Incipient fault diagnosis of rolling element bearing based on wavelet packet transform and energy operator

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Abstract: - This paper mainly deals with the issue of incipient fault diagnosis for rolling element bearing. Firstly, an envelope demodulation technique based on wavelet packet transform and energy operator is applied to extract the fault feature of vibration signal. Secondly, the relative spectral entropy of envelope spectrum and the gravity frequency are combined to construct two-dimensional features vector that characterizes each fault pattern. Furthermore, K-nearest neighbors (KNN) is used to perform faults identification automatically. The experimental results prove that the method could avoid inaccurate diagnosis which only depends on the recognition of characteristic frequency, while the effectiveness of the method in the automatic fault diagnosis of bearing has been proved.

Key-Words: - wavelet packet transform; energy operator; rolling element bearing; incipient fault; envelope spectrum; K-nearest neighbors

1 Introduction

Rolling element bearing is widely used in industrial equipment, and fault diagnosis of such bearing is very important to improve reliability and performance of mechanical equipment. Generally speaking, the faults of rolling element bearing mainly include irregular damage (such as spalling, pitting, cracks, etc.) of inner race, outer race, balls and cage. Due to the affect of the impact force, the vibration signal often displays a complex modulation wave [1-3].

Currently, resonance demodulation is a widely used method of fault diagnosis for rolling element bearing. It mainly adopts envelope analysis through the band pass filter, and then extracts the time-domain characteristics of envelope signal to perform fault diagnosis. One of the key factors to constrain the success of this method is how to select the center frequency and the bandwidth of envelop analysis properly [4-6]. Wu et al. [7] developed an energy operator demodulation method which had been proved better than Hilbert transform, but it still needed to choose rational parameters for band-pass filter. However, because the incipient fault signal of rolling element bearing is weak and is often submerged in noise, it is usually difficult to find out the characteristics of the carrier frequency band for band-pass filter in advance. Therefore, its practical significance is limited. Considering the high precision and speed of wavelet multi-resolution, time-frequency localization and energy operator demodulation, Lei et al. [8] presented the wavelet-energy operator demodulation method. The energy concentration of high frequency modulation was extracted using wavelet transform, and the fault characteristic frequency was obtained through the energy operator demodulation. This method could reduce the interference of noise to some extent. However, because the results of envelope demodulation have multiple spectrum lines, the characteristic frequency of fault may not be obvious, which might cause difficulty to precision of diagnosis.

In general, the incipient fault signal of rolling element bearing is often weak and modulated. In view of both accuracy and fastness of signal envelope demodulation, this paper studies the demodulation method using energy operator. In the pre-processing of signal, wavelet packet transform technique was used to avoid characteristic band selection. Then the relative spectral entropy of envelope spectrum and the gravity frequency are calculated, forming the two-dimensional features to characterize each fault type. Finally, K-nearest neighbors (KNN), which is a very simple but effective method for pattern recognition, is used to identify the fault pattern. The experimental results prove that the method could obtain good performance in incipient fault recognition of rolling element bearing.

2 Mathematical model of vibration signal for rolling element bearing

The modulation phenomenon of vibration acceleration signal acquired from rolling element bearing is quite obvious. Impulse response will be generated due to the fault of rolling element bearing. Assuming that transmitting path from the impact point of fault to the sensor installation position is unchanged, the function of impulse response is expressed as $h(t)$, the vibration signal acquired from the bearing is expressed as $x(t)$, and then the following formula can be obtained [9]:

$$x(t) = x_T(t) + n(t)$$

$$= \sum_{k=0}^{+\infty} D_k h(t-kT) + n(t) \qquad (1)$$

Where: $x_T(t)$ is the vibration impact response signal under fault conditions.

D_k is the strength coefficient of impact response.

$n(t)$ is the vibration signal other than the impact response caused by the fault.

T is the duration of impact response of the fault.

From formula (1), it can be seen that the impact response of vibration signals expressed as $x_T(t)$ is feeble, since the strength coefficient expressed as D_k is weak when incipient fault occurs. Therefore, in order to diagnose incipient fault accurately, it is critical to eliminate the influence of other vibration response signal expressed as $n(t)$ while separating the weak impact response from original signal.

3 Envelope demodulation based on wavelet packet transform and energy operator

3.1 Energy operator demodulation

Energy operator (EO) is a powerful nonlinear operator proposed by Teager, and it is able to extract the signal energy based on mechanical and physical considerations. It has been successfully used in various applications. Energy operator is generally denoted as Ψ , which can be used very well in analyzing and tracking the energy of narrowband signals [8]. Assuming a continuous signal is expressed as:

$$x(t) = a(t)\cos[\int_0^t \omega_i(\tau)d\tau]$$

Then the continuous energy operator can be defined as [7]:

$$\Psi_c[x(t)] = [\dot{x}(t)]^2 - x(t)\cdot\ddot{x}(t) \approx [a(t)\omega_i(t)]^2 \quad (2)$$

According to literature [10], two key formula of energy operator can be obtained:

$$|a(t)| = \Psi_c[x(t)] \Big/ \sqrt{\Psi_c[\dot{x}(t)]} \qquad (3)$$

$$\omega_i(t) = \sqrt{\Psi_c[\dot{x}(t)] \Big/ \Psi_c[x(t)]} \qquad (4)$$

Formula (3) and formula (4) show that energy operator can be used to demodulate the amplitude and instantaneous frequency of signal.

Compared to the envelope demodulation of Hilbert transform, the speed and accuracy of envelope demodulation using energy operators is better [11]. Therefore, it is adopted in this paper to improve discrete-time energy operator demodulation algorithm.

3.2 Analysis of envelope demodulation based on wavelet packet transform and energy operator

Wavelet packet transform is essentially the bandwidth and multi-band filter for the signal, and it can make good performance in signal denoising [12-16]. To select indicators of fault diagnosis for rolling element bearing, we not only need to consider the optimal criteria of wavelet packet basis, but also need to take the best decomposition level of wavelet packet into account[2, 17].

Supposing there is a vibration signal with the sampling length expressed as N , and the sampling frequency expressed as F_s , and then the vibration signal is decomposed by J layer wavelet packet transform, while the J th layer wavelet packet coefficient can be expressed as $c_{J,k}(i)$.

Where $k = 0,1,\cdots,2^J - 1$, $i = 0,1,\cdots,N_J - 1$, $N_J = N/2^J$, and the bandwidth of each band is expressed as $F_b = F_s/2^{J+1}$. If the maximum cut-off frequency of the envelope signal is expressed as F_J , then the F_s , F_J and F_b must satisfy formula

(5), which is determined by the characteristics of the envelope signal.

$$F_b \geq 2F_J \Leftrightarrow F_s / 2^{J+1} \geq 2F_J \qquad (5)$$

Based on formula (5), the upper bound of the maximum decomposition level J can be derived; it also needs to meet $N_J > 2$. Therefore, it needs to calculate the upper bound of J based on formula (6).

$$\begin{cases} J \leq \log_2 \frac{F_s}{F_J} - 1 \\ J < \log_2 N - 1 \end{cases} \qquad (6)$$

After confirming the maximum decomposition level J, the selection criteria of optimal wavelet packet basis can be analyzed. The energy value denoted by wavelet packet transform coefficients $c_{J,k}(i)$ of each layer is used to evaluate the best choice of the wavelet packet basis. Energy expressed as $E_{J,k}$ is calculated by formula (7).

$$E_{J,k} = \sum_{i=0}^{N_J - 1} c_{J,k}(i)^2 \qquad (7)$$

Through the wavelet packet transform, J layer decomposition can be finished, which satisfies formula (8); and the wavelet packet transform coefficients can be reconstructed as below:

$$\begin{aligned} E_j^{\max} &= \max(E_j^0, E_j^1) \\ E_j^{\min} &= \min(E_j^0, E_j^1) \qquad (8) \\ E_j^{\max} &> K_{th} E_j^{\min} \end{aligned}$$

Where K_{th} is generally 1.5 or 2.

Therefore, based on the criteria of wavelet packet transform, and according to formula (1), the m th frequency band component of vibration signals can be easily obtained [9]:

$$x_m(t) = \sum_{k=0}^{+\infty} D_k h_m(t - kT) \qquad (9)$$

Where $h_m(t)$ is the impact response function in the m th sub-band weight, $n(t)$ is zero in relation to high frequency sub-band component. Using the narrow scale to analysis, we can separate the vibration signal from the noise. Therefore, the characteristic function of rolling bearing fault signal can be defined as $s(t)$:

$$s(t) = \sum_{k=0}^{+\infty} D_k \sum_{i=1}^{N} \left| h_{m_i}(t - kT) \right| \qquad (10)$$

Where m_i is the i th sub-band number of the impact response function distribution.

According to formula (10), the characteristic function is acquired to avoid the interference of low frequency noise, which can reflect the degree of impact distribution of the fault of rolling element bearing very well. Therefore, higher signal-to-noise ratio (SNR) can be obtained.

4 Experimental data analysis

This study makes use of experimental data from the bearing data center of the Case Western Reserve University(CWRU)(http://www.eecs.case.edu/laboratory/bearing/download.htm). At first, the test-bed of simulating fault of rolling element bearing is shown in Figure 1.

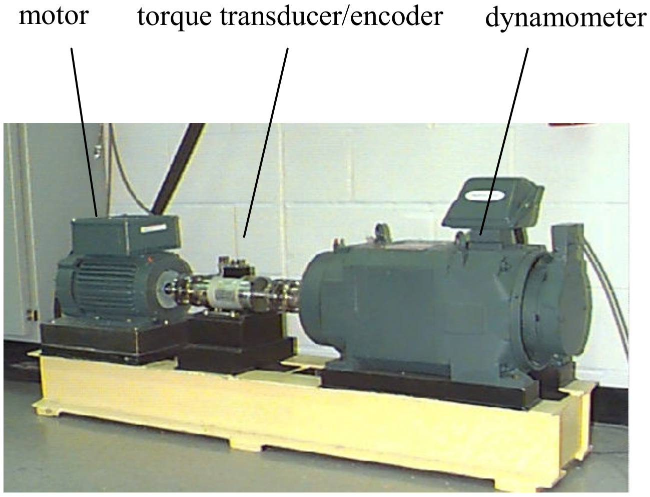

Fig.1 The test-bed to simulate the fault of rolling element bearing

The data acquisition system is used to acquire the data from the drive end bearing on which acceleration sensors are installed. The type of drive end bearing is SKF6205-2RS, the speed is 1796r/mim, the sampling frequency is 12KHz, and the collected data size is 10240. We are concerned with normal, inner race fault, outer race fault and ball fault, which are the four main kinds of fault patterns of rolling element bearing. The radiuses expressed as r of fault damage include 7mils, 14mils, 21mils, 28mils and 40mils, each of which shows varying degree of damage. This paper selects the smallest damage radius to simulate the case of incipient fault, that is to say, we use fault data with 7mils damage degree for research.

According to the specifications of the bearing, we can calculate that the characteristic frequency of inner race fault is 162.1Hz, the characteristic frequency of outer race fault is 107.3Hz, and the characteristic frequency of balls fault is 141.1Hz. As shown in Figure 2, they are the spectrogram of vibration signals under the four operating conditions.

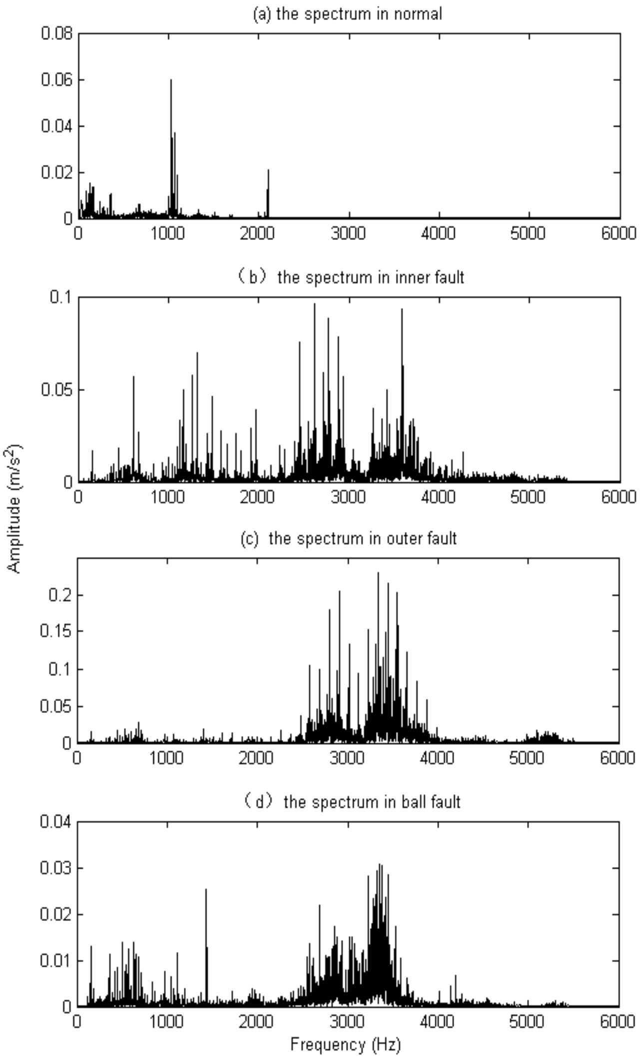

Fig.2 The spectrograms under different fault conditions

It can be seen from Figure 2 that the spectrums of vibration signals under the four operating conditions are rather complicated, which cause difficulty in judging and classifying the fault patterns. According to the range of characteristic frequency of bearing fault, when the working speed is 1796r/mim, the maximum frequency of the envelope signal is 6 times the speed of working frequency, that is to say, the maximum of frequency is 180Hz. According to formula (6), the maximum decomposition level of wavelet packet transform is 7 by calculation, where the decomposition level of the wavelet packet energy operator is chose to 4, and this paper selects the db4 wavelet. The energy operator and the wavelet packet energy operator are both used to analyze the envelope of the signal. As shown in Figure 3, for inner race fault, comparison between the time-domain envelope waveform using energy operator and that using the wavelet packet energy operator envelope is made.

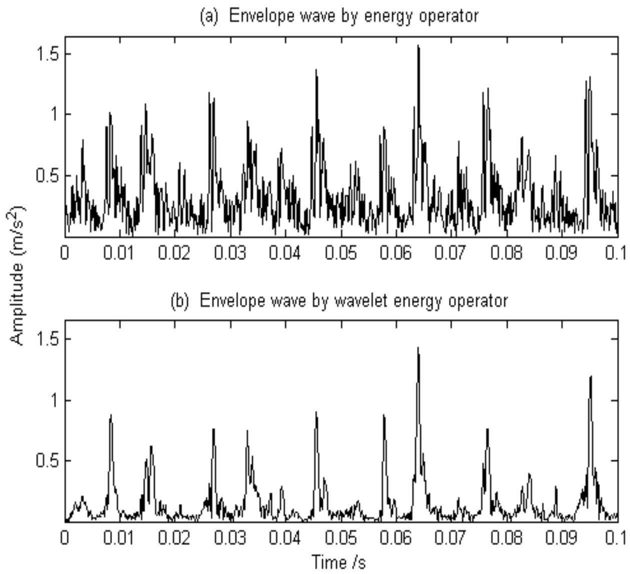

Fig.3 Comparison of envelope waveform with inner - race fault

We can find that there is a lot of clutter when using the energy operator envelope by comparing the time-domain waveforms, and it may bring about a lot of inconvenience to the analysis of signals. However, in view of time-domain waveform, the clutter of envelope domain waveform using wavelet packet energy operator was comparatively less. We can also find that the features are more conspicuous.

Envelope spectrum analysis is often used in analyzing the fault of rolling element bearing because it is essentially the peak value detector, which is also called peak energy spectrum. As the high-frequency amplitude of envelope spectrum is very small, the low frequency below 180Hz of envelope spectrum would be analyzed. The envelope spectrum of vibration signals under the normal, inner race fault, outer race fault and ball fault condition are shown in Figure 4, 5, 6 and 7.

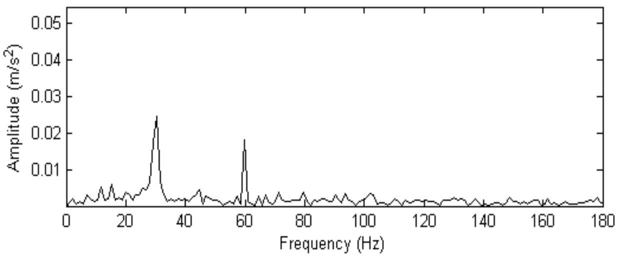

Fig.4 Envelope spectrum of vibration signal of normal state

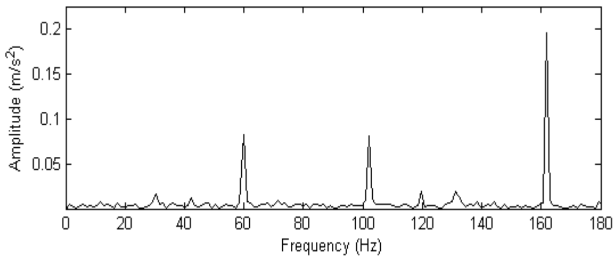

Fig.5 Envelope spectrum of vibration signal of inner race fault

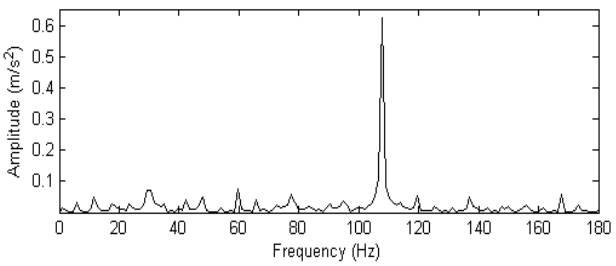

Fig.6 Envelope spectrum of vibration signal of outer race fault

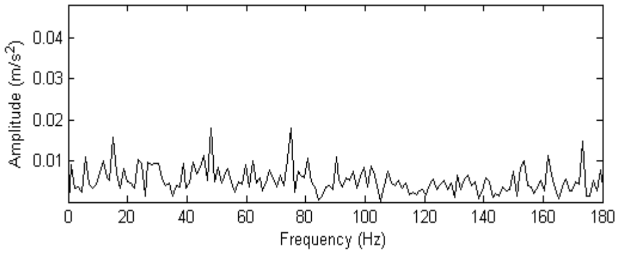

Fig.7 Envelope spectrum of vibration signal of ball fault

Based on the comparisons of the envelope spectrum of the four operational conditions, we can find that the differences among them are obvious. As shown in Figure 6, the characteristic frequency of outer race fault was more obvious by envelope demodulation using wavelet energy operator. However, there are a number of envelope lines under the normal condition and fault condition, especially under the ball fault condition. The envelope spectrum is more complex, because the incipient fault signal of rolling element bearing was feeble, so that the feature of fault is not very clear, which makes the envelope spectrum relatively complex. It is relatively difficult to pinpoint fault characteristic frequency only relying on the characteristic frequency of spectrum by the envelope spectrum analysis, and it is also difficult to get satisfactory results. In order to identify the fault pattern accurately, it is very important to select the appropriate spectral characteristics of the envelope. The spectral entropy and the gravity frequency are commonly used as the features of faults [18-20]. Literature [21] pointed out that the spectrum of one-dimensional spectrum entropy had some limitations, and a two-dimensional vector named spectral entropy and spectral entropy arm was used as the feature parameter, both of which were associated with analysis.

Spectral entropy expressed as H is defined by formula (11), which reflects the concentration of spectrum. The smaller the spectral entropy is, the more concentrated the spectral will be. To compare the spectral entropy of signals with different lengths, the relative spectral entropy expressed as H_r is used as the feature parameter; the relative spectral entropy is calculated by formula (12). The physical significance of spectral entropy arm is the gravity frequency of the spectral entropy. In this paper, the gravity frequency of spectrum expressed as Fc is used directly to replace the spectral entropy arm, and the gravity frequency is calculated by formula

(13). The relative spectrum entropy H_r and the gravity frequency Fc of envelope spectrum are used as two-dimensional feature indexes.

$$H(X) = -\sum \mu(X(K))\log(\mu(X(K))) \quad (11)$$

Where X is the spectral sequence of the time series of $\{x(n)\}$, while in this study it is the envelope sequence. And $\mu(t) = X(K)/\sum X(j)$

$$H_r(X) = H(X)/\log(N/2) \quad (12)$$

Where N is the length of time series.

$$Fc(X) = \sum_{k=1}^{N/2} \frac{K}{N/2}\mu(X(K)) \quad (13)$$

Under the four operational conditions of rolling element bearing, including the normal operation, inner race fault, outer race fault and ball fault, eight sets of data are selected to calculate the characteristic index of envelope spectrum, the results of which are shown in Table 1, and the two-dimensional vectors are drawn in Figure 8. As can be seen from Figure 8, the difference between the normal condition and the other three fault condition could be distinguished clearly.

Table.1 The calculation results of two-dimensional vectors under the four conditions.

Data	Normal		Inner fault		Outer fault		Ball fault	
	H_r	Fc	H_r	Fc	H_r	Fc	H_r	Fc
1	0.8331	0.2155	0.7368	0.1888	0.8511	0.1721	0.9390	0.2070
2	0.8348	0.2144	0.7264	0.1770	0.8396	0.1704	0.9452	0.2184
3	0.8421	0.2072	0.7294	0.1742	0.8487	0.1818	0.9383	0.2026
4	0.8284	0.2112	0.7382	0.1788	0.8428	0.1651	0.9299	0.2130
5	0.8446	0.2248	0.7252	0.1763	0.8543	0.1634	0.9266	0.1861
6	0.8267	0.1997	0.7369	0.1805	0.8507	0.1550	0.9451	0.2153
7	0.8384	0.2108	0.7418	0.1855	0.8456	0.1753	0.9388	0.1915
8	0.8475	0.2223	0.7243	0.1729	0.8410	0.1643	0.9313	0.2053
Mean	0.8370	0.2132	0.7324	0.1793	0.8467	0.1684	0.9368	0.2049

Through the analysis above, it has been proved that the good results could be achieved by wavelet packet transform and energy operator. After performing the wavelet packet transform and envelope demodulation of the energy operator, the two-dimensional vector of the envelope spectrum was constructed as the feature parameters, which can better distinguish the different fault types of rolling element bearing.

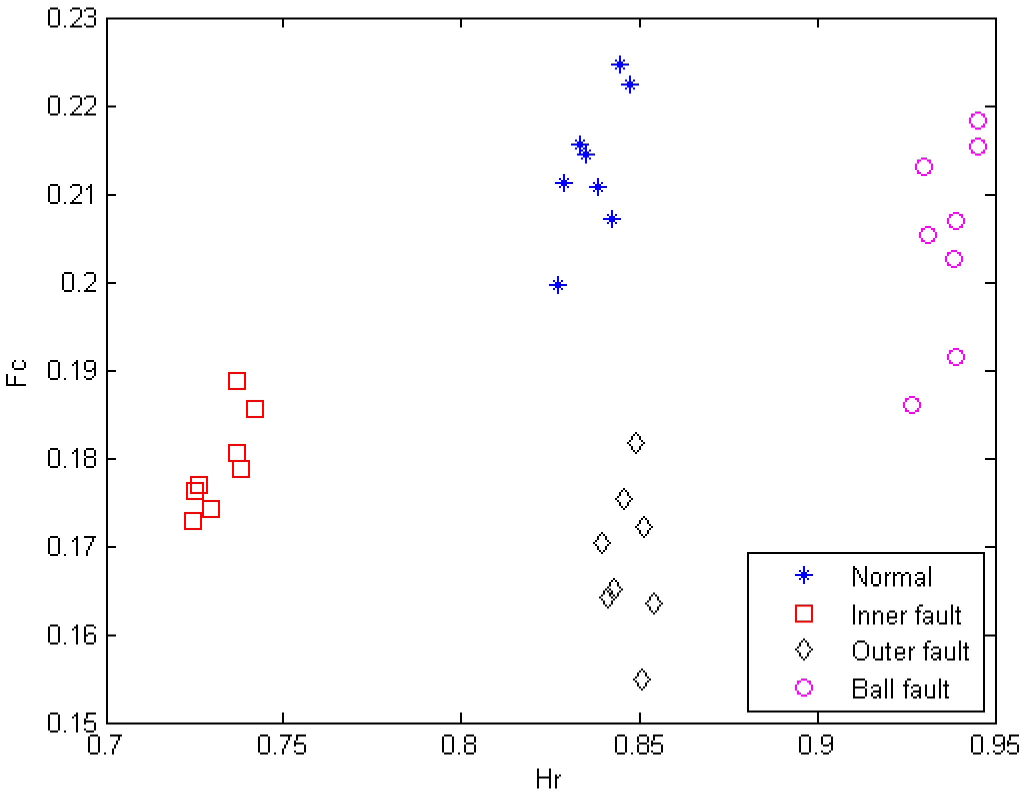

Fig.8 Map of envelope spectrum eigenvalues under the four different conditions

Because the eigenvalues of two-dimensional vector spaces under the four conditions differ greatly from each other, the standard sample expressed as X is constructed by the four categories of feature vectors above. Then, a set of fault data with the spectral envelope characteristics of two-dimensional vector are selected as the test samples expressed as $xTest$, the KNN, which is the very simple and effective method for pattern recognition, is used to identify the test samples $xTest$. Based on formula (14), the standard sample X could be calculated and identified for all sample points in the sample space distance, and its K nearest neighbors could be found according to literature [22, 23].

$$d(x_i) = \sqrt{(c_1^i - c_i)^2 + (c_2^i - c_2)^2 + \cdots + (c_n^i - c_n)^2} \quad (14)$$

Where $i = 1, 2, \cdots, N$

$d(x_i)$ is the distance between the test sample point and the standard sample point. In this paper, the number of nearest neighbor is set to 5 [24, 25]. According to test and analysis, the identification result is shown in Figure 9 using the K- nearest neighbor recognition, and the results of automatic recognition is the ball fault, which is consistent with the actual fault type. Based on the analysis of multiple data measurement, the satisfactory results showed that the proposed method is a simple and effective method for the incipient diagnosis fault of rolling element bearing.

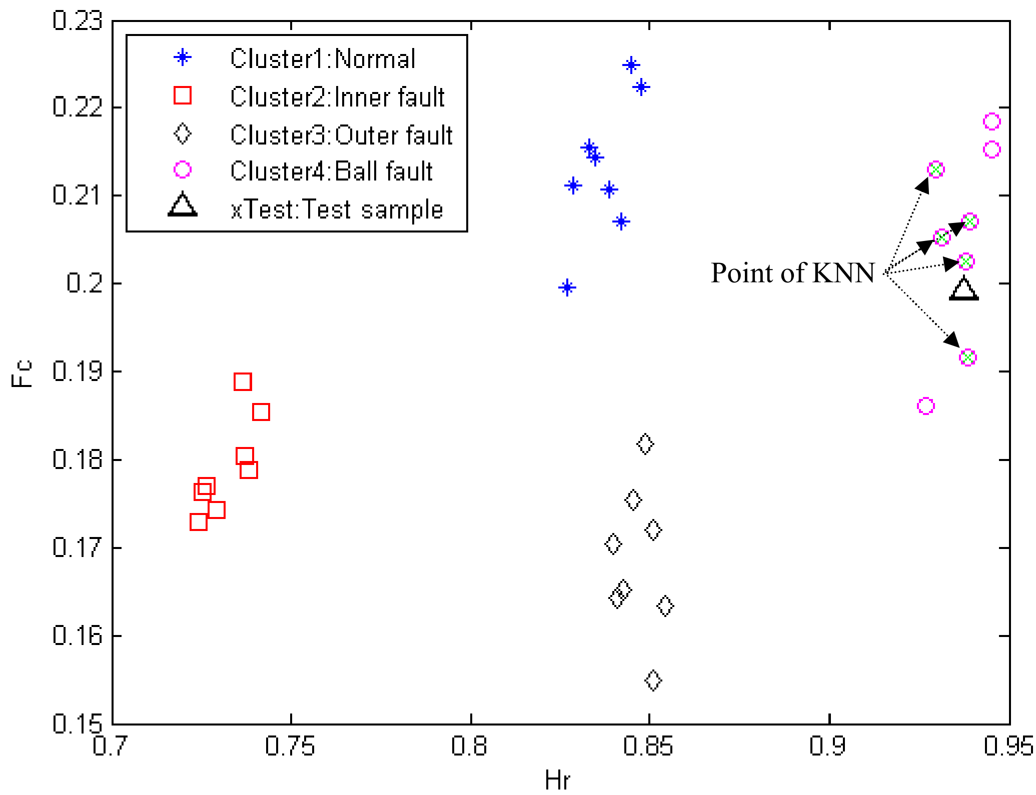

Fig.9 The result of fault Identification with the KNN method

5 Conclusion

In this paper, a method based on wavelet packet transform and energy operator for incipient fault diagnosis of rolling element bearing is proposed and thoroughly studied. The following conclusions can be achieved:

(1) The paper introduces the envelope analysis technique which combines the wavelet packet transform with the energy operator demodulation. This technique not only avoids the need for an artificial carrier signal with a band-pass filtering, but also demonstrates excellent performance in constraining the noise. Through envelope analysis under the four kinds of conditions, the satisfactory results of distinguishing fault can be achieved.

(2) The relative spectral entropy and the gravity frequency of envelope spectrum are combined as the two-dimensional vector feature, which is used to be the characteristics indicator of diagnosis fault for rolling element bearing. Meanwhile, the KNN, which is a very simple but effective method of pattern recognition, is used to identify the faults automatically. The experimental results shows that the technique could avoid only relying on characteristic frequency of fault, and could better distinguish incipient fault of rolling element bearing. Therefore, the method could be used to realize intelligent fault diagnosis and fault identification for rolling element bearing. Experiments have proved that this method has certain application value.

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