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Triple feature extraction method based on multi-scale dispersion entropy and multi-scale permutation entropy in sound-based fault diagnosis

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Fault of rolling bearing signal is a common problem encountered in the production of life. Identifying the fault signal helps to locate the fault location and type quickly, react to the fault in time, and reduce the losses caused by the failure in production. In order to accurately identify the fault signal, this paper presents a triple feature extraction and classification method based on multi-scale dispersion entropy (MDE) and multi-scale permutation entropy (MPE), extracts the features of the signal of rolling bearing when it is working, and uses the classification algorithm to determine whether there is a fault in the bearing and the type of fault. Scale 2 of MDE is combined with scale 1 and scale 2 of MPE as the three features required for the experiment. As a comparison of recognition results, multi-scale entropy (MSE)is introduced. Ten scales of the three entropy are calculated, and all combinations of three feature extraction are obtained. K nearest neighbor algorithm is used for three feature recognition. The result shows that the combination recognition rate proposed in this paper reaches 96.2%, which is the best among all combinations.

KEYWORDS

rolling bearing signal, triple feature extraction, multi-scale dispersion entropy, multi-scale permutation entropy, fault diagnosis

1 Introduction

Today, mechanized equipment fault diagnosis is an unavoidable problem in all walks of life. Rolling bearing fault accounts for a large part of mechanical equipment fault [1, 2]. Rolling bearing, as a basic part of mechanical equipment, is easily damaged under long-term operation, resulting in many different types of faults, which affect the overall operation of equipment. However, early fault identification of bearings has always been a difficult problem to solve. In order to accurately identify and repair faults in time, various fault diagnosis methods have been put forward to distinguish fault types [3–5].

Vibration signals will be generated during normal operation of rolling bearings. By analyzing the characteristics of vibration signals, the fault categories of bearings can be effectively diagnosed. However, due to the influence of bearing load and friction between components, the vibration signals generated are always non-linear and non-stationary [6, 7]. For feature extraction and recognition of such signals, researchers have put forward many time-frequency analysis methods to extract information from the signals. For example, wavelet transform (WT), empirical mode decomposition (EMD) [8] and variational mode decomposition (VMD) [9], however, these methods also have their own disadvantages, such as WT only decomposes low frequency band of signal, mode overlap of EMD, etc. To solve these problems, some improved methods have been put forward successively, such as empirical WT (EWT) [10], complete ensemble EMD with adaptive noise (CEEMDAN) and so on [11, 12].

In recent years, entropy, as a non-linear dynamic method, has also been applied in the fields of fault diagnosis and underwater acoustic signal recognition [13–15]. It is used to describe the complexity of the signal. Sample entropy (SE) [16], approximate entropy (AE) [17], permutation entropy (PE) [18], dispersion entropy (DE) [19] and so on have been put into use successively, and some achievements have been made [20]. However, single-scale entropy cannot completely reflect the fault information, especially the limitations of mutation information. As a result, multi-scale signal analysis methods are gradually applied to signal recognition [21, 22]. MSE was proposed by Costa et al. in 2002 [23], which successfully quantifies the information of time series on multi-scales. Based on the proposal of multi-scale SE (MSE), in 2005, Aziz et al. also made improvements on PE, proposed multi-scale PE (MPE) [24], and made PE obtain higher noise resistance. The proposed multi-scale DE (MDE) is faster to compute and better reflects the characteristics of the real signal than MSE. Both MPE and MDE are widely used in the field of signal recognition [25, 26].

Considering that the DE is faster and more stable, this paper uses the DE to extract fault features, but the DE contains less information. In order to obtain more information about the signal, we introduce the concept of multi-scale and propose a triple feature extraction method based on MDE and MPE in fault diagnosis.

The remainder of this paper is as follows: Section 2 introduces the principle and calculation method of multi-scale and DE; Section 3 describes the specific steps of the triple feature experiments proposed in this paper. Section 4 shows the feature distribution and recognition results of the triple feature extraction experiments, which proves the feasibility of the experiment. Section 5 summarizes the entire experiment.

2 Dispersion entropy

DE is a measure of time complexity. It has a faster calculation speed, is less affected by sudden changes in the signal and can reflect the magnitude relationship. The calculation steps of DE are as follows.

(1) For a given set of time series, $= \{x_1, x_2, \ldots, x_n\}$, the normal cumulative distribution function is used to map the original time series between 0 and 1.

$$y_j = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x_i} e^{\frac{-(t-\mu)^2}{2\sigma^2}} dt \tag{1}$$

The standard deviation σ and mean μ of the time series x are respectively used in the formula.

(2) Use round function to convert the time series mapped in the first step into integers between 1 and c, where c is the number of categories.

$$z_j^c = Round\left(c \cdot y_j + 0.5\right) \tag{2}$$

(3) Construct the embedding vector based on the embedding dimension m and the time delay constant τ as follows:

$$z_j^{m,c} = \left\{z_j^c, z_{j+\tau}^c, \cdots z_{j+(m-1)\tau}^c\right\} \tag{3}$$

(4) Set $z_j^c = v_0, z_{j+\tau}^c = v_1, \cdots z_{j+(m-1)\tau}^c = v_{m-1}$, based on each embedded vector, a corresponding dispersion pattern can be obtained.

$$\pi_{v_0 v_1 \ldots v_{m-1}} \left(v = 1, 2, \cdots c\right) \tag{4}$$

(5) c^m dispersion patterns can be obtained in Step 4) with the following probabilities.

$$p\left(\pi_{v_0 v_1 \ldots v_{m-1}}\right) = \frac{Number\left\{t \,\middle|\, t \le (m-1)\tau, \pi_{v_0 v_1 \ldots v_{m-1}}\right\}}{N-(m-1)\tau} \tag{5}$$

(6) Based on the above steps, the formula for calculating DE is as follows.

$$DE(x, c, m, \tau) = -\sum_{\pi=1}^{c^m} p\left(\pi_{v_0 v_1 \ldots v_{m-1}}\right) \ln\left(p\left(\pi_{v_0 v_1 \ldots v_{m-1}}\right)\right) \tag{6}$$

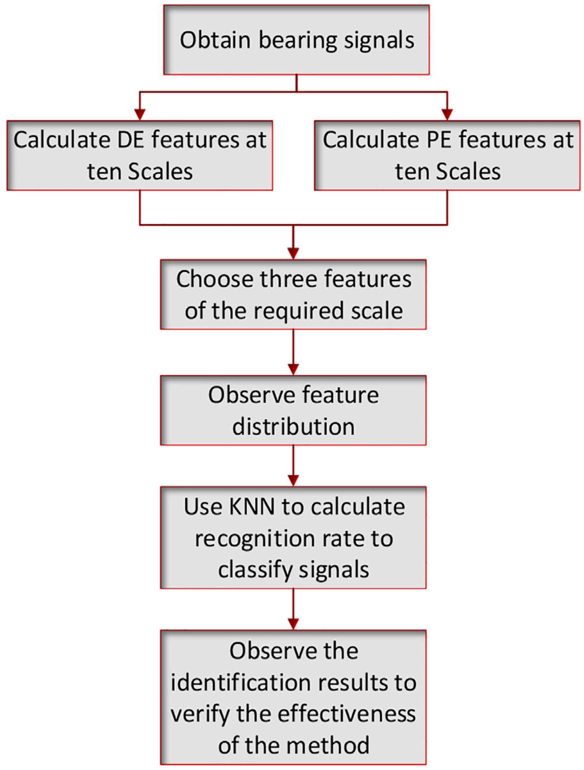

FIGURE 1
Detailed steps of the experiment.

3 Steps of the experiment

The method proposed in this paper is a triple feature extraction method based on MDE and MPE, which is shown in Figure 1. The

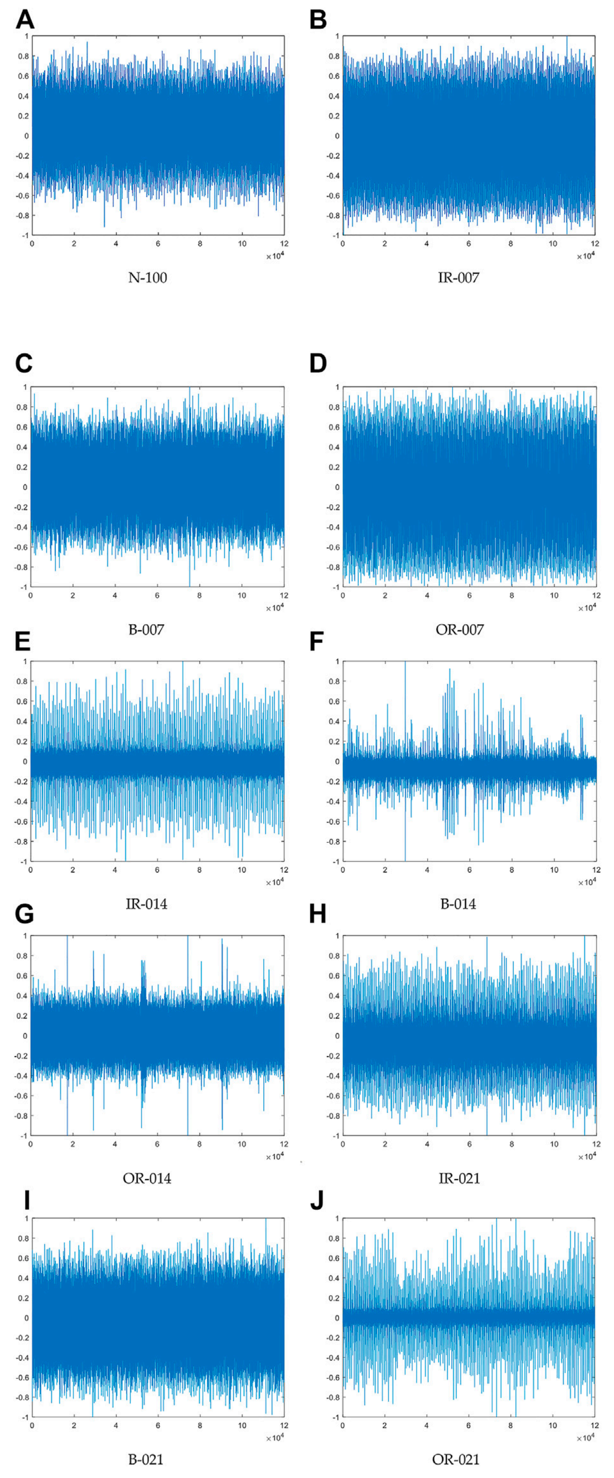

FIGURE 2
Ten types of bearing signals: **(A)** N-100, **(B)** IR-100, **(C)** B-100, **(D)** OR-100, **(E)** IR-014, **(F)** B-014, **(G)** OR-014, **(H)** IR-021, **(I)** B-021, **(J)** OR-021.

method combines scale 2 of MDE with scale 1 and 2 of MPE as three features of the signal, and combines these three features to identify the signal using a classifier. The specific experimental steps are as follows:

(1) Select bearing signals of different fault categories and sizes and divide the samples.
(2) Extract MDE and MPE features at ten scales from samples of these ten types of signals.
(3) Draw the triple feature distribution of the ten types of signals according to the selection principle of the highest recognition rate.
(4) Triple feature recognition by using KNN (k nearest neighbor) algorithm.
(5) Draw the recognition result and calculate the recognition rate to verify the validity of the method.

4 Rolling bearing signals

In order to identify the fault of bearing signal, this article has selected ten bearing signals in different states from Case Western Reserve University [27]. The first one is normal working signal, named N-100, the other nine are working signals in failure state. According to their three sizes (0.007, 0.014 and 0.021 feet) and three different fault locations (ball fault, inner race fault and outer race fault), the nine working signals are named IR-007, B-007, OR-007, IR-014, B-014, OR-014, IR-021, B-021, OR-021. Ten types of bearing signals are shown in Figure 2.

5 Feature extraction experiments

In this experiment, MDE at scale 2 and MPE at scale 1 and 2 are selected as the three features, and the entropy values at ten scales of these ten kinds of signals are calculated. When the scale is 1, the time series is itself. When the scale is larger than 1, the data used to calculate the entropy value is coarsened. The parameters used to calculate the entropy at different scales are the same. It is worth noting that after coarsening, the mean and variance of the data needed for calculating the normal distribution function within the dispersed entropy are still the original data. After calculating the entropy value features, the distribution and recognition of these features are observed and compared, and the feature extraction method used in this paper is verified.

5.1 Single feature extraction

Firstly, the parameters and sampling ranges are determined. The data used are from the ten types of bearing signals selected above. From the 1000th data point of the ten types of signals, 1,024 data points are taken as a sample, and 100 samples are taken for each type of signal. The parameters of these entropy are set as embedding dimension, number of classes, time delay, feature distribution of the ten scales of the two entropy is calculated and plotted. The ten scales of MDE are named as DE1, DE2,.DE10, and MPE is similarly named as PE1, PE2, . PE10. The horizontal coordinates of the graph are the number of samples. The vertical coordinate is the entropy value, and single feature distribution of ten scales of MDE for ten signals are shown in Figure 3.

It can be seen from Figure 3 that at scale 1, entropy values of these ten types of signals are arranged orderly, but there are still different degrees of

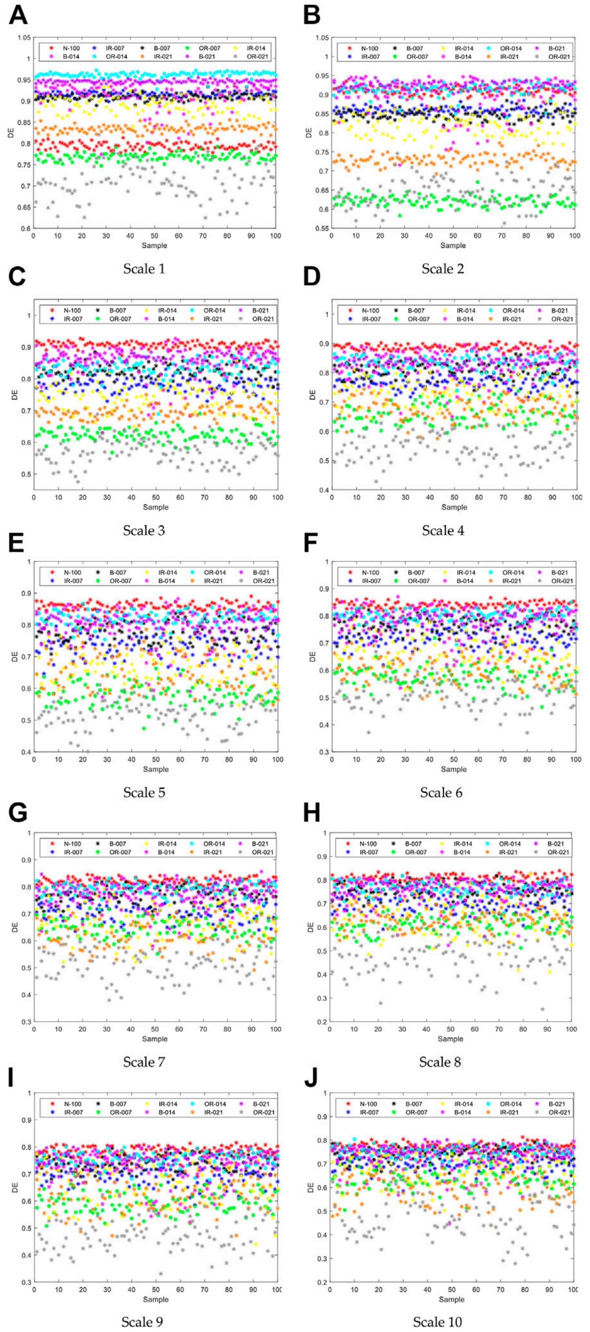

FIGURE 3
Single feature distribution of ten scales of MDE for ten signals: **(A-J)** represent Scale 1 to Scale10.

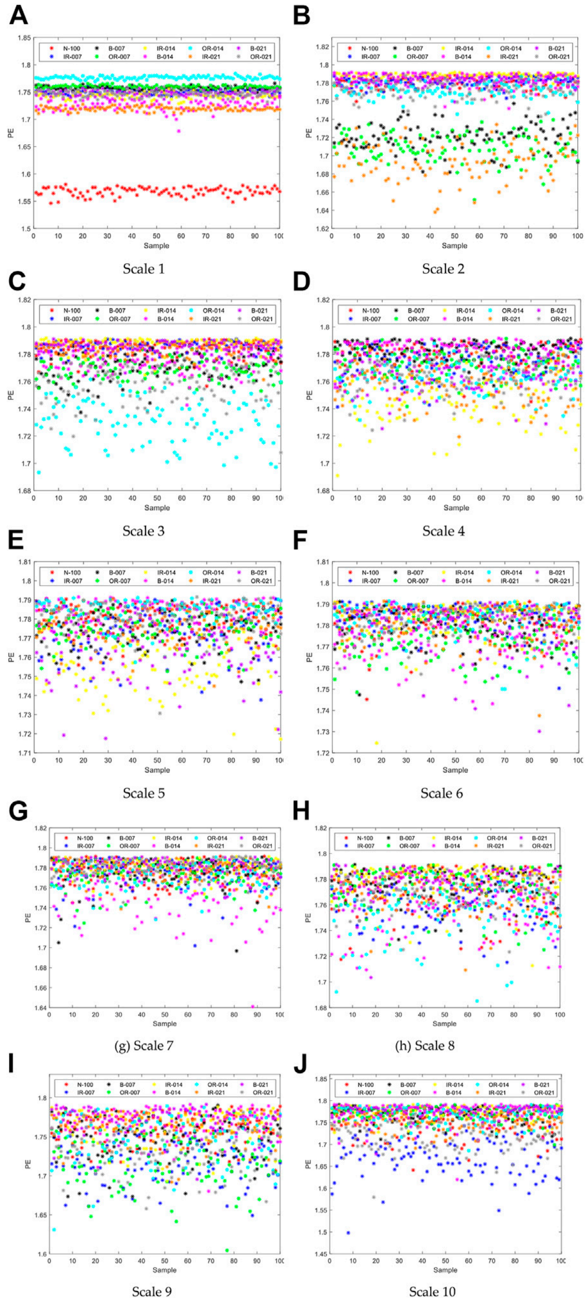

FIGURE 4
Single feature distribution of ten scales of MPE for ten signals: **(A-J)** represent Scale 1 to Scale10.

confusion between two different signals with adjacent distributions. With the increase of scale, the boundaries between various signals become blurred gradually, the effect of feature extraction becomes worse and the phenomenon of aliasing becomes more serious. From the point of view of distribution, the distribution of OR-021 is relatively scattered, while the distribution of other signals mostly concentrates in a certain interval. With the increase of scale, the entropy value gradually concentrates to around 0.8. Single feature distribution of ten scales of MPE for ten signals are drawn in Figure 4.

It can be seen from the Figure 4 that when scale 1 is used, the distribution of the entropy of all kinds of signals is relatively centralized, in which N-100 and OR-014 have less overlap with other signals. In other scales, the signal confusion is more serious. When the scale is 2, the signal entropy concentrates at 1.72 and 1.78. When the scale is greater than 3, the distribution of the ten types of signals is almost confounded. In order to obtain exact results, single feature recognition was performed on these features.

TABLE 1 Single feature recognition results for ten scales of MDE for ten types of signals.

Types	Recognition rate (%)									
	DE1	DE2	DE3	DE4	DE5	DE6	DE7	DE8	DE9	DE10
N-100	80	42	74	70	72	74	50	52	54	34
IR-007	38	60	62	40	22	40	30	34	26	26
B-007	34	38	44	20	40	36	10	18	20	18
OR-007	72	74	50	46	36	32	40	38	44	34
IR-014	62	50	18	28	26	20	20	18	12	8
S-014	30	18	26	22	14	8	6	4	16	10
OR-014	90	24	26	30	38	28	24	8	18	22
IR-021	90	84	74	32	28	32	26	30	10	34
B-021	86	44	54	26	32	26	10	24	6	16
OR-021	90	60	92	82	72	58	80	78	82	68
Average	67.2	49.4	52.0	39.6	38.0	35.4	29.6	30.4	28.8	27.0

According to Table 1, the recognition rate of ten kinds of signals under ten scales of MDE is not high. Except for scale 2 and scale 6, OR-021 had the highest recognition rate. Overall, the recognition rate shows a downward trend with the increase of the scale. When the scale increases to 6, the recognition rate for S-014 starts to be less than 10%. The recognition rate for the ten scales of B-007 and S-014 is less than 50%. Single feature recognition results for ten scales of MPE for ten types of signals are shown in Table 2.

TABLE 2 Single feature recognition results for ten scales of MPE for ten types of signals.

Types	Recognition rate (%)									
	PE1	PE2	PE3	PE4	PE5	PE6	PE7	PE8	PE9	PE10
N-100	100	20	16	16	14	10	20	20	20	16
IR-007	24	24	24	18	10	16	6	14	8	58
B-007	38	38	18	14	16	12	18	18	2	28
OR-007	54	40	24	10	6	16	10	12	46	24
IR-014	36	44	34	26	26	12	18	16	22	8
S-014	48	18	18	26	10	14	26	6	10	8
OR-014	100	32	62	22	14	10	8	22	6	8
IR-021	68	40	10	18	8	12	10	12	10	12
B-021	20	32	22	22	16	16	6	16	16	16
OR-021	20	24	28	12	10	10	8	8	16	20
Average	50.8	31.2	25.6	18.4	13.0	12.8	13.0	14.4	15.6	19.8

As can be seen from the Table 2, the performance of these ten kinds of signals using multi-scale permutation entropy is very poor, with an average recognition rate of 50.8% at scale 1 and less than 40% at the remaining nine scales. When the scale is larger than 3, the recognition rate is lower than 20%. When the scale is 1, the recognition effect is best. The recognition rates of N-100 and OR-014 are 100%, but the recognition rates of the remaining eight signals are not high. The recognition rate decreases significantly with the increase of scale, which is consistent with the feature distribution. The recognition rate of B-007 at scale 9 is only 2%.

5.2 Single feature recognition

After obtaining the characteristic distribution of these ten kinds of signals, a classification algorithm is needed to distinguish them. In this paper, KNN algorithm is selected, 50 of 100 samples are taken as training samples to train the algorithm, and the remaining 50 samples are taken as test samples to observe the classification effect. According to the results of single feature extraction, the single feature recognition results for ten scales with MDE for ten types of signals are shown in Table 1.

5.3 Triple feature extraction

To compare with the feature extraction method proposed in this paper, MSE is introduced in this section, and three features of the ten

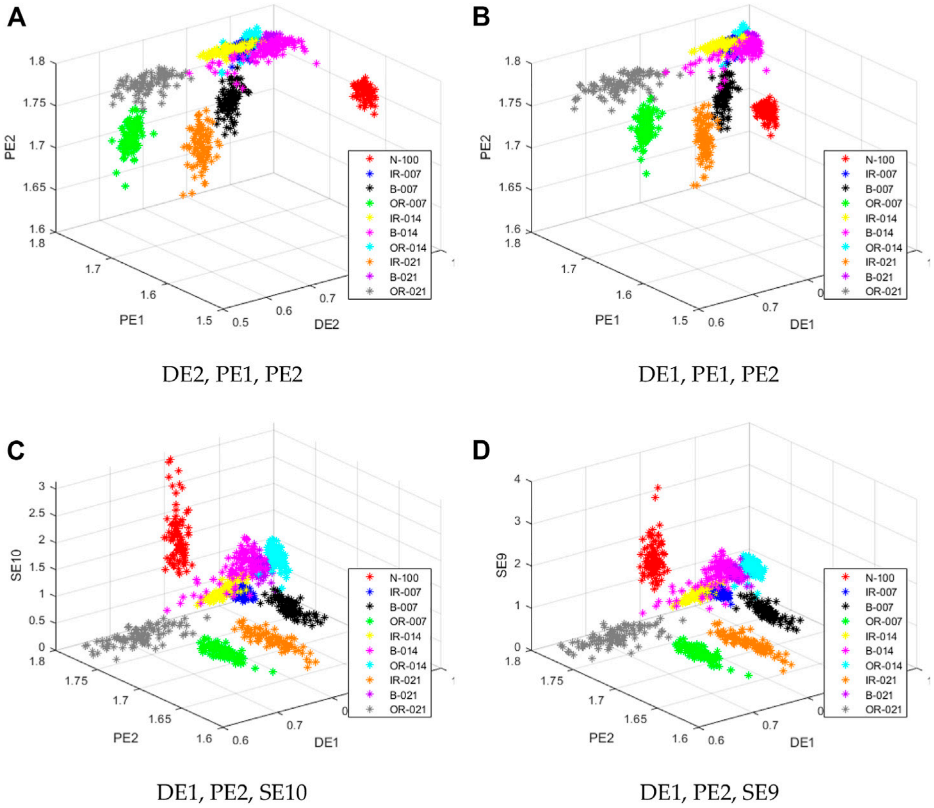

FIGURE 5
The distribution of features for the four best combinations of recognition results: **(A)** DE2, PE1, PE2 ; **(B)** DE1, PE1, PE2; **(C)** DE1, PE2, SE10; **(D)** DE1,PE2,SE9.

scales of the three entropies are combined. Sample selection and parameter setting of the entropy still follow the rules of single feature. Since there are 4,060 methods to select three of the 30 features, the selection of scale combination is based on the highest recognition rate in the experimental results and only four of the best results are obtained in this section: 1) Scale 2 of MDE and scale 1 and 2 of MPE; 2) Scale 1 of MDE and scale 1 and 2 of MPE; 3) Scale 1 of MDE, scale 2 of MPE and scale 10 of MSE; 4) Scale 1 of MDE, Scale 2 of MPE and Scale 9 of MSE. The distribution of features for the four best combinations of recognition results are shown in Figure 5.

From Figure 5, it can be seen that the distribution of all types of signals has been significantly different under the three features, among which N-100, B-007, OR-007, IR-021, OR-021 signals have little mixing with other signals. The remaining five signals have less mixing; All four of the best recognition results have the feature of MPE scale 2. To get a more specific and clear signal distinction, triple feature recognition is used for these features.

5.4 Triple feature recognition

In this section, KNN algorithm is still used to identify the three feature of the feature extraction results. 50 training samples and 50 test samples are still selected. The parameter settings are still the same as those of single feature recognition. Four recognition results maps with the highest recognition rate are drawn. The result figure and recognition rate table of triple feature recognition for ten types of signals are shown in Figure 6 and Table 3.

From Figure 6 and Table 3, it can be seen that the four combinations with the highest recognition rate have a considerable improvement over the recognition rate of single feature recognition, where the combination of scales are chosen based on the highest recognition rate in the experimental results. The average recognition rate of the four combinations has reached more than 90%, and only a few of the 100 samples of each type of signal have been misidentified. In the first combination with the highest recognition rate, the recognition rate of six types of signals is 100%, and the unreachable signals have considerable recognition

TABLE 3 Triple feature recognition rate for ten types of signals.

Combination of scales	DE2, PE1, PE2	DE1, PE1, PE2	DE1, PE2, SE10	DE1, PE2, SE9
Average recognition rate (%)	96.2	95.0	94.0	93.4

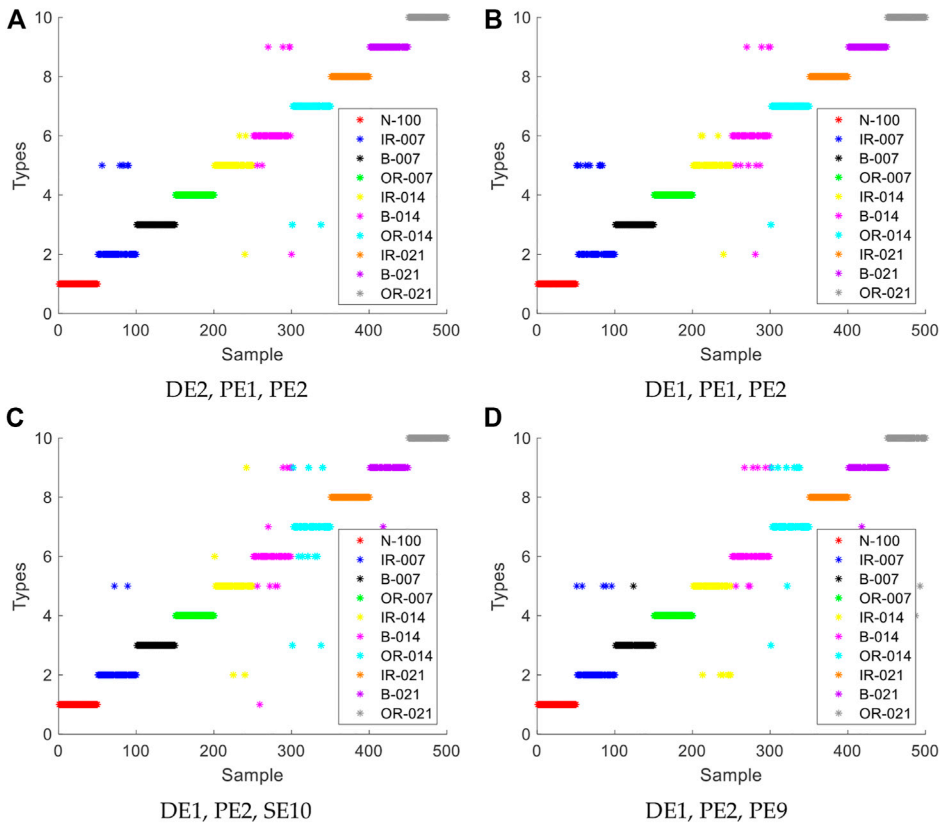

FIGURE 6
Triple feature recognition results for ten types of signals: **(A)** DE2, PE1, PE2 ; **(B)** DE1, PE1, PE2; **(C)** DE1, PE2, SE10; **(D)** DE1, PE2, SE9.

results. The combination of DE2, PE1 and PE2 presented in this paper has the highest recognition rate.

6 Conclusion

Fault signal recognition is the classification of time series, first extracts the features of the fault signal, and then uses the classification algorithm to classify the signal according to the features. In this paper, the multi-scale method is used to obtain the signal features at different scales, where the selection of scale combination is based on the highest recognition rate in the experimental results and only four of the best results are obtained in this section. Combining scale 2 of MDE with scale 1 and 2 of MPE, a triple feature extraction method is proposed to extract and identify the signal features. To verify the superiority of this method, ten types of rolling bearing fault signals are identified. The following are the main research conclusions:

(1) In the field of fault diagnosis, this paper introduces a triple feature extraction method based on scale 2 of MDE, scale 1 and 2 of MPE, and achieves good recognition results with the highest recognition rate of 96.2%.
(2) Combining the three types of entropy which have poor recognition effect in single feature experiment, the recognition ability has been improved significantly, and the recognition rate has been improved by 29%.
(3) The triple feature extraction methods proposed in this paper have a recognition rate of at least 1.2% higher than the other combinations of the three entropies, which can better diagnose the fault.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: [Online]. Available: http://csegroups.case.edu/bearingdatacenter/pages/download-data-file.

Author contributions

NZ and LW jointly discuss and determine the idea and method of the experiment. NZ is responsible for the whole feature extraction experiment, LW is responsible for the writing of the experiment part, and finally, NZ and LW are jointly responsible for the inspection and revision of the article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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