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Structural modal identification through ensemble empirical modal decomposition

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Abstract. Identifying structural modal parameters, especially those modes within high frequency range, from ambient data is still a challenging problem due to various kinds of uncertainty involved in vibration measurements. A procedure applying an ensemble empirical mode decomposition (EEMD) method is proposed for accurate and robust structural modal identification. In the proposed method, the EEMD process is first implemented to decompose the original ambient data to a set of intrinsic mode functions (IMFs), which are zero-mean time series with energy in narrow frequency bands. Subsequently, a Sub-PolyMAX method is performed in narrow frequency bands by using IMFs as primary data for structural modal identification. The merit of the proposed method is that it performs structural identification in narrow frequency bands (take IMFs as primary data), unlike the traditional method in the whole frequency space (take original measurements as primary data), thus it produces more accurate identification results. A numerical example and a multiple-span continuous steel bridge have been investigated to verify the effectiveness of the proposed method.

Keywords: empirical mode decomposition; modal identification; signal processing; narrow frequency bands

1. Introduction

Structural modal identification utilizing vibration test and signal processing technologies has become a practical tool for bridge monitoring and safety evaluation. Vibration tests provide structural response measurements, and signals processing methods identify structural modal parameters (frequency, damping, and mode shapes) from measurements. These identified parameters characterize the investigated structure, thus providing basic information for structural safety evaluation. A number of engineering case studies have been reported in literature to utilize the modal identification technology for bridge safety evaluation (Peeters and Roeck 2001, Ko *et al*. 2002, Brownjohn *et al*. 2003, Grimmelsman *et al*. 2007, Conte *et al*. 2008, Siringoringo and Fujino 2008, Pakzad and Fenves 2009, ASCE 2011). These practical implementations advance the state-of-the-art of the modal identification technology, and illustrate its significant potential in engineering applications.

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However, various kinds of uncertainties involved in vibration test and signal processing still pose a major challenge for accurate and robust structural modal identification, and hinder infrastructure owners' decision to adopt current modal identification technologies in structural maintenance and management (Moon and Aktan 2006, Reynders *et al*. 2008). The following uncertainties, far beyond ambient noise, exist in the modal identification process: (1) Prevailing excitations (wind and traffic) and environmental conditions (humidity, wind and most important, temperature) bring uncertainties into ambient vibration or controlled force experiments; (2) Measurement noises rising from experimental hardware (sensors, cabling and data acquisition system) and experiment design (array density and distribution, data acquisition parameters, on-site quality control, etc.) are unavoidable; (3) various data pre-processing methods with pre-determined parameters for data filtering, re-sampling, windowing and averaging produce different "cleaned" data, and various post-processing methods may produce different identified results, depending on their capabilities to capture signal characteristics in the noisy environment.

A number of data processing methods have been developed aiming at mitigating the uncertainty involved in measurements for modal identification (the subspace system identification method, the complex modal indicator function method etc (Loh *et al*. 2011, Catbas *et al*. 2004)), among which the PolyMAX method is a promising one and it has been widely applied in engineering practices (Peeters *et al*. 2004). It uses multiple-input-multiple-output frequency response functions (FRFs) as primary data to solve denominator polynomial coefficients, and then extracts structural modal parameters. Because FRF peaks in different structural modes may have different levels of magnitudes, and the PolyMAX method uses the least squares method to solve denominator polynomial coefficients by minimizing the FRF estimate errors in the whole frequency range, the identified modal parameters from the PolyMAX method especially those in the modes with small FRF peaks may be inaccurate. Even the weighted least squares method may somehow overcome that deficiency, defining the frequency-dependent weights in the least squares method is still a challenging problem (Verboven 2002). To overcome this deficiency of the traditional PolyMAX method, a Sub-PolyMAX method has been developed to implement LS solvers in subspaces of the whole frequency range independently (Zhang *et al*. 2012). The identification results from a narrow frequency band in the Sub-PolyMAX method are not affected by FRF data in other frequency bands, thus it significantly improves the accuracy of modal identification results. However, the narrow frequency bands have to be manually determined from the whole frequency range in the developed Sub-PolyMAX method. A more efficient method is proposed in this article by employing a novel Ensemble Empirical Modal Decomposition (EEMD) concept (Huang and Wu 2008, Wu and Huang 2008). The EEMD method is recently developed which is able to automatically separate the original data to a set of IMFs with energy in narrow frequency bands, thus the Sub-PolyMAX method can be performed in each narrow frequency band by taking the IMFs as primary data, unlike the traditional PolyMAX method in the whole frequency space by taking original measurements as primary data, for accurate and robust modal identification.

The paper is structured as follows. The theoretical framework of the proposed method is first presented. It includes the EEMD method to decompose the original measurement to a set of signals (IMFs), and the Sub-PolyMAX approach to identify modal parameters by taking the IMFs as primary data. A numerical example is investigated to demonstrate how the proposed method works for modal identification. Subsequently, modal identification of a multiple-span continuous steel bridge is performed to further verify the effectiveness of the proposed method. Finally, some conclusions are drawn.

2. Theoretical framework

In the traditional PolyMAX method, all FRF data in the whole frequency range is used in the Jacobean least squares (LS) implementation to estimate structural modal parameters. Because the LS errors at frequency lines near FRF peaks have crucial influences on the LS solution, while FRF peak values at different structural modes generally are at different magnitude levels, modal identification results especially those in the modes with small FRF peaks identified from the PolyMAX method may be inaccurate. To illustrate such a phenomenon, a two degree of freedoms (DOFs) lumped mass structure is studied here. The mass of the structure lumped to each floor is 2 kg, and the first and second floor stiffness are 1000 kN/m and 2000 kN/m, respectively, which makes the structure has the frequencies of 2.36 Hz and 7.60 Hz in the first and second modes, respectively. The Rayleigh damping with coefficients α = 0.2 and β = 0.0005 is adopted making the structure have damping ratios ξ_1 = 1.05% and ξ_2 = 1.40%. One end of the structure is fixed and the other is free. Vibration responses of the structure under ambient excitations are simulated by the Newmark method. 10% white noise without frequency band limitation is added as observation noise, where 10% means the standard deviation of noise is 10% of that of the simulated data. The frequency response function, H_{11}, of this structure is plotted in Fig. 1. It is seen that the FRF peak value at the second mode is much lower than that in the first mode. Therefore, when minimizing the least square errors of the FRF estimates in the whole frequency range using the traditional PolyMAX method, the accuracy of the estimated structural modal parameters in the second mode will be affected. The weighted LS method is able to improve the accuracy by adopting frequency-dependent weighted factors, however how to define appropriate weight factors is still a problem even much work have been performed on this topic in the literature. It is known that the total FRF can be written as a sum of the FRF values at all modes as shown in Fig. 1. Therefore, if the original data can be decomposed to a set of signals with energy centered in different frequency bands, the PolyMAX will be able to perform modal identification in a subspace of the whole frequency range, thus producing more accurate and robust results. This is the concept of the Sub-PolyMAX method.

2.1 Ensemble empirical mode decomposition

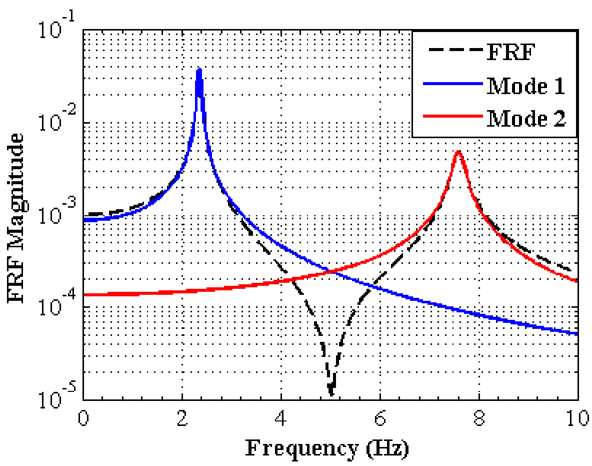

Fig. 1 Typical frequency response function

Empirical Mode Decomposition (EMD) has been developed recently as an adaptive time-frequency data analysis method (Huang and Wu 2008, Lin *et al*. 2005, Xu *et al*. 2003, Yang *et al*. 2004, Yu and Ren 2005, Briwbe *et al*. 2008, Yan and Miyamoto 2006, Nagarajaian and Basu 2009, Zhang *et al*. 2010). It is comparable to other analysis methods like Fourier Transforms and wavelet decomposition. The EMD process decomposes complicated data set into a finite and often small number of signals, known as intrinsic mode functions (IMFs), which are zero-mean amplitude frequency modulation components in the time-domain (Huang *et al*. 1998)

$$x(t) = \sum_{i=1}^{m} c_i(t) + r_m(t) \tag{1}$$

where, $x(t)$ is the original signal, m is the number of the IMFs, $c_i(t)$ is the ith IMF which has the same length as the original signal, and $r_m(t)$ is the residual. A set of IMFs are generated through the EMD process by iteratively averaging the minimum and maximum envelopes of the original signal and subtract the average values from the original data until the defined stoppage criteria are satisfied (Huang *et al*. 1998). From this process, each IMF constructed is a zero-mean time series, and the number of its zero-crossings is a rough indication of the mean frequency of each mode. Namely, the EMD in fact acts as a dyadic filter in stochastic situations involving broadband noise (Flandrin and Gonçalvés 2004).

One of the major drawbacks of the original EMD method is that sometimes mode mixing exists. Namely a single IMF either consisting of signals of widely disparate scales, or a signal of a similar scale residing in different IMF components. To overcome this scale separation problem, the Ensemble Empirical Mode Decomposition (EEMD) has been developed to provide physically unique decompositions (Wu and Huang 2008). The EEMD defines the true IMF components as the mean of an ensemble of trials, each consisting of the signal plus a white noise of finite amplitude. Therefore, it is a noise-assisted data analysis method. The EEMD process is as follows:

(1) Adding white noise into the original data which will populate the whole time-frequency space uniformly. When signal is added to this uniformly distributed white background, the bits of signal of different scales are automatically projected onto proper scales of reference established by the white noise in the background.

(2) Decomposing the noise-added data into a series of IMFs in each trial.

$$x(t) + Randn_j(t,1) = \sum_{i=1}^{M} c_{ij}(t) + r_{Mj}(t) \qquad j = 1,.2,...N \tag{2}$$

with the symbol j denoting the j^{th} trial. Each individual trial may produce very noisy results, for each of the noise-added decompositions consists of the signal and the added white noise.

(3) Averaging a number of trials to remove the noise effect. Since the noise in each trial is different in separate trials, it is canceled out in the ensemble mean of enough trials (Wu and Huang 2008).

$$x(t) = \sum_{i=1}^{M} \frac{\sum_{j=1}^{N} c_{ij}(t)}{N} + \frac{\sum_{j=1}^{N} r_{Mj}(t)}{N} \qquad j = 1,.2,...N \tag{3}$$

Numerous examples in the literature have illustrated that the EEMD process has powerful

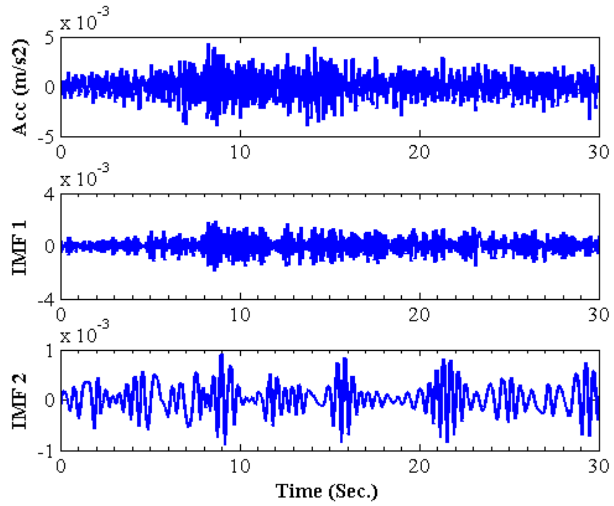

Fig. 2 EEMD of the first floor acceleration; (a) accelerations; (b) the first IMF; (c) the second IMF

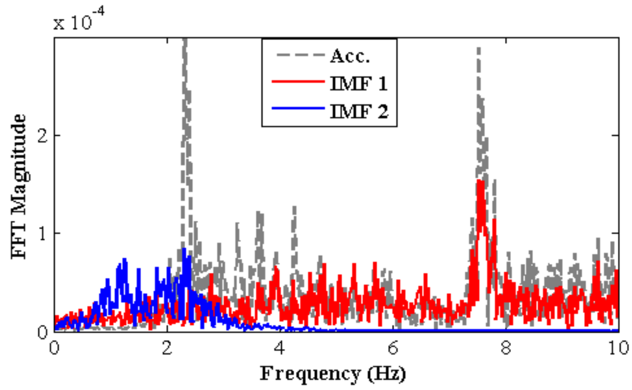

Fig. 3 FFT plots of the IMFs of the first floor accelerations

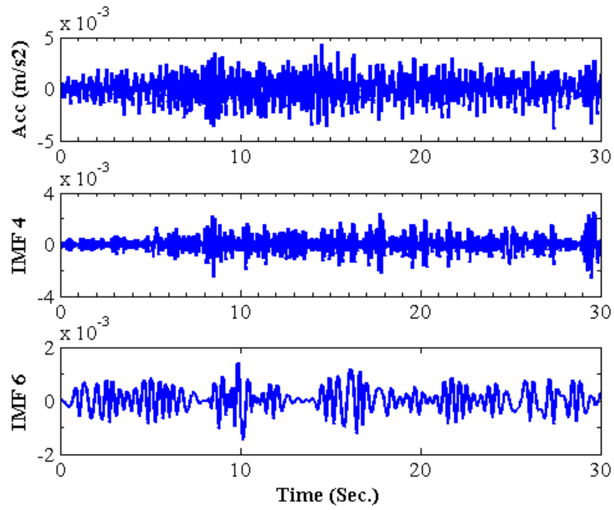

Fig. 4 EEMD of the second floor acceleration; (a) accelerations; (b) the first IMF; (c) the second IMF

property to decompose natural signals to unique IMFs.

Fig. 2(a) plots the acceleration time history of the first floor of the 2-DOF structure described above. An EEMD Matlab toolbox is utilized to decompose it to a set of IMFs, two of which are plotted in Figs. 2(b) and (c). Fast Fourier Transforms of the original data and the IMFs are performed as shown in Fig. 3, which clearly illustrate that each IMF has similar scale corresponding to structural frequency. Similarly, Figs. 4 and 5 show the IMFs of the second floor accelerations and their spectral. It is seen that the structural accelerations have been successfully decomposed to a set of IMFs with energy in narrow frequency bands.

2.2 The Sub-PolyMAX method

As described above, the traditional PolyMAX method identifies modal parameters by minimizing the FRF estimate errors in the whole frequency range, which leads to inaccurate identification results especially for those in the modes with much smaller FRF peaks. It is seen in last section that the EEMD process automatically decomposed structural accelerations to a set of IMFs which are frequency modulation components, thus it is potential to use the IMFs as primary data to perform the Sub-PolyMAX method in narrow frequency bands, which is faster and is able to produce more accurate identification results than the traditional PolyMAX method.

By using the IMFs instead of accelerations as primary data, structural modal parameters are identified from the Sub-PolyMAX method. The details of the method are referred to Zhang *et al.* (2012). The stabilization diagram is used to separate real and spurious modes. Its basic idea is that several runs of the complete pole identification process are made, by using models of increasing order. The pole values of the true eigenmodes always appear at a nearly identical frequency, while false poles tend to scatter around the frequency range. Figs. 6(a) and (b) show the stabilization diagrams from the Sub-PolyMAX method by taking the IMFs in the first and second modes at primary data, respectively. The blue curves in Fig. 6 are FFT plots of the first floor acceleration to provide structural modal information as a reference. It is seen that each Sub-PolyMAX running produces a stable solution in a mode, unlike the traditional PolyMAX method which identifies structural parameters in all modes once. The identified frequencies for the first and second modes are 2.35 Hz and 7.57 Hz, compared to the real frequencies of 2.36 Hz and 7.60 Hz, respectively. The MAC values for the identified mode shapes are 0.99 and 0.95, respectively. After modal

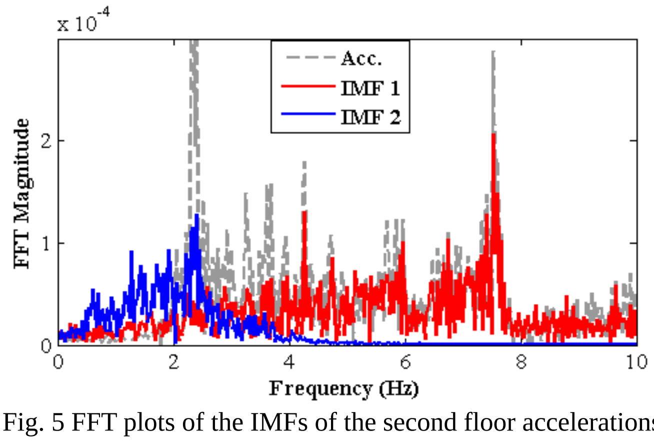

Fig. 5 FFT plots of the IMFs of the second floor accelerations

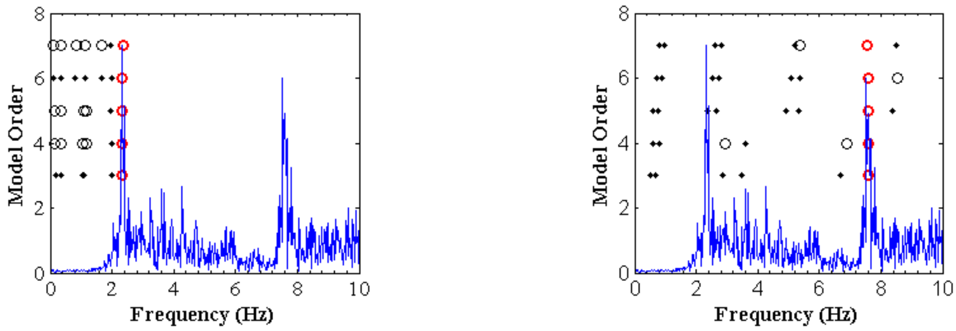

Fig. 6 Stabilization diagrams, (a) the first mode and (b) the second mode (the cycles denotes stable poles, the point denotes unstable poles)

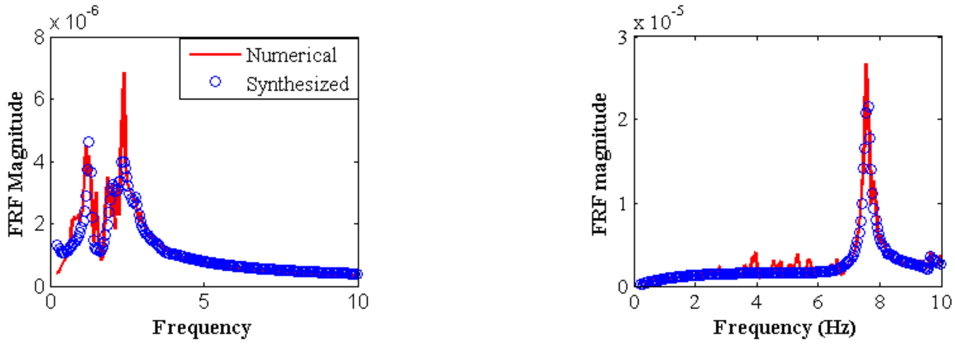

Fig. 7 Synthesized and estimated FRF comparison; (a) the first mode and (b) the second mode

Fig. 8 The investigated continuous steel bridge

parameters are identified, the FRF values are synthesized and compared with the estimated FRF as a way to evaluate the accuracy of the modal identification results. Figs. 7(a) and (b) illustrate that the synthesized FRF curves from the Sub-PolyMAX method have very good agreements with the estimated FRF curves at both modes.

3. Modal ientification of a continuous seel bridge

Modal identification of a real bridge is further investigated to verify the effectiveness of the proposed method. This bridge is a 6-span continuous bridge (Fig. 8) with a length of 944 m. Construction of this bridge is just finished and it has not been open. It has steel box girders with varying sections and reinforced concrete piers. The central pier is connected to the span with earthquake resistant support, while other piers are partially connected to the span allowing sliding in the longitudinal direction. The deck has a width of 33 m with six lanes in two directions, and the allowed maximum vehicle velocity is 100 km/h. The bridge has long approach structures however

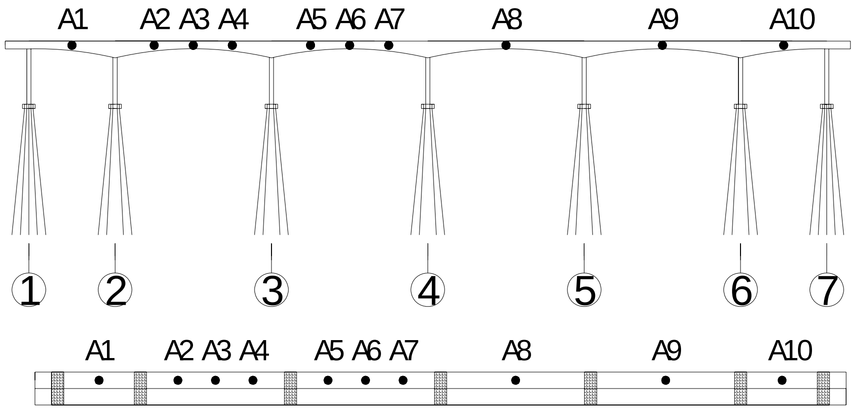

Fig. 9 The instrument plan

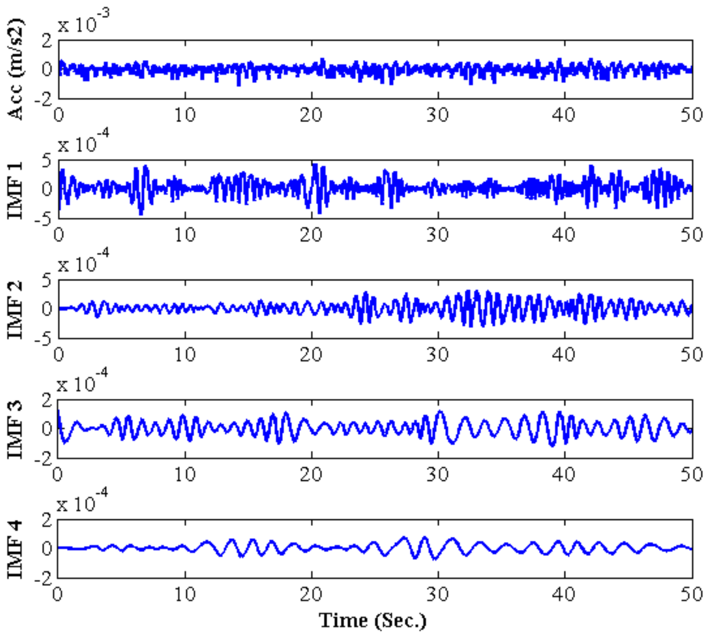

Fig. 10 EEMD of a measured acceleration time history

they are not studied in this study. Ambient vibration test of the bridge has been performed with the instrument plan as shown in Fig. 9. The vibration signals were recorded with a sampling rate of 50 Hz during the testing, and the analog signals were subject to a 10 Hz anti-aliasing filter before they were digitized.

The observed accelerations at 8 locations are processed by the proposed method for modal identification. The EEMD code is first run in the Matlab environment to decompose each acceleration time history to a set of IMFs in the time domain. For instance, Fig. 10(a) shows the acceleration measured at point A in Fig 8. Typical IMFs of this acceleration produced from the EEMD process are plotted in Figs. 10(b), (c), and (d) respectively. It should be noted that only some of the IMFs are plotted here where others are neglected. It is seen from Fig. 10 that each IMF has its special frequency character. The FFT plots of these IMFs further illustrate this feature as shown in Fig. 11, in which the IMFs centered their energy at different frequency bands. It means that the EEMD process has successfully decomposed the original measurement to a series of IMFs with frequency modulation components.

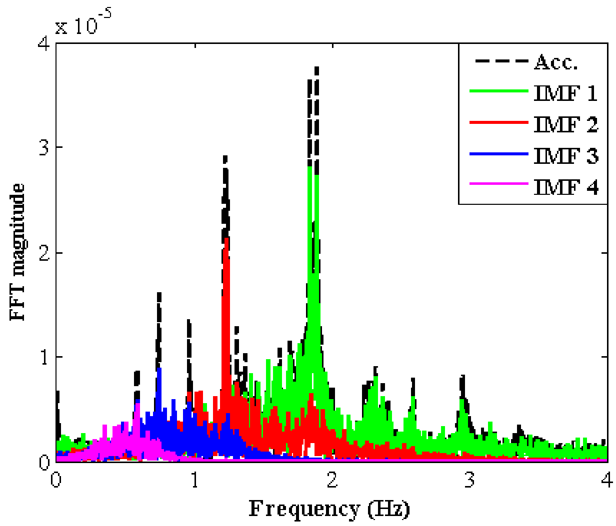

Fig. 11 FFT plots of the IMFs

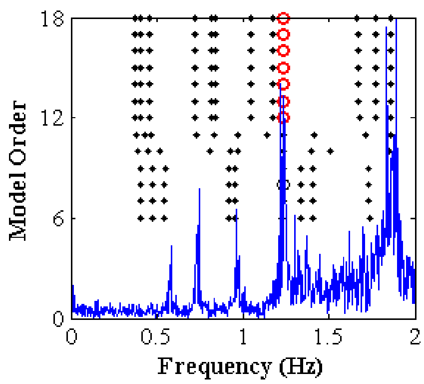

Fig. 12 Stabilization diagram

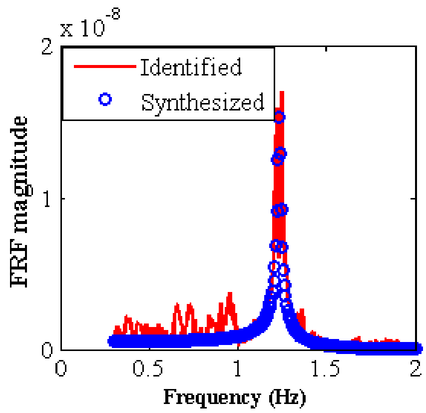

Fig. 13 Synthesized and identified FRF comparison

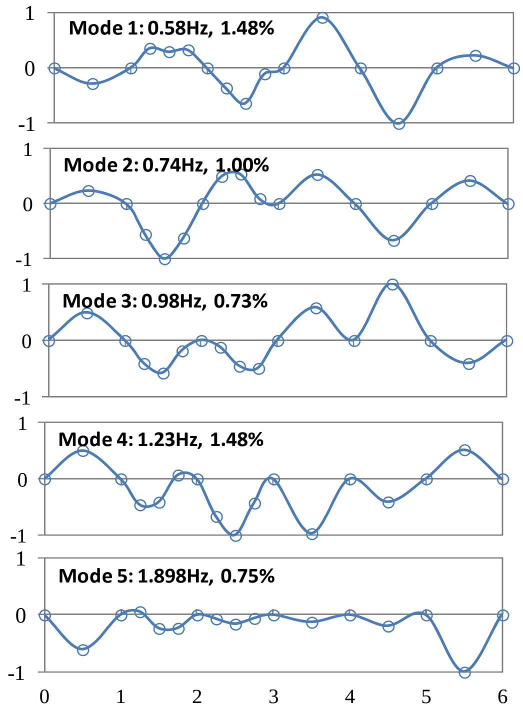

Fig. 14 Modal identification results of the continuous bridge

After the ensemble empirical modal decomposition of the measured accelerations, the Sub-PolyMAX method is performed by taking the IMFs as primary data to identify structural modal parameters from one narrow frequency band to another until parameters in all modes are identified. For instance, Fig. 12 shows the stabilization diagram when using the IMF 2 as primary data in the Sub-PolyMAX method. It is seen that the calculated polynomial poles near the 1.23 Hz are stable, thus structural modal parameters in this mode are identified. The synthesized and estimated FRF for this mode also agreed very well as shown in Fig. 13. Figs. 12 and 13 illustrate the Sub-PolyMAX method has successfully been performed in a narrow frequency band by integrating the EEMD concept to decompose the original measurements. Similarly, by performing the proposed method on other IMFs as primary data, structural parameters of the multiple-span continuous bridge in the first five modes are identified. Each IMF produces structural parameters in one mode, except that the IMF 3 produces structural parameters in both the second and the third modes. The identified structural frequencies, damping ratios and mode shapes are shown in Fig. 14. It should be noted that even the measured accelerations are very weak because the bridge is still not open during the ambient test, structural modal parameters has been successfully identified from the proposed method.

4. Conclusions

A procedure integrating the EEMD method with the Sub-PolyMAX method has been proposed for accurate structural modal identification. The following conclusions are drawn:

(a) The EEMD process decomposes the original measurement to a set of IMFs with special frequency characters, which enable the Sub-PolyMAX method to identify structural parameters in narrow frequency bands by taking the IMFs as primary data, unlike the traditional PolyMAX method which solves structural parameters by minimizing the FRF estimate errors in the whole frequency space.
(b) A multiple-span continuous bridge example has been investigated, whose results demonstrates that the proposed method successfully identify structural modal parameters even though the ambient test data are very weak.
(c) Some details need further investigation in the future work. For instance, the EEMD procedure needs much computation time because a number of trials are required to cancel out noise. The work to improve the EEMD efficiency needs further exploration. In addition, the parameters including the noise level and the trial number needed in the EEMD running may affect the decomposition results. How to select those parameters needs further investigation.

Acknowledgements

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References

ASCE (2012), *Structural Identification of Constructed Facilities: Approaches, Methods and Technologies for Effective Practice of St-Id*, A State-of-the-Art Report. ASCE SEI Committee on Structural Identification of Constructed Systems, In Press.

Browne, T.J., Vittal, V., Heydt, G.T. and Messina, A.R. (2008), “A comparative assessment of two techniques for modal identification from power system measurements”, *IEEE T. Power Syst*., **23**(3), 1408-1415.

Brownjohn, J.M.W., Magalhaes, F., Caetano, E. and Cunha, A. (2010), “Ambient vibration re-testing and operational modal analysis of the Humber Bridge”, *Eng. Struct*., **32**(8), 2003-2018.

Catbas, F.N., Brown, D.L. and Aktan, A.E. (2004), “Parameter estimation for multiple-input multiple-output modal analysis of large structures”, *J. Eng. Mech.- ASCE*, **130**(8), 921-930.

Conte, J.P., He, X., Moaveni, B., Masri, S.F., Caffrey, J.P., Wahbeh, M., Tasbihgoo, F., Whang, D.H. and Elgamal, A. (2008), “Dynamic testing of Alfred Zampa Memorial Bridge”, *J. Struct. Eng.- ASCE*, **134**(6), 1006-1015.

Flandrin, P., Rilling, G. and Gonçalvés, P. (2004), “Empirical mode decomposition as a filter bank”, *IEEE Signal Proc. Let*., **11**(2), 112-115.

Huang, N.E., Shen, Z. and. Long, S.R. (1998), “The empirical ode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis”, *P. Roy. Soc. London. A*, **454**, 903-995.

Huang, N.E. and Wu, Z. (2008), “A review on Hilbert-Huang Transfrom: method and its applications to geophysical studies”, *Rev. Geophys*., **46**, RG2006, 1-23.

Grimmelsman, K.A., Pan, Q. and Aktan, A.E. (2007), “Analysis of data quality for ambient vibration testing of the Henry Hudson Bridge”, *J. Intell. Mater. Syst. Struct*., **18**(8), 765-775.

Ko, J.M., Sun, Z.G. and Ni, Y.Q. (2002), “Multi-stage identification scheme for detecting damage in cablestayed Kap Shui Mun Bridge”, *Eng. Struct*., **24**(7), 857-868.

Lin, S., Yang, J.N. and Zhou, L. (2005), “Damage identification of a benchmark building for structural health monitoring”, *Smart Mater. Struct*., **14**(3), 162-169.

Loh, C.H., Weng, J.H., Liu, Y.C., Lin, P.Y. and Huang, S.K. (2011), “Structural damage diagnoisis based on on-line recursive stochastic subspace identifcation”, *Smart Mater Struct*., **20**(5).

Moon, F.L. and Aktan, A.E. (2006), “Impacts of epistemic (bias) uncertainty on structural identification of constructed (civil) systems”, *Shock Vib*., **38**, 399-420.

Nagayama, T., Fujino, Y., Abe, M. and Ikeda, K. (2005), “Structural identification of a nonproportionally damped system and its application to a full-scale suspension bridge”, *J. Struct. Eng.- ASCE*, **131**(10), 1536-1545.

Nagarajaiah, S. and Basu, B. (2009), “Output only modal identification and structural damage detection using time frequency & wavelet techniques”, *Earthq. Eng. Eng. Vib*., **8**(4), 583-605.

Pakzad, S.N. and Fenves, G.L. (2009), “Statistical analysis of vibration modes of a suspension bridge using spatially dense wireless sensor network”, *J. Struct. Eng.- ASCE*, **135**(7), 863-872.

Pan, Q., Grimmelsman, K., Moon, F. and Aktan, E. (2012), “Mitigating epistemic uncertainty in structural identification”, *J. Struct. Eng.- ASCE*, In Press.

Peeters, B., Auweraer, H.V., Guillaume, P. and Leuridan, J. (2004), “The PolyMAX frequency-domain method: a new standard for modal parameter estimation”, *Shock Vib*., **11**(3-4), 395-409.

Peeters, B. and Roeck, G.D. (2001), “One-year monitoring of the Z24-Bridge: environmental effects versus damage events”, *Earthq. Eng. Struct. D*., **30**, 149-171.

Reynders, E., Pintelon, R. and De Roeck, G. (2008), “Uncertainty bounds on modal parameters obtained from stochastic subspace identification”, *Mech. Syst. Signal Pr*., **22**(4), 948-969.

Siringoringo, D.M. and Fujino, Y. (2008), “System identification of suspension bridge from ambient vibration response”, *Eng. Struct*., **30**(2), 462-477.

Verboven, P. (2002), *Frequency-domain system identification for modal analysis*, Ph.D. Dissertation, Vrije University Brussel, Belgium

Wu, Z. and Huang, N.E. (2008), “Ensemble empirical modal decomposition: A noise assisted data analysis method”, *Adv. Adapt. Data Anal*., **1**(1), 1-41.

Xu, Y.L., Chen, S.W. and Zhang, R.C. (2003), “Modal identificaiton of Di Wang Building under typhoon york using the Hilbert-Huang Transfrom method”, *Struct. Des. Tall Spec*., **12**, 21-47.

Yan, B.F. and Miyamoto, A. (2006), “A comparative study of modal parameter identification based on wavelet and Hilbert-Huang Transforms”, *Comput. Aided Civil Infrastruct. Eng*., **21**(1), 9-23.

Yang, J.N., Lei, Y. and Huang N. (2004), “Hilbert-Huang based approach for structural damage detection”, *J. Eng. Mech.-ASCE*, **130**(1), 85-96.

Yu, D.J. and Ren, W.X. (2005), “EMD-based stochastic subspace identification of structures from operational vibration measurements”, *Eng. Struct*., **27**(12), 1741-1751.

Zhang, J., Yan, R., Gao, R. and Feng, Z. (2010), “Performance enhancement of ensemble empirical mode decomposition”, *Mech. Syst. Signal Pr*., **24**(7), 2104-2123.