

Rolling Bearing Fault Diagnosis Method based on EEMD and GBDBN

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Abstract

Aiming at the complexity, nonlinearity, and non-stationarity of the rolling bearing vibration signal, a fault diagnosis method based on Ensemble Empirical Mode Decomposition (EEMD) and Gauss Bernoulli Deep Belief Network (GBDBN) model is proposed. The method first carries out EEMD on the vibration signal; second, the eigenvalues of each intrinsic mode function (IMF) are statistically analyzed; then, the feature vectors are constructed by selecting less change features; finally, the normalized feature vectors are input into the GBDBN to identify the fault types. The experimental results show that the proposed method achieves more than 90% recognition rate of fault types and has better fault diagnosis ability, which can provide convenience for maintenance.

Keywords: rolling bearing; GBDBN; Gauss Bernoulli restricted Boltzmann machines; fault diagnosis

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1. Introduction

At present, the method of fault diagnosis can be divided into the method based on mechanism modeling, the method based on knowledge engineering, and the data driven method [1]. The vibration signals of the rolling bearing have complex coupling and nonlinearity. Traditional fault diagnosis usually cannot deeply dig data and lacks the related technology to improve the data application.

Empirical Mode Decomposition (EMD) is a time-frequency analysis method proposed by Huang in 1998. EMD has been rapidly developed and widely used in gearbox fault processing [2-3]. EMD has good adaptability and can be decomposed according to its own characteristics of the fault signal to obtain prominent local features in the intrinsic mode components. However, due to the appearance of modal aliasing, the diagnostic accuracy is affected. EEMD is an improvement of the EMD method. Noise-assisted analysis of gearbox fault signals can reduce the effect of modal aliasing and further improve the analysis [4]. The EEMD is an adaptive signal processing method that is well suited for handling nonlinear non-stationary signals. However, in strong noisy environments, the noise often affects the sensitive IMF. The high-frequency weak feature frequencies are easily submerged in the noisy IMF, which is not conducive to fault identification [4]. Some researchers have proposed combining with other classification algorithms for fault diagnosis. References [5-7] combined EEMD and the BP neural network to realize the fault diagnosis of gear and rolling bearing; however, the superficial learning algorithm used has limited ability of expression, which makes it hard to classify high-dimensional and nonlinear features and is apt to fall into the local optimum.

Before the theory of deep learning was proposed, most of the fault recognition techniques were based on a relatively shallow learning structure, which relied on a large amount of signal processing and human experience. However, the model based on deep learning deals with massive data through a multi-hidden network structure model. The neurons in the hidden layer automatically learn the features in the data to obtain more efficient features than artificial selection, thereby removing the dependence on experience and improving the accuracy of classification or prediction. The Deep Belief Network (DBN) has been applied in the field of process monitoring, power grid fault diagnosis, and mechanical equipment fault status recognition in recent years. References [8-9] used the normalized rolling bearing original time-domain signal to train the DBN and completed the fault diagnosis. Reference [10] studied the ball bearing fault diagnosis using a combination of SVD

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and DBN. In reference [11], the double-tree complex wavelet and DBN were used to study the classification of bearing fault types, which extended the application of DBN in fault areas. Reference [12] used the EEMD-Hilbert envelop spectrum and DBN to study the state recognition of rolling bearing and achieved good diagnostic results. However, the number of DBN nodes is relatively large, which results in complex structure and long training time and is not conducive to real-time monitoring. DBN consists of several Restricted Boltzmann Machines (RBMs). RBM is constrained by the two values of input nodes, and it cannot be directly applied in processing data and detecting. Generally, the vibration signal of rolling bearing is a continuous real value, while the Gaussian Bernoulli limited Boltzmann machine (GBRBM) can handle the real value data. Therefore, using GBRBM instead of RBM to build the Gaussian Bernoulli depth belief network (GBDBN) can solve the problem that the vibration signal of rolling bearing is a real value. At present, research on using GBDBN for fault diagnosis is limited. However, when GBDBN is affected by disturbing factors, its output has a certain randomness, so it is easy to misclassify the fault classification. As a result, its performance is not stable.

Aiming at the problem that the traditional method cannot recognize high-frequency weak features after EEMD under a strong noise environment, combined with the advantages of GBDBN where it can directly process real-valued data and adaptively mine deep features of high-dimensional data, a new fault diagnosis method of rolling bearing is proposed. The method firstly carries out EEMD on the vibration signal, then determines the characteristics of each IMF, selects the features with smaller changes as the eigenvectors, and inputs them into GBDBN for fault type identification. Experiments show that this method has a beneficial effect.

2. Modeling Method of Fault Diagnosis based on EEMD and GBDBN

Based on EEMD and GBDBN, a fault recognition model for rolling bearings, inner rings, and outer rings of rolling bearings is established, and it is used to determine whether the ball bearings, inner rings, and outer rings of rolling bearings are faulty. The process of rolling bearing fault diagnosis based on EEMD and GBDBN is shown in Figure 1.

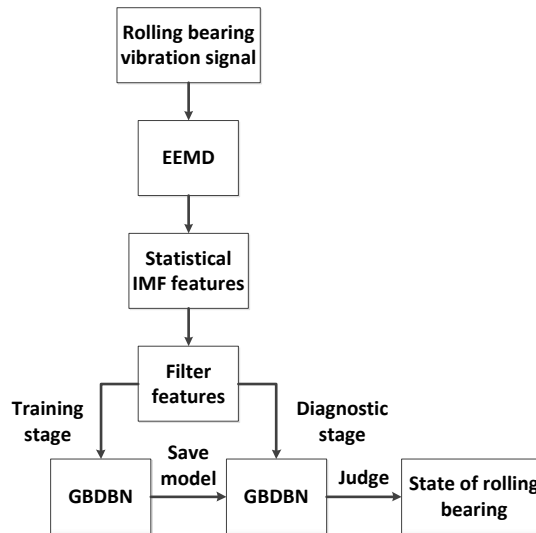


Figure 1. Fault diagnosis model of rolling bearing based on EEMD and GBDBN

This method first draws on the advantages of EEMD, extracts features from nonlinear vibration signals of rolling bearings, and reduces the influence of non-stationary signals and the interference of uncertain factors. Then, the statistical feature of IMFs is used as the input of GBDBN to reduce the number of nodes of GBDBN. Finally, we use the ability of GBDBN to excavate the deep features of high-dimensional data to identify fault types and finally realize the recognition of several types of faults and different fault states of rolling bearings. The implementation process is as follows:

Training stage:

- The vibration data of the rolling bearing is collected and processed by EEDM to obtain each IMF component;
- Using time-domain statistical methods to calculate each IMF component, obtain the statistical characteristics;
- Select the feature vectors with smaller changes and input them to GBDBN for training;
- The trained model is saved to facilitate the diagnosis of the call.

Diagnostic stage:

- The vibration data of the rolling bearing are collected and processed, and the process is the same as the training stage. Then, the features are extracted;
- The feature vectors are extracted and input into the trained GDDBN for fault identification to determine the state of the rolling bearing.

3. The Principle of EEMD and the Method of Time Domain Statistics

3.1. The Principle of EEMD

EEMD overcomes the modal aliasing problem of EMD by adding Gaussian white noise to the original signal and using white noise as an adaptive binary filter in the decomposition [13]. The calculation process is [14]:

- Let the original signal be $x(t)$ and make N the number of polymerization; at the same time, remember $m = 1$;
- A new test signal $x_m(t)$ is generated by adding Gaussian white noise with a magnitude factor of k in $x(t)$:

$$x_m(t) = x(t) + k \cdot n_m(t) \quad (1)$$

- Using the EMD method, decompose $x_m(t)$ into a series of IMFs;
- When $m < N$, steps (2) and (3) are repeated, but the newly added Gauss white noise needs to be distinguished from the previous several times; at the same time, make $m = m + 1$;
- After the above decomposition, several groups of IMFs are produced with the mean value of

$$\bar{c}_i = \sum_{m=1}^N c_{i,m} / N \quad (2)$$

Where N is the number of polymerization and $c_{i,m}$ is the i^{th} IMF obtained by the m decomposition.

The last EEMD intrinsic mode function is the average of the N^{th} decomposition of each IMF above.

3.2. The Method of Time Domain Statistics

Signal characteristics reflect the inherent law of the signal and, to a certain extent, are symbolic. Reference [15] pointed out that the advantage of the characteristic parameter method lies in that only a few indicators are required to explain the bearing state. Statistical characteristics of each IMF are calculated as follows:

Average value:

$$mean = \frac{1}{n} \sum_{i=1}^n x_i \quad (3)$$

Maximum value:

$$m_x = \max(x_i) \quad (4)$$

Peak to peak values:

$$p_x = m_x - \min(x_i) \quad (5)$$

Root Mean Square:

$$X_{rms} = \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2} \quad (6)$$

Kurtosis:

$$\alpha_4 = \frac{\sum_{i=1}^n x_i^4}{n X_{rms}^4} \quad (7)$$

Waveform factor:

$$s = \frac{X_{rms}}{\sum_{i=1}^n |x_i| / n} \quad (8)$$

Peak factor:

$$C = \frac{\max(|x_i|)}{X_{rms}} \quad (9)$$

Kurtosis factor:

$$K = \frac{\alpha_4}{X_{rms}^4} \quad (10)$$

Pulse factor:

$$I = \frac{\max(|x_i|)}{\sum_{i=1}^n |x_i| / n} \quad (11)$$

Margin factor:

$$L = \frac{\max(|x_i|)}{(\sum_{i=1}^n \sqrt{|x_i|} / n)^2} \quad (12)$$

4. Design and Optimization for Planar-Type Voice Coil Motor

GBDBN is a generation model established by training the weights between the neurons of its layers and the layers, so that the whole model can train the data according to the maximum probability to realize the data type identification or classification [16-21]. The components of GBDBN are GBRBMs and consist of multiple GBRBMs stack by stack. Two neurons in each GBRBM correspond to GBDBN. Receiving data involves the explicit layer, while feature extraction involves the hidden layer. Correspondingly, the neurons in the explicit layer and the hidden layer are the explicit element and the hidden element, respectively. Therefore, the process of training GBDBN is the process of training GBRBM [19, 22-23]. In each GBRBM, the explicit layer receives the data to infer the hidden layer and then treats the hidden layer as the explicit layer of the next GBRBM. The explicit element of GBRBM can take a continuous real number, while the hidden element can only take 0 or 1. This feature of GBRBM makes it fit for modeling real value data [10], as shown in Figure 2.

According to reference [3], the system energy function of GBRBM is defined as

$$E(v, h | \theta) = -\sum_{i=1}^n \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_{j=1}^m b_j h_j - \sum_{i=1}^n \sum_{j=1}^m \frac{v_i}{\sigma_i} W_{ij} h_j \quad (13)$$

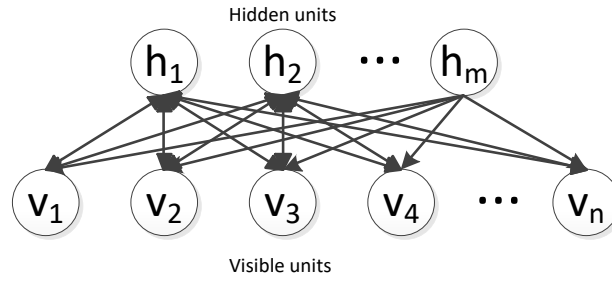


Figure 2. Composition of RBM

Where σ_i is the standard deviation of Gaussian noise corresponding to explicit element v_i , $\theta = \{W_{ij}, a_i, b_j\}$ is the GBRBM structural parameters, W_{ij} represents the connection weight between explicit element v_i and hidden element h_j , a_i represents the offset of the explicit element v_i , b_j represents the offset of the hidden element h_j , and all parameters are real numbers.

Therefore, the joint probability distribution of the explicit and hidden layers is

$$P(h_j = 1 | v, \theta) = \sigma(b_j + \sum_i \frac{v_i}{\sigma_i} W_{ij}) \quad (14)$$

$$P(v_i | h, \theta) = N(a_i + \sigma_i \sum_j W_{ij} h_j, \sigma_i^2) \quad (15)$$

To simplify the model reasoning, it is necessary to normalize the data in advance of the use of GBRBM. For the training of GBRBM, the learning algorithm of Contrastive Divergence is adopted. The specific operations are described as follows:

- First, the excitation value of each hidden unit is calculated:

$$h = Wx \quad (16)$$

- Then, the excitation values of each hidden unit are normalized by the S-shaped function and become the probability value of opening (denoted by 1):

$$P(h_j = 1) = \sigma(h_j) = \frac{1}{1 + e^{-h_j}} \quad (17)$$

- For the S-shaped function, we use the logistic function as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (18)$$

- So far, the probability in the opening state of each hidden unit is calculated. Thus, the probability in the closing state of each hidden unit (denoted by 0) is

$$P(h_j = 0) = 1 - P(h_j = 1) \quad (19)$$

- As to whether the neuron is opened or closed, we need to compare the probability of opening with a random value drawn from a (0,1) uniform distribution:

$$u \sim U(0,1) \quad (20)$$

- As follows:

$$h_j = \begin{cases} 1, & P(h_j = 1) \geq u \\ 0, & P(h_j = 1) < u \end{cases} \quad (21)$$

Then, open or close the corresponding hidden unit according to the above calculation. Similarly, given the hidden layer, the visible layer can be calculated according to the above calculation.

For training RBM, the algorithm shown as follows is the Contrastive Divergence, proposed by Hinton:

- For each record x in the training set, we assign x to the visible layer $v^{(0)}$ to compute the probability that the hidden layer neurons are opened:

$$P(h_j^{(0)} = 1 | v^{(0)}) = \sigma(W_j v^{(0)}) \quad (22)$$

Where superscripts and subscripts are used to distinguish different vectors and dimensions respectively in the same vector.

- Then, a sample is extracted by using Gibbs sampling from the calculated probability distribution:

$$h^{(0)} \sim P(h^{(0)} | v^{(0)}) \quad (23)$$

- Reconstruct the visible layer with $h^{(0)}$:

$$p(v_i^{(1)} = 1 | h^{(0)}) = \sigma(W_i h^{(0)}) \quad (24)$$

- Likewise, a sample of the visible layer is extracted:

$$v^{(1)} \sim P(v^{(1)} | h^{(0)}) \quad (25)$$

- The probability of neurons in the hidden layer being opened is again calculated using visible layer neurons (after reconstruction):

$$P(h_j^{(1)} = 1 | v^{(1)}) = \sigma(W_j v^{(1)}) \quad (26)$$

- The updated weights are as follows:

$$W \leftarrow W + \lambda(p(h^{(0)} = 1 | v^{(0)})v^{(0)T} - p(h^{(1)} = 1 | v^{(1)})v^{(1)T}) \quad (27)$$

$$b \leftarrow b + \lambda(v^{(0)} - v^{(1)}) \quad (28)$$

$$c \leftarrow c + \lambda(h^{(0)} - h^{(1)}) \quad (29)$$

After sufficient training, GBRBM can accurately implement the feature extraction or reducing feature [21].

The GBDBN consists of multiple GBRBM. To obtain a better training effect, the pre-training process uses the unsupervised greedy method, trains from bottom to top layer by layer, and obtains the parameters of each layer.

- Firstly, fully train the first GBRBM;
- Save the weight and offset obtained after training the first GBRBM, and take the state of its hidden element as the input of the next GBRBM;

- After fully training the current GBRBM, the current GBRBM is stacked above the last GBRBM;
- Repeat the third step any number of times until the top level is reached;
- Train data and label classification on top level GBRBM using classified neurons;
- After the GBDBN is trained, the schematic diagram is shown in Figure 3.

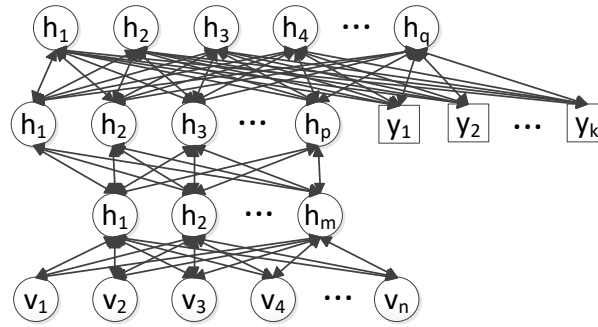


Figure 3. The schematic diagram of training completed GBDBN

The generation model uses the Contrastive Wake-Sleep algorithm to tune, and the process of the algorithm is as follows:

- In addition to the top-level RBM, the weights of the other RBM are divided into an upward cognitive weight and a downward generation weight;
- Wake phase: produce an abstract representation of each layer through the external characteristics and the upward weight, and use gradient descent to modify the downward weights between layers;
- Sleep phase: generate the state of next neurons through the top-level neurons of classification and downward weight, and modify the upward weight between the layers.

5. Experiment and Analysis

The experimental data came from the bearing data center of Case Western Reserve University in the United States. In this paper, only a part of the data was selected as an experimental analysis. The model of the rolling bearing is 6205-2RS, and the drive-end accelerometer data is collected at a 12K sampling rate. The speed of the motor is 1730r/min. The damage conditions of the rolling bearings are single damage, manufactured by artificial EDM, and the damage diameter is 0.007 inches, 0.014 inches, and 0.021 inches, respectively. The state of the rolling bearing is divided into normal, inner ring fault, ball fault, and outer ring fault. Among them, the outer diameter of rolling bearing with damage diameter of 0.007 inches includes three faults in the directions of 3 o'clock, 6 o'clock, and 12 o'clock, and the other two kinds of damaged outer diameters of rolling bearing are all in the direction of 6 o'clock. There is a total of 12 working conditions. The sampling time of each sample is 0.1 seconds, so the number of sampling points for each sample is 1200, and the number of samples for each working condition is 100. 80 samples of each condition were randomly selected for training and the remaining 20 samples were tested. The data is illustrated as follows. The 0.007 inch outer ring fault 6 indicates that the damage diameter is 0.007 inches, the outer ring fault of the rolling bearing is in the 6 o'clock direction, and the other is the analogy shown in Table 1.

Table 1. Data description of rolling bearings

States of the rolling bearing	Numbers of training data	Numbers of testing data	Classification label
Normal	80	20	1
0.007-inner-ring-fault	80	20	2
0.007-ball-fault	80	20	3
0.007-outer-ring-fault-6	80	20	4
0.007-outer-ring-fault-3	80	20	5
0.007-outer-ring-fault-12	80	20	6
0.021-inner-ring-fault	80	20	7
0.021-ball-fault-fault	80	20	8
0.021-outer-ring-fault-6	80	20	9
0.028-inner-ring-fault	80	20	10
0.028-ball-fault -fault	80	20	11
0.028-outer-ring-fault-6	80	20	12

Firstly, EEMD is used to process the vibration signals to extract valid information. The results are shown in Figures 4-9.

Limited to space, only show the decomposition results of normal signals, and the rolling bearing with damage diameter of 0.007 inches includes three fault of inner ring fault, ball fault, and outer ring fault. IMF1~IMF9 represent the decomposition results from high frequency to low frequency.

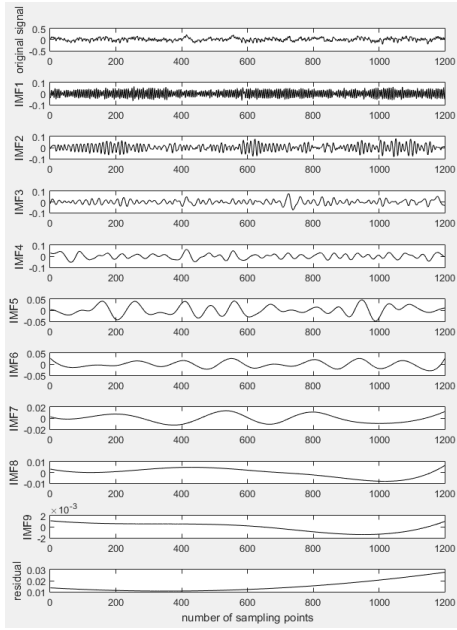


Figure 4. EEMD diagram of normal vibration signals of rolling bearings

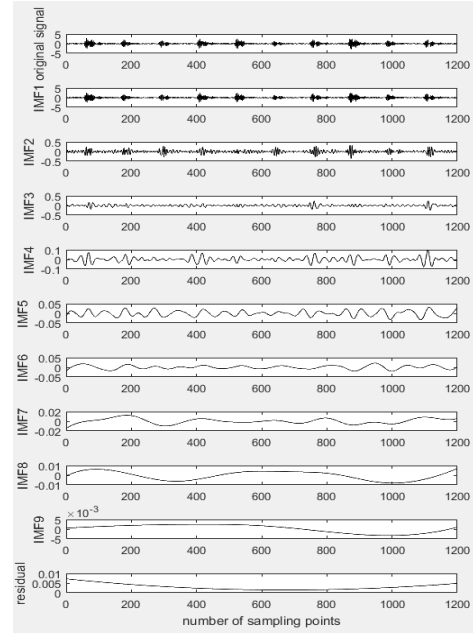


Figure 5. EEMD diagram of inner-ring-fault vibration signals of rolling bearings

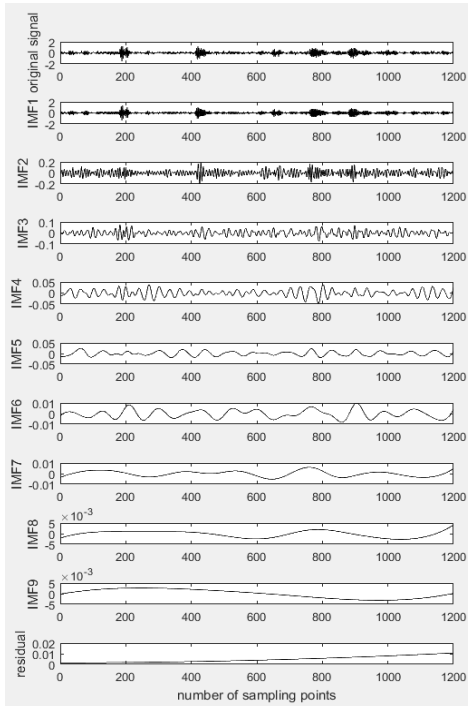


Figure 6. EEMD diagram of ball-fault vibration signals of rolling bearings

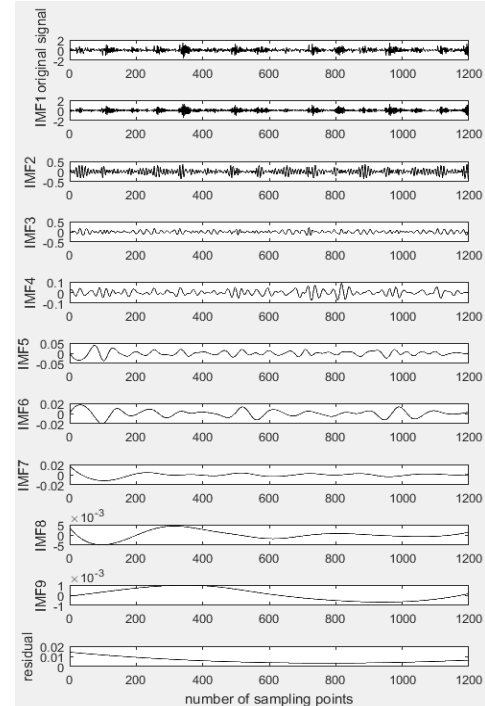


Figure 7. EEMD diagram of outer-ring-fault 3 o'clock vibration signals of rolling bearings

When the rolling bearing has different faults, the distribution of fault signals in each IMF component will change accordingly, so the statistical feature of different frequency bands should be selected as the feature vectors of fault recognition [17, 20, 24-26]. The characteristics of each IMF component are calculated according to the formula in Table 1, and the results are shown in Figure 5. Due to space limitations, only some of the features of the normal signal are listed. It can be seen from the figure that the IMF component varies from high frequency to low frequency, and the characteristic

values change obviously with a difference of several orders of magnitude. Considering the GBDBN method applied in image recognition, each pixel value of the image varies from 0 to 255, so choose the value of the feature that is not too different and not greater than 255. Thus, the paper selects the kurtosis, peak factor, pulse factor, and margin factor of each IMF component as the input of GBDBN.

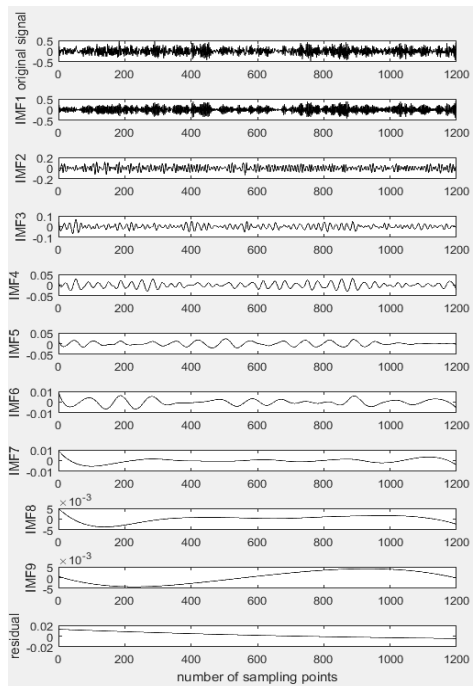


Figure 8. EEMD diagram of outer-ring-fault 6 o'clock vibration signals of rolling bearings

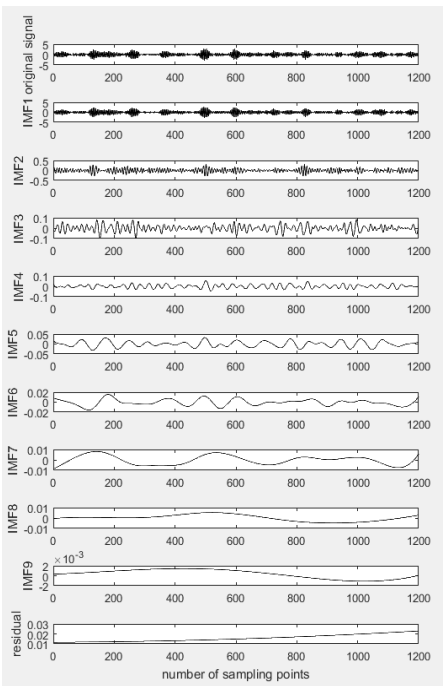


Figure 9. EEMD diagram of outer-ring-fault 12 o'clock vibration signals of rolling bearings

After feature extraction, each sample contains 36 eigenvectors and their corresponding sample tags, which are input to GBDBN for training. The first hidden layer is trained by using the sample feature vector as the input of GBDBN, then the first hidden layer is used as input layer to train the second hidden layers, and the last layer is the classification layer, which constitutes the whole network. The whole GBDBN has four layers, and the structure is 36-120-100-12, that is, the number of neurons in each layer is 36, 120, 100, and 12, respectively. The experiment training times is 1000. During the training process, there usually will be an overfitting phenomenon, so uses Dropout to prevent over-fitting. For better convergence, the learning rate of the model should not be too large, and it is set to 0.1. To make up for the defect that the derivative form of sigmoid function tends to be saturated, a cross-entropy cost function is introduced.

The data of Table 2 are tested and repeated ten times. The results of the experiment are shown in Table 3. After ten times of diagnostic experiments, the method proposed in this paper has a recognition rate of more than 90% for rolling bearing fault types and has good diagnostic capability. To further analyze the effectiveness of the method proposed in this paper, ten experiments are carried out using the same structure of Back Propagation Neural Network (BPNN) and DBN. The comparison results show that the recognition rate of GBDBN is higher than that of BPNN and DBN, which indicates that GBDBN has better classification ability and learning ability than BPNN and DBN.

Table 2. Part of the IMF's statistical features

Feature	IMF1	IMF5	IMF9
Maximum value	0.066067	0.023866	0.002001
Average value	3.337e-05	-0.00166	-0.00037
Peak to peak	0.134285	0.051006	0.003444
Root mean square root	0.028894	0.012619	0.000824
Kurtosis	1.840338	2.110486	3.257759
Waveform factor	865.9293	-7.61671	-2.24890
Peak factor	4.647441	4.041924	4.178347
Kurtosis factor	2640199	83224912	7.057e12
Pulse factor	5.304240	4.703455	5.000333
Margin factor	5.873662	5.278838	5.684202

Table 3. Experimental results

Number of experiments	Recognition rate of BPNN	Recognition rate of DBN	Recognition rate of GBDBN
1	88.33%	89.17%	90.94%
2	80.26%	85.83%	90.21%
3	81.62%	85.83%	90.63%
4	86.25%	87.08%	90.00%
5	84.11%	84.58%	90.63%
6	86.67%	88.75%	91.35%
7	87.92%	89.17%	90.31%
8	85.00%	88.92%	91.36%
9	86.83%	86.67%	90.33%
10	82.95%	85.42%	90.25%

6. Conclusions

The fault diagnosis method of rolling bearing based on EEMD and GBDBN is proposed in this paper. It combines feature extraction with deep learning and makes the most of the advantages of the EEMD and GBDBN methods. Taking the statistical characteristics of IMFs as the training data of GBDBN and avoiding directly inputting the original signal into the deep neural network training reduces the number of neurons and the complexity of the deep neural network to a certain extent and improves the efficiency of diagnosis, resulting in better performance for fault diagnosis. Firstly, the whole model of the rolling bearing fault diagnosis based on EEMD and GBDBN is introduced, and then the methods of feature extraction and processing data of EEMD and modeling method of GBDBN are introduced respectively. Finally, the experiment verifies the effectiveness of the proposed method. Compared with BPNN and DBN, GBDBN has strong ability of data identification and fault diagnosis. To verify the versatility of the method proposed in this paper, we pre-train the data of several types of rolling bearings. The results prove that this method can accurately identify bearing failures.

Acknowledgments

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