Time Series-Based Damage Evaluation Algorithm with Application to Building Structures

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ABSTRACT:

An acceleration-based evaluation approach for building structures under earthquakes using artificial neural networks (ANN) is proposed in this paper. The ground acceleration is included into the input layer of ANN as forced vibration. The approach is modified by using the acceleration at later time steps as the output of the neural network. The time delay is considered as a tuneable band corresponding to different structures.
Based on the numerical simulation for a 5-story shear structure, the appropriate parameter, generality and efficacy of the neural network are studied in. The damage index, relative root mean square (RRMS) error, is observed when the single structural damage occurred, followed by double damages at different damage locations. Variant ground motions is used to certify the generality of this approach. The appropriate parameter of the neural network is proposed according to variant values of damage index corresponding to the different parameters.
The application to a 14-story real building was implemented, and the verification of the proposed approach was obtained as well.

1. 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 hazard.
The amount of literature using statistical discrimination of features for damage detection is quite large. Cawley & Adams proposed the very first damage detection method using the pattern matching approach [1]. A study by Masri et al. has demonstrated that neural networks (NNs) are a powerful tool for the identification of system typically encountered in the structural dynamics fields [2]. Faravelli and Pisano made use of a feed-forward

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neural network to detect and locate damage in a numerical simulation of a two-dimensional nine-bay truss structure [3]. Vanik et al. presented a Bayesian probabilistic methodology for structural health monitoring which uses a sequence of identified modal parameters to compute the probability that continually updated model stiffness parameters [4]. Krawczuk et al. applied a genetic algorithm (GA) to identify and locate damage in a laminated composite beam [5]. An approach using the support vector machine (SVM) to detect local damages in a building structure was proposed by Mita and Hagiwara [6].

There is an approach by directly using dynamic responses in time series without extraction of dynamic properties proposed by Xu et al.[7], which used acceleration, velocity and displacement time histories as the input of the emulator neural network. And this approach was improved by Xu & Chen[8], 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. As the acceleration time histories, which are readily available in real structures, are only required for this method. Thus it is feasible for practical application. Furthermore, the accuracy of AENN is improved significantly by increasing time histories of the response into the input layer, and other modification.

2. Identification of Structural Changes with Neural Network Based on Acceleration Measurement

2.1 ANN Emulator Using Displacement, Velocity and Acceleration as Inputs

The basic idea of identification of structural changes with neural network based on response time histories is to establish an emulator neural network to represent the characteristics of structure. The input of the neural network is the response at the time step of k, and output is the response at time step k+1 as in Fig.1 [7].

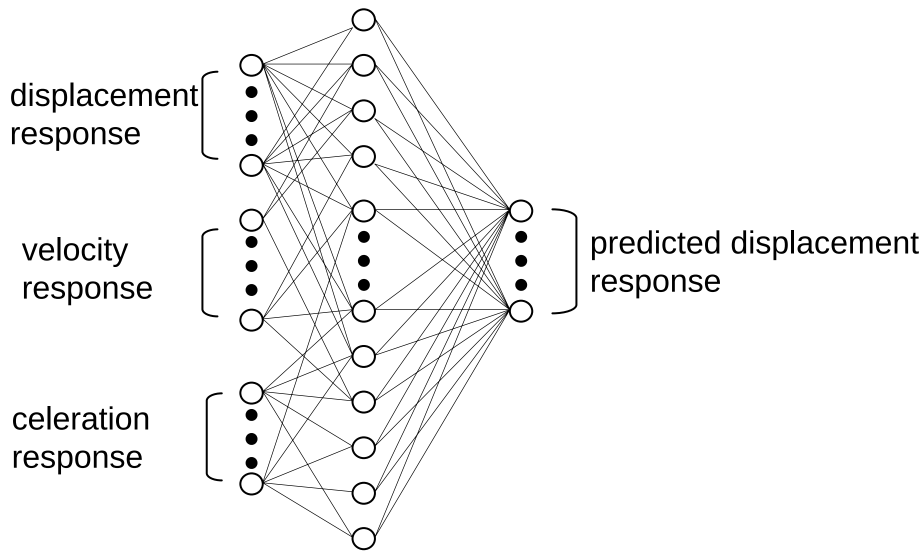


Figure 1. Neural Network to Represent the Characteristics of Structure

The neural network is to be trained by the response time histories under one earthquake excitation. The trained emulator neural network should work to the same structure under the later different earthquake unless there is damage in the structure. In accordance with these, the error between the output of the neural network and the real measurement provides the information of structural damage.

Xu & Chen[8] improved this approach by only using acceleration time histories as the input of the emulator neural network for free vibration. We extended the study beyond the limitation of free vibration by consideration of including ground motion in input layer.

2.2 Proposed ANN Emulator Using Acceleration Only as Inputs

Here, neural networks 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 neural networks. An ARX model[9] 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:

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

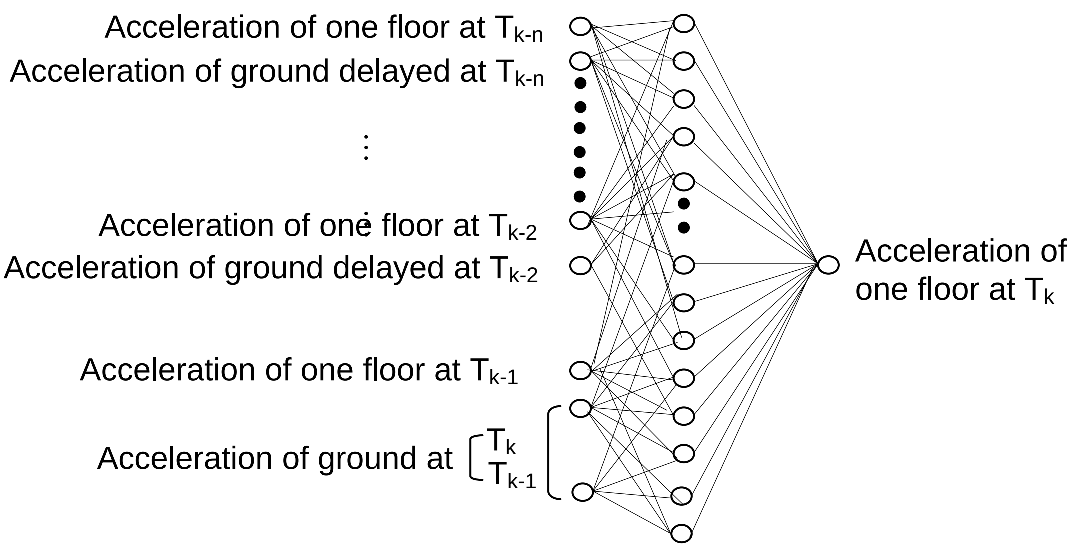


Figure 2. Acceleration-based emulator neural network

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, that 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.

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

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

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

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.

2.3 Modified ANN Emulator

Using acceleration at time 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 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.

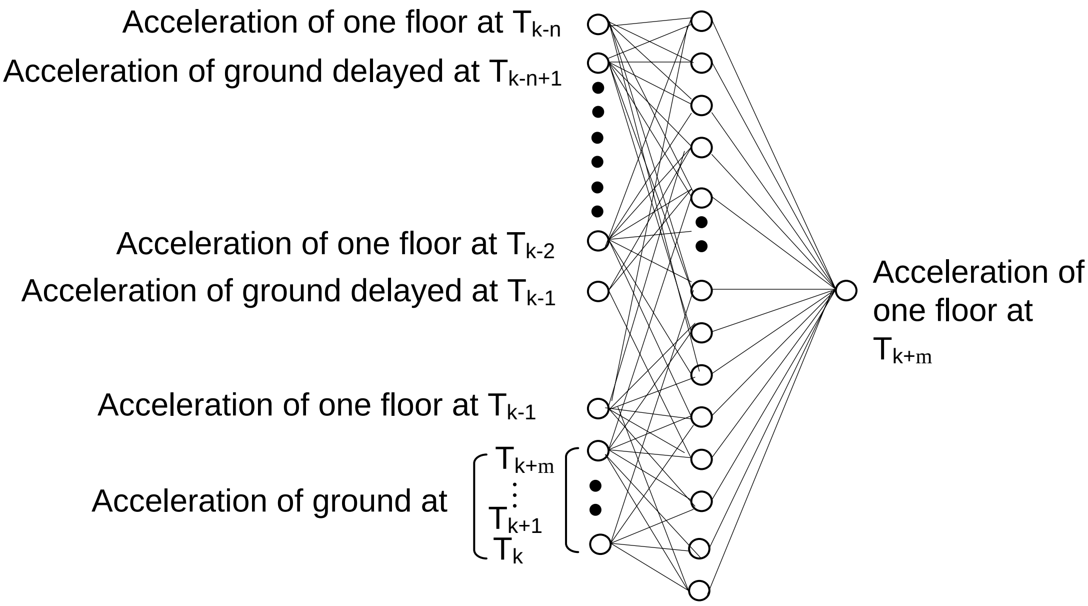


Figure 3. Improved AENN

3. 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. 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.

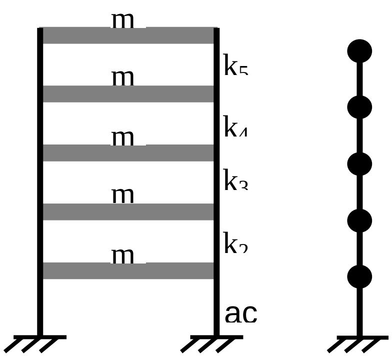


Figure 4.Five-story frame structure

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-story 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 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 a length of 1.

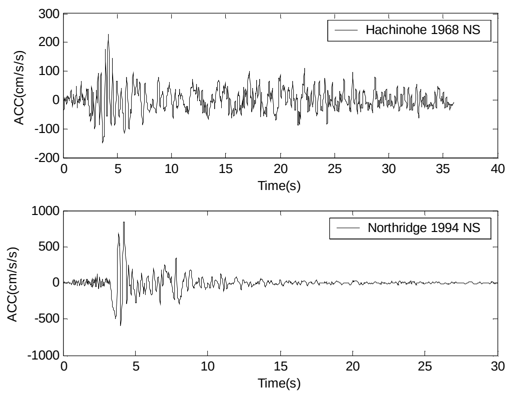


Figure 5. Earthquake records, Hachinohe and Northridge

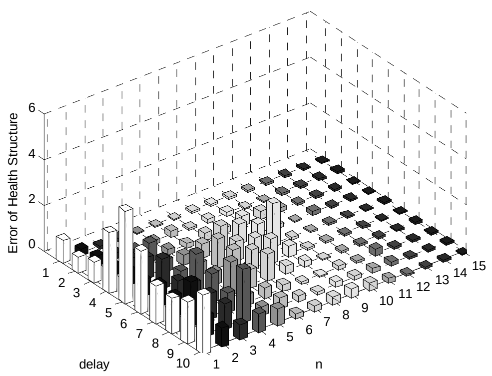


Figure 6. Error for health structure changed by acceleration stream number

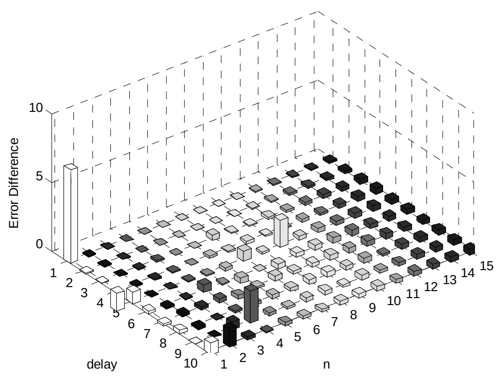


Figure 7. Error difference between health and damage structures

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 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 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 achieves the appropriate value.The error for 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 ten. 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.

4. Discussion on Multi-Input

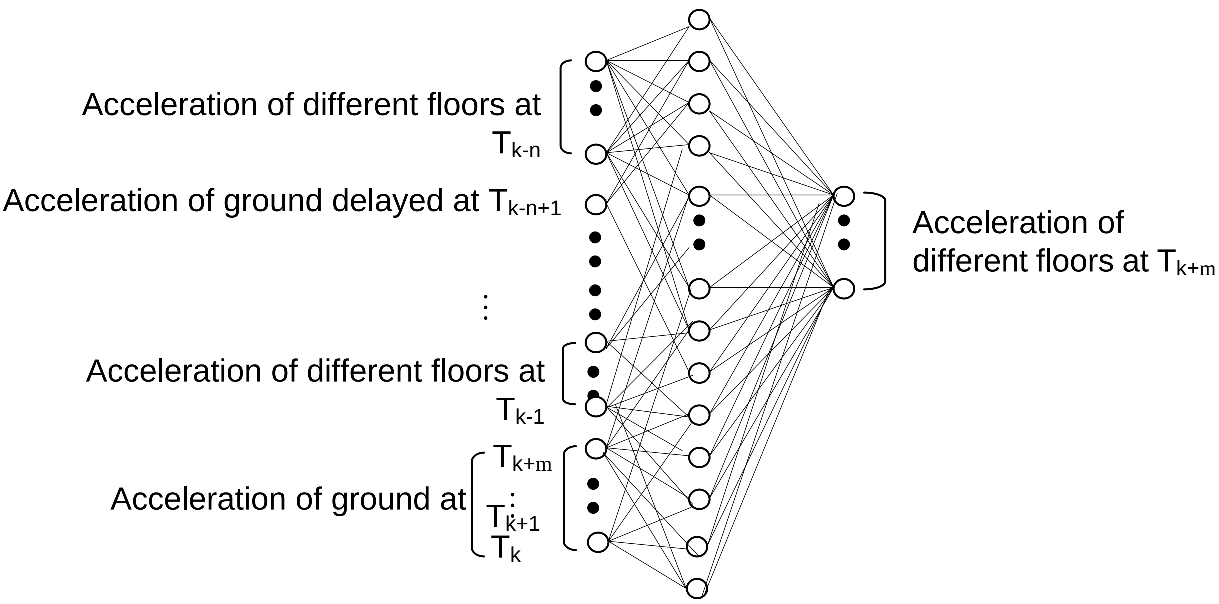


Figure 8. AENN with multi-input

The AENN as in Fig. 3 only use acceleration at one floor. Here, we consider using more accelerations at different floors as in Fig.8.

It is easy to understand that with acceleration at more different floors, the necessary number of acceleration streams at different time steps could be decreased. In Fig. 8, n denotes the number of acceleration streams at different time steps.

Still using the 5-story shear structure in Fig.4, the acceleration time histories for 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 acceleration of the 3rd floor was included together with top floor to consideration, followed by the 2nd, 4th and 1st floor. Along with more acceleration at different floors comprised, the necessary number corresponding to a stably small value of error could be determined from Fig.9-12.

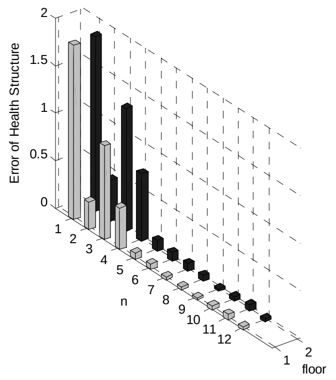


Figure 9. Error changed by n with accelerations of the 3&5th floors

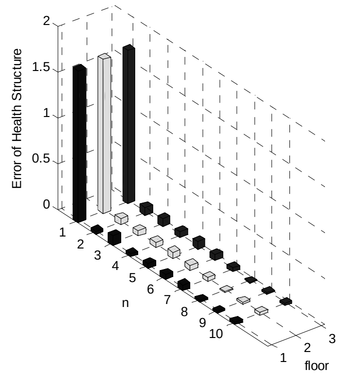


Figure 10. Error changed by n with accelerations of the 2,3&5th floors

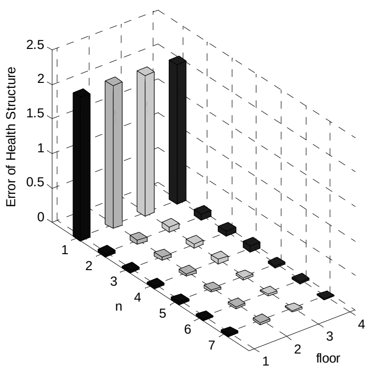


Figure 11. Error changed by n with accelerations of the 2,3,4&5th floors

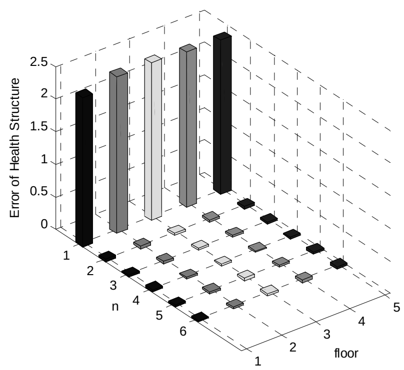


Figure 12. Error changed by n with accelerations of the 1,2,3,4&5th floors

According to the simulation results, when the accelerations of two floors (Fig.9) were included in to neural networks, the necessary number of acceleration streams at different time steps should be 5. When the accelerations of more than two floors were included (Fig.10-12), the necessary number of acceleration streams at different time steps could be decreased to 2 only.

5. Efficacy and Generality of AENN

To verify the efficacy of AENN presented in Fig.8, simulation using the structure described in Fig.4 was performed with acceleration of each floor. The input, hidden and output layers of AENN include 17, 34 and 5 neurons, respectively.

For health structure, the comparison between the output of neural network and the real value decided through the dynamic analysis is shown in Fig. 13. It can be seen that identification can be carried out with high accuracy. This improved AENN can be trained to achieve a desired accuracy for modelling the dynamic behaviour of the healthy structure.

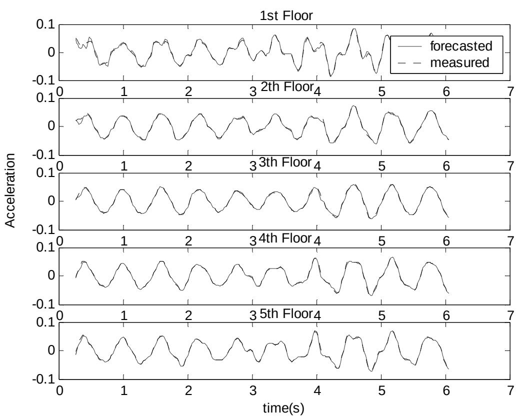


Figure 13. Comparison between the output of neural network and the real value

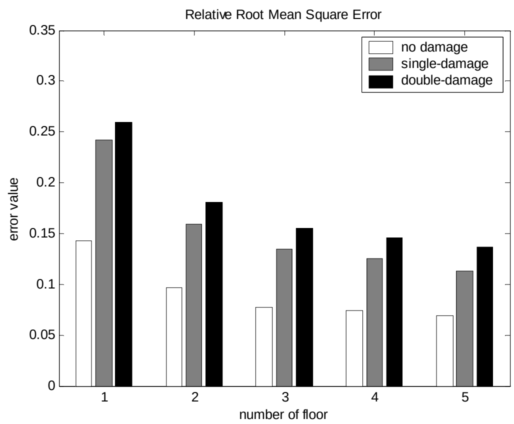


Figure 14. RRMS errors of healthy and damage structures

Further study was carried out considering the existence of structural damage. Firstly single damage of 20% stiffness reduction on the third floor was introduced. The acceleration from the damage structure under Northridge earthquake was as the test data sets of the trained neural network. Using the output of the neural network, RRMS error was calculated according to Eq. 5. Then, damage extended to double-damage of 20% stiffness reduction on the third and fifth floor was considered. Similarly, RRMS error was calculated too. Fig. 14 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 neural network and the real dynamic response, providing the information of structural damage. If this value is quite large, it would be thought that the structure is not healthy. Therefore, the RRMS error could be looked on as a damage occurrence alarm index.

With the purpose of verification of the generality of the proposed AENN, the results under the different ground motions were observed for health structure. It should be realized that the trained AENN could achieve desired accuracy not only for the structure under one ground motion but also for one under others. In accordance with these, the ground motions of Kobe earthquake (Jan. 17, 1995, Kobe Japanese) and white-noise were used as the test data sets, as well as previous Northridge earthquake, to verify the generality of the trained AENN. These three RRMS error values were shown in Fig. 15.

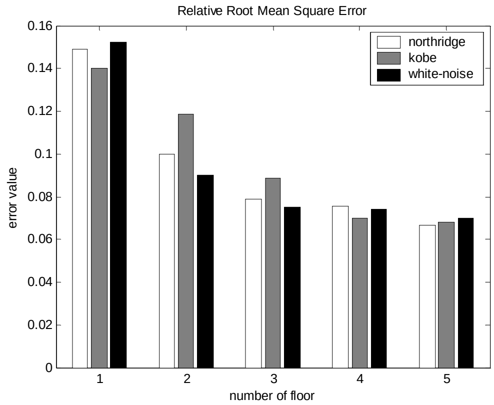


Figure 15. RRMS errors under different ground motions

From Fig. 15, it could be seen that under the different ground motions, this trained neural network achieves the similar accuracy, which certifies the generality of the proposed AENN.

6. Application to real building

6.1 Description of the real building

This study proposed the first application of AENN to real buildings.

Table 3. Data used for structural evaluation

	Date	Maximal value of acceleration in Y direction (cm/s^2)			
		1F	5F	10F	14F
Training data	Oct. 15, 2003	22.1	26.4	22.3	18.4
Test data 1	Nov. 12, 2003	11.9	20.4	19.7	12.4
Test data2	Jul. 23, 2005	35.1	34.3	39.7	41.0

The applied building, Nikken Sekkei Tokyo Building located in Iidabashi of Tokyo, was constructed in March, 2003 [10]. It is 60 meters high, with one-story underground and 14-story overground. The accelerators were installed on the B1F, 1F, 5F, 10F and 14F to measure the acceleration time histories of horizontal two directions and vertical direction. Three sets of acceleration time histories shown in Table 3 would be used for evaluation. The first two identified natural frequencies of this building in horizontal Y direction are about 0.7Hz and 2.3Hz.

6.2 Evaluation of Structure by AENN with the Performance of Filter

A proposed AENN was established for structural evaluation of this real building.
Here, the acceleration time histories of the first floor was considered as the acceleration of ground which would be inputted into the AENN delayed by time T, and the acceleration of the 5, 10, 14^{th} floor was considered as the normal floor, as in Fig. 16.

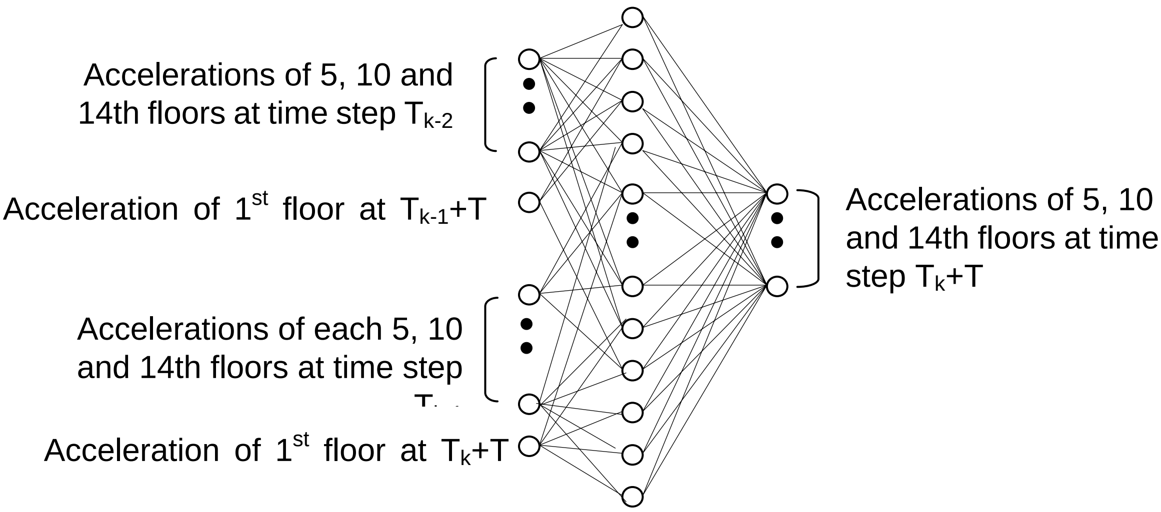
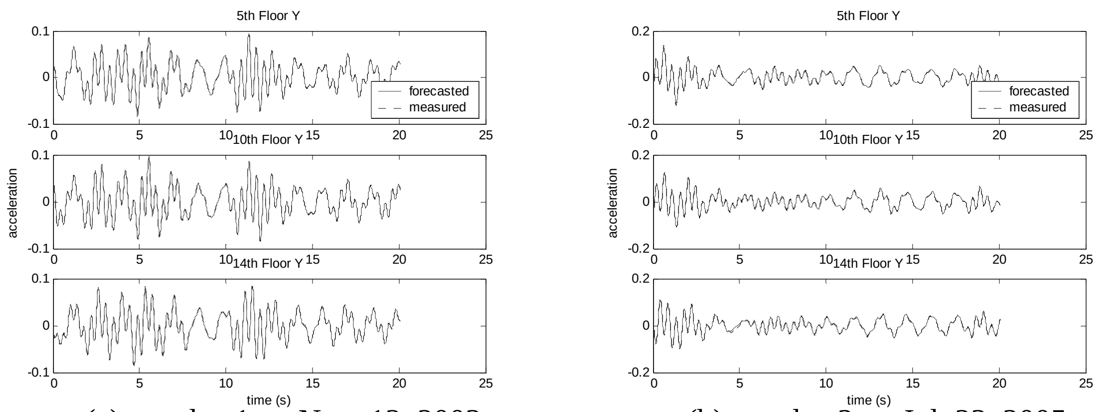


Figure 16. AENN Applied to the Real Building

For a real building, the measured response is unavoidably polluted by noise, which would decrease the accuracy of the structural evaluation. In order to handle this problem, filtering was performed to the measured accelerations. Firstly, lowpass Butterworth filter whose cutoff frequency was 0.8 Hz was applied to obtain the signal near the first-order natural frequency of structure. Then, bandpass Butterworth filter whose passband frequency was [1.8 3] Hz was applied to obtain the signal near the second-order natural frequency of structure. At last, the results of evaluation through these two filters were combined linearly to obtain the final structural evaluation, as in Fig.17.



(a) test data1 on Nov. 12, 2003 (b) test data2 on Jul. 23, 2005

Figure 17. Comparison between the output of neural network and the measured value

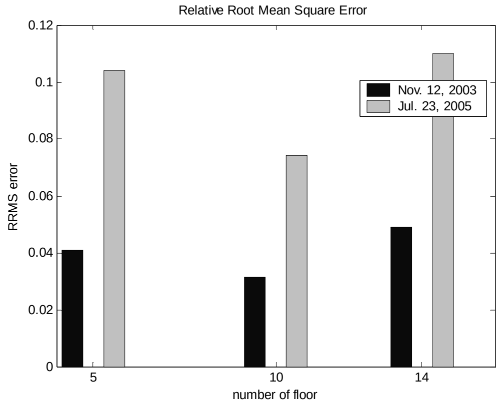


Figure 18. RRMS errors for test data1 and test data2

Using Eq.5, the RRMS error values were calculated for test data1 and test data2, respectively (Fig. 18). Due to only one-month interval between the dates of the training data and test data1, it is reasonable to suppose there would not be much deterioration of this building structure, which means the RRMS error for test data1 would be a small value. However, after almost two years passed, when the test data2 was measured, the thought of some deterioration and change occurring to the building structure could be acceptable and of high possibility, which means the RRMS error for test data2 would be a larger value than before. Therefore, the error value of test data2 should be quite larger than that of test data2. These are consistent with the result shown in Fig. 18.

It is verified that the proposed acceleration-based approach could implement structural evaluation effectively and economically. This characteristic makes the approach very useful for practical application.

7. Concluding Remarks

In this paper, an acceleration-based evaluation approach for building structures under earthquake using neural networks was proposed by including the ground acceleration into the input layer. This approach could be applied to multi-input as well as single input systems.

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 in by comparison of structural evaluation for healthy and damage structures. And the generality was verified by considering the different earthquake acceleration. The application to a 14-story real building were performed, and the verification of the proposed approach was obtained as well.

In our proposed evaluation approach, damage occurrence alarm could be obtained usefully and economically only using readily available acceleration time histories.

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