Multi-fault diagnosis of rolling bearing using fuzzy entropy of empirical mode decomposition, principal component analysis, and SOM neural network

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Multi-fault diagnosis of rolling bearing using fuzzy entropy of empirical mode decomposition, principal component analysis, and SOM neural network

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Abstract

The condition monitoring and multi-fault diagnosis of rolling bearing is a very important research content in the field of the rotating machinery health management. Most researches widely used empirical mode decomposition in tandem with principal component analysis which is applied for feature extraction. But this method may lead to imprecise classification. In this paper, we propose a new method of rolling bearing multi-fault diagnosis, by combining the fuzzy entropy of empirical mode decomposition, principal component analysis, and self-organizing map neural network. The empirical mode decomposition process allows the vibration signal to be decomposed into a series of intrinsic mode functions. For each intrinsic mode function, we obtained the fault feature information. The proposed approach combines the fuzzy function and sample entropy to obtain fuzzy entropy. By this combination, we can reflect the complexity and the irregularity in each intrinsic mode function component. The fuzzy entropy of empirical mode decomposition used to construct the vectors is defined as the input of the principal component analysis. This principal component analysis is used to reduce the dimension of the feature vectors. Finally, the reduced feature vectors are chosen as input of self-organizing map network for automatic fault diagnosis and fault classification. The obtained results show that the proposed approach makes it possible to correctly assess the degradation of rolling bearing and to obtain recognition of high-sensitivity defects for different types of bearing faults.

Keywords

Rolling bearing, empirical mode decomposition, fuzzy entropy, faults diagnosis, principal component analysis, fault classification, self-organizing map

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Introduction

Rotating machinery are considered to be a critical mechanical component in industrial applications in terms of economy, reliability, and safety. The rolling bearings are the most important and frequently used in rotating machinery; their defects usually lead to drop in plant productivity and may cause huge losses in economic field.[1,2] Therefore, to keep the bearings in good operation, it is important to diagnose their faults. Theoretically, rolling bearing fault diagnosis can be divided into three main parts: signal processing to extract the feature information vectors, pattern recognition, and classification according to the extracted fault feature vectors.[3] However, in our approach, we added a necessary step: feature reduction. These steps indicate correctly and efficiently the uncovered fault characteristics in the original signal, which has also an impact on the diagnostic processing and classification results. The variation of working conditions for bearings influences on the feature parameters and may even cause change in the diagnostic method.[4]

Nowadays, the majority of researchers analyze the vibration signal using many conventional methods such as Fourier Transform (FT), Wigner-Ville Distribution (WVD), Short-Time Fourier Transform (STFT), and Wavelet Transform (WT). The FT is

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applied only on linear systems and stationary signals.[5] Therefore, the FT becomes inappropriate for extracting the feature information as in our case, because the vibration signal of rolling bearing is characterized as nonstationary signals.[6] Thus, to analyze the process of nonstationary signals, there are many time-frequency methods such as WT, WVD, and STFT. Furthermore, these methods have limitations. The drawbacks of WVD may assume large negative values. Moreover, it presents some parasitic features called cross-terms interference.[7] The STFT principle's drawback is the finest time location and the best frequency resolution cannot be reached simultaneously. Meanwhile, although the WT has proved its superiority in processing nonstationary signals, it is difficult to choose wavelet base function and the number of levels.[8] Empirical mode decomposition (EMD) was firstly proposed by Huang et al.,[9] which is a temporal frequency analysis method. It has an advantage over the previous methods and it does not use basic functions such as WT where the vibration signal is decomposed into intrinsic mode functions (IMFs). The EMD method is a self-adaptive signal that can be reflected to the local signal feature at different time scales using functions as a filter bank.[10]

The theory of entropy has appeared in the thermodynamics field.[11] Recently, researchers have progressively used feature extraction of nonstationary signals. The sample entropy was proposed by Richman and Moorman[12] to measure the complexity and the similarity of time series domain. The process of sample entropy allows us to calculate the similarity of the time domain signals. It is either one or zero, but without intermediate values. Hence, the similarity degree of a time domain signal is mostly obscured, which leads to neglecting a large amount of information. To eliminate this vague, we should represent the similarity of time domain by a vague concept. The fuzzy entropy contains two functions, sample entropy and fuzzy membership function. This combination is used to measure the irregularity, complexity, and stability of the vibration signals.[13]

The obtained result from fuzzy entropy of EMD for different condition modes is more or less complex. Thus, to enhance the classification and dimensionality reduction, principal component analysis (PCA) can be used.[14] First, we decompose the vibration signal by EMD into IMFs. Then, we calculate the fuzzy entropy for each IMF. Finally, we reduce the dimensionality by using PCA. Moreover, the goal of PCA is to find a lower dimensional space by calculated principal components (PCs) using covariance matrix. In this context, the intelligent classification techniques such as artificial neural networks (ANNs) are widely used.[15]

The neural network self-organizing map (SOM) was introduced by Kohonen.[16] The SOM neural network learning without instructors has self-adaptive and self-learning characteristics.[17] The SOM neural network has the unique ability to efficiently create spatially organized internal representations of several input data characteristics, providing a topology that preserves the high-dimensional spatial map in only two-dimensional spaces.[18] The SOM feature can be used to separate neurons with small similarities, because the neurons with large similarities on the map are very close.[19] Therefore, the SOM is applied for automatic bearings defects identification and classification.

This paper proposes a reliable and improved multi-fault diagnosis for rolling bearings. This method is based on the combined fuzzy entropy of EMD, PCA, and the SOM neural network. The paper is organized as follows: The following section introduces the diagnosis principle of the proposed approach. The next section presents fault identification and classification schemes. The penultimate section shows the experimental benchmark description. The final section presents the obtained results with comments and conclusion.

Fault feature extraction based on fuzzy entropy of EMD

The rolling bearing diagnosis is divided in two main parts, feature extraction and fault classification. During the fault diagnosis, the fault features extraction is the most complicated step. This detected fault is then classified according to the extracted feature. The fault classification is applied when executing the fault feature extraction.

Time-frequency signal decomposition based on EMD

The EMD is used to extract the instantaneous frequency and amplitude data in nonstationary domain. The signal can be decomposed as follows:[20]

Step 1: Identify all the local extrema, and then connect all the local maxima by a cubic spline line as the upper envelope.

Step 2: Repeat the procedure for the local minima to produce the lower envelope. The upper and lower envelopes should cover all the data between them.

Step 3: The mean of upper and lower envelopes value is designated as $mn_1(t)$, and the difference between the signal $s(t)$ and $mn_{11}(t)$ is $h_1(t)$.

$$h_1(t) = s(t) - mn_1(t) \tag{1}$$

Step 4: If $h_1(t)$ is an IMF, then $h_1(t)$ is the first component of $s(t)$. When $h_1(t)$ is not IMF, repeat steps (1–3); we obtain

$$h_1(t) = s(t) - mn_{11}(t) \tag{2}$$

where $mn_{11}(t)$ is the mean of upper and lower envelopes value of $N_1(t)$.

Step 5: Repeat the operation until k times, $h_{1k}(t)$ becomes an IMF, that is

$$h_{1k}(t) = h_{(1k-1)}(t) - mn_{1k}(t) \tag{3}$$

Then, $l_1(t) = h_{1k}(t)$ is designated as the first IMF component from the original data. $l_1(t)$ should contain the finest scale or the shortest period component of the signal.

Step 6: Subtract $s(t)$ from $l_1(t)$, we obtain

$$R_1(t) = s(t) - l_1(t) \tag{4}$$

Step 8: Let us repeat the process as described above for n times, then n-$IMFs$ of signal $s(t)$ could be obtained. Then

$$\begin{aligned} &R_1(t) - l_2(t) = R_2(t) \\ &\dots \\ &R_{n-1}(t) - l_n(t) = R_n(t) \end{aligned} \tag{5}$$

Step 9: The decomposition process can be stopped when R_n becomes a monotonic function, from which no more IMF can be extracted. By summing up equations (4) and (5), we finally obtain

$$s(t) = \sum_{j=1}^{n} l_j(t) + R_n(t) \tag{6}$$

The $R_n(t)$ residue is the mean trend of $s(t)$.

Fuzzy entropy

The process of fuzzy entropy is used to measure the irregularity, complexity, and stability for each IMF component. The steps for the process of fuzzy entropy are as follows[21]:

Step 1: Assume that a time series is denoted as $IMF(i) = (\phi(1), \phi(2), \dots, \phi(N))$, where N is the length of times series. Then, the mean $u_0(t)$ of m consecutive $IMF(i)$ values can be calculated as follows

$$u_0(i) = \frac{1}{m} \sum_{j=0}^{m-1} \phi(i+j) \tag{7}$$

where parameter m is called the embedding dimension and is a positive integer. Then m-dimensional vector $A(i)(i = 1, 2, \dots, n - m + 1)$ is reconstructed as

$$A(i) = [\phi(i), \phi(i+1), \dots, \phi(i+m-1)] - u_0(i) \tag{8}$$

Step 2: The distances of each vector are calculated, and the distance between A_i and A_j can be defined as follows

$$d_{ij}^m(A_i, A_j) = \max(|A_i(k) - A_j(k)|) k = \{1, 2, \dots, m\} \tag{9}$$

Step 3: The similarity between each set of vectors is described using a fuzzy function. An exponential function is used, which is defined as follows

$$D_{ij}^m = e^{-\left(d_{ij}^m / r\right)^n} \tag{10}$$

where n *is* the boundary gradient of the exponential function and r *is* the similar tolerance.

Step 4: The representation function B^m is defined as follows

$$B^m = \frac{1}{N-m} \sum_{i=1}^{N-m} \left| \frac{1}{N-m-1} \sum_{j=1, j \neq i}^{N-m} D_{ij}^m \right| \tag{11}$$

Step 5: Make $m = m + 1$ and repeat step 1 to step 4; B^{m+1} can be obtained and the fuzzy entropy can be expressed as follows

$$fuzzyEn = \ln^{\left(B^m / B^{m+1}\right)} \tag{12}$$

Fault identification and classification based on PCA and SOM neural network

Principal component analysis

The PCA is a statistical analysis method that can be used to reduce the dimensionality of vectors. The PCA is based on finding the space, which represents the direction of the maximum variance of the given data. For a given feature vector, set $x_i = \{x_i, \dots, x_n\}, x_i \in R^n$ which consists of N feature vectors, each one with n dimensions, and the algorithm to extract critical features from the defect conditions is given as follows[22]:

Step 1: Calculate the average value

$$u = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{13}$$

Step 2: Subtract the mean from all samples

$$D_i = \frac{1}{N} \sum_{i=1}^{N} x_i - u \tag{14}$$

Step 3: Compute the covariance matrix

$$C = \frac{1}{N} \sum_{i=1}^{N} D_i D_i^T \tag{15}$$

Step 4: Compute the eigenvalues λ_i and eigenvectors of $v_i(i = 1, 2, \dots, n)$ of the covariance matrix.

$$Cv_i = \lambda_i v_i \tag{16}$$

Step 5: Sort the eigenvectors according to their corresponding eigenvalues.
Step 6: Select the eigenvectors that have the largest eigenvalues $V = \{v_1, v_2, \ldots, v_k\}$, which represent the projection space of PCA.
Step 7: All samples are projected on the lower dimensional space of PCA as defined.

$$P = V^T x \tag{17}$$

where P represents the first PCs. Then the goal is to find a lower dimensional space.

SOM neural network

The neural network SOM introduced by Kohonen is an unsupervised ANN (self-adaptive and self-learning). The SOM neural network has the unique ability to efficiently create spatially organized internal representations of several input data characteristics, providing a topology that preserves the high-dimensional map into only two-dimensional spaces. The SOM consists of input and output layers, as shown in Figure 1. The input layer contains many neurons which are determined by the number of vectors.

Each input layer is connected with an output layer by connection m and each one of these connections has a synaptic weight associated with it $w_k = \{w_{k1}, w_{k2}, \ldots w_{kd}\}$. Each neuron k on the maps is represented by m-dimensional and are connected by a neighborhood relation $P_k = \{P_{k1}, P_{k2}, \ldots P_{km}\}$.[23]

The SOM is trained frequently. Each stage of training, one vector of sample x of the input set is randomly selected and fed to the grid. The distance between all weight vectors from SOM is usually calculated using the Euclidean minimum distance after the weight vectors are formatted to a random value between 0 and 1. The best matching unit is the output neuron, whose weight vector is closest.[24]

$$c = \arg\max \|x - w_i\| \tag{18}$$

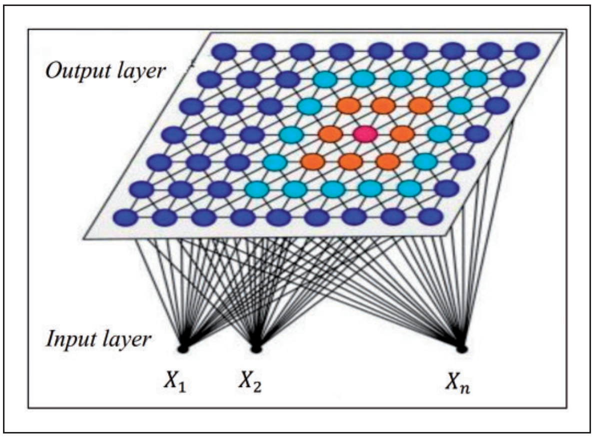

Figure 1. Structural model of self-organizing map neural network.

The weight vectors of the neurons that are close to the best matching unit in the network SOM are adjusted toward the input vector. The SOM weight updating rule of the unit is given as

$$w_i(t+1) = w_i(t) + [\alpha(t) h_{ci}(t)[x(t) - w_i(t)]] \tag{19}$$

where $x(t)$ represents the input vector at time t. The amount of weight vector movement is guided by a learning rate $\sigma(t)$ usually decreasing with time. h_{ci} is the neighborhood function between unit V and unit i. A typical choice is the following Gaussian function.[25]

$$h_{ci}(t) = e^{\left(-\|P_c(t) - P_i(t)\|^2 / 2\sigma(t)^2\right)} \tag{20}$$

$P_c(t)$ and $P_i(t)$ represent the nodes coordinate in the output space and h_{ci} is the neighborhood radius at time t.

Experimental description

In order to validate the efficacy of the proposed approach, we take into consideration the vibration signal data from Bearing Data Center of Case Western Reserve University.[26] The type and geometry of rolling bearing (6205-2RS-SKF, inside diameter 0.9843, outside diameter 2.0472, thickness 0.5906, ball diameter 0.3126, and pitch diameter 1.537) used in this experiment is shown in Figure 2.

The experimental benchmark consists of 1.5 kW motor, torque {sensor-encoder}, dynamo-meter, and electrical control devices. In this experience, the data are collected by various fault load conditions {0 HP (1797 r/min), 1 HP (1772 r/min), 2 HP (1750 r/min)} for the bearing. The vibration signals in various fault type conditions {normal, outer race, inner race, ball fault} are considered. For each fault type condition, the signals are categorized to 10 classes containing three fault loads (0, 1, and 2 HP) and two fault severities (0.007, 0.014 inches).

Table 1 shows the four-mode operation of rolling bearing, normal state, inner-race fault state, outer-race fault state, and ball fault state were considered. These data sets are divided into two sub-data sets to cover all the working conditions except the normal

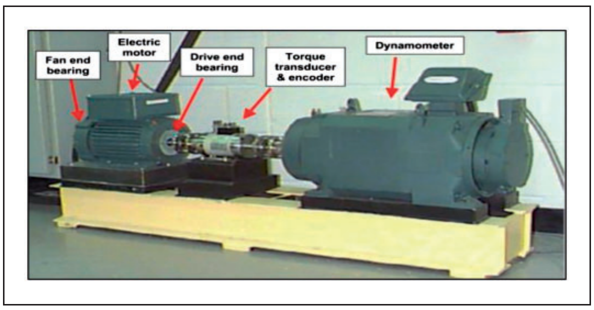

Figure 2. Experimental benchmark.

Table 1. Description of experimental data for bearing.

Label	Fault type	Fault diameter (inches)	Dimension vector	Working condition 0 HP	1 HP	2 HP
1	Normal	—	30	✓	✓	✓
2	Outer race fault	0.007	30	✓	✓	✓
3	Outer race fault	0.014	30	✓	✓	✓
4	Inner race fault	0.007	30	✓	✓	✓
5	Inner race fault	0.014	30	✓	✓	✓
6	Ball fault	0.007	30	✓	✓	✓
7	Ball fault	0.014	30	✓	✓	✓

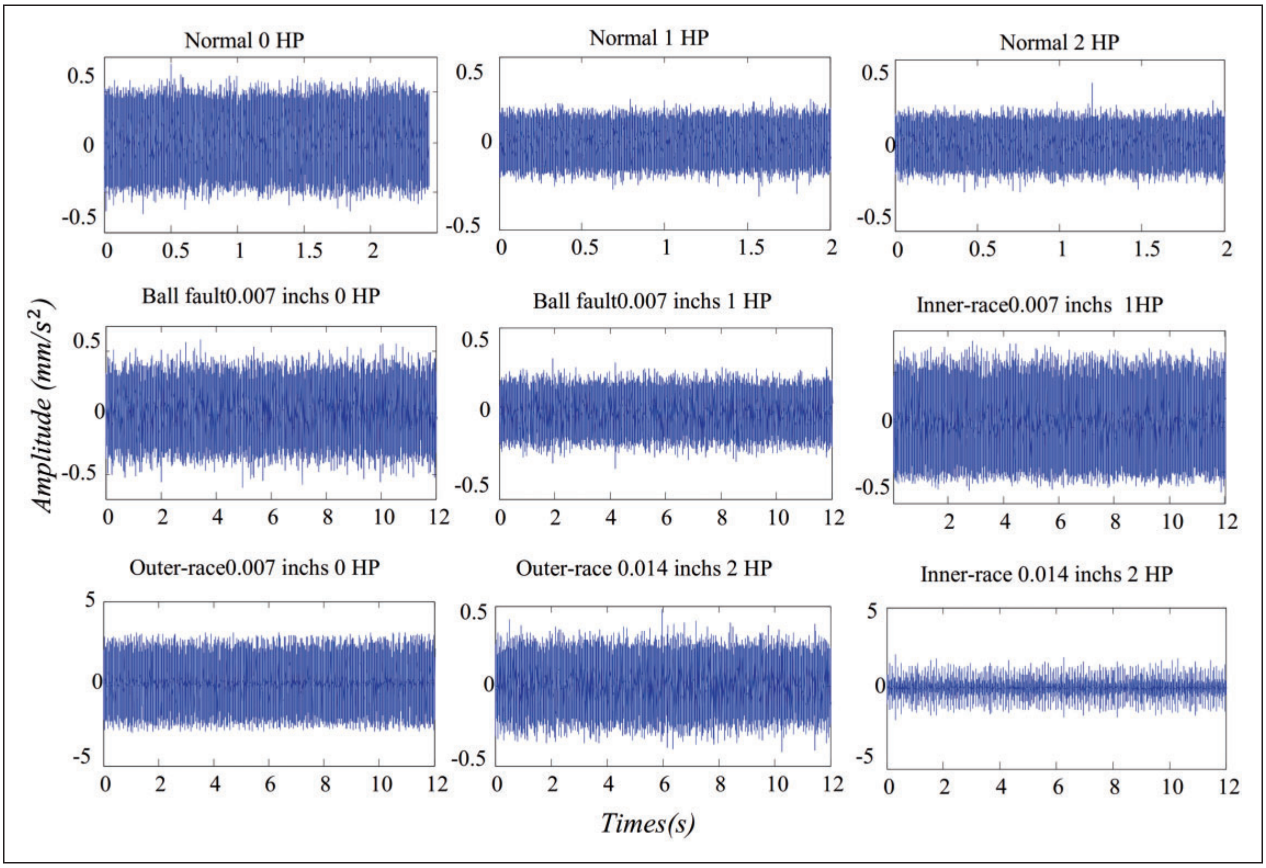

Figure 3. Vibration signals of different rolling bearing behaviors.

state. Each one of these sub data sets contains 30 groups of data. Therefore, we end up with seven data sets, which include 630 samples. The fault feature extraction based on fuzzy entropy of EMD, PCA, and SOM neural network is implemented for each sample.

As shown in Figure 3, the vibration acceleration signals of rolling bearing in different conditions modes, which represent the motor loads varying from 0, 1, and 2 HP, and different diameters (0.007, 0.014 inches) of normal modes, outer race fault, inner race fault, and ball fault are shown in Figure 3. It is shown in this figure that the vibration signals in the four conditions mode are highly complex, which lead to the incapability of making the difference between the faults in each situation.

Experimental results

The proposed method is based on the fuzzy entropy of EMD, PCA, and SOM network to diagnose the vibration signals. The four types of original signals for rolling bearing in different modes condition are

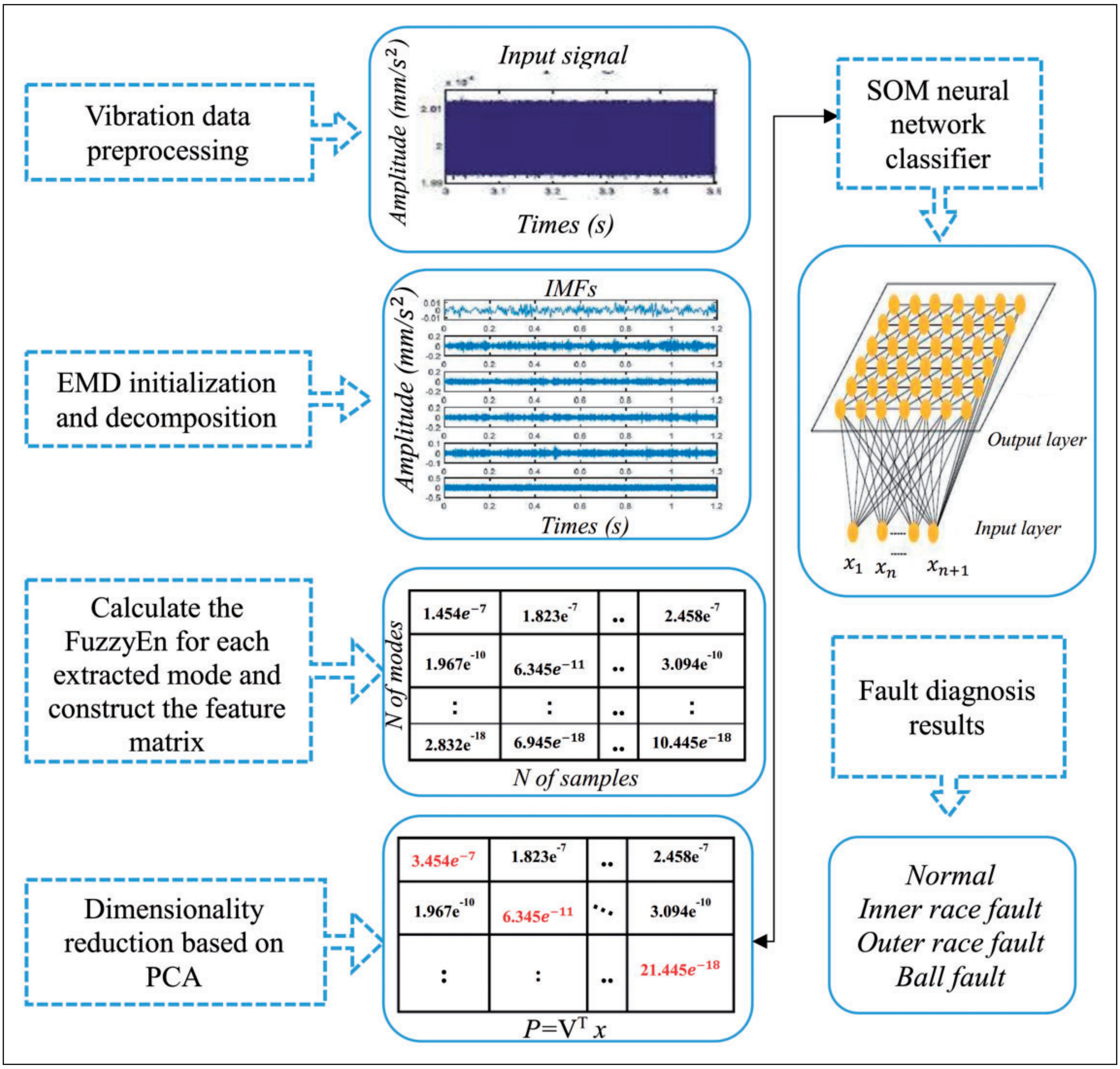

Figure 4. Flowchart of the proposed method.

decomposed into multiple IMF components. To show the process of EMD, we select the vibration signal of the outer race fault as an example. The obtained results of the vibration signal for the outer race fault are shown in Figure 5.

It can be seen in Figure 5 that the EMD method decomposed the vibration signal of the outer-race fault into 10 IMF components and a residual signal. Each IMF component includes information of instantaneous amplitude and frequency. Moreover, this decomposition is classified from high to low frequency. Rolling bearing fault can be detected during changing the feature information in each IMF component. Therefore, the fault feature information analyzed can be complex and vague. The fuzzy entropy is comprised of two functions, sample entropy and fuzzy membership functions. This combination is used to measure the irregularity, complexity, and stability of the vibration signals accurately.

The concept of fuzzy set is introduced by Lotfi Zedah. The fuzzy membership function is used to describe the similarity degree. The exponential function $D_{ij}^{m} = e^{-(d_{ij}^{m}/r)^{n}}$ is a type of fuzzy function employed to measure the similarity of two vectors. To calculate the process of fuzzy entropy, we need to determine the boundary gradient n, which represents the weight of vectors, the threshold tolerance r, which represents the width of the exponential function and the embedding dimension m, which represents the length of the compared vectors, thus the fuzzyEn can be estimated by (m, n, r, N). Notice the similarity for two vectors in sample entropy is based on the Heaviside function which leads to a kind of conventional two-state classifier. To calculate the process of

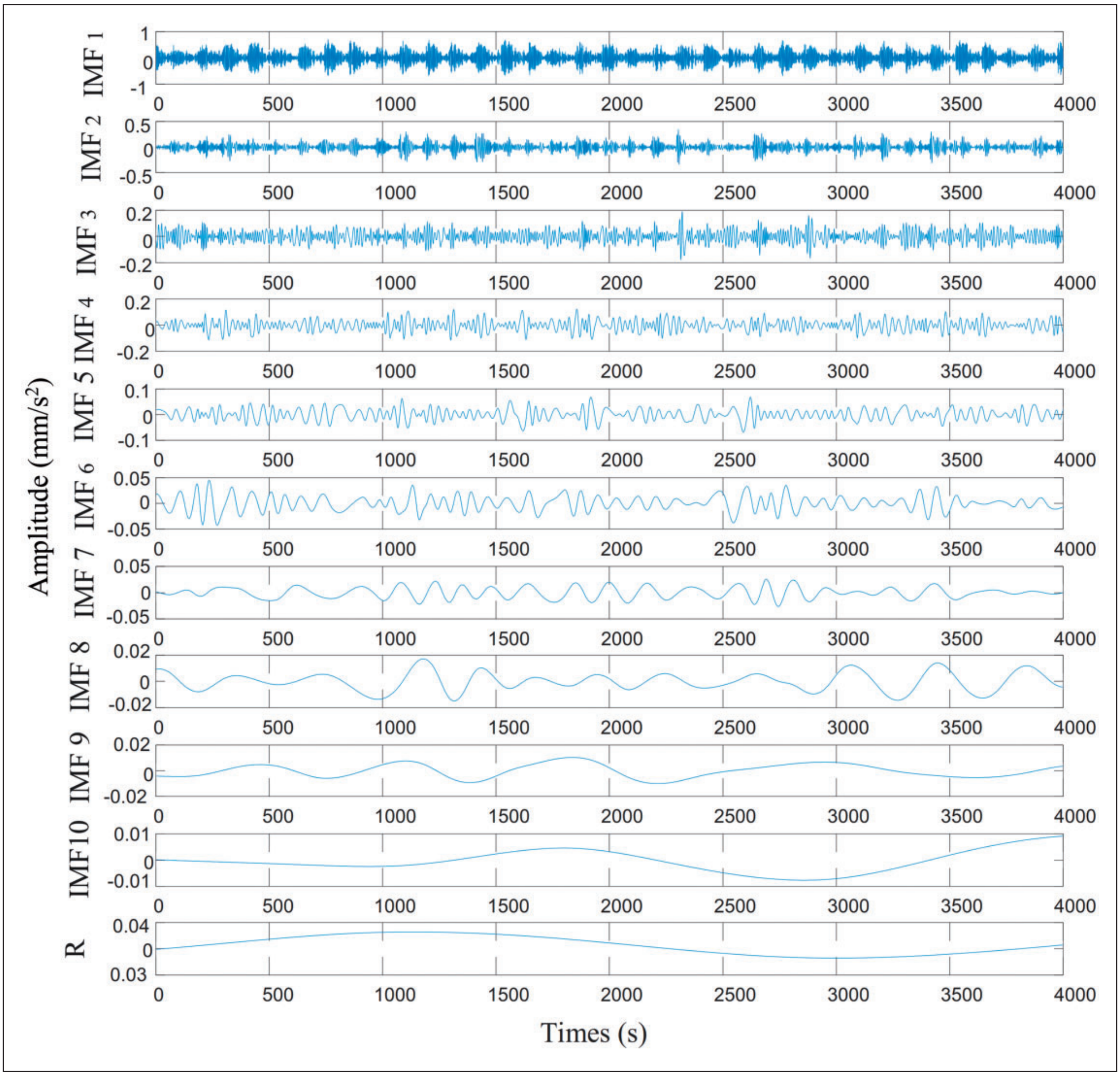

Figure 5. Decomposition results of the vibration signal of outer race fault 0.007 inch for load 1 HP.

sample entropy, we need to determine the threshold tolerance r, which represents the width of the Heaviside function and embedding dimension m, which represents the length of the compared vectors, thus the sampEn can be estimated by (m, r, N).

Generally, r is defined by the signal standard deviation (*std*) to increase the correlation between the time domain and the Heaviside function in sample entropy. On the other side, the correlation is defined between the time domain and the width of the exponential function in the fuzzy entropy. The selected value of r is very important. If this value is too large, it leads to a loss of feature information. On the other side, if the value of r is too small, it leads to an increase of the noise level. The values of boundary gradient confined in the interval between 1 and 3 lead to increase in the probability of similarity degree between the closest vectors weight.

Hence, to avoid the undesired phenomena, we take into consideration the same values for the sampEn and fuzzyEn except for the value of boundary gradient n. The threshold tolerance r is chosen between 0.1 and 0.2 *std*, and the boundary gradient values n is taken either 2 or 3 to keep as much as information details. In this study, we consider the following parameters: length of data $N = 7000$ for each IMF component. Threshold tolerance $r = 0.15$ *std*. Boundary gradient $n = 2$. After some tests, we have chosen the value of $m = 3000$ to appreciate clearly the fault bearing. Figure 6(a) and (b) illustrates, respectively, the comparison between sample entropy and fuzzy entropy for each IMF1-11 components with motor load 1 HP and diameter fault 0.007 inch.

Figure 6(a) shows the trajectory of sample entropy which represents the IMF components for different states of bearing. We observe that there exists a gap

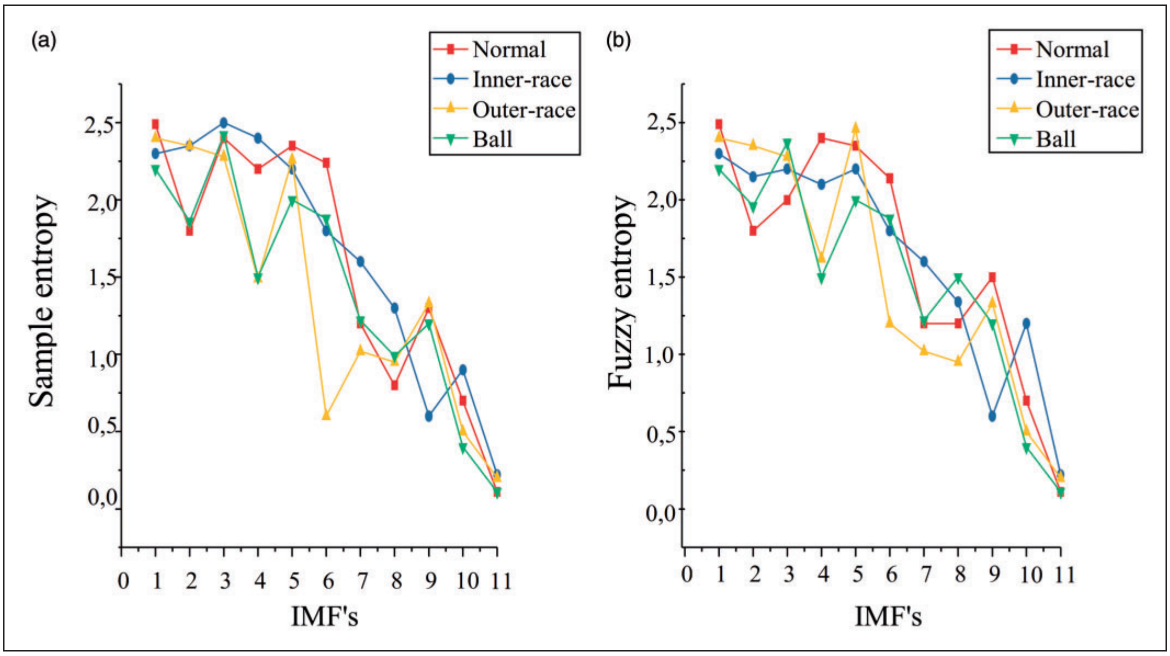

Figure 6. Sample entropy and fuzzy entropy for each intrinsic mode function 0.007 inch for load 1 HP.

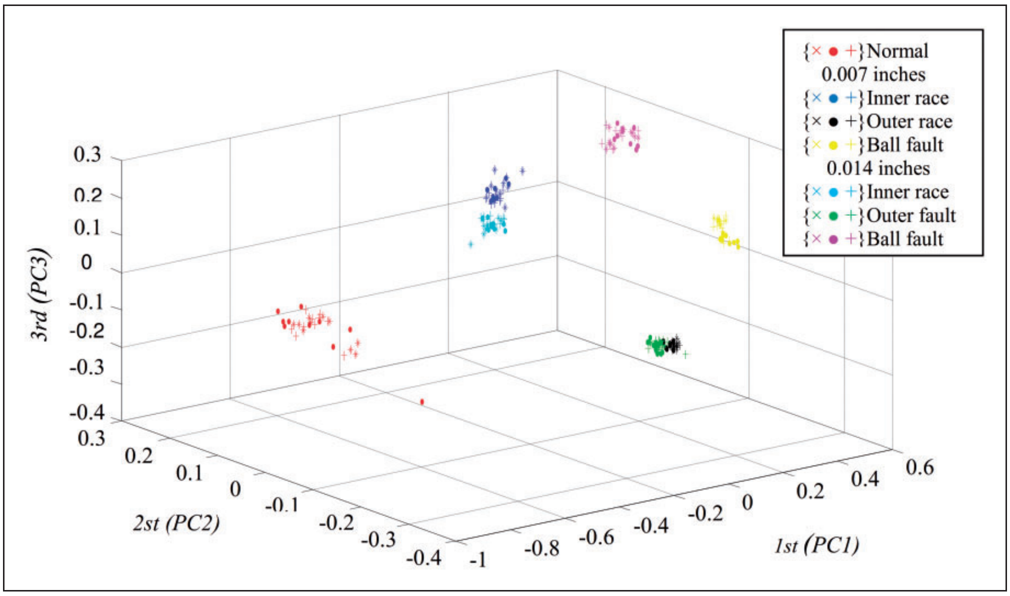

Figure 7. Scatter plots of the first three principal components obtained by empirical mode decomposition–principal component analysis for different faults: {×} load 0 HP, {•} Load 1 HP, {+} Load 2 HP.

only between the sample entropy values of IMF 10 at low frequency for the four rolling bearing states. Nevertheless, most of the IMF overlaps in different points of bearing, such as IMF 2, IMF 4, and particularly in IMF 3. Thus, the sample entropy allows us to measure the stability and the complexity of the vibration signal. But, it cannot distinguish the four rolling bearing states for each IMF components. To eliminate the undesired phenomena, we have proposed the fuzzy entropy method which is based on fuzzy function to measure the irregularity, the complexity, and the stability of the vibration signals which describe the similarity of two vectors. Figure 6(b) shows the fuzzy function measure in most points for each scattered IMFs of rolling bearing state. It appears that there is no overlap except for IMF 11.

Among the advantages of fuzzy entropy is that it provides different points of rolling bearing situation in low- and high-frequency characteristics which is not the case for sample entropy. In sample entropy, the decision rule for vector similarity is based on the Heaviside function and it is very rigid because

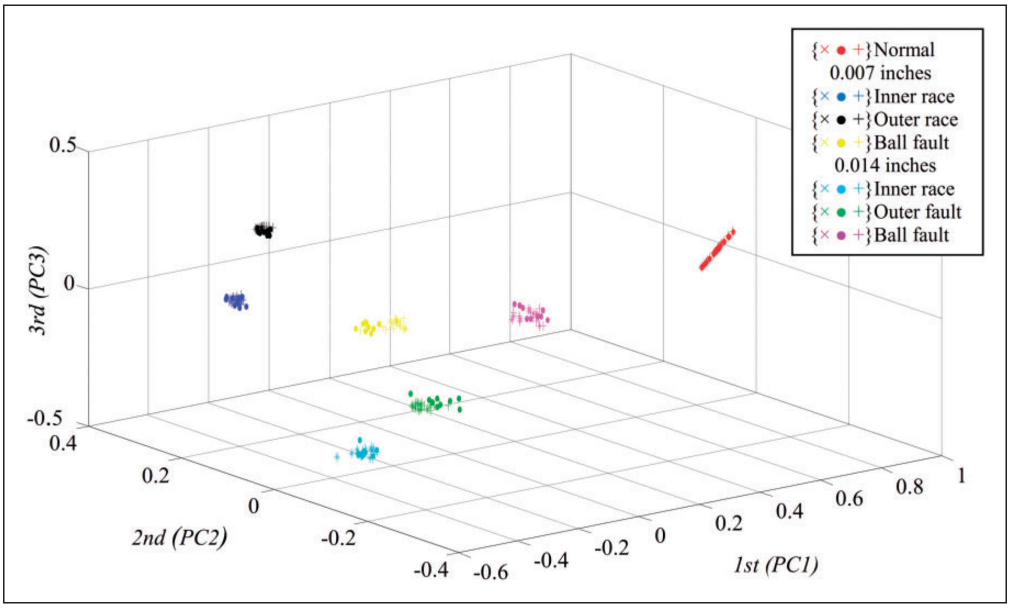

Figure 8. Scatter plots of the first three principal components obtained by FuzzyEn of empirical mode decomposition–principal component analysis for different faults: {×} load 0 HP, {•} Load 1 HP, {+} Load 2 HP.

Table 2. Training data and testing data statistics.

Label	Fault type	Fault diameter (inches)	Training data	Working condition 0 HP	1 HP	2 HP
1	Normal	—	24	✓	✓	✓
2	Outer race fault	0.007	24	✓	✓	✓
3	Outer race fault	0.014	24	✓	✓	✓
4	Inner race fault	0.007	24	✓	✓	✓
5	Inner race fault	0.014	24	✓	✓	✓
6	Ball fault	0.007	24	✓	✓	✓
7	Ball fault	0.014	24	✓	✓	✓

the two vectors are considered as similar vectors only when they are within the tolerance threshold r. To enhance the statistical stability, the fuzzy entropy method which uses the fuzzy function substitutes the Heaviside function to make a gradual entropy variation when the value of r changes monotonously. Another advantage of the fuzzy entropy is that it is efficient when the vibration signal behavior is more complex, which is our case of study. Consequently, the fuzzy entropy is a powerful approach than the sample entropy in the feature extraction domain.

In feature extraction, we may find in the literature EMD-PCA method which is widely used. The EMD allows decomposition of the vibration signal into a set of IMF. The energy of each IMF is then computed to obtain a large feature matrix. For dimensionality reduction, we use the PCA to find new space from the calculated PCs. Figure 7 shows the first three PCs using covariance matrix obtained by EMD-PCA. We can observe that there are major sets of PCs vectors grouped around the rolling bearing in inner-race state and similarly for the outer-race for 0.007 and 0.014 inches. Moreover, distances between inner-race states are relatively small compared to the outer-race where this distance is nonexisting. This leads to an unsatisfactory classification. Consequently, the EMD-PCA is unsuitable to differentiate various states in various condition modes of bearings. The fuzzy entropy of EMD-PCA is used to keep the stability of feature information which can be extracted even in various condition modes of bearing. Thus, this leads to a satisfactory classification. Figure 8 shows clearly the distinguishable seven faults of rolling bearing feature extraction in various condition modes separately for 0.007 and 0.014 inches.

To validate the accuracy of the proposed method, the SOM neural network is used to identify and classify the rolling bearing fault. The most important advantage of the SOM neural network versus the other neural networks is that it provides a two-dimensional space from which the input data distribution could be clearly seen from the clustering region, and each indicative is independent from each other. The fuzzy entropy of EMD-PCA is defined as the input of SOM neural network, and the outputs are represented as classes, which represent normal, inner-race fault, outer-race fault, and ball fault with fault sizes of 0.007 and 0.0014 mils (1 mil = 0.001 inch).The parameters of SOM neural network are as follows: the number of input layer neurons is three. A 5×6 matrix is the output for the competitive layer. The learning rate is 0.02, the neighborhood distance is 1.

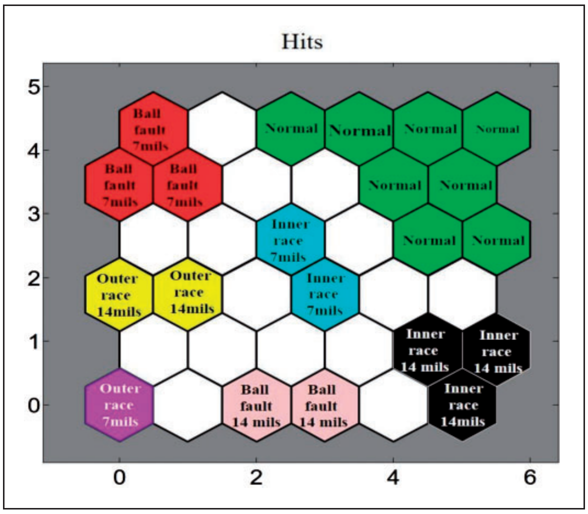

Figure 9. Self-organizing map samples with training data sets, epoch 2000.

Table 2 shows the data sets that are divided into a learning data set with 24 data sets and a test data set with 504 data sets. The U-matrix illustrating the four working conditions of the formed SOM neural network is shown in Figure 9.

Figure 9 shows that the graphs are effective signs showing the distribution of identical units in a single block to a given data set. Thus, the graph can be designed in different colors. This method is used to compare the several data sets by distributing 'hits' on the map.

Figure 9 also shows the existence of a clear bounder between each fault mode. So the abnormality detection which is responsible for deciding whether the rolling bearing is in healthy mode or not could be successfully avoided.

In order to demonstrate the effectiveness of the accuracy of the classification shown in Figure 10, we have remodeled the SOM to get the seven cases of rolling bearings separately. The classification performances of the SOM using the testing data set sets are summarized in this figure.

Furthermore, Figure 10 shows the obtained results of different faults. Therefore, the SOM facilitates the visual comprehension of the fault. In this way, a correct control action can be easily learned depending on the visual output.

The results indicate that the classification of the method that we have proposed—fuzzy entropy of EMD, PCA with SOM neural network—has a good accuracy to diagnose faults for rolling bearing.

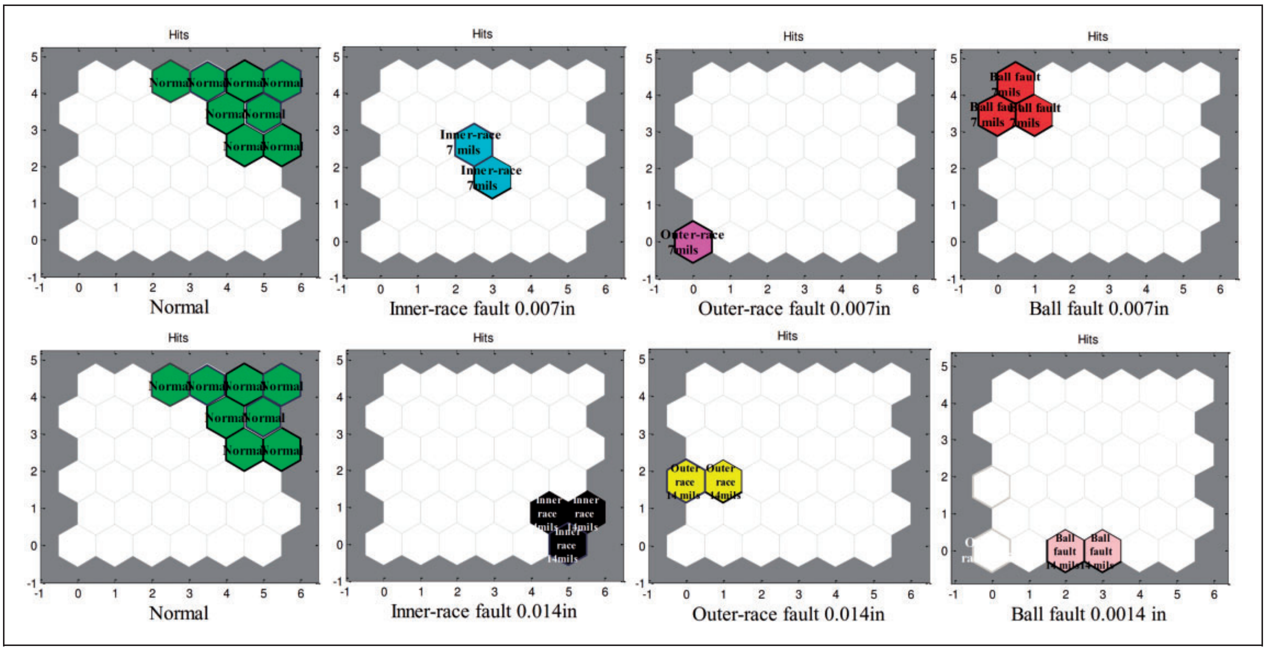

Figure 10. Self-organizing map samples hits for different states.

Conclusion

Rolling bearing diagnosis is considered as one of the most important disciplines in rotating machinery. To keep bearings in a good technical state for various condition modes (various loads and different faults size) this constitutes a new challenge to develop a new method based on fuzzy entropy of EMD-PCA and SOM neural network. The vibration signal is decomposed into set of IMF component by EMD. Each IMF contains feature information such as instantaneous amplitude and frequency. However, through this study the feature information of rolling bearing is difficult to determine the kind of the fault. To overcome this difficulty, we compared fuzzy entropy and sample entropy, and it can be found that the fuzzy entropy has a better outcome than sample entropy in feature extraction accuracy. The result obtained by fuzzy entropy of EMD for each IMF is defined as the input of PCA to extract U-matrix. This method finds out the first three PCs communities of rolling bearing in different conditions modes. Finally, to verify the robustness of the proposed method, we use the SOM network. The obtained results show the efficiency of the proposed approach where the defects and the severities of rolling bearings are clearly classified within different working conditions.

Declaration of Conflicting Interests

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