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GENERATING AN ARTIFICIAL GROUND MOTION USING (RBF) NEURAL NETWORK AND WAVELET ANALYSIS

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ABSTRACT

This paper proposed a new method of constructing artificial ground motion using neural-network and wavelet packet capable of generating an earthquake accelerogram from response spectrum. In this study, the wavelet packet has been used by the best basis search algorithm. This method uses the learning capabilities of neural networks to develop the knowledge of inverse mapping from response spectra to earthquake accelerogram. In the proposed method the neural networks learn the inverse mapping directly from the actual recorded earthquake accelerograms and their response spectra. Several numerical examples of records in Iran are tested to verify the developed models.

Keywords: artificial ground motion, best basis algorithm, neural network, wavelet transform

Introduction

The seismic analysis of many important structures (such as power plants, dams, tall buildings, cable-stayed bridges, etc) is usually done using a step-by-step time history analysis. Dynamic behaviors of inelastic structures during an earthquake are very complex non-stationary processes which are expected by random characteristics of earthquake motions not only in the frequency domain but also in the time domain. In many cases a nonlinear dynamic analysis is done, which requires an accelerogram representative of an earthquake expected at the site. In some cases, it is desirable to develop an artificial earthquake accelerogram, or select an existing recorded accelerogram, compatible with a given response spectrum. Except for very few regions of the world where a set of recorded accelerograms are available, artificial earthquakes are used for the dynamic analysis (Suarez and Montejo 2005). Methods for generating realistic accelerograms are likely to become increasingly important, since the future design codes may require more non-linear dynamic analyses. However, most interesting signals contain numerous non-stationary or transitory characteristics and these characteristics are often the most important part of the signal, Fourier analysis is not suited to detecting them. In an effort to correct this deficiency, Dennis Gabor (1946) adapted Short-Time Fourier Transform (STFT), which maps a signal into a

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two-dimensional function of time and frequency (MATLAB 2004). While the STFT compromise between time and frequency information can be useful, many signals require a more flexible approach. Wavelet analysis represents the next logical step, a windowing technique with variable sized regions. Iyama and Kuwamura(1999), Mukherjee and Gupta (2002a, 2002b), Zhou and Adeli(2003) , Rajasekaran et al(2006), and Ghodrati Amiri et al. (2006) developed the wavelet analysis for generating earthquake accelerograms. Ghodrati Amiri et al. (2006) purposed to generate many artificial records compatible with the same spectrum by wavelet theory. In the other hand, empirical model had been developed with a fixed equation form based on the limited number of data. If new data is little different from original data, then only the regression coefficients with similar features that can be used for this purpose of model are usually modified. But if new data is quite different from original data, then the model should update not only its coefficients but also its equation form. However, artificial neural network (ANN) does not need a specific equation form and the clear internal relation of a function. Instead of that, it needs enough input–output data. Also, it can continuously re-train the new-recorded data and automatically accumulate new experience and knowledge, so that it can conveniently adapt to new data (Lee and Han (2002)). **ANN** has been investigated to deal with the problems involving incomplete or imprecise information. Several authors have used **ANN** in the structural engineering, especially in the structural dynamic problems. Ghaboussi and Lin (1998) proposed a new method of generating artificial earthquake accelerograms using neural networks also Ghodrati amiri et al.(2008) recently present a new methodology based on wavelet packet transform and stochastic neural networks to generate multiple artificial accelerograms that are compatible with target spectrum. A new method of generating artificial earthquake accelerogram is presented in this paper by using (RBF) neural network and wavelet packet.

WAVELET ANALYSIS

A wavelet is a waveform of effectively limited duration that has an average value of zero. Wavelet transform is a very new mathematical tool that cuts up signals into different frequency components, and then studies each component with a resolution matched to its scale (Daubechies 1992). The so called “scale” means the frequency band of the wavelet. The wavelet series used to analysis signals are expanded or shrunk by the mother wavelet automatically. Wavelet transform is a good tool adaptive to time-frequency analysis in earthquake engineering with good time-frequency discrimination ability, wavelet transform can improve the studies of earthquake engineering from conventional frequency spectrum analysis to more accurate time-frequency analysis. Both Fourier and wavelet analysis have limitations. Fourier analysis gives good results for regular periodic signals and wavelet analysis is suitable for highly non-stationary signals that possess sudden picks and discontinuities.

WAVELET PACKET ANALYSIS

The difference between wavelet and wavelet packets is that wavelet packets offer a more complex and flexible analysis, because in wavelet packet analysis, the details as well as the approximations are split. Wavelet packet atoms are waves indexed by time, scale, and frequency. For any orthogonal analyzing function, it is possible to generate a dictionary of wavelet packet bases. In fact the wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. (Strang and Nguyen (1996)).

OPTIMAL DECOMPOSITION

The wavelet packets can be used for numerous expansions of a given signal. The most suitable decomposition of a given signal with respect to an entropy-based criterion was selected. Single wavelet packet decomposition gives a lot of bases from, which can be looked for the best representation with respect to a design objective. It can be done by using an entropy-based criterion to select the most suitable decomposition of a given signal. The best basis algorithm described in Wickerhauser (1994), uses a minimum entropy criterion and gives the most concise description for a signal for the dictionary in hand. This can be done by finding the "best tree" based on an entropy criterion. The best basis search algorithm uses wavelet packets in this approach; the signal is expressed as a linear combination of time-frequency atoms. The atoms are obtained by dilations of the analyzing functions, and are organized into dictionaries as wavelet packets. Wavelet packet analyses have been performed because the coefficients thus obtained have many known uses, de-noising and compression being foremost among them. (Fig. 1)

ARTIFICIAL NEURAL NETWORK (ANN)

Neural networks are a biologically inspired soft computing method that possesses a massively parallel structure (Lin and Ghaboussi (2000)). The unique structure of neural networks gives rise to their learning capabilities, which sets them apart from other mathematically formulated methods, and allows the development of neural-network-based methods for certain mathematically intractable problems. Neural networks are formed by interconnecting many artificial neurons (Ghaboussi and Lin (1998)). It is the learning capabilities of neural networks which set them apart from other mathematically formulated methods, and allow the development of neural-network-based methods for certain mathematically intractable problems. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings. Neural networks are assemblages of interconnected artificial neurons, or nodes. Signals propagate along the connections and the strength of the transmitted signals depends on the numerical weights which are assigned to the connections. Each neuron receives signals along the incoming connection, performs some simple operations, such as calculating weighted sum of the incoming signals and calculating an activation function, and sends signals along its outgoing connections. The knowledge learned by a neural network is stored in its connection weights. The patterns used in training the neural network are called the training set. During the training, a neural network acquires the knowledge from the input-output pairs in the training set, and stores that knowledge in its connection weights. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Neural networks are ideal in dealing with problems which do not have unique and mathematically precise solutions (Lee and Han (2002)).

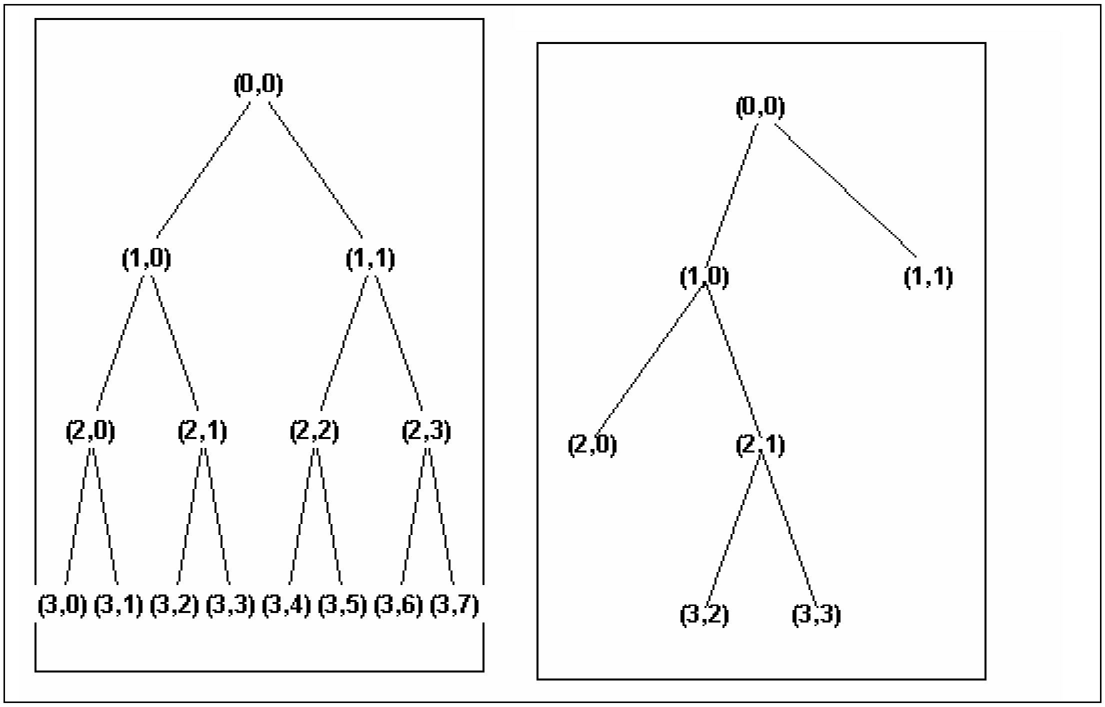

Figure 1: Wavelet packets tree structure and Wavelet packet best tree decomposition

PROPOSED METHODOLOGY

The objective of this study is to develop the methodology for training a new neural network that work with wavelet packet that are capable of generating artificial earthquake ground motion for each input response spectrum. In this paper an adaptive filtering algorithm, based on work by Coifman(1992) and Wickerhauser(1994) have been used. Such algorithms allow the Wavelet Packet tools to include "Best Tree" features that optimize the decomposition both globally and with respect to each node. After training the neural networks, the trained neural networks were tested with the records from the training group. The architecture of generalized regression neural networks was shown in figure 2. A comparison of the input and output earthquake accelerograms and their response spectra clearly indicate that the trained neural networks learned the training cases very well. The trained neural network was tested with the earthquake accelerograms from both the training set and the novel cases from the test set. Figure 3 show the performance of the trained neural network on one of the earthquake accelerograms from the training set and figure 4 show this performance on one test set**.** It is interesting to determine whether the trained neural network is capable of generating reasonable looking accelerograms from design spectra, even though it has been trained with actual recorded earthquake accelerograms. In Figure 5, the trained neural network is provided with a design response spectrum as input, and the generated accelerogram and its response spectrum are shown in the figure. The generated accelerogram is a plausible accelerogram with similar characteristics as those in the training set and its response spectrum is very close to the input design spectrum. This is a useful property of the neural network based methodology, in that it will enable 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.

ANALYTICAL SAMPLES

It is noted that records have been scaled with the maximum acceleration equal to g. Besides, response spectra are calculated by applying Naeim method with ζ=0.05: (Naeim (1999)). In this study, coefficients of wavelet packet and inversion are calculated with an adaptive filtering algorithm, based on work by Coifman (1999) and Wickerhauser (1994). Such algorithms allow the Wavelet Packet tools to include "Best Tree" features that optimize the decomposition both globally and with respect to each node. This study has been accomplished for 40 selected records of Iran with different type of soil (Ramezi (1997)). Table 1 shows list of training and testing records for neural network. It is noted that the records have been decomposed with db-10 wavelet. The 34 accelerograms were used for training and the 6 were used for testing. In this section, the proposed method has been applied with MATLAB software (MATLAB 2004), for neural networks. In this research all records are considered with discrete times of Δt=0.02 sec, and 2^{11}=2048 points consequently.

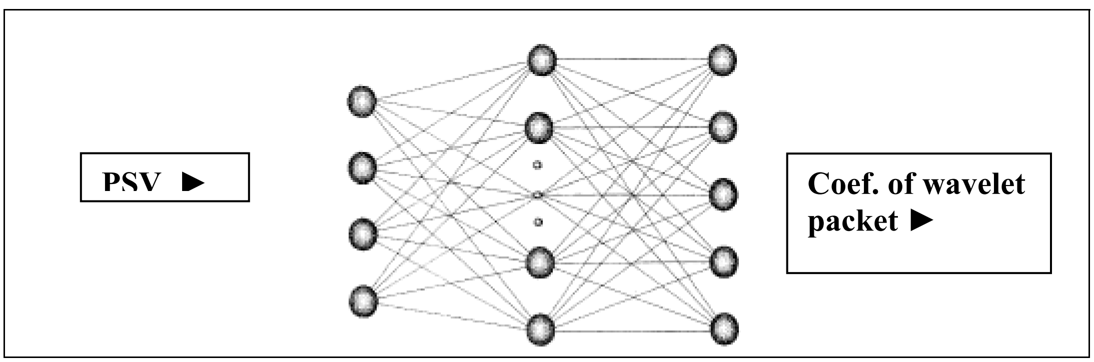

Figure 2: The architecture of studied neural network

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CONCLUSION

In this study, a method of applying neural network with wavelet packet transform for generation of artificial ground motion from pseudo-velocity response spectra is developed. This method shows with computation of the best tree for given entropy, the optimal wavelet packet tree is computed and then by use a trained neural network an artificial ground motion with inverse wavelet packet can be taken. The advantages of this method can be summeraized as follows:

1- High flexibility, so it is possible to answer to a certain input with only a few patterns.

2- High training pace, in a way that it is possible to train all networks in less than a few minutes.

3- Proper use of wavelet packets for thorough identification and extraction of frequency characteristics of each record

Table 1: Data of selected base accelerograms (Ramezi (1997)).

NUMBER	OCCURANCE DATE	NAME OF STATION	AGNITUDEM	MODIFIED PGA (cm/s^2)	GROUND TYPE (TABLE 2)	DURATION (Sec)
1	1976.11.07	Ghaen	6.4	115		19.54
2	1977.03.21	Bandar Abbas	6.9	90	IV	45.22
3	1977.40.06	Naghan	6.1	700	I	20.96
4	1978.09.16	Dayhouk	6.7	272	I	58.38
5	1978.09.16	Tabas	7.3	832	II	49
6	1978.09.16	Bajestan	7.3	78	III	39.58
7	1978.11.04	Moshtabar	6.2	171		18.96
8	1979.01.16	Khaf	6.8	69	III	32.42
9	1978.09.16	Ferdos	7.3	76	IV	53
10	1979.11.27	Kashmar	7.1	70	III	67.92
11	1979.11.27	Bajestan	7.1	104	III	33.20
12	1979.11.27	Ghaein	7.1	186		30.16
13	1979.11.27	Taeibad	7.1	75	III	60
14	1979.11.27	Ghonabad	7.1	69	IV	50.52
15	1979.11.27	Khaf	7.1	127	III	58.04
16	1981.07.28	Gholbaf	7	217	III	59.32
17	1984.06.01	Shalamzar	5	299	III	18.66
18	1985.02.02	Gheer	5.3	290	I	15.34
19	1988.12.06	NourAbad	5.6	85	III	17.28
20	1990.06.20	Abhar	7.7	127		29.48
21	1990.06.20	Roudsar	7.7	91	IV	53.10
22	1990.06.20	Lahijan	7.7	111	IV	60.54
23	1990.06.20	Tonekabon	7.7	130	IV	35.94
24	1990.06.20	Ghachsar	7.7	63		49.48
25	1990.06.20	Zanjan	7.7	125	III	59.78
26	1990.06.20	Robat Kareem	7.7	64	III	12.58
27	1990.06.20	Eshtehard	7.7	71		45.78
28	1991.11.28	Roudbar	5.7	268	I	19.94
29	1994.06.20	Meymand	6.1	394		27.14
30	1994.03.20	Zarrat	5.5	196	I	33.24
31	1994.06.20	zarrat	5.9	289	I	43.50
32	1994.06.20	Firouz Abad	5.9	235	II	38.36
33	1994.06.20	Zanjeeran	5.9	841	II	63.98
34	1994.01.24	Feen	4.9	433		31.96
35	1976.11.24	Mako	7.3	86	I	28.06
36	1977.03.21	Band arAbas	6.9	98	IV	41.06
37	1979.11.14	Khaf	6.8	74	III	39.20
38	1980.01.12	Tabas	5.8	150	II	29.74
39	1979.11.27	Khezri	7.1	94	IV	35.98
40	1981.07.28	Kerman	7	98		38.04

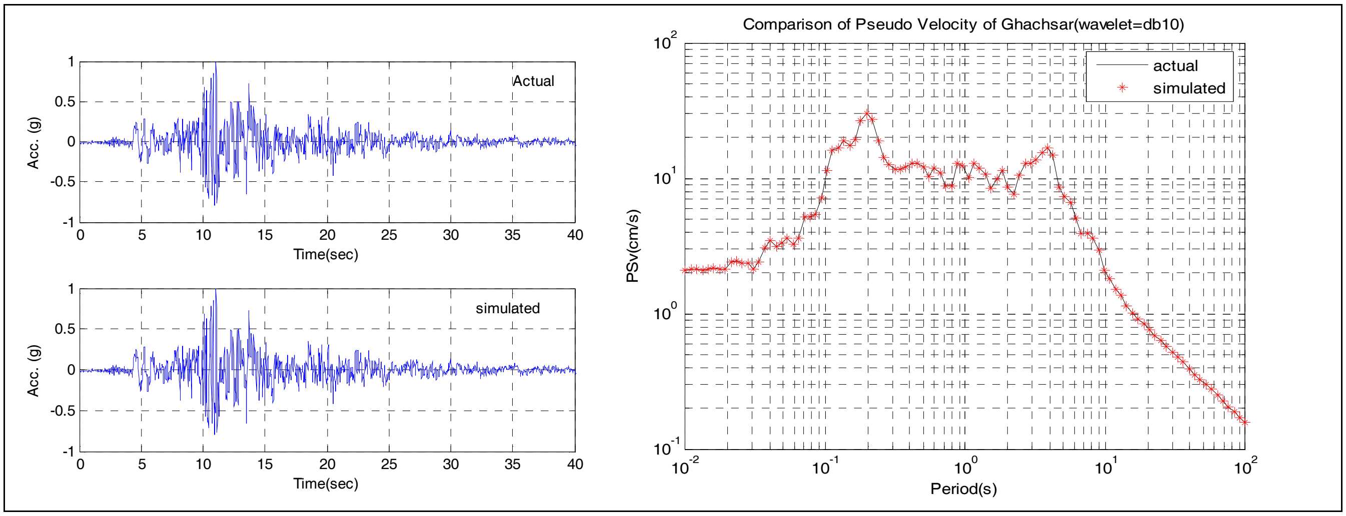

Figure 3 : Accelerogram of Tabas 1978 earthquake (<u>training data</u>) and its pseudo-velocity response spectra of original and generated accelerograms

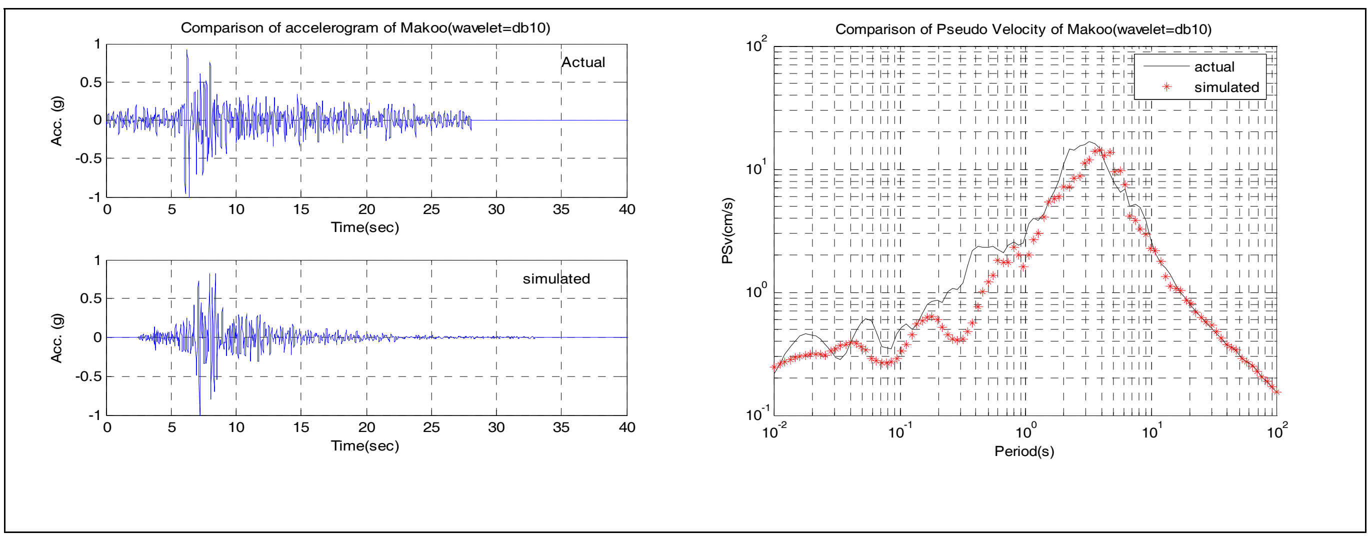

Figure 4: Accelerogram of Makoo 1976 earthquake (<u>test data</u>) and its pseudo-velocity response spectra of original and generated accelerograms

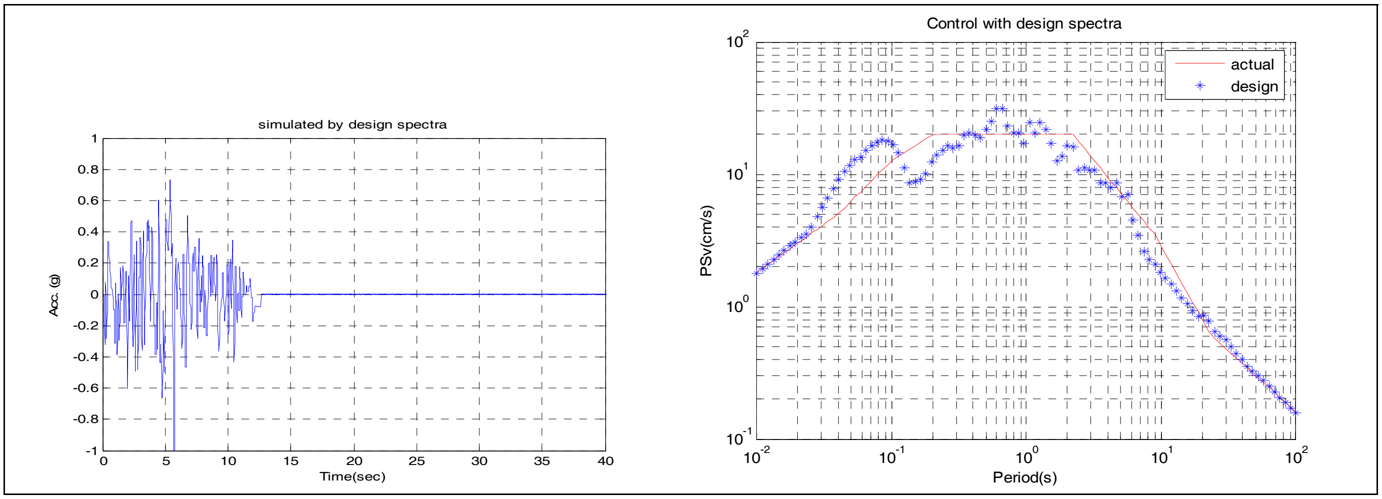

Fig. 10 Neural network generated accelerogram and comparison between design spectrums with pseudo-acceleration response spectrum

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