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Distribution of Peak Ground Velocity in Miyagi Prefecture Estimated from One Accelerogram Using Artificial Neural Network

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Distribution of peak ground velocity Artificial neural network
Back propagation Conjugate gradient algorithm

1. Introduction

This paper deals with the prediction of one component of peak ground velocity (PGV) distribution in Miyagi prefecture based on one accelogram records using Artificial Neural Network (ANN) method.

For this purpose, 37 earthquake records which magnitudes exceed 5 and were detected by 15 Kyoshin Network (K-NET) accelerometers located in Miyagi prefecture are collected, between January 1996 and April 2006.

From the accelogram records of MYG012 and K-NET, peak ground accelerations, peak ground velocities, predominant frequencies, max Fourier amplitudes, energy densities, arias intensities, root mean squares, hsk values of three components and azimuth, depth, earthquake longitude, latitude and magnitudes of each earthquake are estimated and used in ANN as an input.

28 records until 24.08.2005 are used for training and constituting ANN architecture and 9 records detected after this date are used for testing in order to prove the reliability of ANN structure. Namely, after detecting an earthquake in MYG012, all stations of Miyagi prefecture PGV distribution can be obtained in couple of seconds even wave propagation has not finished in investigated area.

2. Method/Application of ANN

One of unique methodology, Artificial Neural Network is continuing its development in various disciplines but has not been widely applied to engineering seismology problems.

This technique fundamentally uses large quantities of data to constitute a model depending on experiences which can then be used to explore the relationship between inputs and outputs or past and future.

In this research, application of ANN method in order to get the distribution of PGV depending on one accelogram is shown. For training the ANN, Training Matrix (TM) and Target Matrix (TRM) are created (Eq.1). 28 earthquake data and 29 various indices are used.

$$\mathrm{TM}=\begin{pmatrix} Var_{11} & \cdots & Var_{1n} \\ \vdots & \ddots & \vdots \\ Var_{m1} & \cdots & Var_{mn} \end{pmatrix} \quad \mathrm{TRM}=\begin{pmatrix} PGV_{11} & \cdots & PGV_{1i} \\ \vdots & \ddots & \vdots \\ PGV_{m1} & \cdots & PGV_{mi} \end{pmatrix} \quad (1)$$

Where; m= number of earthquakes (28)
n=type of indices (root mean square, energy density etc.) (29) i=number of accelerometers (14)

Various numbers and combination (more than 10.000) of hidden layers and neurons in hidden layer is tried more than three times, (Table 1). Designing and training of ANN is computationally expensive but once optimal structure is found, results can be obtained in seconds for different events.

Table 1 Type of used architecture in ANN

Number of Hidden layer	Number of Trials		
•	1~50	-	-
• •	1~50	1~50	-
• • •	23~30	25~30	30~40

Feed-forward, error back propagation neural network and log-sigmoid activation function are employed and for training function the scaled conjugate gradient algorithm (SCG) which was designed to avoid the time-consuming line search is used. The example of architecture of ANN is shown in Fig.1.

Testing of ANN is done by simulating the architecture following training process, (Eq.2).

$$\begin{pmatrix} Var_{11} & \cdots & Var_{1n} \\ \vdots & \ddots & \vdots \\ Var_{m1} & \cdots & Var_{mn} \end{pmatrix} \xrightarrow[\text{simulation}]{\text{ANN}} \begin{pmatrix} {}_{predicted}PGV_{11} & \cdots & {}_{predicted}PGV_{1i} \\ \vdots & \ddots & \vdots \\ {}_{predicted}PGV_{m1} & \cdots & {}_{predicted}PGV_{mi} \end{pmatrix} \quad (2)$$

Recorded values of PGV's are divided by predicted PGV's. Therefore mean values of the ratios, standard deviations and coefficient of variations of training and testing sets are obtained.

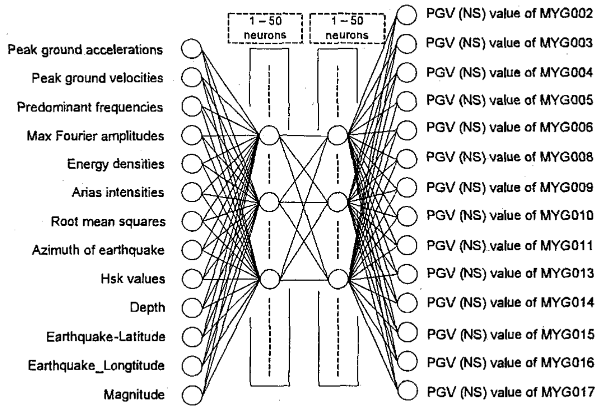


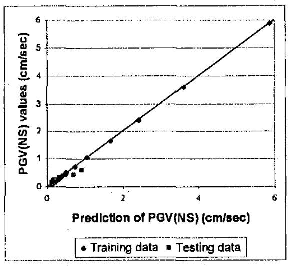
Fig.1. ANN architecture

3. Results

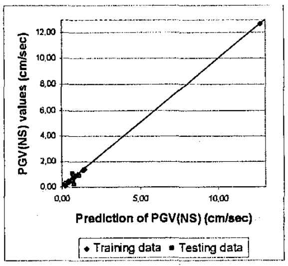
Depending on above description, different type of ANN structures (Table 1.) are employed to get the best result. 2 hidden layers

ニューラルネットワークに基づいた宮城県における
１観測点の記録からの最大速度分布の推定

KUYUK H. Serdar, YAMAMOTO Yu, ARRECIS Francisco, CHEN Jun, OHNO Susumu and MOTOSAKA Masato network with 28 and 26 neurons gave the most reasonable outcomes. Mean values of ratio between predicted and recorded of PGV's detected by MYG003 accelerometer are 1.00 and 0.93, standard deviations are 0.07 and 0.28 for training and testing set, (Fig.2a). For MYG016 these values are 1.00, 0.93 and 0.09, 0.36 respectively, (Fig.2b).



All Earthquake data for MYG003 accelaragram (a)



All Earthquake data for MYG016 accelaragram (b)

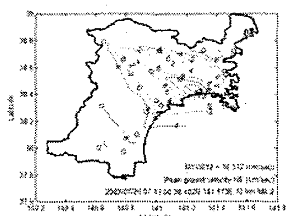
Fig.2. Comparison of obtained and predicted data regarding specific accelograms

Performance of ANN is generally related with the result of testing set; in Table 2 all combination results are shown.

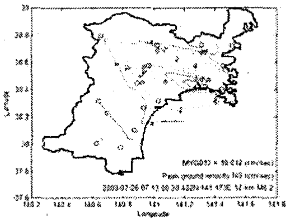
Table 2. Result of ANN

	Average Ratio	Std. Deviation	Coef. of Variation
Training set	1.01	0.01	1.40
Testing set	1.06	0.29	27.53
All data set	1.02	0.08	7.53

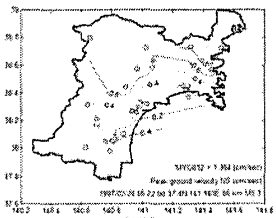
To show how much the results are in agreement, PGV's are contoured for the maximum North-South component of horizontal velocity (in cm/sec) at each station. Two earthquakes used for training of ANN are plotted in Fig.3 and it is clear that recorded data (a), (c) overlap the computed data (b), (d).



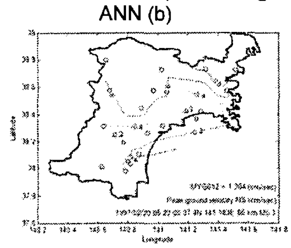
Distribution of PGV(NS) 2003/07/26 Earthquake (a)



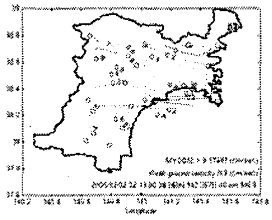
Distribution of PGV(NS) 2003/07/26 Earthquake using ANN (b)



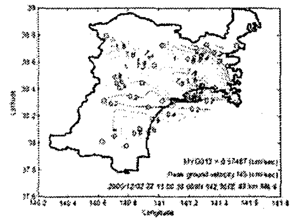
Distribution of PGV(NS) 1997/02/20 Earthquake (c)



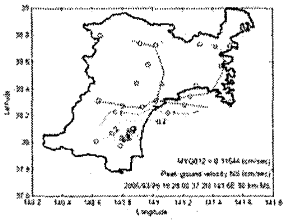
Distribution of PGV(NS) 1997/02/20 Earthquake using ANN (d)



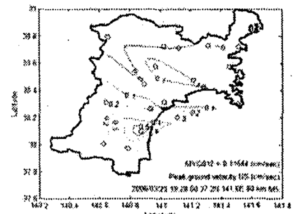
Distribution of PGV(NS) 2005/12/02 Earthquake (e)



Distribution of PGV(NS) 2005/12/02 Earthquake using ANN (f)



Distribution of PGV(NS) 2006/03/29 Earthquake (g)



Distribution of PGV(NS) 2006/03/29 Earthquake using ANN (h)

Fig.3. Comparison of obtained and predicted data regarding specific earthquakes

In (e), (f), (g), (h) of Fig. 3 two of 9 earthquakes used for testing ANN are also demonstrating reasonable results. The current distribution of K-Net seismic station in Miyagi-ken is also shown in Figure 3 with circles.

4. Conclusion and Discussions

In this study some of the advantages of ANN, using experiences, learning capability and constituting relation past and future or inputs and outputs are employed to get the prediction of N-S component of PGV distribution in Miyagi prefecture based on one accelogram records using Artificial Neural Network method is achieved.

The testing result values maybe not exactly fit the experienced data as training sets however the distribution maps show good agreement with real distributions.

It is convenient to use large amount of data in ANN but also it is obvious that as more recorded accelograms or earthquakes become available they can be used to retrain the ANN to get better results.

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