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Nonparametric Identification of a Building Structure from Experimental Data Using Wavelet Neural Network

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Abstract: *This study presents a wavelet neural network-based approach to dynamically identifying and modeling a building structure. By combining wavelet decomposition and artificial neural networks (ANN), wavelet neural networks (WNN) are used for solving chaotic signal processing. The basic operations and training method of wavelet neural networks are briefly introduced, since these networks can approximate universal functions. The feasibility of structural behavior modeling and the possibility of structural health monitoring using wavelet neural networks are investigated. The practical application of a wavelet neural network to the structural dynamic modeling of a building frame in shaking tests is considered 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.*

1 INTRODUCTION

Simulation models aimed at predicting structural behavior are commonly derived from statistics. However, these regression methods cannot be used to construct an optimal model to simulate actual complex engineering behavior. While considering too few factors during regression leads to inaccurate results, considering too many factors complicates the model too much for evaluation.

Structural system identification is an important issue in structural engineering. 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). System identification has its roots in standard techniques and several of the basic routines have direct interpretations as well-known statistical methods such as the least squares and maximum likelihood methods. Astrom and Bohlin (1965) 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 in nonparametric identification. Utilizing a neural network-based approach for system identification is demonstrated to yield more satisfactory results than the traditional approach (Chassiakos and Masri, 1996; Nerrand et al., 1993; Sjoberg et al., 1994, 1995).

However, the implementation of neural networks suffers from the lack of efficient constructive methods. The problems of local minima and convergent efficiency are also important issues and should be addressed when using ANNs. The recently introduced wavelet decomposition (Chui, 1992; Rao and Bopardikar, 1998) emerges

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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 and Benveniste (1992) first proposed this methodology. Thereafter, several studies extended their work to improve the network structure (Jun and Huihe, 1999; Zhang et al., 1995), initialization procedure, parameter adoption law, and learning algorithm (Zhang, 1997; Ciuca and Ware, 1997; Liu et al., 1998; Oussar et al., 1998) of the WNN. Meanwhile, the adoption of the WNN to approximate functions has been considered in various areas of scientific and engineering research (Lu and Li, 1997; Cheng et al., 1998; Adeli and Karim, 2000; Adeli and Samant, 2000; Karim and Adeli, 2002a). 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 et al., 1991; Masri et al., 1996; Abdelghani et al., 1997; Nakamura et al., 1998; Masri et al., 2000). Masri et al. (1996, 2000) and Nakamura et al. (1998) proposed a practical scheme for monitoring the health of real structures. In their works, the artificial neural networks (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 article 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 wavelet neural network 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.

2 THEORETICAL BASIS

2.1 Artificial neural network model with one hidden layer

The multilayered neural network is probably the most frequently used type of network structure in practical applications. The architecture of the network includes an input layer, one or more hidden layers, and an output layer. Frequently considered single hidden layer networks have the following form:

$$f(x) = \sum_{i=1}^{N} w_i h_{\theta_i}(x) \tag{1}$$

where $h_{\theta_i}(\cdot)$ represents the hidden neurons parameterized by θ_i, and $w_i (i = 1 \sim N)$ represents a linear combination of weights of the hidden neurons.

However, implementing neural networks suffers from a lack of efficient constructive methods of determining the parameters of the neurons and choosing network structures. The presence of local minima and low convergent efficiency are also important issues, and must be addressed when using ANNs.

2.2 Wavelet transform

Wavelet transform and wavelet decomposition have been newly discovered as powerful tools and have been applied in many research areas (e.g., Guler et al., 2001; Jang et al., 2001; Zhao et al., 2001; Samant and Adeli, 2000, 2001; Karim and Adeli, 2002b, 2003; Adeli and Ghosh-Dastidar, 2003). 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,

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

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 wavelet transform of a signal $f(x)$ is defined as

$$w(a,b) = a^{-1/2}\int_{-\infty}^{+\infty} f(x)\overline{\psi}\left(\frac{x-b}{a}\right)dt \tag{3}$$

where $\overline{\psi}(x)$ indicates the complex conjugate of $\psi(x)$. The mother wavelet must satisfy an admissibility condition to ensure existence of an inverse wavelet transform

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|F_\psi(\omega)|^2}{|\omega|} d\omega < \omega \tag{4}$$

where $F_\psi(\omega)$ indicates the Fourier transform of $\psi(x)$. The signal $f(x)$ then can be reconstructed by an inverse wavelet transform of $w(a, b)$ as defined by

$$f(x) = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} w(a, b)\psi\left(\frac{x-b}{a}\right)\frac{1}{a^2} da\, db \tag{5}$$

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

$$f(x) = \sum_i w_i a_i^{-\frac{1}{2}} \psi\left(\frac{x-b_i}{a_i}\right) \tag{6}$$

The discretization involves determining the parameters w_i, a_i, b_i in Equation (6), based on a data sample.

2.3 Wavelet neural network

A wavelet neural network (Zhang and Benveniste, 1992), 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, Equation (6) refers to a single hidden layer feedforward network, which is a particular case of network represented by Equation (1). 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 Equation (6) to capture the linear characteristics of nonlinear problems. This modification yields

$$f(x) = \sum_i w_i a_i^{-\frac{1}{2}} \psi\left(\frac{x-b_i}{a_i}\right) + c^T x + d \tag{7}$$

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.

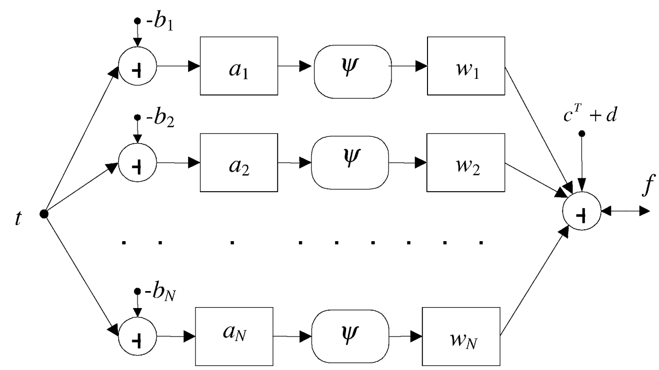

Fig. 1. Wavelet neural network structure for approximation.

2.4 Dynamic modeling using wavelet neural network

According to several publications on system identification (Juang, 1994; Ljung and Glad, 1994), perhaps the most basic relationship between the input u and output y, is the linear difference equation,

$$\begin{aligned} y(t) = {} & f(y(t-1), \ldots, y(t-n_a), u(t-n_k), \ldots, \\ & u(t-n_k-n_b+1)) \end{aligned} \tag{8}$$

where n_a represents the number of poles and $n_b - 1$ is the number of zeros, whereas n_k is the pure time-delay (the dead time) in the system. The equation describes the system in terms of a functional expansion of lagged inputs and outputs. 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

$$\begin{aligned} y(t) = {} & f(y(t-1), \ldots, y(t-n_y), u(t-1), \ldots, \\ & u(t-n_u), e(t-1), \ldots, e(t-n_e)) + e(t) \end{aligned} \tag{9}$$

where

$$\begin{aligned} y(t) &= [y_1(t) \quad y_2(t) \quad \cdots \quad y_m(t)]^T \\ u(t) &= [u_1(t) \quad u_2(t) \quad \cdots \quad u_r(t)]^T \\ e(t) &= [e_1(t) \quad e_2(t) \quad \cdots \quad e_m(t)]^T \end{aligned} \tag{10a–c}$$

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 $f(\cdot)$ is a vector-valued nonlinear function.

Here, the use of WNN was extended to identify the nonlinear system governed by the model:

$$y(t) = f(y(t-1), \ldots, y(t-n_y), u(t-1), \ldots, u(t-n_u)) \tag{11}$$

in which the noise terms in Equation (9) are neglected.

According to Equation (11), 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 characteristics 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.

3 CONSTRUCTING WAVELET NEURAL NETWORK

Figure 2 briefly depicts the processes of constructing a WNN. Before training the WNN (searching for the best parameters, a_i, b_i, and w_i in Equation (7)), some operating parameters should be determined first. They are (1) network architecture parameters, such as number of wavelons; and (2) wavelet initialization parameters, such as number of scale levels scanned and the minimum number of input patterns to be covered by each wavelon.

3.1 Selecting the number of wavelons

Like the number of hidden layers and neurons, the number of wavelons in WNN is critical. The number of wavelons may be selected by relying on appropriate versions of standard model order criteria. A systematic methodology based on information theory and used for system identification to determine the model order can be applied to WNN. Akaike's final prediction error criterion (FPEC) (Akaike, 1969) is adopted here to determine the number of wavelons. The criterion is defined as

$$J_{\mathrm{FPE}}(\hat{f}) = \frac{1 + n_p/N}{1 - n_p/N} \frac{1}{2N} \sum_{k=1}^{N} (\hat{f}(x_k) - y_k)^2 \tag{12}$$

where (x_k, y_k) are training data pairs; N is the sample length of training data, and n_p is the number of parameters in the estimator and is calculated using the following formula.

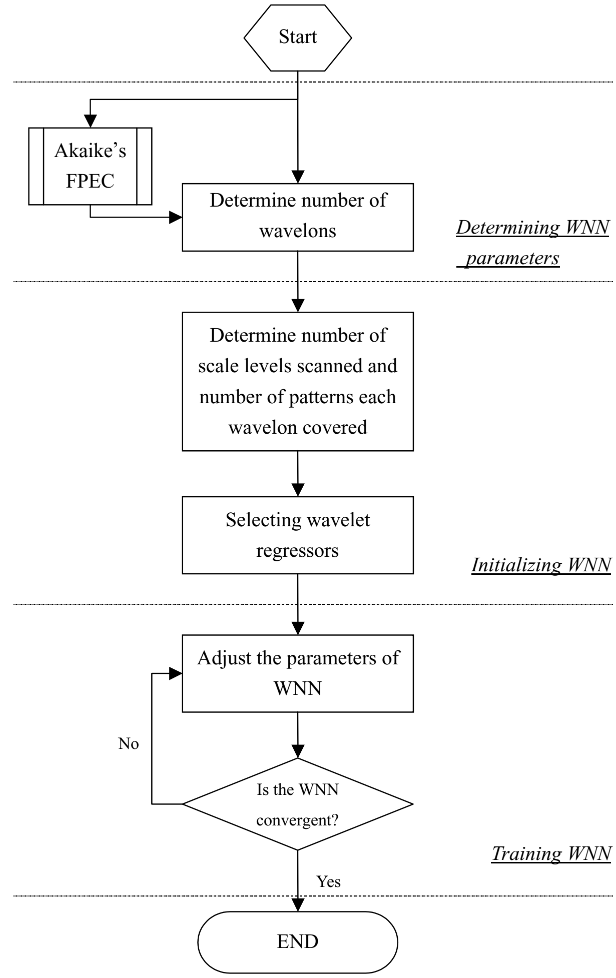

Fig. 2. The processes of approximation using WNN.

$$n_p = M(d+2) + d + 1 \tag{13}$$

where M is the number of wavelets in the network and d is the input dimension.

3.2 Selecting the number of wavelet initialization parameters

Two wavelet initialization parameters, the number of scale levels scanned during initialization and the minimum number of input patterns to be covered by each wavelon, can be determined by experiential rule (Zhang and Benveniste, 1992) as follows:

$$n_c = 2 + n_v; \quad l_v = 4 \tag{14a, b}$$

where n_c is the minimum number of input patterns to be covered by each wavelon; n_v is the number of input variables, and l_v is the number of scale levels scanned during initialization.

3.3 Mother wavelet

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 Equation (6) can be achieved. Therefore, this article uses the following mother wavelet adopted in the WNN to generate a wavelet family:

$$\psi(x) = (x^T x - n) \times e^{-\frac{1}{2}x^T x}, \quad x \in R^n \qquad (15)$$

According to the initialization parameters, the wavelets in the network are selected based on the input/output data of the samples, and the wavelons are initially established after the wavelet is selected using regression. Next, the weights in the net are calculated using quasi-Newton algorithm (Battiti, 1992). After iterative training and adjustment of the parameters a_i, b_i and w_i in Equation (7), the difference between the measured outputs and the calculated output values becomes minimum, and the WNN is established and ready to simulate structural behavior.

4 EXAMPLE

4.1 Problem statement

System identification allows engineers to build mathematical models of a dynamics system, based on measured data. The most commonly used models are difference equations. These include ARX and ARMAX models, and all types of linear state-space models. Lately, black-box nonlinear structures, such as artificial neural networks, fuzzy models, and others, have been extensively applied. In this article, the feasibility of using a WNN to model a five-story 1/2-scaled steel frame 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. The test structure is a 3-m long, 2-m wide, and 6.5-m high steel frame (Figure 3). 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 to various extents. The displacement, 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 rate of sampling the raw data was 1000 Hz. For practical reasons, only the experimental data concerning the acceleration responses in the long span direction are used here.

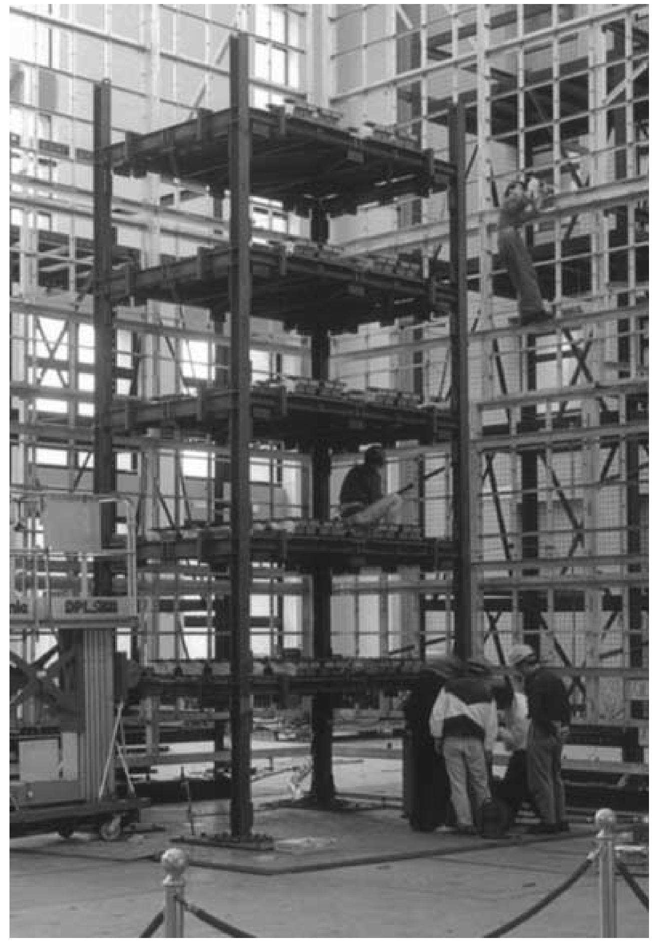

Fig. 3. Photograph of the five-story test structure.

4.2 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.

4.3 Dynamic modeling of the test frame

Figure 4 presents a proposed feedback predictor network. In Figure 4, N_e is number of external inputs to the network; N_s is number 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 5 schematically depicts the network input/output assignment. The response is selected at these degrees of freedom because: (1) the structural element is shaken to yield at the bottom floor under the 60% Kobe earthquake; and (2) practically, only few of the total degrees of freedom are measured for a complex structure. Consequently, only the response data at the first, second, and third floors were considered here.

During the training, 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.

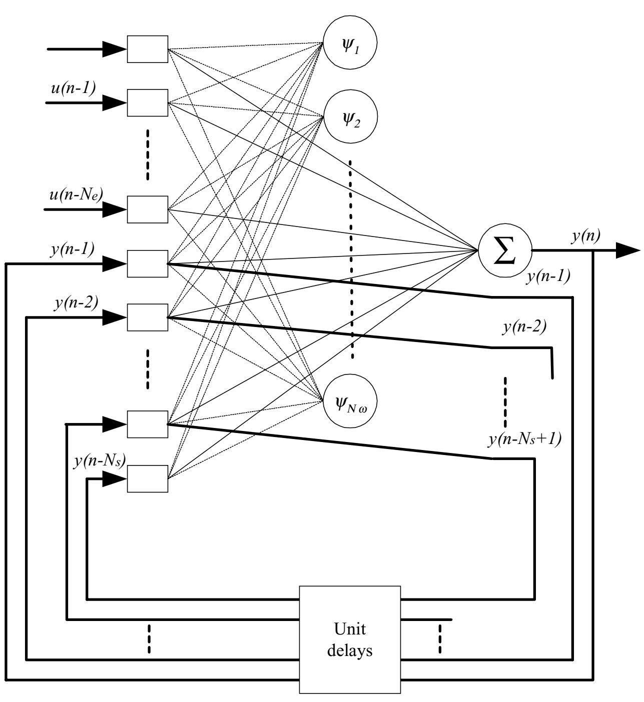

Fig. 4. Feedback predictor networks.

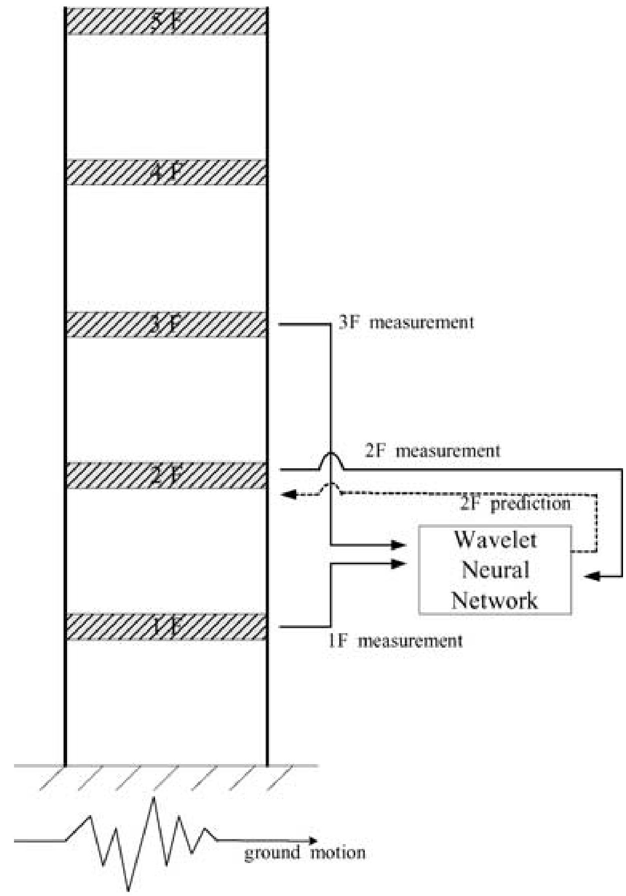

Fig. 5. Schematic diagram of network I/O assignment for steel frame structure.

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

$$\mathrm{RMSE}(\hat{y}) = \frac{\sqrt{\sum(\hat{y} - y)^2}}{\sqrt{\sum(\hat{y} - \bar{y})^2}} \tag{16}$$

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.

4.4 Identification results

The simulation is implemented using the MATLAB WNET toolbox, provided by Zhang (Anonymous FTP), on the Windows 2000 Professional platform, using an AMD Duron-700 PC.

The data concerning the response to a 20% Kobe excitation are used to determine the parameters of the WNN.

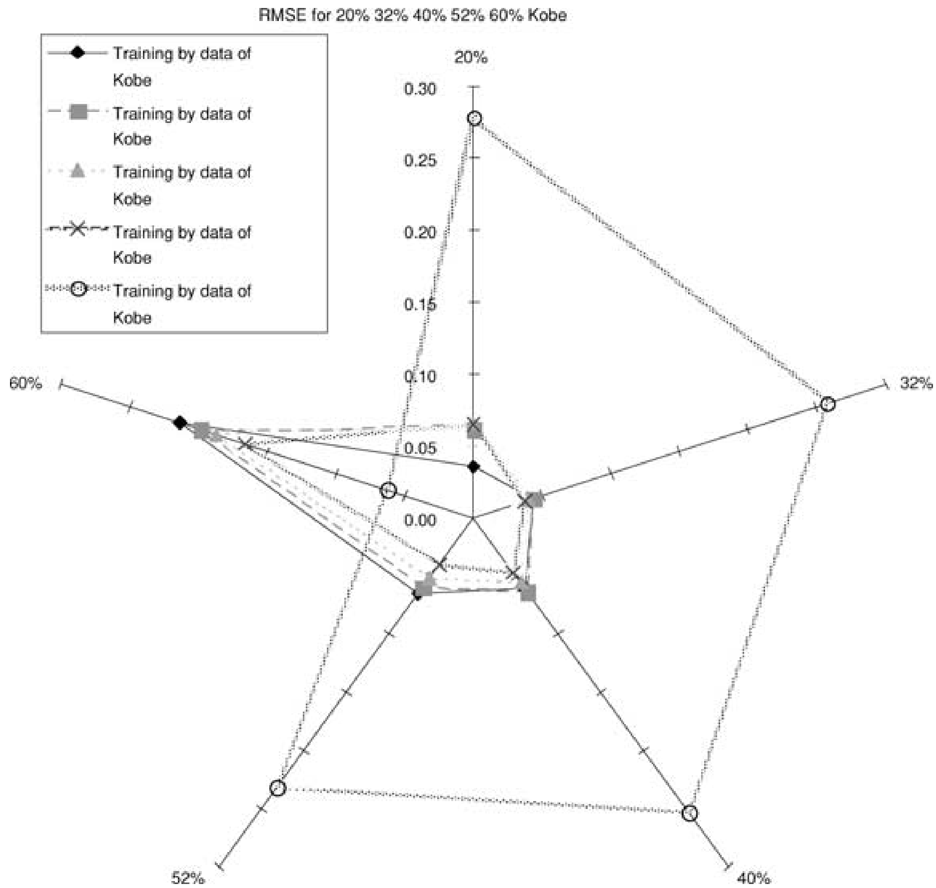

Fig. 6. Radar diagram of RMSE.

First the dynamic model order, n_y, n_u in Equation (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. The accuracy of the prediction, represented by RMSE, and the computational times spent initializing and training are both considered in selecting the order. After trial and error, order ten is selected, since it yields satisfactory accuracy (RMSE) and requires relatively little computational time. The network parameters should be determined. The number of scale levels scanned and the minimum number of input patterns to be covered by each wavelon are determined by the empirical rule, Equation (14). Akaike's FPEC determines that one wavelon suffices in this example. After initialization of the WNN, the WNN was then trained with the quasi-Newton method.

Based on the WNN parameters obtained above, four other 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 6 presents simulation results and the performance indicator RMSE for five difference excitation levels, Kobe 20%, 32%, 40%, 52%, and 60%. Figures 7–10 present and compare the absolute errors between computed and measured acceleration responses of the structure, at various excitation levels. Figures 7 and 8 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. Figures 9 and 10 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 6, the network trained with data concerning responses to 20%, 32%, 40%, and 52% Kobe earthquakes can simulate the structural response under 20%, 32% (Figure 7), 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 0.04 g. However the network cannot

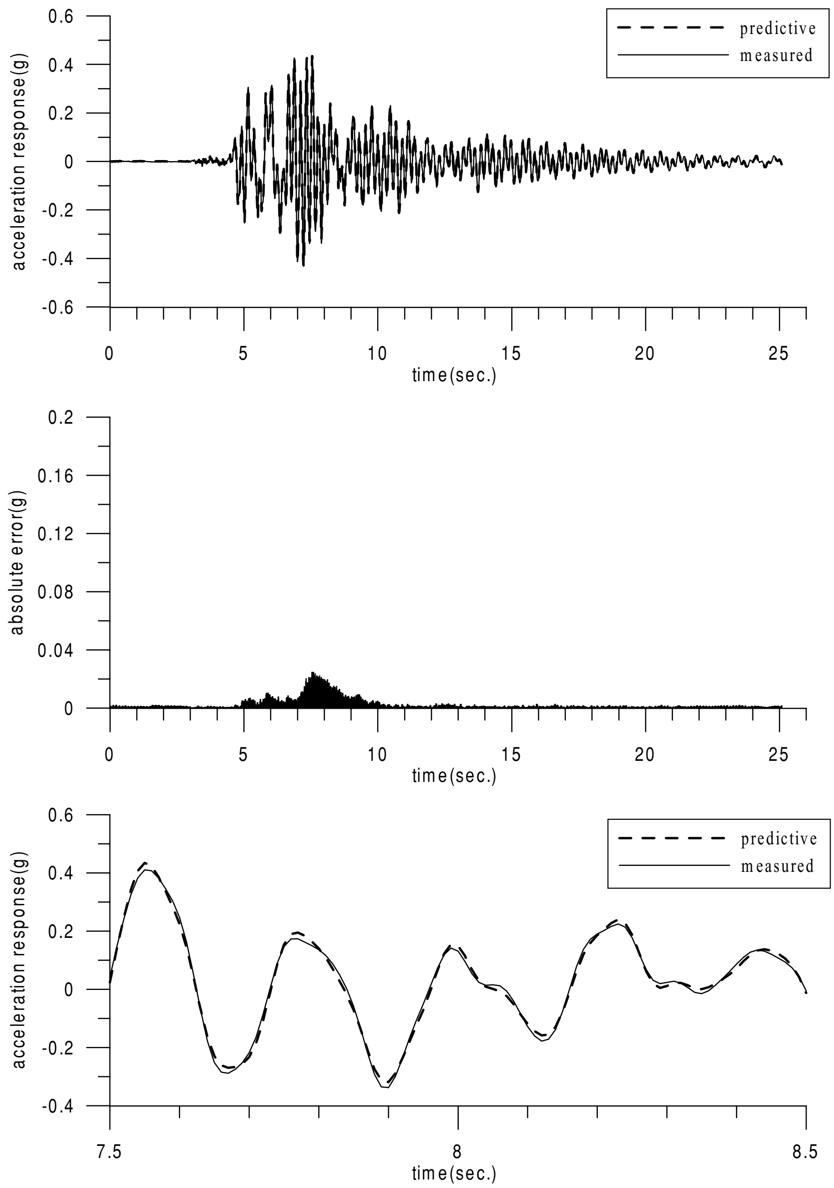

Fig. 7. The WNN system identification results (trained by Kobe NS 20% for forecasting Kobe NS 32%).

perform equally well for the structure under 60% Kobe earthquake (Figure 8). Furthermore, the network trained with the data concerning the response to the 60% Kobe earthquake cannot simulate the structural response under 20%, 32% (Figure 9), 40%, and 52% Kobe earthquakes. The maximum absolute error is around 0.2 g. The RMSE slightly exceeds 15%, very far from the value under 7%. These results 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 et al., 1999) 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

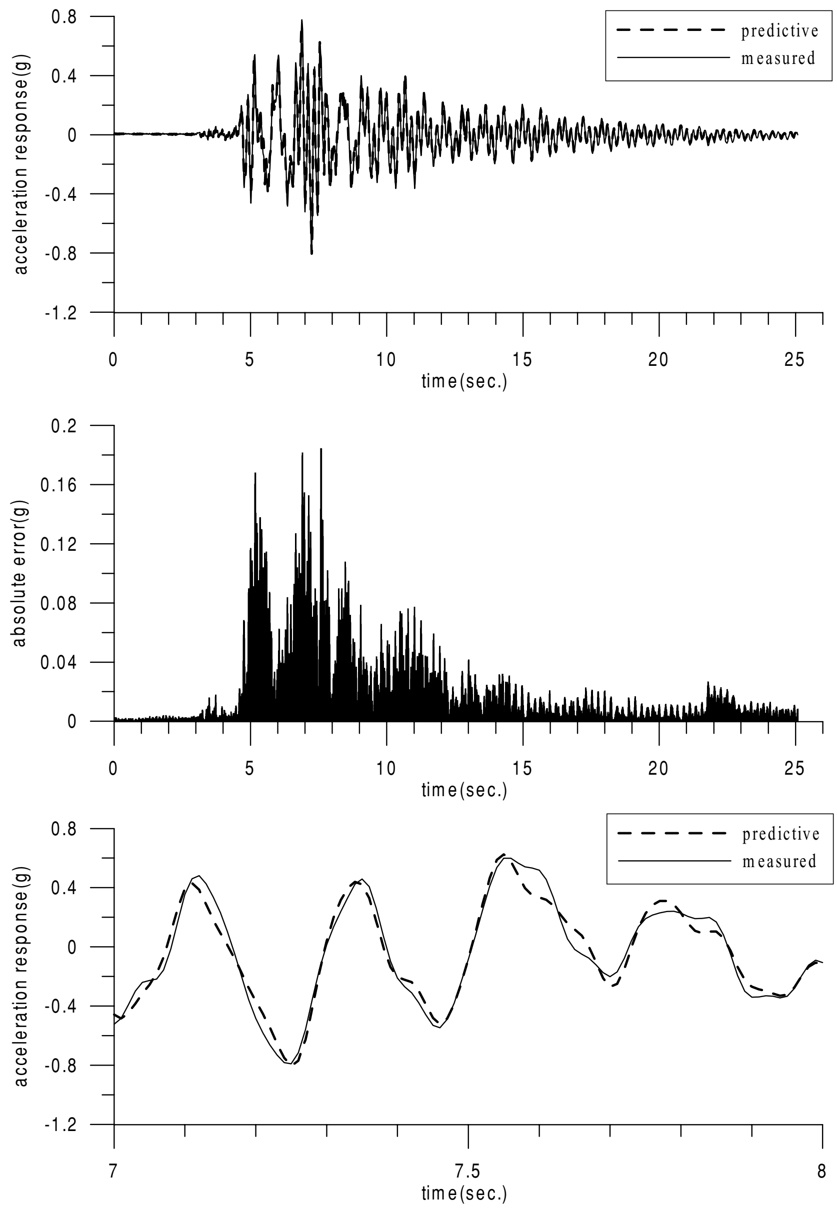

Fig. 8. The WNN system identification results (trained by Kobe NS 20% for forecasting Kobe NS 60%).

steel columns near the first floor to yield. The dynamic modeling results shown in this example seem to reflect such facts.

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 (Hagan and Menhaj, 1994). Figure 11 presents the simulation results of the WNN and ANN that were trained with the 20% and 60% Kobe earthquake data individually. 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, whereas the training time for the ANN to reach the same level of RMSE is more than two hours.

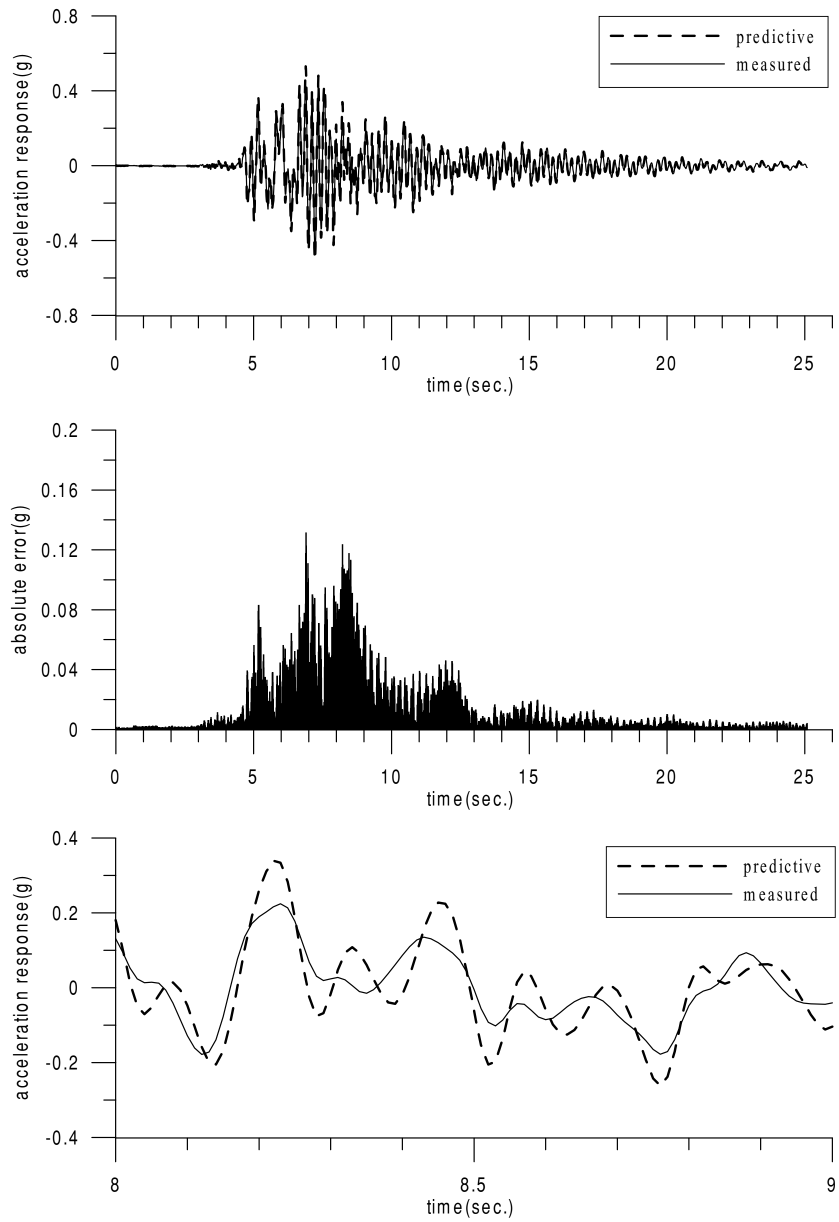

Fig. 9. The WNN system identification results (trained by Kobe NS 60% for forecasting Kobe NS 32%).

5 CONCLUDING REMARKS

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 following conclusions are made:

1. System dynamic models can be obtained by a WNN with a simple network structure (only one wavelon is used in the example) and few training iteration

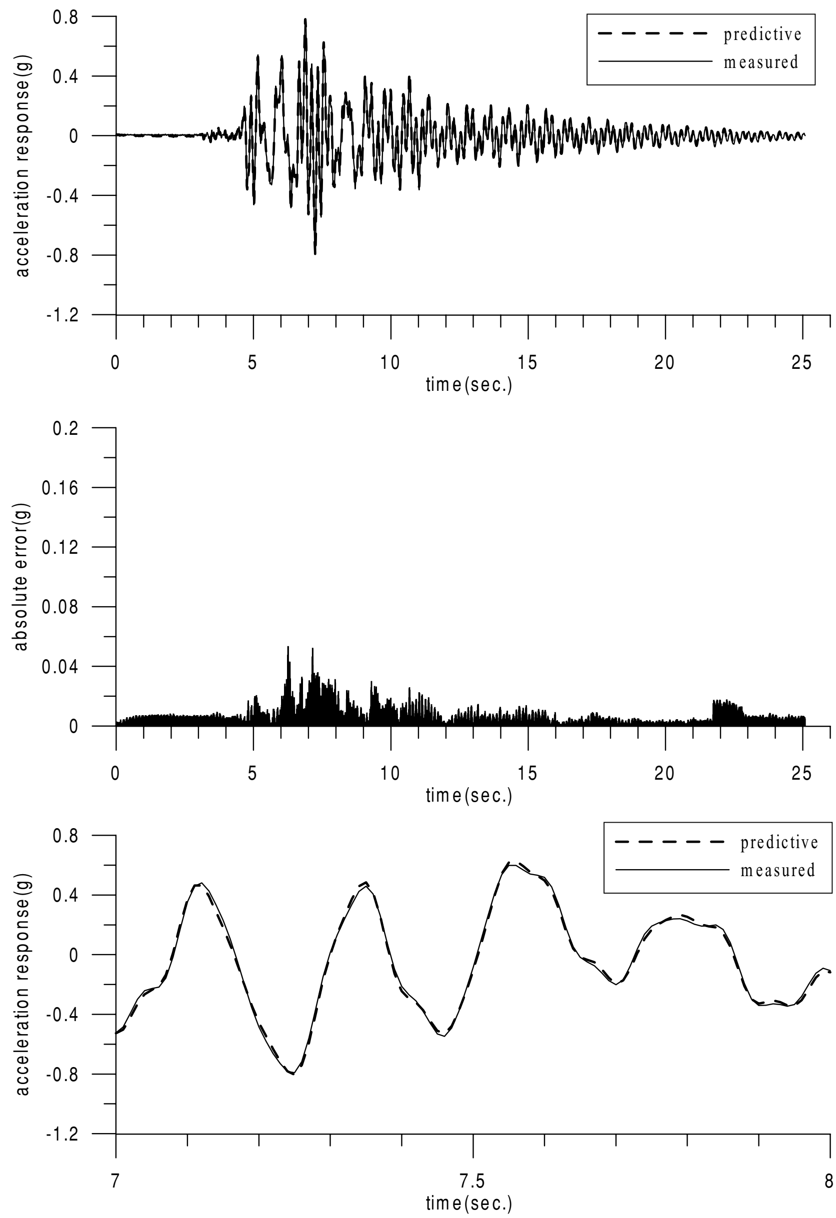

Fig. 10. The WNN system identification results (trained by Kobe NS 60% for forecasting Kobe NS 60%).

epochs, so the computation and cost and time taken is low. Simulation results in the example reveal that the WNN can identify and model a dynamic system.

2. The significant increase in 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 purposes.
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 performs as well as ANN. However, the training time needed for the WNN is much less than the one for the ANN.

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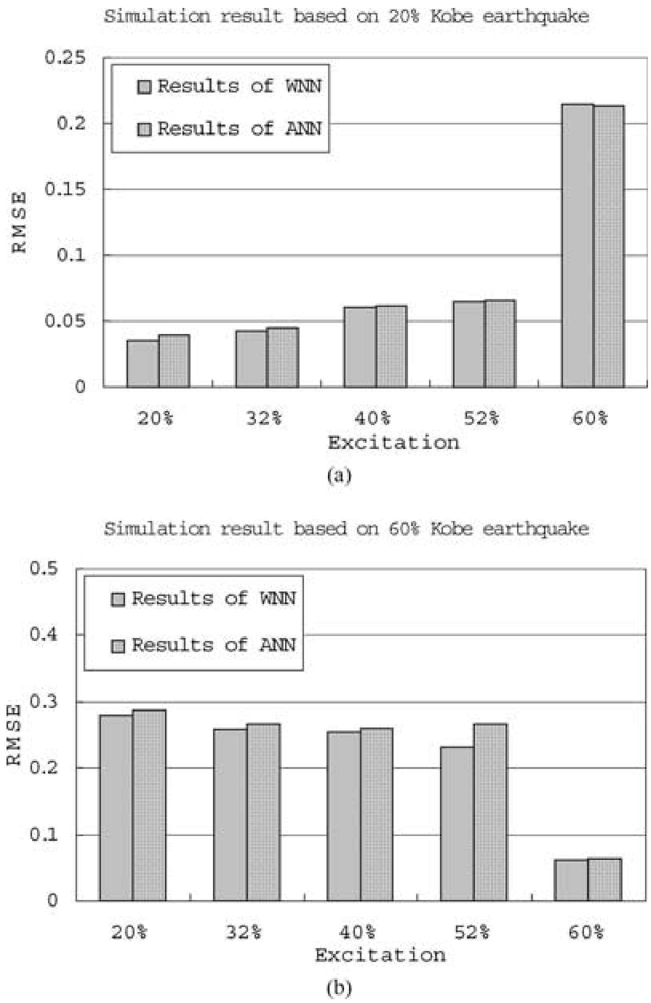

Fig. 11. RMSE comparison between the WNN and ANN: (a) trained with the 20% Kobe earthquake data; (b) trained with the 60% Kobe earthquake data.

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