Bearing fault diagnosis based on wavelet packet energy spectrum and SVM

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Abstract. Aiming at the limitation of wavelet analysis in fault diagnosis, combining wavelet packet energy spectrum and support vector machine algorithm, a fault diagnosis method based on wavelet packet energy spectrum and support vector machine algorithm (SVM) is proposed. This method first performs wavelet packet transformation on the test data, and the vibration signal is decomposed into independent frequency bands. The signal energy changes in different frequency bands reflect the change of the operating state, and the wavelet packet energy spectrum of each frequency band is extracted as a feature vector. Finally, the SVM algorithm is used to test the bearing faults. The test results show that after processing and analysis of a large number of measured bearing data, the fault of the bearing can be diagnosed relatively accurately.

1. Introduction

Bearings are mainly used to support mechanical slewing bodies, reduce friction during the movement of the slewing bodies, and ensure the accuracy of movement. They have been widely used in modern mechanical equipment and transport equipment. Because the load and the environment used by the bearing are usually more complicated, it is also one of the most susceptible parts in mechanical equipment, and its operating state directly affects the safety, reliability and service life of the entire mechanical system. Therefore, it is very important to diagnose bearing faults [1].

As a time-frequency analysis method, wavelet analysis is widely used in the field of fault diagnosis. However, since wavelet packet decomposition contains a large amount of wavelet decomposition information and data, how to use these data to obtain effective fault features is a key issue in fault detection. Chen et al. [2] proposed a rolling bearing fault analysis method based on wavelet packet energy spectrum. This method decomposes the wavelet packet of vibration data into multiple subbands, then reconstructs the fault band, and uses Hilbert transform to demodulate the envelope of the
reconstructed signal. The results verify the feasibility of using wavelet packet energy spectrum to
detect rolling bearing faults.

SVM is a machine learning method developed on the basis of statistical learning theory. It has good
learning ability for small training samples, compared with the requirements of artificial neural
networks for the number of learning samples. Wu et al. [3] proposed a failure mode recognition
method based on zero space tracking algorithm and support vector machine, calculating the statistical
parameters of each narrowband signal, constructing feature vectors and using SVM for failure mode
recognition, this method can effectively realize rolling bearings Failure pattern recognition. In view of
this, a rolling bearing fault feature extraction method based on wavelet packet energy spectrum is
adopted and SVM is proposed for diagnosis. Tests prove that this method can effectively carry out
condition monitoring and fault diagnosis of bearings.

2. Introduction of algorithm

2.1. Wavelet packet decomposition theory

Wavelet packet decomposition can decompose the signal into different frequency bands without
leakage and without overlapping at any time-frequency resolution. After the wavelet packet transform,
the information is complete and all frequencies are retained, which provides a powerful condition for
extracting the main information in the signal. This decomposition can be carried out as many times as
necessary to finally obtain the required frequency [4]. Figure 1 shows the principle diagram of
performing 3-layer orthogonal wavelet packet decomposition on a signal. Record the original signal as
$S$, and after the wavelet packet decomposition passes through filters $H$ and $G$, two sub-bands $S_{10}$
and $S_{11}$ of layer 1 can be obtained; By decomposing the two sub-components of the first layer separately,
the four subbands $S_{20}$, $S_{21}$, $S_{22}$, and $S_{23}$ of the second layer can be obtained; and so on, and the
subbands of the third layer can be obtained.

![Schematic diagram of wavelet packet decomposition](image)

Figure 1. Schematic diagram of wavelet packet decomposition

Many scholars at home and abroad have studied the application of wavelet packet decomposition in
vibration signal processing, and proposed the concept of wavelet packet node energy. It is concluded
that the node energy has better stability than the directly extracted wavelet packet decomposition
coefficient. The wavelet packet node energy is defined as follows:

Assuming that the vibration signal $x(t)$ is decomposed by $j$, $2^j$ subbands are obtained. Then, the
energy of the $\omega$th subband $E_{n_{\omega}}$ can be expressed as:

$$ En_{\omega} = \sum |f_{\omega}|^2, \omega = 0,1,2,\cdots, 2^j - 1 $$

(1)

Where: $f_{\omega}$ represents the $\omega$th component of the vibration signal $x(t)$ after decomposition.

Then the energy spectrum of the wavelet packet of the vibration signal $x(t)$ at the decomposition
level $jth$ $En_j$ is expressed as follows:

$$ En_j = [En_0, En_1, En_2,\cdots, En_{2^j-1}]^T $$

(2)
2.2. Support Vector Machine Algorithm

SVM is a new machine learning method based on the principle of minimizing structural risk. The optimal linear classification surface is established by training the sample set in the original feature space. The kernel function is used to map the non-linear classification interface in the original feature space to the high-dimensional feature space, so that the classification interface becomes linearly separable in the high-dimensional feature space and improve the classification effect [5].

Taking two types of training sample sets as an example, suppose the given training sample set is \( \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \), \( y_i \in \{+1, -1\} \), \( i = 1, 2, \ldots, n \) represents the sample category, and the kernel function is \( K \). Construct the cost function to minimize it:

\[
\min \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{n} \xi_i
\]  
(3)

The constraints are

\[
y_i(\omega^T x_i + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, 2, \ldots, n
\]  
(4)

Among them, \( \xi_i \) is the relaxation factor, which indicates the degree of misclassification of the training samples, and \( C \) is the penalty constant, which controls the degree of penalty for the misclassified samples. \( \omega \) and \( b \) are the weight vector and threshold of the decision function \( f(x) = (\omega \cdot x) + b \), respectively. Construct the Lagrange function as

\[
L(\omega, b, \alpha) = \frac{1}{2} \| \omega \|^2 + C \sum_{i=1}^{n} \alpha_i [y_i(\omega^T x_i + b) - 1 + \xi_i] - \sum_{i=1}^{n} \beta_i \xi_i
\]  
(5)

Among them, \( \alpha_i \) and \( \beta_i \) are Lagrange operators. According to KKT conditions:

\[
\begin{cases}
\alpha_i [y_i(\omega^T x_i + b) - 1 + \xi_i] = 0, i = 1, 2, \ldots, n \\
(C - \alpha_i) \cdot \xi_i = 0, i = 1, 2, \ldots, n \\
\end{cases}
\]  
(6)

\[
f(x) = sgn \left( \sum_{i=1}^{n} \alpha_i^* y_i K(x_i, x) + b^* \right)
\]  
(7)

3. Experimental study

In order to verify the effectiveness of the method proposed in this paper, it is applied to the diagnosis of the fault category and fault diameter of rolling bearings. The bearing data used comes from the Electrical Engineering Laboratory of Case Western Reserve University in the United States [6]. The experimental platform is shown in Figure 2.

![Figure 2. Fault simulation experimental table for rolling bearing](image)

In order to detect bearing faults, the normal and fault signals need to be decomposed by wavelet packets, and the wavelet packet energy spectrum features are extracted as training samples to train the SVM classifier. Then use the decision function generated by the SVM classification algorithm for fault detection. The specific model is shown in Figure 3.
4. Results analysis

4.1. Wavelet packet energy spectrum analysis

Figure 3. Rolling bearing fault detection process

Figure 4. Time domain waveform of the outer circle

Figure 5. Exploded view of wavelet packet

Figure 6. Frequency band energy
Figure 4 is the time domain waveform of the outer ring, N=2048, you can find that the running amplitude has been changing, indicating that there is a fault. In this paper, the wavelet packet is decomposed into 8 layers, and a total of 2^8 frequency bands are obtained. Figure 5 shows the first 4 layers. Wavelet packet decomposition decomposes the signal into 256 sub-bands, and then obtains the energy amplitude for the 256 sub-bands respectively, so the feature corresponding to each sample is 256 dimensions. Fig. 6 is to deal with the energy of the frequency band, it can be seen from the figure that the corresponding frequency doubling feature is quite obvious. This also provides a certain basis for fault diagnosis later.

4.2. Analysis of fault diagnosis results

From the original data, each sample is sampled with 2048 points, and with 100 samples for each fault, the original signal is decomposed using the wavelet packet energy spectrum and its energy characteristics are calculated. A total of 10 faults were diagnosed in this experiment, 9 of which were in fault state and 1 was in normal state. Since there are a total of 10 kinds of faulty rolling bearings, there are a total of 1,000 sets of data. Therefore, the fault characteristic data finally obtained is 1000*5120. There are 700 training sets and 300 test sets. Figure 7 shows the results of fault diagnosis using SVM in the training set. It can be seen from the figure that the accuracy of the training set is 71.43%.

5. Conclusion

Bearing fault diagnosis method based on wavelet packet energy spectrum is a feature that effectively solves the problem that single singular point can not be used for bearing fault diagnosis. It is verified that wavelet packet energy spectrum as a feature can effectively distinguish normal signals and fault signals. The wavelet packet energy spectrum can effectively decompose the vibration signal in different frequency bands, which is convenient for selecting the corresponding sub-channel; signal feature information is preserved after wavelet packet decomposition, which provides strong support for extracting feature information from the signal. Experimental data verification shows that the method proposed in this paper can accurately separate different bearing failure types and realize the recognition of different failure types and degrees of failure. The proposed method is simple and efficient, and can be easily extended to the health monitoring of other engineering structures, and has certain application prospects. The fault diagnosis method based on wavelet packet energy spectrum has the characteristics of simple calculation and good real-time performance, and is also suitable for other fault diagnosis fields.
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References
[1] X.D. Li, W. Zhou, Z.G. Zhao, Y.W. Liao, J.D. Yang, W.J. Yang, “Fault diagnosis of rolling bearings based on EEMD and IGSA-SOM neural network,” Water Resources and Hydropower Express, vol.41, pp.46-52, 2020.
[2] Z.X. Chen, M.S. Jiao, Y. Cai, L.S. Ge, “Fault detection of rolling bearing based on wavelet packet energy spectrum,” Journal of Anhui University of Technology (Natural Science Edition), vol.34, pp.269-274, 2017.
[3] C.G. Wu, J.C. Wang, Q. Hua, “Fault diagnosis method of rolling bearing based on NSP and SVM,” Bearing, vol. 2, pp.39-42+55, 2016.
[4] S.L. Li, Z.L. Liu, “Rolling bearing fault feature extraction based on single-node reconstruction and improved wavelet packet energy and envelope spectrum,” Computer Applications and Software, vol. 35, pp.216-220+236, 2018.
[5] X.L. Jin, Y.R. Zhuo, “Prediction of college entrance examination results based on genetic algorithm and support vector machine model,” Journal of Henan Institute of Technology (Natural Science Edition), vol.32, pp.62-65, 2020.
[6] Bearing Data Center. Case Western Reserve University, Cleveland, OH. [EB/OL]. (2010), (2018-10-20).Available: http://www.eecs.case.edu/laboratory/bearing.