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Study of Planetary Gear Fault Diagnosis Based on Energy of LMD and BP Neural Network

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***Abstract*—Planetary gear box has the characteristics of small volume and large transmission ratio and is widely used in construction machinery. After a long period of operation, the gear fault occurs frequently, which has a great influence on the equipment. However, due to its complex structure, the fault signal is often submerged in the inherent signal of the gearbox. In order to extract the fault feature from the signal, a method based on energy of Local mean decomposition (LMD) and Back Propagation (BP) neural network is proposed to solve this problem in this paper. Original signal is decomposed by LMD into 6 product functions (PF). The energy of each PF component are calculated and defined as the input of the BP neural network. Optimal model of neural network can be obtained based on sample training. The result of experimental shows that the proposed method can achieve an overall recognition rate of 95.5%, which proves that it is an effective method for planetary gear fault diagnosis.**

Keywords- LMD; fault diagnosis; planetary gear; energy; BP neural network

I. INTRODUCTION

Planetary reducer has the characteristics of small size, compact structure, large transmission ratio and high bearing capacity. It has been widely used in low speed, and heavy-duty mechanical systems like wind power generation and helicopter. The planetary gear box is composed of a solar wheel, some planetary gears, an inner gear ring and a planet frame. When it works, it will produce more gear meshing fixed axle gear box, causing superposition of various signals which increases the difficulty of diagnosing faults in planetary gear box.

The diagnosing fault of planetary gear box is a process of feature extraction and signal classification. Because the vibration signal of the planetary gear box is nonlinear and unstable, it is difficult to extract the signal features from the simple time-frequency signal [1]. The method Empirical mode decomposition (EMD) has been proposed by N. E. Huang in 1998. Complex signals can be decomposed into a finite number of intrinsic mode functions (IMF) which contains the local characteristic signals of different time scales of the original signal [2-3]. However, the phenomenon of mode mixing and endpoint leakage exists in the process of EMD [4-5]. In order to solve this problem, methods of Ensemble Empirical Mode Decomposition (EEMD) and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) are successively proposed [6]. However, these methods can not completely suppress the occurrence of mode mixing and endpoint leakage. A new method which is called LMD is proposed by Jonathan S. Smith in 2005.

LMD adaptively decomposes complex non-stationary signal into a number of PF components with instantaneous frequency which has physical meanings [7]. Each PF component is multiplied by an envelope signal and a pure frequency modulation signal. By combining the instantaneous frequency and instantaneous amplitude of all PF components, the complete time-frequency distribution of the original signal can be obtained [8]. A set of energy feature can be obtained by calculating the energy of each component.

Signal classification is realized based on the analysis of the internal relations of signal feature vectors. However, by the interference of noise and other factors, even if the characteristic vector of the same signal will also have some deviations. These deviations have a great impact on the classification of fault types. With the development of computer technology, neural network is widely used in this field to solve the problem mentioned in the preceding sentence. BP neural network is a multilayer feed forward neural network [9]. The main feature of the network is the forward transmission of the signal and the back propagation of error. In forward transmission, the input signal is transmitted from input layer to output by the process of hidden layer. By sample training, the key parameters are updated. Finally the classification of the signal can be realized.

II. MODEL ANALYSIS

A. *Local Mean Decomposition*

LMD adaptively decomposes complex non-stationary signal into several PF components. Each PF component is multiplied by an envelope signal and a pure FM signal [10]. The process of LMD is outlined as follows:

Step 1: All of the local extreme points n_i of signal $x(t)$ are located. The mean value m_i and envelope estimate a_i of an adjacent local extreme are calculated as follows:

$$m_i = \frac{n_i + n_{i+1}}{2} \tag{1}$$

$$a_i = \frac{\left| n_i - n_{i+1} \right|}{2} \tag{2}$$

Local mean function $m_{11}(t)$ and envelope estimation function $a_{11}(t)$ are obtained by moving average.

Step 2: FM signal $s_{11}(t)$ is calculated as follow:

$$s_{11}(t) = \frac{x(t) - m_{11}(t)}{a_{11}(t)} \tag{3}$$

Step 3: FM signal $s_{11}(t)$ is defined as a new signal and its envelope estimation function $a_{12}(t)$ is calculated by step1. If $a_{12}(t)$ is equal to 1, FM signal $s_{11}(t)$ is a pure FM signal. Otherwise, the process step1 and step2 is repeated until the envelope estimate function $a_{1(n+1)}(t)$ of the FM signal $s_{1n}(t)$ is equal to 1. In practical applications, the iteration terminates when $a_{1(n+1)}(t)$ is approximately equal to 1.

$$\lim_{x\to\infty} a_{1(n+1)}(t) \approx 1 \tag{4}$$

Step 4: Envelope signal is multiplied by all the envelope estimation functions generated in the iterative process:

$$\mathrm{a}_1(t) = a_{11}(t)a_{12}(t)...a_{1n}(t) = \prod_{q=1}^{n} a_{1q}(t) \tag{5}$$

Step 5: First PF component is obtained as follows:

$$PF_1(t) = a_1(t)s_{1n}(t) \tag{6}$$

It is a single component AM-FM signal which contains the highest frequency component of the original signal.

Step 6: Residual signal $u_1(t)$ is obtained by extracting the first PF component from the original signal $x(t)$.

$$u_1(t) = x(t) - PF_1(t) \tag{7}$$

$u_1(t)$ is defined as a new signal and the aforementioned steps are repeated k times until $u_k(t)$ becomes a monotonic function.

Finally, original signal can be expressed as follows:

$$x(t) = \sum_{p=1}^{k} PF_p(t) + u_k(t) \tag{8}$$

B. Energy Feature

A number of PF components with physical meaning can be obtained by the LMD. Each component contains a lot of instantaneous amplitude frequency features. As one of the most basic characteristics of vibration signal, energy is highly representative [11]. Energy formula of single is shown as follows:

$$E = \int_{-\infty}^{+\infty} x(t)^2 d_t \tag{9}$$

C. BP Neural Network

Although the feature vector can be used to quantitatively describe the signal, it cannot directly determine the type of signal. As an algorithm of data classification, BP neural network can realize the classification of signal types [12-13]. The BP neural network is composed of input layer, hidden layer and output layer. Its structure is shown in Figure I.

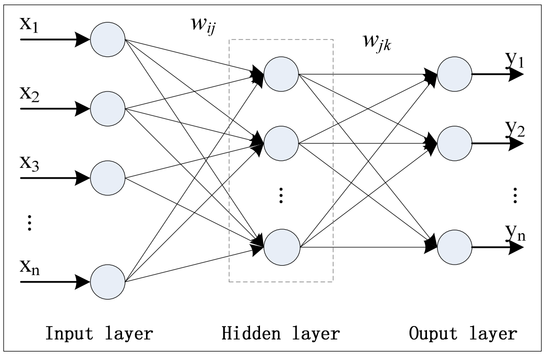

FIGURE I. STRUCTURE OF BP NEURAL NETWOFK

BP neural network must be trained firstly. Through training, the network has the function of memory and prediction [14]. Training process includes the following steps:

Step 1: Initializing neural network. Firstly, set the node number of each layer and the weights w_{ij} , w_{jk} between the adjacent layers. Secondly, initialize the threshold *a* of hidden layer and threshold *b* of output layer. Finally, choose neuron activation function $f(x)$ and set learning rate η. Selected activation function $f(x)$ is shown as follow:

$$f(x) = \frac{1}{1+e^x} \tag{10}$$

Step 2: Output of hidden layer is calculated as follow:

$$H_j = f(\sum_{i=1}^{n} w_{ij}x_i - a_j) \quad j = 1, 2, \cdots, l \tag{11}$$

where *l* is node number of hidden layer, *f()* is activation function of hidden layer.

Step 3: Output prediction of output layer and Network prediction error are calculated as follow:

$$O_k = \sum_{j=1}^{l} H_j w_{jk} - b_k \qquad k = 1,2,\cdots,m \tag{12}$$

$$e_k = Y_k - O_k \qquad k = 1,2,\cdots,m \tag{13}$$

Step 4: Weights w_{ij} , w_{jk} and threshold *a*, *b* are updated according to network prediction error as follow:

$$w_{ij} = w_{ij} + \eta H_j(1-H_j)x(i)\sum_{k=1}^{m} w_{jk}e_k \tag{14}$$

$$w_{jk} = w_{jk} + \eta H_j e_k \tag{15}$$

$$a_j = a_j + \eta H_j(1-H_j)\sum_{k=1}^{m} w_{jk}e_k \tag{16}$$

$$b_k = b_k + e_k \tag{17}$$

where $i = 1,2,\cdots,n \;\; j = 1,2,\cdots,l \;\; k = 1,2,\cdots,m$.

Step 5: Determine that whether the iteration of the algorithm ends, if not, return to step 2.

III. TEST EQUIPMENT AND DATA ACQUISITION

Simulations of planetary gear faults are performed by using the comprehensive mechanical fault simulation bench which is manufactured by Spectra quest in the United States. In this study, the sun gear faults of the second-stage planetary gear are simulated. By changing the sun wheels with different fault types, four types of solar wheel vibration signals are adopted. There are normal gear, wear gear, gear with root crack and broken gear, which are shown in Figure II.The motor output speed is set to 40 Hz and the sampling frequency is set to 3250 Hz, and each sample has 1625 data points.

(A) (B) (C) (D)

FIGURE II. SUN WHEELS WITH DIFFERENT FAULT TYPES

IV. EXPERIMENTAL ANALYSIS

This study proposes a method for diagnosing planetary gear faults based on energy of LMD and BP neural network. The vibration signals of four gear types are shown in Figure III.

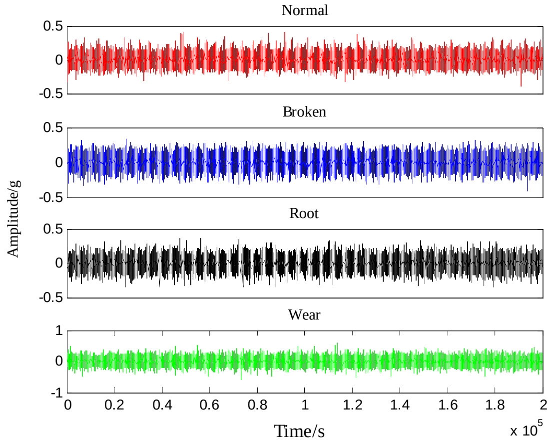

FIGURE III. FOUR TYPES OF GEAR VIBRATION SIGNALS

Given that the structure of planetary gear is complex, the collected signals usually contain the vibration information of many gears. Some fault features are often overwhelmed by these signals [15].

It can be seen that it is difficult to identify the signal types by original signals. LMD adaptively decomposes complex non-stationary signal into a number of PF components with instantaneous frequency which has physical meanings. By decomposing the single, different frequency components of the signal are separated and high-frequency fault features will be highlighted. In this paper, the wear gear is taken as an example. The components of the signal are separated by frequency and contain a large number of signal feature information. By calculating the energy of each layer, original signal can be described by a feature vector. A set of original signal is used as an experiment. Each PF energy of four kinds of gears are shown in Figure IV.

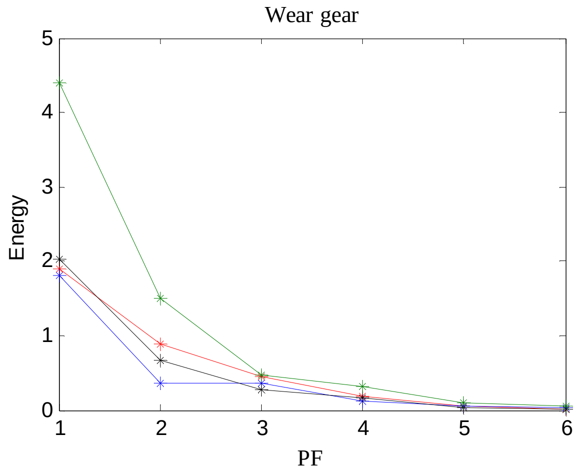

FIGURE IV. PF ENERGY OF FOUR KINDS OF GEARS

By analyzing the line graph of energy feature, It can be seen that the component energy of each signal has its own variation rule. But at the same time, different lines will also exist cross. In this paper, BP neural network is used to process data. By establishing different mapping relations, BP neural network is used to find out the intrinsic relationship between the feature data and the model category. The optimal network parameters are obtained by training samples.

Four kinds of signals are used in experiment. There are normal gear, wear gear, gear with root crack and broken gear. Each signal is decomposed by LMD and 6 PF components are obtained. The number of input nodes is 6 and output node is 4 in BP neural network. The selection of the node number of the hidden layer needs to refer the node number of input and output layers. It will affect the network learning and need to increase the number of training when number of nodes is too small. It will increase the training time and result in over fitting when number of nodes is too many. According to the empirical formula, number 4 is chosen as the number of hidden layer nodes. Then, random function is used to initial connection weights and thresholds. The learning rate is set to 0.1.

In this paper, 400 sets of data are extracted from the original data of the four signal types. Each group consists of 1625 points. 400 groups of data are processed by LMD and energy of each component is calculated to get the 400 sets of feature vectors. The first 200 groups were used as training samples, and the latter 200 groups were used as test samples. The different fault gears are denoted with numbers for training: the broken gear is denoted as 1, the normal gear is denoted as 2, the root-crack gear is denoted as 3 and the wear gear is denoted as 4. The result of test sample identification is shown in Figure V.

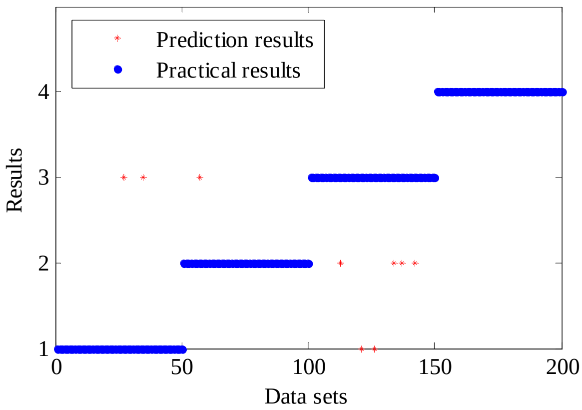

FIGURE V. IDENTIFICATION RESULTS OF TEST SAMPLES

The recognition rates of the four signals are shown in Table I. Using the method proposed in this paper, the recognition rate is up to 95.5%.

TABLE I. RECOGNITION RATES OF GEAR FAULT

Recognition	Gear type			
	normal	***broken***	***root***	***wear***
Rate	96%	98%	88%	100%

V. CONCLUSION

In this paper, a method of diagnosing faults in planetary gear based on energy of LMD and BP neural network is proposed. The vibration signal is adaptively decomposed into 6 PF components by LMD. Energy feature of each PF is calculated as the input of BP neural network. By using training samples to update the parameters, optimal model BP neural network is obtained. The trained neural network is tested by test samples. The fault recognition rates for normal gears, broken gears, root-crack gears and wear gears reached 96%, 98%, 88% and 100%. The overall fault recognition rate is 95.5%, which shows that the trained BP neural network performed well. The results indicated that the proposed method can be used to diagnose faults in planetary gear.

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