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DETECTION OF PROGRESSIVE DETERIORATION OF STRUCTURES USING WAVELET TRANSFORM

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Abstract: Condition assessment of aging structures is of significant importance in detecting structural deterioration that could result in loss of serviceability or structural failure. Over last few decades, modal identification has shown to be an effective method of identifying structural damage. In particular, assessment of discrete and sudden damage has been widely researched. However, initial damage may progressively worsen over time causing an increasing risk of failure in a structure. The time-variant nature of progressive damage makes it difficult to detect faults using traditional methods. Several time-frequency signal-processing methods have shown success in identifying progressive changes by tracking the modal parameters. In this paper, the authors propose continuous Cauchy wavelet transform (CCWT) for detecting progressive damage in structural systems. The Cauchy mother wavelet is selected due to its strong frequency resolution rendering its capability of capturing subtle frequency variations with time. Performance of the CCWT is then validated using several numerical studies.

Keywords: Modal identification; continuous wavelet transform; Cauchy wavelet; progressive damage

1 Introduction

Buildings, bridges and many other large civil infrastructure are subjected to a wide range of loads over their lifecycle. Such time-varying and repeated cyclic loads cause significant deterioration in structural strength. Manual and visual inspection in large structure are costly and time consuming matter. Most recently structural health monitoring (SHM) has come to the forefront as an effective method of damage detection. Vibration based SHM methods (Amezquita-Sanchez and Adeli 2016) are important to detect local as well as global damage that cannot be identified using traditional methods.

Modal identification (Maia and Silva 2001) is a key component of SHM where modal parameters (i.e, frequency, damping and mode shapes) are extracted directly from vibration measurements. The central idea of these techniques is that structural damage causes changes in these modal parameters. Development of modal identification techniques was initiated as input-output analysis in the 1970’s. Due to the feasibility of sensor placement and cost of data collection, output-only methods are more suitable to large structures. While many SHM techniques have been studied, there has been a limited amount of research towards detection of progressive damage of structures.

Recently structural changes due to discrete damage are analyzed using the combination of wavelet transform followed by generalized discrete Teager-Kaiser energy operator (Ulriksen and Damkilde 2016) to locate and quantify damage. Similar studies are performed using wavelet packet transform (Sun and Chang 2004) under pulse loading. Damages due to time-varying and non-stationary excitation are identified using recursive combined subspace identification method (Zhong and Chang 2016), Hilbert transform (Huang et al. 1998), random decrement (Liu et al. 2016), parallel factor decomposition (Friesen and Sadhu 2016), empirical mode decomposition (Darryl and Liming 2006; Sadhu 2015; Bibhas et. al. 2017), and blind source separation techniques combined with auto regressive time-series (Sadhu and Hazra 2013, Musafere et al. 2015; Sadhu et. al. 2017). However, none of the above studies investigates the effects of progressive damage. Recently Valdes-Gonzalez et al. (Valdes-Gonzalez et al. 2015) correlated an undamaged structure with a progressively damaged structure using frequency response functions. A recursive least squares algorithm (Klepka and Uhl 2014) in combination with adaptive wavelet filtration adjusts the wavelet according to the changes in the system, allowing for better tracking of damage.

This paper seeks to demonstrate the ability of continuous Cauchy wavelet transforms (CCWT) for a structure with progressive damage. The continuous wavelet transform (CWT) is a highly adaptable (Amezquita-Sanchez and Adeli 2016) signal processing technique that is used for many applications such as signal noise filtering, image compression, and medical signal processing. Argoul and Le (Argoul and Le 2003) used Cauchy wavelets to test non-linear beam response under an impact force. In this paper, CCWT is explored further to detect time-varying damage in structural systems.

2 Background of CCWT

The Fourier transform is the classical tool for determining the frequency content of a system. One shortcoming of Fourier transform is the lack of its time information that is essential to detect progressive damage. Short-time Fourier transform decomposes a signal into smaller windows and perform frequency domain analysis in each time window. However, there are issues of frequency resolution caused by limiting the size of the window. Use of a wavelet with a limited length helps improving the frequency resolution. Continuous wavelet transform (CWT) is used to separate mixed signals into their components as well as filtering out noise. CWT is given by:

[1] $$Wf(s,\tau) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{s}}\varphi^*\left(\frac{t-\tau}{s}\right)dt$$

Where, s and τ represent scale and translation of the mother wavelet, respectively. s relates to frequency scale, where a larger s relates to a low frequency and smaller s relates to a high frequency. At a location where the signal's spectral component is similar in scale to the value s, the product between the wavelet and signal will be higher. The wavelet shifts along the signal to locate the frequencies within the time domain. The basis function is called 'mother wavelet' $\varphi(t)$. In this paper, Cauchy mother wavelet is used in Eq (2) owing to its strong performance under frequency-modulated signals (Munoz et al. 2003). Fig. 1 shows the Cauchy mother wavelet where the single peak is well suited to signals with non-stationarity in frequency.

[2] $$\varphi_n(t) = \left(\frac{i}{t+i}\right)^{n+1}$$

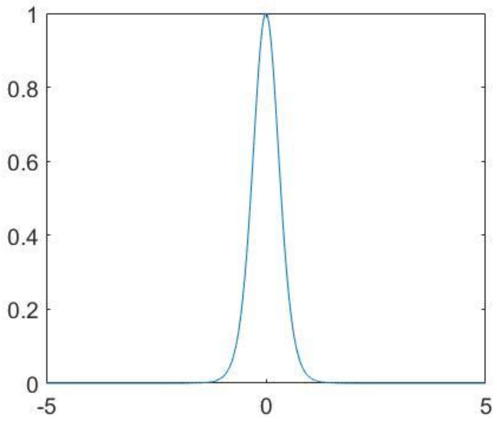

Figure 1: Cauchy mother wavelet

Fig. 2 shows the CCWT of a sine signal that undergoes an instantaneous change in frequency from 8 to 10 Hz as well as a sine sweep signal between 3.0 and 8.0 Hz with 20% noise contamination. The CCWT performs well under both discrete and progressive frequency changes. The results show that the CCWT tracks the signal quite well with the exception of distortion in boundary that cause end-effects similar to previous studies (Depczynski et al. 1999). This ability makes it well suited for identifying progressive damage in structural systems.

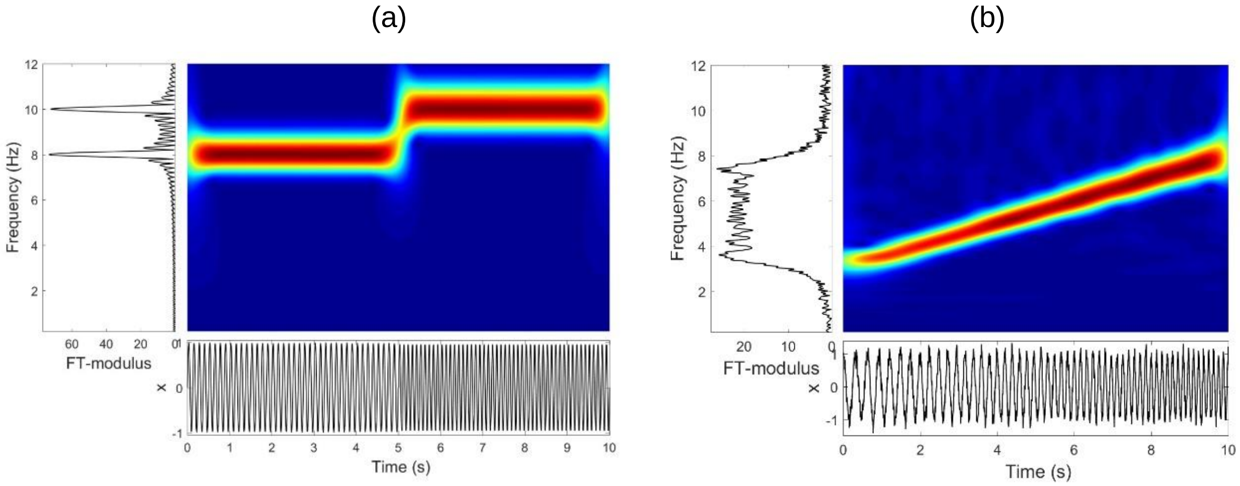

Figure 2: The results of CCWT (a) sine signal changing from 8 to 10 Hz and (b) sine sweep from 3 to 8 Hz with 20% noise

3 Numerical Analysis

A single degree-of-freedom (DOF) system is first selected to test the performance of CCWT. A 10 kg model has a stiffness reduction form 5000 to 1000 N/m. The model has undamaged and damaged natural frequency as 3.56 Hz and 1.59 Hz, respectively. Fig. 3 shows the performance of CCWT using the vibration response of the SDOF model subjected to a harmonic frequency of 2.6 Hz and 5 Hz in Fig. 3(a) and Fig. 3(b), respectively. An increase in amplitude can be seen in Fig. 3(a) as the system's natural frequency matches with the forcing frequency at 65 seconds whereas Fig 3(b) does not have a significant amplitude increase. Therefore, the CCWT provides a better picture of what is happening to the system than any other frequency or time-domain methods.

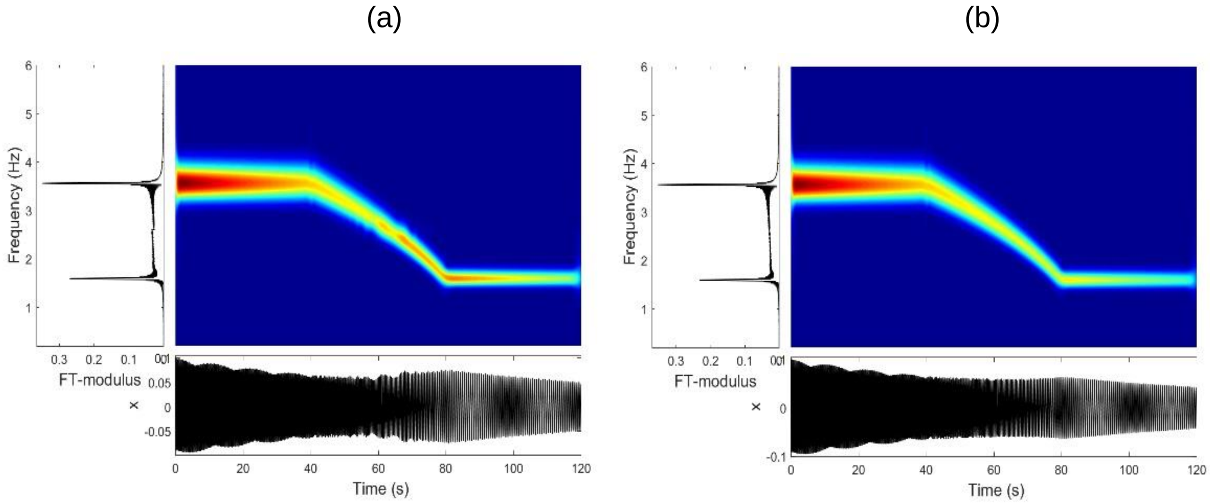

Figure 3: The CCWT results for SDOF system subjected to (a) 2.6 Hz and (b) 5 Hz harmonic excitation.

To further test the performance of CCWT, a 2-DOF model is subjected to an earthquake excitation and the resulting responses are separated using CCWT. The stiffness of the top column is linearly reduced over a period to simulate structural damage as shown in Fig. 4. Table 1 shows the natural frequencies of the model before and after damage. To test the robustness of the CCWT under measurement noise, 10% noise is added to the response signal.

Table 1: Natural frequencies of the 2-DOF model

Modal frequencies	Undamaged (Hz)	Damaged (Hz)
First	1.91	1.44
Second	3.75	3.06

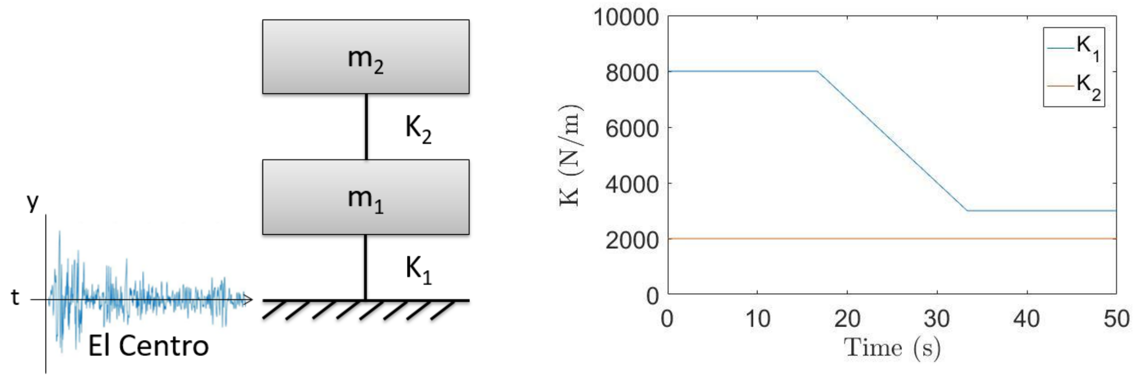
a)
b)

Figure 4: (a) 2-DOF model and (b) stiffness w.r.t time

El Centro earthquake data is used as the base excitation that has a peak ground acceleration of 0.4g and duration of 50 seconds. Fig. 5 shows the CCWT decomposition of the 1st floor revealing clear undamaged, transition and damaged modes. Due to the higher amplitude of the undamaged second mode, the damaged second mode is less apparent. The progressive change in the stiffness can be seen between 16 and 33 seconds.

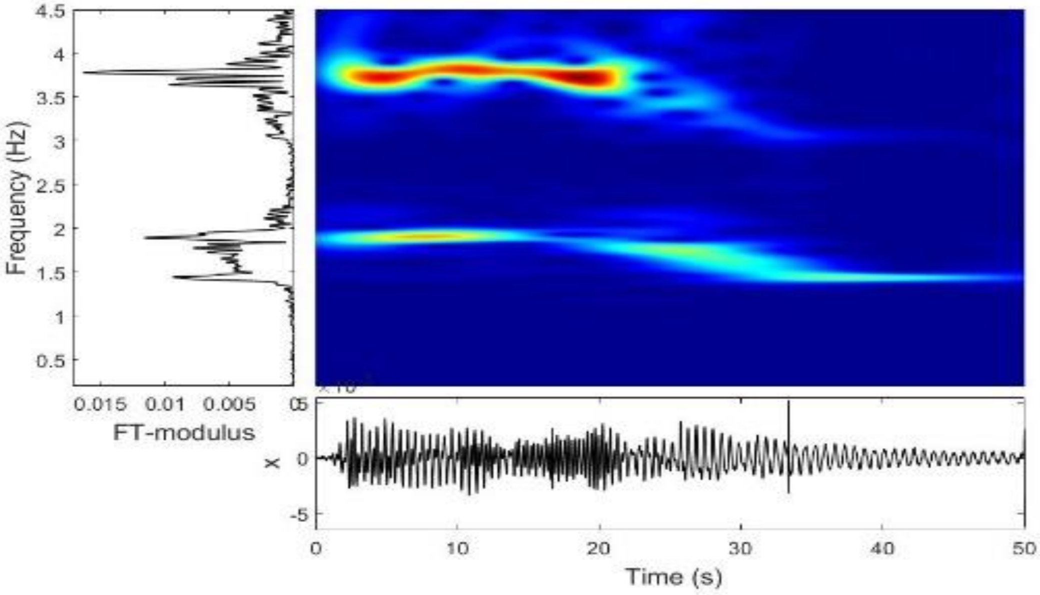

Figure 5: CCWT results of the 1st floor data under El Centro earthquake

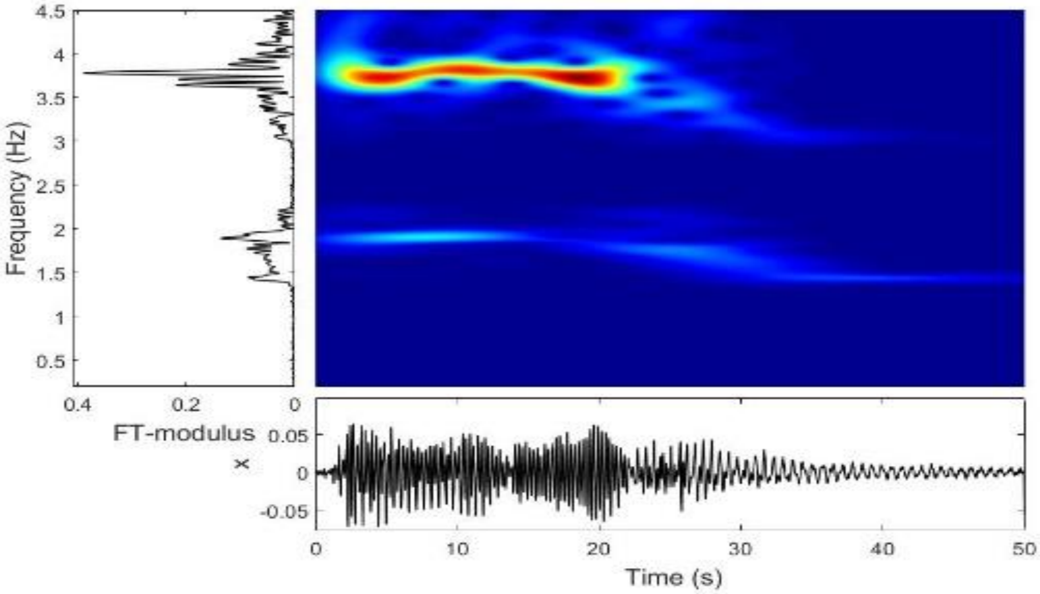

Figure 6: CCWT results of the 2nd floor data under El Centro earthquake

The damage is less clear for the 2nd mode of second floor data. The 2nd modal response can be seen clearly in Fig. 6, whereas the 1st mode is less clear due to the unequal energy distribution in the 2nd mode compared to the 1st mode.

4 Conclusions

In this paper, the CCWT is first time explored as a method for modal identification of progressive damage under several types of excitation. The method is able to separate the signal into its individual components under various loading conditions even with noise contamination. Future work will involve expanding this research for multi-degree-of-freedom models including high-rise buildings and bridges.

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