. Chen et al. [16] designed a dependent feature vector based on 50 time-domain statistical parameters and 50 frequency-domain statistical parameters, and then utilized a probability neural network (PNN) for identifying different faults. Chen et al. [17] presented a feature extraction and selection method, and applied ANN for diagnosing bearing fault severity. Li et al. [18] calculated 1634 feature parameters to reflect bearing conditions, and then the selected 12 sensitive features were used as the input for fault detection. Zarei et al. [19] extracted 4 time-domain feature parameters for revealing bearing operation conditions, and adopted ANN as fault classifier. Lei et al. [20] employed ensemble empirical mode decomposition (EEMD) for feature extraction and wavelet neural network (WNN) for diagnosing bearing faults. Besides, Lei et al. [21] adopted empirical mode decomposition (EMD) and wavelet packet decomposition (WPD) for feature extraction, then selected sensitive features for fault diagnosis using ANN. Tang et al. [22] introduced Shannon entropy and autoregressive model coefficients as input features, and carried out SVM to diagnose the different faults. Liu et al. [23] utilized diagonal spectrum as the feature parameters, and adopted SVM for fault classification. Batista et al. [24] calculated 13 statistical parameters in time domain and frequency domain to reflect bearing health conditions, and then employed SVM for fault identification. Han et al. [25] proposed local mean decomposition (LMD) for feature extraction and constructed SVM for fault diagnosis. EEMD permutation entropy was presented by Zhang et al. [26] as input feature, and then SVM was used as the fault classifier. Saidi et al. [27] calculated eight higher order spectral features for reflecting bearing working conditions, and then the reduced features were fed into SVM for fault identification. Zeng et al. [28] adopted EMD for feature extraction and SVM for bearing fault detection. Zheng et al. [29] introduced multiscale fuzzy entropy as input features and employed SVM as the bearing fault classifier. Liu et al. [30] utilized the most relevance atoms as features and carried out SVM for bearing fault diagnosis.

Although traditional intelligent diagnosis methods have been widely applied in machinery fault diagnosis, they still have three inherent disadvantages: (1) The diagnosis performance of the traditional intelligent methods depends heavily on the quality of the extracted and selected features. In engineering practice, the vibration signals collected from rolling bearing are always complex and non-stationary with heavy noise [5]. Furthermore, the fault categories of bearing often show as not only the single fault but also the compound faults owing to the complexity and correlation of mechanical structures. The compound faults refer to that more than one kind of fault occurs at the same time, and all the fault features are highly coupled together. Thus, very advanced signal processing techniques must be well mastered for effective fault feature extraction. (2) It is a time-consuming and labor-intensive task to select the most sensitive features in different diagnosis issues. In most cases, feature selection depends largely on the engineering experience of diagnostic experts [31]. (3) Traditional intelligent diagnosis methods such as ANN and SVM belong to shallow learning models, which is, with no more than one nonlinear transformation. Several study results have clearly shown that shallow learning models are difficult to effectively learn the complex non-linear relationships [32–35]. Thus, it is necessary to construct deep architectures for automatic and effective fault feature learning of rolling bearing.

Deep learning is a new machine learning method, which has the great capacity to overcome the inherent disadvantages of traditional intelligent methods. The most obvious difference between deep learning methods and traditional intelligent methods is that deep learning methods can automatically learn the valuable features from the raw data [36], instead of extracting or selecting features manually. In other words, deep learning methods can get rid of the dependence on the various signal processing techniques and domain experts. Deep belief network (DBN) and convolutional neural network (CNN) are two kinds of popular deep learning methods, which have been gradually used in machinery fault diagnosis in the last three years [37–39]. DBN is a kind of generative neural network with powerful unsupervised feature learning ability. CNN has several attractive advantages such as shift-invariance and weight sharing through convolutional connections. In order to take full advantages of DBN and CNN, Lee et al. [40] developed a new deep learning model called convolutional deep belief network (CDBN), which has shown better performance compared with standard DBN and CNN [41], however, there still exist two main limitations when applying the standard CDBN for rolling bearing fault feature learning: (1) Binary visible units are always utilized in the standard CDBN, which is difficult to model real data such as the measured vibration data [42]. In addition, standard CDBN learning algorithm has some shortcomings such as error oscillation and slow convergence. Thus, the improvement of CDBN model and the corresponding learning algorithm has become an urgent task. (2) Massive vibration data will inevitably be collected from rolling bearing using advanced data acquisition systems. Thus, balancing the analysis efficiency and the massive data acquisition has been a great challenge for the practical application of CDBN.

In this paper, a novel method called improved convolutional deep belief network with compressed sensing is developed for rolling bearing feature learning and fault diagnosis. The proposed method is applied to analyze the experimental vibration signals. The results confirm that the proposed method can get rid of the dependence on signal preprocessing and manual feature extraction, which is more effective and reliable than the traditional methods. To the best of our knowledge, this paper is the first attempt for carrying out CDBN method in rolling bearing fault diagnosis issue. The main contributions of this paper can be summarized as follows.

(1) In order to reduce the data capacity and improve analysis efficiency, compressed sensing is adopted to compress the measured vibration data.
(2) In order to enhance the feature learning ability for compressed data, Gaussian visible units are employed to construct the new CDBN model.
(3) In order to further improve the convergence and generalization performance of the constructed deep model, exponential moving average technique is used to modify the standard learning algorithm.