16th World Conference on Earthquake Engineering, 16WCEE 2017

Santiago Chile, January 9th to 13th 2017

Paper N° 4765

Registration Code: S-M1471440128

Structural Health Monitoring in Multi-Story Frames Based on Signal Processing and RBF Neural Networks

A. Bakhshi(1), H. Amini Tehrani(2)

(1) *Associate Professor, Department of Civil engineering, Sharif University of Technology, bakhshi@sharif.edu*
(2) *Phd Candidate, Department of Civil engineering, Sharif University of Technology, aminitehrani_h@mehrsharif.ir*

Abstract

In the past few decades, using signal processing tools in structural health monitoring has risen considerably due to recent advances in the field of sensors and other electronic technologies. These advances provide a wide range of response signals such as velocity, acceleration and displacement caused by low to high intensity earthquakes and environmental loads on building structures and bridges. Structural health monitoring i.e. the detection of presence, location and type of damage in structure in order to quantify the amount of damage and predicting the remaining lifetime of structure for service. In this research, wavelet packet transform has been employed in combination with Hilbert transform due to its favorable performance in detection of the structural damages and also its capability for denoising of response signals. In the proposed method, radial basis function (RBF) neural network has been used with the aim of reducing the number of required sensors in order to identify the location and determine the severity of damage caused to the structure. To achieve the proposed goal, the extracted data from each response signal should be increased to provide some information with regard to the higher modes. Finally, the obtained data is used to train the RBF neural network. The performance of the proposed method has been verified by means of numerical examples. To demonstrate the capabilities of the proposed algorithm, numerical simulations are performed on a four-story two-bay shear frame with different damage scenarios using OpenSees. The results show that this method can detect the occurrence, location and severity of damage with good accuracy even in the presence of measurement noise.

Keywords: structural health monitoring; signal processing; wavelet packet transform; neural network; multi-story frames

1. Introduction

Structural health monitoring has become an evolving area over the last few decades with an increasing need to assure the safety and functionality of multi-story structures. Damage may be defined as any deviation in the structure's original geometric or material properties. Any change in dynamic properties of structure leads to changes in modal properties of the structure including changes in natural frequencies, mode shapes and modal damping. Structural health monitoring (SHM) and damage detection denotes the ability to monitor the performance of structures, detect and assess any damage in order to reduce the life-cycle cost of structure and improve its reliability and safety.

Dynamic vibration-based methods rely on the change of vibration characteristics as indication of damage due to the fact that damage changes the physical properties of the structure. Over the last two decades, extensive research has been conducted on vibration-based detection approach. Doebling et al. [1] and Sohn et al. [2] presented comprehensive literature reviews of vibration-based damage detection and health monitoring methods for structural and mechanical systems. The basic premise behind these methods is that a change in stiffness leads to a change in natural frequencies and mode shapes. Although modal-based methods have been applied successfully to identify the dynamic properties of linear and time-invariant structural systems, they still have some problems and challenges[3]. Kim et al. [4] and Hou et al. [5] have pointed to some of these problems. Khoshnoudian and Esfandiari [6] presented an algorithm for damage assessment based on a parameter estimation method, using the finite element and measured modal response of the structures.

Signal-based methods examine changes in the features derived directly from the measured time histories or their corresponding spectra through proper signal processing tools and robust damage detection algorithms. 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. Hou et al. [7] presented the great potential of wavelet analysis for singularity extraction of the signals. The detection results showed that occurrence of damage could be detected by spikes in the details of the wavelet decomposition of response data, and the locations of these spikes could accurately indicate the moments at which the damage occurred. Similar works have been conducted in [8-10]. Several recent studies investigating signal-based methods can be found in [11-13]. They are also affordable and appropriate for online structural health monitoring. Yen and Lin [14] assessed the usage of wavelet packet for the identification and classification of the vibration signals. Biemans et al. [15] used orthogonal wavelet analysis to analyze the measured strain data by piezoelectric sensors in order to detect crack growth in the middle of a rectangular aluminum plate. Sun and Chang [16] suggested a method based on wavelet packet analysis for identification of structural damage. In the proposed method, first, the structural vibration signal decomposes to wavelet packet components, and then the energy component is calculated and used as input to the neural network for damage identification. Yam et al. [17] created a non-dimensional damage index vector for identification of damage in composite structures. Damage index vector is calculated based on changes in the energy of components obtained from the wavelet packet analysis of vibrational response before and after damage occurrence. Sun and Chang [18] presented two damage indices based on the energy of wavelet packet components. In order to show the effectiveness of the proposed method, they studied an experimental model of a cantilevered steel beam. Ovanesova and Suarez [19] used wavelet transform to detect cracks in a one-story plane frame. They investigated the effectiveness of wavelet analysis for the detection of cracks by using numerical examples. Han et al. [20] introduced a damage identification index as the ratio of wavelet packet energy (WPERI). The proposed method was evaluated on a simulated beam with simple supporters and also on steel beams with three damage models in the laboratory. Diao et al. [21] suggested a two-stage technique for the structural damage detection based on wavelet packet analysis and neural network. They used three-dimensional numerical simulation model to verify their measurement method. Li et al. [22] used the combination of empirical mode decomposition (EMD) and wavelet analysis to identify changes in structural responses. They used the method for identifying the damage in a four story shear frame. Ren and Sun [23] used the combination of wavelet transform and Shannon entropy to detect structural damage from vibrational signals. They used wavelet entropy, relative wavelet entropy and time-wavelet entropy as damage-sensitive features for the detection and determination of the damage location.

When comparing the efficiency of the existing techniques for structural health monitoring, one of the important parameters is the number of sensors needed in order to supply the main goals of structural monitoring. In the method presented in this paper, radial basis neural network has been used with the aim of reducing the number of required sensors in order to identify the location and determine the severity of damage caused to the structure. To achieve the proposed goal, the extracted data from each response signal should be increased to provide some information with regard to the higher modes. Finally, the obtained data is used to train the RBF neural network. In this way, the number of required sensors will be remarkably reduced. It is shown that this method can effectively detect the existence, location and severity of damage in multi-story shear frames. Issues related to the robustness of this procedure in different damage scenarios, different damage levels and also in the presence of measurement noise are discussed.

2. Methodology

In this paper, we are looking for a procedure that can effectively satisfy the important goals of structural health monitoring. A combination of wavelet packet transform and fast Fourier transform (FFT) is used in order to achieve mono-frequency components of the acceleration response signals. Then by utilizing the Hilbert transform, the instantaneous mode shapes are also obtained from the recorded acceleration signals on definite floors. Instantaneous mode shapes are considered not to display the instantaneous changes of this parameter, but rather to obtain the final values of this parameter that can be used as an effective indicator in order to train the artificial neural network.

2.1 Wavelet packet transform

The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis and which allows the best matched analysis to a signal. It provides level by level transformation of a signal from the time domain into the frequency domain. It is calculated using a recursion of filter-decimation operations leading to the decrease in time resolution and increase in frequency resolution. The frequency bins, unlike in wavelet transform, are of equal width, since the WPT divides not only the low, but also the high frequency sub band. In wavelet analysis, a signal is split into an approximation and a detail coefficient. The approximation coefficient is then itself split into a second-level approximation coefficients and detail coefficients, and the process is repeated. Fig. 1, shows the level 3 decomposition using wavelet packet transform. However, in the wavelet packet analysis, both the approximation and details at a certain level are further decomposed into the next level, which means the wavelet packet analysis can provide a more precise frequency resolution than the wavelet analysis.

Wavelet Packet is a function with three indexes which can be expressed as a set of following basic functions:

$$W_{2n}\left(2^{p-1}x-l\right)=\sqrt{2^{1-p}}\sum_{m}h(m-2l)\sqrt{2^{p}}W_{n}\left(2^{p}x-m\right) \tag{1}$$

$$W_{2n+1}\left(2^{p-1}x-l\right)=\sqrt{2^{1-p}}\sum_{m}g(m-2l)\sqrt{2^{p}}W_{n}\left(2^{p}x-m\right) \tag{2}$$

where integers p, l and n are the scale, translation and modulation parameters, respectively. The discrete filters h(k) and g(k) are the quadrature mirror filters associated with the scaling function and the mother wavelet function.

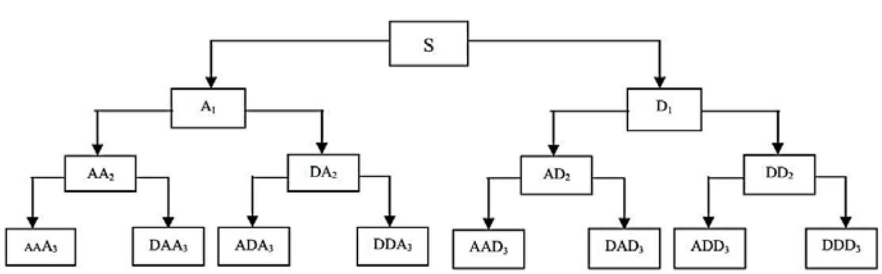

Fig. 1 -Signal decomposition via wavelet packet transform

In wavelet packet decomposition tree for a signal, energy entropy in node i is a special state of P-norm entropy with P = 2. P-Norm entropy is defined as below:

$$e_i = \sum_k \left| c^i_{j,k} \right|^p \ ; \quad (P \geq 1) \tag{3}$$

in which, $c^i_{j,k}$ are wavelet coefficients belong to *j*th level and *i-th* node of wavelet packet decomposition tree. In fact, when P=2, P-norm entropy depicts energy concept and therefore it is named as energy entropy.

2.2 Description of sifting process using wavelet packet decomposition

The applied sifting process is initiated by fitting the cubic spline through the recorded data points. Doing so will increase the time resolution of the recorded signals and thus increase the regularity of the decomposed components. In wavelet packet analysis, the interpolated signals are decomposed into different frequency components. A shape of the decomposed components by wavelet packet analysis depends on the shape of the mother wavelet used for decomposition. A symmetrical wavelet is preferred as a mother wavelet in the process to guarantee symmetrical and regular shaped decomposed components. Daubechies wavelet of higher order shows good symmetry and leads to symmetrical and regular shaped components. In case of the binary wavelet packet tree, decomposition at level n results in 2^n components. This number may become very large at a higher decomposition level and necessitate increased computational efforts. An optimum decomposition of the signal can be obtained based on the conditions required to be an intrinsic mode function (IMF). The IMF is defined as a function which satisfies following two criterions [24]:

(i) The number of extrema and the number of zero crossings in the component must either equal or differ at most by one.

(ii) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by local minima is zero.

In this condition, a particular node N is split into two nodes N1 and N2 if and only if the entropy index of the corresponding node is greater than 1 and thus the entropy of the wavelet packet decomposition is kept as least as possible. For convenience, the difference between the number of extrema and the number of zero crossings is since then called decomposition Index (DI). DI values greater than 1 indicate that, the given node must be decomposed further in order to achieve a mono-frequency component of the signal. In the wavelet packet decomposition tree, nodes with the energy contribution of more than 2 percent of the total signal energy are considered. However, the stated limit can be changed depending on the problem situation.

2.2.1 Steps for wavelet packet sifting process

1) The signal is decomposed in the first level and wavelet packet coefficients are calculated.
2) The energy entropy and decomposition index are computed for each node.
3) In each node of the level of interest, if DI value be more than 1 and also the node energy be greater than the specified limit, this node is decomposed into two other nodes in the upper level.
4) The energy entropy for the new created nodes in the upper level is calculated. If the energy entropy for the two child nodes be less than their parent node, the decomposition process will continue in accordance with the procedure described above for the two child nodes. Otherwise, the parent node will be the end node of the decomposition tree in the intended branch.

   It should be noted that the decrease in entropy will decrease the signal irregularity and thus increases its capability to meet the characteristics of the intrinsic mode functions and mono-frequency components.
5) After completing the decomposition process, the mono-frequency components of the main signal should be extracted among the end nodes of the wavelet packet decomposition tree.

At this stage, Fast Fourier Transform (FFT) is applied to the reconstructed signals of the terminal nodes coefficients in order to determine the mono-frequency components of the main signal.

6) The obtained mono-frequency reconstructed signals from previous step are used to determine the normalized instantaneous mode shapes in accordance with the process described below.

2.3 Normalized Instantaneous (NI) mode shape calculation using Hilbert transform

Briefly speaking, during a moderate or severe earthquake at various moments, stresses reach beyond elastic limit in different sections of structural members and lead to stiffness reduction. A moment later, the earthquake changes its direction of action and thus some of the reduced stiffness is recovered. Indeed, according to the earthquake content, the structure will experience non-elastic deformation, stiffness reduction and partial stiffness recovery again and again. Finally at the end of the earthquake, we have a damaged structure with reduced stiffness and some recorded signals which are directly affected by the time-varying structural behavior. In the present study, despite considering the linear model, we have tried to reduce the structural stiffness at various moments and with different intensities in different members in order to achieve a signal that is most similar to that obtained from the real behavior of the structure.

In modal analysis of time-varying systems, the response history of the building to $P_{eff,n}(\mathrm{t})$, the *n-th* mode component of the effective seismic force $P_{eff}(\mathrm{t})$, is determined by

$$u(t) = \sum_{n=1}^{N} u_n(t) + r(t) \tag{4}$$

where N is the number of DOFs. $u_n(t)$ is the signal component whose energy is concentrated in a band corresponding to the *n-th* natural frequency and $\mathrm{r(t)}$ is a residual signal. In these systems, due to the contribution of different modes other than the *n-th* mode, the *n-th* mode response is determined as:

$$u_n(t) = \sum_{n=1}^{N} \phi_r q_r(t) \cong \phi_n(t) q_n(t) \tag{5}$$

However, since in linear systems $q_r(t) = 0$ for all modes except the *n-th* mode, it is reasonable to expect that $\mathrm{q_r(t)}$ may be small and the *n-th* mode should be dominant even, implying that the elastic modes are, at most, weakly coupled. As is clear from Eq. (4), the original response of each floor is composed of various vibrational modes. Also, based on the valid assumption that led to the right side of Eq. (5), at a certain moment the modal coordinate is the same for different floors in a specific vibrational mode. Therefore the NI mode shape can be calculated as the ratio of modal response vector to one of its components as shown below.

$$\phi_n^{norm}(t) = \frac{u_n(t)}{u_n^p(t)} = \frac{\phi_n(t)}{\phi_n^p(t)} \tag{6}$$

where $u_n^p(t)$ and $\phi_n^p(t)$ are *n-th* mode of vibration response vector and mode shape component at DOF p, respectively. Haung et al. [25] used the concept of instantaneous frequency through the Hilbert transform. For a real signal $u_n(t)$, the analytical signal $Z_n(t)$ is defined as:

$$Z_n(t) = u_n(t) + iHT\left(u_n(t)\right) = a_n(t) e^{i\theta_n(t)} \tag{7}$$

Analytical signal is a complex sequence that has an original signal as its real part and HT of the original signal as its imaginary part. Theoretically, there are many ways of defining the imaginary part but the HT provides a unique way of defining the imaginary part so that the result is an analytic function. The analytic function can also be described in its polar form using two parameters, the instantaneous amplitude $a_n(t)$ and the instantaneous phase angle $\theta_n(t)$. The NI mode shape can be calculated as the ratio of the instantaneous amplitudes given by:

$$\phi_n^{norm}(t) = \frac{Z_n(t)}{Z_n^p(t)} = \frac{a_n(t)}{a_n^p(t)} \tag{8}$$

Hou et al. [5] have reported the advantage of using the analytic signal instead of modal components for normalized mode shape calculation. They have expressed that the advantage of using analytical signal is its non-zero value at any point.

2.4 Artificial neural networks

Artificial neural networks (ANNs) are a family of models inspired by biological neural networks (the central nervous systems of animals, in particular the brain) which are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which exchange messages between each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning.

2.4.1 Radial basis neural network

Radial basis function (RBF) networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The input can be modeled as a vector of real numbers $x \in R^n$. The output of the network is then a scalar function of the input vector, $\varphi : R^n \to R$, and is given by:

$$\varphi(x) = \sum_{i=1}^{N} a_i \rho(\|x - c_i\|) \tag{9}$$

where N is the number of neurons in the hidden layer, c_i is the center vector for neuron i, and a_i is the weight of neuron i in the linear output neuron. Functions that depend only on the distance from a center vector are radially symmetric about that vector, hence they called radial basis function. The norm is typically taken to be the Euclidean distance and the radial basis function is commonly taken to be Gaussian:

$$\rho(\|x - c_i\|) = exp\left[-\beta\|x - c_i\|^2\right] \tag{10}$$

The Gaussian basis functions are local to the center vector in the sense that:

$$\lim_{\|x\|\to\infty} \rho(\|x - c_i\|) = 0 \tag{11}$$

i.e. changing parameters of one neuron has only a small effect for input values that are far away from the center of that neuron. The parameters a_i, c_i and β_i are determined in a manner that optimizes the fit between φ and the data.

An interesting and important property of these radial basis function networks is that they form a unifying link between a number of disparate concepts. One consequence of this unifying viewpoint is that it motivates procedures for training radial basis function networks which can be substantially faster than the methods used to train multi-layer perceptron (MLP) networks. This follows from the interpretation which can be given to the internal representations formed by the hidden units, and leads to a two-stage training procedure. In the first stage, the parameters governing the basis functions (corresponding to hidden units) are determined using relatively fast, unsupervised methods (i.e. methods which use only the input data and not the target data). The second stage of training then involves the determination of the final-layer weights, which requires the solution of a linear problem, and which is therefore also fast.

A significant number of papers presented so far in the field of using neural networks for damage detection, have used excitations with certain frequency content. In fact, the data have been used for network training and also data recorded by the sensors for health monitoring are obtained under the same excitation. As is clear, no two earthquakes are the same and even with the most precise risk analysis studies for a Specific region, it is not

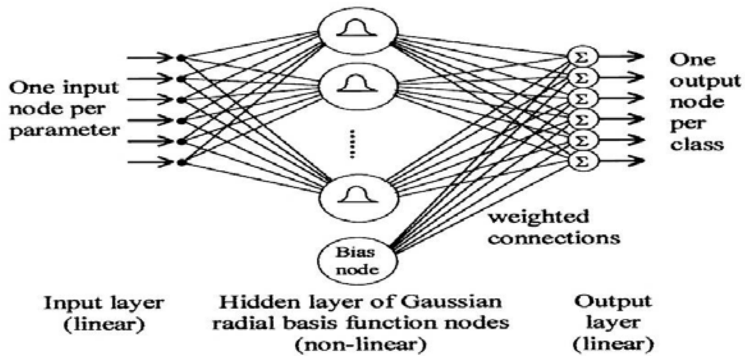

Fig. 2 -Different layers of radial basis function

possible to exactly determine the frequency content and other seismic parameters of the future earthquake. On the other hand, location and intensity of the occurred damage is a function of earthquake record. Therefore the selected damage sensitive feature for neural network training must not be a function of recorded signals amplitude and its derivatives such as energy and entropy.

3. Efficiency assessment of the proposed method

A 4-story-two-bay steel frame with span lengths of 6 m, shown in Fig.3, is used to illustrate the feasibility of the proposed damage detection procedure. This steel frame is designed by closing the rotational degrees of freedom in SAP2000 and section properties of structural members are obtained. The fundamental assumptions considered for steel mechanical properties are as follows: Young's modulus = 200 GPa, Poisson's ratio = 0.3, yield stress = 240 MPa. Then, OpenSees [26] is used in order to perform time history analysis under earthquake excitation. Section properties have been listed in Table 1. In order to investigate the accuracy of the developed model, the dominant frequencies of these two softwares are matched. In OpenSees, all the floors are modeled by the same mass value of 2569 kg and P-Δ effect is also considered. The system damping is assumed to be a Rayleigh damping, which is a mass-stiffness proportional one. The damping constants a_0 and a_1 are set to 0.71635 rad/sec and 2.104×10-3 sec, respectively.

Table 1 - Member sections in the 4-story frame

All Stories	Section
Beam	2IPE220
Column	2IPE180+PL250X8

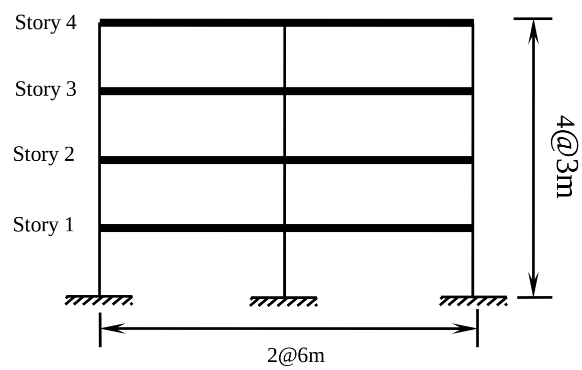

Fig. 3 -Structural model of 4-story shear frame

The corresponding damping ratios are 5% for the first and third modes, 4.08% for the second mode and 5.75% for the fourth mode. The four natural frequencies of the shear frame are 1.399, 4.026, 6.164 and 7.557 Hz, respectively. The structure was base excited by Parkfield earthquake with a sampling frequency of 50 Hz. To study the effect of measurement noise, random Gaussian noise is added to the acceleration response signals. The noise level on each floor is specified at about 5% RMS value of the acceleration response for the total time interval. Damage in the structure is also simulated by stiffness reduction of columns. The time resolution of the acceleration signal is increased using a spline interpolation for interpolating the signal data with finer increment of 0.005 sec instead of 0.02 sec.

In previous section, the procedure for extracting the normalized instantaneous mode shapes was stated. In order to determine the final mode shapes values in different degrees of freedom, we interpolate a horizontal line in the last part of the instantaneous mode shape so that the sum of squared errors would be minimized. It should be noted that the last few steps are not considered in order to eliminate the end effects. To compare the sum of squared errors in different time intervals, these values are normalized with respect to the number of steps. Therefore, the interval which has the lowest sum of squared errors is selected to determine the final mode shape value [24].

For the method presented in this paper, we will not need the final values of mode shapes in all degrees of freedom and also the frequency of damaged structure. In this method, depending on the number of structural floors, it is only necessary to record the acceleration responses of the structure in some degrees of freedom. It should be noted that at least two sensors are needed, but the minimum number of sensors depends directly on the type of structure and also the number of DOFs. In case of using two sensors, one of them is always used to normalize the data obtained from the other one and the second sensor must be installed in the highest floor of the structure to be able to monitor all structural damage occurred in the structure.

In the present study, in order to provide sufficient data for training the neural network, the final values of the first three mode shapes are obtained by combining signal processing tools to carry out the sifting process as described in the previous section. After sensitivity analysis, it was found that only the first and third modes are sufficient in order to achieve the desired accuracy. For the purpose of network training, multilayer perceptron (MLP) neural network and radial basis function (RBF) network were studied. The results showed that RBF networks have better performance in detection of relationships between inputs and outputs. In the mentioned RBF network, "newrb" was selected as a transfer function. This function adds neurons to the hidden layer of a radial basis network successively until it meets the specified sum square error goal or reaches the maximum specified number of neurons. "newrb" transfer function receives matrix of input vectors, matrix of target vectors, mean squared error goal, spread of radial basis functions and maximum number of neurons as an inputs and returns a desired radial basis network as an output. To generate the data required for the training of neural network, four damage severities are considered for each story and then 256 damage patterns are created for whole the structure by permutations of considered damage intensities. In the next step, the mentioned 256 damage patterns are simulated in OpenSees software and the corresponding acceleration responses are recorded. For practical health monitoring of the mentioned structure using the proposed method, we need only two sensors, one of which should be placed on the first floor to normalize the data and the other one must be located on the roof level. In fact, only the obtained data from the fourth floor sensor is used for determining damage existence, location and severity. To investigate the efficiency of the proposed method, five damage patterns with different severities have been considered under Parkfield earthquake record. The mentioned damage patterns have been simulated as both gradual and sudden damage in OpenSees software. Then the mono-frequency components correspond to the first and third modes are extracted from the acceleration signals recorded at the roof level in order to determine the final values of modal parameters. The obtained results are presented in the following tables and figures.

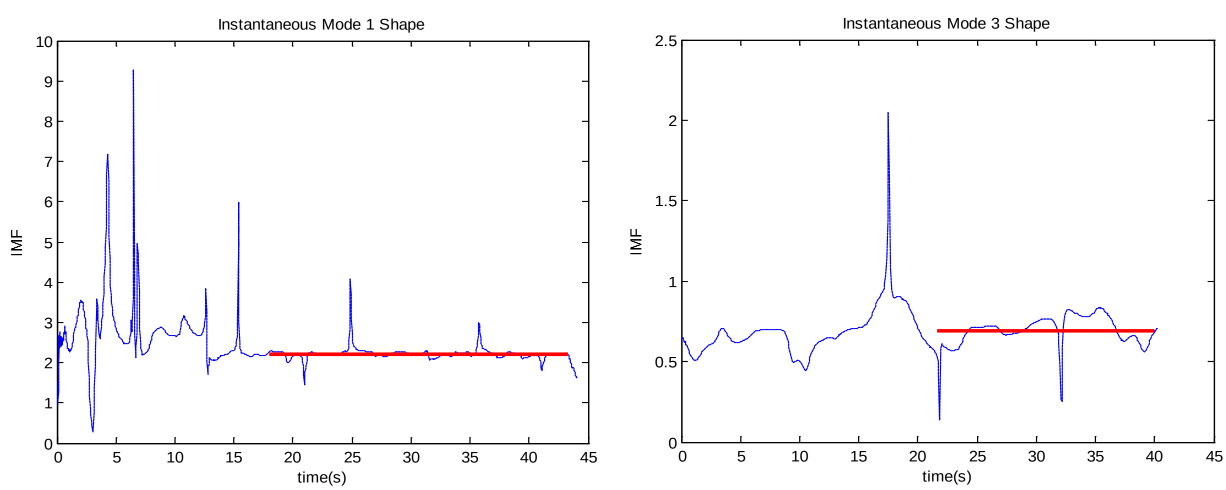

Fig. 4 -Normalized instantaneous mode shapes and the interpolated lines for the first damage scenario

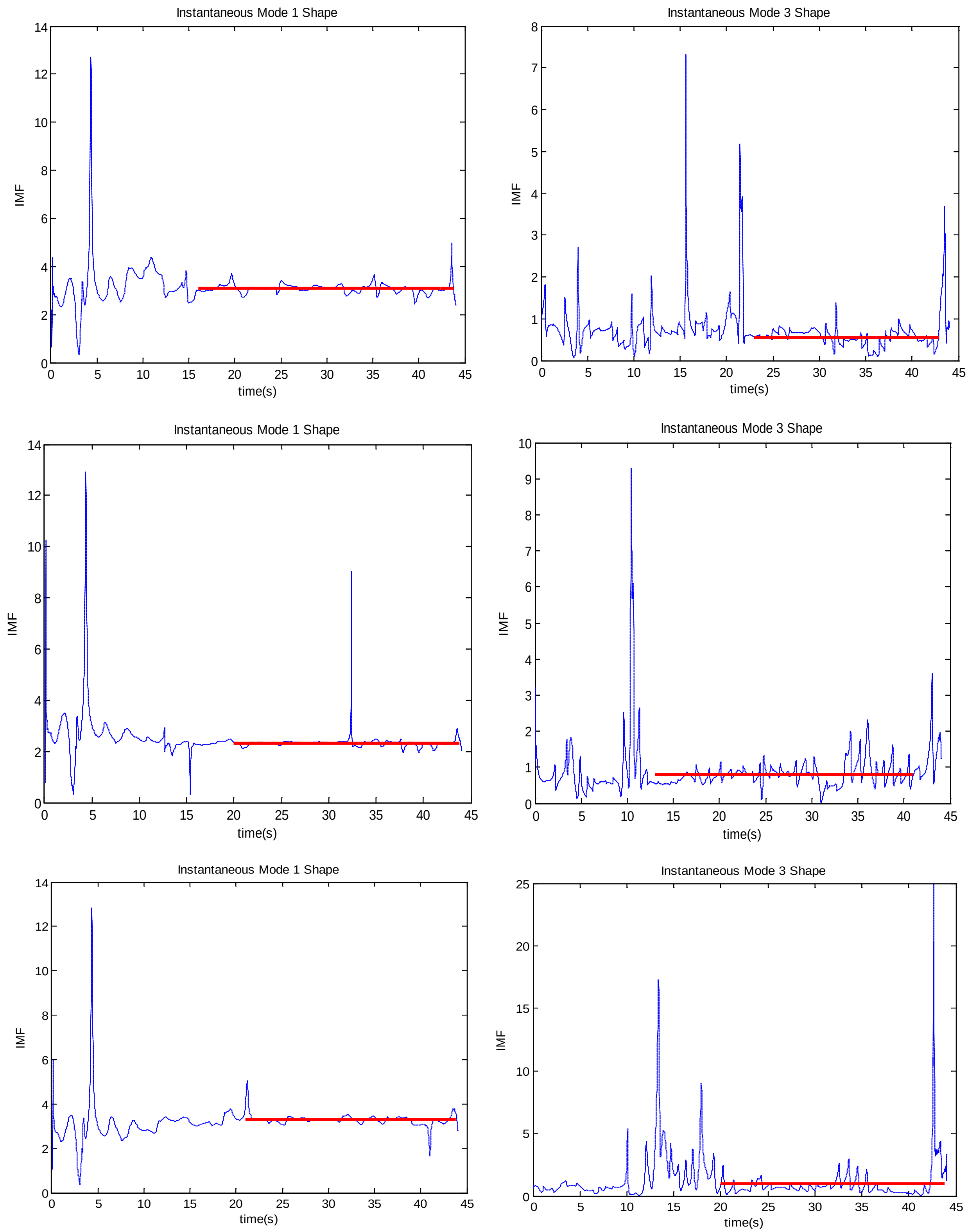

Fig. 5 –Normalized instantaneous mode shapes and the interpolated lines for the second (top), third (middle) and fourth (bottom) damage scenarios

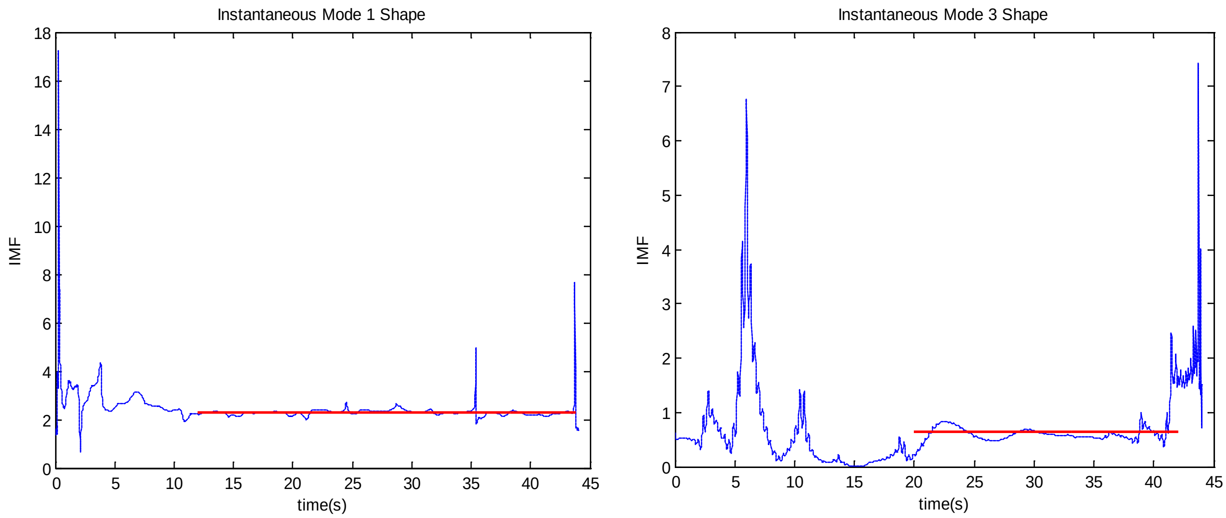

Fig. 6 -Normalized instantaneous mode shapes and the interpolated lines for the fifth damage scenario

Table 2 - error Exact and extracted final mode shapes values of the damaged structure

Data	**Damage Scenario 1**		**Damage Scenario 2**		**Damage Scenario 3**		**Damage Scenario 4**		**Damage Scenario 5**	
	Mode 1st	**Mode 3rd**	**Mode 1st**	**Mode 3rd**	**Mode 1st**	**Mode 3rd**	**Mode 1st**	**Mode 3rd**	**Mode 1st**	**Mode 3rd**
Exact Data	2.226	0.675	3.117	0.541	2.341	0.776	3.304	0.984	2.305	0.636
Extracted Data	2.221	0.693	3.084	0.556	2.326	0.795	3.289	0.981	2.298	0.634
Error (%)	0.226	2.603	1.070	2.831	0.628	0.795	0.454	0.265	0.331	0.368

Table 3 - Considered damage scenarios and the proposed method detection

Damage scenario	**Data**	**Story 1**	**Story 2**	**Story 3**	**Story 4**
1st	Exact Data (%)	40	20	0	10
	Extracted Data (%)	39.94	15.5	5.11	9.79
	Error (%)	0.06	4.5	5.11	0.22
2nd	Exact Data (%)	15	33	20	0
	Extracted Data (%)	18.42	35.41	18.75	5.31
	Error (%)	3.42	2.41	1.24	5.31
3rd	Exact Data (%)	30	0	13	0
	Extracted Data (%)	28.1	3.64	18.67	2.21
	Error (%)	1.9	3.64	5.67	2.21
4th	Exact Data (%)	0	0	35	0
	Extracted Data (%)	4.18	4.53	36.72	2.38
	Error (%)	4.18	4.53	1.72	2.38
5th	Exact Data (%)	40	15	10	30
	Extracted Data (%)	42.76	20.54	5.59	25.36
	Error (%)	2.76	5.54	4.41	4.64

4. Conclusions

One of the main goals of structural health monitoring (SHM) is the determination of the damage location and severity after significant events such as earthquakes, just by utilizing the response signals recorded at the time of the earthquake. To investigate the efficiency of the proposed method, five damage patterns with different severities have been considered under Parkfield earthquake record. The mentioned damage patterns have been simulated as both gradual and sudden damage in OpenSees software.It can be concluded from the obtained result

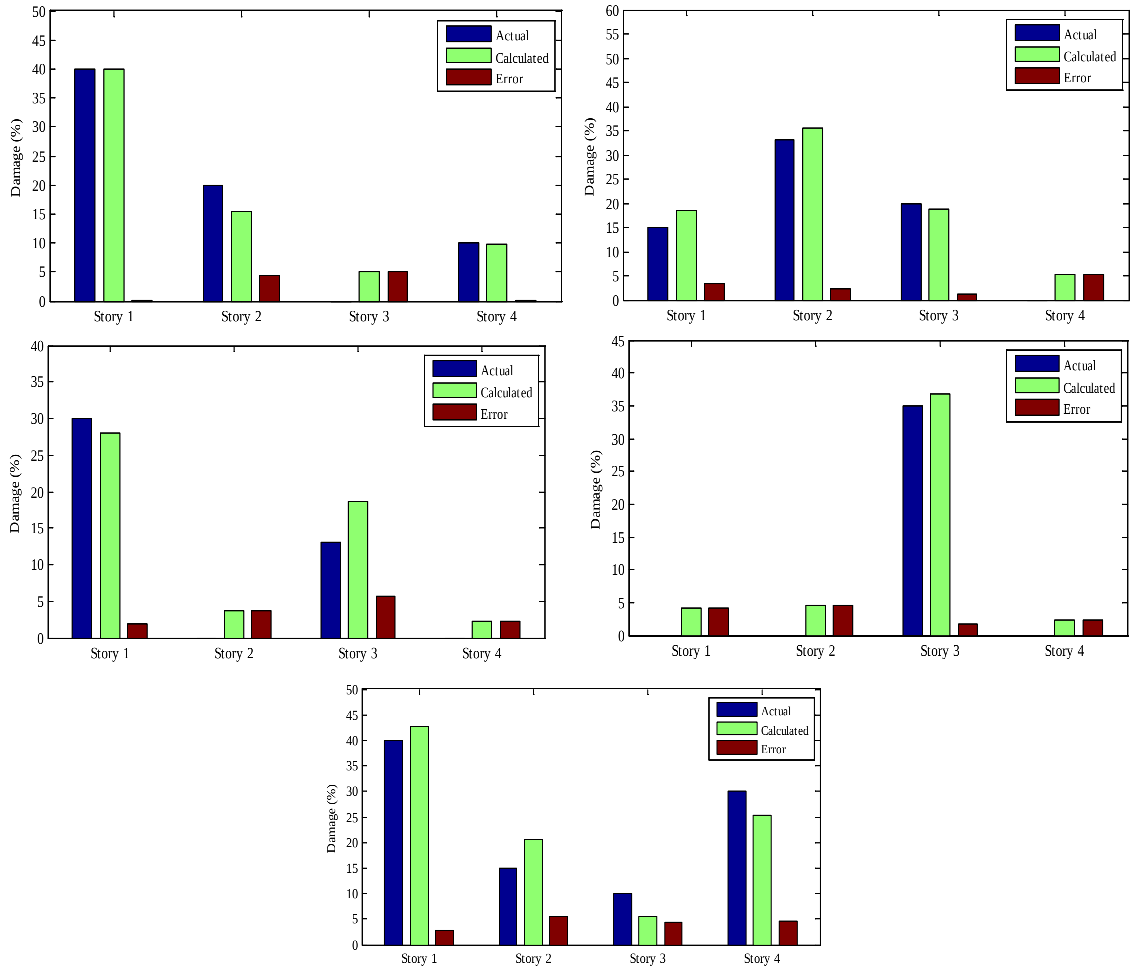

Fig. 7 -Histograms of the actual and calculated damage for the first (top-left), second (top-right), third (middle-left), fourth (middle-right) and fifith (bottom-centered)damage scenarios

that the sifting process via wavelet packet decomposition can properly extract the intrinsic mode functions. It was also shown that the final frequency and mode shape values obtained from the analytical reconstructed signals have a good agreement with the exact values achieved from analysis in OpenSees. In the present study, damage patterns have been selected in such away that is able to evaluate the performance of the proposed method for damage detection in different locations and with different intensities from 10 to 40 percent. The percentage of detection errors observed in most degrees of freedom was less than 5 percent. Also the maximum observed error is 5.7% which is desirable for decision making on structural health situation and also prioritizing the actions required for the repair and strengthening of structures. In the numerical example, it was also shown that damage detection goals was funded only by using the acceleration signals recorded at the roof level. Also the efficiency of the applied sifting process via wavelet packet decomposition was proved for the extraction of third mode vibrational characteristics. The efficiency of the proposed algorithm was investigated for different damage scenarios and intensities and also in the presence of measurement noise in multi-story shear frames. The results indicate the robustness of the applied method in satisfying the triple goals of damage detection.

5. References

[1] Doebling SW, Farrar CR, Prime MB (1996): Damage identification and health monitoring of structural and mechanical systems from changes in their vibration characteristics. a literature review. *Los Alamos National Lab*, NM United States.

[2] Sohn, H, Farrar CR, Hemez FM, Shunk DD, Stinemates DW, Nadler BR, Czarnecki JJ (2004): A review of structural health monitoring literature. *Los Alamos National Laboratory*, Los Alamos, NM, 1996-2001.

[3] Qiao L (2009): Structural damage detection using signal-based pattern recognition. *PH.D Thesis,* Kansas University.
[4] Kim JT, Ryu YS, Cho HM, Stubbs N (2003): Damage identification in beam-type structures, frequency-based method vs mode-shape-based method. *Engineering structures*, **25** (1), 57-67.
[5] Hou Z, Hera A, Shinde A (2006): Wavelet-Based Structural Health Monitoring of Earthquake Excited Structures. *Computer-Aided Civil and Infrastructure Engineering,* **21** (4), 268-279.
[6] Khoshnoudian F, Esfandiari A (2011): Structural damage diagnosis using modal data. *Scientia Iranica,* **18** (4), 853-860.
[7] Hou Z, Noori M, Amand RS (2000): Wavelet-based approach for structural damage detection. *Journal of Engineering Mechanics*, **126** (7), 677-683.
[8] Aguirre DA, Gaviria CA, Montejo LA (2013): Wavelet-based damage detection in reinforced concrete structures subjected to seismic excitations. *Journal of Earthquake Engineering,* **17** (8), 1103-1125.
[9] Su WC, Huang CS, Chen CH, Liu CY, Huang HC, Le QT (2014): Identifying the modal parameters of a structure from ambient vibration data via the stationary wavelet packet. *Computer-Aided Civil and Infrastructure Engineering*, **29** (10), 738-757.
[10] Salehi M, Ziaei-Rad S, Ghayour M, Vaziri MA (2013): A frequency response based structural damage localization method using independent component analysis. *Journal of Mechanical Science and Technology*, **27** (3), 609-619.
[11] Chang M, Pakzad SN (2012): Modified natural excitation technique for stochastic modal identification. *Journal of Structural Engineering,* **139** (10), 1753-1762.
[12] McNeill S (2013): A modal identification algorithm combining blind source separation and state space realization. *Journal of Signal and Information Processing,* **4** (02), 173.
[13] Sadhu A, Hazra B (2013): A novel damage detection algorithm using time-series analysis-based blind source separation. *Shock and Vibration,* **20** (3), 423-438.
[14] Yen GG, Lin KC (2000): Wavelet packet feature extraction for vibration monitoring. *Industrial Electronics,* IEEE Transactions on, **47** (3), 650-667.
[15] Biemans C, Staszewski WJ, Boller C, Tomlinson GR (2001): Crack detection in metallic structures using broadband excitation of acousto-ultrasonics. *Journal of Intelligent Material Systems and Structures,* **12** (8), 589-597.
[16] Sun Z, Chang CC (2002): Structural damage assessment based on wavelet packet transform. *Journal of Structural Engineering,* **128** (10), 1354-1361.
[17] Yam L, Yan Y, Jiang J (2003): Vibration-based damage detection for composite structures using wavelet transform and neural network identification. *Composite Structures,* **60** (4), 403-412.
[18] Sun Z, Chang CC (2004): Statistical wavelet-based method for structural health monitoring. *Journal of Structural Engineering,* **130** (7), 1055-1062.
[19] Ovanesova AV, Suarez LE (2004): Applications of wavelet transforms to damage detection in frame structures. *Engineering structures,* **26** (1), 39-49.
[20] Han JG, Ren WX, Sun Z (2005): Wavelet packet based damage identification of beam structures. *International Journal of Solids and Structures,* **42** (26), 6610-6627.
[21] Diao YS, Li HJ, Wang Y (2006): A two-step structural damage detection approach based on wavelet packet analysis and neural network. *in Machine Learning and Cybernetics 2006 International Conference*, IEEE.
[22] Li H, Deng X, Dai H (2007): Structural damage detection using the combination method of EMD and wavelet analysis. *Mechanical Systems and Signal Processing,* **21** (1), 298-306.
[23] Ren WX, Sun ZS (2008): Structural damage identification by using wavelet entropy. *Engineering structures,* **30** (10), 2840-2849.
[24] Shinde A, Hou Z (2005): A wavelet packet based sifting process and its application for structural health monitoring. *Structural Health Monitoring,* **4** (2),153-170.
[25] Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, Yen NC, Tung CC, Liu HH (1998): The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *in Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, The Royal Society.
[26] McKenna F, Fenves GL, Scott MH (2006): OpenSees: Open system for earthquake engineering simulation. *Pacific Earthquake Engineering Center*, University of California, Berkeley, CA., http://opensees.berkeley.edu.