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Bridges Damage detection Using Deep Learning

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ABSTRACT

Bridges have an important role for a society and its economy. However, bridges are vulnerable and are subject to gradual and sudden deteriorations in operational conditions. Smart management systems are needed to address this issue; this study investigates the possible structural damages and developes innovative solutions to measure the response and to asses the condition of the bridge structure. Sub matrix scaling factors is the algorithm developed to achieve the stated objectives. This study present an application of deep neural network for damage detection. Two bridges were taken into account for the experiments, and acceleration data set were the input of the neural network. The modal analysis of a parametric finite element model computes the analytical modal properties that are compared with the experimental data to train the network. The approach presented, which uses sub-matrix scaling factor, showed good results to characterize damage.

1.Introduction

The aging civil infrastructure has been challenges many researcher to studied the condition civil structures to better face. Maintaining safe and reliable civil infrastructures for daily use is very important to human activities. Knowing the condition and integrity of the structure in terms of its age and usage, and its level of safety from chatastropic event is important and necessary. The process evaluation of determining and tracking structural integrity and assessing the nature of damage in a structure is often referred to as health monitoring.

Generaly, the observation of a structural system over time using periodically sampled response measurements from an array of sensors, the extraction of damage-sensitive features from these measurements, and the statistical analysis of these features to discriminate the actual structural condition for short or long-time periods. Then, once the normal condition has been successfully learned, the model can be used

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for rapid condition assessment to provide, in nearly real time, reliable information regarding the integrity of the structure.

In structural health monitoring, the observation and identification of damage is important. The bridges should be damage free, reliable, and safe. The damage to a structural member causes changes modal properties of the structure: natural frequencies, mode shapes, and damping ratio. It is easy to measure the modal properties, but locating the actual damage is a challenge.

In this study, a new method is proposed by implements machine learning and artificial neural networks is used to locate and quantify the damage. The usefulness of neural networks in finding the damage has been improved due to its ability to deal with the analysis of the structural damage with intensive a computation.

2. Damage Dectection

2.1. Framework Neural Newtork

The natural frequencies and the mode shapes of the real structures were obtained using current state of the art sensing technologies. The signals in time domains were analyzed using autoregressive coefficient algorithm. Although many types of neural network are used in practice. The main advantages using backpropagation algorithm is capable of solving the non linearity separable pattern classification problems; it was first popularized and widely used by (Zivanonic et al 2006). It consists of one output layer of neurons and one or more intermediate layers, referred to as hidden layers. The number of neurons in individual layers may be different, and they may each have a different transfer function. Training is usually done by iterative updating of weights, usually employing the negative gradient of a mean-square error function. The details of the proposed approach are discussed in the following sections.

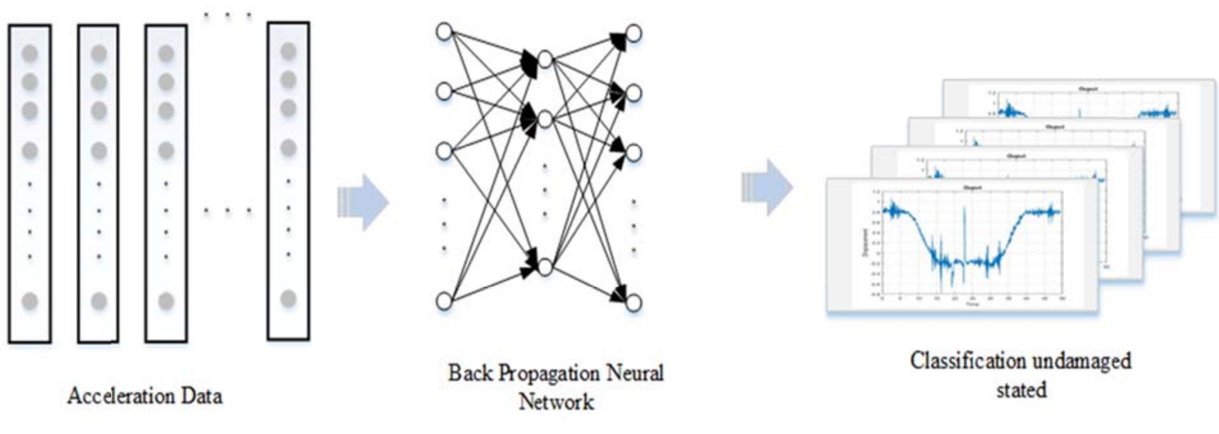

Figure 1. Framework Backpropagation Damage detection

2.2.1 Training

The training and verifying process of neural network started with the learning from experimental data that generated output datasets. Generally, neural network learn by example, learning characteristic of neural network is based on dataset size, larger datasets typically produce networks with enhanced prediction accuracies when compared to neural network produced from limited data[7]. After production, the datasets are divided into training, testing, and validation sets. In the learning process, iterations of connection weight adjustment over the training datasets is important part. Therfore, training datasets help evaluate the prediction accuracy of the neural network on data not applied in the training process. Because multiple network configurations are often considered in neural network analysis, validation datasets are used to reevaluate the top-performing network structures from the training and testing stage. To ensure that the network is exposed to the full range of data in the training process, datasets containing the minimum and maximum values of input parameters are assigned to the training dataset, and the remaining datasets are divided so that the training, testing, and validation subsets receive 50%, 25%, and 25% of the data, respectively (Al Rahmani et al 2012, Dan et al 2014).

2.2.2 Forward propagation

In engineering application multi-layered feed-forward neural networks commonly used in neural networks. These neural networks are used to configure relations between input variables x, and output variable y, within the domain of the training data set $D = \{(xj, yj); j = 1,..., k\}$ in which k indicates the number of the training data set points. The mathematical expression of the problem is a function relating x to y and coinciding with the k points in the (x,y) space. Network architecture is an arrangement of the artificial neurons and their relationships. A multi-layered perceptron consists of an array of input neurons known as the input layer, an array of output neurons called the output layer, and a number of hidden layers. Each neuron receives a weighted sum from each neuron in the preceding layer and provides an input to every neuron of the next layer. The activation of each neuron is governed by a threshold function such as sigmoid function. In order to train the network, the back-propagation algorithm where the error calculated at the output of the network is propagated back through the layers of neurons to update the weights, may be used. Therefore, a multi-layered feed forward neural network is trained with the training set, such that within the domain of the training data it approximately represents the training data set. The approximation in neural networks is represented by the error vectors ej within the domain of the training data.

2.2.3.Back propagation

The most common neural network in use is the multi-layer perceptron (MLP) trained by back propagation. The advantages back propagation learning algorithm is a way of adjusting weights and biases by minimizing the error between predicted and measured outputs of the network. The most commonly applied neural network among many different types is the feed forward, multi-layered, supervised neural network with error back propagation algorithm, which is used in this paper. The neural network model is trained with undamaged condition in order to capture baseline condition.

2.3.Proposed Method

Damage detection method using submatrix scaling factor has been introduced by (yun et al 2004, Lim 1991) . Table 1. Shows comparison of the proposed damage detection method using submatrix scaling factor. This approach can be carried out using simple equipment measurement process (dispalcement, accleration). Based on extracted modal parameter from the experiment, updating finite element is computed using neural network backpropagation propagation. In the proposed method for the model updating tool, the submatrix scaling factor is utilized to figure out the transformed elements. The usage of the submatrix scaling factor is not limited to detect damage location but it takes into account the force level submatrix division: K^N, $K^{My,Vz}$, $K^{Mz,Vy}$ and K^T

Table 1. Proposed Method Submatrix scaling factor

	Conventional Approach	**Proposed Approach**
Procedure	$\beta_{ji} = \dfrac{\varphi_i^T K_j^0 \varphi_i}{\varphi_i^T M \varphi_i} \dfrac{1}{\omega^2}$	$\beta_{ji} = \dfrac{\varphi_i^T K_j^0 \varphi_i}{\varphi_i^T M \varphi_i} \dfrac{1}{\omega^2}$
	$K = \sum_{J=1}^{q} K_j = \sum_{j=1}^{q} s_j K_j^0$	$K = \sum_{J=1}^{q} K_j = \sum_{j=1}^{q} \sum_{i=1}^{m} s_{ij} K_{ij}^0$

3. Numerical Example

Finite element model is used as model update with the aim to minimize the difference between numerical and experimental results. The updating processes used in this paper follows the flowchart shown in Figure 1. Ansys APDL were used for performing modal analysis. The result from numerical modeling were used as input dataset of neural network. The comparison is made to observe the difference between experimental and numerical model.

Numerical modeling was performed using ansys APDL, The Geumdang bridges is selected as model in order to acquire the modal properties. The model were used with the same dimension and same material properties are applied. The finite element model were using two element type beam188 and Shell181. The mesh configuration of the bridge model is shown in figure 2.

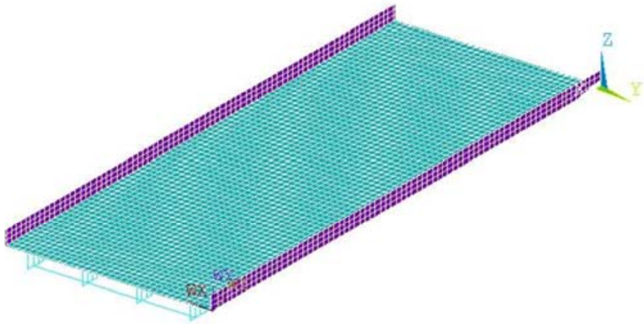

Figure 2. Finite Element Model Geumdang Bridge

In the first stage, the experiments was conducted using short span reinforced concrete bridge. The work done on the bridge is to obtain time series output data in acceleration response of designated spot. In the computaion we assume that the input excitation or external loading on the bridges was ignored when the AR models were built. The temporal data was acquired which constitutes output AR models and burg's algorithm built for multiple AR models gives ARCs for each structured AR models. The eigenvalue decomposition of these ARCs gives modal parameters including natural frequency, mode shape vector and damping ratio. Moreover, In this work it is proposed that the first four mode shape and natural frequencies are applied as inputs of the back propagation neural network for the prediction of damage. Finite element analysis with different damage scenarios was performed.

Table 2. Compariosn of Natural Frequency and Mode shape

Mode Shape	Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)	Mode 4 (Hz)
Experiment	4.667	6.367	11.246	12.486
Initial FE	4.893	6.574	11.589	12.678
Update FE	4.735	6.482	11.354	12.584

Multi-layered back propagation neural network architecture is employed for structural damage detection. Such network consists of an input layer, one or more hidden layers, and an output layer. The network trained using initial training data sets consisting of modal properties as target outputs and their corresponding autoregresion coeficient as inputs.

The feature extraction consists of two key steps. In the first step, the sparse coding algorithm is applied to learn high level features from acceleration data. While in the second step, we use built-in solver function to obtain modal frequencies as complementary features.

Training and testing In previous section, we discuss two steps in feature extraction. The training and testing of classification. In the experiment settings, we define five category of bridge conditions, and in each situation, we perform data preprocessing and feature extraction. By using these data, we can train a classification model so that we could predict which category of condition the bridge belongs to when a new example comes. We build a three layer neural network for data classification, with 160 units in input layer, 75 units in hidden layer and 4 units in output layer. All the data are divided into two parts: 75 % for training and 25 % for testing. We also use ten fold cross validation to find the optimal parameters of classification model.

After training the network, validation dataset to measures of accuracy of the selected architecture, there are many methods in the prediction literature (Haykin 1999, Zhang et al 1998). In this study mean square error (MSE) is used to calculate the accuracy. The ultimate and the most important measure of performance is the prediction accuracy of the output data. An accuracy measure is often defined in terms of the predicting error which is the difference between the actual (desired) and the predicted value. In the Figure 3 its shown different type MSE, based on different model input. It is observed that the location predictions of the networks are correct for all damage cases. The figure shows demonstrate the pattern recognition ability of neural networks.

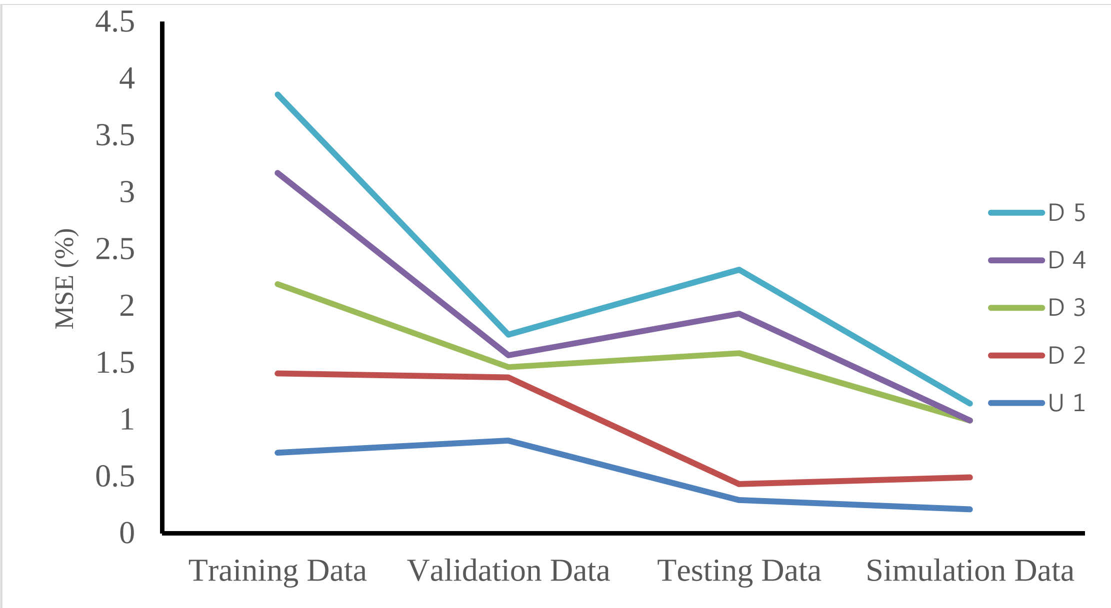

Figure 3. Neural network performance

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4.Conclusion

In this study applied a damage detection approach using Artificial Neural Network and vibrations for bridges. The input dataset from the experiment are performed using time series methods, autoregressive coefficient models were used to model the dynamic responses. Additionally, the numerical simulation using finite element method were perfomed to simulate damage scenario. the following conclusions can be drawn: from the test results, it have been found that the suggested method can effectively calculated the damage detection. However, some larger error that produce by numerical dataset could be minimize during numerical simulation. Further study, to get better result utilized parallel computing using CUDA on GPGU is suggested method because it can effectively compute large matrix and reduce computational time.

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REFERENCES

Dan, D., Yang, T. and Gong, J. (2014), “Intellegent platform for model updating in a structureal health monitoring System”, *Mathematical Problem in Engineering. Hindawi,* Volume 2014.

Zivanovic, S., Pavic, A. and Reynold, P. (2006), “Modal testing and FE model turning of a lively footbridge structure”, *Engineering Structure.,* **28**, 857-858.

Farahani, R.V., and Penumadu, D. (2016), “Full-scale bridge damage identification using time series analysis of a dense array of geophones excited by drop weight”, Structural Control Health Monitoring, 23, 982-997.

Ahmed, M.S. (2016) “Damage Detection in Reinforced Concrete Square Slabs using Modal Analysis and Artificial Neural Network”, Nottingham Trent University.

Haykin, S (1999), “Neural Networks: A Comprehensive Foundation”, Second edition, Pearson Prentice Hall publications.

Zhang, G., Patuwo, E.B. and Hu, Y., (1998),” Forecasting with Artificial Neural networks: he State of the Art”. International Journal of Forecasting, 14(1), 35-62.

Zweiri, Y.H., Whidborne, J F., and Seneviratne, L D (2003), “A Three-Term Backpropagation Algorithm”, Neurocomputing, 50, 305-318.

Abdeljaber, O. and Avci, O., (2016), ‘Nonparametric Structural Damage Detection Algorithm for Ambient Vibration Responses: Utilizing Artifical Neural Networks and Self-Organizing Maps”, Journal Architechture Engineering, 22, 2.

Gul, M and Catbas, F.N., (2010) “Damage Detection with Ambient Vibration Data using Time Series Modelling”, Proceeding IMAC-XXVIII, February