International Journal Of Engineering Research And Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 18, Issue 4 (Jul.-Aug. 2022), PP. 01-08

Wavelet Transformation Analysis for Damage Detection on a Three-Story Building

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ABSTRACT: *Civil structures are susceptible to damages over their service lives due to aging, environmental loading, fatigue and excessive response.Such deterioration significantly affects the performance and safety of structure. In this study, the measured structure vibration signals were decomposed by Fast Fourier Transform (FFT), Continuous Wavelet Transform (CWT) and Wavelet Packet Transform (WPT) to extract the sensitive features of the structural response, and to form one-dimensional or two-dimensional feature patterns.Correlation pattern recognition was used to perform pattern-matching for damage detection.To demonstrate the validity and accuracy of the method, experimental study was conducted on a small-scale three-story building. The results showed that the features of the signal for different damage scenarios can be uniquely identified by these transformations, and correlation algorithm can then be used to identify the most probable damage scenario.*

Date of Submission: 26-06-2022 Date of Acceptance: 08-07-2022

I. INTRODUCTION

Recently, signal-based damage detection methods have received many attentions.These methods involve two main processes: (1) feature extraction and selection, and (2) pattern recognition.Feature extraction and selection is the process of identifying and selecting damage-sensitive features derived from the measured dynamic response, to quantify the damage state of the structure (Sohn et al. 2003).This process often involves fusing and condensing the large amount of available data from multiple sensors into a much smaller data set that can be better analyzed in a statistical manner.Also, various forms of data normalization are employed in the process in an effort to separate changes in the measured response caused by varying operational and environmental condition from changes caused by damage.

Signal-based methods examine changes in the features derived directly from the measured time histories or their corresponding spectra through proper signal processing methods and algorithms to detect damage.Based on different signal processing techniques for feature extraction, these methods are classified into time-domain methods, frequency-domain methods, and time-frequency (or time-scale)-domain methods.Time-domain methods use linear and nonlinear functions of time histories to extract the signal features.Examples of this category are Auto-Regressive (AR) model, Auto-Regressive Moving Average (ARMA) model, Auto-Regressive with eXogenous input (ARX) model and Extended Kalman Filter (EKF). Frequency-domain methods use Fourier analysis and cepstrum (the inverse Fourier transform of the logarithm of the Fourier spectra magnitude squared) analysis to extract features in a given time window.Examples of this category are Frequency Response Functions (FRFs), frequency spectra, cross power spectra, power spectra, and power spectral density.Time-frequency domain methods employ Wigner-Ville distribution and wavelet analysis to extract the signal features. Examples of this category are spectrogram, continuous wavelet transform coefficients, wavelet packet energies and wavelet entropy. As an enhancement for feature extraction, selection and classification, pattern recognition techniques are deeply integrated into signal-based damage detection.Staszewski (2000) and Farrar et al. (2001) presented the detailed descriptions of feature extraction, selection and analysis in the context of statistical pattern recognition. Some cases of successful application of the procedure for damage detection can be found in Sohn et al. (2000, 2001), Trendafilova (2001), Posenato et al. (2008) and Fang et al. (2005). Signal-based methods have received considerable attentions from the civil, aerospace, and mechanical communities because they are particularly more effective for structures with complicated nonlinear behavior and the incomplete, incoherent, and noise-contaminated measurements of structural response (Adeli and Jiang 2006).They are also more cost effective and suitable for online structural monitoring.

Time-domain methods use linear and nonlinear functions of time histories to extract features.Sohn et al. (2000) used an auto-regressive (AR) model to fit the measured time history on a structure.Sohn and Farrar (2001) proposed a two-stage time history prediction model, combining auto-regressive (AR) model and an autoregressive with exogenous inputs (ARX) model. Sohn et al. (2002) developed a unique combination of the

AR-ARX model, auto-associative neural network, and statistical pattern recognition techniques for damage classification explicitly taking the environmental and operational variations of the system in the consideration.

Frequency-domain methods analyze any stationary event localized in time domain.They use Fourier analysis, cepstrum (the inverse Fourier transform of the logarithm of the Fourier spectra magnitude squared) analysis, spectral analysis, frequency response technique, etc to extract features in a given time window.Tang et al. (1991) quantitatively diagnosed gear-wear through cepstrum analysis of gear noise signals.Lee and Kim (2007) used the frequency analysis to detect and localize damage.A signal anomaly index (SAI) which quantified the change of frequency response was developed as damage feature.Fasel et al. (2005) used a frequency domain auto-regressive model with exogenous inputs (ARX) to detect joint damage in steel moment-resisting frame structures.

In contrast to the frequency-domain methods, the time-frequency (or scale) methods can be used to analyze any non-stationary event localized in time domain. Hou et al. (2000) presented the great potential of wavelet analysis for singularity extraction in the signals, and the similar work can also be found on Hera and Hou (2004), Ovanesova and Suarez (2004) and Melhem and Kim (2003). Kim and Kim (2005) used the ratio of the incident wave toward and the reflected wave from the damage as index to assess the damage size. The ratio was estimated by the continuous wavelet transform of the measured signal and the ridge analysis.In the time-frequency plane of the continuous wavelet transform, the ridge was traced to compare the magnitude of the incident wave and the magnitude of the reflected wave from the damage.Sun and Chang (2004) also derived two damage indicators from the WPT component energies.The acceleration signals of a structure excited by a pulse load were decomposed into wavelet packet components.Ding et al. (2008) developed a procedure for damage alarming of frame structures based on energy variations of structural dynamic responses decomposed by wavelet packet transform.

II. Experimental Test

A three-story steel structure was experimentally constructed. As shown in Figure 1, the structure was 36 inches tall and consisted of 3 floors (steel slabs) and 30 columns (steel flat bars). Each floor was supported on ten columns. The steel was cold rolled steel. The clear height for each story was 12 inches.

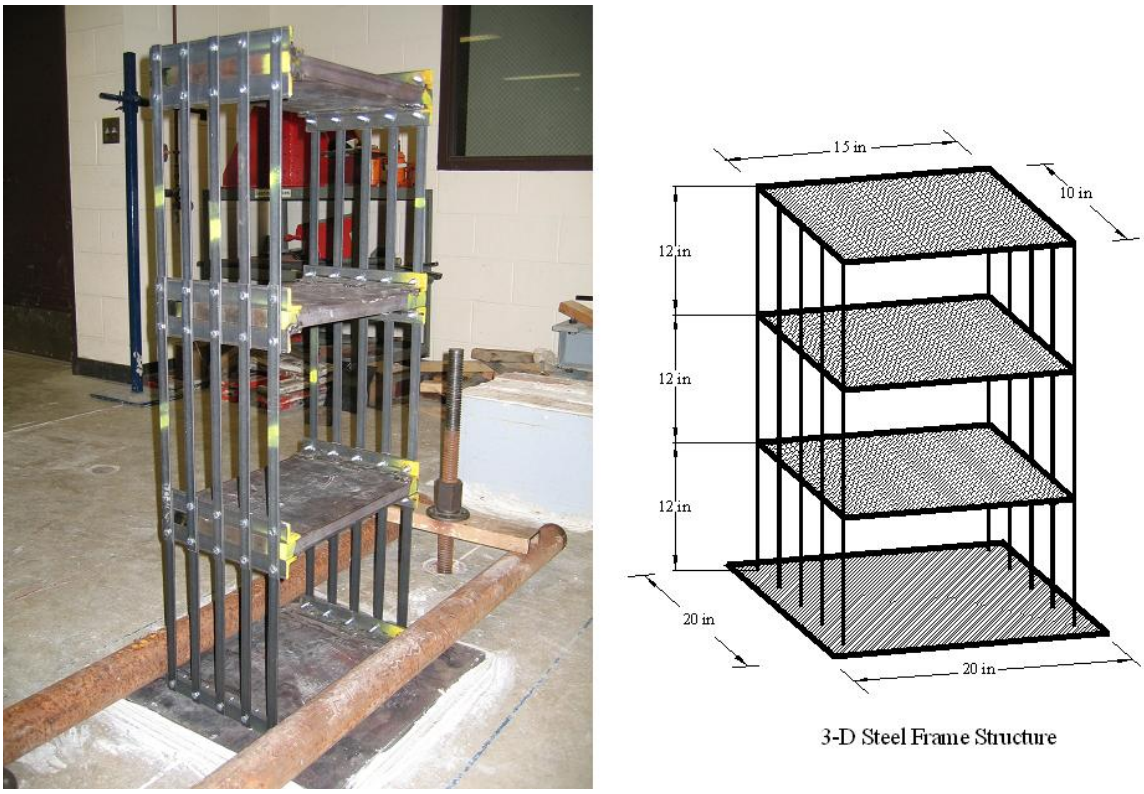


Figure 1: Test three-story steel structure

For easy removal of the columns from the structure and easy replacement of the columns for different damage scenario simulation, bolts were used to connect the steel slab and the steel flat bar.To make the rigid connection between the steel slab and the steel flat column, four pieces of steel angles (¼ ×1 ¼ ×1 ¼; length: 10 inches) were welded on the two faces of the short edges of the floor plates; and two pieces of steel angles (¼ ×1

¼ ×1 ¼; length: 10 inches) were welded on the top face and on the short edges of the foundation slab. A total of fourteen pieces of steel angles were used. The columns were connected to the angles vertical legs using four bolts (1/4; Grade: 5).To prevent rotation and drift, the foundation slab was fixed to the ground by using hydrocal plaster and also two steel pipes

To apply a consistent impulse force on the structure, a steel ball with a diameter of 1.75 inches was used. The steel ball was magnetically adhered to the top of a frame.It was tied by a 20.5 inches chain to this frame so that when the magnet was turned off, the ball dropped 20.5 inches traveling on a circular path to its lowest position, where it hit the third-floor slab and then bounced off the structure to create an impulse force on the structure.

The accelerometer used in the experimental test was MicroStrain, Inc.'s +/-2g G-Link. It has an integral tri-axial accelerometer built onto the board.The full-scale range is approximately +/-2g. G-Link is a complete wireless measurement system that transmits data on a continuous basis for a fixed period of time.In addition, G-Link has the capability to datalog sensor or voltage data to onboard nonvolatile memory.

III. Damage Pattern Database

A 3-D FE model of the structure was constructed by ANSYS, as shown in Figure 2.The element type for floors and columns was shell63 and beam4, respectively. In total, there were 126 elements and 142 nodes in the model.The fully constrained boundary condition and rigid connection between floor and column were also applied to the model. Transient dynamic analysis as detailed described in section 4.2, was carried out to determine the dynamic response of the structure under a step impulse force.The time-step was 0.000488 (1/2048).

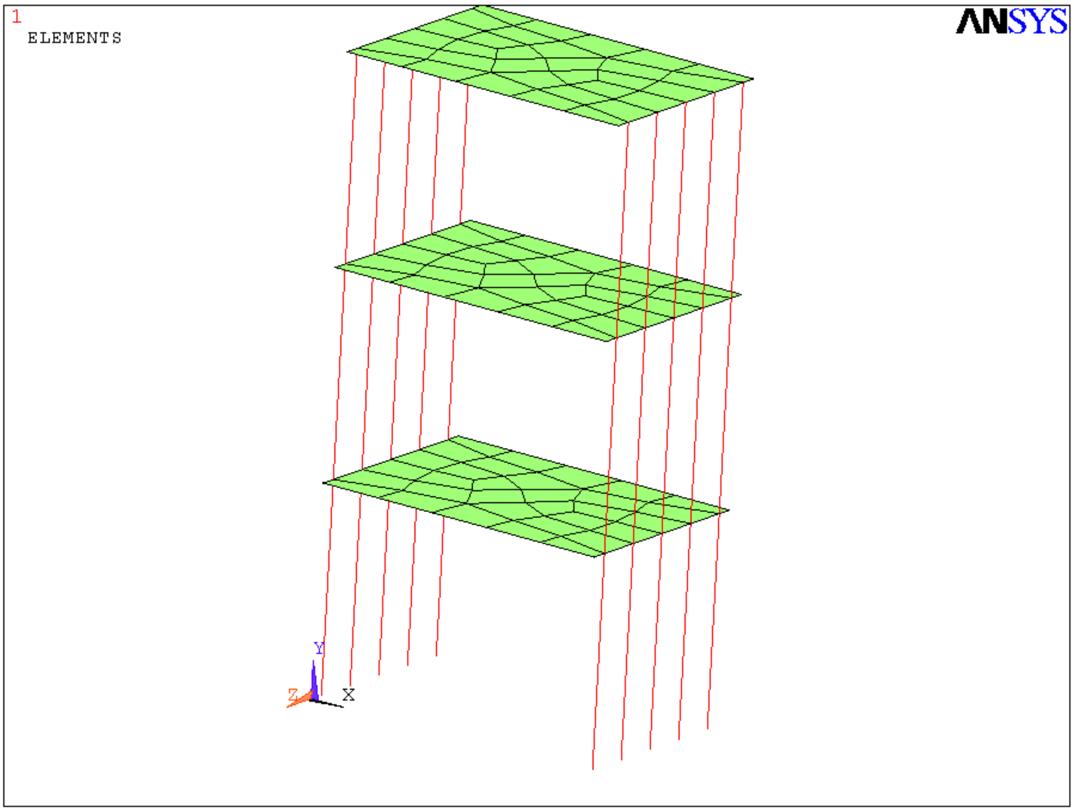


Figure 2: 3-D FE model

Various damage cases were introduced by symmetrically removing columns at different locations, which simulated the failure of one or more columns in the structure.64 damage cases including the baseline condition were designed to represent possible structural damage conditions. In this study, the numerical dynamic responses of the structure under the 64 damage cases were simulated by removing corresponding columns from the 3-D FE model of the structure.The resulting 64 sets of normalized FFT magnitude vectors and 64 sets of CWT coefficient matrices formed the damage feature patterns in the database.

The acceleration signal was also decomposed by WPT using db6 wavelet function.The wavelet packet decomposition level was set to 12 which resulted in a total of 4096 wavelet packet components after decomposition.The energy variationV_j^i for each component was calculated.Such a set of energy variation vectors formed a one-dimensional pattern which presented a unique condition under different damage case. Each energy vector in a pattern was also normalized with respect to the square root of sum of squares of each one in the pattern.

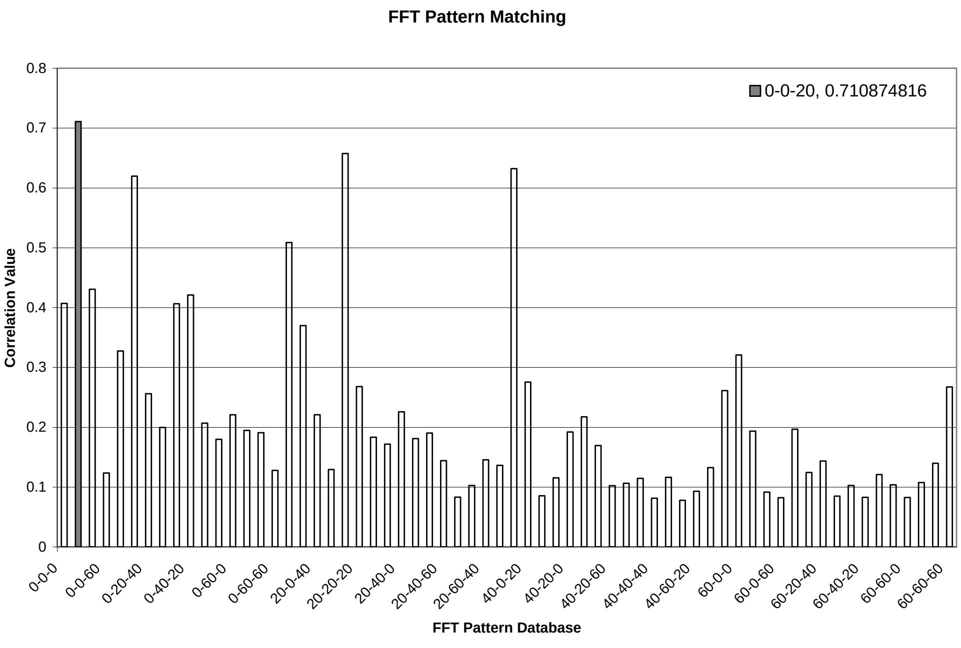
Same as FFT and CWT pattern database construction, the dynamic response of the structure under the 64 damage cases were numerically simulated by removing the corresponding columns from the 3-D FE model. All of the 64 sets of the simulated acceleration response by ANSYS were transformed by WPT into energy variation vectors.The resulting 64 sets of WPT energy variation vectors formed the damage feature patterns in the database.

IV. Case Studies and Pattern Matching

Twenty-eight experimental damage cases, as listed in Table 1 were chosen to test the proposed damage detection procedure and the associated patterns and pattern-matching algorithms.The acceleration response of the structure with each damage case was measured after application of the impulse using the impulse applicator. These acceleration signals were then de-noised and transformed by FFT and CWT.As examples of the test results, Figure 3 shows the FFT and CWT pattern-matching results for damage case 0-0-20 by using correlation.The highest correlation value indicates the most similar pattern in the database which indicates the most probable damage level and location for the unknown case.

Table 1:Experimental test cases

Single Damage Location		Double DamageLocations		Triple DamageLocations	
0-0-20	0-0-60	0-20-20	20-40-0	20-20-20	40-40-40
20-0-0	0-60-0	20-0-20	40-20-0	20-20-40	40-60-20
0-20-0	60-0-0	20-20-0	40-0-20	20-40-20	
0-0-40		40-40-0	0-20-40	20-60-20	
0-40-0		0-40-40	0-40-20	40-20-20	
40-0-0		40-0-40		40-40-20	



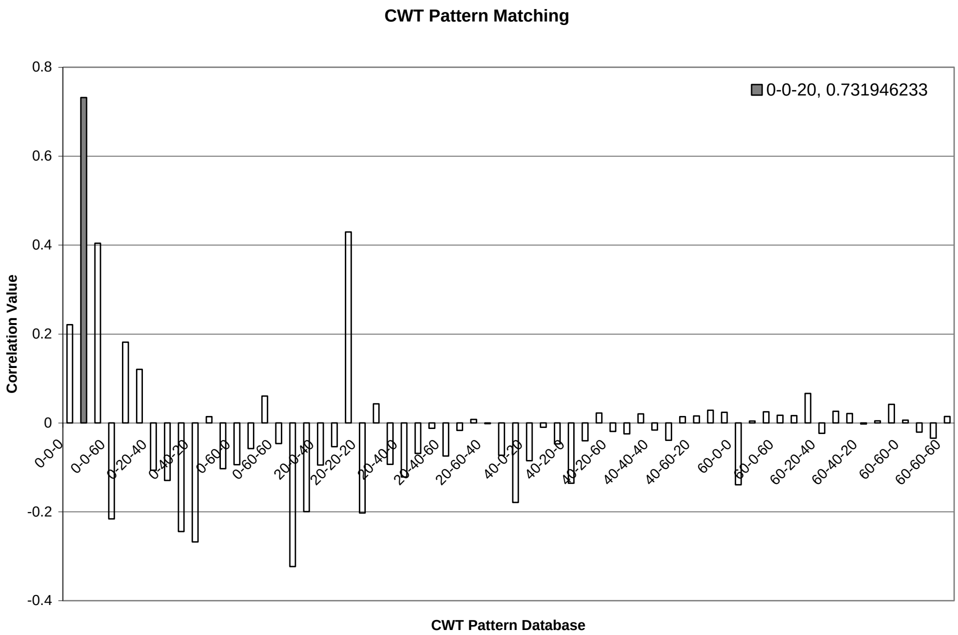


Figure3: Correlation matching for damage case 0-0-20, FFT & CWT pattern matching

All of the experimental test results indicate that both FFT and CWT patterns can preserve the damage information in term of level and location.However, CWT can be more efficient to detect the damage, especially in terms of location when the output signal is from more than one sensor.There are a number of wavelet functions that can be used as the mother wavelet for CWT feature extraction.The choice of wavelet function will affect the computing time and pattern-matching resolution.For demonstration purpose, some widely used wavelet functions were chosen as mother wavelet for CWT- based pattern extraction. Then correlation was used to perform pattern-matching to detect the selected three experimental damage cases: 0-0-20, 20-20-0, and 20-20-40.The successful detection results for all the three experimental damage cases by using different wavelet functions indicated that all of the selected wavelet functions could be used as mother wavelet for CWT-based sensitive feature extraction. The matching resolution based on each wavelet function was calculated as the difference between the two highest correlation values divided by the highest correlation value. It shows that Haar, Daubechies, Symlets and Gaussian wavelets have the best performance. It is also found that Haar, Daubechies and Gaussian wavelets take less computing time.In contrast, Meyr and Dmey wavelets take much longer computing time.

Six experimental damage cases: 0-0-20, 0-0-40, 0-20-0, 20-20-0, 0-20-20, and 20-20-20 were selected to demonstrate the validity and accuracy of WPT method.The results show that WPT-based energy variation vectors can best preserve the dynamic response features of a structure under damage with low level and few locations.And when increasing the level of damage and the number of damage location, the detection result will be overestimated (see Figure 4 to Figure 6).In order to overcome this drawback, increasing the number of sensors and employing an iterative detection process can be explored as a recommended future research work.

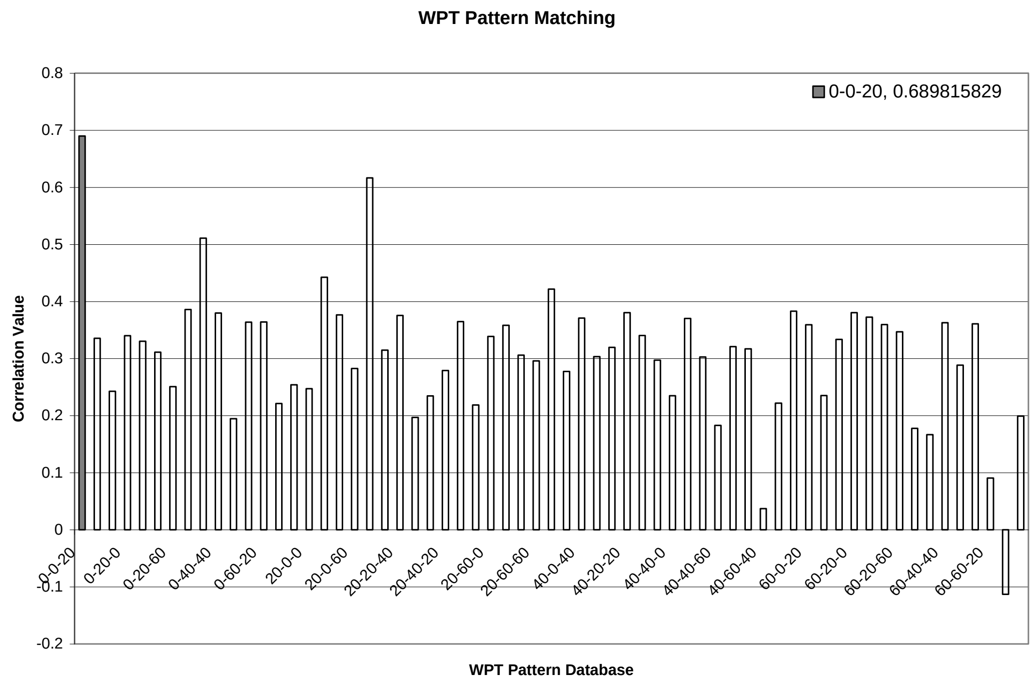


Figure4: Correlation matching for damage case 0-0-20, WPT pattern matching

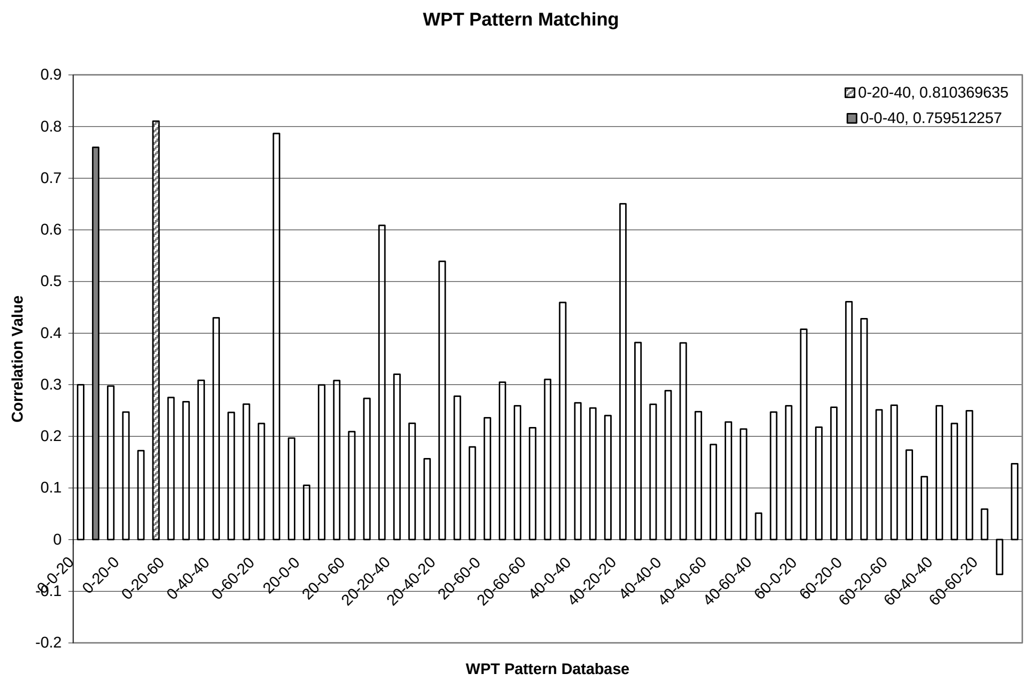


Figure5: Correlation matching for damage case 0-0-40, WPT pattern matching

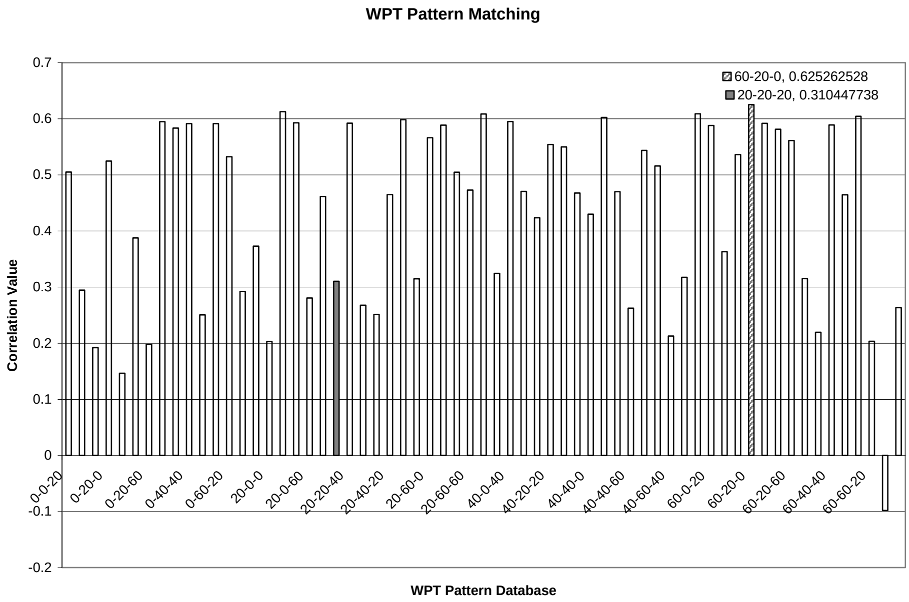


Figure6: Correlation matching for damage case 20-20-20, WPT pattern matching

V. Conclusion

The structure under a specific damage scenario, in terms of location, level and type, has a unique signature and shows a unique pattern in its dynamic response to an excitation.Fourier and Wavelet transforms provide means to extract and preserve the dynamic response features of a structure under various damage conditions.Different damage scenarios can be presented by the features extracted using these transformations. Since FFT preserves the frequency features of the signal, while CWT preserves its frequency as well as its time-sensitive features, CWT pattern results in a higher pattern-matching resolution than FFT pattern.Comparing dynamic response pattern of a damaged structure with a wide range of numerically-generated damage cases stored in a database can serve as a tool to detect the closest damage case in terms of its existence, severity and location.

This study has also shown that WPT-based energy variation vectors can best preserve the dynamic response features of a structure under damage with low level and few locations.Increasing the level of damage and the number of damage locations will result in a wrong detection.Increasing the number of sensors (accelerometers) and employing an iterative process may address this issue and is recommended as a future research work in this field.

The method is particularly effective for large-scale structures due to their complicated nonlinear behavior and the incomplete, incoherent, and noise-contaminated measurements of structural response.Signal-based damage detection has shown great potential in the experimental studies.It should be noted that a structure may experience nonlinear deformations in a severe event; but during detection process, the input, here an impulse, excites the structure within its linear range.This is true for the numerical excitation used for reconstruction of the damage pattern database after a severe event.

REFERENCES

[1]. Adeli, H. and Jiang, X. 2006. Dynamic fussy wavelet neural network model for structural system identification. Journal of Structural Engineering. 132:1,102-111.

[2]. Ding, Y.L., Li, A.Q.and Liu, T. 2008. A study on the WPT-based structural damage alarming of the ASCE benchmark experiments. Advances in Structural Engineering. 11:1,121-127.

[3]. Fang, X.,Luo, H.and Tang, J. 2005. Structural damage detection using neural network with learning rate improvement. Computers and Structures. 83,2150-2161.

[4]. Farrar, C.R., Doebling, S.W.and Nix, D. 2001. Vibration-based structural damage identification. Philosophical Transactions of Royal Society of London Series A: Mathematical, Physical and Engineering Science, London. 359,131-149.

[5]. Fasel, T.R., Sohn, H., Park, G.and Farrar, C.R. 2005. Active sensing using impedance-based ARX models and extreme value statistics for damage detection. Earthquake Engineering and Structural Dynamics. 34,763-785.

[6]. Hera, A.and Hou, Z.K. 2004. Application of wavelet approach for ASCE structural health monitoring benchmark studies. Journal of Engineering Mechanics. 130:1,96-104.

[7]. Hou, Z., Noori, M.and Amand, R.St. 2000. Wavelet-based approach for structural damage detection. Journal of Engineering Mechanics. 126:7, 677-683.

[8]. Kim, I.K.and Kim, Y.Y. 2005. Damage size estimation by the continuous wavelet ridge analysis of dispersive bending waves in a beam. Journal of Sound and Vibration. 287,707-722.

[9]. Lee, J.and Kim, S. 2007. Structural damage detection in the frequency domain using neural networks. Journal of Intelligent Materials Systems and Structures. 18,785-792.

[10]. Melhem, H.and Kim, H. 2003. Damage detection in concrete by Fourier and Wavelet analyses. Journal of Engineering Mechanics. 129,571-577.

[11]. Ovanesova, A.V.and Suarez, L.E. 2004. Application of wavelet transforms to damage detection in frame structures, Engineering Structures. 26,39-49.

[12]. Posenato, D.Lanata, F., Inaudi, D.and Smith, I.F.C. 2008. Model-free data interpretation for continuous monitoring of complex structures. Advanced Engineering Informatics. 22:1,135-144.

[13]. Sohn, H., Czarnecki, J.A.and Farrar, C.R. 2000. Structural health monitoring using statistical process control. Journal of Structural Engineering. 126:11,1356-1363.

[14]. Sohn, H.and Farrar, C.R. 2001. Damage diagnosis using time-series analysis of vibration signals. Smart Materials & Structures. 10:3,446-451.

[15]. Sohn, H., Worden, K. and Farrar, C.R. 2002. Statistical damage classification under changing environmental and operational conditions. Journal of Intelligent Material Systems and structures. 13:9,561-574.

[16]. Sohn, H., Farrar, C.R., Hemez, F.M., Shunk, D.D., Stinemates, D.W. and Nadler, B.R. 2003. A review of structural health monitoring literature: 1996-2001. Report. LA-13976-MS: Los Alamos National Laboratory, NM.

[17]. Staszewski, W.J. 2000. Advanced data pre-processing for damage identification based on pattern recognition. International Journal of Systems Science. 31:11,1381-1396.

[18]. Sun, Z.and Chang, C.C. 2004. Statistical wavelet-based method for structural health monitoring. Journal of Structural Engineering. 130:7,1055-1062.

[19]. Tang, H., Cha, J.Z., Wang, Y. and Zhang, C. 1991. The principal of cepstrum and its application in quantitative fault diagnostics of gears. ASME Design Technical Conference, Miami, FL. 38,141-144.

[20]. Trendafilova, I. 2001. Pattern recognition methods for damage diagnosis in structure from vibration measurements. Damage assessment of structures: proceedings of the 4th International Conference on Damage Assessment of Structures (DAMAS 2001), Cardiff, Wales, UK, June 25th-28th, 2001. Key Engineering Materials. 204-205,85-94.