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Wavelet Package Entropy Threshold Based on Empirical Mode Decomposition (EMD) In the Application of The Rolling Bearing Signal De-noise

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Abstract：Restrain the noise of the vibration signal is an essential preprocessing work of the rolling bearing fault diagnosis. Take the advantages that the empirical mode decomposition (EMD) algorithm can decompose the signal for the intrinsic mode function (IMF), this paper put forward a de-noise method that combined the EMD algorithm with the wavelet package entropy, so that to overcome the drawback such as unable to distinguish useful information in the intrinsic mode function effectively and the wavelet threshold de-noise algorithm threshold selection by the experience. This paper uses the wavelet transform of the intrinsic mode function, related processing for each node coefficient in the underlying factor to highlight the effective information. Based on the characteristics of wavelet packet entropy, divided the new coefficient after set the useful signal to be zero into several components and calculate its wavelet packet entropy, select the average coefficient of wavelet entropy maximum interval as the noise variance to get the node corresponding threshold. The algorithm was applied to the simulation signals and the actual vibration signals of rolling bearing de-noising. The results show that the method is better than that of wavelet threshold de-noise combined with EMD, and at the same time improves the de-noise effect better protect signal effectively.

Key words：*Empirical Mode Decomposition (EMD) Wavelet Package Entropy；Noise Suppression；SNR*

I. INTRODUCTION

One of the most important works for rolling bearing fault diagnosis is the extraction of the fault characteristics. During the acquisition of the bearing fault information, the vibration signal is unavoidable contains noise, so it is very important to do some pretreatment on the vibration signals such as de-noise so that to extract the characteristics effectively. During the study of rolling bearing de-noise, there are some methods, such as singular value decomposition method, digital methods of morphological filtering method[1], and there are also some methods based on joint time-frequency domain analysis such as wavelet transform de-noise and the EMD de-noise [2]. Wavelet transform de-noise by using wavelet decomposition and wavelet packet decomposition, get rid of the noise by threshold quantization process; when calculating the noise variance σ during use the wavelet threshold de-noise method, it gets the mid-value of the high frequency wavelet coefficients directly, without considering the size of the effective signal and noise of the wavelet decomposed coefficients, has a certain speculative. The traditional EMD noise reduction method decompose the signal into IMF components, then according to characteristic that the distribution of stochastic signal general in the high frequency, abandon some of the high frequency components (think they are noises) directly, this method removing noise but lead to the distortion of the signal to a certain extent.

This paper combined the EMD method with wavelet packet entropy, decompose the vibration signal into IMF components, and then decompose each component with multi-scale wavelet packet. After reconstruction of the bottom of the node coefficient，do correlation analysis, then set the useful signal and breakpoint to be zero, divide the coefficients into a number of interval, take the mean value of largest wavelet package entropy values coefficient as the noise variance of the node coefficient, then substitute the noise variance into the threshold formula to calculate the corresponding threshold value, finally get the de-noised signal by reconstruction of the IMF components which are de-noised by threshold function quantization. The method combines the advantages of the EMD and wavelet package entropy, suppress random noise in finer scales, and protect the effective signal effectively.

II. THRESHOLD DE-NOISE PRINCIPLE COMBINED WITH EMD

2.1 EMD algorithm principle and de-noise reconstruction

According to the empirical mode decomposition algorithm theory, any signals are made by a number of intrinsic mode functions (IMF) and a residual component. The decomposition of EMD is a process of obtain the residual component and a number of IMF components. First of all, fitting out their corresponding maximum envelope $e_+(t)$ and minimum envelope $e_-(t)$ according to the maximum and minimum value of the original signal of $x(t)$. Take the mean value $m_1(t)$ of the two envelope curve as the mean value envelope of the original signal. Get the signal $n_1^1(t)$ without low frequency by subtracting the mean value envelope $m_1(t)$ from the original signal $x(t)$. Repeat the above process with $n_1^1(t)$ k times, so that signal $n_1^1(t)$ can meet the IMF screening criteria (in this paper adopts the improved IMF screening criterion put forward by Rilling), then take the signal $n_1^k(t)$ which gets in this process as the first IMF component $\mathrm{c}_1(t)$. Finally get the new signal $\mathrm{r}_1(t)$ by subtracting $\mathrm{c}_1(t)$ from the original signal $x(t)$, repeat the process which $\mathrm{c}_1(t)$ is obtained, get the other IMF components, repeat this process until get the n order IMF components or residual component $\mathrm{r}_\mathrm{n}(t)$ less than the preset value, or the residual component is monotone function or constant, the EMD decomposition process terminated. A limited number of IMF components are obtained by the EMD decomposition of the target signal, and are distributed according to the frequency from high to low. The traditional EMD de-noise process give up the several high frequency components directly according to the characteristic that random signal always distribute in high frequency, and then reconstitute the remaining IMF components directly. So the traditional EMD de-noise principle is remove the first k high frequency IMF components, and reconstitute the remaining IMF components which are distributed in the low and medium frequency.

$$\mathrm{x}'(t) = \sum_{i=k+1}^{n} imf_i(t) + r_n(t) \tag{1}$$

Where $\mathrm{x}'(t)$ is the de-noised signal, $imf_i(t)$ is the remaining intrinsic mode function, $\mathrm{r}_\mathrm{n}(t)$ is the residual component. Thus, the traditional EMD de-noise method removes noise but also leads to a certain loss of signal inevitably.

2.2 Threshold de-noise algorithm combined with EMD

The following algorithm quotes from Ren-ping Shao etc. They combined the EMD and wavelet threshold de-noise, used for rolling bearing signal de-noise. Get the IMF components by EMD decomposition of the target signal, and then remove the noise in the high frequency IMF components by wavelet threshold de-noise method. The algorithm steps are as following:

(1) Decompose the target signal by EMD algorithm; get a number of IMF components;

(2) Choose a kind of threshold determined criteria; calculate the corresponding threshold value of the high frequency IMF components;

(3) Determine the threshold function; remove the noise in some of the high frequency IMF components;

(4) Reconstitute the low frequency components with the de-noised high frequency IMF components, get the de-noised signal.

The signal de-noise effect is affected by the value of the threshold. If the threshold value is large, the de-noise process will damage the useful signal, otherwise, the de-noise process can not remove the noise effectively. The selection of the threshold value of the traditional wavelet threshold de-noise has certain speculative, without considering the change of the decomposition scale effect on noise wavelet coefficients. In order to solve the above problems, select the threshold value by wavelet packet entropy. This paper proposes the de-noise algorithm based on the combination of EMD and wavelet package entropy threshold.

III. WAVELET PACKAGE ENTROPY THRESHOLD DE-NOISE ALGORITHM BASED ON EMD

3.1 The basic concept

The wavelet packet decomposition not only breaks down the high frequency part but also breaks down the low frequency part. Decompose the target signal with noise into N layers, the coefficients of each node represents the characteristic of this frequency band. Since the useful signal with strong correlation and the noise signal correlation is not obvious, the process of correlation analyses of the Nth layer node coefficients can distinguish the position of the useful signal and noise signal. If the correlation analyses were neglected, the de-noised signal resolution will decline since the noise was not distinguished during the de-noise process which leads to the loss of effective signal and narrow band of the signal. Wavelet package entropy is the combination of wavelet packet analyses and information entropy. The threshold selection of the method used in this paper is determined by wavelet package entropy, do correlation analyses after the reconstruction of each node on the Nth layer, the new coefficient is divided into a number of interval, the calculate the wavelet package entropy of each interval, take the coefficient mean value of the maximum interval as the noise variance of the threshold formula. According to the characteristic that the EMD method can decompose the original signal into IMF components adaptively, the algorithm present in this paper combine the EMD with wavelet package entropy in order to finer scales achieve de-noise.

3.2 Wavelet package entropy calculation

According to the Shannon entropy theory, if X represents the state characteristic of an uncertain system, the probability that it take the value a_i is $P(x = a_i)$, the entropy can be expressed as:

$$H(x) = -\sum_{i=1} P(x = a_i) \log P(X = a_i) \qquad (2)$$

Decomposed the signal with j layer wavelet packet, then reconstructed each node on the jth layer get $S_{j,k}$, divided the $S_{j,k}$ (the sampling points for m) into n equal parts, then the wavelet coefficients energy of the ith subinterval can be expressed as

$$E_{j,k}(i) = \sum_{z}^{m/n} \left| S_{j,k}(z) \right|^2 \qquad (3)$$

Where j is wavelet packet decomposition layers $k = 0, 1, \ldots, 2^{j-1}$.

So the probability of the total energy of the nodes is:

$$e_{j,k}(i) = \frac{E_{j,k}(i)}{\sum_{i=1}^{n} E_{j,k}(i)} \qquad (4)$$

According to formula (1), the wavelet package entropy of the ith interval is:

$$H_{j,k}(i) = -e_{j,k}(i) \log e_{j,k}(i) \qquad (5)$$

3.3 Threshold calculation

The threshold selection principle in this paper is as follow:

$$thr = \sigma \sqrt{2 \lg N} \times \left(\frac{1}{2} \right)^{j-1} \qquad (12)$$

Where j is the decomposition scale, N is the length of jth layer wavelet coefficient, σ_j is the mean value of the coefficients of the interval that has maximum wavelet entropy.

3.4 Implementation process of the improve algorithm

The steps of de-noise algorithm are as follow:

Step1: decomposed the target signal $x(t)$ with EMD algorithm, get the IMF components;

Step2: N layers decomposition of the IMF components, get the corresponding wavelet package decomposition coefficients;

Step3: do the correlation analyses to the Nth layer wavelet package decomposition coefficients, then set the useful signal and breakpoint to be zero, divide the coefficients into a number of interval, calculate the wavelet package entropy value of the interval, take the mean value of the coefficients of the interval which have the maximum wavelet package entropy as the noise variance of the node, get the corresponding threshold value of the node; get the de-noised IMF components by wavelet package reconstruction of the coefficients that were quantitative processed

Step4: get the de-noised signal by reconstructing the IMF components used the EMD method.

IV. SIMULATION EXPERIMENT

4.1 Results compare of different signal-noise ratio

In order to evaluate the de-noise performance of the algorithm quantificationally, compare the effect of the algorithm this paper present with the wavelet threshold combined with EMD method.

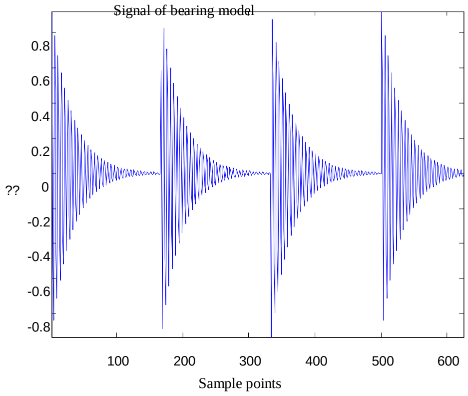

Fig1 Original signal of bearing model

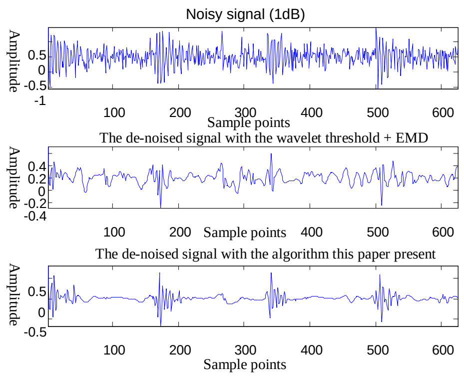

Fig2 Compare of de-noised signal with 1dB SNR

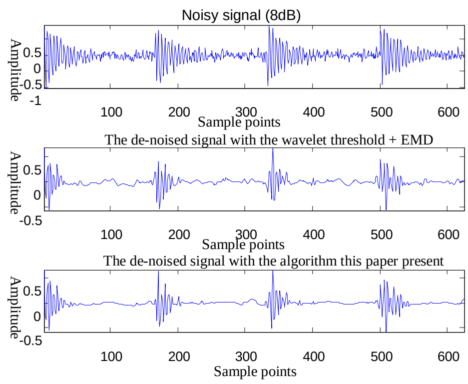

Fig3 Compare of de-noised signal with 3dB SNR

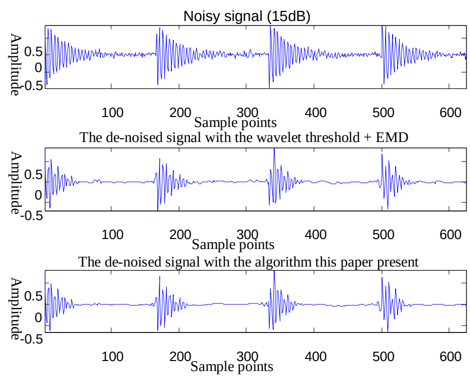

Fig4 Compare of de-noised signal with 15dB SNR

During the simulation experiments, the model of the rolling bearing was added the noise which has the signal-noise ratio of 1dB、8dB and 5dB respectively, the two de-noise methods choose the db3 wavelet function, decomposition scale is 4 layers, adopts the universal threshold selection rules proposed by Donoho, and take the soft threshold function as the threshold function. Fig 1 is the original signal of the rolling bearing model, add to three kinds of signal-noise ratio noises, the de-noised signal as Fig2, Fig3 and Fig4, the figure shows the noisy signal, the de-noised signal with the wavelet threshold combined with EMD, and the de-noised signal with the algorithm this paper present orderly. The signal-noise ratio and root mean square date of the de-noised signal is shown in Table1.

From Fig 2 we can see that the waveform signal loss of the signal in the low signal-noise ratio is very big, such as 1dB SNR, compare with the de-noised signal with the algorithm present in this paper, the de-noised signal with the wavelet threshold combined with EMD distortion is more serious at the periodic attenuation, the algorithm this paper present can retain more fault information. Observe Fig3 and Fig4, in the high signal-noise ratio, such as 8dB and 15dB, the de-noised signal with the algorithm this paper present waveform is more smooth, has little waveform distortion at the periodic attenuation, compare with it, the de-noised signal with wavelet threshold combined with EMD is not smooth since there are residual noise, and has different levels of waveform distortion at the periodic attenuation. The simulation results indicate that the algorithm this paper present has better de-noise effect than the wavelet threshold combined with EMD.

Table 1 the SNR and RMSE of the de-noisied signal

	SNR		RMSE	
SNR	EMD+wavelet threshold	Algorithm	EMD+wavelet threshold	Algorithm
1dB	-0.3073	0.2320	0.0066	0.0041
8dB	4.3208	6.8865	0.0039	0.0022
15dB	7.3161	14.1924	0.0026	0.0011

According to Table1, the de-noise effect with three kinds of SNR , the SNR and RMSE with the algorithm this paper present is smaller than the wavelet threshold combined with EMD, prove that the algorithm this paper present effective, at the same time can protect the effective signal.

4.2 Vibration signal de-noise of actual rolling bearing

During the experimental, use the algorithm this paper present for actual vibration signal de-noise. The experimental data come from QPZZ-II rotary machine vibration analyses and fault diagnosis test platform, obtain the date by running the device with inner ring damage bearing, outer ring damage bearing and ball bearing damage. The parameters are as follow: the sampling frequency is 1000Hz, the sampling points are 8192, and rotate speed N is 1200 $r/\min$. The bearing designation of the experimental is N205. The parameters of the bearing are as follow: the diameter of the rolling body is $d = 7.5mm$, the diameter of bearing section is $D = 39\ mm$, the number of rolling body is $z = 12$, contact angle is $\alpha = 0^{\circ}$

The fault character frequency of inner ring is:

$$f_i = \frac{ZN}{120}(1 + \frac{d\cos\alpha}{D}) = 143\ Hz \tag{6}$$

The fault character frequency of rolling body is

$$f_b = \frac{DN}{120}(1 - \frac{d^2\cos^2\alpha}{D^2}) = 50\ Hz \tag{7}$$

During this experiment choose the db3 wavelet function, decomposition scale is 4 layers, adopts the universal threshold selection rules proposed by Donoho, and take the soft threshold function as the threshold function.
Fig5 and Fig6 shows the original signal of inner ring damage bearing and the corresponding de-noised signal with the algorithm this paper present, Fig7 and Fig8 shows the original signal of rolling ball damage bearing and the corresponding de-noised signal with the algorithm this paper present, Fig9 and Fig10 shows the envelop spectrum of Fourier transform of the de-noised signal of inner ring damage and rolling ball damage bearing.

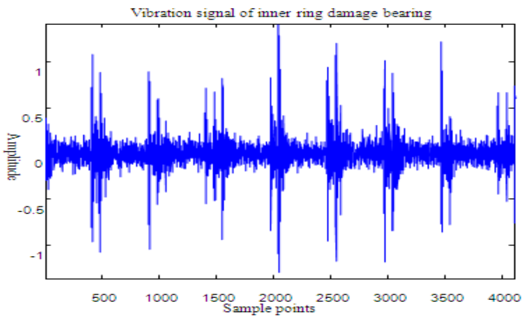

Fig5 original signal of inner ring damage bearing

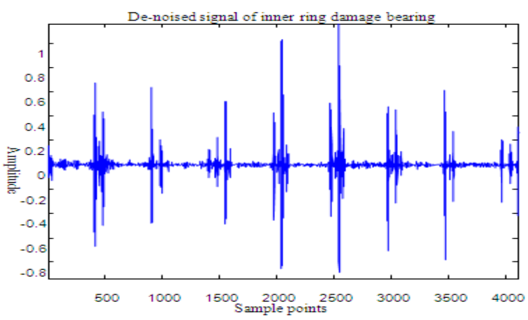

Fig6 De-noised signal of inner ring damage bearing

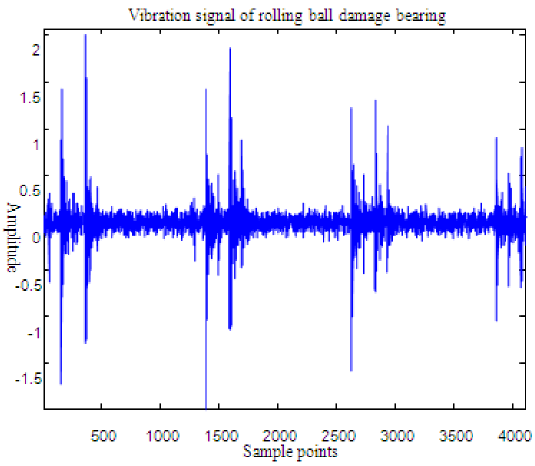

Fig7 Original signal of rolling ball damage bearing

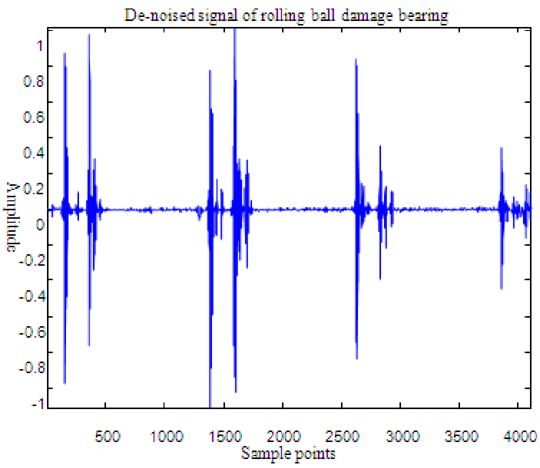

Fig8 De-noised signal of rolling ball damage bearing

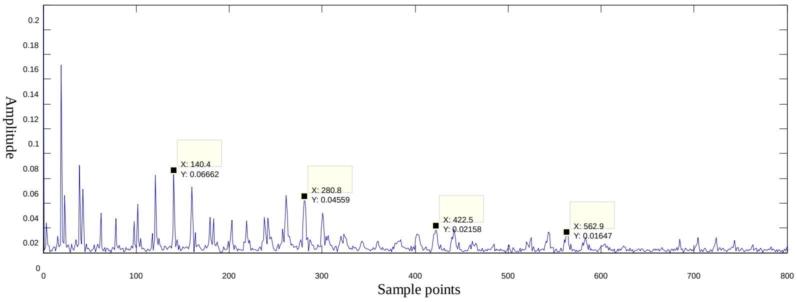

Fig9 Envelop spectrum of De-noised signal with inner ring damage bearing

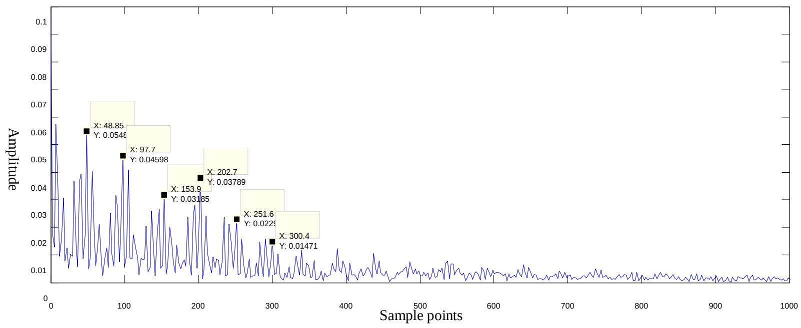

Fig10 Envelop spectrum of De-noised signal with rolling ball damage bearing

From Fig7 and Fig8 we can see that the de-noise effect is obvious with the algorithm this paper present, the de-noised signal retain the cycle waveform of the high speed rotating bearing very well, at the same time reduces the influence of high frequency interference. Extract 4 peak points from the envelop spectrum of Fig9, the corresponding frequencies in order are : 140.4 Hz 、280.8 Hz 、422.5 Hz and 562.9 Hz , the mean value of the two points difference is 141.6 Hz , it is nearly the value of 143 Hz which is calculated from equation (6) at the condition that the bearing rotate speed is 1200 revolutions per minute, so ,we can deduce the fault type is inner ring damage from the envelop spectrum of the de-noising signal. Extract 6 peak points from the envelop spectrum of Fig10, the corresponding frequencies in order are:

48.85 Hz ,97.7 Hz ,153.8 Hz ,202.7 Hz ,251.6 Hz and 300.4 Hz , the mean value of the two points difference is 49.5 Hz , it is nearly the value of 50 Hz which is calculated from equation (7) at the condition that the bearing rotate speed is 1200 revolutions per minute, so ,we can deduce the fault type is rolling ball damage from the envelop spectrum of the de-noised signal. All of the above prove that the algorithm this paper present has good performance for rolling bearing de-noising, it is good for the feature extraction.

V. CONCLUSION

The wavelet package entropy threshold algorithm based on empirical mode decomposition (EMD) was presented in this paper, it take advantages of the EMD that divide the target signal into different characteristic scale mode function adaptively, make use of the feature of the wavelet package entropy that select the threshold according to the energy characteristic adaptively. During the analogy bearing vibration de-noise experiment, the waveform of de-noised signal with the algorithm this paper present is very smooth, and there is almost no distortion at the periodic attenuation. During the experiment of vibration signal de-noised of actual rolling bearing, the algorithm this paper present is effective for signal de-noise, it make the characteristic of the target signal more obvious, diagnose the fault type by the envelope spectrum correctly. All of the above proof that the algorithm this paper present has a good de-noise performance in the aspect of rolling bearing signal de-noising.

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