Rolling Bearing Fault Diagnosis based on DWT-BPNN

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Abstract: - For the fault diagnosis of rolling bearings, it is of great significance to improve the diagnostic accuracy. Therefore, this paper presents a rolling bearing fault diagnosis method which combines Daubechies wavelet (DW) with back propagation neural network (BPNN). Specifically, Daubechies wavelet transform is utilized to decompose the vibration signal of the original data in to different frequency components, which can be implemented to extract more prominent fault features. Then, the extracted features are input into BPNN classification model for fault diagnosis by training and testing. Finally, various experiments are carried out on the rolling bearing dataset of Western Reserve University to verify the effectiveness of this method. The results of this study demonstrate that the proposed method is able to reliably identify different fault categories with higher accuracy in comparison with the FT-BPNN methods based on Fourier transform under different loading conditions, and provides a new and effective method for the fault diagnosis of rolling bearings.

Key-words: Rolling bearing; Fault diagnosis; BP neural network; Wavelet transform.

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1 Introduction

Rolling bearing is one of the indispensable components of mechanical equipment, and it is also one of the most vulnerable components [1, 2]. According to data statistics, about 30% of the malfunctions of rotating machines are caused by rolling bearings [3]. Once the bearing fails, it may affect the safe operation of the whole machinery and equipment, which may cause economic losses or endanger personal safety [4]. Therefore, the research of reliable fault diagnosis methods and accurate diagnosis of the health of rolling bearings can effectively improve the safety and reliability of equipment operation.

The traditional intelligent fault diagnosis methods mainly based on machine learning and statistical inference techniques, such as artificial neural networks, random forest, K-nearest neighbor, Naive Bayesian, support vector machines, fuzzy inference and other developed methods, are almost all need to extract the features of the raw data depended on experience and lacking adaptability [2-7]. To solve this issue, various signal processing methods such as Fourier transform, variational mode decomposition, wavelet decomposition and wavelet packet transform are used to artificially select feature vector as the input of the intelligent classifiers to realize the fault recognition and classification.

This paper proposes a method combining Daubechies wavelet transform and BPNN is proposed for fault diagnosis of rolling bearings. It first utilizes Daubechies wavelet transform (DWT) to decompose the raw data into the low frequency and high frequency components. The frequency signals at different resolution levels can effectively represent the discriminative fault characteristics of the rolling bearing without redundant and leakage owing to its orthogonality. The extracted features are introduced into the BPNN model, and then the health status of rolling bearings is classified by BPNN. The experimental results demonstrate that the proposed method has great merits of high diagnosis accuracy than the FT-BPNN method based on Fourier transform.

The structure of this paper is organized as follows: Section 2 introduces Daubechies wavelet transform and back propagation neural network structure. In Section 3, The method proposed in this paper is introduced in detail. In Section 4, the proposed method is applied to identify the different fault categories of the rolling bearing, and the diagnosis results are utilized to compare with the FT-BPNN method. Finally, Section 5 gives some conclusions of this research and prospects for the future work.

2 Wavelet transform and BPNN

In this section, the concept and properties of Daubechies wavelet basis is first introduced. In the second step, the decomposition of DWT is specifically described in this context. Finally, the structure of BPNN is elaborately described.

2.1 Daubechies Wavelet Basis

Daubechies wavelet has been widely implemented to diagnose faults in various fields as it can match the transient components of the fault characteristics in vibration signals. In this subsection, a family of orthogonal Daubechies wavelets with compact support is elaborately introduced, which has been constructed by Daubechies [2-7].

For every even positive integer N, each Daubechies wavelet family is governed by the two-scale relation

$$\varphi(x)=\sqrt{2}\sum_{k=0}^{N-1}\hbar_k\varphi(2x-k), \qquad (1)$$

where $k=0,1,\cdots,N-1$. Based on the scaling base $\varphi(x)$, the wavelet $\psi(x)$ base function can be written as

$$\psi(x)=\sqrt{2}\sum_{k=0}^{N-1}g_k\varphi(2x-k), \qquad (2)$$

where the $H=(\hbar_k)$ and $G=(g_k)$ are the low pass and high pass filters, respectively, and $g_k=(-1)^k\hbar_{N-1-k}$. For example, Haar wavelet $H=[1,1]/\sqrt{2}$,$G=[1,-1]/\sqrt{2}$, and Daub 3 wavelet $H=[1+\sqrt{3},\ 3+\sqrt{3},3-\sqrt{3},1-\sqrt{3}]/4\sqrt{2}$, $G=[H(3),-H(2),H(1),-H(0)]$, respectively.

Furthermore, the corresponding wavelet base is usually designed with M vanishing moments that are defined as follows.

$$\int x^l\,\psi(x)dx=0,\quad \text{for } 0\le l\le M-1, \qquad (3)$$

which make it orthogonal to the low degree polynomials, and so tend to compress non-oscillatory functions. In addition, the scaling function φ has support in $[0,N-1\ ]$, while the corresponding wavelet ψhas support in the interval $[1-N/2,N/2]$ and has$N/2$vanishing wavelet moments.

2.2 Wavelet Transform

Wavelet transform can be considered as a mathematical tool that converts a signal into a series of scale and wavelet coefficients, respectively [6]. Sample onto the finest resolution level $J$and apply the filters H,G, then the low frequency components $a_{j,k}$ and high frequency components $d_{j,k}$ for resolution levels $j<J$ can be calculated by

$$s_{j,k}=\sum_n\hbar_n s_{j+1,n+2k}, \qquad (4)$$

$$d_{j,k}=\sum_n g_n s_{j+1,n+2k}. \qquad (5)$$

where $s_{j,k}$ and $d_{j,k}$ are the low frequency and high frequency components at the resolution level j, i.e., the approximation and detail coefficients, respectively. Therefore, the signal is decomposed into a hierarchical structure of detail and approximations at the finest level J as follows.

$$f:=\sum_{j=0}^{J}d_{k,jm}+s_{k,0m}. \qquad (6)$$

The DWT is a advanced signal processing technique which decomposes the extracted signal into a range of varying frequencies and mother wavelets that helps in defining the time-frequency multi-resolution analysis (MRA).

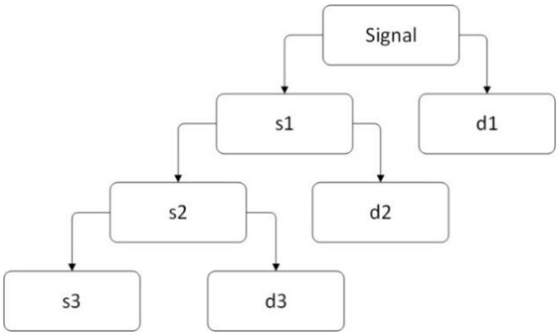

Fig. 1: Decomposition tree of wavelet transform.

The rolling bearing signal measured is decomposed into approximate (s) and detailed (d) coefficients representing the low-frequency and high-frequency components respectively as shown in Fig. 1. By invoking the norm function in MATLAB, calculate d1, d2, d3, and s3 respectively to obtain norm features. Then, these features are introduced into the BPNN model.

2.3 A brief Introduction to BPNN

As one of the most important machine learning structure models, the BPNN model has been widely applied with great success to various fault recognition fields. In this subsection, the structure of the BPNN model is explained in details.

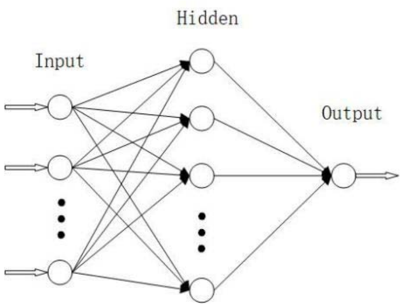

Fig. 2: Basic structure of BP network

The main structure of the BPNN model is a multi-layer network, which consists of one input layer, one or more hidden layers, and one output layer [7]. The input layer receives data, the output layer outputs data, the neurons in the previous layer are connected to the neurons in the next layer, and the information transmitted by the neurons in the previous layer is collected. The information is activated by the activation function, and then the value is passed to the next layer as elaborately depicted in Fig.2.

3 The proposed method

DWT is implemented to decompose the raw vibration signal into different frequency components at different resolution levels, which can improve the diagnosis accuracy by the BPNN model. Correspondingly, the flowchart is shown in Fig. 3 and explained in detail.

3.1 Proposed Algorithm

In this subsection, the vibration signal of the dataset provided of the Bearing Data Center of Case Western Reserve University is first decomposed into $n + 1$ parts, which consist of one low frequency component and n high frequency components, respectively, where n denotes the resolution level. Finally, the $n + 1$ features are dimensionally reduced and then input into the BPNN model for the fault condition identification of the rolling bearing. For the situation of the resolution level $n = 3$,the specific process of the DWT-BPNN model is detailed demonstrated in Fig. 3 as follows.

According to the flowchart demonstrated in Fig. 3, the general steps of the DWT-BPNN method are described in detailed as follows.

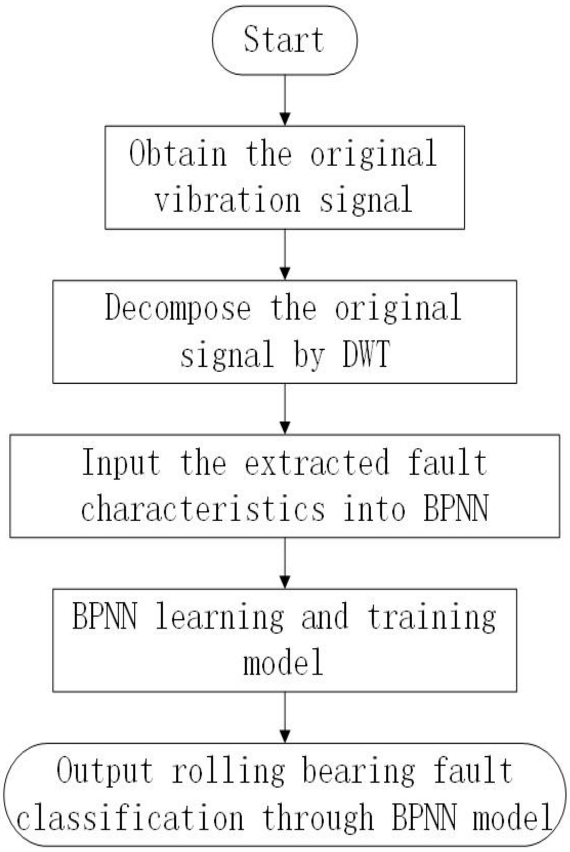

Fig. 3: Flowchart of the DWT-BPNN model for the rolling bearing fault diagnosis

Step 1: The vibration signal of the rolling bearing is collected under different loads for the fault recognition using the DWT-BPNN method in this work.

Step 2: The sample with 4096 points of the vibration signal is decomposed into 4 frequency components by DWT at resolution level 3 as shown in Fig. 1. Then the norm function is invoked in MATLAB to process d1, d2, d3, and s3 to obtain norm features. And they are used as the input of the BPNN model.

Step 3：The sample is randomly divided into 10 parts, 9 of which are used for training and 1 for testing. The experiment was repeated ten times.

Step 4：Finally, the fault features are input into the BPNN model to identify health conditions of the rolling bearing.

4 Diagnosis Results and Analysis

For the situations of different loads, the high diagnosis accuracy obtained by the proposed method is used to compare with FT-BPNN method. The comparison results show that the proposed method is more stable and achieves the higher recognition accuracy. Finally, two-dimensional visualizations of the different classification features extracted by DWT-BPNN fault diagnosis method is elaborately described by the t-SNE method. In addition, all approaches described above are implemented with Python and tested on a computer with an AMD Ryzen 7 5800H CPU @ 3.20 GHz /4.40 GB RAM.

4.1 Description of Experiment Dataset

In this subsection, the vibration signal of the dataset provided of the Bearing Data Center of Case Western Reserve University is detailed described and the corresponding ten fault categories are demonstrated in Fig. 4. Then, how to adopt the configuration of involved parameters and the training samples and the testing samples of the fault identification using vibration data of the rolling bearing are specifically introduced, respectively.

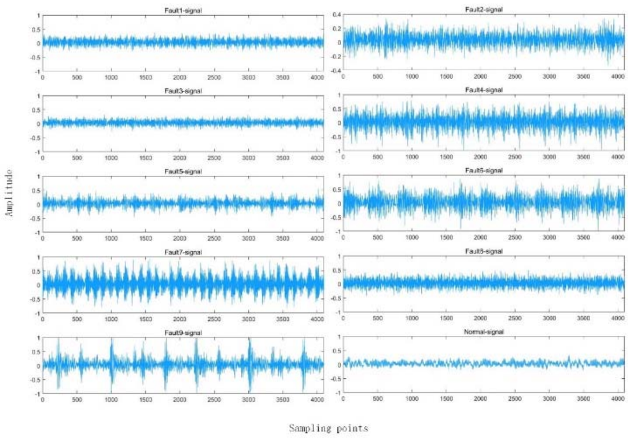

Fig. 4: The raw vibration signal of 10 health conditions of the bearing.

The components of the experimental apparatus are mainly composed of a three-phase induction motor, a torque transducer and a load motor. Each bearing data during testing are measured by acceleration transducers on four different loads (0 hp, 1 hp, 2 hp and 3 hp) and the sampling rate is 12 kHz. The rotating speed changes between 1730 and 1797 rpm based on the applied load. There are four bearing health conditions: healthy condition (H), outer race fault (OF), inner race fault (IF) and ball fault (BF). The diameters of damage size are 0.007, 0.014, 0.021, 0.028 inches, respectively. Therefore, the dataset includes 10 bearing health conditions under the 4 loads. Then, the detailed descriptions of motor bearing are presented in Table 1. For the convenience of analysis and classification, three faults (inner race, outer race and ball) with 0.007 inches are simplified as IR7, OR7 and B7, and abbreviation of other fault types is similar to this, and the 10 health conditions with different fault location and fault size are artificially set as class label 1 to 10 in this paper, respectively.

As shown in Fig. 4, the original data points under 10 health conditions were divided into 100 samples on average, and each sample with 4096 data points is obtained by a sliding window in a manner of partial overlap. Then, 1000 samples can be obtained, each of which is the vibration signal sequence of the bearing.

As illustrated in Fig. 4, the differences of a few fault categories are obvious but the most of fault patterns can not be easy to distinguish. Consequently, it is very necessary to apply DWT-BPNN method to effectively rectify different fault categories of the rolling bearing.

4.2 DWT-BPNN

In this experiment, the raw rolling bearing signal is mapped into high level representative fault characteristics, i.e., the frequency components obtained by DWT at resolution level 3 consist of one low frequency component and three high frequency components without any loss information. Then, 1000 frequency samples can be obtained by this process and are implemented to verify the rolling bearing 10 fault categories by the BPNN model. For the purpose of avoiding particularity and contingency, the experiment is conducted by 10 trials. Finally, the average testing accuracy is detailed listed in Table 2 for 10 trials.

In addition, the configuration parameters of the BPNN model are elaborately illustrated in Table 3. The learning rate is 0.005 and the iteration number is 1000. The optimizer uses Adam.

Table 1. Detailed description of the bearing working conditions.

Bearing state	BF	BF	BF	IR	IR	IR	OR	OR	OR	Normal
Defect size (inches)	0.007	0.014	0.021	0.007	0.014	0.021	0.007	0.014	0.021	–
Abbreviation	B07	B14	B21	IR07	IR14	IR21	OR07	OR14	OR21	Normal
Category labels	1	2	3	4	5	6	7	8	9	10

Table 2. Average test accuracy of the two methods under various load

Method	0hp	1hp	2hp	3hp
DWT-BPNN	0.9940±0.006633	0.9730±0.019519	1.0000±0.000000	1.0000±0.000000
FT-BPNN	0.9520±0.032496	0.9100±0.052536	0.9120±0.023152	0.9610±0.016401

Table 3. The configuration parameters of the highest average diagnosis accuracy.

Input layer	Hidden layer	Output layer	Activation function
4	128-24	10	Sigmoid

In order to avoid contingency, ten trials are carried out for diagnosing the same rolling bearing dataset. Test results indicate that a better classification performance can be obtained by using the proposed fault diagnosis method in comparison with the FT-BPNN method. Correspondingly, the classification results of DWT-BPNN method for 10 trials are elaborately illustrated in Table 4.

4.3 Comparison with FT-BPNN

In this subsection, another one popular fault diagnosis method the FT-BPNN method is implemented to compare with DWT-BPNN method.

FT-BPNN method: First, the raw data is transformed by Fourier transform. By invoking function in , the artificially selected max、min、mean and norm fault features are fed into BPNN for fault diagnosis. The configuration parameters of the BPNN model are elaborately illustrated in Table 3.

As shown in Fig. 5 and Table 5, The results of ten experiments of DWT-BPNN method and FT-BPNN method under four loads and the corresponding histogram comparison are presented. Under each load, the accuracy of the FT-BPNN method fluctuates significantly. In addition, the DWT-BPNN method performs better than the FT-BPNN method. This indicates that the proposed method can efficiently verify different fault categories of the rolling bearing and has higher accuracy than the FT-BPNN method.

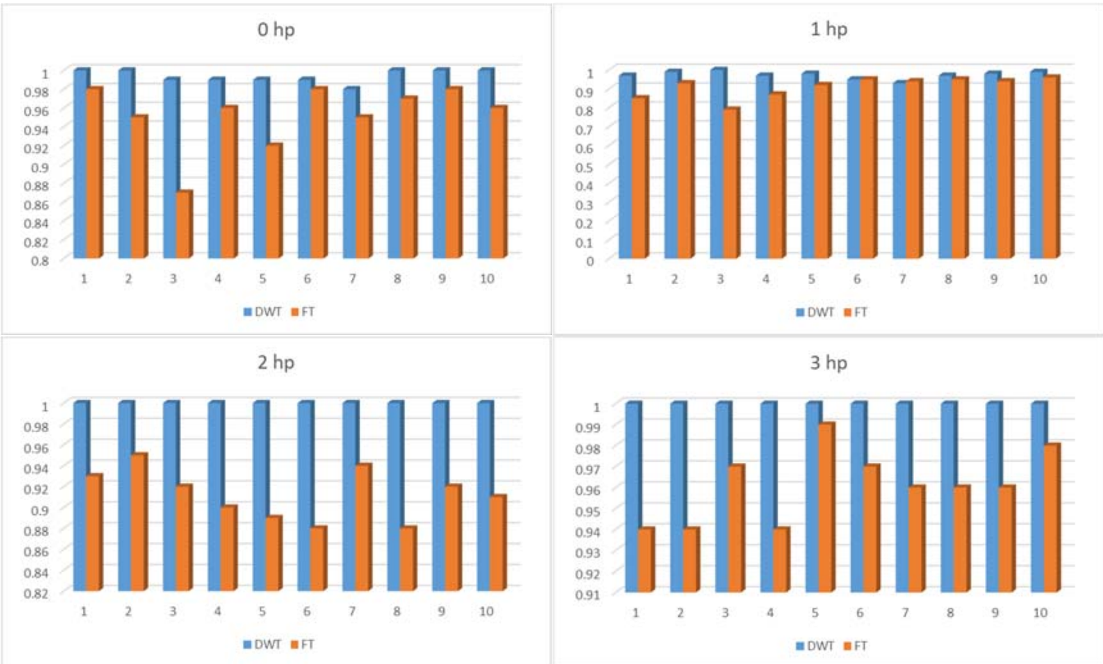

Fig. 5: Diagnosis accuracy of the above methods for 10 trials.

Table 4. Average test accuracy of the two methods under various loads.

Method	0hp	1hp	2hp	3hp
DWT-BPNN	0.9940±0.006633	0.9730±0.019519	1.0000±0.000000	1.0000±0.000000
FT-BPNN	0.9520±0.032496	0.9100±0.052536	0.9120±0.023152	0.9610±0.016401

(Note: the format of recognition result is average testing accuracy ±standard deviation)

Table 5. Diagnosis results of DWT-BPNN methods for each fault type.

Loads	1	2	3	4	5	6	7	8	9	10
0hp	1	1	0.99	0.99	0.99	0.99	0.98	1	1	1
1hp	0.97	0.99	1	0.97	0.98	0.95	0.93	0.97	0.98	0.99
2hp	1	1	1	1	1	1	1	1	1	1
3hp	1	1	1	1	1	1	1	1	1	1

Table 6. Diagnosis results of FT-BPNN methods for each fault type.

Loads	1	2	3	4	5	6	7	8	9	10
0hp	0.98	0.95	0.87	0.96	0.92	0.98	0.95	0.97	0.98	0.96
1hp	0.85	0.93	0.79	0.87	0.92	0.95	0.94	0.95	0.94	0.96
2hp	0.93	0.95	0.92	0.9	0.89	0.88	0.94	0.88	0.92	0.91
3hp	0.94	0.94	0.97	0.94	0.99	0.97	0.96	0.96	0.96	0.98

As illustrated in Fig. 6, the fault conditions can be clearly distinguished at accuracy rate of 100% for 3hp load. This indicates that the proposed method can efficiently recognize different fault categories of the rolling bearing.

As shown in Fig.7, The T-SNE diagram of fault diagnosis experiment using DWT-BPNN method under 3hp load is shown. From the diagram, it can be clearly seen that various fault characteristics are effectively distinguished and has high diagnosis accuracy as a whole.

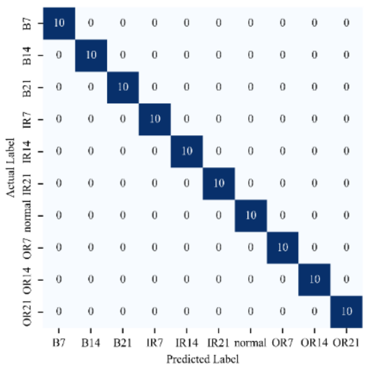

Fig. 6: Multi-class confusion matrices of the DWT-BPNN method for 3hp load.

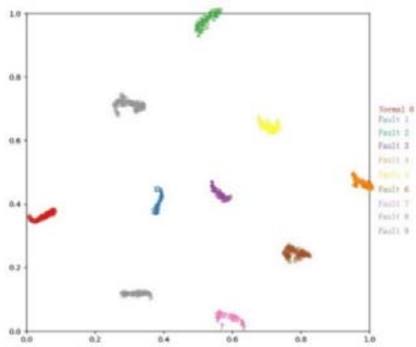

Fig. 7: Features visualization based on t-SNE: DWT-BPNN method for 3hp load.

5 Conclusions

This paper provides a method which can effectively identify the fault of rolling bearing, and compared with FT-BPNN method, it has higher accuracy. The original rolling bearing fault data is processed by wavelet transform, which makes its fault characteristics more representative and has important significance for improving the accuracy of fault diagnosis.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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