Fundamental Study on Damage Detection of Civil Structures Modeled as MDOF System Based on Machine Learning

ATSUSHI MIKAMI

ABSTRACT

In Japan, the deterioration of civil structures constructed during the period of strong economic growth combined with the shortage of engineers has become a serious social problem. One solution to address this issue is to improve the efficiency of structural maintenance and management using sensors. The application of machine learning method is expected to advance such efforts. This research attempts the damage detection of civil structures using an autoencoder, which is a type of unsupervised machine learning. The study revealed that there is a relation between the magnitude of reconstruction error and the degree of damage to the structure.

INTRODUCTION

In Japan, the deterioration of civil structures constructed during the period of strong economic growth (mainly since the 1960s) combined with the shortage of engineers has become a serious social problem. Improving the efficiency of maintenance and management using sensors is one solution to address this issue. The application of machine learning methods to data analysis is expected to advance such efforts. The present research attempts damage detection of civil infrastructures using an autoencoder [1], which is a type of unsupervised machine learning. Although the use of strong motion records observed at an instrumented structure for structural health monitoring is assumed, this study numerically generates seismic responses for a structural model.

Herein, several seismic motions of differently scaled amplitudes were prepared to give input motions to a civil structure modeled as a Multi-Degree-Of-Freedom (MDOF) system. Furthermore, the obtained response records were used for machine learning. Various seismic motions prepared were adjusted to have a maximum amplitude of 50gal. Then, they were used as input ground motions to the structure to calculate the linear structural responses that were used for training the autoencoder. Another earthquake ground motion was then prepared and its maximum amplitude was adjusted in the range of 50 to 1600 gal to be used as input ground motions. The linear and nonlinear structural responses were then calculated to verify the effectiveness of the damage detection method.

Mikami A., Tokai University, 4-1-1 Kitakaname, Hiratsuka, Kanagawa 259-1292, Japan

DAMAGE DETECTION OF CIVIL STRUCTURES USING AUTOENCODER

Herein, it was assumed that structural damage detection is attempted using strong motion observation records obtained from instrumented structures. Although there is a high possibility of obtaining the response records of structures that are subjected to small and medium-sized earthquakes, the possibility of obtaining records with damage to structures is not high. This implies that the probability of obtaining abnormal data is considerably lower than that of obtaining normal data. Thus, as unsupervised machine learning, an autoencoder is used for damage detection of civil structures in this research.

Autoencoder

Machine learning methods are classified into supervised and unsupervised learning. Supervised learning can be appropriately used in fields in which a large amount of training data can be prepared. However, if sufficient damage data are not available as in the field of damage detection of structures, unsupervised learning is preferable. Thus, this research uses an autoencoder, which is an unsupervised machine learning method.

The autoencoder used in this study is a three-layer neural network as shown in Figure 1. The network learns the characteristics of the signal so that the data at the input layer is reconstructed at the output layer. During the training stage, only normal data is used, and the neural network weights are determined. Therefore, when the time series at the input layer is normal data, the original waveform is well reconstructed at the output layer, thus the reconstruction error, which is an index defined as the difference between the original waveform and the reconstructed waveform, becomes small. However, if the time series at the input layer contains abnormal data, the original waveform will not be reconstructed properly at the output layer, causing the reconstruction error to become large. This research attempts to detect structural damage by treating the structural response data unassociated with damage as normal data and the response data associated with damage as abnormal data. It is noted for the application of autoencoder that this research used Deep Learning Toolbox for use with MATLAB [2].

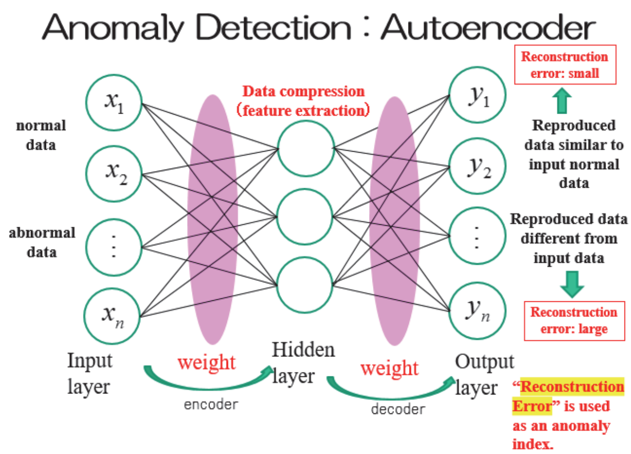


Figure 1. Autoencoder

Civil Structure Modeled as MDOF System

As a model of general civil structure, a MDOF system was prepared. Referring the book by Ohsaki [3], a 5-DOF model was prepared as follows. To simplify the discussion below, mass and stiffness (see Figure 2 and TABLE I) were assumed to be constant for all the layers. For the damping model, stiffness-proportional damping was assumed for simplicity with a first mode damping constant of 5%. The natural frequency of the model is approximately 2.2 Hz. As a method of considering structural damage, a nonlinear model (trilinear model) described in Figure 3 was incorporated throughout the layers.

Input Ground Motions

Five input ground motions (TABLE II) were prepared to calculate the seismic response of the structure to be used for training and verification for the machine learning. The first and second ground motions are El Centro earthquake record and Hachinohe wave provided by The Building Center of Japan. The third one was observed on a stiff ground in Naruto during the 2013 near the Awajishima earthquake. The fourth ground motion was observed at K-NET Urayasu station during 2011 Tohoku earthquake. The last one was observed at K-NET Hakuba station during the 2014 northern Nagano earthquake.

Preparation of Seismic Ground Motions for Structure

Ground motions from No.2 to No.5 in TABLE II were used as the input ground motions for the structure after adjusting their amplitude to 50 gal. The calculated ground

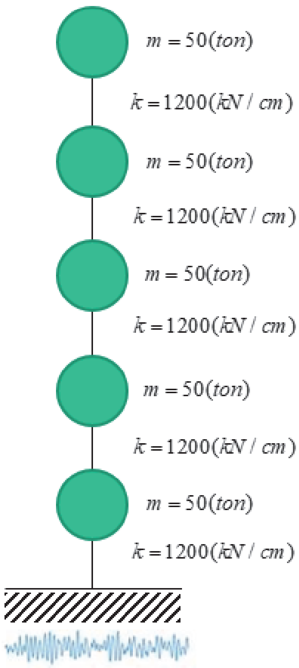


Figure 2. Structural model

TABLE I. PARAMETERS FOR STRUCTURAL MODEL

Parameter	Value
Mass	5.0×10^4 (kg)
Stiffness	1.2×10^6 (N/cm)
Damping constant	0.05 (stiffness-proportional)

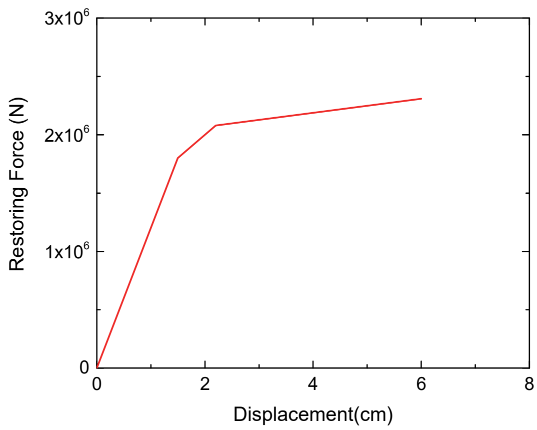


Figure 3. Tri-linear model to describe the nonlinearity of the structural model

TABLE II. GROUND MOTIONS USED TO CALCULATE STRUCTURAL RESPONSES

No.	Earthquake Information	Earthquake Date	Magnitude
1	El Centro earthquake wave	1940.05.18	6.4
2	Hachinohe wave during 1968 Tokachi-Oki earthquake	1968.05.16	7.8
3	Stiff ground in Naruto during earthquake Near Awajishima	2013.04.13	6.8
4	K-NET Urayasu during 2011 Tohoku earthquake	2011.03.11	9.0
5	K-NET Hakuba during 2014 earthquake in Nagano	2014.11.22	6.7

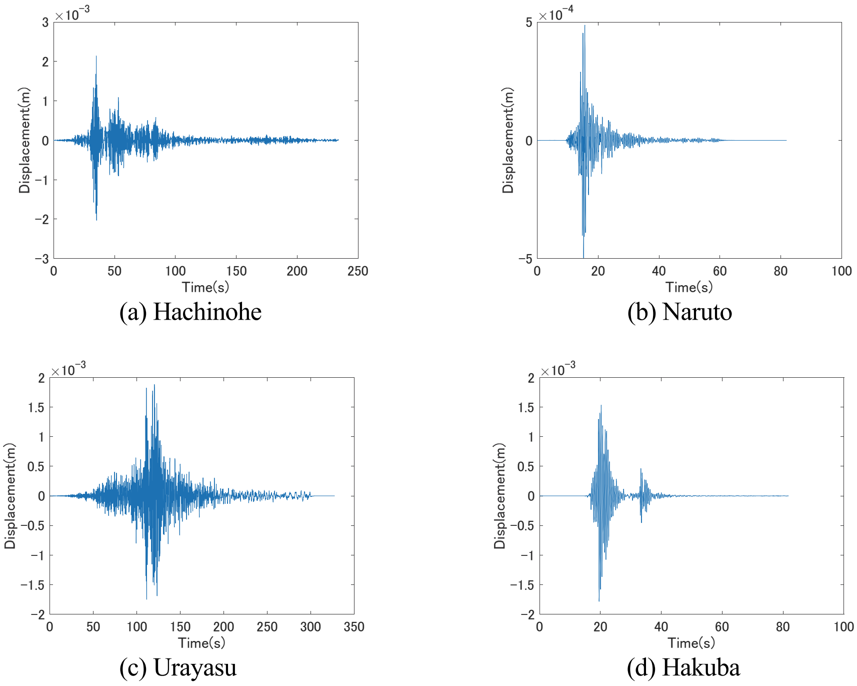


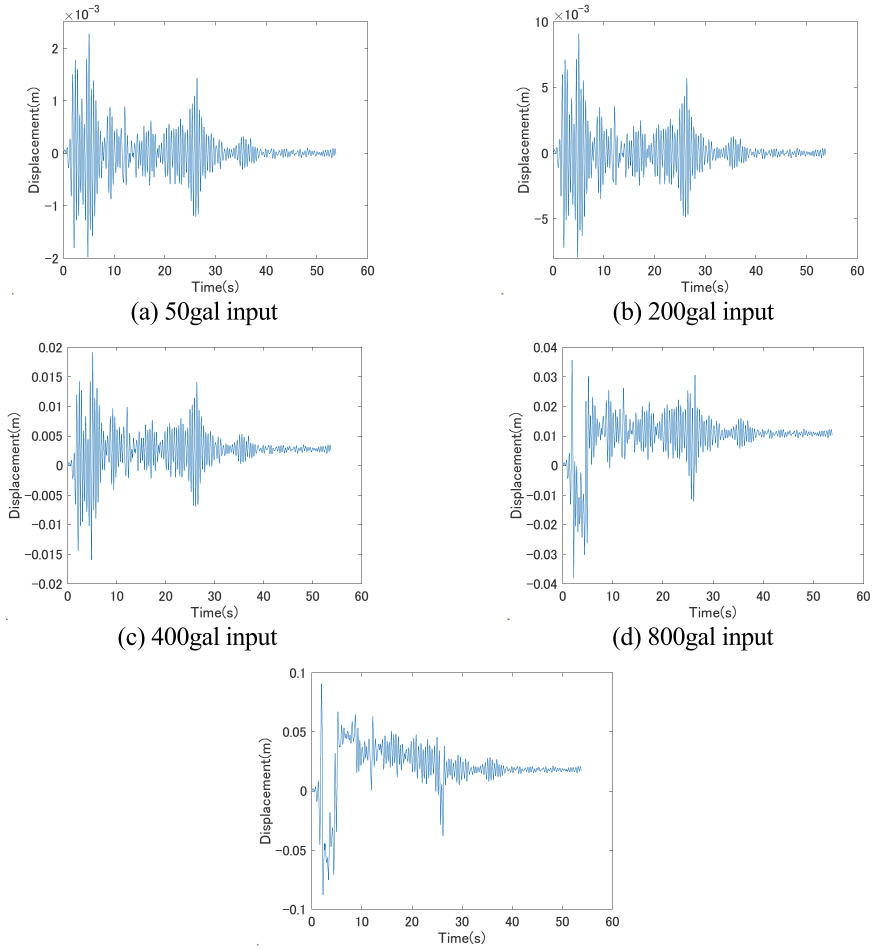
Figure 4. Displacement responses for ground motion No.2 to No.5 scaled as 50gal)

motions were assumed to be linear seismic responses. Input ground motion No.1 was used for the verification of the proposed damage detection method by adjusting its amplitude to 50, 200, 400, 800 and 1600gal.

Seismic Response of Structure

Seismic responses of the structure were calculated as shown in Figure 4 for the input ground motions (No.2 to No.5 in TABLE II). The responses were considered to be linear as the maximum amplitude of these input motion was scaled to 50gal. Figure 5 depicts the seismic responses for the input ground motion No.1 (El Centro wave) with variation in maximum amplitude from 50 to 1600 gal. Residual displacement can be clearly observed in Figure 5 (c), (d) and (e).

Figure 6 depicts the relation between restoring force and displacement. The restoring force characteristics indicate that the structural responses are linear when the maximum amplitudes of the input ground motions are 50 and 200 gal, however, exhibit nonlinear behavior for larger input ground motions (400, 800 and 1600 gal). Note that this study only focuses on the displacement response of the first layer of the MDOF structure.



(a) 50gal input

(b) 200gal input

(c) 400gal input

(d) 800gal input

(e) 1600gal input

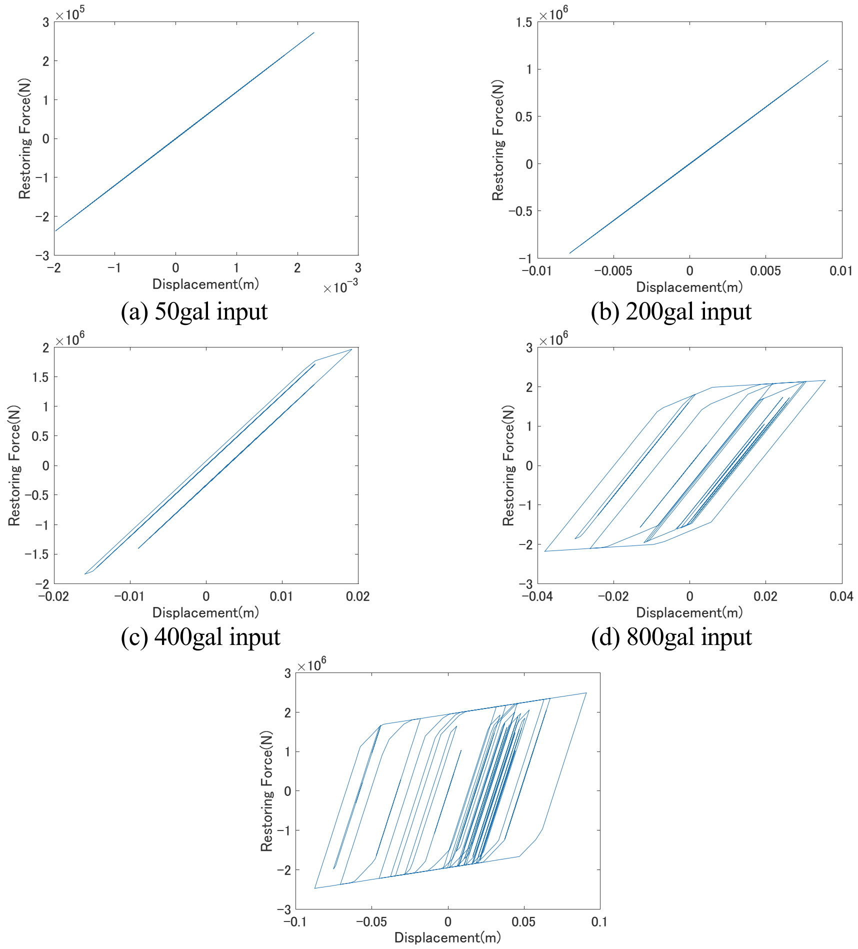
Figure 5. Displacement responses for ground motion No.1 (differently scaled)

COMPUTATIONAL RESULTS OF DAMAGE DETECTION BASED ON AUTOENCODER

Since all the displacement time history records needed for the machine learning were prepared by the previous sections, the autoencoder can be applied to the data in this chapter.

Preprocessing the Data for Training

For the application of machine learning to the time history responses, maximum amplitude of each time series was scaled to 1 (i.e., unit amplitude responses) prior to its application. The time history response data was divided into partial time series of each 1 second comprising 100 data per sample. Thus, reconstruction error values were calculated for each sample (i.e. every 100 data points). It is noted that the hidden layer size of the autoencoder was set as 50.



(a) 50gal input (b) 200gal input
(c) 400gal input (d) 800gal input
(e) 1600gal input

Figure 6. Restoring force characteristics

Calculation Results of Damage Detection

Figure 7 compares the original and the reconstructed waveform for input cases of 50, 200, 400, 800 and 1600 in the increasing order. For larger input case, residual displacements were observed, however the reconstructed waveforms cannot well describe the original waveforms.

Figure 8 shows the reconstruction errors for input cases of 50, 200, 400, 800 and 1600 gal. The reconstruction error was found to be larger for larger input cases despite the standardization of the maximum amplitudes of the time history responses. Notably, the reconstruction error values for the 50 and 200 gal input cases, which were considered to be linear responses, were almost the same. These results indicate a relation between the magnitude of the reconstruction error and the degree of damage to the structure.

Effect of Using Only the Main Part of the Structural Response for Training

Up to this point, almost all data points from the beginning to the end of the structural response were used for training, however, the substantial part of the structural response is usually limited. Therefore, additional consideration is performed here extracting the main part of the response record. TABLE III summarizes which part of the waveform

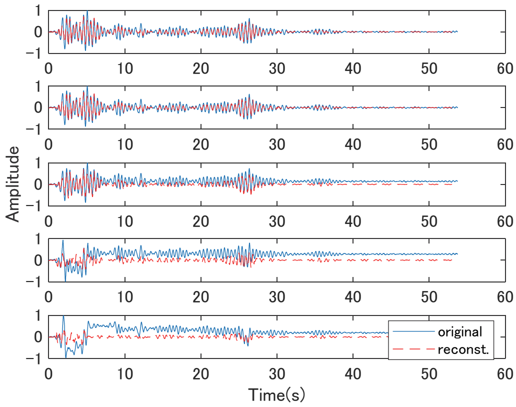


Figure 7. Original and reconstructed waveforms

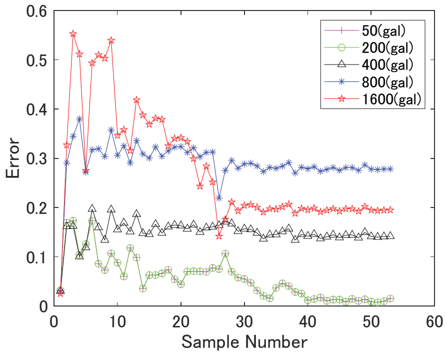


Figure 8. Reconstruction error

was used for training. Approximately half of the data points were extracted from the original response waveform.

Figure 9 shows the reconstruction errors for input cases of 50, 200, 400, 800 and 1600 gal. It can be seen that quite similar results as in Figure 8 was obtained although the amount of data used was reduced approximately by half.

CONCLUSIONS

This study investigated the possibility of using machine learning on the linear seismic response records of civil structures to detect the occurrence of damage from the nonlinear response records of structures during large earthquakes.

Five seismic ground motions were prepared and four of them were adjusted to have a maximum amplitude of 50 gal. Subsequently, they were used as the input ground motions to a 5-DOF structure, and the obtained linear displacement responses were used for training by the autoencoder. Further, the maximum amplitude of the one remaining ground motion was adjusted to 50, 200, 400, 800 and 1600 gal, and these adjusted motions were used as input to the 5-DOF system to calculate linear and nonlinear responses for verification. Structural damage detection was attempted by applying the autoencoder, which was already trained with the linear responses, to these responses. In the training and verification stages, the amplitude of the time history responses was adjusted to 1 (unit response) prior to application of the autoencoder.

TABLE III. EXTRACTED SECTIONS FROM STRUCTURAL RESPONSE USED FOR TRAINING

No.	Earthquake Information and input ground motion	Used structural response data	
		Almost all	Main part only
2	Hachinohe wave during 1968 Tokachi-Oki earthquake	1 – 23400 (234 seconds)	2001 – 13700 (117 seconds)
3	Stiff ground in Naruto during earthquake Near Awajishima	1 – 6000 (60 seconds)	1001 – 4000 (30 seconds)
4	K-NET Urayasu during 2011 Tohoku earthquake	1 – 30000 (300 seconds)	5001 – 20000 (150 seconds)
5	K-NET Hakuba during 2014 earthquake in Nagano	1 – 8100 (81 seconds)	1001 – 5000 (40 seconds)

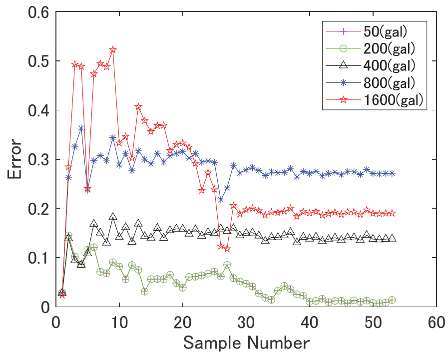


Figure 9. Reconstruction error (main half of structural response)

Reconstruction error was found to be larger for larger input cases despite the standardization of the maximum amplitudes of the time series to 1 (unit response). The reconstruction error values for 50 and 200 gal input cases, for which linear responses were obtained, were almost identical. These results indicate a relation between the magnitude of the reconstruction error and the degree of damage to the structure. Additional examination was conducted extracting the main half part of the structural response record for training the machine learning model, however, quite similar results of damage detection was obtained although the amount of data used for the training was reduced approximately by half.

ACKNOWLEDGMENT

This work was supported by JSPS KAKENHI Grant Number JP19K04583. The author is grateful for the use of seismic motion records provided by The Building Center of Japan and National Research Institute for Earth Science and Disaster Resilience (NIED).

REFERENCES

1. Hinton, G.E. and Salakhutdinov, R.R. 2006. "Reducing the dimensionality of data with neural networks," *Science,* 313(5786):504-507.
2. MathWorks Japan. 2017. "Neural Network for Sensor Data Analysis," The Math Works, Inc. (in Japanese) https://jp.mathworks.com/videos/neural-network-for-sensor-data-analysis-1505494780628.html
3. Ohsaki, Y. 1996. "Architectural Vibration Theory," Shokokusha (in Japanese).