Rolling Bearing Fault Pattern Recognition Method Based on Hht-Svd Parameter Optimization and Hssvm

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ABSTRACT. *A bearing fault diagnosis method based on Hilbert-Huang transform and matrix singular value is proposed. Make Hilbert-Huang transform (HHT) on bearing signals to obtain a spectrum of their 8 components. The sensitive mode functions which are used to reconstruct the signal are selected according to the characteristic frequency of the bearing. Make empirical mode decomposition which was improved by extension method again on the reconstructed signal, get 5 new intrinsic modal components (IMF). Then calculate their singular value de-composition (SVD) to get 5 Singular Values. At last inputting these 5 singular values as characteristic parameters into the Hyper-sphere Support Vector Machine (HSSVM) to learn classification, identify the type of failure of the rolling bearing, and use visualization technology to verify the effect. The experimental results show that the accuracy of the HSSVM classifier established by the method proposed in this paper is about 10% higher than that of the HSSVM classifier without parameter optimization, and the average response speed is increased by 3 seconds. It turns out that this pattern recognition method is advantageous both in terms of response speed and accuracy.*

KEYWORDS: *Hilbert-huang transform (hht), Singular value decomposition (svd), Support vector machine (svm), Pattern recognition*

1. Introduction

Rolling bearings are the key components in rotating machinery. Rolling bearing failure or failure seriously can affect the operation of the equipment and production safety. Therefore, it is very important to study the intelligent faults diagnosis method. At present, the commonly used intelligent diagnosis methods include artificial neural network, extreme learning machine (ELM), hyper-plane support vector machine (HPSVM) and hyper-sphere support vector machine (HSSVM)[1]. Among them, HSSVM is suitable for multi-classification problems, and can better solve practical problems such as small samples and nonlinearities, and overcome the shortcomings such as slow convergence in neural networks and the need for a large number of data samples during training[2].

In actual working conditions, the bearing mode is generally divided into four modes[3]: normal, inner ring fault, outer ring fault, and ball fault, which are multi-classification problems. When the bearing mode changes, its vibration signal can reflect the bearing running characteristics. The vibration mode can be judged by the analysis and clustering of the vibration signal, but the vibration signal of the bearing is nonlinear and non-stationary, and it is difficult to obtain a large sample of typical fault data due to the complexity of working conditions. So the HSSVM is used here as a classifier for analysis in this paper.

The problem with the hyper-sphere support vector machine(HSSVM) is that the classification result depends largely on the model parameters. The commonly used parameters are signal empirical mode decomposition (EMD) component energy entropy, EMD singular value [4] and so on. The singular value can best reflect the inherent characteristics of the matrix, and is suitable for extracting the fault characteristics of various vibration signals. However, a large number of noise interference signals and the end effect of the EMD algorithm itself can reduce the accuracy of classification. Based on this, this paper proposes improved HHT-SVD parameter optimization method[5]. At first, the sample signal is decomposed by HHT to obtain the component spectrum map, select the sensitive component according to the characteristic frequency of the bearing for reconstruction, and then decompose the reconstructed signal twice. The singular value of the quadratic decomposition component is input into the HSSVM as an optimized parameter for cluster analysis.

2. Improved Hht-Svd Parameter Optimization Algorithm

2.1 Hht Decomposition Reconstruction Algorithm Based on Bearing Vibration Mechanism

Fault bearing vibration mechanism: If the bearing is pitting or peeling off, it repeatedly hits other components in contact with the damage point during operation to generate low-frequency vibration components, which we call "by vibration" [4]. These vibrations are periodic with the operation of the bearing, and its theoretical frequency can be calculated from frequency conversion and bearing size. The frequency at which these "by vibration" occurs is called the fault signature frequency. The bearing mainly manifests as three kinds of faults on the inner ring, the outer ring and the rolling element, and the impact caused by the fault induces the high frequency natural vibration of the bearing system, which often plays the role of carrier frequency in the signal. The fault characteristic frequency is its modulation frequency. During the performing spectrum analysis, the frequency band containing the fault frequency is the key analysis frequency band. These types of characteristic frequencies of rolling bearings can be calculated by the formula such as follows[2]:

Working rotation frequency:

$$f_r = \frac{n}{60} \qquad (1)$$

Rolling body pass frequency:

$$f_{rp} = \frac{D}{2d}[1 - (\frac{d\cos\beta}{D})^2]f_r \qquad (2)$$

Inner circle pass frequency:

$$f_{ip} = \frac{Z}{2}(1 + \frac{d\cos\beta}{D})f_r \qquad (3)$$

Outer ring pass frequency:

$$f_{op} = \frac{Z}{2}(1 - \frac{d\cos\beta}{D})f_r \qquad (4)$$

Hilbert Huang transform (HHT) includes empirical mode decomposition (EMD) and Hilbert transform[9]. EMD decomposition can adaptively decompose non-stationary and nonlinear signals of fault vibration into linear and stationary signals, and obtain several intrinsic modal components (IMF). The information of the signal is mined and the characteristics of the signal are preserved, and then the Hilbert transform is performed on each IMF component to obtain a spectrum. However, when EMD is decomposed, the extreme value at the end of the signal is uncertain, which causes the spline difference to produce a large fitting error when decomposing the end points of each component. If it is serious, the decomposed IMF will lose its meaning. At this time, if Hilbert transform is performed on all IMFs, the obtained Hilbert spectrum will generate analysis errors. In order to solve the above problems, the boundary local feature scale extension method is used to suppress the end effect of EMD. At the same time, according to the bearing fault mechanism and the mathematical model and the Hilbert spectrum characteristics of EMD decomposition, it can be seen that the EMD component which contains the fault characteristic frequency is the sensitive component [5], while the other components are mostly the vibration generated by the noise or the natural frequency of the system. Therefore, the HHT-feature frequency analysis method is proposed to select the IMF component sensitive to the fault feature for reconstruction and reject the interference.

The algorithm steps are as follows:

(1) Add two maximum and minimum points respectively at the two ends of the collected vibration signal $x(t)$,Recorded as $S_{max}(1)$, $S_{max}(2)$, $S_{min}(1), S_{min}(2)$.

(2) Taking the mean value of each extreme point at the adjacent end point as the amplitude of the added extreme point, the average time interval of each extreme point near the end point of the original signal $x(t)$ is the time interval of the added extreme point, the expression as follows:

$$AS_{max} = \frac{x_{max}(1) + S_{max}(1) + x_{max}(2)}{3} \qquad (5)$$

$$AS_{min} = \frac{x_{min}(1) + S_{min}(1) + x_{min}(2)}{3} \qquad (6)$$

$x_{max}(1), x_{max}(2), x_{min}(1), x_{min}(2))$ are the first and second maximum and minimum values of the signal $x(t)$.

(3) Use the cubic spline interpolation function to find the upper and lower envelopes of all extreme points, calculate the envelope average, and find the difference between the signal $x(t)$ and the mean of the envelope, recorded as $h_1(t)$:

$$h_1(t) = x(t) - n_1(t) \qquad (7)$$

(4) Determine if $h_1(t)$ meets the two conditions of the IMF: ① The difference between the total number of extreme points and the number of zero crossings does not exceed 1;② About the time axis is symmetrical.If satisfied, then $h_1(t)$ is the first IMF component found, and it is recorded as $c_1(t)$.

If $h_1(t)$ does not meet the above conditions,Then perform the above steps on $h_1(t)$ until $h_k(t) = h_{k-1}(t) - n_k(t)$ satisfies the above conditions. At this time $h_k(t)$ is recorded as $c_1(t)$.and separate $c_1(t)$ from the signal $x(t)$, repeat the above steps. Finally, the signal $x(t)$ can be expressed in the form of an n-th order IMF component and a residual signal sum, ie:

$$x(t) = \sum_{i=1}^{n} c_k(t) + r_n(t) \qquad (8)$$

In this formula,$c_k(t)$is the IMF obtained by EMD with extension method, and $r_n(t)$ is the residual term of the signal.

(5) Hilbert transform is performed on each IMF component to obtain their Hilbert spectrum.

(6) Calculate the characteristic frequency of the common failure mode of the bearing (ball fault, outer ring fault, inner ring fault), and select the IMF component for reconstruction based on this.

2.2 Improved Svd Algorithm

The singular value decomposition (SVD) [10]of matrices is an important matrix decomposition in linear algebra and is a generalization of the normal matrix diagonalization in matrix analysis.

There is a real matrix A of N rows and M columns, and it is singularly decomposed as follows:

$$A = U \wedge V^T \qquad (9)$$

In this formula, $U = [u_1, u_2, \cdots u_N] \in R^{N \times N}, U^T U = I; V = [v_1, v_2, \cdots v_M] \in R^{M \times M}, V^T V = I, \wedge \in R^{N \times M}$ is matrix $[diag\{\sigma_1, \cdots, \sigma_p\}]$ or its transposed form,$p = min(N, M)$

$\sigma_1 \geq \cdots \geq \sigma_P \geq 0, \sigma_1, \cdots \sigma_P$ is called the singular value of the matrix. According to the matrix theory, the singular value of the matrix is an intrinsic feature of the matrix. It has good stability. When the matrix element changes little, the singular value of the matrix changes little. Therefore, the singular value of each vibration signal can be extracted as The fault feature of the mechanical component, so the singular value of each vibration signal can be extracted as the fault feature vector.

After the signal is decomposed by EMD, the IMF components $c_1, c_2, \cdots c_n$, are obtained, and the IMF component is composed into an initial eigenvector matrix C, which is expressed as:

$$C = [c_1, c_2, \cdots c_n]^T$$

In the reference [Field], the singular value decomposition of matrix C is directly performed to calculate the singular values of different frequency components, and these singular values are used as feature parameters to construct a support vector machine.

In this paper, after the obtained vibration signal is decomposed to obtain $C = [c_1, c_2, \cdots c_n]^T$,the Hilbert spectrum of each component is calculated, and the sensitive frequency is analyzed by the bearing characteristic frequency ratio to reconstruct the reconstructed signal. The second EMD with extension method obtains optimized IMFs such as $f_1, f_2, \cdots f_m$ and a residual, and the components which have canceled interference respectively contain different frequency components, and different frequency segments contain different fault information.

So the characteristics of the original vibration signal excluding the high frequency noise can be described by $f_1, f_2, \cdots f_m$,so that by extracting the features of the optimized IMFs $f_1, f_2, \cdots f_m$, the characteristics of the vibration signal can be obtained. Perform singular value decomposition to obtain the singular value of the IMFs . The singular value of the $f_1, f_2, \cdots f_m$ is the fault characteristic of each frequency segment describing the signal in the sampling time, and the difference of the singular value on each different frequency segment reflects the difference of the operating state of the mechanical equipment. These components of the noise interference optimized IMFs contain different time scales, which can make the characteristics of the signal display at different resolutions, and perform singular value decomposition on the optimized IMFs to obtain singular values that best describe the signal characteristics. These singular values will be Enter the SVM classifier as an optimization parameter for machine learning. The flow chart is as follows:
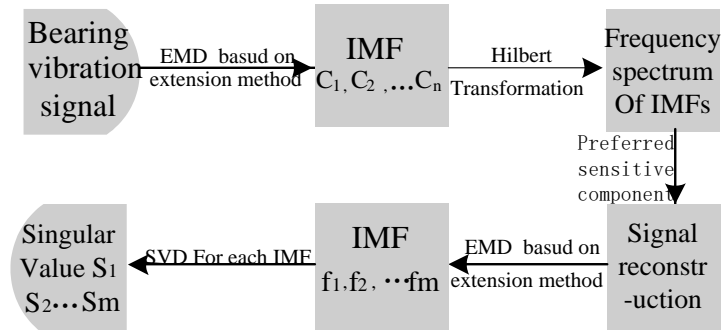
Fig.1 Process for Svd Parameter Optimization

3. Principle for Hyper-Sphere Svm

SVM is a clustering algorithm based on the theory of statistics. Commonly there are two models of hyper-sphere and hyper-plane. The hyper-sphere model is often used to deal with multi-classification problems ($k > 2$)with fast training speed and high detection efficiency[3].

The idea is as follows: Set k element sets $A^m (m = 1,2, \cdots k)$, each set contains n^m points , which belong to the same category. For each set, we look for a ball (a^m, R^m) where a^m is the center of the ball and R^m is the square of the radius of the ball, making the radius as small as possible, and making each ball contain as many samples as possible for each class Point, in order to achieve this aim, we introduce a slack variable, define the Lagrange function with KKT condition , the function like this:

$$L(R^m, a^m, \xi_i^m, x_i^m, \gamma_i^m) = R^m + C\sum_i \xi_i^m -$$

$$\sum_i \alpha_i^m (R^m + \xi_i^m - ((x_i^m \cdot x_i^m) - 2(a^m \cdot x_i^m) + (a^m \cdot a^m))) - \sum_i \gamma_i^m \xi_i^m \quad (10)$$

$a_i^m \geq 0, \gamma_i^m \geq 0$ are a Lagrange multiplier, and partialally deriving the Lagrange function and making them 0:Then the original question trun into a dual problem :

$$maxL(\alpha_I^M) = \sum_i \alpha_i^m (x_i^m \cdot x_i^m) - \sum_{ij} \alpha_i^m \alpha_j^m (x_i^m \cdot x_j^m) \quad (11)$$

Substituting the kernel function, get the formula is as follows:

$$maxL(\alpha_I^M) = \sum_i \alpha_i^m (x_i^m \cdot x_i^m) - \sum_{ij} \alpha_i^m \alpha_j^m (x_i^m \cdot x_j^m)$$

$$\text{s.t.} \begin{vmatrix} \sum \alpha_i^m = 1 \\ 0 \le \alpha_i^m \le C^m \end{vmatrix} \qquad (12)$$

The quadratic programming problem as described above is solved for each classification, thus producing k ball, each ball representing a class. For a new sample point, we need to determine which category it belongs to, and need to calculate the square of its distance to each sphere, ie

$$R^x = k(x,x) - 2k(x,a^m) + k(a^m,a^m) \quad (m=1,\cdots i,\cdots i+j,\cdots k) \quad (13)$$

Then compare and classify sample point according to R^m and R^x.

4. Fault Pattern Recognition Instance

4.1 Experiment

The experimental simulation conditions were carried out in a workshop with a noise decibel of about 60 decibels. The bearing failure test bench used included DEWEtron signal collector, sensor, motor, bearing, etc. The experimental object was a 6312 rolling bearing. The test bench and schematic diagram are shown in Fig 2:
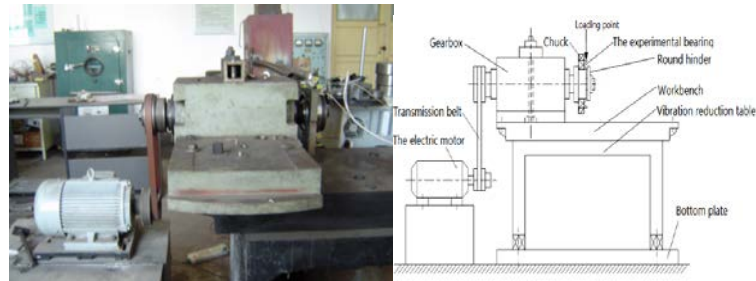

Fig.2 Bearing Failure Test Bench and Its Schematic Diagram

The test bench is composed of four parts: mechanical drive device, loading mechanism, fixing device and base. The power source is three-phase asynchronous motor, rated speed is 1420r/min, rated power is 3kW, rated voltage is 380V, used belt drive , and used dynamic pressure shaft system as spindle system. The diameter is $\Phi = 70$ mm, and the double-point thrusting support is used at both ends. The experimental bearing is fixed on the right end of the main shaft, and the acceleration sensor is directly mounted on the chuck. The experimental object is a normal bearing and a fault bearing of type 6312. The cage is connected by riveting, and a light load is added at the loading point, which is performed by the magnetic powder

brake. The fault bearing is the inner ring pitting diameter of about 4mm, and the experimental parameters are as follows: rolling element diameter $d = 21$ mm, pitch circle diameter $D = 95$ mm, number of rolling elements is 8, contact angle β , spindle speed 1045r/min, frequency conversion 17.5Hz. The common faults are calculated by the formula(1)-(4), that is, the characteristic frequencies of the frequency conversion, the inner ring, the outer ring and the balls, the calculation results are as follows:

$$f_r = 17.5\text{Hz}, f_{ip} = 85\text{Hz}, f_{op} = 54\text{Hz}, f_{bp} = 38\text{Hz}$$

In the vibration signals collected in the four mode states, any one of the signals is subjected to Fourier transform to obtain their spectrum diagrams. As shown in the fig.3, it can be seen that each spectrum diagram has a corresponding peak at the characteristic frequency, but In the presence of noise, high energy (amplitude) peaks may occur randomly in any frequency band, such as 56 Hz ,158 Hz appearing in the inner ring fault signal in the figure, 37 Hz, 70 Hz appearing in the outer ring fault, 20 Hz appearing in the rolling fault, etc. In actual situations, we don't know which mode the bearing is running in before diagnosis, in the case of no fault type, such noise interference may overwhelm the peak of the characteristic frequency, or appear peak in the characteristic frequency where there is no fault, such as the outer ring fault signal of the figure at 37Hz points corresponding to the characteristic frequency of the ball fault, there is a peak of energy, which causes the system to mistake the signal for a ball failure. Under strong noise interference, the spectrum of the signal cannot extract the fault information of the signal. Therefore, before the system learns and clusters a large number of signals, the signal needs to be optimized and denoised.
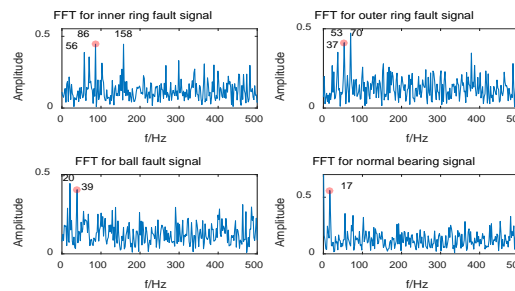

Fig.3 Spectrogram of the Vibration Signal in Different Modes

4.2 Optimization of Characteristic Parameters of Hht-Svd for Bearing Signals

For the bearing signals in the four modes, the HHT transform is performed with the extension method described above, and the Hibert spectrum of each signal IMF component is obtained as shown in the fig.4. It can be observed that in either mode, the first component c1 frequency is mainly distributed in the high frequency band

after 150Hz, the second component c2 frequency is mainly distributed at 50~300Hz, the third component c3 is mainly distributed at 20~150Hz, the fourth component c4 is mainly distributed at 10~80Hz, and the fifth component c5 is mainly distributed at 0~30Hz, the sixth component c6 is mainly distributed in 0~10Hz, and the seventh and eighth components c7 c8 are mainly distributed in 0~5Hz. It can be known by calculation that the four characteristic frequency values distributed in 17Hz~87Hz,so, this four IMF (c2, c3, c4, c5) covers all the characteristic frequencies and they are sensitive components we want to focus on. Let $y(t) = c_2 + c_3 + c_4 + c_5$, y(t) is a signal that is optimized by denoising by the original signal x(t).
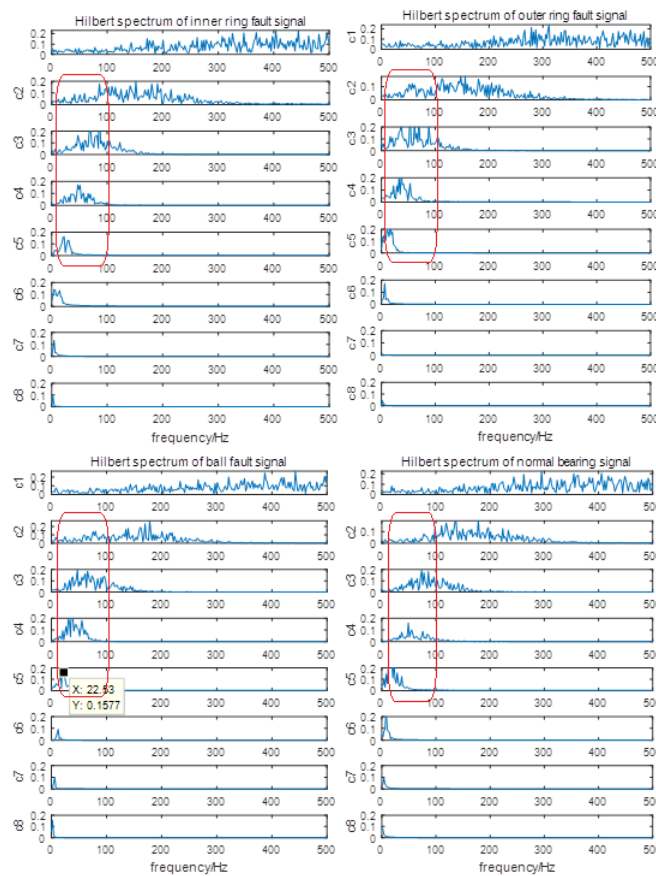
Fig.4 Hht Transformation of Different Modes of Vibration Signals

50 sample points are grouped into one class for each bearing mode, four modes of sampling a total of 200 sample, and each sample has a length of 1 second. The EMD with no improve proposals is performed on each sample signal, and the IMF of the first 8 signals is automatically decomposed. The singular values of the IMF

are obtained as 8 singular values, s1, s2...s8, and 50 samples in each mode. Therefore, each mode has 50 sets of singular values to form a singular value of the polyline trend chart.
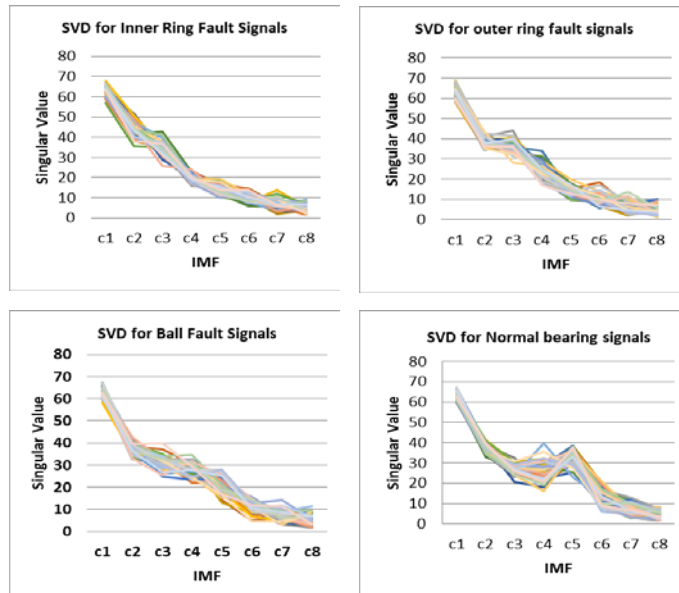
Fig.5 Singular Value Distribution of Bearing Signals Before Optimization

The figure traverses sequentially to indicate the first to eighth IMF components, and the ordinate is the singular value corresponding to the component. According to the basic idea of cluster analysis, the purpose of clustering is to make the parameter sample set of the feature space gather according to each sample, the sample and the sample subset and the only and the sample point subset and the visible acacia measure to get the relationship system between sample points and sub-collections. For more accurate classification and identification of faults, the gap between individuals in the same category needs to be as small as possible, and the gap between individuals in different categories is as large as possible. However, it can be found from Fig. 5 that the unprocessed signal IMF- singular value are relatively similar between inner ring fault signal, outer ring fault signal and ball fault signal, resulting in failure classification.

Taking the average of the eight singular values in the figure, the singular value distribution interval in the four mode states can be obtained. It can be seen that the difference is very small between mean values of the first component, the sixth component, the seventh component, and the eighth component. This small difference is not conducive to machine learning and clustering, especially the first component, the values of the first component singular values in the four modes are very large, but the difference is small. Figure 6 also verifies the effectiveness of the

HHT-feature frequency reconstruction method proposed above: c_2, c_3, c_4, c_5 with large differences are sensitive signals, and other signals are mainly noise or other interfering signals that pass through all frequency bands.
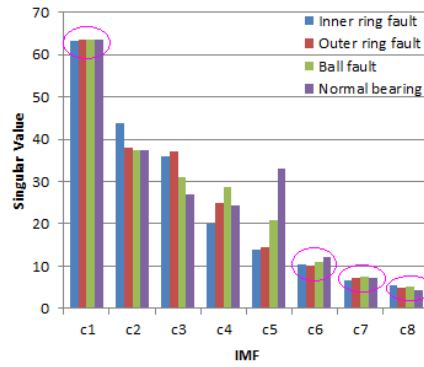

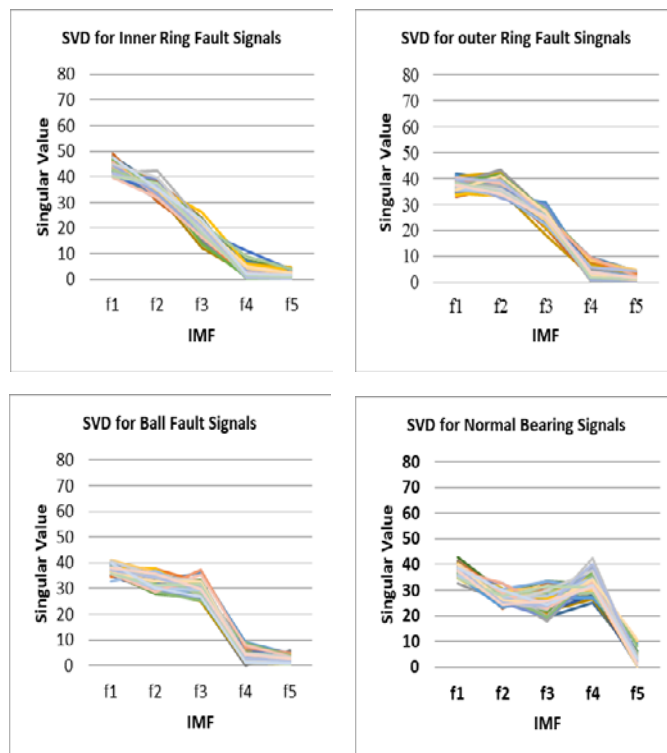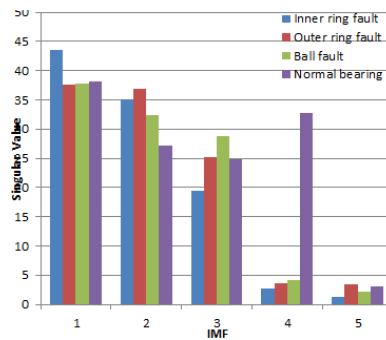*Fig.6 Comparison of 8 Singular Values in Four Bearing Modes Before Optimization*

Fig.7 Singular Value Distribution of Bearing Signals after Parameter Optimization

Therefore, $y(t) = c_2 + c_3 + c_4 + c_5$ is used instead of the original signal for EMD with extension method. Each denoised signal sample can only be decomposed into 6 components (IMF), and take the first 5 IMFs as the main analysis object, make SVD on them. This five singular value are the parameters obtained after optimization. The optimized singular value of the 50 groups in each mode is shown in Figure 7. Compared with Figure 5, the difference of 4 modes in the figure7 becomes obvious, it is more effective to use this 5 singular values as parameters to the SVM. Similarly, the average of 50 sets of singular values in each mode is averaged, and the histogram can be obtained as shown in Fig. 8. It is a significant difference of the singular values between the four modes. In order to clarify the degree of optimization of HHT-feature frequency reconstruction denoising method, the variance value is used to quantify the figure before and after denoising, and the component singular value of the bearing signal in different modes before and after optimization can be obtained. The variance values are shown in Table (1) and Table (2).

Fig.8 Comparison of 5 Singular Values in Four Bearing Modes after Parameter Optimization

The variance of the eight singular values before denoising averaged 11.6666 ($\overline{S}$,) in spite of the number of singular values after optimization decreased, the total variance value increased (from 93.6 to 192.3), and the mean value of variance $\overline{S}$ also increased to 38.4567. Compared with the 8 singular values before denoising, the optimized 5 singular values as the difference of the characteristic parameters of four modes are larger, and the clustering effect after input to the support vector machine is better too.

Table 1 Variance of Singular Values of Signals in Different Modes (Before Optimization)

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	$\overline{S}$	$\sum S$
S	0.0173	7.0025	15.9721	9.7812	55.8803	0.5952	0.1257	0.2243	11.6996	93.6

Table 2 Variance of Singular Values of Signals in Different Modes (after Parameter Optimization)

	IMF1	IMF2	IMF3	IMF4	IMF5	$\overline{S}$	ΣS
S	5.9725	13.3513	10.9715	161.2821	0.7123	38.4567	192.3

4.3 Classification and Pattern Recognition

Use the five optimized singular values in the four mode states as the feature vector (50 sets of singular values for each mode), put them into HSSVM, the sorting machine is constructed. The algorithm steps are as follows:

5. Calculate the Optimized Singular Values for Each of the 50 Sets of Samples in the Four Modes , and Use Them as Feature Vectors.

6. Establishing Optimization Equations Using Radial Basis Kernel Functions

3. Using MATLAB built-in optimization toolbox to solve the quadratic programming problem of four different kernel functions, and find the Lagrangian multiplier α_i^m ,spherical center a^m and radius square R^m of the HSSVM with different states of rolling bearing.

In this paper, 50 sets of training data are represented by Maxwell's triangular plane coordinate chromaticity diagram visualization method in colorimetry. As shown in Fig. 9, the samples in the four states can be accurately separated.

7. Taken 25 Sets of Data in Four Modes in Addition, and a Total of 100 Sets of Data Were Used as Test Samples to Obtain a Diagnosis Result.
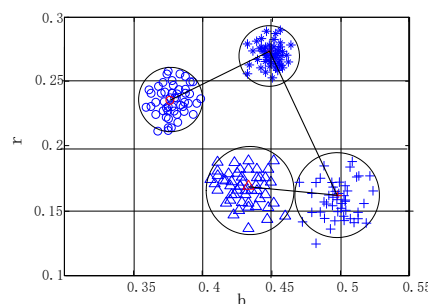

o-inner ring fault   +-ball fault   △-outer ring fault *-normal red - Ball heart

Fig.9 Visualization of Bearing Pattern Clustering Results

For comparison, this paper also uses the unoptimized 8 singular values as the feature vector to construct the Hyper-sphere support vector machine, which is compared with the method adopted in this paper. The results are shown in Table 3. The total accuracy of the method with EMD-SVD is 78%, and the total accuracy obtained by the method in this paper is 89%, the accuracy is improved by 11%, and the average response speed is increased by 3 seconds ,which proves that the singular value optimization method here is effective.

Table 3 Comparison of Two Modes of Discrimination Accuracy

method	Inner fault	Ball fault	Outer fault	normal	Running time	Total accuracy
EMD-SVD	18/25	17/25	20/25	23/25	6.2S	78%
HHT-SVD	21/25	21/25	23/25	24/25	4.7S	89%
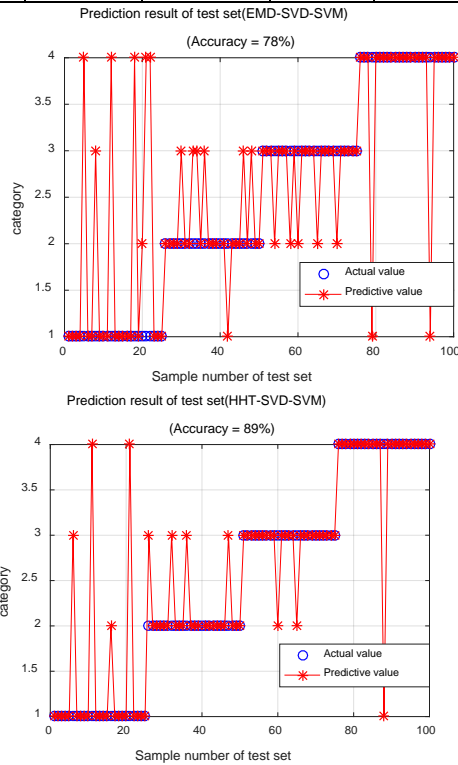
Fig.10 Comparison of Two Modes of Discrimination Accuracy

8. Conclusion

1). The modified HHT transform of signal obtains the Hilbert spectrum of each IMF component. Selecting the sensitive IMF component according to the characteristic frequency of the bearing signal itself can effectively extract the

important components of the signal, thereby eliminating the interference and noise components.

2). The singular value can reflect the inherent characteristics of the signal samples, and has better stability. The signal processed by the HHT-feature frequency reconstruction method performs secondary EMD, and the different IMF components obtained include different frequency bands and components. The singular value describes the fault characteristics of the signal in each frequency band, reflecting the difference in the operating state of the bearing.

3). The singular values obtained by IMFs are input into the hyper-sphere support vector machine (HSSVM)as the characteristic parameter, and effective clustering can be obtained, but the noise interference in the example affects the difference of the singular value, so that the accuracy is decreased., The method based on HHT and characteristic frequency reconstruction can suppress noise interference and optimize singular values. The singular values before and after optimization are input into the SVM as feature parameters, and then cluster analysis is compared. It is proved that the HHT-SVD parameter optimization method is very effective in the cluster analysis of noisy signals.

Acknowledgement

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