BRIDGE SEISMIC DAMAGE RECOGNITION FROM STRUCTURAL ACCELERATION DATA USING MACHINE LEARNING

Saitama University Student Member ○Nikesh Maharjan
Saitama University Regular Member Ji Dang
Saitama University Student Member Ashish Shrestha

1. INTRODUCTION

The need and importance of damage recognition in bridge structures in today's road network is increasing with its aging service life. Bridges are exposed to deterioration and damage during their service life and such damage and deterioration severely affect the safety and serviceability of the structure. Besides its own serviceability factors, such structures are highly vulnerable to damages due to seismic activities. Thus, the recognition of the damages at its early stage has become one of the most important study in the field of civil engineering. Conventional ways of damage recognition are complex, labor intense, time consuming, tedious and lacks standard benchmark for level of damage state detection (Yan *et al*, 2001, Jeong-Tae Kim *et al.*, and X. Fanga *et. al*, 2005). Hence, as an alternative to the conventional methods, studies using machine learning techniques for damage recognition has been an emerging topic.

In this study, performance of Artificial Neural Network (ANN) based algorithm for the damage recognition using acceleration has been studied. The feasibility of using such neural networks for damage recognition with the help of numerical models has been investigated. Simplified models for traverse (3DOF) and longitudinal direction (5DOF) of the bridge are considered for non-linear analysis and numerically simulated to get the structural responses under 18 designed earthquakes. In this neural network, the structural acceleration and calculated displacement are used as the input layer and then the labels (damaged or undamaged) would be obtained from the output layer. Non-linear seismic simulation has been conducted to generate database, which has been used for training the network and classifying the input data into two output classes. Both acceleration and calculated displacement data from 1DOF are used in the training the network and test data set are generated from 3DOF and 5DOF models. Machine learning algorithm trained by using data from simple model has been used in classification of labelled data from complex models.

2. DATA ACQUISITION AND PRE-PROCESSING

The input data (acceleration and displacement) are generated from Non-linear Analysis using 18 different designed earthquakes (Level 1 and Level 2) to excite 3 different models (1DOF, 3DOF and 5DOF with 5% damping ratio). Lumped mass model with the structural parameters as in the Table 1 are considered. All the models are considered as a bilinear model in the analysis (Dynamics of Structure, A.K. Chopra).

Table 1 Non-linear Parameter setting for different models.

Parameters	1DOF	3DOF	5DOF	Remarks
Time Period (T)	0.3 ~ 2 sec	0.5 ~ 2 sec	0.2746 ~ 0.7189	Eigen Value analysis
Stiffness (k)	$(\frac{2\pi}{T})^2 * m$	$(\frac{2\pi}{T})^2 * m$	100	Depends on value of T. (N/m)
Mass (m)	1	1	1	Unit mass (kg)
Stiffness Ratio (alpha)	0.1 ~ 0.6	0.1 ~ 0.6	0.1 ~ 0.6	0.1+0.5*rand
Yield acceleration (ay)	0.2 ~ 1.2	0.2 ~ 1.2	0.2 ~ 1.2	0.2+1*rand

Both displacement and acceleration data are normalized to the length of 300 (150 data from maximum values at both ends). These data are then labelled into damaged and undamaged class with simple condition; when the ratio of maximum value of response displacement (D_{max}) to the Yield displacement (d_y) is greater than 1 and undamaged class (Label 2), if the ratio is less than 1 as shown in the equation (1).

$$\frac{D_{max}}{d_y} > or < 1 \quad (Label\ 1\ or\ Label\ 2) \tag{1}$$

The response data from 1DOF are used for the training the machine learning algorithm. 3 different size of training data set of 5000, 10000 and 20000 (later called as Data-1, Data-2 and Data-3 resp.) are generated. 20% of the training data which are not included in the training are used as test data and the Test Data-1and Test Data-2 from 3DOF and 5DOF respectively are also used for the testing the classification. The data types for both cases can be seen in the tabulated form in Table 2.

Keywords: artificial neural network, algorithm, damage detection, non-linear analysis, seismic
Contact address: 338-8570,255-Shimo-Okubo, Sakura-Ku, Saitama, Japan,
Tel: +81-80-5339-8163 E-mail: nikeshmaharjan383@gmail.com

Table 2 Data types in Case II (acceleration-displacement data)

Model	Training Data	Validation Data	Test Data	Model
1DOF	Data-1 Data-2 Data-3	Val. Data	Test Data-1	3DOF
			Test Data-2	5DOF

3. NEURAL NETWORK BASED DAMAGE DETECTION

ANN has been used for the identifying and classifying the damages in the structure due to ground excitation (earthquakes). Machine Learning Tools like nrptool and nntraintool (MathWorks) has been used for the training the network and classification of the output. Non-linear analysis has been carried out to get the response acceleration from different models under randomly chosen earthquake waves. Response data are then, pre-processed (normalize and label) to train the machine learning algorithm. Once the model has been trained, test data is introduced to the same trained model for the classification.

Two-layer Neural Network (Network-1) and Three-Layer Neural Network (Network-2) has been used for the algorithm training and classification. Network-1 is a multi-layer feedforward network (one input layer, one hidden layer and one output layer), with a sigmoid transfer function in a hidden layer, and a Softmax transfer function in the output layer. Network-2 consists of two different layers of Autoencoder, a Softmax Classifier and a Stacked Network (Autoencoders and Softmax Classifier). In this neural network, the acceleration and calculated displacement has been used in the input layer and then the damage label (damaged or undamaged) would be obtained in the output layer.

4. SYSTEM PERFORMANCE

The network is trained only with the data from 1DOF model and test data are used from other complex models. The normalized acceleration vs. displacement data that has been used in training the model can be visualized as shown in Fig.1. The classification accuracy of the machine learning algorithm has been summarized in the Table 3. The trained algorithm shows very high accuracy (above 90% in all data sets) when the validation data set is used, also, the accuracy is significantly high as 80% in the case of test data (Test Data -1 and Test Data-2) from other models as well.

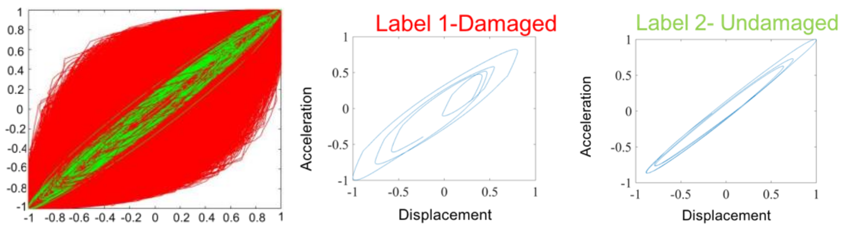
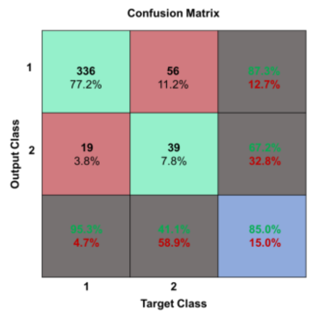


Fig.1: Normalized acceleration-displacement data

Table 3: Classification accuracy in Case II

Train Model Data	Test Data	Data-1	Data-2	Data-3	Classification Architecture
1DOF	20% of the training data size	84.8%	89.8%	93.0%	Network-1
		90.6%	94.7%	95.5%	Network-2
	3DOF (Test Data-1)	84.7%	88.0%	86.0%	Network-1
		83.0%	86.7%	82.3%	Network-2
	5DOF (Test Data-2)	85.0%	82.5%	86.6%	Network-1
		86.8%	85.3%	88.0%	Network-2



5. CONCLUSIONS

The trained network can classify the damage and undamaged data with significant accuracy of 80% or above. Hence, the simpler model can be used for training the network to recognize the damage data from complex models as well. However, the system was found out to be unstable for the structures with high frequencies.

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