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Research article

An enhanced diagnosis method for weak fault features of bearing acoustic emission signal based on compressed sensing

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Abstract: Aiming at the problems of data transmission, storage, and processing difficulties in the fault diagnosis of bearing acoustic emission (AE) signals, this paper proposes a weak fault feature enhancement diagnosis method for processing bearing AE signals in the compressed domain based on the theory of compressed sensing (CS). This method is based on the frequency band selection scheme of CS and particle swarm optimization (PSO) method. Firstly, the method uses CS technology to compress and sample the bearing AE signal to obtain the compressed signal; then, the compressed AE signals are decomposed by the compression domain wavelet packet decomposition matrix to extract the characteristic parameters of different frequency bands, and then the weighted sum of the characteristic parameters is carried out. At the same time, the PSO method is used to optimize the weight coefficient to obtain the enhanced fault characteristics; finally, a feature-enhanced-support vector machine (SVM) fault diagnosis model is established. Different feature parameters are feature-enhanced to form a feature set, which is used as input, and the SVM method is used for pattern recognition of different types and degrees of bearing faults. The experimental results show that the proposed method can effectively extract the fault features in the bearing AE signal while improving the efficiency of signal processing and analysis and realize the accurate classification of bearing faults.

Keywords: compressed sensing; bearing acoustic emission signal; feature enhancement; particle swarm optimization method; support vector machine

1. Introduction

Bearing is an important component of rotating machinery and has been widely used in various fields such as automation and medical treatment. Due to the harsh and complex working environment, it has become one of the most vulnerable parts of mechanical equipment. Its running state directly affects the safety, reliability, and service life of the whole mechanical system [1]. Therefore, it is extremely important to conduct fault diagnosis research on bearings. Bearing fault diagnosis is very complicated, especially since its early fault signal is extremely weak, which is easy to be submerged in the noise signal of other components and cannot be detected [2]. However, the above-mentioned traditional vibration analysis method and current analysis method mainly classify the bearing faults at high speed, and it is difficult to accurately classify the vibration signals buried in noise and the current signals in the low-speed bearing faults. Compared with vibration analysis [3–5] and current signal analysis [6], AE signal has the following advantages: a) It is not affected by mechanical background noise; b) It is more sensitive to early and low-speed bearing faults; c) It is sensitive to the location of the fault; d) It can provide good trend parameters; e) It has the characteristics of high frequency and obvious frequency [7]. Due to the above advantages, bearing fault diagnosis based on AE signals has been widely used, and some research results have been obtained. However, AE technology has the disadvantages of a large amount of time-domain data and difficulty in storage and processing. At the same time, high-frequency AE signals are accompanied by high sampling rates, and the combination of high sampling rates and massive data will bring greater challenges to the cost of acquisition hardware. This time-domain signal obtained based on the Nyquist sampling theorem has a large amount of redundant information, and then the workload of feature extraction and analysis for such a huge amount of data has increased exponentially. Therefore, fundamentally reducing the amount of data becomes an urgent problem to be solved by the AE signal fault diagnosis method.

The CS theory proposed in recent years uses the transform space projection method to realize the compressed sampling of the original signal [8–10]. Most of the information contained in the original signal is obtained with very few measured data, thereby greatly improve the data transmission efficiency and reduce the data storage space, which provides a new idea for bearing AE signal fault diagnosis. At present, the bearing fault diagnosis method based on CS has received widespread attention.

There are many application research of compressed sensing fault diagnosis focus on the optimized feature extraction method. Literature [11] proposed a bearing fault diagnosis method based on CS and matching pursuit (MP) reconstruction algorithm. Literature [12] proposed a CS framework for characteristic harmonics to detect bearing faults. This method uses a compressed MP strategy to detect characteristic harmonics from sparse measurements under the condition of incomplete signal reconstruction. Literature [13] proposed a bearing fault diagnosis method based on CS. This method trains multiple over-complete dictionaries through the dictionary learning method. These dictionaries are effective for the sparse decomposition of signals in each specific state, while signals in other states cannot be sparsely decomposed. This method uses this characteristic to determine the fault state of the bearing. Literature [14] proposed a sparse representation classification strategy, which combined sparse representation with random dimensionality reduction to extract and classify the fault features of rotating machinery. Literature [15] proposed a fault diagnosis method based on sparse representation of time-frequency features, which can reconstruct the time-frequency features of fault signals from a small amount of compressed sampled data containing noise. Literature [16] proposed a method to directly extract the acoustic emission signal compression feature (AECF) from the CS data, and the AECF trend is used to evaluate the running state of the bearing. Literature [22] proposed a fault diagnosis method based on SAE, which combines CS and wavelet packet energy entropy.

Another hot-spot about compressed sensing fault diagnosis focus on the design classification method. Literature [17] uses three methods to process the compressed data and the compressed measured value is directly used as the input of the classifier to diagnose bearing faults. Literature [18] proposed a new intelligent classification method, which uses sparse over-complete features and a deep neural network (DNN) with an unsupervised feature learning algorithm based on sparse autoencoders (SAE) to classify bearing faults in compression measurement. Literature [19] proposed a method for bearing fault diagnosis in a fluctuating environment based on the theory of compressed sensing. The proposed method can effectively reduce the amount of data required for bearing diagnosis and maintain similar accuracy to the current method. Moreover, the reconstructed signal can be used for other fault diagnosis methods. Literature [20] proposed a bearing fault diagnosis method based on CS and heuristic neural networks. Literature [21] proposed a new type of intelligent diagnosis method based on CS and deep learning. It uses the advantages of CS and deep learning to obtain high recognition accuracy with a small amount of measurement data.

The characteristics of bearing fault diagnosis technology based on compression perception above were comprehensively analyzed. Based on the research in reference [16], this paper optimizes and improves the signal decomposition method and feature extraction method in the compressed domain. This method obtains the compressed signal by projecting the signal from the time domain to the compressed domain and is regarded as the original measurement signal; the wavelet packet decomposition of the measured signal is carried out using the wavelet packet change matrix in the compression domain. The characteristic parameters of each frequency band information obtained are taken as feature vectors; the PSO algorithm is used to optimize the weighted coefficient of the feature vector to obtain the fault feature with enhanced feature; the SVM is used to identify and classify bearing fault types. The accuracy and practicability of the method are verified by fault experiments. The contribution of this method is as follows:

a. A fault diagnosis method combining CS technology and AE signals is proposed. Compressed sampling greatly reduces the amount of AE data and retains most of the effective information of the signal for fault diagnosis. The problem of high hardware requirements for the AE signal due to large data volume is solved.

b. The transform matrix of wavelet packet decomposition in the compression domain is derived from the time domain wavelet packet decomposition matrix, which is used to perform wavelet packet decomposition of the compression signal. The fault features of the compression domain of different frequency bands are extracted.

c. Feature weighting is adopted to deal with fault features in the compression domain. The PSO algorithm is used to optimize the weighting coefficient of the fault features. This method realizes the enhancement of weak fault features and avoids the uncertainty of diagnosis results caused by the subjective and one-sided selection of feature information of different frequency bands.

d. Experimental verification shows that the proposed method has a more satisfactory diagnostic performance for bearing fault diagnosis under low-speed conditions compared with the traditional method.

2. Theoretical background

2.1. Compressed sensing theory

CS was proposed by Candes et al. [8,9]. It makes use of the sparse characteristic of signals in a certain transformation domain to compress data while sampling the signal. The compressed data retains most of the information of the original signal, and the reconstruction algorithm uses the observation data to reconstruct the original signal. Most signals in nature are not sparse signals, but a specific transform domain Ψ can be found to make the signal sparse. CS theory points out that if the measured signal $x \in R^N$ is sparse in a certain transform domain Ψ, a measurement matrix $\Phi \in R^{M\times N}$ $(M \ll N)$ that is not related to the transform domain can be used to linearly project the measured signal to obtain the compressed signal $y \in R^N$. Then the original signal $\hat{x}$ is reconstructed with high probability by solving the optimization problem. The sparse representation of a signal x on the orthogonal basis $\Psi \in R^{N\times N}$ is

$$x = \Psi s \tag{1}$$

where the transform coefficient s is sparse and contains only $k(k \ll N)$ non-zero elements. We select the measurement matrix Φ that is not related to Ψ. The signal x is projected to the measurement matrix Φ. Then the reduced-dimensional projection data y is expressed as

$$y = \Phi x = As \tag{2}$$

where $A = \Phi\Psi$ is the perception matrix. To carry out effective and unique signal reconstruction, the expression is often solved by optimizing l_1 norm [23] and the greedy algorithm

$$\hat{x} = arg \quad min\|x\|_1 \quad s.t. \; As = y \tag{3}$$

2.2. Random projection distance preservation

The signal $x \in R^N$ uses a random measurement matrix Φ of size $M \times N$ for compression measurement to obtain compressed data y of size $M \times 1$. Then the relationship between the original signal and the compressed data can be expressed as

$$(1-\varepsilon)\|x-y\|^2 \le \|\Phi(x-y)\|^2 \le (1+\varepsilon)\|x-y\|^2 \tag{4}$$

where $\varepsilon \in (0,1)$, the original signal x has approximate distance preserving in Euclidean space before and after projection. Thus, sufficient effective information of the original signal is preserved in the compressed data, which provides a theoretical basis for the feature extraction method of the compressed domain in this paper.

When the measurement matrix meets the requirement of random projection distance preserving, the signal can be accurately reconstructed. In this paper, the Gaussian random matrix that satisfies the random projection distance preserving property with a high probability is used as the measurement matrix to compress and sample the signal. The measurement matrix is constructed by generating a matrix Φ with the size of $M \times N$, so that each element Φ independently obeys a Gaussian distribution with a mean value of 0 and a variance of $1/M$ [24,25]. This measurement matrix is a random measurement matrix, which is not related to most orthogonal bases or orthogonal dictionaries, and the number of measurements required for accurate reconstruction is small.

3. Compressed domain feature enhancement

The reduction of signal feature information after original signal compression will affect the effect of subsequent fault diagnosis. This paper proposes a week feature enhancement method for improving the accuracy of fault classification.

3.1. Compressed domain transformation matrix based on random projection preservation

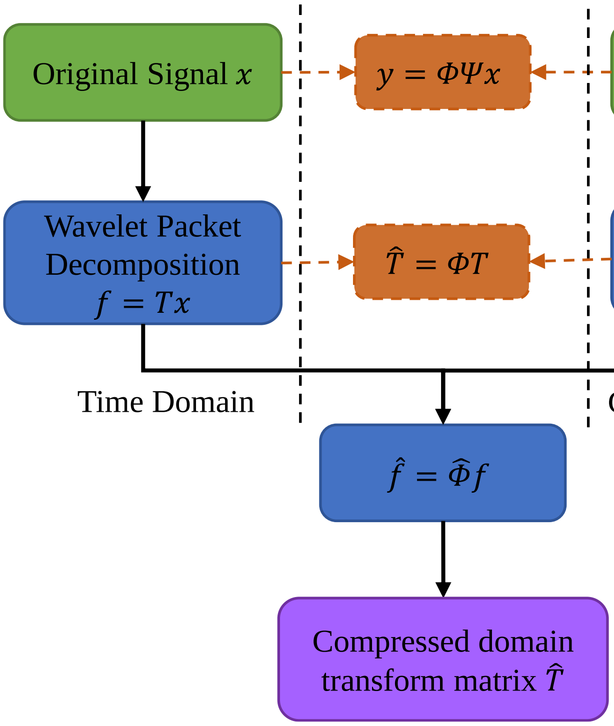


Figure 1. Schematic diagram of the compressed domain transformation matrix based on random projection distance preservation.

Wavelet packet decomposition can decompose the signal into different frequency bands adaptively, without leakage, and without overlapping according to the feature of the signal. It not only improves the time-frequency resolution of the signal but also obtains more detailed information about the signal. In this paper, wavelet packet transform is used to decompose the compressed signal to extract signal features. The time-domain wavelet packet transform matrix of the original signal $x \in R^N$ is $T \in R^{N \times N}$, then the decomposition process of the original signal x can be expressed as

$$f = Tx \tag{5}$$

where $f \in R^N$ is the signal component of the signal x after wavelet packet decomposition in time domain space. Similarly, the wavelet packet transform matrix of the compressed signal $y \in R^M$ is $\hat{T} \in R^{M \times M}$, then the decomposition process of the compressed signal is

$$\hat{f} = \hat{T}y \tag{6}$$

where $\hat{f} \in R^M$ is the signal component of the compressed signal y after the wavelet packet decomposition in the compressed space. According to the distance preserving property of random projection, the dimension reduction observation vector $\hat{f}$ is obtained by projecting the transformation vector f on the random measurement matrix Φ. Similar to the original signal transformation process, the dimensionality reduction observation vector $\hat{f}$ is regarded as the compressed data y obtained through signal transformation, then the compressed domain signal transformation can be expressed as $\hat{f} = \hat{T}y$. The premise of analyzing the dimensionality reduction observation vector is to obtain the compression domain transformation matrix $\hat{T}$, then the solution formula is

$$\hat{f} = \Phi f = \Phi T x = \hat{T} \Phi x \tag{7}$$

$$\hat{T} = \Phi T \Phi^{-1} \tag{8}$$

In Eq (8), the random measurement matrix Φ is not a square matrix, and the least-squares approximation solution needs to be solved by pseudo-inverse Φ^{-1} so as to solve the transformation matrix $\hat{T}$ in the compression domain. In this paper, the compression domain transformation matrix is firstly used to decompose the compressed signal, and then the signal features are extracted. As shown in Figure 1, the schematic diagram of the compression domain transformation matrix based on random projection distance preservation is presented. Therefore, the method in this paper can extract the characteristic information of the compressed signal for diagnostic analysis on the premise of ensuring that the compressed signal retains enough effective information of the original signal.

3.2. Feature enhancement process

The compressed signal is decomposed by wavelet packet to obtain signal features of different frequency bands. Since different frequency bands all contain the local feature information of the signal, if this feature information can be fully utilized, the accuracy of fault classification can be further improved. Therefore, this paper proposes to weight the decomposed signal features, and the PSO method is used to optimize the weight coefficient so as to realize the adaptive selection of the signal features of different frequency bands.

The PSO algorithm is an intelligent optimization algorithm that tracks the optimal particles in the solution space for searching by simulating the predation behavior of birds. Assuming that there are n particles in the D-dimensional search space, where the position of the i-th particle is $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$, and the velocity of the corresponding i-th particle is $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$. The best position experienced by the i-th particle individual is $pbest_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$, the best position experienced by the population is $gbest = (g_1, g_2, \cdots, g_D)$, then the velocity and position update formula of each particle is

$$v_{id}^{k+1} = w v_{id}^{k} + c_1 r_1 (pbest_{id} - x_{id}^{k}) + c_2 r_2 (pbest_d - x_{id}^{k}) \tag{9}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{10}$$

where w is the inertia weight; c_1, c_2 are acceleration factors; r_1, r_2 are random numbers between

[0, 1]; $d = 1, 2, \cdots, D$; $i = 1, 2, \cdots, D$; k is the current iteration frequency.

Table 1. PSO algorithm parameter settings.

Allowable Error	The Maximum Number of Itera-tions	Particle Swarm Size n	Acceleration Factor c_1	Acceleration Factor c_2	Inertia Weight
0.0001	400	700	1.5	1.5	0.8

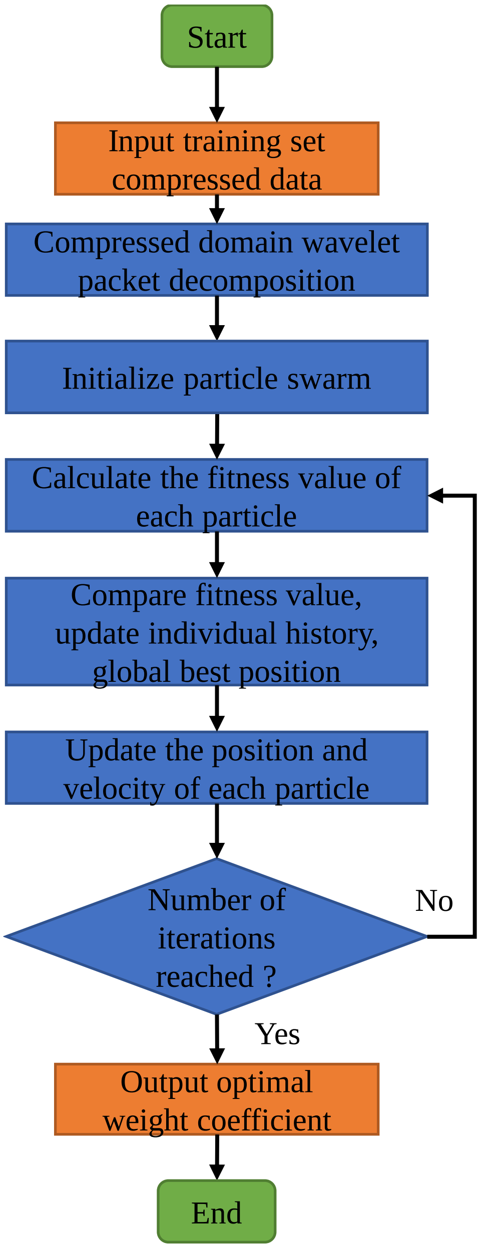


Figure 2. Flow chart of feature enhancement algorithm based on PSO.

In the optimization process of the particle swarm optimization algorithm, each particle has a fitness function to determine whether the position it has experienced so far is optimal, and then the position is updated after comparison. The distribution of signal feature weight coefficients directly affects the fault classification effect. At this time, it is necessary to ensure that the distance between compressed signal feature classes is as large as possible. Therefore, this paper takes the average distance between compressed signal feature classes as the fitness function, and the expression is as follow

$$D_i = \frac{1}{n-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{n} d_{ij} \tag{11}$$

where D_i is the average distance between the i -th type and other classes, d_{ij} is the distance between the i -th type feature and the j -th type feature, and n is the number of fault types.

The particle swarm optimization algorithm steps are as follows:

Step 1: Initialize the particle swarm and set various parameters.

Step 2: Evaluate the fitness of each particle according to the fitness function.

Step 3: Compare the fitness value and update the individual historical best position $pbest$ and the global best position $gbest$.

Step 4: Update the position x and velocity v of each particle according to Eqs (9) and (10).

Step 5: Turn to step 2 to loop iteratively until the number of iterations is satisfied or within the allowable error range, and output the best fitness value and particle position.

The flow chart of the feature enhancement algorithm based on PSO is shown in Figure 2. When setting the parameters of the particle swarm, the main parameter values are shown in Table 1.

4. Fault diagnosis method of bearing acoustic emission signal

By combining CS theory with the PSO algorithm, the problem of AE signal data redundancy can be effectively solved, and the frequency band features containing the main feature information can be adaptively selected to avoid the uncertain influence of subjective parameter setting on experimental results. After the original signal is compressed and sampled, the amount of data is reduced. The compressed signal is decomposed by the wavelet packet in the compressed domain. The PSO algorithm is used to adaptively select the obtained frequency band features, and the fault features are enhanced. Finally, the faults are classified by the SVM. The basic process of bearing AE signal feature enhancement fault diagnosis is shown in Figure 3. The specific steps of the method for enhancing the diagnosis of bearing AE signal weak fault features based on CS are as follows:

a. AE signals of different fault states of the rolling bearing are collected by the AE acquisition system to form a data sample set.

b. The Gaussian random matrix is selected as the measurement matrix Φ. Using Eq (2), the N -dimensional AE signal x is projected to obtain the M -dimensional measurement value y.

c. The wavelet packet decomposition matrix $\hat{T}$ in the compressed domain is obtained by Eq (7). The transformation matrix $\hat{T}$ is used for wavelet packet decomposition of the measured value y. The time domain and frequency domain features of different frequency bands are extracted to form the feature set of the compression domain.

d. The PSO algorithm is used to calculate the weight of signal features of each frequency band so as to obtain feature sets with sufficient distance between classes.

e. Input the enhanced feature set into the SVM classifier for training and testing, and finally realize the fault diagnosis of the rolling bearing.

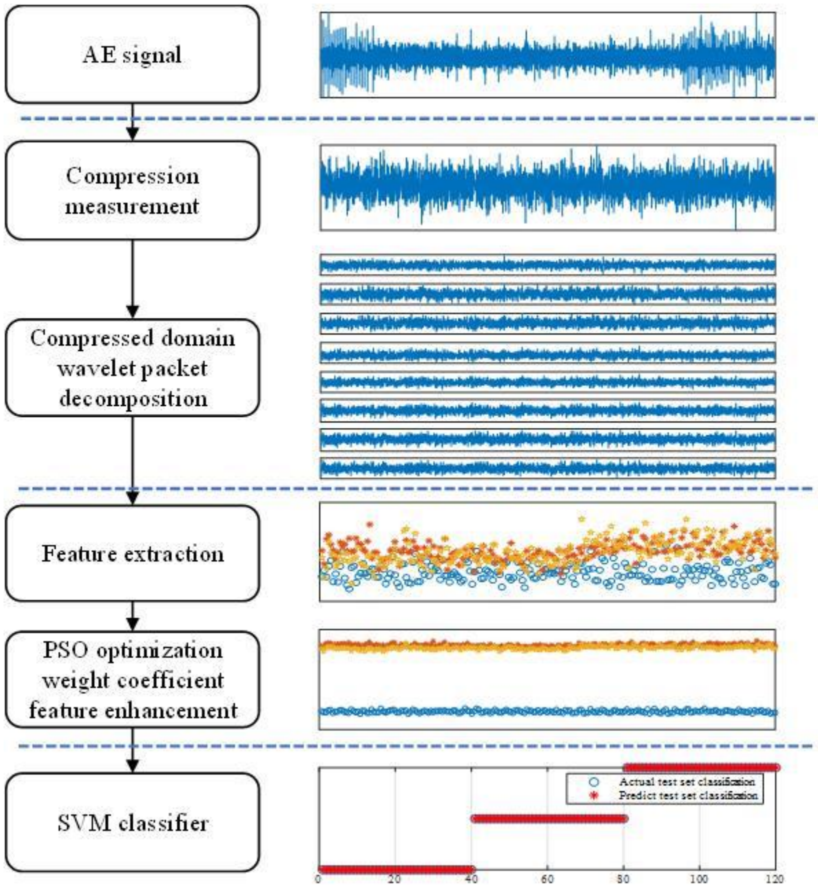


Figure 3. Flow chart of fault diagnosis for bearing AE signal feature enhancement.

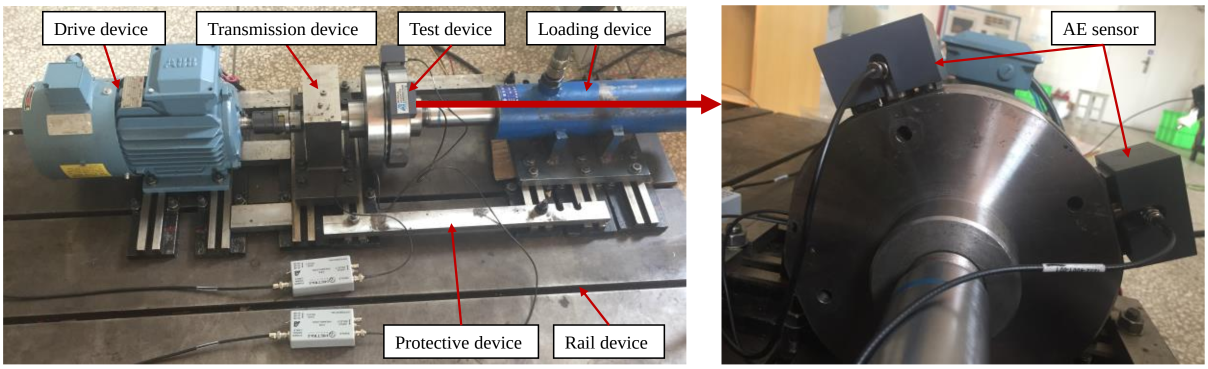


Figure 4. Bearing failure test bench.

5. Experimental verification and analysis

In order to verify the effectiveness of the method in this paper, thrust ball bearings are used for fault simulation experiments, which simulate three states of normal bearing, raceway failure, and rolling element failure. The ball bearing is installed on the bearing failure simulation test bench, which is composed of six parts: drive device, transmission device, test device, loading device, guide rail device, and anti-overload protection device. AE sensors are used to collect bearing AE signals. The AE acquisition system consists of sensors, preamplifiers, data acquisition cards, hosts, and display. The layout of the test bench and sensors is shown in Figure 4. The experiment uses electrical discharge machining technology to process single-point pits on the central position of the bearing raceway and rolling elements to simulate the weak bearing fault. The corresponding fault diameters are 0.5 mm, 1 mm, 1.5 mm, and the depth is 0.65 mm, as shown in Figure 5. The spindle speed of the test bench is 400 rpm, the preamplifier is set to 60 dB, the sampling frequency is 1 MHz, and the number of data points is 1,638,400.

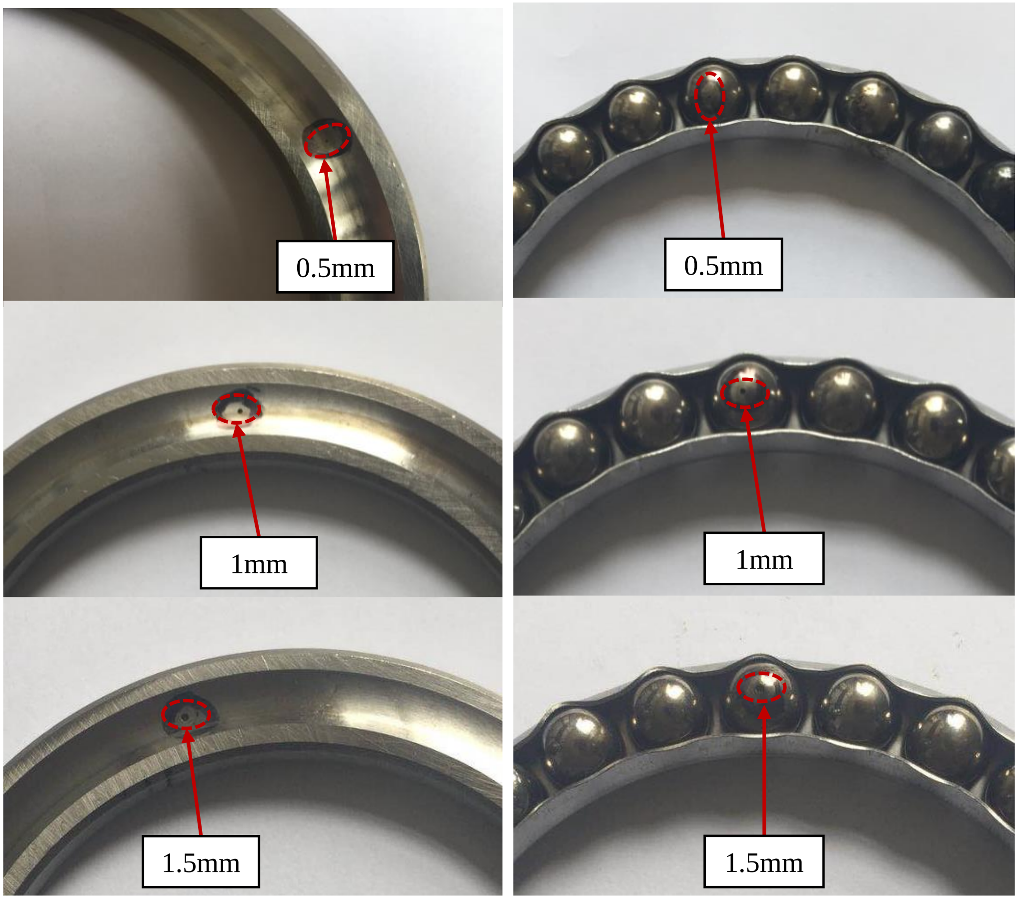


Figure 5. Failure diagram of bearing parts.

5.1. Feature enhancement based on compressed sensing

This paper mainly studies the AE signal with reduced data volume after compression. The AE signal is obtained by constructing a Gaussian random measurement matrix and performing random projection compression on it. Figure 6 shows the time domain waveform diagram and frequency spectrum of the AE signal before and after compression of a sample under the three states of normal, race failure, and rolling element failure. It can be seen from Figure 6 that compared with the original AE signal, the compressed AE signals in the three states exhibit relatively similar random characteristics in both the time domain and the frequency domain. The obvious periodic fault features of the original signal cannot be well-reflected. This is due to the loss of some time-domain features of the signal during the compression measurement process. At this time, conventional AE signal analysis methods cannot accurately and effectively perform feature extraction and classification.

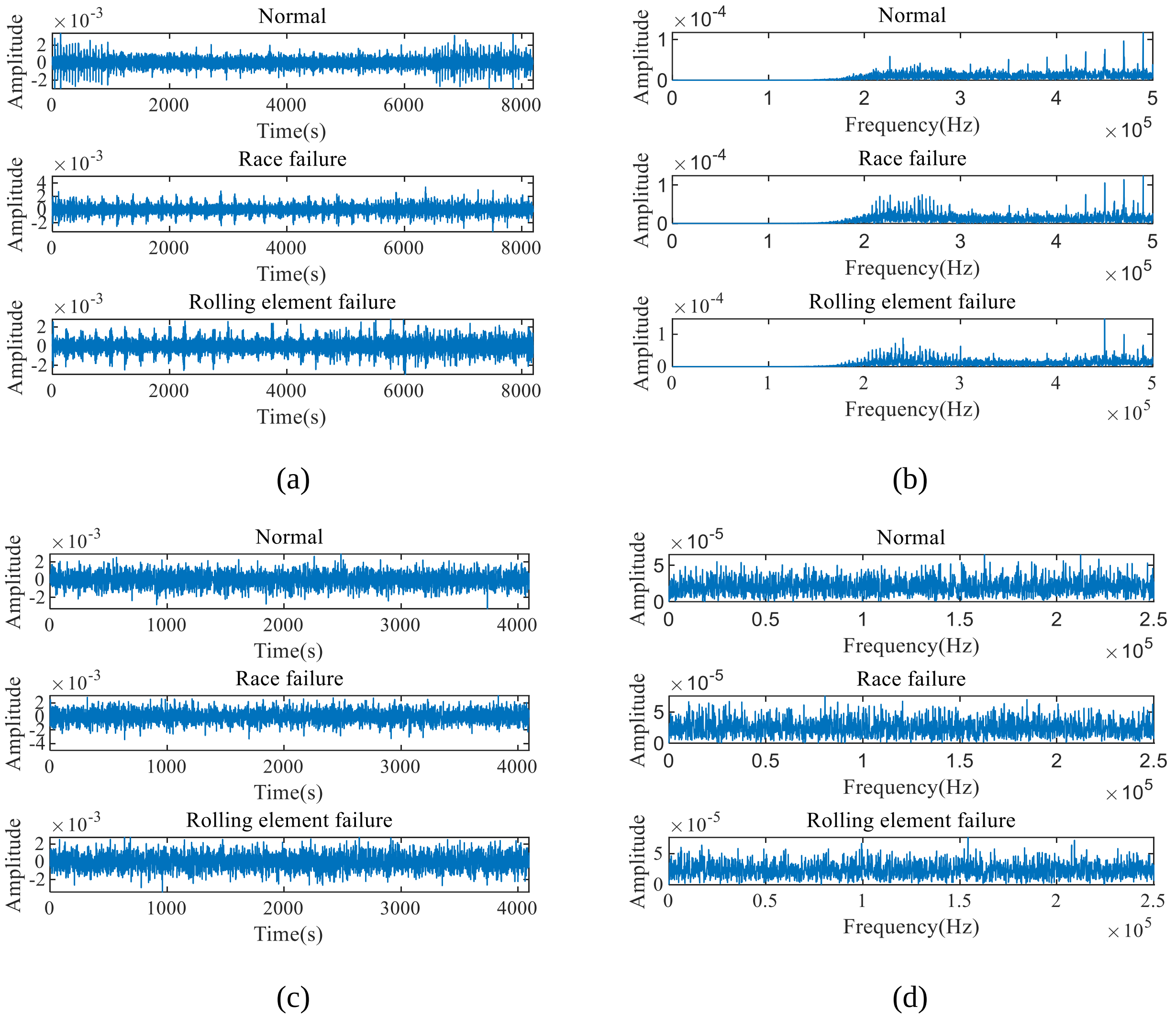


Figure 6. Time-domain waveforms and spectrograms of three states before and after AE signal compression. (a) Original AE signal waveform; (b) Original AE signal spectrum; (c) Compressed measurement data waveform; (d) Compressed measurement data spectrum.

Since compressed data shows randomness in amplitude, in order to obtain enough feature information of compressed domain signals, this paper extracts features from compressed data in the time domain and frequency domain. This paper extracts twenty-eight fault features including thirteen-time domain parameters ($T1 \sim T13$) and fifteen-frequency domain parameters ($T14 \sim T28$) from the wavelet packet decomposition components of the compressed data. The specific feature parameter names and calculation formulas are shown in Table 2. $T19$ and $T20$ indicate the change of the position of the main frequency band and $T21 \sim T25$ indicate the degree of dispersion or concentration of the spectrum. In Table 2, X_k is the spectrum of signal x, where $k = 1, 2, \ldots, N/2.56$ is the number of spectral lines, and N is the number of sampling points of signal x. $PS[k] = 2|X_K|^2 / N^2$, $f = 2.56 f_s * k / N$, $M = 1 + N/2$, $P = PS[0] + \sum_{k=1}^{N/2.56} PS[k]$,

$P0 = (\sum_{k=0}^{N/2.56} PS[k]f)/P$.

Table 2. Characteristic parameter table

Serial Number	Feature Name	Serial Number	Feature Name
$T1$	Absolute mean	$T15$	Spectral mean
$T2$	Mean	$T16$	Spectral skewness index
$T3$	Peak index	$T17$	Spectral kurtosis index
$T4$	Margin index	$T18$	Root mean square frequency
$T5$	Kurtosis index	$T19$	$P1$
$T6$	Skewness index	$T20$	$P2$
$T7$	Zero peak	$T21$	$P3$
$T8$	Impulse indicator	$T22$	$P4$
$T9$	Peak-to-peak	$T23$	$P5$
$T10$	Effective value	$T24$	$P6$
$T11$	Waveform index	$T25$	$P7$
$T12$	Variance	$T26$	Frequency center
$T13$	Square root amplitude	$T27$	Spectral variance
$T14$	Total spectrum	$T28$	Amplitude spectral entropy

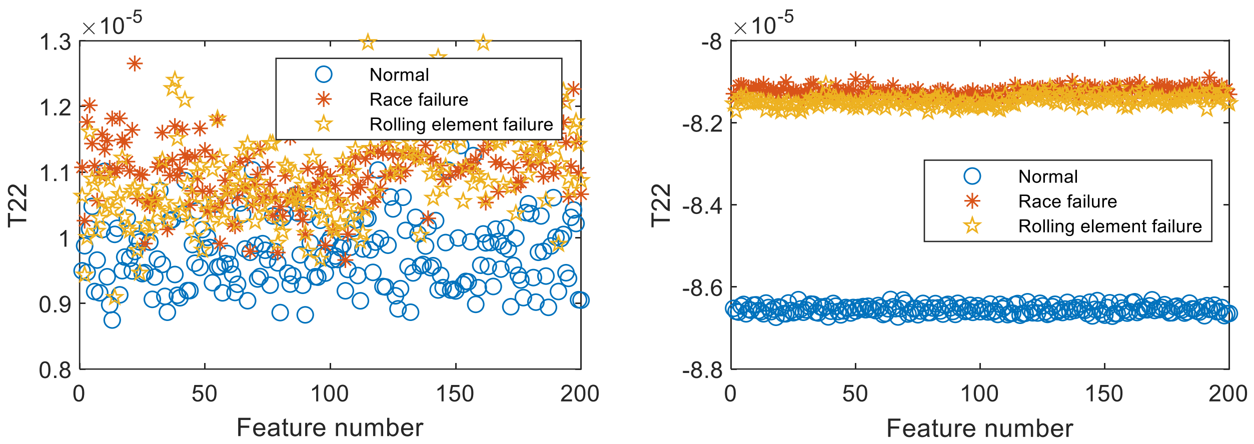
$$P1 = \sqrt{\frac{\sum_{k=0}^{N/2.56}(f^2 * PS[k])}{P}} \quad , P2 = \frac{\sum_{k=0}^{N/2.56}(f^2 * PS[k])}{\sqrt{P * \sum_{k=0}^{N/2.56}(f^4 * PS[k])}} \quad ,$$

$$P3 = \frac{1/M \sum_{k=0}^{N/2.56}(PS[k] - P/M)^3}{\sqrt{(1/M \sum_{k=0}^{N/2.56}(PS[k] - P/M)^2)^3}} \quad , P4 = \frac{1/M \sum_{k=0}^{N/2.56}(PS[k] - P/M)^4}{(1/M \sum_{k=0}^{N/2.56}(PS[k] - P/M)^2)^2} \quad ,$$

$$P5 = \sqrt{\frac{2.56\sum_{k=0}^{N/2.56}((f - P0)^2 PS[k])}{N}} \quad , P6 = \frac{P5}{P0} \quad , P7 = \frac{\sum_{k=0}^{N/2.56}((f - p0)^3 PS[k])}{P5}$$

According to the feature enhancement method in this article, firstly, the AE data of different states are obtained. Two hundred sets of data are taken from each state, and 8192 sample points are intercepted from each set of data. Secondly, the AE data is compressed and measured, and a total of 600 sets of data are compressed and projected to obtain compressed data with a length of 4096 (downsampling rate $R = 2$). Then feature extraction is carried out for the compressed domain data. According to experience, three-layer wavelet packet decomposition is selected, and each group of sample signals will generate 8 component signals of different frequency bands so that there are 4800 component signals of 600 × 8. Twenty-eight eigenvalues of each group of sample wavelet packet decomposition data are calculated to obtain an eigenmatrix of the sample signal compression domain with a size of 4800 × 28. Finally, most of the multi-component signals of these compressed data contain low-frequency information and high-frequency noise signals of bearing operation, and the fault information contained therein is masked, which has a strong interference effect on fault identification. Therefore, in order to improve the classification accuracy of compressed data, weaken the interference of high-frequency noise, and enhance the weak fault characteristic signal, the PSO method can be used to optimize the characteristic weight coefficients of the eight components of the wavelet packet decomposition of each sample to realize the characteristic enhancement and obtain a 600 × 28 eigenvalue matrix.

One feature that is relatively obvious in comparison among the three sample data is selected. As shown in Figure 7, the signal feature is extracted directly after compression and the Characteristic parameters of the signal after the fault feature is enhanced. It can be seen from Figure 7(a) that the compressed feature parameters are in disorder and difficult to classify. In Figure 7(b), the compressed signal is decomposed by wavelet packet by the method of this paper, and the features of each compon-ent signal are extracted for weighted summation. It can be seen that the characteristic parameters of different types of faults obviously have certain laws. Normal and faulty bearings are effectively separated. The two faults of the raceway and rolling element are relatively poor, but they can still be clearly identified. This paper takes different types of fault features as input and selects a suitable proportion of training set and test set. The fault type and classification accuracy are determined by the matching degree of training set prediction classification and test set classification.



(a) (b)

Figure 7. Comparison of features extracted directly from compressed domain and feature parameters after feature enhancement. (a) Compressed domain feature parameters; (b) Feature parameters after fault feature enhancement.

5.2. Bearing fault diagnosis with enhanced compression domain features based on SVM

The feature set is formed by feature extraction and enhancement of the compressed data, and the feature vector matrix is divided into the training set and the test set by 4:1. The kernel function of SVM selects the Gaussian radial basis function, and the results of classification using this method are shown in Table 3. It can be seen from Table 3 that the data samples are divided into three categories. The test sample numbers 1–40, 41–80, 81–120 are a group of samples corresponding to normal, race failure, and rolling element failure. The 120 samples in the test set use the weak fault feature enhancement algorithm to accurately identify various fault samples with a classification accuracy of 100%.

Table 3. Classification results of different types of faults.

Fault Type	Speed/rpm	Fault Diameter/mm	Sample Number	Classification Accuracy Rate/%
Normal	400	0	1-200	100
Race failure	400	0.5	201-400	100
rolling element failure	400	0.5	401-600	100

Table 4. Different degrees of seat ring/rolling element failure parameter table.

Fault State	Speed/rpm	Fault Diameter/mm	Sample Number
Race/rolling element failure degree	400	0	1–200
	400	0.5	201–400
	400	1	401–600
	400	1.5	601–800

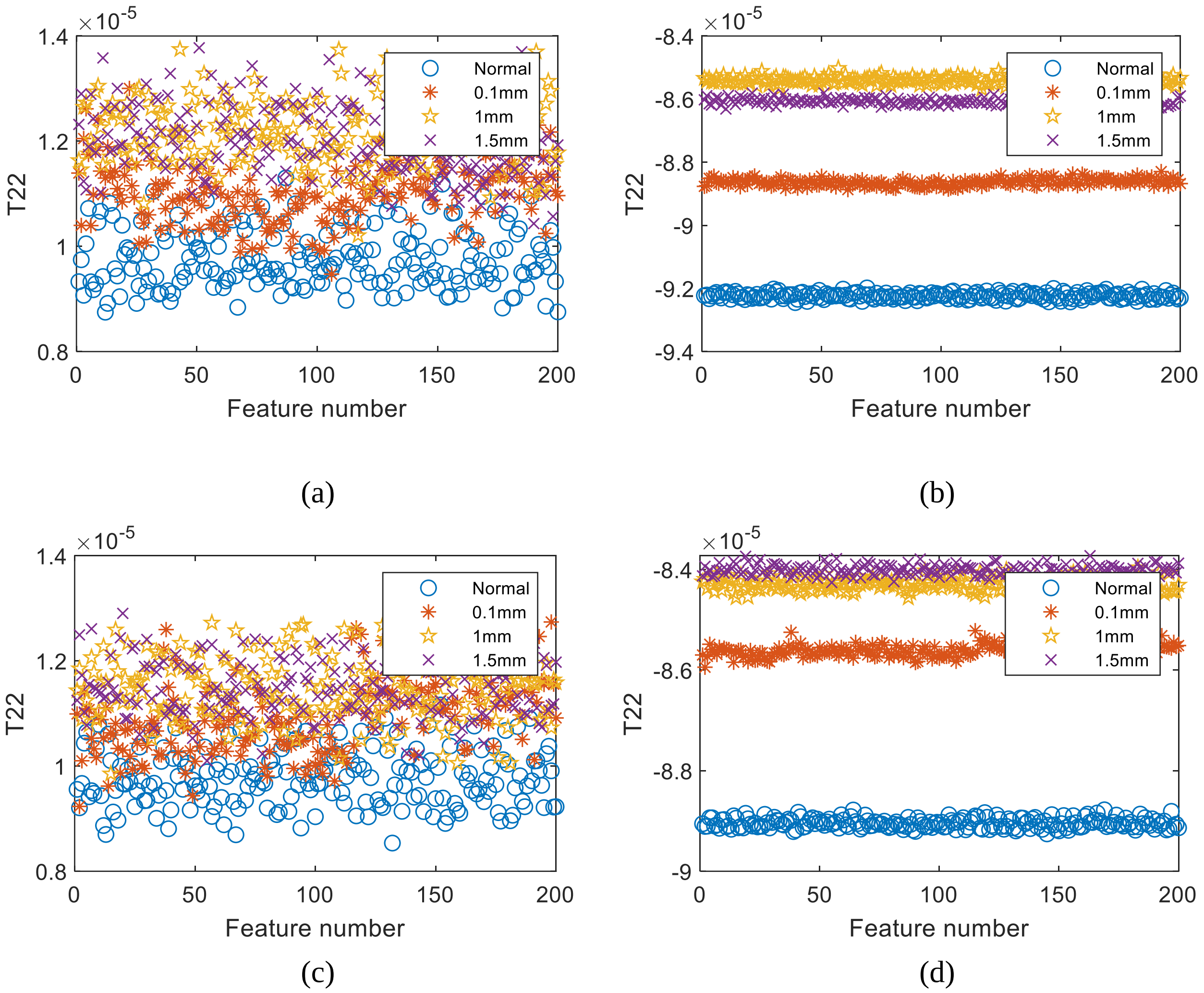


Figure 8. Compressed domain features of different experimental types enhance the front and back feature parameters. (a) Feature parameters directly extracted from race faults; (b) Feature parameters after enhanced race fault features; (c) Feature parameters directly extracted from rolling element faults; (d) Feature parameters after enhanced rolling element fault features.

In order to further verify the effectiveness of the method in this paper, the different faults of bearing races and rolling elements are diagnosed. When the spindle speed is 400 rpm, the diameter of the race failure and the rolling element failure are respectively 0.5 mm, 1 mm and 1.5 mm. There are three types of failure samples. The specific parameter settings are shown in Table 4. After the same compression measurement, three-layer wavelet packet decomposition, feature enhancement, and classification process, the ratio of the training set to the test set is 4:1. The experimental characteristic parameters of different degrees of failure before and after the compression domain feature enhancement are shown in Figure 8. It can be seen from Figure 8(a) and (c) that feature extraction is conducted on the compressed data obtained from the race fault degree experiment and the rolling element fault degree experiment, and the characteristic parameters of different fault types are all mixed, irregular and difficult to separate. From Figure 8(b) and (d), it can be seen that the feature parameters of different fault levels obtained by the feature enhancement method of the PSO algorithm to optimize the weight coefficients show more regularity, better classification and recognition, and larger class spacing. So as to provide more accurate classification information for subsequent bearing fault diagnosis and greatly improve the accuracy of diagnosis. The classification results of the fault feature enhancement diagnosis method are shown in Table 5. The weak fault feature enhancement method based on the proposed method can accurately identify faults of different degrees with 100% classification accuracy for different experimental types. Therefore, the four different degrees of race faults and rolling element faults can be accurately identified with 100% classification accuracy for fault diagnosis using this method.

Table 5. Classification results of different degrees of seat/rolling element failure.

Experiment Type	Training Samples	Test Sample	Identify the Sample	Diagnostic Accuracy Rate/%
Race failure degree test	640	160	160	100
Rolling element failure degree experiment	640	160	160	100

Through the verification of experimental data, we can see that the fault diagnosis method in this paper has obtained perfect results. It can not only correctly classify various faults but also identify different degrees of faults, and the recognition accuracy of each fault can reach 100%. It shows that the method proposed in this paper is effective, which can accurately diagnose different types of bearing faults while reducing the amount of data.

The compression rate reflects the degree of compression of the original signal. Restricted by the constrained equidistance condition, an excessively large compression rate under the condition of a limited number of sampling points will cause serious information loss of the compressed signal. The signal reconstruction error of the normal bearing AE signal under different compression ratios is shown in Figure 9. It can be seen that as the compression rate increases, the reconstruction error of the signal gradually increases, and the reconstruction error is basically in the range of 30 to 50%. When the compression ratio is in the range of 2–4, the OMP method can obtain a smaller reconstruction error, and the reconstruction effect has become better. When the compression ratio is greater than 10, the reconstruction error is large, and the feature information in the compressed data is greatly reduced.

Discrete Cosine Transform (DCT) is an orthogonal projection transformation method that transforms a signal from the time domain to the frequency domain. The key information of the signal is mainly concentrated on a few low-frequency coefficients. DCT is suitable for sparse representation of local singular parts and has a good effect on sparse representation of low-frequency parts. It has strong energy concentration characteristics and decorrelation performance and has good robustness to noise. The Orthogonal Match Pursuit (OMP) algorithm is an iterative greedy algorithm and a classic algorithm for solving the l_1 norm. The algorithm calculates the current optimal solution in each iteration, updates the residuals, and finds the optimal global solution through continuous iterations. The calculation speed is fast, and it is easy to implement. It is very suitable for signal reconstruction.

According to the above analysis, the DCT method is used to sparsely represent the original AE signal, the OMP method is used to reconstruct the signal, and the compression rate R = 2 is selected to reconstruct the original signal. The signal reconstruction error is 0.31, and the signal-to-noise ratio is 5, indicating that the reconstruction method using CS can restore the original signal more accurately. Therefore, the effective key information in the original signal is retained in the compressed measurement data, and the original signal can be reconstructed with a lower reconstruction error. This provides sufficient feature information for feature extraction in the compressed domain.

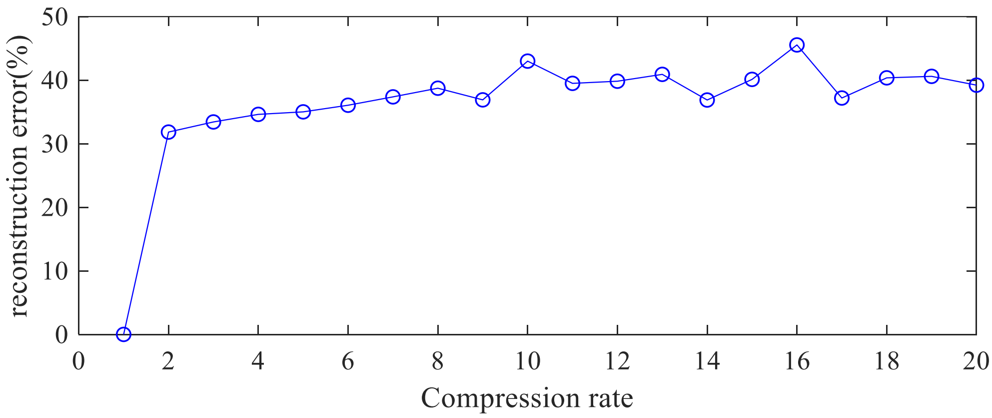


Figure 9. Signal reconstruction errors under different compression rates.

5.3. Compare with existing methods

In order to further verify the effect of the bearing AE signal fault feature enhancement method based on CS, we selected several bearing fault diagnosis methods to compare with the method in this paper. Mainly include: a) Input the compressed data directly into the neural network and use the Softmax classifier to classify; b) Extract the features from the compressed data and input the support vector machine; c) The original AE signal input the support vector machine after extracting the features. Under the conditions of the same parameters, the classification accuracy of the four bearing AE signal fault diagnosis methods is shown in Figure 10.

It can be seen from Figure 10 that four-fault diagnosis methods are used for different degrees of seat ring failure, different degrees of rolling element failure, and different types of failures. The method in this paper has high diagnostic efficiency in the three types of experiments. The accuracy rate reaches 100%, which can realize accurate diagnosis of different fault states. The accuracy of the compressed data input neural network method is low under the three experimental conditions; the method of direct classification of compressed domain feature extraction has the lowest diagnostic accuracy, and the lowest is only 57.5%; the diagnostic accuracy of the method of extracting features from the original AE signals for classification is relatively high, up to 96.67%, but fluctuates greatly under different experiments. In summary, compared with the traditional methods, the method in this paper has obvious advantages by enhancing the weak fault characteristics after CS. No matter in terms of diagnostic accuracy and the wide applicability and stability of the diagnostic method, the method in this paper shows good results.

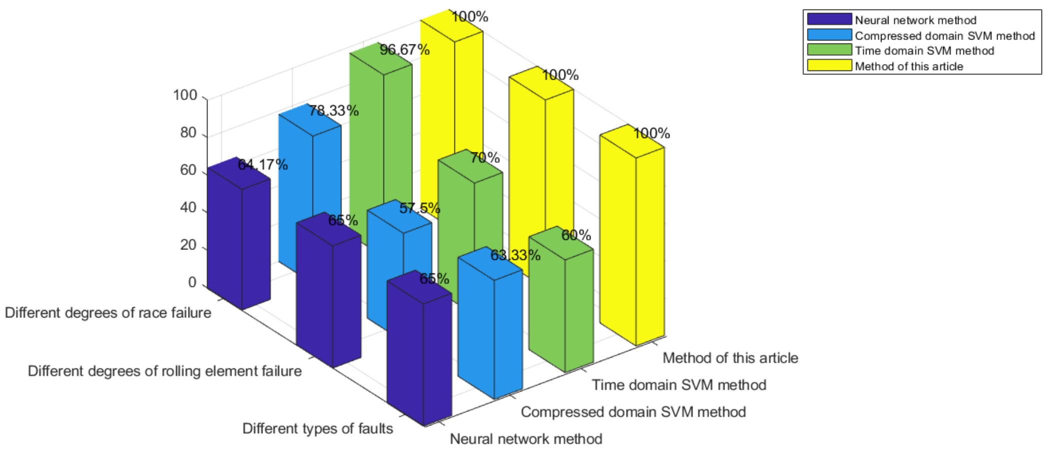


Figure 10. Classification results of different methods under three experimental types.

The reason why the method in this paper is superior to other methods is that the processing object of this paper is to compress the signal, and the less signal contains most of the characteristic information of the original time-domain signal. Then the weak fault features of the compressed signal can be enhanced by some adaptive selection of frequency band information, and the classification accuracy can be higher with fewer data; however, the traditional signal classification method based on time-frequency statistical feature parameters cannot accurately obtain all the information of the signal, so the diagnosis accuracy rate is low when combined with the SVM classifier; in addition, the compression signal classification method based on neural network is limited by the number of hidden layers, the number of training samples and the training method, resulting in unstable network performance and low diagnostic recognition rate.

6. Conclusions

Aiming at the problems of high cost and difficulty in data processing caused by a large amount of data transmission in the fault diagnosis of bearing AE signal, this paper proposes an enhanced diagnosis method for weak fault features of bearing AE signal based on CS. The method presented in this paper is successfully applied to the fault diagnosis of rolling bearings under the condition of ensuring high diagnostic accuracy. The method directly deals with the AE signal in the compression domain of the rolling bearing fault. The wavelet packet decomposition and the PSO method are used to realize the intelligent selection of frequency bands with more fault feature information. It not only solves the problem of the large data volume of AE signal data processing in fault diagnosis but also solves the problem of weak fault characteristics of compressed data. The signal appears in a random and disordered state in the compressed domain. The components decomposed by wavelet packet contain a large amount of feature information. The method of adaptive feature weighting is used to extract effective and enhanced fault information, which avoids the blindness of component selection. The effectiveness of the proposed fault feature enhancement diagnosis method is verified by bearing fault experiments. The method in this paper can accurately identify different types of faults and different degrees of faults. The appropriate compression ratio is selected through the reconstruction error curve of the compression ratio so as to prove that the compression domain signal has enough feature information, and ensure the effectiveness of feature enhancement and the accuracy of fault diagnosis. Finally, compared with the other three traditional fault diagnosis methods, the method in this paper has better performance in terms of the stability of diagnosis and the accuracy of recognition. The method proposed in this paper provides a new idea for the fault diagnosis of compressed signal processing. At the same time, it provides a new diagnosis method for equipment fault diagnosis under big modern data, which has a high engineering application value.

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Conflict of interest

The authors declare no conflict of interest.

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