The Feature Extraction Method based on Hilbert Marginal Spectral Envelope Energy Applied in Gearbox Fault Diagnosis

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Abstract—**For the ship propulsion system health monitoring under multiple working conditions, a gearbox fault diagnosis method based on the vibration energy analysis is proposed in this paper. Firstly, the Hilbert marginal spectrum of gearbox vibration signal is calculated by Hilbert-Huang Transform. Secondly, search the local maximum and minimum values of the Hilbert marginal spectrum to fit the upper and lower envelopes. Thirdly, divide the envelopes into continuous multiple frequency bands and calculate the energy of each frequency band to construct two sets of feature vectors. Finally, train two groups of SVM to classify the samples. Results of the presented method are verified by the case studies of the gearbox test-bed.**

Keywords-Gearbox Diagnostics; Hilbert-Huang Transform; Envelope Energy Analysis; Support Vector Machine; Health Monitoring

I. INTRODUCTION

The gearbox is an important part of the ship propulsion system, which usually works in a severe environment and the work load is heavy. In the gearbox system, the gears and rolling bearings are prone to failure and the failure will lead a serious result. Therefore, the fault diagnosis plays a key role in the marine gearbox health monitoring process. This paper mainly considers the practical application of Marine Parallel-Shaft Reduction Gearbox fault diagnosis method.

Generally, mechanical fault diagnosis generally has 3 steps [1]: The acquisition of the fault signal, feature extraction of the fault mode and fault pattern recognition. In this paper, the acceleration vibration signal of the gearbox is analyzed [2]. For fault pattern recognition, Artificial Neural Network (ANN) and other machine learning methods require a large amount of tag data, but the actual industrial process usually has obtained few tag data samples, which limits the application of this method. Support Vector Machine (SVM) has advantage to classify small samples, which has better performance than many other traditional pattern recognition methods [3]. Therefore, it's a more mainstream fault identification method.

In the process of fault identification, the feature extraction from the signal is a core step. Most signals in the operation of large rotating machinery are non-stationary and non-linear. However, the traditional signal processing method based on Fourier transform is not effective in dealing with gearbox failures such as non-stationary signals with low signal-to-noise ratio and strong interference [4]. Therefore, the advanced time-frequency analysis methods are possible to perform better analysis and fault feature extraction on non-stationary and nonlinear signals [1]. Hilbert-Huang Transform(HHT) and Wavelet Packet Transform(WPT) are commonly used time-frequency analysis methods.

HHT decomposes the signal into a series of Intrinsic Mode Function(IMF) by Empirical Mode Decomposition(EMD). Then, Hilbert marginal spectrum will be constructed from the instantaneous parameters. Jiang[5] extracts the statistical features (mean, variance, etc.) of the Hilbert spectrum and the marginal spectrum as the feature vectors of the SVM. Wang[6] uses the maximum and peak frequencies of the Hilbert marginal spectrum as the SVM feature vector. Ma[7] uses the envelope demodulation method based on Hilbert transform to obtain the characteristics of each fault. WPT is developed from wavelet transform, which can accurately extract the high and low frequency components of the signal. Mariela[8] combines WPT with random forests and genetic algorithms. Li[9,10] use the energy of each bottom layer node decomposed by the wavelet packet as the feature vector of the SVM.

In the traditional HHT and WPT methods, the training and test samples are usually less and the types of faults that can be identified are small. Meanwhile only a single condition is considered [3,11,12]. In this paper, the actual data collected from the professional test-bed, including 9 gearbox working conditions and 10 vibration modes of gearbox. And there's a large number of training and testing samples. The improved Hilbert-Huang Method is discussed in this paper, which extracts feature by Hilbert marginal spectral envelope energy. And applied to gearbox fault diagnosis under multiple working conditions to improve fault pattern recognition accuracy.

This paper is organized as follows: Section II presents the basic method of HHT and proposes an improved feature

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extraction method based on Hilbert marginal spectral envelope energy. Section III presents the principle of SVM and proposes the SVM structure for multiple fault classification. Section IV describes the process of using the method proposed in this paper for gearbox fault diagnosis. The case studies of real gearbox vibration data from the test-bed are presented to verify the proposed approach in Section V. Section VI concludes the paper.

II. THE NEW HILBERT-HUANG METHOD FOR FEATURE EXTRACTION

In this section, a new method of extracting the gearbox vibration feature is proposed. Firstly, the traditional HHT method is applied. Secondly, extract the upper and lower envelopes of the Hilbert Marginal Spectrum(HMS). Thirdly, calculate the energy by frequency band as the feature vectors.

A. Vibration Mode Screening: EMD

Norden E. Huang proposed the concept of IMF based on the conditions that the single-component signal with meaningful instantaneous frequency should be satisfied [14]. EMD[15] algorithm can decompose the original signals into into IMF. The EMD algorithm can be described as follows[4]:

1) Determine all local extreme points of the original signal $x(t)$. Fit the upper and lower envelopes of the signal $x(t)$ with a cubic spline interpolation function[20].

2) Record the mean of the upper and lower envelopes as m_1

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

3) Determine if h_1 is IMF. If h_1 does not satisfy the IMF condition, repeat step (1) with h_1 as the original data until h_1 satisfies the IMF condition. Recorded as

$$c_1 = h_1 \tag{2}$$

where c_1 is the first component of the signal $x(t)$ that satisfies the IMF condition.

4) Separate c_1 from $x(t)$, we can have

$$r_1 = x(t) - c_1 \tag{3}$$

Repeat steps (1) to (3) with r_1 as the original signal and cycle N times. Obtain the N components from the signal $x(t)$, which satisfy the IMF condition, so we have

$$\begin{cases} r_2 = r_1 - c_2 \\ \cdots\cdots \\ r_N = r_{N-1} - c_N \end{cases} \tag{4}$$

End of loop when r_N becomes a monotonic function. The original signal can be reconstructed by these multiple modes.

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \tag{5}$$

where $c_n(t)$ is the IMF decomposed from each layer. N is the number of IMF. $r_N(t)$ is the reconstruction error which can be ignored.

$$x(t) \approx \sum_{n=1}^{N} c_n(t) \tag{6}$$

B. Vibration Mode Description: Hilbert Marginal Spectrum

The vibration frequency will change with time in non-stationary signals. In order to reflect the vibration mode of the signal more accurately, it is necessary to calculate the instantaneous frequency[16]. Hilbert transform on each IMF of the formula (6).

$$c_n'(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{c_n(\tau)}{t-\tau}d\tau = c_n(t) * \frac{1}{\pi t} \tag{7}$$

Construct an analytical signal for each layer of the IMF.

$$z_n(t) = c_n(t) + jc_n'(t) = a_n(t)e^{j\varphi_n(t)} \tag{8}$$

where

$$a_n(t) = \sqrt{c_n^2(t) + c_n'^2(t)} \tag{9}$$

$$\varphi_n(t) = \arctan\frac{c_n'(t)}{c_n(t)} \tag{10}$$

We can calculate the instantaneous frequency as follow.

$$\omega_n(t) = \frac{d\varphi_n(t)}{dt} \tag{11}$$

The above equation gives the distribution of the signal amplitude and frequency with time, called Hilbert spectrum.

$$H(\omega, t) = \mathrm{Re}\sum_{n=1}^{N} a_n(t)e^{j\int \omega_n(t)dt} \tag{12}$$

According to the definition of Hilbert transform, it is essentially the convolution of $x(t)$ and $1/t$. Compared with Fourier transform, the local characteristics of $x(t)$ is emphasized. This paper uses HMS to describe vibration mode.

$$h(\omega) = \int_{-\infty}^{+\infty} H(\omega, t)dt \tag{13}$$

The marginal spectrum reflects the statistically significant cumulative amplitude at each instantaneous frequency point over the entire signal time span[14].

C. Improved Method of Feature Extraction: Band Energy of HMS Extreme Envelope

The HMS has better performance than the Fourier spectrum. On the basis of retaining these advantages, this paper proposes an improved method, which can further improve the accuracy of HMS feature extraction. In order to extract more feature information from the HMS, considering the extreme values can better represent the features, all local maximum and minimum of the HMS are extracted.

According to the existence conditions of extreme values, we have

$$x'(n) = 0, x''(n) \neq 0 \tag{14}$$

1) $x(n)$ is local maximum, if $x''(n) < 0$

2) $x(n)$ is local minimum, if $x''(n) > 0$

In order to keep the data length the same as the original data, cubic spline interpolation[20] is used for maximum and minimum values, generates maximum envelopes $\mathrm{hmax}(\omega)$ and minimum envelopes $\mathrm{hmin}(\omega)$.

Based on the idea that different vibration modes have different vibration energy, this paper divides the maximum and minimum envelopes into multiple continuous frequency bands and calculates the energy in each frequency band to construct the feature vectors.

$$\mathrm{Emax}_i = \sqrt{\sum_{j=1}^{M} \mathrm{hmax}_i^2(\omega_{ij})} \tag{15}$$

$$\mathrm{Emin}_i = \sqrt{\sum_{j=1}^{M} \mathrm{hmin}_i^2(\omega_{ij})} \tag{16}$$

where $i = 1,2,\ldots,N$. N is the number of frequency bands. M is the number of instantaneous frequency points. Emax_i and Emin_i are the energy of envelope in each frequency band. hmax_i and hmin_i are the envelopes. ω_{ij} is the j^{th} instantaneous frequency point in the i^{th} frequency band.

Construct normalized feature vectors.

$$\mathrm{emax}_i = \frac{\mathrm{Emax}_i}{\sum_{m=1}^{N} \mathrm{Emax}_m} \tag{17}$$

$$\mathrm{emin}_i = \frac{\mathrm{Emin}_i}{\sum_{m=1}^{N} \mathrm{Emin}_m} \tag{18}$$

$$\overrightarrow{\mathrm{Tmax}} = [\mathrm{emax}_1\ \mathrm{emax}_2 \cdots \mathrm{emax}_i \cdots \mathrm{emax}_N] \tag{19}$$

$$\overrightarrow{\mathrm{Tmin}} = [\mathrm{emin}_1\ \mathrm{emin}_2 \cdots \mathrm{emin}_i \cdots \mathrm{emin}_N] \tag{20}$$

III. The General SVM for Pattern Recognition

This section first introduces the basic principles of SVM. Then proposes an SVM structure suitable for multiple fault classification.

A. Theoretical Background of SVM

Suppose the training data set L which contains N_1 normal operation data and N_2 faulty data.

$$L = \{(x_1,y_1),(x_2,y_2),(x_3,y_3),\ldots,(x_N,y_N)\} \tag{21}$$

where $N = N_1 + N_2$, $x_i \in R^n$ means classification feature vector, and y_i is category label, we have

$$y_i = \begin{cases} 1 & i \in \{1,2,\ldots,N_1\} \\ -1 & i \in \{N_1+1,\ldots,N_1+N_2\} \end{cases} \tag{22}$$

We want to find a hyper-plane, which can separate the two types of samples and the support vectors have the largest distance from it. Considering the fault tolerance of the system, we introduce the slack vector ξ ,the general support vector machine is formulated in the following optimization form [17].

$$\begin{aligned} &\min_{\omega,b,\xi} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N}\xi_i \\ &s.t.\ \ y_i(w^T x_i + b) \geq 1 - \xi_i, i = 1,2,\ldots,N \\ &\qquad \xi_i \geq 0, i = 1,2,\ldots,N \end{aligned} \tag{23}$$

As for the linearly non-separable data, the kernel function $K(x_i, x_j)$ is adopted to address the original problem in feature space in which the new problem can be handled as a standard linearly separable one [18].

B. Practical Application of SVM

This paper includes 10 vibration modes: Fault-Free, Chipped, Missing, Surface Fault, Eccentric, Crack, Outer, Inner, Ball and Combination.

When training SVM with only one set of feature vectors, the structure of the SVM group is shown in Fig.1. Because SVM can only perform two classifications, it is necessary to train 9 SVMs to distinguish 10 kinds of vibration modes. In this way, it can gradually determine which vibration mode the current input sample belong. The current vibration mode will be determined when the SVM outputs 1 (except for the 9th level SVM).

Two SVM groups are obtained when training by two sets of feature vectors Tmax and Tmin , as shown in Fig.2. The max_SVM group is used to identify the maximum value feature and the min_SVM group is used to identify the minimum value feature. When the two SVM output 1 at the same time (or the output sum is 2), the current mode is determined, otherwise enter the next level SVM (the 9th level SVM output both 2 and -2 can determine mode).

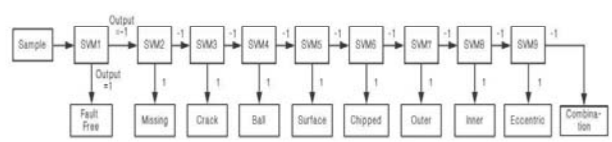


Figure 1. The Structure of One SVM Group

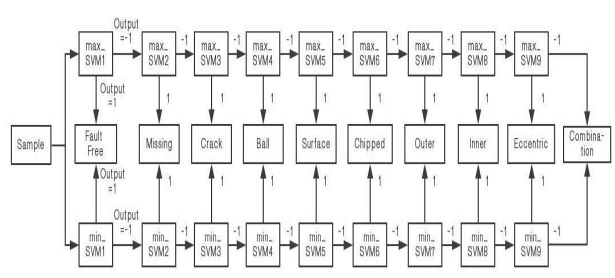


Figure 2. The Structure of Double SVM Groups

IV. THE GLOBAL SCHEME PROCESS FOR THE GEARBOX FAULT DIAGNOSIS

The process of the gearbox fault diagnosis method proposed in this paper is described as follows and shown in Fig.3.

Stage 1: Data Preprocessing.

Obtain the samples' Hilbert Spectrum and get HMS by time integration.

Stage 2: Feature Extraction.

Find the maximum and minimum values of HMS and generate the upper and lower envelopes. Divide the envelope into multiple frequency bands. Calculate the signal energy in each frequency band and construct the feature vectors.

Stage 3: Offline Training.

The SVM structure as shown in Fig.2 is applied. One SVM group uses T_{max} as the feature vectors and the other group uses T_{min} as the feature vectors.

Stage 4: Online Monitoring.

The sample is input into the trained two SVM groups for abnormality detection and fault diagnosis. The current sample vibration mode will be determined when the two groups of SVM output the same result. Otherwise enter the next stage SVM or resampling.

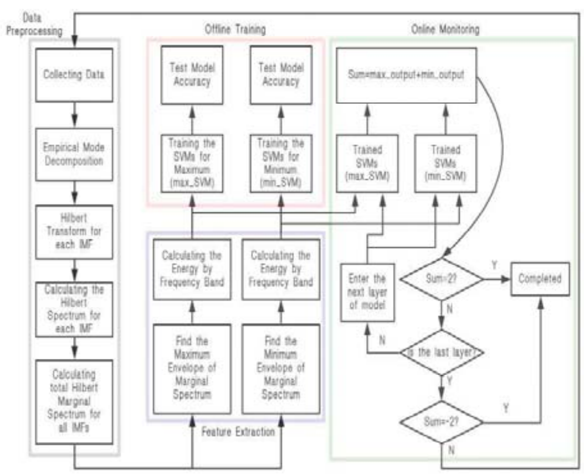
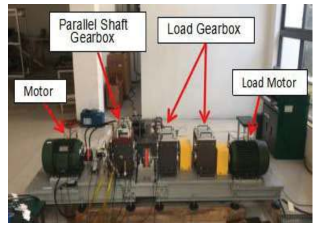


Figure 3. The Procedure of Fault Diagnosis

V. CASE STUDIES OF GEARBOX FAULT DIAGNOSIS IN THE REAL MONITORING PROCESS

A. Experiment Description

The Drivetrain Prognostics Simulator (DPS) is developed by Oceanic Intelligent Technology Center to simulate the actual operation of the gearbox. The lab environment is shown in Fig.4 and Fig.5.



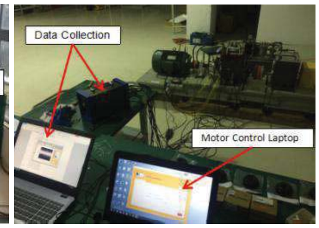


Figure 4. Test-Bed Figure 5. Laboratory Environment

Internal structure of Parallel-Shaft Gearbox as shown in Fig.6. The gearbox input shaft is connected to the output shaft of the drive motor. Fault simulation of gears and rolling bearings on intermediate shaft. The output shaft is connected to the coupling on the right (load motor output).

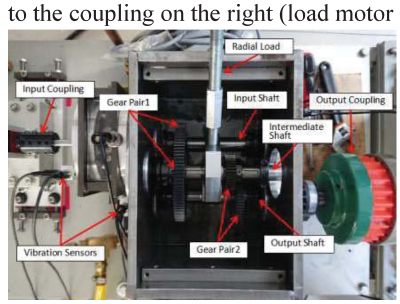


Figure 6. Gearbox Internal Structure Figure 7. Shell Sensor

Acceleration sensors are used to collect gearbox vibration signal. This article uses sensor data on the gearbox shell and the sampling frequency is 12800Hz. The vibration signal sampled by the on-axis sensor is more clearer. Because it's close to the fault source. In contrast, the signal quality of the gearbox shell sensor is worse. However in terms of actual engineering, the shell sensor is more valuable, because in reality the sensor only can be mounted on the gearbox shell. In this paper, analyzing data with more meaningful shell sensor as shown in Fig.7.

Calculate the HMS as shown in Fig.8 from time domain signal.

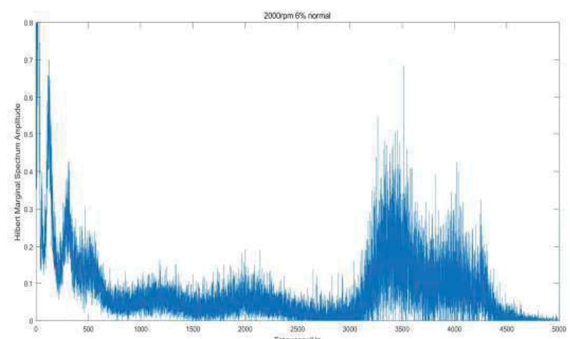


Figure 8. 2000rpm6%load Fault-Free Hilbert Marginal Spectrum

Simulate different operating conditions by changing motors speed. The same mode has different energy distributions under different operating conditions as shown in Fig.9. Therefore, the fault identification algorithm need to be more robust and generalizable.

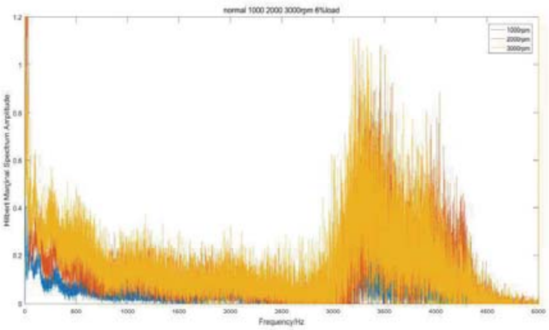


Figure 9. 1000/2000/3000rpm Fault-Free Hilbert Marginal Spectrum

B. Data Processing with Multiple Methods

1) *HMS with Fitting Envelope*

Construct the upper and lower envelopes of the marginal spectrum shown in Fig.8 by the method proposed in Section II. As shown in Fig.10.

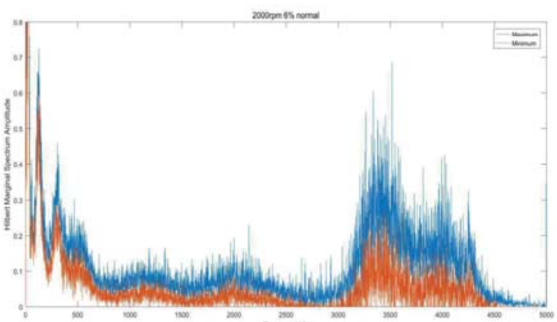


Figure 10. Upper and Lower Envelope

where the blue curve is the maximum envelope of the sample and the orange curve is the minimum envelope of the sample.

Fig.11 and Fig.12 show the upper and lower envelopes of the HMS of the fault-free mode and the rotational eccentricity fault at 2000 rpm 6% load condition. The energy is divided into 16 frequency bands as an example to calculate the energy in each frequency band. Construct feature vectors by the formula(15)~(20). Train the SVM model as process in Fig.3

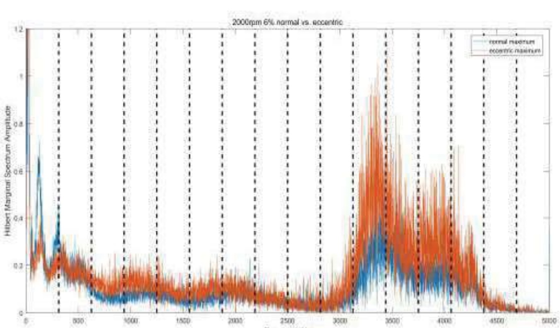


Figure 11. Extracting the Maximum Envelope Feature

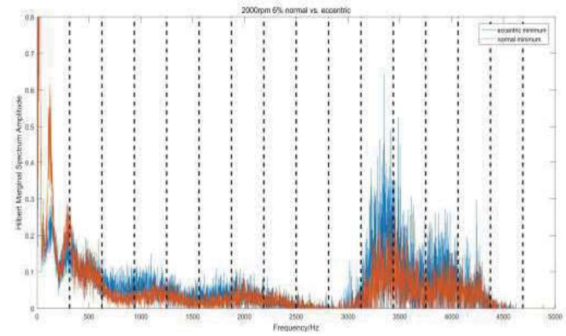


Figure 12. Extracting the Minimum Envelope Feature

2) *HMS without Fitting Envelope*

Directly divide the frequency band without fitting the upper and lower envelopes and calculate the energy for the HMS. This method only needs to train one group of SVM as shown in Fig.1. Fig.13 shows the HMS of fault-free mode and rotational eccentricity fault at 2000 rpm 6% load condition. The energy is divided into 16 frequency bands as an example to calculate the energy in each frequency band.

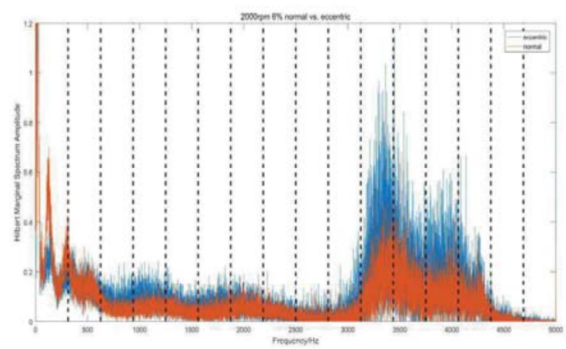


Figure 13. Extracting Features without Fitting Envelope

$$E_i = \sqrt{\sum_{j=1}^{M} h_i^2(\omega_{ij})} \tag{24}$$

where E_i is the energy of i^{th} frequency band. h_i is the HMS belong to i^{th} frequency band. The method of constructing the feature vector is the same as the formula(17)~(20).

3) *Wavelet Packet Decomposition*

The wavelet packet transform is developed on the basis of wavelet transform. Since the traditional wavelet transform can not provide effective analysis for high frequency information, the wavelet packet can further extract the discrete detail signals decomposed by the previous level and extract its low and high frequency components. The schematic diagram of wavelet packet decomposition is as shown in Fig.14.

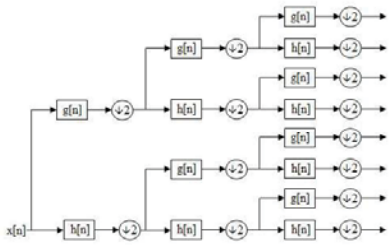


Figure 14. Wavelet Packet Decomposition[19]

where $g[n]$ is low pass filter and $h[n]$ is high pass filter. $\downarrow 2$ means downsampling.

The thought of the wavelet packet transform is completely consistent with the wavelet transform, except that the high frequency information is decomposed once more, but the wavelet transform directly loses the high frequency information. So the wavelet packet transform can perform more accurate feature extraction on the signal. Which can be described as

$$x_{j+1}^{2p}(n) = x_j^p * g'(2n) = \sum_{m=-\infty}^{+\infty} x_j^p(m) g(m-2n) \tag{25}$$

$$x_{j+1}^{2p+1}(n) = x_j^p * h'(2n) = \sum_{m=-\infty}^{+\infty} x_j^p(m) h(m-2n) \tag{26}$$

where p is the subspace of the previous layer. After divide the previous subspace, the low frequency subspace 2p and the high frequency subspace 2p+1 are obtained.

Calculate the energy of the bottom nodes of the wavelet tree as a feature vector[9][10].

$$E_i = \sqrt{\sum_{n=1}^{m} x_i^2(n)} \tag{27}$$

where i is the serial number of the bottom nodes, $i = 1, \ldots, 2^j$. j is the number of wavelet packet decomposition layers. m is the data length of each bottom node which is $1/2^j$ times of the original length of data. x_i is wavelet packet coefficient of i^{th} bottom node. E_i is the energy of i^{th} bottom node.

The method of constructing the feature vector is the same as the formula(17)~(20). This paper bases on the process described in [9], selecting db4 wavelet base and 4 layers wavelet packet decomposition.

C. *Experimental Result and Comparing*

There are 10 vibration modes of gearbox have been considered and 9 operating conditions in each mode have been tested: Drive motor at the speed of 1000 rpm, 2000 rpm, 3000 rpm with 0%, 3%, 6% Load conditions. 288 samples of each vibration mode under 9 operating conditions were collected. 180 samples were used to train SVM and 108 are used to test the accuracy of the SVM.

1) *Hilbert-Huang Methods*

TableI. compares the two Hilbert-Huang methods (Fit the envelope: Improved HHT Method. Not fit the envelope: HHT Method) and calculates the energy of 50 frequency bands. Where the accuracy of each SVM and total accuracy can be calculated as:

$$\mathrm{SVM_i\ Accuracy} = \frac{\text{The number of errors in SVM}_\mathrm{i}}{108 * \text{The number of modes in SVM}_\mathrm{i}} \tag{28}$$

$$\mathrm{Total\ \ Accuracy} \ = \prod_{i=1}^{9} \mathrm{SVM_{\ i}\ \ Accuracy} \tag{29}$$

TABLE I. TWO KIND OF HILBERT-HUANG METHOD

Method	Do not Fit Envelope			Fitting the Envelope		
Feature Vector Dimension	50			50		
Sample Rate / SVM Level Accuracy(%)	12800 Hz	3200 Hz	1600 Hz	12800 Hz	3200 Hz	1600 Hz
SVM 1	100	99.81		100	99.91	97.78
SVM 2	96.09	92.39		100	97.84	97.84
SVM 3	97.22	92.94		99.88	99.88	99.77
SVM 4	97.88	91.93		99.60	98.28	98.28
SVM 5	97.99	92.59		99.38	98.77	96.76
SVM 6	99.07	91.67		99.81	96.85	94.63
SVM 7	99.54	90.74		99.77	99.07	97.69
SVM 8	100	93.83		100	98.15	98.15
SVM 9	100	97.22		100	99.07	99.07
Total Accuracy	88.36	55.35	<50	98.45	88.42	81.59

As can be seen from TableI, under different sampling rates the Improved HHT Method has higher recognition accuracy, indicating whether fit the HMS envelope or not has a great influence on the fault diagnosis result. Because this method extracts two kinds of vibration feature and then uses SVM for cross-comparison. It can greatly improve the identification accuracy .

2) *Hilbert-Huang Methods and Wavelet Packet Transform*

Compare two Hilbert-Huang methods with WPT in Table II. The vibration signal is decomposed into 4 layers by wavelet packets and the energy of 16 bottom nodes is calculated. In other words, the wavelet packet method has a 16-dimensional feature vector. In order to ensure fairness, two Hilbert-Huang methods also extract energy in 16 frequency bands which reduces the feature dimensions compared to Table I.

TABLE II. TWO KIND OF HILBERT METHOD AND WAVELET PACKET

Method	Hilbert Method without Envelope			Wavelet Packet			Hilbert Method with Envelope		
Feature Vector Dimension	16			16			16		
Sample Rate / SVM Level Accuracy(%)	12800 Hz	3200 Hz	1600 Hz	12800 Hz	3200 Hz	1600 Hz	12800 Hz	3200 Hz	1600 Hz
SVM 1	100	97.31		100	99.91	98.89	100	99.35	99.35
SVM 2	95.68	82.51		98.35	97.63	94.65	100	98.35	97.53
SVM 3	95.49	90.74		99.31	97.00	93.10	100	99.77	99.65
SVM 4	96.43	90.08		100	98.28	93.78	99.47	98.94	99.47
SVM 5	97.38	89.51		100	98.77	95.99	99.23	100	95.68
SVM 6	97.96	91.11		99.81	97.22	93.89	99.81	97.22	95.74
SVM 7	95.14	87.50		100	96.53	89.35	99.31	98.15	96.53
SVM 8	99.69	92.90		100	97.84	95.37	99.38	98.46	97.22
SVM 9	100	94.44		100	99.54	93.10	100	97.22	96.76
Total Accuracy	79.71	41.09	<40	97.49	83.94	58.43	97.75	88.10	79.89

It can be seen from Table II. that the identification accuracy of these three methods will decrease as the sampling rate decreases, but the Improved HHT Method has the smallest reduction, so is more robust. In contrast, this method has the highest recognition accuracy at any sampling rate. So it's not sensitive to the length of the training sample. Combined with

Table I, this new method is not sensitive to the dimension of the feature vectors. When the dimensions changes, the Improved HHT has the smaller reduction on the total accuracy. In other words, it's better than WPT and HHT Method.

VI. Conclusion

In this paper, a new method for extracting vibration features of gearbox based on Hilbert marginal spectral envelope energy is proposed. Firstly, the traditional HHT is used to calculate the HMS of the vibration signal, which can describe the vibration state accurately in the frequency domain. Then extract all local maximum and minimum points of the HMS and fit the upper and lower envelopes. Calculate the energy of the upper and lower envelopes in several frequency bands as feature vectors and input the trained SVM for pattern recognition. This new method can extract more feature information from the HMS. Finally, using the real data of the gearbox test-bed for verification, the method of this paper has achieved the excellent effect. This new method has a higher accuracy than the Hilbert method without fitting envelopes and WPT. Meanwhile it is not sensitive to the sampling rate and the dimensions of the feature vector, which has stronger robustness and generalization ability. This method is suitable for practical engineering applications.

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