Rolling Bearing Fault Diagnosis Method Based on Improved Deep Belief Network

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Abstract. The issue of classification accuracy for the fault diagnosis model has received considerable critical attention. In this study, an improved deep belief network was developed and applied to fault diagnosis of rolling bearings. Firstly, the forward training part composed of restricted Boltzmann machines (RBMs) is employed to learn the hidden features of vibration data. Secondly, the samples are synthetized by the reverse generation part according to the weight sharing. The noise time-shift layer can significantly enhance the generalization performance of the model, and the synthesized samples can be utilized to supplement the original dataset to enhance the learning efficiency. Experimental results prove that the improved DBN can manifest remarkable superiority in fault diagnosis against other methods.

1. Introduction
Rolling bearing is prone to failure under the high-speed and heavy-load working environment, which may even cause the fatal accidents and huge economic loss. Therefore, an accurate and effective identification method is essential to improve the running safety of modern machinery.

The vibration signals of rotating machinery contain remarkably abundant information about the health of the rolling bearing, and the efficient analysis of these signals plays an important role in Prognostics Health Management (PHM). The traditional mechanical fault diagnosis methods mainly use signal processing techniques to extract the fault feature and determine the extent of damage and fault location. These methods are time-consuming and laborious, and also requires advanced signal processing knowledge. However, the above problems can be solved by replacing the traditional diagnosis methods with related pattern recognition methods. Artificial neural network (ANN) and support vector machine (SVM) are relatively classic artificial intelligence methods to be used in fault diagnosis. Fault diagnosis methods using SVM and ANN are mainly divided into two steps: the fault features extraction by signal processing techniques, and the fault identification through the pattern recognition. As a result of the high-speed and complex working conditions of machinery and equipment, their key components may produce faults with the characteristics of coupling and concurrency. The vibration data generated by these machinery may also contain more and more non-stationary background noise, hence the shallow machine learning model fails to deal with this problem. Deep learning, a new member of machine learning, overcomes the limitation of shallow model for fault diagnosis.
Deep learning algorithms such as convolutional neural network (CNN) [1], deep belief network (DBN) [2], and long short-term memory (LSTM) [3] are widely employed in fault diagnosis field. Nonlinear deep learning models can reconstruct the input data, so that the proportion of irrelevant signals can be reduced and the effective fault features also can be retained. These methods also have wide applications due to its excellent ability to describe signal characteristics. Shao [4] used Gaussian visible units to establish the model of convolutional deep belief network (CDBN). The complexity of the input vibration signal was reduced by compressed sensing. The results show the excellent generalization ability of this method. Long [5] proposed a CNN based on LeNet-5 for fault diagnosis. The method was verified on a variety of experimental datasets, and the results show higher diagnosis accuracy of this method over the traditional method. Sun [6] proposed a deep neural network (DNN) on the basis of sparse auto-encoder (SAE) for fault diagnosis of induction motor. Chen [7] proposed a fault detection approach founded on SAE and DBN for bearing. The effectiveness of this method was verified by bearing dataset under different working conditions. The results show this method can identify the bearing operating state with high accuracy. Guo [8] put forward a diagnosis method called hierarchical learning rate adaptive deep convolution neural network. Zhang [9] proposed an end-to-end CNN-based model, and achieved satisfied results considering different conditions in fault diagnosis. Lu [10] put forward a diagnosis method on the ground of stacked denoising auto-encoder (SDAE) for rolling bearings. Shao [11] proposed a feature learning approach on the basis of deep auto-encoder (DAE). Jing [12] introduced a CNN-based fault diagnosis method for planetary gearbox. A Convolutional Bi-directional Long Short-Term Memory networks (CBLSTM) was introduced by Zhao [13] for tool wear detection. Zhang [14] proposed a LSTM and recurrent neural network (RNN) method to identify the degradation state of bearings. The results indicate the model is able to accurately predict the remaining service life of bearings.

The deep learning algorithms are developed rapidly in the fault diagnosis. These algorithms not only can get rid of the manual feature extraction, but also represent almost any complex nonlinear problem by multi-layer implicit network. Hinton proposed the deep belief network [15] that recently has widespread application in fault diagnosis, and it performs well because of its strong unsupervised learning ability. However, the existing applications generally focus on the performance of a single standard DBN model. In addition, there are two huge challenges for the diagnosis efficiency of DBN model. One is to collect sufficient fault data in actual conditions, the other is accurately learn the representative fault features of the unbalanced dataset (the ratio between normal data and fault data is unbalanced). Consequently, it is significant to improve the learning efficiency of traditional DBN.

A novel improved DBN for the intelligent fault diagnosis of rotating machinery is proposed in this paper. The general procedure of this method contains three steps: First, the vibration signals of the rolling bearings are employed to forward train the improved DBN. Then, the reverse generation part of the improved DBN generates synthesized samples by weight sharing, and the noise time-shift layer is added to improve the generalization ability of improved DBN in the process. The results prove that improved DBN can mitigate the impact of unbalanced dataset on the diagnosis and improve the generalization ability of the model.

2. The proposed approach
A DBN model is composed of several RBMs in Figure 1. A hidden layer and a visible layer constitute each RBM. The layers are connected by the weight matrix $W$. The RBM limits the units interconnection in peer layer, which is the biggest difference with Boltzmann machine (BM).
In the standard DBN, the insufficient data or the imbalance between normal data and fault data results in low diagnosis efficiency. For this purpose, the improved DBN is proposed based on the generative model theory to address this problem. Figure 2 illustrates the model structure of the improved DBN. This model includes two parts. The first is the forward training, which is used to pre-learn the fault features of input samples. The second is the reverse generation. This part uses the weight of forward training and real labels to generate synthesized samples, and then the forward training part conducts secondary learning on the synthesized samples. Therefore, the method can remarkably enhance the final diagnosis accuracy and generalization performance of the model. More details are as follows:

More specifically, the concept of weight sharing and reverse generation is proposed in improved DBN. The data reverse generation is completed by using the weight matrix and bias obtained in the forward training process. The reverse generation model can be defined as:

\[
V_m = w_{mm}^+ \left[ \text{sigmoid}^{-1}(h) - a_m \right]
\]

\[
H_n = \left[ \text{sigmoid}^{-1}(v) - b_n \right] w_{nn}^+
\]

Where \( \text{sigmoid}^{-1} \) denotes the inverse function, \( a_m \) and \( b_n \) are the bias of corresponding units, \( w_{mm}^+ \) denotes the Moore-Penrose generalized inverse matrix of forward training weight matrix.

The reverse generated samples have highly similar fault features with the original samples, which may lead to the over-fitting problem. This problem is not conducive to the secondary learning process of the forward training part. Hence, the noise time-shift layer is proposed to address it. The noise time-shift layer is adopted to improve the distinction between reverse generation samples and original samples. According to the characteristics of periodicity of fault vibration signals of rotating machinery, each sample is regarded as an independent cycle, and then the whole sample is shifted by several sampling points, and this operation will be over at the end of the cycle. Each sample generated in reverse is moved step by step according to the above principle. In addition, the noise time-shift layer also adds Gaussian distribution matching the dimension of synthesized samples. This layer not only improves the distinction between synthesized samples and original samples, but also preserves the effective features of original samples. Let \( S_t \) be the \( t^{th} \) sampling point of output vector in forward training, the principle of noise time-shift layer can be defined as follows:

\[
S_a = \begin{cases} 
S_t + N_t(a, \sigma^2), & t < a \\
S_t + N_t(a, \sigma^2), & t > a 
\end{cases}
\]

\[ t \in \mathbb{Z}, \sigma^2 = \frac{1}{\sqrt{2\pi}} \]

Figure 1: The structure of DBN and RBM
Where $S_t$ is a synthesized sample, $\alpha$ denotes the time-shift factor, $N(\mu, \sigma^2)$ is the Gaussian distribution with mean $\mu$ and variance $\sigma^2$.

3. Experiment analysis

3.1. Experimental dataset description

The vibration data of rolling bearings from Case Western Reserve University Lab (CWRU) [16] are used to verify the effectiveness of the proposed method. As shown in Figure.3, the experimental devices are composed of an induction motor, an accelerometer, a torque sensor, and a loading motor. The accelerometer and data acquisition equipment are used to obtain the vibration signal of each bearing (6205-2RS). The sampling frequency is 12 kHz. 0.1778mm, 0.3556mm, and 0.5334mm are the chosen bearing fault diameter. Each bearing is tested under four different loads (0, 1, 2 and 3 hp). Four different working conditions for bearings are listed in Table.1.

In this study, ten kinds of rolling bearing working conditions are set according to the fault conditions of the dataset. The same window function is used to process the samples into equal dimension, and each sample contains 1000 sampling points. Table.1 gives the details of dataset as below. It can be obviously seen from the table that there is an imbalance between normal samples and fault samples, and the imbalance ratio is in the region of 1:4.
3.2. Results and analysis
To embody the superiority of improved DBN, two traditional methods are adopted in this paper for comparison: (1) Standard DBN (2) Convolution neural network. (70% of the samples are used for training, and the remainder are used for testing). According to the experimental design, an improved DBN with three RBMs is constructed.

| Table.2 The fault diagnosis results of different methods |
|-----------------------------------------------|
| **Methods** | **Average accuracy (%)** | **Standard deviation** |
| The proposed method | 92.15% | 1.81 |
| Standard DBN | 80.41% | 2.84 |
| CNN | 73.03% | 2.90 |

Each experiment is conducted ten trials to show the stability of this method. The average results of ten trials are shown in the Table.2. The results indicates the average accuracy of improved DBN (92.15%) is slightly superior to that of the standard DBN (80.41%) and CNN (73.03%). It can also demonstrate the improved DBN can learn the characteristic features of the original data. Compared with other deep learning algorithms, the learning efficiency of this method has significant superiority than others. The mean square error of the proposed method is 1.81, which is lower than other two methods (2.84 and 2.90). The results indicate that the stability of the improved DBN has significant superiority. As mentioned above, this method not only can better learn the fault characteristics of the original data, but also can achieve high-precision classification. Moreover, the proposed method can extract more representative features over the traditional deep learning methods and machine learning methods.

4. Conclusions
An improved DBN model for intelligent fault diagnosis of rolling bearings is proposed. First, the original samples are trained by the forward training part of improved DBN, and then the reverse generation part generates synthetized samples by weight sharing to supplement the original dataset. The result indicates the proposed method has higher diagnosis accuracy and effectiveness against other methods, and eliminate the procedure of manual feature extraction. With the highly developed computer technology, the application of deep learning in fault diagnosis will be expanded. Our team would conduct further studies related to this topic.

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