Structural Eng./Earthquake Eng., JSCE, Vol. 13, No. 2, 123s—129s, 1996 October
(J. Struct. Mech. Earthquake Eng., JSCE, No. 549/I—37)

PREDICTION OF PEAK HORIZONTAL ACCELERATION USING AN ARTIFICIAL NEURAL NETWORK MODEL

S.M.R. EMAMI[1], Takanori HARADA[2] and Yushiro IWAO[3]

[1]Member of JSCE, Graduate Student, Dept. of Civil Eng., Saga University (Saga, Japan)
[2]Member of JSCE, Dr. Eng., Associate Professor, Dept. of Civil Eng., Miyazaki University (Miyazaki, Japan)
[3]Member of JSCE, Dr. Sci., Professor, Dept. of Civil Eng., Saga University (Saga, Japan)

In this study, a model on the basis of artificial neural networks is developed to predict the peak horizontal acceleration. The neural network model provides an objective analysis method which requires neither specifying predictive functional forms nor the independence of the inside variables. The Joyner and Boore data set (BSSA, Vol.71, pp.2011-2038, 1981), was used for analysis. For comparison, one- and two-step regression procedures were also applied to the same data set. Various fitness criteria have been considered. Finally, the proposed procedure showed an agreeable capability for the required prediction of ground motion parameters.

Key Words : earthquake, peak horizontal acceleration, regression analysis, neural network

1. INTRODUCTION

Seismic hazard evaluation is commonly based on empirical predictive relations. Such relations are generally expressed as mathematical functions connecting a strong motion parameter to the parameters characterizing the earthquake source, the propagation path distance and the local site conditions. The most important aspect for mitigation of earthquake hazard is probably the prediction of strong motion parameters, likely at a particular site.

One of the special features of the earthquake ground motion, which is of considerable interest to engineers and seismologists, is the maximum peak value of ground acceleration developed at any specific site during an earthquake.

During the past few decades several attempts have been made to estimate the peak acceleration with various pertinent properties of the strong motion records, *e.g.* Gutenberg & Richter[1)], Housner[2)], Trifunac[3)], Campbell[4)], etc.. In order to predict the peak horizontal acceleration, various analytical procedures have been introduced by researchers so far. Among these, regression analysis has been widely used with different techniques, *e.g.* Donovan[5)], Joyner & Boore[6)], Campbell[7)], Fukushima & Tanaka[8)]. Since the 1970s, numerous empirical relations of dependence of peak acceleration on magnitude and distance have been presented, *e.g.* Esteva[9)], where reference to many others can be found in the review articles by Joyner[10)], Joyner and Boore[11)], and Anderson[12)]. Hitherto , all of the abovementioned published studies use parametric models.

In an exploratory data analysis, Brilinger and Preisler[13)] have applied two different techniques to the Joyner and Boore[6)] data for prediction of the peak horizontal acceleration. Carr and Glass[14)] applied the so-called Krieging, a technique of geostatistics which is commonly used to estimate mineral resources, to interpolate the peak acceleration. A nonparametric empirical description was adopted by Anderson and Yutain[15)], to estimate the peak acceleration.

In general, regression analysis is a technique for fitting curves (linear or nonlinear surfaces) to data points. Sympson[16)] points out that the nodal function used in many error correction learning algorithms of neural networks is a family of curves, and the adjustment of the weights that minimizes the overall mean-squared error is equivalent to curve fitting. In this sense, the back-propagation algorithm is an example of an automatic nonlinear regression technique. With

this notion, neural networks could be applied to the predictive issues in earthquake engineering.

In this study a model on the basis of artificial neural networks with the back-propagation algorithm is developed to estimate the peak horizontal acceleration. Neural network models provide an objective analytical outlook which requires neither specifying predictive functional forms nor the independence of the inside variables. The inside variables, for example earthquake magnitude and distance, are somehow related in the observed data, despite their theoretical independence from each other. This fact has a negative effect on the prediction based on the conventional regression procedures. To improve traditional regression procedures (one-step regression), new procedures, *e.g.* Joyner and Boore[6], has been developed to overcome this problem by introducing the so-called two-step regression procedure. In our model, this complexity resulting from the dependence of the inside variables, has no impact on the estimation of the peak horizontal acceleration.

In this paper, in order to demonstrate the potential capability of the neural network models in predicting the peak horizontal acceleration, three different analytical procedures - the conventional regression method (one-step procedure), the Joyner and Boore[6] method (two-step procedure), and a neural network model - have been applied, and compared with each other. The uncertainty involved in the prediction of the peak horizontal acceleration was examined through the analysis of residuals.

2. THE DATA

To demonstrate the reliability of the artifial neural network model for prediction of the peak horizontal acceleration, the Joyner and Boore data set[6] was used in this study. A broad variety of functional forms for such data have been proposed by Joyner and Boore[6], Bolt and Abrahamson[17], and Brillinger & Preisler[13].

The data set consists of 182 recordings of the peak acceleration from 23 earthquakes, and is restricted to shallow earthquakes in the western North America with moment magnitudes M_W greater than 5.0. The number of records for each event vary, with six events having only one record. The magnitude of the earthquakes ranges between 5 and 7.7, but most of the earthquakes are in the range 5.5 to 6.5. The distance in which

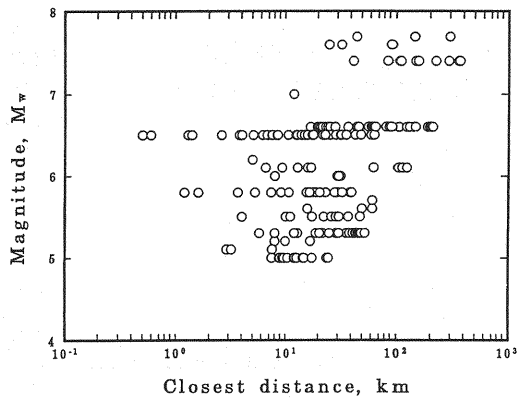

Fig.1 Distribution of the observed data with respect to distance and moment magnitude

the data are obtained ranges from less than 1 km to 300 km. This distance is defined as the closest distance to the fault rupture in kilometers. The larger of the peak horizontal accelerations of two components is selected in each case. The distribution of peak horizontal acceleration data over the magnitude and distance ranges is shown in **Fig.1**.

3. ANALYTICAL PROCEDURES

The aforementioned three analytical procedure - *i.e.* the single- and two-step regression analyses[6], and also the nonparametric neural network approach developed in this article - are examined for the selected data to estimate the peak horizontal acceleration.

A conventional regression analysis begins by assuming the form of the analytical expression for the peak acceleration (A_{max}) as a function of magnitude (M) and distance (R), and possibly other parameters. The analysis then estimates unknown coefficients in this equation which minimize the average misfit of observation. The detailed explanation of traditional analytical procedures can be found in Campbell[18], Kawashima *et al.*[19], and Joyner and Boore[20].

Regression analysis has important limitations. First, it requires a formal expression and second, its inside variables should be fully independent from each other. The latter is of considerable importance from the analytical point of view. Therefore, some functional forms and regression procedures have been introduced so far to reduce the effect of the coupling between magnitude and distance dependence (*e.g.*, Joyner and Boore[6]).

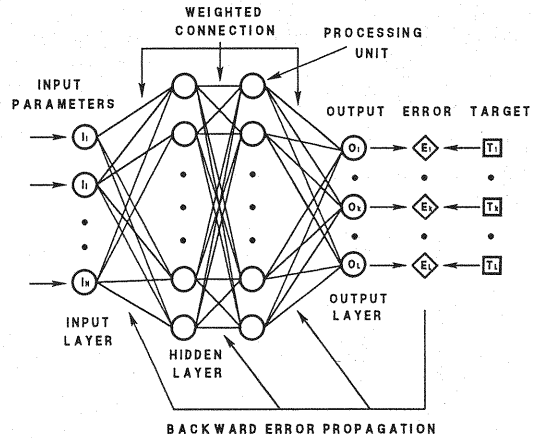

Fig.2 The structure of a typical multilayer neural network with back-propagation error correction

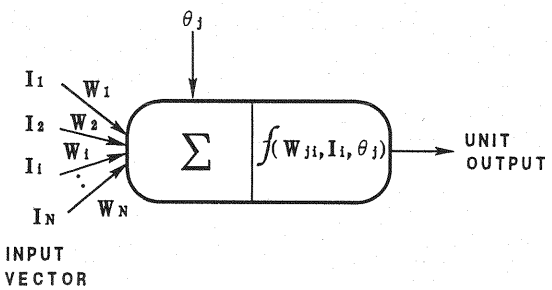

Fig.3 The generic representation of a neural network's processor

On the other hand, neural network models provide an analytical method which requires neither a functional form nor the independence of variables. Such models are based on the function of biological neurons[21].

(1) The neural network model

The concept of artificial neural networks is inspired from neurological system of human body, which consists of a large number of simple processing units. These processing units or nodes have interconnection in the various artificially designed structural models, with varying degrees of analytical strength as indicated by their connection weights. A typical multilayer neural network structure is organized into several layers: an input layer, one or more hidden layers, and an output layer. Each layer is made up of one or more units (neurons). The number of the hidden layers and their nodes would be selected during an effort of trial and error. Neural networks vary in physical design, training model and functionality, depending on the nature of application.

In our approach, a multilayered, forward-chained, and partially connected neural networks is used. Partially connected means, that the neurons in a layer are not connected to each other. It is proven that this kind of network is most useful in engineering applications. **Fig. 2** illustrates a typical architecture of a multilayer neural network, with back-propagation error correction, that consists of an input layer, two hidden layers, an output layer, and three levels of adaptive connections.

Each neuron of a network can be considered as an operator, receiving the real numbers as inputs and transforming them into a single output value. In our network transformation is done through the squashing sigmoidal function as,

$$N_j = \sum_{i=1}^{n} W_{ji} I_i + \theta_j \qquad (1)$$

$$I_j^{next} = f(N_j) = \frac{1}{1 + exp(-\alpha N_j)} \qquad (2)$$

where N_j is the weighted sum of the units i of the input from a previous layer with n units; W_{ji} is the weight between units j and i; I_i is the input element from unit i; θ_j is the bias; I_j^{next} (unit output) is the transformed output from unit j which is considered as an input for next layer; and α is a constant which defines the steepness of the transfer function. A schematic view of an exemplary artificial neuron is shown in **Fig. 3.**

The output is transmitted by a link to connect to the other neurons. For each link a real number and a weight is defined. Before an output value is transmitted, it is multiplied by the corresponding weight. The output from a unit is then transmitted by the link to connect to the other neurons. Finally, the transformed values from the output layer is compared with the corresponding desired value for error calculation, based on the following equation. Let O_r be the output value, for the rth pattern , and let T_r be the desired or target component of the output pattern for this neuron. P and L are the number of samples and units in the output layers, respectively. The error (misfit value) E, depending only of the weights **W**, is defined to be

$$E(\mathbf{W}) = \frac{1}{2}\sum_{r=1}^{P}\sum_{k=1}^{L}(O_r^k - T_r^k)^2 \qquad (3)$$

Modifying the weight values by repeated application learning rules allows the networks to approximate the functional mapping of the inputs on the desired outputs. The classic back-propagation learning algorithm of neural networks was used in our analysis to train a feed-forward network for prediction of the peak horizontal acceleration. The ability of this learning method to automatically capture the nonlinear mapping is significant. The back-propagation learning algorithm uses a least squares error minimization criterion to minimize the error E(W). This can be accomplished by adjusting the weights according to the negative gradient of the error with respect to the weights.

$$\Delta\mathbf{W}^{old} = -\eta\frac{\partial E}{\partial\mathbf{W}^{old}} \qquad (4)$$

$$\mathbf{W}^{new} = \mathbf{W}^{old} + \Delta\mathbf{W}^{old} \qquad (5)$$

where $\mathbf{W}$ is a typical weight which could belong to any layer, and is adjusted from its old value $\mathbf{W}^{old}$ to the new value $\mathbf{W}^{new}$ during an iteration procedure based on the learning rules. The term η is the learning rate which is usually constant during a training. Rumelhart *et al.*[21] who already provided a detailed description of back-propagation learning algorithm.

Analysis and interpretation of neural network behavior is inherently difficult due to the high dimensionality of the solution space. Recent research (*e.g.* Dennis and Phillips[22], Hutton[23], Ripley[24]), has focused on the use of nonparametric and parametric statistical techniques to analyze and interpret the neural network behavior. It has been shown that a forward-chained, multilayer network using a back-propagation learning algorithm is mathematically equivalent to a nonlinear least squares regression fit of the data[25].

Our network model consists of three layers with twelve sigmoidal nodes in the hidden layer and a sigmoidal output unit. Inputs to the network are the earthquake magnitude (Mag.) and distance (Dis.) with three additional combinations (Mag.×Dis., Mag./Dis., and Mag.$^{Dis.}$). These inputs were chosen through an effort of trial and error. As Sympson[16] has pointed out, creating the best possible set of features and properly representing those features is the first step toward success in any neural application. Peak horizontal acceleration is expressed as the logarithm of acceleration (cm/s^2) which was normalized according to the maximum value, and was considered as a target. The input data to the network were also normalized based on maximum values of each input parameter in order to homogenize the weight values. The network has been examined through many training procedures to find out the suitable structure, and finally to get a better adjustment for the root-mean-square error cost function. The trained network results in terms of weights are presented in **Table 1 (a and b)**.

Table 1 Values corresponding to (a) the Input - Hidden, and (b) Hidden - Output connection weights.

a: Input - Hidden weights

Hidden	Bias	Input 1	Input 2	Input 3	Input 4	Input 5
1	0.531	-1.777	1.704	0.070	2.246	-0.406
2	-4.054	6.138	-1.941	0.698	-0.386	-1.202
3	0.371	-1.277	0.865	0.656	1.288	0.043
4	-0.302	-2.454	-6.592	-4.783	6.214	2.394
5	0.439	0.834	0.203	0.805	-0.046	0.747
6	-1.172	1.464	-0.673	0.765	-0.985	0.335
7	-1.917	1.852	-3.425	-0.845	2.499	0.950
8	0.492	0.523	0.509	0.817	0.656	0.755
9	0.553	0.589	0.430	0.283	0.801	1.154
10	-0.057	0.898	0.266	0.747	0.731	1.065
11	0.737	0.328	0.648	0.024	0.089	0.632
12	0.869	0.912	1.012	1.029	0.464	0.798

b: Hidden - Output weights

Bias	Hidden 1	Hidden 2	Hidden 3	Hidden 4	Hidden 5
-2.5831	-1.099	1.964	-0.676	2.756	0.038
	Hidden 6	Hidden 7	Hidden 8	Hidden 9	Hidden 10
	1.053	1.301	0.203	0.398	0.474
	Hidden 11	Hidden 12			
	0.059	-0.119			

Table 2 Fitness criteria and their values for various analytical procedures

Analytical method	Mean square error	Standard error of estimation	Coefficient of determination	$\sigma_{\log Y}$
Neural network model	0.047	0.217	0.822	0.461
One step regression	0.063	0.251	0.767	0.451
Two step regression (Joyner & Boore, 1981)	0.064	0.254	0.770	0.483

4. RESULTS AND DISCUSSION

To evaluate the accuracy of the analytical models, several statistical parameters are calculated,

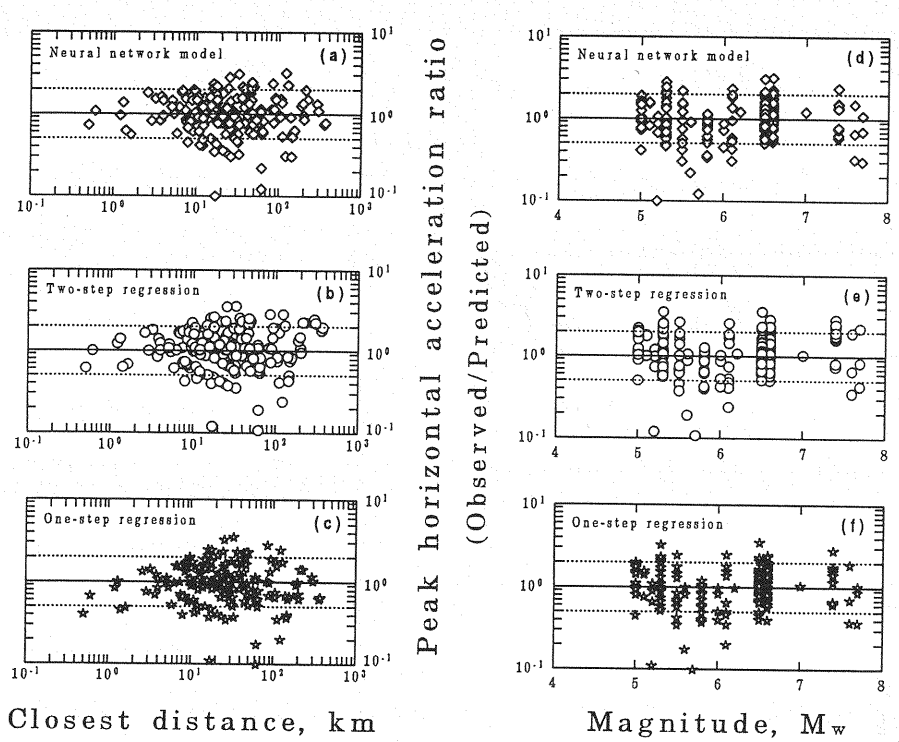

Fig.4 Plots of residuals as functions of distance (a,b,c) and magnitude (d,e,f), according to three analytical procedures

such as the correlation of determination (R^2), mean-square-error (MSE) and standard error of estimation (SEY). The fitness results of analysis for applied methods are given in **Table 2.** The results show that the neural network model is comparable with, and partly superior to the conventional methods. A correlation of determination (the measure of the goodness of fit) of 0.82 is achieved for the neural network model. In comparison, for the Joyner-Boore data[6], the correlation of determination values of 0.76 and 0.77 are found for the one- and two- step regression procedures, respectively.

In order to test for potential biases in the prediction regarding magnitude, distance or predicted accelerations, plots of the residuals with respect to these three parameters were carefully inspected. The residual was simply defined as the ratio of the observed to predicted values. Two examples of these plots appear in **Fig.4 (a,b,c,d,e and f).** If there were systematic trends in the data not accounted for by our statistical analysis, it should be evident from these plots. However, the residuals were found to be uniformly distributed with respect to magnitude , distance, and the predicted accelerations. A correlation analysis confirmed that the residuals were uncorrelated regarding to these variables.

Neural networks can effectively provide an accurate estimate if there is reasonable correlation between input and output data. However accuracy is limited by the available data. Since the neural network system is sensitive to the distribution of training data, the best results can be obtained if the data is well distributed over the magnitude and distance range.

The scatter plot, shown in **Fig.5**, provides a convenient means for assessing the variations in the error of prediction. Prediction curves of the neural network model for magnitudes 6.0 and 7.0 are compared with results of the one- and two-step regression analyses in **Fig.6**. As can be deduced from this Figure, the neural network model is in good agreement with the observed data. For distances less than 10 km, the estimation from one-step regression appears at higher values than other two models, while the estimated acceleration of our model is nearly similar to that of

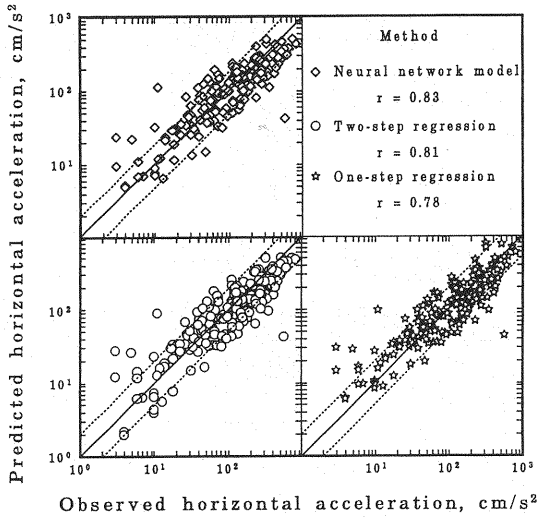

Fig.5 The scatter plot of observed and predicted peak horizontal accelerations

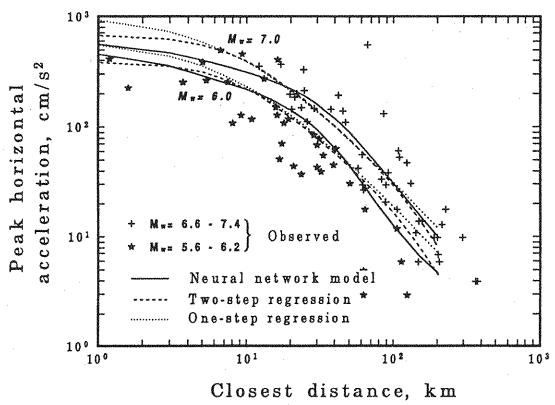

Fig.6 Observed peak horizontal acceleration and model- based predictions for magnitudes 6 and 7

Joyner and Boore[6]. We point out that the graphs prepared by Joyner and Boore[6] and our study, in the case of M=6.0 and 7.0, show that the curves do not differ dramatically. **Fig.7**, is constructed in accordance with our proposed neural network model, and might be used to estimate the peak horizontal acceleration.

5. CONCLUDING REMARKS

The main purpose of this paper was to point out that the neural network model can be directly applied to the earthquake ground motion data. The performance of the neural network model in estimating the peak accelerations can be evaluated

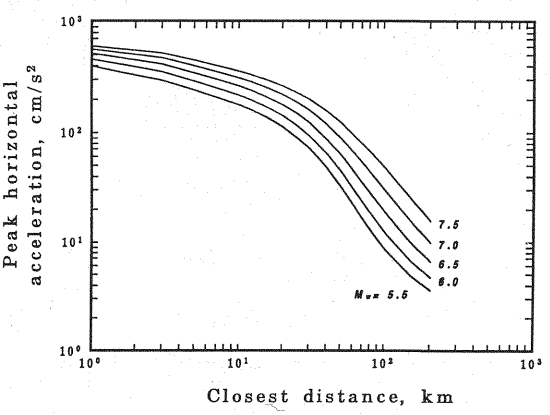

Fig.7 Predicted values of peak horizontal acceleration as a function of distance and moment magnitude, using the neural network model

from the results of this study. This evaluation proves that our approach is capable to predict earthquake ground motion parameters.

A general advantage of this method is that no commitment has been made to prespecified functional forms. Our approach is an objective analytical method which dose not require the independence of estimator parameters, an important condition in conventional analytical procedures. Considering the set of the data used, it is possible to show the capability of the neural network model compared to over conventional predictive methods.

In this paper, the local site effects were not considere because of the lack of available data. However, the neural network model can also take into account the site condition as an input parameter.

Finally, we conclude that the model has the capability for prediction of other ground motion parameters such as estimation of velocity, displacement and acceleration response spectra. The neural network method will be extended to these notions in our future studies.

ACKNOWLEDGMENT: One of the authors (first) is indebted to Dr. M. Niaraki, Mr. H. Sadeghi and Mr. Sh. Miyahara for their kind encouragements. The authors would like to appreciate the kind support of NishiNihon Sogo Consultant Co. Ltd. (Saga, Japan) throughout this study.

REFERENCES

1) Gutenberg, B. and Richter, C. F. : Earthquake magnitude, intensity, energy and acceleration, *BSSA*, Vol.46, pp.105-195, 1956.

2) Housner, G. W. : Engineering estimates of ground shaking and maximum earthquake magnitude, *Proc. 4th World Conf. on Earthq. Eng.*, Santiago, pp.1-13, 1969.

3) Trifunac, M. D. : Preliminary analysis of the peaks of strong earthquake ground motion - dependence of peaks, on earthquake magnitude, epicentral distance, and recording site condition, *BSSA*, Vol.66, pp.189-219, 1976.

4) Campbell, K. W. : The dependence of peak horizontal acceleration on magnitude earthquake in California and eastern North America, *BSSA*, Vol.79, pp.1311-1346, 1989.

5) Donovan, N. C. : A statistical evaluation of strong motion data including the Feb. 9 1971, San Fernando earthquake, *Proc. 5th World Conf. on Earthq. Eng.*, Rome, Vol.2, 1973.

6) Joyner, W. B. and Boore, D. M. : Peak horizontal acceleration and velocity from strong motion records including records from the 1979 Imperial Valley, California earthquake, *BSSA*, Vol.71, pp.2011-2038, 1981.

7) Campbell, K. W. : Near source attenuation of peak horizontal acceleration, *BSSA*, Vol.71, pp.2039-2070, 1981.

8) Fukushima, Y. and Tanaka, T. : A new attenuation relation for peak horizontal acceleration of strong earthquake ground motion in Japan, *BSSA*, Vol.80, pp.757-1346, 1990.

9) Esteva, L. : Seismic risk and seismic design criteria for nuclear power plants, R. J. Hansen (ed.), MIT Press, Cambridge, pp.142-182, 1970.

10) Joyner, W. B. : Strong motion seismology, *Review of Geophysics* , Vol.25, pp.1149-1160, 1987.

11) Joyner, W. B. and Boore, D. M. : Measurement, characterization and prediction of strong motion, *Proc. Earthq. Eng. and Soil Dynamics II*, Park city, ASCE, pp.43-102, 1988a.

12) Anderson, J. G. : Strong motion seismology, *Reviews of Geophysics, Seismology Supplement, U.S. National Report to International Union of Geodesy and Geophysics, 1987-1990*, pp.700-720, 1991.

13) Brilinger, D. R. and Preisler, H. K. : An exploratory analysis of the Joyner-Boore attenuation data, *BSSA*, Vol.74, No.4, pp.1441-1450, 1984.

14) Carr, J. P. and Glass, C. E. : Use of geostatistics for accurate mapping of earthquake ground motion, *Geophisical Journal* , Vol.97, pp.31-40, 1989.

15) Anderson, J. G. and Yutian, L. : Nonparametric description of peak acceleration as a function of magnitude, distance and site in Guerrero, Mexico, *BSSA*, Vol.84, No.4, pp.1003-1017, 1994.

16) Simpson, P. K. : Artificial neural networks, E. Sanchez-Sinencio and C. Lau (ed.), IEEE Press, New York, pp.3-24, 1992.

17) Bolt, B. A. and Abrahanson, N. A. : New attenuation relations for peak and expected acceleration of strong motion, *BSSA*, Vol.72, pp.2307-2321, 1982.

18) Campbell, K. W. : Strong motion attenuation relation: a ten-year perspective, *Earthquake Spectra*, Vol.1, No.4, pp.759-804, 1985.

19) Kawashima K., Aizawa K. and K. Takahashi : Attenuation of peak ground acceleration, velocity and displacement based on multiple regression analysis of Japanese strong motion records, *Earthq. Eng. and Structural Dynamic*, Vol.14, pp.199-215, 1986.

20) Joyner W. B. and D. M. Boore : Methods for regression analysis of strong motion data, *BSSA*, Vol.83, No.2, pp.469-487, 1993.

21) Rumelhart, D. E., Hinton, G. E. and Williams R. J. : Learning internal representations by back propagating errors, *Nature*, Vol.323, pp.533-536, 1986.

22) Dennis, S. and Phillips, S. : Analysis tools for neural networks, *Technical Report 207, Dept. of Computers, Un. of Queensland*, Queensland, 4072, Australia, 1991.

23) Hutton, L. V. : Using statistics to assess the performance of neural network classifiers, *Johns Hopkins Applied Physics Laboratory Technical Digest*, Vol. 13, 1992.

24) Ripley, B. D. : Statistical aspects of neural networks, *Seiminaire European de Statistique*, Sandbjerg, Denmark, pp.25-30, 1992.

25) Golden, R. M. : A unified framework for connectionist system biological cybernetics, Springer-Verlag, Vol.59, pp.109-120, 1988.

(Received November 22, 1995)