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Signal Pattern-Recognition for Damage Diagnosis in Structures

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Abstract: A signal-based pattern-recognition approach is used for structural damage diagnosis with a single or limited number of input/output signals. The approach is based on extraction of the features of the structural response that present a unique pattern for each specific damage case. In this study, frequency-based features and time-frequency-based features were extracted from measured vibration signals by Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) to form one-dimensional or two-dimensional patterns, respectively. Three pattern-matching algorithms including correlation, least square distance, and Cosh spectral distance were investigated for pattern-matching. To demonstrate the validity of the approach, numerical and experimental studies were conducted on a simple three-story steel building.

Results showed that features of the signal for different damage scenarios could be uniquely identified by these transformations, and suitable correlation algorithms could perform pattern matching that identified both damage location and damage severity. Meanwhile, statistical issues for more complex structures as well as the choice of wavelet functions are discussed.

Keywords: Signal-based damage detection; pattern-recognition; feature extraction; damage diagnosis

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Introduction

Civil structures are susceptible to damage over their service life due to aging, environmental factors, fatigue and excessive load. Health monitoring of civil infrastructures aims at monitoring the performance of a system to enhance its safety and reduce its life-cycle cost by detection of possible damage in an early stage. This includes various infrastructures from pavements to bridge decks (Lajnef et al 2011; Cusson et al 2011; Adewuyi et al 2011). Structural Health Monitoring (SHM) monitors the performance of a structural system with an identical goal. In this field, Nondestructive Damage Detection (NDD) techniques are of special interest in monitoring structures for possible damage. Basically, NDD techniques can be classified into either local or global methods. Most currently used methods such as ultrasonic, eddy-current and thermal methods are visual or localized experimental methods that detect damage on or near the surface of the structure. Limitations of local methods are the need to know the vicinity of the damage and accessibility of the portion of the structure being inspected. Chang and Liu (2003) provided detailed information about "local" methods. The need for global damage detection techniques has led to development of vibration-based detection methods that rely on the change of vibration characteristics and signals as indication of damage. Over the last two decades, extensive research has been conducted on this detection approach, leading to various experimental techniques, methodologies, and signal processing algorithms. Doebling et al. (1996) and Sohn et al. (2003) presented comprehensive literature reviews of vibration based damage detection and health monitoring methods for structural and mechanical systems. These methods can be classified into parametric -based or signal–based categories.

Parametric-based methods use changes in measured system or FE modal parameters such as frequencies, damping parameters, stiffness parameters and mode shapes as a sign of damage in structure. Parametric-based methods have been applied successfully to identify the dynamic properties of

linearized and time-invariant equivalent structural systems. (Kosmatka and Ricles, 1999; Ren and Roeck, 2002; Shi et al., 2000; Kim et al., 2003; Moaveni, et al., 2009; Soyoz and Feng, 2009; Jafarkhani R. and Masri S. F., 2011). Various algorithms such as Neural Networks, Wavelets, and Chaos Theory have been successfully used for damage detection, intelligent transportation systems and smart structures (Adeli H. and Jiang X., 2009; Adeli H. and Kim H., 2009). Wavelet-based and Hilbert-based approaches have been developed as enhanced techniques for parametric identification of non-linear and time-variant systems (Staszewski, 1998; Kijewski and Kareem, 2003; Yang et al., 2004; Huang et al., 2005; Hou et al., 2006; Chen et al., 2006; Yan and Miyamoto, 2006; Umesha, et al., 2009). "These methods, however, depend strongly on the accuracy of the measured data. They cannot provide the required accuracy and reliability needed for complex system identifications of real life structures due to complicated nonlinear nature of behavior of civil structures, and incomplete, incoherent, and noise-contaminated measurement of structural response under extreme loadings" (Adeli and Jiang, 2006).

Signal-based (or nonparametric-based) methods examine changes in the features derived directly from measured time histories or their corresponding spectra through proper signal processing methods and algorithms to detect damage. These features may not represent any explicit physical-dynamic parameters. 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 with eXogenous inputs (ARX) model, Auto-Regressive Moving Average (ARMA) model and Extended Kalman Filter (EKF) model (Sohn et al., 2000; Sohn and Farrar, 2001; Nair et al., 2006; Yan et al., 2004; Chen and Liu, 2010; Gul and Catbas, 2011). 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 (Tang et al., 1991; Kamarthi and Pittner, 1997; Lee and Kim, 2007). 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 (Staszewski et al., 1997; Hera and Hou, 2004; Melhem and Kim, 2003; Sun and Chang, 2002; Ren and Sun, 2008). A comparison between parametric-based methods and signal-based methods for damage detection in bridges can be found in Cruz and Salgado (2009).

As an enhancement for feature extraction, selection and analysis, statistical 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 based on pattern recognition. Some cases of successful application of the procedure for damage detection can be found in Sohn et al. (2000; 2001), Trendafilova (2001), Qiao et al. (2009), and Fang et al. (2005), Jiang et al. (2007) , Jiang and Adeli (2005), and Adeli and Jiang (2006). Compared with parametric-based methods, signal-based methods are particularly effective for large-scale structures due to their complicated nonlinear behavior and the incomplete, incoherent, and noise-contaminated measurements of structural response under extreme loadings (Adeli and Jiang, 2006).   In the present study, a signal-based pattern-extraction and recognition method, using a number of signal transformation and pattern matching algorithms, is investigated for damage detection. The vibration signals of a structure excited by a dynamic excitation such as an impulse load were decomposed by Fast Fourier Transform (FFT) or Continuous Wavelet Transform (CWT) for feature extraction. Two types of pattern formed by normalized FFT magnitudes or CWT coefficients of the signal were used in this phase of the study. Three statistical algorithms, correlation, least square distance, and Cosh spectral distance, were also

investigated to perform pattern recognition separately. Damage-pattern database was developed analytically by simulating various damage scenarios. Damage location and level were identified simultaneously by best matching the unknown damage feature with that of known ones in the database. To show the applicability of the method, numerical and experimental case studies were conducted on a three-story steel structure. At the first phase of the numerical study, a 2-D, three-story steel structure model was numerically simulated and the method was applied to detect representative damage cases. The results encouraged the authors to expand the study to a real three-story steel structure, for which a detailed finite element model was developed and tuned against the physical structure. The detailed finite element model of the structure using ANSYS simulated the structural dynamic response excited by an impulsive load; without damage, as well as under different damage scenarios and, the recorded response was processed using MATLAB. The normalized signal features from this detailed model, generated for the base (healthy) structure, as well as various damage cases were collected in a database. The normalized signal features of the real structure under the same type of excitation for an unknown damage case, was then compared against this database, using three different pattern matching methods separately, to detect the most probable damage case.

Fourier transform: This is a frequency-based transform widely used in analysis of linear systems. It decomposes a signal into sine waves of different frequencies which sum to the original waveform, distinguishing different frequency sine waves and their respective amplitudes.

Fast Fourier Transform (FFT) is an efficient algorithm for calculating discrete Fourier transform and its inverse by reducing the number of computations needed for N points from $2N^2$ to $2N\log_2 N$. FFT is of great importance to digital signal processing. It has been widely used to extract the frequency response of structures and has successfully been applied for fault detection in beam and rotating machinery. However, it should be noted that Fourier transform is not capable of preserving the

information on time domain. If there is a local oscillation representing a particular frequency in the signal, its location on the time domain will be lost. Note that while a structure might have been pushed into its non-linear range of response when damaged, the response due to the excitation used for damage detection will be linear, even if the dynamic properties of the structure has been affected by damage. So FFT can theoretically be applied for damage detection as outlined in this method.

Wavelet transform: This is computationally similar to the Fast Fourier Transform. However, unlike the sine waves used in the FFT, the wavelet transform decomposes a signal into a set of orthogonal basic functions, also called mother wavelets. The mother wavelets are typically chosen to have compact supports in both time and frequency domains, so that they have local time-frequency properties. This addresses the aforesaid deficiency mentioned for FFT. In other words, the information on time and frequency will be preserved, depending on the scale-time range used in wavelet transformation, while the information on time is lost using FFT. FFT may serve as a suitable tool for detection of damage in terms of level and location, but fails if damage time is a factor in the algorithm. This includes various structural control systems, or methods in which time is implemented in the algorithm to distinguish concurrent damages at different locations.

The detailed descriptions about mother wavelet and Continuous Wavelet Transform (CWT) can be found in Melhem and Kim (2003). In this study, the Daubechies 6 wavelet was used as the mother wavelet. Meanwhile, other types of mother wavelets were also investigated.

Pattern Recognition Techniques: A pattern can be a set of features recorded as discrete values forming a vector or matrix. The purpose of pattern recognition is to implement the algorithms that operate on the extracted features and qualify the damage state of the structure. In this study, three algorithms were used to perform pattern-matching of the extracted features against the database to identify the damage location and level (severity).

Correlation analysis, as the first method calculates the correlation value C_{ij} of two patterns (Posenato et al., 2008). A correlation value of 1 indicates that the two patterns are identical, a correlation value of -1 means that they are diametrically opposite, and a correlation value of 0 means that they are completely different. A closer value to 1 shows a closer match between the two patterns.

$$C_{ij} = \frac{\sum_{k=1}^{n}(S_i(k) - \bar{S_i})(S_j(k) - \bar{S_j})}{\sqrt{\sum_{k=1}^{n}(S_i(k) - \bar{S_i})^2}\sqrt{\sum_{k=1}^{n}(S_j(k) - \bar{S_j})^2}} \qquad (1)$$

The second method was the Least Square Distance (LSD), which has been widely applied for system modeling and identification, speech recognition, and fingerprint identification. It is defined as

$$d_{ij} = \left(\sum_{k=1}^{n}\left(S_i(k) - S_j(k)\right)^2\right)^{\frac{1}{2}} \qquad (2)$$

The least value shows a closer match and vice-versa.

The third method was the Cosh Spectral Distance (CSD) which gives an indication about the global difference between two patterns (Trendafilova, 2001; Owen, 2003; Haritos and Owen, 2004). It is defined as

$$Co_{ij} = \frac{1}{2n}\sum_{k=1}^{n}\left(\frac{S_i(k)}{S_j(k)} - log\frac{S_i(k)}{S_j(k)} + \frac{S_j(k)}{S_i(k)} - log\frac{S_j(k)}{S_i(k)} - 2\right) \qquad (3)$$

where n is the number of vector points in the pattern; $S_i(k)$ and $S_j(k)$ are the vector values of the patterns i and j at point k; and $\bar{S_i}$ and $\bar{S_j}$ are the average values of the patterns i and j, respectively.

If i is the unknown-damage feature pattern, and j is a known feature pattern in the database, then the highest correlation coefficient, the lowest LSD coefficient, and the lowest CSD coefficient indicate the most similar pattern in the database which shows the unknown case. Figure 1 shows the process of

pattern recognition method for damage detection in this study. It mainly includes five operation stages: numerical simulation of the dynamic response of the structure under different known damage scenarios, signal processing and feature extraction and normalization, damage pattern database construction, signal acquisition on a structure with an unknown damage and pattern matching to find the most probable damage case from the database which indicates the damage location and severity. For continuous structural monitoring, it is necessary to update the numerical model once damage has been found to accurately represent the physical condition of the structure.
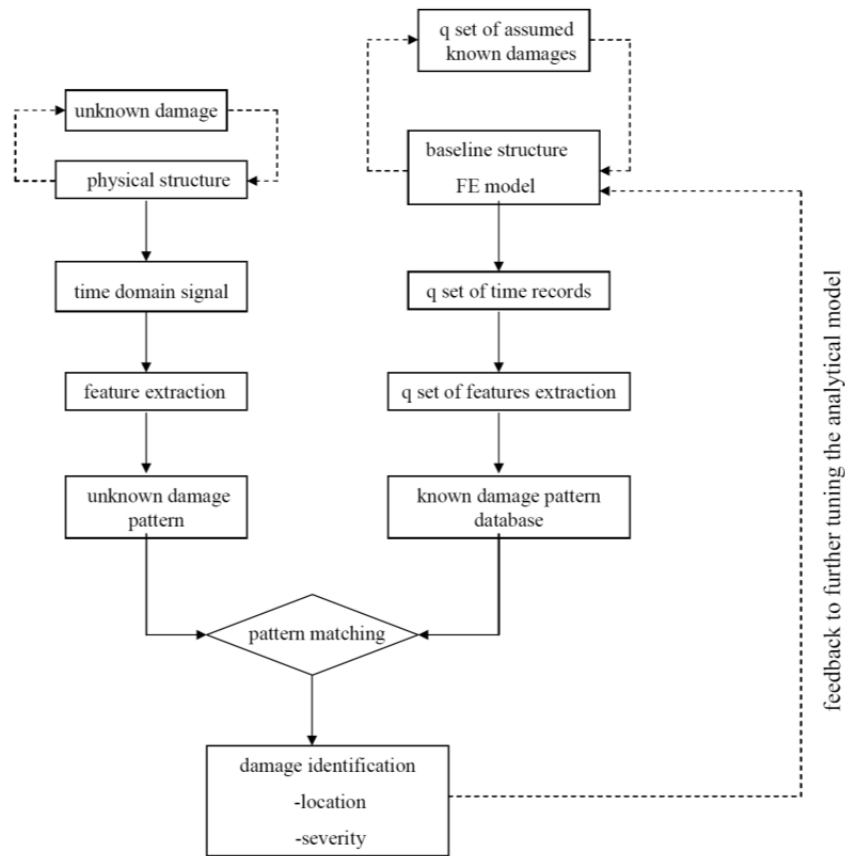

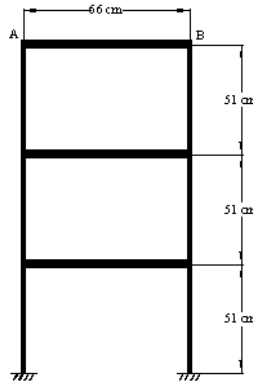**Figure 1. Flowchart of pattern recognition.**

Figure 2. 2-D three-story numerical structure

Preliminary Numerical Investigations

A 2-D steel structure as shown in Figure 2 was numerically simulated to compare the performance of the aforesaid algorithms and illustrate the applicability of the proposed damage detection procedure. The material had a mass density of $7.85 \ g/cm^3$, modulus of elasticity $E = 2 \times 10^5 \ MPa$, and Poisson ration 0.3. The area of each floor cross section was $258 \ cm^2$, with a moment of inertia of $555 \ cm^4$; column cross sectional area was $8.06 \ cm^2$, with a moment of inertia of $0.27 \ cm^4$. This structure was modeled by ANSYS. The element type for floors and columns was 2-D elastic beam (beam3). The floors was rigid compared to columns. The ratio of unit nodal rotation moment of the floor to that of column was more than 1×10^3. All of the connections were assumed to be fixed. Therefore there were a total of 3 noticeable horizontal DOFs in the numerical structure. The damage was simulated by using the baseline model with various dynamic properties, i.e. EI, of the damaged components. Various damage cases were introduced by symmetrically reducing the column stiffness at different stories to preserve the symmetry of the structure. For instance, damage case 0-40-20 refers to a case where stiffness of the columns at second and third stories was reduced by 40% and 20%, respectively.

Transient dynamic analysis was performed by ANSYS to generate the dynamic response of the healthy

structure, and the response under different damage scenarios. The excitation was an impulse force of

0.2 kN with 0.02 second duration acting at the very top corner of the model (point A, Figure 2), and the

numerical acceleration response was recorded at the opposite top corner (point B, Figure 2) for 2

seconds at a sampling frequency of 250 Hz.

In a preliminary effort, frequency-based features were extracted by FFT. The frequencies and

magnitudes corresponding to the three peaks in each of the FFT spectrums are listed in Table 1. The

FFT magnitude vectors in frequency domain were selected as the sensitive features which also preserved

the information of frequency shifting, forming a one-dimension pattern, presenting a unique damage

condition. To eliminate the effects of possible variation of the other factors such as pulse intensity, each

magnitude vector in a pattern was normalized with respect to the square root of the sum of squares of the

corresponding pattern.

Table 1. Peak values on the FFT spectrums

Damage Case	Peak 1		Peak 2		Peak 3	
	frequency (Hz)	magnitude	frequency (Hz)	magnitude	frequency (Hz)	magnitude
0-0-0	1.996	1911.9	5.489	3220.8	7.984	1351.7
20-40-60	1.497	1858	3.992	2468.5	5.988	709.95
60-20-40	1.497	1376.3	3.992	3601.2	6.487	1181.9
60-60-60	1.497	882.4	3.493	2429.4	4.990	1366.1

In the second phase of the preliminary numerical study, time-frequency-based features were extracted by

CWT. The acceleration signal was decomposed by CWT and the extracted features were time-scale-

based CWT coefficients. The CWT is the inner product or cross correlation of the signal $f(t)$ with the

scaled and time shifted wavelet $\psi_{a,b}(t)$. Variable a determines the amount of time scaling or dilation, it

is referred to as the scale or dilation variable. The value of the "scale a" is proportional to the reciprocal

of the frequency. The smaller the value of a, the more the bandpass shifts to a higher frequency,

implying that the CWT at small scales contains information about signal $f(t)$ at the higher end of its

frequency spectrum. The variable b represents time shift or translation and "time b" is the moment of the wavelet along the time axis. The CWT coefficients show the similarity between the signal and the scaled and shifted wavelet. The coefficients can be plotted in 2-dimensional contour with time on the horizontal axis, scale on the vertical axis, and values given by gray-scale colors. Figure 3a, 3b, 3c and 3d show an example of the CWT coefficients contours of acceleration signals of the structure under the selected damage cases.
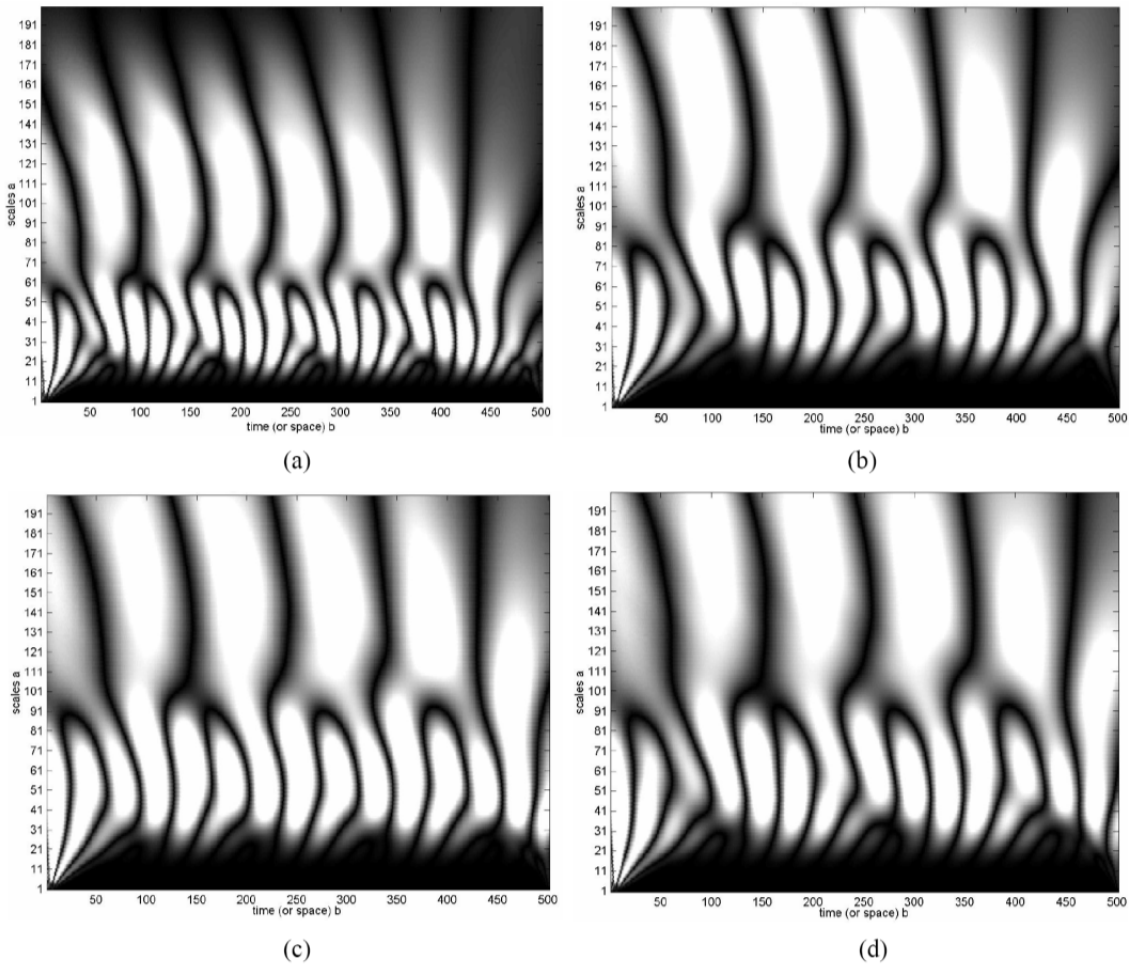

Figure 3. CWT contours for (a) Damage case 0-0-0 (baseline condition). (b) Damage case 40-60-60. (c) Damage case 60-40-60. (d) Damage case 60-60-60

Lighter shading in the contour indicates a higher wavelet coefficient value. Comparison of the four figures shows that the time-frequency-based CWT coefficients were sensitive to different damage cases,

forming a two-dimensional pattern that presents a unique condition for a given damage case. Each coefficient vector in a pattern was also normalized with respect to the square root of the sum of squares of the corresponding pattern.

Damage pattern database construction: As mentioned earlier, different damage levels and locations were numerically simulated by changing the model properties of the structure, i.e. EI, of the damaged components. For demonstration, the damage level was set on a scale of 0 to 60% with increments of 20% at different locations. A total of 64 sets of damage cases, as shown in Table 2, including the baseline condition, were selected to represent the possible structural damage conditions (level and location) for the sample structure.

Table 2. Damage Cases in Database

Case No.	Damage case	Case No.	Damage case	Case No.	Damage case	Case No.	Damage case	Case No.	Damage case
1	0-0-0	14	0-60-20	27	20-40-40	40	40-20-60	53	60-20-0
2	0-0-20	15	0-60-40	28	20-40-60	41	40-40-0	54	60-20-20
3	0-0-40	16	0-60-60	29	20-60-0	42	40-40-20	55	60-20-40
4	0-0-60	17	20-0-0	30	20-60-20	43	40-40-40	56	60-20-60
5	0-20-0	18	20-0-20	31	20-60-40	44	40-40-60	57	60-40-0
6	0-20-20	19	20-0-40	32	20-60-60	45	40-60-0	58	60-40-20
7	0-20-40	20	20-0-60	33	40-0-0	46	40-60-20	59	60-40-40
8	0-20-60	21	20-20-0	34	40-0-20	47	40-60-40	60	60-40-60
9	0-40-0	22	20-20-20	35	40-0-40	48	40-60-60	61	60-60-0
10	0-40-20	23	20-20-40	36	40-0-60	49	60-0-0	62	60-60-20
11	0-40-40	24	20-20-60	37	40-20-0	50	60-0-20	63	60-60-40
12	0-40-60	25	20-40-0	38	40-20-20	51	60-0-40	64	60-60-60
13	0-60-0	26	20-40-20	39	40-20-40	52	60-0-60		

All of the 64 sets of simulated acceleration responses were transformed by FFT and CWT into FFT magnitude vectors and CWT coefficient vectors, respectively. The resulting 64 sets of normalized FFT magnitude vectors and 64 sets of CWT coefficient matrices form the representative damage feature patterns in the database. It should be noted that theoretically, a much larger number of damage cases could have been generated by combining various levels and locations. However, considering the

limitations of the simple test structure, and as a preliminary step in exploring the approach, the damage cases generated and stored in the database was limited to 64.

Case studies and pattern matching: Twenty damage cases listed in Table 3, slightly different from identical cases in the database were analytically simulated, and the corresponding dynamic response under the impulse excitation was numerically generated. Gaussian white noise was added to the generated acceleration signals of the test cases to simulate the condition of signal contaminated with noise. The signal-to-noise ratio (SNR) was 5 dB. The damping ratio (ζ) was 2% when generating the structure dynamic response with damping.

Table 3. Test cases

Single Damage Location G1	Multiple Damage Locations (G2)	Multiple Damage Locations & Severities (G3)	Highest Damage Severity (G4)
0-0-19	0-38-38	19-38-58	0-58-58
0-19-0	38-0-38	19-58-38	58-0-58
19-0-0	38-38-0	38-19-58	58-58-0
0-0-58	38-38-38	38-58-19	58-58-58
0-58-0		58-19-38	
58-0-0		58-38-19	

The pattern-recognition results for all of the test cases by using the three different matching algorithms show that correlation algorithm could best perform pattern matching to identify the damage case even when the signal was highly contaminated with noise and structure had a damping property slightly different from the damping ratio used in the database. As a sample of the damage cases, Figure 4 shows the correlation pattern-recognition results for the test damage case 58-38-19 (environmental condition: damping & noise), by using FFT and CWT pattern, respectively. The highest correlation value was achieved for pattern with damage condition of 60-40-20 in each pattern database, correctly detecting the closest damage case in the database.
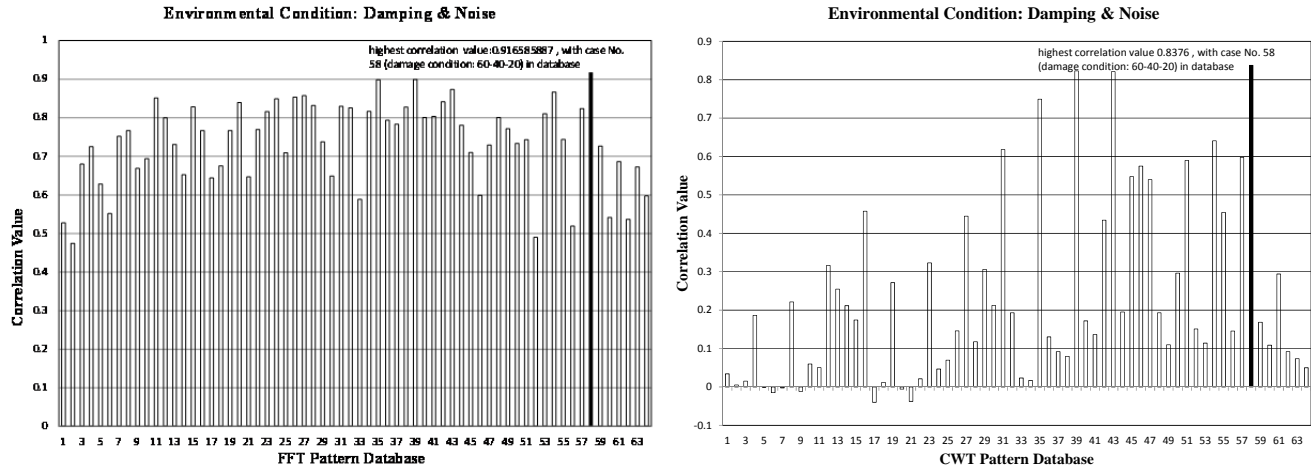
Figure 4. Correlation matching for damage case 58-38-19, FFT & CWT pattern matching.

It should be noted that the process will be more probabilistic and will require a statistical component for more complicated structures, and the probability of a certain damage scenario will be the outcome of the algorithm.

Experimental Tests and Verification

Descriptions of test structure, impulse applicator and signal acquisition: Successful numerical implementation of the proposed damage detection procedure encouraged the authors to experimentally validate it. As shown in Figure 5, the test structure was 91.4 cm tall and consisted of 3 floors and 30 columns. Each floor was supported on ten columns. The floors were steel plates with dimensions of 38.1 cm × 25.4 cm × 2.54 cm and the columns were steel flat bars with dimensions of 41.91 cm × 1.91 cm × 0.32 cm.

To make the rigid connection between the steel slab and the steel flat column, four pieces of steel angles (0.64 cm × 3.18 cm × 3.18 cm; length: 25.4 cm) were welded on the two faces and on the short edges of the floor plates; and two pieces of steel angles (0.64 cm × 3.18 cm × 3.18 cm; length: 25.4 cm) were welded on the top face and on the short edges of the foundation slab. A total of fourteen pieces of

steel angle were used. The columns were connected to the angles vertical legs using four bolts. To prevent rotation and drift, the foundation slab was fixed to the laboratory strong floor.

To apply a consistent impulse force on the structure, a steel ball with a diameter of 4.45 cm was used. The steel ball was magnetically adhered to the top of a frame. It was tied by a 52.07 cm chain to this frame so that when the magnet was turned off, the ball dropped 52.07 cm 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 impulsive force on the structure. The impact was mostly elastic; however, since the response was normalized, the impulse magnitude did not affect the recognition process as long as it did not push the structure into non-linear response range.

Figure 5. Test structure

MicroStrain, Inc.'s G-Link was installed on the top of the third floor to sample and store the acceleration response. The sampled data was sent to the computer by a USB base station through a

wireless connection. Agile-LinkTM software was used to communicate with G-Link and configure data-logging. The sampling rate was 2048Hz.

Numerical model simulation of the structure and its dynamic response: A 3-D FE model of the test structure shown in Figure 5 was constructed by ANSYS. The ANSYS element types for floors and columns were shell63 and beam4, respectively. Transient dynamic analysis was carried out to determine the dynamic response of the structure under a time-varying load. The time-step was 0.000488 s (1/2048 s). The FE model for healthy condition was tuned against test data to fine-tune the value of each parameter in the model. The tuned FE model represented the structure's baseline (healthy) condition and was used in setting damage pattern database.

Damage pattern database construction: Various damage cases were introduced by 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 structure FE model. The resulting 64 sets of normalized FFT magnitude vectors and 64 sets of CWT coefficient matrices formed the damage feature patterns in the database.

Case studies and pattern matching: Twenty-eight damage cases were chosen to test as listed in Table 4. Note that as mentioned earlier, each case is shown by the percentage of damage in the first, second and third stories. As example, 20-60-20 denotes a case where the strength of the columns has dropped 20% in the first story, 60% in the second story and 20% in the third story. The acceleration response of the structure with each damage case was measured after application of the impulsive force on the structure by the ball. These acceleration signals were then de-noised and transformed by FFT and CWT. The three pattern-matching algorithms were used for pattern recognition. The results show that both FFT

and CWT transformations could preserve the damage information enough for distinguished patterns in this study, and the correlation algorithm could perform a better pattern recognition. Figure 6 and Figure 7 show part of these results.

Table 4. Test cases in experimental study

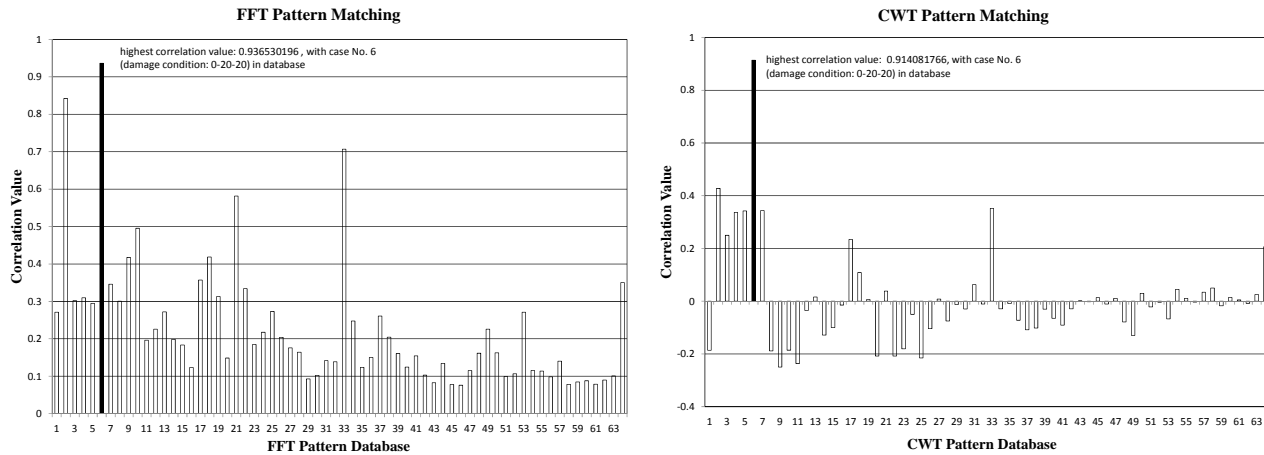| Single Location Damage	Double Location Damage	Triple Location Damage
0-0-20	0-20-20	20-20-20
20-0-0	20-0-20	20-20-40
0-20-0	20-20-0	20-40-20
0-0-40	40-40-0	20-60-20
0-40-0	0-40-40	40-20-20
40-0-0	40-0-40	40-40-20
0-0-60	20-40-0	40-40-40
0-60-0	40-20-0	40-60-20
60-0-0	40-0-20	
	0-20-40	
	0-40-20	

Figure 6. Correlation matching for damage case 0-20-20, FFT & CWT pattern matching.
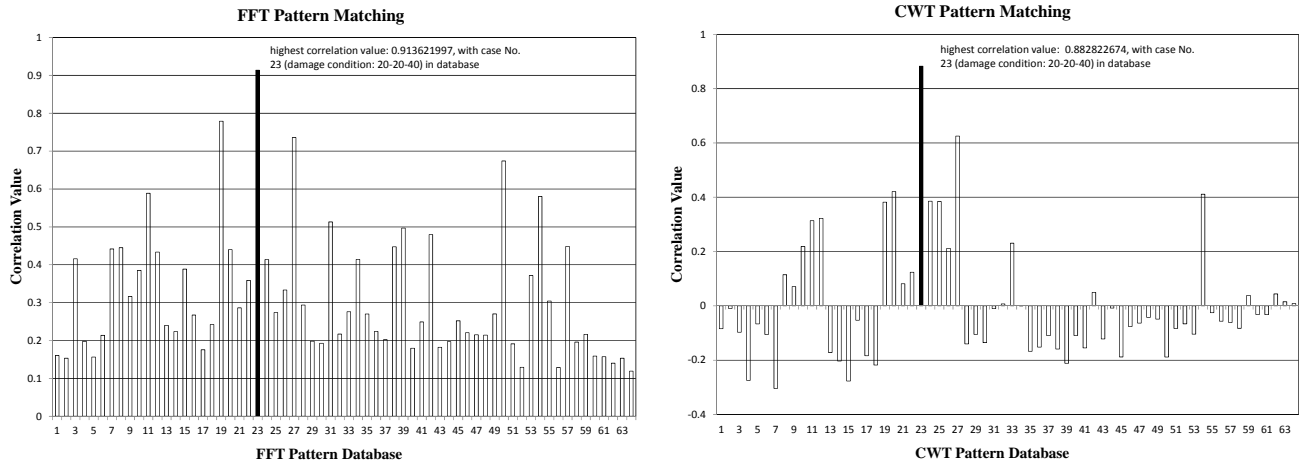
Figure 7. Correlation matching for damage case 20-20-40, FFT & CWT pattern matching.

Discussion and Conclusions

Experimental tests and case studies further validated the overall feasibility of the method for damage detection. Fourier and especially wavelet transforms could well extract and preserve the features of the signal under damage conditions. Since the CWT pattern preserves the frequency and time sensitive features, it results in higher pattern-matching resolution than FFT pattern. The choice of wavelet functions will affect the computing time and detection resolution. In the experimental studies, all the available main mother wavelets were compared. Haar, Daubechies, Symlets and Gaussian wavelets had the best performance. Among the three algorithms used, correlation was the best at performing pattern matching, even when the signal was contaminated with noise. However, the numerical model must be carefully tuned to accurately represent the physical conditions of the structure.

The potential advantages of this approach, as per the results of this study, may be summarized as follows. The method can potentially be used with a single or limited number of input/output signals. It can be used to detect multiple damage locations and also detect the severity of damage at each damage location. It gives good accuracy in the presence of noise. After the case database is generated for the

structure, no additional cases are needed to "train" the system. However, after any physical change including changes due to any possible damage, the database should be updated based on the new dynamic properties of the structure. Note that the method can be implemented in various layers, starting from global (the whole structure) and ending to a structural member for a detailed detection. The process can be automated in terms of detection and continuous fine tuning of the model and database. The study can be advanced further by using a more complicated structure.

It should be noted that in addition to variations in the dynamic response of a structure inflicted by damage, dynamic properties such as damping ratio, stiffness, and mass are not deterministic values and are affected by numerous factors such as temperature and environmental conditions like humidity, etc. So, even if the model should be calibrated against these changes to enhance the accuracy of detection process, the values remain probabilistic and there is a certain level of uncertainty associated with them. Also, for large-scale structures with a large number of details and redundancy, some damage patterns may overlap each other. Therefore, in addition to fine tuning the model used for generation of damage database, a relatively large number of damage cases are needed in order to specify the most probable damage case, once damage in the real structure occurs. In a large structure, while major damage cases can be detected with a good probability, detection of some local damages that may lead to similar patterns in the dynamic response of the structure have a lower probability of being distinctly detected. This issue may be addressed by a multi-layer detection process which needs more damage databases at local levels. The method and algorithm in this study is an elementary step with promising results which can have some merits when it comes to detection of major damages, not detectable by visual inspection, in a large structure with a good probability. The same procedure can be used with more input-output signals to enhance the resolution/probability of damage detection for minor/local damage cases.

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