

Article

A Hybrid Method for Structural Modal Parameter Identification Based on IEMD/ARMA: A Numerical Study and Experimental Model Validation

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Abstract: This article presents a hybrid method of structural modal parameter identification, based on improved empirical mode decomposition (EMD) and autoregressive and moving average (ARMA). Special attention is given to some implementation issues, such as the modal mixing, false modes, the judgment of the real intrinsic mode function (IMF) of classical EMD, and the difficulty of fixing the order of ARMA. To resolve the existing defects of EMD, an improved EMD (IEMD) that combines frequency band filtering and cluster analysis is proposed in this paper, where frequency band filtering divides the signal into several narrowband signals before the EMD process, and cluster analysis is used to determine the real IMFs. Euclidean distance is used to cluster the decomposition results, with no need to adjust any indexes or thresholds, and only by means of using the nearest distance to efficiently determine the real IMF. Moreover, IEMD is used as a pre-processing tool for ARMA, to resolve the difficulty of fixing its order. The capabilities of the proposed method were compared and assessed using a numerical simulation and an experimental model. The numerical simulation and experimental results showed that the improved method could resolve the modal mixing and false modal problems in the classical EMD process and could automatically identified the real IMFs, while the proposed IEMD was combined with ARMA to successfully identify the frequency and mode shape of the structure. Additionally, since each IMF is a single component signal, it is easy to determine the order of the ARMA model.

Keywords: modal parameter identification; EMD; ARMA; natural excitation technique (NExT); improved EMD



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1. Introduction

It is of great practical significance to carry out research on the health monitoring and damage identification of engineering structures based on structural vibration response [1–4], especially the modal analysis of large structures using vibration response data under environmental excitation, which has become a hot issue in current research [5–7].

In recent years, the time-domain method, frequency-domain method, and time-frequency domain method have been commonly used to analyze vibration response, such as the ITD (Ibrahim time domain), stochastic subspace identification (SSI) [8], natural excitation technique (NExT) [9], variational mode decomposition (VMD) [10], and time series analysis method, etc. Among the existing time series analysis methods, ARMA has attracted much attention and been widely used, because of its superior performance [11]. However, in the process of practical application, the ARMA model method often requires that the time series is a series of zero mean stationary random process, which is not consistent with the measured signals of actual engineering [12,13]. Furthermore, it is hard to select the order of an AR/ARMA model according to these limited measurements [14,15].

Aiming at analysis and processing for nonlinear and non-stationary signals, the Hilbert–Huang transform (HHT) [16,17] was proposed, the core of which is the EMD

method. After HHT was proposed, it was widely applied in many fields of engineering. In the actual application of HHT, the scholars found that the HHT method for structural modal parameter identification often encounters problems, such as mode mixing, false mode, and endpoint effects; therefore, many scholars are trying to improve the classic EMD [18,19]. At present, scholars have proposed relevant improvement methods based on independent component analysis (ICA) [20], singular value decomposition (SVD) [21], and empirical mode decomposition (EEMD) [22]. Among them, the most widely-accepted improvement is the EEMD proposed by Huang. Unfortunately, the problems of mode mixing and endpoint effects in EMD have not been fundamentally solved. Many scholars are committed to solving the problem of the endpoint effect of EMD, but the results are often not satisfactory, and many methods have problems of poor adaptivity, a large amount of computation, and long operation time. On the other hand, mode mixing and false modal are other bottleneck problems that hinder the application of EMD. Huang proposed the method of interrupt detection, to solve the phenomenon of mode mixing; namely, the results are directly observed and re-decomposed if modal mixing occurs. This method required human posterior judgment, and the decomposition efficiency was greatly reduced. Therefore, it is still necessary to efficiently solve the mode mixing of EMD. Inspired by recent auto-ID (automatic identification) technology [23–25], this paper tries to use cluster analysis to automatically identify the real IMFs.

In summary, in order to improve the above mentioned shortcomings of ARMA and EMD and to also further expand the application of these methods, this paper proposes a new hybrid automatic method for structural modal parameter identification based on IEMD and ARMA, and the effect of the proposed method was verified using a seven-story steel frame test apparatus in the laboratory. This paper is organized as follows: in Section 2, the algorithms of ARMA and EMD are introduced. The improved ARMA based on IEMD is discussed in detail in Section 3. A numerical simulation and a seven-story steel test frame in the laboratory to verify its effects are discussed in Sections 4 and 5. The conclusions are given in the last part.

2. Theoretical Background of Proposed Method

2.1. EMD

The EMD was first proposed by Huang et al. [16], in 1998, and uses a sifting process to extract intrinsic mode functions (IMFs) and a final residue, from a complicated multi-component signal $x(t)$, i.e.,

$$x(t) = \sum_{i=1}^m y_i(t) + r(t) \quad (1)$$

where m is the total number of IMFs, $y_i(t)$ ($i = 1$ to m) is the i th IMF, and $r(t)$ is the final residue. Each IMF represents a different type of frequency in theory, and each IMF satisfies the following two features: (1) The maximum difference between the number of extreme points and the number of zero crossings is one; (2) At any data point, the average value of the local minimum envelope and the local maximum envelope of data are zero. The point is that the decomposition process of EMD is adaptive, which means that it does not need to select a basis function in the decomposition process, and is superior to wavelet transform.

However, there are still some drawbacks to the results of EMD, i.e., the end-point effect, mode mixing, and real IMF determination [18,19,22]. Here, mode mixing is defined as any IMF consisting of oscillations of dramatically disparate scales, or similarly featured time scales that are distributed in different IMFs, resulting in the mixing and mutual influence of two adjacent IMFs, which is difficult to identify. Owing to the phenomenon of mode mixing, the decomposition of EMD loses its meaning, let alone the accurate identification of modal parameters, so mode mixing is a limitation of EMD. Therefore, it is necessary to improve the classical EMD to obtain a greater accuracy of modal parameter identification. To solve the limitations of mode mixing and real IMF determination in classical EMD, an IEMD is proposed in this paper.

2.2. IEMD

The occurrence of mode mixing destroys the physical meaning of the subsequent IMF. In addition, the issue of the judgement of real IMFs is also worth studying. Therefore, in this study, in order to improve the mode mixing problem, frequency band filtering was used to improve the classical EMD, so as to effectively suppress the occurrence of mode mixing in the process of classical EMD. However, many false modes are generated at the same time. For this reason, cluster analysis was used to obtain the real IMFs in this paper. Hence, combining a band-pass filter and cluster analysis, an IEMD (as shown in Figure 1) is proposed.

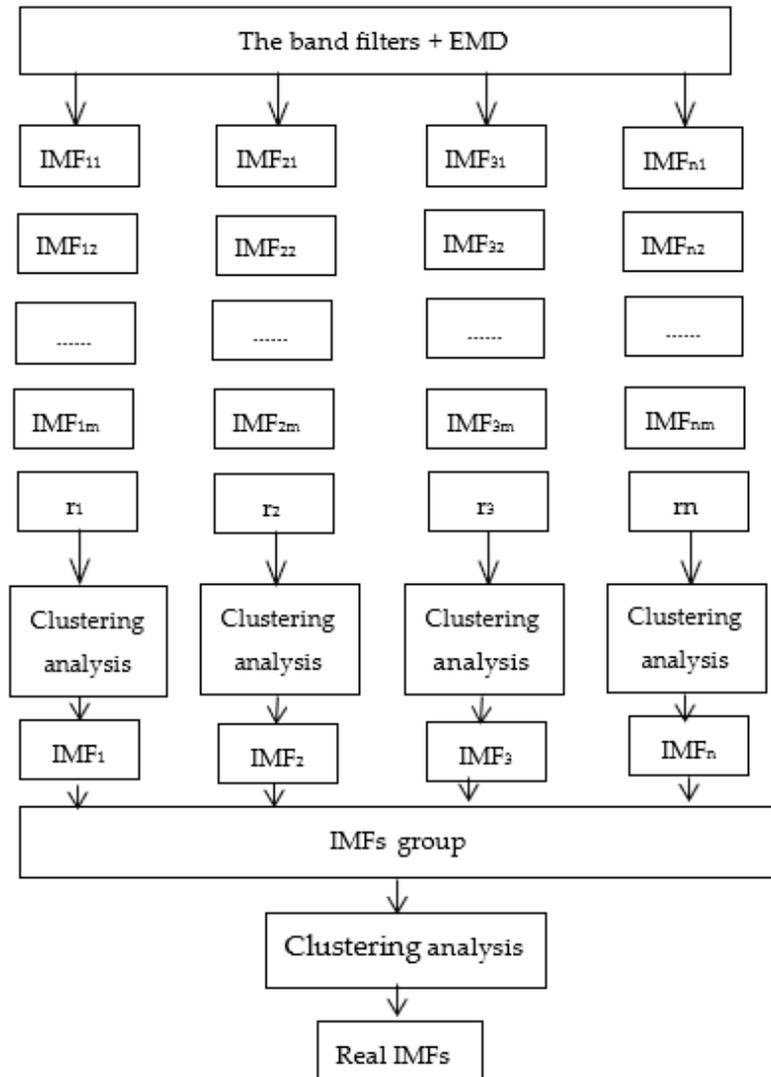


Figure 1. The proposed IEMD method.

The specific steps are as follows:

- (1) Use fast Fourier transform (FFT) to obtain the spectrum of the acceleration response signal, seeking each peak frequency as the center frequency of the band-pass filter, and then let the signal go through to the specific frequency-band filter. Namely, using FFT to analyze the acceleration signal $\ddot{x}_p(t)$, utilizing the frequency spectrum of FFT to choose the peak frequency, and then roughly estimate each frequency range, for example, $\mu_{jL} < \mu_j < \mu_{jH}$, then let the signal $\ddot{x}_p(t)$ pass the band-pass filter with specific bandwidth $\mu'_{jL} < \mu_j < \mu'_{jH}$, (here $\mu_{jL} < \mu'_{jL}$, $\mu'_{jH} < \mu_{jH}$) eventually, the signal $\ddot{x}_p(t)$ will be differentiated into limited sub-band acceleration signals.

- (2) After filtering, each sub-band signal is processed by EMD, and IMFs component of each sub-signal are obtained successively.
- (3) After the signal is processed according to the two steps mentioned above, multiple IMF groups are obtained. The key problem is how to identify the real IMFs from multiple IMF groups. In view of this, cluster analysis [26] using the multivariate data analysis method is introduced in this paper to solve the problem of the determination of the real IMF. Through a two-time cluster analysis, the screened IMF can be guaranteed to be the real IMF, and there is no mode mixing among the IMFs.

2.3. ARMA

The basic principle of ARMA [12] is as follows:

- (1) In a practical application, a high-order differential equation can be used to describe the relationship between an incentive and response for the N degrees of freedom linear system in a discrete time domain, which is composed of a series of time series in different times; namely, the ARMA time-series model in Equation (2), this equation can be used to represent specific relations between x_t (response data sequence) and x_{t-k} (history value).

$$\sum_{k=0}^{2N} a_k x_{t-k} = \sum_{k=0}^{2N} b_k f_{t-k} \tag{2}$$

where the left side of the equation is the AR model; namely, the autoregressive difference polynomial. The right side of the equation is the MA model; namely, the sliding average difference polynomial. $2N$ is the order of the autoregressive and sliding mean models. a_k is the autoregressive coefficient of the system to be identified, b_k is the sliding mean coefficient to be identified, and f_t is excited by white noise. When $k = 0$, a_0 and b_0 are regarded as 1.

- (2) According to the generalized Yule–Walker equation (Equation (3)), the least squares solution (Equation (4)) of the system can be obtained using the pseudo-inverse method, and the autoregressive coefficient a_k ($k = 1, 2, \dots, 2N$) can be obtained.

$$[R]_{(L-M) \times M} \{a\}_{M \times 1} = [R']_{(L-M) \times 1} \tag{3}$$

$$\{a\} = ([R]^T [R]^{-1}) ([R]^T \{R'\}) \tag{4}$$

where R is the autocorrelation function of x_t .

- (3) The sliding average model coefficient b_k ($1, 2, \dots, 2N$) can be obtained by using the nonlinear equations (Equation (5)).

$$\begin{cases} b_0^2 + b_1^2 + \dots + b_M^2 = c_0 \\ b_0 b_1 + \dots + b_{M-1} b_M = c_1 \\ \vdots \\ b_0 b_M = c_M \end{cases} \tag{5}$$

- (4) a_k and b_k can be obtained from Equations (4) and (5), and the modal parameters of the system can be calculated through the transfer function expression of the ARMA model. The transfer function of the ARMA model is shown in Equation (6):

$$H_z = \frac{\sum_{K=0}^{2N} b_k z^{-k}}{\sum_{k=0}^{2N} a_k z^{-k}} \tag{6}$$

Using a high-order algebraic equation to solve the poles of the transfer function, and the relationship between the modal frequency ω_k and damping ratio ζ_k of the system is shown in Equation (7):

$$z_k = e^{sk\Delta t} = e^{(-\zeta_k \omega_k + j\omega_k \sqrt{1-\zeta_k^2})\Delta t} \tag{7}$$

- (5) Modal frequency ω_k and damping ratio ζ_k obtained using Equation (7), as shown in Equation (8):

$$\begin{cases} \omega_k = |R_k|/\Delta t, R_z = \ln z_k = s_k \Delta t \\ \zeta_k = \sqrt{\frac{1}{1+[Im(R_k)/Re(R_k)]^2}} \end{cases} \quad (8)$$

3. The Principle of IEMD and ARMA

Based on the IEMD, a hybrid method for structural modal parameter identification is proposed, its identification process is shown in Figure 2; first, using IEMD to address two groups of acceleration response signals, to obtain two sets of IMFs, with one group as the reference signal and the obtained cross-spectral density function corresponding to every IMF; then, using Fourier inverse transformation to obtain the cross-correlation function, then, using NExT to obtain the free vibration response; finally, ARMA is used to identify the modal parameters of the structure.

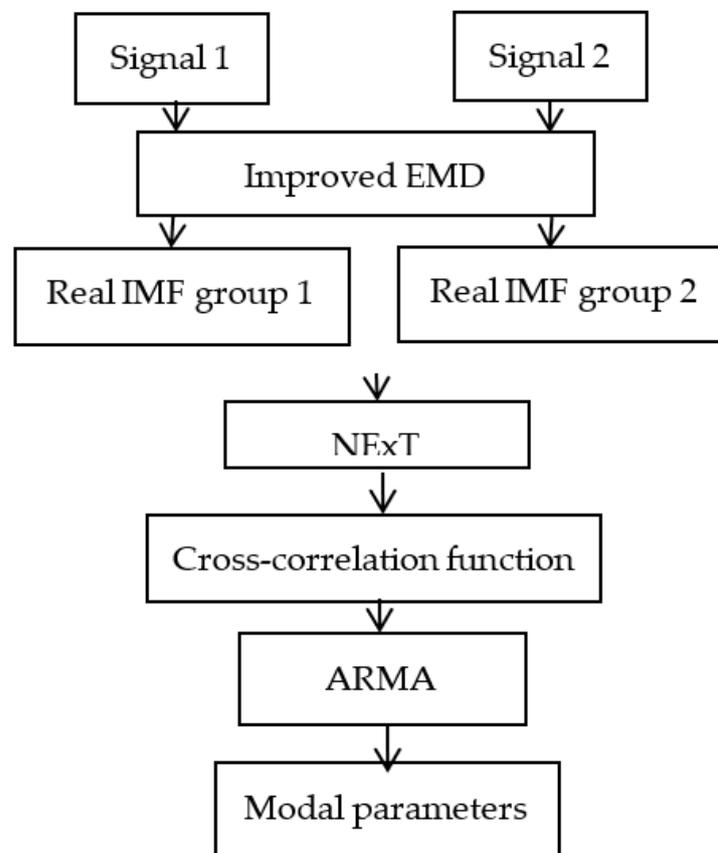


Figure 2. Diagram of using IEMD and ARMA to identify structural parameters.

ARMA was used to extract the modal parameters of the structure, assuming the cross-correlation function was expressed by R_j , which was obtained using the inverse Fourier transform of the j th cross-spectral density function and taken as the free vibration response of the structure x_j .

According to literature [11], the GREEN function of the ARMA model can be used to solve the frequency and damping ratio of the system, while the residue can be used to obtain the structural mode shapes. Assuming the excitation point is at the point q , and the

k th residue corresponding to the transfer function $H_{pj}(s)$ of the response at point p as $A_{k pq}$, then the residue can be obtained from the following equation:

$$A_{k pq} = \lim_{z \rightarrow z_k} H_{pq}(z)(z - k) = \frac{\sum_{k=0}^{zN} b_k z^{-k}}{\sum_{k=0}^{zN} a_k z^{-k}} \Bigg|_{z=z_k} \tag{9}$$

Thereby, the vibration pattern vector can be obtained by processing the residues obtained from all response measurement points. If a structure contains n response measurement points, it is necessary to determine the corresponding measurement points of the maximum absolute value of the remaining number of n corresponding modes of the same order. If the measurement point is m , the normalized complex mode shape vector corresponding to the k th mode is:

$$\{\phi_k\} = [A_{k1q} \ A_{k2q} \ \dots \ A_{knq}]^T / A_{kmq} \tag{10}$$

4. Numerical Validation

To study the effectiveness of the proposed method, a simulated signal, denoted by $x(t)$, was applied. The signal is a mathematical model, used to describe the displacement response of a damped system under free vibration [27]. It can be written as follows:

$$x(t) = 5e^{-2.2t} \sin(78.5t + 0.46) + 20e^{-3.4t} \sin 500.5t + 20e^{-2.24t} \sin 1401.1t + 5e^{-3.84t} \sin(2745.6t + 0.1) \tag{11}$$

where A_n is the amplitude, ξ_n is the damping ratio, f_n is the natural frequency, and θ_n is the phase angle of the n th mode. N is the total number of modes. Here, the number of modes is 4. The parameters used for generating $x(t)$ are as follows: $f_1 = 12.5$ Hz, $f_2 = 79.7$ Hz, $f_3 = 223.1$ Hz and $f_4 = 437.2$ Hz, Amplitudes are $A_1 = A_4 = 5$, $A_2 = A_3 = 20$. Phase angles are $\theta_1 = 0.46$, $\theta_4 = 0.1$, and $\theta_2 = \theta_3 = 0$, and the correlated damping ratios are $\xi_1 = 2.8\%$, $\xi_2 = 0.68\%$, $\xi_3 = 0.16\%$, and $\xi_4 = 0.14\%$.

Here, the sampling frequency is 4096 Hz, and the sampling points total 8192. Classical EMD was performed on the simulated signals of the displacement response, and eight IMFs and one residual term were obtained. The first four order IMFs and their corresponding spectrum are shown in Figure 3. It can be seen from Figure 3 that the displacement simulation signal was not decomposed into four single IMF components, but into eight IMFs, and the decomposed low frequency components were not what we had expected and should not have appeared, this was evidence of false modes. In addition, it can also be seen from Figure 3 that the first generated IMFs covered a wide frequency range and obviously contained three frequency components. The second decomposed IMF component was a single frequency component; however, mode mixing appeared again in the third IMF component obtained by EMD; namely, two frequency values appeared in the single component of the third IMF.

The displacement simulation signal of Equation (11) was also analyzed using the EEMD method. The first six orders of IMFs decomposed using the EEMD method are shown in Figure 4. In the process of EEMD, the added white noise level was set to 0.1, and the overall average mean number was 50. As can be seen from Figure 4, EEMD could almost decompose signals into single components, except the first IMF, and there was very obviously two frequency components (around 100 Hz); that is, modal mixing occurred. It can also be seen from Figure 4 that energy leakage existed in the decomposition process of the EEMD method, and it was obvious that the two different IMFs generated in the low-frequency domain contained the same frequency component (labeled by the red dotted rectangle). Meanwhile, one positive aspect was that EEMD successfully identified low order frequency components, which is of great significance for modal analysis and structural damage detection of large structures.

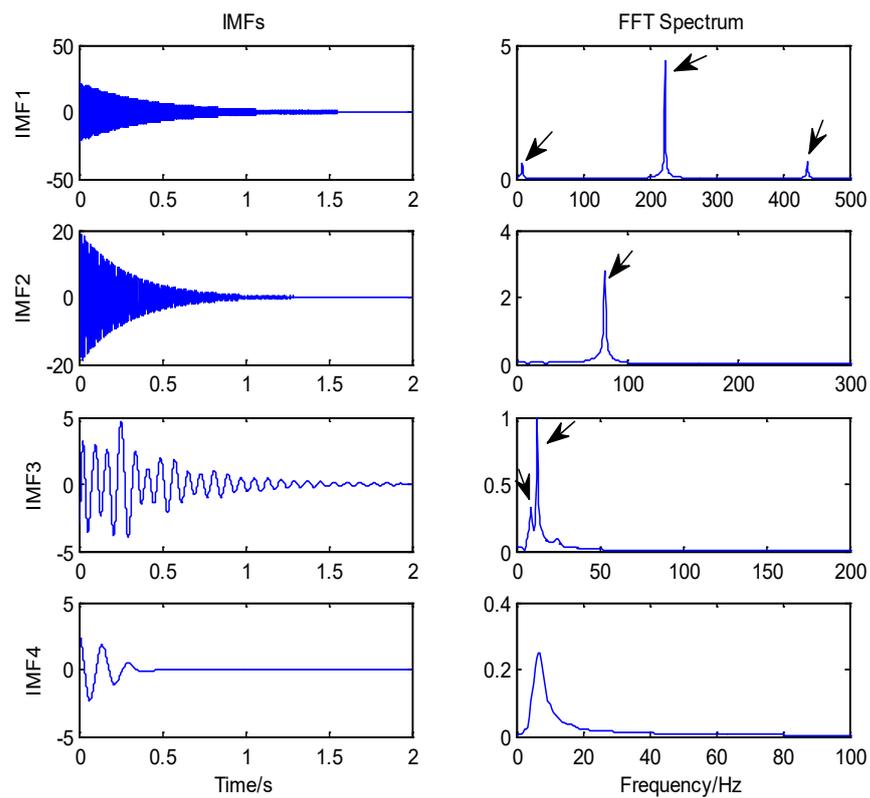


Figure 3. Partial IMFs obtained using EMD and the corresponding FFT frequency–spectrum.

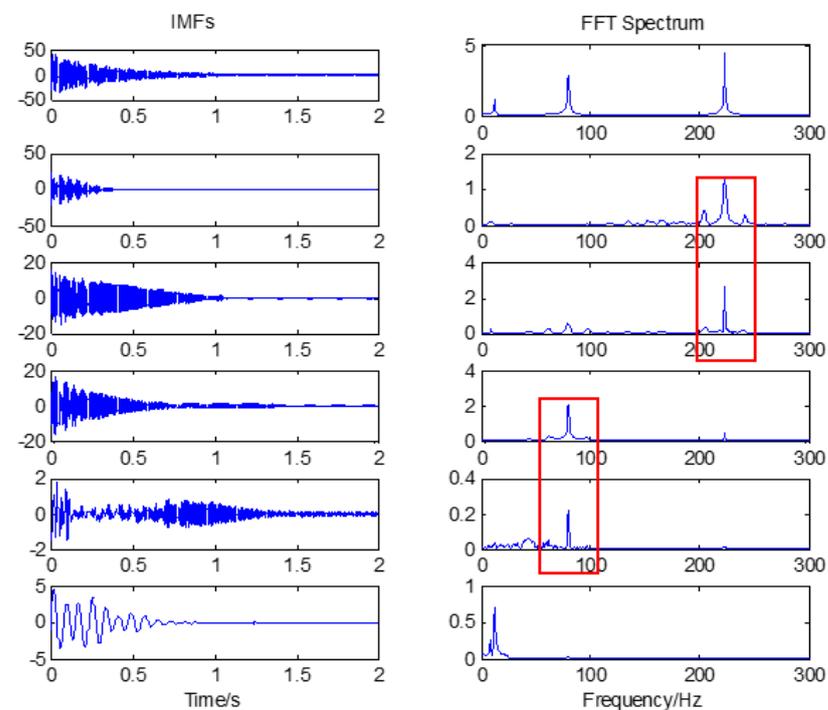


Figure 4. Partial IMFs obtained using EEMD and the corresponding FFT frequency–spectrum.

IEMD was also used to analyze the simulated signals of Equation (11), and the obtained four order IMFs are shown in Figure 5. First, the FFT spectrum was used to estimate the frequency range quickly and roughly, four frequency ranges were defined from the four peak frequencies in the Fourier spectrum; here, four band-pass filters with the center of the peak frequency were formed, and each frequency range can be expressed as $j_L < j < j_R$.

The frequency range is theoretically the difference between two adjacent frequencies of the Fourier spectrum, but the smaller the frequency range is, the better the band-pass filtering effect will be. Therefore, in this paper, the frequency range is no more than 5%. Then, the simulated signal was processed by filtering through the band-pass filters with four specified frequency bands and IMFs, after the processing of each filter were obtained accordingly. For instance, there were 10 IMFs, and a residual could be obtained from the first frequency-band after the processing of EMD, as shown in Figure 6. Finally, the required IMF was automatically identified using clustering analysis shown in Figure 7. Here, Euclidean distance was used to cluster the decomposition results, with no need to adjust any indexes or thresholds, and only the nearest distance default in MATLAB was used to efficiently determine the real IMF.

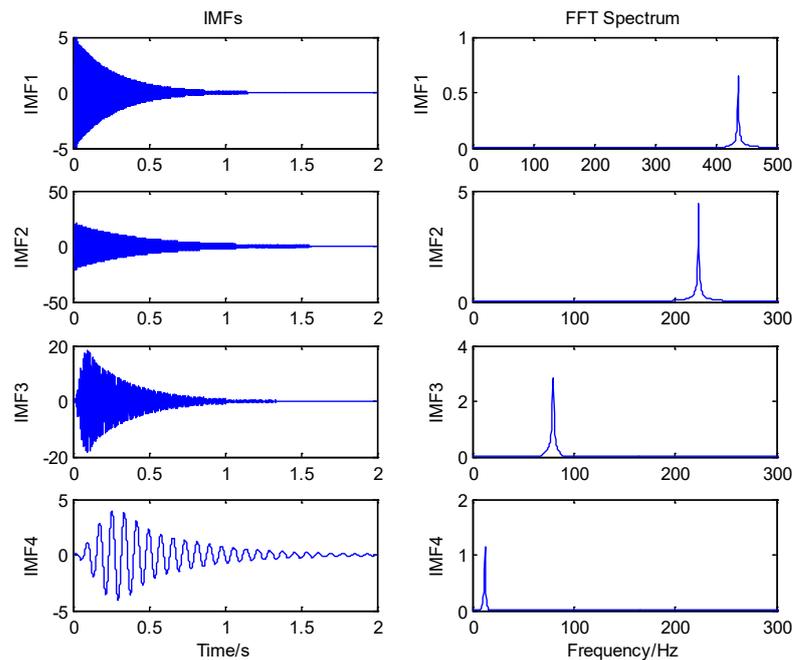


Figure 5. IMFs obtained by IEMD and the corresponding FFT frequency–spectrum.

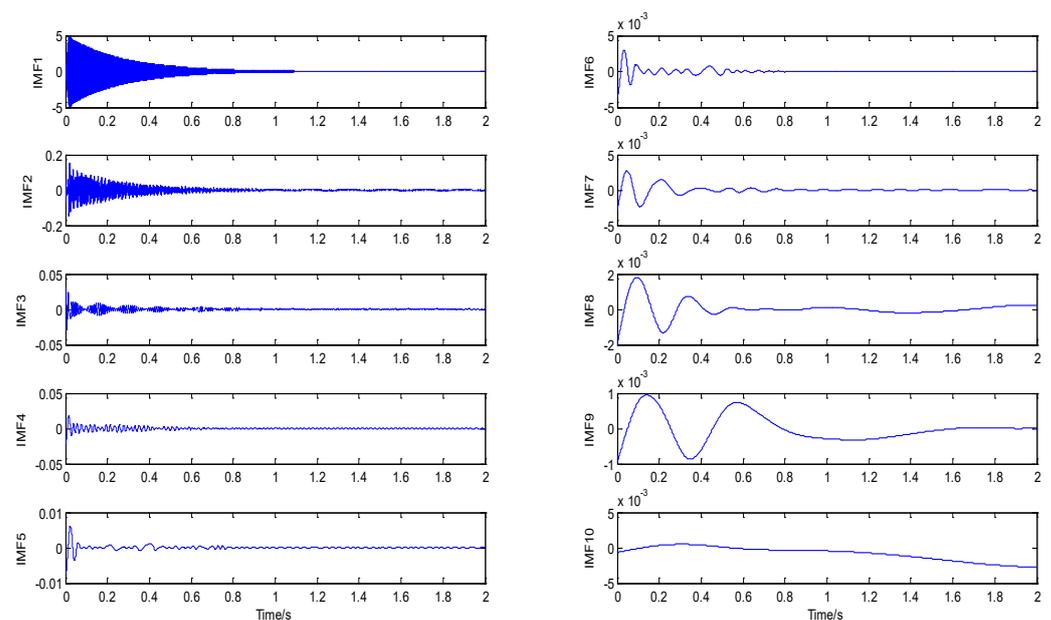


Figure 6. IMFs obtained by the first band–filtering.

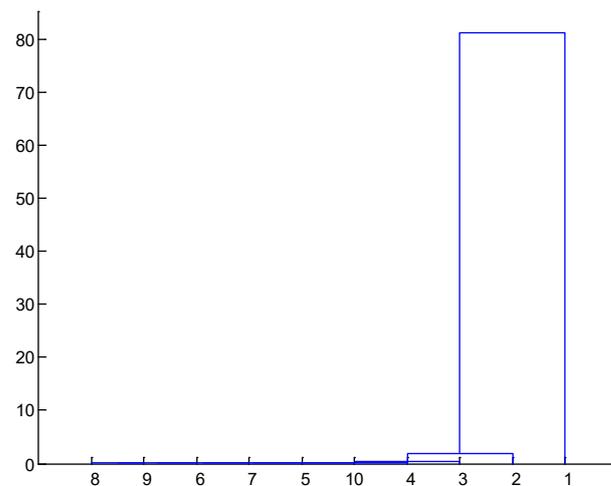


Figure 7. Cluster analysis results of IMFs in Figure 6.

From Figure 7, it can be seen that the first IMF was required, this process was repeated at each frequency-band, and the required IMF group was formed. Finally, the real IMFs were obtained using a clustering analysis (Euclidean Distance) of the IMFs group again, as shown in Figure 8. It can be seen from Figure 8 that the four IMFs obtained from IEMD were independent of each other, and there was no mode mixing. By comparing Figures 3–5, it can be seen that the proposed IEMD can improve the phenomenon of mode mixing and could accurately identify each IMF, as well as make preparations for the subsequent identification of structural modal parameters.

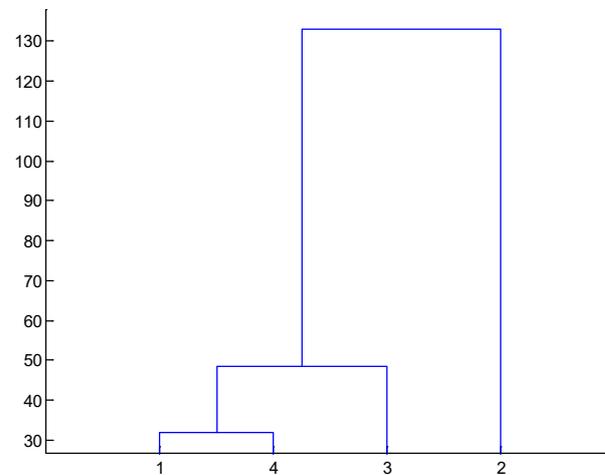
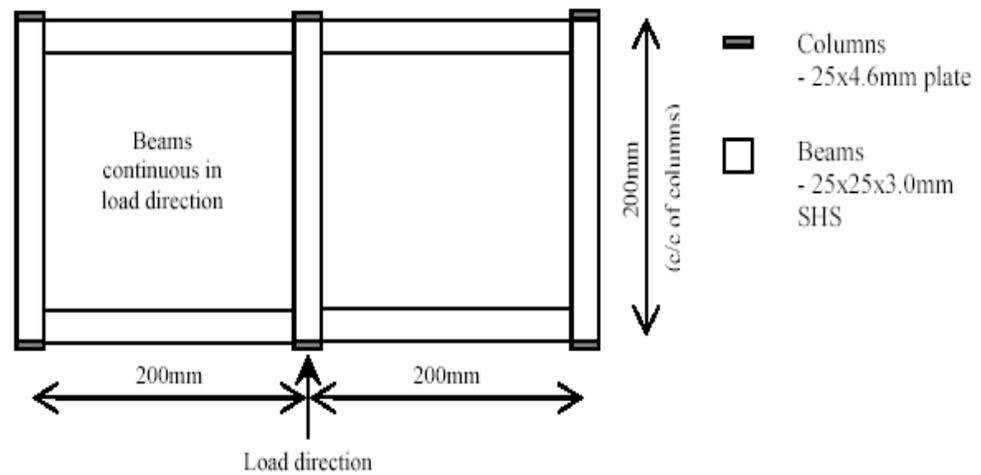


Figure 8. Cluster analysis results of IMFs of IEMD.

5. Test Verification

5.1. Experiment

As shown in Figure 9, a seven-story steel-frame structure laboratory scale model [28] was constructed, and the plane size of this model was $0.4 \text{ m} \times 0.2 \text{ m}$, and it was 1.4125 m in height. Using hot-rolled 300 w grade steel ($f_y = 300 \text{ Mpa}$), the section size of the beam, column, and the characteristics of the cross-section were as shown in Table 1. The beam was continuous in the loading direction. Random excitation (hammering method) was applied in the direction perpendicular to the beam at the rigid joints in the middle span of the top floor of the steel frame structure. An acceleration sensor was arranged at the middle beam end of each layer, parallel to the excitation direction, so that a total of seven sensors were arranged to collect acceleration signals (Figure 10), and the sampling frequency was 2000 Hz.



Plan View

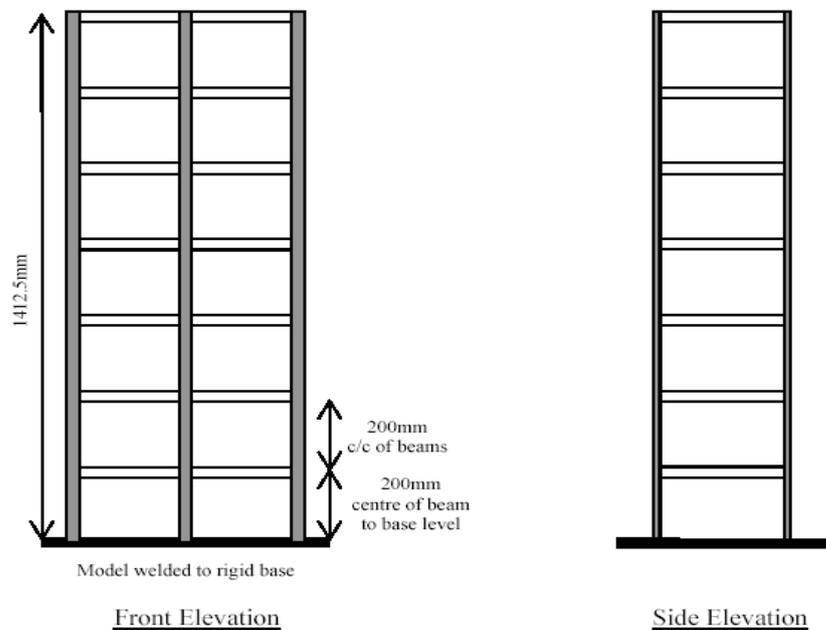


Figure 9. Seven-story steel frame model.

Table 1. Structural member characteristics.

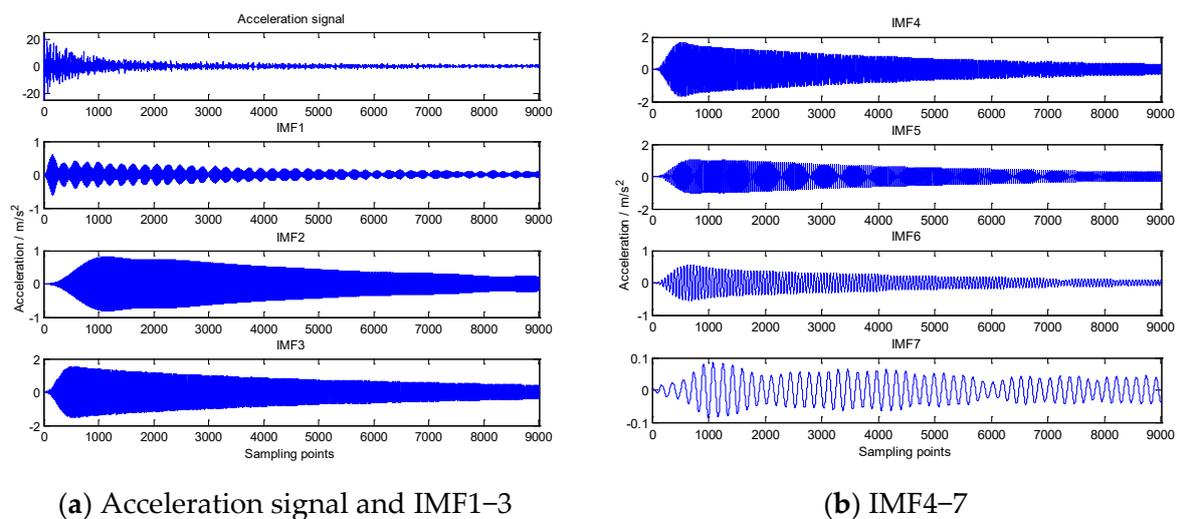
Geometrical Features	Beam	Column
Sectional dimension	25 mm × 25 mm × 3 mm (SHS)	25 mm × 4.6 mm
Sectional area A/m^2	286×10^{-6}	115×10^{-6}
Inertia moment I/m^4	2.41×10^{-8}	7.78×10^{-10}
Young modulus E/Pa	206×10^9	206×10^9
Volume density $\rho [kg/m^3]$	7850	7850



Figure 10. Testing of a seven-story steel frame structure.

5.2. Identification Results and Discussion

The measured acceleration response signal of the seven-story frame structure in a healthy state is shown in Figure 11, the proposed hybrid method of IEMD and ARMA was used for modal parameter identification, and the detailed identification process was shown as follows:



(a) Acceleration signal and IMF1–3

(b) IMF4–7

Figure 11. Acceleration signal and IMF1–7 using IEMD.

First, the acceleration signal was measured by means of IEMD for preprocessing; namely, choosing two groups of the acceleration response in a structural healthy condition. Then, a FFT process was performed, followed by picking up the peak frequency of the Fourier spectrum as the central frequency of the band-pass filter. Two sets of acceleration response signals separately passed through the band-pass filter with a specified frequency band, and frequency range can be expressed as $j_L < j < j_R$, in this paper, while the frequency range was no more than 5%. Finally, a two-time cluster analysis was used to determine the real IMFs. Second, the cross-correlation function was obtained using the NEXt method. Obviously, two sets of acceleration response signals can obtain two groups of IMFs (The first seven order IMFs are shown in Figure 11). With one set of IMFs as the reference signal, the corresponding cross-spectral density function of each IMF was solved, and the inverse Fourier transform was carried out to obtain the cross-correlation function, as the free vibration response of the structure (as shown in Figure 12).

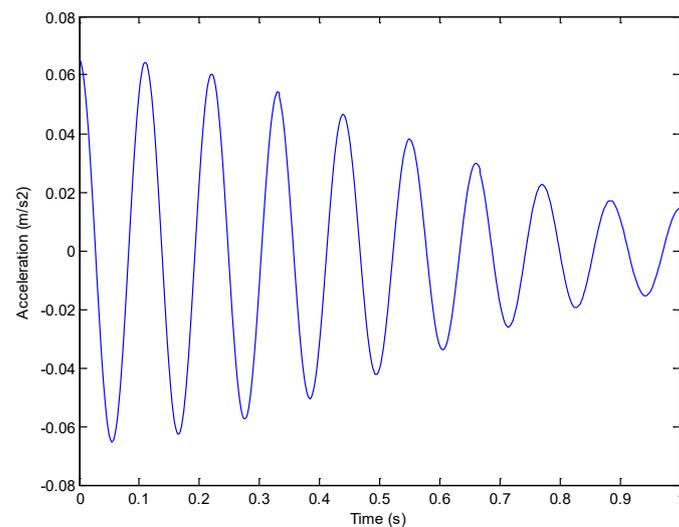


Figure 12. Free vibration curves of IMF6 obtained using the NExT method.

Finally, by using an ARMA(2, 2) model to simulate the free vibration response (cross-correlation function), the sixth IMF was taken as an example, as shown in Figure 13, for identifying the modal frequency of the structures (as shown in Table 2). As mentioned above, ARMA-based modal identification is one of the most popular methods, since it offers a high accuracy of modal parameters, with the main obstacle in ARMA-based modal identification being the determination of proper system order. This defect has attracted a large number of scholars to complete a lot of related research [13–15], but the problem of model order determination is still very difficult. However, in this paper, since the components of the IMFs are all single-order modes after disposing of the IEMD, the order of the model is two, which is twice the order of the mode. In order to identify the mode shape, the vibration response signals of all freedom degrees should be measured. For different measuring points, the coefficients of the vibration mode are obtained using the residue and normalized to obtain the mode shape.

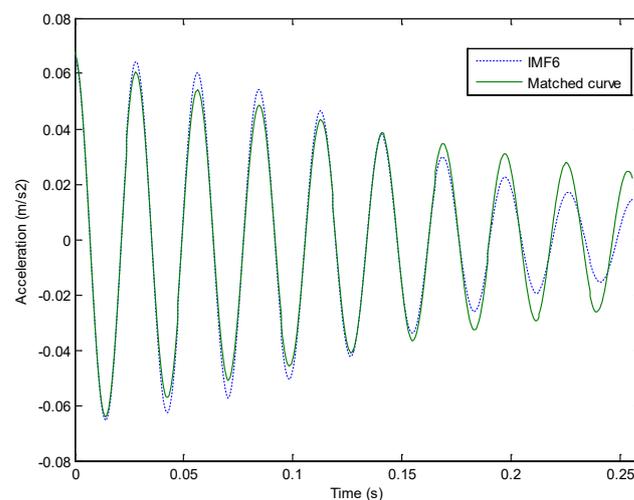


Figure 13. Corresponding to Figure 11, the fitting curve used in the ARMA model.

Table 2. Comparison of the modal frequency identification results (Hz).

Mode	Theoretical Value [28]	Proposed Method	HHT	NExT/ARMA
1	11.7	11.86	13.35	–
2	35.2	35.5	8.96	35.6
3	58.6	58.58	35.56	58.54
4	80.1	79.94	58.30	80.75
5	99.6	98.71	99.48	98.76
6	113.3	113.4	67.92	113.27
7	123.0	122.84	293.22	122.94

In order to further illustrate the effect of the IEMD method, the IMFs obtained by classical EMD decomposition are shown in Figure 14. From Figures 11 and 14, it can be seen that mode mixing occurred for the six and seventh IMFs obtained by EMD locally, i.e., some data with the same, or nearly the same, frequency are decomposed into more than one IMF (labeled by the red dotted rectangle), while in Figure 11 the modes are well separated from original signal. A Hilbert spectrum analysis and cluster analysis of IMFs obtained using IEMD are shown in Figures 15 and 16, respectively. It can be seen from these two figures that the IEMD resolved the problems of modal mixing, and the identified IMFs were all single independent components. Therefore, the IEMD/ARMA methods could obtain more accurate recognition results (as shown in Table 2). It can also be concluded that EEMD cannot completely improve the mode mixing problem of classical EMD based on the frequency identification results. However, EEMD can obtain more accurate frequency identification results than classic EMD in the low frequency domain. It is worth noting that during the process of EEMD, both the amplitude standard deviation σ of white noise and the number N of adding white noise need to be selected artificially. The selection of this value will affect the decomposition result, and the decomposition of EEMD is very time-consuming. Here, in order to facilitate calculation, $\sigma = 0.1$ and $N = 50$. It should be pointed out that, when NExT/ARMA was directly used for modal parameter identification, the reason why the ideal frequency recognition results could be obtained, excepting that the low-order frequency was not successfully identified, was because this paper used a trial calculation method to determine the order of the ARMA model. However, with the help of IEMD, the order of the ARMA model can be easily determined.

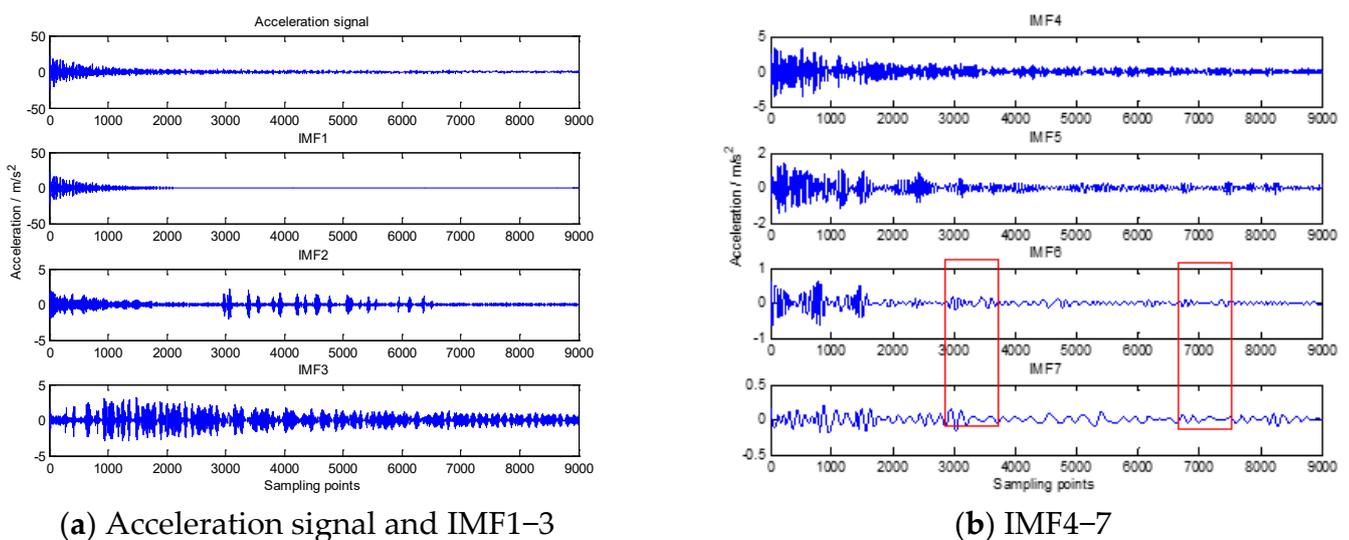


Figure 14. Acceleration signal and IMF1–7 using EMD.

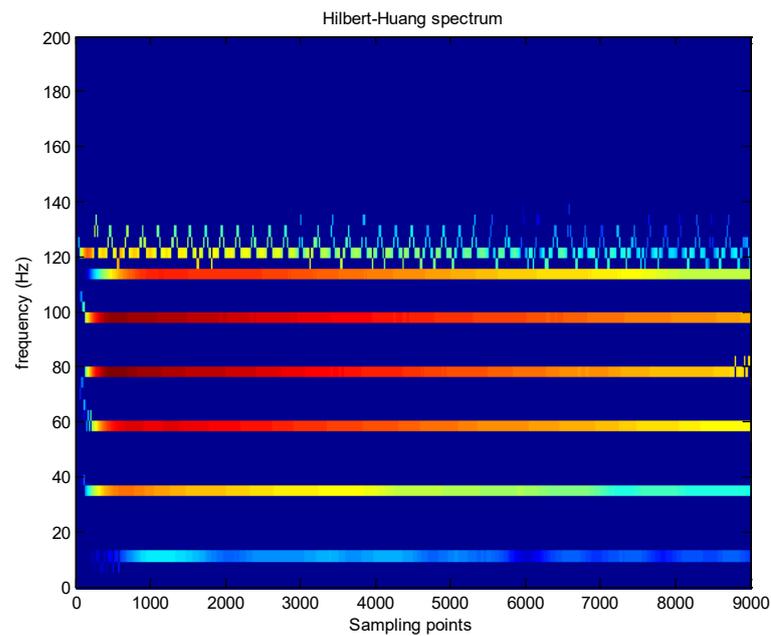


Figure 15. Hilbert spectrum using IEMD + Hibert.

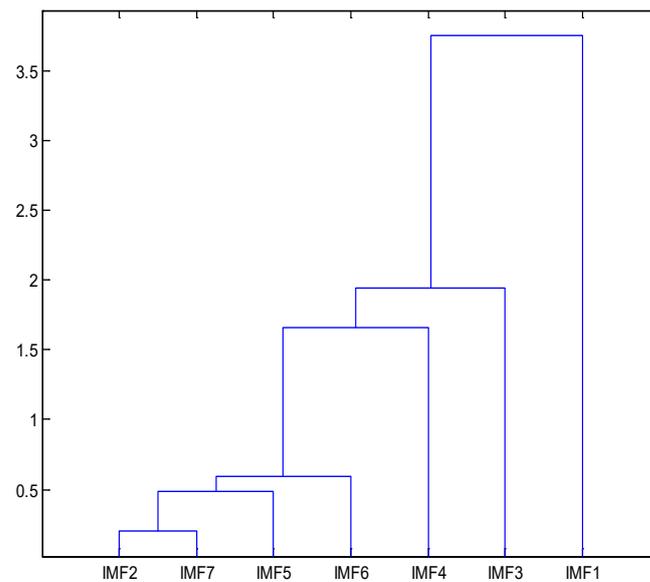


Figure 16. Cluster analysis results of IMF.

Regarding identifying the mode shapes, it is necessary to obtain the acceleration responses of all degrees of freedom; and repeating the above identification process, the complex mode vectors corresponding to each mode of the measuring points were obtained. The real part of the complex modal vector was the modal shape coefficient. The modal vector can be obtained by normalizing the modal coefficients. The recognition results of the first six order mode shapes are shown in Figure 17. From Figure 17, it is not difficult to see that the identified mode shapes were in good agreement with the theoretical shapes, and the overall shapes were basically consistent with the theoretical shapes.

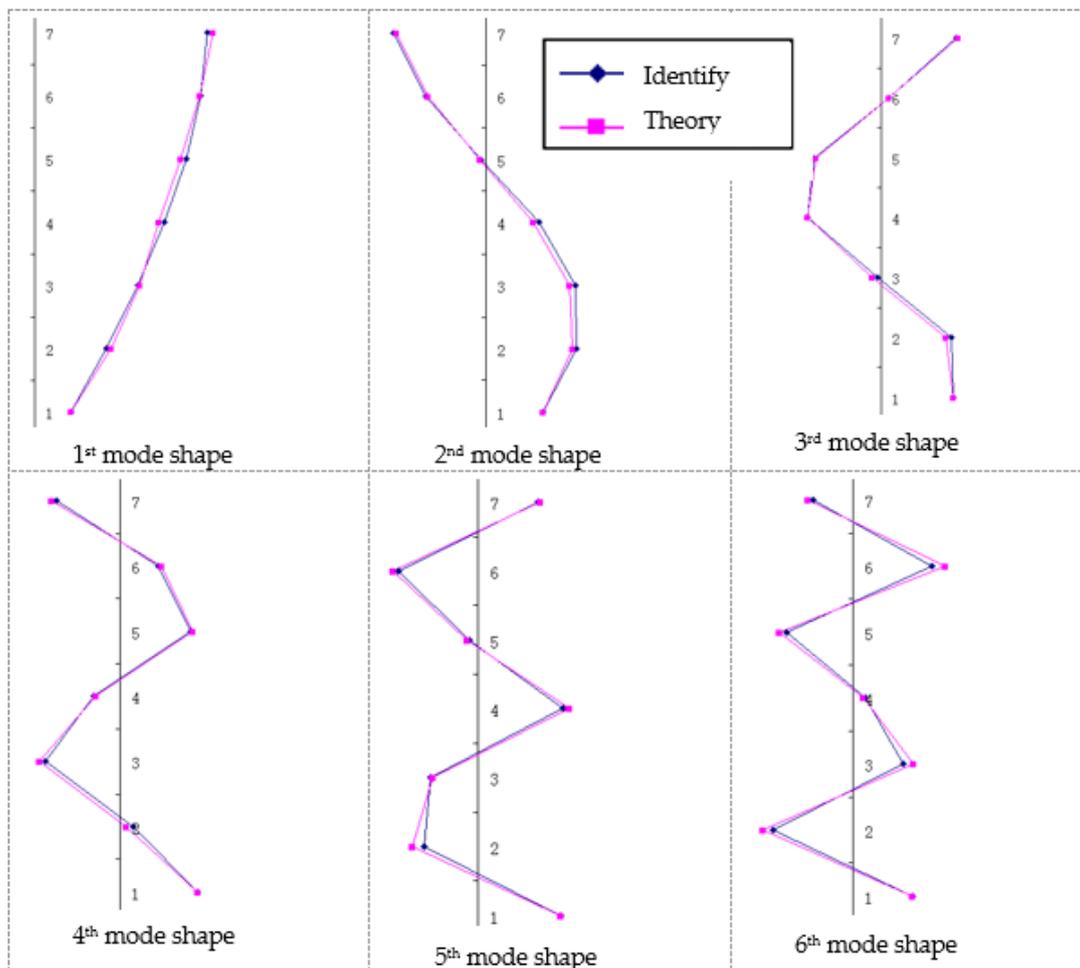


Figure 17. The first six vibration modes identified using the IEMD/ARMA method.

6. Conclusions

In view of the practical difficulties of the classic EMD and ARMA methods in practical applications, such as mode mixing, and determination of real IMF and the model order, as well as ARMA requiring the time series to be a series of stationary random processes with a zero mean value, this paper proposed a hybrid method to improve the structural modal parameter identification, by means of combining IEMD and ARMA. IEMD was used to preprocess the signal, and a cluster analysis was used to determine the real IMFs. The free vibration response was obtained using the NExT method and used as the input signal for the ARMA method. The modal test of a seven-story steel frame showed that IMFs, which were used as an input signal for ARMA and were obtained by preprocessed of IEMD, which could resolve the mode mixing problem and make the determination of ARMA order easier. Thus, the structure frequency and modal shape were identified successfully, which proved the effectiveness of the proposed method and further expands the application range of ARMA. However, the application of this proposed method will be limited in the case of some dense modal vibration signals, when FFT cannot correctly divide the frequency band. In addition, recognition of time-varying signals was not considered in this paper, and continuous research work will be devoted to this aspect in the future.

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