Internal Combustion Engine Fault Diagnosis Method Based MICEEMD-PWVD

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Abstract. As to multi-signals, the figure of time-frequency distribution becomes difficult to understand due to cross-terms in the Wigner-Ville distribution (WVD). At present time, cross-terms suppression of time-frequency analysis is one of the top interests in signal processing, and more and more research had been put on this topic, but the present research on cross-terms suppression exist conflicting problem that these methods couldn’t suppress the cross-terms while holding high time-frequency resolution. A novel method of cross-terms suppression in the WVD based on Complementary Ensemble Empirical Mode Decomposition (CEEMD) was proposed to solve the above problem. Firstly, multi-component signals were decomposed into intrinsic mode functions (IMFs) which were single component signal by CEEMD; Secondly, the Mutual Information values of IMFs and original signal were calculated to judge and delete the CEEMD false components; Thirdly, these Wigner-Ville distributions of true component of IMFs were computed; Finally, WVDs of each single component signal were added linearly to reconstruct the WVD of original signal. Test on synthetic data shows the effectiveness of the proposed method, which can suppress the cross-terms while holding high time-frequency resolution. Apply MICEEMD - PWVD in internal combustion engine valve clearance fault diagnosis, useTD-2DPCA method to extract MICEEMD-PWVD time-frequency image feature, then classify the characteristic parameters with the nearest neighbor classifier. The results show that the IC Engine Fault Diagnosis Method Based MICEEMD-PWVD and TD-2DPCA can accurately diagnose IC engine valve fault.

1. Introduction
In the internal combustion engine fault diagnosis, the vibration signal often contains the rich breakdown information, therefore the internal combustion engine vibration diagnosis is its breakdown diagnosis important research domain. However, there are many shortcomings in the traditional vibration diagnosis method. The Fourier transform based spectrum analysis is based on the assumption of signal stationary, and the result of the analysis is frequency domain information and time domain feature. Most of the mechanical failure vibration signals are non-stationary and non-linear. For these non-stationary signals, the essential defect of the Fourier transform makes the extracted fault feature information defective, thus reducing the accuracy of fault diagnosis. Therefore, the time-frequency analysis method has become the main method of engine fault diagnosis, such as short time Fourier transform [1, 2], Wigner-Ville Distribution [3, 4], wavelet transform [5, 6] and Hilbert-Huang
transform. These time-frequency analysis methods for processing internal combustion engine vibration signal mutations, discontinuities, non-stationary signal provides the necessary means. In these methods, Wigner-Ville Distribution method has been widely used in the field of mechanical equipment fault diagnosis, with this method of signal analysis, the edge of the signal characteristics, instantaneous frequency and localization are good, but the cross-terms become the bottleneck of the application. It is difficult to express the signals with multiple frequency components in the presence of cross terms. In this paper, the vibration signal of internal combustion engine is analyzed by MICEEMD-PWVD, which not only avoids the cross-term interference, but also retains all the excellent features of the WVD distribution, and can effectively extract the vibration characteristics of the cylinder head of the internal combustion engine.

The essence of feature extraction is a dimension reduction process. Images are stored and represented in the form of matrices, which can be compressed by matrix theory. Commonly used methods are principal component analysis (PCA), non-negative matrix factorization (NMF) and so on. The common drawback of PCA and NMF methods is that the two-dimensional image matrix needs to be vectorized before dimensionality reduction, and the image matrix can not be directly processed [7]. Yang et al [8] proposed two-dimensional PCA (2DPCA) and applied it to face image compression and reconstruction, and achieved good results. Although the 2DPCA can effectively reduce the image dimension, but its data compression is one-way, the dimensionality of the image is still larger. In order to solve the above problems, this paper uses the two-directional 2DPCA(TD-2DPCA) method to extract the features of the generated time-frequency images, and obtains good results.

2. MICEEMD-PWVD Time-frequency Analysis

2.1. Ensemble Empirical Mode Decomposition

Although EMD has many merits, its decomposition is unstable and modal aliasing exists, which leads to the inclusion of different scale signals in some intrinsic modal function components, or similar scale signals exist in different IMF components. In view of the above problems, the paper [9] proposes the Ensemble Empirical Mode Decomposition (EEMD), which first adds white noise to the original signal, and then collects the IMF components obtained by EMD decomposition. The EEMD method suppresses the modal aliasing problem of EMD to a certain extent and improves the stability of the EMD algorithm. However, it can not guarantee that each IMF component satisfies the IMF component condition. The white noise added to the signal will be in each IMF to be residual, and the number of EEMD lumping the average number of times in general hundreds of times, very time-consuming.

In order to solve the above problems, Complementary Ensemble Empirical Mode Decomposition (CEEMD) is proposed in paper [10]. The CEEMD method is to decompose EMD by adding two pairs of opposite white noise signals to the original signal, and then combine the results to get the final IMF.

The steps for CEEMD are as follows:

Step 1: Add the positive and negative auxiliary white noise to the original signal to generate two sets of IMF;

\[
\begin{bmatrix}
M_1 \\
M_2 
\end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix}
S \\
N 
\end{bmatrix}
\]

In the formula, \(S\) is the original signal; \(N\) is the auxiliary noise; \(M_1, M_2\) are the signals after adding the positive and negative pairing noise respectively. Thus, the number of ensemble signals is \(2n\).

Step 2: Each signal in the set is subjected to EMD decomposition, and each signal yields a set of IMF components, where the \(j\) IMF component of the \(i\) signal is denoted as \(c_{ij}\).

Step 3: The decomposition results are obtained by the way of multi-component combination:
\[ c_j = \frac{1}{2n} \sum_{i=1}^{2n} c_{ij} \]  

(2)

In the formula, \( c_j \) is the \( j \) IMF component finally obtained by CEEMD decomposition. Generally \( j = \log_2 N - 1 \), where \( N \) is the length of original signal after discretization[11].

2.2. Mutual Information

The number of IMF, in order to determine which component is a pseudo component, we use the mutual information method proposed in paper [12] to remove the pseudo-component of IMF.

Mutual Information (MI) is the concept proposed by Shannon, the founder of information theory, which is derived from the concept of entropy. The mutual information of \( I(X|Y) \) is defined as follows [13-14]:

\[ I(X|Y) = -\sum_{i,j} P(x_i, y_j) \log \frac{P(x_i, y_j)}{P(x_i)P(y_j)} \]  

(3)

In the formula, \( P(x_i, y_j) \) is the joint probability of \( x_i \) and \( y_j \), the joint information entropy of \( X \) and \( Y \) is introduced \( H(X,Y) = -\sum_{i,j} p(x_i, y_j) \log p(x_i, y_j) \), mutual information is \( I(X|Y) = H(X) + H(Y) - H(X,Y) \), \( I(X|Y) \) represents the value of \( Y \) after the relevant information provided by \( X \).

Assume that the original signal \( S \) is composed of \( n \) basic mode components, namely: \( S = \sum_{i=1}^{n} C_i \), after CEEMD decomposition, the theoretical decomposition of \( n \) basic mode components \( C_i \), respectively, corresponding to the original signal \( n \) basic mode components. Due to the errors in the decomposition process and the characteristics of the CEEMD algorithm itself, \( n \) basic mode components \( \hat{C}_i \) and \( m \) dummy components \( x_k \) are decomposed, and \( \hat{C}_i \) and \( C_i \) are not exactly the same, \( m \) pseudo-component \( x_k \) is formed by the difference between the two, namely:

\[ S = \sum_{i=1}^{n} \hat{C}_i + \sum_{k=1}^{m} x_k \]  

(4)

First, the mutual information \( MI_i \) of the fundamental mode component \( C_i \) and the original signal \( S \) after EMD decomposition is calculated, the normalization of \( MI_i \), so that:

\[ \lambda_i = \frac{MI_i}{\max(MI_i)} \]  

(5)

\( \lambda_i \) is the normalized mutual information value, \( 0 \leq \lambda_i \leq 1 \).

It can be seen from the definition of mutual information that the mutual information of the false component \( x_k \) and the original signal \( S \) is much smaller than the mutual information of the real component \( \hat{C}_i \) and the original signal \( S \), using this feature, the mutual information value \( \lambda_i \) of each component and the original signal is taken as an index to evaluate the reliability of each basic mode component. When \( \lambda_i \) is small, it can be judged that the component is a false component. Here, the false component determination threshold value \( \delta \) is set, if the mutual information value \( \lambda_i \) of the IMF
component and the original signal is greater than $\delta$, then the component is regarded as the true component, otherwise the false component is eliminated. Define the false component to determine the threshold $\delta$ is

$$\delta = 0.5 \ast \text{mean}(MI_1, MI_2, \cdots, MI_n)$$  \hspace{1cm} (6)

2.3. MICEEMD-PWVD algorithm

The basic principle of CEEMD-PWVD time-frequency analysis (MICEEMD-WVD) algorithm based on mutual information is shown in Fig.1, the calculation steps are as follows:

![Diagram of MICEEMD-PWVD time-frequency analysis flow chart](image)

**Figure 1.** MICEEMD-WVD time-frequency analysis flow chart

Step 1: The CEEMD decomposition method is used to decompose the signal $s(t)$ to obtain a finite number of basic mode components.

$$s(t) = \sum_{i=1}^{n} c_i + r_n$$  \hspace{1cm} (7)

Step 2: Calculating the normalized mutual information $\lambda_i$ and the false component judgment threshold $\delta$ of each intrinsic mode component $\hat{C}_i$ and the original signal $s(t)$ and discriminating and eliminating the pseudo component of $\lambda_i \leq \delta$ according to the magnitude relation of $\lambda_i$ and $\delta$;

Step 3: The PWVD of each component is calculated after the Hilbert transform of the true intrinsic mode component $\hat{C}_i$, and the result is linearly superposed, which is the MICEEMD_PWVD distribution of the signal $s(t)$. The MICEEMD_PWVD time-frequency distribution of the signal $s(t)$ is defined as:
MICEEMD_PWVD\_a(t, f) = \sum_{j=1}^{N} \int_{-\infty}^{\infty} fPWVD_C(t, f) df \over \int_{-\infty}^{\infty} PWVD_C(t, f) df \tag{8}

3. TD-2DPCA

2DPCA is the essence of horizontal compression of the image, the basic idea is to image the overall degree of dispersion as the goal, by looking for a set of optimal unit orthogonal projection vector as the optimal projection vector group, in order to achieve the image feature extraction [8].

Suppose there is a C class pattern: w\_1, w\_2, \cdots, w\_c, a total of M training sample images: A\_1, A\_2, \cdots, A\_M, Each size is m\times n. The general distribution matrix \( G\_i \) of the model is

\[
G\_i = \frac{1}{M} \sum_{i=1}^{M} (A\_i - \bar{A})^T (A\_i - \bar{A})
\]

\[
\bar{A} = \frac{1}{M} \sum_{i=1}^{M} A\_i
\]

is the mean matrix of the training pattern, easy to prove that \( G\_i \) is the non-negative n\times n set.

The image matrix \( A\_i \) is projected onto \( X \) by a linear transformation \( Y = A\_i X (i = 1, 2, \cdots, k) \) to obtain the eigenvector \( Y \). In the formula: \( X \) is the n dimensional unitized column vector; \( Y \) is the feature vector after projection. The projection direction \( X \) is selected such that the projected feature vector has better separability. Define a criterion function

\[
J(X) = tr(G\_i) = X^T G\_i X
\]

In the formula: \( tr(G\_i) \) is the trace of \( G\_i \).

In order to achieve the maximization of the criterion function \( J(X) \), we need to find the optimal projection vector \( X \). In fact, the optimal projection vector is the unit eigenvector corresponding to the largest eigenvalue of \( G\_i \). Since \( G\_i \) is a non-negative definite matrix, there are \( n \) standard orthogonal eigenvectors, assumed

\[
G\_i X\_i = \lambda X\_i, \quad (\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \geq 0)
\]

The orthogonal eigenvectors corresponding to the first \( d \) largest eigenvalues can be used as the optimal projection matrix \( P = [X\_1, X\_2, \cdots, X\_d] \). The feature coding matrix \( B \) of the image sample \( A \) is obtained by using the optimal projection matrix to extract the known image sample \( A, B = AP \).

The feature \( B\_i (i = 1, 2, \cdots, M) \) of the first extraction is used as the training matrix to extract the second feature, that is, \( B\_i^T \) as \( A\_i \) into formula (9), a new distribution matrix is

\[
\hat{G}\_i = \frac{1}{M} \sum_{i=1}^{M} (B\_i - \bar{B})(B\_i - \bar{B})^T
\]

In the formula: \( \bar{B} = \frac{1}{M} \sum_{i=1}^{M} B\_i \) is the population mean matrix of the training sample set after the first compression.
Using the criterion function similar to formula (10), we can get the standard orthogonal eigenvector $Z_1, Z_2, \cdots, Z_h$ of the first $h$ largest eigenvalue of $\hat{G}_t$, as the second best projection matrix $Q$, then the feature matrix $U$ extracted by the TD-2DPCA algorithm for any image $A$ is

$$U = B^T [Z_1, Z_2, \cdots, Z_h] = P^T A^T Q$$  \hspace{1cm} (13)$$

The dimension of the characteristic matrix $U$ vector is $h \times d$, and the feature dimension extracted for the first time is $m \times d$, so that $h$ is much smaller than $m$, thereby reducing the extracted feature dimension, and further improving the classification efficiency.

4. Simulation analysis

In order to analyze the performance of this method and combine the characteristics of internal combustion engine vibration signal, a multi component intermittent implus simulation signal is established, the simulation signal $x(t)$ is composed of two different amplitude, frequency and phase of the sinusoidal signal and an intermittent implus signal $v(t)$, sampling frequency is 200Hz. The intermittent implus signal simulates the impact vibration of each valve of the internal combustion engine which is opened or seated, the analytical expression is

$$x(t) = \sin(20\pi t + \frac{\pi}{2}) + 0.8\sin(2\pi t - \frac{\pi}{4}) + v(t)$$  \hspace{1cm} (14)$$

The signal and the three components shown in Figure 2.

EMD decomposition of the signal $x(t)$, mutual information method to remove the pseudo component of the results shown in Figure 3, as can be seen from the figure, due to the presence of intermittent implus signal $v(t)$, the first sinusoidal component of the IMF1 had a distortion, that is, many of its parts by $v(t)$ in the implus part of the replacement, while the replaced sinusoidal component is shifted into the IMF2 component, in the corresponding position, this should be the IMF2 component was moved to the IMF3. Thus in the three IMF components have appeared in the model aliasing, the above results illustrate the shortcomings of EMD on the intermittent implus signal processing.
Figure 3. Simulation results of EMD decomposition

Figure 4. The MICEEMD Decomposition Results of Simulated

The MICEEMD result of signal $x(t)$ is shown in Figure 4, the results clearly show that MICEEMD does solve the problem of modal aliasing in EMD, the better decomposition of the three components of $x(t)$.

Figure 5 ~ Figure 8 are the WVD, PWVD and MICEEMD-WVD three kinds of methods to analyze the simulation signal generated time-frequency images, it can be seen from the figure that the WVD method has the best time-frequency aggregation, but a frequency domain cross-interference term is generated at 5 Hz, 12.5 Hz, and 17.5 Hz, and a time domain cross-interference term is generated for an intermittent vibration signal of 25 Hz, difficult to distinguish the true frequency of the signal components; PWVD method suppresses the time domain cross-interference term of the intermittent vibration signal at 25Hz, but can not suppress the 5Hz, 12.5Hz and 17.5Hz frequency domain cross-interference terms; The time-frequency image generated by MICEEMD-WVD method effectively suppresses the cross-interference term in the frequency domain, and has higher time-frequency aggregation, but it is not possible to suppress the time-domain cross-interference term of the intermittent signal; The MICEEMD-PWVD method effectively suppresses the cross-interference term in the frequency domain and time domain, and has high time-frequency aggregation.
5. Fault diagnosis of internal combustion engine

The experiment in this paper is carried out on the 6135 internal combustion engine. Respectively, with the acceleration sensor and pulse sensor to measure the internal combustion engine vibration signal and the TDC signal, the location and installation of the sensor are shown in Figures 9-11.

The internal combustion engine cylinder head vibration signal acquisition on the internal combustion engine fault diagnosis, sampling frequency 25kHz, speed 1500r/min, during the test, the engine was run without load. In the experiment, several typical failures of the valve mechanism are simulated: gap is too large, too small, serious valve wear, air leakage and so on. Table 1, 0.30mm, 0.50mm and 0.06mm, respectively represent internal combustion engine valve clearance is normal, too large, too small three states; "Hatch" means that the valve clearance is 0.30mm, but in the valve opened a 4mm×1mm hole, the simulation valve serious air leakage fault; "New valve" means the valve clearance is 0.30mm, the valve without grinding, simulated valve slightly leak fault. Eight kinds of working conditions of the specific valve clearance shown in Table 1. Each set of measurement data records the vibration signals within 360° of the crank angle before and after the TDC of the 2nd cylinder compression. A total of 480 samples of 60 vibration signals were collected from 8 kinds of fault conditions of internal combustion engine valves.
Figure 9. Experimental setup and sensor position

Figure 10. Electromagnetic pulse sensor position

Figure 11. Acceleration sensor position

Table 1. Eight states of internal combustion engine’s valve train (mm).

| State code | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Clearance of intake valve | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.06 | 0.06 | 0.50 |
| Clearance of exhaust valve | 0.30 | 0.36 | 0.50 | Hatch 4×1 (0.3) | New valve (0.30) | 0.06 | 0.50 | 0.50 |

Fig. 12-14 and Fig. 15 (a) show the WVD time-frequency, PWVD time-frequency, HHT time-frequency and MICEEMD-PWVD time-frequency diagrams of cylinder head vibration signals for state 1 (normal valve clearance). The left side of each graph is the power spectrum of the signal, the right is the time domain map, time domain map below is contour line time-frequency image, the lower
right corner is the contour color scale, and different colors represent different amplitude. Compared with the time-frequency images, it can be known that the WVD method is used to analyze the vibration signals of the cylinder head. The PWVD method can suppress the cross-interference term of WVD to some extent. The MICEEMD-PWVD method suppresses the WVD. The time-frequency resolution is the highest, and the HHT method can not analyze the vibration signal of internal combustion engine correctly.

**Figure 12. State 1 WVD Image**

**Figure 13. State 1 PWVD image**

**Figure 14. State 1 HHT image**
Figure 15. Time-frequency Image of MICEEMD - PWVD in Internal Combustion Engine
Figure 15 shows the MICEEMD-PWVD time-frequency images of the internal combustion engine valve mechanism under different conditions. When the valve train is in different states, the time-frequency images obtained from the cylinder head vibration signals are different. Value, etc., different state vibration vibration signal information is clearly reflected in the time-frequency image.

Therefore, we can use the TD-2DPCA method to extract and classify the generated MICEEMD-PWVD time-frequency image to realize the fault diagnosis of the valve mechanism of the internal combustion engine. Firstly, 60 images in each state are transformed into grayscale images, and then bilinear interpolation is used to compress the images into pixels $56 \times 42$. Then 30 images in each state are randomly selected as the training set, and the remaining 30 images as the test set, the TD-2DPCA algorithm for time-frequency image feature extraction, the dimension of feature is $d$ and $h$ respectively, and the value of $d = h$ is set to $[2, 3, \ldots, 10]$; To test the versatility of the method, a relatively simple Nearest Neighbor classifier was used to classify it. To ensure the accuracy of the results, the above process was repeated 30 times and the mean value was calculated as the final result Figure 16 shows.

It can be seen from Fig.16 that the recognition rate of MICEEMD-PWVD method is 96.92% when the feature dimension is $6 \times 6$, $7 \times 7$ and $8 \times 8$, The recognition rate of WVD method is 94.92% when feature dimension is $8 \times 8$, The recognition rate of the PWVD method is 90.58% at the feature dimension $10 \times 10$. The recognition rate of the MICEEMD-PWVD method is higher than that of the WVD method, and the PWVD method has the lowest recognition rate. PWVD suppresses the cross-interference term in the time domain of WVD, but the recognition rate is lower than that of the WVD method. The reason is that the WVD cross-interference term is serious and is not sensitive to some noise interference of the internal combustion engine, while PWVD suppresses it to a certain extent Cross-interference terms, but the noise of the internal combustion engine becomes sensitive. The MICEEMD-PWVD time-frequency image not only suppresses the cross-interference term of WVD, but also has high time-frequency resolution and lowers the influence of engine noise on recognition rate, so the MICEEMD-PWVD method has the highest recognition rate.

![Figure 16. Recognition Results of Different Feature Dimension](image)

6. Conclusion

(1) MICEEMD-PWVD time-frequency analysis method can effectively suppress the cross-interference term of WVD method, obviously distinguish the time-frequency distribution characteristics of different valve clearance conditions, and can be used for fault diagnosis of valve clearance of internal combustion engine.

(2) The feature parameters of the MICEEMD-PWVD time-frequency image are extracted by TD-2DPCA method, and the fault classification is performed by the nearest neighbor classifier. The results show that the TD-2DPCA method can effectively reduce the dimension of the data and can not lose
the effective information of the image. The TD-2DPCA method can extract the characteristic parameters of the time-frequency image with good self-adaptability and high fault recognition accuracy, and can be used in the engine valve clearance diagnosis.

References

[1] Kim Y H. Fault detection in a ball bearing system using a moving window [J]. Mechanical Systems and Signal Processing, 1991, 5 (6): 461-473.
[2] Samin B, Rizzoni G. Engine knock analysis and detection using time-frequency analysis [C]// SAE960618, 1996.
[3] Xiao J, Flandrin P. Muitaper time-frequency reassignment for nonstationary spectrum estimation and chirp enhancement [J]. IEEE Transaction on Signal Processing, 2007, 55 (6): 2851-2860.
[4] Mao Y F, Qin S. Re-allocation of spectrum and multi-spectral windows and its application in machinery fault diagnosis [J]. Journal of Vibration and Shock, 2009, 28 (1): 161-165.
[5] Bo L, Qin S R, Liu X F. Theory and application of Wavelet analysis instrument library [J]. Chinese Journal of Mechanical Engineering: English Edition, 2007, 19 (3): 464-467.
[6] Cary S, Akujuobi C M. An approach to vibration analysis using wavelets in an application of aircraft health monitoring [J]. Mechanical Systems and Signal Processing, 2007, 21: 1255-1272.
[7] Zhai Junhai, Zhao Wenxiu, Wang Xizhao. Rasearch on the image feature extraction [J], Journal of Hebei University, 2009, 29 (1): 106-112.
[8] Yang Jian, Zhang D, Yang Jingyu. Two-dimensional PCA: a new approach to appearance-based face representation and recognition [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2004, 26 (1): 131-137.
[9] Zhaohua Wu, et al., Enhancement of lidar backscatters signal-to-noise ratio using empirical mode decomposition method [J]. Advances in Adaptive Data Analysis, 2008, 1 (1).
[10] Yeh J R, Shieh J S, Norden e, et al. Complementary ensemble empirical mode decomposition: a noise enhanced data analysis method [J]. Advances in Adaptive Data Analysis, 2010, 2 (2): 135-156.
[11] Hu Guangshu. Modern signal processing tutorial [M]. Bei Jing: Tsinghua University Press, 2015.
[12] Cai Yanping. Research on improved Empirical mode decomposition algorithm and its application in machinery fault diagnosis [D]. Xi’an: Rocket Force University of engineering, 2011.
[13] Shen Lu, Yang Fuchun, Zhou Xiaojun, et.al. Gear fault feature extraction based on improved EMD and more phological filter [J]. Journal of vibration and shock, 2010, 29 (3): 154-156.
[14] Hu Aijun. Research on the application of Hibert-Huang transform in vibration signal analysis of rotating machinery [D]. Bao Ding: North China electric power university, 2008.