Time-domain Feature Extraction and Neural Network Identification of Structure Crack Based on Surface-mounted Active Sensing Network

Chunling Du, Jianqiang Mou, Landong Martua, Shudong Liu, Bingjin Chen,
Guopeng Cao, Wen Xiang Yock, Jingliang Zhang
*A*STAR, Data Storage Institute(DSI)*
5 Engineering Drive 1,
Singapore 117608
Email: DU_Chunling@dsi.a-star.edu.sg

Frank L. Lewis
Automation and Robotics
Research Institute,
University of Texas,
Arlington, TX76019, USA

***Abstract*—In this work, the condition of a metallic structure is classified based on the acquired sensor data from a surface-mounted piezoelectric sensor/actuator network. The structure under consideration is an aluminum plate with riveted holes and possible crack damage in these holes is investigated. The sensor/actuator network uses diagnostic signals injected to piezoelectric actuators and received sensor signals to detect the crack. The damage classification system consists of three major components: sensitive signal acquisition, principal feature extraction and damage classification. An appropriate sine wave burst is used as diagnostic signals for actuators to transmit to sensors in order to detect the integrity of the structure. The combination of time-domain S0 waves from all sensitive sensor signals is directly used as features to detect damage. Since the time sequence of the extracted S0 waves is selected as the feature and has a high dimension, principal component estimation is applied to reduce the data dimension before entering the neural network training. Finally, in structure condition classification, a LVQ (learning vector quantization) neural network is used to classify structure conditions as healthy or damaged. In this paper, a number of FEM (finite element modeling) simulation results of sensor signals are taken as inputs to the neural network for training, since it is found that the FEM results have a good agreement with the experimental testing results on real plates. The performance of the classification is then validated by using these testing results.**

***Keywords*-active sensing; damage classification; feature extraction; finite element modeling; Lamb wave; principal component analysis; structure health monitoring; sensor network.**

I. Introduction

Early detection of damages such as cracks in metallic structures due to cyclic loads and environmental corrosion is critical for preventing catastrophic failure and prolonging the life of aircraft structures. To reduce the cost of maintenance, structural health monitoring (SHM) has been proposed as an alternative approach to replace traditional time-consuming inspection for maintenance. The wave propagation method for structural health monitoring has been demonstrated to be effective in detecting debonding in composites and cracks in metallic structures. Therefore, in this work, wave propagation method based on surface-mounted piezoelectric sensor arrays is adopted to monitor crack growth at riveted holes.

In general, the structural health monitoring system consists of two major parts: hardware and software. The hardware includes the distributed sensor network and the data acquisition system. In this work, the active sensing network with actuators excited by known diagnosis signals is adopted. And the software part for diagnosis includes signal analysis for sensitive feature extraction and intelligent algorithms for damage interpretation and classification, which actually result in the physical condition of a given structure from the raw sensor measurements. Our research reported in this paper is concentrated on feature extraction and structure condition classification.

Neural network methods are widely used to solve classification problem, since when properly trained they easily map the extracted feature space to structure condition space. Designing an effective neural network has always been a challenging task. In [6], a three-layer propabilistic neural network is applied to classify the sensor data into several categories relative to the damage location in the circular plates using resonance frequency shifts of E/M (electro/mechanical) impedance as damage features. In [7], a backpropagation neural network is trained to categorize cracks according to their lengths using FE modeling data for scattering of ultrasound by the cracks emanating from rivet holes in a thin aluminum plate. An impedance-based damage detection combined with a backpropagarion neural network is developed in [8] to locate and identify the structure damages. In [9], with independent component analysis for vibration features, a multi-layer perceptron neural network, trained using an error backpropagation algorithm, is able to detect the undamaged and damaged states with very good accuracy and repeatability.

Lamb wave is much more sensitive to structure damages than other structural responses such as modal shape, natural frequency, etc., and the artificial neural network technique based on Lamb wave testing is able to lead to precise identification of the damages. In [10], the authors developed an identification technique for debonding in ad-

 ISBN: 978-1-61208-144-1

hesively bonded joints using Lamb wave signals interpreted by neural network training. In [11], different crack lengths at four locations in a PVC sandwich panel were numerically simulated and the percentage shifts in structural energy were used to train a backpropagation neural network. Good identification precision was achieved for another numerically simulated damage cases, while poor precision was attained using measurement signals. In [12], the so-called DDFs (digital damage fingerprints) are extracted from the spectrographic characteristics of Lamb wave signals and serve as damage features. Various numerical simulation results are employed to train the NN (neural network) and then experimentally validated by identifying cylinder through-holes and delamination in the composite laminates. In most of these papers, the artificial NN employs the method of supervised feedforward backpropagation.

This paper presents a method based on neural network for the classification of an aluminum plate with and without crack damage at reveted holes. The time-domain sensor signals are directly used as damage features, and key features having reduced data size are extracted after principal component estimation. The estimated key features are then considered as the input at the neural network, which is trained according to the learning vector quantization method. The NN training uses FEM (finite element modeling) data of Lamb wave propagation in the active sensor network system, and the classification performance is evaluated through the validation using the experimental testing data.

II. Active sensing system for structure crack detection

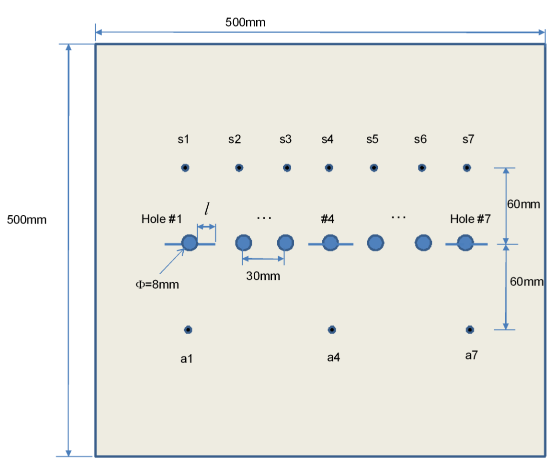

Figure 1. Active sensing system for an aluminum plate with riveted holes with cracks.

The aluminum plate with riveted holes illustrated in Fig. 1 is studied on crack detection using the active sensing system, which consists of sensors denoted as s1, s2, $\cdots$, s7, and actuators denoted as a1, a2, $\cdots$, a7. The cracks in the hole are indicated in Fig. 1 with length l. The actuators excited by the diagnosis signal, which is here the windowed sinewave burst as shown in Fig. 2, transmit the signal to the sensors. The received signal on the sensor contains the information about the integrity of the structure between the actuator and the sensor, and will be used to detect any crack occurrence by investigating any change in the received signal. Based on the analysis of the sensor signals, information can be retrieved concerning the extent of the damage and used to assess and classify the health condition of the structure.

In this work, we take actuator a4 as one case which is excited by the diagnosis signal in Fig. 2. Signal propagation is simulated with FEM method, and will be verified by testing on real plates.

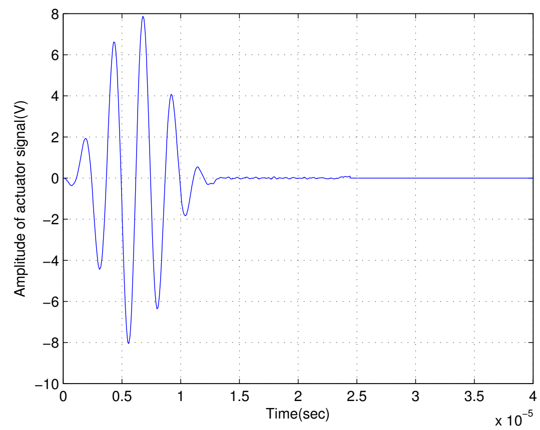

Figure 2. 400 kHz sinewave burst injected to the actuator in simulation.

A. FEM simulation

The FEM result of sensor signals for the pristine plate is shown in Fig. 3. The fundamental symmetric (S0) mode is widely used to detect surface crack in metallic structures due to its sensitivity to crack growth [1] and thus in this work it is utilized for crack detection. As indicated in Fig. 3, S0 wave is obviously fetched by the sensors.

When the plate has a crack with l=6mm at the hole #4, the signals of sensors 1 to 4 are shown in Fig. 12. It is obviously noticed that the S0 wave amplitude of sensor 4 is reduced compared with that of the pristine plate. In this case, because sensors s5, s6 and s7 are symmetric to sensors s3, s2 and s1, their signals are respectively the same as those of sensors s3, s2 and s1 and thus omitted here.

With different crack lengths, the maximum amplitude of S0 wave of each sensor signal is plotted in Fig. 5. As expected, sensor s4 is most sensitive to crack at hole #4, which is proved from Fig. 5 as the curve corresponding to s4 drops most significantly even for a small crack l=2mm.

 ISBN: 978-1-61208-144-1

Other sensors s2 and s3 are sensitive to bigger cracks, while s1 signal does not change much and thus it is not able to detect the crack at hole #4.

Simulation results of sensor signals for cracks located respectively at holes # 3, 2 and 1 have been obtained. The S0 wave maximum amplitude versus different crack lengths is displayed in Fig.s 6-8. In Fig. 6, s3 and s2 are most sensitive to cracks, and s1 is also possibly useful to detect crack. In Fig. 7 for the crack at hole #2, s1 and s2 are able to detect it. However, for crack at hole #1, none of the four sensors is capable of detecting the crack. This implies that excitation to an actuator closer to it is required. In this work, we study the case of actuator a4 excited. As for other actuators, the processing to sensor signals is similar.

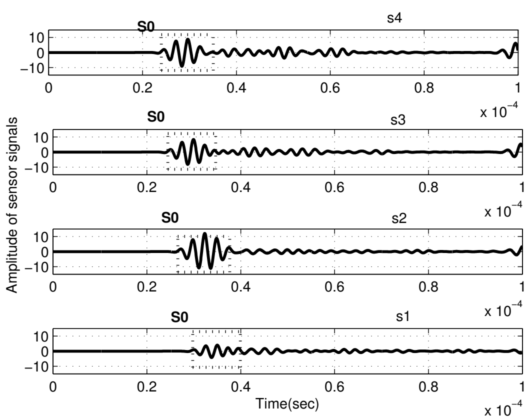

Figure 3. Sensor signals for the pristine plate.

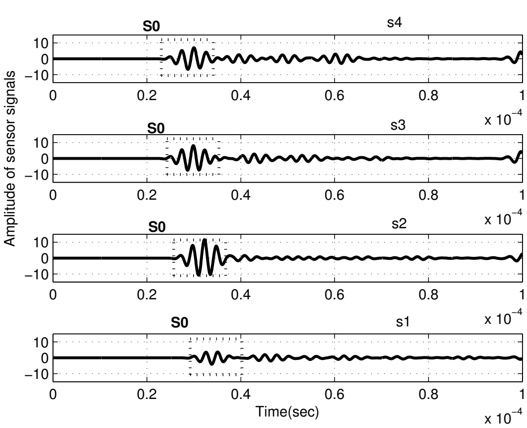

Figure 4. Sensor signals for the plate with crack l=6mm at hole#4.

The above analysis shows that the sensors are all useful to crack detection. It is also noticed that S0 wave amplitude as well as its time delay (or, time of flight [2]) relative to actuator signal are sensitive to the crack. Therefore the time

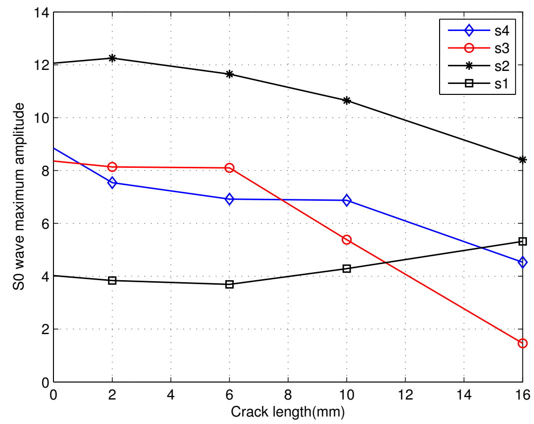

Figure 5. Maximum amplitude of S0 wave versus crack length for crack at hole #4.

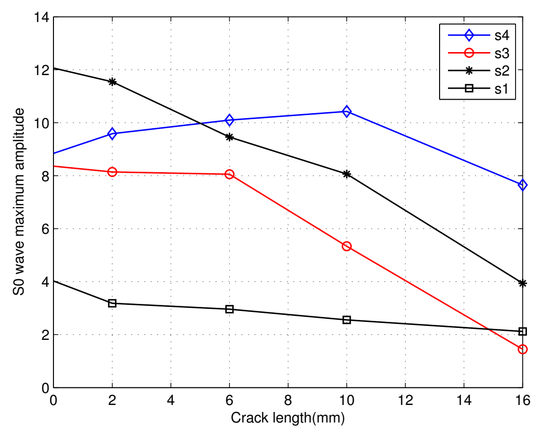

Figure 6. Maximum amplitude of S0 wave versus crack length for crack at hole #3.

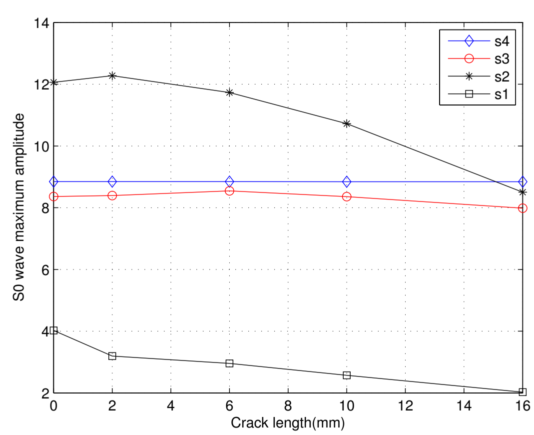

Figure 7. Maximum amplitude of S0 wave versus crack length for crack at hole #2.

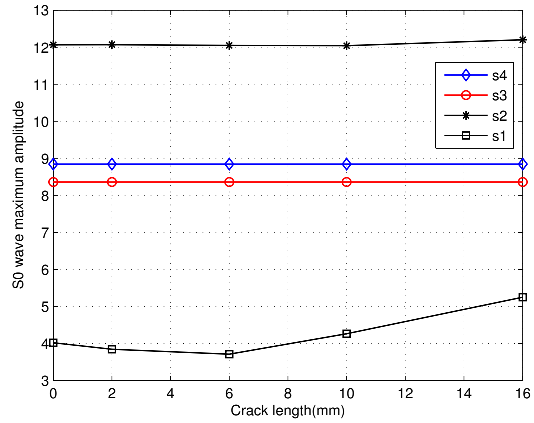

Figure 8. Maximum amplitude of S0 wave versus crack length for crack at hole #1.

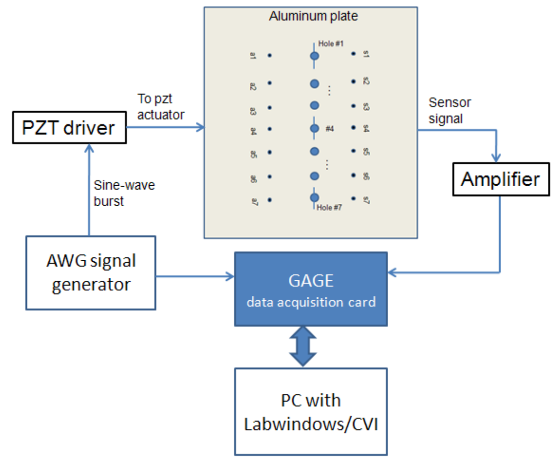

Figure 10. Experimental setup.

sequences of S0 waves of sensors s1-s4 will be used as features for classification in this paper. Take the crack at hole #4 as an example. The combined S0 wave time sequence of sensors s1-s4 is shown in Fig. 9.

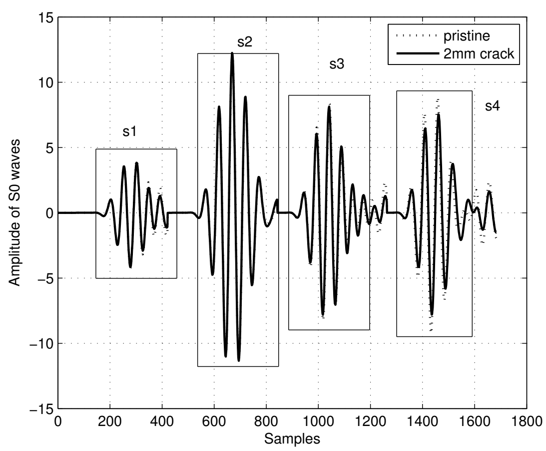

Figure 9. S0 waves for crack at hole #4.

B. Experimental verification

The experimental setup consists of an Arbitrary Wave Generator (AWG) 2041, PZT driver, sensor signal amplifiers, and a programmable GAGE Compuscope 82G card connected to a PC running Labwindows/CVI. The actuation and the sensor signals are amplified by high bandwidth amplifiers. The data acquisition subsystem includes a PCI interface controlled with the PC running Labwindows/CVI, and the data are saved in PC through the GAGE card. The schematic diagram of the experimental setup is shown in Fig. 10.

Experimental testing on a real plate has been conducted. Circular transducers as sensors and actuators are mounted to the surface of the plate by using epoxy. Excitation signal to the actuator is the same as that in Fig. 2. The sensor signal is collected via the data acquisition card with 20MHz sampling rate. For the pristine plate, sensor signals are displayed in Fig. 11, which agrees well with the simulation results in Fig. 3. We take the plate with crack l=6mm at hole#4 as one example with crack. Fig.s 12-13 show the simulation and experimental results, where it is observed that the S0 mode agrees quite well to each other.

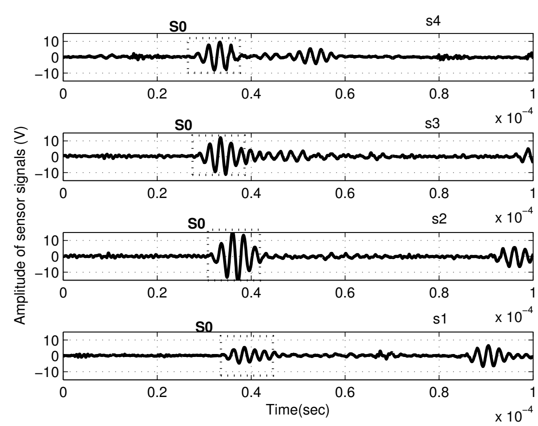

Figure 11. Experimental sensor signals for the pristine plate.

Since the FEM result agrees well with the experiment data, in the next section the FEM results together with some of the experiment data will be used in the neural network training for damage classification.

III. CLASSIFICATION ARCHITECTURE

This section presents the system architecture being used for the crack classification methodology. The key steps

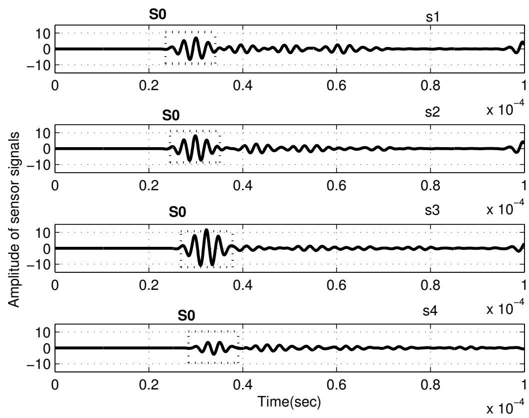

Figure 12. Simulated sensor signals for the plate with crack *l*=6mm at hole#4.

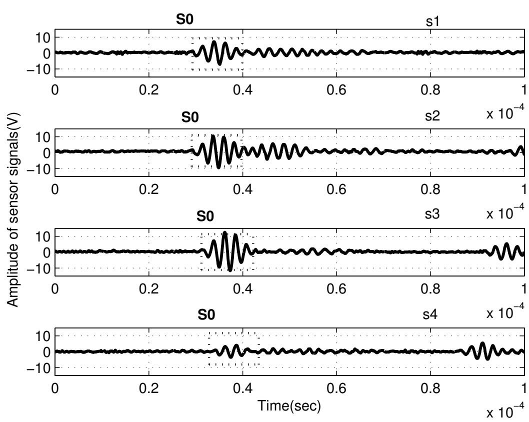

Figure 13. Experimental sensor signals for the plate with crack *l*=6mm at hole#4.

involved in the methodology are 1) S0 wave extraction, 2) Estimation of principal components, 3) Structure condition classification using a neural network.

The proposed approach makes use of an architecture that consists of a neural network to classify different structure conditions. The scheme employed in the approach is shown in Fig. 14, and is detailed in subsequent sections and outlined below.

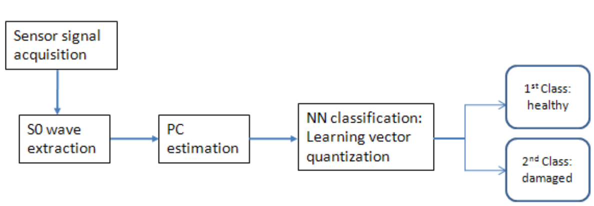

Figure 14. Classification architecture.

The first step of the methodology involves the extraction of S0 wave. The time sequences of S0 waves from several sensors are used as inputs to the stage of principal component estimation. This step directly uses the time-domain signal of the sensors, which reduces the processing time for the sensor signals.

The second step given in the proposed approach involves the dimension reduction of the sensor signal using Principal Component Estimation. Principal component analysis (PCA) is a statistical technique used for data compression by determining a linear transformation matrix $W \in R^{m\times n}$ $(m < n)$. The data $X \in R^{n\times 1}$ is compressed and a lower dimension data $y \in R^{m\times 1}$ is yielded and given by

$$y = WX. \qquad (1)$$

The PCA technique is to reduce the number of features representing a data by discarding the ones which have small variance and retains only those that have large variance. It uses singular value decomposition method in calculating the eigenvectors of the co-variance matrix formed by analyzing the sensor data. Only those eigenvectors are selected which give the maximum information about the data. These chosen eigenvectors form the matrix W.

The last and the main step of classifying structure conditions are obtained from the methodology of neural network. The neural network is based on Learning Vector Quantization (LVQ) nets. The LVQ network is trained using Kohonen learning rule to classify structure conditions.

IV. Classification performance analysis

The time domain data of S0 waves from sensors 1 to 4 discussed in Section II is used as feature to classify the cases into categories relative to the structure condition. In this paper, two classes are assigned: 1 representing no damage, and 2 representing damage with crack.

As shown in Table 1, the shaded parts are the types of plates under investigation. It is shown that the data used for principal component estimation and neural network training are mostly coming from FEM results. Only one case is from a real specimen as the pristine plate. For principal component estimation and neural network training, these data are expanded as 1019 pristine plate and 736 damaged plates, which means the sensor data for pristine plate is repeatedly used for 1019 times, and the sensor data for each damaged case is repeatedly used for 46 times. The dimension of S0 wave combination from the four sensors is 1684. After principal component estimation, the dimension is reduced from 1684 to 13.

The used LVQ neural network ('newlvq' function in Matlab) is a a two-layer network. The first layer is a competitive layer that uses the compet transfer function and calculates the distance from an input to each row of the input weight matrix. The second layer is a linear layer having purelin neurons. In this application, the number of hidden neuron

 ISBN: 978-1-61208-144-1

of the first layer is 4 and the class percentages are 45% and 55%.

As shown in Table 1, testing results from 10 real plates (indicated by the shadow) are used to verify the classification method. Based on the trained LVQ neural network, 8 plates are classified correctly, and 2 plates are not classified correctly. It is noted the NN training is mainly based on the FEM simulation results. The trained NN leads to such a classification results for the tested specimens is acceptable and promising. It is also noticed that the trained NN is potentially able to identify combined cracks, although it is solely based on the single crack cases.

Table 1. Health classification with sensor data from s1-s4.

Plates	Crack length l (mm)	FEM simulation plates	Tested plates	Classification results
Pristine	0	T	T	1
	0			1
Crack at Hole #4	2	T		
	6	T		
	10	T		2
	16	T		2
Crack at Hole #3	2	T		2
	6	T		1
	10	T		2
	16	T		2
Crack at Hole #2	2	T		
	6	T		
	10	T		
	16	T		
Crack at Hole #1	2	T		
	6	T		
	10	T		
	16	T		
Cracks: 2mm@hole#4, 6mm@hole#1				2
Cracks: 6mm@hole#4, 2mm@hole#1				1

Classification results: 1- healthy; 2- damaged
T: used for principal component estimation and NN training

V. Conclusion

In this paper, the aluminum plates with the riveted holes and possible crack damage at these holes have been studied and the surface-mounted piezoelectric sensor/actuator network has been utilized to detect the crack. The 400 kHz sine wave burst has been used as diagnostic signals and injected to actuators and it propagates to sensors in order to detect the integrity of the structure. The combination of time-domain S0 waves from all sensitive sensor signals has been directly used as features to detect the crack damage. After the principal component estimation, the reduced-size data work as input for the LVQ neural network training. The neural network training has utilized a series of FEM simulation results, since it has been found that the FEM results have a good agreement with the experimental testing results on real plates. The performance of the classification has been finally validated by using the testing results from 10 real plates.

References

[1] J. -B. Ihn, and F. -K. Chang, “Detection and monitoring of hidden fatigue crack growth using a built-in piezoelectric sensor/actuator network: I. Diagnostics”, *Smart Materials and Structures*, vol. 13, pp. 609-620, 2004.

[2] J. -B. Ihn, and F. -K. Chang, “Detection and monitoring of hidden fatigue crack growth using a built-in piezoelectric sensor/actuator network: II. Validation using riveted joints and repair patches”, *Smart Materials and Structures*, vol. 13, pp. 621-630, 2004.

[3] P. Dang, H. Stephanou, F. Ham, and F. L. Lewis, “Facial expression recognition using a two stage neural network”, *Proceedings of the 15th Mediterranean Conference on Control & Automation*”, Athens, Greece, 27-29 Jul., 2007.

[4] T. Kohonen, Self-Organizing Maps, Second Edition, Berlin: Springer-Verlag, 1997.

[5] Z. Su, L. Ye, and Y. Lu, “Guided Lamb waves for identification of damage in composite structures: A review”, *Journal of Sound and Vibration*, vol. 295, pp. 753-780, 2006.

[6] V. Giurgiutiu, Structural Health Monitoring with Piezoelectric Wafer Active Sensors, Burlington, MA: Academic Press/Elsevier, 2008.

[7] K. Zgonc, and J. D. Achenbach, “A neural network for crack sizing trained by finite element calculations”, *NDT & E International*, vol. 29, no. 3, pp. 147-155, 1996.

[8] V. Lopes Jr., G. Park, H. H. Cudney, and D. J. Inman, “Smart structures health monitoring using artificial neural network”, *Structural Health Monitoring*, pp. 976-985, 1999.

[9] C. Zang, M. I. Friswell, and M. Imregun, “Structure damage detection using independent component analysis”, *Structural Health Monitoring*, vol. 3, pp. 69-83, 2004.

[10] U. Bork, R. E. Challis, “Artifitial neural networks applied to Lamb wave testing of T-form adhered joints”, *Proc. of the Conference on the Inspection of Structural Composites*, Bentham Press, 1994.

[11] L. H. Yam, Y. J. Yan, J. S. Jiang, “Vibration-based damage detection for composite structures using wavelet transform and neural network identification”, *Composite Structures*, 60, pp. 403-412, 2003.

[12] Z. Su, L. Ye, “Lamb wave propagation-based damage identification for quasi-isotropic CF/EP composite laminates using artificial neural algorithm, part I: methodology and database development”, *Journal of Intelligent Material Systems and Structures*, 16, pp. 97-111, 2003.

[13] L. Ye, Z. Su, C. Yang, Z. He, and X. Wang, “Hierarchical development of training database for artificial neural network-based damage identification”, *Composite Structures*, 76, pp. 224-233, 2006.