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A fault diagnosis method based on local mean decomposition and multi-scale entropy for roller bearings

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ABSTRACT

A novel fault feature extraction method based on the local mean decomposition technology and multi-scale entropy is proposed in this paper. When fault occurs in roller bearings, the vibration signals picked up would exactly display non-stationary characteristics. It is not easy to make an accurate evaluation on the working condition of the roller bearings only through traditional time-domain methods or frequency-domain methods. Therefore, local mean decomposition method, a new self-adaptive time-frequency method, is used as a pretreatment to decompose the non-stationary vibration signal of a roller bearing into a number of product functions. Furthermore, the multi-scale entropy, referring to the calculation of sample entropy across a sequence of scales, is introduced here. The multi-scale entropy of each product function can be calculated as the feature vectors. The analysis results from practical bearing vibration signals demonstrate that the proposed method is effective.

1. Introduction

The roller bearings are the most common components in rotating machines. Kinds of factors such as wear, fatigue, corrosion, overloading and so on can cause the local defects of bearings while the machines are running. Even a minor fault may have distinct and pernicious influence on the whole system, so it is important to monitor the bearing condition and diagnose the fault of bearings.

It has always been being a crux in the fault diagnosis how to obtain fault feature information from the vibration signals. Traditional fault diagnosis methods are performed by analyzing the vibration signals only in the time or frequency domain and then recognizing the working condition of bearings [1–3]. However, because of the influence of the non-linear factors including loads, clearance, friction, stiffness and so on, the fault signals usually display strong nonlinear, non-Gaussian and non-stationary features, so it is difficult to accurately recognize the working condition of bearings only in the time or frequency domain [4,5].

Common time frequency analysis methods include the Wigner Ville distribution (WVD), the short time Fourier transformation (STFT), the wavelet transform (WT), etc., but each of these methods has its limitations. For example, the Wigner Ville distribution would cause cross-term interference when dealing with the multi component signals [6,7]; the analysis window of STFT is fixed [8]; the WT has been well applied in fault diagnosis [9–11] but different mother wavelets should be predefined for each component. So they are still not self-adaptive in nature. Empirical mode decomposition (EMD) and local mean decomposition (LMD), different from the above methods, are self-adaptive time-frequency decomposition techniques. EMD is usually combined with the Hilbert transform, turning into the HHT method. However, there still exist some deficiencies in EMD such as the modes

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mixing problem and end effects that are still underway [12,13]. In addition, sometimes the unexplainable negative instantaneous frequency would appear when computing instantaneous frequency by performing Hilbert transform to the decomposition results of EMD and meanwhile the end effects would be more serious [14].

Local mean decomposition algorithm was developed by Smith in 2005 and originally used as a time-frequency analysis tool of the electroencephalogram signals [14]. LMD method is similar to EMD method but it turns out that the former is better than the latter in some aspects [15]. LMD method can be used to adaptively decompose any complicated multi-component signal into a series of product functions (PFs), each of which is the product of an amplitude envelope signal and a purely frequency modulated signal. Specially, each PF, whose instantaneous amplitude (IA) is the amplitude envelope and instantaneous frequency (IF) can be derived from the frequency modulated signal, has physical meaning. LMD method is suitable for analyzing non-stationary signals, so it is introduced to perform fault feature extraction of roller bearings in this paper.

After the original signal is decomposed, it is very likely that different fault conditions can be recognized by dealing with the decomposition results such as the PFs, IFs or IAs which may contain useful fault information. In the past, FFT and other spectrum analysis methods such as the power spectrum analysis have been used to transform the decomposition results to extract fault features [16,17]. However, traditional spectrum analysis methods are suitable for stationary signals rather than non-stationary ones, so the analysis results may not be so satisfactory. Kinds of fault extraction methods, in which LMD is combined with the order tracking method, PCA or AR model, have been put forward and applied to the diagnosis of rotary machines [18–20]. But establishing a new model after performing LMD analysis to the original signal would make the process of fault diagnosis longer or more complex.

Obviously, for the roller bearings, vibration signals of different fault patterns will show varying complexity and therefore the entropy of vibration signals varies. Costa proposed the multi-scale entropy (MSE) on the basis of sample entropy, which was originally used for heart rhythm variability research [21]. Later the multi-scale entropy was applied in the field of fault diagnosis. Zhang has proposed a bearing fault diagnosis method based on MSE and adaptive neuro-fuzzy inference system [22]. MSE is also chosen as the feature extractor in the fault diagnosis of shafts [23]. Compared with the approximate entropy and sample entropy, MSE can analyze the series complexity under different scales. Furthermore, the computation of MSE is simple. Therefore, in this paper MSE is used as the feature extractor. And based upon the above analysis, the recent development of demodulation technique LMD and multi-scale entropy are combined and applied to the roller bearing fault feature extraction.

This paper is organized as follows. The theory of the LMD method is given briefly in Section 2. In Section 3 a fault diagnosis approach in which LMD and multi-scale entropy are combined is put forward. In Section 4, the proposed approach is applied in the fault diagnosis of the roller bearings, which demonstrates that the method is effective and feasible. Conclusions are given in Section 5.

2. LMD analysis method

The purpose of LMD is to obtain a series of frequency modulated signals and envelope signals by decomposing the original multi-component signal. The product of each frequency modulated signal and the corresponding envelope signal is called a product function (PF) which has physical meaning. After all needed product functions are obtained, the completed time-frequency distribution of the original signal can be derived. Given any signal $x(t)$, it can be decomposed as follows [14,18]:

(1) The first step of the decomposition involves finding out all the local extrema n_i and calculating the mean of two successive extrema n_i and n_{i+1}. So the ith mean value m_i is given by

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

All mean values m_i of two successive extrema are connected by straight lines. The local means are then smoothed using moving averaging to form a smoothly varying continuous local mean function $m_{11}(t)$.

(2) The ith envelope estimate a_i is given by

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

The local envelope estimates are smoothed in the same way as the local means to derive the envelope function $a_{11}(t)$.

(3) Subtract the local mean function $m_{11}(t)$ from the original signal $x(t)$ and the resulting signal, denoted by $h_{11}(t)$, is given by

$$h_{11}(t) = x(t) - m_{11}(t) \tag{3}$$

$h_{11}(t)$ is then divided by the envelope function $a_{11}(t)$, resulting in $s_{11}(t)$.

$$s_{11}(t) = h_{11}(t)/a_{11}(t). \tag{4}$$

If the envelop function $a_{12}(t)$ of $s_{11}(t)$ equals to 1, the procedure will end and $s_{11}(t)$ is a purely frequency modulated signal. If not, regard $s_{11}(t)$ as the original signal and repeat the above procedure until $s_{1n}(t)$ is a purely frequency modulated signal, namely, the envelop function $a_{1(n+1)}(t)$ of $s_{1n}(t)$ equals to 1. Therefore

$$\begin{cases} h_{11}(t) = x(t) - m_{11}(t) \\ h_{12}(t) = s_{11}(t) - m_{12}(t) \\ \quad\vdots \\ h_{1n}(t) = s_{1(n-1)}(t) - m_{1n}(t) \end{cases} \tag{5}$$

where

$$\begin{cases} s_{11}(t) = h_{11}(t)/a_{11}(t) \\ s_{12}(t) = h_{12}(t)/a_{12}(t) \\ \quad\vdots \\ s_{1n}(t) = h_{1n}(t)/a_{1n}(t) \end{cases}. \tag{6}$$

(4) An envelope signal is derived by multiplying together the successive envelope estimates obtained during the iterative process described above.

$$a_1(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{q=1}^{n} a_{1q}(t). \tag{7}$$

This final envelope signal is then multiplied by the frequency modulated signal to form the first product function PF_1, actually which is a mono-component amplitude-modulated and frequency-modulated signal.

$$PF_1 = a_1(t)s_{1n}(t). \tag{8}$$

The instantaneous amplitude of PF_1 is $a_1(t)$ and the instantaneous frequency of it can be derived from the purely frequency modulated signal $s_{1n}(t)$ as

$$f_1(t) = \frac{1}{2\pi}\frac{d[\arccos(s_{1n}(t))]}{dt}. \tag{9}$$

(5) $PF_1(t)$ is then subtracted from the original data $x(t)$, resulting in a new signal. Repeat the whole process k times until $u_k(t)$ is a constant or monotonic.

$$\begin{cases} u_1(t) = x(t) - PF_1(t) \\ u_2(t) = u_1(t) - PF_2(t) \\ \quad\vdots \\ u_k(t) = u_{k-1}(t) - PF_k(t) \end{cases}. \tag{10}$$

Up to this point, the original signal can be reconstructed according to

$$x(t) = \sum_{P=1}^{k} PF_P(t) + u_k(t). \tag{11}$$

The time-frequency distribution can be constructed based on the results of LMD, namely displaying the instantaneous amplitude and instantaneous frequency of all PF components together.

3. The fault feature extraction method based on LMD and MSE

In order to realize the recognition of machine conditions there is a need to extract features from the fault vibration signals. As previously mentioned, multi-scale entropy is based on the sample entropy and it can measure the complexity of signals under different scales. Therefore, MSE can be regarded as the indexes and feature parameters of judgment in order to characterize the complexity of vibration signals under different scales and fault conditions.

Thus, after the vibration signal is analyzed by LMD method, the MSE of different PF components varies and can reflect the complexity of vibration signals at multi scales. Therefore, the fault feature extraction method in which LMD and MSE are combined is proposed in this paper and the steps of this method are listed as follows:

(1) Different vibration signals are sampled by an acceleration sensor at a certain sampling frequency f_s under different working conditions of the machine including the normal conditions and different fault conditions.
(2) Use LMD method to decompose the original signal under each working condition, thus a series of PF components can be acquired. After the decomposition, different vibration signals may have different numbers of PF components, so the first m PF components which contain useful fault information are chosen for research.

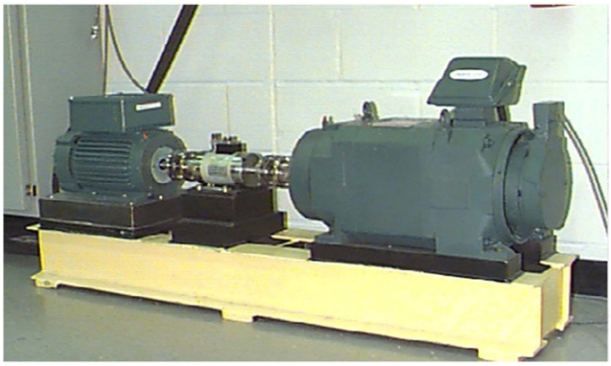

Fig. 1. Experimental setup.

(3) Determine the scale factor τ and calculate the multi-scale entropy of chosen PF components. The computation method of MSE is as follows [22]: assuming the data of a PF component is $\{x_1, x_2, \cdots, x_N\}$, data length N. Predetermine the embedding dimension m and the tolerance $r = 0.15 \times SD$, where m and r are the needed parameters when computing the sample entropy and SD is the standard deviation of the original data. Then construct consecutive coarse grained vectors $\{y(\tau)\}$ with scale factor τ ($\tau = 1, 2, \cdots$ and is a positive integer), according to the following equation:

$$y_j(\tau) = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, 1 \le j \le N/\tau. \tag{12}$$

Obviously, when $\tau = 1$, the coarse grained time series is the original time series. For a nonzero τ, the length of each coarse-grained time series is N/τ.

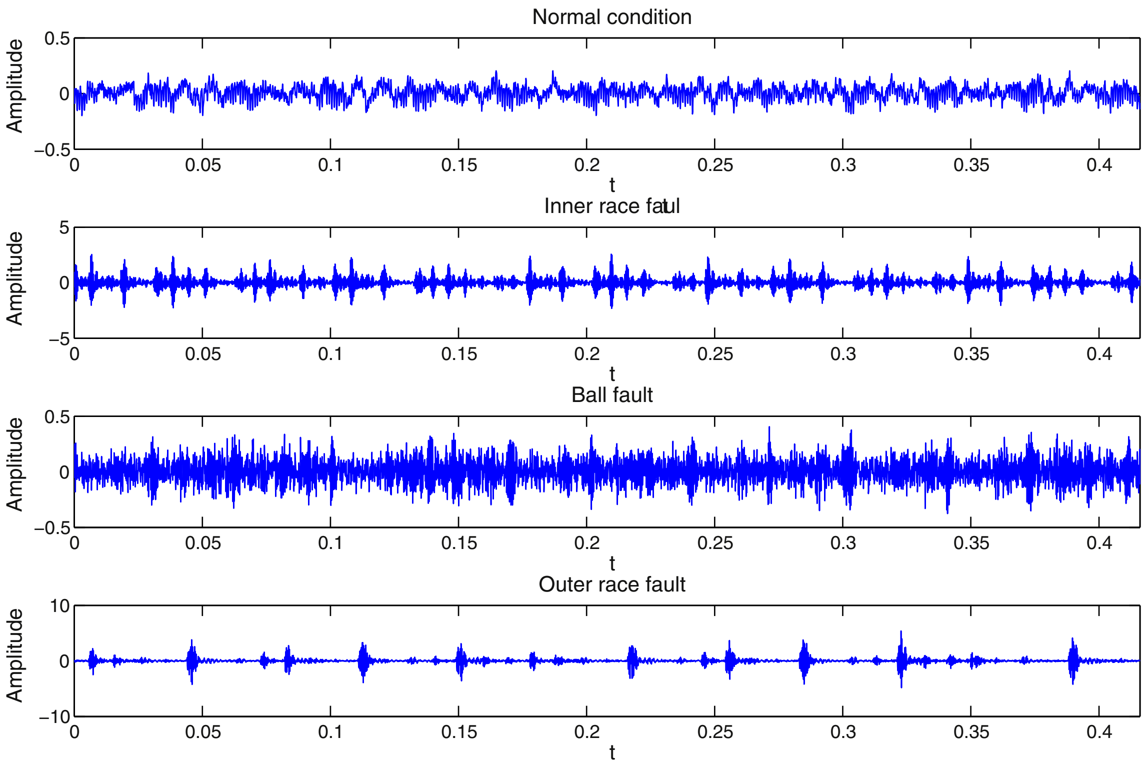

Fig. 2. Vibration signals of each bearing condition.

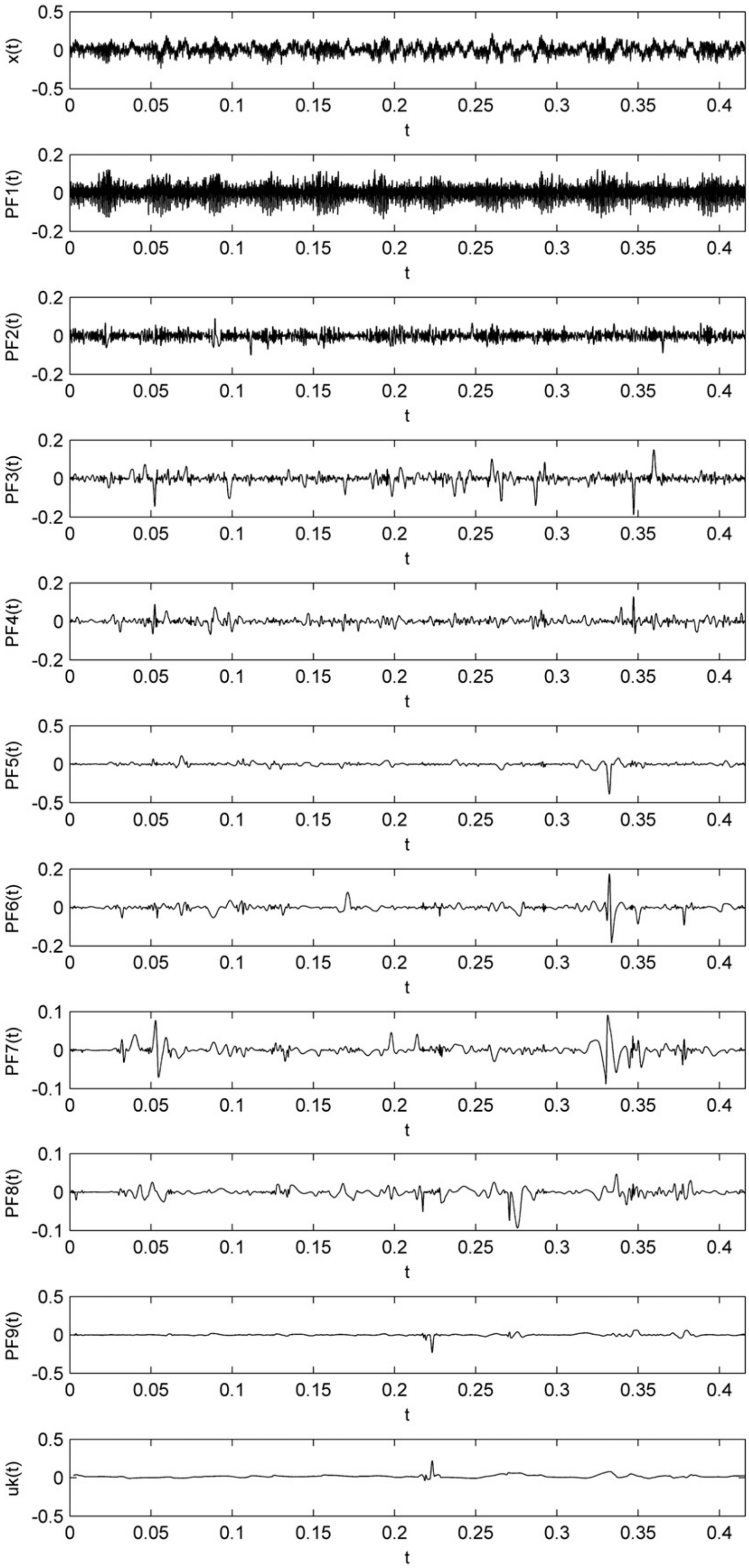

Fig. 3. LMD results of the vibration acceleration signal of the normal roller bearing.

Then the sample entropy is computed for the coarse-grained time series at each scale, and sample entropies over multiple scales are plotted as a function of the scale factor. The sample entropies over multiple scales are the so-called multi-scale entropy.

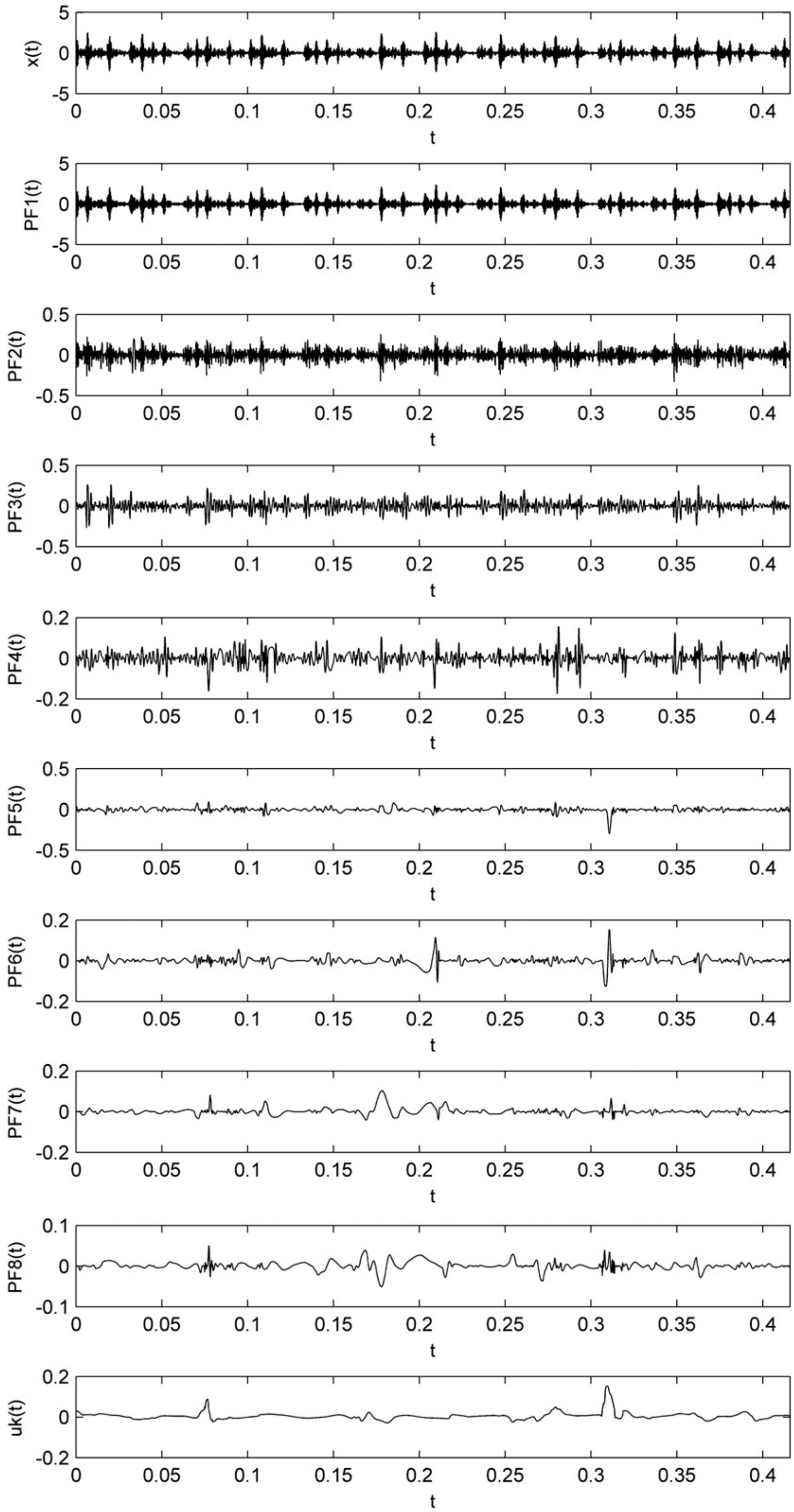

Fig. 4. LMD results of the vibration acceleration signal of the roller bearing with inner race fault.

(4) Compare the multi-scale entropy curves of different PF components and choose the multi-scale entropy which can most significantly and effectively reflect fault characteristics, namely which can distinguish itself from the other vibration signals, as the fault feature vector.
(5) Adopt a proper fault classifier such as neural networks or support vector machines and so on and take the chosen fault feature vector as input of the fault classifier in order to recognize different fault conditions.

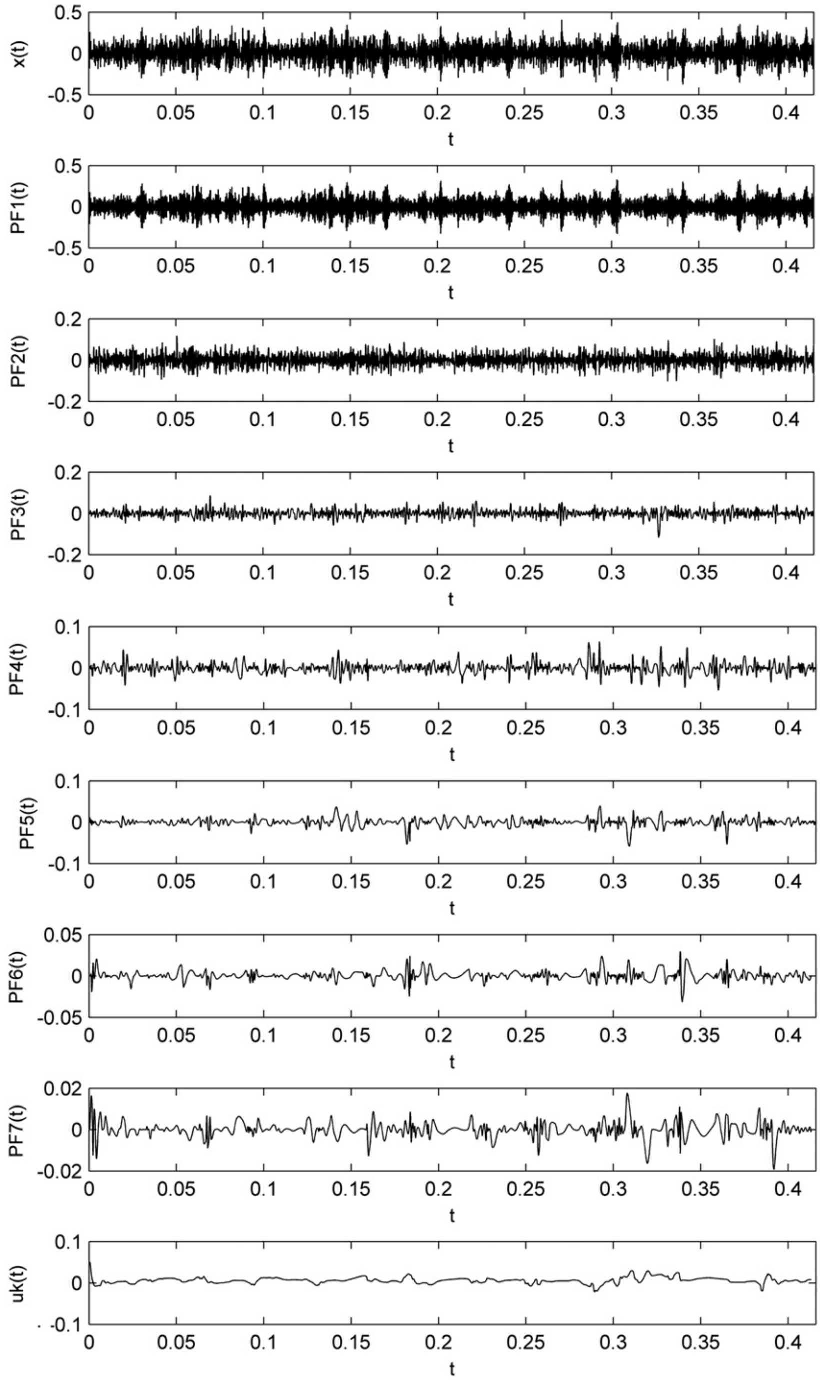

Fig. 5. LMD results of the vibration acceleration signal of the roller bearing with ball fault.

4. Application

The roller bearing vibration shows strong nonlinear and non-stationary feature because of the complicated working environment and LMD method is suitable for analyzing this kind of data, so the fault extraction method mentioned in Section 3 would be suitable for the fault diagnosis of roller bearings.

To verify the effectiveness of the proposed approach, the fault extraction method based LMD and the multi-scale entropy was applied to the experimental bearing vibration signals analysis. In this paper all the roller bearing vibration data analyzed are from the website of Case Western Reverse Lab. Experiments were conducted using a two hp, three-phase induction motor (left), a torque sensor (middle) and a dynamometer (right) connected by a self-aligning coupling (middle), as is shown in Fig. 1. The dynamometer is controlled so that desired torque load levels can be achieved. The test bearing supports the motor shaft at the drive end. Single point faults were introduced into the test bearing using electro-discharge machining. Bearing faults under consideration cover outer race fault, inner race fault and rolling element (ball) fault.

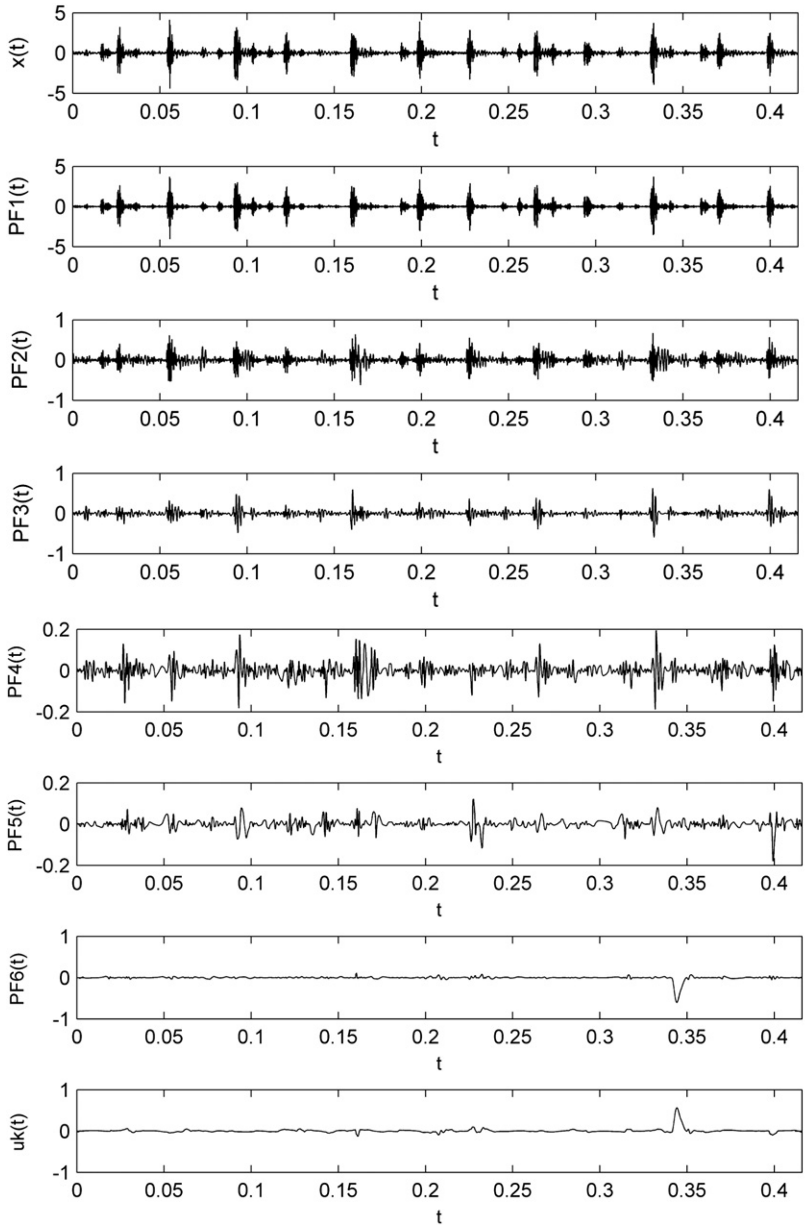

Fig. 6. LMD results of the vibration acceleration signal of the roller bearing with outer race fault.

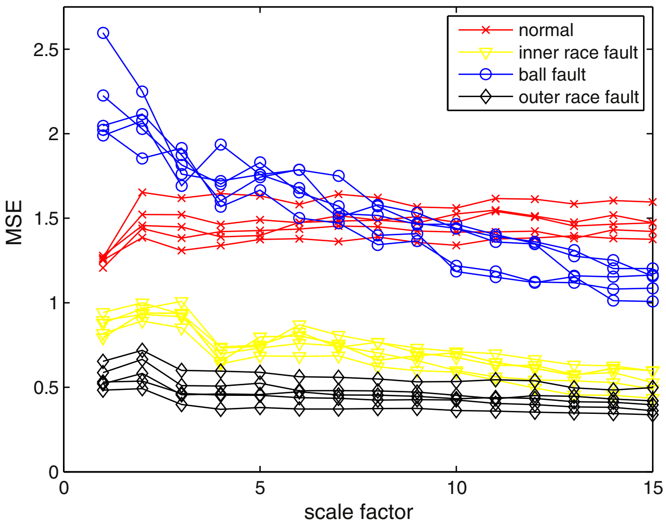

Fig. 7. MSE over 15 scales of the original signals.

We choose the data from the experiments in which SKF bearings are used and the approximate motor speed is 1750 rpm. The data set consists of 80 data samples in total, 20 data samples under each fault condition and every data sample has 5000 data points in it.

The time domain waveforms of vibration signals under the four working conditions are shown in Fig. 2. Because of the non-stationary and nonlinear characteristics of the vibration signals, which can be reflected from the time domain analysis, LMD method is used to decompose them into a set of mono-component PFs. Figs. 3, 4, 5 and 6 give the decomposition results of four kinds of working conditions including the normal state and the conditions with inner race fault, with ball fault and with outer race fault. From the figures we can see the number of PFs derived from the original signals varies with different original signals. Signals with more complexity will be decomposed into more PFs. According to the steps in Section 3, after LMD method is performed to different fault signals and the PF components have been gotten under different conditions, multi-scale entropy of each PF component can be derived. The parameters including m and the max of τ that are needed in calculating the multi-scale entropy are respectively set as 4 and 15. Multi-scale entropies are calculated by using data from the original signals and their PF components. It

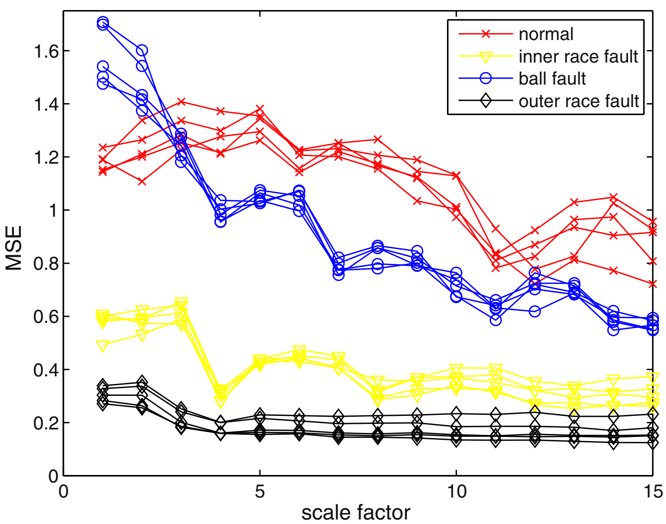

Fig. 8. MSE over 15 scales of the PF1 components.

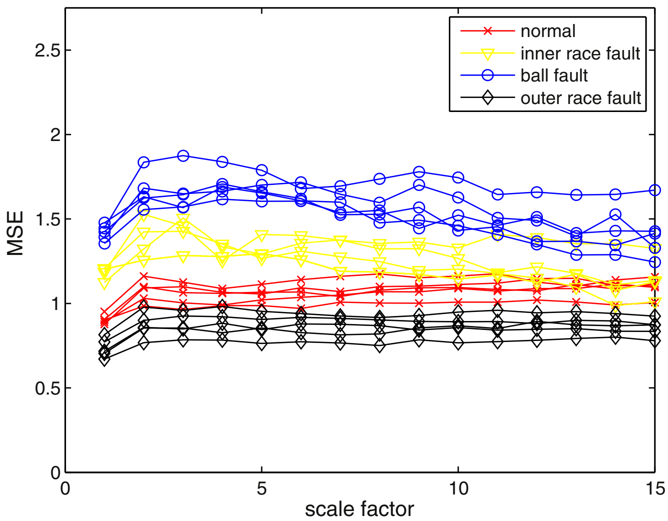

Fig. 9. MSE over 15 scales of the PF2 components.

turns out that the first a few PF components are more useful for the analysis. Figs. 7, 8 and 9 respectively show the multi-scale entropy curves of the original signals, PF1 components and PF2 components under the four kinds of working conditions.

As can be seen from the figures, it is not easy to recognize the four kinds of working conditions just from the multi-scale entropy curves of the original signals, especially the normal states and the conditions with ball fault. In Fig. 7, obviously, the lines which represent conditions with ball fault cannot be separated from the ones which represent normal states. On the one hand, it is because the complexity of signals under normal states and the conditions with ball fault is similar. In other words, the feature of the two kinds of signals is alike. On the other hand, much noise hidden in the signals may affect the identification of them. However, the multi-scale entropy curves of PF1 components can recognize the four states clearly in Fig. 8, especially when $\tau = 8$. So the multi-entropy when $\tau = 8$ can be chosen as a measurement factor, just like the spectral kurtosis. But the appropriate value of scale-factor τ may vary from different operating conditions. We can see from Fig. 9 that the separation effect is not so good, either, when the multi-scale entropy curves of PF2 are used as the fault features. It is known that the decomposition process of LMD analysis method is a process of removing the high frequency components gradually. Thus the PF1 component contains the highest frequency of the original signal and meanwhile it accounts for the most energy compared with the other PF components. Therefore the feature of PF1 component can reflect the feature of the original signal to some extent and the PF1 component can be chosen to recognize different working conditions of the roller bearings.

Take the extracted multi-scale entropy vectors as the inputs of the chosen fault classifier, a BP neural network, which has an input layer with 15 nodes, a hidden layer with 9 nodes and an output layer with 4 nodes. Set the mean square error of the neural network as 0.1. As previously mentioned, there are 20 groups of data in total. Use 15 groups of them as training samples, the others as testing samples and the testing results are shown in the Appendix Table. The simulation experiment shows that the feature vectors chosen in this paper can recognize different working conditions of the roller bearings effectively. Also, the fault extraction method proposed in this paper is effective.

5. Conclusion

A fault extraction method based on LMD analysis method and MSE is put forward in this paper. LMD method is suitable for analyzing complex multi-component signals. Targeting the fact that the vibration signals have the features of being non-linear, non-stationary and so on, the LMD method is chosen to preprocess the vibration signals of the roller bearings, resulting in a set of PF components. The diagnosis process varies with the analysis method performed to the PF components. In this paper it is the multi-scale entropy that is introduced and LMD method is combined with MSE. Calculate multi-scale entropies of the PF components and take the multi-scale entropies, namely the feature vectors, as the inputs of a BP neural network classifier. In this way, different working conditions of the roller bearing are recognized correctly. The analysis to practical bearing vibration signals demonstrates that the fault extraction method proposed in this paper is effective.

Acknowledgments

The authors thank Case Western Reserve University for providing the Bearing Fault Data Files freely over the web.

Appendix A

Appendix Table
Testing results of the BP neural network.

No.	Working condition	Testing samples	Theoretical output	Actual output	Classification results
1	Normal	{1.2516, 1.3354, 1.4340, 1.4294, 1.4219, 1.2257, 1.3712, 1.3450, 1.2430, 1.2008, 0.8693, 0.8099, 0.9546, 1.0662, 1.0514}	{1, 0, 0, 0}	{0.997, 0.008, 0.002, 0.000}	Normal
2		{1.1885, 1.1080, 1.2260, 1.2765, 1.2952, 1.1562, 1.2523, 1.1674, 1.1244, 1.0117, 0.7821, 0.8253, 0.9637, 0.9741, 0.8080}	{1, 0, 0, 0}	{1.015, 0.008, 0.004, 0.000}	
3		{1.1636, 1.2666, 1.2794, 1.3307, 1.3080, 0.9492, 1.2355, 1.1825, 1.1492, 0.9932, 0.7084, 0.6473, 0.8084, 0.8405, 0.8268}	{1, 0, 0, 0}	{1.024, 0.006, 0.002, 0.000}	
4		{1.2351, 1.2650, 1.3365, 1.2982, 1.3814, 1.2066, 1.2008, 1.1550, 1.0345, 1.0031, 0.8386, 0.7219, 0.8127, 0.7722, 0.7220}	{1, 0, 0, 0}	{0.954, 0.008, 0.002, 0.000}	
5		{1.1448, 1.3139, 1.4354, 1.3644, 1.4569, 1.2560, 1.1943, 1.1104, 1.0721, 1.0208, 0.7192, 0.7882, 0.8718, 0.8340, 0.8925}	{1, 0, 0, 0}	{0.988, 0.008, 0.002, 0.006}	
6	Ball fault	{1.6613, 1.4411, 1.2542, 0.9586, 1.0614, 1.0017, 0.6728, 0.7241, 0.6777, 0.6498, 0.5226, 0.6654, 0.6342, 0.5101, 0.5632}	{0, 1, 0, 0}	{0.006, 1.021, 0.005, 0.000}	Ball fault
7		{1.6368, 1.3942, 1.2215, 0.8794, 0.9791, 0.9232, 0.6625, 0.6875, 0.7237, 0.6540, 0.4285, 0.6087, 0.6345, 0.4832, 0.5079}	{0, 1, 0, 0}	{0.006, 0.984, 0.005, 0.000}	
8		{1.6030, 1.4115, 1.1306, 0.9910, 0.9920, 1.0223, 0.7433, 0.7705, 0.7319, 0.6735, 0.5745, 0.6706, 0.6122, 0.5883, 0.5800}	{0, 1, 0, 0}	{0.006, 1.030, 0.005, 0.000}	
9		{1.6138, 1.5881, 1.3715, 0.9951, 1.1198, 1.0582, 0.8782, 0.8509, 0.7842, 0.7778, 0.6585, 0.7342, 0.6832, 0.6495, 0.5643}	{0, 1, 0, 0}	{0.006, 1.001, 0.004, 0.000}	
10		{1.6260, 1.3909, 1.2248, 0.9383, 1.0629, 0.9740, 0.6718, 0.7518, 0.7697, 0.7072, 0.5872, 0.6593, 0.6390, 0.5351, 0.5427}	{0, 1, 0, 0}	{0.006, 1.011, 0.005, 0.000}	
11	Inner race fault	{0.5703, 0.5645, 0.5446, 0.2855, 0.3845, 0.3899, 0.3554, 0.2818, 0.3014, 0.3391, 0.3282, 0.2980, 0.2831, 0.3007, 0.3076}	{0, 0, 1, 0}	{0.002, 0.002, 1.066, 0.021}	Inner race fault
12		{0.5164, 0.5225, 0.5106, 0.2557, 0.3677, 0.3847, 0.3827, 0.3176, 0.3222, 0.3759, 0.3691, 0.3436, 0.3128, 0.3560, 0.3320}	{0, 0, 1, 0}	{0.002, 0.000, 0.893, 0.050}	
13		{0.5770, 0.5751, 0.5941, 0.2705, 0.4132, 0.4420, 0.4294, 0.3291, 0.3779, 0.3888, 0.3884, 0.3394, 0.3380, 0.3656, 0.3478}	{0, 0, 1, 0}	{0.003, 0.003, 1.075, 0.005}	
14		{0.5889, 0.5705, 0.5515, 0.3268, 0.3820, 0.4004, 0.3778, 0.3059, 0.3031, 0.3391, 0.2915, 0.2727, 0.2423, 0.2616, 0.2428}	{0, 0, 1, 0}	{0.002, 0.003, 1.051, 0.017}	
15		{0.5488, 0.5714, 0.4979, 0.2868, 0.3653, 0.3867, 0.3636, 0.2864, 0.2810, 0.3221, 0.2942, 0.2679, 0.2362, 0.2594, 0.2445}	{0, 0, 1, 0}	{0.001, 0.001, 0.875, 0.040}	
16	Outer race fault	{0.2772, 0.2736, 0.1962, 0.1689, 0.1816, 0.1849, 0.1879, 0.1905, 0.1927, 0.1922, 0.1968, 0.2037, 0.2009, 0.1936, 0.2050}	{0, 0, 0, 1}	{6.148e−5, 1.696e−5, 0.003, 0.974}	Outer race fault
17		{0.4431, 0.4621, 0.3555, 0.3169, 0.3251, 0.3233, 0.3000, 0.3052, 0.3032, 0.2903, 0.2936, 0.2967, 0.2757, 0.2734, 0.2823}	{0, 0, 0, 1}	{0.000, 0.000, 0.072, 0.902}	
18		{0.2794, 0.2769, 0.2026, 0.1698, 0.1728, 0.1650, 0.1564, 0.1552, 0.1494, 0.1484, 0.1452, 0.1459, 0.1416, 0.1384, 0.1413}	{0, 0, 0, 1}	{5.017e−5, 2.045e−5, 0.003, 0.999}	
19		{0.4302, 0.4742, 0.3413, 0.3093, 0.3206, 0.3252, 0.2938, 0.2938, 0.2951, 0.2828, 0.2789, 0.2872, 0.2810, 0.2687, 0.2739}	{0, 0, 0, 1}	{0.000, 0.000, 0.052, 0.945}	
20		{0.4755, 0.4595, 0.3372, 0.2807, 0.3015, 0.2910, 0.2521, 0.2541, 0.2511, 0.2553, 0.2436, 0.2454, 0.2456, 0.2316, 0.2440}	{0, 0, 0, 1}	{0.000, 0.000, 0.055, 0.890}	

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