Assessment of seismic performance of structures by health monitoring

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2007 NZSEE Conference

ABSTRACT: The performance of existing structures can be assessed in real-time using Structural Health Monitoring (SHM). In this study, a SHM method is proposed and experimentally tested on a 3-storey laboratory structure mounted on a shake-table. Several damage conditions were simulated in the structure by a reduction in lateral stiffness. Typical stiffness reductions were between 7% - 10%. The structure was excited using a series of earthquake records. Examination of the acceleration time histories, using time series analysis and pattern recognition, enabled accurate detection, location and quantification of damage.

1 INTRODUCTION

In the past decade a vast amount of research has been conducted on Structural Health Monitoring (SHM) for the purposes of developing methods for detecting, locating and quantifying damage in structures. SHM can be broadly defined as a process involving firstly, tracking any aspect of structural performance or health by measuring data and secondly, interpreting changes so that structural condition and reliability can be quantified objectively (Aktan et al., 2002). Of particular importance for seismically active regions, such as New Zealand, is the assessment of seismic induced damage in structures. SHM can be used for this task. Contemporary SHM methods include the use of mode shapes (Pandey et al., 1991), frequency response functions (Zang & Imregun, 2001, Ni et al., 2006) and time series analysis (Omenzetter & Brownjohn, 2006, Nair et al., 2006) techniques. Modal parameters, such as natural frequencies or mode shapes, have been shown to be either insensitive to observable amounts of damage or usually corrupted with large amounts of noise (Farrar et al., 2000). On the other hand, time series analysis techniques are inherently suited to SHM, where data is sampled at discrete time intervals over long periods of time. Despite this, the application of time series methods is yet to be fully explored.

In this paper, a time series based SHM method is proposed and verified on a 3-storey laboratory structure mounted on a shake-table. The experimental structure was approximately 2.1m high and constructed from equal angle aluminum sections for columns and stainless steel floor plates. Earthquake records were used to excite the structure in an undamaged and several damaged states. Damage was defined as a reduction in lateral stiffness and was simulated by replacing the columns with those of a thinner section. Four damaged states were considered; these were 1) no damage, 2) damage localized at the 1st storey, 3) damage localized at the 2nd storey, and 4) simultaneous damage at 1st and 2nd stories. Acceleration time histories were recorded at each storey when the structure was in a particular damage state. Time series models were used to fit these acceleration time histories. By examining changes in the time series models, damage in the structure could be identified using a pattern recognition technique.

2 THEORY

2.1 *Time series models*

Autoregressive (AR) modes are often used to model stationary time series processes. A stationary process is a stochastic process, which obeys probabilistic laws and is centered about a constant mean and variance. While the response of a structure excited by an earthquake record would generally be considered non-stationary, the response can be analyzed by dividing it into small sections that are stationary. An AR model basically relates the current value of the time series x_t to the p previous values x_{t-1}, …, x_{t-p}, or;

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + \phi_p x_{t-p} + a_t \qquad (1)$$

where p is the model order, ϕ_1, … , ϕ_p are the AR coefficients and a_t is a random error.

2.2 *Pattern recognition using Artificial Neural Networks*

In this study the AR coefficients were used together with a pattern recognition technique to detect damage. An Artificial Neural Network (ANN) (Kecman, 2001) approach was chosen as the pattern recognition technique. ANNs are data processing structures designed to mimic the function of the biological brain. ANNs can be considered as systems with an input, some processing and an output. By showing the ANN input-output pairs the ANN can be 'calibrated' to give the desired output. In this study the inputs were the AR coefficients and the output was the damage at each storey, quantified as the percentage remaining stiffness.

3 LABORATORY STRUCTURE AND DATA ACQUISTION

The laboratory structure used in the experiments is shown in Figure 1a. The structure was approximately 2.1m high and constructed from equal angle aluminum column sections and stainless steel floor plates bolted together with aluminum brackets see Figure 1b. The column sections were 30×30mm equal angles, 0.7m in height and fastened at each end with two M6 bolts to the brackets. Two column section thicknesses were used, either 4.5mm or 3mm for the undamaged and damaged states respectively. The stainless steel floor plates were 4mm thick and 650×650mm square. Additional brackets were installed at the base of the structure to mitigate torsional motion. The whole structure was mounted on a 20mm sheet of plywood and bolted with M10 bolts to the shake-table.

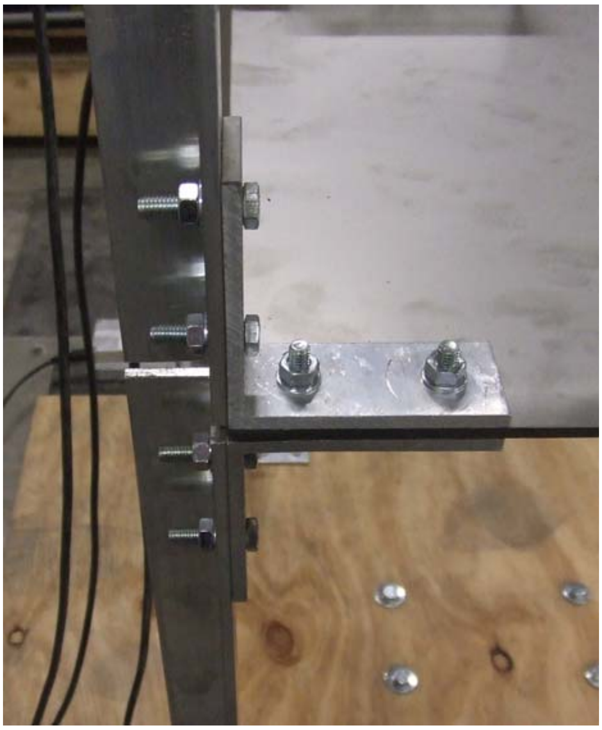
(a)  (b) 

Figure 1. Photographs of the structure: (a) laboratory structure on shake-table, and (b) column-floor joint.

The structure was instrumented with four 2.5Vg^{-1} uniaxial accelerometers, one for measuring the table acceleration and one for each storey. Accelerations were measured in the direction of shaking at 400Hz using a computer fitted with a data-logging card. All data was filtered with a zero phase shift 50Hz low pass filter. Afterwards the acceleration data was decimated by a factor of four for modal analysis and eight for time series modeling. This reduced the original 400Hz signal down to 100Hz and 50Hz respectively. The decimate procedure implemented in MATLAB Signal Processing Toolbox (Mathworks, 2006) uses an eight order Chebyshev Type I low pass filter with cutoff frequency (0.8/R) $\times(F_s/2)$, where F_s was the initial sampling frequency and R the decimate factor, before resampling the data.

4 APPLICATION OF SHM METHOD TO EXPERIMENTAL DATA

The proposed SHM method, outlined in Figure 2, was applied to the laboratory structure. AR time series models were used to fit the acceleration time histories from each storey and an ANN was used to relate the AR models to the damage at each storey. Such a method could be applied to a real-world structure and used to assess performance in real time. Damage was considered to be a reduction in lateral stiffness and was simulated by replacing the columns at the particular storey with thinner ones. Four damage states were investigated; these were named D0, D1, D2 and D3 corresponding to no damage, 1st storey damage, 2nd storey damage, and simultaneous 1st and 2nd storey damage. The lateral stiffnesses k_1, k_2 and k_3 of each storey in each damage state were unknown and had to be estimated by updating a simple mass-spring analytical model of the structure. The analytical model was updated on natural frequencies and checked with mode shapes obtained from experimental modal analysis. In a real-world application a similar problem would arise and an undamaged analytical model would have to be developed based on experimental data. Natural frequencies, damping ratios and mode shapes were estimated from identification of a discrete state-space model. The natural frequencies, f, of the structure in each state together with percentage changes in frequency, Δf, for states D1, D2 and D3 are given in Table 1. Modal damping ratios in the D0 state were estimated at approximately 1% for all three modes. Mode shapes normalized for a maximum response of 1 are shown in Figure 3 for all four damage states. Both natural frequencies and mode shapes appear to remain relatively unchanged to damage. From the analytical model updating procedure, a set of lateral stiffnesses for the structure in each damage state were obtained, see Table 2. Reductions in lateral stiffness in the order of 7% - 10% were obtained.

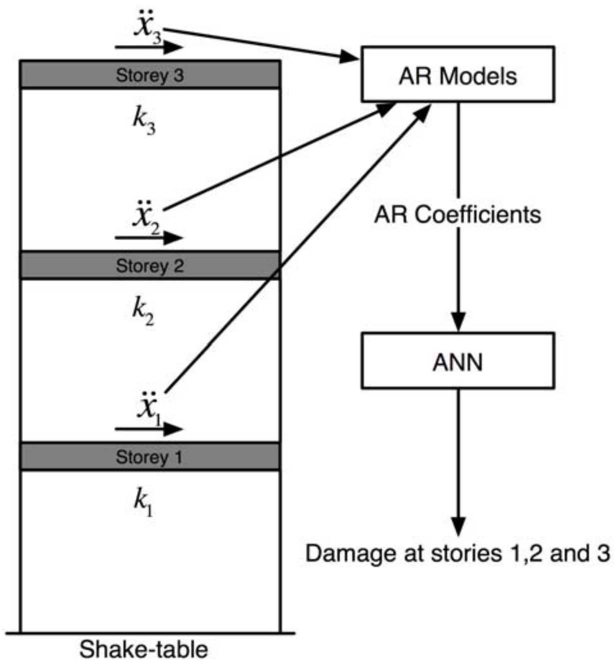


Figure 2. Diagram of proposed SHM method.

Table 1. Natural frequencies and their relative changes at different damage states.

	f (Hz)				Δ*f* %*		
Mode	D0	D1	D2	D3	D1	D2	D3
1^{st}	1.928	1.879	1.837	1.840	-2.5%	-4.7%	-4.6%
2^{nd}	5.517	5.426	5.464	5.417	-1.6%	-1.0%	-1.8%
3^{rd}	8.548	8.303	8.093	8.152	-2.9%	-5.3%	-4.6%

* Based on D0.

Table 2. Estimated lateral stiffness for each damage state.

Stiffness	**D0**	**D1**	**D2**	**D3**
k_1 (N/m)	3.77×10^4	3.49×10^4	3.77×10^4	3.49×10^4
k_2 (N/m)	0.60×10^4	0.60×10^4	0.54×10^4	0.54×10^4
k_3 (N/m)	0.77×10^4	0.77×10^4	0.77×10^4	0.77×10^4

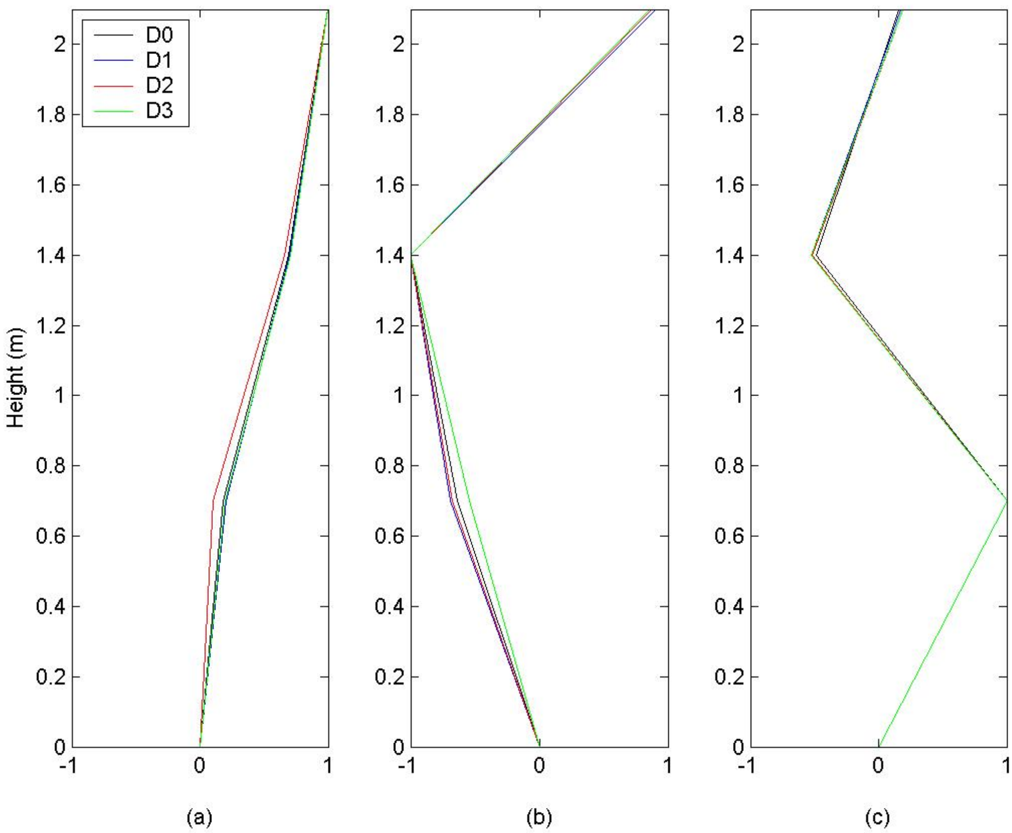


Figure 3. Mode shapes of the experimental structure in each damage state: (a) 1^{st} mode, (b) 2^{nd} mode, and (c) 3^{rd} mode.

Eight scaled earthquake records were used to excite the structure in the four damage states. Table 3 lists the earthquakes used, the PGA of the original and scaled records, the duration of the record and the frequency at which the earthquake was sampled. The earthquakes were scaled so that a range of response amplitudes was obtained, while ensuring no yielding of the structure occurred. From AR time series modeling of the recorded acceleration time histories of the structure a set of 388 data points was obtained, 97 points for each damage state. This data set was randomly divided into 300 points to calibrate the ANN and 88 points to test the proposed SHM method.

4.1 *Damage quantification and localization using experimental data*

Using the estimated lateral stiffnesses in Table 2, the damage at each storey was defined as the current, remaining stiffness divided by the original undamaged stiffness. Table 4 shows the damage at each storey for all four states. The amount of damage was relatively small, with a 7% - 10% reduction in stiffness. After the ANN was calibrated it was tested on the remaining 88 data points. The results are shown in Figure 4, where the damage detected has been plotted against the actual damage found through the updating procedure for all three stories. For perfect predictions, the data points should lie on (0.93, 0.93) and (1.00, 1.00) for the 1st storey, (0.90, 0.90) and (1.00, 1.00) for the 2nd storey, and (1.00, 1.00) for the 3rd storey. The figure shows that the proposed SHM method has correctly detected the damage at each story with a small amount of scatter about the actual damage.

4.2 *Integration of experimental and analytical data*

As mentioned briefly above, any SHM method applied to a real-world structure would most likely require an analytical model of the undamaged structure as it would be unlikely that an undamaged structure would be damaged to obtain experimental data. Instead various damage scenarios would be simulated using the analytical model. Experimental data collected from actual monitoring of the structure would be compared with the simulated analytical data and thus damage could be detected.

Table 3. Earthquake records.

Earthquake	PGA (g)	Scaled PGA (g)	Duration (sec)	Sampling frequency (Hz)
Duzce 12/11/1999	0.535	0.027	25.885	200
Erzincan 13/3/1992	0.496	0.033	20.780	200
Gazli 17/5/1976	0.718	0.048	16.265	200
Helena 31/10/1935	0.173	0.035	40.000	100
Imperial Valley 19/5/1940	0.313	0.031	40.000	100
Kobe 16/1/1995	0.345	0.035	40.960	100
Loma Prieta 18/10/1989	0.472	0.047	39.945	200
Northridge 1/17/1994	0.568	0.038	40.000	50

Table 4. Damage (remaining stiffness) at each storey for the four damage states.

Storey	D0	D1	D2	D3
1st	1.00	0.93	1.00	0.93
2nd	1.00	1.00	0.90	0.90
3rd	1.00	1.00	1.00	1.00

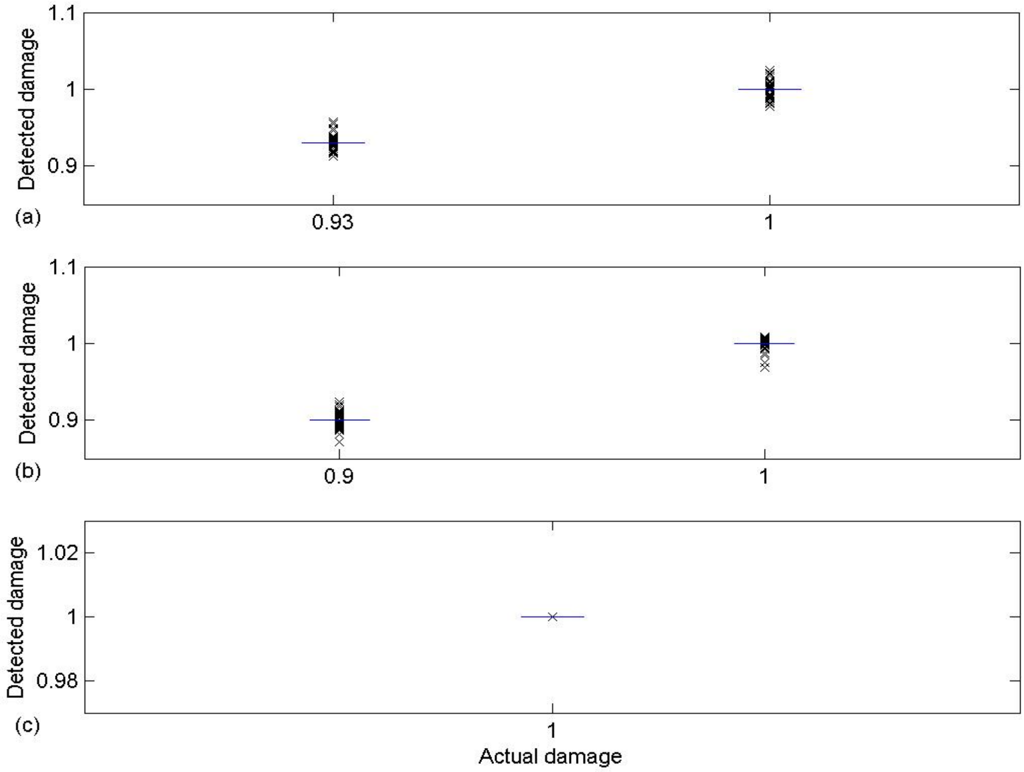


Figure 4. Detected vs. actual damage using experimental data at (a) 1st storey, (b) 2nd storey, and (c) 3rd storey.

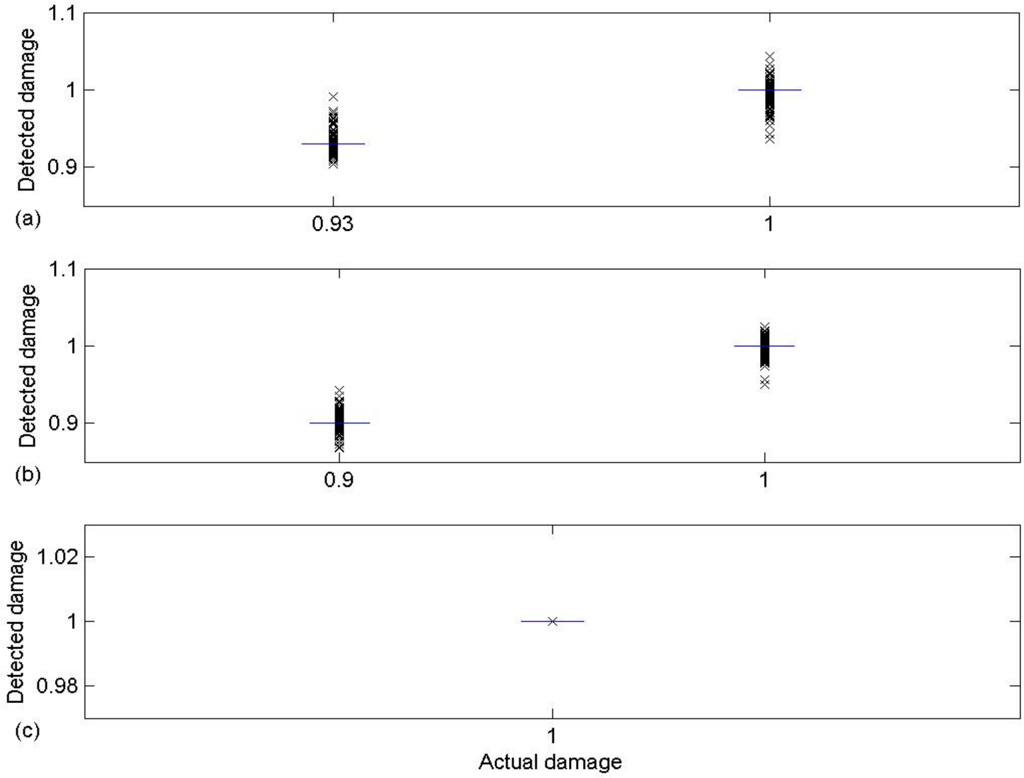


Figure 5. Detect vs. actual damage using a combined analytical and experimental data set (a) 1st storey, (b) 2nd storey, and (c) 3rd storey.

To demonstrate the proposed SHM method's applicability to real-world structures the analytical models developed above were simulated on a computer under random ground excitation. AR time series models were fitted to these analytical acceleration time histories giving 388 data points. This 388 point analytical data set was randomly combined with the existing 388 point experimental data set giving a total of 776 points. This mixed analytical and experimental data set was divided into 500 points to calibrate the ANN and 276 for testing. The results are shown in Figure 5. Compared to Figure 4 there is more scatter about the actual damage indicating that the use of analytical data decreases the efficiency of the method and more research on this issue is required.

5 CONCLUSIONS

In this study a SHM method capable of detecting, locating and quantifying damage has been developed using AR models and ANNs. The method was successfully applied to a 3-storey laboratory structure mounted on a shake-table. Damage was simulated as a reduction in lateral stiffness and was introduced in the laboratory structure by replacing the columns with those of a thinner thickness. The proposed SHM method was able to detect between a 7% - 10% reduction in lateral stiffness. This SHM method could be used to assess the condition of critical civil infrastructure in real-time.

Future research will focus on applying the proposed method to more realistic structures with more complex patterns and possibly structures exhibiting a non-linear response. The integration of experimental and analytical data will also be explored in depth.

ACKNOWLEDGMENT

The authors would like to express their gratitude for the Earthquake Commission Research Foundation for their financial support of this research (Project No. UNI/535).

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