A Novel PCA-DBN Based Bearing Fault Diagnosis Approach

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Abstract. This paper is concerned with fault diagnosis problem of a widely used component in vast rotating machinery, rolling element bearing. We propose a novel intelligent fault diagnosis approach based on principal component analysis (PCA) and deep belief network (DBN) techniques. By adopting PCA technique, the dimension of raw bearing vibration signals is reduced and the bearing fault features are extracted in terms of primary eigenvalues and eigenvectors. Parts of the modified samples are trained by DBN for fault classification and diagnosis and the rest are tested to examine the algorithm. A distinctive feature of this approach is that it requires no complex signal processing procedure of bearing vibration signals. The experimental results demonstrate the effectiveness of the PCA-DBN based fault diagnosis approach with a more than 90% accuracy rate.

Keywords: PCA · DBN · Rolling element bearing · Fault diagnosis

1 Introduction

Rolling element bearings are widely used in numerous rotating machinery. As the high precision requirement in practical applications, it is of significant importance to monitor bearing components and maintain them in good conditions. Bearing component in general is likely to encounter impact, oscillation, fracture, structure change and clearance chang, etc. For most cases, these failures may degrade the component efficiency and lifetime, even lead to catastrophic accidents, which pose great challenge to the implement of rotating machinery.

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With the development of fault diagnosis techniques, nevertheless, various bearing fault diagnosis schemes have been proposed over the last two decades (see [1,13,18], and the references therein). An overwhelming majority of the available results are obtained in virture of analyzing the vibration signal of bearings, where the vibration is measured by an accelerometer directly [12,17]. Sorts of advanced signal processing and parameter identification methods are utilized, such as short-time Fourier transform [4], wavelet time-scale decomposition [21], cumulant spectrum [8], to name a few. Among those achievements, it is worth noting that [10] proposed a wavelet-based feature extraction method based on minimum Shannon Entropy Criterion to extract statistical features from wavelet coefficients of raw vibration signals; [15] developed a new fault diagnosis scheme utilizing the wavelet transform to process vibration signals and using an adaptive neuro-fuzzy system to classify the fault data; [17] presented a localized bearing defects detection method based on wavelet transform; [24] classified bearing fault categories and identified the fault level by adopting the Hilbert-Huang transform. These results somehow shed light on the signal-processing based bearing fault diagnosis. Frankly speaking, however, the difficulty in processing the vibration signal arises from the complicate and unclear formulation of the involved dynamic model, especially the nonlinearity in vibration signals and the uncertainty in fault state information. It is hard to get a precise model representation either from time domain or frequency domain aspects, rendering a dilemma of extracting fault-related features from bearing vibration signals. Furthermore, with the increasing scale and complexity of industrial control systems, vibration signals are partial to be with high dimensions and numerous data, making it far more intricate to process bearing vibration signals [14].

To this end, we propose an intelligent fault diagnosis method in this paper to extract the fault features from raw vibration signals in spirit of PCA technique. PCA is a statistical procedure and widely used for dimensionality reduction [16]. The idea that applying PCA to deal with bearing fault diagnosis was first advocated in [11], where a PCA-based decision tree was introduced and proved to have better classification performance compared with normal decision tree. In [19] and [5], a PCA and support vector machine (SVM) fusion bearing fault feature extraction method was proposed. [9] applied spectral kurtosis and cross correlation techniques to extract bearing fault features and developed a health index using PCA and a semi-supervised k-nearest neighbor distance measure. In [25], PCA was used to get description features from the combination of energy spectrums and statistical feature and then a BP based neural network model is established for the diagnosis of rolling bearing faults. Our work reinforces these existing results and develop the intelligent fault diagnosis approach further. We propose a novel approach based on PCA method and DBN technique. We use PCA to reduce dimensions of raw vibration signals, extract bearing fault features, and then generate fault feature vectors. Parts of these fault feature vectors are then input into a DBN as the training set, while the rest are tested to examine the proposed algorithm.

The rest of the paper is organized as follows. In Sect. 2, we introduce the basic theories on PCA and DBN. Section 3 presents our results on PCA-DBN based bearing fault diagnosis approach. Experiments are carried out to show the effectiveness of the proposed algorithm. In the end, Sect. 4 concludes the whole paper.

2 Preliminary Theories of PCA and DBN

2.1 Dimensionality Reduction by PCA

PCA is a multi-variate statistical method that transforms a large number of possibly correlated variables into a smaller number of uncorrelated variables. It is widely used in dimensionality reduction algorithm to reduce signal dimension by the following steps:

– Step 1. Given a set of vibration signal $X \in R^{N\times M}$, in which each row vector in X refers to one measurement and each column vector in X to refers to a samples $x_i \in R^{N\times 1}, i = 1, ..., M$. Compute the average value vector of all the training sets, which is denoted by A

$$A = \frac{1}{M}\sum_{i=1}^{M} x_i \tag{1}$$

– Step 2. Compute the covariance matrix P

$$P = \frac{1}{M-1}\sum_{i=1}^{M}(x_i - A)(x_i - A)^T \tag{2}$$

It is worth noting that since $P \in R^{N\times N}$, there are N eigenvectors in P. Calculate the eigenvalue $\lambda_i, i = 1, ..., N$ and eigenvectors $v_i, i = 1, ..., N$ of the covariance matrix P.
– Step 3. Sequence the eigenvalues from big to small as $\lambda_1 \geqslant \lambda_2 \geqslant \ldots \geqslant \lambda_N$ along with the corresponding eigenvectors $v_i, i = 1, ..., N$. The cumulative contribution rate α is consequently calculated in terms of the first r principal components

$$\alpha = \sum_{i=1}^{r}\lambda_i / \sum_{i=1}^{N}\lambda_i \tag{3}$$

– Step 4. If $\alpha \geqslant 0.85$, construct a new matrix $E \in R^{N\times r}$ composed of eigenvectors $v_i, i = 1, ..., r$, i.e., $E = (v_1, v_2, \ldots, v_r)$. The new sample set X' can be obtained by mapping the raw data through matrix E

$$X' = E^T X \tag{4}$$

where $X' \in R^{r\times M}$.

As such, a modified bering vibration signal set is generated which has lower dimension compared with the original one but maintains the primary feature information at the mean time.

2.2 Feature Classification by DBN

As is known to all, DBN technique has been frequently used in face recognition and hyperspectral image classification [20,23]. It was applied for aircraft engine health diagnosis and electric power transformer health diagnosis as well [22]. In [3], DBN was directly adopted for bearing fault diagnosis using raw measured vibration signal. Upon this, we propose an intelligent bearing fault diagnosis approach by using DBN to train the modified samples (i.e. the dimensionally reduced vibration signals) obtained by PCA. This can be viewed as the key step to the proposed intelligent bearing fault diagnosis approach. In what follows, we shall illustrate the main strategy of DBN technique.

DBN is a probabilistic multi-layer neural network consist of a plurality of Restricted Boltzmann Machines (RBMs), which are constructed by connections of visible layers and hidden layers [7]. The visible units (denoted by v) and the hidden units (denoted by h) are symmetrically connected upon weights w_{ij}. There is no connection among units within the same layer [2]. In this paper, we consider a DBN model consist of two RBMs, where the structure is as shown in Fig. 1.

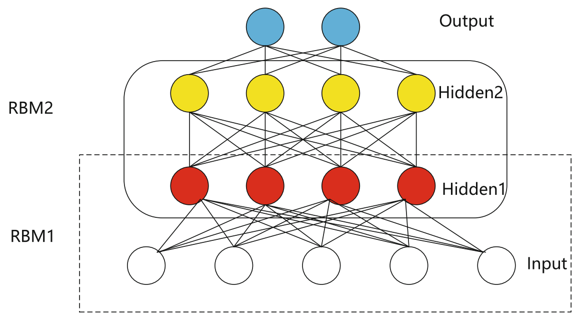

Fig. 1. Architecture of DBN

Define the energy function $E(v, h)$ of a RBM as

$$E(v,h;\theta) = -\sum_{i=1}^{n_v} a_i v_i - \sum_{j=1}^{n_h} b_j h_j - \sum_{i=1}^{n_v}\sum_{j=1}^{n_h} h_j w_{ij} v_i \tag{5}$$

where v_i and h_j are the states of visible units and hidden units respectively with a_i, b_j being corresponding biases. Let $\theta = \{w_{ij}, a_i, b_j\}$ refer to the parameter of RBM.

The joint probability of the visible units and hidden units is

$$P(v,h;\theta) = \frac{e^{-E(v,h;\theta)}}{Z(\theta)}, Z(\theta) = \sum_{v,h} e^{-E(v,h;\theta)} \tag{6}$$

where $Z(\theta)$ is the normalization factor. Besides, we have

$$P(h|v) = \frac{e^{-E(v,h)}}{\sum_{j=1}^{n_h} e^{-E(v,h)}} \tag{7}$$

$$P(v|h) = \frac{e^{-E(v,h)}}{\sum_{i=1}^{n_v} e^{-E(v,h)}} \tag{8}$$

Since that $v, h \in \{0, 1\}$ and there is no connection between the same layer, the probabilistic version of the neuron activation functions are derived as

$$P(h_j = 1|v) = \frac{P(h_j = 1|v)}{P(h_j = 1|v) + P(h_j = 0|v)} = sigmoid(b_j + \sum_{i=1}^{n_v} w_{ij} v_i) \tag{9}$$

$$P(v_i = 1|h) = \frac{P(v_i = 1|v)}{P(v_i = 1|v) + P(v_i = 0|v)} = sigmoid(a_i + \sum_{j=1}^{n_h} w_{ij} h_j) \tag{10}$$

The objective of training RBM is to increase the probability of input data $P(v)$ by following the parameters update laws

$$\begin{aligned} \Delta W_{ij} &= \eta(< v_i h_j >_{data} - < v_i h_j >_{recon}) \\ \Delta a_i &= \eta(< v_i >_{data} - < v_i >_{recon}) \\ \Delta b_j &= \eta(< h_j >_{data} - < h_j >_{recon}) \end{aligned} \tag{11}$$

where η is the learning rate, the notation of $< \cdot >_{data}$ refers to the expectation with respect to the distribution of observed data and $< \cdot >_{recon}$ refers to the expectation with respect to the distribution of reconstructions produced.

Due to the existence of normalization factor $Z(\theta)$, it is complex to calculate the joint probability distribution $P(v, h; \theta)$. In [6], a Contrastive Divergence (CD)-k solution was developed. It has been proved that $k = 1$ works well in practical applications. The CD-K algorithm is as shown in Algorithm 1.

3 Intelligent Bearing Fault Diagnosis Approach

The bearing fault diagnosis problem typically is regarded as a class of pattern classification problem, thus contains four main steps as data acquisition, feature extraction, feature selection and health condition identification. Our fault diagnosis scheme in this paper is carried out by following the procedure stated in Table 1. In the first place, we acquire bearing vibration signals. In the next, we define normal and fault types of the bearing component. Three types of fault

Algorithm 1. CD-k algorithm

Require: $k, S, RBM(W, a, b)$
Ensure: $\Delta W, \Delta a, \Delta b$
  $Initialize : \Delta W = 0, \Delta a = 0, \Delta b = 0;$
  for all $v \in S$ **do**
    $v^{(0)} := v;$
    for $t = 0, 1, \cdots, k-1$ **do**
      $h^t = sample\_h\_given\_v(v^{(t)}, RBM(W, a, b));$
      $v^{t+1} = sample\_v\_given\_h(v^{(t)}, RBM(W, a, b))$
    end for
    for $i = 1, 2, \cdots, n_h; j = 1, 2, \cdots, n_v$ **do**
      $\Delta W_{j,i} = \delta W_{j,i} + [P(h_j = 1|v^{(0)})v_i^{(0)} - P(h_j = 1|v^{(k)})v_j^{(k)}];$
      $\Delta a_i = \Delta a_i + [v_i^{(0)} - v_i^{(k)}];$
      $\Delta b_j = \Delta b_j + [P(h_j = 1|v^{(0)}) - P(h_j = 1|v^{(k)})];$
    end for
  end for

categories are considered including inner race fault, outer race fault and ball fault with diameters ranging from 0.007, 0.014 to 0.021 in., which eventually leads up to 10 kinds of state conditions totally. Then we use PCA method to reduce the dimension of all the vibration signals and normalize the data within the range [0, 1]. In the followed step, the modified data are divided into two parts, training set and testing set. Then we initialize the parameters of DBN. The DBN is trained by training set and then examined by testing set. In the last, we analyze and obtain the final fault diagnosis result. We shall present our PCA-DBN based intelligent bearing fault diagnosis approach detailedly in the following paragraph.

Table 1. Procedure of our intelligent bearing fault diagnosis method

Step	Description
Step 1	Acquire bearing vibration data
Step 2	Define normal and fault types
Step 3	Apply PCA to reduce data dimension
Step 4	Divide data into training set and testing set
Step 5	Initial parameters of the DBN
Step 6	Train DBN by training set and diagnose on testing set
Step 7	Analyze and obtain the final fault diagnosis result

3.1 Data Description and Reduction

We get the bearing vibration signals from Case Western Reserve University Bearing Data Center and use 2 hp reliance electric motor to conduct the experimental simulations, where the acceleration data are measured at locations near to and remote from motor bearings.

In most rotating machinery, the diameter of bering component ranges from 0.007 in. to 0.021 in. We consider three common sorts of bearings with diameter being 0.007, 0.014 and 0.021 in., respectively. At the meanwhile, three typical fault categories such as ball fault, inner race fault, outer race fault are concerned. Consequently, there are 10 state conditions in total including normal state, or in other words, 10 feature classifications in all. Parts of the time-domain response are as shown in Fig. 2. Obviously, it is hard to observe and classify these signal state features directly from their time-domain response. Alternatively, on the other hand, it is useful to collect all these points to extract feature by using the eigenvalues and eigenvectors of the generated fault feature matrix. To this effect, PCA technique is adopted to reduce the dimension of raw bearing vibration signals instead of common vibration signals processing.

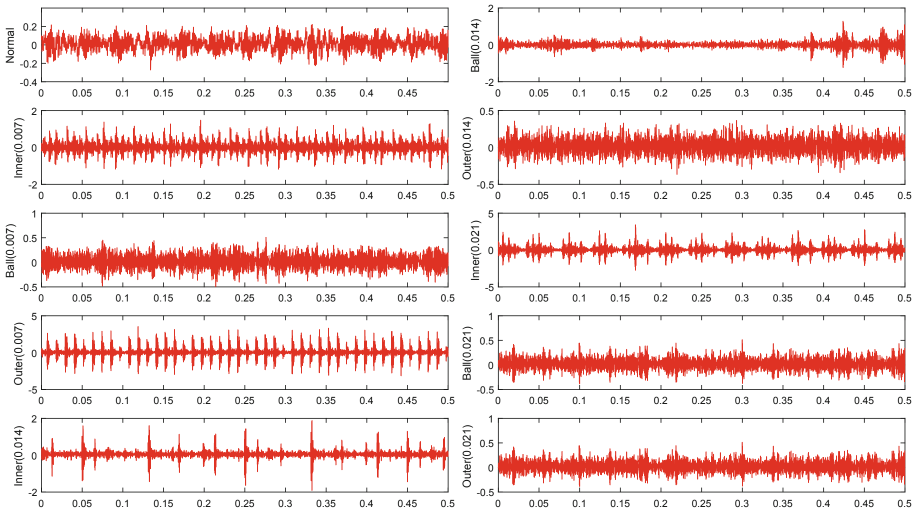

Fig. 2. Time-domain responses of different bearing vibrations signals

3.2 Experimental Results and Discussion

In this part, we use experimental results to examine the effectness of our proposed approach. The experiment data are collected at 12 kHz. All the datasets are collected upon four different loads as 0, 1, 2, 3 hp. Let the motor speed be close to 1800 rpm, and each sample contain 400 data points.

We consider four different situations. The dataset A and C are with 12000 original samples and the remaining dataset B and D are with 12120 original samples. In other words, we examine our fault diagnosis scheme under different sample sizes. On the other hand, we compare the DBN based and PCA-DBN based fault diagnosis schemes between the dataset with same sample size. The vibration signals in dataset A and B are directly input into DBN to diagnose the state condition and those data in dataset C and D are input into DBN after a PCA procedure. The four experimental dataset are described as in Table 2. From Table 2 we can conclude dataset A and B are with 400 dimension, and the dimension of dataset C and D is reduced from 400 to 123 since that the cumulate contribution rate of prior 123 dimension eigenvalues exceeds 95%. In what follows, we divide dataset A, B, C, D into two parts, training set and testing set, and normalize all the datasets into the range of [0, 1].

Table 2. Description of four experimental datasets

Fault diameter	Conditions	Dataset A and C		Dataset B and D	
		Training data	Testing data	Training data	Testing data
None	Normal	840	360	909	303
0.007	Inner	840	360	909	303
	Ball	840	360	909	303
	Outer	840	360	909	303
0.014	Inner	840	360	909	303
	Ball	840	360	909	303
	Outer	840	360	909	303
0.021	Inner	840	360	909	303
	Ball	840	360	909	303
	Outer	840	360	909	303

Table 3. Classification rate of four experimental datasets

Dataset	Training accuracy rate	Testing accuracy rate
Dataset A	85.96%	69.66%
Dataset B	88.38%	76.94%
Dataset C	94%	88.78%
Dataset D	99.6%	91.16%

The DBN model for Dataset A and B has a 400-300-100-10 structure, while that for Dataset C and D has a 123-100-100-10 sturcture. The learning rate of η of forward stacked RBM is set to 0.1. The momentum is set to 0.9 and the dropout is set to 0.1. The fault classification rates of four experimental datasets are as demonstrated in Table 3. From Table 3, we can see dataset C and D exhibit better accuracy rate than dataset A and B, which means the PCA-DBN based fault diagnosis scheme is better than the pure DBN based fault diagnosis scheme. In addition, dataset D shows the best accurate rate among all, indicating a larger number of sample contributes a better accurate rate. However, it is worth noting that PCA-DBN base intelligent bearing fault diagnosis approach hearing is not exempt from overfitting phenomena.

4 Conclusion

This paper presents a novel PCA-DBN based fault diagnosis approach for bearing component. We firstly utilize PCA technique to reduce samples dimensions, extract fault features, and then adopt DBN for fault classification and diagnosis. The effectiveness of the proposed intelligent bearing fault diagnosis approach is examined by experimental results. In addition, the PCA-DBN based fault diagnosis strategy can be applied into other large scale industrial fault diagnosis systems without manual feature selection.

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