Fault Diagnosis of Composite Features Rolling Bearing Based on Variational Mode Decomposition

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Abstract. In order to extract the vibration signal feature of rolling bearing with non-steady feature and improve the fault diagnosis rate accurately and stably, a variational mode decomposition (VMD) feature extraction method is proposed. Particle swarm optimization (PSO) is used to optimize the parameters of support vector machine to construct a fault diagnosis model to achieve fault diagnosis of rolling bearings. Firstly, change the modal decomposition of the known fault signal under the same load to get the modal function, and the modal function is further extracted by the singular value decomposition. The time domain, frequency domain feature and modal feature of the original signal are extracted. Constructing hybrid features to achieve efficient fault feature extraction. Optimizing SVM parameters through PSO algorithm to construct fault diagnosis models to achieve efficient fault diagnosis. Finally, by comparing with EMD-based feature extraction methods in the same load, the method shows better classification performance and the overall fault recognition rate remains above 99.17%, which verifies the reliability and effectiveness of the method.

1. Introduction
Rolling bearing is a component with a high failure rate in the operation of mechanical equipment. If it can extract effective fault information as soon as possible and determine the type of fault, and timely repair or replacement, it can prevent safety accidents and reduce economic losses. When the rolling bearing fails, the vibration signals it generates tend to exhibit strong non-linear, non-Gaussian, and non-causal smoothness features \cite{1-2}. It is difficult to diagnose faults in the time domain or frequency domain alone \cite{3}. Rolling bearing fault diagnosis process is essentially a pattern recognition process, which mainly includes feature extraction and fault classification. When the rolling bearing fails, the energy of each frequency band of the vibration signal will change. If the signal feature of each frequency band can be effectively extracted, the fault diagnosis and classification of the rolling bearing can be performed. Therefore, the effective extraction of fault features is the key to fault diagnosis.

The empirical mode decomposition (EMD) \cite{4} was widely used in the fault feature extraction of rolling bearings in the early days. However, the modal aliasing phenomenon \cite{5} exists in the EMD method, so that the frequencies cannot be completely separated when the signal is decomposed. The method of variational mode decomposition \cite{6} has been applied in the field of feature extraction in
recent years. The method shows the excellent performance and has important theoretical and application values. Zheng Xiaoxia et al. [7] studied the influence of the number of modal components on the signal characteristic information from the frequency aspect based on the VMD method, selected the best modal component for envelope demodulation analysis, and neglected the research on the fault diagnosis process [8]. Gao Hongkai et al. [9] used kurtosis method and envelope demodulation to select components with relatively large kurtosis to analyze, and finally identified the working status and fault type of the rolling bearing through the envelope spectrum, but the stability and accuracy of fault diagnosis is lower than that of the support vector machine. Wang Xin et al. [10] combined the advantages of the VMD method and the support vector machine, and select the components containing the main fault information as the input of the support vector machine from several modal function components that are decomposed. Judging the bearing's working status and fault type, lack of the original fault signal itself of the time domain and frequency domain features, and these features can improve the accuracy of the support vector machine training, as well as the optimization of the parameters of the support vector machine.

In this paper, the VMD method is used to decompose the state information of the rolling bearing, the singular value of each mode is extracted as the feature vector, and the time-domain, and frequency-domain features are combined to form the composite feature. The particle swarm optimization algorithm and the genetic algorithm are used to optimize the parameters of the support vector machine. Finally, diagnoses the type of signal failure.

2. Data Feature Extraction Method

2.1. Variational Mode Decomposition

Firstly, In the VMD algorithm, the intrinsic modal function (IMF) is redefined as an am-fm signal with the expression [11]:

$$u_k(t) = A_k(t) \cos(\phi_k(t))$$  \hspace{1cm} (1)

Where: $A_k(t)$ is the instantaneous amplitude of $u_k(t)$ and $\omega_k(t)$ is the instantaneous frequency of $u_k(t)$. $\omega_k(t) = \phi'_k(t) = d\phi_k(t)/dt$. $A_k(t)$ and $\omega_k(t)$ are gradually changed with respect to phase $\phi_k(t)$, that means within the range of interval $[t - \delta, t + \delta]$, $u_k(t)$ can be regarded as a harmonic signal with amplitude $A_k(t)$ and frequency $\omega_k(t)$.

When the VMD algorithm obtains the IMF component, it gets rid of the signal processing method used by the EMD algorithm to remove the cyclic screening. Instead, the signal decomposition process is transferred to the variational frame, and the adaptive decomposition of the signal is realized by searching the optimal solution of the constrained variational model. The frequency center and bandwidth of each IMF component are continuously updated during the iterative solution of the variational model. Finally, the signal band can be adaptively segmented according to the frequency domain feature of the actual signal to obtain several narrow-band IMF components. Assuming that the original signal is decomposed into $K$ IMF components, the corresponding constraint variational model expression is:

$$\begin{align*}
\min \left\{ & \| \delta(t) + \frac{j}{\pi t} \ast u_k(t) \|_2^2 \right\} \\
\text{s.t.} & \sum_k u_k = f
\end{align*}$$  \hspace{1cm} (2)
In the formula, \( \{u_k\} := \{u_1, \ldots, u_K\} \) represents the K IMF components obtained by decomposition. 
\( \{\omega_k\} := \{\omega_1, \ldots, \omega_K\} \) Represents the frequency center of each component.

In order to obtain the optimal solution to the above constrained variational problem, an augmented Lagrange expression is introduced:

\[
L(\{u_k\}, \{\omega_k\}, \lambda) := \alpha \sum_k \left| \partial_t \left[ (\delta(t) + \frac{j}{\pi t}) * u_k(t) \right] e^{-j\omega_k t} \right|^2 + \\
\left\| f(t) - \sum_k u_k(t) \right\|^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle
\]

Where: \( \alpha \) is the penalty parameter, \( \lambda \) is the Lagrange multiplier.

The saddle point of the augmented Lagrange function is obtained by using an alternating direction multiplier algorithm, which is the optimal solution of the above model, and the original signal is decomposed into \( K \) narrow-band IMF components. VMD needs to predetermine the modal number \( K \). The difference of each mode is mainly the difference of the center frequency. The literature [12] uses the method of observing the center frequency to obtain the center frequency corresponding to different \( K \) values, and finds that starting from \( K \) is 5, a mode with a similar center frequency appears, and it’s considered that over decomposition occurs, so the modal number is selected as 4.

2.2. Composite Feature Selection

Using the VMD decomposition method, the original signal is decomposed to obtain four IMF components, and singular values of each component are taken as IMF1, IMF2, IMF3, and IMF4. In order to extract feature values effectively, appropriate statistical feature values are selected to characterize the processed information. The statistical characteristic values selected in this paper are standard deviation, mean square root, kurtosis, mean and mean square error of each data group [13]. Combining with the decomposition of IMF1-4 to form a 9-dimensional composite feature (abbreviated as FH).

| Statistical Feature Name | Calculation Formula |
|--------------------------|---------------------|
| Standard deviation       | \( \sigma = \sqrt{\frac{1}{T} \sum_{i=1}^{T} (x_i - \bar{x})^2} \) |
| Root mean square         | \( \sqrt{\frac{1}{T} \sum_{i=1}^{T} x_i^2} \) |
| Kurtosis                 | \( a_4 = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^4}{N\sigma^4} \) |
| Mean                     | \( \bar{x} = \frac{1}{T} \sum_{i=1}^{T} x_i \) |
| Variance                 | \( \frac{1}{T} \sqrt{\sum_{i=1}^{T} (x_i - \bar{x})^2} \) |
3. Prediction And Classification Based On PSO SVM

3.1. Support Vector Machine
Support vector machine realizes the transformation of linear non-separable linear reparability through kernel functions. Research shows that the radial basis kernel function shows good generalization ability in SVM [14], and its form is like the formula (4).

\[ K(y_i, z_j) = \exp\left(-\frac{|y_i - z_j|^2}{\sigma^2}\right) = \exp(-\gamma |y_i - z_j|^2) \]  

The input vector is mapped from the original space to the high-dimensional feature space \( H \), and an optimized hyper plane is established in the feature space \( H \). The classification line equation is as follows:

\[ \omega \cdot x + b = 0 \]  

\[ y_i(\omega \cdot x_i + b) \geq 1, \quad i = 1, 2, \ldots, I \]

In the formula, \( \omega \) is a weight, \( x \) is an input vector, \( b \) is a threshold, \( I \) are the number of vectors.

According to Karush-Kuhn-Tucker, optimizing each coefficient to get the best classification function:

\[ f(x) = \text{sgn}\left(\sum_{i=1}^{I} y_i a_i \sigma(x, x_i) + b\right) \]  

The fitness function is:

\[ f(\sigma^2, C) = \frac{1}{R(\sigma^2, C)} \]  

From the above equations, it can be seen that when constructing the SVM classification model, the key factor of the performance lies in the choice of the penalty parameter \( C \) and the function \( \sigma \).

3.2. Particle Swarm Optimization for SVM
Particle swarm optimization is a global optimization method based on swarm intelligence. It achieves optimal solution search in complex solution space through cooperation and competition among individuals. It is suitable for SVM parameter optimization [15]. Taking the kernel function parameter \( \sigma \) and the penalty parameter \( C \) as parameters to be optimized, the optimization goal is to obtain the highest classification accuracy. The test sample set is input into the trained SVM to identify the status category to which the fault belongs, thereby realizing the diagnosis of different faults. Based on the VMD method of fault diagnosis flow chart shown in Fig. 1:
Figure 1. Flowchart of the VMD-FH-PSO-SVM model

4. Case Studies
To verify the feasibility and validity of the algorithm model, the data of the rolling bearing experimental platform of the Electrical Engineering Laboratory of Case Western Reserve University in the US [16] was used in this paper. The bearing tested in the experiment was a 6205-2RS deep groove ball bearing manufactured by SFK.

4.1. Data Feature Sample
Compare the fault data with normal data under the same experimental conditions to determine the type and location of the fault better. The rolling bearing is selected to work at load of 0-3, a speed of 1797 rpm (load 0), 1772 rpm (load 1), 1750 rpm (load 2), and 1730 rpm (load 3). Sampling frequency is 12 kHz, and damage point diameter 0.18 mm. Inner ring fault, rolling element fault and outer ring fault data in 6 o'clock direction in 4 states, 50 sets of data each, each set of data intercepted 2048 sampling points, and the first 70% (35 groups) of data were used as training samples, the last 30% of the data (15 groups) as test sample data, through the support vector machine for fault diagnosis, specific data in Table 2.
4.2. Comparison and Analysis of Different Models

In order to verify the superiority of the proposed method, the following comparisons were based on the different feature extraction methods and different parameter optimization model under the VMD and EMD decomposition methods:

1) SVM model: Using the VMD/EMD decomposition method to obtain modal feature, taking the singular value IMF1-4 as the input feature to train the training set, and SVM classification prediction is performed respectively.

2) PSO-SVM model: Using the VMD/EMD decomposition method to obtain modal feature, taking the singular value IMF1-4 as the input feature to train the training set. The PSO algorithm is used to optimize the parameters of the classifier, and SVM classification prediction is performed with the optimal parameters.

3) FH-PSO-SVM model: Using the VMD/EMD decomposition method to obtain modal feature, taking the singular value IMF1-4, and then select the data standard deviation, root mean square, kurtosis, mean and the mean square error to form composite features for training the training set. The PSO algorithm is used to optimize the classifier parameters, and SVM classification prediction is performed with the optimal parameters.

4) FH-GA-SVM model: Using VMD/EMD decomposition method to obtain the modal feature, taking the singular value IMF1-4, and then select the data standard deviation, root mean square, kurtosis, mean and the mean square error to form composite feature for training the training set. The genetic algorithm (GA) algorithm is used to optimize the classifier parameters [17], and the SVM classification prediction is performed with the optimal parameters. The experimental data are shown in Table 3 (the results are 5 averages):

According to the data in Table 3, the average prediction accuracy of the SVM model, PSO-SVM model, and FH-PSO-SVM model based on the VMD decomposition method are higher than the accuracy rate of 6.4%, 10.3%, and 7.6% in the EMD decomposition method respectively. It shows that the modal feature obtained by VMD decomposition method are better than EMD decomposition, and the features from VMD decomposition method have better training effect on SVM to obtain higher accuracy. Secondly, the prediction accuracy rate of FH-PSO-SVM model under the decomposition of VMD and EMD is higher than that of the PSO-SVM model with the same load and same decomposition mode of 2.6% and 5.3%, indicating that the composite feature compensates the modal feature of the original signal to a certain degree, and the SVM training effect and prediction accuracy are better. In addition, the prediction accuracy of the PSO-SVM model under the VMD and EMD decomposition methods is higher than that of the SVM model without parameters optimization of 7.8% and 3.9%, indicating that the parameter optimization has significantly improved the SVM training and prediction results. The prediction accuracy of the FH-PSO-SVM model under the EMD decomposition method is
higher than that of the FH-GA-SVM model by 7.9% and 4.2%, indicating that the PSO algorithm is superior to the GA in the SVM parameter optimization effect. As a result, a higher prediction accuracy rate is achieved.

Table 3. Forecast accuracy of each model under load 1-3

| Decomposition Method | Fault Diagnosis Model | Operating Conditions | Accuracy (%) |
|----------------------|-----------------------|----------------------|--------------|
| VMD                  | SVM                   | Load 1               | 88.3333      |
|                      |                       | Load 2               | 88.3333      |
|                      |                       | Load 3               | 90           |
|                      | PSO-SVM               | Load 1               | 92.5         |
|                      |                       | Load 2               | 98.3333      |
|                      |                       | Load 3               | 99.1667      |
|                      | FH-PSO-SVM            | Load 1               | 99.1667      |
|                      |                       | Load 2               | 99.1667      |
|                      |                       | Load 3               | 99.5         |
|                      | FH-GA-SVM             | Load 1               | 90           |
|                      |                       | Load 2               | 89.1667      |
|                      |                       | Load 3               | 95           |
| EMD                  | SVM                   | Load 1               | 75           |
|                      |                       | Load 2               | 84.1667      |
|                      |                       | Load 3               | 88.3333      |
|                      | PSO-SVM               | Load 1               | 83.3333      |
|                      |                       | Load 2               | 88.3333      |
|                      |                       | Load 3               | 92.5         |
|                      | FH-PSO-SVM            | Load 1               | 83.3333      |
|                      |                       | Load 2               | 92.5         |
|                      |                       | Load 3               | 99.1667      |
|                      | FH-GA-SVM             | Load 1               | 74.1667      |
|                      |                       | Load 2               | 90.8333      |
|                      |                       | Load 3               | 97.5         |

Under the same working conditions, by comparing the experimental data of each model, combining the singular values of the modal feature after VMD decomposition with the time domain and frequency domain features to form a composite feature, the PSO algorithm is used to optimize the classifier (FH-PSO-SVM model). The highest accuracy rate was obtained by predictive classification under three loads, showing the best diagnostic effect.

5. Conclusion
A fault signal feature extraction method based on variational modal decomposition combined with time domain and frequency domain features was proposed. The particle swarm optimization algorithm was used to optimize the classification parameters of the support vector machine for fault diagnosis of rolling bearings. VMD decomposition of the vibration signal avoids the modal aliasing phenomenon of EMD decomposition and accurately extracts the signal features. By combining the time domain and frequency domain features, it can quickly and accurately obtain the effective sample features in large data volumes. The PSO algorithm optimizes the SVM parameters, and has a higher recognition rate than the traditional genetic algorithm, achieving efficient and stable fault diagnosis. The experimental analysis shows that using this algorithm model is a feasible approach to fault diagnosis.

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