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A NEWER TIME-FREQUENCY DECOMPOSITION-BASED MODAL IDENTIFICATION TECHNIQUE FOR STRUCTURES

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Abstract: In last few decades, vibration-based structural health monitoring has gained significant popularity to perform condition assessment of civil structures. A wide range of system identification methods has been developed by different researchers to identify modal parameters accurately from the measured vibration data. One of the time-frequency methods, namely empirical mode decomposition (EMD), has been very popular owing to its basis-free nature and applicability to any nonlinear and nonstationary signals of dynamical systems. However, the EMD results in significant mode-mixing in the separated signals that causes inaccuracies in the estimated modal parameters. In this paper, two different newer classes of EMD methods are explored and compared to undertake ambient modal identification using just single channel measurement. The proposed method is perfectly suitable for automation and has significant potential for real-time monitoring since it uses only one channel of data at a time. The performance of the proposed EMD method is verified using a suite of numerical and experimental studies.

1 INTRODUCTION

Large-scale infrastructure such as bridges, buildings, wind turbines, dams and tall towers may lose structural integrity due to exposure to severe earthquakes, strong winds or other operational loads. Structural Health Monitoring (SHM) is an essential tool to evaluate the current state of the structure, predict the future damage, and conduct appropriate maintenance and retrofitting. SHM is primarily consisted of sensor-intensive data collection and signal processing-based system identification followed by condition assessment and hazard mitigation. In this paper, two different classes of signal processing methods are explored as a possible tool for modal identification of civil structures.

System identification (SI) addresses the problem of deriving mathematical models to describe dynamical systems based on the observed measurement of civil and mechanical structures (Reynders 2012). Consequently, condition assessment and retrofitting are undertaken based on current modal parameters of the structures. In spite of significant development of a wide range of modal identification methods, time-frequency (TF) analysis is considered as a prominent SI method that shows the variation of modal parameters in time and frequency domain simultaneously. Linear TF methods include short-time Fourier transforms (STFTs), and wavelet transforms (WTs), whereas most quadratic methods are variations of the Wigner-Ville distribution and Cohen's class distribution. However, none of these approaches leads to a unique transform that can be used in all scenarios independent of its own characteristics. Due to the uncertainty relation that links time and frequency, the results from any transformation depend not only on the intrinsic characteristics of the signal but also on the properties of the chosen transform (Auger *et al.* 2013). In last two decades, time-frequency domain methods have acquired a considerable interest, particularly in civil and mechanical systems. Wavelet transform (Hou *et al.* 2000), blind source separation (BSS) (Sadhu *et al.* 2017) and EMD (Huang *et al.* 1998) are used as modal identification techniques for large-scale civil infrastructure.

EMD is one of the popular time-frequency domain methods which is a data-driven in nature that does not require any basis functions and can work with nonlinear and nonstationary signals (Li *et al.* 2017). EMD decomposes the signal into a set of oscillatory waveforms known as intrinsic mode functions (IMF). IMFs are extracted by using successive averaging and interpolation steps which are known as *sifting* operation. However, sifting operations cause considerable mode mixing in the IMFs. Recently, many studies are developed within EMD to solve this issue. (Qin *et al.* 2015) developed an output-only modal analysis method using improved EMD to solve mode-mixing problems with closely spaced frequencies. Wavelet-bounded empirical mode decomposition was used to solve the problem of mode mixing in EMD (Moore *et al.* 2018). (Zhang *et al.* 2012) developed a frequency modulated EMD to determine the variations in the modal parameters of a bridge-air system. (Li *et al.* 2007) combined EMD and wavelet transform for damage detection. Multi-variate EMD was explored with ensemble EMD (Sadhu 2017) and BSS (Barbosh *et al.* 2018) to alleviate mode-mixing in multichannel measurements. Synchro-squeezing transform (SST) was considered as an evolved EMD with reassignment allowing reconstruction of the signal (Daubechies *et al.* 2010). This article presents the theoretical background and application of the newer EMD methods that can be considered as a potential modal identification method for civil structures. The novel aspect of the presented techniques lies in improving the frequency separation performance, as well as achieving stability under lower sampling rates. On the similar lines, the SST improves the traditional CWT by re-allocating each value of the original transform to a new frequency during squeezing on the time-frequency plane.

2 NEWER CLASS OF EMD

2.1 Empirical mode decomposition

The empirical mode decomposition (EMD) is a popular method which is a unique time-frequency domain method to decompose a signal that could be nonlinear and nonstationary in nature. In general, EMD decomposes the signal into a set of oscillatory waveforms known as intrinsic mode functions (IMF). An IMF is a function that satisfies following two conditions (Huang et al. 1998):

(a) In the whole data set, the number of extrema and the number of zero crossings must be either equal or differ but not more than one.
(b) At any point, the average of the envelope set by the local maxima and the envelope set by the local minima is zero.

The fundamental steps of EMD to decompose a signal $y(t)$ are as follows (Huang et al. 1998):

1. Select all the local extrema then prepare a cubic spline line on all of the local minima and local maxima as the lower and upper envelopes. All the data between them have to be covered by the lower and upper envelopes. Their mean is denoted as k_1 and the difference between the data $y(t)$ and $k_1$is defined by

$$[1]\; h_1 = y(t) - k_1$$

If h_1 satisfies the two conditions of IMF that are mentioned above, then h_1 should be the first IMF of signal $y(t)$.

2. Otherwise, presume h_1 as the original data $y(t) = h_1(t)$ and repeat the sifting process with $imf_1 = h_1$ until the requirements are realized, and the first IMF is obtained.

3. $y(t)$ is then deducted from the IMF and another IMF is obtained by applying the sifting process again to the remaining signal. The process is reiterated to gain *n* IMFs, as shown in:

$$[2]\; y(t) = \sum_{j=1}^{n} imf_j(t) + p_n(t)$$

Where $imf_1(t)\;(i = 1,2, \ldots\ldots, n)$ represents the IMFs of the signal $y(t)$ from high to low frequency components and each $imf_j(t)$ includes a different frequency component. p_n is the mean residual trend of the signal or a constant.

2.2 Time-Varying Filter EMD (TVF-EMD)

In traditional EMD method, the estimation of the local mean can be observed as a unique form of low pass filtering (Flandrin *et al.* 2004). In Time-Varying Filtering-based EMD method (TVF-EMD), a B-spline approximation is adopted as a TVF which is easier to be constructed from the filter cut-off frequency. In general, B-splines is mostly used as an interpolation tool. However, a B-spline approximation is used as a filter in the TVF-EMD method, whose cut-off frequency is time-varying. The B-spline approximation creates polynomial splines that approximate the input signal and uses B-spline functions which are piecewise polynomials. In order to form the desired signal, the polynomial portions are joined together. The joining points of the polynomial sections are denoted as knots. Every signal (i.e., IMF) in B-spline space is determined by (Li *et al.* 2017)

$$[3]\ g_m^n(t) = \sum_{j=-\infty}^{+\infty} r(j)\,\beta^n\,(t/m - j)$$

Where $r(j)$ is the B-spline coefficients and it is enlarged by a factor of m. The signal (or approximation result) is determined by n, m, and $r(j)$. Therefore, given the B-spline order and knots, the B-spline approximation is used to determine the B-spline coefficients $r(j)$ that minimizes the approximation error. Let $b_m^n\,(t) = \beta^n\,(t/m)$ and the asterisk denotes the convolution operator, For any signal $y(t)$, $r(j)$ is determined by minimizing the approximation error ε_m^2:

$$[4]\ \varepsilon_m^2 = \sum_{t=-\infty}^{+\infty} (\,y(t) - [r]_{\uparrow m} \times b_m^n(t))^2$$

where $[\,.\,]_{\uparrow m}$ is the up-sampling operation by *m*.

2.3 Synchro-squeezing transform (SST)

The majority of time-frequency decomposition methods fall under linear or quadratic methods. However, with few setbacks due to lack of interpretation or reconstruction of signals in case of quadratic methods (Daubechies *et al.* 2010), advancements are always sought to improve time-frequency representation. A general SST is an adaptive and invertible transform developed to improve the quality or readability of the wavelet-based time-frequency representation by squeezing it along the frequency axis. It is a particular case of relocation methods which aim to sharpen a time-frequency representation by allocating its value to a different point in the time-frequency plane determined by the local behaviour. The SST uses these steps (Deubechies *et al.* 2010):

1. Obtain the continuous wavelet transform (CWT) of the input signal. The CWT must be an analytical wavelet to capture instantaneous frequency information.
2. Extract the instantaneous frequencies from the CWT output, W_f, using a phase transform, ω_f. This phase transform is proportional to the first derivative of the CWT with respect to the translation, *u*. In this definition of the phase transform, *s* is the scale.

$$[5]\ \omega_f(s,u) = \frac{\partial t W_f(s,u)}{2\pi i W_f(s,u)}$$

The scales are defined as $s = \frac{f_x}{f}$, where f_x is peak frequency and f is the frequency.

3. "Squeeze" the CWT over regions where the phase transform is constant. The resulting instantaneous frequency value is reassigned to a single value at the centroid of the CWT time-frequency region. This reassignment results in a sharpened output from the SST when compared to the CWT.

Recently (Mihalec *et al.* 2016) studied the usability of SST in obtaining damping ratio of a vibrating system, whereas (Hazra *et al.* 2017) investigated bearing fault diagnosis using the SST. However, there has been a limited research on the applicability of SST for structural health monitoring application, particularly in the vibration-based health monitoring of civil infrastructure.

3 NUMERICAL STUDIES

In this section, a three degrees-of-freedom (DOF) model is used to explore the applicability of TVF-EMD and SST on a dynamic system. The lumped mass and stiffness are assumed to be 144 tonnes, and 2×10^8 N/m, respectively in each floor. The natural frequencies of this model are 2.66, 7.45 and 10.76 Hz, respectively. The dynamic system was excited at its base using Imperial Valley earthquake. Fig. 1 shows Fourier spectra of the 3-DOF model, whereas the signal decomposition of the SST is shown in Fig. 2. As shown in the figures, the third mode has significantly low energy and it is not delineated by the SST in Fig. 2.

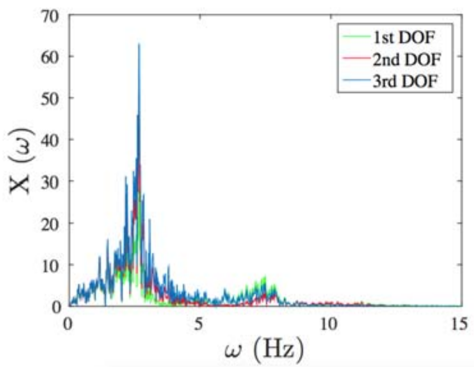

Figure 1: Fourier spectrum of the floor vibration data

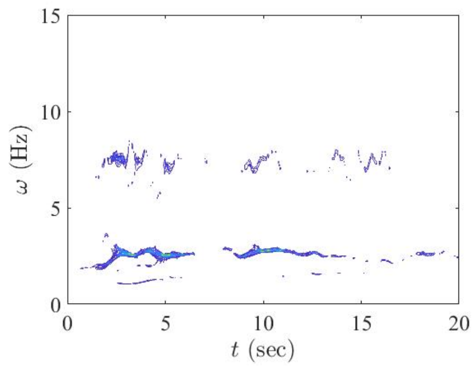

Figure 2: SST of the vibration data

Fig. 3 shows IMFs obtained from the second-floor vibration measurements by using the TVF-EMD method. It is clearly seen that all IMFs are mono-component signal and the TVF-EMD method has successfully separated the modal responses of the model even with extremely low energy modes. Once the modal responses are obtained, auto-correlation function of modal responses is used to extract modal damping ratio as shown in Fig. 4. The true and estimated frequencies as obtained from the TVF-EMD and SST are compared and shown in Table 1.

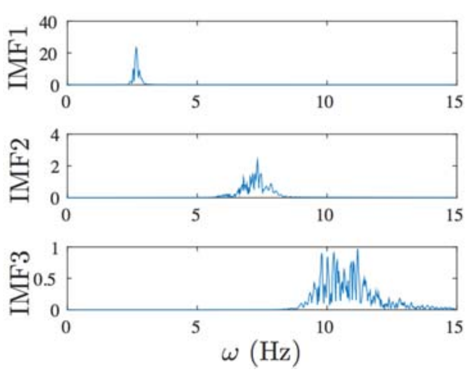

Figure 3: IMFs obtained from the TVF-EMD

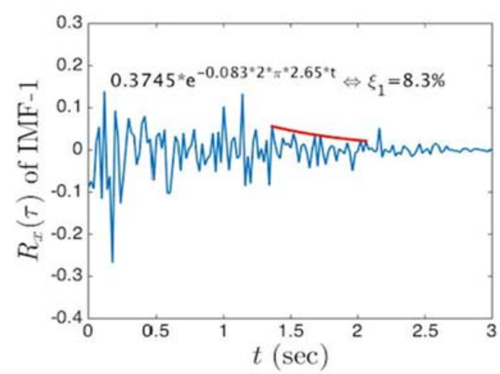

Figure 4: Estimation of damping ratio of IMF-1

Table 1. Identification results (frequencies in Hz) of the EMD methods

Mode #	ω_1	ω_2	ω_3
Analytical	2.66	7.45	10.76
TVF-EMD	2.65	7.33	10.26
SST	2.79	7.55	-

4 EXPERIMENTAL RESULTS

In this section, a six-story experimental model as shown in Fig. 5 is utilized to demonstrate the proposed method. The mass of first three floors is 2.47 Kg for each, and the other three floors have masses of 1.12 kg. In order to collect the vibration data, the model was placed on a shake table, and the shaking table was connected to a shaker as shown in Fig. 5. The data was collected by using a wireless sensor that was placed in the middle of the fourth floor. The model was excited using a random shaking for 30 seconds via a control system attached to the modal shaker, and then the data was collected using the sensor at a sampling frequency of 200 Hz. Finally the data is analyzed using the TVF-EMD and SST methods. Fig. 6 shows the Fourier spectrum of fourth floor response. The theoretical frequencies and frequencies obtained from the TVF-EMD and SSI are shown in Table 2.

Figure 5. Experimental model

Fig. 7 shows the IMFs of the fourth floor measurement obtained from the TVF-EMD. It can be observed that the TVF-EMD method has extracted the mono-component modal responses successfully. However, the SST method could not delineate all the natural frequencies. For example, the first three modes with low energy content are not identified by the SST in Fig. 8.

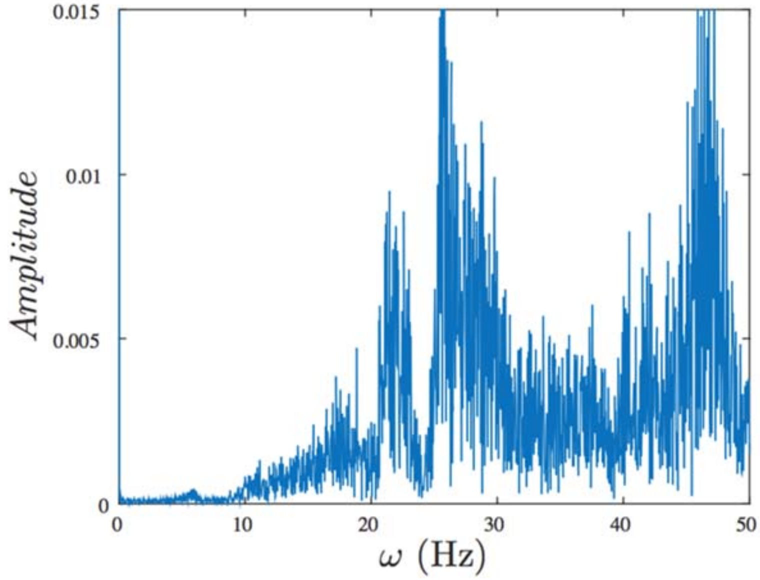

Figure 6. Fourier spectrum of the floor vibration data

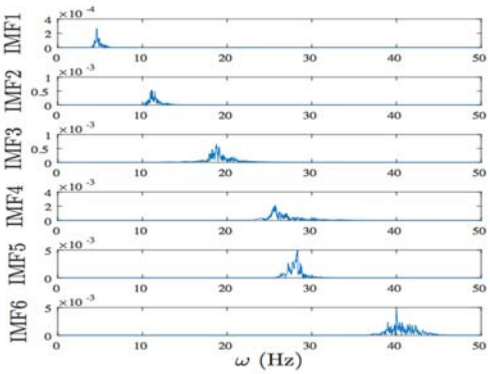

Figure 7. IMFs obtained from TVF-EMD

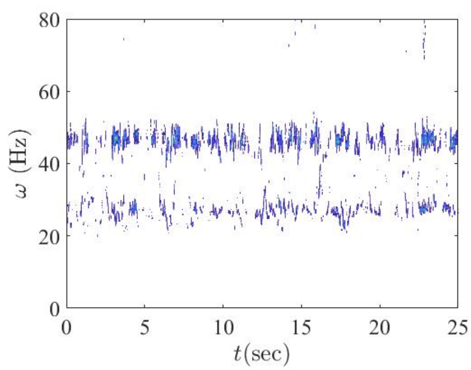

Figure 8. SST of the floor vibration data

Table 2. Identification results (frequencies in Hz) of the experimental model

Mode #	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6
Analytical	4.6	11.3	18.6	25.6	28.8	39.2
TVF-EMD	4.6	11.2	18.8	25.7	28.3	40.0
SST	-	-	-	26.0	29.2	45.01

5 CONCLUSIONS

In this paper, two different EMD methods are utilized as a possible tool for modal identification method using a single channel measurement. Both the methods, TVF-EMD and SST, are validated using a numerical simulation and an experimental model subjected to random base excitation. The TVF-EMD method shows excellent capabilities of identifying structural modes with low energy content, however the performance of the SST method is shown to be limited only to higher energy modes. The limitation of SST method is attributed to the instability arisen while squeezing the frequencies of the CWT. As a result, a low energy signal with noise compromises the capability of SST to extract low energy modes. Future work is reserved to validate the performance of these methods under a wide range of dynamical systems as well as full-scale structures. Since TVF-EMD method is capable of identifying modal parameters using just a single sensor, it could be considered as a potential system identification tool for real-time SHM in decentralized or mobile sensing network. In future, with the aid of a reference sensor, modeshape estimation will be pursued using the TVF-EMD.

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