A DATA DRIVEN STRUCTURAL HEALTH MONITORING APPROACH INTEGRATING COGNITIVE CONCEPTS

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Abstract**—** The most crucial step of the structural health monitoring (SHM) methodology is the detection stage where a decision on the existence of damage has to be made. Without a very detailed and refined finite element model of the system, data driven approaches have the potential for rapid assessment of the structure at the damage detection stage of the more encompassing SHM problem. Change in the dynamic properties of structures offers a real-time structural health monitoring technique which detects damage at low cost and with little or no human intervention. Whether the changes in the identified parameters are due to the onset of damage or due to factors introducing non-linearity to the system, such as closing and opening of micro-cracks in concrete structures, environmental conditions or noise present in the data is a challenge that needs to be faced. This study presents a pattern recognition type of approach that will help with the distinction of true and false positives. The first step of the model-free methodology includes the linearity check of the system. The recorded vibration measurements recorded from the structure is divided into time segments and with each data set modal parameters are identified. The variability of the identification results are used as a measure for the existence of confounding factors that may mask accumulation of damage revelation. An 'expert' knowledge gained through this allows better treatment of the uncertainties in the problem and mimic the human decision process. The results of the numerical simulations are promising for the effectiveness of the procedure to minimize 'false negative' identifications.

Keywords**—** *Data Driven Damage Detection, Structural Health Monitoring, Cognitive, Cognitive Concepts*

1. INTRODUCTION

THE need for a rapid assessment of the state of the critical and conventional civil structures have been demonstrated during recent earthquake disasters. The problem with the current practice is the shortage of experienced inspectors and inevitable time delays. These problems are compounded when the signs of damage are not visible and the structure being inspected is not readily accessible.

Structural health monitoring (SHM) methodologies are being explored extensively as a possible means to an automated damage characterization strategy for detecting, locating, quantifying damage and if possible predicting the remaining service life of a structure in a timely manner. SHM employs both local and global methods of damage identification to achieve this objective. The local methods include visual inspections and non-destructive evaluation tools whereas global methods work with measured vibration data and data mining methods [1-5] for achieving this objective.

The limitation of the local methods is that they are not practical for application to large and complex structures but more so to investigate specific components of a structure. Most of the global methods, on the other hand, exploit changes in modal parameters and to identify the extent and location of damage in large structures. The basic idea behind these techniques is that the vibration characteristics or the so-called modal parameters (frequencies, mode shapes and modal damping) are functions of the physical properties of the structure (mass, energy dissipation mechanisms and stiffness) and damage will in turn cause changes in the modal properties. The problem that is most commonly considered is the one where data are recorded at two different times and it is of interest to determine if the structure suffered damage in the time interval between the observations. *Damage*, within this context, is defined as any unfavorable changes in the physical properties of the structure. The behavior of the system during the data collection is typically assumed linear and the damage, which may result from an extreme event occurring inside the time segment, is characterized as changes in the parameters of a linear model. Hence linear methods are utilized to analyze the two signals, namely before and after the damage. In Civil Engineering applications, however, the assumption of linearity is hardly ever satisfied. Even in cases of relatively low excitation amplitudes, closing and opening of micro-cracks in concrete structures, yielding of regions with high residual stresses in steel structures, and the ever present interaction between the structural framework and non-structural elements, introduces nonlinearity in the response which will definitely affect the accuracy of the analysis. Furthermore, most of the damage detection techniques generally neglect the effect of environmental factors including changes in loads, boundary conditions, temperature, and humidity, on modal parameters. Whether the changes in the identified parameters are due to the onset of damage or due to such other factors is the most challenging aspect of the damage identification problem. This paper examines cognitive concepts to discriminate the changes of modal parameters due to inherent non-linearity of the system from those caused by structural damage. We attempt to establish a systematic approach to distinguish the differences in the identified natural frequencies due to damage versus natural variation due to the existence of mild non-linearities.

2. MODAL IDENTIFICATION WITH OBSERVER KALMAN FILTER

A theoretical framework that has proved convenient and fruitful for the development of mathematical models from input/output data is the state-space approach. Among methods that operate entirely in time domain, the Observer/Kalman Filter Identification (OKID) algorithm has shown to be efficient and robust. The most noteworthy feature of the algorithm is the introduction of an observer that transforms the mathematical structure to one where the eigenvalues of the

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system matrix are zero for noiseless data or nearly zero when noise is present. A consequence of the modification introduced by the observer is that the non-zero length of the modified system's pulse response functions is drastically reduced when compared to those of the original system, with important gains in efficiency and robustness resulting. In effect, the OKID algorithm treats the output data as resulting from a modified input on a modified system. The matrices of a minimum realization for the actual system are then subsequently obtained for the modified system. The name Observer/Kalman derives from the fact that the gain of the introduced observer is that of a Kalman filter [6].

The eigensystem realization algorithm (ERA) was first proposed by Juang and Pappa (1985) for modal parameter identification and model reduction of linear dynamical systems and was later refined and ERA with data correlations (ERA/DC) was formulated to handle the effects of noise and nonlinearities [8].Operating on pulse response functions, also known as Markov Parameters, this technique produces an input/output mapping having the smallest state vector dimension that is compatible with a given accuracy. This mapping is known as a realization and has the form

$$\dot{x} = Ax + Bu \tag{1a}$$

$$y = Cx + Du \tag{1b}$$

where x = state vector, y = output vector, and the matrices A,B,C and D are the result of the realization. Since the same input/output mapping of Eqs.(1) is also given by:

$$\dot{z} = T^{-1}AT\,z + T^{-1}Bu \tag{2a}$$

$$y = CT\,z + Du \tag{2b}$$

It is evident that the matrices that define the realization are not unique (except for D which is independent of the non-singular transformation matrix T). Note, however, that since the system matrices of any two realizations are related by a similarity transformation, the eigenvalues are preserved.

In order to carry out the system realization with the extracted impulse response data, the discrete counterpart of the continuous state-space model can be expressed as

$$x(k+1) = A_1 x(k) + B_1 u(k) \tag{3a}$$

$$y(k) = Cx(k) + Du(k) \tag{3b}$$

For a system with r input and m measurement vectors, the system response, $y_j(k)$ at time step k due to unit impulse u_j can be written as

$$Y(k) = [y_1(k) \quad y_2(k) \quad \cdots \quad y_r(k)],\ k=1,2,\ldots \tag{4}$$

and form the $ms \times rs$ Hankel matrix

$$H(k-1) = \begin{bmatrix} Y(k) & Y(k+1) & \cdots & Y(k+s-1) \\ Y(k+1) & Y(k+2) & \cdots & Y(k+s) \\ \vdots & \vdots & \ddots & \vdots \\ Y(k+s-1) & Y(k+s) & \cdots & Y(k+2(s-1)) \end{bmatrix} \tag{5}$$

where s is an integer that determines the size of the matrix. By definition, the submatrices $\boldsymbol{Y}(k)$ correspond to the system Markov parameters and can be expressed as

$$Y(0) = D \tag{6a}$$

$$Y(k) = CA^{k-1}B \qquad k=1,2\ldots \tag{6b}$$

The basic formulation of ERA starts with the factorization of the Hankel matrix using the singular value decomposition,

$$H(0) = U\ S\ V^T \tag{7a}$$

$$H(1) = U\ S^{1/2} A\ S^{1/2} V^T \tag{7b}$$

Thus, the following triplet is a minimum realization:

$$\hat{A} = S^{-1/2} U_1^T H(1) V_1\ S^{-1/2} \tag{8a}$$

$$\hat{B} = S^{1/2} V_1^T E_r \tag{8b}$$

$$\hat{C} = E_m^T U_1 S^{1/2} \tag{8c}$$

where E_m^T is $[I_m\ O_m \cdots O_m]$ and E_r^T is $[I_r\ O_r \cdots O_r]$ and *Oi* is a null matrix of, Ii is an identity matrix of order i.

The basic formulation of the ERA requires the system's Markov parameters. An accurate identification of the Markov parameters is vital for accurate system realization. Identification of the system Markov Parameters has traditionally been carried out by Discrete Inverse Fourier Transformation (IDFT) of Frequency Response Functions (FRF). The approach used here, however, solves for the Markov Parameters directly in the time domain. The approach avoids the well-known difficulties associated with time-domain deconvolution by the introduction of an observer. The observer, when appropriately selected, leads to a state-space representation where the output is mapped to a modified input by a system whose pulse response functions decay much faster than those of the original system. As one anticipates, the Markov Parameters of the original system can be recovered from the observer gain and the Markov Parameters of the Observer Model.

The State-Space Observer Model is readily obtained from Eqs. (1). Specifically, adding and subtracting Gy to Eq. (1a) and defining

$$v = \begin{bmatrix} u \\ y \end{bmatrix} \tag{9}$$

one gets

$$\dot{x} = \overline{A}\,x + \overline{B}\,v \tag{10a}$$

$$y = Cx + Du \tag{10b}$$

where;

$$\overline{A} = A + GC \tag{11}$$

and

$$\overline{B} = [B + GD \quad -G] \tag{12}$$

Provided the system is observable, the eigenvalues of the modified system matrix Eq. (11) can be placed arbitrarily. One very attractive alternative is to select G such that all the eigenvalues of $\overline{A}$ are zero. In this case the resulting system matrix is nilpotent and the Markov Parameters of the Observer Model become identically zero after a finite (typically small) number of time steps. Because of the close relationship between the gain G that leads to zero eigenvalues in $\overline{A}$ (dead-beat observer) and the Kalman Filter, the foregoing approach is known as the Observer/Kalman Filter Identification (OKID) technique. In practice, the term is in fact generally used to refer to the complete process of identifying the pulse response functions followed by the generation of a minimum realization, typically using ERA/DC [8]. Once the system realization is obtained, the eigenvalues () and eigenvectors () of the state matrix A and the state-to-output influence matrix C can be used to obtain the modal parameters.

3. NUMERICAL SIMULATIONS

The numerical simulations are performed on the shear building model of a one-story one bay frame given in Figure 1. For the perfectly linear healthy state, the modal parameters of the structure are listed in the figure. The input excitation is taken as horizontal ground motion.

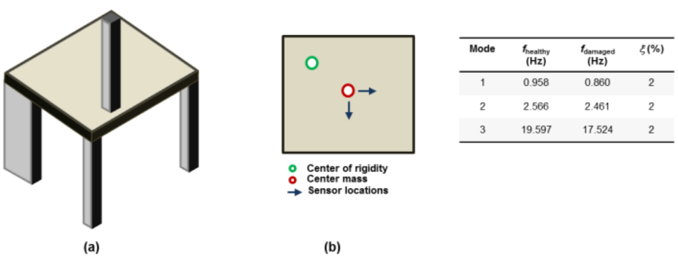

Fig.1. Simplified 3-D model for the numerical simulations: (a) Elevation view (b) Plan view

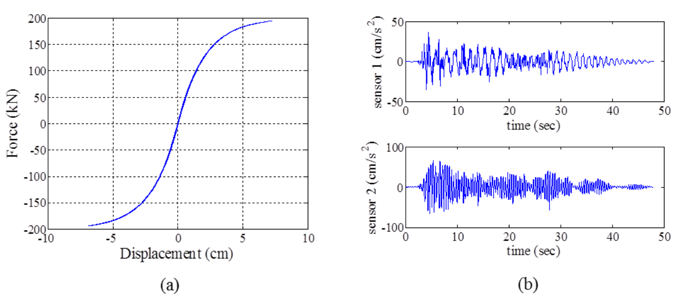

Fig.2. (a) Restoring force vs displacement relationship for the wall (b) Simulated acceleration measurements at the mass center of the floor

As part of the attempt to discriminate the changes in the modal parameters due to non-linearity of the system versus those caused by structural damage, the restoring force relationship for the shear wall is assumed to display Bouc-Wen [9] type non-linear behavior with parameters that result in smooth transition to non-linear softening behavior as shown in Figure 2. The acceleration response at the indicated sensor locations are analytically computed and sensor noise is simulated by contaminating both the input and the analytically computed acceleration response for all four floors with white noise having an RMS equal to 10%. The simulated acceleration measurements are also plotted in Figure 2. The 2500 point, 50 sec. long response data set is divided into 14 sec. long segments and consecutive segments are overlapped by a ratio of 5/7. ERA-OKID procedure is carried out for each segment and the modal parameters displayed in Table 1 are identified.

TABLE I
MODAL IDENTIFICATION RESULT

Data Set	Linear: No Damage		Linear: Damage		Non-Linear: No Damage	
	f_1(HZ)	ξ_1 (%)	f_1(HZ)	ξ_1 (%)	f_1(HZ)	ξ_1 (%)
1	0.96	2.09	0.83	2.13	0.69	13.88
2	0.96	2.10	0.83	2.02	0.70	12.67
3	0.96	2.19	0.83	2.14	0.74	14.04
4	0.96	2.21	0.83	2.11	0.77	16.50
5	0.96	2.38	0.83	2.22	0.80	12.47
6	0.96	2.31	0.83	2.59	0.81	9.31
7	0.96	2.73	0.83	2.68	0.81	7.75
8	0.96	3.14	0.83	3.24	0.82	6.79
9	0.96	3.00	0.84	3.46	0.86	5.80
10	0.96	3.10	0.84	2.25	0.90	3.91

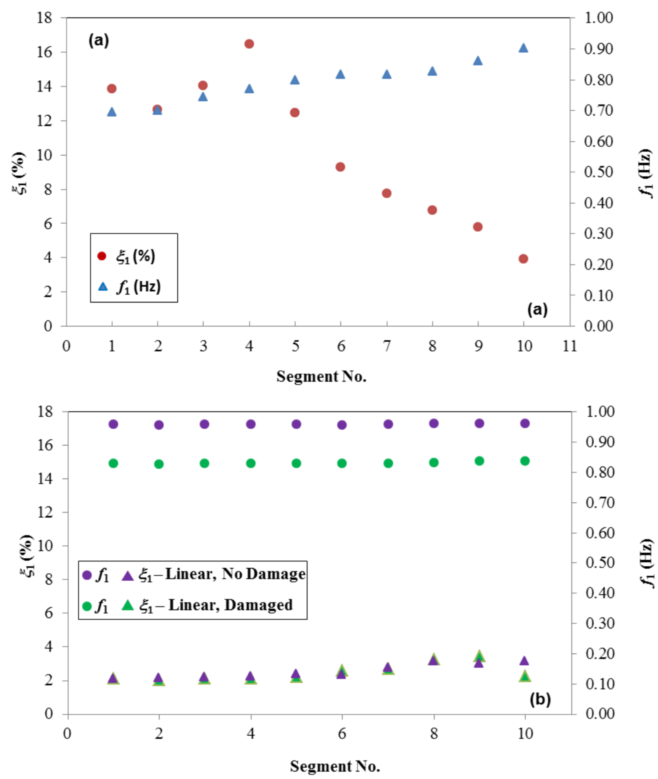

Fig.3. Identified Parameters for Mode 1: (a) Non-linear case (b) Linear case

Figure 3(a) and 3(b) display the variation of the estimated damping ratios and the natural frequencies for the first mode using different data segments with ERA-OKID algorithm for the linear damaged and non-linear cases, respectively. As clearly indicated in the figure, for the linear case, both for healthy and damaged states, the variability in the modal

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parameter estimates are small. The mean estimated values for the fundamental mode are f_1=0.96 Hz and ξ_1=2.52% with a standard deviation of 0.42% for the undamaged case and f_1=0.83 Hz and ξ_1=2.48% with a standard deviation of 0.50% for the damaged linear case. For the nonlinear case however, nonlinearity in the response manifests itself with increased damping ratio estimations having high variability (μ=4.17, σ=10.31). For the linear damaged case, however variability in the damping ratios is much smaller (μ=2.48, σ=0.50). It should also be mentioned that although the singular value decomposition of the Hankel matrix indicates the order of the system clearly during realization for the perfectly linear case, with nonlinear behavior it becomes harder to determine the order using the singular values and nonlinearity starts appearing as fictitious modes.

4. CONCLUSIONS

In this work, a damage detection methodology has been introduced. The proposed methodology is just an initial step in a damage characterization problem where a decision has to be made on the existence of damage. The initial examination with simulated data had promising results its capability for detection stage. Although the training data included loss of stiffness as the simulated damage and mild non-linear softening restraining force-displacement relationship, it can be easily expanded to different damage scenarios and force-displacement relationships including inelastic behavior. The variability in the extracted information proved to be very useful in discriminating between the simulated cases of ‘nonlinear behavior’ versus ‘damage’. Although this work did not focus on the further localization of damage but just the distinction between presence or absence of damage, this type of ‘insight’ may allow the ‘expert’ to better treat the uncertainties and provide reliable detection of damage. Further work will have to involve different structural configurations with different damage scenarios including multiple locations so that the ‘training data’ includes a more comprehensive data base content.

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