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USING WAVELET NEURAL NETWORK FOR THE IDENTIFICATION OF A BUILDING STRUCTURE FROM EXPERIMENTAL DATA

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SUMMARY

A wavelet neural network-based identification approach is presented in this paper to dynamically modeling a building structure. By combining wavelet decomposition and artificial neural networks, wavelet neural networks (WNN) are used for solving chaotic signal processing. The theoretical basis and basic operations of WNNs are first briefly introduced. Then the feasibility of structural behavior modeling and the possibility of structural health monitoring using WNNs are investigated and discussed. A practical application of WNNs to the structural dynamic modeling of a building frame in shaking tests is presented in an example. Structural acceleration responses under various levels of the strength of the Kobe earthquake were used to train and then test the WNNs. The results reveal that the WNNs not only identify the structural dynamic model, but also can be applied to monitor the health condition of a building structure under strong external excitation.

INTRODUCTION

An important issue involved in structural engineering is the identification of structural system. The aim of system identification is to identify a predefined simulation model that approximates a real world system. Hence, the process of system identification can be treated as a kind of function approximation (or mapping). Astrom [1] applied Maximum Likelihood estimation to difference equations (Auto Regressive Moving Average with eXogenous input models, ARMAX). Thereafter many estimation techniques and model parameterizations were developed. However, the complex nature of civil structures is such that the available measurements of their responses are typically incomplete, incoherent, and noise-polluted. Consequently, conventional system identification methods cannot yield the required accuracy, reliability, and feasibility for current structures. Recently, developing approaches to providing more accurate models for analyzing civil engineering structures has received considerable attention. Of these approaches, artificial neural network (ANN)-based methods have become highly effective for use non-parametric

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identification. Utilizing a neural network-based approach for system identification is demonstrated to yield more satisfactory results than the traditional approach (Chassiakos [2]; Nerrand [3]; Sjoberg [4]).

However, the implementation of neural networks suffers from some problems, such as the lack of efficient constructive methods, the local minima, and the convergent efficiency, when using ANNs. The recently introduced wavelet decomposition (Chui [5]; Rao [6]) emerges as a highly effective approach for function approximation. Furthermore, wavelet decomposition combined with the neural network structure, namely, wavelet neural networks (WNN) has been recently discovered as a more powerful tool for signal analysis. Zhang [7] first proposed this methodology. Thereafter, several studies extended their work to improve the network efficiency. However, until now, few studies have addressed WNNs in the area of dynamics of civil engineering structure.

Another relevant issue in structural engineering, which has actively been studied in recent years, is the health monitoring of structures. Structural health monitoring schemes based on a system identification approach have been extensively studied during the past decade (e.g. Agbabian [8]; Masri [9][10]; Abdelghani [11]; Nakamura [12]). Masri [9][10] and Nakamura [12] proposed a practical scheme for monitoring the health of real structures. In their works, the ANN was first trained using the dynamic responses of a healthy (undamaged) structure. Then, the well-trained ANN was fed with the dynamic responses under various scenarios for the same structure. The condition of the structure can be diagnosed and evaluated by monitoring the system output errors of the ANN. The concept behind their proposed method is adopted in this paper to explore the relevance of WNN to monitoring structural health, based on the dynamic model identification results for the structure.

This work attempts to demonstrate the feasibility of adapting a WNN to model the behavior of a structure in an earthquake. Not requiring information concerning physical parameters, the proposed model can easily simulate structural behavior, based only on the input and the output data of the structure. An example of a five-story 1/2-scaled steel frame in different scales of the Kobe earthquake is considered to elucidate the power of the proposed model. Illustrative examples indicate that the proposed WNN system identification model can yield an exact structural dynamic response. WNN and ANN approaches will also be compared, using the same experimental data. The proposed example will also clarify the potential of using WNNs for monitoring structural health, according to the computed output errors of WNNs under various levels of excitation.

THEORETICAL BASIS

Introduction to wavelet transform

Wavelet transform together and wavelet decomposition have been newly discovered as powerful tools. Wavelet theory states that functions of L^2 space can be represented by their projections onto the space linearly spanned by a family of wavelet functions. The wavelet functions are typically chosen to have compact supports in both time and frequency domains, so that they have local time-frequency properties. Functions can be approximated by the truncated discrete wavelet decomposition because of their local time-frequency properties.

A wavelet family associated with the mother wavelet $\psi(x)$ is generated by two operations – dilation and translation. It can be written as,

$$\psi_{a,b}(x) = a^{-1/2}\psi\left(\frac{x-b}{a}\right) \tag{1}$$

where a and b are dilation and translation parameters, respectively. Both are real numbers and a must be positive.

Using the mother wavelet function $\psi(x)$, the continuous inverse wavelet transform of a signal $f(x)$ is defined as,

$$f(x) = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} w(a,b) \psi\left(\frac{x-b}{a} \right) \frac{1}{a^2} dadb \tag{2}$$

where $w(a,b)$ is the wavelet transform of a signal. Note that, the mother wavelet must satisfy an admissibility condition to ensure existence of an inverse wavelet transform

To meet the requirement for digital computation, the continuous inverse wavelet transform is normally transformed to the discrete form,

$$f(x) = \sum_i w_i a_i^{-\frac{1}{2}} \psi(\frac{x-b_i}{a_i}) \tag{3}$$

The discretization involves determining the parameters w_i, a_i, and b_i in Eq. (3), based on a data sample.

If the function $f(x)$ is mostly compact in both time and frequency domains, and the mother wavelet is well concentrated in both time and frequency domains, then good approximation of $f(x)$ using a finite number of terms in Eq. (3) can be achieved. Therefore, this paper uses the following mother wavelet adopted in the WNN to generate a wavelet family.

$$\psi(x) = \left(x^T x - n \right) \times e^{-\frac{1}{2} x^T x}, \ x \in R^n \tag{4}$$

More details about the wavelet theory can be seen in related literature (e.g. ref. [6] and [7]).

Wavelet neural network

A wavelet neural network, which logically connects an artificial neural network with wavelet decomposition, is based on a novel neural network structure, and involves the wavelet transform. As a matter of fact, Eq. (3) refers to a single hidden layer feedforward network. Here, a hidden neuron is a dilated and translated wavelet. Sometimes, the function to be approximated is partially linear. Some additional terms were introduced to the network specified by Eq. (3) to capture the linear characteristics of nonlinear problems. This modification yields,

$$f(x) = \sum_i w_i a_i^{-\frac{1}{2}} \psi(\frac{x-b_i}{a_i}) + c^T x + d \tag{5}$$

Figure 1 shows the architecture of the wavelet neural network. In Figure 1, the combination of translation ($-b_i$), dilation (a_i), and wavelet (ψ_i), all lying on the same line, is called a wavelon.

The wavelets are considered as a family of parameterized nonlinear functions which can be used for nonlinear regression. Their parameters are estimated through a training procedure. In general, the adopted training algorithm is similar to the one in a back-propagation procedure. Details for the training procedure of the WNN are not mentioned in this paper and can be found in related literatures (Zhang [7][13][14]; Battiti [15]).

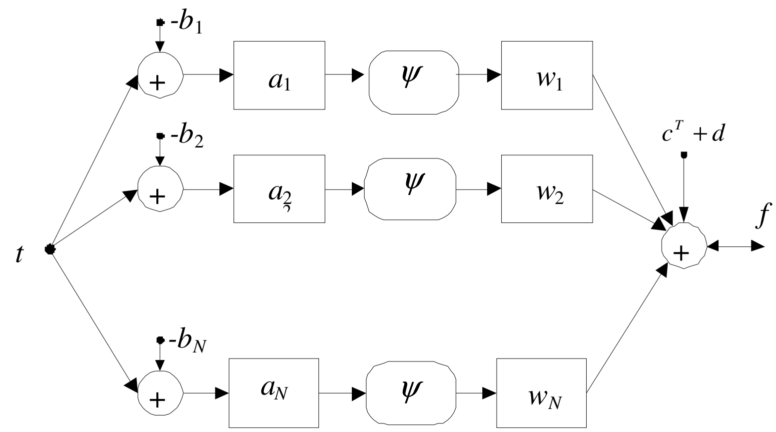


Figure 1. WNN model.

Dynamical system modeling using WNN

Several studies have shown that a large class of discrete-time nonlinear systems derived from the difference equation can be represented by the nonlinear ARMAX (NARMAX) model. Its ability to approximate a system to a desired accuracy depends on an appropriately selected set of known functions. Wavelet functions are then involved in an NARMAX model.

The NARMAX model representation of nonlinear discrete time systems with *r* input and *m* output can be expressed as,

$$y(t) = f\big(y(t-1), \ldots, y(t-n_y), u(t-1), \ldots, u(t-n_u), e(t-1), \ldots, e(t-n_e)\big) + e(t) \quad (6)$$

where $y(t)$, u(t), and $e(t)$ are the system output, input and noise vectors, respectively; n_y, n_u and n_e are the maximum delay time (lags) of the output, input and noise, respectively; $e(t)$ is the zero-mean noise signal, and $f(.)$ is a vector-valued nonlinear function.

In this study, the use of WNN was extended to identify the nonlinear system governed by the model:

$$y(t) = f\big(y(t-1), \ldots, y(t-n_y), u(t-1), \ldots, u(t-n_u)\big) \quad (7)$$

in which the noise terms in Eq. (6) are neglected.

According to Eq. (7), the output at the present time is a functional representation of the past input and output data. When the WNN is well-trained using a training set of the system input-output responses, the network structure parameters associated with the WNN can be considered as the dynamic characteristics of the system. If the dynamic characteristic of the system do not change, the trained WNN will perform just like the measured response of a real structure. However, if the dynamic characteristics of the system change due to damage or deterioration of structural elements, the network structure parameters associated with the WNN can no longer represent the dynamic characteristics of the system, and the WNN will exhibit a marked difference between computed and measured responses.

EXAMPLE

Introduction to the experiment setup

In this paper, the feasibility of using a WNN to model a five-story 1/2-scaled steel frame (Figure. 2) at the National Center for Research on Earthquake Engineering (NCREE) is examined by processing the dynamic responses of this test structure to different scales of the original Kobe earthquake, in shaking table tests.

Figure 2. Photo of the five-story steel frame.

The five-story test structure is a 3 m long, 2 m wide, and 6.5m high steel frame. Several lead blocks were piled on each floor such that the mass of each floor was approximately 3664 kg. Table 1 shows a brief description about the structural elements of the steel frame.

Table 1. Member section of the five-story steel frame

Direction (unit)	Short span (mm)	Long span (mm)
Column(1F~5F)	H125x125x6.5x9	H125x125x6.5x9
Beam(1F~5F)	H150x75x5x7	H100x100x6x8
Girder(1F~5F)	H100x50x5x7	H100x50x5x7

After the test frame is installed on the shaking table, the frames were subjected to the base excitation of the Kobe earthquake, weakened to various extents. The structural responses histories of displacement, velocity, and acceleration 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 1000 Hz. For practical reasons, only the experimental data concerning the acceleration responses in the long span direction are used in this study.

Data processing

The measured story acceleration responses are the input/output data for system identification using WNN. Five sets of experimental data, which are structural acceleration responses under 20%, 32%, 40%, 52%, and 60% Kobe earthquakes, were considered. The originally measured data were recorded at a frequency of 1000 Hz. In order to reduce the dimensionality of the data without losing the features of the dynamic response, the original data were processed by changing the sampling rate of the signal. The data were resampled at ten times the original sample rate, 100 Hz. A lowpass FIR filter was used in resampling. Thus, about 2000 records were used to identify the system. Moreover, all input/output data of WNN were normalized by being transformed into a hypercube $[-1, 1]^n$. The learning procedure was applied to this hypercube, and the computed output recovered by transforming the data back to their original shape.

Dynamic modeling of the test structure

In this paper, a feedback predictor network is adopted for the identification purposes of the test structures. Figure 3 presents the proposed feedback predictor network. In Figure 3, N_e is numbers of external inputs to the network; N_s is numbers of state inputs variables to the network. The WNN is used to identify the acceleration response of the second floor from the data obtained above and below that floor.

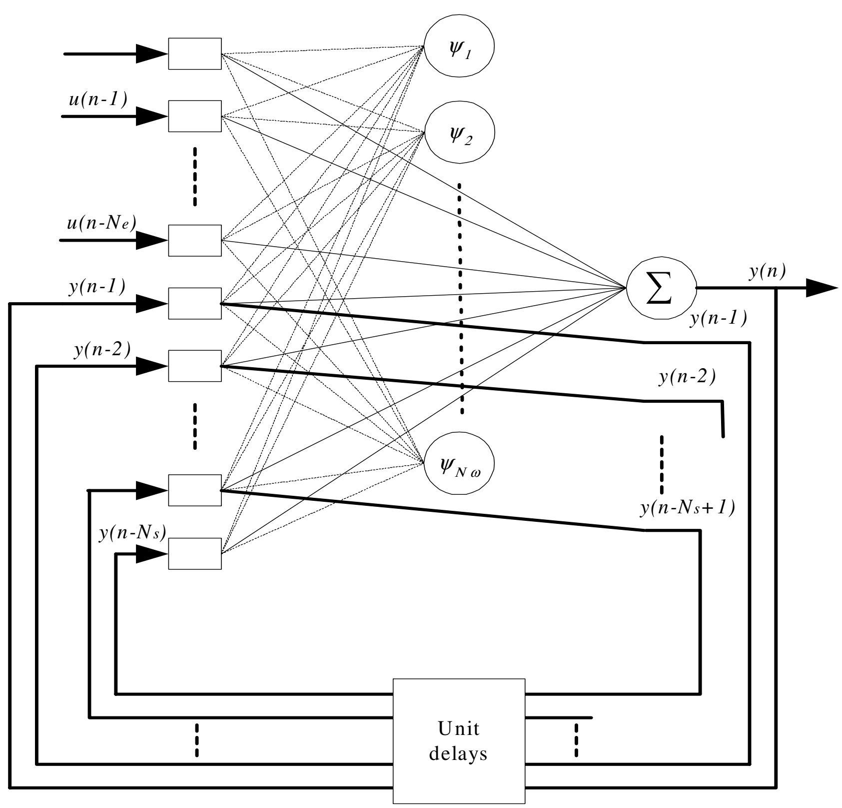


Figure 3. A feedback predictor network.

Figure 4 schematically depicts the system input/output assignment. The response is selected at these degrees-of-freedoms because of the reasons: (i) the structural element is shaken to yield at the bottom floor under the 60% Kobe earthquake; and (ii) practically, only few of the total degree-of-freedoms are measured for a complex structure. Consequently, only the response data at the first, second, and third floors were considered here.

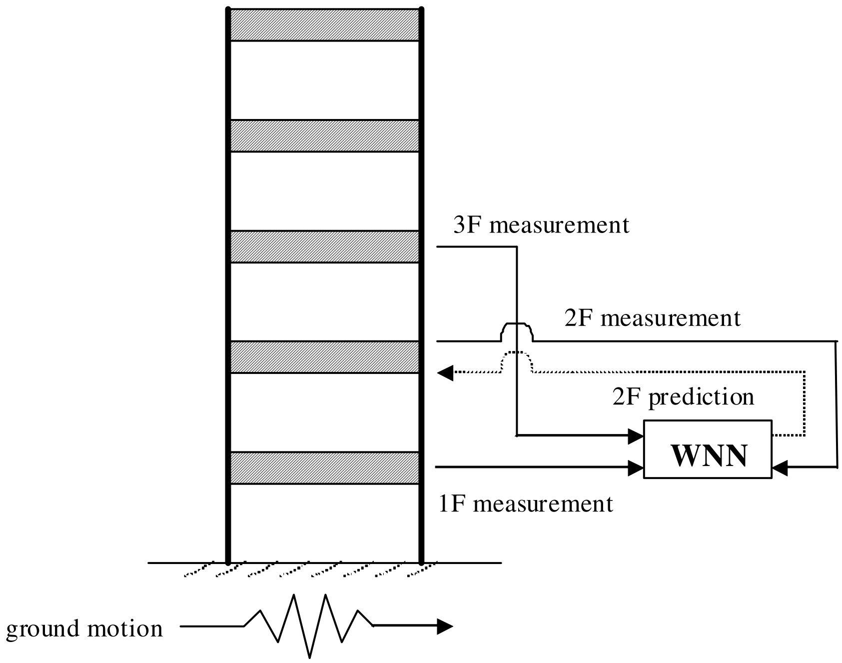


Figure 4. Network I/O assignment for the test frame.

In the training stage, the originally measured data of the test structure are treated as input-output data. After training, the computed output and originally measured data are used as the past time input data to determine the subsequent output. For example, the acceleration responses of the first, second, and third stories during the previous time interval are used as inputs to the WNN, and the current acceleration response of the second story is used as the output of the WNN. After training, the acceleration response is computed using the trained WNN. The measured acceleration response of the first and third stories, and the computed previous acceleration response of the second story are input to the input nodes to calculate the current acceleration response of the second story.

The normalized root-mean-square-error (RMSE) value is employed as a performance indicator of the performance of the WNN.

$$RMSE(\hat{y}) = \frac{\sqrt{\sum(\hat{y} - y)^2}}{\sqrt{\sum(\hat{y} - \bar{y})^2}} \tag{8}$$

where y is the desired output; $\hat{y}$ is the computed output; and $\bar{y}$ is the mean of computed output. A smaller RMSE implies a better performing WNN.

RESULTS AND DISCUSSION

The data concerning the response to a 20% Kobe excitation are used to determine the working parameters of the WNN. First the dynamic model order, n_y, n_u in Eq. (11), suitable for describing the structural behavior is determined. According to the authors' experience, the WNN can have good performance when the values n_y and n_u are set to be the same. Then the WNN is trained based on the response data under the 20% Kobe excitation.

Based on the WNN working parameters obtained above, other four sets of experimental data obtained at different excitation levels (i.e. 32%, 40%, 52%, and 60% Kobe earthquakes) were also used to train their own WNNs. After training, each trained WNN is tested with the five sets of experiment data in sequence. Figure 5 presents simulation results and the performance indicator RMSE for five difference excitation levels, Kobe 20%, 32%, 40%, 52%, 60%.

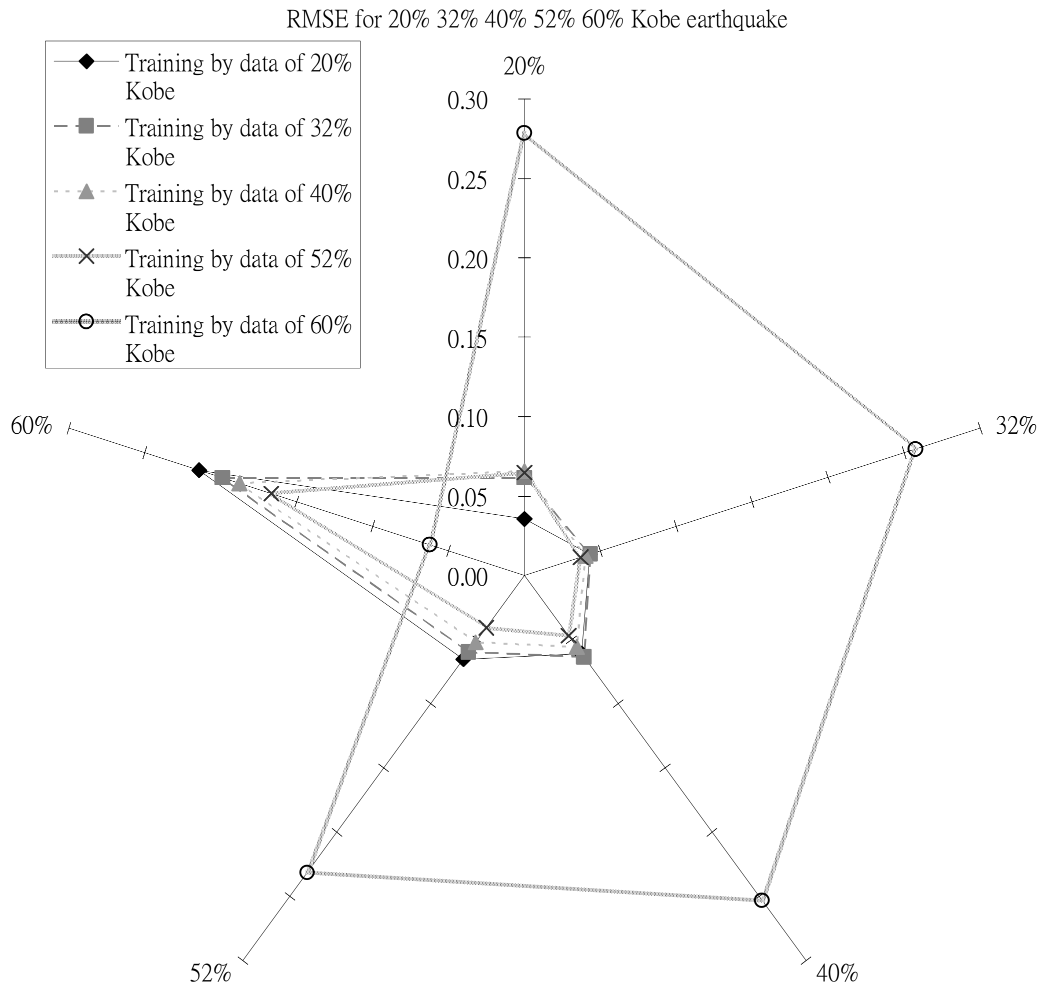


Figure 5. RMSE radar diagram of the WNN for the test frame under different excitations.

Figures 6 to 9 present and compare the absolute errors between computed and measured acceleration responses of the structure, at various excitation levels. Figures 6 and 7 present the results concerning the structural response to Kobe 20% excitation, used as a training source to simulate the structural responses to Kobe 32% and 60% excitations. Figure 8 and 9 present the results concerning the structural response to Kobe 60% excitation, used as a training source to simulate the structural responses to Kobe 32% and 60% excitations.

According to the results shown in Figure 5, the network trained with data concerning responses to 20%, 32%, 40%, and 52% Kobe earthquakes can simulate the structural response under 20%, 32% (Figure 6), 40%, and 52% Kobe earthquakes. The performance indicators (RMSE) are under 7% and the maximum absolute errors between the computed and measured response are around 0.04g. However the network cannot produce perform equally well for the structure under 60% Kobe earthquake (Figure 7).

Furthermore, the network trained with the data concerning the response to the 60% Kobe earthquake cannot simulate the structural response under 20%, 32% (Figure 8), 40%, and 52% Kobe earthquakes. The maximum absolute error is around 0.2g. The RMSE slightly exceeds 15%, very far from the value under 7%.

These results showed above imply that the structural behavior may change when the input excitation exceeds that of a 52% Kobe earthquake. The results also imply that, if the structural element does not change (or yield), then WNNs can obtain almost the same response as would be measured. However, if the structural element does change (or yield), then the WNNs trained with the response of a baseline (undamaged) structure will no longer be sufficient to represent the dynamic behavior of this structure, and the outputs of the WNNs significantly differ from the measured response. Interestingly, the frame has been reported (Yeh [16]) to respond linearly to 20%, 32%, 40%, and 52% Kobe earthquakes. Measured strains and visual inspection revealed that a 60% Kobe earthquake input caused the steel columns near the first floor to yield. The dynamic modeling results shown in this example seem to reflect such facts.

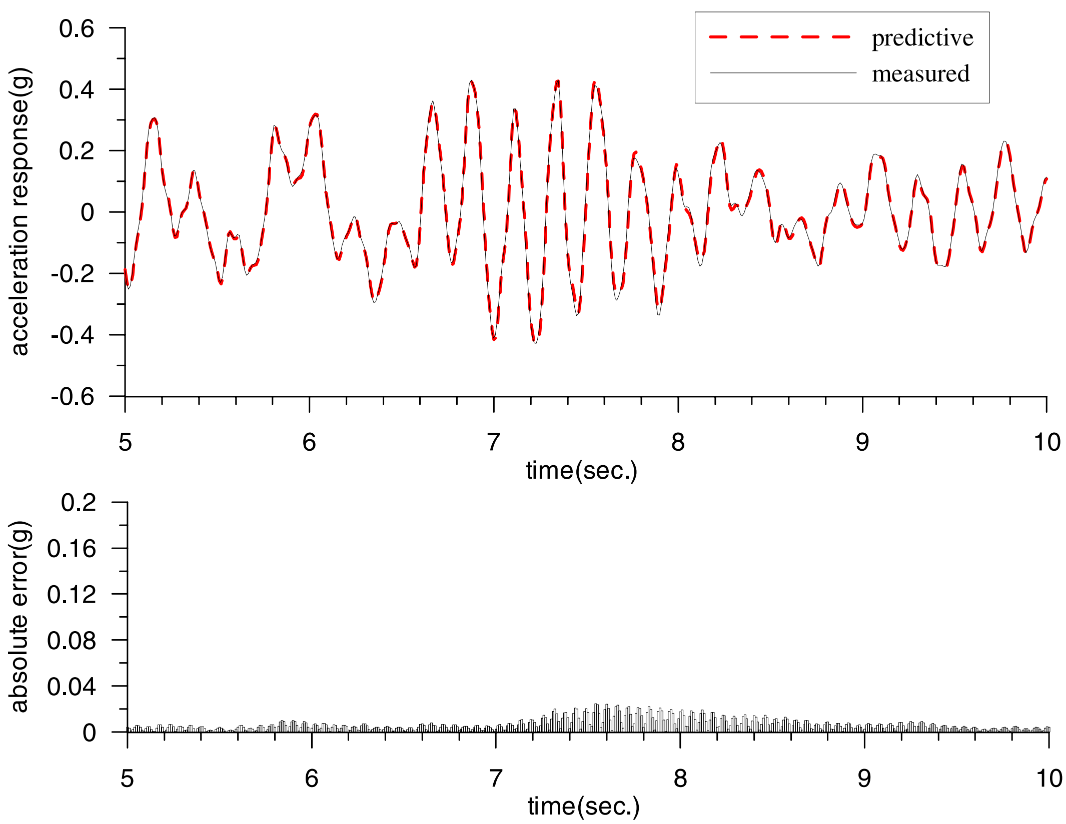


Figure 6. The WNN system identification results. (trained by Kobe 20% for forecasting Kobe 32%)

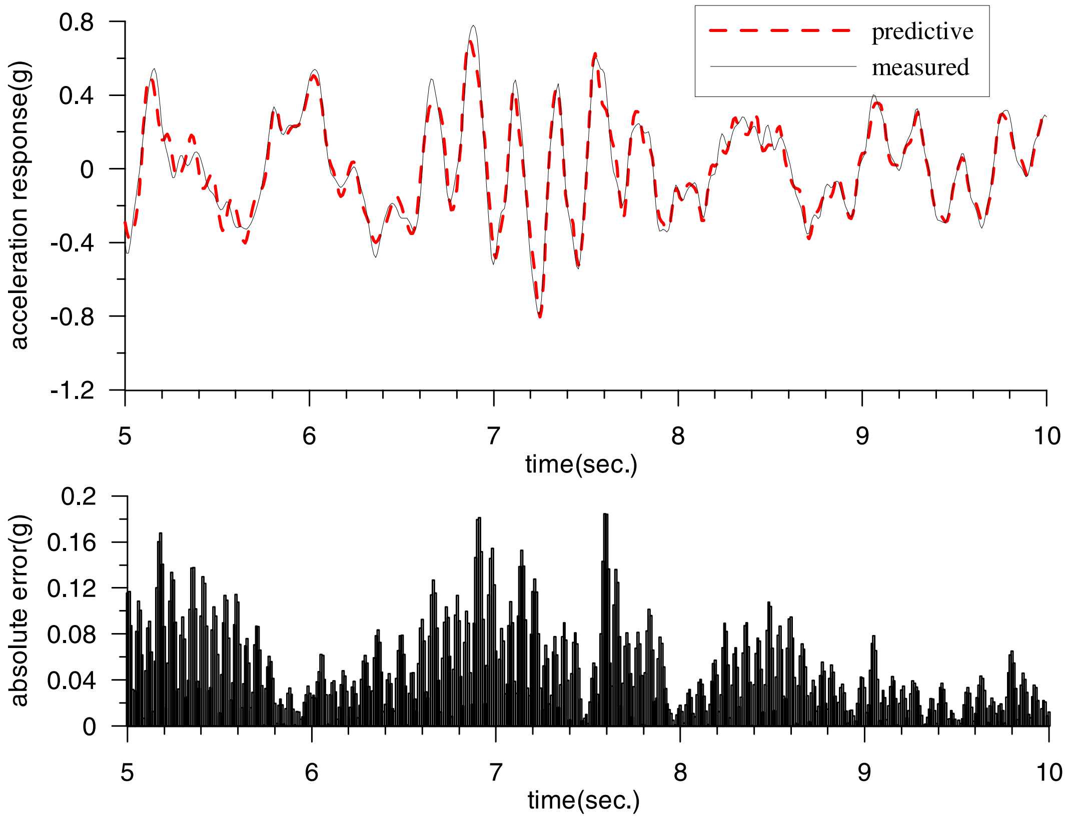


Figure 7. The WNN system identification results.(trained by Kobe 20% for forecasting Kobe 60%)

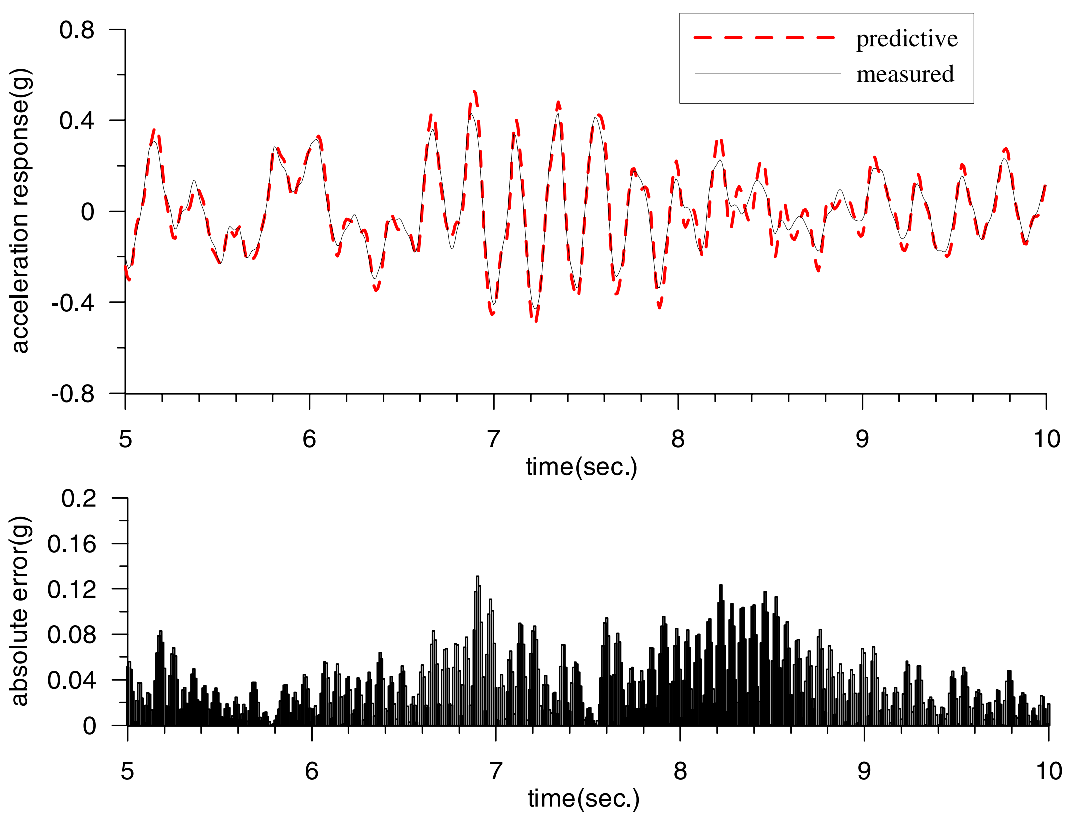


Figure 8. The WNN system identification results.(trained by Kobe 60% for forecasting Kobe 32%)

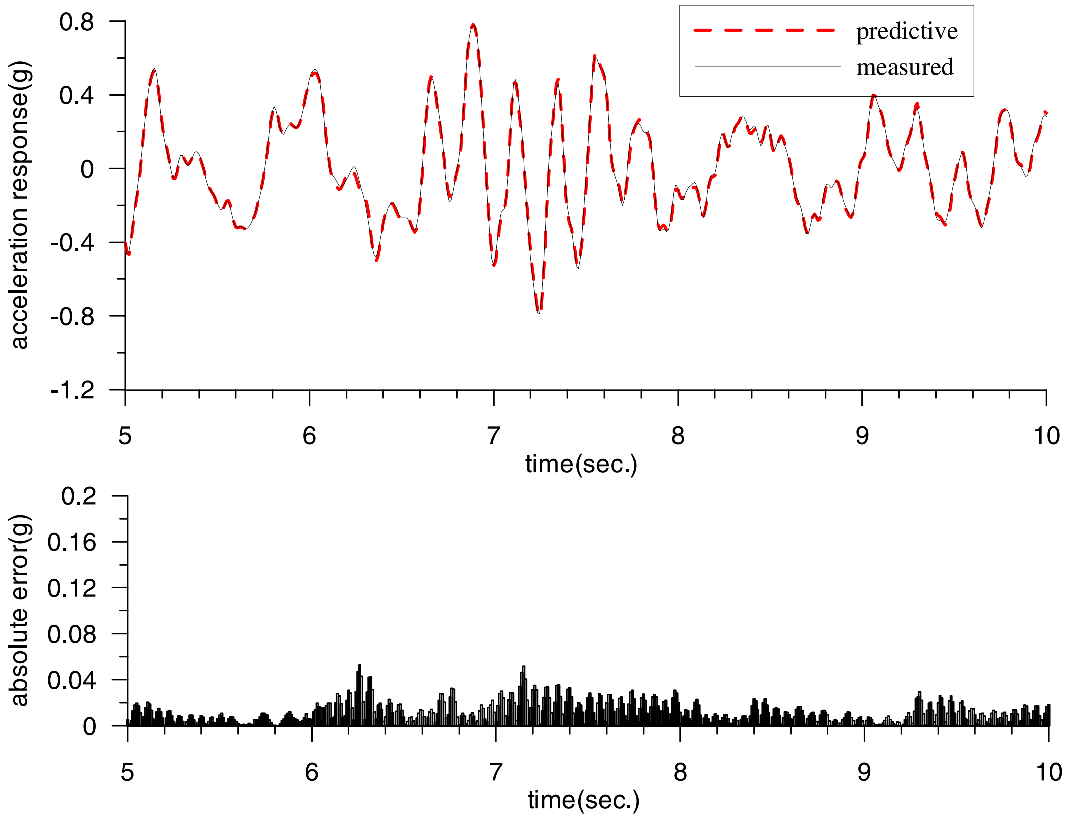
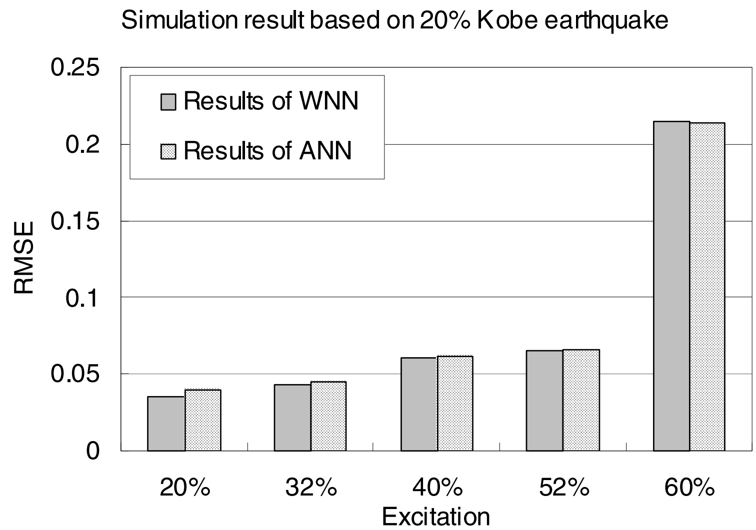


Figure 9. The WNN system identification results.(trained by Kobe 60% for forecasting Kobe 60%)

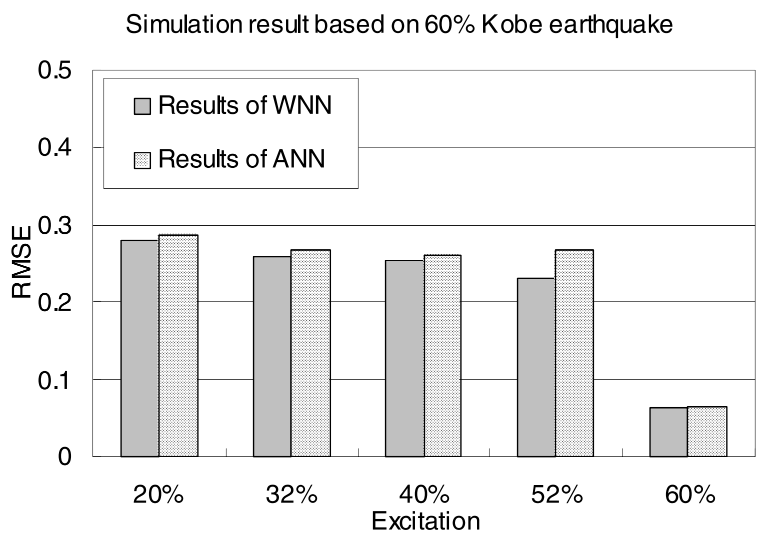
The structural response is also determined by ANN to compare the result of system identification using ANN and WNN. The architecture of the ANN used included one hidden layer with 4 hidden nodes, and the training algorithm was the Levenberg-Marquardt (LM) algorithm [17]. The simulation results of the WNN and ANN that were individually trained with the 20% and 60% Kobe earthquake data are shown in Fig. 10. The figure shows that the WNN gives simulation results that are similar to those obtained using the ANN. Although the values of RMSE by the ANN are very close to those obtained using the WNN, the WNN provides a more systematic approach to determining the network structure. Moreover, after the networks are initialized, a longer training period is needed for the ANN to perform as well as the WNN in this example. The training time for the WNN is about 100 seconds, while the training time for the ANN to reach the same level of RMSE is more than two hours.

CONCLUSIONS

This work presents a wavelet neural network-based approach to dynamically identify and model a building structure. The proposed approach is applied to analyze the response of a structure to an earthquake, to verify the feasibility of modeling structural behavior. The wavelet neural network, which combines wavelet decomposition and neural networks, has a very strong mathematical foundation, rooted in wavelet transformation for solving chaotic signal processing. The basic operations and method of training of the wavelet neural network are introduced owing to its effectiveness in approximating universal functions. A practical application of the wavelet neural network to structural dynamic modeling of a building frame in the shaking tests is illustrated. Structural acceleration responses to different levels of the Kobe earthquake were used to train and then test the WNNs. Based on the results in this study, the conclusions are made:



(a)



(b)

Figure 10. RMSE comparison between the WNN and ANN.
(a) trained with the 20% Kobe earthquake data.
(b) trained with the 60% Kobe earthquake data.

1. System dynamic models can be obtained by a WNN with a simple network structure (only one wavelons is used in the example) and few training iteration epochs, so the computational and cost and time take is low. Simulation results in the example reveal that the WNN can identify and model a dynamic system.
2. The significant increasing of the RMSE can be used to monitor the health of a structural system and detect the failure of the structure. The example in this study shows the possibility of using WNNs for monitoring structural health purpose.
3. Comparing the RMSE of the WNN with that of ANNs in previous research shows that WNN is highly suitable for identifying a system and perform as well as ANN. However, the training time need for the WNN is much more less than the one for the ANN.

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