Structural Engineering and Mechanics, Vol. 37, No. 6 (2011) 575-592
DOI: http://dx.doi.org/10.12989/sem.2011.37.6.575

Application of neural networks and an adapted wavelet packet for generating artificial ground motion

A. Asadi[1a], M. Fadavi[2b], A. Bagheri[3c] and G. Ghodrati Amiri*[3]

[1]*Department of Civil Engineering, Yazd University, Yazd, Iran*
[2]*Department of Computer Engineering, Shomal University, Amol, Iran*
[3]*Center of Excellence for Fundamental Studies in Structural Engineering, School of Civil Engineering, Iran University of Science & Technology, PO Box 16765-163, Narmak, Tehran 16846, Iran*

(Received August 15, 2009, Accepted November 17, 2010)

Abstract. For seismic resistant design of critical structures, a dynamic analysis, either response spectrum or time history is frequently required. Owing to the lack of recorded data and the randomness of earthquake ground motion that may be experienced by structure in the future, usually it is difficult to obtain recorded data which fit the requirements (site type, epicenteral distance, etc.) well. Therefore, the artificial seismic records are widely used in seismic designs, verification of seismic capacity and seismic assessment of structures. The purpose of this paper is to develop a numerical method using Artificial Neural Network (ANN) and wavelet packet transform in best basis method which is presented for the decomposition of artificial earthquake records consistent with any arbitrarily specified target response spectra requirements. The ground motion has been modeled as a non-stationary process using wavelet packet. This study shows that the procedure using ANN-based models and wavelet packets in best-basis method are applicable to generate artificial earthquakes compatible with any response spectra. Several numerical examples are given to verify the developed model.

Keywords: artificial ground motion; wavelet packet transform; best basis algorithm; generalized regression neural network; target spectrum.

1. Introduction

The major imperfect of the response spectrum analysis in seismic design of structures lies in its inability to provide temporal information of the structural responses. Such information is sometimes necessary in achieving a satisfactory design. Because of the complex nature of the formation of seismic waves and their travel path before reaching recording station, and considering lack of enough earthquake records, generation of artificial earthquake recodes is the best method in this regard. The natural phenomena are usually nonlinear and the majority of the signals have changing frequency contents so separated time analysis and frequency analysis by themselves do not fully

*Corresponding author, Professor, E-mail: ghodrati@iust.ac.ir
[a]Assistant Professor, E-mail: aasadi@yazduni.ac.ir
[b]Faculty Member, E-mail: fadavi@shomal.ac.ir
[c]Graduate Student, E-mail: abbagheri@hotmail.com

describe the nature of these non-stationary dynamic loads. However, a rigorous detailed study on the dynamic behavior of a linear or nonlinear structure requires a time domain analysis along with the use of an accelerogram consistent with the design response spectra of the particular site under investigation.

The problem of generating such artificial accelerograms has been studied by researches using a variety of methods (Karabalis *et al.* 2000). The natural phenomena are usually nonlinear and the majority of the signals have changing frequency contents. There are, however, several instances where acceleration time histories are required as seismic input instead. For example, to determine the ultimate resistance and to identify modes of failure of structures, a nonlinear time history analysis is needed. In other cases, acceleration time histories are required for linear analyses. For instance, many seismic codes require this type of analysis for buildings witch pronounced irregularities. In these cases, it is common to use acceleration time histories whose response spectra are compatible with the code-prescribed design spectrum. To provide input excitations to structural models for sites with no strong ground motion data, it is necessary to generate artificial accelerograms. It has long been established that due to parameters such as geological conditions of the site, distance from the source, fault mechanism, etc. different earthquake records show different characteristics. Thus, the simulated earthquake records must have realistic duration, frequency content, and intensity, representing the physical conditions of the site (Refooei *et al.* 2001). Thus, there is need for generating ensembles of realistic artificial earthquake ground motion to cover a variety of uncertainties in seismic design of structures (Fan and Ahmadi 1990).

Spectral analysis using the Fourier Transform has been one of the most important and most widely used tools in earthquake engineering. Over the past few years, however, researchers have become aware of the limitations of this technique, especially in the case of non-stationary signals, and of nonlinear systems (Jaffard *et al.* 2001). As a new method with obvious advantage for time-frequency analysis, wavelet transform is now applied in many fields of study. Wavelet transform is a good tool adaptive to time-frequency analysis in earthquake engineering with good time-frequency discrimination ability (Benedetto and Frazier 1994). Wavelet transform can improve the studies of earthquake engineering from conventional frequency spectrum analysis to more accurate time-frequency analysis. With good time-frequency discrimination ability and flexible time-frequency windows, wavelet transform are now widely used to analysis various signals in time and frequency domain simultaneously.

The recently developed wavelet analysis has emerged as a powerful tool to analyze temporal variations in frequency content. Recent applications of the wavelet transform to engineering problems can be found in several studies that refer to dynamic analysis of structures, damage detection, system identification, etc. Newland (1994) applied wavelets for analyzing vibration signals, and developed special wavelets and techniques for engineering purpose. Ghodrati Amiri *et al.* (2006, 2007, 2008), Ghodrati Amiri and Bagheri (2008), Suarez and Montejo (2005, 2007), Rajasekaran *et al.* (2006), Hancock *et al.* (2006), Mukherjee and Gupta (2002a, b) and Iyama and Kuwamura (1999) developed the wavelet analysis for generating earthquake accelerograms.

In the other hand, 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. Recently, Ghaboussi and Lin (1998), Lin and Ghaboussi (2000), Lee and Han (2002), Rajasekaran *et al.* (2006), Ghodrati Amiri and Bagheri (2008) and Ghodrati Amiri *et al.* (2008) have developed innovative methodologies for the generation of artificial earthquake accelerograms using neural networks. Lin and Ghaboussi (2000) proposed using stochastic neural networks to generate the same artificial accelerogram compatible with the response spectrum. Ghodrati Amiri and Bagheri (2008) proposed generating one artificial accelerogram compatible with the response spectrum using wavelet theory and radial basic function neural networks. Ghodrati Amiri *et al.* (2008) proposed to generate multiple spectrum compatible earthquake accelerograms using the wavelet packet transform and stochastic neural networks.

In this paper, the decomposing capabilities of wavelet packet with best-basis transform and the learning abilities of Generalized Regression Neural Network (GRNN) are used to develop a method for generating accelerogram from response spectra. The proposed method validated using 40 accelerograms to train the neural networks. The performance of the trained GRNN is estimated by generating accelerogram for new response spectra and design spectra.

2. Overview on wavelet packet transform

Wavelet transform is a mathematical tool, which transforms sequential data in time axis such as earthquake accelerations to spectral data in both time and frequency. Therefore, wavelet transform provides information on non-stationary time dependent intensity of motions regarding a particular frequency of interest. Wavelets are mathematical functions that cut up data or function into different frequency components, and then study each component with a resolution matched to its scale (Benedetto and Frazier 1994). Wavelets, which are oscillatory functions of zero mean and of finite energy, can be used to obtain a time-frequency representation of a process.

As a result of decomposition of only the approximation component at each level using the dyadic filter bank, the frequency resolution in higher-level e.g., A1 and D1 (Fig. 1). Discrete Wavelet Transform (DWT) decompositions in a regular wavelet analysis may be lower. It may cause problems while applying DWT in certain applications, where the important information is located in higher frequency components. The frequency resolution of the decomposition filter may not be fine enough to extract necessary information from the decomposed component of the signal. The necessary frequency resolution can be achieved by implementing a wavelet packet transform to decompose a signal further. The wavelet packet analysis is similar to the DWT with the only difference that in addition to the decomposition of only the wavelet approximation component at

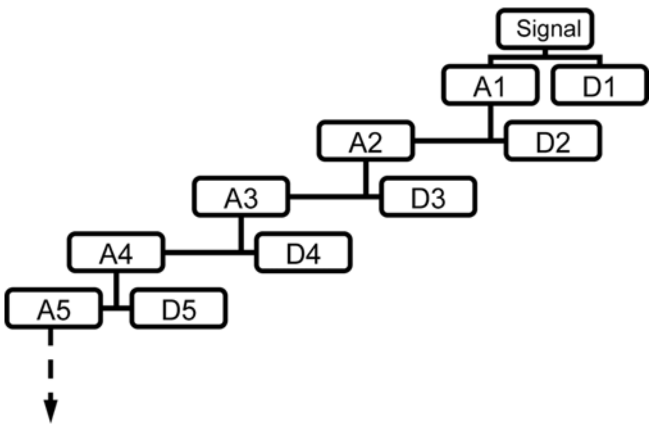

Fig. 1 Wavelet decomposition tree

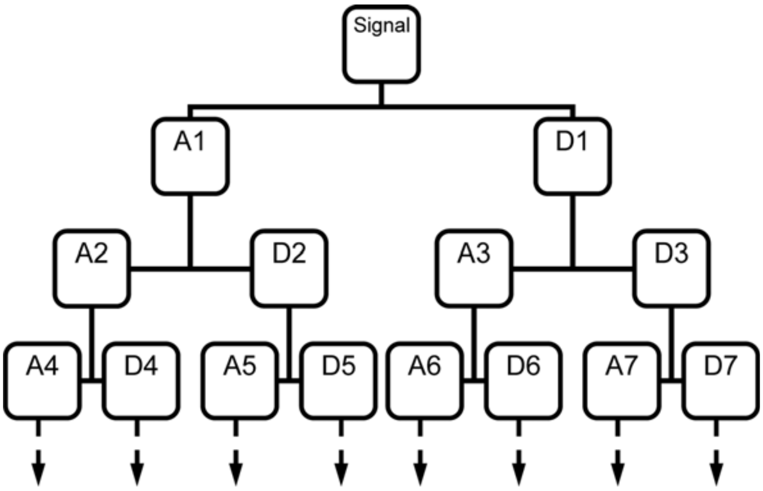

Fig. 2 Wavelet Packet decomposition tree

each level, a wavelet detail component is also further decomposed to obtain its own approximation and detail components as shown in Fig. 2.

Each component in this wavelet packet tree can be viewed as a filtered component with a bandwidth of a filter decreasing with increasing level of decomposition and the whole tree can be viewed as a filter bank. At the top of the tree, the time resolution of the WP components is good but at an expense of poor frequency resolution whereas at the bottom of Thus with the use of wavelet packet analysis, the frequency resolution of the decomposed component with high frequency content can be increased. As a result, the wavelet packet analysis provides better control of frequency resolution for the decomposition of the signal (Abhijeet Shinde 2004).

A wavelet packet function $\psi_{j,k}^{i}(t)$ is defined as (Ogden 1997)

$$\psi_{j,k}^{i}(t) = 2^{j/2}\psi^{i}(2^{j}t-k) \tag{1}$$

where j and k are the scaling parameter and the translation parameter, respectively; $i = 0, 1, \ldots$ is the oscillation parameter; and $\psi^{i}(t)$, without any subscript, is understood to be $\psi_{j,k}^{i}(t)$ with $j = k = 0$.

The wavelet is obtained by the following recursive relationships

$$\psi^{2i}(t) = \frac{1}{\sqrt{2}}\sum_{k=-\infty}^{\infty} h(k)\psi^{i}\left(\frac{t}{2}-k\right) \tag{2}$$

$$\psi^{2i+1}(t) = \frac{1}{\sqrt{2}}\sum_{k=-\infty}^{\infty} g(k)\psi^{i}\left(\frac{t}{2}-k\right) \tag{3}$$

where $\psi^{i}(t)$ is called as a mother wavelet and the discrete filters $h(k)$ and $g(k)$ are quadrature mirror filters associated with the scaling function and the mother wavelet function. These two filters, $h(k)$ and $g(k)$, are also called group-conjugated orthogonal filters (Fan and Zuo 2006).

The wavelet packet coefficients C corresponding to the signal $f(t)$ can be obtained as

$$C^i_{j,k} = \int_{-\infty}^{\infty} f(t)\,\psi^i_{j,k}(t)dt \tag{4}$$

Provided the wavelet coefficients satisfy the orthogonality condition.

The wavelet packet component of the signal at a particular node can be obtained as

$$f^i_j(t) = \sum_{k=-\infty}^{\infty} c^i_{j,k}\psi^i_{j,k}(t)dt \tag{5}$$

After performing wavelet packet decomposition up to jth level, the original signal can be represented as a summation of all wavelet packet components at jth level as shown in equation

$$f(t) = \sum_{i=1}^{2^j} f^i_j(t) \tag{6}$$

In wavelet packet, standard structure composed of low and high pass filters is used in perfect reconstruction filter bank (Strang and Nguyen 1996).

2.1 Best basis algorithm in wavelet packet transform

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.

The best basis search algorithm uses wavelet packets. In this model 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. 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. The application of the best basis search for the wavelet packet dictionary is equivalent to an optimal filtering of the signal. For any given signal, the best basis algorithm decides which base represents the signal more efficiently. Comparisons with other methods of analysis such as wavelet analysis using harmonic wavelets and classic Fourier analysis have been conducted. As expected, this adaptive method gives better results (Ghodrati Amiri and Asadi 2009). Wavelet packet atoms are waveforms indexed by three naturally interpreted

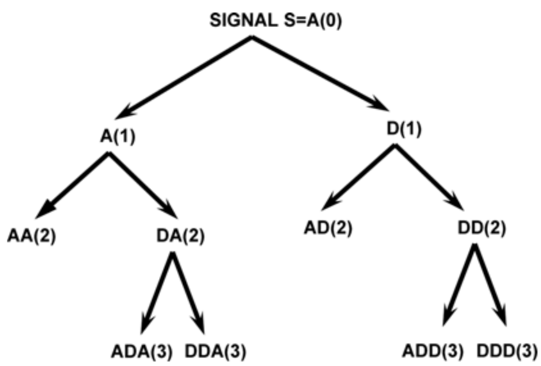

Fig. 3 Wavelet packet tree (Best-tree)

parameters: position, scale (as in wavelet decomposition), and frequency. For a given orthogonal wavelet function, a library of bases can be generated called wavelet packet bases. Each of these bases offers a particular way of coding signals, preserving global energy, and reconstructing exact features. The wavelet packets can be used for numerous expansions of a given signal. The most suitable decomposition of a given signal can be selected with respect to an entropy-based criterion. The application of the best basis search for the wavelet packet dictionary is equivalent to an optimal filtering of the signal. For any given signal, the best basis algorithm decides which base represents the signal more efficiently (Fig. 3).

3. Artificial neural networks

Neural networks are biologically inspired soft computing methods that possess a massively parallel structure. Neural networks are ideal for solving problems that do not have unique and mathematically precise solutions proposed method (Ghaboussi and Lin 1998). Neural networks solve complex problems by training sets. Neural networks have been used as an effective method for solving engineering problems in a wide range of application areas (Haykin 1998). Neural networks include the following important topics that are useful for complex problem solving such as nonlinearity, input-output mapping, adaptability, evidential response, and contextual information (Ghaboussi 1999).

3.1 Generalized regression neural networks

GRNNs are feed-forward networks trained using a supervised training algorithm. A generalized regression neural network is often used for function approximation. This network may require more neurons than standard feed-forward back-propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available. Generalized regression neural network have several advantages, for example they usually train much faster than back propagation networks and also they are less susceptible to problems with non-stationary inputs because of the behavior of the radial basis function hidden units. The architecture of generalized regression neural networks as was shown in Fig. 4 contains three layers: input and output layers and one hidden layer.

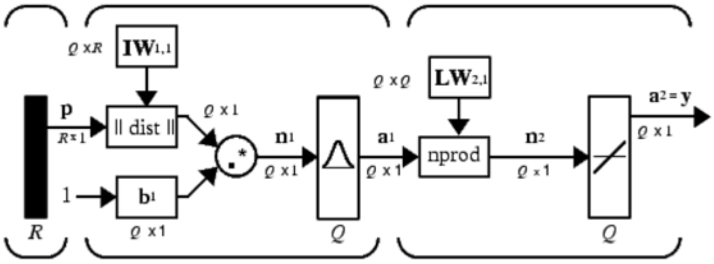

Fig. 4 The architecture of GRNN

4. Proposed methodology

Although the recently developed wavelet analysis has emerged as a powerful tool to analyze temporal variations in frequency content that traditional approaches miss, but 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. Other approaches have been examined, and several algorithms and analyzing functions have been proposed (Jaffard *et al.* 2001). One of them is the best basis search algorithm which using wavelet packets. As were shown the wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. 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. The best basis algorithm uses a minimum entropy criterion and gives the most concise description for a signal for the dictionary in hand.

The main objective of this study is to present a new way based on wavelet packet transform in best basis algorithm and GRNN to generate artificial accelerograms which has a response spectrum close to a specified response spectrum used as the input of the neural network. Further, the accelerogram generated from a given response spectrum should also have the characteristics like the group of accelerograms used in the training of the neural network. The suggested method is based on expanding a GRNN which takes discretized ordinates of the pseudo-velocity response spectrum of accelerogram as input, and the output of the neural network produces the wavelet packet coefficients of the earthquake accelerograms in best basis method with defined entropy.

Fig. 5 shows the proposed method for generating accelerograms compatible with response or design spectrum. In the first step, wavelet packet transform is used to decompose earthquake accelerograms to several levels that each level covers a special range of frequencies. It was interesting that by using wavelet packet transform with best basis method and choosing only one coefficient the results are too near to actual signal. So in this research only one network is proposed that gives only the nodes with the maximum energy in wavelet packet tree with best basis algorithm. After training the neural network, the trained neural network was tested with the records from the training group. The trained neural network was tested by using the training response spectra. A comparison of the input and output earthquake accelerograms and their response spectra clearly indicate that the trained neural network learned the training cases very well.

As was shown in Fig. 5 the input layer of neural network has the pseudo-velocity response spectrum of accelerogram

$$PSV(\omega, \xi) = \omega \max_t |x(t)| \tag{7}$$

$$\ddot{x}(t) + \zeta\omega_i\dot{x}(t) + \omega_i^2 x(t) = -\ddot{x}_g(t) \tag{8}$$

where ω, ξ and $\ddot{x}_g(t)$ are the fundamental frequency and the damping ratio of the single degree of freedom system and the earthquake ground acceleration, respectively.

The input layer of the GRNN has 100 nodes; because they receive the values of the pseudo-velocity response spectrum of accelerogram at 100 discrete frequencies.

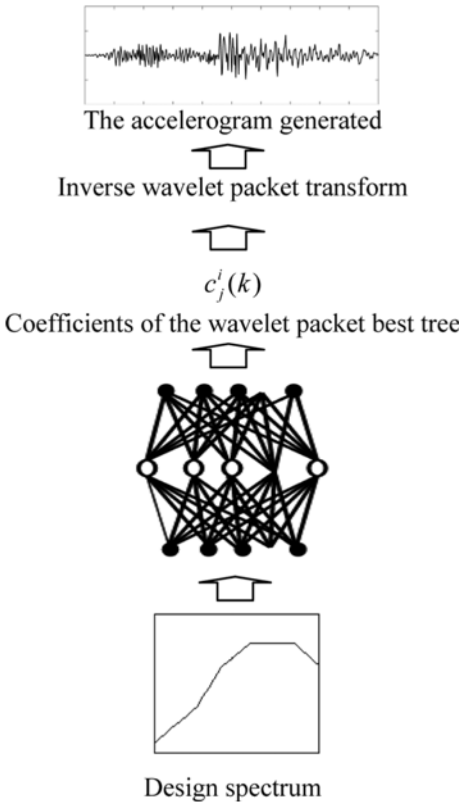

Fig. 5 The proposed method for generating accelerogram

The output layer of GRNN has the wavelet packet coefficients in best tree with maximum energy. Wavelet packet coefficients of the earthquake ground acceleration $\ddot{x}_g(t)$ are embedded in the inner product of the earthquake ground acceleration with every wavelet packet function, and given below

$$c_j^i(k) = \sum_{k=-\infty}^{+\infty} \ddot{x}_g(t)\,\psi_{j,k}^i(t) \tag{9}$$

where $c_j^i(k)$ denotes the ith set of wavelet packet decomposition coefficients at the jth scale parameter and k is the translation parameter.

The Daubechies wavelet mother of a high order which is used in this study gives a relatively small overlap, which means that it has a good resolution in the frequency domain. Based on resent work (Ghodrati Amiri and Asadi 2009) the DB10 was chosen as mother wavelet so that it gives more better and efficient results because of its orthogonality and satisfactory resolution in both time and frequency.

There are many variations of algorithms for training of neural networks. Faster algorithms are divided into two categories. The first category uses heuristic techniques, which were developed from an analysis of the performance of the standard steepest descent algorithm. The second

Table 1 Data of selected base accelerograms (Ramezi 1997)

Number	Occurance date	Name of station	Magnitude (Ms)	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	Bandar Abas	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

category of fast algorithms uses standard numerical optimization techniques. In this study, the fast algorithm of Levenberg-Marquardt applied for training of neural network.

The GRNN was trained by 34 earthquake accelerograms shown in Table 1. Given a response spectrum as input, the GRNN will produce multiple wavelet packet coefficients and the generated accelerograms using inverse wavelet packet transform are obtained.

The wavelet packet component of the generated accelerogram $\ddot{x}_{g\ j}^{s\ i}(t)$ can be represented by a linear combination of wavelet packet functions $\psi_{j,k}^{i}(t)$ as follows

$$\ddot{x}_{g\ j}^{s\ i}(t) = \sum_{k=-\infty}^{+\infty} c^{s\ i}_{\ j}(k)\,\psi_{j,k}^{i}(t) \tag{10}$$

where $c^{s\ i}_{\ j}(k)$ is the wavelet packet decomposition coefficient of the generated accelerogram by GRNN.

Finally, the generated accelerogram $\ddot{x}_g^s(t)$ can be obtained as

$$\ddot{x}_g^s(t) = \sum_{i=1}^{2^j} \ddot{x}_{g\ j}^{s\ i}(t) \tag{11}$$

5. Analytical sample

The most important issue related to most neural networks is the lack of proper educational records. Various records have been registered and modified in different centers in Iran for past years. Usage of accelerogram for training is not proper, since selected records have to include information related to a relatively strong and noticeable earthquake. Therefore, this proposed method for generating accelerogram compatible with response or design spectrum in this study has been applied to a sample including 40 selected records of Iran with different type of soil (Ramezi 1997). As was shown the type of soil has no influence in results. Tables 1 and 2 show lists of

Table 2 Ground classification according to “Iranian Earthquake Code of practice, Standard No. 2800”

Ground type	Explanation of materials	Shear wave velocity (m/s)
I	Un-weathered igneous rocks, hard sedimentary rocks and metamorphic rocks (as gneisses and crystalline silicate rocks) Very hard conglomerates very compact and very hard sediment	Vs > 750
II	Soft igneous rocks e.g., tuffs, clay stones, shale and semi-weathered or altered rocks Crushed (but not hardly) hard rocks , foliated metamorphic rocks, conglomerate and compact sand and gravel	375 < Vs < 750
III	Weathered rocks, semi-compact sands and gravels, other compact sediments Compact sandy clay soils, with low ground water level	175 < Vs < 375
IV	Soft sediments, clay soils, weak cemented and un-cemented sands, incompact soils with high ground water level Any kind of soft soils	Vs < 175

training and testing records for neural network and the type of their soil (Iranian Code 2006), respectively. These records were scaled with their peak ground acceleration to 1g. Besides, response spectra are calculated with $\zeta = 0.05$ and the values of the pseudo-velocity response spectra were calculated at 100 discrete frequencies. It is noted that the records have been decomposed with db-10 wavelet. The 34 accelerograms were used for training and the 6 accelerograms were used for testing. In this section, the proposed method has been applied with MATLAB software for neural networks. All records have $\Delta t = 0.02$ sec, and $2^{11} = 2048$ points consequently. Therefore, a series of zeros is added to the records which are shorter than desired length ($2048 \times 0.02 = 40.96$ sec) to gain proper length and for the longer ones, the strong duration of records of longer length is considered according to MacCann and Shah Algorithm (1979). The output layers of neural networks have the

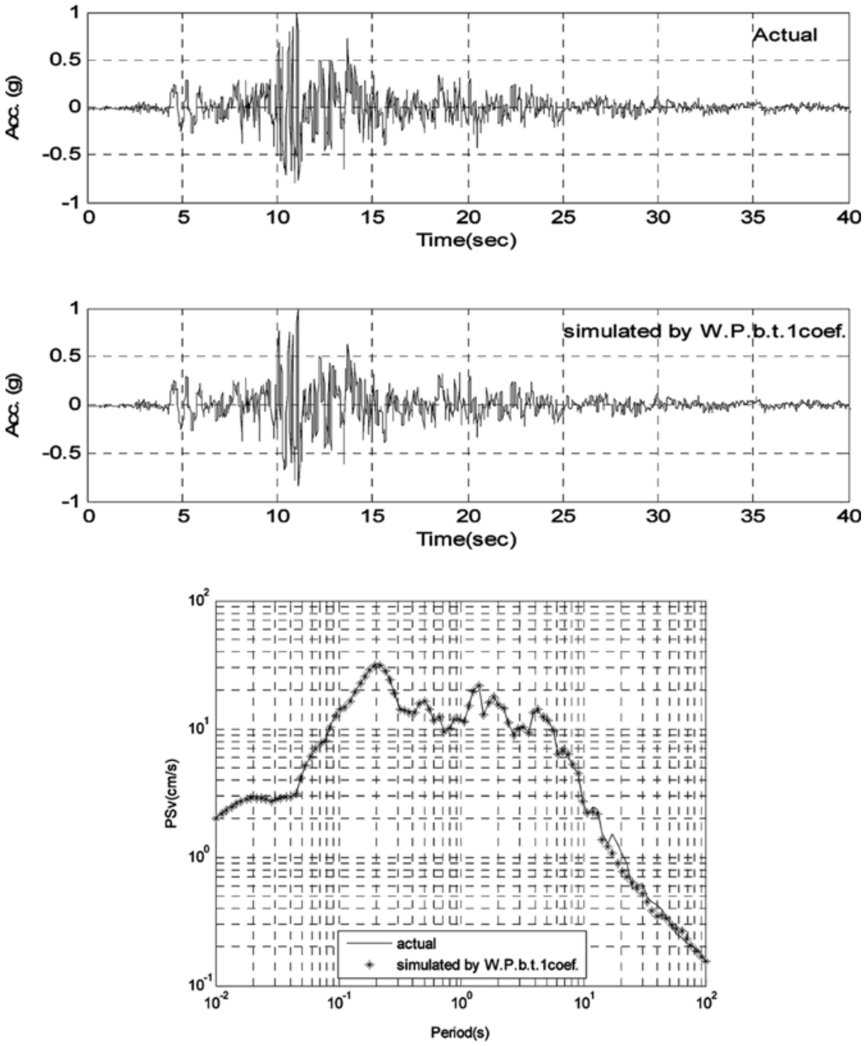

Fig. 6 Accelerogram of Tabas 1978 earthquake (top), neural network generated accelerogram (middle) and comparison between pseudo-acceleration response spectra of original and generated accelerograms (below)

wavelet packet coefficients best tree of the wavelet packet transform of the earthquake accelerograms. In this section, 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. By the results of our last paper (Ghodrati Amiri and Asadi 2009) here the third level of the wavelet packet transform was chosen and used so eight neural networks were trained. After training the neural network, the trained neural network was tested with the records from the training group. The trained neural network was tested by using the training response spectra.

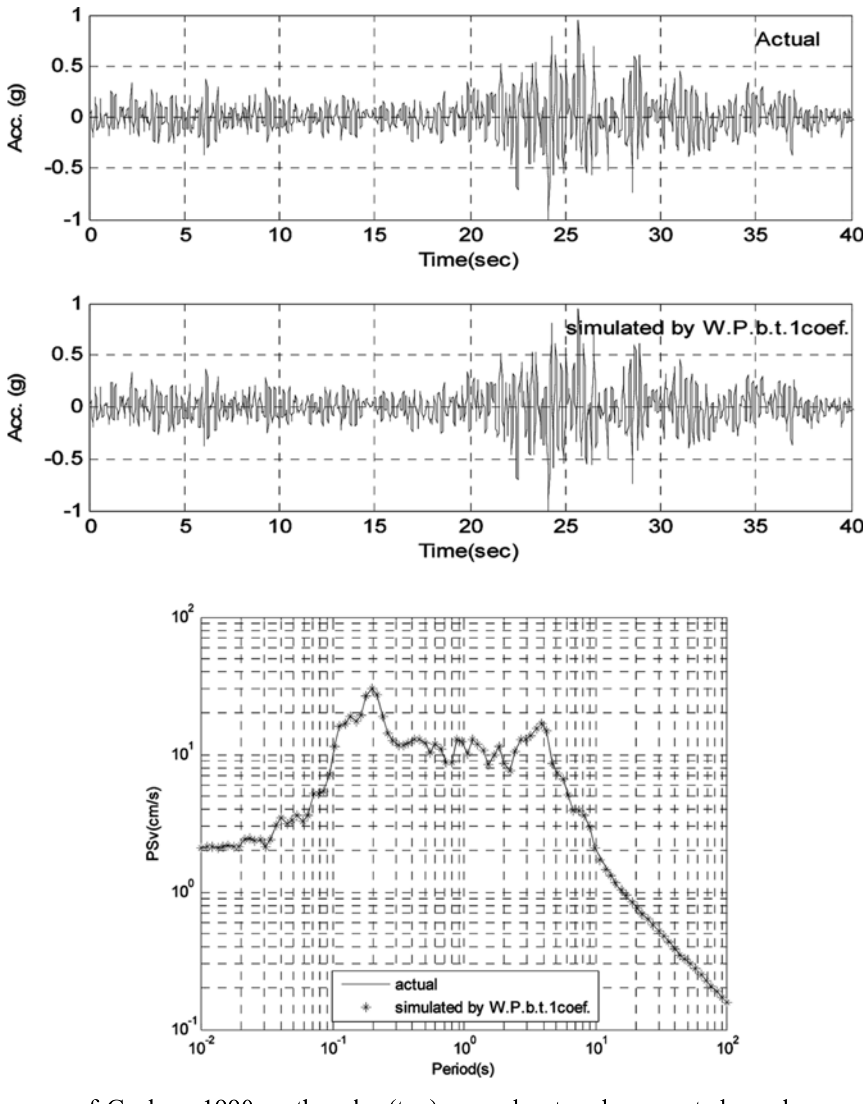

Fig. 7 Accelerogram of Gachsar 1990 earthquake (top), neural network generated accelerogram (middle) and comparison between pseudo-acceleration response spectra of original and generated accelerograms (below)

A comparison of the input and output earthquake accelerograms and their response spectra clearly indicate that the trained neural network learned the training cases very well. Figs. 6-8 show the performance of the trained neural network on two of the earthquake accelerograms from the training set Figs. 6-8 shows the results of Tabas, Gachsar and Rudbar-1, tests of the trained neural networks from the training group, with comparison of the actual and generated accelerograms, and their pseudo-velocity response spectra clearly displays that the trained neural networks have learnt the training cases very well.

In case there are no earthquake accelerograms in the neural network's training set which have a response spectrum close to the input response spectrum, the trained neural network generates a reasonable accelerogram shape from its training set.

Figs. 9-10 show tests of trained neural networks with novels accelerogram with the accelerogram of Bandar Abas 1977 and Khaf 1979 earthquakes and the generated accelerograms are very close to

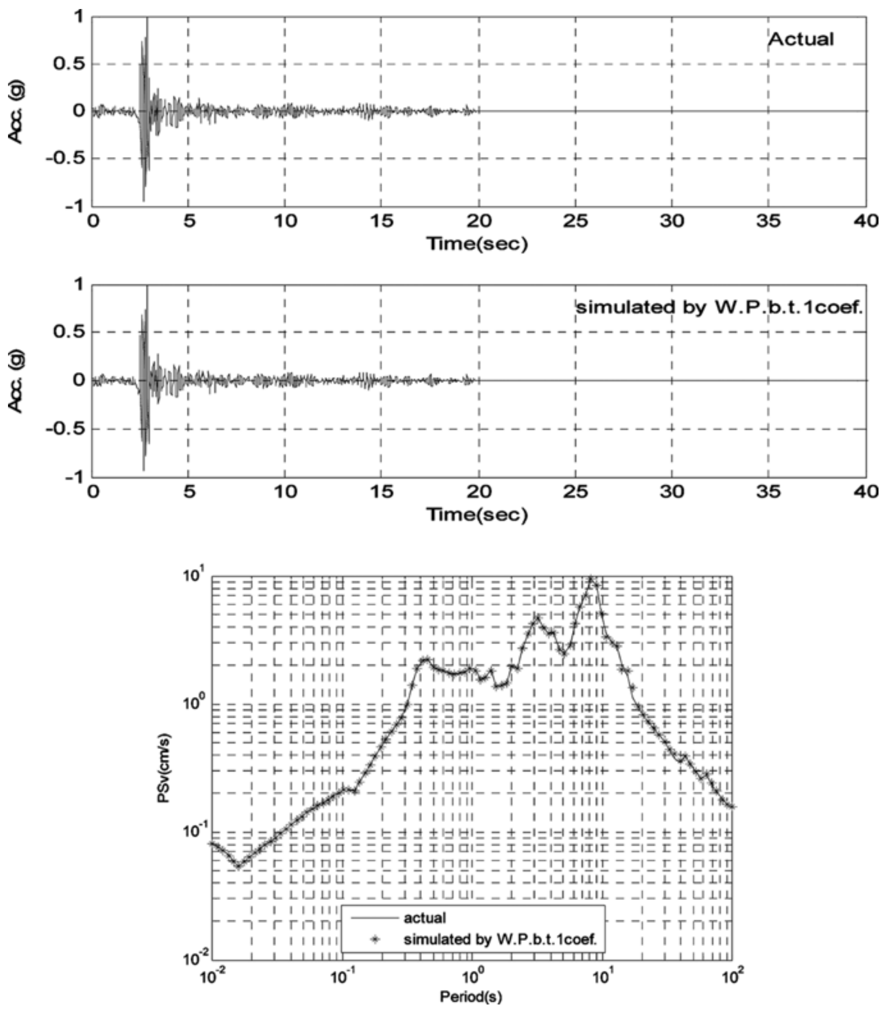

Fig. 8 Accelerogram of Rudbar-1 1991 earthquake (top), neural network generated accelerogram (middle) and comparison between pseudo-acceleration response spectra of original and generated accelerograms

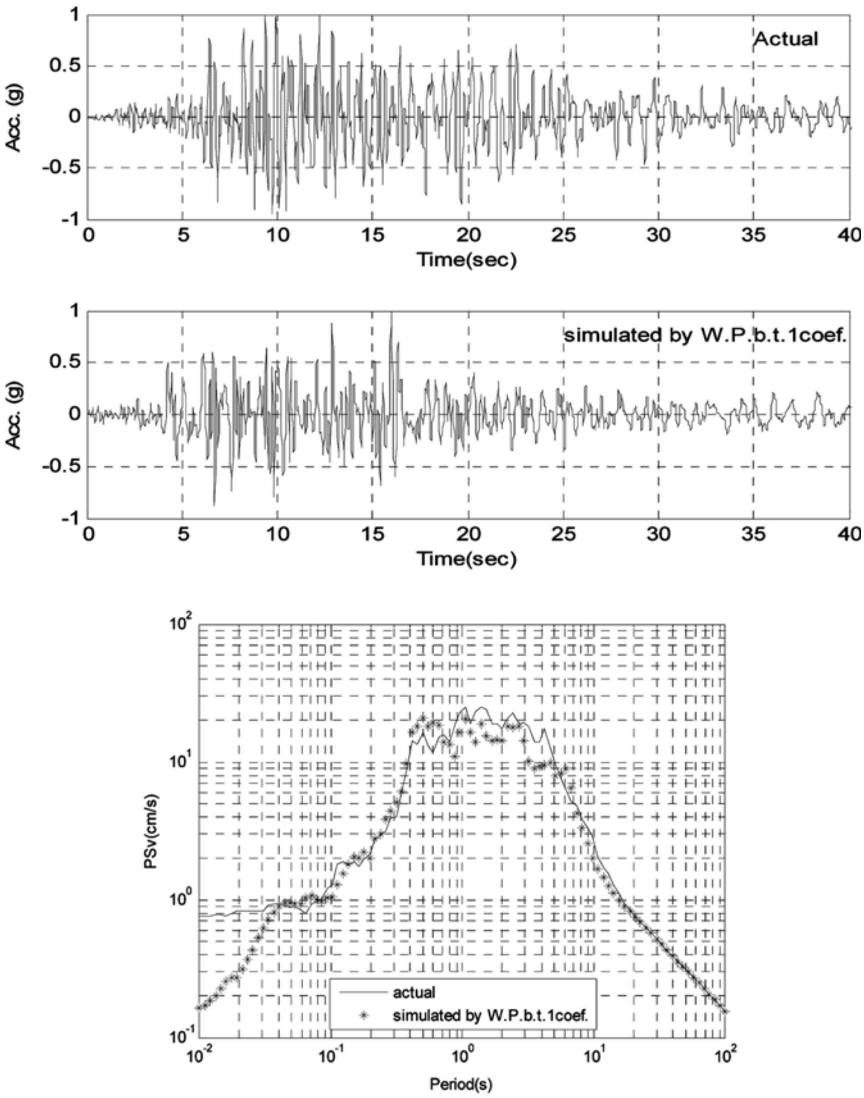

Fig. 9 Accelerogram of Bandar Abas-1 1977 earthquake (top), neural network generated accelerogram (middle) and comparison between pseudo-acceleration response spectra of original and generated accelerograms (below)

the earthquake records. From these and other tests examples it is reasonable to conclude that the trained neural network is able of generating accelerograms for any novel response spectra. The generated accelerograms are plausible accelerograms with similar characteristics as those in the training set and their response spectrums are very close to the input design spectrum. Finally, it is interesting to determine whether the trained neural networks are capable of generating reasonable looking accelerograms from design spectra, even though it has been trained with actual recorded earthquake accelerograms. In Fig. 11, the trained neural network is provided with a design response spectrum as input, and the generated accelerogram and the comparison of the response spectra of

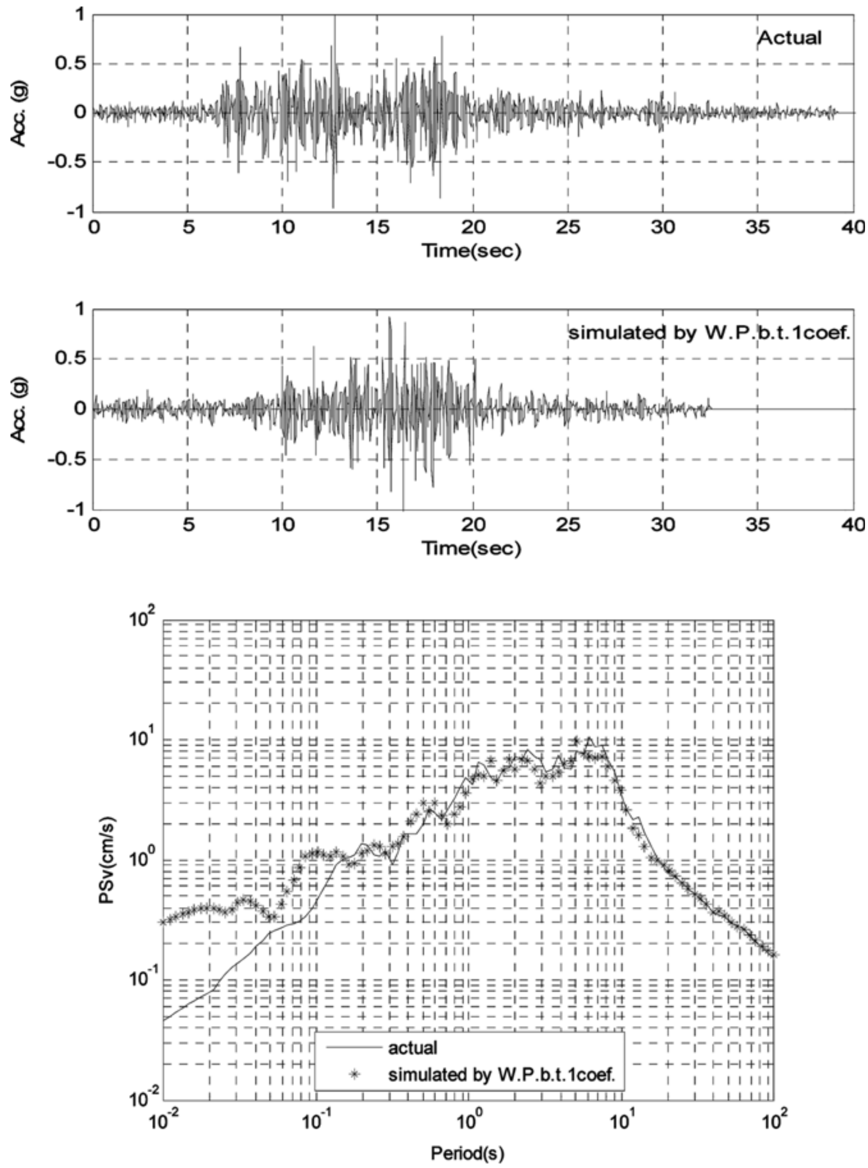

Fig. 10 Accelerogram of Khaf 1979 earthquake (top), neural network generated accelerogram (middle) and comparison between pseudo-acceleration response spectra of original and generated accelerograms (below)

the generated accelerograms with the design spectrum are shown in the top portion of the figure. As were shown although thse training sets in this method is not much, but the results are suitable. The GRNN that introduce in this paper was trained in less time than other methods. This is a useful property of this 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.

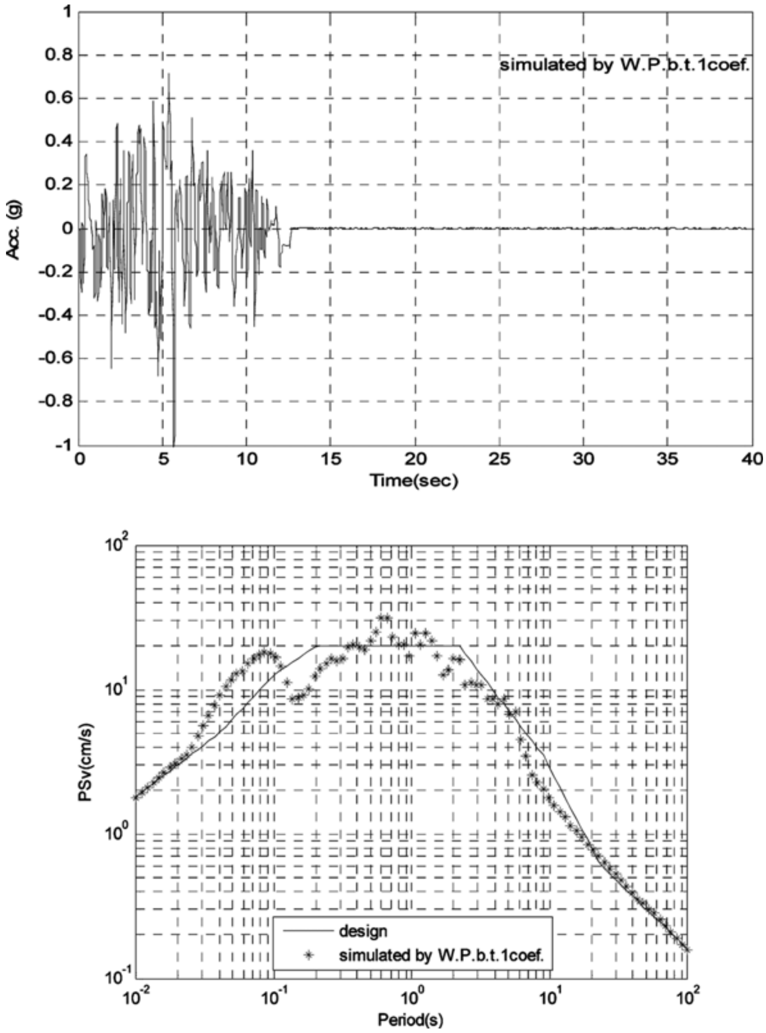

Fig. 11 Neural network generated accelerogram (top) and comparison between design spectrums with pseudo-acceleration response spectrum (below)

6. Conclusions

In this study, a new neural network-based methodology by using wavelet packet transform with best-basis algorithm for generation of artificial accelerograms from the pseudo-velocity response spectra has been proposed. This method shows with computation of the best-tree for given entropy, the optimal wavelet packet tree is computed to balance the amount of compression and retained energy. By using this method the results can be optimized. The proposed method is validated by using 34 accelerograms to train the GRNNs and 6 accelerograms for testing it. In testing the trained neural networks, it was found out that, when given a pseudo-velocity response spectrum as input, the generated neural network either generates an accelerograms very similar to one from its training set; one which has a pseudo-velocity response spectrum close to input, or it synthesizes a new and realistic looking accelerogram. The performance of the trained GRNN is estimated by generating accelerogram for new response spectra. It is shown that both the time domain characteristics and the response spectra of the generated accelerograms are similar to the original recorded accelerograms.

The advantages of this method can be summeraized as follows:

- High flexibility, so it is possible to answer to a certain input with only a few patterns.
- High training pace, in a way that it is possible to train all networks in less than a few minutes.
- Proper use of wavelet packets for thorough identification and extraction of frequency characteristics of each record.
- Non-random characteristic of outputs, in a way that each record is considered to be the product of two or more

Finally, with the proposed method, an artificial earthquake accelerogram compatible with a single design spectrum is generated. The generated accelerogram can then be used in time history analysis of linear and nonlinear structures

References

Abhijeet Shinde, D. (2004), "A wavelet packet based sifting process and its application for structural health monitoring", Master Thesis, Faculty of Worcester Polytechnic Institute.

Benedetto, J.J. and Frazier, M.W. (1994), *WAVELETS: Mathematics and Applications*, CRC Press, Boca Raton.

Building and Housing Research Center (BHRC) (2006), Iranian Code of Practice for Seismic Resistance Design of Buildings, Standard No.2800, 3rd Edition, Tehran, Iran.

Chui, C.K. and Wang, J.Z. (1992), "On compactly supported spline wavelets and a duality principle", *T. Am. Math. Soc.*, **330**, 903-915.

Coifman, R.R. and Wickerhauser, M.V. (1992), "Entropy-based algorithms for best-basis selection", *IEEE T. Inform. Theory,* **38**(2), 713-718.

Daubechies, I. (1992), "Ten lectures on wavelets", *CBMS-NSF Conference Series in Applied Mathematics*, Montpelier, Vermont.

Daubechies, I. (1988), "Orthonormal bases of compactly supported wavelets", *Commun. Pure Appl. Math.,* **41**, 909-996.

Fan, F.G. and Ahmadi, G. (1990), "Nonstationary Kanai-Tajimi models for El Centro 1940 and Mexico City 1985 earthquake", *Prob. Eng. Mech.*, **5**, 171-181.

Fan, X. and Zuo, M.Z. (2006), "Gearbox fault detection using Hilbert and wavelet packet transform", *Mech. Syst. Signal Pr.,* **20**, 966-982.

Chopra, A.K. (1995), *Dynamics of Structures*, Englewood Cliffs, NJ, Prentice-Hall.

Ghaboussi, J. and Lin, C.J. (1998), "New method of generating spectrum compatible accelerograms using neural networks", *Earthq. Eng. Struct. D.*, **27**, 377-396.

Ghaboussi, J. (1999), "Biologically inspired soft computing method in structural mechanics and engineering", *Proceeding of the 1st International Conference of Artificial Neural Networks in Engineering* (ANNIE'97), Seoul, Korea.

Ghodrati Amiri, G., Bagheri, A. and Fadavi, M. (2007), "New method for generation of artificial ground motion by a nonstationary Kanai-Tajimi model and wavelet transform", *Struct. Eng. Mech.,* **26**(6), 709-723.

Ghodrati Amiri, G. and Bagheri, A. (2008), "Application of wavelet multiresolution analysis and artificial intelligence for generation of artificial earthquake accelerograms", *Struct. Eng. Mech.,* **28**(2), 153-166.

Ghodrati Amiri, G., Ashtari, P. and Rahami, H. (2006), "New development of artificial record generation by wavelet theory", *Struct. Eng. Mech.,* **22**(2), 185-195.

Ghodrati Amiri, G., Bagheri, A. and Razaghi, A. (2008), "Generation of multiple earthquake accelerograms compatible with spectrum via the wavelet packet transform and stochastic neural networks", *J. Earthq. Eng.*

(Accepted for publication).
Ghodrati Amiri, G. and Asadi, A. (2009), "Processing ground motion records by using an advanced method in wavelet packet", *Intl. J. Eng. Sci., Iran University of Science & Technology* (Submitted for review).
Hancock, J., Waston-Lamprey, J., Abrahamson, N.A., Bommer, J.J., Markatis, A., Macoy, E. and Mendis, R. (2006), "An improved method of matching response spectra of recorded earthquake ground motion using wavelets", *J. Earthq. Eng.,* **10**(special issue 1), 67-89.
Haykin, S. (1998), *Neural Networks: A Comprehensive Foundation*, 2nd Edition, Pearson Education.
Iyama, J. and Kuwamura, H. (1999), "Application of wavelets to analysis and simulation of earthquake motions", *Earthq. Eng. Struct. D.*, **28**, 255-272.
Jaffard, S., Meyer, Y. and Ryan, R.D. (2001), "Wavelets: tools for science & technology", *Soc. Ind. Appl. Math.,* Philadelphia.
Karabalis, D.L., Cokkinides, G.J. Rizos, D.C. and Mulliken, J.S. (2000), "Simulation of earthquake ground motions by a deterministic approach", *Adv. Eng. Soft.*, **31**, 329-338.
Lee, S.C. and Han, S.W. (2002), "Neural-network-based models for generating artificial earthquakes and response spectra", *Comput. Struct.,* **80**, 1627-1638.
Lin, C.J. and Ghaboussi, J. (2000), "Recent progress on neural network based methodology for generating artificial earthquake accelerograms", *Proceedings of the 12th World Conference on Earthquake Engineering,* Auckland, New Zealand, January-February.
Mac Can, W.M. and Shah, H.C. (1979), "Determining strong-motion duration of earthquake", *B. Seismol. Soc. Am.,* **69**, 1253-1265.
Mallat, S.G. (1989), "A theory of multi-resolution signal decomposition, the wavelet representation", *IEEE T. Pattern Anal.,* **11**, 674-693.
MATLAB Reference Guide (2004), The Math Works Inc.
Meyer, Y. (1989), *Orthonormal Wavelets in Wavelets,* Springer, Berlin.
Mukherjee, S. and Gupta, K. (2002a), "Wavelet-based characterization of design ground motions", *Earthq. Eng. Struct. D.*, **31**, 1173-1190.
Mukherjee, S. and Gupta, K. (2002b), "Wavelet-based generation of spectrum-compatible time-histories", *Earthq. Eng. Struct. D.*, **22**, 799-804.
Naeim, F. (1999), *The Seismic Design Handbook*, Van Nostr.
Newland, D.E. (1994), *Random Vibrations, Spectral and Wavelet Analysis*, 3rd Edition, Longman Singapore Publishers.
Ogden, R.T. (1997), *Essential Wavelets for Statistical Applications and Data Analysis,* Birkhauser, Boston.
Rajasekaran, S., Latha, V. and Lee, S.C. (2006), "Generation of artificial earthquake motion records using wavelets and principal component analysis", *J. Earthq. Eng.,* **10**(5), 665-691.
Ramezi, H. (1997), "Base accelerogram data of iranian accelerograph network", Building and Housing Research Center, BHRC-PN S 253, Tehran, Iran.
Refooei, F.R., Mobarake, A. and Ahmadi, G. (2001), "Generation of artificial earthquake records with a nonstationary Kanai-Tajimi model", *Eng. Struct.*, **23**, 827-837.
Strang, G. and Nguyen, T. (1996), *Wavelets and Filter Banks*, Wellesley-Cambridge Press, Wellesley, Massachusetts
Suarez, L.E. and Montejo, L.A. (2005), "Generation of artificial earthquake via the wavelet transform", *Solid. Struct.,* **42**, 5905-5919.
Suarez, L.E. and Montejo, L.A. (2007), "Applications of the wavelet transform in the generation and analysis of spectrum-compatible records", *Struct. Eng. Mech.,* **27**(2), 185-198.
Wickerhauser, M.V. (1994), *Adapted Wavelet Analysis from Theory to Software*, (Ed. Peters, A.K.), Wellesley, MA.