Acceleration-based damage indicators for building structures using neural network emulators

Yuyin Qian1,∗,†,‡ and Akira Mita2,‡

1 Department of System Design Engineering, Keio University, 3-14-1 Hiyoshi, Kohoku-ku, Yokohama 223-8522, Japan
2 Department of System Design Engineering, Keio University, Yokohama, Japan

SUMMARY

In this paper we propose the use of artificial neural network (ANN) emulators for an acceleration-based approach to evaluating building structures under earthquake excitation. The input layer of the ANN is a forced vibration, described as ground acceleration and the acceleration data of several floors. The approach is improved by using the acceleration at later time steps as the output of the neural network (NN). This time delay is optimized as a tunable band to provide the most sensitive signals.

Minimally, this approach requires only one sensor, making it highly practicable and flexible. It is applicable to structures under diverse excitations including even very small impacts.

Based on numerical simulation of a 5-story shear structure, we determined appropriate parameters for use of an NN and studied the generality and efficacy of the approach. The damage index, the relative root mean square error, was calculated for the case of a single structural damage as well as for cases of double damages at different damage locations, and appropriate parameters for the NN emulator were proposed according to the damage patterns. Variant ground motions were used to certify the generality of the approach.

The numerical simulations of the proposed approach were verified experimentally. Copyright © 2007 John Wiley & Sons, Ltd.

KEY WORDS: structural health monitoring; damage indicators; building structures; damage identification; neural network emulator

1. INTRODUCTION

Structural health monitoring (SHM) for the prediction of onset damage and deterioration of building structures has increasingly received attention and interest because of the rising numbers
of aged infrastructure and high damage costs caused by unpredictable hazards. The importance of SHM has been especially underlined and exposed to the public by many recent occurrences of structural failure. In July 2007 alone, Japan was struck by a major earthquake in the Niigata region that destroyed wooden structures and caused fire in a nuclear power plant, New York suffered from the explosion of an 83-year-old steam pipe, and Americans were horrified to see a bridge filled with commuter traffic collapse across the Mississippi River.

The amount of literature using statistical discrimination of features for damage detection is quite large. Cawley and Adams [1] proposed the very first damage detection method using the pattern matching approach. A study by Masri et al. [2] has demonstrated that neural networks (NNs) are a powerful tool for the identification of systems typically encountered in the structural dynamics fields. Faravelli and Pisano [3] made use of a feed-forward NN to detect and locate damage in a numerical simulation of a two-dimensional nine-bay truss structure. Vanik et al. [4] presented a Bayesian probabilistic methodology for SHM, which uses a sequence of identified modal parameters to compute the probability of continually updated model stiffness parameters. Krawczuk et al. [5] applied a genetic algorithm (GA) to identify and locate damage in a laminated composite beam. An approach using the support vector machine (SVM) to detect local damages in a building structure was proposed by Mita and Hagiwara [6].

An approach directly using dynamic responses in time series without extraction of dynamic properties, which used acceleration, velocity and displacement time histories as the input of an emulator NN, was proposed by Xu et al. [7] and was improved by Xu and Chen [8], through the use of acceleration time histories only as the input of the emulator NN. The method was called an acceleration-based emulator neural network (AENN) for free vibration.

In this paper, the AENN is extended beyond the limitation of free vibration to allow for arbitrary forced vibration. Minimally, only a single sensor is needed for response measurement for the damage alarm. Acceleration time histories, which are readily available in real structures being the only necessity, this method is feasible for practical application. Furthermore, the accuracy of AENN is improved significantly by increasing time histories of the response into the input layer.

2. IDENTIFICATION OF STRUCTURAL CHANGES USING AN ACCELERATION-BASED NEURAL NETWORK

2.1. ANN emulator using displacement, velocity and acceleration as inputs

The basic idea of identification of structural changes using an NN based on response time histories is to establish an emulator NN that represents the characteristics of the structure. Input of the NN is the response at time step \( k \), and output is the response at time step \( k + 1 \) as in Figure 1 [7].

The NN is to be adapted using an existing response time history from a past earthquake excitation. Provided the structure has incurred no damage, the trained emulator NN should be applicable to the same structure under subsequent earthquakes. Given this, the error between the output of the NN and the real measurement provides information regarding structural damage.

Xu and Chen [8] improved this approach by using acceleration time histories only as the input of the emulator NN for free vibration. We have extended the study beyond the limitation of free vibration.
vibration by considering the inclusion of ground motion in the NN input layer so that the applied structure can be under arbitrary excitation, and the number of required response measurements can possibly be minimized.

2.2. Proposed ANN emulator using acceleration only as inputs

NNs may work as good black-box models even for nonlinear systems. Although ARX (auto-regressive extra input) models represent linear system dynamics, it could offer some revelation to application of NNs. An ARX model \[9\] is given by

\[
A(q)y(t) = B(q)u(t) + e(t)
\]

where \(q\) is the shift operator. The auto-regression model \(A(q)\) in terms of \(q\) is defined by

\[
A(q) = 1 + a_1 q^{-1} + \cdots + a_{na} q^{-na}
\]

Similarly, the function \(B(q)\) is defined by

\[
B(q) = b_1 q^{-1} + \cdots + b_{nb} q^{-nb}
\]

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

\[
y(t) = -a_1 y(t-1) - \cdots - a_{na} y(t-na) + b_1 u(t-1) + \cdots + b_{nb} u(t-nb) + e(t)
\]

This representation indicates that the prediction of the response requires several previous time steps for response as well as inputs. NNs can be used as an alternative to the ARX model, to represent the relationship determining the next output value given previous observations and extra input. The advantage of NNs is applicability to nonlinear systems as well as linear systems.

An AENN adapted to represent the mapping between acceleration at different time steps can be established as in Figure 2. Here we use acceleration time histories as observations. Since they are readily available in real structures, using accelerations provides much convenience. The
acceleration of ground is beyond the consideration of the NN’s target, so it is included as $T_k$, into the NN input layer.

The trained AENN is a nonparametric model of the structure and can be used to forecast the acceleration response under a later earthquake.

Relative root mean square (RRMS) error $e$ is defined by

$$e = \frac{\sqrt{\sum_{m=1}^{M} (\hat{x}_m^f - \tilde{x}_m)^2}}{\sqrt{\sum_{m=1}^{M} (\tilde{x}_m)^2}}$$

(5)

where $M$ is the number of sampling data; $\hat{x}_m^f$ the output of trained NNs at sampling step $m$; $\tilde{x}_m$ the acceleration corresponding to the real dynamic response under earthquake excitations at sampling step $m$.

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

2.3. Modified ANN emulator

Using acceleration at time steps $k - 2$ and $k - 1$ to forecast the acceleration at time step $k$, RRMS error is frequently too small to be regarded as an index of damage occurrence alarm. Considering this, the approach was improved by using the acceleration at later time steps, including $k - 2$ and $k - 1$ as the output of the NN.

The acceleration of the ground floor is not synchronous with the accelerations of the above-ground floors in the input layer, as shown in Figure 3. The acceleration of ground has a time delay of $m \times \Delta t$ such that the emulator NN can forecast the acceleration of each floor at later time steps. The delay $m \times \Delta t$ is considered as a tunable band corresponding to different structures.
3. PARAMETERS DETERMINATION BASED ON SIMULATION

Acceleration stream number and ground delay, $n$ and $m \times \Delta t$ in Figure 3, are chosen parameters. The number of acceleration streams, $n$, should be large enough to make the RRMS error for healthy structures a stably small value, while the appropriate ground delay $m \times \Delta t$ should make the RRMS error between healthy and damaged structures a comparatively large value. The search for appropriate values for these two parameters was based on numerical simulation and will be discussed in this section.

Because the goal of this section is to search for appropriate parameters for an AENN that is generally applicable, a basic structure is used for simplicity and generality. We used a 5-story shear frame structure shown in Figure 4 and modelled it as a 5 degree-of-freedom lumped mass system with structural parameters shown in Table I. The natural frequencies of the frame structure are 1.6521, 4.1120, 6.1565, 8.1085 and 12.2932 Hz, as shown in Table II. The damping matrix is assumed to be Rayleigh damping which can be expressed in the following form:

$$
C = aM + bK
$$

(6)
where $a$ and $b$ are estimated to have damping ratios 0.005 for the first mode and 0.013 for the second mode.

The AENN is trained using a network training function that updates weight and bias values according to Levenberg–Marquardt optimization. The output layer includes 1 neuron. In this structure, the acceleration at the fifth floor is measured. The neuron number of the input layer is decided by $n$ and $m \times \Delta t$ in Figure 3, and the neuron number of the hidden layer is two times that of the input layer.

Acceleration time histories obtained from the top floor of the 5-story shear structure under Hachinohe earthquake (16 May 1968, Hachinohe City) ground motion were used as training data sets. Test data sets were under the Northridge earthquake (17 January 1994, Northridge, California). These two earthquake records are shown in Figure 5. The sampling time is 0.02 s, and all time histories were normalized.

During numerical simulation, the acceleration stream number, $n$, was incrementally changed from 1 to 15. The delay, $m \times \Delta t$, was changed from 0.02 to 0.2 s, say, 1–10 times the sampling time. The two values, RRMS error for healthy structure and difference of RRMS errors between healthy structure and damaged structure, are shown in Figures 6 and 7 to reach a stably small value for the former RRMS and comparatively large value for the latter RMSS. The difference of RRMS errors was defined by

$$\Delta e = e_{\text{damage}} - e_{\text{health}}$$  \hspace{1cm} (7)

With the goal of more easily deciding the proper AENN parameters, severe damage, stiffness reduction of 20% at each floor was utilized.

Prediction accuracy is raised by incrementing the number of acceleration streams at different time steps to an appropriate value. The value of RRMS error decreases to a stable value if the number of acceleration streams achieves some appropriate value. The information in Figure 6 showing error for healthy structures vs acceleration stream number and delay was used to decide an appropriate acceleration stream number. In Figure 6, it can be seen that the error for the healthy structure is stably small for acceleration stream numbers 10 or above. Therefore, the necessary acceleration stream number for the 5-story shear structure should be 10, which is understandable and reasonable considering this methods analogy with ARX Models.

The error difference between healthy and damaged structures in Figure 7 was used to decide an appropriate ground delay. In Figure 7, it can be seen that the error difference corresponding to $n = 10$ is comparatively large with ground delay seven times of sampling time, say, 0.14 s. So

Table I. Structural parameters of the object structure.

<table>
<thead>
<tr>
<th>DOF</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass (kg)</td>
<td>4000</td>
<td>3000</td>
<td>2000</td>
<td>1000</td>
<td>800</td>
</tr>
</tbody>
</table>

Table II. Modal parameters of the object structure.

<table>
<thead>
<tr>
<th>DOF</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency (Hz)</td>
<td>1.65</td>
<td>4.11</td>
<td>6.16</td>
<td>8.11</td>
<td>12.3</td>
</tr>
<tr>
<td>Damping ratio</td>
<td>0.005</td>
<td>0.013</td>
<td>0.019</td>
<td>0.026</td>
<td>0.039</td>
</tr>
</tbody>
</table>
the appropriate ground delay is 0.14 s for this structure. The first-order natural frequency of this structure is 1.6521, our decided ground delay suggests that ground delays of approximately $\frac{1}{4}$ of the structural periodic time are appropriate.
4. CONSIDERATION OF NOISE EFFECT

Damage is introduced to the structure as shown in Figure 4 with the intent of demonstrating whether the RRMS errors can provide an effective damage alarm. To evaluate the effect of measurement noise on the accuracy of damage detection, the accelerations are corrupted with 2 and 5% RMS noise. The structural parameters and the earthquake excitations are the same as in the previous section. Only minimal output, the acceleration at floor 5, is used. Damage detection results for clean, 2% RMS corrupted, and 5% RMS corrupted signals are shown in Figures 8, 9 and 10, respectively. Figure 8 shows that in the no-noise case the values of RRMS error are 0.0540, 0.0995 and 0.2133 for the healthy structure, for the structure with 10% damage at the 2nd floor and for the structure with 20% damage at the 2nd floor. In the 2%-noise case, i.e. in Figure 9, the RRMS errors were 0.0724, 0.1187 and 0.2288, again for the healthy structure, for the structure with 10% damage at the 2nd floor and for the structure with 20% damage at the 2nd floor. And finally, in the 5%-noise case, i.e. in Figure 10, the analogous values of RRMS error were 0.0947, 0.1504 and 0.2405. For these three cases, the differences between no damage and 10% damage were 0.0455, 0.0463 and 0.0557. The differences between no damage and 20% damage were 0.1593, 0.1564 and 0.1458. There are consistent and detectable differences between the healthy and damaged cases.

For SHM, the objective is not to identify exact index values but to detect variations in a relative sense and/or changes in magnitude in the absolute sense. The results of the damage detection simulation with clean signals and corrupted signals showed the relative values of RRMS errors for damage scenarios to be detectable. Thus, a damage alarm is provided by the observation of RRMS error, regardless, within reason, of signal corruption level.
Figure 8. Damage detection with clean signals.

Figure 9. Damage detection with 2% noise signals.
5. DISCUSSION ON MULTI-OUTPUT

The AENN described in Figure 3 has only acceleration at a single floor as output. Here, we consider using more accelerations at different floors in a multi-output NN as shown in Figure 11.

Utilizing acceleration at more multiple floors in this manner decreases the necessary number of acceleration streams at different time steps, denoted by $n$ in Figure 11.

Still using the 5-story shear structure depicted in Figure 4, the acceleration time histories for excitation under Hachinohe earthquake (16 May 1968, Hachinohe City) (Figure 5) ground motion were used as training data sets, and those under the ground motion of the Northridge earthquake (17 January 1994, Northridge, California) (Figure 5) were used as test data sets. Consideration was given to the acceleration of the 3rd and 5th floors, followed by consideration to the 2nd, 4th and 1st floors.

From Figures 12–15 it is seen that increased utilization of acceleration at multiple floors decreases the necessary number of acceleration streams at different time steps, $n$, needed for ensuring stably small values of error.

According to the simulation results, when the accelerations of two floors (Figure 12) are included in the NNs $n$ should be 5. When the accelerations of more than two floors are included (Figures 13–15), this number is reduced to only 2.

The proposed method does not require the use of accelerations from multiple floors. The minimum is only one, and using just one floor acceleration provides high convenience and practicability, though longer time series periods for time series are needed. On the other hand, increasingly low-cost microelectromechanical sensors (MEMS) and wireless solutions have been...
fabricated for structural measurement allowing for a dense network of sensors to be deployed in structures to obtain multi-floor accelerations which can give our approach higher reliability. Our approach is flexible, and on either end, using a single output or multi-outputs shows practicality.

Figure 11. AENN with multi-output.

Figure 12. Error changed by \( n \) with accelerations of the 3rd and 5th floors.
Figure 13. Error changed by $n$ with accelerations of the 2nd, 3rd and 5th floors.

Figure 14. Error changed by $n$ with accelerations of the 2nd, 3rd, 4th and 5th floors.
6. AENN EFFICACY AND GENERALITY OF AENN

To verify the efficacy of the AENN presented in Figure 11, simulation using the structure described in Figure 4 was performed with acceleration of each floor. The input, hidden and output layers of the AENN include 17, 34 and 5 neurons, respectively.

For the healthy structure, the comparison between the output of the NN and the real value decided through dynamic analysis is shown in Figure 16. It is seen that identification using the NN can be carried out with high accuracy. The improved AENN can be adapted to achieve a desired accuracy for modelling the dynamic behaviour of the healthy structure.

Further study was carried out considering the existence of structural damage, firstly instituting single damage of 20% stiffness reduction on the 3rd floor. As before, the acceleration of the damaged structure under the Northridge earthquake was used as the test data. Using the output of the NN, RRMS error was calculated according to Equation (5). Consideration was then extended to double-damage: 20% stiffness reduction on the 3rd and 5th floors. Similarly, RRMS error was calculated as before. Figure 17 shows the different values of RRMS errors of healthy, single-damage and double-damage structures. RRMS error shows the change between the output of the NN and the real dynamic response, providing information regarding structural damage. If this value is quite large, it is thought that the structure is not healthy. Therefore, the RRMS error can be used as a damage occurrence alarm index.

To verify the generality of the proposed AENN, the results under different ground motions were observed for a healthy structure, to show that the trained AENN can achieve desired accuracy not just for a specific ground motion. Ground motions of the previously used Northridge earthquake, the Kobe earthquake (17 January 1995, Kobe Japanese), and white-noise were used as the test data sets for this purpose. These three RRMS error values are shown in Figure 18.

Figure 15. Error changed by $n$ with accelerations of the 1st, 2nd, 3rd, 4th and 5th floors.
From Figure 18, it is seen that under the different ground motions, the adapted NN achieves similar accuracy, certifying the generality of the proposed AENN. Similarity of damage errors under the different earthquake excitations also shows the stability and reliability of the proposed method.

7. ACCELERATION-BASED DAMAGE EVALUATION SYNTHESIS

This key points of our acceleration-based damage evaluation of building structures with NNs are summarized as follows:

- The damage evaluation approach uses only acceleration time histories, and only with consideration of similarity to ARX models.
- A time delay was introduced to the ground acceleration in order that the emulator NN could forecast the acceleration of the each floor at later time steps.
- The necessary number of acceleration streams at different time steps for the single-output network is 10. We suggest a ground delay, which is $\frac{1}{4}$ of the structural periodic time.

Figure 16. Comparison between the output of neural network and the real value.
Figure 17. RRMS errors of healthy and damaged structures.

Figure 18. RRMS errors under different ground motions.
It is proposed that more acceleration histories from different floors are used for the multi-output emulator NN in order to decrease multi-output. The necessary number of acceleration streams at different time steps could be decreased.

8. EXPERIMENTAL VERIFICATION

A series of physical experiments were performed to verify the performance of our proposed approach. The model structure is depicted in Figure 19. Damage was introduced by replacing columns with weaker columns. By replacing two columns in the story, the story stiffness was reduced by 33%.

Under the base of the structure were bearings (in Figure 20) to allow back-and-forth base excitation applied by hand. Accelerometers were installed on each floor plate to measure acceleration response, and one was installed on the base to measure ground motion.

The 5-story structure was initially healthy with all original columns intact. Two acceleration sets were recorded, one of which was used as training data to establish the artificial neural network (ANN) (Figure 11). The other set was healthy test data used for comparison with damage data. Two columns of the 4th floor were then replaced by weak columns (of the same material and integrity as healthy columns, but with smaller cross-sectional area) to simulate the single-damage case. The double-damage case was simulated by replacing two columns of the 2nd floor as well as 4th floor. Finally, two columns of the 3rd floor were also replaced to simulate the triple-damage case.

Figure 19. Five-story structural modal and columns.
Figure 21 is the prediction of the test data for the healthy structure using the trained ANN emulator. Figure 22 shows RRMS errors of healthy, single-damage, double-damage and triple-damage structures. These RRMS errors represent the difference between the output of the NN and the real dynamic response, thus providing an indication of structural damage. The magnitude of the RRMS error corresponds to the severity of damage and therefore can be looked at as a damage occurrence alarm index.

Figure 20. Basement with bearings.

Figure 21. Prediction of test data for healthy structure.
A redundant experiment was performed on a different 5-story steel structure using a shake table (Figure 23) to further verify the proposed method. This 5-story steel frame structure had a height of 5 m and a floor plate 3 m \times 2 m. Damage was introduced by removing splice at different locations, loosening bolts and damaging beams.

The detection results for this redundant experiment are shown in Figure 24. The analysis of the results contained in Figure 24 leads to observations in concordance with the first experiment: The value of RRMS error can be considered as a damage occurrence alarm index. We may conclude that the ANN emulator method is indeed applicable to realistic problems.

9. CONCLUDING REMARKS

We have proposed an acceleration-based evaluation approach for building structures subjected to earthquakes using NN emulators. This approach takes into account ground acceleration by including it in the input layer up to the most recent time step. It requires only a limited number
of acceleration time histories and can be applied to single- or multi-output systems. Furthermore, we found that increasing the previous time steps of the acceleration can effectively reduce the necessary number of acceleration histories at different floors. This, and the minimal requirement of only a single sensor, gives the method high practicability and flexibility. Input excitations are not limited, i.e. the structures can be under diverse excitations, even very small impacts.

Based on numerical simulation of a 5-story shear structure, appropriate parameters of the NN emulators were suggested. The efficacy of the approach was studied by comparing healthy and damaged structures. Its generality was verified by considering different earthquake

Figure 23. Shake-table experimental set-up.
accelerations. Experiments using two 5-story shear structure models were performed, and the effectiveness of the proposed approach was well verified.

In our proposed evaluation approach, alarms of damage occurrence can be obtained practically and economically using readily available acceleration time histories only.

REFERENCES