State Monitoring and Early Fault Diagnosis of Rolling Bearing based on Wavelet Energy Entropy and LS-SVM

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Abstract— **Rolling bearing is one of the most widely used elements in rotary machines. In this paper, a novel method is proposed to extract early fault features and diagnosis the early fault accurately for rolling bearing. Wavelet Energy Entropy is introduced as a feature parameter for bearing state monitoring and least square support vector machine (LS-SVM) is used for early fault diagnosis. In order to test the effectiveness of the method, a series of bearing whole life cycle test are performed on the accelerated bearing life tester. The result shows that Wavelet Energy Entropy has better performance and can forecast fault development earlier compared to conventional signal features. LS-SVM method can distinguish early bearing fault modes more accurate and faster than classic pattern recognition methods.**

Index Terms—**state monitoring, early fault diagnosis; wavelet energy entropy, least square support vector machine (LS-SVM), rolling element bearing**

I. INTRODUCTION

Rolling element bearing is one of the most widely used and important parts of varieties of rotating machinery, whose running condition often directly affects the performance of the whole machine, which makes the state monitoring and fault diagnosis of rolling bearing becomes hot research focus. According to former studies [1], most rolling bearing faults occur in the surface of outer race, inner race or rolling elements. In recent years, many state monitoring techniques based on temperature, optical, vibration have been developed. However, because of the cost, effective and convenience reasons, vibration signal analysis is the most widely studied and practical used state monitoring approach for rolling bearing [2].

Generally, the key problem of vibration signal monitoring is feature extraction. Many techniques have been developed in the area, conventional feature extraction techniques can be concluded as time domain analysis [3], frequency domain analysis [4] and time-frequency domain analysis [5-6]. However, in most cases, vibration signals are too noisy to use these techniques because the signal collected from rolling bearing is mixed with many other signal sources. The features generated by the incipient fault are usually very weak and might be covered by other signals. That makes the diagnosis methods based on vibration signal becomes unreliable. Thus, effective extraction of early fault symptom is still a critical challenge. In recent years, wavelet transform has been widely adopted in signal process area [7]. It is basically a time-frequency domain analysis method. But different from Short Time Fourier Transform (STFT) and Wigner-Ville Distribution (WVD), its time–frequency window is changeable as required. Because of the flexibility of wavelet basis, the wavelet transform presents better performance to process non-stationary signals than conventional signal analysis methods. Meanwhile, entropy introduced by Thermodynamics has been applied in many signal processing methods [8-9]. Entropy indicates the order degree of information stored in the signal. When early fault occurs, the vibration signal order degree will be fluctuate firstly which makes entropy has potential sensitivity in fault prediction. In this study, Wavelet packet energy entropy is applied in state monitoring of rolling element bearing. The results indicate that Wavelet Energy Entropy has better performance than conventional signal features and has well fault prediction ability.

Early fault diagnosis is the extension of early warning. Because of the difficulty of early fault feature extraction and accurate failure type classification, the early fault diagnosis is still a critical research challenge. Generally, Fault diagnosis is a type of pattern recognition problem. In recent years, many algorithms based on artificial intelligence techniques have been successfully applied in mechanical fault diagnosis problem. The LS-SVM algorithm is developed from standard support vector machine. It is fast and accurate in classification. In this paper, wavelet packet coefficients are obtained from each

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faulty signal, and then energy value is calculated for each signal separately. Then energy values are used for training and testing of LS-SVM. The results indicate that the combination of Wavelet relative energy and LS-SVM can effectively distinguish bearing early fault type.

This paper is an extension study based on literature [10]. The former research discussed the Wavelet Energy Entropy and SOM methods in rolling bear condition monitoring. Compared to that, this study makes three innovations:

(1) Discuss the Wavelet energy entropy deeper by compare the method with conventional time-domain features and present the program statement to calculate it.

(2) More bearing accelerate life experiments have been done which formed a more sufficient and reliable dataset.

(3) A more effective algorithm, LS-SVM is introduced for fault diagnosis.

II. Wavelet Energy Entropy Theory

The wavelet packet method is developed from classic wavelet decomposition. For classic wavelet transform [11], signals split into detail and approximation sections. The main improvement from Wavelet Transform (WT) to Wavelet Packet Transform (WPT) is that WPT splits both approximations and details. Therefore, a better frequency resolution can be obtained for high frequency bands of the decomposed signal. In another word, WPT can extract much more detail features from the signal. For early fault diagnosis of rolling bearings, high frequency sections of signal (1000-10000 Hz) is sensitive to early fault, while low frequency sections (<1000 Hz) is more suitable for accurate fault diagnosis[12].

Generally, wavelet packets can be organized in trees (Fig.1), Fig.1 shows the level 3wavelet packet decomposition.

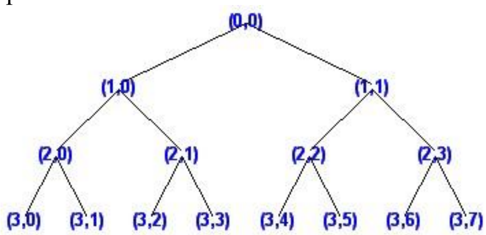

Figure1. Level 3 wavelet packet decomposition

Define S_{3i} as the reconstructed signal of X_{3i}.Then original signal S can be expressed as:

$$S = S_{30} + S_{31} + \cdots + S_{37} \tag{1}$$

Assume the lowest frequency of S is 0 and the highest frequency is 1. Table I shows the frequency band.

TABLE I.
THE FREQUENCY BAND RANGE

Signal	Frequency
S_0	0-0.125
S_1	0.125-0.25
S_2	0.25-0.375
S_3	0.375-0.5
S_4	0.5-0.625
S_5	0.625-0.75
S_6	0.75-0.875
S_7	0.875-1

The wavelet energy is defined as the sum of square of detailed wavelet decomposition coefficients. Different input signals will make different scale wavelet coefficients. The wavelet energy is defined as follow equation:

$$E_{3j} = \int |S_{3j}(t)|^2 dt = \sum_{k=1}^{n} |x_{jk}|^2 \tag{2}$$

Where E_{3j} is the energy of S_{3j} and X_{jk} is the amplitude of discrete points.

The feature vector can be defined as follows:

$$T = [E_{30}, E_{31}, E_{32}, E_{33}, E_{34}, E_{35}, E_{36}, E_{37}] \tag{3}$$

Entropy indicates the order degree of information which is stored in observed signal. The sum of all signals energy at scale j is defined as:

$$E_j = \sum_{k=1}^{N} E_{jk} \tag{4}$$

Define relative wavelet energy as:

$$p_{jk} = E_{jk} / E_j \tag{5}$$

Obviously, $\sum p_{jk} = 1$. According to the definition of Shannon entropy, the Wavelet Energy Entropy along scales is defined as below:

$$W_{EEj} = -\sum_{k=1}^{2^j} p_{jk} \log p_{jk} \tag{6}$$

The MATLAB program function to calculate wavelet e nergy entropy is as follows:

```
function S_wt=waveletentropy(ECG,n,wpname)

wpt1=wpdec(ECG,n,wpname);
for i=1:2*n %wpcoef(wpt1,[n,i-1])
%disp('energy of every tree nodes E(i)');
E(i)=norm(wpcoef(wpt1,[n,i-1]),2)*norm(wpcoef(wp
t1,[n,i-1]),2);
end
%disp('total energy of wavelet packet E_total');
E_total=sum(E);
%disp('probability of each nodes P');
for i=1:2*n
p(i)= E(i)/E_total;
end
%The calculation of wavelet energy entropy is calcul
ate as below —sum（pj*lnpj），

for i=1:2*n
m(i)=p(i)*log(p(i));
end

S_wt = sum(m)*(-1);
disp(['valve of wavelet energy entropy',num2str(S_w
t)]);
```

```
    figure;
    subplot(1,2,1);
    plot(ECG);
  subplot(1,2,2);
    plot(E);
```

III. Least Square Support Vector Machine

LS-SVM is developed from standard SVM [13]. It transformed inequality constraint to equality constraint and transformed quadratic programming to solve linear equations. These improvements enhance the rate of convergence and the accuracy of classification.

Define a m samples data set (x_i, y_i), (i=1,2,…,m), x_i is input data and y_i is output classification. The optimization object function of LS-SVM is:

$$\begin{cases} \min J(\mathrm{w},\xi)=\frac{1}{2}w^T w+\frac{1}{2}f\sum_{i=1}^{m}\xi_i^2 \\ s.t.\ \mathrm{y}_i\left[w^T\varphi(\mathrm{x}_i)+\mathrm{b}\right]=1\text{-}\xi_i, i=1,2,...,m \end{cases} \quad (7)$$

Where ξ is relaxation factor, w is weight vector, b is offset constant, f is penalty factor or regularization factor which control the complexity of the algorithm. The x from the original space is mapped as a vector by nonlinear function $\varphi(\mathrm{x})$ which solves linearly inseparable problem.

Equation (7) is transformed to optimization problem by Lagrange equation:

$$L(w,b,\xi,a)=J(w,\xi)\text{-}\sum_{i=1}^{m}a_i\left\{y_i\left[w^T\varphi(\mathrm{x}_i)+\mathrm{b}\right]\text{-}1+\xi_i\right\} \quad (8)$$

Where α_i is Lagrangian. Accroding to Karush Kuhn Tucher (KKT) optimal condition:

$$\begin{cases} \frac{\partial L}{\partial w}=0 \Rightarrow w=\sum_{i=1}^{n}\alpha_i\varphi(x_i) \\ \frac{\partial L}{\partial b}=0 \Rightarrow \sum_{i=1}^{n}\alpha_i=0 \\ \frac{\partial L}{\partial \xi_i}=0 \Rightarrow \alpha_i=f\xi_i \\ \frac{\partial L}{\partial \alpha_i}=0 \Rightarrow y_i[w^T\varphi(x_i)+b]-1+\xi_i=0 \end{cases} \quad (9)$$

Then eliminate w and ξ:

$$\begin{bmatrix} 0 & \mathrm{y}^T \\ 1 & \Omega+f^{-1}I \end{bmatrix}\begin{bmatrix} b \\ a \end{bmatrix}=\begin{bmatrix} 0 \\ y \end{bmatrix} \quad (10)$$

Where $1=[1,...,1]_{1\times m}^T$, I is unit matrix, $\mathrm{y}=[\mathrm{y}_1,\mathrm{y}_2,...,\mathrm{y}_m]^T$, $a=[\alpha_1,...,\alpha_m]^T$, $\Omega=ZZ^T$, $Z=[y_1\varphi(\mathrm{x}_1),...,y_N\varphi(\mathrm{x}_N)^T]$. After solved b and α from eqution (10). The classific function can be obtained:

$$f(\mathrm{x})=\mathrm{sgn}[\sum_{i=1}^{m}a_i K(\mathrm{x},\mathrm{x}_i)+\mathrm{b}] \quad (11)$$

Where K(x,x_i) is kernel function. Most widely used kernel function include Radial Basis function (RBF), Polynomial kernel function and Sigmoid function. RBF is adopted in this paper for its well effect in paper [12]. Thus $K(\mathrm{x},\mathrm{x}_i)=\exp\left\{\text{-}\|x\text{-}x_i\|^2/\sigma^2\right\}$, where σ is the width factor.

General steps for rolling bearing early fault diagnosis based on relative wavelet energy and LS-SVM are as follows:

(1) Select the typical normal and early fault samples.

(2) Use 3 level db4 Wavelet Packet to analysis the signal.

(3) Calculate the relative wavelet energy by equation (5).

(4) Use relative wavelet energy as input data of LS-SVM to classify the fault modes, and optimize the regularization factor and width factor by minimize the misclassification rate.

(5) Classify the failure modes of unkown samples by classification function.

IV. Bearing Life Accelerated Test

The accelerated bearing life tester (ABLT-1A) (Fig. 2) is produced by Hangzhou Bearing Test & Research Center (HBRC). Four test bearings on one shaft are simultaneously hosted in the tester. The shaft is driven by an AC motor and coupled by rub belts. During the experiment, the rotation speed is constantly 3000 rpm. An oil circulation system that regulates the flow and the temperature of the lubricant is applied to lubricate the bearings. An accelerometer was installed on the bearing housing to continuously collect vibration signals.

Figure 2. Accelerated bearing life test-ABLT-1A

The bearing type is 6208-2RS. It is a typical deep groove ball bearing. Detailed parameters are listed in Table II.

The radial load is added by a 100 times weight-oil pressure amplifying unit (Fig.3). The weight is 17.7 Kg. For each bearing, the radial load is P/2=(17.7×100)×9.8/2/1000=8.67 kN.

The vibration data is collected with sampling frequency of 20 kHz and saved per minute. The total experiment time is 683 hours. The tester is automatically stopped because of vibration valve and bearing temperature exceeds the limit threshold. After disassemble the bearing, an inner race defect is found (Fig. 4A) which indicate the experiment has recorded the the complete life test data.

The data of rolling element failure (Fig. 4B) is collected by another experiment under the same experimental conditions.

TABLE II.
DETAILED PARAMETERS OF THE ROLLING ELEMENT BEARING

Type	6208-2RS
Pitch diameter /mm	60
Inside diameter /mm	40
Rolling element diameter /mm	12
Roller number	9

V. RESULTS AND DISCUSSION

A. Vibration Data Analysis

The Root Mean Square (RMS) of vibration signal is shown in Fig. 5 and the Kurtosis of vibration signal is shown in Fig. 6. These two parameters are most widely used in practice because they are simple and effective.

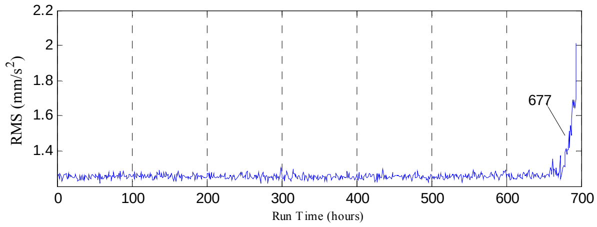

Figure 5. Root mean square of the vibration signal

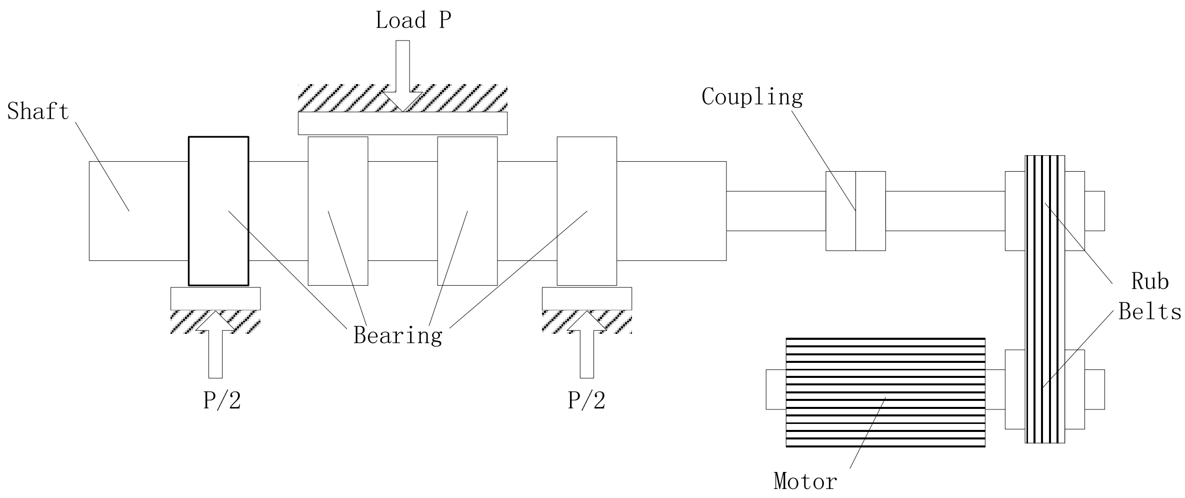

Figure 3. Load diagram of test bearings

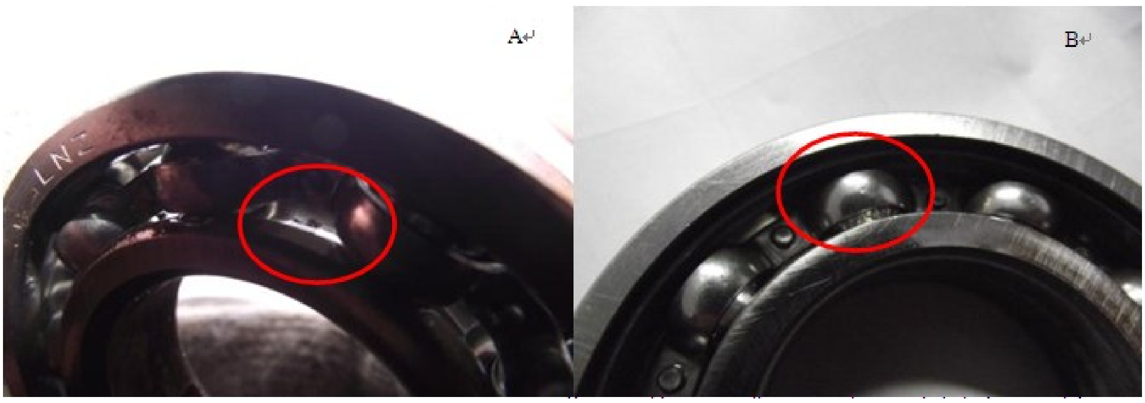

Figure 4. Failure bearings (A. inner race defect; B. rolling element failure)

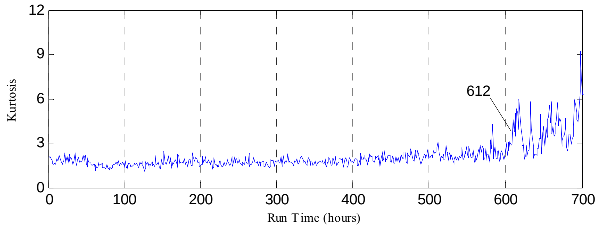

Figure 6. Kurtosis of the vibration signal

As shown in Fig.5, the vibration signal is smooth and stable before 650 h which indicates the bearing is in normal condition. Then the value begins to increase from 677 h and in 683 h the test bed is shut down because of excessive vibration. During the whole life cycle of the rolling element bearing, the time from fault symptom to complete failure is extremely short. This will cause terrible maintenance effect because of the relatively short reaction time. Fig.6 indicates that the Kurtosis valve which represents the amount of impact energy can find the fault symptom in 612 h which is still have potential to improve. If the fault symptom is found earlier, there will be more time to prepare the maintenance resources and keep the production process working stability and safety.

B. Wavelet Energy Entropy Analyses

In this work, the signal is analysised by level 3 wavelet packet decomposition using db4 wavelet. The wavelet packet reconstruction is computed based on the approximation coefficients and modified coefficients at level 3 to calculate the energy of every frequency band. Then calculate the valve of wavelet energy entropy. The result is concluded in Fig. 7.

The total time span can be divided into two periods: the front period (0 h-542 h) indicates the signal of normal condition and the back period (542 h-683 h) indicates the bearing fault and degradation period. During normal condition period, the valve of Wavelet Energy Entropy is stable. Meanwhile, during fault and degradation period, the signal has a more diverse distribution, and its amplitudes have an obvious decreasing trend. Compared to RMS (677 h) and Kurtosis (612 h), Wavelet Energy Entropy changed apparently in 542 h. Thus, Wavelet Energy Entropy is a better early fault feature and can detect the early failure ahead of time. Furthermore, its calculation is based on time domain vibration data which do not need to upgrade the monitoring hardware. These advantages will make the Wavelet Energy Entropy method easily adopted in practice.

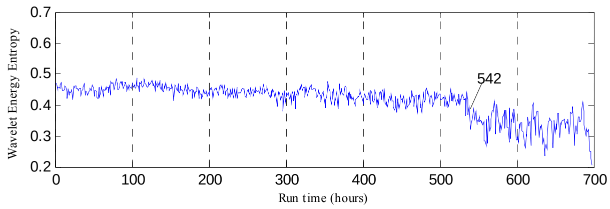

Figure 7. Wavelet Energy Entropy of the vibration signal

C. LS-SVM Analysis

Bearing early fault features are sensitive in high frequency band while accurate fault diagnosis has to analysis the low frequency band. Wavelet Packet can divide the signal frequency into 2^n sections (n is the wavelet packet decomposition level) and extract relative energy as eigenvalue to analysis the signal detailly and comprehensively.

Vibration signals are analysised by db4 Wavelet Packet 3 level decomposition. Then relative energy of each frequency band is used as input data of LS-SVM.

20 sets of inner race defect data (560 h-600 h), 20 sets of rolling element failure data (560 h-600 h) and 20 sets of normal data (100 h-200 h) are put into the LS-SVM model as training dataset. In the identification procedure, other 15 sets of date are identified by the trained LS-SVM model. Meanwhile, Artificial Neural Network (ANN) and standard support vector machine (SVM) are chosen as comparation methods. The results are concluded in Table.III.

Wavelet Packet relative energy is an effective beating early fault eigenvalue because all classsify algorithms perform high accuracy rate. Compared to ANN and SVM, LS-SVM has the highest accuracy rate and shortest CUP time. Consider bigger dataset commonly in practice, the speed advantage of LS-SVM will be more significant. The computer hardware used in the test is: CPU: Intel Dual-Core 3.20 GHz; RAM: 1.96GB. The matlab version is R2009b.

TABLE III.
CLASSIFICATION ACCURACY RATE AND SPEED OF LS-SVM, ANN, SVM

	LS-SVM	ANN	SVM
Accuracy Rate（%）	93.7	88.2	90.6
CPU time（s）	1.1	1.9	1.5

CONCLUSION

In this paper, a novel condition monitoring and early fault diagnosis method for rolling bearing based on wavelet energy entropy and LS-SVM is proposed. The result shows that wavelet energy entropy has better performance and can forecast earlier fault development than RMS and Kurtosis. Then LS-SVM model is introduced to distinguish bearing early fault type. This method has higher classification accurate rate and faster calculate speed than conventional recognition methods. For no hardware update required, the proposed method can adapt to most practice bearing monitoring systems and improve the reliability of the diagnosis system.

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