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Research of Mechanical Fault SVM Intelligent Recognition Based on EEMD Sample Entropy

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Abstract: The extraction of fault information is the key of fault intelligent recognition of support vector machine for rolling bearing. Because of the non-adaptive and mode mixture of wavelet transform and empirical mode decomposition, ensemble empirical mode decomposition (EEMD) and sample entropy have been adopted to extract fault information of rolling bearing. For three kinds of conditions and pitting diameters, the vibration signal of rolling bearing has been acquired by experiment. Then by wavelet transform to reduce noise, the noise reduction signal has been decomposed into several intrinsic mode function components by EEMD, and the complexity of major components has been described by sample entropy. In addition, a SVM rolling bearing fault classification recognizer which EEMD sample entropy has been adopted as training and recognition samples is proposed. The experiment result shows that under small sample, the inner race, outer race and ball fault of bearing can be accurately recognized and the accuracy for reorganization enhance with the number of samples increasing. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: EEMD, Sample entropy, SVM, Rolling bearing, Intelligent diagnosis.

1. Introduction

Application of SVM for intelligent fault diagnosis in rotating machinery can effectively solve the practical problems, such as small sample, nonlinear and high dimensional pattern recognition, and overcome the defects of traditional BP neural network intelligent diagnosis, such as requires a large sample, determines the network structure difficultly, converges slowly and converges to local minimum easily [1-3]. However, when the bearing or other parts in mechanical equipment breaks down, the vibration signals often have the feature of nonlinear, non-stationary and signal interference [4, 5]. How to extract the fault information from above vibration signal and be used as a feature vector of SVM classification recognizer is the key to realize mechanical fault SVM intelligent diagnosis. Wavelet transform and EMD (Empirical Mode Decomposition, EMD) have been used for extracting fault information by many researchers, but wavelet transform is not self-adaptation as well as there will be modal mixture and false components after the signal has been decomposed by EMD [6, 7]. In this paper, firstly, the bearing signal is multi-scale decomposed into several IMF components by EEMD, then the sample entropy of major components is calculated, as a result the fault information is extracted effectively. Secondly, the EEMD sample entropy can be used as a feature vector of SVM bearing fault classification recognizer, after that SVM is trained and recognized.

2. Acquisition of Bearing Signal

Fig. 1 shows the experimental platform to acquire the bearing signal. Experimental platform is mainly composed by drive motor, test motor, torque sensor, acceleration sensor, acquisition card, encoder and counter, computer. The acceleration sensor has been mounted on the shaft end of test motor at x-direction and Y-direction which the bearing vibration signal can be measured and transported to acquisition card; On this experimental platform, the acquisition card is PCI-1718HGU with the characteristics of 100 KS/s, 12 bits/16 channels high gain multi-function. All signals can be A/D conversed and transmitted to a computer office access database by PCI-1718HGU. Motor speed information can be obtained by PCI-1784. In addition, the torque information can be tested by torque sensor.

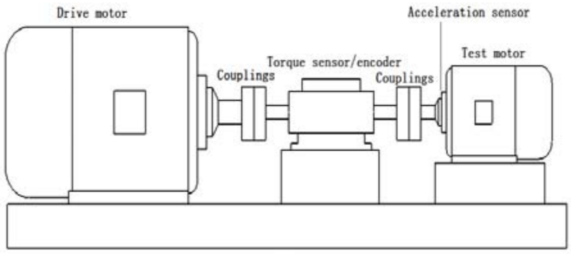


Fig. 1. The experimental platform of bearing signal acquisition.

The model of rolling bearing is 6205 on the shaft end of test motor. In order to recognize different fault, the bearing is artificially set four cases: bearing normal, inner race single pitting, outer race single pitting, ball single pitting. The pitting diameter has three kinds: 0.2 mm, 0.4 mm and 0.7 mm, pitting depth is 0.25 mm, the three kinds of fault are denoted by fault 1, fault 2, fault 3. Its fault characteristic frequency is determined by the rotational speed of the shaft, the bearing geometry and fault position:

Fault characteristic frequency of outer race:

$$f_o = \frac{z}{2} f_r (1 - \frac{d}{D} \cos \alpha), \tag{1}$$

Fault characteristic frequency of inner race:

$$f_i = \frac{z}{2} f_r (1 + \frac{d}{D} \cos \alpha) \tag{2}$$

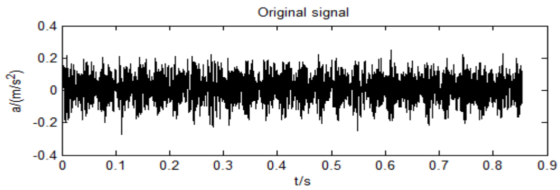
Fault characteristic frequency of ball:

$$f_b = \frac{D}{2d} f_r (1 - \frac{d^2}{D^2} \cos^2 \alpha), \tag{3}$$

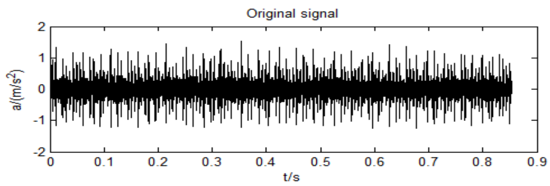
where z is the number of ball equal to 9; f_r is the rotational frequency of the shaft equal to 29.12 Hz; d is the diameter of ball equal to 7.95 mm; D is pitch diameter equal to 39 mm; α is touch angle equal to 0°.

So it can calculate that the fault characteristic frequency of outer race, inner race and ball respectively is 104.4 Hz, 157.5 Hz and 137.3 Hz.

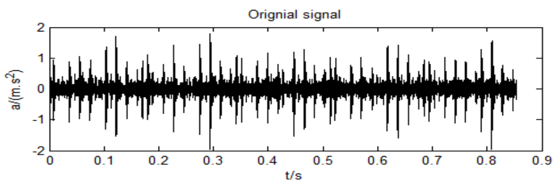
According to Shannon sampling theorem, the sampling frequency has been defined as 10 K. 20 groups of normal and fault 1 bearing vibration signal are collecting at the case of 0 kW, 1750 r/min; 40 groups of each normal and fault 2 bearing vibration signal are collecting at the case of 1.5 kW, 1750 r/min; 60 groups of each normal and fault 3 bearing vibration signal have been collected at the case of 1.75 kW, 1750 r/min. Fig. 2(a)~Fig. 2(d) show the original signal of normal bearing, bearing inner race at fault 1, bearing outer race at fault 1 and bearing ball at fault 1 respectively.



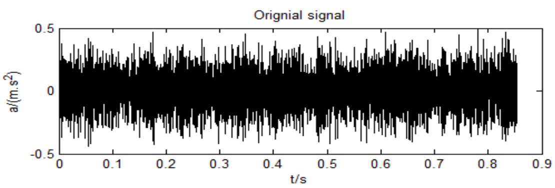
(a) Normal bearing



(b) Bearing inner race at fault 1



(c) Bearing outer race at fault 1



(d) Bearing ball at fault 1

Fig. 2. Original signal of bearing vibration signal.

From Fig. 2, it can obviously to see there have noise signal in bearing vibration signal and when fault occurs on any component of bearing, its vibration signal appears a characteristic of nonlinear, non-stationary with cyclical shocks.

3. Noise Reduction by Wavelet Transform

Since the signal presence of noise pollution, in order to prevent end effects and accumulation errors which generate at the noised signal is decomposed by EMD, the noise must be reduce [7]. Wavelet transform can effectively realize signal noise separation by taking advantage use of the difference between signal and noise in the time domain and the frequency domain, and obtain a better noise reduction effect. If the signal $s^*(t)$ is noise pollution, it changes into $s(t)$, just as the formula (4):

$$s(t) = s^*(t) + \sigma e(t), \quad (4)$$

where $e(t)$ is the noise; σ is the noise intensity.

Step 1: 3 layers db4 wavelet is used to decompose the signal $s(t)$, according to multi-scale analysis algorithm, the signal $s(t)$ can be decomposed into two parts: approximate coefficients and detail coefficients. After a translational telescopic, the scale function as follows:

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t - k), \quad (5)$$

$$\theta_{j,k}(t) = 2^{-j/2}\theta(2^{-j}t - k), \quad (6)$$

Expanding the signal on formula (5) and (6), we will get the calculation formula of approximate coefficients and detail coefficients about above scale functions.

$$A_j(n) = [s(t), \phi_j(t - 2^j n)], \quad (7)$$

$$D_j(n) = [s(t), \theta_j(t - 2^j n)], \quad (8)$$

The signal decomposition model is shown in Fig. 3 which is following the above multi-scale decomposition method.

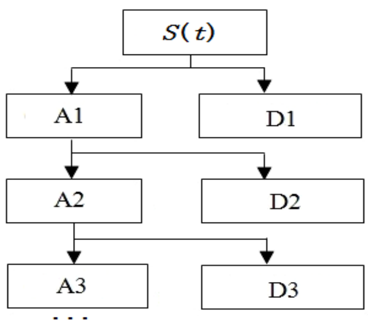


Fig. 3. The model of signal decomposition.

Finally the decomposition the signal $x(t)$ can be expressed as formula (9):

$$x(t) = \sum_k c_{j,k}\phi_{j,k}(t) + \sum_k d_{j,k}\theta_{j,k}(t), \quad (1)$$

where $c_{j,k}$ and $d_{j,k}$ are the scaling coefficients and wavelet coefficients of scale space respectively.

Step 2: In the wavelet transform, the threshold of each layer coefficient noise reduction based on the original signal to noise ratio. The threshold of each layer is determined by the Birge-Massart strategy after getting the noise intensity [8]. The Birge-Massart strategy as follows:

Specifying the decomposition level j, for j+1 and higher level, all the coefficients are retained; For i ($1<i<j$), retaining the coefficients of maximum absolute value and its number is n_i;

$$n_i = E(j + 2 - i)^3, \quad (10)$$

where E is the empirical coefficient.

The threshold in wavelet transform can be expressed as:

$$T = |c_{i^*}|, \quad (11)$$

where c_{t^*} is the $t^{*\text{th}}$ larger wavelet decomposition coefficients after sorting, t^* is determined by follow formula:

$$crit = -\sum_{k \le t} c_k^2 + 2\sigma^2 t[a + \lg(J/t)], \quad (12)$$

where: J is the total number of coefficient; a is the empirical coefficient, equals to 2.

Step 3: Setting the threshold by soft threshold:

$$d(t) = \begin{cases} t - T & t > T \\ t + T & t < -T \\ 0 & else \end{cases} \quad (13)$$

Step 4: Similarly to the above method, reconstructing the signal by formula (9) in the opposite direction after processing threshold.

As a result, the noise reduction vibration signal of bearing is obtained. Fig. 4(a) is the noise reduction signal of normal bearing, Fig. 4(b) is the noise reduction signal of inner race at fault 1, Fig. 4(c) is the noise reduction signal of outer race at fault 1, Fig. 4(d) is the noise reduction signal of ball at fault 1. Compared to Fig. 2, using wavelet transform to process the noise pollution signal can not only remove the noise, but also almost all maintain the fault information.

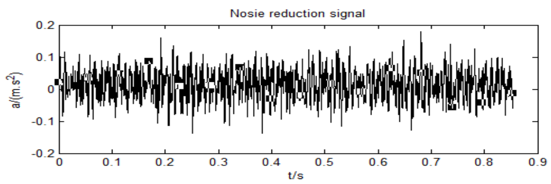
4. Fault Information Extraction with EEMD

EEMD combines with neural network or support vector machine has already been widely used in machinery fault intelligent diagnosis [9, 10]. However, studies have shown that modal mixture and false components are easily generated because of

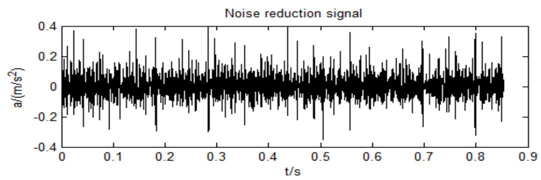
Empirical Mode Decomposition. EEMD is a method that white noise which has the statistical characteristic of frequency uniformly distributed is added into the signal, as a result, the signal can maintain continuity at different scales. So EEMD can not only promote anti-aliasing decomposition, but also maintain the characteristic of EMD. EEMD is applied to extract bearing fault signal in this article, the algorithm as follows:

Step 1: White noise $n_i(t)$ is added into bearing signal x(t) several times, the standard deviation of white noise takes 0.4 times the standard deviation of bearing signal, then signal x(t) changes into $x_i(t)$:

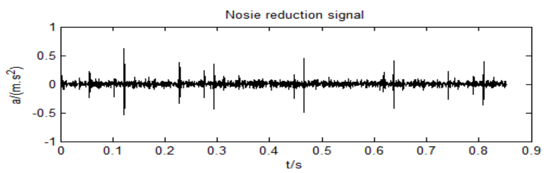
$$x_i(t) = x(t) + n_i(t) \tag{14}$$



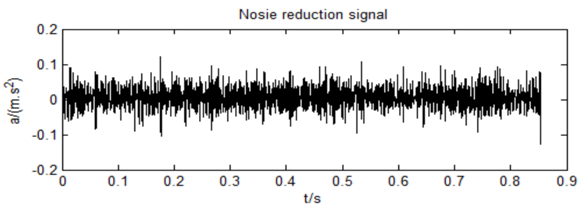
(a) Normal bearing



(b) Bearing inner race at fault 1



(c) Bearing outer race at fault 1



(d) Bearing ball at fault 1

Fig. 4. Noise reduction signal by wavelet transform.

Step 2: Signal $x_i(t)$ is decomposed into 6 IMFs by EMD, components $c_{ij}(t)$ and the remainder $r_i(t)$ which satisfy two assumptions of EMD are gained, the subscript i, j means the j^{th} IMF component with white noise adds i times. At the end of decomposition, the signal can be expressed as follows:

$$x_i(t) = \sum_{i}^{6} c_{ij}(t) + r_i(t)\,, \tag{15}$$

Step 3: Calculating ensemble average of each IMF component, the result of above calculation is EEMD IMF components:

$$c_j(t) = \frac{1}{N}\sum_{i=1}^{N} c_{ij}(t) \tag{16}$$

According to above algorithm, we finally gain 6 IMF components of each group of signal. Since the bearing fault characteristic frequency is in the middle-high frequency, former three IMF components are enough. Due to the paper limitation, only some IMF components are given in Fig. 5.

In order to extract the fault frequencies, each IMF component $c_i(t)$ which is decomposed by EEMD does Hilbert transform:

$$H[c_i(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{c_i(\tau)}{t-\tau} d\tau \tag{17}$$

Then structuring analysis functions $w_i(t)$:

$$w_i(t) = c_i(t) + jH[c_i(t)] \tag{18}$$

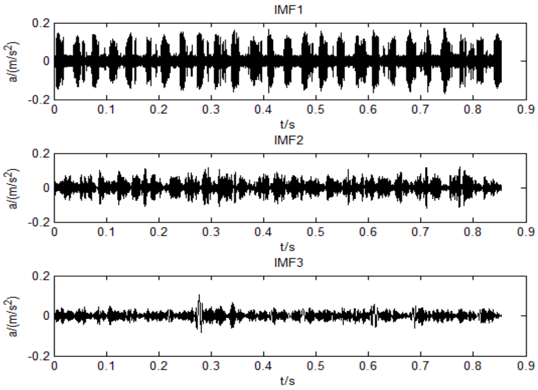
At last calculating the envelope spectrum of each $u_i(t)$:

$$u_i(t) = \sqrt{c_i^2(t) + H^2[c_i(t)]} \tag{19}$$

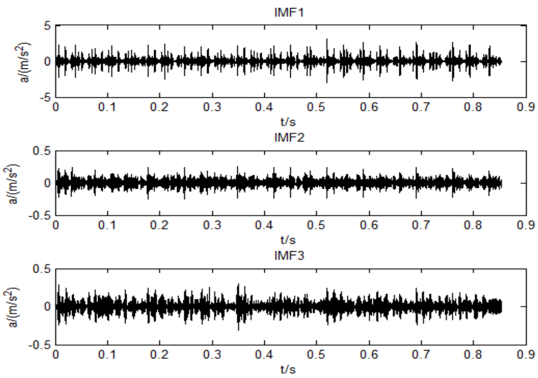
Fig. 6(a)~Fig. 6(d) is the envelope spectrum of the former three IMF components, We can find in Fig. 6(a) only 30.3 Hz and its double times 60.6 Hz which is close to the rotational frequency of the shaft f_r=29.12 Hz; However, in Fig. 6(b) we can see there are fault characteristic frequency of inner race 157.7 Hz very close to the calculation value 157.5 Hz, besides there are several frequency multiplication in IMF1, IMF2 and IMF3, especially in IMF1, and there are 30.3 Hz and its double times 60.6 Hz within the 100 Hz in Fig. 6(b) which are highlighted peak value.

Similarly, we can also find 104.4 Hz and its frequency multiplication, 137.3 Hz and its frequency multiplication exist in the envelope spectrum of outer race at fault 2 and ball at fault 2, the results pictures does not give in this article.

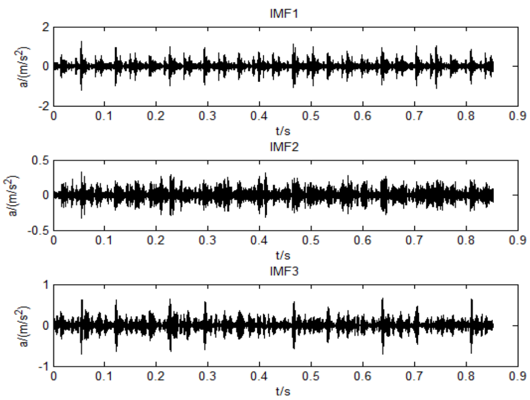
According to above analysis, it show that each fault has its own fault feature, so the sample entropy can be applied to describe the complexity of bearing vibration signal, details in following part.



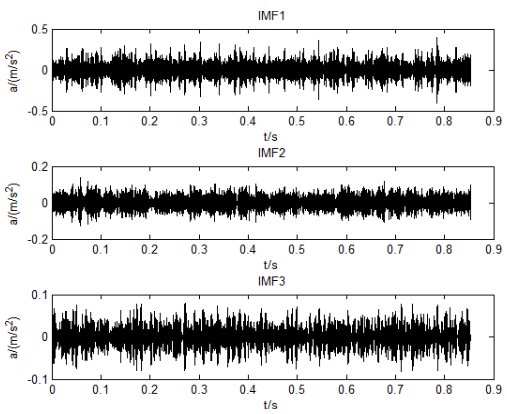
(a) Normal bearing at 1.5 kW, 1750 r/min



(b) Inner race at fault 2

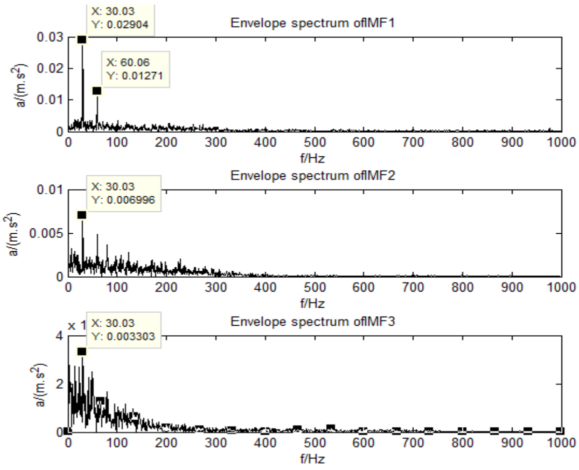


(c) Outer race fault 2

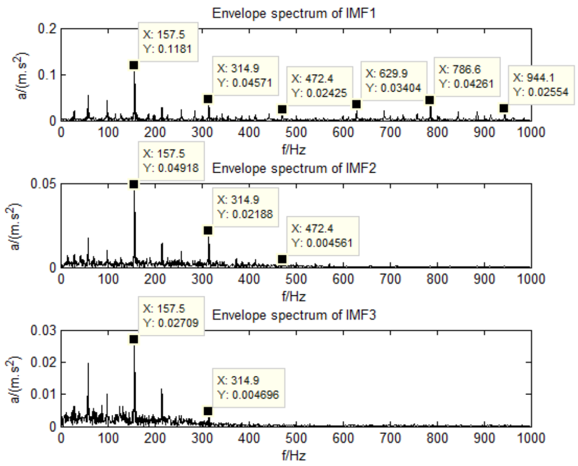


(d) Ball fault 2

Fig. 5. Former three IMF components of EEMD decomposition.



(a) Normal bearing at 1.5 kW, 1750 r/min;



(b) Inner race bearing at fault 2

Fig. 6. The envelope spectrum.

5. Complexity Evaluation by Sample Entropy

Sample entropy uses a non-negative number to represent the complexity of time series, the more complex time series, the larger sample entropy; the more regular time series, the smaller sample entropy. The sample entropy of bearing signal is calculated by the following algorithm:

Step 1: Intervally takes 3000 data point in signal $c_j(t)$, and takes similar tolerance coefficient r=0.25SD(c), SD(c) is the standard deviation of $c_j(t)$, takes pattern dimension m=2, reconstructs m-dimensional vector:

$$c(k) = [c_k, c_{k+1}, \cdots c_{k+m-1}], \quad (20)$$

Step 2: Calculating the distance d_{kl} between c(k) and c(k+l):

$$d_{kl} = \max\left|c(k) - c(k+l)\right|, \quad (21)$$

where l=0,1….M-m.

Step 3: Statisticing the number of each d_{kl} which is smaller than r, and $B_k^m(r)$ which is the ratio of this number and total number of distance M-m-1:

$$B_k^m(r)=\frac{1}{M-m-1}\{the\ number\ of\ d_{kl}<r\}, \quad (22)$$

Step 4: Calculating average of each $B_k^m(r)$:

$$B^m(r)=\frac{1}{M-m-1}\sum_{k=1}^{M-m}B_k^m(r), \quad (23)$$

Step 5: According to dimension m, repeat step 1-4 to obtain $B_k^{m+1}(r)$ and $B^{m+1}(r)$.

Step 6: Calculating SampEn(m,r):

$$SampEn(m,r)=\ln B^m(r)-\ln B^{m+1}(r), \quad (24)$$

According to this algorithm, the sample entropy of all the former three IMF components of any group which have been decomposed by EEMD can be calculated. The results show in the Tables 1-4.

Table 1. EEMD SampEn of normal bearing.

Condition	EEMD SampEn		
	IMF1	**IMF2**	**IMF3**
0 kW, 1750 r/min	0.7245	0.6357	0.6011
1.5 kW,1750 r/min	0.7789	0.6987	0.6438
1.75 kW,1750 r/min	0.8162	0.7026	0.6792

Table 2. EEMD SampEn of bearing at fault 1.

Fault Position	EEMD SampEn		
	IMF1	**IMF2**	**IMF3**
Inner race	1.1143	0.9528	0.7452
Outer race	0.9787	0.8513	0.6923
Ball	1.1670	1.0452	0.8498

Table 3. EEMD SampEn of bearing at fault 2.

Fault Position	EEMD SampEn		
	IMF1	**IMF2**	**IMF3**
Inner race	1.0379	0.9071	0.6954
Outer race	0.9358	0.8013	0.6432
Ball	1. 0159	0.9588	0.7139

Table 4. EEMD SampEn of bearing at fault 3.

Fault Position	EEMD SampEn		
	IMF1	**IMF2**	**IMF3**
Inner race	1.1576	1.0123	0.8515
Outer race	1.0312	0.9365	0.7986
Ball	1.2084	1.1058	0.9239

1) Tables 1-4 show that EEMD sample entropy of any IMF component, fault bearing is much larger than normal bearing. It means fault information generates in vibration signal when bearing breaks down, and the larger EEMD sample entropy, the more fault information generated.

2) EEMD sample entropy of normal bearing is small, EEMD sample entropy of bearing at fault 1 increased, at fault 2 decreased, at fault 3 increased again. This changing trend indicates that there is a larger shock between each component of bearing at fault 1, result in generating much fault information; the shock between each component of bearing decreased at fault 2, result in the fault information decreased; the shock between each component of bearing increased again at fault 3, the fault information increased again. Therefore, the changing trend of EEMD sample entropy can reflect the bearing vibration signal changing with fault accurately, and can be used as a feature vector of SVM.

3) According to the above tables, EEMD sample entropy of each group, IMF1>IMF2>IMF3. Its changing trend not only consistent with the changing trend of IMF components which are decomposed by EEMD, but also conform the law the more complex signal, the larger sample entropy; the more regular signal, the smaller sample entropy.

6. Design of Classification and Recognition

Mapping the input vector to a high dimensional feature space and constructing The optimal separating hyperplane through nonlinear mapping (kernel) is the core idea of SVM [11]. Taking an example of two-dimensional input space, shown in Fig. 7: circles and squares represent the two types of samples, H is the classification line, H_1 and H_2 are lines which across the samples and nearest H, the distance between H_1 and H_2 is the classification margin. The optimal separating hyperplane not only can separate the two types of samples correctly, but also can maximum classification margin.

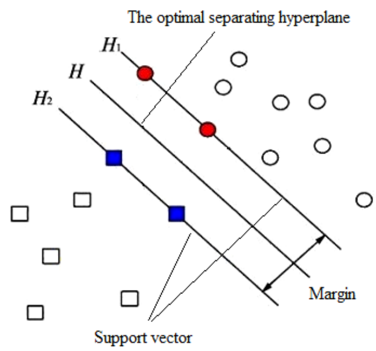


Fig. 7. The diagram of optimal classification.

For maximum margin that is equivalent to the minimum $\|w\|$ using the Lagrange multiplier α_i>0, i=1, 2, n, equation (9) can be changed into follows:

$$\min L(w,b,\alpha)=\frac{1}{2}\|w\|^2-\sum_{i=1}^{l}\alpha_i[(x_i \bullet w+b)-1], \quad (25)$$

Constraints as follows:

$$\sum_{i=1}^{n} y_i\alpha_i = 0, \quad \alpha_i \geq 0, i=1,2,n \quad (26)$$

The nonlinear signal can be calculated by defining the Kernel Function which can transform the nonlinear signal into a high dimensional space [12]. Commonly used kernel functions are Polynomial Kernel Function, Radial Basis kernel Function, Sigmoid Kernel Function, Splines Kernel Function. Radial Basis kernel Function is used:

$$k(x_i \bullet x_j)=\exp(-\frac{\|x_i-x_j\|^2}{2\sigma^2}), \quad (27)$$

The optimization function which under the quadratic inequality constraints can be expressed as follows:

$$Q(\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j k(x_i \bullet x_j), \quad (28)$$

We can obtain the optimal classification function after solving the above function:

$$f(x)=sign[\sum_{i=1}^{n}\alpha_i * y_i k(x_i \bullet x)+b*], \quad (30)$$

The final discriminant function only includes the inner product of the support vector machine and summation actually, therefore, the computational complexity of recognition depends on the number of support vectors.

The classification method of support vector machine such as one-to-one, one-to-many, directed acyclic graph, decision directed acyclic graph, binary tree [13]. According to signal acquisition and extraction of normal bearing, inner race fault, outer race fault, ball fault, choosing the method of one-to-many, and requiring four two scores support vector machine classifier. When SVM 1=1, it means bearing normal; When SVM 2=1, it means bearing inner race fault; When SVM 3=1, it means bearing outer race fault; When SVM 4=1, it means bearing ball fault; otherwise, they are all 0.

7. SVM Classifier Training and Recognition

EEMD sample entropy is used as feature vector of SVM:

$$x^T=[IMF1, IMF2, IMF3]^T, \quad (30)$$

11 groups of EEMD sample entropy, total are 44 groups at bearing normal and at fault 1 are used as training sample, 9 groups, total 36 groups are used as recognition sample. SVM1=1 it indicates bearing normal, while SVM1= 0 it means abnormal in SVM 1 training. SVM2, SVM3, SVM4 are trained in the same way. In order to verify the impact of sample size on SVM recognition, 30 groups of each sample at fault 2 are used as training sample, 10 groups of each sample at fault 2 are used as recognition sample, 50 groups of each sample at fault 3 are used as training sample, 10 groups of each sample at fault 3 are used as recognition sample, they are all trained and recognized in the same way. Table 5-7 are the results of above research.

Table 5. The classified result of fault 1.

Name	Sample	Identification sample									Accuracy
		1	2	3	4	5	6	7	8	9	
SVM1	80	1	1	1	1	1	1	1	1	1	100 %
SVM2	80	1	1	1	1	0	1	1	1	1	88.8 %
SVM3	80	1	0	1	0	1	1	1	1	0	66.7 %
SVM4	80	1	1	1	0	1	1	0	1	1	100 %

Table 6. The classified result of fault 2.

Name	Sample	Identification sample									Accuracy
		1	2	3	4	5	6	7	8	9	
SVM1	160	1	1	1	1	1	1	1	1	1	100 %
SVM2	160	1	1	1	1	1	1	1	1	1	100 %
SVM3	160	1	0	1	0	1	1	1	1	1	80 %
SVM4	160	1	1	1	1	1	0	1	1	1	90 %

Table 7. The classified result of fault 3.

Name	Sample	Identification sample									Accuracy
		1	2	3	4	5	6	7	8	9	
SVM1	240	1	1	1	1	1	1	1	1	1	100 %
SVM2	240	1	1	1	1	1	1	1	1	1	100 %
SVM3	240	1	1	1	1	1	1	1	1	1	100 %
SVM4	240	1	1	1	1	1	1	1	1	1	100 %

Compared each other, the normal and fault bearing can be intelligent recognized by EEMD sample entropy as feature vector of SVM. When sample size increases to a certain number, the recognition accuracy rate increases to 100 %.

8. Conclusions

In this paper, fault information extraction has been researched as a feature vector of SVM. The different fault bearing vibration signal was acquired in experiment, wavelet transform was used to reduce the noise, then the IMF components, envelope spectrum, SampEn of each bearing signal were calculated by EEMD, Hilbert transform and sample entropy. Meanwhile, a bearing fault SVM classification and recognition was development, different sizes of EEMD sample entropy were trained and recognized, all of them can be intelligent identified by SVM. In this method EEMD can promote anti-aliasing decomposition, as a result modal mixture and false components were eliminated, sample entropy can represent the complexity of any signal, both of them combine with SVM will have a wider application space in mechanical fault intelligent identification.

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References

[1]. Nello Cristianini and John Shawe Taylor, An introduction to support vector machines and other kernel-based learning methods, *Machinery Industry Press*, 2005.

[2]. Lin Jipeng and Liu Junhua, Algorithm research on wavelet support vector machine, *Journal of Xi'an Jiaotong University*, Vol. 39, Issue 8, 2005, pp. 816-819.

[3]. Norden E Huang, Zheng Shen and Steven R Long, The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis, *Proceedings of Royal Society London A*, Vol. 454, 1998, pp. 903-995.

[4]. Wu Zhonghua and Norden E. Huang, Ensemble empirical mode decomposition: a noise-assisted data analysis method, *Advances in Adaptive Data Analysis*, Vol. 1, Issue 1, 2009, pp. 1-41.

[5]. J. S. Richman and J. Randall Moorman, Physiological time series analysis using approximate entropy and sample entropy, *Am. J. Physiol. Heart Physiol.*, Vol. 278, 2000, pp. 2039-2049.

[6]. Xu Renlin and An Wei, Application of wavelet noise reduction in signal based on EMD Hilbert Transform, *Noise and Vibration Control*, Vol. 6, 2008, pp. 74-77.

[7]. Wang Ya, Lv Xinhua and Wang Haifeng, An improved wavelet threshold noise reduction method and Matlab realization, *Microcomputer Information*, Vol. 22, Issue 6, 2006, pp. 259-261.

[8]. Yang Yu, Yu Dejie and Cheng Junshen, Bearing fault diagnosis method based on EMD and neural networks, *Journal of Vibration and Shock*, Vol. 24, Issue 1, 2005, pp. 85-88.

[9]. Lv Jianxin, Wu Husheng and Wu Lushan, Study on fault diagnosis for rolling bearing based on EMD complexity feature and SVM, *Mechanical Transmission*, Vol. 35, Issue 2, 2011, pp. 20-24.

[10]. Zhang Chao and Chen Jianjun, Contrast of ensemble empirical mode decomposition and empirical mode decomposition in modal mixture, *Journal of Vibration and Shock*, Vol. 29, 2010, pp. 87-90.

[11]. V. N. Vapnik, The nature of statistical learning theory, *Springer Verag*, New York, 1995.

[12]. Rong Haina, Zhang Gexiang and Jin Weidong, Selection of kernel functions and parameters for support vector machines in system identification, *Journal of System Simulation*, Vol. 18, Issue 11, 2006, pp. 3204-3208.

[13]. Chih Weihsu and Chih Jenlin, A comparison of methods for multiclass support vector machines, *IEEE Transactions on Neural Networks*, Vol. 13, Issue 2, 2002, pp. 415-425.

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