INTRODUCTION

1.1 General

There is a need for continuous assessment of the level of performance and safety of civil engineering structures when subjected to earthquakes, hurricanes and other extreme loads. Various methods have been developed in recent years for structural damage detection (Doebling et al. 1998), many of which rely on cumbersome finite element modeling processes and/or linear modal properties for damage diagnosis. For practical applications, these methods have been shown to be ineffective because of labor intensive tuning, excessive computational effort, and significant uncertainties caused by user interaction and modeling errors.

1.2 Overview of existing methods

Current methods of health monitoring of instrumented buildings include statistical signal processing techniques to examine the signatures obtained from recorded vibration signals. More recently, signal processing techniques such as the wavelet transforms (Hou et al. 2000) and the Hilbert Huang transforms (Yang & Lei 2000) have been employed for damage detection. These approaches are based on detecting the discontinuities in the acceleration data using the aforementioned transforms. However, the efficiency of these methods depends on the noise level of the signal and the severity of damage. Thus, damage detection and localization is still a daunting problem in structural health monitoring and extreme event damage evaluation (Chang 1998, 2000).

Recently, a damage detection approach using time series analysis of vibration signals was proposed by Los Alamos National Laboratory (LANL) (Sohn et al. 2001a, b). It is based on the ‘statistical pattern recognition’ paradigm. This damage detection approach has shown great promise in the identification of damage in the hull of a high-speed patrol boat as well as in several relatively simple laboratory test specimens. The method is very attractive for the development of an automated monitoring system because of its simplicity and its minimal interaction with users. However, before it can be embedded into a health monitoring system and used in practice the model needs to be tested with records obtained from a wide range of operational and environmental cases as well as different damage scenarios. Thus, a study was conducted by the authors (Lei et al. 2003), testing a modified version of the algorithm on the benchmark problem proposed by the ASCE Task Group on Health Monitoring (Johnson et al. 2000).

In this paper, the earlier algorithm developed by the authors (Lei et al. 2003) is further modified to increase the reliability of the damage prediction. For this purpose, the reference database is populated using an ensemble of normalized relative interstory accelerations of adjacent floors as opposed to the absolute acceleration signals at individual sensor loca-
2 DAMAGE DETECTION ALGORITHM OF VIBRATION SIGNALS USING TIME SERIES

2.1 Introduction

The damage diagnosis approach proposed by LANL is based solely on the statistical analysis of vibration signals from a structure of interest. In this approach, the structural health monitoring problem is posed in a statistical pattern recognition framework (Farrar et al. 2000), which consists of four parts: (i) the evaluation of a structure’s operational environment, (ii) the acquisition of structural response measurements, (iii) the extraction of features that are sensitive to damage, and (iv) the development of statistical models for feature discrimination. In this paper, the LANL algorithm has been modified and applied to the ASCE benchmark problem to detect and localize damage.

2.2 Description of algorithm

An ensemble of acceleration responses \( x_l(t) \) \((l=1, 2, \ldots, N)\) at one of the measurement locations (the accelerometer measurement shown in Fig.1) of the undamaged structure subject to different excitation samples is generated using the MATLAB program. \( N \) is the total number of sensor locations in the structure. All the time signals are normalized as follows:

\[
x_{s,l}(t) = \frac{x_l(t)}{\sqrt{\sum_{j=1}^{nsamp} [x_j(t)]^2}}
\]  

(1a)

where \( x_{s,l}(t) \) is the normalized signal and \( nsamp \) is the number of data points of the signal at the \( l \)th location. This signal is then standardized by using the following relation

\[
x_{m,l}(t) = \frac{x_{s,l}(t) - m(x_{s,l})}{\sigma(x_{s,l})}
\]  

(1b)

where, \( m(x_{s,l}) \) and \( \sigma(x_{s,l}) \) are the mean and standard deviation of \( x_{s,l}(t) \) respectively. This standardization-normalization procedure is applied to all signals employed in this study, reducing the signals to a zero mean and unit standard deviation processes.

From Figure 2, in the y direction and face 1, for the first, second, third and fourth stories, the relative interstory accelerations are \( a_1(t) \), \( a_5(t) \), \( a_9(t) \) and \( a_{13}(t) \) respectively. This is done for all the four faces of the structure.

The database is populated with the new set of interstory acceleration signals, \( x_j(t) \), \( j=1,2,\ldots,N-1 \). The hypothesis for introducing this new signal is
that after the structure is damaged at a particular story, the relative acceleration between these two stories will be significantly different and this would provide a more robust measure of damage. Interstory drifts have been shown (Krawinkler and Gupta 1998) to be well correlated to damage. However, it is difficult to use interstory drift ratios in practical situations because of errors in the signals with base line correction and double integration of the acceleration signals (Boore et al. 2002). Thus, direct use of the acceleration signal can potentially be a better approach for damage detection as introduced in equation 1c.

For each time series \( x_i(t) \) in the reference database, an AR (auto-regression) model with \( p \) AR terms is constructed as (Ljung 1987)

\[
x_i(t) = \sum_{i=1}^{p} \alpha_{ji} x_i(t-i) + e_i(t)
\]  

(2)

where \( \alpha_{ji} \) is the \( i^{th} \) AR coefficient, \( e_i(t) \) is a random process and \( p \) is the order of the AR model. The order of an AR model is determined based on the partial auto-correlation analysis of the signal (Box et al. 1994, Chatfield 1994).

A new acceleration response \( y(t) \) is obtained from the undamaged structure with operational condition close to one of the reference signals (Sohn et al. 2001a, 2001b). If the new signal is closest to the new signal is referred to ‘data normalization’ (Sohn et al. 2001a, 2001b). If the new signal \( x_k(t) \) ‘closest’ to \( y(t) \) determined by minimizing the following difference of the AR coefficients:

\[
\text{Difference} = \sum_{i=1}^{p} (\alpha_{ji} - \alpha_{ji})^2
\]  

(4)

The selected signal \( x_k(t) \) is defined as the reference signal. The procedure of finding a reference signal closest to the new signal is referred to ‘data normalization’ (Sohn et al. 2001a, 2001b). If the new signal is obtained from the undamaged structure with operational condition close to one of the reference signals, the AR coefficients of the new signal should be similar to those of the reference signal.

Second, an ARX (auto-regressive with exogenous inputs) model is constructed from the selected reference signal as

\[
x_k(t) = \sum_{i=1}^{na} a_{ki} x_k(t-i) + \sum_{i=1}^{nb} b_{ki} e_{x}(t-i) + e_k(t)
\]  

(5)

where \( na \) and \( nb \) are the orders of the ARX model, \( a_{ki} \) and \( b_{ki} \) are the coefficients of the AR and the exogenous input, respectively, and \( e_{x}(t) \) is the residual error of the ARX(\( na, nb \)) model. This model is employed to predict the new signal \( y(t) \).

\[
y(t) = \sum_{i=1}^{na} a_{ki} y(t-i) + \sum_{i=1}^{nb} b_{ki} e_{y}(t-i) + e_y(t)
\]  

(6)

where \( e_y(t) \) is given in Equation 3, \( a_{ki} \) and \( b_{ki} \) are coefficients associated with \( x_k(t) \) in Equation 5 and \( e_{y}(t) \) is the residual error of the new signal. If \( y(t) \) is obtained from the damaged structure, the ARX prediction model developed from the reference signal \( x_k(t) \) cannot reproduce the new signal. Thus, the residual error \( e_{y}(t) \) is significantly changed in comparison to \( e_{x}(t) \). Also, a larger increase in the residual error would indicate that the location where the measurement is made is near the damage source.

The ratio of the standard deviation of the residual errors \( h \), is defined as the damage-sensitive feature (Hoon et al, 2001) given by

\[
h = \frac{\sigma(e_y)}{\sigma(e_x)}
\]  

(7)

where \( \sigma(e_y) \) and \( \sigma(e_x) \) are the standard deviations of the signal under consideration and the reference signal respectively.

Threshold limits and damage decisions are based on the empirical distribution of \( e_{x}'(t) \) (Sohn et al. 2001a, 2001b, Worden et al. 2002). However, it is found that this damage-sensitive feature \( h \) has both the effects of excitation variability and damage. Also, the damage sensitive feature, \( h \), is highly dependent on the order of the ARX model given by \( na \) and \( nb \). As defined by equation 7, the value of \( h \) will increase as the order of the ARX model increases. In order to eliminate this non-uniqueness of \( h \), the original algorithm is modified by considering the effects of excitation variability and the orders of the prediction model on the residual errors.

The ARX model in Equation 5 is again employed for the remaining signals \( x_l(t) \) (\( l=1, 2, ..., k+1, ..., N-1 \)) in the reference database.

\[
x_l(t) = \sum_{i=1}^{na} a_{li} x_l(t-i) + \sum_{i=1}^{nb} b_{li} e_{x}(t-i) + e_l(t)
\]  

(8)

where \( e_{l}(t) \) is the residual error of the signal \( x_l(t) \) associated with the ARX model defined by Equation 5. A new parameter \( h'(l) \) is defined as the ratio of the standard deviation of residual errors of \( e_{x}'(t) \) and \( e_{l}(t) \), i.e.,

\[
h'(l) = \frac{\sigma(e_{x}'(t))}{\sigma(e_l(t))}
\]  

(9)

for all values of \( l \), leading to \( N-1 \) values of \( h' \). Thus, \( h' \) is considered to be random variable and the values \( h'(l) \) are realizations of this random variable. Thus, the mean value \( m(h') \) and standard deviation \( \sigma(h') \) can be evaluated from the observations of \( h'(l) \). Treating \( h' \) as a random variable with its probability distribution provides a more standard test for damage detection and localization since it accounts
for the effects of excitation error as well as the variability of the orders $na$ and $nb$ in the prediction model.

For instance, if we assume $h'$ to be normally distributed and consider a 97.5% confidence one-sided interval, then the $m(h') + 1.96 \sigma(h')$ may be used as the threshold limit for the damage condition. Thus, if the value of $h$ is greater than this threshold limit, then there is a 97.5% confidence in stating that the structure is damaged at that particular section in the structure. Similarly, if the value of $h$ is less than the threshold limit, there is a 97.5% confidence that if there is damage to the structure, the damage is smaller than the threshold value.

3 ASCE HEALTH MONITORING BENCHMARK PROBLEM

3.1 Description

In order to coordinate research activities in the area of damage detection, a benchmark problem was proposed by the ASCE Task Group on Health Monitoring (Johnson et al. 2000). The benchmark structure is a 4-story 2-bay by 2-bay steel frame scale model structure. Figure 1 is a schematic drawing of the benchmark building from Johnson, et al. (2000), in which the $w_i$ are excitations, and $\dot{y}_{ia}$ and $\ddot{y}_{ib}$ are accelerometer measurements ($\dot{y}_{ic}$ and $\ddot{y}_{id}$ in the x-direction are omitted for clarity).

Two analytical models for the structure were proposed for numerical simulation: a 12DOF shear building model and a 120DOF model with more structural details. Both models are finite element based. Structural damage can be simulated by removing the stiffness of various elements in the finite element models. Five damage patterns defined in the benchmark study are: (i) removing all braces in the 1st story, (ii) removing all braces in both the 1st and 3rd stories, (iii) removing one brace in the 1st story, (iv) removing one brace in each of 1st and 3rd story, and (v) damage pattern 4 with the floor beam partially unscrewed from the column in the 1st floor. These damage modes are shown by the braces and beams drawn in dashed lines in Figure 1. Excitation to the structure is either ambient wind loading at each floor in the $y$-direction or a shaker force applied on the roof at the center column position. To account for the uncertainty of environmental loads, the loads are modeled as filtered Gaussian white noise. More information on the benchmark problem can be obtained from http://wuscel.cive.wustl.edu/asce.shm/benchmarks.htm

A MATLAB program was provided by the ASCE Task Group to numerically simulate dynamic responses at the measurement locations on each floor as shown in Figure 1. Different combinations of structural finite element models, excitation conditions and damage patterns results in various dynamic response histories.

4 DAMAGE LOCALIZATION RESULTS

In this paper, three damage patterns have been studied. These are damage pattern 1-3. The 12dof model has been used to generate the structural responses for the benchmark structure.

Ten time series of acceleration responses at each measurement location of the damaged structure are tested. Damage localization results are shown in the following tables where DI is the damage indicator, ‘0’ denoting no damage and ‘1’ denoting damage. Results of two of these time series has been included in Table 1-3.

4.1 Detection and localization of pattern 1

Damage pattern 1 pertains to the structural condition when all braces of the first story are broken. For each measurement location at the floor level of the benchmark structure as shown in Figure 1, 30 acceleration response time histories from the undamaged structure are generated. They form the ensemble of reference database. Figure 3 shows the normal probability plots of $h'$ from the measurements at the first floor level of case 1, where the plus signs show the empirical probability versus the data value for each point in the samples $h'$. Since the data points fall near the line, it is reasonable to assume that $h'$ is asymptotically normally distributed.

Table 1 shows the damage detection results of case 1 with damage pattern 1. Damage is detected on the first floor, whereas no damage is found in other stories.

The results presented here indicate that current damage detection algorithm is less model-dependant in the sense that only measurement signals are required in the analysis. No prior knowledge on the
4.2 Detection and localization of pattern 2

Damage pattern 2 pertains to the structural condition when all braces from the first and third story are broken. The results are illustrated in Table 2 and results are consistent with the damage pattern 2.

Table 2: Damage detection and localization results for damage pattern 2

<table>
<thead>
<tr>
<th>No.</th>
<th>Test 1</th>
<th>Test 2</th>
<th>DI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$h$</td>
<td>$m(h')$</td>
<td>$\sigma(h')$</td>
</tr>
<tr>
<td>1</td>
<td>3.22</td>
<td>1.41</td>
<td>0.15</td>
</tr>
<tr>
<td>2</td>
<td>2.04</td>
<td>1.06</td>
<td>0.07</td>
</tr>
<tr>
<td>3</td>
<td>2.57</td>
<td>1.29</td>
<td>0.17</td>
</tr>
<tr>
<td>4</td>
<td>2.02</td>
<td>1.05</td>
<td>0.07</td>
</tr>
<tr>
<td>5</td>
<td>1.01</td>
<td>1.03</td>
<td>0.05</td>
</tr>
<tr>
<td>6</td>
<td>1.05</td>
<td>0.98</td>
<td>0.09</td>
</tr>
<tr>
<td>7</td>
<td>0.99</td>
<td>1.06</td>
<td>0.12</td>
</tr>
<tr>
<td>8</td>
<td>1.08</td>
<td>0.99</td>
<td>0.07</td>
</tr>
<tr>
<td>9</td>
<td>2.02</td>
<td>1.13</td>
<td>0.08</td>
</tr>
<tr>
<td>10</td>
<td>2.00</td>
<td>1.08</td>
<td>0.11</td>
</tr>
<tr>
<td>11</td>
<td>1.75</td>
<td>0.97</td>
<td>0.08</td>
</tr>
<tr>
<td>12</td>
<td>2.23</td>
<td>0.85</td>
<td>0.05</td>
</tr>
<tr>
<td>13</td>
<td>1.22</td>
<td>1.24</td>
<td>0.22</td>
</tr>
<tr>
<td>14</td>
<td>0.99</td>
<td>1.22</td>
<td>0.15</td>
</tr>
<tr>
<td>15</td>
<td>1.07</td>
<td>1.09</td>
<td>0.13</td>
</tr>
<tr>
<td>16</td>
<td>1.00</td>
<td>1.22</td>
<td>0.11</td>
</tr>
</tbody>
</table>

4.3 Detection and localization of pattern 3

Damage pattern 3 pertains to the structural condition when one of the braces from the first story is broken. This is a case of minor damage, where element 24 in the y direction has been broken. As in the previous case, five time series of acceleration responses at each floor of the damaged structure are tested. Table 3 shows results consistent with the damage pattern.

The results indicate that damage occurs near 2 and 4, both on the y faces of the structure. However, the algorithm cannot predict that the damage is near sensor 2. However, it does predict that the damage is on floor 1 in the y direction.

Table 3: Damage detection and localization results for damage pattern 3

<table>
<thead>
<tr>
<th>No.</th>
<th>Test 1</th>
<th>Test 2</th>
<th>DI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$h$</td>
<td>$m(h')$</td>
<td>$\sigma(h')$</td>
</tr>
<tr>
<td>1</td>
<td>1.06</td>
<td>1.06</td>
<td>0.06</td>
</tr>
<tr>
<td>2</td>
<td>2.51</td>
<td>1.58</td>
<td>0.26</td>
</tr>
<tr>
<td>3</td>
<td>1.04</td>
<td>1.04</td>
<td>0.09</td>
</tr>
<tr>
<td>4</td>
<td>3.26</td>
<td>1.55</td>
<td>0.16</td>
</tr>
<tr>
<td>5</td>
<td>1.19</td>
<td>0.99</td>
<td>0.13</td>
</tr>
<tr>
<td>6</td>
<td>1.43</td>
<td>1.43</td>
<td>0.17</td>
</tr>
<tr>
<td>7</td>
<td>1.03</td>
<td>1.15</td>
<td>0.13</td>
</tr>
<tr>
<td>8</td>
<td>1.66</td>
<td>1.41</td>
<td>0.19</td>
</tr>
<tr>
<td>9</td>
<td>0.97</td>
<td>1.36</td>
<td>0.12</td>
</tr>
<tr>
<td>10</td>
<td>1.16</td>
<td>1.14</td>
<td>0.10</td>
</tr>
<tr>
<td>11</td>
<td>1.32</td>
<td>1.30</td>
<td>0.19</td>
</tr>
<tr>
<td>12</td>
<td>1.05</td>
<td>1.63</td>
<td>0.32</td>
</tr>
<tr>
<td>13</td>
<td>0.94</td>
<td>1.15</td>
<td>0.14</td>
</tr>
<tr>
<td>14</td>
<td>1.16</td>
<td>1.32</td>
<td>0.19</td>
</tr>
<tr>
<td>15</td>
<td>1.30</td>
<td>1.20</td>
<td>0.08</td>
</tr>
<tr>
<td>16</td>
<td>1.29</td>
<td>1.37</td>
<td>0.13</td>
</tr>
</tbody>
</table>

5 CONCLUSIONS

A new damage detection algorithm, based on a recently proposed methodology by LANL (Sohn et al. 2001) was modified to consider the effect of excitation variability and the orders of the prediction model on the originally extracted damage-detection feature (Lei et al. 2003). However, this algorithm was not able to detect minor damage patterns. Thus, a new measure is introduced in the form of a normalized relative interstory acceleration, which is found to be more robust and detects damage pattern 3. The algorithm is solely based on signal analysis of the vibration data and it is less model-dependant. It is very attractive for the development of an automated health monitoring system because of its simplicity and computational efficiency. The authors are presently investigating to use extreme value statistics to fit the values of $h'$ in order to be able to make more consistent damage decisions and to more reliability differentiate between minor and major damage. These algorithms will also be applied to experimental data of the benchmark problem (Dyke et al. 2001) with additional damage patterns. Furthermore, the algorithms will be tested with building response data from past earthquakes for building for which damage information is also available. The computational efficiency of these algorithms makes them particularly suitable for emergency response damage assessment. As sensors become increasingly less costly, a structure can be densely popu-
lated with such sensors making it easier to localize as well as to identify damage since individual sensors have location identifiers.

ACKNOWLEDGMENTS

This research is supported by the National Science Foundation through Grants No. CMS-9988909 and CMS-0121842. The authors would like to express thanks to Dr. Sohn Hoon and Dr. Charles Farrar at the Los Alamos National Laboratory in New Mexico for valuable discussions with them.

REFERENCES


