Extented Intelligent Recognition of Rolling Bearing Early Faults Using Multiscale Permutation Entropy

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***Abstract*—Considering the diversity, complexity and uncertainty existing in bearing vibrations, an extended intelligent identification paradigm for bearing faults was proposed based on multiscale permutation entropy (MPE) and extension theory. MPE can reflect the random degree and detect the dynamic mutation of time series over subsequent scales, while extension theory provides an approach to address the extensibility and regularity of complicated problems. In the present paradigm, MPE was employed to compute the entropies over multiple scales as an original feature vector to represent bearing vibrations, which were then graded using Fisher ratio to choose the most informative features. The chosen features were exploited to determine the classical domain and joint domain of matter elements associated with various bearing health conditions. Bearing fault pattern was assigned to the one with maximum dependence degree among the afore-constructed matter elements. An experiment was conducted on an electrical motor involving four bearing conditions including normal, inner race, outer race and rolling element faults. The test was repeated 100 times with an averaged rate of 92.2% by the proposed method which outperforms the method using multiscale sample entropy and extension theory.**

Keywords- rolling bearings; multiscale permutation entropy; extension theroy; Fisher ratio; fault recognition

I. INTRODUCTION

Rolling element bearing is among the most important and frequently encountered components in the vast majority of rotating machinery. In fact, more than 50% of mechanical failures are related to bearing defects [1], and once the rolling bearing fails, it will seriously affect the reliable operation of mechanical equipment. Therefore, how to accurately judge the bearing health status online have been attracting significant attention over the years. At present, the fault diagnosis methods of rolling bearings are in full bloom. According to the different nature of test signals, they can be divided into vibration method, noise method, electrical signal method, oil sample analysis method and acoustic emission method [2]. Vibration signal has become prevalent in bearing fault diagnosis due to its advantages of large amount of information and easy acquisition. The vibration method usually involves three steps: feature extraction, feature selection or feature compression and fault recognition. Among them, feature extraction refers to extract the most representative feature vectors from original signals. Feature selection or feature compression is to obtain the most informative features which reflect the pattern to be recognized from the original feature vectors. Fault recognition is the automatic classification and recognition of fault patterns through pattern recognition or machine learning.

Feature extractions remain an open issue in fault diagnosis. Zhang et al. [3] used Morlet wavelet to filter the vibration signal and then made use of envelope spectrum analysis to extract the features of the filtered signal. A crest factor of envelope spectrum was proposed as a measure to choose an optimal frequency band of filters. Li et al. [4] employed MED (Minimum entropy deconvolution) to denoise bearing vibration signals, followed by cepstrum analysis to extract features from envelope signals. Although the foregoing methods have achieved certain success, the inability of revealing nonlinear information inherent in vibration signals still remain to be improved. In practice, once rolling bearings come out with faults, their vibration signals often show non-stationary and non-linear characteristics [5,6]. At present, a variety of methods available for non-linear time series analysis including correlation dimension, approximate entropy, sample entropy and permutation entropy. However, the fractal dimension is time-consuming in computation and thus unsuitable for on-line monitoring [7]. The approximate entropy is of poor consistency [8], while sample entropy is susceptible to the influence of non-stationarity and outliers of time series [7]. Permutation Entropy is a method to detect the randomness and dynamic mutation of time series. It has the advantages of simple calculation and strong anti-noise ability, making the applications in the field of fault diagnosis has been founded [9,10]. For example, Yan et al. [10] applied permutation entropy for feature extraction and condition monitoring of rotating machinery using vibration signals. The results show that permutation entropy can effectively detect dynamic changes of vibration signals and characterize health states of rolling bearings under different conditions. Such applications have reported with promising results, but only the time series with permutation entropy is described. In the case of fault stage, the randomness and dynamic behavior of the vibration signal change dramatically. Due to the complexity of background noise as well as micro

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and macro coupling in mechanical systems, fault-related feature information in vibration signals is often distributed in different time scales. Meanwhile, the randomness of vibration signal and the change of dynamic behavior also occur at different scales. Therefore, multi-scale permutation entropy is employed to extract features of bearing vibration signals in the present work.

The pattern recognition approach popular in fault diagnosis including neural network, expert system and support vector machine [11]. Although the above diagnosis methods can achieve intelligent diagnosis of bearing fault, shortcomings are also obvious. It is difficult to select the structure of neural network, and the accuracy of diagnosis is affected by the convergence rate [12]. Expert systems suffer from poor adaptability, knowledge acquisition bottleneck and poor real-time performance [11]. Supporting vector machines requires a large amount of optimization for model parameter estimation [13]. Extension theory is a novel method proposed by Cai Wen in 1983 [14]. Compared with the above pattern recognition methods, extension theory not only has the advantages of simple structure, strong extensibility and without complicated parameter determination, but also can analyze contradictions and regularity enabling it to be application in the field of fault diagnosis by the scholars. [15-17].

In view of the multi-scale correlation and non-linearity within rolling bearing vibration signals and the advantages of extension in pattern recognition, an extended intelligent recognition method for early bearing fault is proposed based on multi-scale permutation entropy and extension theory. Firstly, multi-scale permutation entropies of bearing vibration signal is calculated as original feature vectors, and then the Fisher ratio is used to choose the most salient features. Finally, the resulted feature vectors with a reduced size serve to determine the classical domain and joint domain of the matter-element models in the context of extension theory for different health states of bearings. In test stage, feature vectors are presented to the bearing matter element models of different health states to calculate correlation degrees. The element model with the largest correlation degree is expected to give a diagnosis result. The proposed method is validated by motor bearing data.

II. THEORETICAL BASIS

A. *Multiscale permutation entropy*

Multiscale permutation entropy was first proposed by Aziz et al. [18] in 2005 to measure the complexity and randomness of time series at different scales. It overcomes the disadvantage that permutation entropy can only describe the complexity of signals on a single scale, and has the ability of anti-interference and anti-noise. The specific algorithm is as follows.

According to the given embedded dimension m and the time delay λ, the original time series $X=\{x_1, x_2,\dots, x_n\}$ that length is n is coarsely grained, and then the coarse grained sequence can be obtained.

$$y_j^{\tau} = \frac{1}{\tau}\sum_{i=(j-1)\tau}^{j\tau} x_i,\ j = 1 \quad 2 \quad \cdots \quad \frac{N}{\tau} \qquad (1)$$

In the above formula, τ is the scaling factor. The length of each coarsening sequence changes to $1/\tau$ of the original time series length, When the scale factor is 1, the coarse granulation time series is the same as the original time series.

For each scale of coarse grained time series, the permutation entropy is calculated, and all the permutation entropy values are regarded as the function of scale factor, which is called multiscale permutation entropy analysis. The function is expressed as

$$MPE(x,\tau,m,\lambda) = PE(y^{(\tau)},m,\lambda) \qquad (2)$$

In the calculation of multi-scale entropy in this paper, two parameters that are embedding dimension m and time delay n need to be considered. Bandt et al. [19] believe that the value range of the embedded dimension m is best from 3 to 7, because if m is 1 or 2, the reconstructed time series contains too few states, losing the significance and effectiveness of the algorithm and failing to effectively detect the dynamic mutation of the time series. If m is too large, the time series of the reconstructed phase space will be homogenized. At this time, the algorithm is not only more time-consuming, but also unable to effectively reflect the subtle changes in the time series [20]. In view of the small influence of time delay lambda on the calculation of time series [7], in summary, the embedded dimension m of this paper is set as 6, time delay λ is set as 1, and data length n is set as 2000.

B. *Extension theory*

Extension theory (early called matter-element analysis) is a new discipline established by Chinese scholar CAI wen in 1983 [14]. It takes the incompatible problem as the research center and seeks the internal mechanism of the contradiction of things. The logic cell of extension theory is matter-element, and it uses matter-element to describe things and their changing rules. The matter-element can be expressed as R=(N,C,V), where N is the thing to be studied, C is the feature of the thing N, and V is the quantity value of the thing N about the feature C, which is called the three elements of the matter-element composed by N, C and V. In practical situations, multi-dimensional features are generally used to describe the properties of things N, so as to constitute n-dimensional matter-element Rn.

$$R_n = (N,C,V) = \begin{bmatrix} N & c_1 & v_1 \\ & c_2 & v_2 \\ & \vdots & \vdots \\ & c_n & v_n \end{bmatrix} \qquad (3)$$

In the formula, $C=(c_1, c_2, \dots, c_n)$represents the feature set of N, and $V=(v_1, v_2, \dots, v_n)$ represents the magnitude corresponding to feature C.

Correlation function is another important concept in extension theory, which can describe the degree and change of a certain property of the characteristics of things qualitatively and quantitatively. Elements in the same domain can be divided into different levels of association according to the numerical value of the association function. The relationship of "same within class, different between classes" is developed into "different levels within class". Distance, as the basis of correlation function and the extension of qualitative description to quantitative description, is defined as the distance between any point x_0 on the real axis and a finite real interval X=<a, b >. The expression is as follows

$$\rho(x_0, X) = \rho(x, < a, b >) = \left| x - \frac{a+b}{2} \right| - \frac{b-a}{2} \tag{4}$$

On the basis of distance, the correlation function expands the qualitative description of " P with a certain property" to the quantitative description of "degree of P with a certain property" Let x_0 be any element in the real domain, interval X=<a, b >, X_0=<c, d >, and $X \subset X_0$, X、X_0 have no common endpoint, and take its best advantage as the midpoint of the interval, then its elementary correlation function can be expressed as

$$k(x_0) = \begin{cases} \dfrac{-\rho(x_0, X)}{|X|} & x_0 \in X \\ \dfrac{\rho(x_0, X)}{\rho(x_0, X_0) - \rho(x_0, X)} & x_0 \notin X \end{cases} \tag{5}$$

In the formula, $\rho(x_0, X)$ and $\rho(x_0, X_0)$ respectively represent the distance between the element x_0 and the interval X and X_0. $k(x_0)$ represents the correlation degree of element x_0 with respect to interval X, and its positive and negative sum indicates the degree to which x_0 belongs to or does not belong to X.

C. Fisher ratio

In pattern recognition, Fisher criterion is the distance between the largest categories obtained by projecting eigenvectors in the optimal direction [21]. Fisher ratio is improved on the basis of Fisher criterion, and its main content is the ratio of inter-class dispersion and intra-class dispersion of features in the same dimension, which has the function of removing redundant information. The expression is as follows

$$F_{(k)} = \frac{S_b^{(k)}}{S_w^{(k)}} \tag{6}$$

Whereas $F_{(k)}$ represents the Fisher ratio of the k-dimensional feature, $S_b^{(k)}$ represents the inter-class dispersion of the k-dimensional feature, and $S_\omega^{(k)}$ represents the intra-class dispersion of the k-dimensional feature. The inter-class dispersion of feature components reflects the degree of difference between feature samples of different scales, while the intra-class dispersion reflects the degree of density between feature samples of the same scale. When Fisher ratio is larger, that is, the greater the inter-class dispersion is, the smaller the intra-class dispersion is. This shows that the feature components have better distinguishing effect and better representativeness.

Assuming that there are L samples in class $\boldsymbol{c}$ mode, $L=L_1+L_2+\cdots+L_c$, and there are L_c samples in class $\boldsymbol{c}$ mode, then class $\boldsymbol{c}$ mode can be expressed as $\omega_c=\{x_k^{(c)}, k=1,2\cdots, L_c\}$ by a set, so that $m_k^{(i)}$ and m_k are the average values of the dimension characteristics of all samples in class i model and the K dimension characteristics of all samples, i=1，2，…，c.

$$\begin{aligned} S_b^{(k)} &= \sum_{i=1}^{c} \frac{L_i}{L} \left(m_k^{(i)} - m_k \right)^2 \\ S_w^{(k)} &= \frac{1}{L} \sum_{i=1}^{c} \sum_{x \in w_i} \left(m_k^{(i)} - m_k \right)^2 \end{aligned} \tag{7}$$

III. METHOD FLOW

Early bearing failure based on multi-scale entropy permutation proposed extension recognition method for the processes shown in Figure 1, the following steps:

(1)A rolling bearing species c health states is provided in here, each have N samples for training, all computing c×N samples arranged on m entropy scale, consisting of a multi-scale entropy arrayed configuration (c×N)×m original training feature matrix;

(2) Using the Fisher scoring ratio permutation entropy of the m scales training samples, according to the high and low scores sequentially sorting, selecting the highest scoring permutation entropy on the scale of k as final feature, finally to give (c×N)×k Training feature matrix, where k<m;

(3) Using the elements in the above training matrix as the characteristic parameters, construct the classical domain and the local domain of the bearing elements in different health states, and then establish the matter element model of bearing different health states;

(4) Calculated by the Fisher test signal selected permutation entropy than on a scale k, constituting the test sample feature vectors and successively substituted into the bearing element model was different health status, using the calculated correlation functions are different from the test sample and the bearing correlation health matter element model values;

(5) According to the determined value associated with a different state of health thereof bearing rolling element model health status, i.e., what type of fault or trouble.

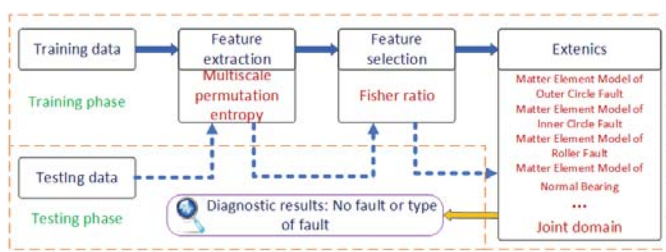

Figure 1. Rolling bearing fault extension intelligent diagnosis flow chart

IV. EXPERIMENTAL DATA PROCESSING AND ANALYSIS

The early fault experiment of rolling bearing is carried out on the bearing gear comprehensive fault simulation test bench shown in Figure 2. The test bench is driven by frequency conversion motor through belt. Test station comprises two parts, wherein the upper half part of the transmission gear, rotor bearing failure in the experimental part under half that was used in the experiment. The bearing model used in the experiment is NU205EM.The bearing is a roller bearing inner ring detachably mounted in the bearing housing experiment rightmost end. Three different types of early faults, including inner ring fault, outer ring fault and rolling element fault, were simulated by EDM. The fault size was 0.05mm. An acceleration sensor attached to the bearing housing over the test, the sampling frequency of the sensor is set to 12kHz, the bearing inner ring rotation speed of 1218 r/min, a load of 40kg is applied to the rotor by a coil loading mechanism. The fault-free signal and the three fault signals are divided into sample data of length 20000, and each of the four types of signals has 60 sample data.

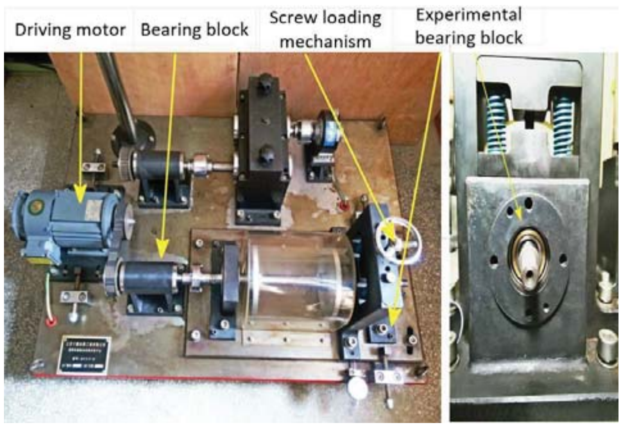

Figure 2. Bearing gear comprehensive fault simulation test bench

A. *Feature extraction and feature selection*

Forty samples of bearing signals in four different states are randomly selected as training samples and all data samples as testing samples. The above training samples are analyzed by using MPE, and the scale factor is obtained. The results are shown in Figure 3. The length of the vertical line in the figure indicates the standard deviation of the sample entropy value of various bearing samples on this scale. From Figure 3, it can be seen that the change trend of the entropy values of the four different bearing health states is approximately the same, and all decrease with the increase of scale factor. It shows that the main information of bearing vibration signals in the four states is stored in small scale. The entropy value of the original bearing signal in the healthy state is higher than that in the other three states, which indicates that the irregularity of the bearing vibration signal sequence in the fault-free state is the highest. In fact, the vibration of bearing in fault-free state is mainly caused by the surface roughness of rolling contact pair, clearance and the position change of rolling body, so the vibration signal is close to random signal. It can also be seen from Figure 3 that the PE values of four different types of signals are almost the same when the scale factor τ is greater than 6. This shows that different types of early fault vibration signals have little difference in large-scale time series, and their main information is stored in small-scale time series. This is because in the process of coarsening, the mean value of time series to a certain extent "neutralizes" the dynamic catastrophe behavior of the original signal, and to a certain extent reduces the ability of permutation entropy to detect the dynamic catastrophe of time series. Ability, It can also be seen from Figure 3 that the MPE values of the four types of vibration signals are not very different, and have the phenomenon of overlap. If the bearing fault classification and recognition is based on the MPE values directly, there are obvious limitations and information redundancy.

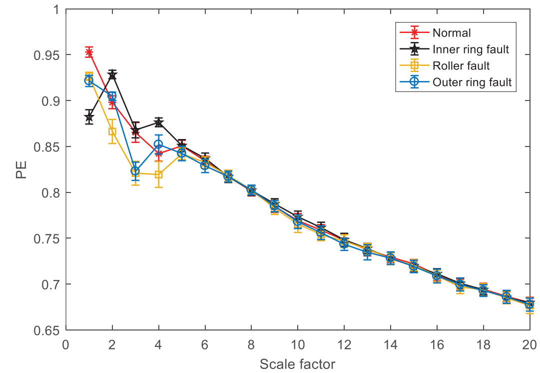

Figure 3. MPE mean and standard deviation curve of bearing under four health conditions

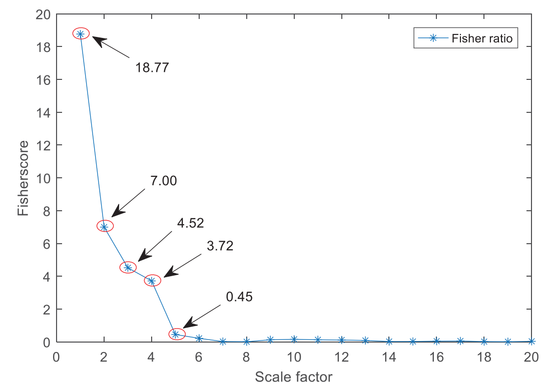

Figure 4. Fisher ratio of permutation entropy on scales

In order to solve the above problems, it is necessary to reduce the dimension of eigenvectors and use pattern recognition method to discriminate the bearing health status. The Fisher ratio of permutation entropy on 20 scales of training set is calculated as shown in Figure 4. It can be seen that the Fisher ratio decreases gradually with the increase of scale factor when scale factor is 1-7, and tends to be zero when scale factor is 7-20, and the fluctuation is small. The Fisher ratio of the first five scale factors is the largest in Figure. 4, which shows that the main information of bearing vibration signal sequence in four states is stored in the first five scale vibration signal sequence, which is consistent with the result of Figure. 3 analysis.

B. *Establishment of classical domain and joint domain*

In the extension pattern recognition, how to determine the classical domain and joint domain of matter-element model is the key to establish matter-element model, and also is a premise to realize extension pattern recognition of rolling bearing fault. Combining the above feature extraction and feature selection methods, the first five scales of permutation entropy are selected as feature vectors. Forty samples randomly selected from samples in various health states were used as the training data to establish the bearing matter-element model under different health states. The classical domain matter element models of fault-free, inner-ring fault, rolling element fault and outer-ring fault are R1, R2, R3 and R4 respectively. According to Chebyshev inequality, 95% of the samples are required to fall into the classical domain, so it can be determined that the classical domain of matter element model is the standard deviation of the training sample mean plus minus 4.47 times [22]. That is to say, the classical domain of each characteristic parameter is [Z-4.47σ, Z+4.47σ]. Z is the average value of the characteristic parameter and σ is its standard deviation .The Z and σ values of the characteristic parameters in the four matter-element models are determined by 40 training samples randomly selected in the health status samples of each bearing. The concrete expressions of the four matter-element models are expressions (8) to (11).

$$R_1=(N_1,C,V)=\begin{bmatrix} N_1 & c_1 & \langle 0.9277 \quad 0.9780\rangle \\ & c_2 & \langle 0.8696 \quad 0.9298\rangle \\ & c_3 & \langle 0.8167 \quad 0.9138\rangle \\ & c_4 & \langle 0.8052 \quad 0.8793\rangle \\ & c_5 & \langle 0.8233 \quad 0.8779\rangle \end{bmatrix} \tag{8}$$

$$R_2=(N_2,C,V)=\begin{bmatrix} N_2 & c_1 & \langle 0.8753 \quad 0.9155\rangle \\ & c_2 & \langle 0.9106 \quad 0.9479\rangle \\ & c_3 & \langle 0.8274 \quad 0.9075\rangle \\ & c_4 & \langle 0.8555 \quad 0.8982\rangle \\ & c_5 & \langle 0.8242 \quad 0.8791\rangle \end{bmatrix} \tag{9}$$

$$R_3=(N_3,C,V)=\begin{bmatrix} N_3 & c_1 & \langle 0.9064 \quad 0.9471\rangle \\ & c_2 & \langle 0.8042 \quad 0.9278\rangle \\ & c_3 & \langle 0.7590 \quad 0.8839\rangle \\ & c_4 & \langle 0.7539 \quad 0.8854\rangle \\ & c_5 & \langle 0.8137 \quad 0.8715\rangle \end{bmatrix} \tag{10}$$

$$R_4=(N_4,C,V)=\begin{bmatrix} N_4 & c_1 & \langle 0.8907 \quad 0.9520\rangle \\ & c_2 & \langle 0.8865 \quad 0.9236\rangle \\ & c_3 & \langle 0.7867 \quad 0.8624\rangle \\ & c_4 & \langle 0.8010 \quad 0.9038\rangle \\ & c_5 & \langle 0.8104 \quad 0.8753\rangle \end{bmatrix} \tag{11}$$

Based on the classical domain matter element model determined by the four different bearing states mentioned above, the joint domain matter element model R_p of rolling bearing health state can be obtained. Among them, N_p represents the set of rolling bearings in four different states. C is the multi-scale permutation entropy of rolling bearings which can characterize different states. V_P is the range of permutation entropy of four kinds of bearings under the same scale factor, which can be expressed as [$C_{\min}$, $C_{\max}$]. $C_{\min}$ and $C_{\max}$ are the minimum and maximum values of the classical field of permutation entropy of all States at the same scale, respectively. The expression is (12).

$$R_p=(N_P,C,V_p)=\begin{bmatrix} N_p & c_1 & \langle 0.8753 \quad 0.9780\rangle \\ & c_2 & \langle 0.8042 \quad 0.9479\rangle \\ & c_3 & \langle 0.7590 \quad 0.9138\rangle \\ & c_4 & \langle 0.7539 \quad 0.9038\rangle \\ & c_5 & \langle 0.8104 \quad 0.8791\rangle \end{bmatrix} \tag{12}$$

C. *Extension intelligent recognition of rolling bearing faults*

The running state of rolling bearing is divided into four kinds: fault-free state (j=1), failure state of inner ring (j=2), failure state of rolling body (j=3) and failure state of outer ring (j=4).At this point, the correlation degree function changes from equation (5) to equation (13).

$$k_j(x_i)=\begin{cases} \dfrac{-\rho(x_i,V_{ji})}{|V_{ji}|} & x_i\in V_{ji} \\ \dfrac{\rho(x_i,V_{ji})}{\rho(x_i,V_{pi})-\rho(x_i,V_{ji})} & x_i\notin V_{ji} \end{cases} \tag{13}$$

Where $k_j(x_i)$ denotes the correlation between the sample x to be measured and type j rolling bearings at the i characteristic scale (i = 1, 2,..., c), V_{ji} represents the value interval of the i characteristic scale in the state of class j , V_{pi} represents the value interval of the j characteristic scale in joint domain. Furthermore, the comprehensive correlation degree function of the five characteristic scales can be written out to obtain the comprehensive correlation degree function between the sample to be tested and each kind of health state. The specific expression is formula (14).

$$K_j(x)=\sum_{i=1}^{5}\omega_i K_j(v_i) \tag{14}$$

$K_j(x)$ represents the comprehensive correlation between the sample data x to be measured and the health status of rolling bearing class j. ω_i is the weight coefficient, which is expressed as the weight of the characteristic entropy of the i characteristic scale in the five eigenvalue scales, and $\sum\omega_i=1$. In this paper, the ratio of Fisher's ratio to total Fisher's ratio of each feature scale is taken as the weight of the scale. The expression is as follows

$$\omega_i=\frac{FS_i}{\sum_{i=1}^{5}FS_i} \tag{15}$$

Take all samples including training samples as test samples. According to the order of normal state, outer ring fault, inner ring fault and rolling element fault, it is brought into the matter element model of four previous bearing health states in turn, relevance values with four matter-element models can be obtained. By comparing the size of four correlation values, complete extension intelligent recognition of samples to be measured. Extension intelligent recognition of all samples as Figure. 5. The recognition results 1, 2, 3 and 4 represent the normal state, outer ring fault, inner ring fault and rolling element fault respectively. From Figure. 5, it can be see that there are no misjudgments in the normal state and the inner ring fault, but there are two misjudgments in the inner ring fault and the rolling element fault, and the recognition rate can reach 93.3%.

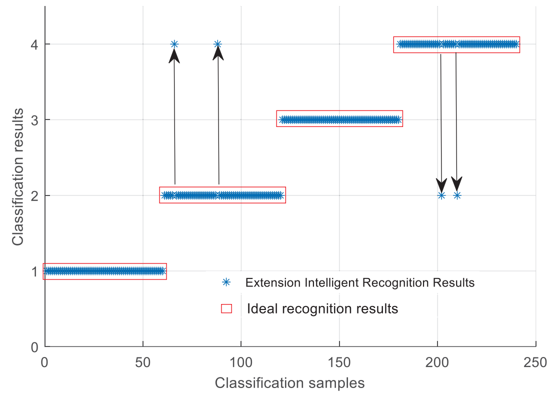

Figure.5 Extension intelligent recognition results of all samples to be tested

In order to avoid the impact of accidental errors on the experiment and improve the reliability of the experiment results, 40 samples were randomly selected from bearing data of different states as training samples again, all data samples are taken as testing samples. The process is repeated 100 times to obtain 100 test results. The results are shown in Figure 6. As can be seen from Figure 6, 466 misjudgments occurred in 100 repeated experiments, with an average recognition rate of 92.2%. This shows that the method based on extension pattern recognition and MPE is reliable in this experiment.

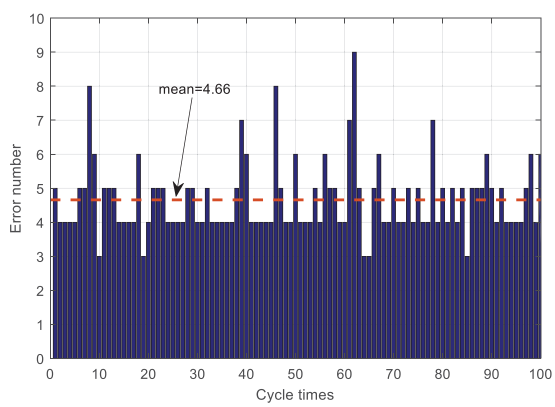

Figure.6 Number of misjudged samples in 100 test cycles

D. *Method comparison*

In order to verify the effectiveness and superiority of the proposed method, a comparative experiment was carried out by combining multi-scale entropy with extension. Among them, the embedding dimension m of sample entropy is 1, the similarity tolerance r is 0.15S, and S is the standard deviation of the original signal. The flow chart of the comparative experiment method is consistent with this method. Each time, 40 samples are randomly selected from the health status of each bearing as training samples, all data as testing samples, and 100 times are repeated. The number of samples identified each error is shown in Figure 7. Among the results of 100 cycles, 2460 errors occurred, with an average error rate of 24.6 and an average recognition rate of 59% leading the recognition effect to be low-quality. In contrast, the early extension intelligent diagnosis method of rolling bearing based on MPE has certain advantages in the analysis of experimental data.

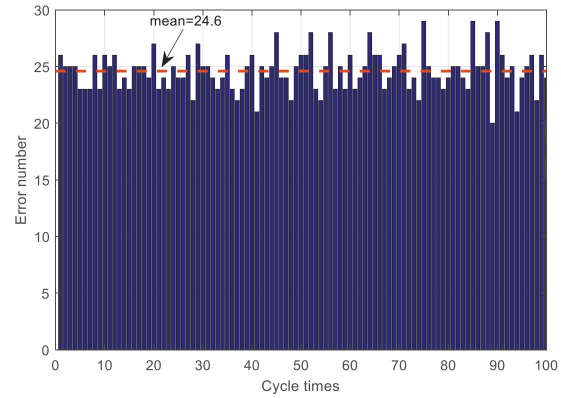

Figure.7 Number of misjudged samples in 100 test cycles

V. CONCLUSION

(1) The feature extraction of bearing vibration signals in different health states is realized by using MPE method, and the feature selection is realized by using Fisher ratio, which lays a foundation for the determination of classical domain and joint domain of extension matter-element model.

(2) Extension pattern recognition is applied to rolling bearing fault diagnosis. The permutation entropy of five scales obtained by feature selection is taken as the feature vector. Qualitative and quantitative analysis of bearing diagnosis is realized according to the correlation degree between test samples and matter element models of rolling bearings in different health states.

(3) The experimental results show that the proposed extended intelligent diagnosis method for early fault of rolling bearings has better effect under the experimental data, and the fault recognition rate reaches 92.2%. Compared with the combination of multi-scale entropy and extension, it has certain advantages.

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