International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

IJIEMR Transactions, online available on 27th Oct 2018. Link

:http://www.ijiemr.org/downloads.php?vol=Volume-07&issue=ISSUE-11

Title: **STRUCTURAL DAMAGE LOCALIZATION USING PROBABILISTIC NEURAL NETWORK**

Volume 07, Issue 11, Pages: 88-93.

Paper Authors

MS. DHANALAKSHMI & MR. E RAKESH REDDY

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

STRUCTURAL DAMAGE LOCALIZATION USING PROBABILISTIC NEURAL NETWORK

MS. DHANALAKSHMI & MR. E RAKESH REDDY
Malla Reddy Engineering College (Autonomous) Department of Civil Engineering

Abstract

This paper presents a study of using the probabilistic neural network (PNN) to identify the damage type and region in the cable-stayed Ting Kau Bridge from the simulated noisy modal data. The essence of the PNN for damage type and region identification is to judge the pattern class of damage types and regions to which the test vectors of unknown source should belong. In the present study, a total of 17 pattern classes are defined for the Ting Kau Bridge to depict various damage types and different damage locations. The simulated damage cases involve the damage occurring at the main stay cables, longitudinal stabilizing cables, transverse stabilizing cables, main girders, cross-girders, and bearings. The characteristic ensembles for each pattern class (training samples) are obtained by computing the natural frequency change ratios when incurring the corresponding damage in a validated finite element model of the bridge and then corrupting the analytical frequencies with random noise. The testing samples for damage localization exercises are obtained in a similar way except that the damage is incurred at a different location of the same region for each pattern class.

INTRODUCTION

The Ting Kau Bridge, as shown in Figure 1, is a 1177m long cable-stayed bridge with two main spans of 448m and 475m respectively, and two side spans of 127m each (Bergermann and Schlaich 1996). A unique feature of the bridge is its arrangement of the three single-leg towers which are strengthened by longitudinal and transverse stabilizing cables. As a part of a sophisticated long-term monitoring devised by the Hong Kong SAR Government Highways Department, more than 200 sensors of The present study attempts to develop a method of using the probabilistic neural network (PNN) to identify damage type and region in the Ting Kau Bridge from the noisy measurement modal data. The PNN performs the Bayesian decision analysis with the Parzen windows estimator cast into an artificial neural network framework. Because the PNN describes measurement data in a Bayesian probabilistic approach, it shows great promise for structural damage detection in noisy conditions. In this paper, the simulation study of damage localization is conducted by means of a validated three-dimensional finite element model of the bridge (Ni et al. 2000). A three-layer PNN is developed for the damage type and region identification, in which a total of seventeen pattern classes are configured and only the natural frequencies are used for describing the pattern characteristics and for damage identification. The

influence of noise level on the identification accuracy is evaluated in the simulation study.

Civil engineering technology has grown at a tremendous rate over the past few decades. Structures are built on a scale that has never been seen before. The societies in which such structures reside, rely heavily on them for transportation, economic growth, and even housing. As such, a new field of engineering research has attracted great interest among the civil

engineering research community. Structural Health Monitoring (SHM) is the field of engineering research in which researchers develop techniques that are used to monitor the health of a structure by assessing structural damage extent and location. As a structure ages it is susceptible to damage that can occur from settling, constant vibrations, or weakening materials. Unpredictable natural disasters can cause extreme damage in structures, which if left undetected could lead to structural failure. Detecting structural damage can prevent catastrophic loss of life and can save cities from immense economic losses. It is for these reasons that SHM is such an important civil engineering research topic.

SHM techniques, historically, compare structural parameters (natural frequencies, mode shapes, etc...) to detect damage. Local techniques often require that the existence and approximate location of damage be known. In order for these local techniques to be used, damaged members usually have to be accessed, which means that barriers (e.g. walls) must be removed and structural use must be limited or completely restricted.

One such local technique, A piezoelectric Impedance-Based SHM technique, was developed at the Center for Intelligent Material Systems and Structures. This technique utilizes advantageous properties of piezoelectric materials which allow them to act as both actuators and sensors (Kabeya, 1998). This technique, although able to detect rather small damages such as cracks, has many severe limitations. The technique is easily influenced by ambient temperature change, the actuator and the sensor must be situated rather closely (the sensing area must be small), and the ability to identify damage location is poor.

Global SHM techniques use low frequency methods to assess damage extent and location of the entire structure. Unlike local SHM techniques, approximate damage location does not need to be known, and access to members being tested is not required. The goal of SHM research is to develop a continuous, on-line, global SHM system which monitors structures from a central location.

Many global SHM techniques use multiple steps to identify damage throughout a structure. One technique uses the MODE-ID, developed by Beck et al. (1994), to obtain modal parameters. This two step technique reduces the error between the measured response of the structure and the response calculated from the numerical modal to obtain the most accurate values of the natural frequencies. The second step to this method utilizes model updating to obtain the mass and stiffness matrices of the structure via a Bayesian probabilistic framework (Beck, 1998).

This paper introduces research performed at Keio University in Tokyo, Japan, on the capabilities of Probabilistic Neural Networks (PNNs) for damage detection, specifically detecting the locality and the extent of damage. In order to successfully produce a PNN, a model must be created with parameters resembling the parameters of the experimental structure. Accordingly, a comparative study was performed on two model updating techniques, the Element-Equation Arrangement (EEA) technique and the Least Squared of the Eigenvalue Problem (LSEM) technique.

II. NEURAL NETWORKING

Neural networks are systems that attempt to function as the biological learning system of the human brain. In 1943 a neurophysiologist by the name of Warren McCulloch, and mathematician Walter Pitts, published a paper in which they presented how neural networks could work. With advancements made in computer research during the 1950's it was possible to model a neural network. Although there were many successful attempts during this period, neural networking research was pushed aside due to immense interest in advancements made in the field of computer technology.

Due to exaggerations made with regards to the capabilities of neural networks, paired with the lack of technology, neural networking research disappeared until the early 1980s. Since then neural networking has been a popular research subject because of its extensive application to various fields. In 1982 a US-Japanese joint conference on cooperative/competitive neural networking was held in Kyoto, Japan. Upon worry that the United States would be left behind, in the wake of Japan's research efforts into neural networking, US researchers re-instituted a focus on the subject (Anderson, 1992).

Possibly because of their ability to learn (or be trained) with vasts amounts of information in a relatively short amount of time, they have been applied to many fields. In the medical field, networks are trained with models of various conditions and information that could be gained from patients checkups. The network can then identify a patients condition when it is given information about a patient (such as sex, age, blood pressure, etc...). One program, Computer Aided Tracking and Characterization of Homicides (CATCH), has been applied to tracking criminals. The program uses previous cases to train the network and then when a crime occurs, data from the case can be used to test the network and investigators can sift through applicable information; the network matches similar cases and repeat offenders can be questioned or possible leads can be investigated. Even corporations involved in the stock market use neural networking to predict the markets future (Clabaugh, 2000).

Existing method

SHM techniques, historically, compare structural parameters (natural frequencies, mode shapes, etc...) to detect damage. Local techniques often require that the existence and approximate location of damage be known. In order for these local techniques to be used, damaged members usually have to be accessed, which means that barriers (e.g. walls) must be removed and structural use must be limited or completely restricted.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Proposed method

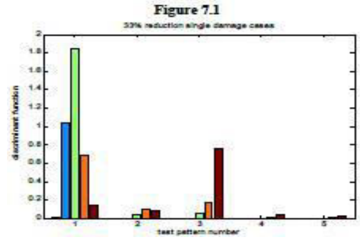
The probabilistic neural network (PNN) is applied to the identification of damage type and region in the cable-stayed Ting Kau Bridge. A total of 17 pattern classes representative of various damage types and regions are established and both the training and testing samples are generated in a noisy condition. The damage identification study is conducted by taking the natural frequencies of the first 20, 10 and 5 modes respectively as input vectors to the PNN and under 11 different noise levels.

RESULTS

In order to determine the most accurate implementation of the PNN for damage detection, including locality and extent, several scenarios were investigated. For single damage cases (damage in one floor), training data was produced without model updating, using the EEA method for model updating, and using the LSEP method for model updating. This data was used to train the PNN and test data was used to determine if the PNN could classify the damage. In addition, double damage data (response of structure from damage on two (2) floors) was acquired from the experimental structure and used to test the PNN.

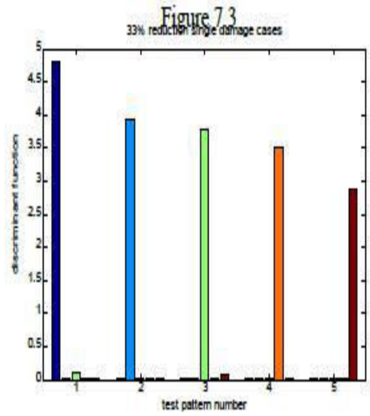
The PNN was tested with five (5) single damage cases, where the first case represented damage on the first floor, the second represented damage on the second floor, and so on and so forth. The following figures represent the results of the aforementioned scenarios:

Figure 7.1



The PNN was trained without updating the stiffness matrix of the model and was unable to detect damage;

Using the LSEP method, which implements mode shapes as well as natural frequencies to? update the models stiffness matrix, damage detection was unsuccessful



The PNN trained with natural frequency change rates produced from the stiffness matrix dated using the EEA method, was successful in classifying the test data into damage categories.

The PNN was trained with fifty (50) natural frequency change rates. This training data represented various permutations of damage (1st floor and 2nd floor, 1st floor and 3rd floor, etc...). Results obtained are shown below:

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Figure 7.2

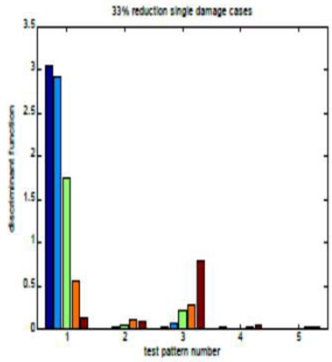
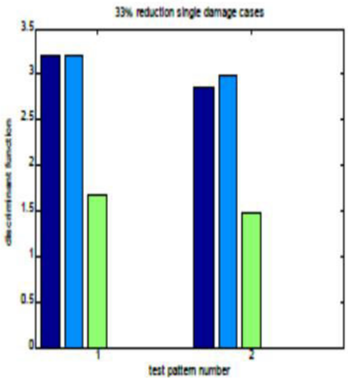


Figure 7.4



The PNN was unsuccessful in classifying double damage experimental data.

CONCLUSIONS and FUTURE WORK

The future of the world's civil infrastructure relies heavily on the development of a successful global SHM

technique. Before PNNs can be implemented as one such SHM technique, much research must be done to investigate the many aspects of PNNs that are unclear

to today's pattern classification researchers.

It is known that PNNs can be easily trained with data for pattern classification. This research was successful in developing a PNN, trained with data obtained via the EEA method of model updating, that could classify single damage test data into 5 distinct damage categories, and give the extent of that damage.

However, there are many intricacies of PNNs that need further development before they can be used as a successful global SHM technique. The PNN trained using data acquired from the LSEP method of model updating could quite possibly produce more accurate results because it uses mode shapes and natural frequencies obtained from experimental data to update the model's stiffness matrix. Future research into the use of PNNs for SHM should include training the PNN with

mode shapes as well as natural frequencies, and implementing the LSEP method of model updating.

Future research should also include the development of a PNN that is successful in classifying double damage test data. This is a difficulty because of the vast number of permutations that are possible in an actual structure. However, PNNs are easily trained with large amounts of data so the only difficulty is developing a method for obtaining double damage training data.

This research has shown the applicability of PNNs to single damage classification. Because PNNs use probability to classify damage, that is they classify a data point by it's distance from a known category unit via a density function, they can be used to classify damage when space (memory) is a limiting factor. It is for these promising reasons that research should continue into the implementation of PNNs as a SHM technique.

REFERENCES

1. Anderson, D. and McNeill, G., “Artificial Neural Networks Technology”, Data and Analysis enter for Software. Project No. F30602-89-C-0082. Rome, NY. 1992.
2. Beck, J.L., May, B.S., and Palidori, D. C., “Determination of Modal

Parameters from Ambient Vibration

3. Data for Structural Health Monitoring", First World Conference on Structural Control, California, USA, 3-5 August, 1994.
4. Beck, J.L., Katafygiotis, L.S., "Updating Models and Their Uncertanties- Bayesian Statistical Framework", Journal of Engineering Mechanics, Vol. 124, pp. 455-461, 1998.
5. Caicedo, Juan Martin 2003. "Structural Health Monitoring of Flexible Structures", Ph D Thesis, Sever Institute of Technology, Department of Civil Engineering, Washington University, St. Louis.
6. Clabaugh, C., Myszewski, D., and Pang, J., "The intellectual excitementofComputer Science."Stanford Computer Science Education. 2000. <www-
7. Duda, R.O, Hart, P.E., Stork, D.G. Pattern Classification, 2nd Edition. 2001, NewYork: Wiley & Sons, USA. pp. 164-174.
8. Kazuhisha,Kabeya1998. "Structural Health Monitoring Using Multiple Piezoelectric Sensors and Actuators." Master's Thesis, Department of Mechanical Engineering, Virginia Polytechnic Institute and State University.
9. Qian, Yuyin & Mita, Akira. DamageIdentificationof StructuresBasedonPattern Classification using Limited Number of Sensors. 2005.
10. Zhang, D.W. & Li, Y.M. 1989. A generalMethodofElement-Equation Arrangement. Structure & Environment Engineering. 6:9-15.