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Fault Diagnosis for Rolling Bearing Based on the (SVM) Combined with (EMD) Instantaneous Power Spectral Entropy

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Abstract: The dynamic characteristics of the bearing will be complex and nonlinearity when the bearing failure and the fault signal will also exhibit non-stationary. This paper presents a kind of rolling bearing feature extraction method based on the empirical mode decomposition (EMD) and instantaneous power spectral entropy, since the EMD decomposition is adaptive and suitable for processing the nonlinearity and non-stationary signal. The steps of the method are as follow: first decompose the bearing signal into a finite number of IMF components, second process these components with power spectrum, third calculate the information entropy of the power spectrum, at last take the power spectrum entropy as the feature vector, and classify the failures into different type by support vector machine (SVM). Experiments show that 96.25% of the classification is correct which verify that the feature extraction method proposed in this paper is feasible and effective.

Key Words: *EMD, SVM, Fault Diagnosis of Bearing*

Rolling bearing is widely used in most rotating machinery, it is an important component since its operating status will effects the performance of the whole machine directly, so it is necessary to diagnose the failure of the bearing. Most of the actual bearing signals are non-stationary and nonlinearity signal. An effect method used for processing such kind of signals is time-frequency analysis, such as short-time Fourier transform (STFT), Winger-Ville distribution (WVD), Wavelet transform (WT), empirical mode decomposition (EMD) and Hilbert-Huang transform (HHT) [1]. These time-frequency analysis methods are widely used for extracting the features of the bearing signal in recent years. Then diagnose the fault by artificial neural networks[2] or support vector machine[3-4] according to the features. Support vector machine (SVM) is a kind of machine learning method proposed by Vapnik based on the statistical learning theory, it has the advantages of solving the small sample study, high-dimensional and nonlinear problems, avoiding the problems of structure selection and local minima compare with neural network method.

This paper present a feature extraction method based on the EMD and instantaneous power spectral entropy, so that to solve the problems of complexity and non-stationary signal of the rolling bearing when it is running. The steps of the method are as follow: first decompose the bearing signal into a finite number of IMF components, second process these components with power spectrum, third calculate the information entropy of the power spectrum, at last take the power spectrum entropy as the characteristic vector, and classify the failures into different type by support vector machine (SVM). Simulation and experiments verify the effectiveness of the method.

I. THE FEATURE EXTRACTION METHOD BASED ON EMD AND INSTANTANEOUS POWER SPECTRAL ENTROPY

1.1 Empirical mode decomposition (EMD)

Empirical Mode Decomposition(EMD) is a new method used in non-stationary signal processing, it was proposed by American scholar Huang in 1998, it decompose the signal into a finite number of intrinsic mode functions(IMF). EMD decomposition is a continuous screening process, has self—adaptive, can get the intrinsic mode function on different frequency bands[6-8], so it is widely used in fault diagnosis of mechanical equipment.

The EMD decomposition is based on the following three assumptions:

（1）the extreme points of the signal is no less than two, a maximum and a minimum;

（2）define the characteristic time scale according to the time between two extreme points

（3）if the signal is unfilled by extrema but contains inflection points, a differentiation process applied once or more may reveal the extrema.

On the basis of these assumptions, the step of EMD decomposition is as follow: find all the maximum points of the signal $x(t)$, determine the upper envelope of the original signal by cubic spline curve; the same process, find all the minimum points, determine the lower envelop of the signal by cubic spline curve, the mean value of the upper and lower envelop is m_1, the difference between the original signal $x(t)$ and the mean envelop m_1 is a new signal named h_1:

$$x(t) - m_1 = h_1 \qquad (1\text{-}1)$$

Ideally, h_1 is the first IMF component of the original signal when it meets the two conditions of IMF component.

Take h_1 as the original signal if it can not meets the conditions of IMF component, then repeat step(1), get the mean value m_{11} of the upper and lower envelop , then judge whether $h_{11} = h_1 - m_{11}$ meets the conditions of IMF, if not , repeat the above process for several times until get $h_{1(k-1)} - m_{1k} = h_{1k}$, and h_{1k} meets the conditions. Set $c_1 = h_{1k}$,then c_1 is the first IMF component of the original signal.

After the repeated "screening", the IMF components will have constant amplitude which are useless, so termination condition must be set up. The termination condition of this paper is calculate as the standard deviation SD of two continuous "screening" IMF components $h_{1(k-1)}(t)$ and $h_{1k}(t)$, SD is expressed as:

$$SD = \sum_{t=o}^{T} \left[\frac{\left| h_{1(k-1)}(t) - h_{1k}(t) \right|^2}{h_{1(k-1)}^2(t)} \right] \qquad (1\text{-}2)$$

In general, the smaller SD is, the better linearity and stability that the intrinsic mode function has. But, it will meaningless if SD is too small, so the suggested range of SD is 0.2~0.3.

Separate c_1 from the original signal, get

$$r_1 = x(t) - c_1 \qquad (1\text{-}3)$$

Do the above mentioned screening process to r_1, get the following relations:

$$r_1 - c_2 = r_2 ; r_2 - c_3 = r_3 ; \cdots ; r_{n-1} - c_n = r_n \quad (1\text{-}4)$$

If r_n is a monotonic function, can not decompose, the loop end. According to equation (1-3) and (1-4),the original signal $x(t)$ can be expressed as :

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (1\text{-}5)$$

Here r_n is residual function, take as the mean value of the signal.

The IMF components decomposed from the EMD decomposition includes different frequency band information, when the rolling bearing failure, the signal in some frequency band will change, at the same time, the instantaneous power spectral will fluctuation. So, the fault features of the rolling bearing can be extracted from the calculation of the power spectrum entropy of the IMF components.

1.2 Power spectrum calculation

Power spectrum analysis is a commonly used mechanical fault diagnosis method. The process of power spectrum analysis is as follow: First, obtain the amplitude spectrum of the signal by Fourier transform; then obtain the power spectrum of the signal by calculating the square of the amplitude spectrum.

Combined with the rolling bearing fault diagnose, first decompose the bearing signal with EMD decomposition, obtain a finite number of IMF components $\sum_{i=1}^{n} c_i(t)$, calculate the Fourier transform of each component $C_i(f)$, the power spectrum of each IMF components are obtained via:

$$S_i(f) = \frac{1}{N} \left| C_i(f) \right|^2 \quad (1\text{-}6)$$

Here, N is sample amount.

1.3 Power spectrum entropy calculation

Information entropy is the uncertainty quantitative evaluation of the information source; it can indicate the general characteristic of the information source. The information entropy is widely used since it can indicate the intrinsic information of the modulation signal, so it is used for extracting the fault features of the bearing signal. The information entropy is obtained via:

$$H(X) = -\sum_{i=1}^{n} p_i \log \ p_i \quad (1\text{-}7)$$

Here $p_i = S_i(f) / S(f)$ is the proportion that the ith IMF component power spectrum in the overall power spectrum.

$S(f) = S_1(f) + S_2(f) + \cdots + S_n(f)$ is the sum of all the IMF component power spectrum

1.4 The feature extraction steps

(1) Decompose the bearing signal by EMD technique; obtain a finite number of IMF components $c_i(t)$;

(2) Calculate the Fourier transform of each IMF component $C_i(f)$;

(3) calculate the power spectrum $S_i(f)$ according to equation (1-6);

(4) Calculate the power spectrum entropy according to equation (1-7)

(5) Take the power spectrum entropy as feature vector; extract the features of the bearing signal.

II. PERFORMANCE ANALYSIS OF BEARING FEATURE EXTRACTION ALGORITHM

2.1 Noise permission ability analysis

The vibration signal will appear modulation phenomenon when different rolling bearing failure occurs. Specific phenomenon is that sideband exists around the resonant frequency, and the sideband interval is the modulation frequency, is also the characteristic frequency of the bearing fault. Take the following signal as the simulation signal of the rolling bearing:

$$x(k) = e^{-at} \times \sin 2 f_c kT \tag{2-1}$$

$$t' = \mathrm{mod}\left(kT, \frac{1}{f_m}\right) \tag{2-2}$$

Here α , is the index frequency, fm is modulation frequency, fc is carrier frequency and T is sampling interval respectively. Fig 1 shows the original signal When α =800，fm=100Hz，fc=5000Hz， T =1/25000s，signal length is 8192 points. Calculate the power spectrum entropy of each IMF component which gets from the EMD decomposition. Add noises with SNR of 0.1,1,5,10 respectively so that to test the effect of noise. Fig 2 shows the bar chart of the EMD power spectrum entropy with different SNR.

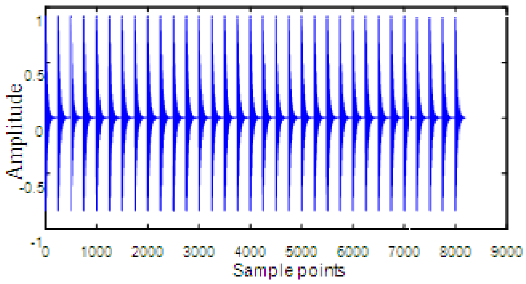
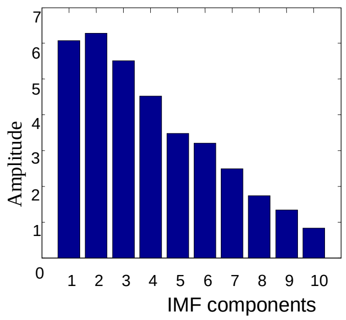
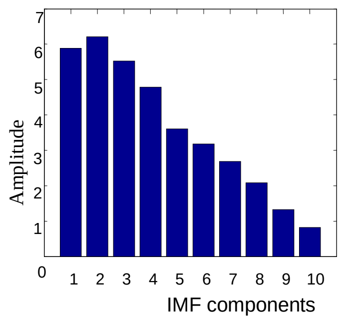


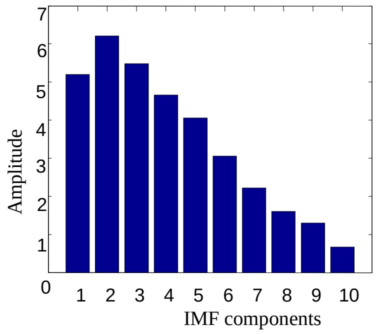
Figure 1 the orignal signal



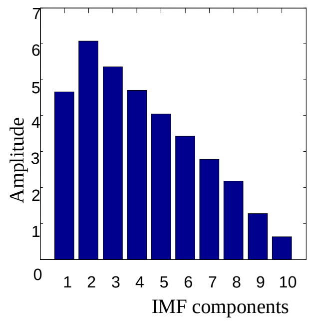
（a）entropy chart with SNR 0.1



（b）entropy chart with SNR 1



（c）entropy chart with SNR 5



（d）entropy chart with SNR 10

Figure 2 bar chart of EMD power spectrum entropy with different SNR

As shown in Fig2, the EDM instantaneous power spectrum entropy of the FMI components is different at the first frequency band and instability for different SNR noise, but at the other frequencies almost the same. Since the noise has a greater impact on the first frequency band, the other frequency bands are taken as the characteristic vectors to reduce the effect of the noise. Therefore, this method can eliminate the influence of noise on the signal.

2.2 Stability analysis

In order to demonstrate the stability of the method, different type of fault data were collected from the cylindrical roller bearing N205. 40 sets of data were obtained for each type of rolling bearing failure such as the normal running; inner race failure, outer race failure and ball bearing failure etc, calculate the EMD instantaneous power spectrum entropy of each set of data, take the mean value of repeated experiments as the feature vector used for making fault classification. The EMD instantaneous power spectrum entropy are summarized in Tab1.

Table 1 the EMD instantaneous power spectrum entropy value

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9
Normal signal	6.5344	6.3258	6.4671	6.2103	5.7590	5.4639	4.7177	4.2058	3.5608
Normal signal	6.6144	6.0245	6.3841	6.2952	5.6855	5.4365	4.7627	4.1766	3.4929
Normal signal	6.9193	6.4322	6.3633	6.2616	5.7718	5.5329	4.6724	4.0598	3.4351
Inner race fault	6.5482	6.7431	6.9336	6.4059	6.0430	5.3025	4.7902	3.8519	3.0475
Inner race fault	6.6732	6.9401	7.0277	6.5029	5.9571	5.2755	4.8277	3.9548	3.1613
Inner race fault	6.7940	6.5585	7.1468	6.5146	5.9585	5.3425	4.8237	3.9880	3.2621
outer race fault	7.6937	7.5248	6.6348	5.3499	5.8028	5.2531	4.4097	3.4241	3.0360
outer race fault	7.6956	7.3607	6.7015	5.4096	5.8299	5.3389	4.4167	3.5905	2.9938
outer race fault	7.7672	7.2927	6.6645	5.3156	5.7745	5.2397	4.5042	3.4792	3.1204
rolling elements fault	6.3562	6.9001	6.8154	6.3361	5.7034	5.0171	4.2146	3.7928	2.9888
rolling elements fault	6.6523	7.2478	6.8937	6.3451	5.6582	5.1070	4.2204	3.6337	2.9155
rolling elements fault	6.3556	6.9980	6.7207	6.3054	5.7447	5.1379	4.1527	3.6079	2.9451

As show in Tab1, the instantaneous power spectrum entropy of the IMF components are stable for the rolling bearing at the same condition, have some difference at different conditions, so the power spectrum entropy can be used for fault diagnosis. In addition, the instantaneous power spectrum entropy are quite different for the first two components although the rolling bearing at the same condition because the influence of the noise. Take the instantaneous power spectrum entropy except the first two components as the feature vectors so that reduce the effect of the noise and improve the diagnosis accuracy. To verify the validity of the method utilizing support vector machine for fault classification.

III. ROLLING BEARING FAULT DIAGNOSIS BASED ON SVM

3.1 SVM binary classifier

The classification process of SVM is to find the optimal classify hyper plane in the space that satisfy the classification request. The hyper plane not only separate the data correct but also make the distance of the two data sets maximum. Convert the SVM learning process to an optimization problem. Given a training sample $\{(x_i,y_i), i=1,2,\ldots\ldots l\}$,where $x_i \in R^n$ is the input, $y_i \in \{+1,-1\}$ is the expected output, +1 and -1 represent the different classification. Under the linear separability $wgx+b=0$, the optimal hyper plane can be constructed by solving an optimization problem:

$$\Phi(w,\xi)=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{l}\xi_i$$

$$s.t.\quad y_i(w_i \cdot x+b)\geq 1-\xi_i$$

$$\xi_i \geq 0, i=1,2,\cdots,l \qquad (3\text{-}1)$$

Here w is the normal vector of the hyper plane, C is the error penalty factor, ξ is the slack variable, $\xi_i > 0$ when the prediction of the machine is wrong, $b \in R$ is the threshold.

Solve equation (3-1) by Lagrange multiplier methods, converts the quadratic programming problems with linear constraints to the corresponding dual problem:

$$\max Q(a)=\sum_{j=1}^{l} a_j-\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} a_i a_j y_i y_j K(x_i,x_j) \qquad (3\text{-}2)$$

Where, $K(x_i, x_j)$ is a kernel function. There are several commonly used kernel functions, such as polynomial kernel function, radial basis function, multilayer perceptron and dynamic kernel functions etc. [8,9] In this paper radial basis function is used.

3.2 SVM multi-classifier

Although support vector machine classifier is originally developed for two-category problems, it can be extended to multi-class classification since the type of the bearing faults more than two. Multi-class classification is based on the two-category classification, and mostly used algorithms are mainly one-against-one, one-against-all and directed acyclic graph. The algorithm one-against-one is adopted in this paper.

The one-against-one method creates a classifier between two classes. For k-class classification roblem the one-against-one method needs $k(k-1)/2$ classifiers, each of which is trained on samples from the two corresponding classes. After all the classifiers are trained, a voting strategy is used for test. The unlabelled sample is assigned to the class with the largest vote. Compared with the one-against-rest method, the classification accuracy is improved; however, there are still unclassified samples.

3.3 Bearing fault diagnosis experiments

In order to verify the practicability of the methods, take 20 sets of the original signal as training samples at each condition, the other 20 sets as test samples. Extract the feature vector from the instantaneous spectrum entropy of the training samples. Take the normalization processed feature vector as the input of the support vector machine, the classification results is shown in Tab 2.

Table2 test results of the support vector machine

Actual state	Normal signal	Inner race fault	Outer race fault	rolling elements fault	Accuracy
Normal signal	20	0	0	0	100%
Inner race fault	0	18	0	2	90%
Outer race fault	0	0	20	0	100%
rolling elements fault	0	1	0	19	95%
Overall accuracy	96.25%				

As shown in Tab2, there are 2 samples misclassified in the 20 test samples of inner race fault, 1 sample misclassified in the 20 test samples of rolling elements fault, the accuracy is 96.25%. The results of the experiments demonstrate that the rolling bearing faults extraction based on EMD instantaneous spectrum entropy is effective, good stability, immune to noises and classification accurate, utility.

IV. CONCLUSION

With the improvement of the degree of modern industrial automation, the fault diagnose is wildly used in the mechanical equipment. In this paper, combined with the characteristic of the rolling bearing vibration signal, a characteristic vector extraction method based on the advantages of EMD decomposition, power spectrum analysis and information entropy is proposed. The numerical experiments shows that the method has a good noise-tolerant ability and stability, and it can extract the characteristic of the fault signal accurately. In addition, the rolling bearing fault signal classification with SVM classification method has a high recognition rate. Therefore, this paper research has the important academic value and the project application value.

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