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Fault Diagnosis of Locomotive Wheel-bearing Based on Wavelet Packet and MCA

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Abstract. Fault diagnosis of locomotive wheel-bearing is directly related to the locomotive performance and the safe operation of train. Owing to the fault signal of locomotive wheel-bearing being difficult to separate, the fault diagnosis method was proposed, which based on wavelet packets and morphological component analysis combined with the vibration signal characteristics of locomotive wheel-bearing. The simulation results show that the fault diagnosis of the locomotive wheel-bearing under low signal-to-noise ratio (SNR) case is achieved by wavelet packet and morphological component analysis. It provides a theoretical basis for the fault diagnosis and condition monitoring for the locomotive wheel-bearing.

Introduction

Wheel-bearing plays a vital role in running parts of locomotive. High speed and heavy load for the railway transportation industry have become an irresistible trend. As the key part of locomotive running gear, the condition of wheel-bearing is directly related to the performance of locomotive and the safety of train. Therefore, fault diagnosis on locomotive wheel-bearing is of great significance to prevent fault and ensure safe operation. Furthermore, it provides technical foundation for remote condition monitoring of locomotive running parts [1].

In the past decades, rolling bearing for fault diagnosis has gained more attention with the fast development of manufacturing industry. Nowadays, the blind source separation for fault diagnosis of rolling bearings has been applied to many fields [2-3]. The fault diagnosis for rolling bearing based independent component analysis has been achieved [4-5]. The characteristics of the ICA are that original signal has been decomposed into several independent components according to the principle of statistical independence. Each signal component is recovered only by the original signal to achieve the separation and the extraction of signal. However, the limitation of this method is that it has certain requirements for the original signal. The composite fault of rolling bearing was successfully distinguished by morphological component analysis. However, this method took more time [6]. The resonant component and impact component of rolling bearing was separated successfully with the morphological component analysis. But the analysis time was too long. The blind source signal was separated perfectly in combination with the wavelet packet and the variational Bayesian independent component analysis method.

We have proposed a fault diagnosis method, which consists of wavelet packet transform and morphological component analysis, to separate blind source signal under low signal-to-noise ratio case in this paper. Firstly, the wavelet packet decomposition and reconstruction are used to reduce the noise of original signal. Then, the signal is separated by morphological component analysis. Finally, the pulse signal is demodulated with Hilbert transform and the fault position of locomotive wheel-bearing is identified according to the characteristic frequency.

Wavelet Packet Transform

Wavelet packet transform takes further decomposition for unfinished high frequency part [7]. In multi-resolution analysis, V_i is the scale function space, W_i is the wavelet function space. i represents the scale factor, k represents the translation factor. The scaling function $c_{2p}(n)$ and wavelet function $c_{2p+1}(n)$ are defined as:

$$\begin{cases} c_{2p}(n) = \sqrt{2}\sum_{k\in Z} h(k)c_p(2n-k) \\ c_{2p+1}(n) = \sqrt{2}\sum_{k\in Z} g(k)c_p(2n-k) \end{cases} \tag{1}$$

Where, $p \in Z$, $n \in R$, $h(k)$ and $g(k)$ represent the low and the high pass of conjugate mirror filter respectively, $g(k) = (-1)^k h(1-k)$.

Wavelet packet decomposition algorithm is:

$$\begin{cases} d_{il}^{2n} = \sum_{k\in Z} \overline{h}_{k-2l} d_{i+1,k}^{n} \\ d_{il}^{2n+1} = \sum_{k\in Z} \overline{g}_{k-2l} d_{i+1,k}^{n} \end{cases} \tag{2}$$

Where, $i \in Z_+$, $l \in [1,i]$.

Wavelet packet reconstruction algorithm is:

$$d_{i+1}^{n} = \sum_{k\in Z} (h_{l-2k} d_{ik}^{2n} + g_{l-2k} d_{ik}^{2n+1}) \tag{3}$$

Morphological Component

The key of the MCA method is to find the dictionary of sparse representation of each signal component. It can be assumed that, the input signal $S(S \in R)$ consists of k component signal Sk, that is $S = \sum_{k=1}^{K} Sk$. At the same time, each Sk has the dictionary of sparse representation ϕk relatively, that is $Sk = \phi k \alpha k$, α_k is the transform coefficient. It can be calculated using

$$\left\{\alpha_1^{opt}, \bullet\bullet\bullet, \alpha_K^{opt}\right\} = \arg \min_{\{\alpha_1, \bullet\bullet\bullet, \alpha_k\}} \sum_{k=1}^{K} \|\alpha_k\|_0 \quad \left(s = \sum_{k=1}^{K} \phi_k \alpha_k \right) \tag{4}$$

The $\arg\min_x f(x)$ is the return value of x when $f(x)$ is the minimum.

Simulation Analysis

Aimed to inspect feasibility of wavelet packet combined with morphological component analysis method, to show the noise reduction effect of wavelet packet decomposition and reconstruction as well as the impact of signal separation of morphological component analysis method, we set the simulation signal as follows:

$$f(t) = \sin(t) \tag{5}$$

$$x(t) = \begin{cases} 1 & kT < t < \frac{T}{2} + kT(k \in Z) \\ -1 & \frac{T}{2} + kT < t < T + kT(k \in Z) \end{cases} \tag{6}$$

Where $f(t)$ is sinusoidal function, which is used to simulate the periodic signal. $x(t)$ is piecewise function, which is used to simulate the pulse signal. T is the period of $x(t)$.

The sampling period of sinusoidal signal is 2π and there are 3142 sampling points. The sampling frequency of the pulse signal is 50 Hz and there are 3142 sampling points. The noise signal is random signal, which ranges from 0 to 1, and includes 3142 sampling points. The simulation synthetic signal is vector sum of sinusoidal signal, pulse signal and noise signal. Figure 1 shows the simulation signal.

As the signal shown in the Figure 2, the simulation synthetic signal is carried out by the MCA directly. The separated pulse signal is shown as the upper left and the upper right is the synthetic signal. The lower left is the sinusoidal signal and the lower right is the noise signal. Compared with the Figure 1, we can find that each component of the signal is different in the amplitude and contains many noise signals. So the separation effect isn't ideal.

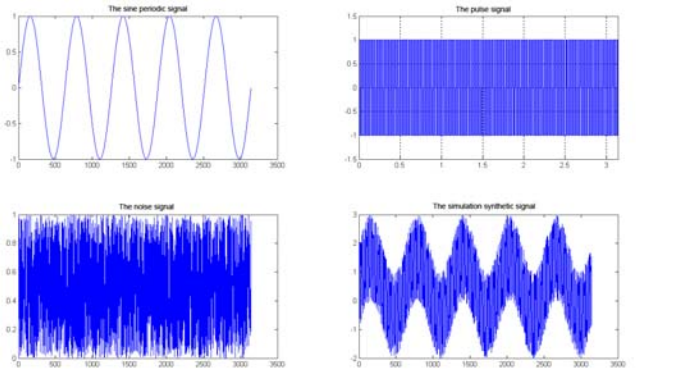

Figure 1.Simulation component signal and synthetic signal

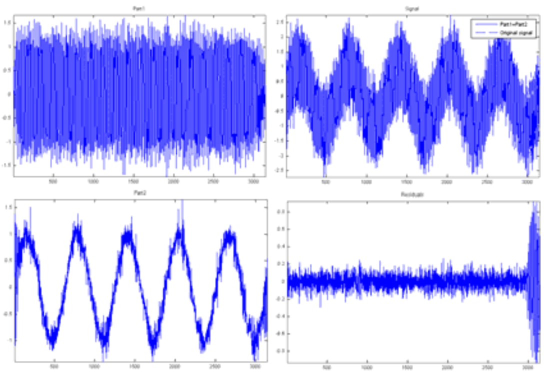

Figure 2. The MCA results of simulation signal

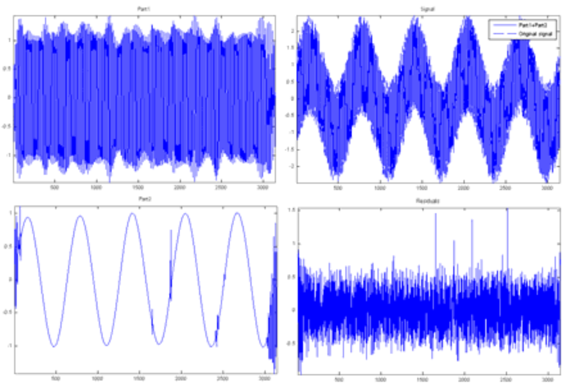

Figure 3. The MCA results of denoising signal

As the signal shown in the Figure 3, the simulation synthetic signal is denoised with wavelet packet decomposition and reconstruction, and then it is made by the MCA. We choose db10 wavelet basis function to implement three layers wavelet packet transform for the signals. Compared the Figure 3 with the Figure 1, each component of separation in Figure 3 is different in the amplitude slightly, the noise is decreased obviously and the image is smoother, which proves the validity of the method of combining wavelet packet with morphological component analysis.

Analysis the Fault Signal of Locomotive Wheel-bearing

The fault of locomotive wheel-bearing consists of wear fault and surface damage fault. The wear fault is a kind of gradual fault. In general, it will not damage the bearing immediately and its damage degree isn't obvious. The harm of surface damage fault is more serious than that of the surface wear fault, which is also the main object of fault diagnosis of locomotive wheel-bearing. The impact frequency of the surface damage is periodic and it is associated with the geometry size and rotating speed of the bearing. Since the fault occurred in different parts, the obtained frequency is different. The effective characteristic value can be obtained by calculation and equation. Experimental data comes from drive rolling of locomotive running gear in this article. The type of bearings is 552732QT.

The vibration signal's sampling frequency is 1k Hz and bearing speed is 1850rpm. Experimental data of four conditions are contained, which are normal signal, outer ring fault signal, inner ring fault signal and rolling body fault signal, sampling rate is 2048, in other words, each data contains 2048 vibration acceleration signal. According to the equation of rolling bearing failure frequency, the failure frequency of out ring is 104.56 Hz, the failure frequency of inner ring is 157.94 Hz.

The locomotive wheel-bearing fault diagnosis model based on the wavelet packet and the MCA is constructed by three steps. First, Wavelet packet decomposition and reconstruction can reduce noise. Second, morphological component analysis enables separation. Third, the envelope demodulation analysis is based on Hilbert transform.

The decomposition and reconstruction of Wavelet packet are used for noise reduction of inner ring fault signal and outer ring fault signal of locomotive wheel-bearing respectively. The result is shown in the Figure 4. The noise reduction effect is obvious compared with original signal in Figure 1.

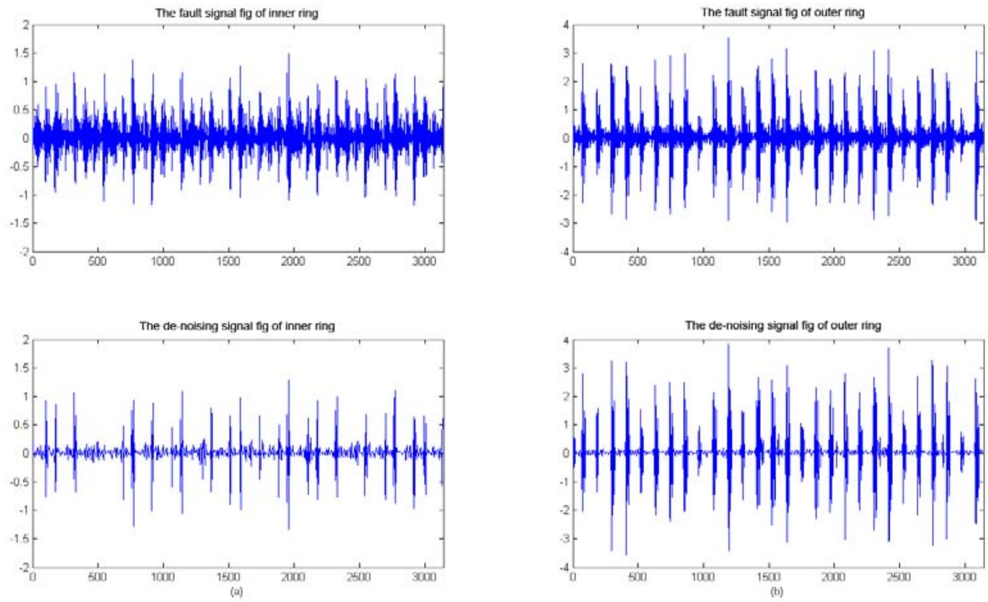

Figure 4. The comparison chart of before and after noise elimination for the inner ring and outer ring fault signal

Separating the inner ring and outer ring fault signal for locomotive wheel-bearing by MCA after noise reduction. The separation result is shown in the Figure 5 and the Figure 6. The upper left and upper right are isolated impact signal and the fault signal after noise reduction respectively. The lower left is isolated periodic signal and the lower right is isolated noise signal.

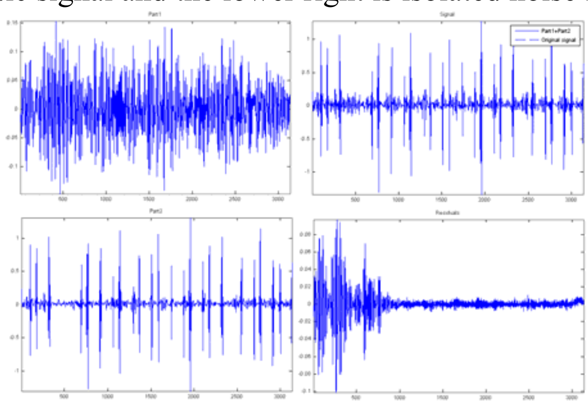

Figure 5. The MCA separation results of inner ring fault signal

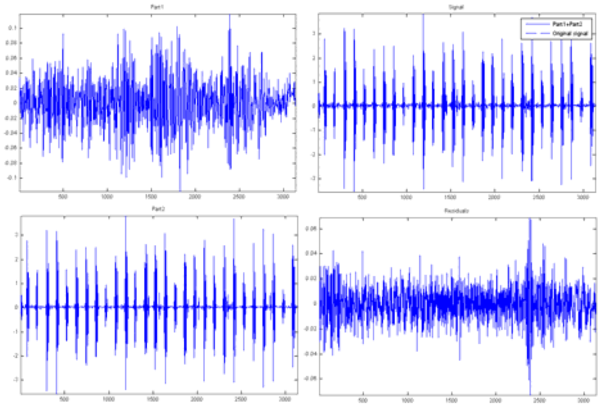

Figure 6. The MCA separation results of the outer ring fault signal

The impact of component is extracted by the MCA method and the shock signal is analyzed by Hilbert envelope demodulation. The Figure 7 and the Figure 8 show the results.

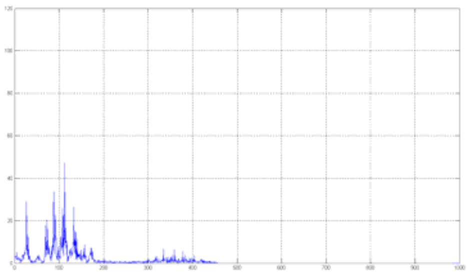

Figure 7. The Hilbert transform of the outer ring fault signal

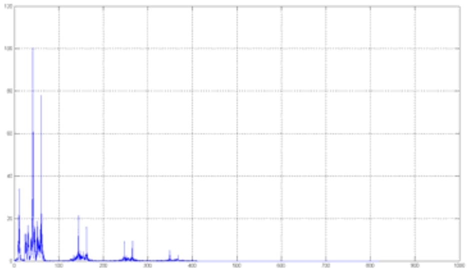

Figure 8. The Hilbert transform of the inner ring fault signal

As shown in the Figure 7, through Hilbert envelope demodulation analysis for impulse signal, 105Hz frequency components and harmonic components is close to 104.56Hz, which is the outer race fault frequency. So the outer race fault signal is separated effectively and outer ring fault is identified successfully. Figure 8 shows that through the Hilbert envelope demodulation analysis for impulse signal, 160Hz frequency components and harmonic components is close to 157.94Hz, which is the inner race fault frequency. So the inner race fault signal is isolated effectively and inner ring fault is identified successfully. Therefore, the proposed method combined with wavelet packet and morphological component analysis can separate the locomotive wheel-bearing fault signal and realize fault diagnosis effectively.

Conclusions

The wavelet packet and morphological component analysis are applied to fault diagnosis of locomotive wheel-bearing. Firstly, the inner and outer ring fault signal of locomotive wheel-bearing are separated. The impact and harmonic component are isolated successfully combined with their advantages of wavelet packet and the MCA. Then, the isolated impact signal is analyzed by Hilbert transform. Finally, the fault diagnosis for inner ring and outer ring of rolling bearing is accomplished, which indicates the validity of this method under low SNR environment.

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References

[1] D S HUANG, J X DU. A constructive hybrid structure optimization methodology for radial basis probabilistic neural networks. IEEE Transactions on Neural Networks. 19(2008)2099-2115.

[2] X G ZHENG, C RITZ, J T XI. Collaborative blind source separation using location informed spatial microphones. IEEE Signal Processing Letters. 20(2013)83-86.

[3] J THIAGARAJAN, K N RAMAMURTHY, A SPANIAS. Mixing matrix estimation using discriminative clustering for blind source separation. Digital Signal Processing. 23(2013)9-18.

[4] Cheng W, Zhang Z S, Zhang J, Lu J T. Acoustical Source Tracing Using Independent Component Analysis and Correlation Analysis, Shock and Vibration, 2015(2015)1-8.

[5] Zhao Z H, Yang S P. Machinery fault feature extraction based on independent component analysis and correlation coefficient," JOURNAL OF VIBRATION AND SHOCK, 32(2013) 67-72.

[6] Bobin J, Starck J L, Fadili J M, Moudden Y, Donoho D L, Morphological Component Analysis: An Adaptive Thresholding Strategy, IEEE Transactions on Image Processing, 16(2007)2675-2681.

[7] Yiakopoulos C T, Antoniadis I A, Wavelet Based Demodulation of Vibration Signals Generated by Defects in Rolling Element Bearings, Shock and Vibration, 9(2002) 293-306.