Structural damage identification by neural networks and modal analysis

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STRUCTURAL DAMAGE IDENTIFICATION BY NEURAL NETWORKS AND MODAL ANALYSIS

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ABSTRACT

The basis for the approach to damage identification is that changes in the structure's physical properties. This paper proposes a nondestructive testing technique based on modal analysis is discussed in order to develop a new, efficient and simple damage detection method for civil structures. This paper presents a sensitivity study comparing the sensitivities of frequencies, mode shapes, and modal flexibilities. Sensitivity-based analysis for the features vectors extraction. The neural networks (NNs) are introduced in this study, the combined parameters of the "frequency change ratios (FCRs) and shifts in modal flexibilities (SMFs)" are presented as the input features of NNs in structural damage identification. It is also shown, through a simulation, that this method is verified to be practical for the location and extent of structural damage identification.

NOMENCLATURE

$[\boldsymbol{M}],[\boldsymbol{K}]$	mass, stiffness matrices
$[\boldsymbol{\Phi}],[F]$	mass-normalized mode shape, modal flexibility matrix
$[\boldsymbol{\Lambda}]$	eigenvalues diagonal matrix
$\{\phi\}_r$	r^{th} mode shape
ϕ_{jr}	j^{th} element of r^{th} mode shape
$\{f\}_r$	r^{th} mode of the modal flexibility matrix
ω_r, k_{ij}	r^{th} mode frequency, i^{th} row j^{th} column element of stiffness
n	the number of DOFs

1 INTRODUCTION

Over the past 30 years damage identification in a structure from changes in global dynamic parameters has received considerable attention from the civil, aerospace and mechanical engineering communities [1-6]. the basis for the approach to damage identification is that changes in the structure's physical properties (i.e., stiffness, mass and/or damping) will, inturn, alter the dynamic characteristic(i.e., resonant frequencies, modal damping, and mode shapes) of the structures.

The amount of literature related to damage detection using shifts in resonant frequencies is quite large. It should be noted that just frequency shifts don't hold sufficient damage information for the structures[5]. The experiment's data of the mode shapes (or mode shape derivatives) have often been used to the identification of the damage location[7,8]. The modal assurance criteria (MAC) is used to localize the structural damage by the author[8], Fox [9] shows that single-number measures of mode shape changes such as the MAC are relatively insensitive to damage in a beam with a saw cut. Another class of damage identification methods uses the dynamically measured flexibility, Aktan and Pandey [10-12] present a damage-detection and location method based on changes in the measured flexibility of the structure.

In recent years there has been increasing interest in using neural networks to estimate and predict the extent and location of damage in complex structures. A study by Masi et al.[13] has demonstrated that NNs are a powerful tool for the identification of systems typically encountered in the structural dynamics field. Several researchers have dealt with NN approaches for damage estimation of simple degrees-of-freedom models. Kudva, et al. used a backprop neural network to identify damage in a plate stiffened with a 4 x 4 array of bays[14]. Wu, et al. applied the NNs to identify damage in a simple three-story frame[15]. Elkordy, et al. and Worden, et al. used a back-propagation neural network to identify damage in a framework structure[16,17]. Noteworthy publications in this area are the works of Kirkegaard and Rytter [18], Nakamura, et al.[19], Szewczyk and Hajela[20], Schwarz, et al.[21], Chung-Bang Yun [22].

It is verified theoretically that this parameter is a function of the severity of deterioration and the location of the damage in a structure, but which can't be expressed by a simple linear formulary. The neural network (NN) is introduced in this paper to map the non-linear problem[23].

It is commonly acknowledged that the selecting high sensitive features play a great role in the damage identification process. In this paper, the features extraction technique employs sensitivity-based methods. The results demonstrate that modal flexibilities are more sensitive to damage than the others, so, the FCRs and SMFs are used as input patterns to the NNs. Use of the most sensitive diagnostic features for structural damage identification will provide the most reliable result for damage occurs.

Damage generally produces changes in the stiffness of the structure. These changes are reflected by changes in some of the dynamic properties. These properties include the natural frequencies, mode shapes, and their derivatives, such as the modal flexibility. The modal flexibility involves functions of both the natural frequencies and mode shapes. Some researchers have found experimentally that the modal flexibility can be a more sensitive parameter than natural frequencies or mode shapes alone for damage detection[10].

The following presents a sensitivity study to determine which dynamic parameters are best for identification purposes for application to the input patterns of NNs.

2 SENSITIVITY COEFFICIENT ANALYSIS

For the purpose of efficient parameterization of the structure, the sensitivity-based method is adopted in this study. Using the method, three Modal parameter sensitivities are evaluated.

The Modal parameter sensitivities represent a linearized estimate of the change in the modal parameters, principally frequencies, damps and mode shapes, due to perturbations of the stiffness and mass matrices of the model. Many methods have been proposed for accurate and efficient computation of these sensitivity coefficients[24-27]. Stubbs and Osegueda[28,29] developed a damage detection method using the sensitivity of modal frequency changes. Lam and Wang[30] employed the sensitivity analysis to the detection of Damage Location.

The sensitivity problem is important because the sensitivities of the modal parameters are useful for determining the sensitivity of dynamic responses and for gaining insight into the behavior of physical systems and for the features extraction.

2.1 Assessment of the Parameters Sensitivity

For a n-DOF vibration system, the relationship between the modes and the stiffness matrix can be written as

$$[\boldsymbol{K}][\boldsymbol{\Phi}] = [\boldsymbol{M}][\boldsymbol{\Phi}][\Lambda] \tag{1}$$

where $[\boldsymbol{M}]$ is the mass matrix, $[\boldsymbol{\Phi}]$ is the mass-normalized modal matrix, and $[\Lambda]$ is the diagonal containing the eigenvalues. The modal matrix $[\boldsymbol{\Phi}]$ and $[\Lambda]$ can be assumed as

$$[\boldsymbol{\Phi}] = [\{\phi\}_1, \{\phi\}_2, \cdots, \{\phi\}_n] \tag{2}$$

$$[\Lambda] = \begin{bmatrix} \ddots & & \\ & \omega_r^2 & \\ & & \ddots \end{bmatrix} \qquad (r = 1,2,\cdots n) \tag{3}$$

respectively.

To determine the dynamical flexibility of the system, based on the condition of mass- normalized mode shape and equation (1) gives

$$[\boldsymbol{F}]=[\boldsymbol{\Phi}][\boldsymbol{\Lambda}]^{-1}[\boldsymbol{\Phi}]^T \\ =[\{f\}_1,\{f\}_2,\cdots\{f\}_n] \tag{4}$$

Suppose the structural damage occurs based on a local stiffness reduction, the sensitivities of the modal parameters (where for mode r and considering instrumentation points i and j) can be shown[31]

Sensitivity Coefficients for Frequency

$$\frac{\partial\omega_r}{\partial k_{ij}}=\begin{cases}\dfrac{\phi_{ir}\phi_{jr}}{\omega_r} & (i\neq j)\\ \dfrac{\phi_{ir}^2}{2\omega_r} & (i=j)\end{cases} \tag{5}$$

Sensitivity Coefficients for Mode Shapes

$$\frac{\partial\{\phi\}_r}{\partial k_{ij}}=\sum_l^n\alpha_l\{\phi\}_l \tag{6}$$

where

$$\alpha_s=\begin{cases}\dfrac{\phi_{is}\phi_{jr}+\phi_{js}\phi_{ir}}{\omega_s^2-\omega_r^2} & (i\neq j)\\ \dfrac{\phi_{js}\phi_{jr}}{\omega_s^2-\omega_r^2} & (i=j)\end{cases} \quad \text{for } s\neq r$$

$\alpha_s=0$ for $s=r$

Sensitivity Coefficients for Modal Flexibility

$$\frac{\partial f_{lr}}{\partial k_{ij}}=\sum_{s=1}^n\left[\begin{array}{l}\dfrac{1}{\omega_s^2}\left(\dfrac{\partial\phi_{sl}}{\partial k_{ij}}\phi_{sr}+\dfrac{\partial\phi_{sr}}{\partial k_{ij}}\phi_{sl}\right)\\ -\dfrac{2}{\omega_s^3}\dfrac{\partial\omega_s}{\partial k_{ij}}\phi_{sl}\phi_{sr}\end{array}\right] \tag{7a}$$

For a special case with $l=r$,(8a) becomes

$$\frac{\partial f_{lr}}{\partial k_{ij}}=\sum_{s=1}^n\left[\frac{2}{\omega_s^2}\frac{\partial\phi_{sr}}{\partial k_{ij}}\phi_{sr}-\frac{2}{\omega_s^3}\frac{\partial\omega_s}{\partial k_{ij}}\phi_{sr}^2\right] \tag{7b}$$

2.2 Evaluation of the Sensitivities

In this section, a 5 layers shear frame structure (fig.1) is introduced to evaluate the parameter sensitivities (previous section). The results are used to select which diagnostic features should be used for the input patterns.

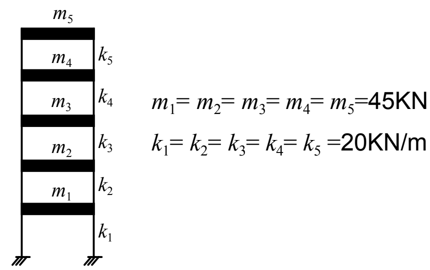

Figure 1: 5 Layers simulated shear frame system

In the following, for the simulated system introduced, the difference in sensitivities (maximum values) between natural frequencies, mode shapes and modal flexibilities due to k_1, k_2, k_3, k_4 and k_5 based on Equ.5, Equ.6, and Equ.7 are shown in Fig 2. which shows that the dynamic flexibility is more sensitive to local stiffness reduction than the other parameters.

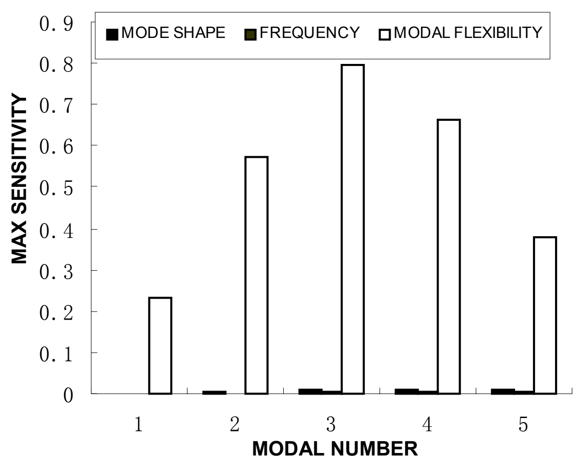

Figure 2: MAX Sensitivities of frequency, mode shape modal flexibility

The results show that the larger values in the sensitivity coefficients for the modal flexibilities are more likely to indicate damage than either natural frequencies or mode shapes.

3 NEURAL NETWORKS APPROACH

NNs[23] have been viewed as potential saviors for solution of the difficult problems in damage location. In this paper the possibility of using a Multilayer Perceptron (MLP) network trained with the Back-propagation Algorithm as a non-destructive damage assessment technique to locate and quantify damage in Civil Engineering structures is investigated. Since artificial neural networks are proving to be an effective tool for pattern recognition, the basic idea is to train a neural network with simulated values of modal parameters in order to recognize the behavior of the damaged as well as the undamaged structure. Subjecting this trained neural network to measure modal parameters should imply information about damage states and locations.

3.1 **Input Patterns to NNs**

A way of choosing the patterns representing the characteristics of the structure, which are to be used as the input to NNs, is one of the most important subjects in this approach. Such as: Wu et al.[15] used the frequency spectrum, Povich et al.[32] used FRFs. Nonetheless, to characterize those spectral properties, many sampling data are required. Accordingly, a large number of input neurons in the NNs are needed, which may reduce the efficiency and accuracy of the training process[22]. Therefore, it is desirable to use the input patterns which are more suitable for the case with partial measurement data.

In this paper, partial FCRs and SMFs are used as the input patterns. The choice has been made based on the following advantages:

- The length of the input pattern is limited.
- The FCRs and SMFs have high sensitivity to the global and local characteristics of the structure.

Definition of the FCR and SMF

$$FCR = \Delta\omega / \omega \tag{8}$$

$$SMF = \sum_{l=1}^{n} \left| \frac{\Delta f_{lr}}{f_{lr}} \right| \tag{9}$$

where $\Delta\omega$, Δf_{lr} means the change of the natural frequency, modal flexibility after and before of the damage occurs, respectively.

The input patterns can be defined as

Input pattern vector $= \{(FCR_r, SMF_r), r = 1, 2, \cdots, m\}$ (10)

Where m is the number of modes to be included in the identification.

It is important to choose the proper network size. If the network is too small, it may not be able to represent the system adequately. On the other hand, if the network is too big, it becomes over-trained and may provide erroneous results for untrained patterns. In general, it is not straightforward to determine the best size of the networks for a given system. It may be found through trial and error process using knowledge about the system. The number of the neurons in the input and output layers varies depending on the number of modes and damage (extant and location) included. A three-layer NN ($6 \times 15 \times 5$) was selected for the present example.

3.2 **Illustrative numerical example**

The 5-DOF simulated shear frame system (which is same with fig.1) is used to demonstrate the NNs method by the input patterns of combined features vector (FCRs, SMFs).

In the following, the initial stiffness and mass assumed that m_1=2kg, m_2=m_3=m_4=m_5=1kg, k_1=50N/m, k_2=k_3=k_4= k_5=40N/m. the damage in this system is simulated by reducing the stiffness k by various degrees. The training and testing data set were prepared for the case with 0, 30, 50, 70, and 90% reduction of the stiffness (k_1, k_2, k_3, k_4, k_5), respectively. The first three modes were used as input patterns to the NNs, an example (due to 25% and 40% reduction in k_1, k_2, k_3, k_4, k_5, respectively) of the tested outputs was listed in the

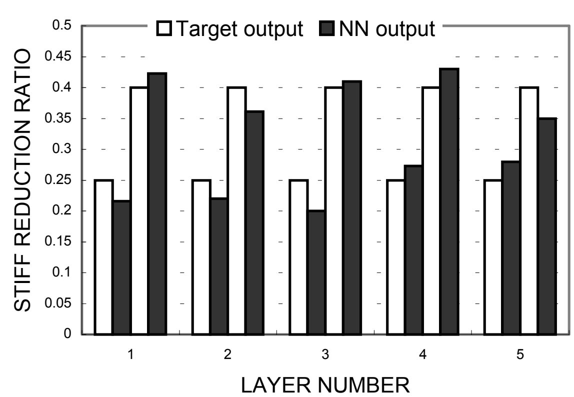

Fig3.

Figure 3: Example of test outputs

The training process took about epochs to learn the pattern representation using BP(L-M)[33] algorithm. Fig 3. shows that the NNs approach employs the FCRs and SMFs data to identify damage is efficient for engineering application.

4 CONCLUSION

In this study a sensitivity-based features extraction method is presented and applied to evaluate the parameter sensitivities of a 5 layers shear frame structure. The larger values for the modal flexibility sensitivity coefficients indicate that the SMFs will more suitable for the input patterns of NNs than either the natural frequencies or mode shapes alone.

The NNs approach is applied to diagnostics, which employs the combined parameters of the "FCRs and SMFs" to identify damage in structures. The results show that a neural network trained with simulated data is available for detecting location and size of a damage.

REFERENCES

[1] Adams, R.D., P. Cawley, C.J. Pye and B.J. Stone, “A Vibration Technique for Non-Destructively Assessing the Integrity of Structures,” Journal of Mechanical Engineering Science, 20, 93–100, 1978.

[2] Penny, J.E.T., D.A.L. Wilson, and M.I. Friswell, “Damage Location in Structures Using Vibration Data,” in Proc. of the 11th International Modal Analysis Conference, 861–867, 1993.

[3] Hearn, G. and R.B. Testa, “Modal Analysis for Damage Detection in Structures,” Journal of Structural Engineering, 117(10), 3042–3063, 1991.

[4] Kim, H.M. and T.J. Bartkowicz, “Damage Detection and Health Monitoring of Large Space Structures, Sound and Vibration, 27(6), 12–17, 1993.

[5] Doebling, S. W., Farrar, C. R., Prime, M. B., and Shevitz, D. W., “Damage identification and health monitoring of structural and mechanical systems from changes in their vibration characteristics: a literature review, ” Los Alamos National Laboratory report LA-13070-MS, April 1996.

[6] Zimmerman, D. C., M. Kaouk, and T. Simmermacher, “On the Role of Engi-neering Insight and Judgement Structural Damage Detection,” in Proc. of the 13th International Modal Analysis Conf., 414–420, 1995.

[7] Pandey, A.K., M. Biswas, and M.M. Samman, “Damage Detection from Changes in Curvature Mode Shapes,” Journal of Sound and Vibration, 145(2), 321–332, 1991.

[8] West, W. M., “Illustration of the use of modal assurance criterion to detect structural changes in an orbiter test specimen,” in Proc. Air Force Conference on Aircraft Structural Integrity, 1–6, 1984.

[9] Fox, C. H. J., “The location of defects in structures: a comparison of the use of natural frequency and mode shape data,” in Proc. of the 10th International Modal Analysis Conference, 522–528, 1992.

[10] Aktan, A. E., K. L. Lee, C. Chuntavan and T. Aksel, “Modal Testing for Structural Identification and Condition Assessment of Constructed Facilities,” in Proc. of 12th International Modal Analysis Conference, 462–468, 1994.

[11] Pandey, A. K., and M. Biswas, “Damage detection in structures using changes in flexibility,”Journal of Sound and Vibration, 169(1), 3–17, 1994.

[12] Baruh, H. and S. Ratan, “Damage Detection in Flexible Structures,” Journal of Sound and Vibration, 166(1), 21–30, 1993.

[13] Masri, S. F., Chassiakos, A. G., and Caughey, T. K., “Identification of nonlinear dynamic systems using neural networks,” J. Of Appl. Mech.,Trans., ASME, 60, 123-133, 1993.

[14] Kudva, J., N. Munir, and P. Tan, “Damage Detection in Smart Structures Using Neural Networks and Finite Element Analysis,” in Proc. of ADPA/AIAA/ASME/SPIE Conference on Active Materials and Adaptive Structures, 559–562, 1991.

[15] Wu, X., J. Ghaboussi, and J.H. Garrett, “Use of Neural Networks in Detection of Structural Damage,” Computers and Structures, 42(4), 649–659, 1992.

[16] Elkordy, M.F., K.C. Chang, and G.C. Lee, “Neural Network Trained by Analytically Simulated Damage States,” ASCE Journal of Computing in Civil Engineering, 7(2), 130–145, 1993.

[17] Worden, K., A. Ball, and G. Tomlinson, “Neural Networks for Fault Location,” in Proc. of the 11th International Modal Analysis Conference, 117,47–54, 1993.

[18] Kirkegaard, P. and A. Rytter, “Use of Neural Networks for Damage Assessment in a Steel Mast,” in Proc. of the 12th International Modal Analysis Conference, 1128–1134, 1994.

[19] Szewczyk, P.Z. and P. Hajela, “Damage Detection in Structures Based on Feature-Sensitive Neural Networks,” ASCE Journal of Computing in Civil Engineering, 8(2), 163–178, 1994.

[20] Mitsuru Nakamura, Samif. Masri, Anastassios G. Chassiakos and Thomas K.Caughey, “a Method for Non-parametric Damage Detection Through the Use of Neural networks,” Earthquake Engng. Struct. Dyn, 27,997-1010,1998.

[21] Schwarz, B.J., P.L. McHargue, and M.H. Richardson, “Using SDM to Train Neural Networks for Solving Modal Sensitivity Problems,” in Proc. of the 14th International Modal Analysis Conference, 1285–1291, 1996.

[22] Chung-Bang Yun, Eun Young Bahng, “Substructural identification using neural networks,” Computers & Structures, 77, 41-52, 2000.

[23] Bishop, C.M., Neural Networks and Their Applications,” Review of Scientific Instrumentation, 65(6), 1803–1832,1994.

[24] Fox, R. L., and Kapoor, M. P., “Rates of Change of Eigenvalues and Eigenvectors,” AIAA Journal, 6(12), 2426-2429, 1968.

[25] Nelson, R. B., “Simplified Calculation of Eigenvector Derivatives,” AIAA Journal, 14(9), 1201-1205,1976.

,

[26] Wang, B. P., “Improved Approximate Methods for Computing Eigenvector Derivatives in Structural Dynamics,” AIAA Journal, 29(6), 1018-1020, 1991.

[27] Zhang, O., and Zerva, A., “Iterative Method for Calculating Derivatives of Eigenvectors,” AIAA Journal, 34(5), 1088-1090, 1996.

[28] Stubbs, N. and R. Osegueda, “Global non-destructive damage evaluation in solids,” Modal Analysis: The International Journal of Analytical and Experimental Modal Analysis, 5(2), 67–79,1990.

[29] Stubbs, N. and R. Osegueda, “Global damage detection in solids experimental verification,” Modal Analysis: The International Journal of Analytical and Experimental Modal Analysis, 5(2), 81–97, 1990.

[30] Lam, H.F., J.M. Ko, and C.W. Wong, “Detection of Damage Location Based on Sensitivity Analysis,” in Proc. of the 13th International Modal Analysis Conference, 1499–1505, 1995.

[31] Zhao, J., and John T. DeWolf, “Sensitivity Study for Vibration Parameters Used in Damage Detection,” Journal of Structural Engineering, 125(6),410-416, 1999.

[32] Povich, C., and T. Lim, “An Artificial Neural Network Approach to Structural Damage Detection Using Frequency Response Functions,” in Proc. of 35th AIAA/ASME/ASCE /AHS/ASC Structures, Structural Dynamics, and Materials Conference, 151–159, 1994.

[33] Neural Network Toolbox User’s Guide. The Mathworks, Inc, 1994