Real-Time Damage Monitoring Using Output-only Acceleration Data

JEONG-TAE KIM[1)], JAE-HYUNG PARK[2)], HAN-SUNG DO[3)], YONG- HWAN LEE[4)]

ABSTRACT:

In this study, an ANN-based algorithm using acceleration signals is developed for alarming locations of damage in beam-type structures. First, theoretical backgrounds are described. The problem addressed in this paper is defined as the stochastic process. Also, an ANN-algorithm using output-only acceleration responses is newly designed for damage detection in real time. The cross-covariance of two acceleration-signals measured at two different locations is selected as the feature representing the structural condition. Neural networks are trained for potential loading patterns and damage scenarios of the target structure for which its actual loadings are unknown. The feasibility and practicality of the proposed method are evaluated from laboratory-model tests on free-free beams for which accelerations were measured before and after several damage cases.

INTRODUCTION

Structural health monitoring (SHM) has become the important research topic for securing the safety of infra-structures. Many researchers have focused on developing reliable vibration-based techniques that use vibration characteristics of a structure to detect, locate and size the damage in the structure [3-6]. Up-to-date, vibration-based damage detection methods are implemented by a series of signal acquisition, data analysis in time and frequency domains, pattern recognition and system identification process. In order to fulfill the existing damage detection methods which are either signal-based or model-based methods, at least three significant amounts of works are needed: (1) to obtain acceleration-response signals measured at selected multiple locations, (2) to extract modal parameters such as natural frequencies and mode shapes from the signals, and (3) to modify the measured modal information suitable for certain

[1)] Pukyong National University, idis@pknu.ac.kr
[2)] Pukyong National University, cross96@pknu.ac.kr
[3)] Pukyong National University, hssu1217@pknu.ac.kr
[4)] Korea Infrastructure Safety & Technology Corp., joymaker006@naver.com

damage detection algorithms such as damage index methods, genetic algorithm (GA)-based methods, and artificial neural networks (ANN)-based methods.

Recently, ANN algorithms have been studied for vibration-based damage detection due to the advantage in dealing with various types of input and output and the efficient pattern-recognition capability with various training patterns. Many researchers have made efforts to develop ANN techniques for identifying the location and the extent of damage [11-12], to develop a substructural identification method for complex structures using multilayer perceptron [13], to implement the ANN techniques using modal data to health monitoring of bridges [1, 8-10].

However, several problems still remain to be resolved before the ANN techniques can be successfully implemented for damage detection in large structures. Most of signal process and modal analyses need off-line works that are time-consuming depending on the number of sensors involved and the amount of signals recorded. Also, errors in baseline FE models cause errors in modal parameters used for the input of neural networks and those errors have effects on the accuracy of damage detection. The error in the baseline model is critical since modal parameters are to be generated for various perturbed cases of the baseline model and used as training patterns for the neural networks. Those problems hinder the implementation of on-line damage monitoring into real structures. For the realization of the on-line health monitoring, therefore, it is needed to develop a ANN-based damage detection method that uses real-time signals measured from a limited number of sensors, without any further frequency-domain data-process, to identify the changes in structural conditions.

In this study, an ANN-based algorithm using acceleration signals is developed for locating and estimating severity of damage in beam-type structures. The following approaches are used. Firstly, theoretical backgrounds are described. The problem addressed in this paper is defined as the stochastic process. Also, an ANN-algorithm using output-only acceleration responses is newly designed for damage detection in real time. As the feature representing the structural condition, we select the cross-covariance of two acceleration-signals measured at two different locations. By means of the feature, neural networks are trained for potential loading patterns and damage scenarios of the target structure for which its actual loading histories are not available. The feasibility and practicality of the proposed method are evaluated from laboratory-model tests on free-free beams for which a series of accelerations were measured before and after several damage cases.

THEORITICAL BACKGROUNDS

Problem Statement

The problem addressed here may be defined as follows: Given a structural system that exhibits the stochasticity in some physical parameters and a set of the dynamic responses of that structural system; then estimate the physical parameters by knowing the dynamic responses [2]. Here the parameter of interest will be some form of stiffness, e.g., bending or axial. In this paper, the discussion is limited to a wide sense stationary discrete process $\{X_k(t)\}$. Each particular function $X_k(t)$, where t is variable and k is fixed, is a sample function.

For a pair of stationary random processes $\{X_k(t)\}$ and $\{Y_k(t)\}$, the mean and variance values are defined as

$$\mu_X = E[X_k(t)], \quad \mu_Y = E[Y_k(t)] \tag{1}$$

$$\sigma_X^2 = E[X_k(t)X_k(t)], \quad \sigma_Y^2 = E[Y_k(t)Y_k(t)] \tag{2}$$

where μ_X and μ_Y are the means; σ_X^2 and σ_Y^2 are the variances. For arbitrary fixed t and τ, the cross-correlation function, $R_{XY}(\tau)$, between $\{X_k(t)\}$ and $\{Y_k(t)\}$ is given by

$$R_{XY}(\tau) = E[X_k(t)Y_k(t+\tau)] \tag{3}$$

Furthermore, the normalized cross-covariance function, $\rho_{XY}(\tau)$, is estimated by

$$\rho_{XY}(\tau) = \frac{R_{XY}(\tau) - \mu_X \mu_Y}{\sigma_X \sigma_Y} \tag{4}$$

where the function $\rho_{XY}(\tau)$ measures the linear dependency between $\{X_k(t)\}$ and $\{Y_k(t)\}$ for a displacement of τ in $\{Y_k(t)\}$ relative to $\{X_k(t)\}$.

Acceleration-Based ANN Algorithm

Suppose that we are given an arbitrary structure with NE elements and N nodes. By assuming that the structure behaves linearly, the acceleration response at a certain location (e.g., a node) evaluated at time t for a multi-degree-of-freedom system can be given by

$$\ddot{X}_t = [M]^{-1}\left(\{F\} - \dot{X}_t[C] - X_t[K]\right) \tag{5}$$

where [M], [C] and [K] are, respectively, the mass, damping and stiffness matrices of the system; {F} the external force vector; and X_t, $\dot{X}_t$, and $\ddot{X}_t$ the displacement, velocity, and acceleration at a certain location.

As described in Eq. (5), the dynamic responses change due to the perturbation of the structural parameters. With the known force vector {F}, the patterns of the dynamic responses at a location can be recognized as the consequence of the changes in physical parameters at all other locations in the structure. Consequently, the acceleration measured before and after damage can be used as the input for the ANN-based damage detection [8]. However, this approach is limited only when the external forces that are applied for the real structure is known and identical to the ones that are used for training the neural networks. In order to overcome the above-mentioned limitation for the use of the acceleration as the direct input, the cross-covariance function is selected to represent two acceleration signals measured at two different locations.

In this study, the standard back-propagation algorithm is employed. The networks consist of an input layer, a hidden layer, and an output layer. The input layer contains the cross-covariance function of two acceleration signals at two different locations measured before and after damage. The output layer consists of the element-level stiffness indices to be identified as [9]

$$S_j = k_{j,d} / k_{j,u} \tag{6}$$

where j denotes the element number; d damaged state; and u undamaged state. The severity of the element is defined as

$$\alpha_j = 1 - S_j \tag{7}$$

The acceleration-based neural networks algorithm is schematized as shown in Figure 1. It consists of two parts: (a) Training neural networks (TNN) and (b) Alarming damage location (ADL) using the neural networks. TNN is performed in the following four steps.

Firstly, a baseline finite element (FE) model with NE elements is selected for the target structure. Secondly, N numbers of excitation patterns characterized by the intensity, frequency and duration are selected on the basis of potential loading scenarios of the structure. Thirdly, M numbers of damage patterns characterized by the loss of element-level stiffness are decided on the basis of the potential damaging scenarios of the structure. Finally, for each of the N excitation patterns, a set of neural networks are trained for the M damaging patterns. The cross-covariance values are computed from two acceleration signals measured before and after damage. The ratios of the cross-covariance values between before and after damage are the inputs to the neural networks. TNN is repeated until the N sets of neural networks are trained for the N excitation patterns, in which each set of neural networks is corresponding to a specific excitation pattern.

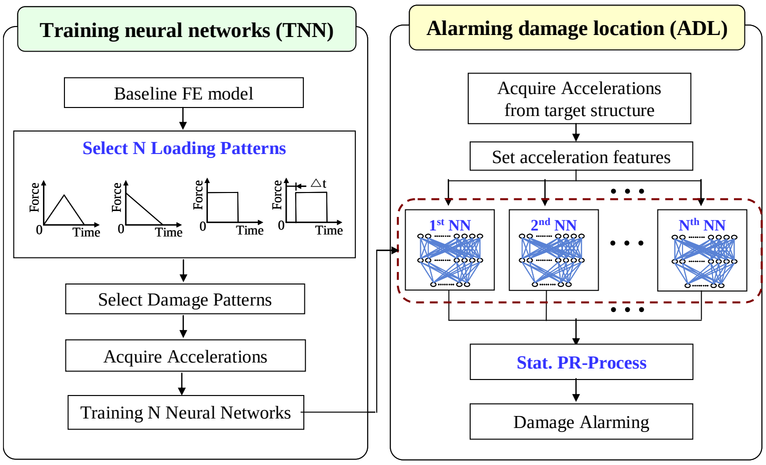


Figure 1: Schematic of Acceleration-Based Neural Networks for Damage Detection

ADL is performed in the following procedures. First, accelerations are measured at two different locations before and after damage occurred in the structure. Next, the ratios of the cross-covariance values of the two accelerations between before and after damage is computed and input into the neural networks trained by TNN. Thirdly, element stiffness indices and severity indices are estimated for NE output elements from the soft computing process. ADL is repeated for the N sets of neural networks, from which stiffness indices and severity indices are estimated, respectively.

We realize that the values computed for the damage indices will always contain many uncertainties. Here, we propose accounting for the impact of these uncertainties by using a statistical-based method to assign damage to an element.

To account for all available N sets of neural networks (i.e., the N sets of excitation patterns) we form a single indicator (DI) for the jth element as [7]:

$$DI_j = \left(\sum_{i=1}^{N} \alpha_{ji}^2 \right)^{-1/2} \tag{8}$$

where $0 \le DI_j \le \infty$ and the damage is located at element j if DI_j approaches the local maximum point. Next, the elements are assigned to a damage class via a statistical-pattern-recognition technique that utilizes hypothesis testing. The following statistical criteria are established for damage localization. For the given set of DI results, the locations of damage are selected on the basis of a rejection of hypothesis in the statistical sense. First, the collection of values DI_j ($j = 1,2,3,..., NE$) associated with each element and each neural networks set is treated as a random variable. In other words, the collection of the damage indices DI_j is treated as a sample population of damage indices. We first normalize the damage indices DI_j according to the standard rule

$$Z_j = \left(DI_j - \mu_{DI}\right) / \sigma_{DI} \tag{9}$$

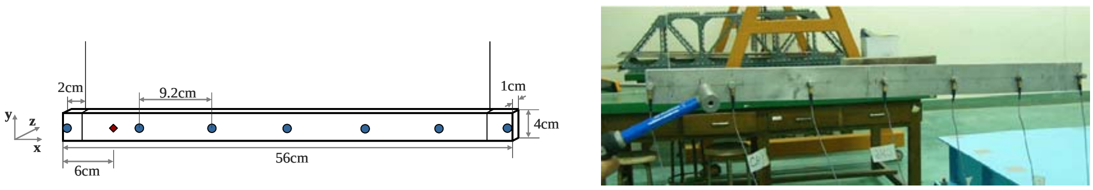
in which μ_{DI} and σ_{DI} represent, respectively, the mean and standard deviation of the collection of DI_j values. The null hypothesis (i.e., H_O) is taken to be that the structure is undamaged at the jth element and the alternate hypothesis (i.e., H_1) is taken to be that the structure is damaged at the jth element. In assigning damage to a particular location, we utilize the following decision rule: (1) choose H_1 if $Z_j \geq z_o$; and (2) choose H_O if $Z_j < z_o$, where z_o is number which depends upon the confidence level of the localization test.

EXPERIMETAL VERIFICATION

Test Structure and Experimental Setup

Experiments were performed to evaluate the feasibility and the practicality of the present acceleration-based ANN algorithm. As described in Figure 2, a free-free, aluminum beam was selected and dynamic responses of the structure were measured before and after damaging episodes. The geometrical properties of the test structure are as follows: the length $L = 56$ cm and the rectangular cross-section $t \times H = 1cm \times 4cm$. The material properties of the test structure are as follows: the elastic modulus $E = 70GPa$, Poisson's ratio $\upsilon = 0.33$, and mass density $2700\, kg/m^3$.

The locations and arrangements of the accelerometers are shown in Figs. 2(a) and 2(b). 7 accelerometers were selected to measure the motion of the structure in the z-direction and equally distanced along the longitudinal direction. Each accelerometer was mounted along the center line. Sampling frequency was set to 8.0 kHz and total 8,450 discrete data were acquired for each measure.



(a)Free-Free Beam (b) Experimental Setup

Figure 2: Experimental Setup on Free-Free Beam

Training Neural Networks (TNN) for Damage Detection

In order to train neural networks and further to utilize those for damage detection, we selected a baseline free-free beam model which consists of 12 beam elements with equal size ($L^{EL} = 4.6$ cm) and with uniform bending rigidity ($EI = 233.3 N.m^2$). Figure 3 shows the lay-out of acceleration-signal acquisition in the free-free beam model. From FE analyses, exciting impulses were applied to $0.1L$ and accelerations were obtained at $0.3214L$ (i.e., node 5) and $0.5L$ (i.e., node 7). Sampling frequency of accelerations was set to 8 kHz and total 8,450 discrete acceleration data were numerically analyzed for each measure.

Next, several excitation types were selected to simulate unknown impulse-loadings. As shown in Figure 4, four excitation types were selected as follows: (1) Excitation 1 is triangular pulse with 0~0.01 sec duration, (2) Excitation 2 is right-triangular pulse with 0~0.01 sec duration, (3) Excitation 3 is rectangular pulse with 0~0.01 sec duration, and (4) Excitation 4 is rectangular pulse with 0.005~0.015 sec duration. Pulse intensity was set to 5 percent of self-weight of the beam model. Also, damage scenarios were selected to train neural networks for damage detection. Total 127 scenarios were selected as follows. Single-damage-location cases were selected for each of all 12 elements. For each case, the element stiffness loss was simulated between 0.1 and 0.5 with a step size of 0.1. Also, two-damage-location cases were selected for all combinations of the 12 elements.

Neural networks should be trained for the 4 excitation types and the 127 damage scenarios that included an undamaged case; therefore, totally 505 training patterns were considered for damage detection in the test structure. As shown in Figure 5, the neural networks consisted of three layers.

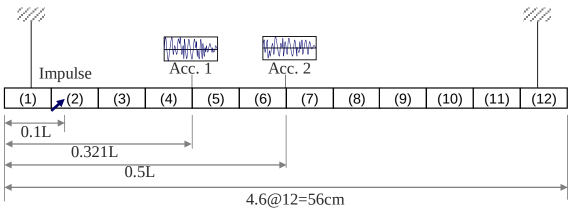
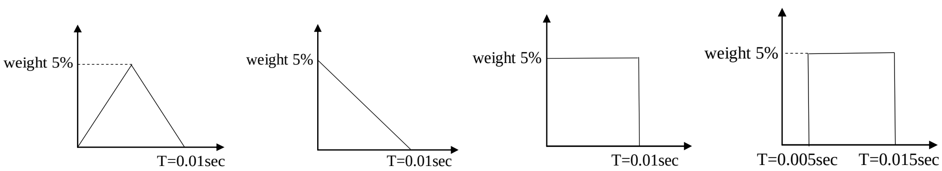


Figure 3: Baseline Free-Free Beam Model



(a) Excitation 1 (b) Excitation 2 (c) Excitation 3 (d) Excitation 4

Figure 4: Excitation Patterns to Train for Unknown External Loads

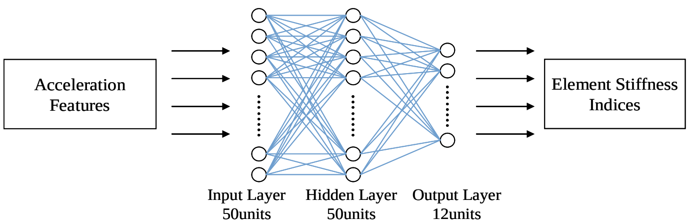
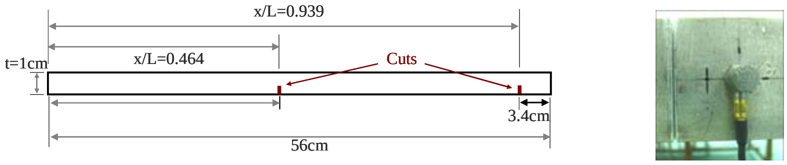


Figure 5: Acceleration-Based Neural Networks

Alarming Damage Location (ADL) using Neural Networks

As shown in Figure 6, damage was inflicted by sawing two levels of cuts at two different locations of the beam. Four different scenarios of damage were introduced as follows: (1) Case 1 is a single damage at $x/L = 0.464$ with severity $a/t = 0.25$; (2) Case 2 is a single damage at $x/L = 0.464$ with $a/t = 0.5$; (3) Case 3 is two damages at $x/L = 0.464$ and $x/L = 0.939$ (3.4cm distance from the right edge) with $a/t = 0.5$ and $a/t = 0.25$, respectively, and (4) Case 4 is two damages at $x/L = 0.464$ and $x/L = 0.939$ with $a/t = 0.5$ and $a/t = 0.5$, respectively.

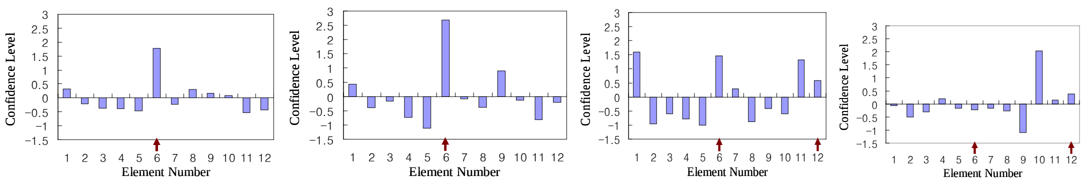
As described previously, accelerations were measured at the 7 locations before and after each damage scenarios. The impulse was applied to a location 6cm distanced from the left edge by hand-hammering but not controlled or recorded. For each damage case, 50 cross-covariance ratios of accelerations measured between before and after damage were input into the neural networks and stiffness indices of the 12 elements of the test structure were estimated as the output.



(a) Damage Locations (b) Saw Cut

Figure 6: Damage Inflicted in Test Structure

The elements 7 and 12 are the parallel identical elements in the free-free beam corresponding to the real cut locations $x/L = 0.464$ and $x/L = 0.939$, respectively. In each damage case, stiffness indices of 12 elements were estimated by the four different excitation patterns, respectively. Finally, damage indices were computed according to Eq. (8). On assuming the damage indices distributed normally, normalized damage indices were generated in accordance with Eq. (9) (note that the analysis indicates that the damage indices approximately fit into normal distribution by excluding the damaged elements which are the special causes). The confidence level for the localization corresponded to $z_0 = 1.5$. This criterion corresponds to a one-tailed test at a confidence level of 93.3%. The damage localization results for the four damage cases are shown in Figures. 7(a)-(d). In damage cases 1 and 2, element 7 was predicted, which is identical to the damaged element. In damage case 3, elements 1 and 7 were predicted, in which the first one is false-alarm and the second one is correct. Also, by setting the confidence level $z_0 = 1.3$ which gives 90.3% confidence level, element 11 could be also predicted, which shows about 8% localization error. In damage case 4, element 10 was predicted, which shows about 16% localization error. Damage localization was not successful in this case.



(a) Damage Case 1 (b) Damage Case 2 (c) Damage Case 3 (d) Damage Case 4

Figure 7: Damage Localization Results for Test Structure

CONCLUSIONS

In this study, an ANN-based algorithm using acceleration-related features was developed for locating and estimating severity of damage in beam-type structures. Firstly, theoretical backgrounds were described. The problem addressed in this paper was defined as the stochastic process. Also, an ANN-algorithm using output-only acceleration responses was newly designed for damage detection in real time. As the feature representing the structural condition, we selected the cross-covariance of two acceleration-signals measured at two different locations.

The feasibility and practicality of the proposed method were evaluated from laboratory-model tests on a free-free, aluminum beam for which its actual loading histories were unknown. Four (4) excitation types and 127 damage scenarios were selected to train neural networks of a baseline free-free beam model with 12 beam elements. Initial 50 signal data measured from two accelerometers were input into the neural networks and stiffness indices of the 12 elements of the test structure were estimated as the output. From the damage localization process, single-damage cases were predicted correctly but dual-damage cases resulted in relatively high localization errors.

ACKNOWLEDGEMENTS

The authors would like to appreciate to Smart Infra-Structure Technology Center (SISTeC) granted by KOSEF for the financial support.

REFERENCES

1. Barai, S.V. and Pandey, P.C., “Vibration signature analysis using artificial neural networks”, *ASCE, Journal of Computing in Civil Engineering*, Vol. 9, No. 4, 1995, pp. 259-265.
2. Bendat, J.S. and Piersol, A.G., “Random Data Analysis and Measurement Procedures”, John Wiley & Sons, 1991, Singapore.
3. Catbas, F.N. and AKtan, A.M., “Condition and damage assessment: issues and some promising indices”, *ASCE, Journal of Structural Engineering*, Vol. 128, No. 8, 2002, pp. 1026-1036.
4. Chen, Y. and Feng, M.Q., “Condition assessment of bridge sub-structure by vibration monitoring”, *2nd International Workshop on Advanced Smart Materials and Smart Structures Technology*, Co-edited by C.B. Yun and B.F. Spencer, Gyeongju, Korea, 21-24 July, 2005, pp. 651-676.
5. Doebling, S.W., Farrar, C.R. and Prime, M.B., “A summary review of vibration-based damage identification methods”, *Shock and Vibration Digest*, Vol. 30, No. 2, 1998, pp. 91-105.
6. Kim, J.T. and Stubbs, N., “Model uncertainty impact and damage-detection accuracy in plate-girder”, *ASCE, Journal of Structural Engineering*, Vol. 121, No. 10, 1995, pp. 1409-1417.
7. Kim, J.T., Ryu, Y.S., Cho, H.M., Stubbs, N., “Damage identification in beam-type structures: frequency-based method vs mode-shape-based method”, Engineering Structures, Vol. 25, 2003, pp. 57-67.
8. Lee, I.W., Oh, J.W., Park, S.K. and Kim, J.T., “Damage assessment of steel box-girder bridge using neural networks”, *Journal of Korean Society of Steel Construction*, Vol. 11, No. 1, 1999, pp. 79-88.
9. Lee, J.J., Lee, J.W., Yi, J.H., Yun, C.B, and Jung, J.Y., “Neural networks-based damage detection for bridges considering errors in baseline finite element models”, *Journal of Sound and Vibration*, Vol. 280, No. 3, 2005, pp. 555-578.
10. Ni, Y.Q., Wang, B.S. and Ko, J.M., “Constructing input vectors to neural networks for structural damage identification,” *Smart Materials and Structures*, Vol. 11, 2002, pp. 825-833.
11. Szewczyk, Z.P. and Hajela, P., “Damage detection in structures based on feature-sensitive neural networks”, *ASCE, Journal of Computing in Civil Engineering*, Vol. 8, No. 2, 1994, pp. 163-178.
12. Wu, X., Ghaboussi, J. And Garret Jr., J.H., “Use of neural networks in detection of structural damage”, *Computers and Structures*, Vol. 42, No. 4, 2001, pp. 649-659.
13. Yun, C.B. and Bhang, E.Y., “Joint damage assessment of Framed Structures using Neural Networks Technique”, *Engineering Structures*, Vol. 23, No. 5, 2001, pp. 425-435.