Application of integrated wavelet-EEMD in cylinder wall clearance Detection of internal combustion engine

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Abstract. Non-detectability and wear resistance for cylinder wall clearance of internal combustion engines, this paper takes DA462 gasoline engine as the object of study, and collects the vibration signal of engine cylinder surface under different cylinder wall clearance. According to the excellent effect of wavelet transform on signal denoising, the Ensemble Empirical Mode Decomposition has good adaptability to non-stationary signals. A wavelet-Ensemble Empirical Mode Decomposition signal processing method is proposed, and the characteristic signal in the signal is expressed by using approximate entropy, and finally the cylinder wall clearance is verified by using neural network. The verification results show that the wavelet-Ensemble Empirical Mode Decomposition method has a good effect on the detection of engine cylinder wall clearance, and provides a good theoretical basis for the detection of engine mechanical component technical conditions without disintegration.

1. Introduction

The piston and the cylinder are one of the most important cooperation pairs of the engine. The clearance of the cylinder wall directly affects the technical performance of the engine. Therefore, detecting the clearance of the cylinder wall becomes an important part of detecting the technical condition of the engine. In the case of non-disassembling the engine, the detection of the engine cylinder wall clearance can be realized, so that the technical condition of the engine can be known in time, the mileage of the engine can be predicted, and the correct use and maintenance of the engine, and provides the reference for the appraisal of the old motor vehicles.

The vibration signal measured by the sensor is used to diagnose the running state of the machine, which is the most common and effective method in the current mechanical fault diagnosis. The vibration parameters generated during engine operation contain a wealth of fault information and are important indicators for evaluating the technical performance of the engine[1]. Single signal de-noising method has its disadvantages in signal processing, so combining the advantages of different methods to process the signal can get good results. Wavelet threshold denoising can remove noise well when it is used for signal noise reduction. The Ensemble Empirical Mode Decomposition has good adaptability to the signal decomposition by time scale, and can be linear and smooth in the processing of nonlinear and non-stationary signals. However, it is affected by noise. Therefore, the vibration threshold has a good effect on noise signal removal[2]. Firstly, the wavelet signal is denoised by wavelet threshold, and then the denoised signal is subjected to Ensemble Empirical Mode Decomposition. It is equivalent to filtering with the wavelet threshold before performing EEMD noise reduction on the signal, which can achieve good noise reduction effect.
2. Wavelet threshold de-noising
The data correlation of the signal after orthogonal wavelet transform is very strong. For the signal with noise, after wavelet decomposition, the wavelet coefficient component of the signal obtained is usually large. The wavelet coefficient component of the noise is small, and for the resolved wavelet coefficients, the signal is usually larger than the noise[3]. According to this characteristic, generally, as long as the appropriate number is selected as the critical threshold, the obtained wavelet decomposition coefficient is compared with the value, and the component corresponding to the decomposition coefficient smaller than the value is regarded as noise, thereby filtering out; the component corresponding to the decomposition coefficient greater than this value is considered to be the original signal and is retained. The method to achieve denoising based on this criterion is wavelet threshold denoising. According to this principle, it can be seen that the factors affecting the wavelet threshold denoising are the selection of the wavelet basis function, the selection of the decomposition layer number and the selection of the wavelet threshold.

Because the dbN wavelet has the Mallat algorithm, it can perform fast calculation on signal analysis, and has good orthogonality and tight support. Therefore, the dbN wavelet is selected as the basis function. When the threshold rule is selected, the selection rule is a heuristic threshold rule, which is a threshold selection rule combining the common threshold rule and the Stein unbiased risk threshold rule, which has the advantages of both[4], and is the optimal selection rule when the threshold is selected. The hard threshold function better preserves features such as spikes in the real signal when processing the signal. The selection method based on wavelet threshold denoising is wavelet hard threshold heuristic noise reduction.

3. Ensemble Empirical Mode Decomposition (EEMD)
Ensemble Empirical Mode Decomposition method is an adaptive signal processing method proposed by Huang et al. in solving unsteady signals. The core idea of this method is to think that any signal is composed of several Intrinsic Mode Functions (IMF). The signal can contain several eigenmode functions at any time. Therefore, using EMD to process the signal is to decompose the signal into different IMFs. If the eigenmode functions of the signal decomposition are overlapped with each other, the original signal will be obtained.

The empirical mode decomposition method has good adaptability by performing IMF decomposition on the signals and arranging the signals in the order of high frequency to low frequency, but since the IMF component will contain different time feature scales during decomposition, or one time scale contains multiple IMF components, the phenomenon known as modal aliasing. In order to suppress the appearance of modal aliasing, by adding Gaussian white noise before performing empirical mode decomposition on the signal, and then IFM decomposition of the signal, the resulting set of IFM components is averaged to obtain the final IMF component. Due to the added noise signals cancel each other out after time-frequency decomposition, which does not affect the signal, and improves the appearance of modal aliasing. This method is to integrate empirical mode decomposition[5]. This paper selects 10 IMF components for EEMD to process.

4. Experimental diagnosis
The experiment selected the DA462 gasoline engine. The test point is located at the work position of the top end of the 1 cylinder piston during the commutation process, and the lateral impact response of the piston during the commutation of the piston is recorded. The test bench is mainly composed of DA462 engine, sensor, B&K vibration acquisition module, and computer. The test schematic is shown in Figure 1. In order to comprehensively consider various operating conditions of the engine, the engine is simulated under three different cylinder wall clearances at engine speeds of 800r/min, 1500r/min, and 2200r/min respectively.
4.1 Analysis of experimental results

When the engine is running at 800r/min, the comparison and time-frequency diagram of the first four orders of IMF components in the EEMD decomposition process corresponding to the vibration signal at the cylinder wall clearance of 0.06mm and 0.09mm are as follows:

Figure 2. cylinder wall clearance 0.06mm IMF1–2 time-frequency diagram
Figure 3. Cylinder wall clearance 0.09mm IMF1~2 time-frequency diagram

Figure 4. Cylinder wall clearance 0.06mm IMF3~4 time-frequency diagram
It can be seen from Fig. 2 to Fig. 5 that the amplitude of the frequency of each order IMF component changes under different cylinder wall clearances at the same speed. As the clearance of the cylinder wall increases, the amplitude of the spectrum of each IMF component increases correspondingly, that is, as the clearance of the cylinder wall increases, the amplitude of the lateral impact response of the 1-cylinder piston increases significantly. It is indicated that the difference of the rotational speed and the difference of the cylinder wall gap will affect the vibration signal, but the IMF component of each step of the signal can not predict the size of the cylinder wall gap. Therefore, some characteristics of the signal need to be extracted.

4.2 Feature vector extraction and recognition

Approximate entropy is a complexity measure analysis method that can measure the complexity and regularity of time series without coarse graining\cite{6}. The physical meaning is the probability of generating a new pattern in the time series when the dimension changes. The greater the probability of generating a new pattern, the more complex the sequence, and the corresponding approximate entropy. The EEMD method realizes the decomposition of the signal on the time scale. The approximate entropy can describe the complexity of the information to the time series. It can be used to describe the signal level of the IMF component, and the approximate entropy has lower requirements on the length of the data. It has strong resistance to noise, wide application range of signals, and can be used as feature extraction of signals. Therefore, the approximate entropy theory is used to approximate the entropy quantization of each order IMF component to construct the feature vector.

The algorithmic process of approximate entropy is as follows:

1. For a signal sequence $x_i$, it consists of an m-dimensional vector in order, namely:
   \[ X(i) = (x_i, x_{i+1}, \cdots, x_{i+m-1}) \]  
   among them $i = 1, 2, \cdots, N - m + 1$.

2. The distance between each $x_i$ and the remaining element $x_j$ is calculated, and the distance between the two is the largest absolute value of the corresponding element difference. Which is:
Calculating the degree of association $r$ between any two vectors: given a similar tolerance, counting the number $\text{Num}(D_{m}[X_i, X_j] < r)$ of the distance from the remaining vector $X_j$ of each $i$-value corresponding vector $X_i$ that is less than the threshold; the ratio of the value to the total number of vectors is the degree of association between the two vectors.

$$C^m(r) = \frac{1}{N - m + 1} \text{Num}(D_{m}[X_i, X_j] < r), i, j = 1, \cdots, N - m + 1, i \neq j$$

4. Calculate the degree of autocorrelation for each vector sequence:

$$\Phi^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} \ln C^m_i(r)$$

5. Increase the dimension to $m+1$ and find $\Phi^{m+1}(r)$ by the above steps.

6. In the actual case where $N$ has a finite value, the value of the approximate entropy is:

$$ApEn(m, r, n) = \Phi^m(r) - \Phi^{m+1}(r)$$

The embedding dimension $m$ is generally taken as 1 or 2. The similar tolerance $r$ takes 0.1 to 0.25 times the standard deviation of the sequence.

After the wavelet noise reduction and EEMD decomposition of the engine vibration signal, the approximate entropy of the IMF components of the signal is obtained. The following figure shows the approximate entropy of the IMF components of each order when the cylinder wall gap is 0.06mm and the speed is 1500r/min:

![Figure 6. Approximate entropy size diagram of the cylinder wall clearance of 0.06mm at 1500r/min](image)

It can be seen from the figure that the approximate entropy of the first six IMF components is large, indicating that the fault features are obvious. Therefore, the first 6-order IMF component approximate entropy is selected to construct a set of feature vectors.

### 4.3 Verification process

| Serial number | Cylinder wall clearance | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 |
|---------------|-------------------------|------|------|------|------|------|------|
|               |                         |      |      |      |      |      |      |
Table 2. Set of reference vectors at 1500r/min

| Serial number | Cylinder wall clearance | IMF1  | IMF2  | IMF3  | IMF4  | IMF5  | IMF6  |
|---------------|-------------------------|-------|-------|-------|-------|-------|-------|
| A1            | 0.03mm                  | 0.1226| 0.0162| 0.0183| 0.0146| 0.0114| 0.0081|
| A2            | 0.06mm                  | 0.0284| 0.0145| 0.0153| 0.0135| 0.0095| 0.0077|
| A3            | 0.09mm                  | 0.1342| 0.0186| 0.0172| 0.0142| 0.0101| 0.0082|
| A4            | 0.12mm                  | 0.1085| 0.0193| 0.0176| 0.0143| 0.0098| 0.0082|
| A5            | 0.15mm                  | 0.0594| 0.013  | 0.0161| 0.0152| 0.0118| 0.0082|
| A6            | 0.18mm                  | 0.0141| 0.0186| 0.0152| 0.0111| 0.0074| 0.0058|

Table 3. Set of reference vectors at 2200r/min

| Serial number | Cylinder wall clearance | IMF1  | IMF2  | IMF3  | IMF4  | IMF5  | IMF6  |
|---------------|-------------------------|-------|-------|-------|-------|-------|-------|
| C1            | 0.03mm                  | 0.0165| 0.0201| 0.0256| 0.0215| 0.0191| 0.0114|
| C2            | 0.06mm                  | 0.0188| 0.0216| 0.0361| 0.0347| 0.0219| 0.0133|
| C3            | 0.09mm                  | 0.0103| 0.0125| 0.0260| 0.0271| 0.0199| 0.0132|
| C4            | 0.12mm                  | 0.0124| 0.0149| 0.0306| 0.0278| 0.0204| 0.0114|
| C5            | 0.15mm                  | 0.0325| 0.0116| 0.0152| 0.0153| 0.0129| 0.0093|
| C6            | 0.18mm                  | 0.0306| 0.0109| 0.0163| 0.0154| 0.0121| 0.0085|

Table 1, Table 2, and Table 3 are a set of vectors below the cylinder wall clearance of the engine at 800 r/min, 1500 r/min, and 2200 r/min.

After the eigenvectors are constructed, the eigenvectors need to be identified and analyzed. In terms of pattern recognition, prediction analysis, etc., BP neural network can map the nonlinearity relationship between data well in the nonlinear system composed of simple units of data, and has good adaptability; also has good ability to learn memory and predict. Therefore, this paper selects BP neural network to learn and identify feature vectors.

When the engine speed is the same, the eigenvectors of the different cylinder wall gaps are each set of ten groups. BP neural network is used to randomly select 8 sets of data of each size as the learning training samples, and the other two groups are test samples, to construct a double hidden layer learning model, the number of nodes per layer is 5, and the thresholds and weights of each layer are set by function calculation to identify the feature vectors. Figure 10, Figure 11, and Figure 12 show the results of different cylinder wall clearances at 800r/min, 1500r/min and 2200r/min.
It can be seen from Fig. 7 to Fig. 9 that the BP neural network can be used for learning recognition at different speeds, and the engine cylinder wall gap can be identified with good results. The accuracy is 91.7%. Therefore, using wavelet denoising and EEMD decomposition to solve the approximate entropy as the eigenvector can realize the detection and identification of engine cylinder wall clearance.

5. Conclusion
When the engine is running, the wear of the cylinder wall clearance is not easy to be found, but it has a great influence on the performance of the engine. This paper takes the DA462 engine as the research object, and manually changes the cylinder wall clearance of the engine. The vibration excitation generated by the lateral impact of the engine piston during the commutation of the top dead center is collected, and the signal is analyzed by the wavelet-collective empirical mode decomposition method to realize the detection of the engine cylinder wall gap.

When processing the signal, the wavelet threshold denoising method with the best effect in signal denoising in wavelet transform is used to remove the noise of the vibration signal first, and then the EEMD method is used to decompose the denoised vibration signal to obtain the corresponding IMF. Component, EEMD decomposition realizes the processing of the signal from high frequency to low frequency. Then, for each order IMF component, the feature vector is extracted by approximate entropy. By analyzing and observing the approximate entropy of each IMF component, the feature vector is constructed. The fault vector is modeled by BP neural network for the eigenvectors. By training the sample features and then identifying and detecting the feature vectors, the resolution is better, and the engine is not disintegrated. Although the final fault diagnosis rate has not reached 100%, it is basically possible to correctly diagnose and identify the engine cylinder wall clearance. It can be easily and simply applied to engineering practice.
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