Soil Dynamics and Earthquake Engineering 31 (2011) 866–872

Contents lists available at ScienceDirect

Soil Dynamics and Earthquake Engineering

journal homepage: www.elsevier.com/locate/soildyn

Neural network estimation of duration of strong ground motion using Japanese earthquake records

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ARTICLE INFO

Article history:
Received 26 December 2009
Received in revised form
24 October 2010
Accepted 2 January 2011
Available online 3 April 2011

Keywords:
Duration of strong motion
Geophysical properties
Neural network
Hypocentral distance
Shear wave velocity

ABSTRACT

The duration of strong motion has a significant influence on the severity of ground shaking. In this work, a combination of average values of four geophysical properties of site (Standard Penetration Test (SPT) blow count, primary wave velocity, shear wave velocity, and density of soil) including hypocentral distance of less than 50 km and magnitudes more than 5.0 from Japanese ground motion records were used for development of neural network model, to estimate duration of strong ground motion. Since majority of strong motion databases provide only average shear wave velocity for site characterization, an attempt has also been made to train the neural network with magnitude, hypocentral distance and average shear wave velocity as three input variables. Results obtained from this study show that the duration of strong motion is mostly dependent on average shear wave velocity rather than other geophysical properties of site.

1. Introduction

Engineers are primarily interested in strong ground motion. Ground motion associated with a peak ground acceleration of 0.05*g* or higher is considered as strong ground motion [1]. Duration of strong ground motion is one of the key parameters that will contribute to the seismic performance of structural systems. A ground motion with moderate peak acceleration and a long duration may cause more damage than a ground motion with a larger acceleration and a shorter duration [2]. An earthquake accelerogram is generally composed of rise, strong motion, and decay time. For all engineering applications, only the strong motion portion of an accelerogram is of interest. Strong-motion duration play an important role in assessing the damage potential of earthquake ground motion. Several researchers in the past have proposed procedures for computing the strong motion duration of an accelerogram [3–5, 6]. In literature, there are more than 30 definitions of strong-motion duration [7]. The most commonly used definition is the bracketed duration [8], which is defined as the time interval between the first and last exceedances of a specified acceleration (usually 0.05*g*). Another definition of duration [9] is the time interval in which significant contribution to the integral of the square of acceleration ($\int a^2\,dt$) referred to as the accelerogram intensity takes place. In this study the strong motion duration is defined as the interval between the times at which 5% and 95% contributions of the total integral is achieved.

This paper provides a neural network based approach for estimating the duration of strong ground motion based on earthquake records and site characteristics. In the foregoing sections of the paper, the compilation and processing of strong motion data for the Japanese earthquake records from Kyoshin-Net database and the application of artificial neural networks to estimate duration of strong motion have been discussed.

2. Compilation of strong motion data

The main goal of this study is to develop neural network based model to estimate the duration of strong earthquake ground motion using Japanese earthquake records. For this purpose, the first step in network training is to generate a sufficiently large database for which, compiling and processing of strong motion data is required. The ground motion records used in the study are obtained from Kyoshin Net (K-NET) database. Kyoshin Net is a dense strong-motion networking consisting of over 1000 observatories deployed all over Japan at free-field sites at intervals of approximately 25 km covering the country. A map of Japan with all K-NET station locations is presented in Fig. 1. These instruments are located on the ground surface. Each station has a digital strong-motion seismograph (accelerometer) with a wide frequency-band and wide dynamic range. In this study, a total of 84,456 horizontal components of earthquake records from 609 earthquakes of Japan have been downloaded from the internet, which have a magnitude of 5 and above. All K-NET data is openly available on registration through their Web-site [10]. The type of magnitude scale used by Kyoshin Net in Japan is the magnitude,

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doi:10.1016/j.soildyn.2011.01.001

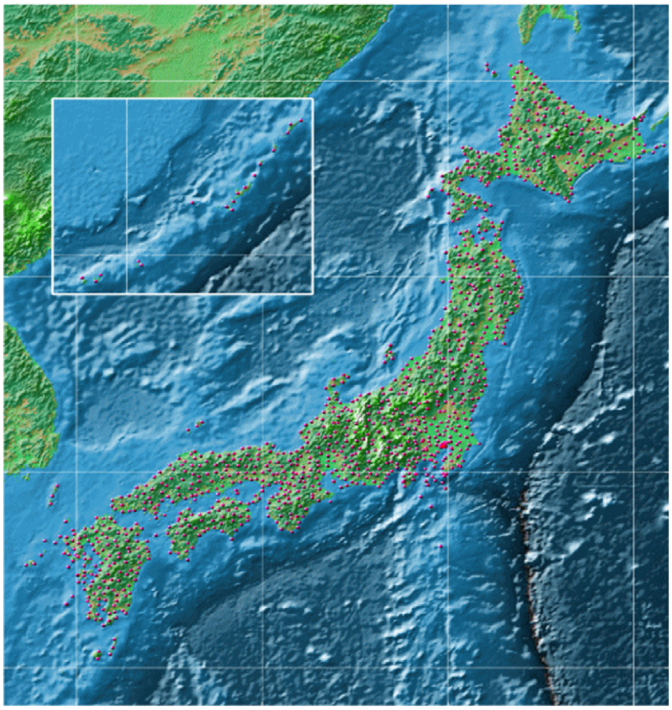

Fig. 1. Locations of strong motion stations operated by K-NET in Japan [10].

Table 1
Typical soil condition at Nagoya station, Japan [10].

Depth (m)	N-value	Velocity (m/s)		Density (gm/cm^3)	Soil column
		P	S		
1	9	260	120	2.02	0.00–1.00 m Fl
2	13	550	280	1.75	1.00–4.60 m S
3	14	550	280	1.78	4.60–4.90 m S
4	18	550	280	1.8	4.90–5.70 m S
5	20	550	280	1.83	5.70–7.80 m S
6	16	550	280	1.79	7.80–9.50 m C
7	18	960	280	1.81	9.50–11.65 m SF
8	16	960	280	1.83	11.65–14.85 m M
9	18	960	280	1.8	14.85–16.70 m C
10	29	960	280	1.83	16.70–17.90 m M
11	31	1520	340	1.84	17.90–18.80 m GF
12	19	1520	340	1.84	18.80–19.60 m M
13	15	1520	290	1.71	19.60–20.00 m C
14	29	1520	290	1.73	
15	25	1520	290	1.84	
16	38	1770	350	1.88	
17	33	1770	350	1.79	
18	39	1770	350	1.87	
19	21	1770	350	1.93	
20	22	1560	270	1.87	

M_{JMA}, estimated by the Japan Meteorological Agency (JMA). Almost all sites have the data on soil conditions (Standard Penetration Test Value, Density), including P and S wave velocities recorded, except a few stations where this soil data is not available. A typical soil data format at one of the recording stations is presented in Table 1. The variation of soil condition along the depth at this station is shown in Fig. 2.

2.1. Processing of strong motion data

All stations operated by K-NET have K-NET95 accelerometers, with 108 dB dynamic range having a maximum measurable acceleration of 20 m/s^2 (2000 Gals). The resolution of A/D converter is 18 bits with a sampling frequency of 100 Hz. The resolution of accelerometer is 15 mGal. For processing the strong motion data, a computer program was used [11]. In this program, the raw data available in terms of counts in the data format of K-NET are converted into acceleration using the scale factor given in the header of data. As the natural frequencies of all accelerographs were very high (about 200 Hz), there was no need of instrument response correction.

A baseline correction of all acceleration time histories has been performed by using the least square line of the time history. Corrections have also been applied in frequency domain by filtering high and low frequency components of the accelerograms. All accelerograms were bandpass filtered by removing frequencies below 0.1 Hz and above 30 Hz. A sixth order Butterworth bandpass filter was used for this filtering operation.

The average values of shear wave velocity, primary wave velocity, Standard Penetration Test (SPT) blow count, and the density of soil have been used. The averaging of these parameters has been done as per FEMA [12]. These values were calculated as shown below

$$\overline{v_s},\overline{v_p},\overline{N},\overline{\rho} = \frac{\sum_{i=1}^{n} d_i}{\sum_{i=1}^{n} \frac{d_i}{v_{si}}, \frac{d_i}{v_{pi}}, \frac{d_i}{N_i}, \frac{d_i}{\rho_i}} \quad (1)$$

where v_{si} is the shear wave velocity, v_{pi} is the primary wave velocity, N_i is the SPT blow count, and ρ_i is the density of soil, in the layer 'i', d_i is the depth of layer 'i', and n is the number of layers of similar soil materials for which data is available.

3. Fundamentals of neural network

Artificial neural networks (ANNs) are based on the current understanding of the biological nervous systems. An artificial neural network is a massively parallel-distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain [13]. ANNs are extremely useful tool when there is no well-defined functional relationship between dependent and independent variables. The theoretical background on neural networks (NN) and its applications can be found in a large volume of literature [13–18]. A neuron is the information-processing unit of the neural network, much like the brain in human beings [13]. Fig. 3 shows the block diagram of a neuron.

A neuron consists of three main parts: A set of synapses, which connect the input signal (x_j) to the neuron via a set of weights (wk_j), an adder (u_k) which sums up the input signals, weighted by the respective synapses of the neuron and an activation function ($\phi(.)$) for limiting the amplitude of the output of the neuron. At times, a bias (b_k) is added to the neuron to increase or decrease the net output of the neuron.

Mathematically [10], a neuron k is described as

$$u_k = \sum_{j=1}^{n} wk_j x_j \quad (2)$$

$$y_k = \phi(u_k + b_k) \quad (3)$$

where $x_1, x_2, x_3, \ldots, x_n$ are the input signals, $wk_1, wk_2, \ldots, wk_n$ are the weights for neuron k, b_k is the bias, u_k is the adder or the linear combiner, $\phi(.)$ is the activation function, and y_k is the output signal of the neuron.

The output range of the neuron depends on the type of activation function used. There are four types activation functions [18] commonly used namely: hard-limit activation function, log-sigmoid