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A Multi-component Signal Decomposition Application Research on Improved Algorithm Based on Improved Wavelet Ridge

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Abstract: Multi-component signal decomposition method with noise has become a research hotspot of equipment condition monitoring. Aiming at the iterative divergence problem of traditional wavelet ridge extraction algorithm for multi-component harmonic signals widely existing in mechanical and electrical systems, in order to achieve the goal of high decomposition accuracy and anti-noise performance of multi-component signals, the relationship between the initial scale and the extracted components is analyzed. Compared with the time domain of noisy harmonic signals, an improved wavelet ridge extraction algorithm is proposed （WRSD） After the instantaneous frequency of a component is obtained by this extraction algorithm, the component can be separated from the original signal and its instantaneous amplitude can be obtained by using the synchronous demodulation method. This method has high accuracy and certain anti-noise performance for instantaneous frequency estimation. Through simulation analysis and engineering application, the key zero point in intelligent manufacturing equipment of high-performance composite parts can be realized Fault detection of components.

Keywords: Wavelet Ridge Extraction Algorithm, Neural Network, Signal Denoising, Fault Diagnosis, Measurement and Control System

1. Introduction

In the past decades, signal decomposition method has become a research hotspot. Discrete wavelet transform has been used to decompose signals earlier [1-3], but its frequency resolution is not high due to rough binary scale division. Scholars at home and abroad have successively proposed double density wavelet transform, high density wavelet transform and dense frame wave transform, which have been well applied in mechanical fault diagnosis [4, 5]. Empirical Mode general (EMD) is a signal decomposition method widely used in the field of mechanical fault diagnosis [6]. However, it has the problems of mode aliasing and boundary effect. Among them, mode aliasing seriously affects the frequency resolution of EMD. In response to this problem, Feldman proposed a Hilbert vibration decomposition (HVD) method [7, 8]. This method has good frequency resolution and can recognize different narrow-band components. However, both EMD and HVD are sensitive to noise. In this paper, the instantaneous frequency of each component is extracted by the wavelet ridge line, and then the signal components are obtained by the synchronous demodulation method [9-11]. Because wavelet transform has good performance in time-frequency localization, the instantaneous frequency of each component is extracted by wavelet ridge, and then each characteristic signal component is obtained by synchronous demodulation. This method has good self-adaptability, high decomposition accuracy and frequency resolution, and has high accuracy and advantages for weak fault feature extraction. 2. Wavelet Ridge Theory [12-15]. So as to realize the fault detection of key components of composite materials in intelligent manufacturing equipment.

2. Wavelet Ridge Theory

2.1. Analytic Wavelet Transform of Asymptotic Signal

Any single component real signal s(t) can be expressed as

$$s(t) = A(t)\cos(\varphi(t)) \tag{1}$$

in the formula A(t)≥0，It can be called instantaneous amplitude，$\varphi(t) \in [0, 2\pi)$，This is called the instantaneous phase.

The analytical signal of signal s(t) can be defined as

$$Z_s(t) = (1 + iH)s(t) = A_s(t)\exp(i\varphi_s(t)) \tag{2}$$

Where H represents the HILBERT transformation of the signal. In particular,

If s(t) is an asymptotic signal, Then the analytical signal can be approximately expressed as

$$Z_s(t) \approx A(t)\exp(i\varphi(t)) \tag{3}$$

2.2. Wavelet Ridge and Wavelet Curve

The wavelet ridge is the set of all points (a, b) that satisfy $t_s(a,b) = b$ in the phase plane

$$P = \{(a,b) \in R^2;\ a > 0,\ t(a,b) \overline{\overline{s}}\ b\}$$

The point (ar (b),b) on the wavelet ridge line is called the wavelet ridge point, The instantaneous frequency of the analyzed signal can be easily obtained from the wavelet ridge line, The wavelet curve is the passing point (ar (b0),b0) in the phase plane, And all of the points that satisfy $t_s(a,b) = b0$

$$C = \{(a, b) \in R^2;\ a > 0,\ t(a, b) = b\}$$

The wavelet curve is completely determined by the phase function φψ (t) of the analysis wavelet.

3. Improved Wavelet Ridge Extraction Algorithm

The wavelet ridge can be obtained by taking the maximum value of the wavelet system modulus on the time-frequency plane. It is found that the wavelet ridge can be accurately obtained by the phase information of the wavelet transform. Establish below:

$$\varphi(a,b) = \arg[W_s(a,b)]$$

Along a given wavelet curve, the partial derivative of the phase angle of the wavelet transform relative to the translation B is equal to the center frequency of the telescopic wavelet at the intersection with the wavelet ridge. Through this fast algorithm of wavelet ridge iterative extraction, the specific methods are as follows: For a discrete sequence $T_s = 1\ f_s$ with a sampling period of $s(t_k)$, $k = 0,1,\dots N-1$, $t_k = t_0 + kT$s,; *Let its wavelet transform at a given scale a be $W_s(a, t_k)$ and its phase be $\varphi(a, k)$, and define Db as a discrete differential operator with respect to translation parameters,* Let $a_0(t_k)$ be the initial estimate of $a_r(t_k)$, then the wavelet ridge is calculated by the following iterative method

$$a_{i+1}(t_k) = \omega_0 / Db\varphi(a_i, k) \tag{4}$$

$$a_0(t_{k+1}) = a_r(t_k)\ k = 0, 1, \dots, N-1 \tag{5}$$

According to the required accuracy, It can be considered that a_i is the final convergence value.

For a given wavelet curve, at the intersection with the wavelet ridge, $\varphi(a, b)$ has the following characteristics, Along a given wavelet curve, the partial derivative of the phase Angle of the wavelet transform with respect to the translation b is equal to the central frequency of the extensional shrinking wave at the intersection with the wavelet ridge.

The research shows that the root cause of iteration divergence is the adoption of a fixed threshold in the iteration process, which leads to the fact that there is still no convergence of the method at some sampling points for multiple iterations.

To solve this problem, this paper proposes an improved method to ensure the accuracy of calculation and avoid iteration divergence. The basic idea of this algorithm is to set a maximum number of iterations in the iteration process, and when the overlap divergence occurs at a certain point, the estimation value with the minimum relative error calculated in each iteration estimation is selected as the calculation result of the wavelet ridge at that point. This is an adaptive way to change the iteration threshold. In addition, the algorithm can calculate the instantaneous amplitude of the signal.

The improved wavelet ridge extraction algorithm can be well used to calculate the instantaneous frequency of single component signal. But what happens if the algorithm is used to analyze noisy multi-component signals? The following will be discussed through simulation experiments.

4. Simulation Example

Vibration signals of rotating machinery such as fault gearbox and bearing are usually multi-component am-fm signals. In order to extract fault features, the modulation frequencies of certain components need to be calculated. So we need to decompose the signal first. The following simulation of multi-component AM-FM signal is investigated.

$$x(t) = x_1(t) + x_2(t) + x_3(t) + n_s(t) \tag{6}$$

$$x_1(t) = [0.8 + 0.4\sin(2\pi\times 10t)]\cos[2\pi\times 400t + \sin(2\pi\times 20t)] \tag{7}$$

$$x_2(t) = [1 + 0.3\sin(2\pi\times 10t)]\cos[2\pi\times 200t + \sin(2\pi\times 10t)] \tag{8}$$

$$x_3(t) = [2 + 0.4\cos(2\pi\times 10t)]\cos[2\pi\times 100t + \sin(2\pi\times 10t)] \tag{9}$$

Where, *ns* (*t*) is gaussian white noise with standard deviation of 0.3. The sampling frequency is 2048hz and the time interval is [0, 1.995]s, then the time domain waveform of the signal is shown in figure 1.

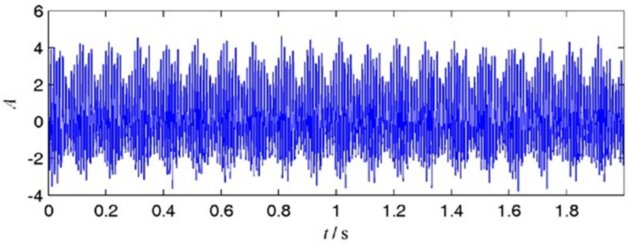

Figure 1. *Time domain waveform of noisy multi-component AM-FM signal.*

Similarly, WRSD method is used to decompose the signal at first, but the center frequency of complex Morlet wavelet is set as 3π, and three components as shown in Figure 2a, are obtained through WRSD. The corresponding error signal is shown in Figure 2b.

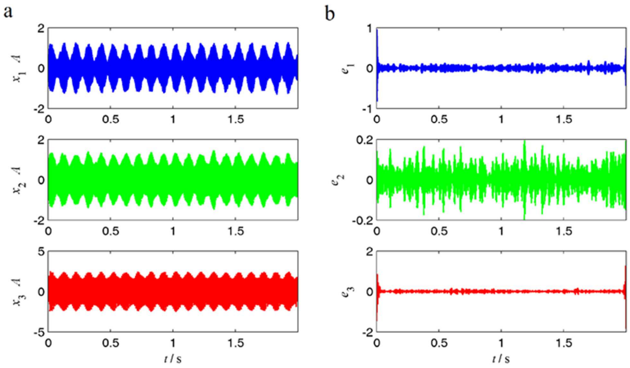

Figure 2. *The results of multi-component AM-FM signal decomposition were obtained by using WRSD (a) components obtained by decomposition; (b) decomposition error.*

As can be seen from the figure, the three components are separated effectively, but the errors at both ends of the first and third components are relatively large. Then HVD and EMD are used to analyze the multi-component AM-FM signal respectively.

For HVD, the normalized filter cutoff frequency is set to 0.07, and the three components obtained and the corresponding errors are shown in figure 3.

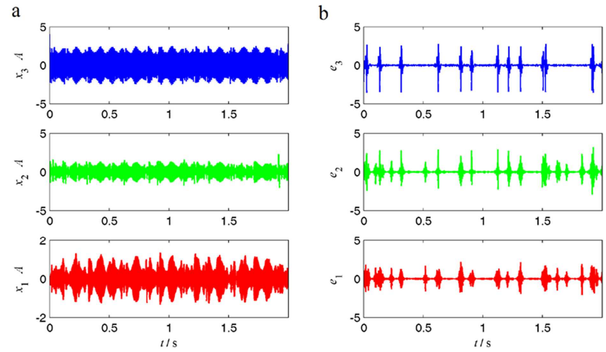

Figure 3. *The results of multi-component AM-FM signal decomposition were obtained by using HVD (a) components obtained by decomposition; (b) decomposition error.*

As can be seen from figure 3, the three components are not separated correctly and the decomposition accuracy is low.

Ten IMF were obtained by using EMD, among which the first, second and third IMF represent three components respectively $x_1(t)$, $x_2(t)$, $x_3(t)$, The three IMF and their errors are shown in figures 4(a) and 4(b) respectively.

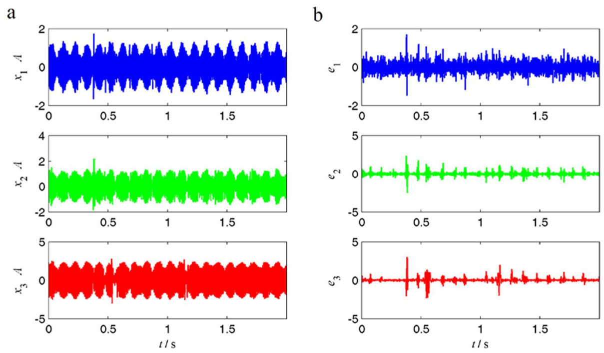

Figure 4. *The results of multi-component AM-FM signal decomposition were obtained by using EMD (a) components obtained by decomposition; (b) decomposition error.*

Table 1. *The comparison of the three methods in the example.*

evaluation index	**WRSD**			**HVD**			**EMD**		
	$x_1(t)$	$x_2(t)$	$x_3(t)$	$x_1(t)$	$x_2(t)$	$x_3(t)$	$x_1(t)$	$x_2(t)$	$x_3(t)$
	0.0038	0.0031	0.0092	0.0234	0.2501	0.2235	0.0596	0.0726	0.0972
variance	0.0039	0.0031	0.0091	0.0234	0.2501	0.2235	0.0596	0.0726	0.0980
	0.9945	0.9971	0.9975	0.9639	0.9373	0.7721	0.9245	0.9303	0.9763

It can be seen from the figure that component $x_1(t)$ cannot be separated effectively, and there is a large error between the other two IMF and component $x_2(t)$ and $x_3(t)$. The comparison results further verify the advantages of EMD compared with HVD and EMD. It can be seen that EMD method has the highest computational efficiency.

5. Conclusion

By comparing the three methods of simulation examples, it is easy to get that WRSD method successfully decomposed the simulation signal, while HVD and EMD failed to decompose the signal correctly. In addition, it is worth noting that HVD will first extract the components of the maximum energy, while WRSD and EMD extract the components of the highest frequency first.

The comparison results further validate the advantages of the proposed method over HVD and EMD. Similarly, this paper calculates the operation time of WRSD, HVD and EMD, which are 3.9758, 2.4257 and 0.1843 s respectively. It can be seen that EMD method has the highest computational efficiency. Aiming at the iterative divergence of traditional wavelet ridge extraction algorithm, an improved wavelet ridge extraction algorithm was proposed, and the relationship between the initial scale and the extracted components was analyzed. Then, an adaptive multi-component signal decomposition method, the wavelet ridge signal decomposition method, is proposed by using the algorithm and synchronous demodulation method (WRSD). Simulation and experimental results show that this method has better decomposition accuracy than EMD and HVD.

Through simulation analysis and engineering application, the effectiveness and advance of this method is verified, and the fault detection of key components in intelligent manufacturing equipment of high performance composite components can be successfully realized. The improved wavelet ridge extraction algorithm verifies that when an initial scale is given, the algorithm can automatically obtain the ridge of a component closest to the scale. After obtaining the instantaneous frequency of a component, the component can be separated from the original signal by synchronous demodulation method, and its instantaneous amplitude can be obtained at the same time. It has excellent time-frequency localization, high precision and certain anti-noise performance.

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