NEW METHODOLOGY OF GENERATING MULTIPLE SPECTRUM COMPATIBLE EARTHQUAKE ACCELEROMETER FOR TAIWAN AREA USING NEURAL NETWORKS

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ABSTRACT

Taiwan is located in an earthquake prone region. The geology constitution of Taiwan is constantly changing. There are at least 42 active faults in Taiwan area based on published literature. Since the beginning of the 20th century, eight catastrophic earthquakes had struck Taiwan; a magnitude 7.3 Chi-Chi earthquake hit central Taiwan in 1999 and caused serious irreversible damages such as split ground, wrecked roads and collapsed bridges as well as taking more than 2300 lives. In the same time, the huge number of earthquake accelerograms of 921 Chi-Chi earthquake and its aftershocks were also recorded. Therefore, we need a method to systematically process and utilize these massive volumes of the recorded accelerograms for structural design and analysis.

Earthquake response spectra are often used in analysis and design of structures. In some cases, it is desirable to develop an artificial earthquake accelerogram compatible with a given design spectrum. As more non-linear dynamic analyses are being performed, the need for developing accelerograms from design spectra is increasing and the method for generating realistic accelerograms become more and more important.

A new neural network based methodology for generating spectrum compatible artificial earthquake accelerogram is proposed by Lin and Ghaboussi on 1999 and developed using the historical US earthquake records as well as the learning capabilities of neural networks to extract the knowledge of the inverse mapping directly from the response spectra to earthquake accelerograms. In its two-stage approach, the “replicator neural networks (RNN)” (as a data compression tool) and the “stochastic neural networks (SNN)” were used and a multi-layer feed-forward neural network learns to relate the response spectrum to the compressed Fourier spectrum. The methodology is capable of generating multiple earthquake accelerograms from a single design spectrum. Using historical Taiwan earthquake records and MATLAB software, the methodology is modified based on the original method and proposed to generating artificial earthquake accelerograms for Taiwan area.

This research will provide a systematic methodology to utilize the massive volumes of the recorded accelerograms as well as to generate a stochastic ensemble of spectrum compatible artificial earthquake accelerograms for Taiwan area from any design spectrum to be used in nonlinear dynamic time history analysis.

Keywords: Taiwan, Earthquake, ground motions, neural networks, stochastic, accelerograms

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INTRODUCTION

Taiwan is located in an earthquake prone region. Therefore, the geology constitution of Taiwan is constantly changing. Based on published literature, there are at least 42 active faults identified in Taiwan area. Started from 1990, the Taiwan Strong Motion Instrumentation Program (TSMIP) installed 82 real-time stations and 650 strong motion stations. In the mean time, 51 structures were monitored. All these data are digitalized and maintained by the Central Weather Bureau (CWB). Therefore, the density of the strong motion station in Taiwan is the highest in the world. From historical records, eight catastrophic earthquakes had struck Taiwan since the beginning of the 20th century. In 1999, a magnitude 7.3 Chi-Chi earthquake hit central Taiwan and caused serious irreversible damages such as split ground, wrecked roads and collapsed bridges as well as taking more than 2300 lives. Meanwhile, due to the above mentioned dense strong motion stations, the huge number of earthquake accelerograms of 921 Chi-Chi earthquake and its aftershocks were also recorded. Therefore, we need a method to systematically process and utilize these massive volumes of the recorded accelerograms for structural design and analysis.

“Response spectrum” is commonly used by structural engineers to evaluate the seismic response of structures and to design structures to withstand earthquakes. Defined as the maximum response of an idealized damped single degree of freedom (SDOF) structure subjected to an earthquake accelerogram as the ground motion ($x(t)$), a response spectrum ($S_v(\omega, \zeta)$) is normally plotted as a function of the frequency ($\omega$) and damping ratio ($\zeta$) (Newmark and Hall, 1982). Usually the actual recorded accelerograms will be used for a given site and earthquake source when they are available. Otherwise, artificially generated earthquake accelerograms are used. As the design codes require more nonlinear analyses, the need for generating artificial earthquake accelerograms is increasing.

When used for the seismic design of structures, the design spectrum has a pre-determined statistical relationship with the recorded accelerogram for the specific postulated event. This statistical relationship can be an average mean (plus one sigma) or the envelope of the accelerograms. Furthermore, the artificial earthquake accelerograms are required to be compatible with the design spectrum, i.e. the response spectra of the generated accelerograms should closely approximate the design spectrum. Since 1964, Housner and Jennings; Tsai (1972); Levy and Wilkinson (1976); Iyengar and Rao (1979); Polhemus and Cakmak (1981); Kimura and Izumi (1989); Spanos and Mignolet, (1990); Haddon (1996); and many researchers have participated the research of generating artificial earthquake accelerograms.

A new methodology for generating multiple artificial earthquake spectrum compatible accelerograms from design spectra was first proposed in 1997 and modified in 1999 by Lin and Ghaboussi (2001) using the learning capabilities of neural networks with the historical US earthquake records. In which, various types of the neural networks were used to develop the knowledge of the inverse mapping from the response spectra to earthquake accelerograms. This method has been proved capable of generating multiple earthquake accelerograms from a single design/response spectrum for the North American area as well as the Himalayan region (Pathak, Kumar, and Narayan, 2004) successfully.

Recently, using historical Taiwan earthquake records and MATLAB software, this method has been modified and further applied to generate artificial earthquake accelerograms for Taiwan area. The proposed method produces a stochastic ensemble of earthquake accelerograms from a design spectrum developed by Taiwan’s seismic code. An example is presented that used 60 recorded accelerograms to train the neural network and several design spectra and response spectra to test this improved methodology.

SOLVING ENGINEERING PROBLEM USING NEURAL NETWORKS

Many engineering problems are inverse problem while they were not solved in this way. For example, if we look at the sequence of input-system-output as forward, then to solve the input while both system and output are known, or to solve the system while both input and output are known can be taken as inverse problems. Most of the problems in engineering such as analysis, design, system identification, diagnosis, prediction, classifying, control, planning, etc. can be separated into two categories: the first one is obtaining the result
through prediction and evaluation. The second one is to find the reason through the result. For example, when applying the loading on a system and calculate the deformation of that system is a forward problem. On the other hand, identifying the system via the applied loading and its deformation, or evaluating the applied loading through the system and its deformation can both be classified into inverse problems.

If we consider calculating the spectrum from an accelerogram a forward problem, determining an accelerogram from its spectrum is an inverse problem. This problem of calculating the response spectrum is irreversible since a huge amount of information is lost while going from the accelerogram to its response spectrum. Therefore, the unique solution cannot be found in this inverse problem and the accelerogram cannot be determined uniquely from its response spectrum. In fact, most of the inverse problems share the same property of having no unique solutions. Mathematically based methods are not suitable for solving these inverse problems particularly due to the lack of unique solutions. However, biologically inspired soft computing methods, such as neural networks, can imitate the robust problem solving strategies applied in nature when dealing with these inverse problems. The imprecision tolerant learning capabilities of neural networks offer opportunities to solve non-unique inverse problems (Ghaboussi, 1999).

Inspired by the operational mechanism of the human beings’ brain and neural system, neural networks are a soft computing method that possess a massively parallel structure. Neural networks are formed by interconnecting many artificial neurons. Signals propagate along the connections and the strength of the transmitted signal depends on the numerical weights that are assigned to the connections. Each neuron receives signals from the incoming connections, calculates the weighted sum of the incoming signals, computes its activation function, and then sends signals along its outgoing connections. The knowledge learned by a neural network is stored in its connection weights. To solve difficult engineering problems, it is necessary to design a task-specific neural network rather than just apply a simple neural network. The complexity of the problem and the very large size of the neural networks used in this study required special attention to the architecture and training of the neural networks. However, to make this application popular and well accepted by structural engineers in Taiwan, adopting the original methodology using MATLAB software with Taiwan earthquake records become the main task of this study.

THE PROPOSED NEURAL NETWORK BASED METHODOLOGY

Neural networks are ideal for solving problems that do not have unique and mathematically precise solutions. Any neural network representing a functional association is only expected to learn that association approximately, over the range of parameters represented in the training cases. In this sense, the inverse problem investigated in this research can be stated as follows: Given a design or response spectrum, the proposed neural network based method will generate multiple accelerograms that are similar to the accelerograms with which it was trained. Besides, the objective of this study is to develop the methodology using neural networks (MATLAB toolbox) that are capable of generating multiple accelerograms for each input response spectrum of Taiwan area. We expect that the mean of the generated accelerogram should closely approximate the input response spectrum. Furthermore, the overall characteristics of the generated accelerograms (such as their duration and envelope) should be similar to those recorded earthquake accelerograms in Taiwan area used to train the neural networks.

Among the methodology developed by for Lin and Ghaboussi (2001), various types of the neural networks were used. The creation of the main neural network in the proposed method consists of three stages. In the first stage, a “replicator neural networks (RNN)” (as a data compression tool) is used to efficiently compress the Fourier spectra of the actual recorded earthquake accelerograms. Then, a “stochastic neural networks (SNN)” is used to relate the discrete response spectra to the compressed Fourier spectra in the second stage. Finally in the third stage, the SNN and the upper part of the RNN are combined to form a Multiple Accelerograms Generator Neural Network (MAGNN). The MAGNN is trained using a set of grouped recorded accelerograms and the performance of the trained MAGNN is evaluated by generating accelerograms using the input of several novel design spectra.

In this study, the MATLAB neural network toolbox is used to develop the RNN in the first stage (Lo, 2001). Then the SNN developed by Lin (Lin and Ghaboussi, 2001) using Fortran 90/95 is included at the second
Eventually, the Multiple Neural Network Accelerograms Generator (MNNAG) is formed and trained using a set of grouped recorded accelerograms in Taiwan area. The performance of the trained MNNAG is evaluated by generating accelerograms using the input of novel design spectra based on Taiwan’s construction code. The details of each stage are described in the following paragraphs.

**REPLICATOR NEURAL NETWORKS FOR DATA COMPRESSION**

The replicator neural network (RNN) is a unique 5 layers neural network. It consists of identical input and output layers and three hidden layers with a much smaller number of neurons specified in the middle hidden layer. The RNN is trained to replicate the same vector given at its input layer in its output layer. In 1996, Hecht-Nielsen indicated that the RNN performs a mapping from the $n$-dimensional input vector space to a unit cube in the $k$-dimensional vector space of the middle hidden layer, where $k$ is much smaller than $n$, and showed that the middle hidden layer of the RNN produces optimal source codes. To utilize this feature, the RNN is used to accomplish the data compression of the Fourier spectra from the earthquake accelerograms in this research. Both the real and imaginary parts of the Fourier spectra were used together to train the RNN for better efficiency (Lin and Ghaboussi, 2001).

The procedure for training and using the RNN is as follow: First, the Fourier spectrum of the earthquake accelerogram is computed using Fast Fourier Transform, and the real and imaginary parts of the Fourier spectrum are provided as input to the RNN. The input layer for the RNN has 4096 (2^{12}) nodes, which is the number of discrete points contained in the Fourier spectra, for the accelerogram with 80 sec duration. The output layer has the same number of nodes as the input layer. The RNN has three hidden layers with different activation functions within neurons (Hecht-Nielsen, 1996). The middle hidden layer, which is the compression layer, has around 40 nodes. The output of the RNN represents the real and imaginary parts of the Fourier spectrum of the replicated accelerogram.

The sixty earthquake accelerograms of Taipei Basin were used to train the RNN. The trained RNN was tested by presenting accelerograms as input and comparing them with the RNN replicated accelerograms. Comparisons (of both accelerogram and their response spectra) were first performed for the accelerograms in the training set, and then for novel accelerograms that were not included in the training set. The trained RNN generally learns the cases in its training set far more accurately than the novel cases. However, the trained RNN is able to produce reasonable results for the novel cases.

Each half of the trained RNN can be considered an independent neural network that performs a special function. The lower part of the RNN (input layer to the middle hidden layer) performs data compression while the upper part (middle hidden layer to the output layer) performs data decompression (Lin and Ghaboussi 2001). The activations of the middle hidden layer can be considered to represent the compressed Fourier spectra. It is the upper part of the trained RNN that are used in the MNNAG (Figure 1.).

**RANDOM VARIABILITY OUTPUT WITH STOCHASTIC NEURAL NETWORK**

Since 1985, researchers have introduced random variability in several neural networks in different ways. Some of the early neural networks, including the Boltzmann machine (Ackley et al 1985) and the Gaussian machine (Akiyama et al 1989), used probabilistic functions. Inspired by that, Lin proposed a stochastic neural network composed of a new type of stochastic neuron model in 1999. The proposed stochastic neuron is a modification of those used in the Gaussian machines. In this research, Lin’s stochastic neurons were implemented in the multi-layer feed-forward back propagation neural network to form the Stochastic Neural Network (SNN), which is able to produce the desired random variability in the output for earthquake ground motion applications. Lin’s (Lin and Ghaboussi, 2001) stochastic neuron model enables the neural network to escape from the local minima and is capable of generating different outputs according to a specified statistical distribution. The new stochastic neuron model is formed using the truncated normal distribution to the activation function of the neuron described in the following equations.
\begin{align}
U_i &= \sum_{j=1}^{\infty} W_{ij} V_j + I_i \\
f(U_i) &= \frac{1}{1 + \exp(-U_i)} + \epsilon \\
V_i &= \begin{cases} 
0 & \text{if } f(U_i) \leq 0 \\
1 & \text{if } f(U_i) \geq 1 \\
\text{otherwise} & 
\end{cases} \\
\end{align}

Where \( \epsilon \sim N(0, \tau^2) \) is the normal distribution with standard deviation \( \tau \) and temperature parameter \( \epsilon \).

The random variability from the compressed Fourier spectrum of the generated accelerogram is accomplished by the SNN, which learns to relate the response spectrum to the compressed Fourier spectrum of the accelerogram. The architecture of the SNN consists of four layers with stochastic neurons in the output and two hidden layers. The SNN are trained to generate a set of similar output with some random variability from a single input vector of a response spectrum. In going from the input layer to the output layer the signals pass through the stochastic neurons of different layers. Although the stochastic neurons produce some random variability in the output of the SNN, the mean value of the output ensemble should be very close to the output of a deterministic neural network due to the normal distribution and its standard deviation. As shown in Figure 2, given a design or response spectrum as its input, the SNN creates a random ensemble of output and produces multiple compressed Fourier spectra from a single design or response spectrum. Any of the compressed Fourier spectra can be used to generate an accelerogram by passing through the upper part of the RNN described in the previous section. The input layer of the SNN receives the values of the pseudo velocity response spectrum at discrete frequencies. The output layer has nodes representing the compressed Fourier spectrum. The number of nodes in the hidden layers of the SNN was determined during the training of the neural network using the adaptive architecture determination method (Joghataie, Ghaboussi and Wu, 1995). The SNN was also trained using the same earthquake accelerograms which were used to train RNN. Since Lin’s stochastic neurons will produce stochastically different output values during the training, the neural network will learn the underlying knowledge between the response spectra and the compressed Fourier spectra and store that knowledge in its connection weights. Given a single design or response spectrum as input, the SNN will generate multiple compressed Fourier spectra within reasonable range of error. The SNN performs an one-to-many inverse mapping task.

**MULTIPLE NEURAL NETWORK ACCEL. GENERATOR FOR TAIWAN AREA**

The Multiple Neural Network Accelerograms Generator (MNNAG) is developed to generate the real and imaginary parts of the Fourier spectra from synthesized accelerograms for Taiwan area from the vector of the pseudo velocity design spectrum at discrete frequencies. As shown in Figure 1, the MNNAG is composed of two neural networks. The lower four layers define the SNN and the upper three layers of the MNNAG is formed by the upper part of the RNN. When given a design spectrum as input, the lower part of the MNNAG (the SNN) generates many compressed Fourier spectra. Each of the compressed Fourier Spectra is passed through the upper part of the MNNAG (the upper part of the RNN), which outputs Fourier spectrum of the generated accelerogram for Taiwan area. This process allows the MNNAG to generate multiple reasonable artificial spectrum compatible earthquake accelerograms for Taiwan area from one design spectrum directly. The MNNAG was also trained using the CWB recorded earthquake accelerograms from Taiwan Strong Motion Instrumentation Program (TSMIP).

**EXAMPLE FOR TAIPEI BASIN**

The methodology proposed in this research has been applied to a data sample consisting of grouped earthquake accelerograms recorded in Taiwan area (training data set of the neural networks), and several design spectra for testing of the trained neural networks (test data set). All of these accelerograms were recorded from events with magnitudes greater than 5.0 and strength greater than 4
since 1993 in Taipei basin (Taiwan area). All of the accelerograms were discrete data at 0.02 seconds and the durations of the strong shaking were variable. Arbitrary durations of 81 seconds were chosen for all the accelerograms and sufficient points with zero amplitude were added at the end of each accelerogram to bring the total duration of all accelerograms to 80 seconds, which correspond to 4000 discrete points. For the purpose of computing the Fast Fourier Transforms of the earthquake accelerograms, the number of discrete point had to be extended to 4096 ($2^{12}$), again by adding zero amplitude points to the end of the accelerograms. The values of real and imaginary parts of the Fourier spectra are defined at 4096 discrete frequencies. Computing the Fast Fourier Transforms of the earthquake accelerograms produced the values of real and imaginary parts of the Fourier spectra. Only half of each of spectra were used because of symmetry on the Fourier spectrum. All the points were used as the input and output of the RNN since complete reversibility is essential.

The values of the response spectra were computed at 50 discrete frequencies, which were equally spaced within the frequency range of 0.02 and 50 Hz in log scale. All the design spectra used as input for testing the training neural networks were created following the seismic code of Taiwan. The values of the design spectra were also computed at 50 discrete frequencies equally spaced.

The trained RNN (lower part) was used to obtain the compressed Fourier spectra of the accelerograms in the training set. Then the compressed data and the response spectra of the earthquakes were then used to train the SNN. The trained neural networks were tested using the response spectra in the training set and then some novel design spectra. A comparison of the input and output accelerograms and their response spectra clearly indicates that the trained neural networks learned the training cases very well.

It is interesting that the trained neural network is capable of generating reasonable looking accelerograms from design spectra, even though it was trained with actual recorded earthquake accelerograms. A number of design spectra are presented as novel cases to the trained MNNAG. The MNNAG synthesized an ensemble of accelerograms such that the mean value of their response spectra closely approximates the input design spectrum for all frequencies. In Figure 2, the trained neural network is provided with a design response spectrum as input and the generated accelerograms and their response spectra are shown in the Figures 3 and 4. Even though the input design spectrum is conservative at long period region (displacement sensitive period), the neural network generated earthquake accelerograms is plausible and realistic looking. The generated accelerograms shown in Figures 3 are accelerograms with similar characteristics as those in the training set and their response spectra are very close to the input design spectrum although their individual response spectra in Figure 4 are not closely compatible with the input design spectrum. The average of all the response spectra is very close to the input design spectrum in the acceleration sensitive and velocity sensitive periods.

From this example the authors conclude that the trained MNNAG are capable of producing different but reasonable and realistic earthquake accelerograms from a single design spectrum for Taiwan area. This is a useful property of the neural network based methodology, in that it will enable the generation of accelerograms compatible with any specified design spectra. The generated accelerograms can then be used in time history analysis of linear and nonlinear structures.

**SUMMARY**

Generating spectrum compatible earthquake accelerogram using neural network were proved successfully in North America (Lin et al. 2001) and Himalayan Region (Pathak et al. 2004). If we can collect more recorded earthquake data in Taipei Basin or other area in Taiwan, and trained with proposed MNNAG for Taiwan Area, the more realistic artificial earthquake accelerogram can be provided. The neural network based methodology for generating multiple artificial spectrum compatible earthquake accelerogram has been presented and proved feasibly for Taiwan area. The RNN, which is simulated using the MATLAB NN toolbox, is trained to learn the data compression of the Fourier spectra from the accelerograms. The Lin’s stochastic neuron is included to form the SNN, which is trained to learn to associate the response spectra with the compressed Fourier spectra (using Fortran 90/95). The SNN is able to produce a random ensemble of output from a single input. The
multiple neural network accelerograms generator (MNNAG) is then formed by combining the upper part of the trained RNN and the trained SNN. The methodology was applied to a sample of recorded earthquake accelerograms in Taiwan area (Taipei basin). The results indicated that the MNNAG is able to synthesize one ensemble set of spectrum compatible and realistic looking accelerograms when given a single design spectrum as input.

It is envisioned that in the future applications of the proposed method many neural networks can be developed, each capable of generating accelerograms with specified characteristics, such as duration, distance from source and the source mechanism. Accelerograms can be grouped into different training sets by different region with specific site characteristics in Taiwan area. However, the performance is not as good as the neural network program developed by Lin using Fortran 90/95. A friendly user interface between structural engineer and MAGNN should be developed using Visual Basic or Visual C++. The neural network based methodology also offers a systematic way of processing and utilizing the increasingly large number of the earthquake accelerograms being recorded with each new earthquake, as well as providing a new direction of solving a difficult one-to-many inverse mapping problem by its stochastic feature.

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Figure 1. The methodology of MNNAG

Figure 2. Random variability output from SNN

Figure 3. Samples of generated accelerograms

Figure 4. Comparison of design spectrum with response spectra of generated accelerograms