# STRUCTURAL DAMAGE DETECTION USING FREQUENCY RESPONSE FUNCTIONS AND NEURAL NETWORKS

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This paper illustrates the damage identification and condition assessment of a three story bookshelf structure using a new frequency response functions (FRFs) based damage index and Artificial Neural Networks (ANNs). A major obstacle of using measured frequency response function data is a large size input variables to ANNs. This problem is overcome by applying a data reduction technique called principal component analysis (PCA).

In the proposed procedure, ANNs with their powerful pattern recognition and classification ability were used to extract damage information such as damage locations and severities from measured FRFs. Therefore, simple neural network models are developed, trained by Back Propagation (BP), to associate the FRFs with the damage or undamaged locations and severity of the damage of the structure. Finally, the effectiveness of the proposed method is illustrated and validated by using the real data provided by the Los Alamos National Laboratory, USA. The illustrated results show that the PCA based artificial Neural Network method is suitable and effective for damage identification and condition assessment of building structures. In addition, it is clearly demonstrated that the accuracy of proposed damage detection method can also be improved by increasing number of baseline datasets and number of principal components of the baseline dataset.

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ABSTRACT: This paper illustrates the damage identification and condition assessment of a three story bookshelf structure using a new frequency response functions (FRFs) based damage index and Artificial Neural Networks (ANNs). A major obstacle of using measured frequency response function data is a large size input variables to ANNs. This problem is overcome by applying a data reduction technique called principal component analysis (PCA).

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## 1 INTRODUCTION

Structures are subjected to natural disasters such as earthquakes, floods, typhoons, as well as from daily loading, corrosion, fatigue, structural deterioration with age and suffer distress. As an example, more than 6,400 people killed and over 110,000 buildings collapsed because of Hyogo-ken Nanbu earthquake in 1995 (Aiko et al., 2006). If appropriate retrofitting is not carried out, such as the repair (cracks) and strengthening (jacketing) of buildings the building can suffer partial or complete collapse without prior warning resulting in loss of human lives and large economic impact.

Existence of structural damage of a structure changes dynamic characteristics of the structure such as natural frequency, mode shapes, modal damping and vibration responses. Therefore detection, localization and quantification of damages within the

structure can be done using the changes of these characteristics. Sometimes a modal identification can be a time-consuming task and the curve fitting process always adds some unavoidable errors. In most practical cases obtaining complete modal data is difficult because they often require a large number of sensors. Utilization of mode shapes requires a lot of information. Also, when using just mode shapes, sometimes it is difficult to detect structural damage when the damage is located close to a node. Among all sorts of methods developed for damage detection in structures, the use of frequency response functions (FRFs) seems very promising for damage detection in recent years. The direct use of measured frequency response functions data for damage detection in most cases give a considerable advantage (Maia et al., 2003) because the FRF is one of the easiest to obtain in real-time as it only requires a small number of sensors and little human involvement (Yanfei, 2009). Furthermore, the FRFs are less contaminated because they are directly measured from structures (Banks et al., 1996). Therefore it is more reasonable and reliable to use directly-measured FRF data for structural damage detection.

This paper proposes a methodology to deal with a real engineering data. Measured FRFs from a three story bookshelf structure provided by Los Alamos National Laboratory, USA are used. Usage of all available FRF data as an input to artificial neural networks makes the training and convergence impossible. Therefore one of the data reduction techniques, the principal component analysis (PCA) is used to reduce the FRF data. The measured FRF is reconstructed using only a few PCs which are most significant. These PCs are used as input vector for ANNs instead of the raw FRF data. The method is validated using available data in Los Alamos National Laboratory web site. The results obtained are discussed in detail.

## 2 PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a dimension-reduction tool that can be used to reduce a large set of variables to a small set that still contains most of the information in the large set. Principal component analysis (PCA) transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

Using available FRFs data of the intact structure, matrix H= [$h_{ij}$ (ω)] which has *m* rows of FRFs (*m* observations from different sensors); each with *n* frequency points is formed. In the present study, numbers of observations (*m*) depend on number of baseline datasets use for the matrix H. As an example there are 96 numbers of observations (*m*) and 8192 frequency points (*n*) for case 1 and *m* numbers of observations change with different cases as shown in Table 3. Each column of H is adjusted to have a zero mean by subtracting the mean of each column of FRFs of the intact structure and dividing each column by its standard deviation to get a unit variance to yield a response variation matrix $[\tilde{H}(\omega)_{mxn}]$ as follows.

The mean response of the *j*th column is given as:

$$\overline{H_j} = \frac{1}{m}\sum_{i=1}^{m} h_{ij}(\omega) \qquad (1)$$

The corresponding standard deviation $S_j$ can be defined as

$$S_j^2 = \frac{1}{m}\sum_{i=1}^{m}(h_{ij}(\omega) - \overline{H}_j)^2 \quad (2)$$

A typical element of the FRF matrix can now be replaced by:

$$\tilde{h}_{ij}(\omega) = \frac{h_{ij}(\omega) - \overline{H}_j}{S_j\sqrt{m}} \quad (3)$$

The correlation matrix can be defined as:

$$[C]_{nxn} = [\tilde{H}]^T_{nxm}[\tilde{H}]_{nxn} \quad (4)$$

By definition, the principal components are the eigenvalues and associated eigenvectors of the correlation matrix:

$$[C]\{\Psi_i\} = \lambda_i\{\Psi_i\} \quad (5)$$

where *i* is the principal component index.

The first principal component, i.e. the highest eigenvalue and its associated eigenvector, represents the direction and amount of maximum variability in the original data. The next principal component, which is orthogonal to the first component, represents the next most significant contribution from the original data, and so on.

New FRFs for the detection stage is obtained and it is represented as new. This new complete observation $(H_{new})_{1xn}$ will be reconstructed based on $\tilde{H}_j$, $S_j$ and $\{\Psi_i\}$ of the intact structure. In this algorithm FRFs of testing stage are not transferred to PCs. Element $(H_{new})_{1xj}$ of the FRF matrix $(H_{new})_{1xn}$ is transformed into

$$(\tilde{H}_{new})_{1j} = \frac{(H_{new})_{1j} - \overline{H}_j}{S_j} \quad (6)$$

The projection of the response variation matrix $(\tilde{H}_{new})_{1xn}$ on the *n* principal components derived from baseline FRFs of the intact structure is written as (Ni et al., 2006)

$$(A)_{1xn} = (\tilde{H}_{new})_{1xn}(\Psi)_{nxn} \quad (7)$$

The projection matrix [A] and the eigenvector matrix $(\Psi)$ can be partitioned into two sub-matrices with *p* principal components and (*n-p*) principal components. Setting those sub-matrices representing principal components (*n-p*) to zero, one obtained:

$$(\tilde{H}_R)_{1xn} = [A][\Psi]^T = [[A_{1xp} : [0_{1x(n-p)}][[\Psi]_{nxp} : [0]_{nx(n-p)}]^T \approx [A]_{1xp}[\Psi^T_{pxn}] \quad (8)$$

Finally, the element $(\tilde{H}_R)_{1xj}$ of the reconstructed response variation matrix is used to obtain element $(H_R)_{1xj}$ FRF for the new observation,

$$(H_R)_{1xj} = S_j[\tilde{H}_R]_{1xj} + \overline{H}_j \quad (9)$$

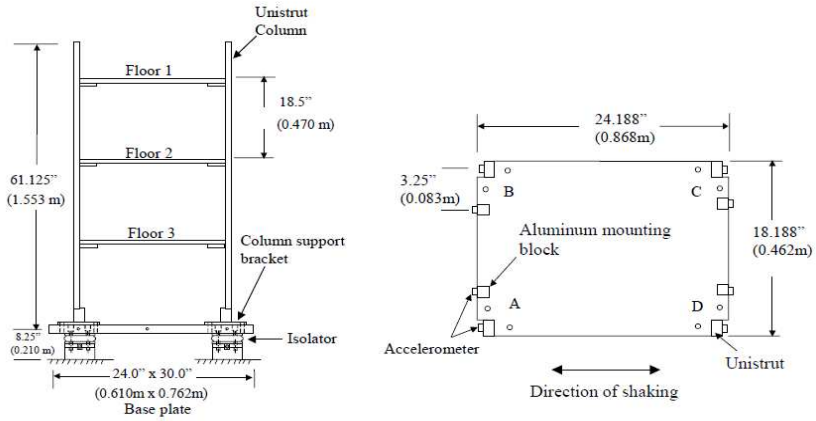
In order to reduce the high dimensionality of FRF dataset, the complete FRF is divided into sub-observations with low dimensionality where each sub-observation contains *r* consecutive frequency points ($r<n$). To compare the new constructed signal $(H_{new})_R$ with the baseline signal H which is the mean response of the m observations of the intact structure, the damage index (*DI*) is defined as,

$$DI = (H_{new})_R/(H)_{baseline} \quad (10)$$

## 3 CASE STUDY: BOOKSHELF STRUCTURE

### 3.1 Experimental Test

A three story bookshelf structure, shown in Figure 1 (a) and (b) is investigated to verify the method. This structure is a well defined benchmark structure tested by Los Alamos National Laboratory. The background and the time history data are available on the Los Alamos website (http://institute.lanl.gov/ei/). The structure is constructed of Unistrut columns and aluminium floor plates with two bolt connections to brackets on the Unistrut and is instrumented with 24 piezoelectric single axis accelerometers, two per joint, eight in each plate.




(a) Basic dimensions (b) Floor layout

Figure 1. Bookshelf structure available from (http://institute.lanl.gov/ei/).

The nominal sensitivity of each accelerometer is 1 V/g. The whole system is excited using a shaker attached at corner D and in each test case, excitation signals were random. A force transducer is mounted between the stringer and the base plate to measure the excitation input. Each time signal is consisted of 8192 data points captured from each accelerometer and data was sampled at 1600Hz. The amplitude of excitation was adjusted from 2 to 7 V. The numbers of FRFs were calculated from both the measured force and response signals.

The configuration of all structural damage cases are listed in Table 1. 21 cases are considered in this study, which are divided into two groups as known states (reference state) and unknown states as shown in Table 2. For each case, there are several excitation levels as shown in following tables.

Table 1: Structural damage cases

| Damage extent | Description |
|---|---|
| D00 - HS | No damage |
| DB0 - DS1 | Bolts removed between the bracket and the plate at location |
| DBB - DS2 | Bracket completely removed at location 1C |
| DB0 - DS3 | Bolts removed between the bracket and the plate at location |
| DBB - DS4 | Bracket completely removed at location 3A |
| DB0 - DS5 | Bolts removed between the bracket and the plate at location |
| DBB - DS6 | Bracket completely removed at location 1C and 3A |

Table 2: List of known and unknown states

| Case | Structural State | Damage | Damage extent | Excitation Level |
|---|---|---|---|---|
| 1, 2, 3 | Healthy states | - | D00 | 2, 5, 7 |
| 4, 5, 6 | DS1 | 1C | DB0 | 2, 5, 7 |
| 7, 8, 9 | DS2 | 1C | DBB | 2, 5, 7 |
| 10, 11, 12 | DS3 | 3A | DB0 | 2, 5, 7 |
| 13, 14, 15 | DS4 | 3A | DBB | 2, 5, 7 |
| 16, 17, 18 | DS5 | 1C ,3A | DB0 | 2, 5, 7 |
| 19, 20, 21 | DS6 | 1C ,3A | DBB | 2, 5, 7 |

### 3.2 Feature extraction by principal component analysis

The FRFs are transferred to principal component values using “princomp” function in MATLAB (The Math Works 2009b). Available FRFs data of intact structure are arranged in a matrix of *m x n*, where *m* is the number of observations (no of sampled

damage cases) and *n* is the dimension of the observations (8192 FRF data points obtained from the experiment). Then using the mean value and standard deviation of FRFs of baseline structure, FRFs of damaged structure is reconstructed using Equation 6. The ratio between reconstructed FRFs of damaged structure and baseline structure is calculated and it is called FRFs based damage index (As discussed in previous section).
A total of 672 FRFs, 96 corresponding to state HS, 96 from each DS1 to DS6, are used to calculate damage indices for each measured FRF with 2V, 5V and 7V excitation levels (Case 1 in Table 3). The damage index values are first divided into a training group with 336, testing data group with 112, validation data group with 112 and simulation data group with 112 FRFs. The training group consists of 48 damage indices of each healthy and different damage cases and testing, validation and simulation groups consist of 16 damage indices of each healthy and damage cases, as described in Table 4. Back propagation neural networks are used which consist of 3 layers, the input layer, one hidden layer and one output layer. These networks are trained using training group and validation data set is provided for early stopping (avoid over-fitting) and testing data set is provided for estimating a network's ability to generalize. The mean squared performance function is used to measure the network's performance according to the mean of squared error.

The derived principal components of the baseline data set represent a certain contribution for the certain data set. It is concluded that in this case the first four principal components (PCs) accounted for about 84.57% of the whole variance while the first 25 PCs contained 95.20% of the whole variance. The FRF containing 4096 spectral lines are illustrated in Figure 2 for healthy state and various damage cases. The figure legend "L00-D00-V02" denotes the L00 state with D00 damage extent and 2V excitation level as shown in Table 2. D00 indicates the no damage occurs. Other legends in the following figures can be recognized similarly.

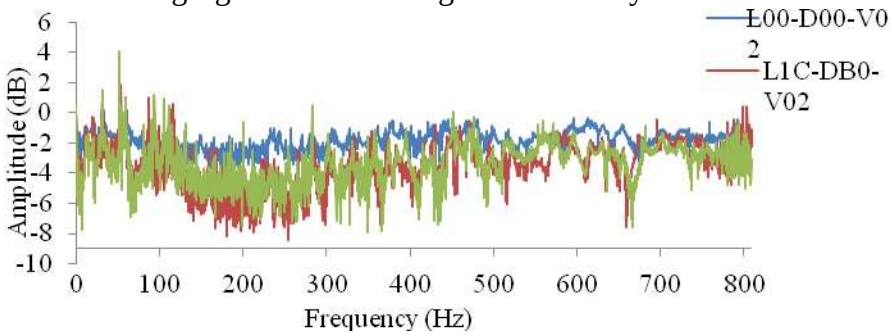



Figure 2. FRFs containing 4096 spectral lines for case 1, case 4 and case 7.
96 sets (i.e. *m*=96) of FRFs data of the intact structure, each set having 8192 (i.e. *n*=8192) frequency points are used. In order to apply PCA to utilize only a few PCs to capture the main features of the baseline signals, each complete observation including 8192 frequency points is divided into 16 groups (i.e. 16 sub observations) where each group consists of 512 consecutive frequency points (i.e. *r*=512). This procedure gives 16 numbers of damage indices for each damage case. Each sub observation of FRF data is reconstructed only using the first 25 PCs as first 25 principal component values gives 95.2% contribution to the original data set. 16 damage indices obtained from the proposed method for different damage cases and undamaged case is plotted in Figure 3.

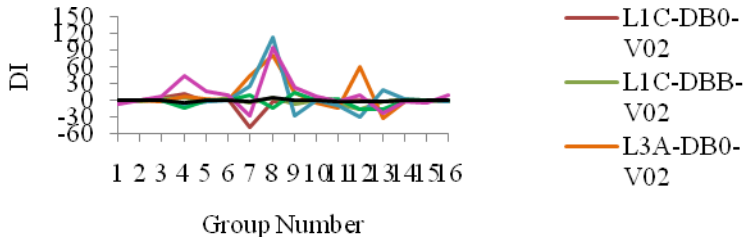



Figure 3. DI of reconstructed FRFs of different damage cases and undamaged case corresponding to 2V excitation level.

### 3.3 Neural Network Architecture

Selecting ANN architecture depends on the application domain and is usually determined by trial and error method. The neural network architecture used in this study consists of 3 layers, the input layer, one hidden layer and one output layer. The number of nodes for the input and output layers is determined by the nature of the problem to be solved. The output neurons are used to classify whether the structure is damaged or not, damage location and damage severity. Training function TRAINLM and transfer function TANSIG (which is recommended in most of back propagation applications) are used in this study.

### 3.4 Number of baseline data sets

In order to find the number of baseline data sets with accuracy of the proposed method it is tested with different number of baseline data sets. 4, 3, 2 and 1 baseline data sets are used in this study as shown in the Table 3 and for all these cases 25 principal components, which account 95.2% of original data set are used.

Table 3 Details of baseline datasets

| | Number of baseline data | Number of testing data sets (for each HS, DS1- | Number of FRFs in each data set (equal to number of FRFs |
|---|---|---|---|
| Case | 4 | 4 | 24 |
| Case | 3 | 4 | 24 |
| Case | 2 | 4 | 24 |
| Case | 1 | 4 | 24 |

Table 4 Number of damage indices for training group, validation group, testing group and simulation group corresponding to different cases.

| | Training group | | Validation group | | Testing group | | Simulation | |
|---|---|---|---|---|---|---|---|---|
| | HS | DS1-DS6 | HS | DS1-DS6 | HS | DS1-DS6 | HS | DS1- |
| Case 1 | 48 | 48 | 16 | 16 | 16 | 16 | 16 | 16 |
| Case 2 | 36 | 36 | 12 | 12 | 12 | 12 | 12 | 12 |
| Case 3 | 24 | 24 | 8 | 8 | 8 | 8 | 8 | 8 |
| Case 4 | 12 | 12 | 4 | 4 | 4 | 4 | 4 | 4 |

First, ANNs are trained with data from training group at the same time validation data group and testing data group are introduced. Then trained ANNs are tested with simulation data group which has not been used during the training stage. The difference between actual neural network output and desired output value is calculated as mean squared error. Expected error should be 0% in order to get accurate results which mean the accuracy of the trained neural networks is 100%. Therefore the output error can be used to test the accuracy of the proposed method. The output results are shown in Table 5 and 6. It is clearly shown that increasing number of baseline data sets can improve the

detectability of damage effectively. Even though the 24 baseline datasets give 6.285% simulation error of damage severity for 2V excitation level 96 baseline data sets give 3.256%.simulation error, which prove that the number of baseline data sets can affect the accuracy of the outputs.

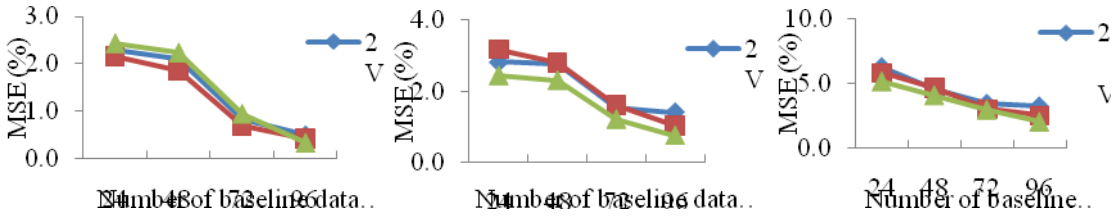
Table 5 Neural network performance (in mean squared error (MSE)) trained with data to identify damage location and severity with 96 and 72 baseline data sets.

| | Simulation error (%) with 96 data sets | | | Simulation error (%) with 72 data sets | | |
|---|---|---|---|---|---|---|
| | 2(V) | 5(V) | 7(V) | 2(V) | 5(V) | 7(V) |
| Damage or not | 0.501 | 0.438 | 0.347 | 0.845 | 0.698 | 0.956 |
| Damage location | 1.407 | 1.035 | 0.758 | 1.552 | 1.612 | 1.206 |
| Damage severity | 3.256 | 2.497 | 2.046 | 3.452 | 3.002 | 2.982 |

Table 6 Neural network performance (in mean squared error (MSE)) trained with data to identify damage location and severity with 48 and 24 baseline data sets.

| | Simulation error (%) with 48 | | | Simulation error (%) with 24 | | |
|---|---|---|---|---|---|---|
| | 2(V) | 5(V) | 7(V) | 2(V) | 5(V) | 7(V) |
| Damage or not | 2.102 | 1.865 | 2.236 | 2.287 | 2.156 | 2.432 |
| Damage location | 2.751 | 2.806 | 2.302 | 2.823 | 3.179 | 2.436 |
| Damage severity | 4.547 | 4.625 | 4.095 | 6.285 | 5.815 | 5.156 |

In order to get the clear idea of the output results of the artificial neural networks with different number of baseline data sets, the output results are plotted in the Figure 4.




(a) (b) (c)

Figure 4. Simulation performance (MSE %) subdivided by excitation level with different numbers baseline data sets to identify (a) damaged or not, (b) damage location and (c) damage severity.

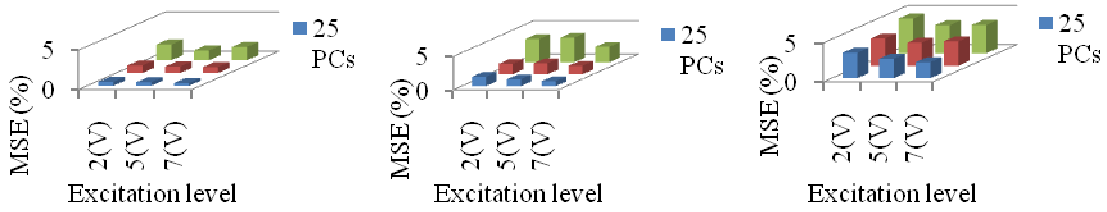
The results clearly show that the output error of ANNs can be decreased with a large number of baseline data sets; hence damage detection accuracy using proposed method can be increased.

### 3.5 Number of principal components

In order to determine effect of number of principal components with the accuracy of simulation output of artificial neural networks, different numbers of principal components are used with the proposed method. In this study 4, 15 and 25 principal components which give 84.57%, 89.07% and 95.2% contribution of original data set respectively are tested. Damage detection results obtained from 15 and 4 principal components and 96 baseline data sets of the simulation group are listed in Table 7. Simulation performance is plotted in Figure 5 to get the better idea of changing output results with different number of PCs.

Table 7 Neural network performance (in mean squared error (MSE)) trained with 15 and 4 principal components and 96 baseline data sets to identify damage location and severity.

| | Simulation error (%) with | | | Simulation error (%) with | | |
|---|---|---|---|---|---|---|
| | 2(V) | 5(V) | 7(V) | 2(V) | 5(V) | 7(V) |
| Damage or not | 0.954 | 0.821 | 0.755 | 2.004 | 1.246 | 1.692 |
| Damage | 1.567 | 1.635 | 1.269 | 3.503 | 3.709 | 2.322 |
| Damage | 3.489 | 2.956 | 3.123 | 4.452 | 3.598 | 3.632 |




(a) (b) (c)

Figure 5. Neural network simulation performance (MSE %) subdivided by excitation level with different PC numbers to identify damaged or not, damage location and damage severity.

Using few principal components of baseline datasets can lose some important characteristics of the data that the neural network would find useful in the detection phase. The results of the proposed method show that the proposed method can still give good results with few PCs. Even with 4 PCs of the baseline data set ANNs give more than 95% accurate results for severity estimation. The output results increase to 97% with 25 PCs which elaborate the effect of number of PCs with the given method.

## 4 CONCLUSIONS

An effective algorithm has been formulated using the advantageous features of using FRF data over using modal data. FRF data measured prior and posterior to damage of the structure are utilized for structural damage detection. The developed algorithm can lead to a solution of a damage detection indicating location and magnitude of damage. The validity, accuracy and applicability of the proposed method have been assessed by experimental study using a three story bookshelf structure. Data from three excitation levels are used in this study. The proposed method is a promising tool for structural assessment in a real structure because it shows reliable results with the trained ANNs using laboratory experimental data.

The following conclusions are made after going through the results. First, PCA is a powerful technique for reducing the size of measured FRF data. Second, accuracy of the proposed method can be improved by increasing the number of baseline data sets, which means when the number of baseline data sets is higher accuracy of the outputs of ANNs is higher. Furthermore, effect the number PCs with the proposed method is also investigated in this study. Results clearly demonstrate that even the first few PC values can give accurate results. Moreover, damage detection can be improved significantly with increasing number of principal components which is used in the proposed algorithm.

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