DAMAGE IDENTIFICATION OF CONCRETE ARCH BEAM UTILISING RESIDUAL FREQUENCY RESPONSE FUNCTION

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ABSTRACT

One of the critical missions for bridge structural health monitoring (SHM) is to provide a reliable assessment technique to potential hazards caused by structural damage or other structural defects using continuously monitored vibration data. Recognising the needs and shortcomings of SHM, a project was established by NICTA, the University of Technology Sydney and The University of Sydney to develop reliable damage detection methods to provide robust and accurate assessment techniques for critical bridge infrastructure in Australia. This paper presents the progress of research and development of a vibration-based damage detection technique and its experimental validation in the laboratory. The proposed technique uses residual frequency response functions (FRFs) combined with principal component analysis (PCA) to form damage specific features (DSFs) that are incorporated in pattern recognition using artificial neural networks (ANNs). In the method, FRFs are obtained using modal analysis techniques and damage is identified using ANNs that innovatively map the DSF to damage characteristics, such as damage location and severity. The results of the experimental validation show that the proposed technique can successfully locate and quantify damage induced to a concrete arch beam simulating a real life structural component of the Sydney Harbour Bridge.

KEYWORDS

Structural health monitoring, frequency response function, principal component analysis, artificial neural network, non-destructive testing

INTRODUCTION

The National ICT of Australia (NICTA), in collaboration with the Road and Maritime Services (RMS) in NSW, have developed and installed a large number of custom-designed sensors on the Sydney Harbour Bridge to monitor the performance of critical structural components and to thereby ensure their safety and reliability. The system aims to provide a robust and reliable warning and evaluation system to detect structural deficiencies on a series of concrete arch beam components. A critical issue is how to reliably detect structural damage using continuous real-time monitored data of the bridge components under ambient vibration conditions as well as to provide an accurate evaluation on the bridge loading capacity based on the estimated bridge condition. This on-going project is in its first stage focusing on the exploration of the effectiveness of various damage detection algorithms through numerical and experimental investigations.

For Structural Health Monitoring (SHM), the idea of using vibration response for detecting damage has always been an attractive approach. A great deal of vibration-based research has been devoted to the use of modal parameters (i.e. modal frequencies, modal damping and mode shapes) and their derivatives to form damage specific features (DSFs) for damage detection. Among the three modal parameters, modal frequencies are the simplest DSFs for detecting damage. Research undertaken in recent years, however, focused primarily on the use of directly measured data such as frequency response functions (FRFs) to assess the condition of a structure and identify damage. Contrary to processed data, such as modal parameters, direct measurements from numerical and experimental modal testing have the advantage of retaining abundance of information on a structure's dynamic behaviour as well as of avoiding labour intensive experimental modal analysis. Thereby, operational human induced errors can be eliminated and crucial damage sensitive information is preserved. Further, using direct measurements from real-time can make these methods favourable for online monitoring. Artificial neural networks (ANNs), a form of artificial intelligence, have strong abilities to learn from experience, generalize from examples, and identify underlying information from noisy data. In the presented method, the joint use of directly measured FRF data and ANNs is employed. Similar approaches have already been applied by some researchers and promising results have been obtained (Das and Parhi 2009; Li, Dackermann, Xu and Samali 2009; Dackermann, Li and Samali 2013). A challenge in utilising FRFs as inputs for ANNs is the large size of the FRF data. Utilising full-size FRFs in neural networks will cause problems in training convergence and computational efficiency. Principal component analysis (PCA) is a statistical technique that is known for its capability of reducing the dimension of data as well as its ability of reducing the influence of uncertainties by filtering unrepeatable random features. Hence, a technique is proposed that jointly uses FRFs, PCA and ANNs for the damage detection of a concrete arch beam replica of the Sydney Harbour Bridge.

PROPOSED DAMAGE IDENTIFICATION APPROACH

The proposed damage identification approach uses PCA to compress residual frequency response function to obtain a unique DSF. Once the DSF is identified, the proposed approach utilises ANNs for damage identification by means of pattern recognition. A schematic diagram of the proposed method is shown in Figure 1. The approach features a 3-step process: i) detecting the existence of damage (undamaged or damaged), ii) determining the damage category (e.g. Light, Medium, Severe and Extra Severe), and iii) identifying the actual severity of the damage.

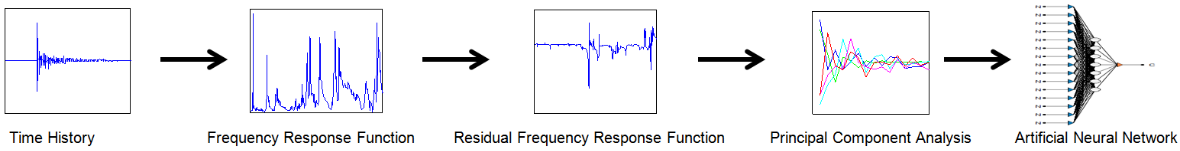

Figure 1. Schematic diagram for proposed damage identification approach.

EXPERIMENTAL SETUP

A concrete cantilever beam with an arch section, shown in Figure 2a, was manufactured and tested in the UTS Structural Laboratory. The test structure simulates a structural component of the Sydney Harbour Bridge located under the bus lane. It consisted of a 200UB18 steel I-Beam with a 50 mm concrete cover on both ends and was 2 m long. 15 accelerometers were installed on the specimen to measure the vibration response resulting from impact excitation. The cross-section of the beam and the location of the accelerometers are shown in Figure 2b. The structure was excited at three different locations, shown in Figure 2a, using an impact hammer with a steel tip. Thereby, different modes of the structure were excited. The impact points were located 50 mm away from the front face of the specimen with impact locations 1 and 3 being 50 mm distanced from the side edges and location 2 being located on the central axis. For each impact location, 18 hammer strikes were executed and the structural response was recorded with a sampling rate of 8 kHz over a period of two seconds.

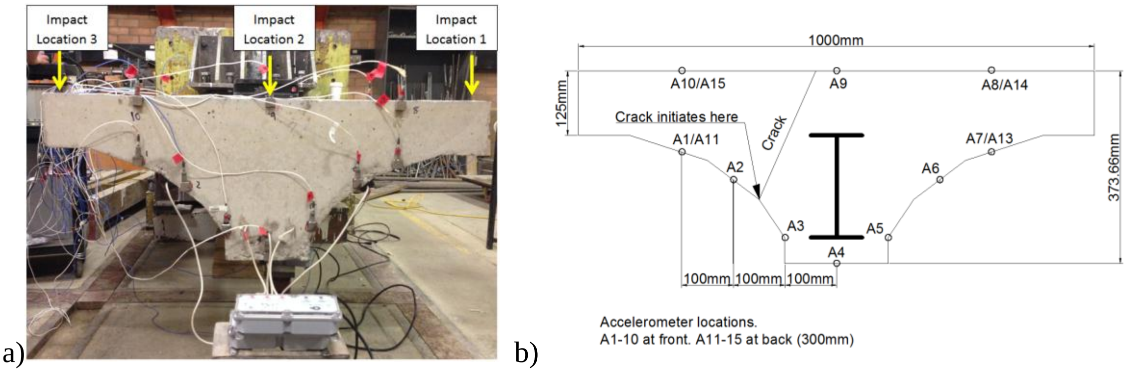

Figure 2. (a) Photograph of test specimen with indicated impact locations, and (b) cross-sectional geometry of the structure with accelerometer locations.

After testing the structure in its undamaged state, damage was seeded on the specimen using a saw blade inducing a cut between accelerometer 2 and 3 as indicated in Figure 2b. The cut had a depth of 55 mm and was induced in four incremental stages with four different lengths. The structure was tested again after each damage stage. In total, five different structural conditions were tested:

- Condition case 1: No damage
- Condition case 2: Light damage with a crack length of 75mm
- Condition case 3: Medium damage with a crack length of 150mm
- Condition case 4: Severe damage with a crack length of 225mm
- Condition case 5: Extra severe damage with a crack length of 270mm

DAMAGE IDENTIFICATION PROCEDURE

Frequency Response Functions

In the proposed damage identification procedure, first, residual FRF data was determined to obtain the unique DSF. Residual FRFs emphasise the difference between FRF measurements of a baseline structure (undamaged condition case) and a damaged structure (damaged condition case) and can be calculated using Eq. 1.

$$\text{Residual FRF} = \text{FRF}_{\text{undamaged}} - \text{FRF}_{\text{damaged}} \tag{1}$$

As an example, the FRFs and correlating residual FRFs of accelerometer 9 for impact location 3 are shown for all five condition cases in Figure 3 a and b, respectively. As it can be seen, the residual FRFs enlarge the changes in the FRFs of the different condition cases.

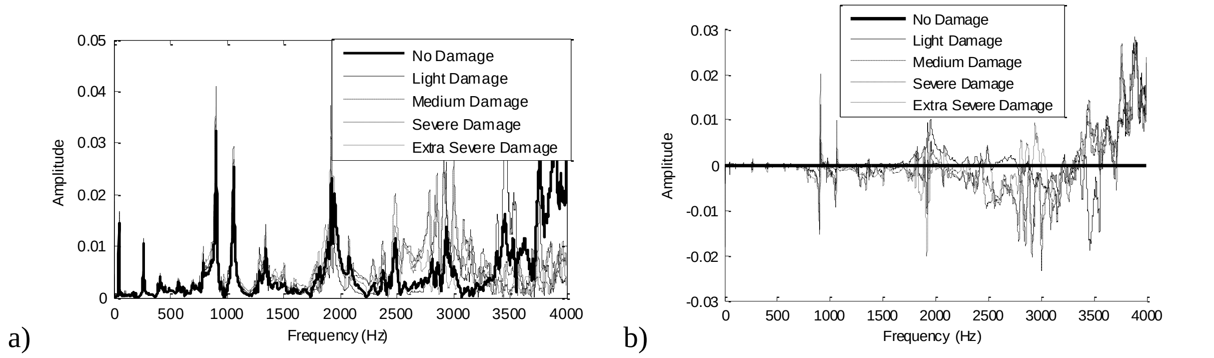

Figure 3. (a) FRFs and (b) residual FRFs of accelerometer 9 (impact location 3) for all condition cases.

To select typical FRF data, the FRFs of the 18 hammer impacts (measurement samples) were correlated with each other for all three impact locations. It was found that the ten samples with the highest correlation to the average of the 18 measured samples possessed a correlation of at least 75%. Thus, the FRFs of these ten hammer hits were selected, giving a total of 50 FRFs for the five condition cases (10 hammer hits × 5 condition cases). When calculating the residual FRFs, the FRF of each undamaged case was subtracted from the FRF of each condition case using Eq. 1. Thereby, a total of 500 residual FRFs were generated for each impact location and accelerometer (10 hammer hits of undamaged case × 10 hammer hits of each condition case × 5 condition cases).

Principal Component Analysis

PCA can overcome issues associated with using large-size data in ANNs and are capable of reducing measurement noise and other uncertainties. PCA is a statistical technique that projects data onto its most important principal components, and thereby, it greatly reduces its size without significantly affecting the data. Eigen value decomposition of the covariance matrix forms the basis of PCA. In the presented study, PCA is applied to linearly transform residual FRFs into a smaller set of uncorrelated values. In the resulting data, the first Principal Component (PC), which is the largest eigenvalue, represents the direction and amount of maximum variability of the residual FRF. The subsequent PCs have lower contribution to the data. The contributions of the derived PCs of the data from accelerometer 9 (impact location 3) is depicted in Figure 4 a. To ensure that at least 90% of data is represented, the first 15 PCs were considered as input to the ANN models. PCA was used for all residual FRF data of all accelerometers and impact locations. Figure 4 b illustrates the derived PCs of the residual FRFs of accelerometer 9 (impact location 3). It can be seen that the PCs of the five condition cases show unique and distinguishable features.

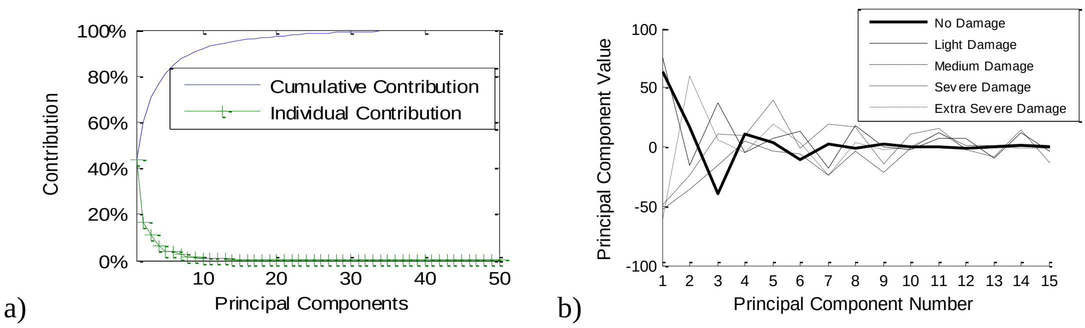

Figure 4 (a) PCA contribution, and (b) PC values of accelerometer 9 (impact location 3).

Artificial Neural Networks

ANNs mimic biological networks and use weighted interconnected processing elements called neurons to learn and map set input variables to output variables by adjusting the inputs weights and biases of the neuron connections according to the adjusted transfer functions. The Alyuda NeuralIntelligence© software was used in this study to for the ANN modelling. The ANNs are used to detect damage and to identify the corresponding severity in a three-step process. In step one; different numbers of PCs were used as network inputs to identify a structure as being damaged or undamaged. When the structure is identified as damaged, then the step two of the ANN model applies, classifying the damaged structure into four different damage categories including light, medium, severe and extra severe damage. The severe and extra severe cases then proceeded to step three, which determines the numeric length of the damage crack. A schematic diagram of this hierarchical ANN system is depicted in Figure 5.

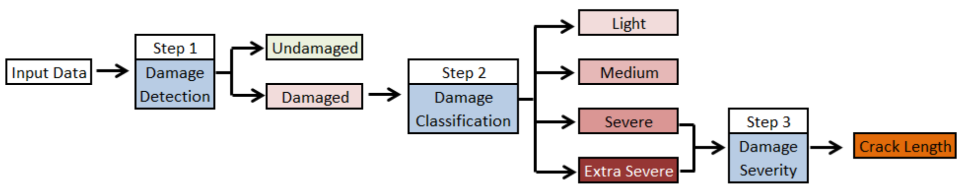

Figure 5: Three-step ANN system for damage detection, classification and severity identification.

For the ANN training, the 500 residual FRFs of each impact location and accelerometer were divided into 200 training samples, 150 validating samples and 150 testing samples. In this study, one network was trained for each impact location and each accelerometer. While the networks were trained with the training samples, its performance was supervised utilizing the validation set to avoid over-fitting. The testing data was used to test the trained networks with before unseen data. All networks consisted of an input layer made up of 15 nodes representing the first 15 PCs. This was followed by a hidden layer of 7 nodes, which was followed by the output layer. For the output layer, step one had a single categorical node, step two had four categorical nodes and step three had a single numeric node. The transfer functions used were logistic sigmoid functions. Steps one and two used the quick-propagation training algorithm and step three used the Levenberg-Marquardt training algorithm.

RESULTS AND DISCUSSION

Step one of the three-step ANN system aimed at damage detection. Here, all data of the five condition cases were used in the ANN model. The networks of step one classified the data either as undamaged or damaged. Depending on the number of PCs used as inputs to the networks, the accuracy of the damage detection results increased as shown in Figure 6 a. For the shown data, an accuracy of 100% was reached after three PCs were used. Up to 15 PCs were used in this study as ANN inputs.

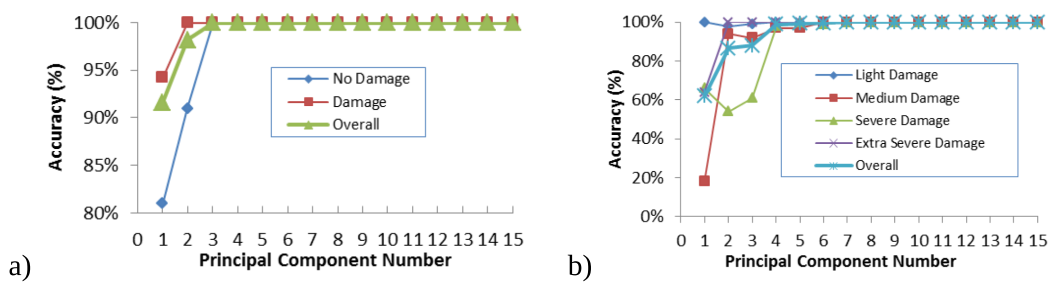

Figure 6: Network accuracy vs. number of used PCs of data from accelerometer 9 (impact location 1) for (a) step one damage detection, and (b) step two damage classification.

Data that was identified as damaged in step one, proceeded to step two, aimed at classifying the damaged samples into four different categories including light, medium, severe and extra severe damage. Similar to step one, the overall accuracy of the network results increased with an increase of the used number of PCs as seen in Figure 6 b. For data of accelerometer 9 (impact location 1), a 100% accuracy was achieved after using seven PCs. The result accuracy varied among the different data cases. For all impact locations and accelerometers, a 100% accuracy in damage classification was achieved using all 15 PCs. Step three of the damage identification procedure deviates from the previous steps since it calculates a numerical value for the severity of the damage rather than classifying the data into categories. Figure 7 a, b and c shows the obtained percentage errors of the step three networks trained with all considered data of the severe case for impact locations 1, 2 and 3, respectively. It can be seen that the data from accelerometer 7 resulted in the largest percentage errors (up to 13.38%). This is possibly due to human error, as this accelerometer may not have been calibrated correctly or connected to the specimen as rigidly as the other accelerometers. This could be reflected on the actual bridge where an accelerometer may not have been installed properly or it may be damaged.

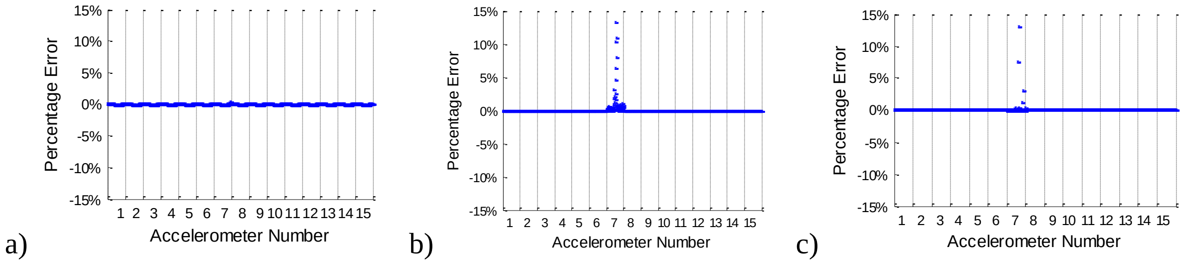

Figure 7. Network errors of the severe condition case for each accelerometer from (a) impact location 1, (b) impact location 2, and c) impact location 3.

Much of the success of the proposed method is attributed to its application in a controlled laboratory environment with five clear defined condition cases. In the field, however, there are many factors that can influence the measurements of the accelerometers including temperature, traffic, humidity, wind, solar-radiation and even improper placement or damage to accelerometers.

CONCLUSION

In this paper, a three-step hierarchical system was proposed as a potential technique for the damage detection of the Sydney Harbour Bridge. The steps of the proposed system include: i) detecting the existence of damage (undamaged or damaged), ii) determining the damage category (e.g. Light, Medium, Severe and Extra Severe), and iii) identifying the actual severity of the damage. The presented method used residual FRF, PCA and ANNs for the damage identification algorithm. PCA was used to compress residual FRFs to obtain DSFs, which were used in combination with ANNs for damage identification using pattern recognition. The network outcomes showed that steps one and two of the identification system, can give results of 100% accuracy using 15 PCs as ANN inputs. Step three presented good identification results with the exception of accelerometer 7, which showed errors of up to 13.38%. This on-going project of implementing a SHM system on the Sydney Harbour Bridge is currently in its initial stage and further research and development will be conducted in the future.

REFERENCES

Dackermann, U., Li, J. and Samali, B. (2013) “Identification of member connectivity and mass changes on a two-storey structure using frequency response functions and artificial neural networks”, *Journal of Sound and Vibration*, Vol. 332, No. 16, pp. 3636-3653.

Das, H.C. and Parhi, D.R. (2009) “Application for Neural network for fault diagnosis of cracked cantilever beam”, *World Congress on Nature and Biologically Inspired Computing*, pp. 1303-1308.

Li, J., Dackermann, U., Xu, Y. and Samali, B. (Eds.) (2009) “Damage identification in civil engineering structures utilizing PCA-compressed residual frequency response functions and neural network ensembles”, *Structural Control and Health Monitoring*, Vol. 18, No. 2, pp. 207-226.