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Damage Diagnosis in Bridges Using Wavelet

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Abstract. It is hopeful to detect damage in a fast and reliable way in order to increase the safety, extend the working life and reduce the maintenance cost of long-span bridges. This paper presents an effective method for damage estimation based on statistical moments of the energy density function of the vibration responses in the time–scale (or time–frequency) domain. The proposed damage identification method is verified and demonstrated using vibration response of a finite element model of a real structure. The results of applying this algorithm to different damage severities demonstrated that the proposed method has the capability to detect even minor damages in a structure.

Keywords: continues wavelet transform (CWT), damage index, hypothesis test, railway bridge, structural health monitoring.

1. Introduction

Bridges are an important and integral part of modern transportation systems and play a vital role in the lives of a community. They are normally designed to have long life spans. Changes in load characteristics, deterioration with age, environmental influences and random actions may cause local or global damage to structures. Bridge failure or poor performance will disrupt the transportation system and may result in loss of lives and property. It is therefore very important to ensure that bridges perform safely and efficiently at all times by monitoring their structural integrity and undertaking appropriate remedial measures.

Structural Health Monitoring (SHM) and damage detection denotes the ability to monitor the performance of structure, detect and assess any damage at the earliest stage in order to reduce the life-cycle cost of structure and improve its reliability and safety.

Structural damage causes changes in structural physical properties, mainly stiffness and damping, at damaged locations. These changes in structural properties in turn alter the dynamic response behaviour of the structure from its initial pre-damage condition. Therefore, it is common practice in structural condition assessment to monitor the structural physical dynamic characteristics of the structure under test to identify damage at the earliest stage of development.

In the last few decades, changes in the vibration responses have been widely used for damage identification. Detailed literature reviews concerning these techniques and response parameters used for damage identification can be found elsewhere [1].

Many existing vibration-based approaches for damage detection require the modal properties with the aid of the traditional Fourier transform. There are a few inherent characteristics of the Fourier transform that might affect the accuracy of damage identification. Firstly, the Fourier transform is in fact a data reduction process and information on the structural condition might be lost during the process. Secondly, the Fourier transform is a global analysis technique, and its basis functions are global functions. Any perturbation of the function at any point in the time domain will influence every point in the frequency domain. This means that the Fourier transform does not exhibit the time dependency of signals and it cannot capture the evolutionary

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characteristics that are commonly observed in the measured signals from structures under random excitation[2]. The Fourier transform is often used to characterize the overall frequency content of the signal and cannot deal with the local changes, discontinuities, and time-varying signal. All these factors add difficulty to the implementation of Fourier-transform-based damage detection techniques [3].

In order to eliminate these difficulties wavelet-based damage detection has been considered by several researchers over the last decade. While Fourier analysis consists of the breaking up of a signal into sine waves of various frequencies and phases, wavelet analysis is a breaking up of a signal into shifted and scaled versions of a mother wavelet or basis function. These results in variable sizes of a window function and make it possible to detect the discontinuities and breakdown points of data that other analysis methods usually miss. The applications of wavelet analysis in the areas of damage identification and health monitoring have been widely reported. The first researcher known to have applied wavelet to vibration analysis is Newland [4], [5]. He applied a wavelet analysis to the study of vibration of buildings caused by underground trains and road traffic by which he found the similarities between the response signals in each floor. Moyo and Brownjohn [6] applied wavelet analysis for characterization of the response behavior of a bridge during and after construction by using long-term strain measurement data. W.L. Bayissa [3] proposed a damage identification method based on the zeroth-order moment (ZOM) known as the total energy of the joint density function. Long Qiao [7] used damage sensitive feature extracted from continuous wavelet transform (CWT) that presented a unique pattern for any particular damage scenario for damage estimation.

In this paper, a method based on energy content of the wavelet coefficients in damaged and pre-damaged state has been used for damage identification in a numerical analysis of Rafsanjan-Bafghrailway bridge.

2. Theoretical Background

2.1. Wavelet transform

.Wavelet analysis is a signal processing method, which relies on the introduction of an appropriate basis and a characterization of the signal by the distribution of amplitude in the basis. Detailed information regarding wavelet analysis and its application can be found elsewhere [8]. The wavelet is a smooth and quickly vanishing oscillating function with good localization in both frequency and time. A wavelet family $\psi_{a,b}(t)$ is the set of elementary functions generated by dilations and translations of a unique admissible mother wavelet$\psi(t)$:

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

Where a, b € R, a $\neq$ 0, are the scale and translation parameters, respectively, and t is time. As the scale parameter a increases, the wavelet becomes wider.

The continuous wavelet transform of a signal (CWT) is defined as the sum over all time of the signal multiplied by a scaled, shifted version of the wavelets function where both the time and frequency windows can be changed. The CWT is given

$$Q(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} y(t)\psi^*\left(\frac{t-b}{a}\right)dt \quad (2)$$

Where the index $Q(a,b)$ comprises the wavelet coefficients and a and b are the scale (dilation) and translation (position) parameters, respectively. “y(t)” is the vibration response signal. $\psi^*$is the complex conjugate of the basis function (or mother wavelets function), ψ.

2.2. Wavelet energy

The wavelet coefficients obtained using the continuous wavelet transform (CWT) are employed for computation of the energy density functions, over the time–scale domain as follows:

$$C(t,f) = |Q(a,b)^2| \quad (3)$$

The total energy of the time–frequency function of the signal equates to the area under the joint time–scale variation given by

$$E[C(t,f)] = \iint_{-\infty}^{+\infty} C(t,f)\,dtdf \quad (4)$$

3. Damage Identification Method

First, the CWT is performed on the time-series response data at each of the simulated response measurement points. The Symlet wavelet family of order 8 (sym8) from the MATLABs wavelet toolbox is then employed for the wavelet analyses. The wavelets coefficients obtained at each measurement point are used to determine the energy distribution as a joint function of time and scale (or frequency). Then, the damage index is formulated based on the energy ratios obtained at the measurement points from the undamaged and damaged states of the structure:

$$DI_j = \left(E_j^d / \textstyle\sum_{j=1}^{j=n} E_j^d\right) / \left(E_j^u / \textstyle\sum_{j=1}^{j=n} E_j^u\right) \tag{5}$$

Where E_j^d and E_j^u are the total energy of the time–frequency density function of the damaged and undamaged state respectively, at measurement point j, and n is the number of measurement points.

The statistical analysis is then implemented within DI values. The mean value $\mu_{DI}$and standard deviation $_{DI}$ can be calculated. In order to test the hypothesis, the damage index given by Eq. (5) is first standardized as follows:

$$NDI = (DI_j - \mu_{DI}) /_{DI} \tag{6}$$

We classified damage using a one-tailed hypothesis test as follows: if NDI > C, we state that location j is undamaged. If NDI < C, we state that location, j is damaged. The typical value of C widely used in the literature for damage localization is 1.28 for 90% confidence level for the presence of damage. In this paper, the classification of damage is conducted by using the threshold value of 1.28 for damage cases.

4. Example Study on Truss Railway Bridges

4.1. Bridge structural characteristics

In order to evaluate the validity of the proposed damage detection strategy, a numerical example on a truss railway bridge, is carried out in ANSYS software.

This model is a finite element model of railway bridges in Rafsanjan, Iran as shown in Fig. 1. The bridges are on the Abbas - Bafq railway line in the desert of stones of Iran. It is two double-track railway bridges without ballast, located in curves. The structures are 360m and 440m long respectively, including 5 and 6 spans of 60m and 80m each respectively. The bridge has been constructed in 1988.

Fig. 1: Overview of the Railway bridges in Rafsanjan.

Damage estimations were carried out for 6 damage scenarios, as described in TABLE 1. The first 5 damage scenarios are cases with a single damage location (DS1–DS5), while 6th case (DS6) has two damage locations. Damage is assumed to affect the stiffness properties and is simulated by reducing Young's modulus at a particular element location. The damage locations are shown in Fig. 4.

Table. 1: Damage scenarios

Damage scenario	Damage location	Damage severity(percent reduction in stiffness)
DS1	Elements on the center of deck (1)	10
DS2	Elements on the center of deck (1)	30
DS3	Elements on the left of deck (2)	30
DS4	Elements on the center of deck (1)	50
DS5	Elements on the left beam of deck (2)	50

DS6	Elements on the left and right on deck (2),(3)	30

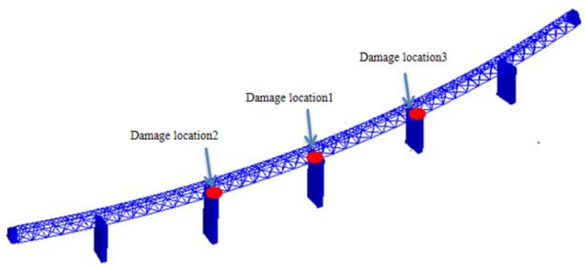

Fig. 2: Damage locations.

The principal aim was to study the feasibility of using the measured ambient vibration of a bridge before and after damage to see if the data could be used for detecting the onset or existence of damage. In practice, the most frequent dynamic loading would be from traffic and wind. Moreover, traffic vibration would be continuous, whenever the bridge was in use. Therefore, traffic induced vibration was simulated by passing a 80 kN train across the structure at speed of 20m/s was modelled as a series of force impulses acting at points along the structure at short time increments corresponding to the train motion. Then, transient analysis is conducted on the bridge subjected to various damage scenarios. Consequently, acceleration response-time histories are determined at each of the simulated response measurement points. A sampling period of 45 s, ITS values of 0.01s is used to obtain 4500 samples at each measurement points.

Nine accelerometers were assumed to be mounted on the bridge's deck to monitor accelerations due to traffic loading. The sensors are denoted S1, S2 to S9 as indicated on Fig. 3. The number of sensors significantly affects the accuracy of the model. Although model sensitivity to the sensors' number and location was not part of this study, it is evident that large sensor arrays are capable of providing sufficient details about regional behaviour under loading and identifying patterns of dynamic behaviour from different regions of the bridge. However, for purposes of continuous monitoring of a bridge, it is desirable that the number of instruments and their associated data are minimized. The output signals of these accelerometers are obtained from the finite element model as the z-axis acceleration component at the nodes located at the accelerometer positions.

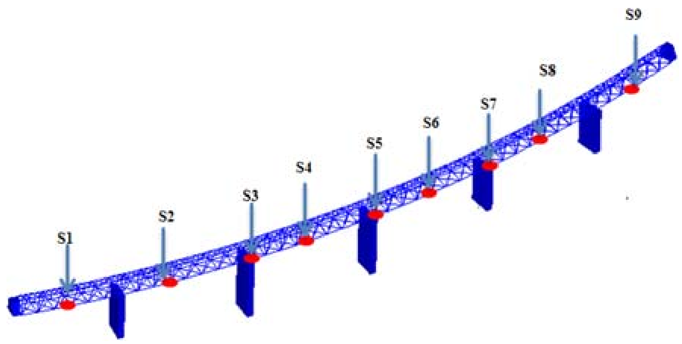

Fig. 3: Sensor locations.

4.2. Discussions on damage identification results

Passing the train on the bridge lasted for 37 seconds. We used acceleration response of the bridge after passing the train for our damage identification purpose. In Fig. 4 the transient time history at a typical measurement grid point for damaged and undamaged state respectively, is presented.

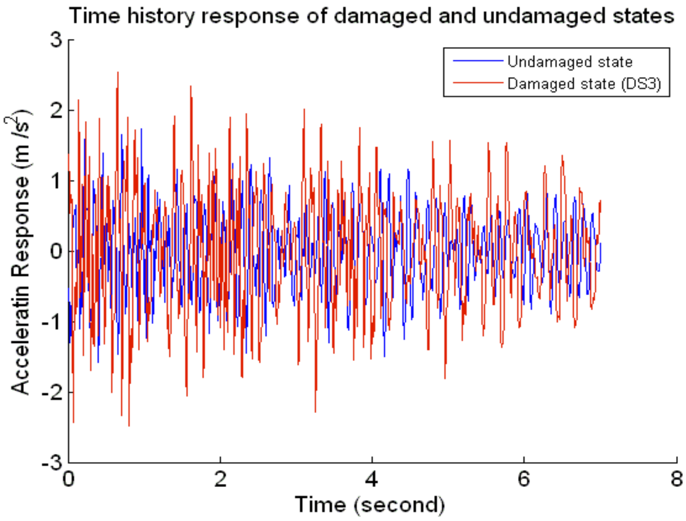

Fig. 4: Acceleration response at typical measurement point for damaged and undamaged state.

In Fig. 5, contour of difference wavelet coefficients of damaged and undamaged signal is shown. As can be seen, the difference at scales between 5 and 15 is more significant than the other scales, so we used scales between 5 and 15 for our damage identification purpose. Wavelet coefficients of damaged and undamaged signal have been shown in Fig. 6. Discussions of the results obtained are presented in section 5.

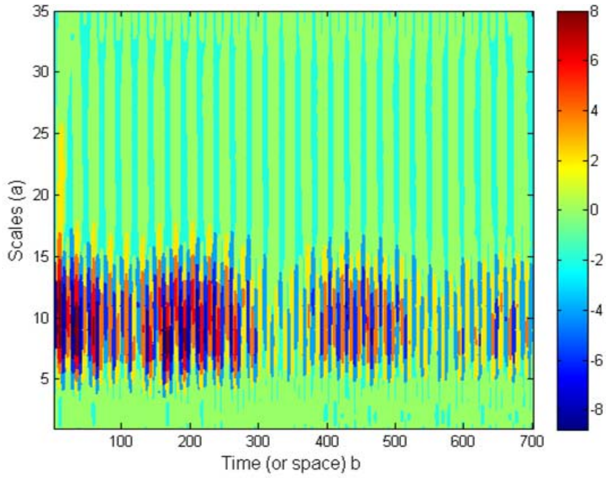

Fig. 5: Contour of difference between wavelet coefficient of damaged and undamaged state.

5. Results and Discussion

A cubic spline interpolation method was employed to determine damage indexes at a refined set of grid points between sensors. The results presented in Fig. 6 shows damage indexes at nine sensor locations. It is clear from the Fig. 6 that our damage index effectively detects and localizes damages. This shows that the proposed technique is able to localize single and multiple damages accurately. As discussed in section 3, normalized damage index more than 1.28 for confidence level of 90% indicates a damage occurrence. In some damage scenarios the adjacent locations has been influenced by damage as well as exact damage location. However, the exact damage location is clear.

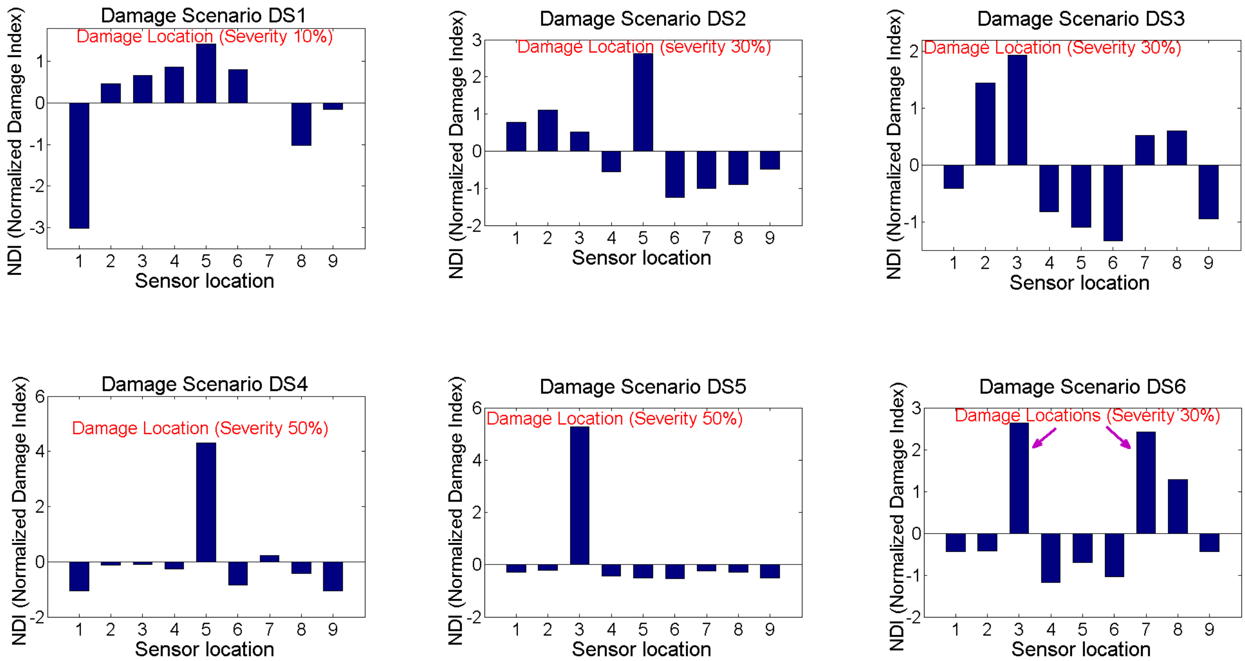

Fig. 6: Damage identification results for different damage scenarios.

6. Conclusion

A wavelet-based technique is used for damage assessments of bridge using energy of wavelet coefficients. CWT is first conducted to damaged and undamaged states. Then, total energy of wavelet coefficients is used as damage sensitive index.A cubic spline interpolation method was employed to determine damage indexes at a refined set of grid points between sensors. One-tailed hypothesis test is used to classify damaged and undamaged locations depending on the pre-defined damage threshold value. The methodology has been verified by acceleration responses extracted from finite element model of RafsanjanRailway Bridge. Some damage scenarios with different severities and locations are carried out. The method was successful in detecting and localizing these damage scenarios.

7. References

[1] H. Sohn, C. R. Farrar, F. M. Hemes, D. D. Shunk, D. W. Stinemates, B. R. Nadler, J. J. Czarnecki, A Review of Structural Health Monitoring Literature: 1996-2001 Report no. LA-13976-MS Los Alamos National Laboratory, Loa Alamos (USA), 2004.

[2] S. S. Law, X. Y. Li, X. Q. Zhu, S. L. Chan “Structural damage detection from wavelet packet sensitivity” Engineering Structures 27, 2005, pp1339-1348.

[3] W. L. Bayissa, N. Haritos, S. Thelandersson, “Vibration based structural damage identification using wavelet transform” Mechanical Systems and Signal Processing 22, 2008, pp 1194-1215.

[4] D. Newland “Wavelet analysis of vibration. Part 1: theory”, ViberAcoust 116, 1994, pp 409-416.

[5] D. Newland “Wavelet analysis of vibration. Part 2: wavelet maps”, ViberAcoust 116, 1994, pp 417-424.

[6] P. Moyo, J. M. W. Brownjohn, “Detection of anomalous structural behavior using wavelet analyses , Mechanical Systems and Signal Processing 16, 2002, pp 429-445.

[7] L. Qiao, *Structural damage detection using signal based pattern recognition* Ph.D. Theses, Kansas State University, Manhattan, Kansas, 2009

[8] S. Mallat, A wavelet tour of signal processing, Academic Press, San Diego, 1999.