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EXPERIMENTAL EVALUATION OF UNCERTAINTY EFFECT ON REAL-TIME DAMAGE MONITORING IN PRESTRESSED CONCRETE GIRDERS

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Abstract

In this study, a new damage monitoring method using a set of parallel ANNs and acceleration signals is developed for alarming locations of damage in PSC girders. The problem addressed in this paper is defined as the stochastic process. In addition, a parallel ANN-algorithm using output-only acceleration responses is newly designed for damage detection in real time. The cross-covariance of acceleration-signals is selected as the feature representing the structural condition. Neural networks are trained for uncertain loading patterns and damage scenarios of the target structure for which its actual loadings are unknown. The uncertainty effect on real-time monitoring using the proposed method is evaluated from model tests on PSC beams for which accelerations were acquired before and after several damage cases.

INTRODUCTION

To date, many researchers have focused on developing reliable vibration-based techniques that need to implement a series of signal acquisition, data analysis in time and frequency domains, pattern recognition and system identification process[3-6]. 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 damage detection algorithms such as damage index methods, GA-based methods, or 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 [8], to implement the ANN techniques using modal data to health monitoring of bridges [1], [6-8]. However, 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 models cause errors in modal parameters and those errors have effects on the accuracy of damage detection.

For the realization of on-line health monitoring, therefore, it is necessary 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 alarming location of damage in PSC girders. Firstly, theoretical backgrounds are described. The problem addressed in this paper is defined as the stochastic process. In addition, 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 of the proposed method is evaluated from numerical model tests on PSC beams for which a series of accelerations were acquired before and after several damage cases.

REAL-TIME DAMAGE MONITORING METHOD

Problem Statement

Given a structural system that exhibits the stochasticity in some physical parameters and a set of the dynamic responses of that structural system, estimate the physical parameters by knowing the dynamic responses. 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

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

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

For arbitrary fixed t and τ, the cross-correlation, $R_{XY}(\tau)$ is given by

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

Furthermore, the normalized cross-covariance function, $\rho_{XY}(\tau)$, which measures the linear dependency between $\{X_k(t)\}$ and $\{Y_k(t)\}$ for a displacement of τ in $\{Y_k(t)\}$ relative to $\{X_k(t)\}$ is estimated by

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

ANN Algorithm using Acceleration Signature

Suppose that we are given an arbitrary structure with NE elements and N nodes, which 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. With the pre-assumable force vector {F}, the patterns of the dynamic responses at a location may 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. We select the normalized cross-covariance function, which is described in Eq. (4), to represent two acceleration signals measured at multiple locations. So the input layer contains the measured acceleration features, and the outputs are element's physical features as described in Eq. (5). By assuming the mass and damping properties are not changed before and after damage, the output layer consists of the element-level stiffness indices to be identified as

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

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

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

Figure 1 schematizes the neural networks algorithm using acceleration features as the input data. It consists of two parts: (a) Training neural networks (TNN) and (b) Alarming damage location (ADL) using the neural networks.

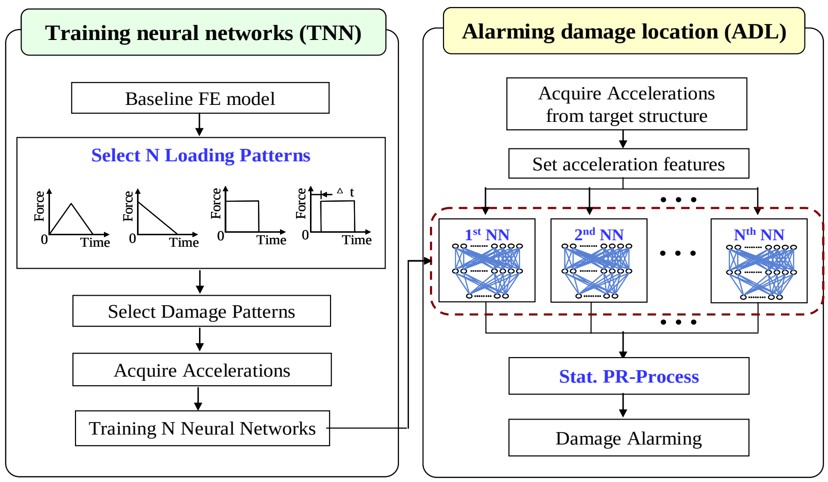


Figure 1. Schematic of Acceleration-Based Neural Networks for Damage Detection

We realize that the values computed for the damage indices will always contain many uncertainties. Three major sources of uncertainty are as follows: first, there are uncertainties associated with the difference between excitation-force models in TNN and actual loading conditions of the target structure; second, there are variations resulting from environmental fluctuations during the test; and third, there are uncertainties associated with the data extraction process. 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 [4]:

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

where $0 \le DI_j \le \infty$ and the damage is located at element j. Next, we 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.

VERIFICATION EXAMPLE

Description of Test Structure

Numerical tests were performed to evaluate the feasibility of the present ANN algorithm using acceleration features as the input. For the verification, a PSC beam was selected as shown Fig. 2 and dynamic responses of the structure were numerically analyzed before and after damaging episodes. The beam length L is 6.4m and the span length L_r is 6.0m. The T-type cross-section is $B \times H = 71cm \times 60cm$. The FE model of the PSC beam is schematized in Fig. 2. We divided the beam into 15,200 block elements. The elastic modulus of concrete is $E_c = 21.52GPa$ and the linear mass density of concrete is $\rho_c = 2400 kg/m^3$. The linear mass density of steel tendon is $\rho_c = 7850\, kg/m^3$. The elastic modulus of steel tendon for *n*th mode under tension is estimated by equivalent flexural rigidity formula as following Eq. (10) [9].

$$E_s = \frac{L^2 N}{n^2 \pi^2 I_s^2} (\mathrm{kN/m^2}) \tag{10}$$

where I_S is the second moment of area of the steel tendon element. The dynamic responses for each mode are combined by using superposition method. For the acquisition of the dynamic responses, we used the commercial software MIDAS/Civil and MATLAB.

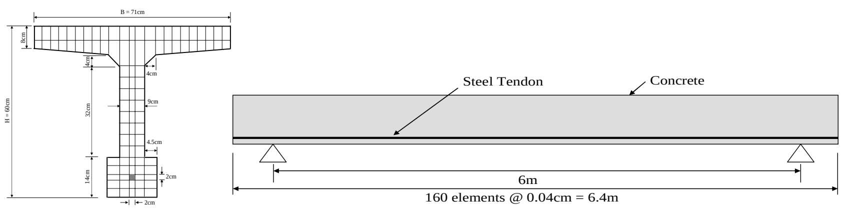


Figure 2. Geometry and schematization of FE model for simply-supported PSC beam

Trained Neural Networks

In order to train neural networks, a total of 7 groups are divided as shown Fig. 3. The groups 1~6 are the concrete elements and group 7 indicate the tendon elements. For generation of training patterns, exciting impulses were applied to $0.1L$ on the flange and accelerations were obtained at $0.3214L$ (i.e., station 1) and $0.5L$ (i.e., station 2) on the flange as shown Fig. 3. The sampling frequency of accelerations was set to 1 kHz and total 2,000 discrete acceleration data are obtained in 2 seconds duration. Next, several excitation types were selected to simulate unknown impulse-loadings.

Four excitation types were selected as shown in Fig. 4. Neural networks should be trained for the 4 excitation types (i.e., Excitations 1-4) and the 43 damage scenarios that included an undamaged case; therefore, a total of 172 training patterns were considered for damage detection in the test structure. As shown in Fig. 5, the neural networks consisted of three layers: (1) an input layer with 50 units where the first 50 cross-covariance ratios of accelerations between before and after damage were input, one after another, (2) a hidden layer with 50 units, and (3) an output layer with 7 units which were allocated to the 7 groups of the beam model.

Damage Location

As shown in Fig. 7, damages were applied by reducing two levels of stiffness at three different groups of the beam. Six different scenarios of damage were introduced as follows: (1) Case 1 is a single damage at group 3 with severity $\Delta E / E = 0.17$; (2) Case 2 is a single damage at group 3 with severity $\Delta E / E = 0.27$; (3) Case 3 is a single damage at group 6 with severity $\Delta E / E = 0.17$; (4) Case 4 is a single damage at group 6 with severity $\Delta E / E = 0.27$; (5) Case 5 is a single damage at group 7 with severity $\Delta E / E = 0.17$; and (6) Case 6 is a single damage at group 7 with severity $\Delta E / E = 0.27$.

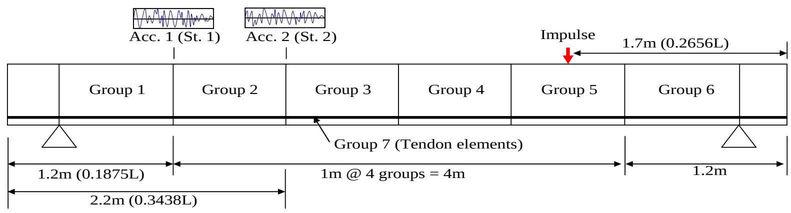
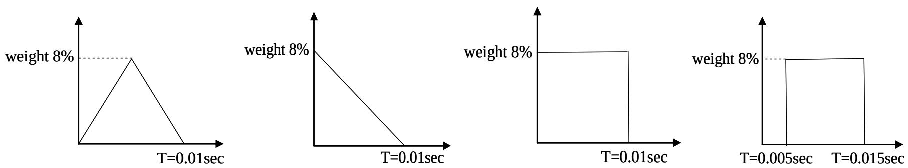


Figure 3. Group definition and scheme for acceleration acquisition



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

Figure 4. Excitation patterns to train for unknown external loads

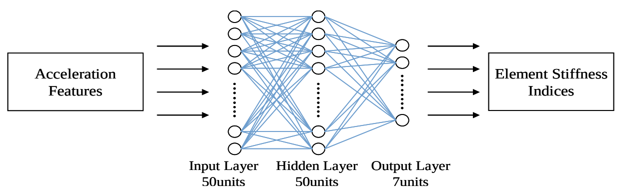
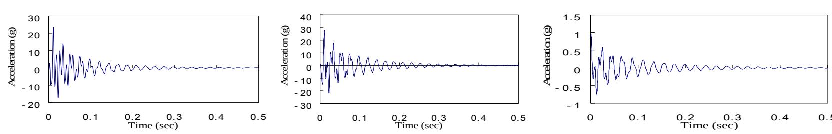


Figure 5. Acceleration-based neural networks



(a) Acceleration 1 (b) Acceleration 2 (c) Cross-Covariance

Figure 6. Two acceleration signals and cross-covariance signal for TNN

Accelerations were acquired at the 2 locations (see Fig. 3) before and after each damage scenarios. The impulse was applied to a location 1.7m distanced from the right end by triangular pulse with 0~0.5 sec duration.. Figure 9 shows acceleration signals measured at station 1 and station 2 and their cross-covariance signal, respectively. 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 7 groups of the test structure were estimated as the output.

Figure 10 shows the estimated stiffness indices of the test structure for the damage case 1. In this damage case, stiffness indices of the 7 groups were estimated by the four different excitation patterns (i.e., Excitations 1-4), respectively. For Eq. (8), we set $z_0 = 1.5$ corresponding to a confidence level of 93.3%. As shown in Figs. 11(a)-(e), damage cases 1 and 2, group 3 was predicted, which is identical to the damaged element. In damage cases 3 and 4, group 6 was predicted correctly. However, in damage cases 5 and 6, damage localization was not successful.

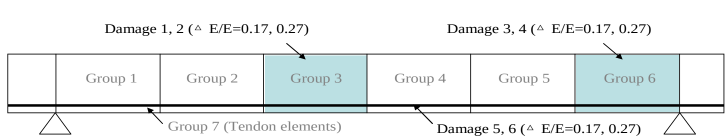
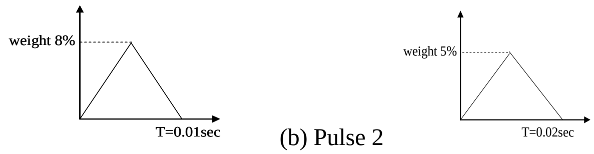
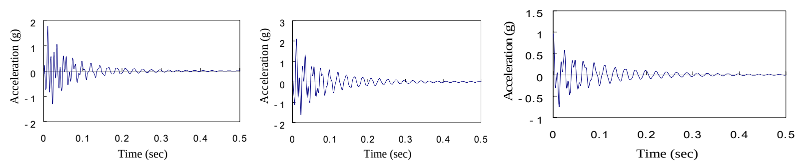


Figure 7. Damage scenarios for test structure



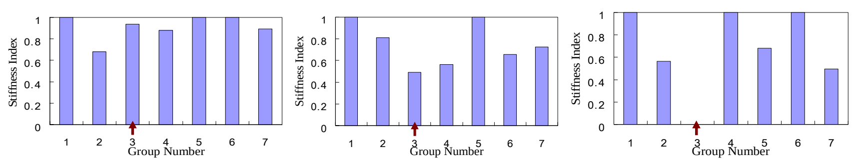
(1) Pulse 1 (b) Pulse 2

Figure 8. Comparison of two triangular pulses used for TNN and ADL



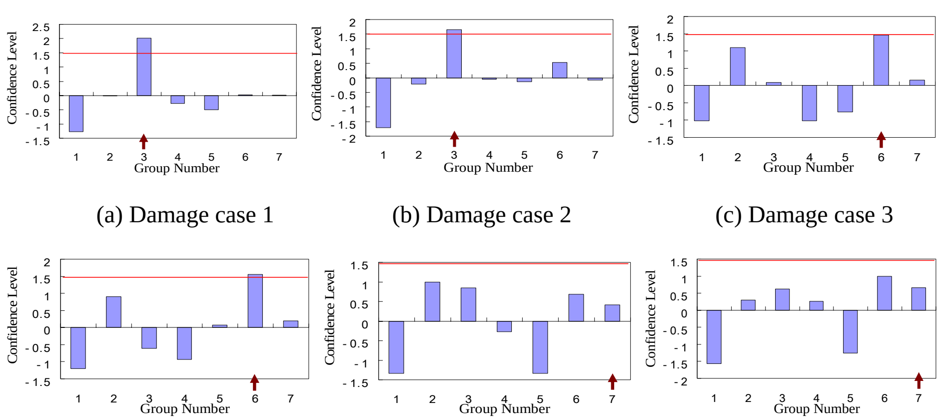
(a) Acc. 1 (b) Acc. 2 (c) Cross-covariance

Figure 9. Two acquired acceleration signals and cross-covariance signal for ADL



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

Figure 10. Estimated stiffness indices for damage case 1



(a) Damage case 1 (b) Damage case 2 (c) Damage case 3

(d) Damage case 4 (e) Damage case 5 (f) Damage case 6

Figure 11. Damage localization results for test structure

SUMMARY AND CONCLUSIONS

In this study, a new damage monitoring method using a set of parallel ANNs and acceleration signals was developed for alarming locations of damage in PSC girders. A parallel ANN-algorithm using output-only acceleration responses was newly designed for damage detection in real time. The cross-covariance of acceleration-signals was selected as the feature representing the structural condition. Neural networks were trained for uncertain loading patterns and damage scenarios of the target structure for which its actual loadings are unknown. The uncertainty effect on real-time monitoring using the proposed method was evaluated from model tests on PSC beams for which accelerations were acquired before and after several damage cases.

A PSC girder model was selected and dynamic responses were acquired by accelerometers before and after damaging episodes. Four (4) excitation types and 43 damage scenarios were selected to train neural networks of a PSC girder model. Initial 50 signal data measured from two accelerometers were input into the neural networks and stiffness indices of the 7 groups of the test structure were estimated as the output. From the damage localization process, single-damage cases for cracks were predicted correctly but the damage detection for prestress-loss was not successful. In the future, it is needed to select efficient excitation models for damage detection of PSC girder and to evaluate the practicability of the proposed method by experimental tests.

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