PREDICTION ON THE AMPLITUDES OF SEISMIC UNDERGROUND MOTIONS BASED ON DEEP NEURAL NETWORK

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Abstract

The underground structures were significantly damaged in the 1995 Kobe Earthquake, and since then the seismic safety of underground structures has received lots of attentions. In the dynamic nonlinear analysis of underground structures, one of key issues is how to determine the amplitudes of seismic underground motions (e.g., peak acceleration of underground record). Because the number of recorded underground records is far less than that of ground motions, there is no reliable prediction tool for the amplitude of seismic underground motions. Recently, the deep learning has become a popular and powerful tool to predict the behavior of complicated systems. The amplitudes of seismic underground motions depend on the characteristics of soil and earthquake, making the prediction very complicated. This paper aims to predict the peak acceleration of seismic underground records using the deep neural network (DNN). The total of 86880 underground records (including two horizontal components for each station) recorded by 4258 earthquake events (magnitude varies from 4.0 to 9.0) on 639 stations (epicentral distance varies from 0.74 km to 135 km), are collected from the Kik-net database. The average shear wave velocity of top 30 m soil (V_{S30}) varies from 111.11 m/s to 2100 m/s, and the peak ground acceleration (PGA) varies from 1.57 gal to 1080 gal, in order to cover the nonlinear site response. The seismic underground records in the east-west (EW) direction (i.e., the total of 43440 records) are randomly split into training (80% of the database), validation (10% of the database) and test (10% of the database) datasets, respectively, to check the overfitting of the DNN model (consisting of 5 layers and 256 neural in each layer) by monitoring the loss of the validation and testing datasets. The Adam optimizer is used as the optimization algorithm to reduce the error of the output with a batch size of 512 and 150 epochs of training. Note that the deep learning in this study was performed using Tensorflow. The input parameters include magnitude, epicentral distance, depth of the underground receiver (varies from 99 m to 2003 m), the classic site-characterization term Vs30, PGA, peak ground velocity (PGV) and peak ground displacement (PGD). The generalization ability of DNN model based on the database in the EW direction is also studied with the database in the north-south (NS) direction, and the results are summarized in Table 1. The results in Table 1 indicate that the DNN model provides good prediction on the peak acceleration of seismic underground records, and the generalization ability of DNN model is also accepted.

Key words: prediction; amplitude; underground motion; Kik-net; deep neural network

1. Introduction

Seismic hazard analysis is a critical part in the field of earthquake engineering. Underground motion amplitude is recognized as the basis for the seismic design of underground structures.
Recent years, more and more researchers have shown an increasing interest in deep neural network and extended the applications including the image classification, speech recognition and so on. Earlier studies have proven that neural networks have universal approximation properties [1,2]. Deep nets can approximate more functions than shallow nets and possess better approximation capability for some functions expressible by shallow nets [3-6].

An important advancement among artificial neural network (ANN) architecture is the construction of the deep neural network (DNN). This is, in fact, an improved form of ANN with multiple hidden layers between the input and output layers that has an excellent learning ability in terms of complex and non-linear relationships. It has been massively employed in civil engineering applications. Particularly in attenuation relationships correlating the peak ground acceleration (*PGA*), peak ground velocity (*PGV*), and peak ground displacement (*PGD*) with a number of independent predictors including earthquake magnitude, source to site distance, local characteristics of the site, and properties of earthquake source [7-10].

In this study, we consider a new robust artificial intelligence-based approach to apply deep neural network (DNN) models for predicting underground motion amplitudes, Compared with the traditional methods of studying the regular pattern of underground motion amplitude in the soil profile, such as developing equivalent-linear or nonlinear site response models and ground motion prediction equations. The new models are built upon the KiK-net database, which have both surface and downhole seismometers.

2. Method

Deep Neural Network (DNN) has extended the applications of conventional neural networks, which is a machine learning technique that does not need a feature extraction step. It can improve the learning of complex and nonlinear features by increasing number of layers and number of neurons in each layer. Increasing the number of layers and neurons can increase the run-time of the algorithm and require more training dataset. Another noticeable feature of DNN is transferring learning by training a set of data, and the weights of the network is refined by a different dataset. Two challenging requirements of DNN are large training datasets and high-performance computing platforms. With the help of public database and high-performance computers, more researchers use DNN to overcome complex and nonlinear pattern recognition problems. Typical applications of DNNs include object recognition, classification in the field of image processing and speech recognition [11-16]. In this study, we employ DNN to train, learn and predict the underground motion amplitude parameters.

If there is a network with m layers and n neurons in the ith layer, the output of the jth neuron is obtained by Eq. (1).

$$u_{ij} = \sigma(\sum w_{ji} \cdot x_j + b_j) \tag{1}$$

In Eq. (1), w_{ji} and b_j are the weight and bias corresponding to the jth neuron of the ith layer. The weights and the biases are initialized randomly (for instance by the normal distribution) and optimized through an iteration scheme. The input data is passed through the network layers. At the output, the obtained result is compared to the measured one. The difference between the observed and calculated outputs are used to correct the weights and biases using a backward propagation scheme, Fig.1 demonstrates the architecture of a deep neural network.

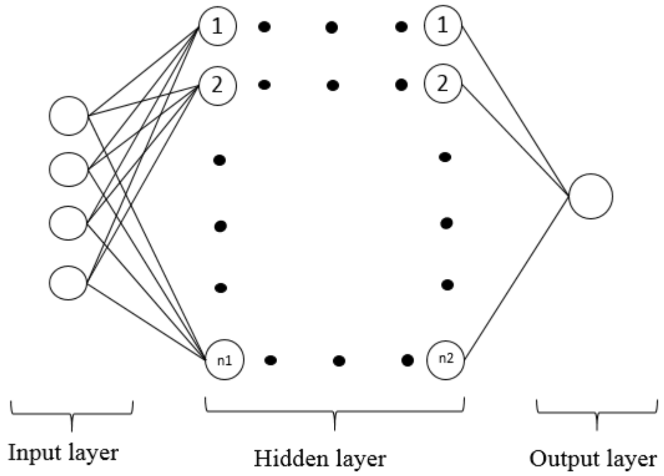


Fig. 1 – The architecture of a deep neural network.

3. Model

Underground motion parameters are governed by various seismic variables, including source (e.g., magnitude), path (e.g., source-to-site distance), site (e.g., average shear-wave velocity to various depths) and ground-motion parameters (e.g., observed *PGA*). The source effect is considered by different parameters regarding the source of earthquake event. The path effect is taken into account by a number of definitions representing the distance of the site from the source. The site effect is related to the local ground type and can be accounted for by the shear wave velocity in the soil. The attenuation relationships are frequently the functions of the earthquake magnitude, source to site distance, geotechnical properties of site, and ground-motion intensity.

We exploit DNNs to model the relationships between each input parameter and the predictors. We consider three different models corresponding to three independent output parameters (i.e., peak underground acceleration *PUA*, peak underground velocity *PUV*, and peak underground displacement *PUD*,). Each model is a 6-layer network consisting of 7×128×256×256×128×1 neurons. The input neurons represent magnitude, epicentral distance, average shear wave velocity of top 30 m soil, depth, *PGA*, *PGV*, *PGD* and the output is the estimated peak underground motion parameter.

Due to complex and nonlinear features of input parameters, we increased the number of layers and the number of neurons in each layer. The final decision on the hyper-parameters of the model was based on the validation set. We use Adaptive Moment Estimation (Adam) as the learning method that automatically adjusts the learning rate for every parameter.

The total of 86880 underground records (including two horizontal components for each station) recorded by 4258 earthquake events (magnitude varies from 4.0 to 9.0) on 639 stations (epicentral distance varies from 0.74 km to 135 km), are collected from the Kik-net database. The V_{S30} varies from 111.11 m/s to 2100 m/s, and the peak ground acceleration (PGA) varies from 1.57 gal to 1080 gal, in order to cover the nonlinear site response. The seismic underground records in the east-west (EW) direction (i.e., the total of 43440 records) are randomly split into training (80% of the database), validation (10% of the database) and test (10% of the database) datasets, respectively.

We initialized the weights of the network by a Normal distribution. The activation functions of the neurons were Rectified Linear Units (ReLUs). The loss function of the optimization was the ''Mean Square Error'' using Eq. (2).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \tag{2}$$

We calculated the natural logarithm of the input data and normalized them in the range of [0,1] using Eq. (3).

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

In Eq. (3), X, Xmax, and Xmin are the natural logarithm of the input parameter, the maximum and the minimum values of X, respectively. Fig. 2 demonstrates the architecture of the developed ground motion model (GMM).

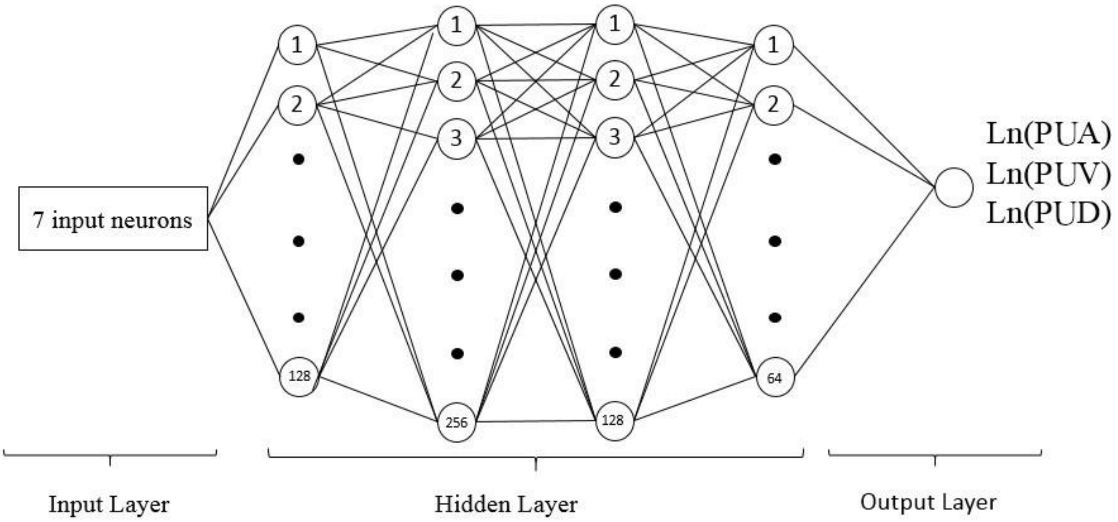


Fig. 2 – The architecture of the developed ground motion model (GMM).

The formulations of peak underground motion parameters (in natural logarithmic form) are selected as follows:

$$\begin{Bmatrix} \ln PUA \\ \ln PUV \\ \ln PUD \end{Bmatrix} = f(M_w, Epid, V_{S30}, Depth, PGA, PGV, PGD) \tag{4}$$

where,

M_w: Earthquake moment magnitude

Epid: Source-to-site distance

V_{S30} (m/s): Average shear wave velocity over the top 30 m of site

Depth: Depth of downhole seismometers

PGA: Peak ground acceleration

PGV: Peak ground velocity

PGD: Peak ground displacement

The best DNN models are selected based on the best fitness values on the training and testing data sets. Variety of standard measures are available for evaluating the performance of the prediction models. The indices used for the performance analysis in this study, are correlation coefficient (R), mean absolute error (MAE), and root mean squared error (RMSE). These measures are calculated by the following formulae for each dataset.

$$R = \frac{\sum (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum (x_i - \overline{x})^2 \sum (y_i - \overline{y})^2}} \tag{5}$$

$$MAE = \frac{\sum_{i=1}^{N} (|x_i - y_i|)}{N} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N} \sum (x_i - y_i)^2} \tag{7}$$

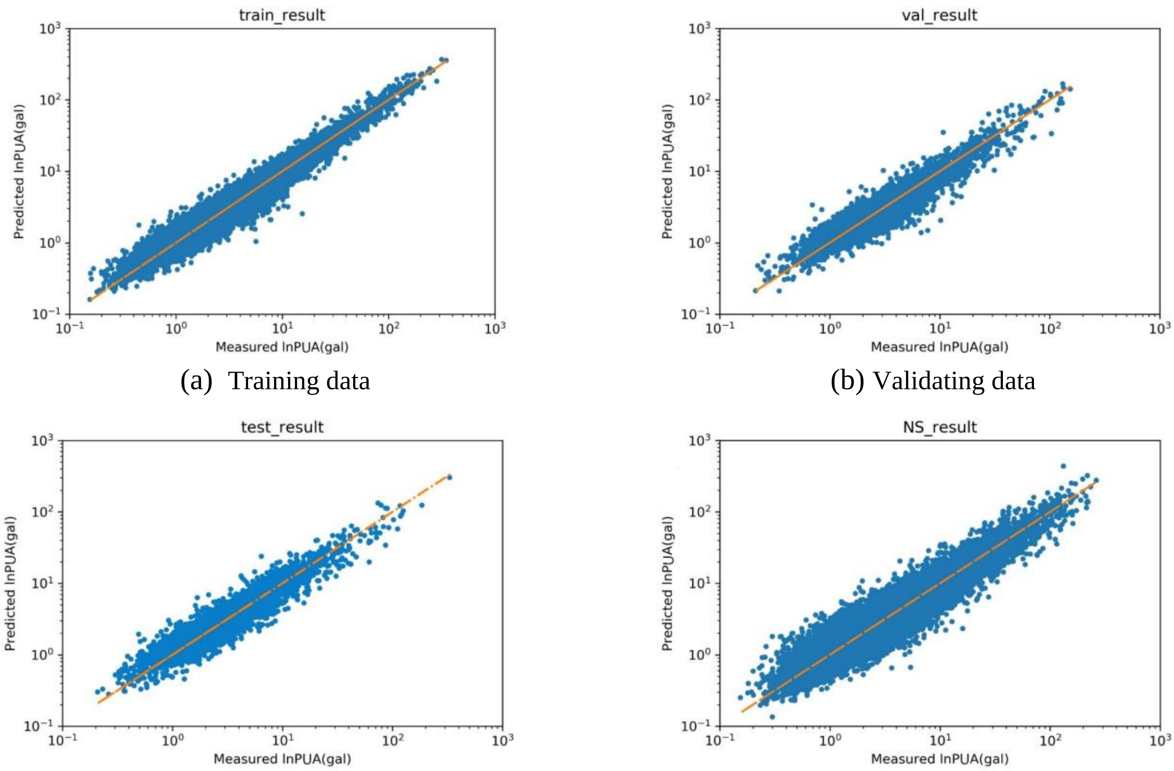
Where,

N, x_i, y_i, x and y are the total number of data, measured output, estimated output, the average value of measurements and the average value of estimations, respectively

4. Result and Discussion

The observed surface record is used as the input parameters to the DNN model, and the motion is propagated through the soil profile to predict the ground motion at the downhole. With the training of amplitude of seismic underground motions, the predicted downhole ground motion is then compared with the observed downhole ground motion.

The Fig. 3-Figure 5 show the comparisons between the predicted and observed values for the PUA, PUV and PUD respectively. It can be seen that the DNN model developed in this work show the similar prediction ability for different parameters.

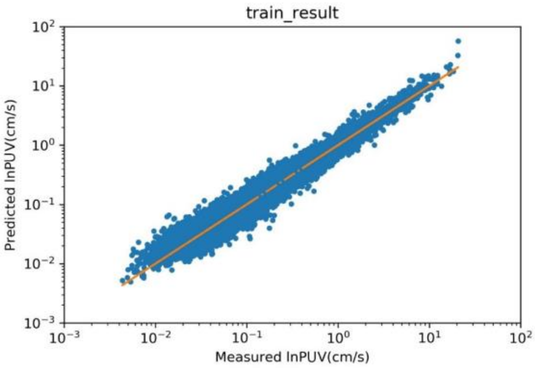


(a) Training data (b) Validating data

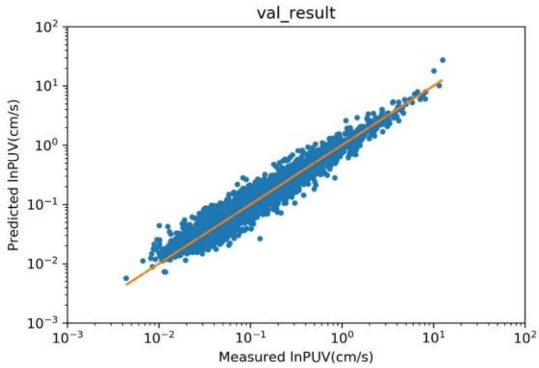
(c) Testing data-EW (d) Testing data-NS

Fig. 3 – Predicted versus measured values of PUA

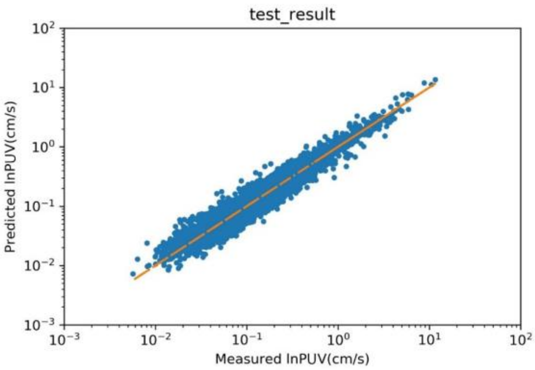
Table 1 shows the correlation and bias results between the predicted and observed values for PUA. The results in Table 1 indicate that the DNN model can provide the precise prediction for underground motion amplitude parameters. The generalization ability of DNN model based on the database in the EW direction is also studied with the database in the north-south (NS) direction, and the results indicate that the generalization ability of DNN model is also accepted.



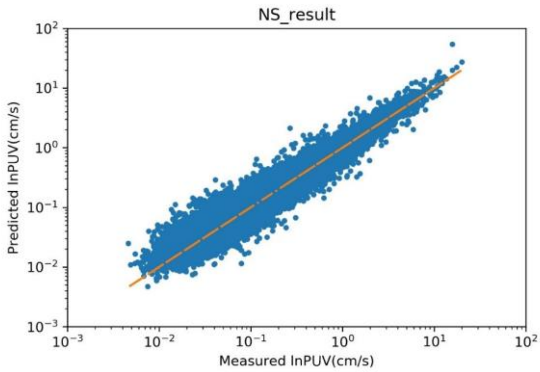
(a) Training data



(b) Validating data

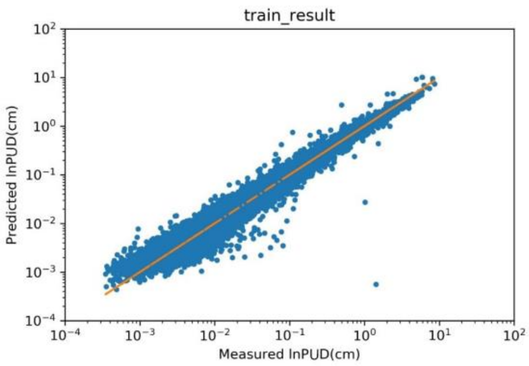


(c) Testing data-EW

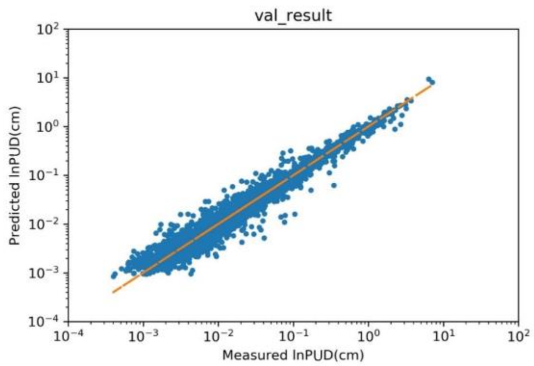


(d) Testing data-NS

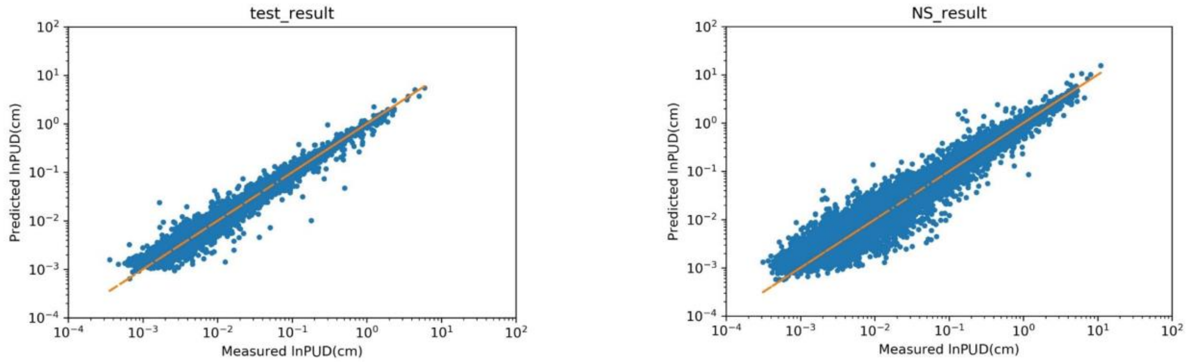
Fig. 4 – Predicted versus measured values of PUV



(a) Training data



(b) Validating data



(c) Testing data-EW (d) Testing data-NS

Fig. 5 – Predicted versus measured values of PUD

Table 1. The values of coefficient of determination R^2, MSE and MAE

Direction	Datasets	R^2	MSE	MAE
EW	Training	0.946	0.047	0.167
	Validation	0.887	0.100	0.244
	Testing	0.884	0.098	0.244
NS	All	0.876	0.106	0.251

5. Conclusion

The KiK-net database in Japan used in this study is the most extensive network of vertical seismometer arrays in the world, which have both surface and downhole seismometers. In this study, we exploit the DNN to develop robust models for estimating the time-domain underground motion parameters. The DNN can represent more complicated functions using large number of layers, and neurons each layer. The presented models depend on a large database including a great amount of earthquake data collected from KiK-net database,

The proposed models give reliable estimates of the amplitudes of seismic underground motions. This is verified based on the appropriate values of several important statistical indices such as correlation coefficient(R^2), mean absolute error (MAE), and root mean squared error (RMSE).

The generalization ability of DNN model based on the database in the EW direction is also studied with the database in the north-south (NS) direction, and the results indicate that the generalization ability of DNN model is also accepted.

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