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Damage Detection of Moment Frames using Ensemble Empirical Mode Decomposition and Clustering Techniques

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Abstract

Most of the damage detection methods implement dynamic response of linear structures for indication of damage. Time-frequency methods employ signal processing techniques to detect temporal changes in frequency characteristics of vibration response of the system. However, most of these techniques fail facing with nonlinear systems due to consecutive changes in stiffness that lead to fake damage indications. This study is divided into two parts. First, the Empirical Mode Decomposition method (EMD) is compared to Ensemble EMD (EEMD) to clarify the capability of these methods as signal processing tools. For this reason, the acceleration responses of a nonlinear steel moment frame are extracted by EMD and EEMD. Second, Hilbert transform based on EEMD is employed in conjunction with a density-based clustering technique to classify the changes in frequency and amplitude patterns to identify and estimate the extent of damage. Simulation results demonstrate that frequency is not an appropriate parameter to determine the extent of damage for nonlinear systems.

Keywords: *damage detection, nonlinear, HHT, EMD, EEMD, clustering*

1. Introduction

Damages in modern aerospace, mechanical and civil systems has always received considerable attention from engineering society since it has led to unwanted major economical loss and loss of life. Therefore, periodic inspection of engineering constructions is needed for identification of damage. Structural health monitoring is a robust approach to monitor the structure to detect damage in the early stages. The use of vibration data to find a reliable, efficient, and cost effective approach to quantify structural damage in engineering structures has attracted considerable research attention during the last decade. The basic idea of vibration-based methods is that the change in structural conditions such as stiffness, mass and damping is related to dynamic response of the structure under excitation. So, the change in modal parameters can indicate damage occurrence. Previous researches report the successful implementation of these methods on damages of civil structures including failures of beam-columns elements, joints and braces (Kawiecki, 2001; Shi *et al.*, 2002; Abdo and Hori, 2002; Sampaio *et al.*, 2003). Comprehensive literature reviews on vibration-based damage identification techniques for structures are provided by Salawu (1997), Doebling *et al.* (1998), Jingxiang (2004), Zou *et al.* (2000) and Fan and Qiao (2011).

Among the diverse vibration-based methods, the time-frequency based types are more concerned today. They employ signal processing techniques and data mining to detect damage from vibration response. Thus, an appropriate signal processing tool is the key element, since it extracts signal characteristics recorded by sensors to make investigation of structure integrity possible. Most of the traditional time-frequency signal processing methodologies are based on the fact that signal is linear and stationary. For example, Short-time Fourier Transform (SFFT) is a Fourier-based transform multiplied by a sliding time window function in the continuous-time case (Cohen, 1995).

However, data in real world can be simultaneously nonlinear and nonstationary in most cases which makes many of these procedures inappropriate for analysis. Spectrogram and Wigner-Ville procedures are able to analyze non-stationary but linear data (Flandrin, 1999). Also, several methods are proposed which deal with stationary but nonlinear data (Tong, 1990; Diks, 1999). Wavelet Transform (WT) is similar to SFFT and also provides variable-sized regions for windowing. Therefore, it can capture higher frequency resolutions and is able to provide a uniform resolution for all scales (Li *et al.*, 2009). However adaptivity is needed to adequately fit all the variety originating from nonlinear and non-stationary data. Huang *et al.* (Huang *et al.*, 1996; 1998) developed a time-frequency method based on combination of Empirical Mode Decomposition (EMD) and Hilbert Transform

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(HT), termed Hilbert-Huang Transform (HHT), to represent nonlinear and non-stationary data.

Vincent *et al.* (1999) compared EMD and wavelet analysis for structural damage detection. They concluded that EMD is superior to wavelet due to its adaptive nature. Quek *et al.* (2003) investigated damage in beams and plates based on the wave propagation fundamentals and HHT as a signal processing tool. To verify their technique they conducted several experimental tests on an aluminum beam, a sandwiched aluminum beam and a reinforced concrete slab. Yang *et al.* (2004) utilized EMD to identify damage time instants and its locations employing ASCE benchmark structure. They demonstrated that abrupt changes in stiffness due to structural damage cause appearance of spikes in EMD when signal is filtered. They also employed HHT for damage detection and system identification of the structure in the presence of noise. Xu and Chen (2004) investigated the effect of sudden stiffness change in the elements of a three-story shear building based on shaking table tests. They processed the time-history acceleration response of the stories by EMD to identify damage. Li *et al.* (2007) combined EMD and wavelet analysis. They first extracted signals by EMD to its components and then implemented wavelet on monocomponents to identify location and severity of damage. Cheraghi and Taheri (2007) proposed a new EMD-based damage index. They conducted some experimental tests and analytical modelings based on finite element method to detect damage in pipelines. Rezayi and Taheri (2009) conducted an experimental test on steel pipes. They recorded vibration data of a pipe via piezoelectric sensors and used a novel damage index based on EMD to detect damage. Chen (2009) reprocessed some available experiences of special civil structures and carried out several experimental investigations for system identification and damage detection. He concluded that EMD is a robust tool for structural health monitoring of tall buildings.

However, EMD has a major drawback. To overcome the mode mixing problem of EMD various improved methods are proposed which include the well-known Ensemble EMD (EEMD) (Wu and Huang, 2009). EEMD utilizes the benefits of properties of white noise to distribute components with more proper scales. On the other hand, most of the effective present techniques use wavelet or HHT to detect spikes due to stiffness changes in a structure. However, for nonlinear structures seismic excitation causes continuous transitions from elastic to plastic behavior which creates similar spikes. This fake damage spikes can incorrectly be considered as damage and make identification of damage impossible (Saadat *et al.*, 2004).

In this study, a methodology is proposed to detect damage and its severity in moment frames with nonlinear behavior under earthquake excitation. Response acceleration time-histories are processed by EEMD and Hilbert transform to extract instantaneous frequencies and amplitudes. A dimensionality reduction technique is implemented to reduce the amount of data. Instead of filtering the signal, a density-based clustering technique is used to classify data to detect changes due to damage.

2. Introduction to the Hilbert-Huang Transform

2.1 Empirical Mode Decomposition

In 1998, Huang *et al.* (1998) proposed Empirical Mode Decomposition (EMD) as a time-series demodulation method that is able to extract any arbitrary signal to a combination of intrinsic simple oscillatory signals referred to as 'IMF'.

IMFs are defined so that to satisfy the two following conditions (Huang *et al.*, 1998)

1) In the whole dataset, the number of extrema and the number of zero-crossings must either equal or differ at most by one

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

The first condition presents in many decomposition techniques which ensures oscillation. However, the new idea of EMD comes from the second condition that forces IMFs to be locally symmetric. Therefore, it prevents asymmetric signals to include which can lead to unwanted vacillations. Also, in contrast to harmonic waves, amplitude and frequencies of IMFs can change during the time. Therefore, these simple intrinsic mode functions can be nonlinear or nonstationary that would result in a well-behaved Hilbert transform. Extraction of IMFs is possible via 'sifting process' and consists of the following steps:

1) The first step is to find the local exterma of the time-series, $x(t)$.

2) A cubic spline is passed through maximum points to find an upper envelope. The second cubic spline is passed through minimum points as lower envelope. Then their mean curve, m_1, is calculated

3) m_1 is subtracted from the initial signal to find the first component, h_1:

$$h_1 = x(t) - m_1 \tag{1}$$

4) Ideally, h_1 is an IMF. However the aforementioned conditions must be satisfied. Thus, the above steps are repeated as many times as needed, denoted by k:

$$h_{1k} = h_{1(k-1)} - m_{1k} \tag{2}$$

A stopping criterion can be checked at the end of each iteration. As an example, the following threshold can be used:

$$SD = \sum_{t=0}^{T} \frac{|h_{(k-1)}(t) - h_{(k)}(t)|^2}{h^2_{(k-1)}(t)} \tag{3}$$

If the difference between two successive components is less than the pre-defined threshold, the last component is an IMF and is designated as c_1. The first IMF has the highest oscillation frequency contents of the original signal:

$$h_{1k} = c_1 \tag{4}$$

5) The residue, r_1, is obtained from extraction of the IMF from the signal

$$r_1 = x(t) - c_1 \tag{5}$$

6) Residue is considered as the initial signal and the process of steps (1) to (5) is repeated to find more IMFs. This process is

repeated to reach a residue that is less than the threshold. Thus, the residue is constant or a monotonic signal. The original signal can be reconstructed by summation of intrinsic modes and the residue:

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{6}$$

2.2 Ensemble Empirical Mode Decomposition

EMD is proven to be an applicable algorithm for many purposes. However, one of its major drawbacks is mode mixing problem. It can consequence to IMFs with widely disparate time scales or analogous time scales in separate IMFs, as discussed by Wu and Huang (2004). Mode mixing is mainly due to signal intermittency that not only can lead to time-frequency alias but also makes IMFs physically meaningless. To overcome this problem Wu and Huang (2009) proposed a noise assisted data analysis method referred to as Ensemble EMD (EEMD). EEMD utilizes the statistical characteristics of white noise in conjunction with an ensemble of trials to improve the scale separation problem in sifting process. In fact, by implementation of uniform white noise background, signal components with distinct scales are more accurately populated to proper scales of reference. Adding noise to the ensemble yields noisy IMFs for each trial but it helps all possible solutions to be examined in the ensemble. The effect of included white noise is eliminated by utilizing ensemble mean. In brief, EEMD can be defined by the following steps:

1) White noise with a pre-defined amplitude, $m_i(t)$, is added to the initial signal, $x(t)$:

$$x_i(t) = x(t) + m_i(t) \tag{7}$$

2) EMD is applied to decompose the signal to IMFs, c_j

3) Steps (1) to (2) are repeated with different white noise for each try

4) The obtained corresponding component means are the final decomposed IMFs:

$$c_j(t) = \lim_{N\to\infty} \frac{1}{N} \sum_{i=1}^{N} c_{ji}(t) \tag{8}$$

where, i and j are ensemble number and component number, respectively.

2.3 The Hilbert-Huang Transform

The Hilbert-Huang Transform (HHT) is an adaptive signal decomposition tool that utilizes combination of EMD and Hilbert transform to extract instantaneous amplitude and frequencies. The Hilbert transform of a signal, $x(t)$, is defined by (Huang *et al.*, 1998):

$$\mathrm{H}[x(t)] = \frac{1}{\pi} PV \int_{-\infty}^{+\infty} \frac{x(t)}{t-\tau} d\tau \tag{9}$$

where, PV is the Cauchy principal value, and t is the time variable.

The analytic signal is obtained as:

$$z(t) = x(t) + iy(t) = a(t)e^{i\theta(t)} \tag{10}$$

in which,

$$a(t) = \sqrt{x^2(t) + y^2(t)}$$

$$\theta(t) = \arctan\left(\frac{y}{x}\right) \tag{11}$$

$a(t)$ is the instantaneous amplitude. Instantaneous frequency is the derivative of phase function:

$$\omega = \frac{d\theta}{dt} \tag{12}$$

HHT initially utilizes EMD to extract IMFs from the original signal. Then, Hilbert transform is applied on IMFs to find instantaneous frequencies and amplitudes.

3. Dimensionality Reduction

Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) are the most popular methods used for dimensionality reduction (Martinez and Martinez, 2005). They are successfully used in statistics, pattern recognition and machine learning for classification and dimensionality reduction. PCA maps correlates data to principal components in such a way that the highest variance is obtained on the first component and the other components that satisfy orthogonality condition of Eigen vectors. Unlike the PCA, LDA is a supervised procedure and does not ignore data labels. LDA tries to separate differences of data classes by an effective projection, $J(W)$, which is mathematically defined by the maximum of (Welling, 2005):

$$J(W) = \frac{W^T S_B W}{W^T S_W W} \tag{13}$$

where, S_B is 'between-class scatter matrix' and S_W is 'within-class scatter matrix' of variable W, defined by:

$$S_B = \sum_c (\mu_c - \bar{x})(\mu_c - \bar{x})^T$$

$$S_W = \sum_c \sum_{i \in c} (x_i - \mu_c)(x_i - \mu_c)^T \tag{14}$$

where, $\bar{x}$ is data mean and μ_c is the mean vector of the class. For convenience, Eq. (13) can be transformed to an optimization problem:

$$\min: -\frac{1}{2} W^T S_B W$$

$$W^T S_W W = 1 \tag{15}$$

According to lagrangian equation:

$$L_P = -\frac{1}{2} W^T S_B W + \frac{1}{2}\lambda(W^T S_W W - 1) \tag{16}$$

The solution is obtained from:

$$S_B W = \lambda S_W W \Rightarrow S_W^{-1} S_B W = \lambda W \quad (17)$$

If S_B is assumed to be a symmetric positive matrix which is also definite, one can conclude:

$$S_B = S_B^{\frac{1}{2}} S_B^{\frac{1}{2}}$$

$$S_B = U \Lambda U^T \Rightarrow S_B^{\frac{1}{2}} = U \Lambda^{\frac{1}{2}} U^T \quad (18)$$

By definition of $v = S_B^{\frac{1}{2}} W$, Eq. (18) changes to:

$$S_B^{\frac{1}{2}} S_W^{-1} S_B^{\frac{1}{2}} v = \lambda v \quad (19)$$

The eigenvalue problem of the above equation, λ, can be solved by finding the maximum eigenvalue according to definition of J.

4. Density-based Clustering

So far, many types of clustering algorithms have been proposed for different purposes. However, traditional algorithms are suitable for small databases and require large runtime for large data sets. Several methods are recently proposed to increase the efficiency of clustering of large databases (Zhang *et al.*, 1996; Raymond and Han, 1994; Shafer *et al.*, 1996). 'Density Based Spatial Clustering of Applications with Noise' (DBSCAN) procedure proposed by Ester *et al.* (1996) is a well known density-based technique which is able to find arbitrarily shaped clusters and also has a notion of noise. DBSCAN defines three types of points including: (1) core point: a point inside a cluster (2) border point: a point that is not inside a cluster but within the neighborhood of a core point (3) noise point: a point that is neither a core nor a border (Tan *et al.*, 2006). Fig. 1 depicts point definitions for a two-dimensional data set. A cluster in DBSCAN is defined by a collection of data, larger than a pre-defined minimum number, *Mpts*, in vicinity, *Eps*.

DBSCAN algorithm can be briefly described by the following steps

1) Classify all points in the data set
2) Discard all points classified as noise

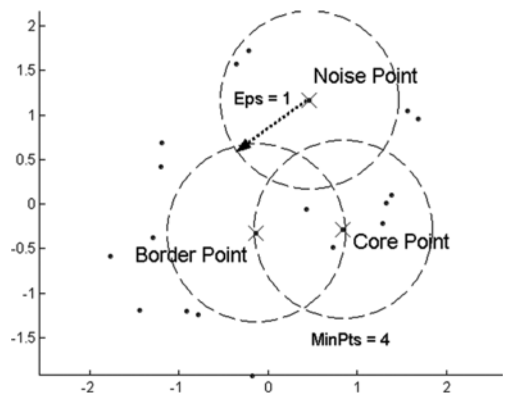

Fig. 1. Definition of Points in DBSCAN (Tan *et al.*, 2006)

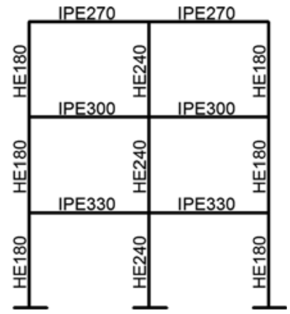

Fig. 2. Sections of Beam-Column Elements

3) Find the core points density reachable within *Mpts* and *Eps.* Each group of core points makes a cluster
4) Include the remaining border points to their corresponding core points

5. Modeling of the Structure

A three-story intermediate steel moment frame is selected for analysis. Building is assumed to be located on a high seismic area (D_{max}) and on site class D according to ASCE7-05 (2005). It is supposed that steel's yield stress is 2400 Kg/cm^2. Floor's dead and live loads are 600 Kg/m^2 and 200 Kg/m^2, respectively. Design of the building is carried out based on AISC360-05 (2005) and AISC341-05 (2005). The model structure has 4.0 m bay length and 3.2 m story height. Dominant period of the structure is 0.81 second. Fig. 2 depicts beam-column sections of the structure. The open source finite element program, Opensees (McKenna and Feneves, 2009) is used for nonlinear dynamic analysis. 'zerolength' element is used to connect elastic beam-column members at each beam-column connection face to characterize nonlinear behavior of connections. No cyclic degradation is defined. 'Steel01' material is utilized to model bilinear moment-rotation relationship of moment connections. 3% strain hardening is defined for connections. Nonlinear dynamic analysis is performed on a 2D centerline model. 5% Rayleigh damping is considered. P- effect is ignored to prevent second order displacements during the analysis. Panel zone inelastic deformations are neglected since it significantly affects the drift responses of the structure and makes the interpretation of results complicated.

6. Damage Detection Procedure

In this section a promising damage detection procedure is proposed based on a combination of signal processing and data mining. The procedure is based on the comparison of linear and nonlinear response of the structure for different intensity levels, as mentioned in the last section. Fig. 3 plots the process proposed method. Each step of this procedure is described in details in the next steps.

6.1 Nonlinear Dynamic Analysis

Moment frames experience nonlinear behavior during seismic

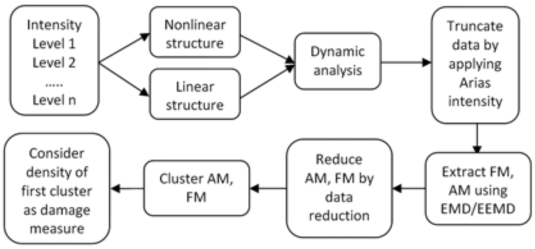

Fig. 3. Damage Detection Method

actions due to formation of plastic hinges in beam-column elements. During a seismic excitation several beam-column elements tolerate nonlinear behavior. Thus, damage is not localized. In order to capture the damage it is possible to monitor the roof response of the structure. It may be rational for low-rise buildings. But, higher modes effect cannot be neglected for higher buildings which makes problem of sensor location complicated. To appropriately capture this outspread damage we monitored entire responses of the stories.

The total interstory drift angle is related to the sum of the plastic rotations originating from flexural deformation of the members in each story (FEMA350, 2000). Thus, the maximum interstory drift is designated as a measure of damage in this study. Gillory Array#3 ground motion recorded from Loma Prieta earthquake is randomly selected from SAC/BD-97/04 (1997) time histories for site class D. To study the extent of damage in the structure, we defined 8 ground motion intensity levels. These levels cover the behavior of the structure from elastic (i.e. 1% maximum interstory drift according to FEMA350) to near collapse capacity (i.e. 10% maximum interstory drift). Plastic rotations of moment connections are monitored to ensure the elastic behavior of the structure at intensity level 1. Ground motion intensity is increased and acceleration response of stories is monitored using a nonlinear time-history analysis for each level. Table 1 lists the intensity levels and their corresponding response of the structure for linear and nonlinear behaviors.

6.2 EMD vs. EEMD

In this section performance of EMD and EEMD procedures in extraction of amplitudes and frequencies is investigated. Response acceleration of the stories is considered as inputs for EMD/EEMD and the extracted results are compared in a contrast.

Fig. 4 shows the input ground motion record and the output acceleration response of stories during nonlinear time-history analysis for level 1.

The total ground motion record length can be used for analysis. However, we used Husid diagram of ground motion record to reduce the amount of data. Husid diagram is the ratio of earthquake time history energy content (Arias intensity) to total energy of ground motion record defined by (Trifunac and Brady, 1975):

$$H(t) = \frac{\int_0^t (\ddot{x}_g)^2 dt}{\int_0^{t_e} (\ddot{x}_g)^2 dt} \tag{20}$$

where, t is time and t_e is duration of ground motion record. According to the Husid diagram, significant duration of a strong motion is calculated by duration between normalized Arias intensities of 5% and 95%. This considerably reduces the data size and consequently computational effort needed for EEMD. Fig. 5 plots Husid diagram of the ground motion record.

We assigned 100 iterations as ensemble number and also added noise with ratio of the standard deviation of 10% of original signal as proposed by Wu and Huang (2009). HHT Matlab program (Zhaohua, 2010) is implemented for EMD/EEMD analyses. It is

Table 1. Interstory Drift Results of Nonlinear Dynamic Analysis

	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
nonlinear	0.010	0.018	0.025	0.039	0.046	0.052	0.061	0.069
elastic	0.010	0.018	0.023	0.039	0.047	0.051	0.057	0.062

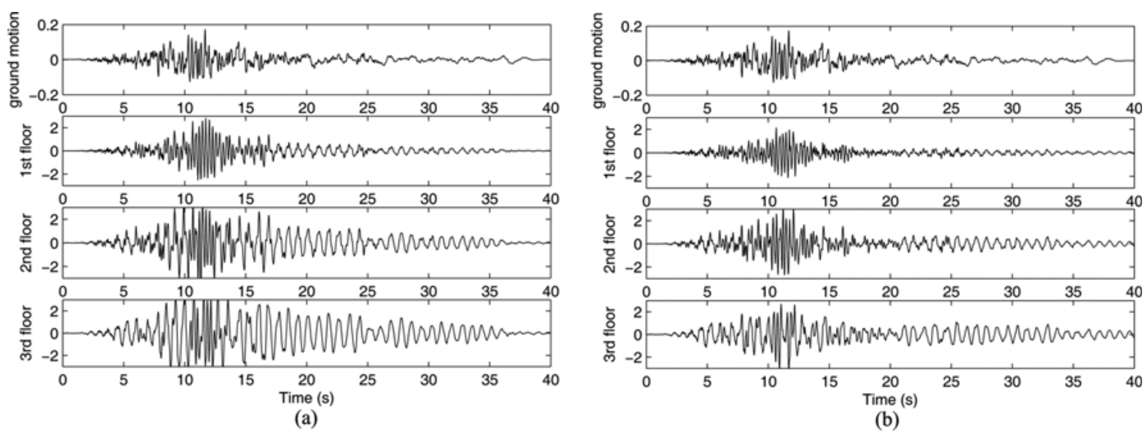

Fig. 4. Ground Motion Acceleration and Acceleration Response of Stories for Level 1 based on Ground Acceleration (g): (a) Elastic Structure, (b) Nonlinear Structure

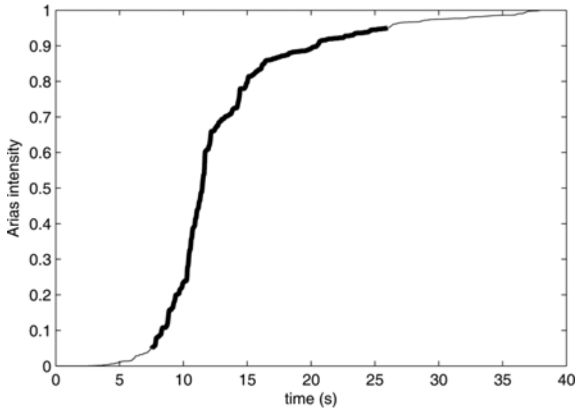

Fig. 5. Significant Duration of the Ground Motion Record

worth to note that we do not filter the response accelerations. Although signal filtering can eliminate unwanted frequencies or noise, however parts of signal that contain important information about flaw can be made of multiple frequencies which can unintentionally be removed by filtering. Therefore, indication signal strength may be weakened. Fig. 6 shows the first eight components obtained from EMD and EEMD. EEMD extracted components seem noisy. Although, the second and third components of EEMD are very noisy but the amplitudes of components are very low in comparison to the first component. As the first EEMD component shows, EEMD yields considerable improved signal extraction since the components of EEMD has more uniform scales.

To investigate the improved capability of EEMD, Hilbert-Huang transform is performed based on EMD and EEMD as shown in Figs. 7 and 8. It is obvious that HHT yields improved frequency extraction based on EEMD than EMD, since dispersion in frequencies is considerably reduced and extracted frequencies are mainly populated between the first and the third natural vibration frequencies of the structure (i.e. 1.22 and 6.85 Hz).

Previous studies show that EEMD extracted components are

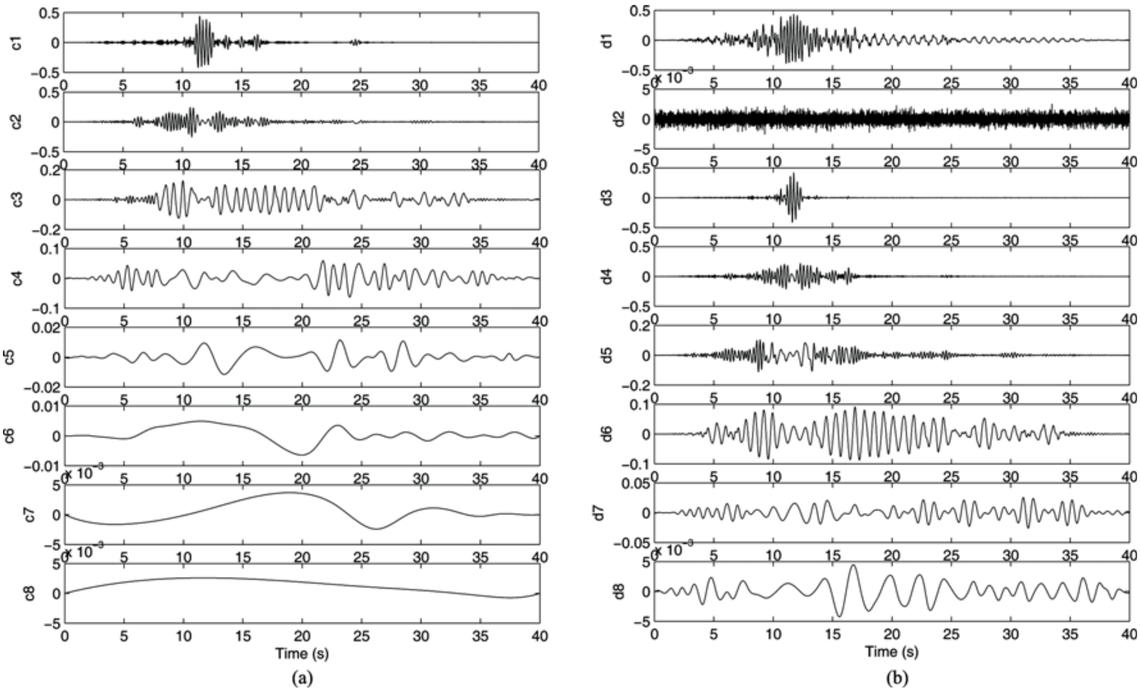

Fig. 6. Intrinsic Mode Functions of 3rd Story Acceleration Response under Level 1: (a) EMD, (b) EEMD

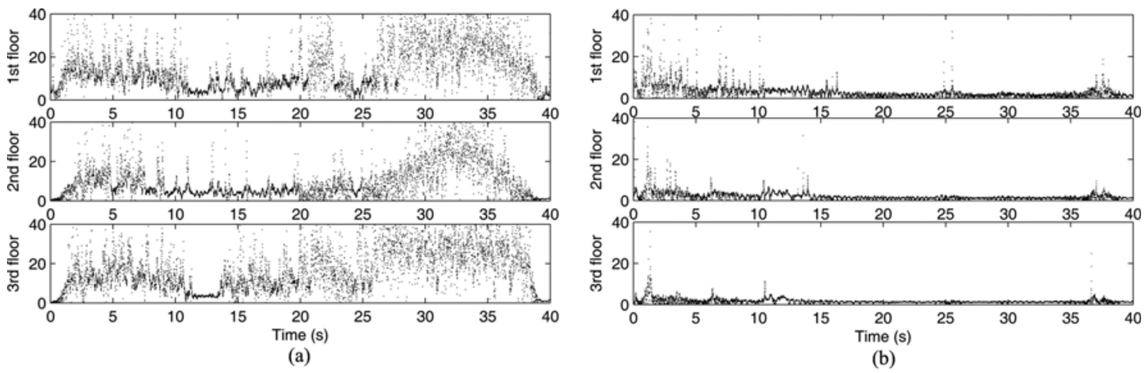

Fig. 7. Instantaneous Frequencies of 3rd Story Acceleration Response under Level 1: (a) EMD, (b) EEMD

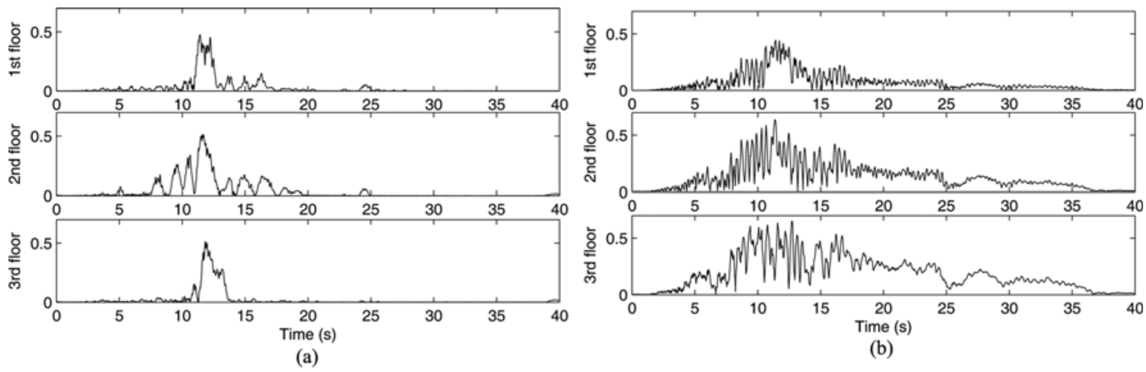

Fig. 8. Instantaneous Amplitudes of 3rd Story Acceleration Response under Level 1: (a) EMD, (b) EEMD

not necessarily IMFs due to scale mixing which can be as a result of high-frequency intermittence (Wu and Huang, 2009). This is illustrated in Fig. 6, especially for the second component. The physically meaningful IMFs can be extracted by further post-processing. However, the first IMF in EMD or EEMD has the highest oscillation frequency content of the original signal (see Eq. 1). Thus, we used the first component for analysis since the other components may not be suitable for Hilbert spectral analysis. HHT is applied on each story response acceleration to extract frequencies and amplitudes at each level.

6.3 Dimensionality Reduction

In the next step, LDA is applied on response frequencies and amplitudes of stories at each level to reduce the dimensionality of data. LDA not only reduces the dimensionality but also can merge the frequency response of stories to create a more indicative data by finding a robust projection which can eliminate noisy directions. The Matlab Toolbox for dimensionality reduction (Van der Maaten, 2007) is utilized for calculations. Thus, further analysis is performed on one dimensional data including frequencies and amplitudes. Fig. 9 compares story time-frequencies and LDA results.

6.4 Clustering

DBSCAN is a robust technique dealing with clusters of arbitrary shape and can relatively resist to noise which makes it suitable for this study. However, it does not respond well faced with clusters with widely varying densities. Furthermore, detection of noise and outliers is sensitive to specified radius. To evaluate the validity of clustering, several cluster validation methods are proposed. However, each clustering technique has a diverse concept for clustering which makes it difficult to employ the same evaluation criteria for different clustering techniques. For instance, SSE may be suitable for K-means clustering but not for density-based clusters since they need not to be globular. Consequently, the important issue in DBSCAN is selection of proper *Eps* and *Mpts* parameter values. To find rational values, one approach is to monitor the behavior of changes in distances between k^{th} nearest neighbor points, called *k-dist*, for some *k*. An appropriate *Eps* corresponds to a value of *k-dist* with abrupt change (Tan *et al.*, 2006). As an example, Fig. 10 plots calculated *k*-dist values corresponding to $k = 4$ for all data set sorted in ascending order. The diagram seems a bit noisy. However, the k-dist values do not vary a lot which means the densities are relatively uniform. There is a sharp change around the 4th nearest distance of 0.01. As a result, we chose the value of 0.01 for *Eps* and 4 for *k*.

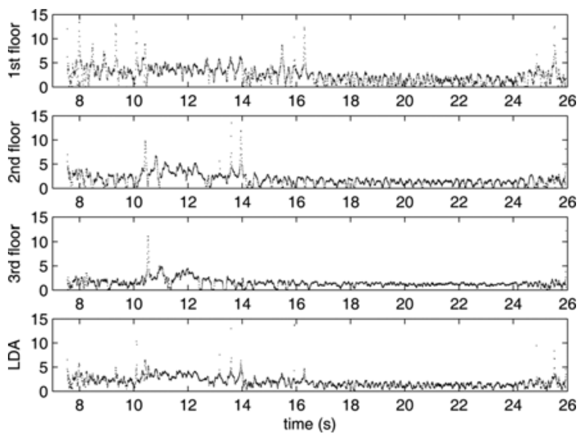

Fig. 9. Comparison of Instantaneous Frequency of Stories and LDA Results

6.5 Detection of Damage

Change in ground motion intensity does not change response

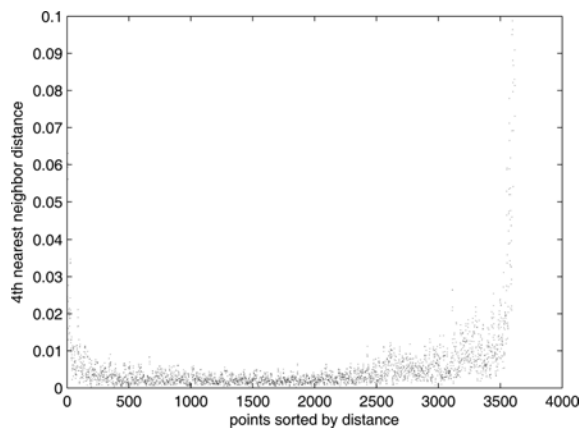

Fig. 10. k-dist Plot for Frequencies

Table 2. Results of Clustering of Levels 1 and 8 for Nonlinear Structure

Cluster No.		1	2	3	4	5	6	7	8	9
Level 1	frequency	3632	40	10						
	amplitude	787790	3179	1708						
Level 8	frequency	3589	46	14	5	5	5	5	7	6
	amplitude	2914581	6571	3248	890	1811	538	875	3098	1538

frequencies of the structure when it behaves linearly. Also, the amplitudes linearly increase with increase in ground motion intensity. However, when a structure tolerates nonlinear behavior its response frequencies change due to consecutive stiffness change. Change in the pattern of time-frequencies, which leads to change in cluster densities can be used for identification of damage. For instance, Table 2 compares clustered frequency densities of nonlinear structure for levels 1and 8. Only 3 clusters are classified for level 1but 9 clusters for level 8. Thus, by increase in damage level the dispersion of frequencies is increased which yields more clusters with lower densities. The largest cluster contains the most frequency content of vibration. Therefore, it is rational to consider the number of data points presented in the largest cluster as a damage measure. Fig. 11 shows the changes in this damage measure for different levels. We plotted frequency damage measure vs. drift ratios to be able to compare the drift ratio as a traditional damage measure and frequencies. As long as the structure is linear, frequency damage criterion remains constant but when damage occurs it reduces. But, damage indicator is not continuously decreased by increase in ground motion level that denotes the frequency is a suitable parameter for indication of damage but not for extent of damage. To investigate the capability of amplitudes to detect damage, we defined the sum of amplitudes corresponding to the largest cluster frequencies as a damage criterion as follows:

$$DM_a = \sum_{i=1}^{n} a_{i,1} \tag{21}$$

where, DM_a is the amplitude damage measure, $a_{i,1}$ is the amplitude of the ith data point in the first cluster and n is the number of data points of the first cluster.

Table 2 also lists the aforementioned corresponding sum of amplitudes for the above intensity levels.

The values of frequency and amplitude damage measures are listed in Table 3 for different damage levels to be able to quantitatively investigate the results for different intensity levels. It is clear that frequency measure irrationally changes by increase in damage level. Therefore, frequency damage measure which is the difference of frequency measure for linear and nonlinear cases do not correlate the damage level. Instead, amplitude measure shows a monotonic reduction in the growth due to increase in

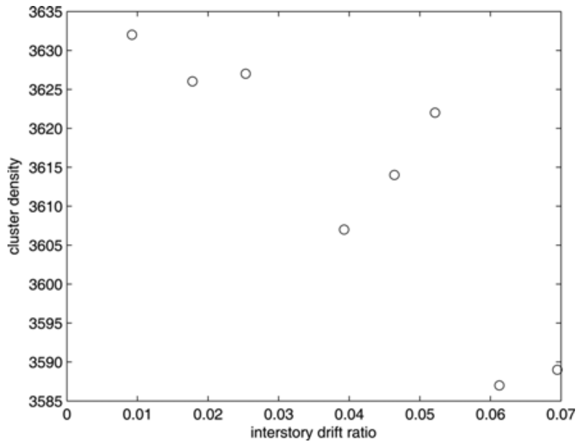

Fig. 11. Density of Frequencies of the Largest Cluster vs. Story Drift Ratios

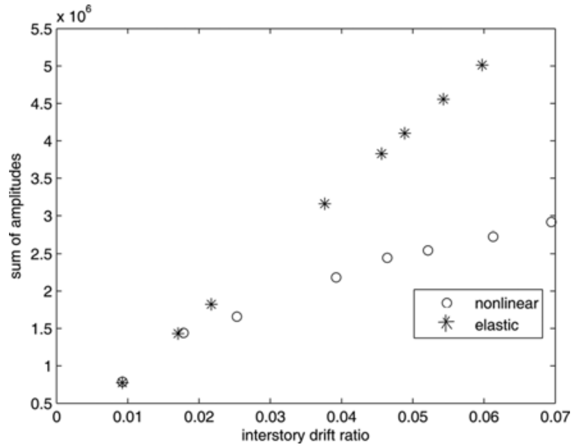

Fig. 12. Variations of Damage Criterion vs. Story Drift Ratios

Table 3. Comparison of Amplitude and Frequency Damage Criteria for Different Damage Levels

Damage level		1	2	3	4	5	6	7	8
Frequency measure	Linear	3632	3626	3627	3607	3614	3622	3587	3589
	Nonlinear	3635	3634	3632	3636	3638	3637	3637	3638
Amplitude measure	Linear ($\times 10^6$)	0.774	1.444	1.823	3.159	3.828	4.101	4.557	5.013
	Nonlinear ($\times 10^6$)	0.742	1.431	1.658	2.183	2.446	2.545	2.727	2.915
Frequency damage measure		3	8	5	29	24	15	50	49
Amplitude damage measure ($\times 10^6$)		0.032	0.013	0.165	0.976	1.382	1.556	1.83	2.098

Table 4. Selected Ground Motion Records

Earthquake	Year	Mw	Mech	Stn	R-Km	Site
Loma Prieta	1989	7.0	ob	gil3	12.4	D
Northridge	1994	6.7	th	sylm	6.4	D
Imperial Valley	1979	6.5	ss	ar05	4.1	D

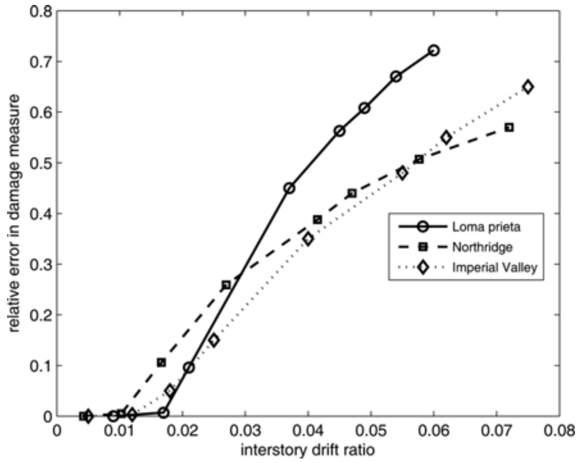

Fig. 13. Relative Error of Damage Measure for Different Ground Motions

nonlinearity. To clear this issue, Fig. 12 compares the amplitude damage measure versus story drift responses for nonlinear and linear cases. The figure depicts that the more increase in ground motion intensity the more decrease in the amplitude damage measure.

6.6 Ground Motion Effect

In previous section, one ground motion record was utilized to investigate changes in features of the output response of the structure. In this section, three different ground motion records are employed to be able to study the effect of dispersion in characteristics of different ground motions on the proposed damage measure. The ground motion records are selected from SAC/BD-97/04 bin, as listed in Table 4. The relative error of the amplitude damage measure is depicted in Fig. 13 for the ground motion records. It is clear that there is a relatively large dispersion in different ground motions. However, there is a similar trend in nonlinear behavior of the structure for all cases. In general, damage measure increases by increase in nonlinear behavior of the structure.

7. Conclusions

A novel technique based on combination of a time-series method and data mining is presented which is capable to overcome the limitations of time-frequency methods for damage detection of nonlinear structures. Using clustering techniques instead of filtering the signal not only does not weaken indication signals but also helps to monitor the structure vibrations in a timeframe to obtain a cumulative behavior. In a time-frequency approach signal processing is a key parameter. Implementation of an EMD-based method with an adaptive characteristic of decomposition of non-linear and nonstationary data helps to improve the efficiency of signal processing. Also, EEMD is proven to be able to more appropriately decompose a signal to its components with different scales. Simulations indicate that amplitude is more suitable as a measure for damage detection of nonlinear structures than frequency.

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