Fault Diagnosis of Motor Bearings Based on Ensemble Empirical Mode Decomposition and Minimum Support Vector Machine

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Abstract: This paper proposes a bearing fault diagnosis method based on integrated empirical mode decomposition and Bayesian criterion using least squares support vector machine to address the issues of poor accuracy and reliability in the diagnosis of wind turbine motor bearing faults. The collected vibration signals are processed using wavelet denoising method, and the integrated empirical mode decomposition method is used to extract features from the signals. The intrinsic mode functions of each state are selected based on correlation as the evaluation index. Then, the energy entropy of the corresponding mode is calculated as the characteristic phasor of the vibration signal. Finally, a Bayesian based least squares support vector machine classifier is established to complete fault diagnosis. The experimental results show that the EEMD based and Bayesian based least squares support vector machine methods can effectively improve the accuracy of bearing fault diagnosis.

Keywords: Ensemble Empirical Mode Decomposition; Least Squares Support Vector Machine; Motor Bearing; Fault Diagnosis

1. Introduction

As the main power component of wind turbines, the operational stability of bearings is crucial. If the bearing fails, it will have a significant impact on the operation of the entire rotating machinery and even the entire fan. Therefore, in order to ensure the reliability and safety of rolling bearings, reduce maintenance costs, and diagnose their faults, it is of great practical significance [1].

Traditional fault diagnosis techniques based on vibration signal analysis, such as short-time Fourier transform, require appropriate window functions that are difficult to obtain; Wigner distribution, this method is prone to secondary aliasing; Cohen class analysis, this method is difficult to select suitable kernel functions; Wavelet transform, this method does not have adaptive characteristics; The Hilbert Huang transform uses empirical mode decomposition (EMD) algorithm to decompose signals into a set of intrinsic mode functions (IMFs) with strong single variable adaptability, high time-frequency resolution, and good time-frequency clustering [2]. It has the advantage of transforming nonlinear and non-stationary signals into linear and stationary signals, but this method has problems such as mode aliasing and endpoint effects. Ensemble Empirical Mode Decomposition (EEMD) is a method that adds new white noise to assist data analysis on the basis of EMD. It can suppress the shortcomings of EMD, such as severe endpoint effects and mode aliasing, while also having the advantages of EMD in processing nonlinear and non-stationary signals [3]. Based on this, this article proposes an EEMD energy entropy algorithm for feature vector extraction, which improves the accuracy of vibration signal feature vector extraction. Support Vector Machine (SVM) is an intelligent fault pattern recognition method developed on the basis of statistical learning theory. It adopts the principle of structural risk minimization and can effectively avoid problems such as under learning, over learning, and curse of dimensionality. SVM has shown excellent characteristics in solving problems such as small sample, nonlinear, and high-dimensional pattern recognition [4]. Due to the fact that the judgment results of traditional support vector machines are usually hard classification results with a high misclassification rate, this paper adopts Bayesian criteria and proposes a method to obtain the posterior probability of support vector machines. Based on Bayesian criteria, the Least Squares Support Vector Machine (LS-SVM) method is proposed [5].

In summary, this article proposes a wind turbine rolling bearing fault diagnosis method combining EEMD energy entropy and LS-SVM based on Bayesian criteria, and applies the diagnostic model to bearing experimental data to verify the effectiveness of the proposed method.

2. Fault Feature Extraction Based on EEMD Energy Entropy Method

2.1 EEMD Method

EEMD can adaptively decompose nonlinear and non-stationary multi-mode signals into several IMF components of stationary single mode and a remainder term according to the characteristics of the signal itself [6]. The algorithm is as follows:

(1) Add p random additive Gaussian white noises with zero mean and equal variance to the original signal $x(t)$, with a sequence of $(n_1(t), n_2(t), \cdots n_p(t))$, to form a signal sequence of $(x_1(t), x_2(t), \cdots x_p(t))$.

$$\begin{cases} x_1(t) = x(t) + n_1(t) \\ x_2(t) = x(t) + n_2(t) \\ \cdots \\ x_p(t) = x(t) + n_p(t) \end{cases} \tag{1}$$

(2) Perform empirical mode decomposition on p signals after adding white noise. The IMF of a signal must meet the following two conditions: (1) The number of extreme points and the number of zero crossings in the entire signal series must be equal or at most differ by one point; (2) At any point in time, the mean of the envelope of the maximum and minimum points is equal to zero.

(3) EEMD processing consists of the following four steps:

Step 1: Apply the cubic spline algorithm to find the envelope lines of all local maximum and minimum points of signal $x_i(t)(i = 1,2,\cdots, p)$, and then calculate the average value $m_1(t)$ of these two envelope lines. Subtract $m_1(t)$ from $x_i(t)$ to obtain h_1.

$$h_1 = x_i(t) - m_1 \tag{2}$$

Step 2: If h_1 satisfies the two conditions of IMF, then h_1 is the first IMF component c_1. If h_1 does not meet the conditions, use it as raw data and repeat step 1, that is, first obtain the average value $m_{1,1}$ of the upper and lower envelope lines, then subtract $m_{1,1}$ from h_1 to obtain $h_{1,1}$, and then determine whether the conditions are met. If it is still not satisfied, repeat step 1 again. If the condition is satisfied after repeating k times, let $c_1 = h_{1,k}$ be the first IMF component.

$$h_{1,k} = h_{1,k-1} - m_{1,k} \tag{3}$$

Step 3: Separate the first IMF component c_1 from the original signal $x(t)$ to obtain the residual term r_1.

$$r_1 = x_i(t) - c_1 \tag{4}$$

Step 4: Repeat the above three steps with r_1 as the raw data to obtain the second IMF component c_2 of $x_i(t)$ that satisfies the condition. Repeat this process n times to obtain n IMF components of $x_i(t)$ and one residual component $R_{i,es}$. Thus, the matrix c of IMF and the residual function matrix R_{es} of $R_{i,es}$ can be obtained.

$$c = \begin{pmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,n} \\ \vdots & \vdots & & \vdots \\ c_{p,1} & c_{p,2} & \cdots & c_{p,n} \end{pmatrix} \tag{5}$$

$$R_{es} = \begin{pmatrix} R_{1,es} \\ R_{2,es} \\ \vdots \\ R_{p,es} \end{pmatrix} \tag{6}$$

Calculate the average value $C_i(i = 1,2,\cdots, p)$ of each row of the IMF component matrix c and the average value $R_{0,es}$ of the residual function matrix elements:

$$C_i = \frac{1}{n}\sum_{k=1}^{n} c_{i,k} \tag{7}$$

$$R_{0,es} = \frac{1}{p}\sum_{i=1}^{p} R_{i,es} \tag{8}$$

So the original signal $x(t)$ can be reconstructed as:

$$x_0(t) = \sum_{i=1}^{p} C_i + R_{0,es} \tag{9}$$

2.2 Energy Entropy

Different types of bearing faults result in changes in the frequency components of the extracted vibration signals and the amplitude energy of the signals within each frequency band. In this paper, the energy entropy obtained from EEMD decomposition is used as the feature vector, and the amplitude energy E_i of the IMF component $c_i(t)$ is shown in the following equation:

$$E_i = \int_{-\infty}^{\infty} \left| c_i(t) \right|^2 dt \tag{10}$$

Normalize the amplitude energy E_i of each IMF component to obtain the energy entropy of each IMF component.

$$T_i = E_i / E, E = (\sum_{i=1}^{5} \left| E_i \right|^2)^{\frac{1}{2}} \tag{11}$$

3 Least Squares Support Vector Machine Support Vector Machine and Its Improvement

3.1 Support Vector Machine

Support Vector Machine (SVM) is a branch of machine learning that belongs to neural network classifiers. It is suitable for small sample analysis and has been widely used in mechanical equipment fault pattern recognition [7-9]. The selection of SVM kernel function, the size of penalty factor, the value of insensitivity coefficient, the width of kernel function, and the size of training samples directly affect the performance of classification and the accuracy of fault diagnosis. According to the theory of universal functions, using an appropriate inner product function in the optimal classification surface can achieve linear classification of a nonlinear problem after transformation, such as using Gaussian radial basis function (RBF). Gaussian RBF is shown in the following equation:

$$K(x_i, x) = \exp(-\gamma \left\| x_i - x \right\|^2 \tag{12}$$

The classification function is:

$$f(x) = \text{sgn}(\sum_{i=0}^{n} a_i y_i K(x_i, x) + b) \tag{13}$$

Where, γ is the hyperparameter, x_i and x are sample vectors, $a_i y_i$ weights, and b is the bias.

3.1 Least Squares Support Vector Machine Based on Bayesian Criterion

The judgment results of traditional support vector machines are usually hard classification results, with a high misclassification rate, especially for point recognition in boundary regions. Therefore, this article fully considers obtaining the posterior probability of support vector machines and proposes a method for obtaining the posterior probability of support vector machines using Bayesian criteria [10-12]. This method maps the classification results of the least squares support vector machine using Bayesian criteria to obtain a probabilistic representation. The classification function of support vector machine, that is, the output without threshold is $f(x) = h(x) + b$, where $h(x) = \sum_i y_i a_i k(x_i, x)$. Based on Bayesian criterion, the classification result is mapped to the interval [0, 1] through a $sigmoid$ function to represent the output probability, as shown in the following equation.

$$P(y = 1 | f) = \frac{1}{1 + \exp(Cf + D)} \tag{14}$$

In the equation, parameters C and D are used to adjust the size of the mapping value. The idea of this method is that the probability value depends on the distance between the sample point and the boundary. Points farther away from the boundary are considered to have a higher probability of correct classification, while points closer to the boundary are considered to have a lower probability of correct classification. Parameters C and D are obtained through maximum likelihood estimation. Firstly, a training set (f_i, t_i) is defined, where t_i is the target probability:

$$t_i = \begin{cases} \dfrac{N_+ + 1}{N_+ + 2} & y_i = +1 \\ \dfrac{1}{N_- + 2} & y_i = -1 \end{cases} \quad i = 1, 2, \cdots, l \tag{15}$$

In the formula, N_+ is the number of positive samples, $N\_$ is the number of negative samples, and y_i is the target discrimination category. Obtain C and D by solving a negative logarithmic likelihood function.

$$\min - \sum_i t_i \log(p_i) + (1 - t_i) \log(1 - p_i) \tag{16}$$

Where, $p_i = \dfrac{1}{1 + \exp(Cf_i + D)}$. By using this mapping method, the posterior probability of the support vector machine classification result can be obtained.

4. Fault Diagnosis Process Based on the Combination of EEMD and LS-SVM

Step 1: Collect vibration signals using vibration signal sensors.

Step 2: Use wavelet transform to denoise the original signal and minimize the interference after modal decomposition.

Step 3: Perform EEMD decomposition on the denoised signal to obtain IMFs. Calculate the correlation coefficients for each IMF. Screen IMFs and select the components with high correlation to the original signal.

Step 4: Calculate the energy entropy of the screened IMFs as the extracted fault feature vector.

Step 5: Use vibration signals of different types of faults to obtain characteristic vectors of different types of faults in steps one to four. Use the obtained fault feature vectors as input training data for SVM classifiers, and construct a one to many classifier of "one type and other types" with the same number of constructs as the number of fault types.

Step 6: Collect the vibration signal to be detected, process the vibration signal using the same method as described above to obtain the feature vector.

Step 7: Use the feature vector as the detection data input for the SVM classifier to obtain the classification result.

5. Experimental Verification

To verify the effectiveness of the proposed method, data from the Bearing Data Center of Case Western Reserve University was used. The bearing type is SKF6205, and the vibration signal of the bearing is measured using an accelerometer. The data contains multiple sets of data under different conditions. Here, the vibration signal of the bearing drive end with a load of 3HP, a speed of 1730 rpm, and a sampling frequency of 12 kHz is selected for simulation verification. The operating status of the bearings corresponding to the data used includes four types: normal, inner ring fault, outer ring fault, and rolling element fault, with damage diameters of 0.007 inches and 0.021 inches. As shown in Figure 1, the EEMD method is used to extract features from the obtained outer ring fault signal.

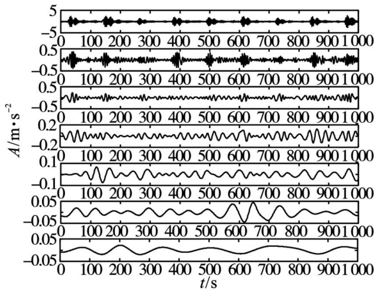


Figure 1. Results of Feature Extraction of Outer Ring Fault Signals Obtained by EEMD Method Solution

EEMD can evenly distribute the various frequencies of the signal over the entire time axis, eliminate signal frequency discontinuities, effectively reduce signal mode aliasing, and achieve the goal of improving signal resolution without obvious endpoint effects. The EEMD algorithm also inevitably produces false or IMF components that are not closely related to the original signal, which affects the accuracy of fault identification and diagnosis. Since each IMF component is orthogonal to the original signal, the correlation is used to evaluate the relationship between each IMF component and the original signal. Here, the correlation coefficient ρ is used for evaluation, where a larger ρ indicates a higher correlation between the IMF component corresponding to ρ and the original signal. This article selects IMF components based on the size of ρ . According to the formula for calculating the correlation coefficient in probability theory:

$$\rho_k = \frac{\sum_{i=1}^{\rho}\sum_{t=0}^{\infty} c_{i,k}(t)x(t)}{\sqrt{\sum_{i=1}^{\rho}\sum_{t=0}^{\infty} c_{i,k}^2(t)x^2(t)}} \tag{17}$$

Where, $c_{i,k}(t)$ represents each IMF component, and $x(t)$ represents the signal after wavelet denoising. As shown in Table 1, the correlation coefficients between the 7 IMF components and the original signal are presented.

This article selects 0.5 as the correlation coefficient threshold. As shown in Table 1, only IMF1, IMF2, IMF3, and IMF4 have correlation coefficient values greater than 0.5. Therefore, this article selects the above IMF as the final feature component to calculate its energy entropy value and uses Bayesian and LSSVM methods to achieve fault diagnosis.

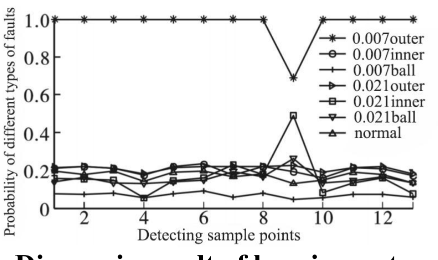
Table 1. Correlation Coefficients between 7 IMF Components and the Original Signal

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7
correlation coefficient	0.72	0.68	0.53	0.62	0.42	0.39	0.21

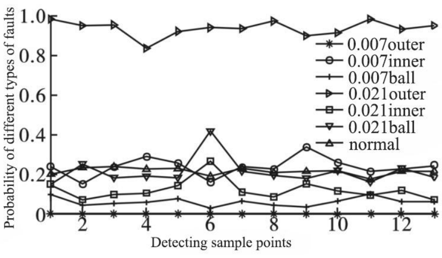
6. Analysis of Experimental Results

After using the EEMD and energy entropy methods proposed in this paper to extract features from outer, inner, and ball faults with a damage diameter of 0.007 and outer, inner, and ball faults with a damage diameter of 0.021, as well as normal state data from Western Reserve University, 7 sets of sample data were obtained. Each set of sample data contains 300 sample feature vectors, and the first 200 features were selected for each sample as training samples and input into LSSVM for training. Thirteen features were selected as detection samples to test the classification performance of LSSVM. The hard classification results of LSSVM were mapped to the posterior probability of each point using Bayesian criteria and plotted as a curve. The results are shown in Figure 2.

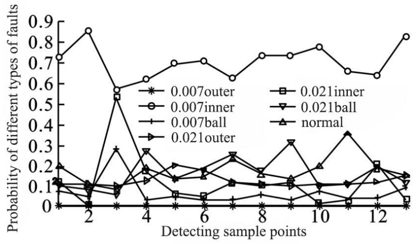
From Figure 2 (a) to Figure 2 (f), it can be seen that for each detection category, the corresponding posterior probability curve is the highest curve and does not intersect with the curves of other categories. This avoids the occurrence of false positives caused by individual points being too close to the SVM classification hyperplane. The diagnostic effect is good, which verifies the effectiveness of the proposed method.



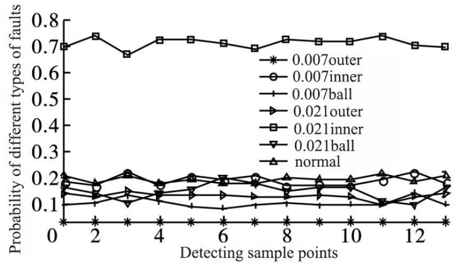
(a). Diagnosis result of bearing outer ring 0.007



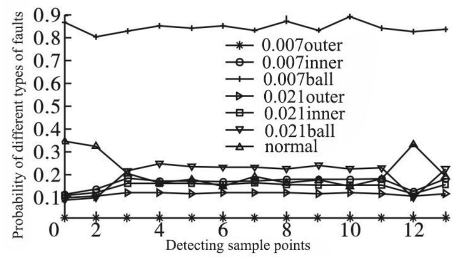
(b). Diagnosis result of bearing outer ring 0.021



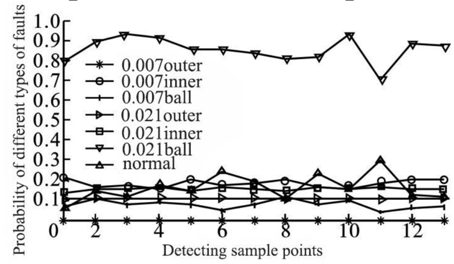
(c). Diagnosis result of bearing inner race 0.007



(d). Diagnosis result of bearing inner ring 0.021



(e). Diagnosis result of bearing ball 0.007



(f). Diagnosis result of bearing ball 0.021

Figure 2. Diagnosis Result

7. Conclusion

This paper proposes a new method for fault diagnosis of wind turbine bearings, which combines EEMD energy entropy feature extraction and LS-SVM based on Bayesian criteria, to address the nonlinear and non-stationary characteristics of vibration signals in wind turbine bearings. The method was applied to fault diagnosis of data from Western Reserve University. Firstly, EEMD and energy entropy methods were used to extract features from bearing vibration signals, obtaining corresponding feature vectors. To reduce the dimensionality of the obtained feature vectors, remove redundant components, and reduce computational complexity, the correlation number criterion was used to screen the obtained feature vectors. Finally, a Bayesian based least squares support vector machine was used to achieve bearing fault diagnosis. The results showed that the method can effectively extract fault features of bearings with strong robustness.

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