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VOTING NEURAL NETWORK CLASSIFIER FOR DETECTION OF FATIGUE DAMAGE IN AIRCRAFTS

Ziemowit Dworakowski¹, Lukasz Ambrozinski¹, Krzysztof Dragan^{1,2}, Tadeusz Stepinski¹, Tadeusz Uhl¹

¹ AGH University of Science and Technology, al. Mickiewicza 30, 30-059 Cracow, Poland

² ITWL Instytut Techniczny Wojsk Lotniczych, ul. Księcia Bolesława 6 01-494 Warsaw, Poland

zdw@agh.edu.pl, ambrozin@agh.edu.pl, krzysztof.dragan@itwl.pl, tstepin@agh.edu.pl

ABSTRACT

An ANN based method for detection and localization of fatigue damage in aircraft structures is presented in the paper. Damage indices are calculated from Lamb-wave measurements conducted by the network of piezoelectric transducers. Data gathered by the sensors is used as an input to the proposed voting neural network classifier. A set of neural network electors of different architecture cooperates to achieve consensus concerning the state of each monitored path. Sensed signal variations in the ROI, detected by the networks at each path, are used to assess the state of the structure as well as to localize detected damage and to filter out ambient changes. The classifier has been extensively tested on large data sets acquired in the tests of specimens with artificially introduced notches as well as the results of numerous fatigue experiments. Effect of the classifier structure and test data used for training on the results is evaluated. It is shown that the developed classifier performs better than individual ANNs in terms of damage detection. The classifier structure, composed of different networks working together, yields an increased reliability, mainly due to the lower impact of the initial weights distribution on the final result.

KEYWORDS : *SHM, ANN, Lamb Waves, Fatigue tests*

INTRODUCTION

The problem of the structural integrity monitoring of aircraft structures for the operation and maintenance strategy is not easy task due to the several engineering and certification limitations. In the article the approach for the built of integrated monitoring system validated for the operational phase is presented. The aircraft used is turbo propeller training aircraft used by armed forces for the preliminary pilot training. The aircraft undergo Full Scale Fatigue Test (FSFT) which will continue up to mid-2014. The FSFT of the structure is necessary in connection with the structure modification as well as with the change of the maintenance system (from the Safe Life to Condition Based Maintenance). Main part of the operational and maintenance phase is Non Destructive Inspection delivery. In particular an alternative approach which may support or in future partially replace the scheduled NDI inspections is the SHM system for that aircraft based on PZT sensors which was designed and verified during FSFT. The principle of its operation is to monitor key areas of the aircraft with use of Lamb Waves. It is a well-known approach, as Lamb-waves allow to monitor large structures due to their long range propagation and sensitivity to structural changes. However, the interpretation of obtained time-domain signals is often difficult due to the complexity of a monitored structure and dispersive nature of Lamb waves. A possible solution to this problem is to employ Artificial Neural Networks (ANN). Proper training on data obtained from various experiments allows the network to properly respond to damage in a monitored structure. ANNs have been extensively researched during last decades, which resulted in vast amount of network structures and types. Different networks have their advantages and

disadvantages. It is often hard to point out the one, which is best suited for the given task. In order to increase reliability and versatility of the classifier several networks can be employed to perform one task simultaneously. The result of such process tend to be more robust and invulnerable to issues afflicting single ANNs such as high impact of initial weights distribution on results. The most common realization of this idea encompasses decomposition of a problem into sub-problems which are later solved by differently specialized networks [1, 2]. In this article authors will provide a different solution, in which a group of different ANNs is used to solve the same task and achieve decision by voting.

Article will present some parts of data processing from the FSFT of the aircraft and other experiments performed on specimens. Data processing and classification was designed to automatically detect damage presence, progression and localization.

1. THEORETICAL BACKGROUND

1.1 Damage Indices

Damage occurrence in a structure affects the propagation of the LWs which influence the acquired signals. The aim of DIs evaluation is to extract and quantify damage-related features. In this section five damage indices, used to quantify difference between a signal $y(t)$ and a baseline $x(t)$, are presented. Note that although the DIs are calculated in a discrete time domain, continuous time domain is used here for brevity. The first feature, presented here, is the normalized squared error between the signal and the baseline, calculated in the time-domain according to the formula:

$$DI_{TDRMS} = 1 - \frac{\int_{t_1}^{t_2} [y(t) - x(t)]^2 dt}{\int_{t_1}^{t_2} x(t)^2 dt}, \quad (1)$$

where t_1 and t_2 denote time intervals in which the integration is performed [5].

The following two DIs were based on the cross correlation of the signal and the baseline, which can be estimated as

$$\hat{R}_{xy}(\tau) = \int_0^T x(t) \cdot y(t + \tau) dt, \quad (2)$$

where $x(t)$ is baseline, $y(t)$ is current signal, T is the length of these signals, and τ is time-lag applied to one of the signal.

In the first approach the DI quantifies the difference between two signals as the drop in cross-correlation coefficient between the signal and baseline using the following expression where $\hat{R}_{xy}(\tau = 0)$ is the cross correlation coefficient of the baseline and the response obtained for the lag of 0.

$$DI_{XCOR} = 1 - \frac{\hat{R}_{xy}(0)}{\sqrt{\hat{R}_{xx}(0)\hat{R}_{yy}(0)}}, \quad (3)$$

The main feature of this DI is that if the baseline and response are identical, the cross correlation becomes the autocorrelation with peak at level of 1 at $\tau = 0$. The main advantage of this DI is that it is sensitive only to changes in the shape of the signals, not to their amplitudes [4]. In the second approach the DI is evaluated similarly to the previous one, however, in this case the maximum value of the cross correlation is used, regardless of τ at which it occurs. Therefore, the formula 3 may be rewritten as:

$$DI_{maxXCOR} = 1 - \frac{\max|\hat{R}_{xy}(\tau)|}{\sqrt{\hat{R}_{xx}(\tau)\hat{R}_{yy}(\tau)}}, \quad (4)$$

The $DI_{maxXCOR}$ is insensitive to time-shifts between the baseline and the response.

Two last DIs were evaluated as a difference between the envelope of the signal and the baseline. It can be calculated using the following expression:

$$DI_{ENV} = 1 - \frac{\int_{t_1}^{t_2} [Y(t) - X(t)]^2 dt}{\int_{t_1}^{t_2} X(t)^2 dt}, \quad (5)$$

where $X(t)$ and $Y(t)$ denote envelopes of the baseline and the signal respectively. Two methods for envelope evaluation were used: Hilbert transform and continuous wavelet transform (CWT). In the implementation based on CWT complex Morlet wavelet was used as the mother wavelet.

1.2 Artificial Neural Networks

1.2.1 Voting Classifier

Damage Indices are sensitive to different changes in signals which means that various cases of damage can be detected by different DIs. Therefore, damage detection based on Lamb-wave signals can be described as data classification problem in n-dimensional data space, where n is the number of DIs used. Artificial Neural Networks are commonly used to solve such problems. Their ability to generalize over an incomplete set of data allows the classification system to react to states that had not been used in training process. In this problem, for the classification purposes the ANNs should observe the data from different experiments and exploit tendencies that are present in majority of data sets. This should allow them to perform successful damage detection in specimens which state is unknown and which had not been presented to the network in the training phase.

The authors decided to use two types of networks: Multilayered Perceptron Network (MLP) and Self-Organizing Kohonen Map. (SOM) The former are trained in supervised mode and thus divide the data space into regions that correspond with interpretation of input data provided by the operator. The latter are trained in unsupervised way and respond to natural data clustering present in the data space. The performance of both types of network is different. However, it is difficult to point out the better type, as they outperform one another for different cases investigated.

Another important issue is that results obtained by the networks are strongly affected by randomly generated initial weights distribution. For instance, several networks of the same architecture and trained with the same set of data may provide different classification results. Both issues can be solved by use of a set of network working together. This allows the classifier to be reliable as the differences caused by initial weights distribution are averaged.

The voting ANN classifier is organized as follows: Five ANN electors with structure of MLP and two of SOM are trained on the same data and used in classification purposes. The number of MLP networks is higher than those trained with Kohonen algorithm as the diversity caused by initial weights distribution in MLP networks tend to have higher influence on results than those in SOM. For each piece of data (set of DIs calculated from the time-domain signal) each of networks returns the answer in the range of 0-1, where 0 respond to structure in reference state and 1 denotes the damage. The results of electors are averaged in each class of network and between classes with respect to equation:

$$C = 0.5 * \frac{MLP_1 + MLP_2 + \dots + MLP_n}{n} + 0.5 * \frac{SOM_1 + SOM_2 + \dots + SOM_k}{k}, \quad (6)$$

Where C denotes the final classification result, MLP_n denotes the result of classification with n-th MLP elector and SOM_k denotes the result of classification with k-th SOM elector. Such proportions allow both classes of networks remain of similar importance for calculations.

1.2.2 Damage localization and ambient filtration

The detection performed with use of one signal captured in one point of a structure is subjected to changes in environmental condition. Variations in humidity or temperature may significantly affect the result of calculations. These changes occur for all signals captured. In contrast, the damage is usually present in one distinct location and thus affect only some of the signals captured. The developed damage detection and localization algorithm exploits this feature.

Each of the key areas of the aircraft is monitored with use of a net of embedded sensors. The signal captured between each pair of sensors arranged in pitch-catch mode is evaluated with use of a voting algorithm described in sec. 1.2.1. The state of the structure is thus obtained for all measurement paths and used to assess and localize the damage with respect to equation (7) where $C_{k,max}$ represent k-th maximal damage value detected in sensor network with use of the voting algorithm, while C_{min} represent the minimal value obtained in calculations.

$$C = \min(C_{1,max}, C_{2,max}, C_{3,max}) - C_{min}, \quad (7)$$

In case of environmental condition changes affecting the result, the damage should be detected in each path, but as the minimal value is high, the resulting damage index should remain below the level of detection. In case of one false detection on one path caused by noise the result should be similar. However, the value of damage index rapidly increase if the damage is detected on more than one measurement path. Graphical interpretation of this idea is presented in fig. 1.

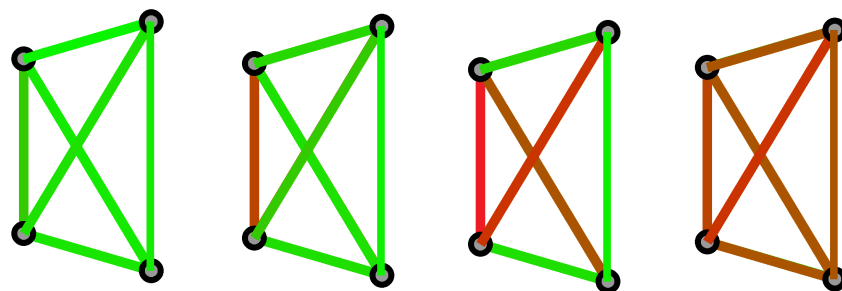


Figure 1 : Different states of structure: Intact keypoint (a), damage detected on one path (possibly due to noise) (b), damage detected on three paths (c) and damage detected in the whole area - due to change in environment (d)

2. INPUT DATA ACQUISITION

2.1 Experimental setup - laboratory experiment

The first experiment was performed on an aircraft wing panel to obtain experimental data for ANN training and classification. The specimen was an aluminium structure, consisting of a part of skin and an omega-shaped stiffener. The sample was instrumented with 8 PZT transducers from Steminc, USA. Transducers layout can be seen in figure 2(a). The aim of the experiment was to monitor the stiffener, which carries most of loads, using transducers coupled to skin panel, which can easily be accessible for transducers installation. Since the sample was a part of aircraft's fuel tank, sealing was present between the skin and the stiffener. Therefore, according to the previous tests, the ultrasonic wave could be transmitted between the bounded components. [7]

The signals were acquired using the following parameters:

- Excitation frequencies: 100, 200 kHz

- Window modulation: Hanning
- Length of excitation: 8 periods

For each measurement cycle, the subsequent transducers were used as actuators whereas the remaining PZTs were used as sensors. Therefore, for each damage level a set of 112 time signals was acquired.

In the first step of the experiment, a set of baselines was captured. Next, a small notch was introduced to the stiffener, along the path between transducer 1 and 2. The cut was deepened in several increments and a number of measurements for the different crack sizes was acquired. The same procedure was repeated introducing notches in the stiffener on the paths between the transducers 3-4, 5-6 and 7-8. An example of two cuts in the specimen can be seen in fig. 2.

The time signals captured during the experiments, were processed according to section 1.1, to extract the damage indices further used for ANN training and classification.

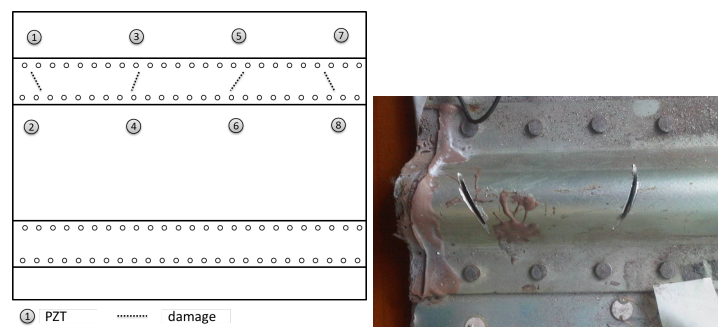


Figure 2 : Transducers and crack locations in specimen (a), Two exemplary cracks introduced in specimen (b)

2.2 Experimental setup - fatigue experiment

Two independent piezoelectric transducers (PZT) networks, containing 4 sensors each were bonded to the opposite sides of the structure (Fig. 3). One of the network was deployed on the same element (Fig. 3(a)), the other had two transducers placed on the riveted reinforcement (Fig. 3(b)) and in that case the Lamb waves were transmitted to the rest of the transducers through the sealant present between the two elements. The signals were acquired with setup from previous experiment (See sec. 2.1). Detailed evaluation of this specimen is given in [6].

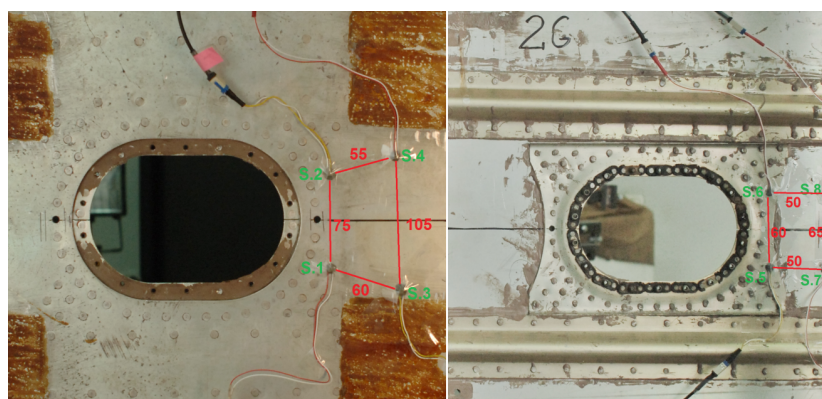


Figure 3 : The specimen and the deployed transducers. Dimensions are given in mm

2.3 Experimental setup - full-scale fatigue test

Complete SHM system was used in FSFT to monitor key areas of the whole aircraft. The structures state evaluation was performed according to procedure described in sec. 1.2, the setup of data acquisition unit was similar to one described in sec. 2.1. The monitoring encompassed 14 keypoints selected on a basis of previously performed simulations. Each of selected keypoints was evaluated by the net of embedded sensors containing 4 - 6 transducers. The experiments were performed in the intervals between scheduled load cycles. The aircraft placed in a hangar was subjected to natural temperature variations that affected its whole structure and thus measurement results.

3. ANN EVALUATION

3.1 ANN configuration and learning

According to the procedure described in sec. 1.2 five MLP networks and two SOM networks were used as electors in voting classifier. MLP networks consisted of 2 hidden layers with 24 and 12 neurons while SOM networks consisted of 32 neurons placed in five layers. Numbers of neurons in both networks were chosen based on authors experience with the similar classifier performance in different classification tasks [7].

For the purpose of ANN training and evaluation, the state of structure in each experiment was given the value of damage ranging from 0 to 1, where 0 denoted undamaged state, while 1 denoted damage.

Three sets of data were used in training and testing process. The data for training and testing were arranged in different configurations:

- "Experimental" (E_{CV}) dataset used for training and testing with respect to Cross Validation method
- "Experimental" dataset used for training, "Fatigue2" ($F1$) dataset used for testing
- "Fatigue1" dataset used for training and testing with respect to Cross Validation method
- "Fatigue1" ($F1$) dataset used for training, "Fatigue2" ($F2$) dataset used for testing

Evaluation of each configuration (training and testing on the chosen sets) were performed 100 times in order to gain statistical knowledge of networks performance. Classifier trained on a fatigue sets ($F1$ and $F2$) was used to evaluate the data acquired from FSFT. The layouts of sensors were introduced to the system in order to build a maps that allow damage localization.

3.2 Classification results

The ANN evaluation is presented in figures 4 - 5. In each configuration of training and testing datasets voting classifier outperforms other networks in terms of efficiency. This is due to the fact, that initial weights distribution have lower impact on results obtained if the network outputs are averaged. It is worth noting, that in cases where one class of elector components performs worse, it usually do not affect the overall result.

Trained classifiers were used to evaluate the state of structure undergoing FSFT in all of the selected keypoints. Results of autonomous state evaluation were similar to one performed by an expert in all but one keypoint: 9 out of 10 keypoints were classified correctly. The classifier successfully filtered out the influence of ambient condition changes which resulted in lowering overall "level of damage" detected in intact keypoints. An example of this (Keypoint 4) can be seen in Fig. 6(a). However, the filtration does not affect the damage detection capabilities of the algorithm, which can be observed in Fig. 6(b) (Keypoint 10).

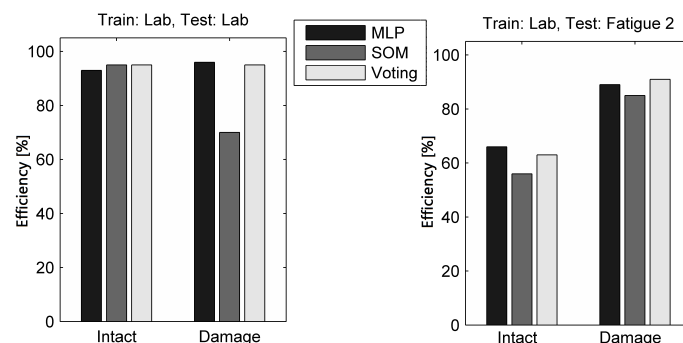


Figure 4 : Results of ANNs training on "Laboratory" dataset. Testing performed on "Laboratory" dataset with respect to Cross-Validation method (a), and on "Fatigue2" dataset (b).

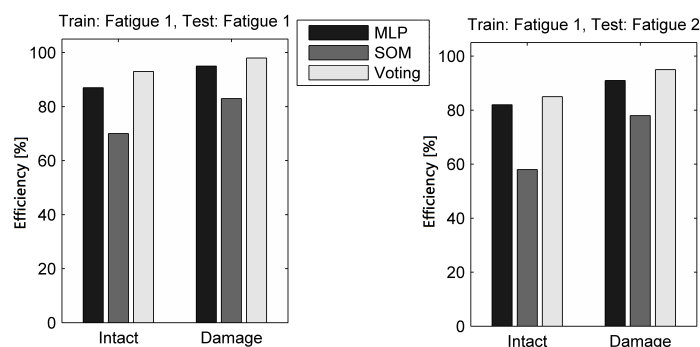


Figure 5 : Results of ANNs training on Fatigue1" dataset. Testing performed on "Fatigue1" dataset with respect to Cross-Validation method (a), and on "Fatigue2" dataset (b).

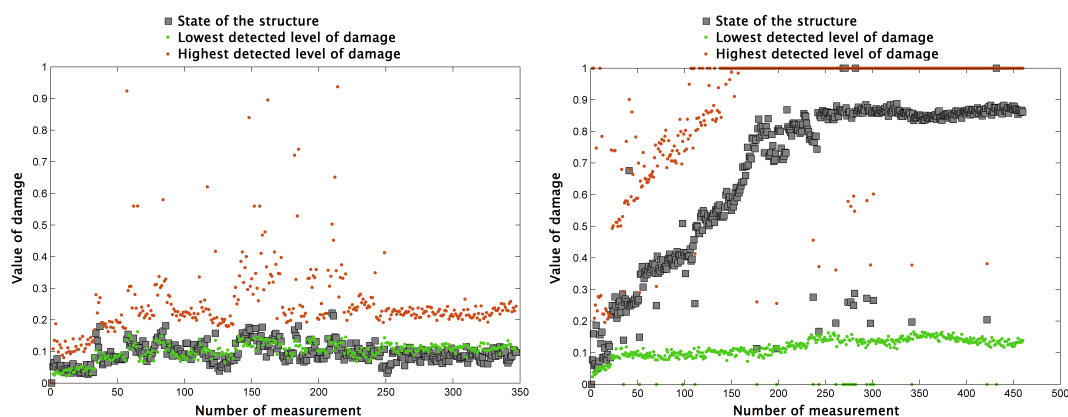


Figure 6 : Structure evaluation in two exemplary keypoints during Full Scale Fatigue Test for undamaged (a) and damaged keypoint (b)

4. CONCLUSIONS

The authors have developed a method which has potential to detect damage in planar structures. A pitch-catch measurements of Lamb-waves are used to calculate damage indices which are later used as an input to the voting ANN classifier. It has been proven by the authors, that usage of several cooperating networks can lead to better and more reliable results. Signals acquired by several sensor pairs embedded in one area can be used to distinguish local structural change caused by damage from a global one caused by environment variations. The developed method has been tested on damaged specimens as well as on data acquired during full-scale fatigue test of a whole aircraft.

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