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ACCELERATION-BASED DAMAGE EVALUATION OF BUILDING STRUCTURES WITH NEURAL NETWORKS AND PARTICLE SWARM OPTIMIZATION

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Abstract

An evaluation approach for building structures under earthquakes is proposed to provide damage alarm and identification. It is a time-domain evaluation procedure capable of alarming, localizing and quantifying damage using limited acceleration measurements. The technique is a combination of the damage detection based on artificial neural networks (ANN) and the system identification using the particle swarm optimization (PSO).

To implement the concept, a two-phase approach is used. In the first phase, the ANN emulator used for emulating the structural response is tuned to properly model the hysteretic nature of a building response. To facilitate the most realistic monitoring system using accelerometers, the acceleration streams at the same location but at different time steps are utilized. The prediction accuracy can be raised by the increment of a number of acceleration streams at different time steps. Damage occurrence alarm can be obtained practically and economically only using readily available acceleration time histories in this phase. In the second phase, damage localization and quantification can be achieved by the system identification using PSO. Based on the numerical simulation for a 5-story shear structure, the adaptability, generality and appropriate mass of parameters for the technique are studied.

INTRODUCTION

Structural health monitoring (SHM) has received great attention and interest to predict the onset of damage and deterioration of building structures because of the increasing number of aged buildings and unpredictable natural hazards.

Most currently available damage detection methods are global in nature, i.e., the dynamic properties (natural frequencies and mode shapes) are obtained for the entire structure from the input–output data using a global structural analysis [1]. However, natural frequencies and mode shapes are not sensitive to minor damage and local damage. The techniques using time-domain dynamic responses are appealing and promising. Furthermore, the dynamic responses of structures under environmental excitation or small-scale earthquakes are very economical information for structural identification and health monitoring, especially in the places where small-scale earthquakes occur very frequently. Some information about structural parameters and dynamic properties can be identified by the direct use of these time-domain responses. Naira et al. proposed a damage detection and localization algorithm based on time series modeling [2]. There is an approach by directly using dynamic responses in time series without extraction of dynamic properties proposed by Xu et al. [3], which used acceleration, velocity and displacement time histories as the input of the emulator neural network. This approach was improved by Xu & Chen[4], which only used acceleration time histories as the input of the emulator neural network, called acceleration-based emulator neural network (AENN) for free vibration.

In this paper, the AENN is extended to forced vibration beyond the limitation of free vibration. The acceleration time histories, which are readily available in real structures, are only required. This is the first phase, through which the damage occurrence alarm can be obtained by observing the relative root mean square (RRMS) error between the output of AENN and the real value.

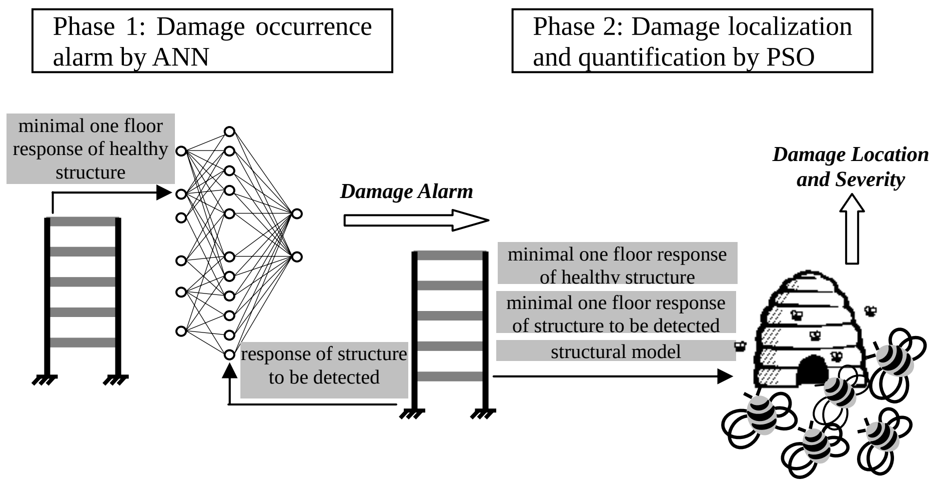

Figure 1. Two-phase damage evaluation approach

After knowing the damage occurrence, the next phase is to determine the damage localization and quantification. Most currently available damage localization approaches are using pattern recognition methods to classify the different damage location. However, such approaches need analytical data for all damage case situations, which can be computationally expensive and even impossible. Therefore, the system identification is utilized. Most of the currently available system identification techniques are based on the frequency-domain approach; in this paper the system identification problem is transferred to optimization problem with the convenience for time-domain. The PSO is utilized.

The proposed approach is carried out in two phases as briefly described in Fig. 1. The detailed and theoretic analysis is in the following sections.

IDENTIFICATION OF STRUCTURAL CHANGES WITH NEURAL NETWORK BASED ON ACCELERATION MEASUREMENT

Proposed ANN Emulator Using Acceleration Only as Inputs

Here, neural networks may work as good black-box models for nonlinear systems, as well as linear systems. Although ARX (Auto-Regressive eXtra input) models represent linear system dynamics, it could offer some revelation to application of neural networks. An ARX model [5] is given by

$$A(q)y(t) = B(q)u(t) + e(t) \tag{1}$$

where q is the shift operator. Auto-Regression model $A(q)$ in terms of q is defined by

$$A(q) = 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a} \tag{2}$$

Similar function is defined by

$$B(q) = b_1 q^{-1} + \cdots + b_{n_b} q^{-n_b} \tag{3}$$

A pragmatic and useful way to see (1) is to view it as a way of determining the next output value given previous observations:

$$y(t) = -a_1 y(t-1) - \cdots - a_{n_a} y(t-n_a) + b_1 u(t-1) + \cdots + b_{n_b} u(t-n_b) + e(t) \tag{4}$$

Instead of ARX model, neural networks may represent the relationship of determining the next output value given previous observations and extra input. And the advantage of neural networks is that it may work for nonlinear systems, as well as linear systems. This representation indicates that the prediction of the response requires several previous time steps for response as well as inputs.

So an acceleration-based emulator neural network (AENN), which can be trained to represent the mapping between the acceleration at different time steps, could be established as in Fig.2. Here we use acceleration time histories as observations. Since they are readily available in real structures, using accelerations only provides much convenience. The acceleration of ground is out of the consideration of neural networks' target, so we include the acceleration of ground at T_k, which is already available, into the input layer of neural networks.

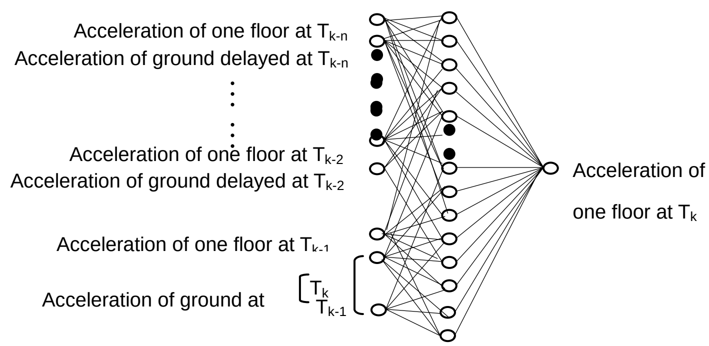

Figure 2. Acceleration-based emulator neural network

The trained AENN is a non-parametric model for the structure and can be used to forecast the acceleration response under later earthquakes.

Relative root mean square (RRMS) error, e, s defined by [6]

$$e = \frac{\sqrt{\sum_{m=1}^{M} \left(\ddot{x}_m^f - \ddot{x}_m\right)^2}}{\sqrt{\sum_{m=1}^{M} (\ddot{x}_m)^2}} \tag{5}$$

where, M is the number of sampling data; $\ddot{x}_m^f$ the output of trained neural networks at sampling step m; $\ddot{x}_m$ the acceleration corresponding, which is the real dynamic response under earthquake excitations at sampling step m.

RRMS shows the change between the output of the neural network and the real dynamic response, and provides the information of structural damage. If this value is quite large, it would be thought that the structure is not healthy.

Modified ANN Emulator

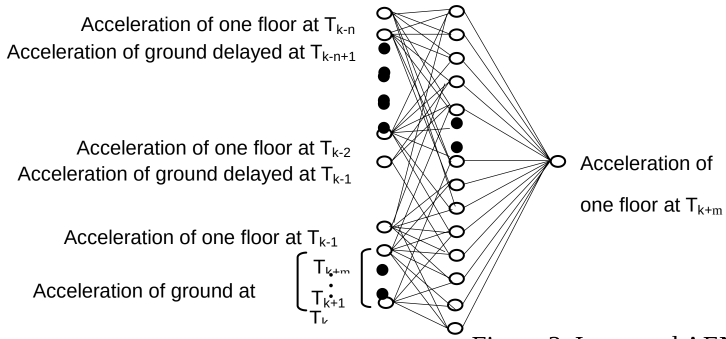

Figure 3. Improved AENN

Using acceleration at time of steps k-2 and k-1 to forecast the acceleration at time step k, it would be common that the RRMS error is too small to be regarded as the index of a damage occurrence alarm. Therefore, the improvement of the approach was carried out by using the acceleration at later time steps as the output of the neural network. The accelerations of ground floor and the other floors in the input layer are not synchronous as shown in Fig. 3. The acceleration of ground has a delay of time $m \times \Delta t$ in order that the emulator neural network could forecast the acceleration of the each floor at later time steps. The delay $m \times \Delta t$ is considered as a tunable band corresponding to different structures.

SEARCH FOR APPROPRIATE PARAMETERS BASED ON SIMULATION

Acceleration stream number and ground delay, n and $m \times \Delta t$ in Fig.3, are to be decided in this section. The necessary number of acceleration stream, n, should make the RRMS error for health structures be a stably small value. The appropriate ground delay $m \times \Delta t$ should make RRMS error difference between health structures and damage structures be a comparatively large value. The search for these two appropriate parameters would be performed in this section based on numerical simulation.

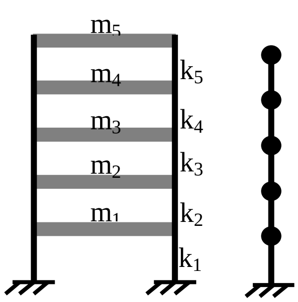

Figure 4.Five-storey frame structure

Table 1. Structural parameters of the object structure

DOF	1	2	3	4	5
Mass (kg)	4000	3000	2000	1000	800
Stiffness (kN/m)	2000	2000	2000	2000	2000

Table 2. Modal parameters of the object structure

DOF	1	2	3	4	5
Frequency (Hz)	1.65	4.11	6.16	8.11	12.3
Damping Ratio	0.005	0.013	0.019	0.025	0.039

In this study, a 5-storey shear frame structure shown in Fig.4, is considered as the object structure. The structure is modelled as a 5 degree-of-freedom lumped mass system. The structural parameters of the 5-mass structure are shown in Table 1. The natural frequencies of the frame structure are 1.6521Hz, 4.1120Hz, 6.1565Hz, 8.1085Hz, and 12.2932Hz, as shown in Table 2. The damping matrix is assumed to be Rayleigh damping, which can be expressed in the following form,

$$\mathbf{C} = a\mathbf{M} + b\mathbf{K} \tag{6}$$

where a and b are selected to have damping ratios 0.005 for the first mode and 0.013 for the second mode..

Using the network training function that updates weight and bias values according to Levenberg-Marquardt optimization, AENN is trained firstly. The output layer includes 1 neuron. The neuron number of input layer is decided by n and $m \times \Delta t$ in Fig.4, and the neuron number of hidden layer is two times of that of the input layer.

Here, the acceleration time histories obtained from the top floor of the 5-story shear structure under the earthquake ground motion of Hachinohe earthquake (May, 16, 1968, Hachinohe City) was used as training data sets. And the acceleration time histories under the ground motion of Northridge earthquake (Jan. 17, 1994, Northridge, California) was used as test data sets. These two earthquake records are shown in Fig.5. The sampling time is 0.02 second. All of these time histories were normalized to the length of 1.

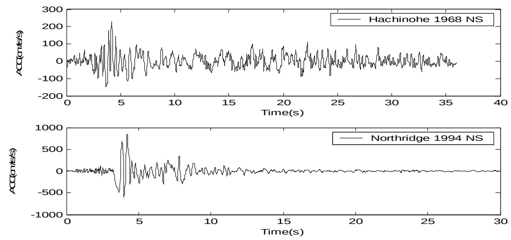

Figure 5. Earthquake records, Hachinohe and Northridge

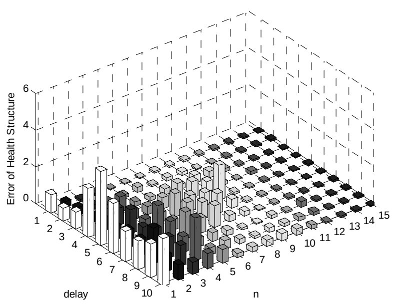

Figure 6. Error for health structure changed by acceleration stream number and delay

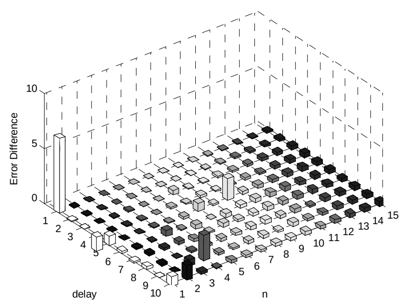

Figure 7. Error difference between health and damage structures

During the numerical simulation, acceleration stream number, n, was changed from 1 to 15. The delay, $m \times \Delta t$ was changed from 0.02 to 0.2second, say, 1~10 times of sampling time. The two values, RRMS error for health structure and the difference of RRMS errors between health structure and damage structure, would be observed in Fig.6 and Fig.7, to obtain stably small value for the former one and comparatively large value for the latter one. The difference of RRMS errors was defined by

$$\Delta e = e_{damage} - e_{health} \tag{7}$$

Here, the damage structure was with stiffness reduction of 20% at each floor.

The prediction accuracy could be raised by the increment of a number of acceleration streams at different time steps to an appropriate value. The value of RRMS error would decrease to a stable value if the number of acceleration streams reaches the appropriate value.The error for a health structure changed by acceleration stream number and delay in Fig.6 was observed to search for necessary acceleration stream number firstly. In Fig.6, it could be seen that error for health structure would be stably small with acceleration stream number larger than 10. Therefore the necessary acceleration stream number is 10 in this case. For 5-story shear structure, the appropriate value of acceleration stream number should be 10, which is understandable and reasonable on this method bearing an analogy with ARX Models.

The error difference between health and damage structures in Fig.7 was observed to search for appropriate ground delay secondly. In Fig.7, it could be seen that error difference corresponding to *n*=10 would be comparatively large with ground delay 7 times of sampling time, say, 0.14 second. So the appropriate ground delay is 0.14 second for this structure. The first order natural frequency of this structure is 1.6521, so the ground delay, which is 1/4 of structural periodic time, is suggested here.

SYSTEM IDENTIFICATION AS AN OPTIMIZATION PROBLEM USING PSO

The identification problem can be understood as an optimization problem in which the error between the actual physical measured response of a structure and the simulated response of a numerical model is minimized. In order to show this in more detail, let us consider a physical system as shown in Fig. 4 with q outputs of acceleration responses y_j^M for $j=1,2,\cdots,q$. Let y_j^M for $j=1,2,\cdots,q$ denote the value of the acceleration responses of the actual system.

Suppose that a model that is able to capture the behaviour of the physical system is developed and that this model depends upon a set of *n* parameters, contained in a vector $\mathbf{x}=\{x_i\}$ for $i=1,2,\cdots,n$. Call the newly formed model of the system and its parameters the identified system or candidate system, and let y_j for $j=1,2,\cdots,q$ denote the value of the acceleration responses of the identified system. At this point, let us now built the vectors y_j^M and y_j as

$$\mathbf{y}_j^M=\lfloor y_j^M(0) \quad y_j^M(1) \quad \cdots \quad y_j^M(T)\rfloor \tag{8}$$

$$\mathbf{y}_j=\lfloor y_j(0) \quad y_j(1) \quad \cdots \quad y_j(T)\rfloor \tag{9}$$

containing all sampled values of the *j*th output of the actual and identified systems, respectively. Now consider the vectors y_j^M and y_j, without subindex, as the stacked vectors of all available output records for each system, which can be written as

$$\mathbf{y}^M=\lfloor y_1^M(0) \quad y_1^M(1) \quad \cdots \quad y_1^M(T) | y_1^M(0) \quad \cdots | \cdots | y_q^M(0) \quad \cdots \rfloor \tag{10}$$

$$\mathbf{y}=\left[y_1(0) \quad y_1(1) \quad \cdots \quad y_1(T) | y_1(0) \quad \cdots | \cdots | y_q(0) \quad \cdots \right] \tag{11}$$

and compute the error norm of all the simulated outputs of the identified system with respect to those measured from the actual system, defined as:

$$F(\mathbf{x})=\sqrt{\left(\mathbf{y}^M-\mathbf{y}\right)\left(\mathbf{y}^M-\mathbf{y}\right)^T} \tag{12}$$

In order to obtain a successful identification, the candidate system must be able to accurately reproduce the output of the physical system for any given input. Therefore, our interest lies in minimizing the error norm of the outputs. Formally, the optimization problem requires finding a vector $\mathbf{x}\in S$, where S is the search space, so that a certain quality criterion is satisfied, namely that the error norm $F:S\to R$ is minimized. The function F is commonly called a cost function or objective function. Vector $\mathbf{x}^*$ will be called a solution to the minimization problem if $F\left(\mathbf{x}^*\right)$ is the global minimum of F in S, or

$$\mathbf{x}^*\in S \,|\, F\left(\mathbf{x}^*\right)\le F(\mathbf{x}) \qquad \forall \mathbf{x}\in S \tag{13}$$

The search space S is defined by a set of maximum and minimum values for each parameter. It is conceived as an n-dimensional domain that is delimited by vectors $\mathbf{x}_{max}$ and $\mathbf{x}_{min}$ containing the upper bounds of the n parameters and the lower bounds respectively or

$$S = \left\{ x \in R^n \middle| x_{min,i} \le x_i \le x_{max,i} \qquad \forall i = 1,2,\cdots,n \right\} \tag{14}$$

The problem of identification thus interpreted is treated as a linearly constrained, (due to the delimited n-dimensional search space) nonlinear (due to the nonlinear cost function) optimization problem.

Particle Swarm Optimization (PSO)

Particle swarm adaptation has been shown to successfully optimize a wide range of continuous functions [7]. The algorithm, which is based on a metaphor of social interaction, searches a space by adjusting the trajectories of individual vectors, called "particles" as they are conceptualized as moving points in multidimensional space. The individual particles are drawn stochastically toward the positions of their own previous best performance and the best previous performance of their neighbors.

A population of particles is initialized with random positions $\vec{x}_i$ and velocities $\vec{v}_i$, and a function, f, is evaluated When a particle discovers a pattern that is better than any it has found previously, it stores the coordinates in a vector $\vec{p}_i$. The difference between $\vec{p}_i$ (the best point found by i so far) and the individual's current position is stochastically added to the current velocity, causing the trajectory to oscillate around that point. Further, each particle is defined within the context of a topological neighborhood comprising itself and some other particles in the population. The stochastically weighted difference between the neighborhood's best position $\vec{p}_g$ and the individual's current position is also added to its velocity, adjusting it for the next time-step. These adjustments to the particle's movement through the space cause it to search around the two best positions.

An important source of the swarm's search capability is the interactions among particles as they react to one another's findings. Analysis of interparticle effects is beyond the scope of this paper, which focuses on the trajectories of single particles.

NUMERICAL VERIFICATION

In order to verify the performance of the proposed methods, let us analyze the structure described in former sections represented in Fig. 4. The minimal output, only acceleration at floor 5, is used. In the first phase, the damage index increases, while the damage becomes severe, as shown in Fig. 8.

To verify the performance of the second phase and compare it with other global search methods, the results obtained with the usage of the Simulated Annealing (SA) and Genetic Algorithm (GA) are presented in Tables 3, along with the results obtained with the PSO, for the sake of comparison. The unit of the stiffness value is 100kN/m.

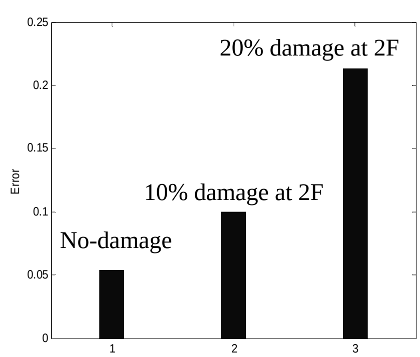

Figure 8. Damage alarm

		no noise			5% noise			10% noise			20% noise		
	Value	PSO	SA	GA	PSO	SA	GA	PSO	SA	GA	PSO	SA	GA
k_1	20	20.555	19.513	20.522	19.153	17.051	21.576	17.950	17.086	17.201	22.008	16.955	16.845
k_2	20	19.457	20.555	19.485	21.223	25.541	18.807	22.740	24.463	24.298	18.576	29.465	27.960
k_3	20	19.090	20.880	19.183	20.833	26.421	17.058	25.899	30.824	29.245	16.034	18.110	20.581
k_4	20	20.513	19.622	20.292	20.853	19.595	24.663	16.138	15.499	16.082	30.413	37.935	37.319
k_5	20	21.018	18.909	21.403	17.325	12.506	19.867	22.518	17.610	17.079	17.936	15.418	10.028
Error		3.54%	3.39%	3.55%	6.43%	22.81%	10.51%	17.07%	25.09%	23.18%	19.88%	36.92%	38.99%

Table3. Results of numerical simulation

For square competition, these three methods are with the same termination criterion, 1000 maximum generation; the same upper bound of the search space, twice the actual value of the parameters, lower bound, one tenth of their actual values; and the same random values added as noise.

The analysis of the results contained in Tables 3 leads to the following observations: in general, in the minimal output information scenario, the PSO performed similarly to the SA and GA in the noise-free case. However, the PSO performed better than the SA and GA at all levels of noise tested. The system identification based on PSO is feasible and of advantage for damage localization and quantification with possibly few response outputs.

CONCLUDING REMARKS

In this paper, an evaluation approach for building structures under a earthquake was proposed to provide damage alarm and identification. This was a two-phase time-domain technique capable of alarming, localizing and quantifying damage using limited acceleration measurements. The damage alarm can be firstly obtained using ANN. The damage location and severity can be determined secondly with the system identification using the particle swarm optimization (PSO).

Based on the numerical simulation for a 5-story shear structure, the appropriate parameters of the neural network were searched for and suggested. The effectivity of this method was also studied by comparison of structural evaluation for the healthy structures with the damaged structures. The verification of two phases was conducted as well. In our proposed evaluation approach, damage occurrence alarm and identification could be obtained accurately and economically only using readily available acceleration time histories.

REFERENCES

1. DoeblingW., Farrar C.R., Prime M.B., 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, Los Alamos National Laboratory, Los Alamos, NM 87545, 1996.
2. Krishnan Nair K., Kiremidjian A. S., Law K. H.. Time series-based damage detection and localization algorithm with application to the ASCE benchmark structure. Journal of Sound and Vibration 291 (2006) 349–368.
3. Xu, B., Wu, Z.S. & Yokoyama, K. Response Time Series Based Structural Parametric Assessment Approach with Neural Networks, Proceedings of the First International Conference on Structural Health Monitoring and Intelligent Infrastructure, Tokyo, Japan, Vol.1. (2003) 601-609.
4. Xu, B. & Chen, G. Acceleration-Based Identification of Structural Parameters with Neural Networks, Proceedings of the 5th International Workshop on Structural Health Monitoring, Stanford Univ., Stanford, CA (2005) 1073-1080.
5. Mita, A. Structural Dynamics for Health Monitoring, SANKEISHA Co.,Ltd. Nagoya, Japan. (2003).
6. Qian, Y. & Mita, A. Time Series-Based Damage Evaluation Algorithm with Application to Building Structures, Proceedings of the 1st Asia-Pacific Workshop on Structural Health Monitoring, Keio Univ., Yokohama, Japan. (2006).
7. Angeline, P. Evolutionary optimization versus particle swarm optimization: Philosophy and performance differences. In V. W. Porto, Saravanan, N., Waagen, D., and Eiben, A. E. (Eds.), Evolutionary Programming VII, Berlin: Springer. (1998). 601-610.