APPLICATION OF NEURAL NETWORKS IN STRUCTURAL HEALTH MONITORING

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Abstract

A neural network based-approach for structural health monitoring was presented. The proposed approach involves two steps. The first step, system identification, uses NARX (Non-linear Auto-Regressive with eXogenous) neural networks to identify the undamaged and damaged states of a structural system. The second step, structural damage detection, uses the aforementioned trained NARX neural networks to generate free vibration responses with the same initial condition or impulsive force. Comparing the periods and amplitudes of the free vibration responses of the damaged and undamaged states allows the extent of changes to be assessed. Furthermore, numerical and experimental examples demonstrate the feasibility of applying the proposed method for structural health monitoring.

INTRODUCTION

Conventional neural-network-based structural damage assessment methods (Ghaboussi et al., 1991; Wu et al., 1992; Elkordy et al., 1993; Szewczy and Hajela, 1994; Pandy and Barai, 1995) use artificial neural networks (ANNs) to extract and store the knowledge of the patterns in the response of undamaged and damaged structure. Thus, the need for construction of the mathematical models and the comprehensive inverse search is avoid. The inputs of the neural network are usually structural responses in time or frequency domain, or structural modal parameters (frequency, damping ratio, and mode shape), and the outputs are usually the damaged levels of members in the structure. However, Masri et al. (1996, 2000) indicated that the failure modes of the test structure are so varied and so unpredictable; thus, it is not feasible to train the neural network by furnishing it with pairs of failure states and corresponding diagnostic response.

ANNs are robust and fault tolerant (Rumelhart et al., 1986). ANNs can also effectively deal with qualitative, uncertain, and incomplete information, thereby making them highly promising for identifying systems that are typically encountered in structural dynamics. Studies by Masri et al. (1996, 2000) complemented conventional ANN-based structural damage assessment methods by concentrating on a class of problems where knowledge of the failure states is not available. They presented an ANN-based system identification (SI) approach for detecting changes in the characteristics of systems where the structure is unknown from predicted error. Similar work can be found in Huang and Loh (2001). Moreover, the weights of the approximating neural network store the knowledge of the structural properties. Hung and Kao (2002) presented an ANN-based SI approach for detecting changes in the characteristics of systems where the structure is unknown from the optimum weights of the NARX neural network.

The periods and amplitudes of a structural free vibration responses contain information on structural properties, meaning structural damage can be detected based on changes in the periods and amplitudes of the structural free vibration response. This work develops a neural network-based approach for detecting changes in the characteristics of structure-unknown systems. The proposed approach involves two steps. The first step, system identification, uses NARX neural networks to identify the undamaged and damaged states of a structural system. The second step, structural damage detection, uses the aforementioned trained NARX neural networks to generate free vibration responses with the same initial condition or impulsive force. Comparing the periods and amplitudes of the free vibration response of the damaged state with those of the undamaged state allows changes to the physical system from its undamaged state to be detected. Moreover, numerical and experimental examples are presented to demonstrate the feasibility of using the proposed method for structural health monitoring.

HEALTH MONITORING STRATEGY

This neural network-based approach, as shown in Fig. 1, for detecting changes in the characteristics of structure-unknown systems involves two steps. The first step, system identification, uses NARX (Non-linear Auto-Regressive with eXogenous) neural networks to identify the undamaged and damaged states of a structural system. The second step, structural damage detection, uses the aforementioned trained NARX neural networks to generate free vibration responses with the same initial condition or impulsive force. Comparing the periods and amplitudes of the free vibration response of the damaged and undamaged states can reveal the extent of changes. The following presents the details of the above approaches.

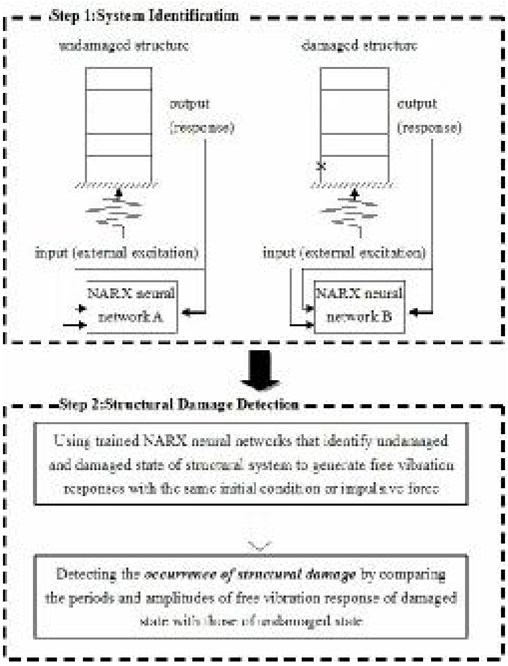

Fig 1: Schematic diagram of the proposed approach

NARX Neural Network

ANN models have been extensively applied to identify dynamic systems. Cybenko (1989) and Funahashi (1989) rigorously demonstrated that, even with only one hidden layer, neural networks can uniformly approximate any continuous function. Consequently, this theoretical basis for modeling linear or nonlinear systems by neural networks is sound. The NARX neural network, as shown in Fig. 2, approximates the following equation:

$$y(t) = g(y(t-1),\cdots,y(t-n_y),x(t),\cdots,x(t-n_x)) \tag{1}$$

where x and y are the system input and output vectors, respectively; n_x and n_y are the maximum lags in the input and output, respectively; g is a linear or nonlinear function. The inputs of the NARX neural network are $y(t\text{-}1)$, …, $y(t\text{-}n_y)$, and $x(t)$, …, $x(t\text{-}n_x)$. The output of the NARX neural network is $y(t)$. Notably, approximation by the NARX neural network in a discrete linear structural system is analogous to identifying the mass, damping and stiffness coefficients in the equation of motion.

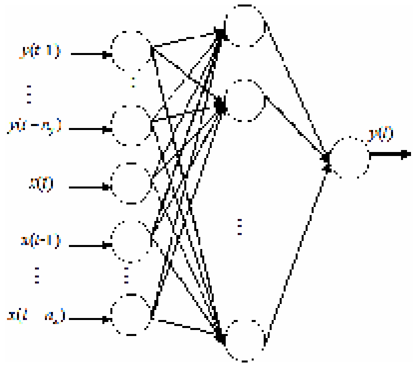

Fig 2: The architecture of the NARX neural network

Generating a free vibration response using the trained NARX neural network

The periods and amplitudes of a structural free vibration response contain information on structural properties, meaning it is feasible to detect structural damage from changes in the periods and amplitudes of the structural free vibration response. However, generating a structural free vibration is difficult if the structural properties are unknown. Recently, Hung et al. (2001) have developed a method for simulating the seismic response of a nonlinear hysteretic structure using the approximating ANN. This approach can be used to generate the free vibration response of a structure-unknown system. The generation on a free vibration response using the trained NARX neural network which identifies the undamaged or damaged state of the system is as follows:

(1) Provide an initial input vector (initial condition or impulsive force) to the trained NARX neural network.
(2) Feed forward the initial input vector in step (1) through the trained NARX neural network to compute the output vector.
(3) Feed back this computed output vector to the input layer of the trained NARX neural network as the next input vector.
(4) Feed forward the next input vector in step (3) through the trained NARX neural network to compute the next output vector.
(5) Return to step (3) and repeat until the maximal number of iterations is reached.

The free vibration response generated by the NARX neural network which identifies the undamaged state is compared to that generated by the NARX neural network which identifies the damaged state. If the network has been well trained, and if the system characteristics have not changed, the periods and amplitudes of both free vibration responses will match. On the other hand, if the system has changed, the above statement will no longer stand. The deviations between the periods and amplitudes of the two free vibration responses provide a quantitative measure of the changes in the physical system relative to its "healthy" condition.

ILLUSTRATIVE EXAMPLES

Example 1: The Numerical Example

In this example, a 5-story shear building was chosen to demonstrate the feasibility of using the proposed approach for health monitoring of linear MDOF structure systems. The structural properties of the building are assumed to be as follows: floor mass $m=8\times10^4$ kg, floor stiffness $k=4\times10^7$ N/m, and floor damping $c=1.5\times10^6$ N-s/m for all floors. EL-Centro earthquake was used as the external excitation. The sampling period Δt is 0.01 second. In this example, only the relative acceleration time histories of the five floors, computed by SSP (State Space Procedure), were used as measured responses of the structure.

First, relations between the changes of structural properties (floor stiffness and damping) and those of the periods and amplitudes of the structural free vibration response were discussed. Figure 3 shows the comparison of the free vibration responses (relative accelerations), with initial ground acceleration 0.01g, of three cases (floor stiffness reduction varies from 0 to 40% every 20%) between 0.5 and 6.5 seconds. It shows that the more the floor stiffness reduction, the longer the periods of the free vibration response. Figure 4 shows the comparison of the free vibration responses, with initial ground acceleration 0.01g, of the three cases (floor damping increase varies from 0 to 40% every 20%) between 0.5 and 6.5 seconds. It shows that the more the floor damping increase, the smaller the amplitudes of the free vibration response.

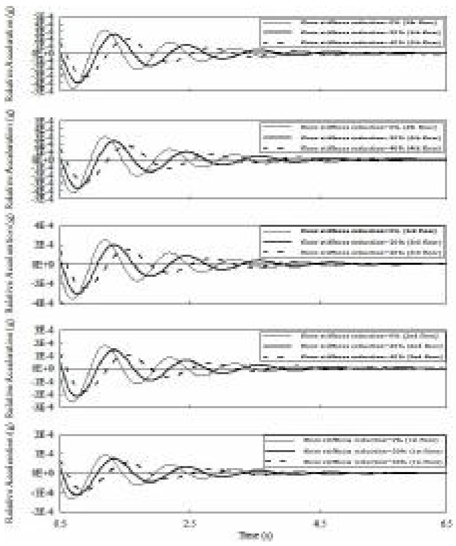

Fig. 3: Comparison of the free vibration responses, with initial ground acceleration 0.01g, of three cases (floor stiffness reduction varies from 0 to 40% every 20%)

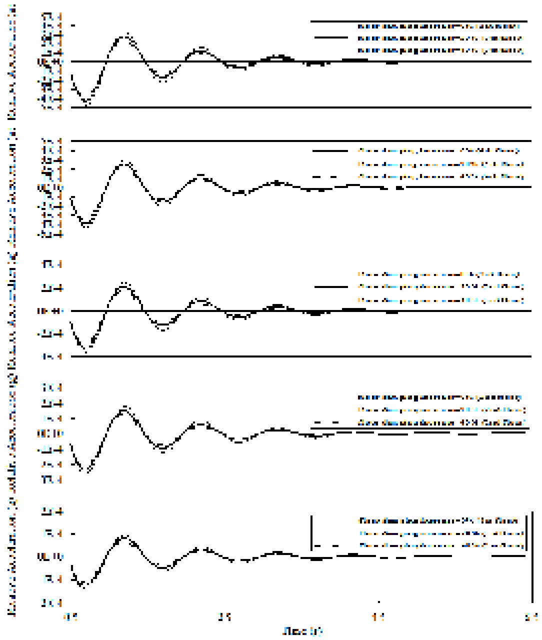

Fig. 4: Comparison of the free vibration responses, with initial ground acceleration 0.01g, of the three cases (floor damping increase varies from 0 to 40% every 20%)

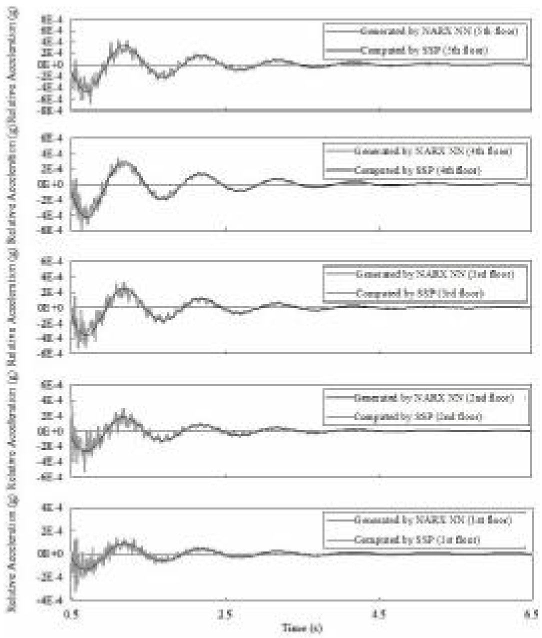

Fig. 5: Comparison of the numerical solutions and generated free vibration responses, with initial ground acceleration 0.01g, from the trained NARX neural network

Second, the undamaged case was used to compare the free vibration response generated by the trained NARX neural network with the numerical solution (computed by SSP). The training data set of the NARX neural network is the 2000 records of EL-Centro Earthquake. The NARX neural network consists of 301, 0, and 5 nodes in input layer, hidden layer, and output layer, respectively, and denoted as NARX(301-0-5). The 301 input data are 250 the structural relative accelerations of the five floors in (*k*-1) back-to (*k*-50) time steps, and 51 external excitations in *k* back-to (*k*-50) time steps. The five outputs are the structural relative accelerations of the five floors at time *k*. The complete off-line training process took 1000 cycles and the system error converges to 1.2085×10^{-18}. After training, the NARX neural network was used to generate free vibration responses of the building system. Figure 5 is the comparison of the two free vibration responses (between 0.5 and 6.5 seconds) with initial ground acceleration 0.01g, which shows the excellent correspondence between the numerical solutions and the generated free vibration responses from the trained NARX neural network for the five floors.

Example 2: The Experimental Example

In this example, the dynamic responses of a five-story steel frame, subjected to various strengths of the Kobe earthquake in shaking table tests, were processed to demonstrate the applicability of the proposed method. This series shaking table tests were undertaken by The National Center for Research in Earthquake Engineering in Taiwan on a 3 meters long, 2 meters wide, and 6.5 meters high steel frame (Fig. 6) to generate a set of earthquake response data for this benchmark model of a five-story steel structure. Lead blocks were piled on each floor such that the mass of each floor was approximately 3664 kg. The frames were subjected to the base excitation of the Kobe earthquake, weakened by various levels. The displacements, velocity, and acceleration response histories of each floor were recorded during the shaking table tests. Additionally, some strain gauges were also installed in one of the columns and near the first floor. The sampling rate of the raw data was 1000Hz.

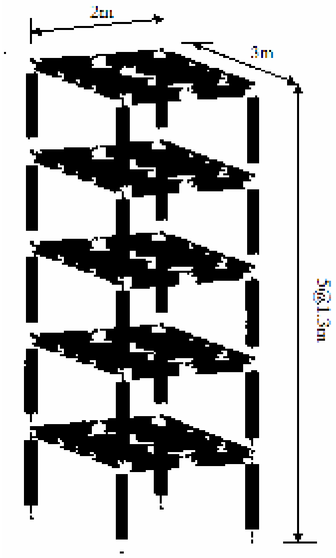

Fig. 6: Simple sketch of a five-story steel frame

Notably, it is reported (Yeh et al., 1999) that the frame responded linearly when it subjected to 8%, 10%, 20%, 40%, and 52% of the strength of the Kobe earthquake. Measured strains and visual inspection revealed that 60% of the strength of the Kobe earthquake input caused the steel columns near the first floor to yield.

NSINs Training: In the following, only the responses (relative accelerations) and inputs in the long span direction were addressed. The significant responses between 4.5 and 12.5 seconds were used to train ANNs and thus, to some extent, reduce the noise effect. Five NARX neural networks were used to identify five different states (from state 1 to state 5). States from 1 to 5 are the states that the frame subjected to 10%, 20%, 40%, 52%, 60% Kobe earthquake, respectively. Networks with the same topology of the previous example were employed in this example. That is, the topology of each NARX neural network is NARX(301-0-5). The 301 inputs and the five outputs are the same as that in the previous example. The complete off-line training process took 3000 cycles.

Structural Health Monitoring: After training, the five NARX neural networks were used to generate free vibration responses to investigate the changes of the structural properties with excitation magnitude. First, the comparison of the free vibration responses of state 1, state 2, and state 3, with initial ground acceleration 0.01g, is shown in Fig. 7. It reveals that the periods of the three free vibration responses were almost identical, but the amplitude becomes smaller and smaller with the increasing of excitation magnitude. According to results of example 1, it shows that the stiffness values of the three states were almost the same, and the damping values increase with the increasing of excitation magnitude. Second, the comparison of the free vibration responses of state 3 and state 4, with initial ground acceleration 0.01g, is shown in Fig. 8. It displays that the periods of the free vibration of state 4 were slightly longer than that of state 3, and the amplitudes of the two free vibration responses were almost the same. According to results of example 1, it exposes that the stiffness values of state 4 were a little smaller than those of state 3, but the damping values of the two states were almost the same. Finally, the comparison of the free vibration responses of state 4 and state 5, with initial ground acceleration 0.01g, is shown in Fig. 9. It reveals that the periods of the free vibration of state 5 were longer than those of state 4, and the amplitudes of the free vibration of state 5 were larger than those of state 4. Based on results of example 1, the stiffness and damping values of state 5 were smaller than those of state 4. In addition, it has to be pointed out that the free vibration response of the fifth floor of state 5 obviously deviates the central line (relative acceleration=0), which may be a massage that some elements of the frame were yield under such strong excitation magnitude. The result completely corresponds with the evidence investigated in the lab.

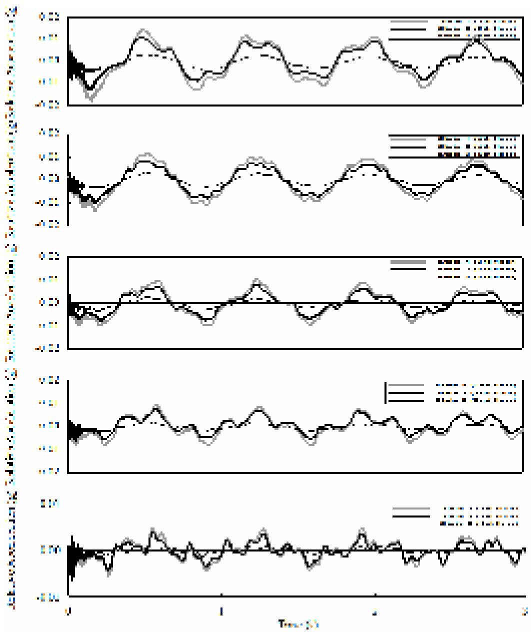

Fig. 7: Comparison of the free vibration responses of state 1, state 2, and state 3, with initial ground acceleration 0.01g

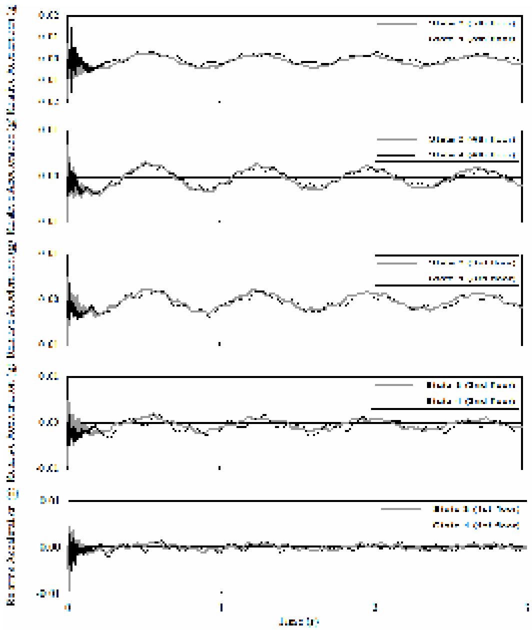

Fig. 8: Comparison of the free vibration responses of state 3 and state 4, with initial ground acceleration 0.01g

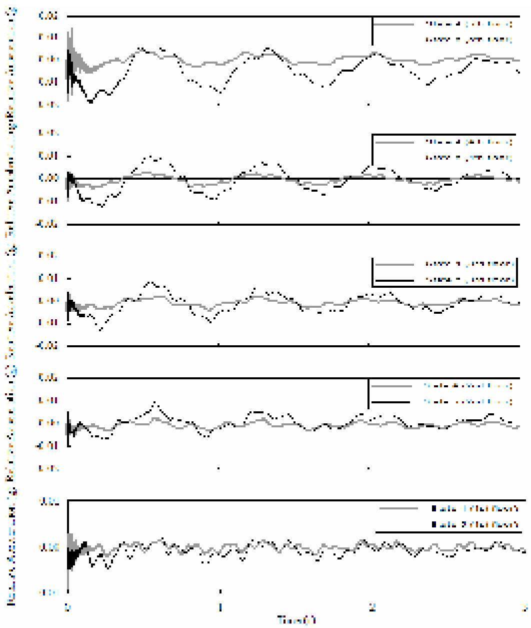

Fig. 9: Comparison of the free vibration responses of state 4 and state 5, with initial ground acceleration 0.01g

CONCLUSIONS

This study presented a novel neural network based-approach for structural health monitoring. Noteworthy, the proposed approach is practically feasible for structural health monitoring. The practical feasibility of the proposed approach is supported by the following two reasons. First, ANNs are a promising tool for system identification of real-world structures. Second, the results of numerical and experimental examples prove the practical feasibility of the proposed approach for structural health monitoring. The following important conclusions can be drawn from the results presented in this research.

1. Changes on structural properties (stiffness and damping) cause changes on periods and amplitudes of the free vibration of the structure system. Therefore, periods and amplitudes of the free vibration are useful indices to reflect changes of structural properties.
2. The proposed approach makes it easy to accurately generate a free vibration response of a structure-unknown system using neural networks.
3. The proposed approach has the ability to detect changes of structural properties. Especially, this approach can reveal clear massage when some structure elements were yield, which can't be achieved by other analytical methods.

Some limitations expected to be complemented in future studies were summarized as follows:

1. A drawback of proposed approach is the accumulation of simulation error. Since the accumulated simulation error was not obvious in results of illustrative examples, this problem wasn't discussed in this paper. In fact, Hung et al. (2001) had addressed a sensitivity analysis method to decrease the accumulated simulation error. Nevertheless, this interesting topic could be further researched.
2. Future investigations should apply the proposed approach to measurements in the field to examine its capacity to deal with incomplete measurements and noise corruption. Furthermore, the ability of the proposed approach to detect the location of damage should be further researched.

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