Running State Evaluation Method of Turbine Bearing Based on Feature Vector

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Due to the high modal coupling of the cooling turbine bearing in environment control system, it is very difficult to extract the vibration signal feature and construct the recognition model on different feature. A running state evaluation method of the turbine bearing is proposed based on the feature vector with limited testing data in this paper. Firstly, aiming at some failure modes in several typical faults of turbine bearing, three time domain feature parameters and seven frequency domain feature parameters are chosen to construct feature vector for discrimination. Then, the feature vectors of different fault testing data are dimensional reduced based on the principal component analysis method. Based on above, the support vector machine (SVM) model of the turbine bearing running state is proposed for monitoring and predicting the occurrence and development of typical turbine bearing failure modes. Experimental results suggest that the bearing running state evaluation method proposed in this paper can improve the prediction accuracy effectively.

Key words: turbine bearing; feature vector; reducing dimensional analysis; state evaluation method

1 Introduction

The rolling bearing widely used in rotating machinery is an extremely critical component that usually determines the useful lifetime of equipment, especially in cooling turbine. The unexpected fault of rolling bearing could lead to critical damage of rotating machinery, thus its effective and reliable bearing running state evaluation method is needed to guarantee the healthy state of rolling bearing.

Generally, the current bearing running state evaluation method can be categorized into three major classes, namely model-based (or physics-based) and data-driven methods [1-2]. For a specific system (such as a rolling bearing), the model-based method establishes a mathematical model to generate prediction estimates, however, the accurate model is very difficult to derive and hardly meets the requirement of real-time running in practice. Considering a bearing as a single-degree-of-freedom vibratory system, Qiu [3] built a stiffness-based prognostic model to predict the failure lifetime of bearing. Through analyzing the measured condition data, the data-driven method can estimate the health degradation and fault evolution of rolling bearing. Through combining with particle filtering and Bayesian algorithm, Chen [4-5] proposed neuro-fuzzy-based integrated prediction methods to carry out machine health condition prediction.

Besides, some advanced prediction methods are also applied to bearing running state evaluation. Liu [6] presented multistep neuro-fuzzy predictor to forecast the future states of the bearing health condition. Considering uncertainty, Chen [7] studied on the bearing condition prediction based on an interval type-2 fuzzy neural network approach. Zhang [8] developed a degradation indicator of rolling bearing based on HMM. Support vector regression is also used to monitor the bearing degradation and predict the remaining useful life of bearing [9-10].

In the paper, the state evaluation methods of turbine bearing in environment controlling system is investigated. Especially, the feature extraction and processing methods of bearing vibration signals are also studied, which can predict the occurrence and development of typical bearing faults and obtain the reliable state evaluation methods. The method provided in this paper will provide the references for enhancing the accuracy of rolling bearing running state judgment.

2 Bearing running state evaluation methods

2.1 The extraction of bearing vibration feature vectors

Bearing running state can be divided into 4 levels: normal, abnormal, fault and failure. With the evolution of the bearing state, the bearing vibration feature parameters will change according to certain rules.

The damage fault of rolling bearing generally bring up periodic pulse impact and modulation phenomenon of vibration signals, which represents modulation sidebands spacing evenly on the both sides of characteristic frequency in the frequency spectrum. After employing the envelope spectrum analysis method to extract modulation information, it can estimate the damage location and degree of parts by analyzing its strength and frequency.

A feature vector is selected to accomplish the estimate analysis of bearing running state, which is consisted of three time domain feature parameters extracted from time domain signals and seven frequency domain feature parameters abstracted from envelope spectrum of the signals.

Time domain feature parameters:

1. Peak-peak value v1- the difference value between the minimum and maximum values of a signal in one cycle, which describes the variation range of signal value and is suitable for fault diagnosis like pitting damage with instantaneous impact and low rotating speed.

$$v1=x_{max}-x_{min} \tag{1}$$

2. Effective value (RMS) v2- the root of the vibration energy in a cycle, which reflects the magnitude of vibration energy. It is suitable for recognizing the fault whose vibration amplitude changes slowly with time such as wear fault. The effective value is sensitive to the random abnormal vibration waveform on surface crack and it can make a proper evaluation of its measurement value.

$$x_{rms} = \sqrt{\frac{1}{T}\int_0^T x^2(t)\,\mathrm{d}t} \tag{2}$$

3. Kurtosis v3, the 4th order center distance normalization. Due to various uncertain factors, the vibration signal amplitude distribution approaches normal distribution, and the kurtosis is about 3. With the developing of fault, the kurtosis value increases. The advantage of this method is independent of the rotating speed, size and load of bearing, and it is especially keenness to the impact signal. Kurtosis is suitable for surface damage, such as pitting fault, particularly the diagnosis of early fault.

$$K = \frac{\int_{-\infty}^{+\infty}\left[x(t)-\bar{x}\right]^4 p(x)\,\mathrm{d}x}{\sigma^4} \tag{3}$$

where, x(t) is instantaneous amplitude, $\bar{x}$ is the mean value of amplitude, p(x) is probability density, σ is the standard deviations .

The characteristic frequency of bearing is determined by shaft rotating speed, bearing geometry dimension and damage position (outer ring, inner ring, rolling body). According to the fault characteristic frequency, it is detected that whether there is a fault and determined where the fault location is. Assuming there is no relative sliding between the raceway and rolling, and there is no deformation when they are under radial and axial load. The main feature frequency is as follows:

Inner ring rotating frequency f_r :

$$f_r = n/60 \tag{1}$$

The passing frequency of the rolling body on the outer raceway f_{bo} :

$$f_{bo} = \frac{1}{2}\left(1-\frac{d}{D}\cos\alpha\right)f_r \tag{2}$$

The passing frequency of the rolling body on the inner raceway f_{bi} :

$$f_{bi} = \frac{1}{2}\left(1+\frac{d}{D}\cos\alpha\right)f_r \tag{3}$$

The passing frequency of the rolling body on the cage (i.e. the autorotation frequency of the rolling body) f_b :

$$f_b = \frac{D}{2d}\left[1-\left(\frac{d}{D}\right)^2\cos^2\alpha\right]f_r \tag{4}$$

Rotating frequency of cage (i.e. the revolution frequency of the rolling body) f_c :

$$f_c = \frac{1}{2}\left(1-\frac{d}{D}\cos\alpha\right)f_r \tag{5}$$

where, d is ball diameter, D is bearing pitch diameter, α is contact angle.

Accordingly, the amplitudes of inner ring rotating frequency fr, and its 2, 3 times frequency; the passing frequency of the rolling body on the outer raceway f_{bo}; the passing frequency of the rolling body on the inner raceway f_{bi}; cage rotating frequency f_c and autorotation frequency of the rolling body f_b are selected and defined as 7 frequency characteristic parameters (v4- v10), respectively.

Hence, the feature vector of bearing vibration signals are employed as follows:

$$\mathbf{v} = \{v1 \quad v2 \quad \cdots \quad v10\} \tag{6}$$

2.2 Feature vector processing method based on principal component analysis (PCA)

The eigenvalues of bearing test signals are not isolated, but with a high degree of correlation between each other. Under the normal conditions, this correlation is controlled by basic rules, such as mass conservation and energy conservation. It would be destroyed if certain feature vectors change. The correlativity between each feature vector can be obtained by PCA method for fault detection and diagnosis.

At normal operation conditions, supposing $\mathbf{v}_i \in R^{10}$ indicates the feature vector of bearing vibration signals in state i, $X \in R^{10\times\mathrm{n}}$ represents a measurement matrix consisted of feature vectors of n samples, what would be gained by normalizing X as follows,

$$\overline{X} = \left[X - I_n u^T\right] D_\sigma^{-1/2} \tag{7}$$

where, I_n is n-dimensional column vector composed of 1, $u = \left[u_1, ..., u_p\right]^T$, $D_\sigma = diag(\sigma_1^2, ..., \sigma_m^2)$ are mean vector and variance matrix. In order to simplifying the deviation, $\overline{X}$ is still represented as X.

According to PCA method, matrix X is decomposed as follows:

$$X = \chi + X = TP^T + T P^T \tag{8}$$

where, $T \in R^{\mathrm{n}\times\mathrm{l}}$, $P \in R^{\mathrm{m}\times\mathrm{l}}$ are partition matrix and load matrix of principal element; $T \in R^{\mathrm{n}\times(\mathrm{n\text{-}l})}$, $P \in R^{\mathrm{m}\times(\mathrm{m\text{-}l})}$ are partition matrix and load matrix of residual error, respectively. The column vectors of P are the feature vectors corresponding to the top l largest eigenvalues λ_{j} of covariance matrix R . l is the number of principal components contained in the PCA model, which have direct effect on the quality of model, and the effective of fault detection and diagnosis. There are two methods to confirm the number of principal components, which is principal component contribution rate and minimum reconstruction error variance. The former is relatively simple, and the result would be much more preferable as long as the threshold contribution rate is reasonable. The criterion of selecting principal component by the principal component contribution rate method is as follows:

$$\frac{\sum_{k=1}^{i} \lambda_k}{\sum_{1}^{m} \lambda_j} \ge Cl \qquad (9)$$

where, Cl is threshold contribution rate, $Cl \in [0,1]$. Because the principal components contribution rate is generally large, Cl can be set as Cl=95%.

Once the model is built, a new sample vector can be decomposed into two parts:

$$x = x + x \qquad (10)$$

where,

$$x = PP^T x = Cx \qquad (11)$$

$$x = PP^T x = (I - C) x = Cx \qquad (12)$$

where, I is an identity matrix .

x and x are the projection of x on principal component subspace (*PCS*) and residual subspace (*RS*) respectively. C and C are corresponding projection matrix. Consequently, measurement data space is divided into *PCS* and RS by PCA method, where the normal values are contained in *PCS*, and the fault and noise data are contained in *RS*.

3 Experiment investigation

3.1 Introduction of test rig

The rotator test rig is shown in Fig.1, which is simplified environment control turbine system and driven by a motor, and the working speed is 200-3000rpm which is controllable.

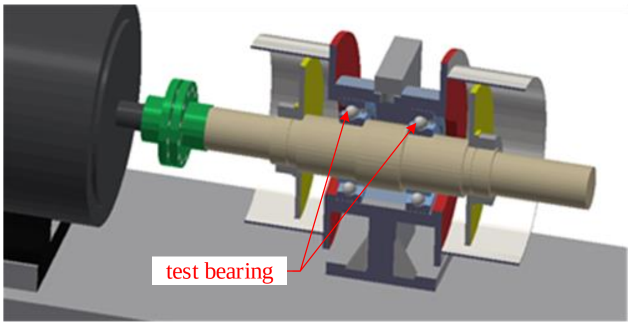


Fig.1 Test rig

The transducers arrangement is shown in Fig.2. Sensor 1 is eddy current transducer, which is placed horizontally perpendicular to the axis; Sensor 2 and 3 are acceleration transducer, which is laid vertically and horizontally perpendicular to the axis respectively. The parameters of bearing is shown in Table 1.

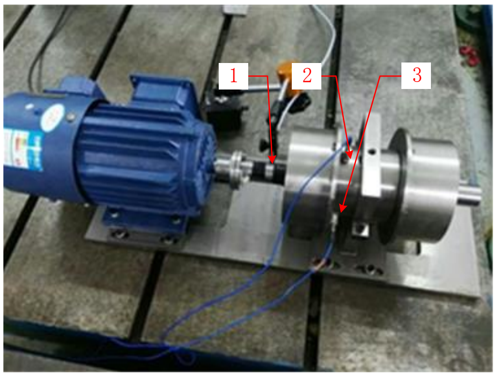


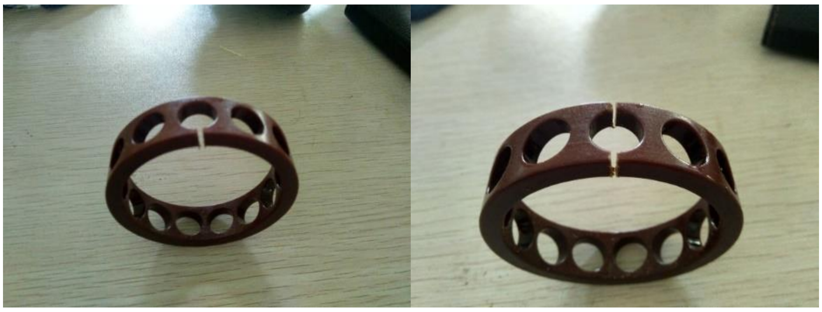
Fig.2 Test rig

Table 1 bearing parameters

Pitch radius	Diameter of rolling body	Quantity of rolling body	Contact angle
61.4	11.1	13	25

3.2 Comparison of fault features

Different cracks are arranged on the cage, inner and outer raceway of the test bearing, which are shown in Fig.3-5.



（a） Half slit （b） Complete slit

Fig.3 Different crack at cage

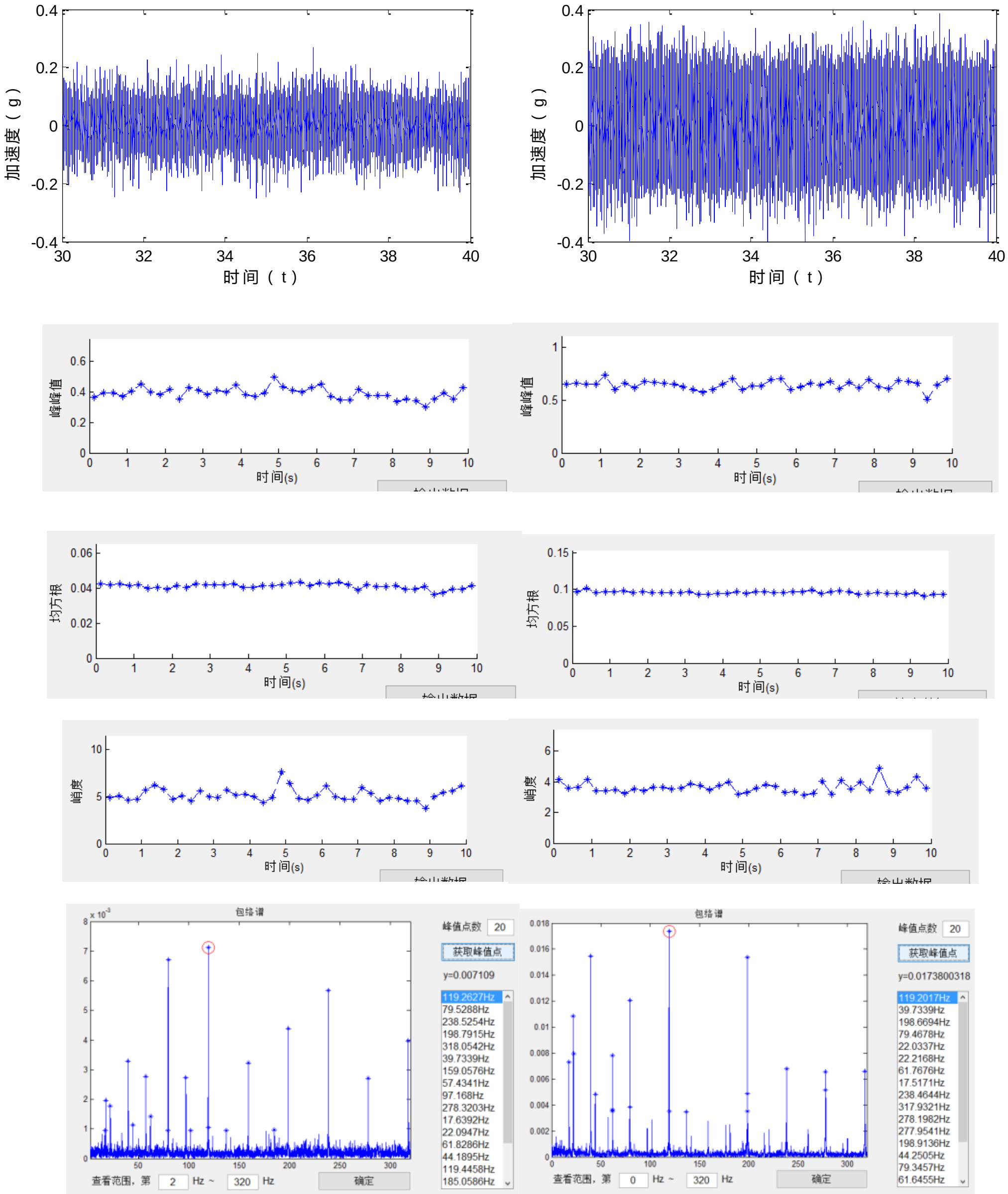
（a） 0.5mm width （b） 2mm width

Fig.4 Different crack at inner ring

（a）0.5mm width （b）2mm width

Fig.5 Different crack at outer ring

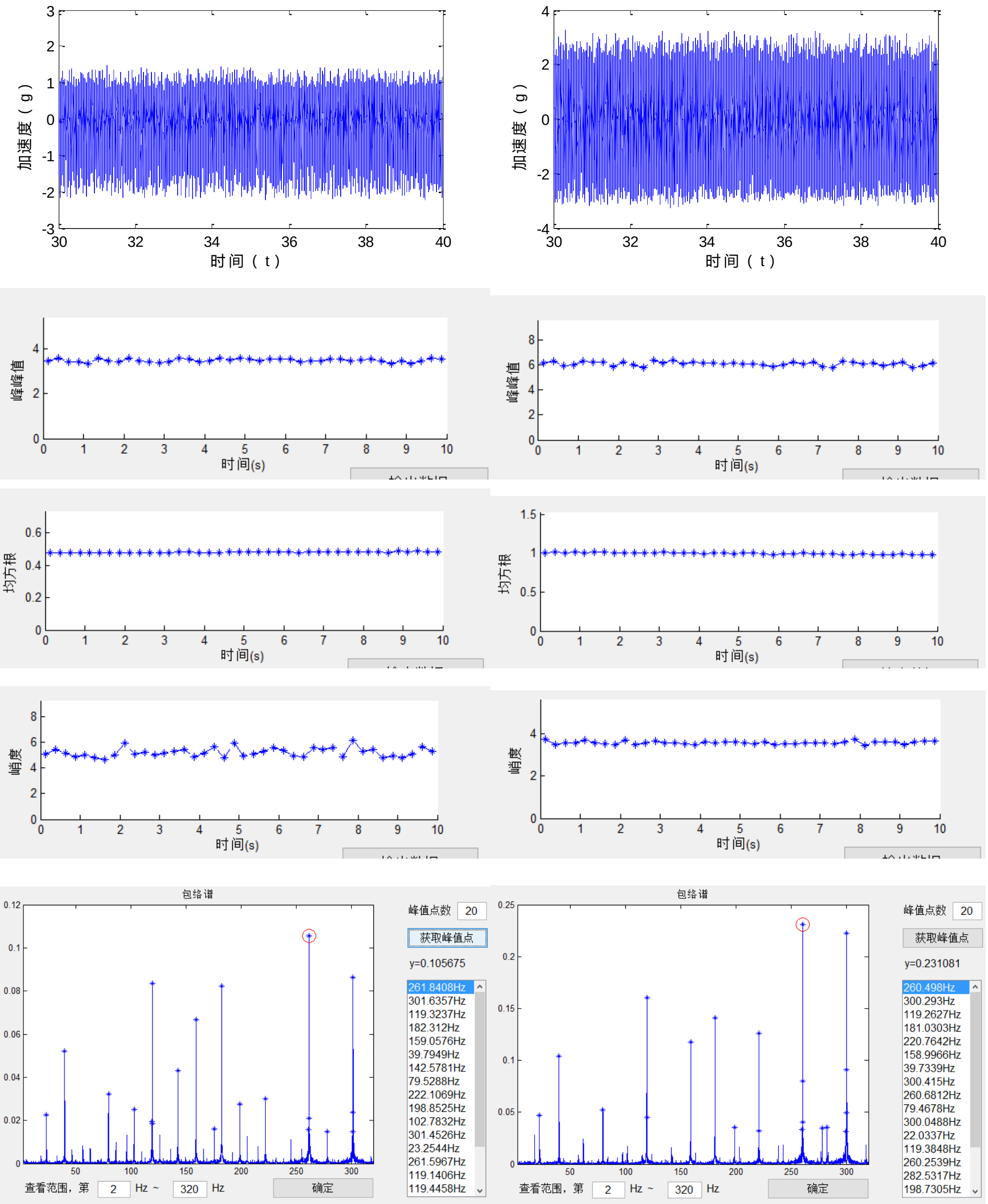
The corresponding vibration signals and its analysis results of sensor 3 are shown in Fig. 6-8.



（a）Half slit （b）Complete slit

Fig.6 Vibration signals comparison under different preseted crack on cages

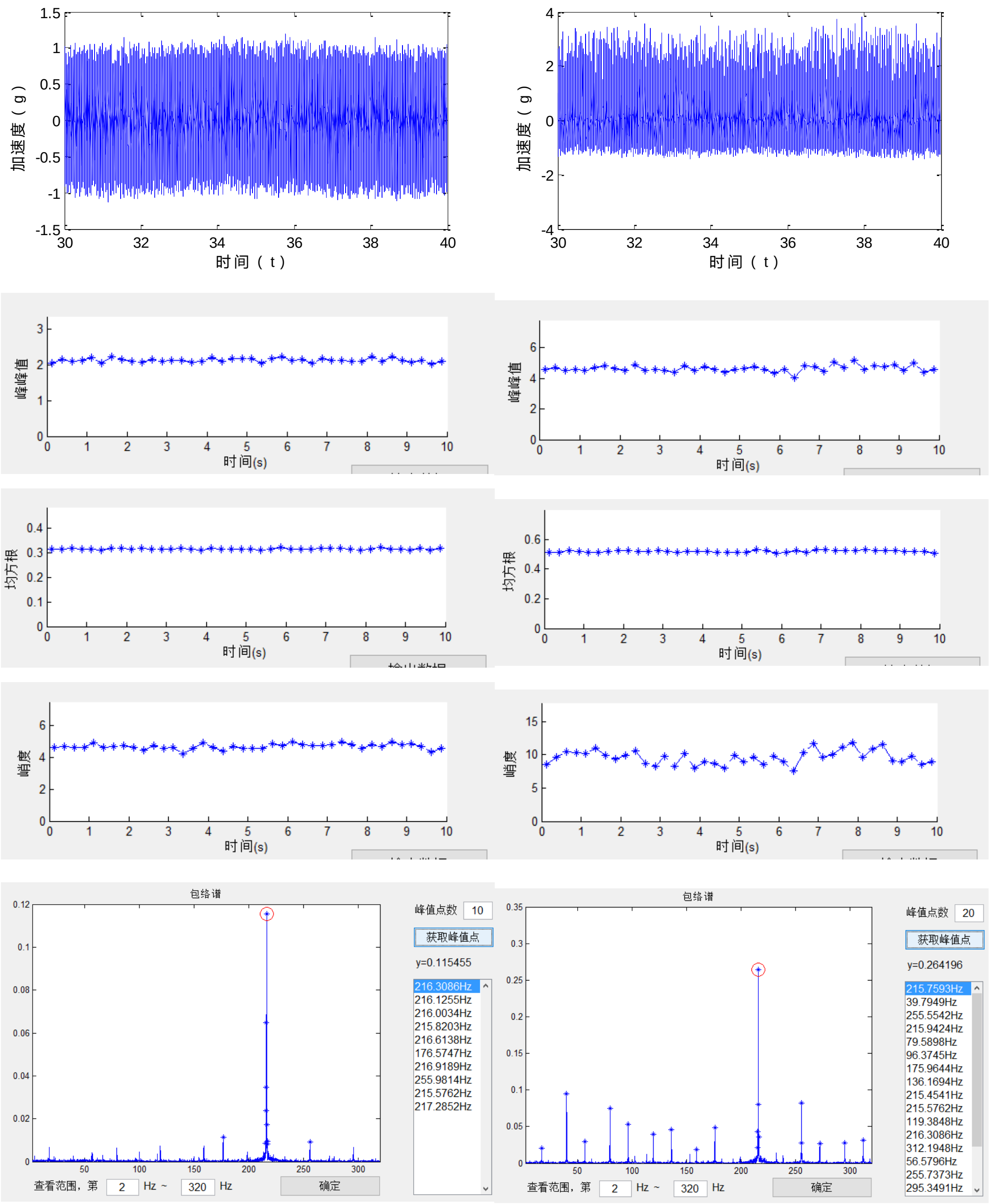
By comparing the characteristic of the signals when slit the bearing cage from half to complete, it is obvious that Peak-peak value and RMS value increase significantly, but kurtosis decreases from 5 to 4 with the crack is growing up. From the envelope spectrum results, the peak values of double rotating-frequency, together with inner and outer ring passing frequency of rolling ball increase significantly, but rotating frequency of cage decrease slightly.



（a）0.5mm width （b）2mm width

Fig.7 Vibration signals comparison under different preseted crack on inner ring

By comparing characteristic of the signals when the crack of inner ring increases from 0.5mm to 2mm, it is obvious that Peak-peak value and RMS value increase significantly, but kurtosis decreases from 5 to 4. The amplitude of each frequency raises obviously at the envelope spectrum results.



（a）0.5mm width　　（b）2mm width

Fig.8 Vibration signals comparison under different preseted crack on outer ring

By comparing characteristic of the signals when the crack of outer ring increases from 0.5mm to 2mm, it is obvious that Peak-peak value and RMS value increase significantly. Meanwhile, the kurtosis value increases from 5 to 10. The envelope spectrum results shows the most of its frequency component is the outer ring passing frequency of rolling ball, and the frequency characteristic is more obvious companying with the expansion of the crack .

3.3 State analysis and prediction

30 groups of feature vectors are selected, among which, 10 groups belong to normal bearing, 10 groups belong to outer ring slight damage fault and 10 groups belong to outer ring severe damage fault. The feature vectors are shown in Table 2.

Table 2. Feature vectors of the test results

v1	v2	v3	v4	v5	v6	v7	v8	v9	v10
0.293	0.036	2.925	0.001	0.001	0.001	0.002	0.002	0.002	0.001
0.336	0.038	3.011	0.001	0.001	0.001	0.001	0.001	0.002	0.001
0.328	0.037	3.021	0.001	0.001	0.001	0.002	0.002	0.002	0.002
0.313	0.038	3.019	0.001	0.001	0.001	0.002	0.001	0.002	0.001
0.305	0.038	2.920	0.001	0.001	0.001	0.002	0.001	0.002	0.001
0.297	0.036	3.045	0.001	0.001	0.001	0.002	0.002	0.002	0.002
0.334	0.039	2.980	0.001	0.001	0.001	0.003	0.001	0.004	0.003
0.392	0.041	3.191	0.001	0.000	0.001	0.003	0.001	0.001	0.003
0.334	0.038	2.998	0.001	0.001	0.001	0.002	0.001	0.002	0.002
0.174	0.017	3.172	0.000	0.000	0.000	0.001	0.000	0.001	0.000
1.344	0.194	4.378	0.028	0.004	0.003	0.101	0.004	0.001	0.001
1.405	0.195	4.275	0.030	0.003	0.004	0.097	0.003	0.001	0.001
2.278	0.312	4.778	0.005	0.005	0.007	0.134	0.009	0.001	0.003
2.287	0.317	4.652	0.002	0.003	0.003	0.012	0.002	0.001	0.001
2.313	0.316	4.752	0.001	0.004	0.002	0.012	0.002	0.001	0.001
2.326	0.317	4.657	0.001	0.004	0.002	0.012	0.003	0.001	0.001
2.432	0.324	4.590	0.001	0.004	0.002	0.012	0.002	0.002	0.002
2.320	0.316	4.665	0.003	0.006	0.007	0.115	0.007	0.001	0.002
2.298	0.316	4.606	0.004	0.007	0.008	0.154	0.009	0.001	0.001
2.379	0.322	4.761	0.003	0.003	0.006	0.153	0.008	0.002	0.002
4.953	0.511	9.694	0.092	0.077	0.035	0.276	0.033	0.007	0.018
5.109	0.517	9.312	0.140	0.105	0.045	0.394	0.037	0.008	0.019
5.089	0.518	9.273	0.095	0.071	0.031	0.277	0.032	0.005	0.016
4.956	0.513	9.533	0.093	0.074	0.039	0.226	0.026	0.011	0.022

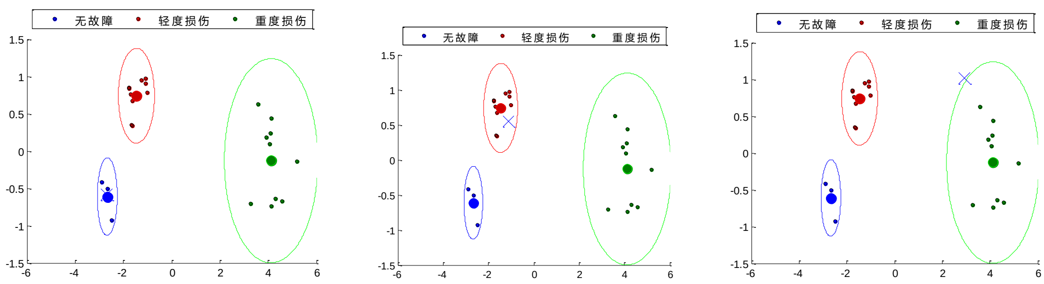
4.948	0.516	9.466	0.096	0.074	0.038	0.276	0.030	0.011	0.021
5.275	0.520	9.810	0.095	0.076	0.041	0.273	0.029	0.011	0.025
5.165	0.513	10.047	0.089	0.082	0.040	0.274	0.034	0.004	0.026
5.184	0.516	10.458	0.091	0.079	0.037	0.238	0.032	0.006	0.025
5.106	0.514	10.309	0.092	0.075	0.035	0.243	0.032	0.007	0.023
4.669	0.468	7.683	0.051	0.069	0.027	0.223	0.025	0.009	0.029

The high dimensional data should be handled by dimension reduction by PCA method, and a proper number of principal components should be selected to ensure the minimum of the feature information loss. By calculating, the variation information of first two principle components are 91.7% and 4.3%, which should be reversed.

Table 3 Validating data

Group	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10
1	0.34	0.04	3.01	0.001	0.001	0.001	0.001	0.001	0.002	0.001
2	2.28	0.31	4.73	0.003	0.006	0.007	0.116	0.001	0.002	0.007
3	5.27	0.52	9.64	0.095	0.075	0.039	0.264	0.001	0.002	0.021

To validate the evaluation method, three feature vectors shown in Table 3 are selected, which belong to normal bearing, outer ring slight damage fault and outer ring severe damage fault, respectively. From the results shown in fig.9, it is effective using the evaluation method to give the fault mode and running state.



(a) Group 1 (b) Group 2 (c) Group 3

Fig. 9 Diagnosis results

4 Conclusion

In this paper, a running state evaluation method of the turbine bearing is proposed based on the feature vector with limited testing data.

The feature vector constructed by three time domain feature parameters and seven frequency domain feature parameters is effective in recognizing the fault type and the state of the running bearing.

Experimental results suggest that the proposed method in this paper has potential in improving the accuracy to predict the state of running bearings

References

[1] Jardine AKS, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical systems and signal processing 2006; 20: 1483–1510.
[2] Jay Lee, Fangji Wu, Wenyu Zhao, Masoud Ghaffari, Linxia Liao, David Siegel. Prognostics and health management design for rotary machinery systems – Reviews, methodology and applications, Mechanical systems and signal processing, 2014,42: 314–334.
[3] Qiu J, Seth BB, Liang SY, Zhang C. Damage mechanics approach for bearing lifetime prognostics, Mechanical systems and signal processing, 2002, 16(5): 817–829.
[4] Chen C, Zhang B, Vachtsevanos G, Orchard M. Machine condition prediction based on adaptive neuro-fuzzy and high-order particle filtering. IEEE Transactions on Industrial Electronics 2011; 58(9):4353–4364.
[5] Chen C, Zhang B, Vachtsevanos G. Prediction of machine health condition using neuro-fuzzy and Bayesian algorithms. IEEE Transactions on Instrumentation And Measurement 2012; 61(2):297–306.
[6] Liu J, Wang W, Golnaraghi F. An enhanced diagnostic scheme for bearing condition monitoring. IEEE Transactions On Instrumentation And Measurement 2010;59(2): 309–321
[7] Chaochao Chen, George Vachtsevanos. Bearing condition prediction considering uncertainty: An interval type-2 fuzzy neural network approach, Robotics and Computer-Integrated Manufacturing, 28 (2012) 509–516.
[8] Shuai Zhang, Yongxiang Zhang, Lei Li, Jieping Zhu. Rolling elements bearings degradation indicator based on continuous Hidden Markov Model, J Fail. Anal. and Preven, 2015, 15:691–696.
[9] Theodoros H. Loutas, Dimitrios Roulias, George Georgoulas. Remaining Useful Life Estimation in Rolling Bearings Utilizing Data-Driven Probabilistic E-Support Vectors Regression, IEEE Transactions on Reliability, 2013, 62(4): 821–832.
[10] Abdenour Soualhi, Kamal Medjaher, Noureddine Zerhouni. Bearing Health Monitoring Based on Hilbert–Huang Transform, Support Vector Machine, and Regression, IEEE Transactions on Instrumentation and Measurement, 2015, 64(1): 52–62.