TELKOMNIKA, Vol. 11, No. 10, October 2013, pp. 5867 ~ 5875
ISSN: 2302-4046

Study on Fault Feature Extraction of High-Speed Automaton

Aiyu Wang, Hongxia Pan*, Huiling Liu
School of Mechanical Engineering and Automation, North University of China
Taiyuan 030051, China
*Corresponding author, e-mail: panhx1015@sohu.com

Abstract

In order to effectively extract the weak fault feature of high-speed automaton (HSA) in the environment with strong noises, a method of fault feature extraction was proposed based on wavelet packet energy entropy and fuzzy clustering algorithm. In this paper, wavelet packet was utilized to denoise the vibration signals of three working conditions of automaton, to decompose the signals and then to obtain eight frequency band energy entropies of each signal. Through processing and analyzing the features, the results show that there are obvious differences between three conditions, and the fuzzy clustering algorithm can identify the fault pattern of HSA accurately. The feature proposed by this extraction approach is proved to be able to effectively reflect the working state of the automaton, therefore the wavelet packet energy entropy could be considered as the feature parameters of HAS for fault identification and diagnosis. The fault feature extraction method can also provide a certain engineering application value for real-time monitoring and early fault diagnosis of this type HSA.

Keywords*: High-speed automaton (HSA); wavelet packet energy entropy; fuzzy clustering algorithm; feature extraction*

1. Introduction

High-speed automaton (HSA) is a key component of a gun system, as its working environment is high temperature, high pressure and high speed, its working reliability and components' crack and wear gradually become the focus the gun system monitoring and diagnosis field. The method of fault diagnosis through analyzing the vibration signal of the complex mechanical equipment is an effective fault diagnosis method. However fault feature extraction is the key to the fault diagnosis, it will be related to the reliability and the accuracy of early fault diagnosis [1].

As the poor working environment of HSA, and its vibration response signal is short-time and transient , in addition the cracks and wear of some members make the vibration response is very weak [2-4], so it this is difficult to identify these weak signal. Many methods of processing and analyzing vibration signals are generally for stationary signal, which often is not applicable for short-time and transient signals [5]. So studying the method of processing and analyzing the short-term and transient signal, which can combine with vibration response mechanism and effectively extract the features seem to be extremely necessary.

The premise of the automaton fault diagnosis is the extraction of fault feature; it will directly affect the reliability of early fault prediction and diagnostic accuracy of HSA. The vibration signal generated in firing action is a short-time and transient and non-stationary signal, so the traditional spectrum analysis method-fast Fourier transform (FFT) can not reflect the change of response spectrum over time. Because the FFT can only be effective to the stationary random signal, and it gives the statistical average results from the time domain or the frequency domain, but cannot obtain the signal's overall and local features both in time domain and frequency domain. Even the short-time Fourier transform (STFT) [6] also cannot satisfy the different requirements of high and low frequencies because of the fixed size and shape of time window. But the wavelet packet transform (WPT) method can decompose any signal (smooth or non-smooth) into a wavelet basis function family, which contains a large number of intact information, and by decomposing and reconstructing the signal in different scales, the distribution of detailed information of the original signal in different frequency bands can be

Received April 19, 2013; Revised July 4, 2013; Accepted July 17, 2013

obtained [7]. Currently the WPT has become an effective signal processing technology. In addition, the information entropy is an effectual quantitative evaluation indicator for the uncertainty degree of signal's or system's state, which can effectively extract the signal features in different transform space combined with different signal processing approaches [8].

Therefore, we present a fault feature extraction method based on wavelet packet energy entropy and fuzzy clustering algorithm In this paper. First, processing the vibration signals by wavelet packet decomposition and calculating each band's energy entropy and establishing the feature vectors. Then analyzing and comparing the wavelet packet energy entropies of three working conditions. Finally combining the fuzzy clustering algorithm to classify the automaton's working states and identify the fault pattern. By example, the method is proved to be reasonable and effective.

2. Research Method

2.1. Principle of Wavelet Packet Transform

Wavelet packet transform (WPT) is based on the wavelet transform of further development, and has more flexibility [9]. The structure of (WPT) is similar to discrete wavelet transform (DWT). Both have the framework of multi-resolution analysis. We know that the main difference in the two techniques is that wavelet transform just decompose the part of low frequency rather than high frequency, so the resolution of the high frequency is low, but the WPT not only can process orthogonal decomposition in the low frequency component but also in the high frequency component [10]. Therefore, the WPT have the same frequency bandwidths in each resolution and DWT does not have this property. The mode of decomposition does not increase or lose the information within the original signals. Therefore, the signal with great quantity of middle and high frequency signals can offer superior time-frequency analysis. The WPT suits signal processing especially no stationary signals because the same frequency bandwidths can provide good resolution regardless of high and low frequencies [11-13].

2.2. Wavelet Packet Energy Entropy Extraction [14]

Firstly, getting the sequence $S_{j,k}$ by wavelet packet decomposition of the original signals, in which *j* is the decomposition level, and $k = 0, 1, 2, \cdots, 2^j - 1$. Then according to the time characteristic of the signal, the obtained sequence $S_{j,k}$ is divided into *N* segments, and calculating each segment's energy.

$$Q_{i(j,k)} = \int_{t_{i-1}}^{t_i} |A_i(t)|^2 \, dt \tag{1}$$

Where $A_i(t)$ ($i = 1, 2, \cdots, N$) is the signal amplitude of sequence $S_{j,k}$, *i* is the coefficients of the subspace after wavelet packet decomposition, t_{i-1}, t_i are respectively the beginning and the ending time of the *i*th segment signal.

Then normalizing each segment's energy, method is as follows:

$$e_{j,k}(i) = \frac{Q_{i(j,k)}}{\sum_{i=1}^{N} Q_{i(j,k)}} \tag{2}$$

Information entropy is a measurement of information based on a positioning system under a certain state, it is also a measure of the degree of system disorder, and is applied to the signal analysis, which can be used to estimate the uniformity or complexity of stochastic signal. According to the information entropy theory, wavelet packet energy entropy of the *j*th layer and the *k*th frequency band after wavelet packet decomposition can be defined as follows [15, 16]:

$$H_{j,k} = -\sum_{i=1}^{N} e_{j,k}(i) \lg e_{j,k}(i) \tag{3}$$

2.3. Fuzzy Clustering Algorithm [17, 18]

The basic idea of clustering analysis is to measure the degree of closeness between things by similarity, and then achieve the classification. The main steps of fuzzy clustering are described below:

Step 1. The establishment of the original data matrix. Assume that $U=\{x_1,x_2,\cdots,x_n\}$ is a set which contains *n* objects to be classified, and each object has *m* elements $x_i=\{x_{i1},x_{i2},\cdots,x_{im}\}$, $i=1,2,\cdots,n$, which are required to describe the classification object's characteristics well.

Step 2. The standardization of the sample data. In this paper, range transformation method is used as follows:

$$x_{ik}^{'}=\frac{x_{ik}-\min\limits_{1\le i\le n}\{x_{ik}^{'}\}}{\max\limits_{1\le i\le n}\{x_{ik}^{'}\}-\min\limits_{1\le i\le n}\{x_{ik}^{'}\}},\quad (k=1,2,\cdots,m) \tag{4}$$

After transformation, the value of $x_{ik}^{'}$ ensures $0\le x_{ik}^{'}\le 1$, and the impact of dimension can be eliminated.

Step 3. Calibration. Calibration is to establish a fuzzy similarity matrix R, and in this paper Euclidean distance calibration was used and is given by:

$$r_{ij}=1-cd(x_i-x_j)=1-c\sqrt{\sum_{k=1}^{m}(x_{ik}-x_{jk})^2} \tag{5}$$

Where c is a coefficient, and it should be appropriately selected in order to ensure $0\le r_{ij}\le 1$.

Step 4 Cluster Analysis. For a finite set, suppose $\tilde{R}=[r_{ij}]$ is a fuzzy similarity matrix (FSM), if it satisfies reflexivity, symmetry and transitivity, the matrix $\tilde{R}=[r_{ij}]$ is a fuzzy equivalence matrix (FEM), and then it can be used to classify. If the FSM does not meet the transitivity, it needs to be transformed. The transform method as follows [19]: $R^2=R\circ R=(S_{uv})_{n\times n}$, $R^4=R^2\circ R^2\ldots$, Where $S_{uv}=\mathop{\vee}\limits_{w=1}^{n}(r_{uw}\wedge r_{wv})n$, ($u=1,2,\cdots,n; v=1,2,\cdots,n$), "$\vee$"、"$\wedge$" means "choosing the bigger "、" choosing the smaller". Once $R^{2k}=R^k=R^*$, R^* can be regardered as a FEM. For any truncated matrix R_λ^*, $\lambda\in[0,1]$, where R_λ^* must also is a FEM, during classification each element value can be chosen like this: the element which is greater than or equal to λ should be changed to 1, else be changed to 0. Then according to the arrangement of 1 and 0, classification can be achieved.

3. Experimental Analysis

3.1. Experimental Method

In this paper two kinds of faults of high-speed automaton (HSA) were set, including fault 1 (scored atresia impact fillet fault) and fault 2 (scored rotary fillet fault). The three bursts fire test was completed in the shooting experimental stage under three operating conditions of HSA (normal, fault 1 and fault 2). Vibration signals of HAS under each working condition were measured with triaxial acceleration sensor of type 44987 produced in PCB company. The installation site of the measuring point and the corresponding coordinate is shown in Figure 1, where the coordinate origin was set in the muzzle position, and the measuring point was located in the top of the gun breech. The sampling frequency in this experiment was 51.2 KHz, and the vibration signals in three states (normal, fault 1 and the fault 2) were obtained by DSP system.

This experiment is three bursts fire, and the time of commencing firing of the first bullet was as the triggering time of data acquisition. The effective length of the signal is extracted from the beginning of the first shot to the third shot is completed.

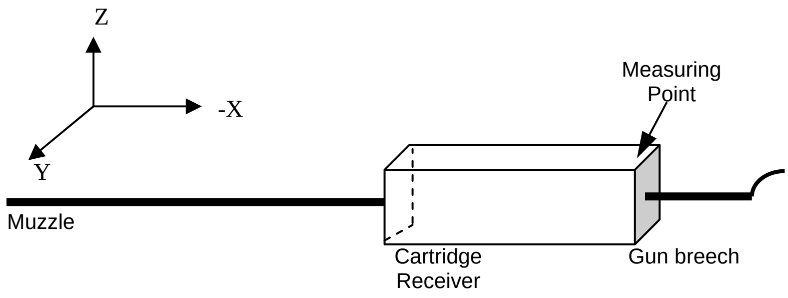


Figure 1. The installation site of measuring point and corresponding coordinate

Figure 2 shows the time domain signals of three working states acquired in y direction of measuring point. As can be clearly seen from Figure 2, there are obvious differences in acceleration amplitude of three states. In order to distinguish automaton's working state more accurately, wavelet packet transform method was applied, and the energy entropy of each vibration impulse signal was extracted as fault characteristic parameters, and combined with fuzzy clustering algorithm, shock and vibration signals generated by HAS were analyzed and compared.

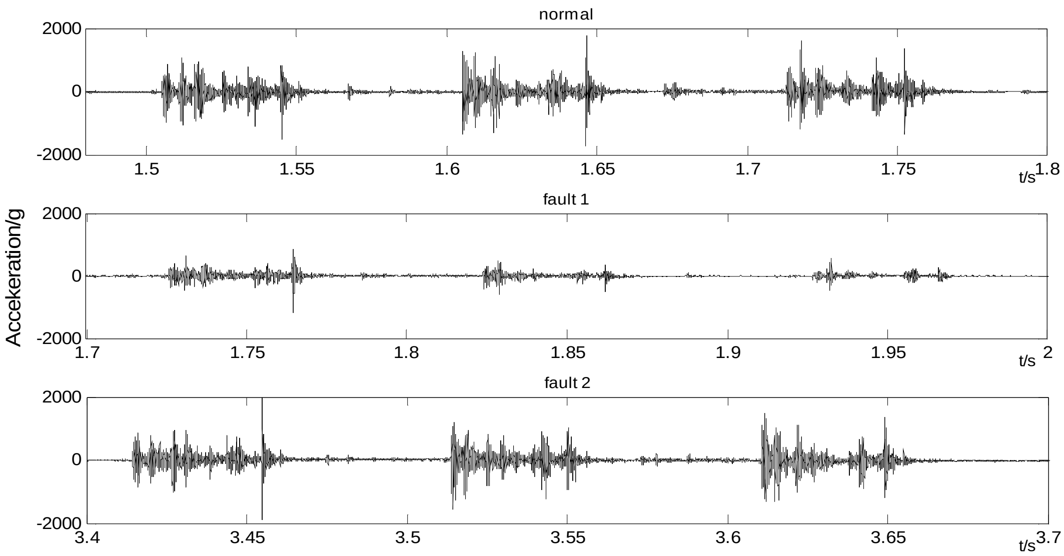


Figure 2. The original vibration acceleration signals of each working condition

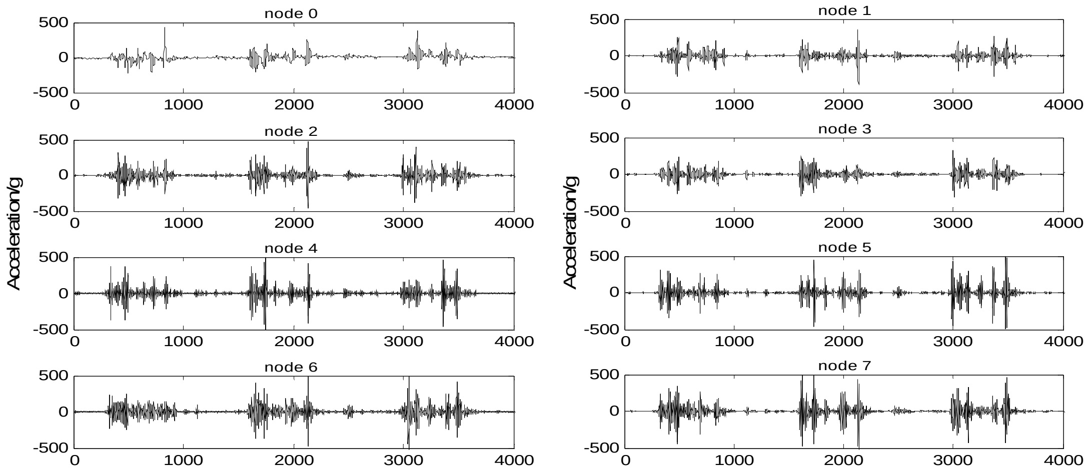
3.2. Feature Extraction of Vibration Signals

Step 1. Denoising and decomposing the normal vibration signals and two fault signals to the third level using wavelet packet with db10 wavelet, then obtain eight different frequency band signals, plotted in figure 3.

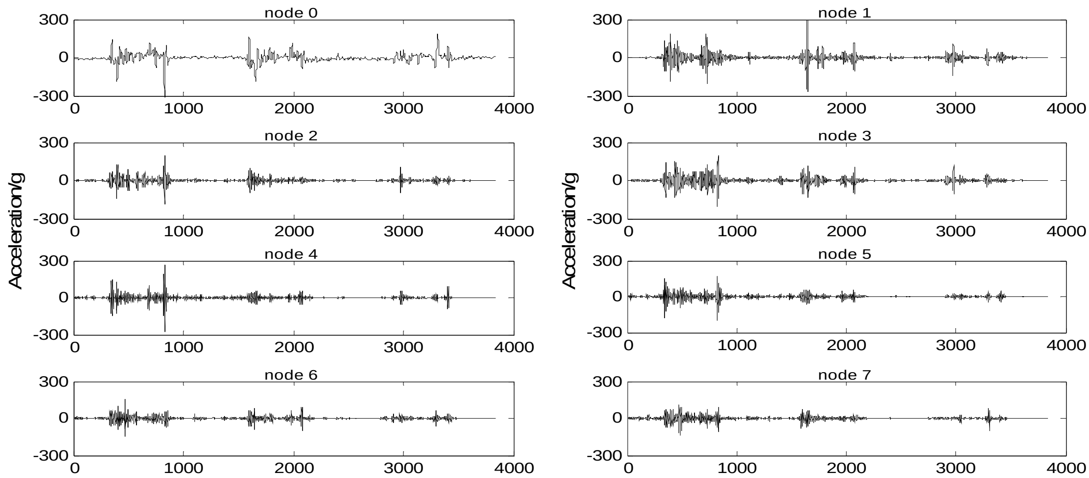
Step 2. In accordance with the principle of energy balance, dividing each frequency band signals into 10 sections. Then utilizing the formula (1), (2), (3) to obtain eight frequency band wavelet packet energy entropies of the third layer, the calculation results are shown in Table 1.

Step 3. Construct the feature vector. The feature vector T is composed of 8 wavelet packet energy entropies sequence of the 3^{rd} layer and was shown by:

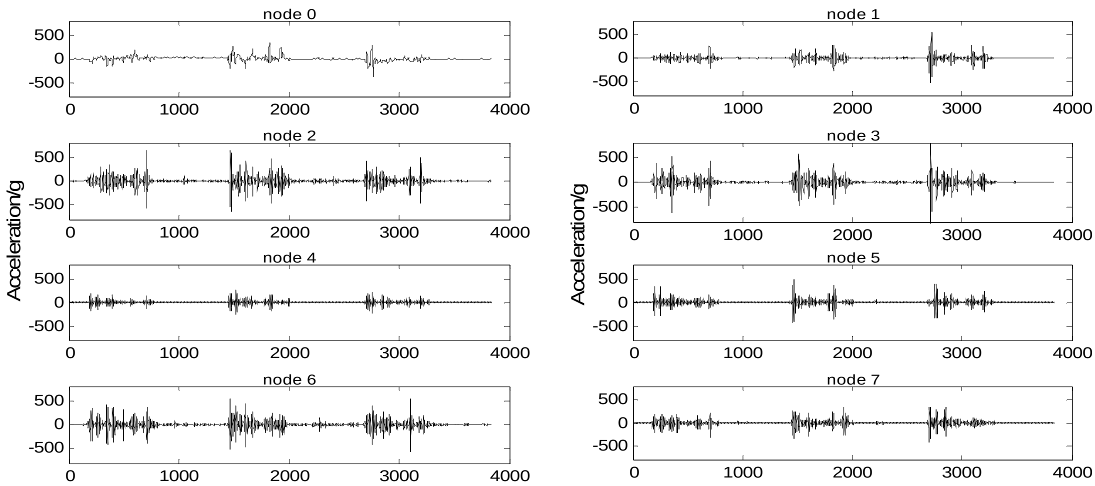
$$T = [H0, H1, H2, H3, H4, H5, H6, H7] \quad (6)$$



(a). Eight frequency bands of normal signal



(b). Eight frequency bands of fault 1 signal



(c). Eight frequency bands of fault 2 signal

Figure 3. The wavelet packet decomposed results of three conditions

Table 1. The features of different vibration signals

Samples		H0	H1	H2	H3	H4	H5	H6	H7
Normal signals	x_1	2.8643	2.8888	2.9673	2.9269	3.0191	2.9339	3.0119	2.8014
	x_2	2.6334	2.8347	2.9681	2.8966	2.6735	2.8509	2.9055	2.6724
Fault 1 signals	x_3	2.5096	2.4037	2.2504	2.3163	2.1314	2.0842	2.3279	2.2248
	x_4	2.5829	2.3235	2.4005	2.21	2.407	2.4608	2.4416	2.3337
Fault 2 signals	x_5	2.6502	2.4139	2.7651	2.5313	2.5766	2.562	2.7644	2.6579
	x_6	3.2081	2.4722	2.6081	2.6038	2.5056	2.4823	2.7528	2.5551
Strange sample	x_7	3.1673	2.6537	2.7004	2.5732	2.7295	2.6114	2.6491	2.4844

Careful contrast of the wavelet packet energy entropy values of each frequency band in three working conditions of HSA shows up some obviously differences. But in the same kind of state, each group signal features are very close, and it exists similarities between them. The characteristics of the normal state are distributed uniformly, and each group energy entropies of fault 1 and fault 2 are clearly smaller than the normal state, and the distribution of them is more scattered, which indicates the energy distribution of each frequency band at these two fault states is interferenced by a certain degree. In addition, it also can be found energy entropy values of fault 1 are generally less than the fault 2. Accordingly the description of table 1, wavelet packet energy entropy can be used as the feature parameters of HAS for fault identification and diagnosis.

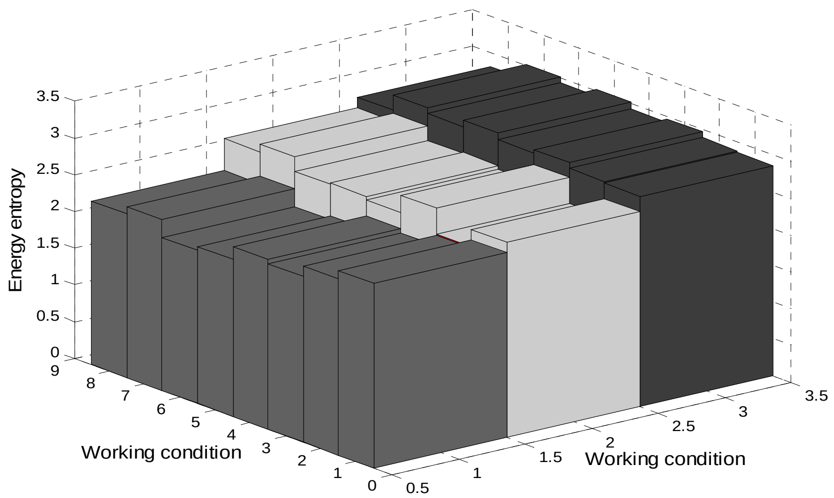


Figure 4. Three-dimensional histogram

Selecting any one group feature vector from each state in Table 1, and they are used to plot a three-dimensional histogram, shown in Figure 4. Where "1", "2", "3" in the x-axis respectively represents fault 1, fault 2 and normal state, digits 1-8 shown in the y-axis express eight frequency bands after wavelet packet decomposition with three levels, and z-axis represents corresponding energy entropy of each frequency band in each state. The differences of energy entropy in three states are more intuitively seen from the figure 4. The energy entropies in normal state are generally higher than other two fault states, especially in frequency band 3, 4, 5 6, 7 i.e. corresponding H2, H3, H4, H5, H6, the differences are most significant, and in another frequency bands it also has a little of differences. Thence the wavelet packet energy entropy as the characteristic parameters of HSA for fault diagnosis is reasonable.

3.3. Cluster Analysis and Results

According to the previously mentioned fuzzy clustering algorithm, the source code was programmed with computer software. Then, the feature vectors extracted from the vibration signals were constituted into a sample set of fuzzy clustering, as shown in Table 1. Finally, processing the feature vectors using equation (4) and formula (5), then the fuzzy equivalent matrix R^* can be acquired under the reconstructed method of transitive closure and is given by:

$$R^* = \begin{bmatrix} 1.0000 & 0.8340 & 0.7127 & 0.7127 & 0.7127 & 0.7127 & 0.7127 \\ 0.8340 & 1.0000 & 0.7127 & 0.7127 & 0.7127 & 0.7127 & 0.7127 \\ 0.7127 & 0.7127 & 1.0000 & 0.7962 & 0.7143 & 0.7143 & 0.7143 \\ 0.7127 & 0.7127 & 0.7962 & 1.0000 & 0.7143 & 0.7143 & 0.7143 \\ 0.7127 & 0.7127 & 0.7143 & 0.7143 & 1.0000 & 0.7583 & 0.7583 \\ 0.7127 & 0.7127 & 0.7143 & 0.7143 & 0.7583 & 1.0000 & 0.8609 \\ 0.7127 & 0.7127 & 0.7143 & 0.7143 & 0.7583 & 0.8609 & 1.0000 \end{bmatrix} \tag{7}$$

Then using the truncated matrix method to analyze the fuzzy equivalent matrix R^*, the analysis results show that the classification result is accurate when $\lambda \in (0.7143,\ 0.7583)$. Moreover when $\lambda = 0.7583$, the classification result is most detailed, the corresponding sectional matrix $R^*_{\lambda=0.7583}$ is as follows:

$$R^*_{\lambda=0.7583} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix} \tag{8}$$

From $R^*_{\lambda=0.7583}$, it can be seen that the samples are clearly divided into three categories: $\{x_1, x_2\}$, $\{x_3, x_4\}$ and $\{x_5, x_6, x_7\}$, where x_1, x_2 belong to the normal state, x3 and x4 belong to fault 1, x5, x6 and the strange sample x7 are all fault 2 signals, it is visibly that the standard samples can been classified accurately into three categories by sectional matrix $R^*_{\lambda=0.7583}$ and the strange sample can also be identified exactly.

The method of feature extraction and fuzzy cluster algorithm proposed above show that the wavelet packet energy entropy can be used as the feature characteristic of HAS for fault diagnoses and identification, and the clustering algorithm can identify the fault state effectively, which further illustrate the wavelet packet energy entropy used as the characteristic parameters of HAS for fault diagnosis is feasible. The integrated of the feature extraction method of energy entropy and the data acquisition system, and the features extracted in this experiment are established as a standard database sample, we can achieve real-time testing for early fault and present a reference method of fault diagnose for HAS.

4. Conclusion

Firstly, the proposed feature extraction method of wavelet packet energy entropy is very effective, and we can see that there are clear differences in energy entropies of three working conditions of HAS. So it is reasonable to use wavelet packet energy entropy as feature values, and which also provides a theoretical foundation for fault diagnose of HAS.

Secondly, the sample set can be classified by selected threshold value λ with fuzzy cluster algorithm, and the strange sample can also be identified, which further indicates this feature extraction method is valid.

Finally, the experimental results obtained in this study provide a reliable data for early fault detection and diagnose of HSA. Meanwhile the proposed method could also supply a certain reference value for fault feature extraction, faults diagnose and maintenance of other type automaton.

Acknowledgment

This research was supported by National Natural Science Foundation of China (Grant No. 51175480).

References

[1] Su Wensheng, Wang Fengtao, Zhu Hong, et al. Feature Extraction of Rolling Element Bearing Fault Using Wavelet Packet Sample Entropy. *Journal of Vibration, Measurement & Diagnosis*. 2011; 31(2): 162-166.

[2] HU Jiashun, Feng Xin, LI Xin, et al. State-of-Art of Vibration Analysis and Crack Identification of Cracked Beams. *Journal of Vibration and Shock*. 2007; 26(11): 146-152.

[3] Yaguo Lei, Zhengjia He, Yanyang Zi. A new approach to intelligent fault diagnosis of rotating machinery. *Expert Systems with Applications*. 2008; 35: 1593-1600.

[4] Anthony J, Bishara, B, Keith P. Multinomial process tree models of control and automaticity in weapon misidentification. *Journal of Experimental Social Psychology*. 2009; 45: 524-534.

[5] Li Qiang, Wang Taiyong, Leng Yonggang. Engineering signal processing based on adaptive step-changed stochastic resonance. *Mechanical Systems and Signal Processing*. 2007; 21: 2267-2279.

[6] Xu Yuxiu, Yuan Peixin, Yang Wenping. Fault Diagnosis fractal and wavelet method of Complex Machine. Edition 1. Beijing: China Machine Press, 2003.

[7] Cheng Zhengxing. Wavelet Analysis Algorithm and Application. Xi'an-Xi'an Jiaotong University Press, 1998.

[8] Xie Ping, Du Yihao, Huang Shuangfeng. Research On Non-linear Feature Extracting Method Of Complex Mechanical System Based On Information Entropy. *Journal of Vibration and Shock*. 2008; 27(7): 135-137.

[9] Wei Feng, Wenxing Bao. A New Technology of Remote Sensing Image Fusion. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(3): 551-556.

[10] Li Sheng, Xue Huijun, Lu Guohua, et al. Enhancement of non-air conducted speech based on wavelet-packet adaptive threshold. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013: 130-135.

[11] C Li, Z Song, P Li. *Bearing fault detection via wavelet packet transform and rough set theory.* Proceedings of Fifth World Congress on Intelligent Control and Automation. 2004: 1663–1666.

[12] E Ortiz, V Syrmos. Support vector machines and wavelet packet analysis for fault detection and identification. *IJCNN 06. International Joint Conference on Neural Networks*. 2006: 3449–3456.

[13] GG Yen, KC Lin. Wavelet packet feature extraction for vibration monitoring. *IEEE Transactions on Industrial Electronics*. 2000; 47: 650–667

[14] Chen weigen, Deng Bangfei. Applying wavelet packet energy entropy and neural networks to diagnose circuit breaker faults. *Journal of Chongqing University*. 2008; 31(7): 744-748.

[15] Gui Zhonghua, Han Fengqin. *Neural network based on wavelet packet-characteristic entropy for fault diagnosis of draft tube*. Proceeding of the CSEE. 2005; 25(4): 99-102 (in Chinese).

[16] He Zhengyou, Cai Yumei, Qian Qingquan. *A study of wavelet entropy theory and its application in electric power system fault detection*. Proceeding of the CSEE. 2005; 25(5): 38-43.

[17] Yang Lunbiao, Gao Yingyi. The fuzzy mathematical principles and applications. Guangzhou: South China University of Technology Press; 2005.

[18] Li Hongji.The fuzzy mathematical foundation and practical algorithm. Beijing: Science Press; 2005.

[19] Yao Zhuting, Pan Hongxia. Application of wavelet package analysis on fault diagnosis of vehicle. International Symposium on Test and Measurement (ISTM). Beijing: Published and Distributed by International Academic Publishers Beijing World Publishing Corporation; 2003.