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Research Article

Rolling Bearing Diagnosing Method Based on Time Domain Analysis and Adaptive Fuzzy C-Means Clustering

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Vibration signal analysis is one of the most effective methods for mechanical fault diagnosis. Available part of the information is always concealed in component noise, which makes it much more difficult to detect the defection, especially at early stage of the development. This paper presents a new approach for mechanical fault diagnosis based on time domain analysis and adaptive fuzzy C-means clustering. By analyzing vibration signal collected, nine common time domain parameters are calculated. This lot of data constitutes data matrix as characteristic vectors to be detected. And using adaptive fuzzy C-means clustering, the optimal clustering number can be gotten then to recognize different fault types. Moreover, five parameters, including variance, RMS, kurtosis, skewness, and crest factor, of the nine are selected as the new eigenvector matrix to be clustered for more optimal clustering performance. The test results demonstrate that the proposed approach has a sensitive reflection towards fault identifications, including slight fault.

1. Introduction

Rolling bearing element is a key component in engineering machinery and any slight damage may lead to unexpected suspension of production, even industrial accidents. Common bearing faults develop for variety of reasons, such as unpredictable heavy loads and insufficient lubrication. It is of vital importance to know its defect before it is too late. As a rule, faults, which often occur in rolling elements, such as the ball and inner and outer race, generate and grow during bearing operation. It is very necessary to diagnose faults at early stage of their development. So far, for lack of cyclostationarity [1] of the vibration signal, a number of diagnosis methods have been proposed, which are variedly classified as vibration analysis [2], wear debris detection [3], current and temperature monitoring [4], and so on. Acoustic emission (AE) [5] is considered as one of the most effective acoustic-based bearing health monitoring techniques. It is a high frequency, transient impulse emitted by the rapid local stress redistributions in solid material under working load conditions. Examples of AE applications are crack growth, corrosion, and wear [6]. Compared to other methods, it has special advantages, but the situation that no acoustic emission signal will be detected for a stable defection limits its application.

Vibration analysis, another one of the most effective rolling bearing fault diagnosis techniques, hops off the limitation of AE. A periodic shock impulse appears every time one component contacts another if there is a local fault. It is vibration analysis that makes the detection of the fault quantitatively. Time domain analysis, frequency domain analysis, and time-frequency domain analysis are the three main branches. Time domain analysis has the disadvantages of low sensitivity and low accuracy, but its simple calculations and direct signal processing contribute to shortening of the processing time. Simple time domain method is not suitable for effective fault diagnosis, but it is much better when combined with other approaches, for example, neural network [7], pattern recognition, and artificial intelligence. Muralidharan et al. [8] finished fault diagnosis of self-aligning carrying idler in different conditions, by using statistical measures to get useful features and then to classify them with decision tree algorithm.

Frequency domain analysis, also called spectral analysis, is used to transform the signals acquired from time domain into frequency domain through fast Fourier transform (FFT). Each component of bearing has a fault characteristic frequency calculated according to a series of empirical formulas. Monitoring these fault characteristic frequencies and their low-frequency harmonics is a classic method for bearing fault diagnosis [9]. However, the background noise makes it difficult to identify valid frequency component. To weaken the noise level and strengthen the signal to noise ratio, researchers have adopted some new approaches, like amplitude spectrum, power spectrum, cepstrum, and Hilbert demodulation [10–13], for bearing detection. However, the accuracy of these methods highly depends on the bearing dimensions and rotational speed [6].

Time-frequency analysis provides the joint distribution information of time and frequency domain, which clearly illustrates frequency of the signal varying as a function of time. To characterize the energy intensity of one signal at different time and frequency, a variety of approaches have been proposed, such as short time Fourier transform [14], Wigner-Ville distribution [15], and continuous wavelet transform [16]. However, the computation of these methods takes too much time so that the classification process becomes more complicated. Though a lot of researches have been carried out in the field of fault diagnosis, it is evident that very few literatures reported the enhancement of the algorithms to effectively recognize faults of micro size.

In order to analyze the vibration signal, new unpitched sound would be unexpectedly added by complex approaches to weaken the original noise, either frequency domain analysis or time-frequency analysis, which makes it difficult to detect micro fault. Hence, relatively original time domain analysis method becomes a potential one for micro size fault. Moreover, more reliable and robust diagnoses will be acquired if multiple methods associated with vibration analysis like fuzzy C-means (FCM) clustering and singular entropy. Fuzzy C-means clustering is a clustering algorithm based on division, ensuring the maximal similarity among the data points divided into one cluster and minimum similarity among different clusters. Furthermore, feature weighted FCM cluster analysis [17] is applied to recognize different fault categories and fault severities but no exposition about the corresponding relationship between fault category and clustering center. X. He and Q. He [18] proposed a fault diagnosis approach based upon principal component analysis (PCA) method and fuzzy C-means (FCM) clustering. However, it is stretched thin by the case of unpredictable operating conditions.

The present paper proposes a new method based on time domain analysis and adaptive fuzzy C-means clustering. Nine feature parameters of the vibration signals are extracted as the eigenvectors to be clustered. Then these data points will be separated into different piles using the adaptive algorithm. To further bear fault related feature extraction from the signal, five parameters of the nine are selected as the new eigenvector matrix to be clustered. And the experiment results showed the validity and robustness of the method in the application of fault detection of micro size, which would be potential for diagnosing faults at early stage of their development.

2. Theoretical Basis of the Analysis

2.1. Time Domain Feature Parameters. As we know, acquired vibration signal is amplitude as a function of time. Its mean equals the average value of the absolute value of amplitude, which is calculated as

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n}\left|x_i\right|. \tag{1}$$

Variance, a physical quantity which reflected stability level of data, is the average of quadratic summation, which sums the square value of difference value of each data and the mean:

$$X_{\text{var}} = \frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{X}\right)^2. \tag{2}$$

Standard deviation shows dispersion of a group of data with respect to the mean, and its magnitude equals arithmetic mean value of the variance.

Root mean square (RMS) indicates the energy of the signal and has a positive effect on wear fault and a weak sensitivity to early fault. Consider

$$X_{\text{RMS}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}. \tag{3}$$

Kurtosis reflects the characteristic of random variable distribution, and the kurtosis value of bearing vibration signal generally varies between 3 and 45. It indicates that there is a certain degree of damage when the value is up to 4. Compared with RMS, kurtosis is sensitive to early fault; expect its poor stability. Consider

$$X_{\text{kur}} = \frac{1}{n}\frac{\sum_{i=1}^{n}x_i^4}{X_{\text{RMS}}^4}. \tag{4}$$

Peak, maximum amplitude at some time, is always used to detect breakdown accompanied by instantaneous impact. Consider

$$X_p = \frac{1}{n}\sum_{i=1}^{n}X_{pi}. \tag{5}$$

Crest factor is defined as the ratio of peak value and RMS. The threshold value to judge physical condition of bearing is approximately 1.5. Generally speaking, there is local defect if the crest factor value exceeds 1.5 [19]. Consider

$$X_{\text{cf}} = \frac{X_p}{X_{\text{RMS}}}. \tag{6}$$

Skewness is the characteristic parameter to attribute asymmetry degree of probability density curve relative to the mean. Skewness is, by definition, the order three standard moments of the sample. Consider

$$X_{\text{skew}} = E\left[\left(\frac{x-\mu}{\sigma}\right)^3\right]. \quad (7)$$

Kurtosis [19, 20] is a measure of the heaviness of the tails in the distribution of the signal. It is the non-Gaussianity of the signal that makes the tails of the distribution heavier and destroys the symmetry of the distribution, resulting in high values of the kurtosis parameter, which is suitable for flaking failures. Crest factor [19] is usually used for faults like local spalling, scratching, and nick. The two above have a good sensitivity for discrete faults and are unacted on bearing rotating speed, dimension, and load. Skewness [21] is a measure of the asymmetry of the data around the mean. Variance [21] and RMS [19] have well reliability on continuous faults like wearing. In general, kurtosis and crest factor are used for discrete faults, while variance and RMS are used for continuous faults. Hence, the five time domain parameters were picked out for the consideration of the complement among different types of parameters and also the gains of the same type. According to their complementarity and consistency, the optimal combination contained with five parameters (variance, RMS, kurtosis, skewness, and crest factor) was selected as the eigenvector matrix to be clustered.

2.2. Adaptive Fuzzy C-Means Clustering. The aim to cluster is to get as large between-class distance and as small in-class distance as possible when classifying data. To avoid the validation problem of giving the number of clusters in advance, adaptive fuzzy C-means clustering is applied, and its basic idea is as follows.

The central vector of population sample is calculated as

$$\overline{x} = \frac{\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} x_j}{n}. \quad (8)$$

Membership matrix $U^{(k)}$ is calculated as

$$u_{ij}^{(k)} = \frac{1}{\sum_{r=1}^{c}\left(d_{ij}^{(k)}/d_{rj}^{(k)}\right)^{2/(m-1)}}. \quad (9)$$

Clustering center matrix $V^{(k+1)}$ is calculated as

$$v_i^{(k+1)} = \frac{\sum_{j=1}^{n}\left(u_{ij}^{(k)}\right)^m x_j}{\sum_{j=1}^{n}\left(u_{ij}^{(k)}\right)^m}. \quad (10)$$

Adaptive function of clustering-C is as follows:

$$L(c) = \frac{\sum_{i=1}^{c}\left(\sum_{j=1}^{n} u_{ij}^{m}\right)\left\|v_i-\overline{x}\right\|^2/(c-1)}{\sum_{i=1}^{c}\left(\sum_{j=1}^{n} u_{ij}^{m}\right)\left\|x_j-v_i\right\|^2/(n-c)}. \quad (11)$$

In function (11), the numerator shows between-class distance, while the denominator shows in-class distance. It is obvious that the larger $L(c)$ would get, the more reasonable clustering would be. Figure 1 shows the adaptive process of clustering number-C.

3. Experimental Analysis and Verification

3.1. Data Sources. The data is from the Case Western Reserve University Bearing Data Center Website, which provides access to ball bearing test data for normal and faulty bearings. As shown in Figure 2, the test stand consists of a 2 hp motor, a dynamometer, and control electronics (not shown). Testing bearing, located in the driving end, is deep groove ball bearing of SKF6205. Single point faults are introduced to the test bearings using electrical discharge machining, and accelerometers are attached to the housing with magnetic bases to collect vibration data.

3.2. Diagnosis in Condition of Nine Time Domain Parameters. Analysis based upon four cases of bearing conditions (health, inner race, ball, and outer race) is conducted. There are 28 groups of signals for four bearing conditions and two fault diameters of 0.007 inches and 0.014 inches. The sample frequency is 12 kHz. Nine statistic parameters at time domain of the 28 groups of vibration signals are shown in Table 1.

In allusion to four types of bearing signals, a 9×16 data matrix (9 means nine time domain feature parameters and 16 represents the fact that there are four groups of signal data for each bearing condition and the total is sixteen) is constituted to be the eigenvector matrix for clustering analysis after taking 16 groups of signals as a data sample. In the course of clustering analysis, $\varepsilon = 0.001$, the center of clustering is being constantly revised through iterative algorithm until convergence. As shown in Figure 3, 16 groups of signals are clustered into four sorts, which represents four conditions of bearing, and accordingly adaptive function of clustering-C in Table 2 values the maximum only when the number clustering is four, which means consistent results. Sixteen groups of sample data distribute around four clustering centers, each of which denotes one kind of bearing condition. It evolves that the diagnosing method proposed in the paper has good effects on the recognition of mechanical fault. In fact, there are many alternative array modes for a 9×16 data matrix from the 28 groups of data, and the rate of accurate diagnosing is not as satisfying as we have expected after dozens of experiments.

3.3. Diagnosis in Condition of Five Optimal Time Domain Parameters. In the previous section, because of the data redundancy of different parameters, nonideal bunching result was gotten in Figure 3, where sample data of the same bearing condition is not in such concentrating distribution. Meanwhile, adaptive function of clustering-C in Table 2 did not occupy obvious advantages with respect to the situation of 5 clusters, which probably implied poor robustness.

Effective feature parameters should be chosen to constitute the new eigenvector matrix. For further study, two 5×16 data matrices (5 means five time domain feature parameters and 16 represents the fact that there are four groups of signal data for each bearing condition and the total is sixteen) are constituted to be the eigenvector matrix for clustering analysis after taking 16 groups of signals as a data sample. One is for the fault size of 0.014 inches, and

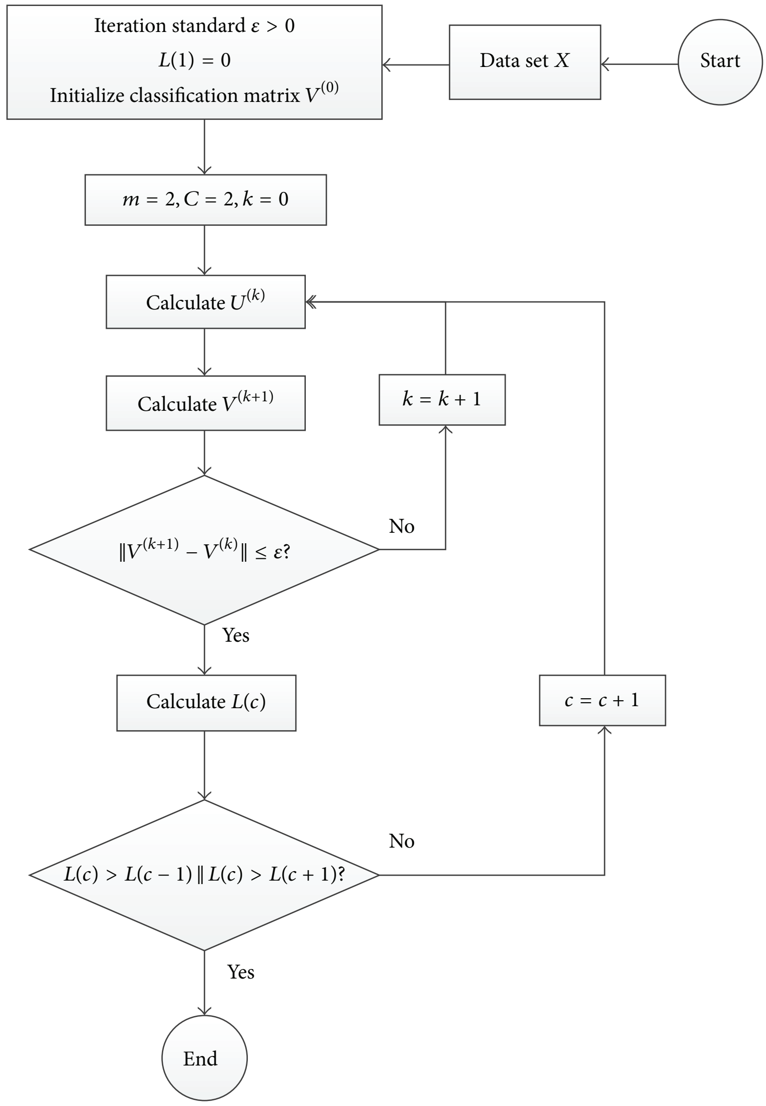


Figure 1: Adaptive fuzzy C-means clustering flow chart.

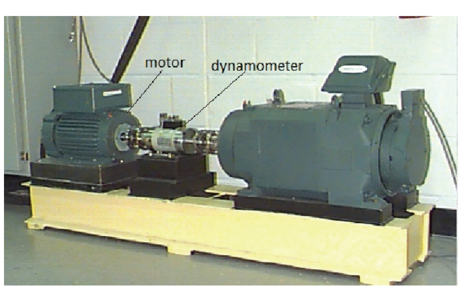


Figure 2: The test stand (bearing data center of CWRU).

the other is for the fault size of 0.007 inches. As shown in Figure 4(a), 16 data sets (0.014 inches), which contained four bearing conditions of health, inner race, ball, and outer race, were divided into four groups, one of which means one bearing condition, and the clustering functions in Table 3 verify the availability of the clustering. The other 16 data sets (0.007 inches) in Figure 4(b) were clearly clustered into four piles.

There is no obvious aliasing phenomenon among different distributed data in Figure 4, which shows the two different cases when the defection is of, respectively, micro size of 0.007 inches and 0.014 inches. Obviously, four types of bearing conditions could be easily identified from Figure 4 and corresponding data points gathered together around the four clustering centers. Moreover, the fact that adaptive clustering-C function $L(c)$ gets the value at $c = 4$ much larger than others in Tables 3 and 4 declared the validity and rationality of the new eigenvector matrix of the five parameters.

Then, the method with five-parameter feature matrix was applied to the situation of single fault. Thereinto, the diagnosis of inner and outer race single fault of 0.007 inches was shown in Figure 5. The result shown in Figure 5 and

Table 1: Statistic parameters in time domain of the vibration signals.

Fault diameter (inch)	Name	Mean	Var.	RMS	Median	Kur.	Skew.	Std.	Peak	Crest
0	H-P0	0.0126	0.0053	0.0738	0.0125	2.7642	−0.0354	0.0727	0.0765	1.0372
0	H-P1	0.0126	0.0042	0.0664	0.0150	2.9306	−0.1730	0.0652	0.0578	0.8708
0	H-P2	0.0123	0.0040	0.0643	0.0146	2.9251	−0.1671	0.0631	0.0592	0.9196
0	H-P3	0.0125	0.0042	0.0659	0.0144	2.9572	−0.1275	0.0647	0.0613	0.9297
0.007	I7-P0	0.0134	0.0848	0.2915	0.0071	5.3959	0.1640	0.2912	0.2750	0.9432
0.007	I7-P1	0.0058	0.0858	0.2929	−0.0003	5.5423	0.1304	0.2928	0.2687	0.9173
0.007	I7-P2	0.0046	0.0897	0.2995	0.0013	5.5638	0.0904	0.2995	0.2728	0.9107
0.007	I7-P3	0.0047	0.0983	0.3136	0.0023	5.2911	−0.0132	0.3136	0.2892	0.9222
0.007	B7-P0	0.0126	0.0192	0.1392	0.0128	2.9847	−0.0089	0.1387	0.1597	1.1473
0.007	B7-P1	0.0039	0.0193	0.1391	0.0037	2.9638	0.0075	0.1390	0.1529	1.0994
0.007	B7-P2	0.0046	0.0217	0.1473	0.0039	2.8314	0.0271	0.1472	0.1628	1.1054
0.007	B7-P3	0.0042	0.0236	0.1536	0.0037	2.8897	0.0204	0.1536	0.1669	1.0861
0.007	O7-P0	0.0232	0.4477	0.6695	0.0219	7.6494	0.0569	0.6691	0.5767	0.8614
0.007	O7-P1	0.0041	0.3504	0.5919	0.0004	7.5950	0.0334	0.5919	0.5128	0.8663
0.007	O7-P2	0.0039	0.3251	0.5702	0.0032	7.8522	0.0195	0.5702	0.4780	0.8383
0.007	O7-P3	0.0045	0.3368	0.5804	0.0037	7.9637	−0.0021	0.5804	0.4857	0.8369
0.014	I14-P0	0.0344	0.0380	0.1978	0.0339	21.957	−0.0588	0.1948	0.1746	0.8824
0.014	I14-P1	0.0036	0.0274	0.1655	0.0031	22.084	0.0030	0.1655	0.1299	0.7849
0.014	I14-P2	0.0037	0.0266	0.1631	0.0026	21.686	0.0235	0.1630	0.1301	0.7976
0.014	I14-P3	0.0030	0.0327	0.1808	0.0034	18.164	0.0334	0.1808	0.1483	0.8203
0.014	B14-P0	0.0047	0.0233	0.1527	0.0045	17.769	0.2251	0.1526	0.1293	0.8469
0.014	B14-P1	0.0045	0.0198	0.1409	0.0041	8.8371	0.0157	0.1408	0.1255	0.8909
0.014	B14-P2	0.0046	0.0206	0.1435	0.0044	9.7522	0.1433	0.1434	0.1298	0.9049
0.014	B14-P3	0.0045	0.0179	0.1337	0.0065	14.859	0.1638	0.1336	0.1157	0.8652
0.014	O14-P0	0.0144	0.0099	0.1007	0.0142	3.0560	0.0006	0.0996	0.1121	1.1130
0.014	O14-P1	0.0031	0.0087	0.0936	0.0028	2.9403	0.0089	0.0935	0.0967	1.0339
0.014	O14-P2	0.0032	0.0094	0.0968	0.0035	3.0241	0.0002	0.0968	0.0992	1.0249
0.014	O14-P3	0.0025	0.0090	0.0947	0.0027	3.7970	0.0042	0.0947	0.0918	0.9691

Table 2: Adaptive clustering-C function for Figure 3.

c	1	2	3	4	5	6
$L(c)$	0	123.96	163.15	328.48	314.45	0

Tables 5 and 6 indicates that the method is able to recognize bearing fault of micro size, namely, at early stage of defection.

4. Result and Discussion

From the experiments above, we could know that the method proposed in this paper can be applied to diagnosis of bearing faults of micro size, no matter single or multiple faults.

Next, in order to verify the correction and superiority of the method, diagnosing method based on Hilbert transformation and wavelet denoising was applied to the same vibration signals of Figure 5. After preliminary calculation of empirical equation, the fault character frequencies of the inner race and outer race are 162.18 Hz and 107.37 Hz.

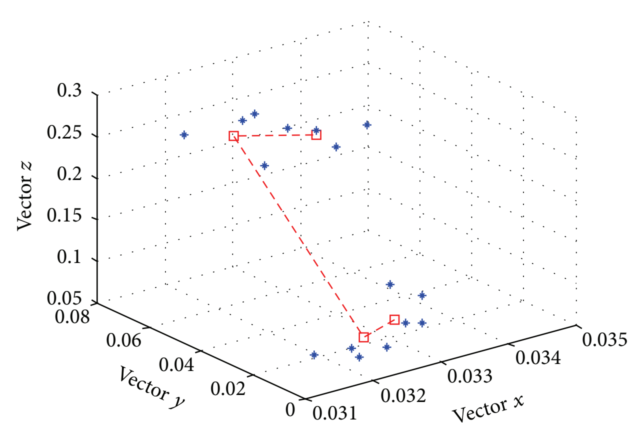
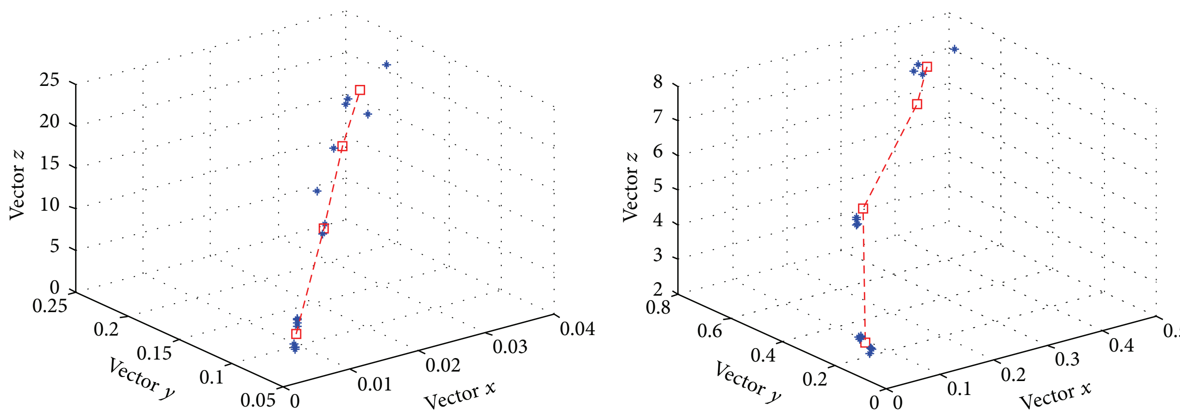


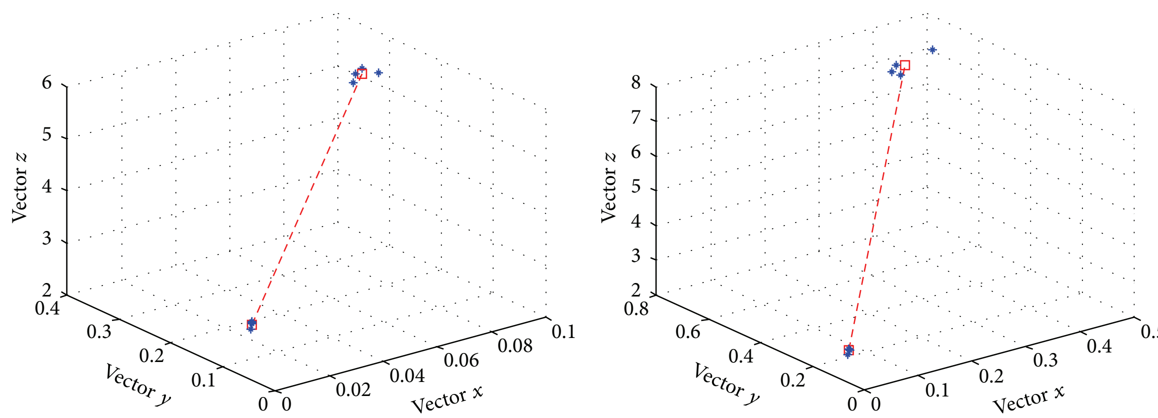
Figure 3: The 3D diagram of four types of bearing conditions (9×16 matrix).

The spectrogram after Hilbert envelope demodulation and wavelet denoising is displayed in Figure 6. As shown in



(a) The 3D clustering diagram (0.014 inches)
(b) The 3D clustering diagram (0.007 inches)

Figure 4: The 3D diagram of four types of bearing conditions with five parameters.



(a) The 3D clustering diagram (inner)
(b) The 3D clustering diagram (outer)

Figure 5: The 3D diagram of two types of bearing conditions.

Table 3: Adaptive clustering-C function for Figure 4(a).

c	1	2	3	4	5	6
$L(c)$	0	129.7	180.17	566.53	437.1	0

Table 4: Adaptive clustering-C function for Figure 4(b).

c	1	2	3	4	5	6
$L(c)$	0	13.30	38.06	531.49	165.06	0

Figure 6(a), the frequency domain diagnostic approach is able to detect the inner race point faults of 0.007 inches, except for several unfathomed frequency components. There is no evident frequency value and homologous frequency multiplication in the other diagram of Figure 6(b). The fact that no resultful information was extracted from the signal with noisy environment implies the shortage of the approach.

By contrast, the method present in this paper is an efficient and robust way to detect the micro size fault.

Table 5: Adaptive clustering-C function for Figure 5(a).

c	1	2	3	4
$L(c)$	0	671.69	498.06	0

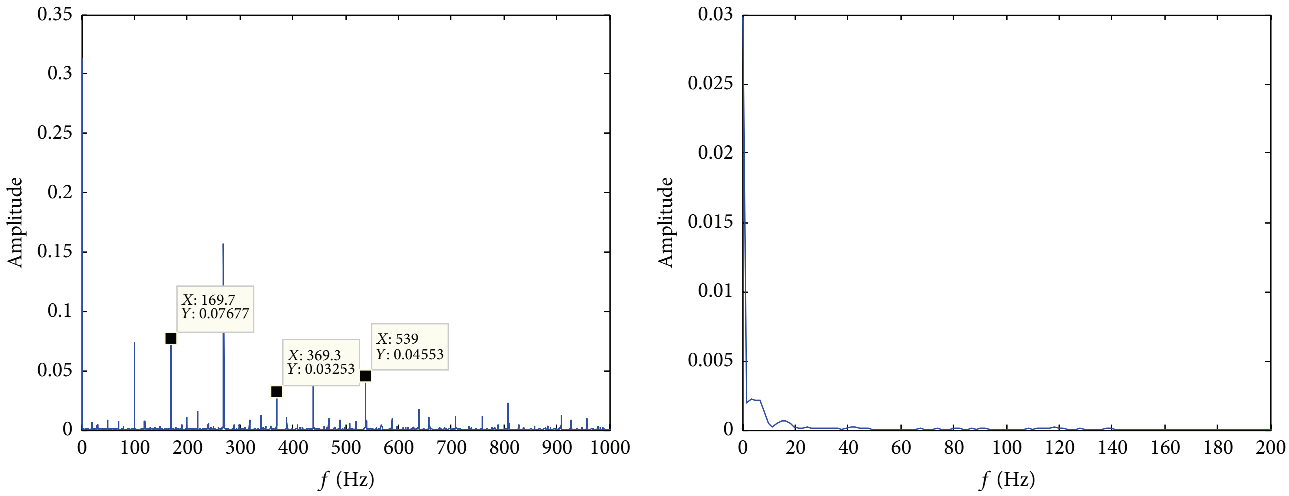
Table 6: Adaptive clustering-C function for Figure 5(b).

c	1	2	3	4
$L(c)$	0	1840.54	1074.56	0

5. Conclusion

Time domain analysis is a direct signal processing method with simple calculations, and each of the nine time domain parameters can reflect the different characteristics of the signal to be extracted as significant basis for initial diagnosis to some extent.

In this paper, a method based on time domain analysis and adaptive fuzzy C-means clustering was proposed. Judging by the complementarity and consistency of the nine time domain parameters, five of them, namely, variance,



(a) The spectrogram (inner)

(b) The spectrogram (outer)

Figure 6: The spectrogram of the fault signals (0.007 inches).

RMS, kurtosis, skewness, and crest factor, were selected as the feature matrix for clustering algorithm. Benefiting from the adaptivity of the clustering algorithm, unknown operating conditions of the bearing could be detected fast and accurately, to estimate whether the rolling bearing is healthy or not, even single fault or multiple faults. The experiments proved the validity and robustness of the method in the application of fault detection of micro size, which would be potential for diagnosing faults at early stage of their development.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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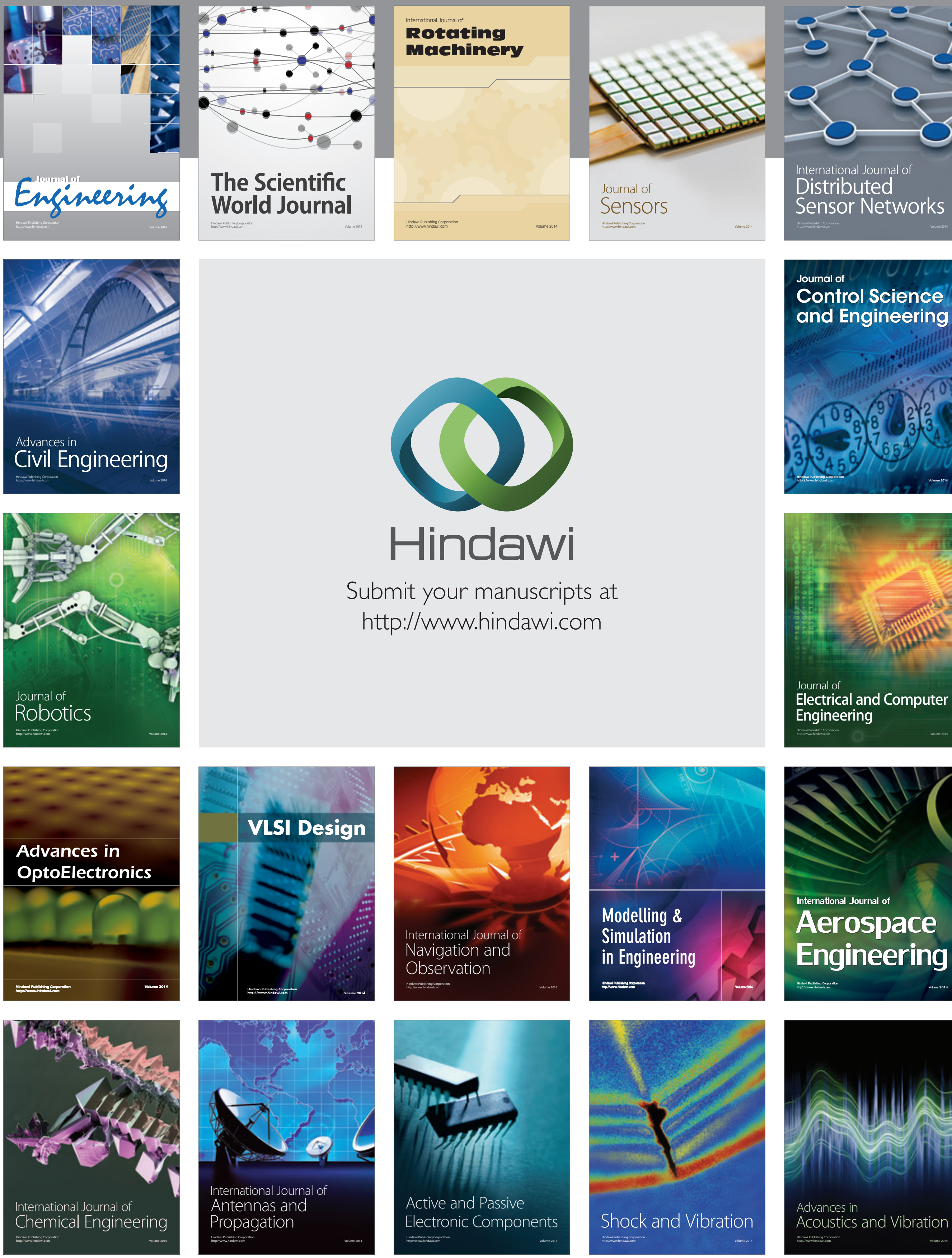
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