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A Fault Diagnosis Solution of Rolling Bearing Based on MEEMD and QPSO-LSSVM

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ABSTRACT The vibration signals of rolling bearing are often non-stationary and non-linear, and consequently it is much more difficult to extract the deep characteristics in the time domain. In this paper, a new fault diagnosis method is proposed to identify the fault types of rolling bearings combined the benefits of the modified ensemble empirical mode decomposition (MEEMD), quantum particle swarm optimization (QPSO) and least squares support vector machine (LSSVM) algorithms. In this method, the vibration signals are decomposed by the MEEMD algorithm to obtain the intrinsic mode function (IMF) components. After normalizing the energy moment characteristics of each IMF component, the feature vectors can be obtained and conveniently input into the LSSVM model optimized by the QPSO algorithm to perform training and identification. It can effectively improve the performance on decomposition and extraction of vibration signals, and further improve the accuracy of the fault diagnosis. The proposed method is verified by the results of the experiments. It shows that this technique can extract the characteristics of the vibration signals effectively and identify them accurately.

INDEX TERMS Rolling bearing, MEEMD, feature extraction, QPSO, LSSVM, intelligent fault diagnosis.

I. INTRODUCTION

Rolling bearings are important parts of rotating machinery equipment. Monitoring and diagnosing their internal latent faults timely and correctly are of great significance for ensuring their safe operation [1], [2]. Rolling bearings are often exposed to harsh environments during long-term operation, deteriorating bearing with failure conditions can cause abnormalities in mechanical equipment, and even terribly serious injuries or deaths [3]. Therefore, it is very important to identify the fault state timely, necessarily and accurately.

Rolling bearing fault diagnosis has a long history of development, and has made great progress. At present, it has formed a multi branch research structure. Its detection and diagnosis technologies mainly include vibration diagnosis technology, acoustic diagnosis technology, temperature diagnosis technology, oil film resistance diagnosis technology [4]. The vibration diagnosis is one of the most commonly used techniques. The main objective of these methods is to extract the essential characteristics from the vibration signals.

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Traditional methods of analyzing rolling bearing fault signals, such as Fourier transform [5], Wigner-Ville [6], and wavelet transform [7], are inherently flawed in the analysis of non-linear steady state. Most of these methods cannot accurately reflect the fault characteristics from the bearing signals [8]. Once Wu and Huang [9] proposed the EMD algorithm which can adaptively process the time-frequency signals, it has been widely used in many fields, including the process of vibration signals [10]. However, the EMD algorithm has some problems, mainly the modal aliasing phenomenon. In response to this problem, many scholars have proposed a series of solutions. Among them, Wu and Huang [11] proposed the EEMD algorithm by studying the characteristics of white noise signals. In this method, the signals are firstly subjected to adding white noise multiple times, and then the EMD algorithm is performed to decompose the preprocessed signals to obtain the IMF components. However, the treatment of adding white noise will increase the amount of calculation. In addition, the unreasonable choice of the amplitude and the number of iterations of white noise will lead to the appearance of pseudo components. Yeh *et al.* [12] proposed a complementary ensemble empirical mode decomposition (CEEMD) algorithm which mainly adds two opposite white noise signals to the original signal to be analyzed, and performs EMD decomposition respectively. CEEMD can reduce the reconstruction error caused by white noise when the decomposition effect is equivalent to EEMD. However, the amount of computation is too large, and due to the limitation of the number of iterations, the decomposed components may not meet the conditions of IMF. The modified CEEMD algorithm was put forward by adding a pair of white noise signals to the original vibration signals, namely MEEMD [13]. The modal aliasing phenomenon and reconstruction errors are effectively suppressed. Then, the pseudo components are eliminated by calculating the permutation entropy. Finally, EMD decomposition is performed on the obtained residual signals, and all the components are arranged from high frequency to low frequency. This method can not only suppress the modal aliasing phenomenon to a certain extent in the decomposition process, but also reduces the amount of calculation, which is a modification on the EEMD algorithm and has huge advantages [14]. Due to these mentioned above, this paper adopts the MEEMD algorithm to decompose the vibration signals to be detected adaptively, and then the energy moment normalization is performed to obtain the feature vectors that can reflect the potential characteristics of the signals, which are used as the input for later fault diagnosis.

In the field of pattern recognition, neural networks, expert systems, and support vector machines are widely used with the rapid development of machine learning [15] and deep learning [16] in recent years. Although the fault diagnosis methods based on expert systems [17] have achieved a very good diagnostic performance in theory and applications, the reasoning process is quite complicated and it is difficult to meet the needs of practical issues. The fault diagnosis methods based on neural networks [18], [19] are widely known for its self-learning and can handle many complex problems, however its diagnostic capacity is quite limited by the number of samples. When the sample data is insufficient, the process of fault diagnosis is a little slow and it's difficult to converge. LSSVM, as an improved optimization algorithm of classical SVM, not only has the same supervised learning ability as SVM, but also performs fast calculations without specifying the approximation accuracy [20]. The generalization ability of LSSVM is closely related to its kernel function parameter and penalty factor, so choosing the appropriate parameters is the core to the successful establishment of the LSSVM model. At present, the selection of parameters is mainly based on experience and it depends too much on the user's level, which greatly limits its application. In recent years, fast cross-validation, genetic algorithm, neural network, ant colony algorithm, particle swarm optimization and other improved algorithms have appeared to optimize the parameters of support vector machines, but the effect of optimization has a great relationship with the choice of optimization algorithm. The particle swarm optimization (PSO) algorithm [21] is an effective cluster intelligent optimization algorithm. It shows outstanding advantages in solving practical application problems, however, the particles trajectory is a limited and gradually shrinking area, it cannot cover the entire feasible region, and it inevitably has the defect of premature convergence. With the continuous study of it, people have proposed a modified PSO model from the perspective of quantum mechanics, namely the QPSO algorithm [22]. It is believed that the particles have quantum behaviors, which has higher search efficiency, stronger robustness and shorter calculation time. For the period of fault diagnosis and classification, the LSSVM model optimized by the QPSO algorithm is used to perform the state discrimination from the feature vectors extracted by the MEEMD algorithm and the energy moment normalization.

The above comprehensive technique which combines the MEEMD algorithm and QPSO-PNN model so far have not been applied in the field of rolling bearing fault diagnosis. In this paper, the MEEMD algorithm is used to decompose the vibration signals to a series of IMFs, and the IMF components are normalized to obtain the energy moment feature vectors. Then the QPSO algorithm is introduced to iteratively optimize the parameters in the LSSVM model. Finally, the QPSO-LSSVM model is performed to train and diagnose the vibration signals. The technique is validated by the experimental datasets as well.

The main contributions in this paper are summarized as follows:

1) The MEEMD algorithm is an improved algorithm of the EEMD and the CEEMD, and it has better completeness and orthogonality. It can not only decompose and reconstruct the original signals more accurately, but also reduce the calculation time and reconstruction errors compared with the EEMD and CEEMD. By combining the energy moment normalization, it is very suitable for extracting and analyzing the useful characteristics of vibration signals, which is more conducive to later model input and fault discrimination.
2) Due to the iterative optimization by the QPSO algorithm, the search ability and the quality of the candidate solutions are greatly improved, which makes the parameters decision in the LSSVM model more accurate and the model construction more reasonable.
3) A comprehensive algorithm combining the MEEMD algorithm and the QPSO-LSSVM model is used to discriminate faults, which greatly improves the diagnostic accuracy and is applied to the classification of fault signals acquired from the rolling bearings.

II. METHODOLOGY

A. THE PROPOSED METHOD

The proposed fault diagnosis process of rolling bearing based on MEEMD and QPSO-LSSVM is shown in Fig.1. Firstly, the original signals are decomposed into a series of IMF components from high to low frequency by the MEEMD algorithm, the energy moment feature vectors can be extracted by integrating the transverse axis of all IMF components. Then

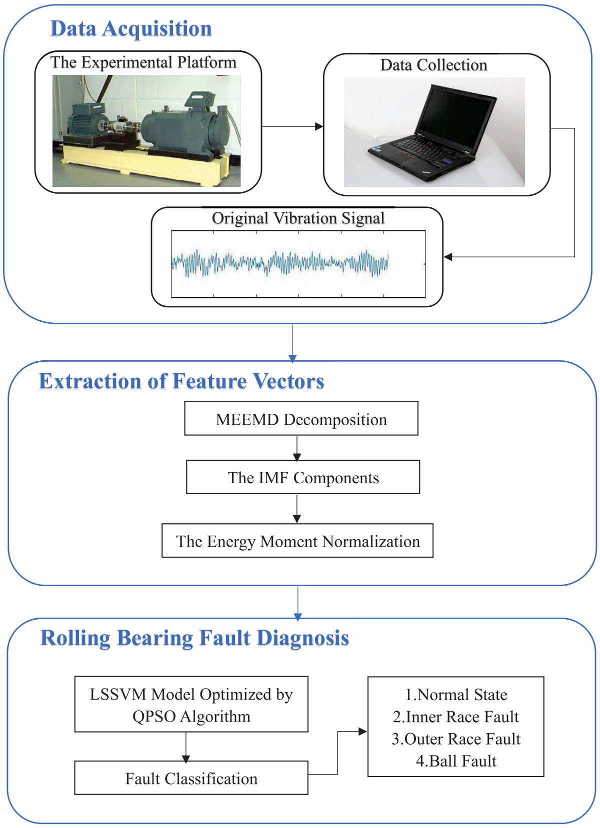

FIGURE 1. The overall design of the proposed fault diagnosis process.

the QPSO algorithm is introduced to iteratively optimize the parameters of the LSSVM model. Finally, train and identify the fault types using the LSSVM model optimized by the QPSO algorithm.

B. THE PRINCIPLE OF THE MEEMD ALGORITHM

MEEMD algorithm is a modified algorithm for EEMD and CEEMD algorithms. EMD algorithm can adaptively decompose complex non-stationary signals. The processed signals can be decomposed into several intrinsic mode function (IMF) components which mainly characterize the signals and a residual component. Each IMF component from high frequency to low frequency can effectively reflect the characteristics of different frequency bands of the original vibration signals [23]. In the EMD algorithm, the original vibration signal $x(t)$ can be decomposed into the following forms:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

where $\{c_i(t), i = 1, 2, \ldots, n\}$ is the i th IMF component, n is the total of the IMF components, $r_n(t)$ is the residual component which can reveal the mean trend of the $x(t)$.

Although the EMD algorithm shows a good result when processing non-stationary signals, however due to the existence of noise signals and pulse interference in the acquired signals, the EMD also has many disadvantages, such as modal aliasing phenomenon. The impact signals are often mixed in the vibration signals, so modal aliasing phenomenon is more likely to occur when using the EMD algorithm to process these signals, which will cause each IMF component to not truly reflect its own physical meaning and reduce the accuracy of the decomposition results. As a modified algorithm, the MEEMD algorithm [24] can not only effectively suppress the modal aliasing phenomenon, but also eliminate the effects of pseudo components and solve the problem of modal splitting. It mainly calculates the permutation entropy (PE) of each IMF component based on the EEMD and CEEMD algorithms, sets a corresponding threshold, removes the IMF components larger than the threshold, and then performs EMD decomposition on the remaining signals, finally arranges all the IMF components from high frequency to low frequency. For non-stationary signals, the steps of the MEEMD algorithm are briefly explained as follows:

1) Add the positive and negative paired white noise $n_i(t)$ and $-n_i(t)$ to the original signal $x(t)$, that is:

$$\begin{cases} x_i^+(t) = x(t) + a_i n_i(t) \\ x_i^-(t) = x(t) - a_i n_i(t) \end{cases} \tag{2}$$

where a_i represents the amplitude of the white noise; $n_i(t)$ represents the noise signal, and its amplitude generally takes 0.1 to 0.2 times the standard deviation of the original signal; $i = 1, 2, 3, \cdots, n$, n is the logarithm of the white noise, the number of the ensembled signals is $2n$.

2) EMD algorithm is performed on the signals $x_i^+(t)$ and $x_i^-(t)$ in the set, and each signal can be decomposed into a set of IMF components.

$$\begin{cases} x_i^+(t) \xrightarrow{\text{EMD}} c_{ij}^+(t) \\ x_i^-(t) \xrightarrow{\text{EMD}} c_{ij}^-(t) \end{cases} \tag{3}$$

where $c_{ij}^+(t)$ and $c_{ij}^-(t)$ represent the jth IMF component of the ith signal.

3) The IMF components of each order can be obtained by means of multi-component ensemble averaging.

$$c_j(t) = \frac{1}{2n} \sum_{i=1}^{n} \left[c_{ij}^+(t) + c_{ij}^-(t) \right] \tag{4}$$

where $c_j(t)$ is the jth IMF component.

4) Check whether the $c_j(t)$ is an abnormal signal in turn. Detect the randomness of the signal by using permutation entropy. The larger the entropy value, the greater the randomness of the signal. The signal can be determined whether it is randomly abnormal by setting the permutation threshold θ_0. Calculate the permutation entropy of $c_j(t)$, and those with values greater than θ_0 are considered abnormal signals.

5) The abnormal signals are separated from the original signal, and then the remaining is decomposed by the EMD algorithm.

$$s(t) = x(t) - x'(t) \tag{5}$$

$$s(t) \xrightarrow{\text{EMD}} \sum_{k=1}^{m} c_k(t) + r(t) \quad (6)$$

where $x'(t)$ indicates the sum of all abnormal signals, $s(t)$ indicates the remaining signals, and $c_k(t)$ indicates the kth IMF component obtained through the MEEMD algorithm.

6) The process of the MEEMD algorithm can be expressed briefly as follows:

$$x(t) \xrightarrow{\text{MEEMD}} \sum_{k=1}^{m} c_k(t) + r(t) \quad (7)$$

The above decomposition process shows that the MEEMD algorithm can avoid unnecessary ensemble averaging in the EMD and the EEMD algorithms. It can make the decomposed IMF components more meaningful. The calculation amount of CEEMD and the reconstruction errors caused by adding white noise are reduced which guarantees the completeness of the decomposition. This method can effectively extract the characteristics of the vibration signals, which is very beneficial to the fault diagnosis of rolling bearings by intelligent methods in the later stage.

C. THE EXTRACTION OF FEATURE VECTORS BY ENERGY MOMENT NORMALIZATION

After the decomposition of vibration signals by the MEEMD algorithm, a series of IMF components can be obtained. In order to simplify the calculation, only the first six IMF components with large correlation coefficient are selected, which is enough to ensure the accuracy of reconstruction. These IMF components contain some important information that reflect the characteristics of the original signals. In order to mine the deep feature information hidden in each IMF component, the energy moment normalization [25] is used to extract valid vectors of the vibration signals. The steps are as follows:

1) Since the rolling bearing fault signals are discrete, the energy of each IMF component is calculated according to the following equation:

$$E_i = \int_{-\infty}^{+\infty} |d_i(t)|^2 dt = \sum_{j=1}^{n} \left|D_{ij}\right|^2 \quad (8)$$

where $d_i(t)$ is the energy of the ith IMF component, D_{ij} is the amplitude of the ith IMF at its jth discrete point, the number of the discrete points is n.

2) Add the energy of all IMF components obtained in the first step and perform normalization calculation by the following equations to obtain the characteristic vectors of the rolling bearing fault signals:

$$E = \sum_{i=1}^{6} E_i \quad (9)$$

$$T = (E_1/E, E_2/E, \cdots E_6/E) \quad (10)$$

The energy moment calculation reflects the distribution characteristics of each IMF energy on the time axis, which can extract the essential characteristics of the signals effectively and accurately. It can be seen that the calculation of the energy moment takes into account not only the magnitude of the IMF energy, but also the distribution of the IMF energy over time. Therefore, compared with the simple calculation of IMF energy, the energy moment calculation can better reveal the energy distribution characteristics and facilitate the extraction of fault characteristics.

D. THE PRINCIPLE OF THE LSSVM

1) SVM

The main idea of SVM is to take non-linear samples as input vectors and transform them into high-dimensional feature space through mapping transformation [26]. Then search for a globally optimal hyperplane in the feature space and classify the samples. Let the sample training set $T = \{(x_1, y_1), \cdots, (x_n, y_n)\}$, where x_i is the input vector and $x_i \in R^n$, y_i is the classification label and $y_i \in \{1, -1\}(i = 1, 2, \cdots, n)$.

The problem of finding the optimal classification surface can be transformed into solving a quadratic programming problem. The objective function and the constraint are as follows:

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\xi_i$$
$$\text{s.t. } y_i\left(< x_i, \omega > + b\right) \geqslant 1 - \xi_i \quad (11)$$

where ω is the adjustable weight vector, b is bias coefficient, $< \cdot >$ is inner product, ξ_i is a non-negative relaxation variable which is used to measure the degree of deviation of data points, C is penalty factor, the larger the value, the greater the penalty for misclassification.

According to Mercer's theorem, non-linear classification can be achieved by using different kernel functions $K(x, x_i)$, and the Lagrange multiplier α_i is introduced. The decision function of the optimal classification hyperplane can be expressed as follows:

$$f(x) = \text{sgn}\left[\sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + b\right] \quad (12)$$

The schematic of the SVM model is shown in Fig.2.

2) LSSVM

The sample training of the standard SVM needs to solve the quadratic programming problem, the training speed is slow and greatly affected by the number of training samples. To overcome these shortcomings, an extended SVM model namely LSSVM comes into being. The LSSVM is a kernel-based machine learning algorithm and has the principle of risk minimization [27]. By solving linear equations instead of solving the quadratic programming problem, it greatly reduces the calculation complexity, and improves the operation efficiency and convergence accuracy. The optimization problem can be expressed as follows: given a set of samples

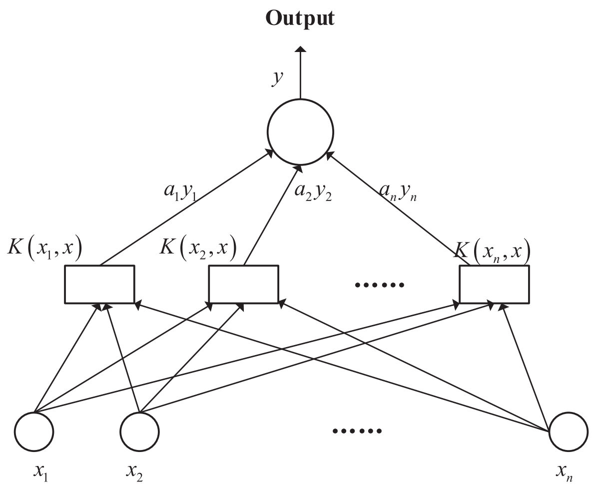

FIGURE 2. The schematic of the SVM model.

$\{x_i, y_i\}_{i=1}^{m}$, where x_i is the input vector and y_i is the corresponding output of the samples. ϕ is nonlinear transformation function which maps the given input data to a higher-dimensional feature space. It is represented as follows by approximate linear approximation:

$$f(x) = \omega^T \phi(x) + b \tag{13}$$

where ω is the adjustable weight vector, b is the bias coefficient.

In the original feature space, as an extension of the SVM model, the LSSVM objective function under the constraint condition is as follows:

$$\min J(\omega, \xi_i) = \frac{1}{2}\left(\omega^T\omega + C\sum_{i=1}^{m}\xi_i^2\right)$$
$$s.t.\ y_i = \omega^T\phi(x) + b + \xi_i \tag{14}$$

where C is the penalty factor that balances the minimum classification boundary and the minimum classification error, ξ_i is a non-negative relaxation variable which is used to measure the degree of deviation of data points, ϕ is nonlinear transformation function which maps the given input data to a higher-dimensional feature space.

At this time, the Lagrange function used is as follows:

$$L = \frac{1}{2}\omega^T\omega + \frac{1}{2}C\sum_{i=1}^{m}\xi_i^2 - \sum_{i=1}^{m}a_i\left\{\omega^T\varphi(x) + b + \xi_i - y_i\right\} \tag{15}$$

where a_i is the Lagrange multiplier, this function transforms a constrained optimization problem into an unconstrained optimization problem.

According to KKT conditions, find the partial derivative of ω, b, ξ_i, a_i and set it 0 to get:

$$\frac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^{m}a_i\varphi(x_i)$$
$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{m}a_i = 0$$
$$\frac{\partial L}{\partial \xi_i} = 0 \rightarrow a_i = C\xi_i$$
$$\frac{\partial L}{\partial a_i} = 0 \rightarrow \omega^T\varphi(x_i) + b + \xi_i - y_i = 0 \tag{16}$$

After eliminating ω, ξ_i, the optimization problem can be transformed into the following linear equations:

$$\begin{bmatrix} 0 & Q^T \\ Q & K + C^{-1}I \end{bmatrix}\begin{bmatrix} b \\ A \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{17}$$

where

$$Q = \begin{bmatrix} 1, \ldots & 1 & 1 \end{bmatrix}^T$$
$$A = \begin{bmatrix} a_1 & a_2, \ldots & a_{m-1} & a_m \end{bmatrix}^T$$
$$Y = \begin{bmatrix} y_1 & y_2, \ldots & y_m \end{bmatrix} \tag{18}$$

After the solution, a_i, b can be obtained, then the optimal linear regression function of the corresponding LSSVM is:

$$f(x) = \sum_{i=1}^{m}\alpha_i K(x_i, x) + b \tag{19}$$

where $K(x_i, x)$ is the kernel function that satisfies the Mercer's theorem. In this paper, the BRF Gaussian Kernel is chosen as the kernel function:

$$K(x_i, x) = \exp\left(-\frac{\|x_i - x\|^2}{\sigma^2}\right) \tag{20}$$

where σ^2 is the kernel width of the kernel function.

When using LSSVM for classification prediction, the choice of the parameter σ of the RBF kernel function and the penalty factor C has a greater impact on the learning ability and classification results of the model. It's necessary to choose the appropriate parameters in order to get a better classification accuracy [28]. These parameters are generally obtained by the cross-validation method, which is not only time-consuming but also blind. In this paper, the quantum particle swarm optimization (QPSO) is introduced to determine the parameters to improve the accuracy and computation speed of the fault diagnosis.

E. DESIGNED PRINCIPLE OF QPSO ALGORITHM

1) PARTICLE SWARM OPTIMIZATION (PSO)

PSO algorithm is a cluster intelligent algorithm based on iterative optimization. It was proposed by Dr. Kennedy and Dr. Eberhart in 1995 when simulating the migration and cluster behavior of birds foraging [29].

The mathematical model of the PSO algorithm is as follows:

In the d-dimensional search space, a population is composed of N particles. The speed vector and position vector of the ith particle are denoted as $V_i = (v_{i1}, v_{i2}, \cdots, v_{id})$ and $X_i = (x_{i1}, x_{i2}, \cdots, x_{id})$, respectively. The optimal historical position searched by this particle is $p_i = (p_{i1}, p_{i2}, \cdots, p_{id})$, and the optimal position searched by the entire population is $p_g = (p_{g1}, p_{g2}, \cdots, p_{gd})$. For each generation of particles, update their speed and position according to the following equations respectively:

$$\begin{aligned} v_{id}(k+1) = \omega v_{id}(k) & \\ + c_1 r_1 \left[p_{id}(k) - x_{id}(k)\right] & \\ + c_2 r_2 \left[p_{gd}(k) - x_{id}(k)\right] & \quad (21) \end{aligned}$$

$$x_{id}(k+1) = x_{id}(k) + v_{id}(k+1) \quad (22)$$

where ω is the inertia weight; k is the number of iterations; c_1 and c_2 are positive learning factors; r_1 and r_2 are random numbers uniformly distributed between 0 and 1; p_{id} is an individual extreme value; p_{gd} is a global extreme value.

2) QUANTUM PARTICLE SWARM OPTIMIZATION (QPSO)

The PSO algorithm has several defects such as easy to premature, poor global optimization capability, and slow convergence speed. From the perspective of quantum mechanics, Sun put forward the evolutionary algorithm based on the standard PSO to solve these problems, namely QPSO algorithm [30]. In quantum space, the QPSO algorithm has the advantages of fewer parameters and less randomness. Therefore, it effectively solves the problems of the limited search space and falling into the local optimal solution easily in the PSO algorithm, which improves the search accuracy and search speed. The QPSO algorithm can search across the entire feasible solution space, so its global search performance is far superior to the standard PSO algorithm. The wave function is used to describe the state of the particles, and the probability density function of the particles at a certain point of space is obtained by solving the Schrodinger equation, and then the position equation of the particles is obtained by Monte-Carlo method:

$$x(t) = P \pm \frac{L}{2} \ln\left(\frac{1}{u}\right) \quad (23)$$

where u is a random number that ranges from 0 to 1; L is the characteristic length of potential well, and the changing rules with time t are as follows:

$$L(t+1) = 2\beta \left|m_{best} - x(t)\right| \quad (24)$$

$$m_{best} = \sum_{i=1}^{M} \frac{P_i}{M} = \left(\sum_{i=1}^{M} \frac{P_{i1}}{M}, \sum_{i=1}^{M} \frac{P_{i2}}{M} \cdots, \sum_{i=1}^{M} \frac{P_{iD_{\text{dim}}}}{M}\right) \quad (25)$$

$$P_{\text{d}} = \phi \cdot P_{\text{id}} = (1-\phi) P_{\text{gd}} \quad (26)$$

where β is called the contraction expansion coefficient, M is the number of particles, D_{dim} is the dimension of the particles, ϕ is a random number uniformly distributed between 0 and 1, m_{best} is the average best position of all particles in the population, and P_i is the P_{best} of the ith particle, the position equation of the particle is finally described as follows:

$$x(t+1) = P \pm \beta \left|m_{\text{best}} - x(t)\right| \ln\left(\frac{1}{u}\right) \quad (27)$$

In the QPSO algorithm, the state of the particles is described only by the position vectors, and there is only one controlled parameter in the algorithm. The selection and control of this parameter is very important, it is related to the convergence speed of the entire algorithm.

F. THE PROCESS OF THE QPSO-LSSVM ALGORITHM FOR THE FAULT DIAGNOSIS

The QPSO algorithm has parallel global optimization capabilities. It can improve the classification accuracy using the QPSO algorithm to perform parameters optimization of LSSVM. In the process of parameters optimization of the kernel function parameter σ and penalty factor C of LSSVM, the QPSO algorithm can guarantee the convergence of the algorithm during the search process and ensure that the algorithm can avoid premature convergence while the algorithm is convergent [31]. It has a very important impact on improving the learning ability and generalization ability of the LSSVM algorithm. Therefore, this paper proposed a LSSVM model optimized by the QPSO algorithm. The specific steps are as follows:

1) Set the number of particles to M, the dimension of the quantum particle swarm to d, and the maximum number of iterations to $T_{\max}$ and other related parameters.
2) According to the LSSVM algorithm and the parameters to be optimized, the adaptive value of each particle in the quantum population is evaluated, and the local optimal value P_i and the global optimal value P_g are updated.
3) Calculate the m_{best} of quantum particle swarm according to Equation 25. Calculate the P_i according to m_{best} and the global optimal particle P_g by Equation 26, and then substitute P_i and m_{best} into Equation 27 to update the position of each particle. In Equation 27, take a negative when $u < 0.5$ and take a positive when $u > 0.5$.
4) Determine whether the current number of iterations t has reached the maximum number of iterations; if not, go to Step 2 until the iteration termination condition is met.
5) The parameters optimization is implemented based on the QPSO algorithm, and the optimal particles are used as parameters of the LSSVM model to construct the QPSO-LSSVM model.

The flowchart of the QPSO-LSSVM is shown in Fig.3.

In this paper, the QPSO algorithm is introduced to iteratively optimize the parameters in the LSSVM model to establish a fault diagnosis model. The fault feature vectors extracted by the MEEMD algorithm and the energy moment normalization are used as the input vectors of the QPSO-LSSVM model to train and identify the fault of rolling bearing.

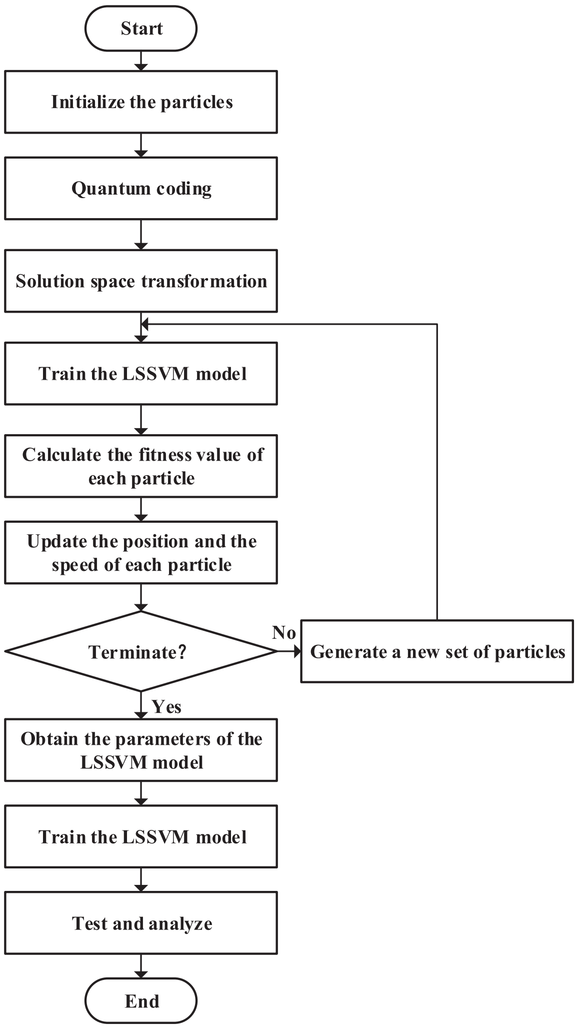

FIGURE 3. The flow chart of the QPSO-LSSVM model.

III. EXPERIMENTS VALIDATION

In order to verify the effectiveness and practicability of the proposed method for rolling bearing fault diagnosis based on the MEEMD algorithm for adaptive decomposition and the QPSO-LSSVM algorithm for classification, two experimental schemes were proposed for practical verification. Firstly, the experimental data from the Case Western Reserve University laboratory in the United States was used for verification. In order to further demonstrate the universality and representativeness of the proposed method, the data in the experimental bench was acquired for experiments. We also analyzed them in combination with practical engineering problems.

A. EXPERIMENT 1

Firstly, the experimental data of the Case Western Reserve University laboratory in the United States was used for verification [32]. The experimental platform is shown in Fig.4. The left side of the figure is a 2-hp motor, the middle is a torque transducer, the right is a load motor, and some

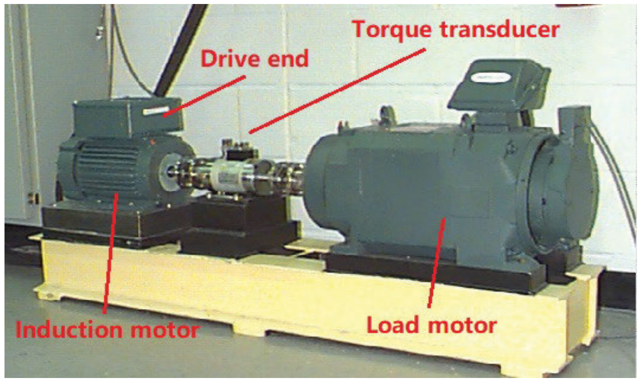

FIGURE 4. The experimental platform of CWRU.

TABLE 1. The classification of the experimental data.

States	total	train	test	classification
normal state	90	40	50	1
inner race fault	90	40	50	2
outer race fault	90	40	50	3
ball fault	90	40	50	4

electronic controls are not included in the figure. The bearing to be tested supports the motor shaft. The designation of the bearing is SKF-6205 deep groove ball bearing.

Three types of faults, including inner race fault, outer race fault and ball fault, were all subjected to single-point damage of electro-discharge machining to simulate the state of natural evolution damage. The speed of the bearing is $r = 1797r/\min$, the balls number of the bearing is $n = 8$, the contact angle of the rolling elements is $\alpha = 0°$, the ball diameter is $d = 6.75mm$, and the bearing pitch diameter is $D = 28.5mm$. The sampling frequency of the digital signal is $12000S/s$. In each state, 90 sets of data was randomly selected, the first 40 sets as training data, and the last 50 sets as test data to verify the accuracy of the classification. In this way, there was 360 sets of data including the normal state, and each group of data contains 1024 sampling points. See Table 1 for details of datasets.

The time-domain diagram of bearing vibration signals in different states and the IMF components diagram obtained after the MEEMD algorithm are shown in Fig.5-8. Among them, Fig.5 is in a normal state, as a comparison group, and Fig.6-8 are respectively in an inner race fault, an outer race fault, and a ball fault, as a fault group.

The energy moment normalization calculation can be used to obtain the energy moment feature vectors. The histogram of the IMFs is shown in Fig.9. These vectors obtained can be used as the input of the later QPSO-LSSVM model. In the selected experimental data, each state contains 90 sets of data. After decomposition, 90 sets of vectors can be obtained. There are 4 states, a total of 360 sets, and the data is relatively large. Here, only 3 sets of data randomly selected for each state are listed in Table 2.

In order to more intuitively see the difference between the input vectors decomposed by the MEEMD algorithm and the energy moment normalization, we use the multidimensional

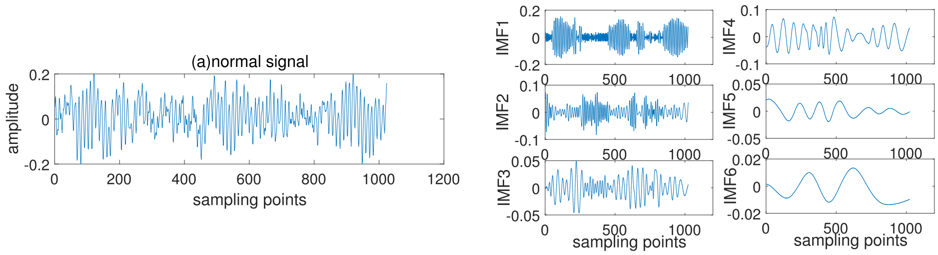

FIGURE 5. The original vibration signal and the decomposed IMF components of the normal signal.

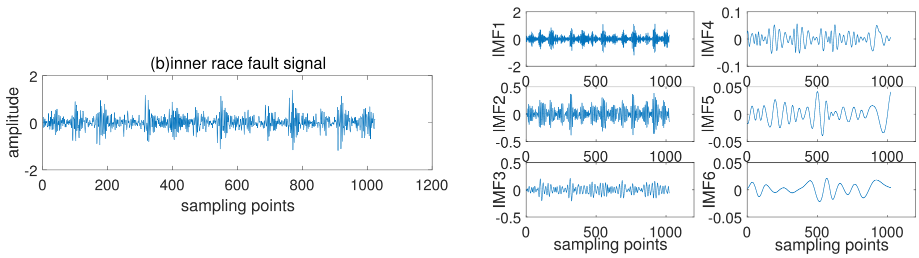

FIGURE 6. The original vibration signal and the decomposed IMF components of the inner race fault signal.

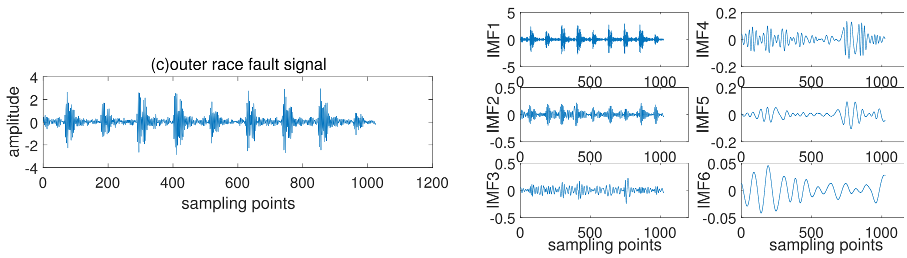

FIGURE 7. The original vibration signal and the decomposed IMF components of the outer race fault signal.

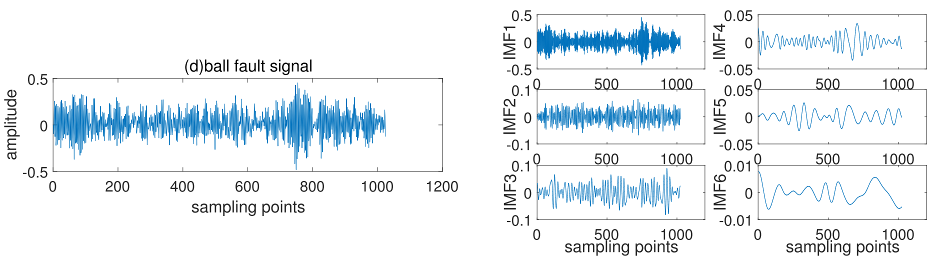

FIGURE 8. The original vibration signal and the decomposed IMF components of the ball fault signal.

scaling method (MDS) to observe the distribution characteristics of the training data in a 2-dimensional space which is shown in Fig.10. The effect of feature extraction is very helpful for later fault identification.

Subsequently, the LSSVM model optimized by the QPSO algorithm was used to classify and discriminate the data. In the process of QPSO, the number of particles is $M = 30$, the dimension of the quantum particle swarm is $d = 2$, which represents the kernel function parameter σ and the penalty factor C respectively, where $\sigma \in [10, 100]$, $C \in [0.1, 1]$ and the maximum number of iterations is $T_{\max} = 200$. It can be seen from the simulation experiments, the best value σ and C of the LSSVM model optimized by the QPSO algorithm is 98.0905 and 0.1013 respectively in this experiment. Compared with the SVM and LSSVM and PSO-LSSVM models. The detailed output results and the accuracy are shown in Table 3. It can be seen that the accuracy rate of fault diagnosis performed by the QPSO-LSSVM model is 98.5% better than several other comparison methods. It shows that the method proposed in this paper has a good performance on feature extraction and classification diagnosis.

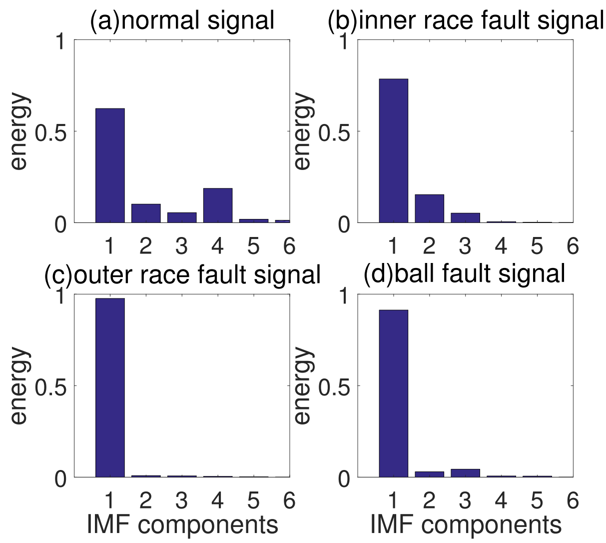

FIGURE 9. The histogram of the IMFs.

TABLE 2. The feature vectors by energy moment normalization.

States	energy feature vectors
normal state	0.5959 0.1614 0.0547 0.1157 0.0435 0.0288
	0.5785 0.1284 0.0619 0.1184 0.0948 0.0180
	0.5756 0.1476 0.0518 0.1010 0.1098 0.0142
inner race fault	0.7851 0.1534 0.0523 0.0055 0.0026 0.0011
	0.7434 0.1775 0.0688 0.0065 0.0030 0.0008
	0.7385 0.1819 0.0581 0.0162 0.0045 0.0009
outer race fault	0.9765 0.0086 0.0073 0.0046 0.0022 0.0007
	0.9720 0.0129 0.0107 0.0030 0.0011 0.0004
	0.9638 0.0224 0.0079 0.0038 0.0014 0.0006
ball fault	0.9131 0.0299 0.0438 0.0067 0.0060 0.0005
	0.8715 0.0530 0.0562 0.0100 0.0084 0.0009
	0.9168 0.0351 0.0377 0.0060 0.0042 0.0002

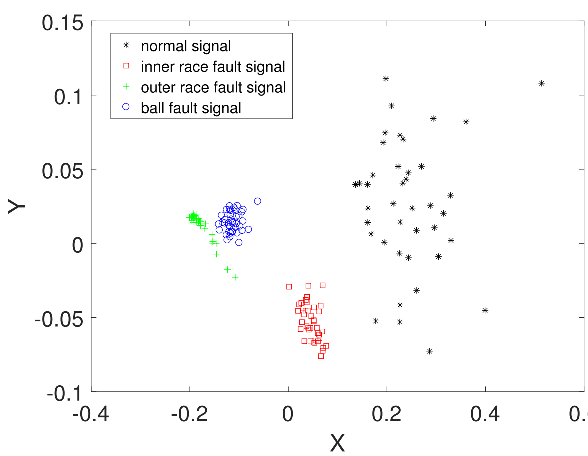

FIGURE 10. The MDS distribution of the processed data.

B. EXPERIMENT 2

In order to further verify the universality and representativeness of the proposed method, the experimental data of the QPZZ-II platform in the laboratory was used in this section, and it is analyzed in combination with actual engineering problems. The experimental platform is shown in Fig.11. It consists of a variable-speed drive motor, bearings,

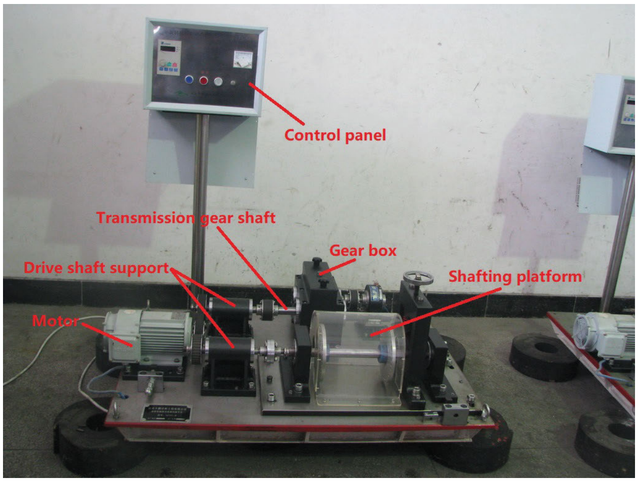

FIGURE 11. The QPZZ-II experimental platform in the laboratory.

gearboxes, shafts, eccentric turntables, and speed governors. The designation of the bearing is N205. In order to maintain the consistency, 360 sets of data were also selected for experimental verification. The classification information is the same as the Experiment 1, and is still shown in Table 1.

In the process of MEEMD decomposition, 100 sets of white noise sequences are added to the vibration data, the amplitude is 0.1, and the maximum number of modes is set to 6. The time domain diagram and the MEEMD decomposition diagram of bearing vibration signals under the four states including the normal state, the inner race fault, the outer race fault, and the ball fault are shown in Fig.12-15. Based on the energy moment normalization calculation, the histogram of the energy moment feature vectors is shown in Fig.16, and the detailed values are shown in Table 4. The MDS method is used to observe the distribution characteristics of the training data which is shown in Fig.17.

Subsequently, the LSSVM model optimized by the QPSO algorithm was used to classify and discriminate the data. In the process of QPSO, the number of particles is also chosen as $M = 30$, the dimension of the quantum particle swarm is $d = 2$, which also represents the kernel function parameter σ and the penalty factor C respectively, where $\sigma \in [10, 100]$, $C \in [0.1, 1]$ and the maximum number of iterations is $T_{\max} = 200$. The settings of these parameters are the same as the Experiment 1. It can be seen from the simulation experiments, the best value σ and C of the LSSVM model optimized by the QPSO algorithm is 49.858 and 0.8009 respectively in this experiment. Compared with the SVM, LSSVM and PSO-LSSVM models, the output results of which are shown in Fig.18-21.

The accuracy of the fault diagnosis using the QPSO-LSSVM model is 98.0%, meanwhile, the accuracy of SVM is 95.0%, the accuracy of LSSVM is 95.5%, and the accuracy of PSO-LSSVM is 97.5%. The results are shown in Table 5. We also compared the training time of the two methods.

TABLE 3. The outputs by different models.

Method	normal state	inner race fault	outer race fault	ball fault	accuracy
SVM	50/50	49/50	42/50	49/50	95.0%
LSSVM	50/50	50/50	45/50	49/50	97.0%
PSO-LSSVM	49/50	50/50	47/50	50/50	98.0%
QPSO-LSSVM	50/50	50/50	47/50	50/50	98.5%

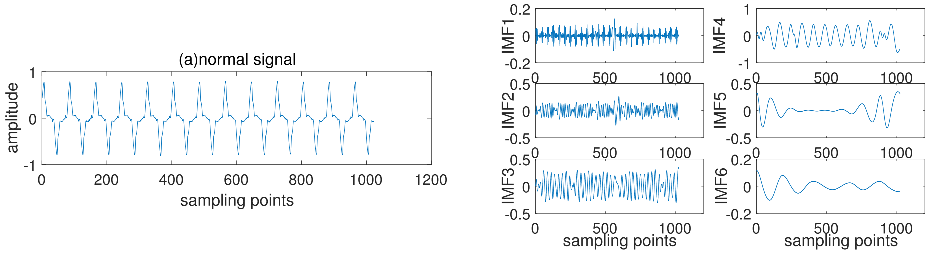

FIGURE 12. The original vibration signal and the obtained components by MEEMD algorithm of the normal signal.

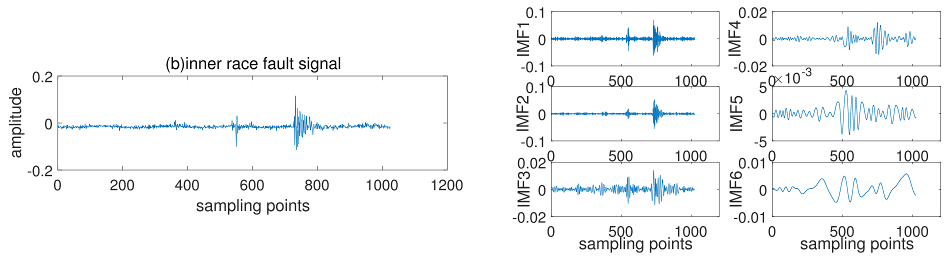

FIGURE 13. The original vibration signal and the obtained components by MEEMD algorithm of the inner race fault signal.

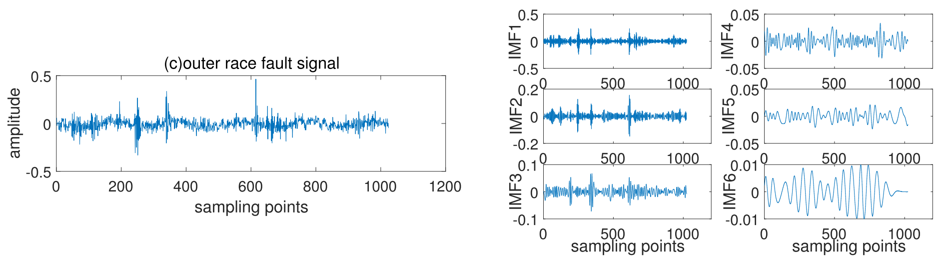

FIGURE 14. The original vibration signal and the obtained components by MEEMD algorithm of the outer race fault signal.

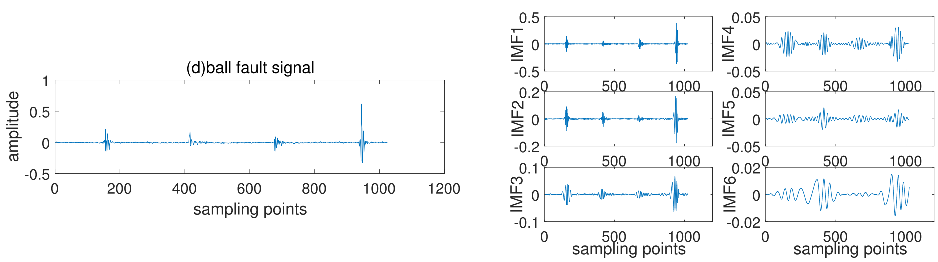

FIGURE 15. The original vibration signal and the obtained components by MEEMD algorithm of the ball fault signal.

The results show that the training time of the QPSO-LSSVM model is 6.397s, while that of the PSO-LSSVM model is 10.982s. Obviously, the proposed method in this paper is more efficient. In order to illustrate the superiority of the proposed model in this paper, RBF neural network algorithm was used to compare with it. Its diagnostic accuracy is only

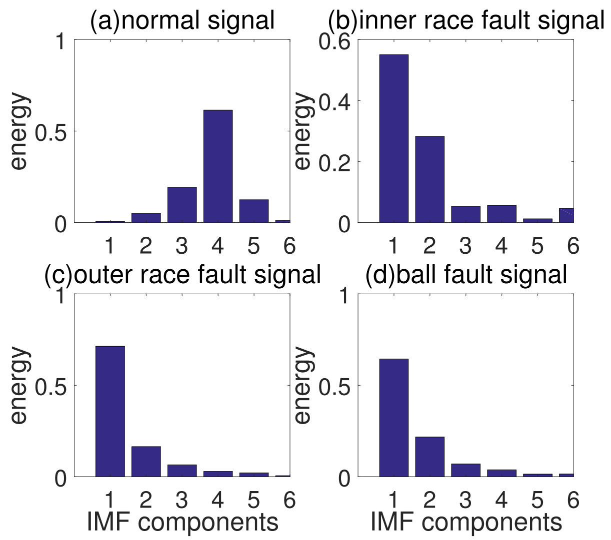

FIGURE 16. The histogram of the feature vectors.

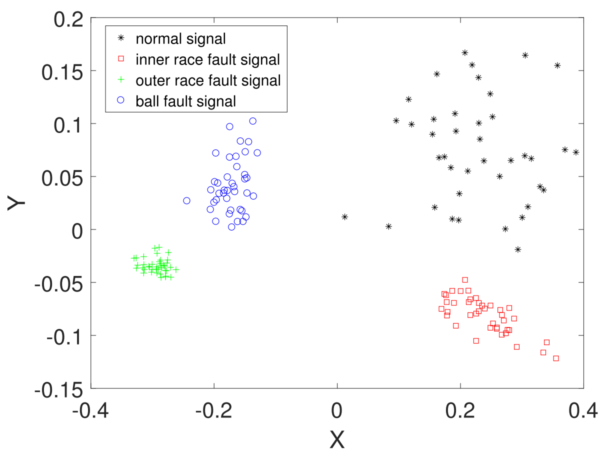

FIGURE 17. The distribution of the data by MDS.

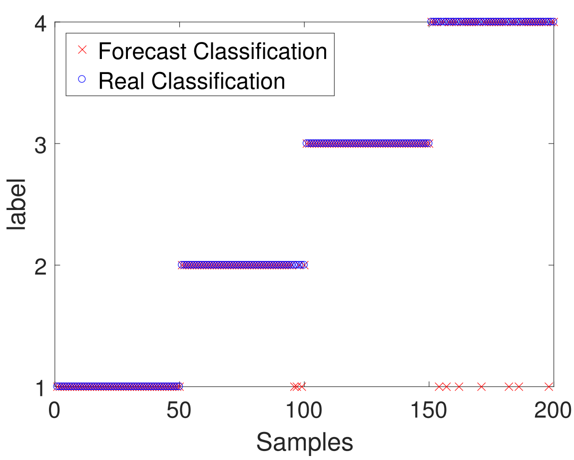

FIGURE 18. The forest classification and the real classification by the SVM model.

90.0%, and the performance is far less than the method proposed in this paper.

At the same time, in order to highlight the advantages of the proposed algorithm, the EMD-QPSO-LSSVM algorithm

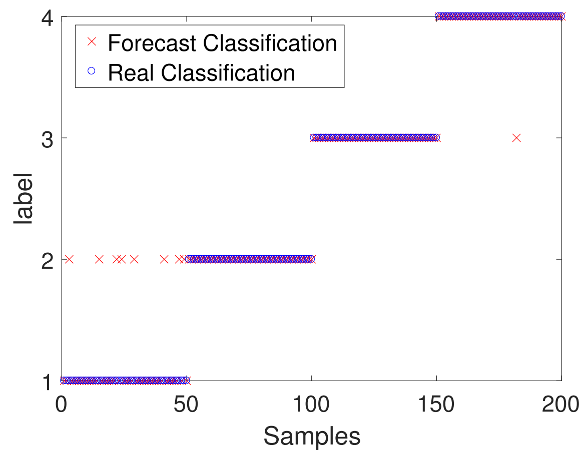

FIGURE 19. The forest classification and the real classification by the LSSVM model.

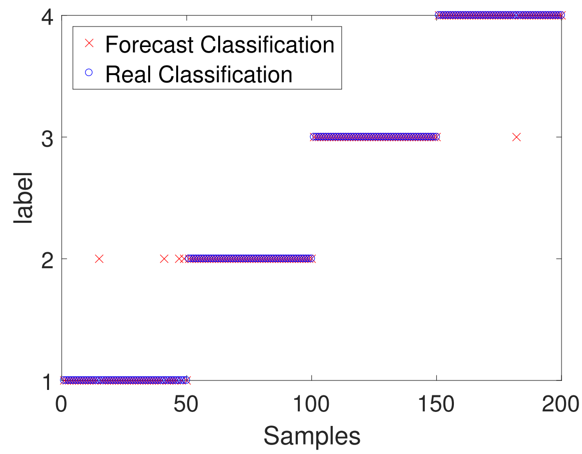

FIGURE 20. The forest classification and the real classification by the PSO-LSSVM model.

TABLE 4. The energy moment feature vectors.

States	energy feature vectors
normal state	0.3755 0.2997 0.0798 0.1791 0.0472 0.0188
	0.2676 0.3302 0.1006 0.2032 0.0964 0.0020
	0.3071 0.3590 0.1579 0.0880 0.0665 0.0215
inner race fault	0.4401 0.4278 0.1029 0.0198 0.0081 0.0014
	0.4625 0.3643 0.1439 0.0215 0.0066 0.0012
	0.4268 0.4438 0.0994 0.0218 0.0049 0.0034
outer race fault	0.8479 0.0884 0.0330 0.0213 0.0056 0.0037
	0.8778 0.0590 0.0306 0.0187 0.0102 0.0037
	0.8909 0.0613 0.0301 0.0107 0.0057 0.0013
ball fault	0.7038 0.1011 0.1321 0.0397 0.0203 0.0030
	0.7188 0.0687 0.1362 0.0468 0.0228 0.0067
	0.7360 0.1023 0.0929 0.0399 0.0220 0.0068

and the EEMD-QPSO-LSSVM algorithm were carried out for fault diagnosis, with the accuracy of 94.5% and 96.0%, respectively. It can be seen that the accuracy of the proposed method is indeed higher than other EMD-based algorithms mentioned in this paper.

The IMF components obtained by the MEEMD algorithm can reflect the signal characteristics from different frequency bands, and its decomposed time-frequency characteristics can effectively reveal the differences from different states. We can see from the data distribution characteristics of the

TABLE 5. The classification of the fault diagnosis by different models.

Method	normal state	inner race fault	outer race fault	ball fault	accuracy
SVM	50/50	47/50	50/50	43/50	95.0%
LSSVM	42/50	50/50	50/50	49/50	95.5%
PSO-LSSVM	46/50	50/50	50/50	49/50	97.5%
QPSO-LSSVM	47/50	50/50	50/50	49/50	98.0%

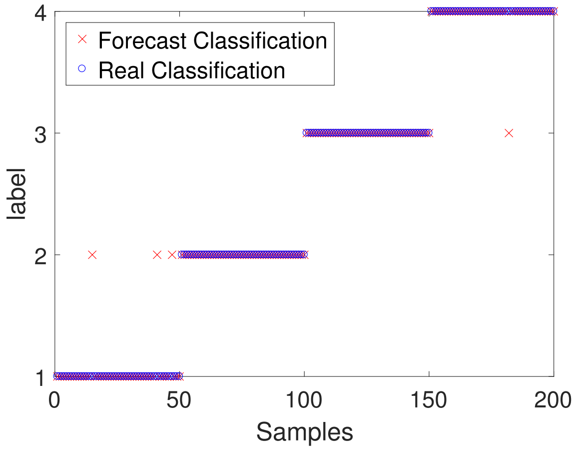

FIGURE 21. The forest classification and the real classification by the QPSO-LSSVM model.

2-dimensional space that several known faults can be effectively distinguished, but there will be a few overlapping phenomena, which does not affect the overall accuracy of the fault diagnosis. In the later period, the parameters of the LSSVM model are iteratively optimized by the QPSO algorithm, and the optimal solution can be found in a limited sample space, avoiding the blindness of parameters selection. In short, from the perspective of experimental verification, the fault diagnosis algorithm comprehensively combining the MEEMD algorithm and the QPSO-LSSVM model does have a good performance on signal characteristic extraction and fault classification, and it can give ideal results intuitively.

IV. CONCLUSION

In this study, a new technique which comprehensively combines the MEEMD algorithm for feature extraction and the QPSO-LSSVM model for classification is applied in the fault diagnosis of rolling bearing. The feature vectors of vibration signals extracted by the MEEMD algorithm and the energy moment normalization can more effectively reflect the potential information which can be easily put into the QPSO-LSSVM model. Due to the introduction of the QPSO algorithm, the candidate solutions in the LSSVM model are better chosen. The performance on the accuracy of the fault diagnosis is improved accordingly. The experiments validate the effectiveness of the proposed method, which provides a reference for the future study in feature extraction and fault classification.

Future research will apply this method to the diagnosis of mixed faults and complex faults. Even it can be applied to other fields, such as inverter fault diagnosis, power load prediction, power fault diagnosis and so on.

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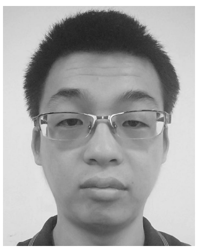

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