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Research on Feature Extraction and Classification Method of Vibration Signal of Escalator Sprocket Bearing

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Abstract

In order to improve the accuracy of escalator sprocket bearing fault diagnosis, the problem of the feature extraction method of bearing vibration signal is addressed. In this paper, empirical mode is used to decompose the original signal, and the optimal modal component among the multiple modal components is obtained after the optimization decomposition is selected by the envelope spectrum method, and the multi-angle feature measure is introduced to extract the fault characteristic value. According to the vibration characteristics of the bearing vibration signal data, a bearing signal feature group that is more inclined to the fault feature category information is established, which avoids the absolute problem of extracting a single metric feature. The fuzzy C-means clustering algorithm is used to cluster the sample data with similar characteristics into the same cluster area, which effectively solves the problem that a single measurement analysis cannot characterize the complex internal characteristics of the bearing vibration signal.

Keywords: Bearing; Vibration; Multi-Angle Feature Measurement; Signal Feature Group; Empirical Mode; Fuzzy C-Means Clustering

1 INTRODUCTION

With the rapid acceleration of urbanization and the continuous construction and development of infrastructure, the demand for escalator is more and more in public places, and the safety and stability of escalator sprocket bearing is particularly important. The traditional fault diagnosis technology of escalator sprocket bearing is that maintenance personnel rely on technical experience to regularly inspect or regularly replace the bearing fault. The empirical method can be used in the equipment with simple structure and low technical index, but it is insufficient in front of the escalator sprocket bearing with high precision. Regular replacement of bearings will require a large amount of labor and increase equipment maintenance costs [1]. Therefore, researchers conducted a large number of studies on vibration signal data. Wu and Huang aimed at the limitations of many Intrinsic Mode functions (IMF) in EMD decomposition. Ensemble Empirical Mode Decomposition (EEMD) method is proposed. By analyzing the parameters of EEMD algorithm, it is helpful to anti-mixing decomposition and restrain the mode aliasing phenomenon, but it is not effective in processing a single IMF. Jiang et al [2] studied and improved empirical mode decomposition algorithm on the basis of EMD algorithm, which effectively solved the problem of mode aliasing and highlighted the fault information of the characteristic components of IMF component. Yan et al studied the singular value decomposition algorithm in depth, and performed the singular value decomposition on two matrices to efficiently calculate the orthogonal basis of intersection. However, the complexity was much lower than most of the latest technologies. After numerical simulation, the feasibility of the algorithm was verified [3]. Tian et al studied signal data from the standpoint of mathematical differential geometry, deeply understood the intrinsic characteristics of various characteristic types of vibration signals, derived their relevance and substance through mathematical formula, and simulated virtual characteristic signals [4]. Ioan deeply studies entropy theory extraction methods, and obtains eigenvalues that can better characterize fault categories through entropy extraction of original data, thus improving the accuracy of fault diagnosis algorithm [5]. Yu et al used the singular value denoising method to improve the defects of the local wave decomposition algorithm. Through the singular value decomposition of the phase space reconstruction matrix of vibration signals, the singular entropy method was used to set the order and retain the singular value, effectively reducing the interference of noise signals [6]. Yang Gongyong et al obtained many inherent modal functions by using the improved Hilbert Yellow transform, measured the inherent modal functions by the singular value algorithm, obtained bearing fault characteristics, and finally identified fault types effectively through Mahalanobis distance [7]. For existing or emerging problems, researchers need to make continuous breakthroughs and innovations, and in-depth study of vibration signal feature extraction methods for bearing faults is of great significance for improving the accurate diagnosis and prediction of bearing fault categories.

2 BEARING VIBRATION ORIGINAL SIGNAL DECOMPOSITION

2.1 Vibrational Original Signal

In normal condition, the main failure types of escalator sprocket bearing include inner ring fault, outer ring fault and rolling body fault. When the structure in the bearing fails, some weak impact signals will be generated, resulting in abnormal resonance vibration of other structures in the bearing, gradually deteriorating the performance of the sprocket bearing and eventually damaging it.

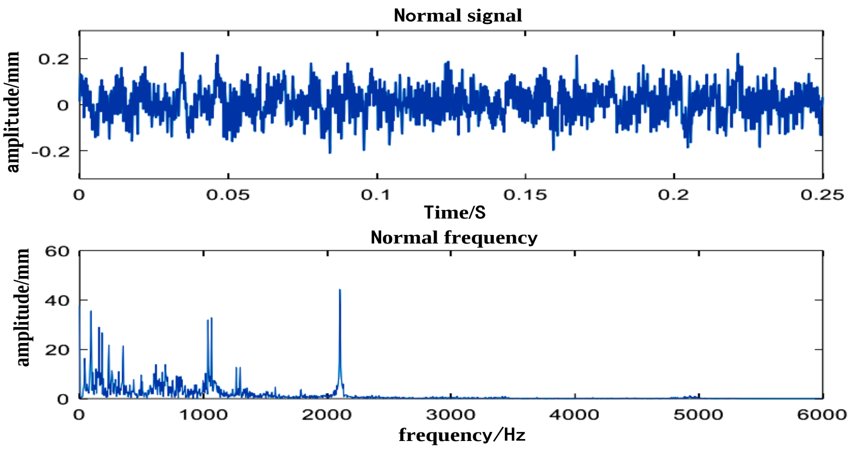


FIGURE 1 TIME-DOMAIN WAVEFORM AND FREQUENCY DIAGRAM OF NORMAL SIGNAL OF ROLLING BEARING

Figure 1 shows the time domain waveform and spectrum diagram of normal sprocket bearing signals. Because the vibration signal of sprocket bearing is affected by its own attributes and external factors, it generates vibration amplitude, but its amplitude is not affected by abnormal signals, so that the amplitude generated is relatively small and the signal fluctuation is stable.

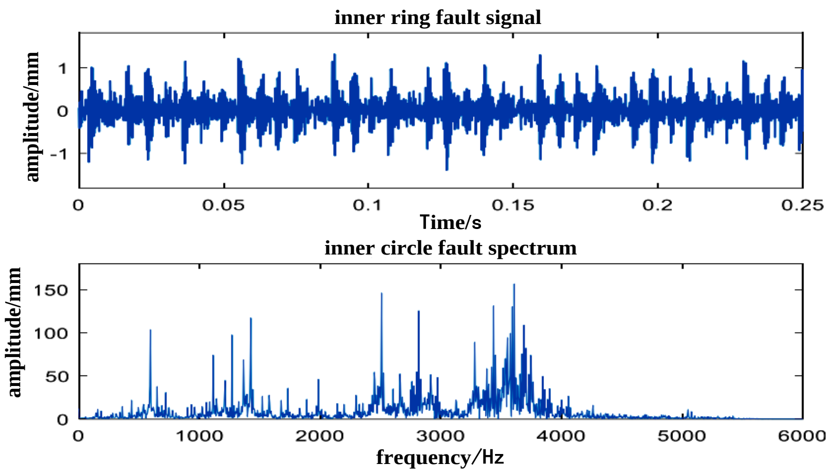


FIGURE 2 TIME-DOMAIN WAVEFORM AND FREQUENCY SPECTRUM OF THE FAULT SIGNAL OF THE INNER RING OF THE ROLLING BEARING

Figure 2 shows the time domain waveform and spectrum diagram of the sprocket bearing inner ring fault signal. The vibration amplitude of the fault signal is relatively large. When the inner ring is running, because the inner ring is in contact with the rolling body, the fault point of the inner ring constantly carries out friction with the rolling body, and the pulse signal generated changes periodically.

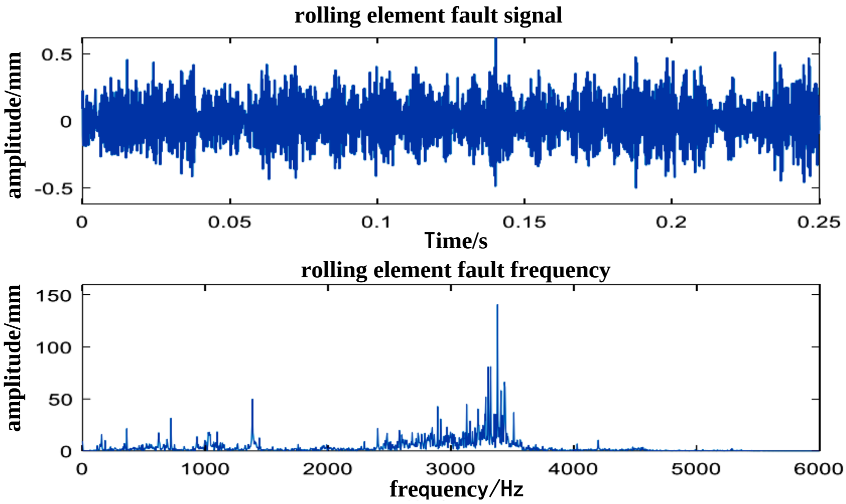


FIGURE 3TIME-DOMAIN WAVEFORM AND FREQUENCY SPECTRUM OF THE FAULT SIGNAL OF THE ROLLING ELEMENT OF A ROLLING BEARING

Figure 3 shows the time domain waveform and spectrum diagram of sprocket bearing roller fault signal. The waveform corresponding to the fault point on the rolling body is similar to that of the fault point on the inner ring. Because the contact position between the fault area and raceway of the rolling body changes from time to time, the contact condition of each position is different, and the pulse amplitude changes periodically.

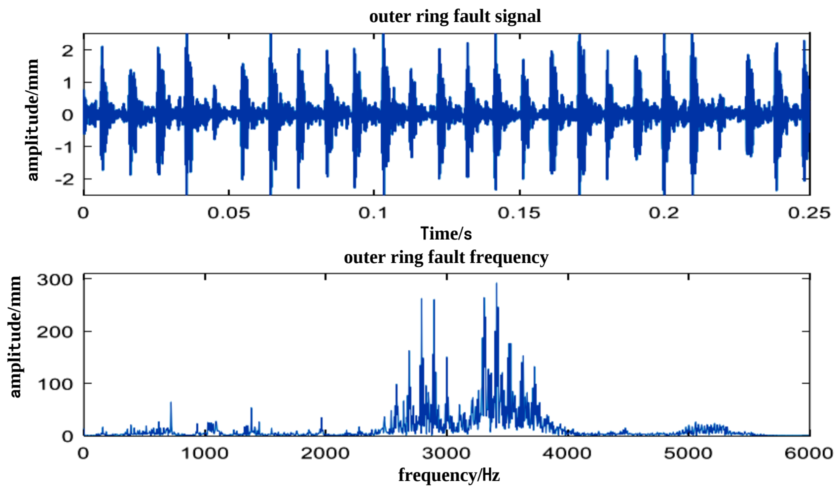


FIGURE4 TIME-DOMAIN WAVEFORM AND FREQUENCY SPECTRUM OF THE FAULT SIGNAL OF THE OUTER RING OF THE ROLLING BEARING

Figure 4 shows the time domain waveform and spectrum diagram of the fault signal of the sprocket bearing outer ring. Because the outer ring is in the peripheral position of the bearing and is easily affected by the impact of the external environment, the amplitude fluctuation range of the fault vibration signal of the outer ring in the time domain obviously increases, resulting in a periodic and high amplitude impact state.

2.2 Empirical Mode Decomposition

The principle of empirical mode decomposition is to decompose the original signal into multiple inherent mode functions that represent local features at different time scales, linearize the nonlinear data, and obtain the time-spectrum diagram that represents the characteristics of the actual signal through Hilbert transform [8]. The essence of this algorithm is the process of continuous screening of modal components, solving the envelope to remove the mean value, to achieve the pattern of the margin signal asymptotically to the inherent modal function. The specific algorithm steps are as follows:

(1) Obtain all maximum and minimum points in the original signal;

(2) Carry out cubic spline interpolation on the upper and lower extremum points of the original signal to obtain its envelope, so that the signal to be solved is between the two envelope lines.

(3) Average the data of the points on the envelope to get the mean sequence. For example, the upper and lower envelope lines and mean lines of a certain component are shown in Figure 5. Normal bearing signal data are selected for the experiment, and the sampling point is 600. The upper and lower envelope lines and mean lines are analyzed briefly.

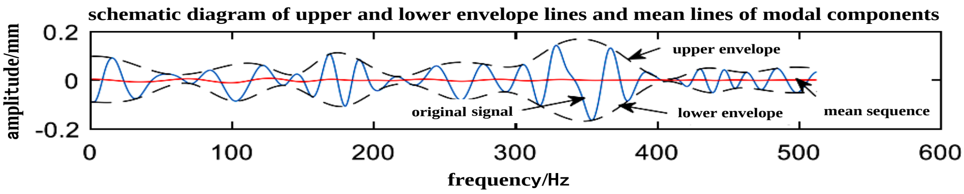


FIGURE5 SCHEMATIC DIAGRAM OF THE UPPER AND LOWER ENVELOPES AND MEAN VALUE LINES OF MODAL COMPONENTS

(4) After subtracting the mean sequence from the original signal, the remaining part of the signal is obtained, and the low-frequency component information is effectively eliminated. The obtained signal is also similar to the inherent mode function.

$$h_1(t) = x(t) - m(t) \tag{1}$$

When the modal function $h_1(t)$satisfies the conditions, one is the same number of extremums and zeros, the other is the average value of the local maximum and minimum extremums is zero. If this is true, $h_1(t)$ is the intrinsic IMF weight of the original signal. Otherwise, it is taken as the signal to be processed again, and then envelope de-mean screening is carried out until the two conditions of IMF component are met and IMF component of $c_1(t)$ is obtained.

$$c_1(t) = \mathrm{h}_1(t) \tag{2}$$

（5）Subtract the decomposed intrinsic modal component of $c_1(t)$ from the original signal to obtain the residual signal $r_1(t)$, and then repeat the above screening process.

$$r_1(t) = x_1(t) - c_1(t) \tag{3}$$

(6) Repeat steps (2), (3) and (4) for the remainder signal in the formula, and solve the component of a mode function of is, until the remainder signal can no longer be decomposed, and the final original signal remainder is. Its expression is as follows:

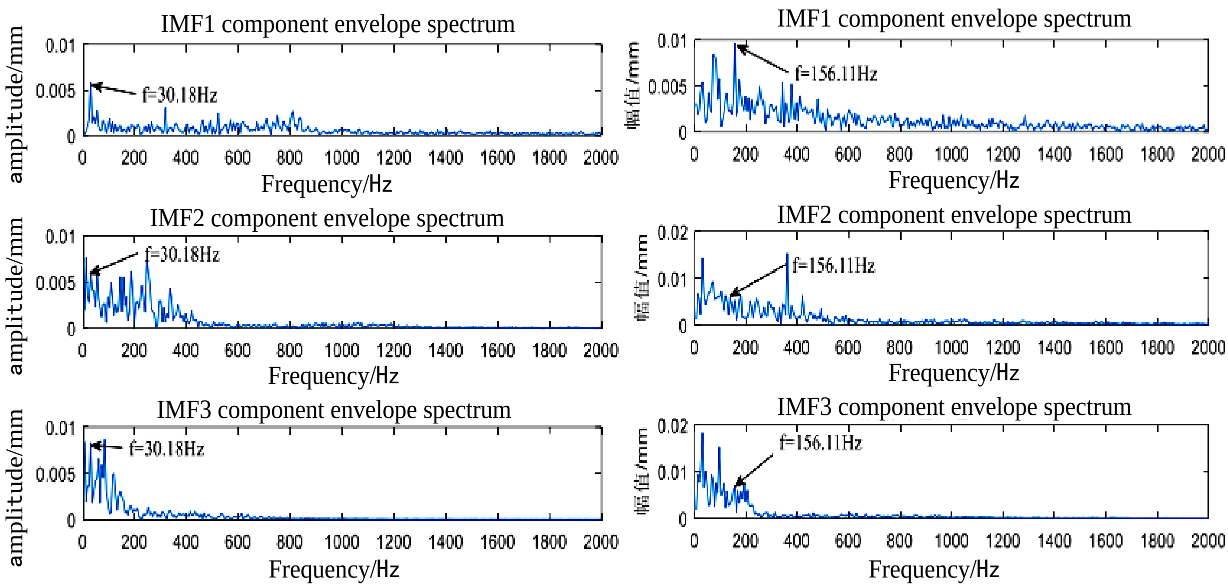
$$x_1(t) = \sum_{i=1}^{n} c_1(t) + r_n(t) \tag{4}$$

3 FEATURE SELECTION ANALYSIS OF VIBRATION SIGNAL

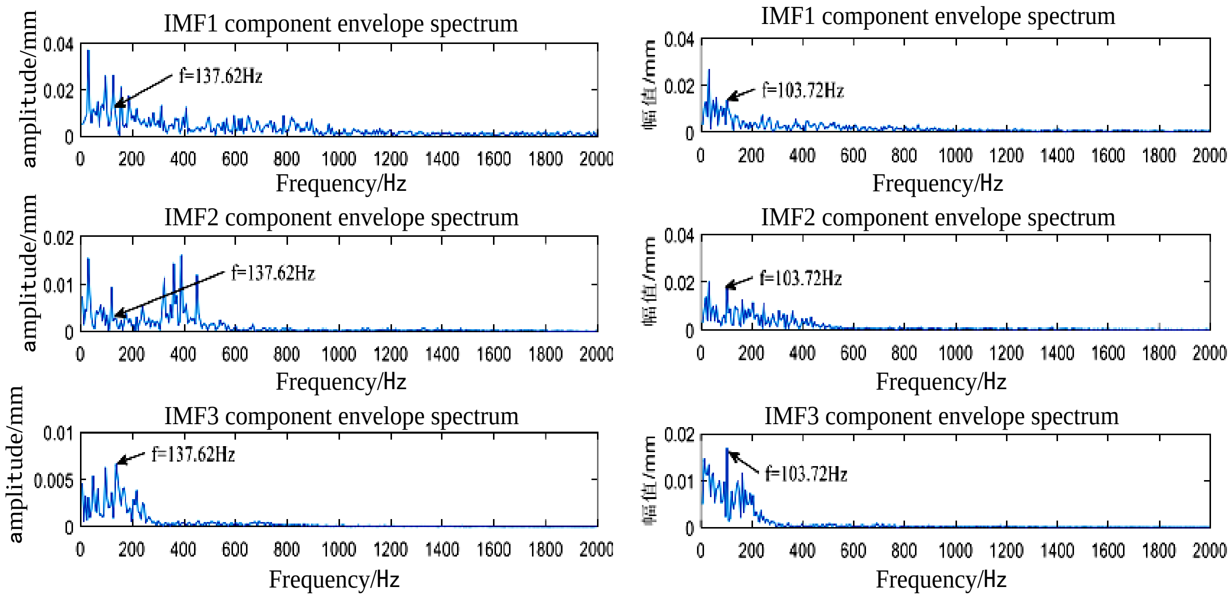
3.1 Selection of Modal Components of Envelope Spectrum

Before constructing the signal feature set, we first consider which component of the decomposed modal component can best represent the fault feature information. The envelope spectrum is the signal data obtained from the original signal transformation, which is particularly sensitive to the pulse fault signal, and the peak fault characteristic frequency is easy to identify. Therefore, the envelope spectrum method can effectively optimize many modal components [9]. Bearing data from Case Western Reserve University in the United States are selected as experimental support based on the envelope spectrum method, and the optimal first three components are selected from the multiple modal components obtained from the decomposition of normal state, inner ring fault, roller fault and outer ring fault signals. The horizontal axis is frequency /Hz, and the vertical axis is amplitude /mm.

As can be seen from Figure 6, the envelope spectrum method is used to decompose many natural modal functions decomposed by the empirical mode decomposition algorithm, and the first three natural modal functions are relatively stable in the amplitude and period of the normal state signal. Among them, the peak frequency characteristics of the selected IMF1 are more obvious than those of the other two components in (a). The fault signal will appear different amplitude shock oscillations in a specific period, and the peak frequency of the fault signal is significantly higher than that of the normal signal. For the selection of the optimal modal component of the fault signal, IMF1, IMF3 and IMF3 can be selected as the optimal modal component of the inner ring fault, the roller fault and the outer ring fault respectively through the frequency characteristic peak provided in the simulation diagram, because their peaks are the most prominent. Therefore, the measurement feature extraction of the optimal modal component can accurately reflect the real state of sprocket bearing.



（a）selection of optimal modal components for normal signals （b）optimal modal component of inner ring fault signal



（c）optimal modal component of rolling element fault signal （d）optimal modal component of outer ring fault signal

FIGURE 6 SELECTION DIAGRAM OF SIGNAL OPTIMAL MODAL COMPONENTS

TABLE 1 COMPARISON TABLE BETWEEN THE DECOMPOSITION FREQUENCY AND THE INHERENT FAULT FREQUENCY VALUE OF THE CHARACTERISTIC SIGNAL

Characteristic Frequency /Hz	Normal Signal	Inner Ring Fault	Roller Fault	Outer Ring Fault
Natural frequency	30.25	156.14	137.49	104.57
Decomposition frequency	30.19	156.11	137.38	103.72

It can be seen from Table 1 that there are certain errors in the comparison of the four signals, especially the outer ring fault. In addition to certain deviations in the research algorithm, the influence of inherent attribute defects of the sprocket bearing itself cannot be excluded. If the signal feature category can be effectively characterized within the range of feasibility.

3.2 Feature Measurement Selection Method of Vibration Signal

For the complex sprocket bearing fault vibration signals, the vibration signals are measured and analyzed from multiple angles, and the fault feature groups of a variety of mixed domains are established. By analyzing and measuring the pros and cons of each combination, it is helpful to comprehensively characterize the essential mechanism characteristics of sprocket bearing. As shown in Table 2, according to the above feature extraction methods of time-domain index and entropy theory, multiple groups of optimal modal components of the four signals obtained by envelope spectrum method were measured by mean square value, standard deviation, margin factor, sample entropy, permutation entropy and singular value entropy, so as to form the sprocket bearing signal feature group.

TABLE 2 TABLE OF SIX SIGNAL CHARACTERISTIC GROUPS OF SPROCKET BEARINGS

Characteristic Index	Normal Signal	Inner Ring Fault	Roller Fault	Outer Ring Fault
Mean square Value	0.0026	0.1031	0.0251	0.0461
Standard Deviation	0.5412	0.1833	0.2014	0.1927
Margin Factor	18.0127	12.1103	12.1095	16.9782
Sample Entropy	0.0012	0.0258	0.0215	0.0242
Permutation Entropy	4.5721	3.4125	2.6016	3.8736
Singular Value Entropy	1.1209	0.9148	0.8591	0.8173

As can be seen from Table 2, the difference of mean square values among the four characteristic signals is obvious; the difference of eigenvalues of standard deviation of inner ring fault, rolling body fault and outer ring fault is not obvious; the characteristic values of inner ring fault and rolling body fault are close to each other in margin factor, and the effect is poor; the difference between various features of singular value entropy is small, and the effect is poor. Permutation entropy is better than sample entropy. Therefore, the fault characteristic information cannot be effectively characterized only from a single feature, and the six feature indexes can be analyzed in pairs to establish a variety of combinations of sprocket bearing vibration signal feature group, which can fully reflect the actual signal characteristic state of sprocket bearing.

3.3 Fuzzy C-Means Clustering

Fuzzy C-means clustering algorithm is a clustering method with better performance by introducing fuzzy set theory proposed by Ruspini into cluster analysis. Its essence is to determine which cluster a sample data belongs to with the help of membership degree. After the error square and iterative operation of the objective function, the optimized objective function can accurately classify the data sample, so as to minimize the distance between the sample point and the matching clustering center point and the weighted sum of fuzzy membership degree, so as to ensure that the sample data with similar characteristics are clustered into the same cluster region [10].

Set the sample set $X=\left(x_1,x_2,\cdots,x_n\right)$, $X=\left(x_{i1},x_{i2},\cdots,x_{im}\right)$,From this, its classification matrix is:

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{5}$$

Divide the sample set $X=\left(x_1,x_2,\cdots,x_n\right)$ into $D=\left(\left\{d_1,d_2,\cdots d_c\right\}\right)$ to obtain c clustering center vectors, and the constructed matrix V is：

$$V=\begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_c \end{bmatrix}=\begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1m} \\ v_{21} & v_{22} & \cdots & v_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ v_{c1} & v_{c2} & \cdots & v_{cm} \end{bmatrix} \tag{6}$$

The algorithm minimizes the objective function by finding the division matrix U and the cluster center matrix V, and the constraints are:

$$\sum_{i=1}^{c} u_{ij}=1, j=1,2,\cdots,n \tag{7}$$

$$v_i=\frac{\sum_{j=1}^{n}\left(u_{ij}\right)^m x_j}{\sum_{j=1}^{n}\left(u_{ij}\right)^m}, 1\le i\le c \tag{8}$$

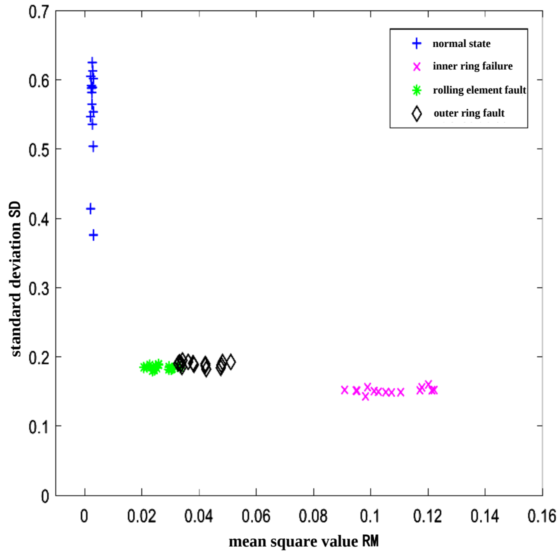
$$u_{ij}=\left[\sum_{k=1}^{c}\left(\frac{\left\|x_j-v_i\right\|^2}{\left\|x_j-v_k\right\|^2}\right)^{\frac{1}{m-1}}\right]^{-1}, 1\le i\le c, 1\le j\le n \tag{9}$$

The expression of the optimization problem is calculated iteratively by (19) and (20):

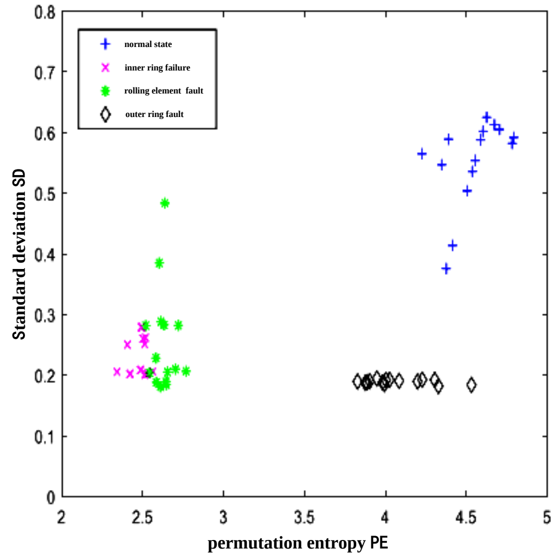
$$J_m\left(X,U,V\right)=\sum_{j=1}^{n}\sum_{i=1}^{c}u_{ij}^m\left\|x_j-v_i\right\|^2 \tag{10}$$

According to formula (10), the value of the objective function is the sum of squares of the weighted distance between each sample data object and the clustering center point. The smaller the value, the more accurate the clustering center of the data sample will be. The essence of fuzzy C-means clustering algorithm is to satisfy the process of classification matrix and clustering center calculation when the objective function reaches the minimum [11].

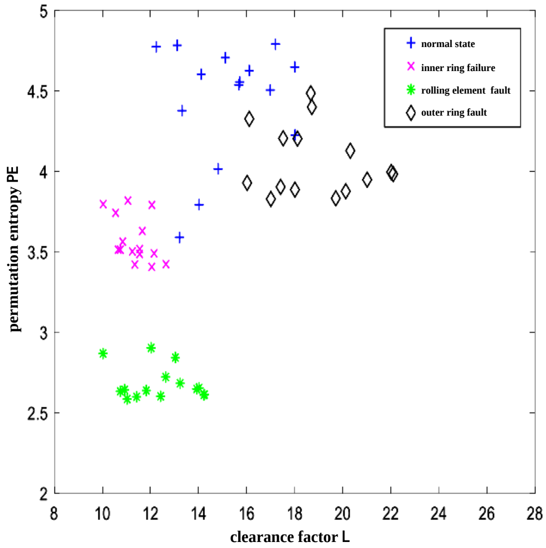
Through the decomposition of the original signal and the decomposition of multiple natural modal components according to the envelope spectrum method to select the optimal modal component, and then the multi-angle feature combination analysis, in order to obtain the bearing normal state, inner ring fault, roller fault and outer ring fault signal feature data sets of 15 groups, a total of 60 groups of data. The fuzzy C-means clustering algorithm is used to conduct experimental evaluation on the extracted data of each measurement feature group. The clustering results of each feature group are shown in Figure 7. The horizontal and vertical axes represent the measurement values of various indicators.



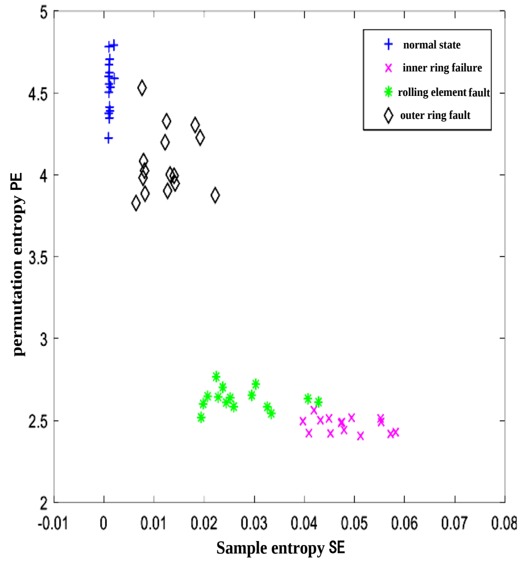
(a) AN SQUARE VALUE AND STANDARD DEVIATION



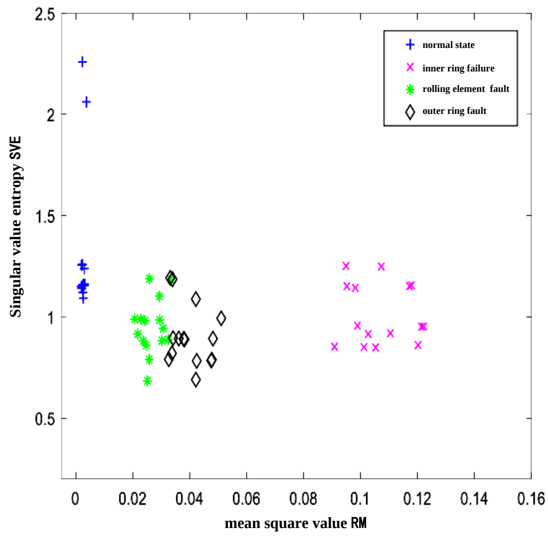
(b) PERMUTATION ENTROPY AND STANDARD DEVIATION



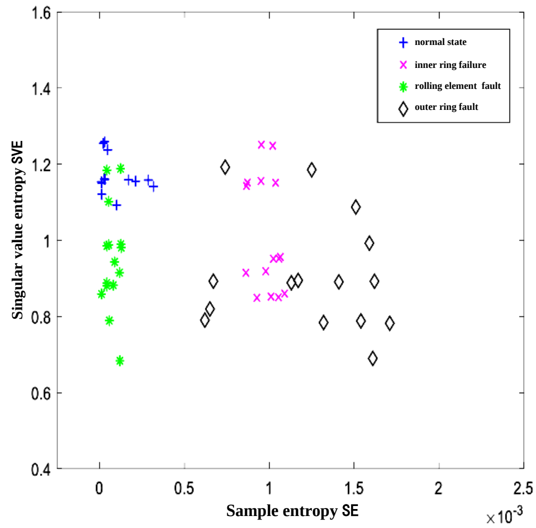
(c) MARGIN FACTOR AND PERMUTATION ENTROPY



(d) SAMPLE ENTROPY AND PERMUTATION ENTROP



(e) MEAN SQUARE VALUE AND SINGULAR VALUE ENTROPY



(f) SAMPLE ENTROPY AND SINGULAR VALUE ENTROPY

FIGURE7 CLUSTERING RESULT GRAPH OF FEATURE GROUPS

As can be seen from FIG. 7, each measurement feature group is processed by fuzzy C-means clustering algorithm, and the four types of sample data present different clustering results in the set space. (a) In the clustering results of group mean square value and standard deviation, some cluster points of the rolling element fault signal feature cluster overlapped with that of the outer ring fault signal, and the distribution of the normal signal feature cluster points was relatively discrete; (b) In the clustering results of group permutation entropy and standard deviation, part of the inner circle fault and the roller fault signal feature cluster also overlap, and the distribution of the normal state and the roller fault feature cluster is relatively scattered; (c) In the clustering results of group margin factor and permutation entropy, partial cluster points of the normal state and the outer circle fault signal feature cluster overlap seriously, and the four clustering clusters are scattered, and the clustering effect is obviously poor. (d) In the clustering results of sample entropy and prearrangement entropy, the clustering effect of the fault signal feature cluster points of the normal state and the rolling element fault signal feature cluster is better. There is no obvious overlap between the fault signal feature cluster points of the outer ring fault and the inner ring fault, but the distance between the two types of clusters is too close, and there are some errors. (e) In the clustering results of group mean square and singular entropy, some cluster points of outer ring fault signal feature cluster and roller fault signal feature cluster overlap, and the distribution of four kinds of feature cluster points is scattered; (f) In the clustering results of sample entropy and singular value entropy of the group, cluster points of the four types of feature clusters are scattered, and multiple cluster points overlap, indicating that there are certain errors in the clustering results.

TABLE 3 FUZZY C MEAN CLUSTERING DATA RESULT TABLE

Characteristic Indicators	Normal Signal	Inner Ring Failure	Rolling Element Failure	Outer Ring Failure
Mean square value - standard deviation	90%	95%	81%	75%
Permutation entropy-standard deviation	75%	82%	70%	90%
Margin factor - permutation entropy	45%	83%	87%	52%
Sample entropy - permutation entropy	96%	93%	90%	89%
Mean square value - permutation entropy	76%	80%	75%	73%
Sample entropy - singular value entropy	65%	60%	53%	37%

It can be concluded from Figure 7 and Table 3 that: In terms of feature selection strategy, the sample entropy-permutation entropy feature extraction method has a higher accuracy than the four types of feature signals extracted by the other five methods, indicating that the correlation between other feature groups and bearing fault feature class data is closer, so it is more appropriate to use the combination of sample entropy-permutation entropy to extract signal feature values. It provides more accurate characteristic data for the subsequent comparative experiments of various methods.

4 CONCLUSION

In this paper, empirical modes are used to decompose the original signals. The envelope spectrum method is used to select the optimal modal component among the multiple modal components optimized for decomposition. Multi-angle feature measurement is introduced to extract fault feature values, and the bearing signal feature set is established which is more inclined to the fault feature category information. The complex intrinsic characteristics of sprocket bearing vibration signals can not be effectively characterized by a single metric analysis. Fuzzy C-means clustering algorithm is used to accurately cluster bearing fault characteristic types, which effectively solves the problem that a single metric analysis cannot characterize the complex inherent characteristics of bearing vibration signals, and has certain research and application value in the field of bearing fault diagnosis.

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