ISSN 1726-5479

SENSORS & TRANSDUCERS

3/12 vol. 14-2 Special

Physical and Chemical Sensors & Wireless Sensor Networks

International Frequency Sensor Association Publishing

IFSA

Sensors & Transducers

Volume 14-2, Special Issue
March 2012

www.sensorsportal.com

ISSN 1726-5479

Sensors & Transducers Journal (ISSN 1726-5479) is a peer review international journal published monthly online by International Frequency Sensor Association (IFSA). Available in electronic and on CD.

Sensors & Transducers Journal

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Volume 14-2
Special Issue
March 2012

www.sensorsportal.com

ISSN 1726-5479

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Sensors & Transducers Journal, Vol. 14-2, Special Issue, February 2012, pp. 283-296

Sensors & Transducers

ISSN 1726-5479

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Structure Crack Identification Based on Surface-mounted Active Sensor Network with Time-Domain Feature Extraction and Neural Network

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Received: 15 November 2011 /Accepted: 20 December 2011 /Published: 12 March 2012

Abstract: In this work the condition of metallic structures are classified based on the acquired sensor data from a surface-mounted piezoelectric sensor/actuator network. The structures are aluminum plates with riveted holes and possible crack damage at these holes. A 400 kHz sine wave burst is used as diagnostic signals. The combination of time-domain S0 waves from received sensor signals is directly used as features and preprocessing is not needed for the dam age detection. Since the time sequence of the extracted S0 has a high dimension, principal component estimation is applied to reduce its dimension before entering NN (neural network) training for classification. An LVQ (learning vector quantization) NN is used to classify the conditions as healthy or damaged. A number of FEM (finite element modeling) results are taken as inputs to the NN for training, since the simulated S0 waves agree well with the experimental results on real plates. The performance of the classification is then validated by using these testing results. *Copyright © 2012 IFSA.*

Keywords: Active sensing network, Damage classification, Feature extraction, Lamb wave, Principal component analysis.

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1. Introduction

To reduce the cost of maintenance, SHM (structural health monitoring) 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. And early detection of such damages due to cyclic loads and environmental corrosion is critical for preventing catastrophic failure and prolonging the life of aircraft structures. Therefore, in this work, wave propagation method based on surface-mounted piezoelectric sensor arrays is adopted to monitor cracks 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 [1], 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 [2], 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 back propagation neural network is developed in [3] to locate and identify the structure damages. In [4], with independent component analysis for vibration features, a multi-layer perceptron neural network, trained using an error back propagation algorithm, is able to detect the undamaged and damaged states with very good accuracy and repeatability.

Lamb wave [5, 10] 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 [6], the authors developed an identification technique for debonding in adhesively bonded joints using Lamb wave signals interpreted by neural network training. In [7], 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 case, while poor precision was attained using measurement signals. In [8], 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 neural network and then experimentally validated by identifying cylinder through-holes and delamination in the composite laminates. In most of these papers, the artificial neural network 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 riveted holes. The time-domain sensor signals are directly used as damage features without preprocessing, and key features having reduced data size are extracted after principal component estimation. The estimated key features are then considered as the input to the neural network, which is trained according to the learning vector quantization method. The neural network training mainly uses FEM 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.

2. Active Sensing System for Structure Crack Detection

The aluminum plate with riveted holes illustrated in Fig. 1 is studied for crack detection using the active sensing system, which consists of sensors denoted as s1, s2,···, s7, and actuators denoted as a1, a4, and a7. The cracks at the hole are indicated in Fig. 1 with length *l*. The actuators excited by the diagnosis signal, which is the windowed sinewave burst as shown in Fig. 2, transmit the signal to the sensors. The received signal by 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. It is mentioned that the distance between the sensor, the actuator and the hole, and the diagnostic signal frequency are determined with the help of analytical and numerical simulation, which is detailed in the accompanying paper [15].

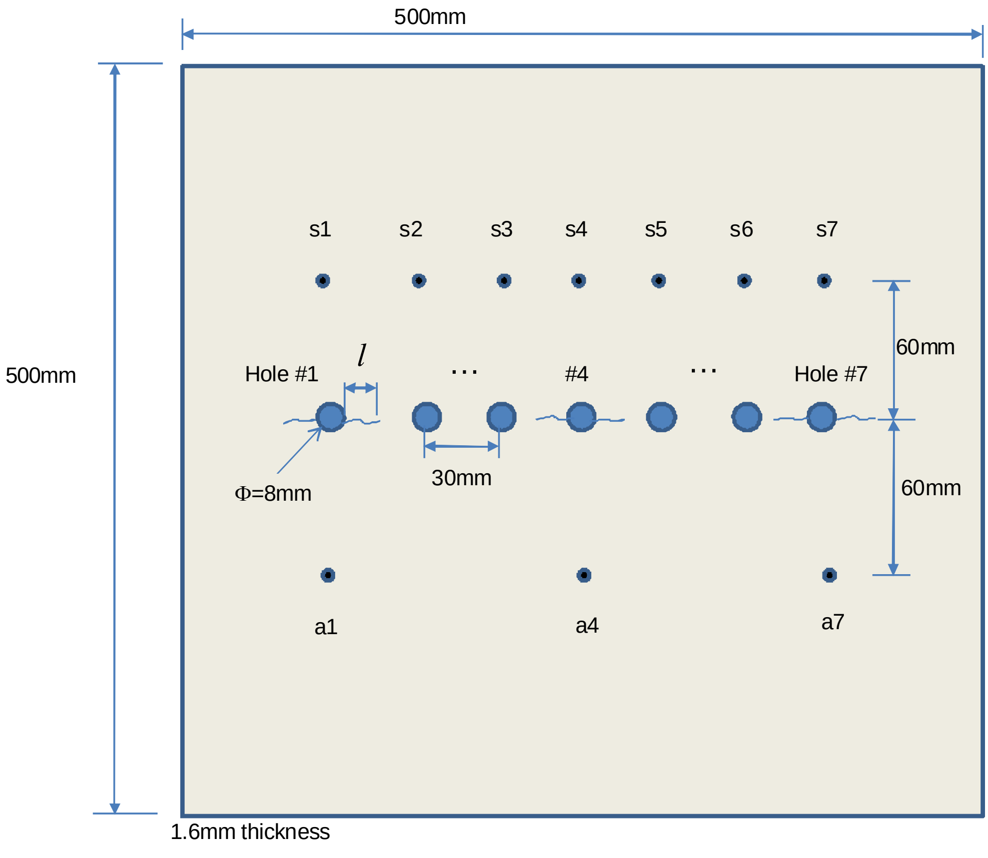

Fig. 1. Active sensing system for an aluminum plate with riveted holes with cracks.

The experimental testing 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. 3.

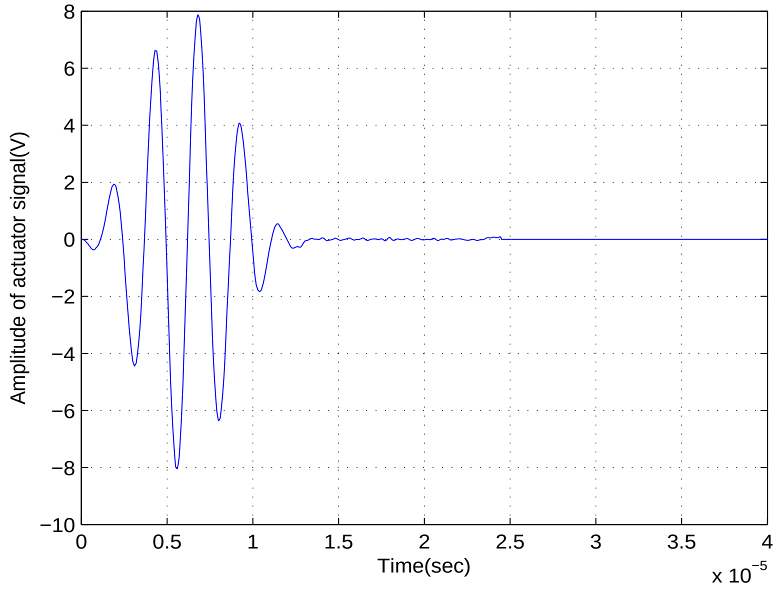

Fig. 2. 400 kHz sinewave burst injected to the actuator.

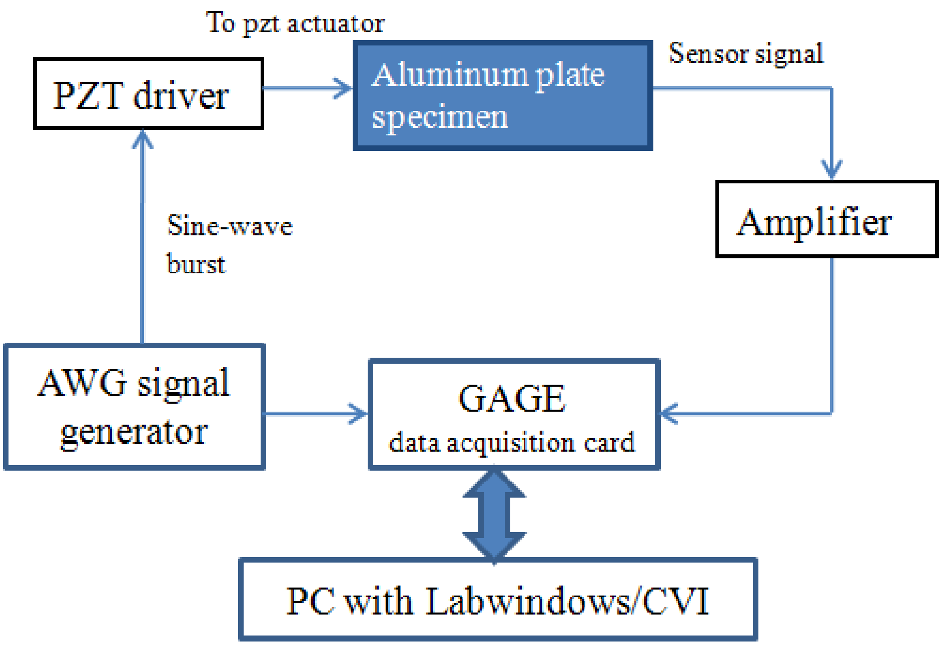

Fig. 3. Schematic diagram of experimental setup.

Experimental testing on real plates has been conducted. Circular transducers working as sensors and actuators are mounted to the surface of the plate using epoxy. The sensor signal is collected via the data acquisition card with 20 MHz sampling rate. As one example, the experimental sensor signals for the pristine plate are displayed in Fig. 4. We also take the plate with cracks l = 6 mm at hole #4 and l =2 mm at hole #1 as another example for comparison. Fig. 5 shows the testing results, where the differences of S0 waves from those in Fig. 4 for the pristine plate are observable, e.g., the peak value is reduced, especially for s1 and s4. In next sections, we shall made use of these differences to detect the damage via feature extraction and condition classification.

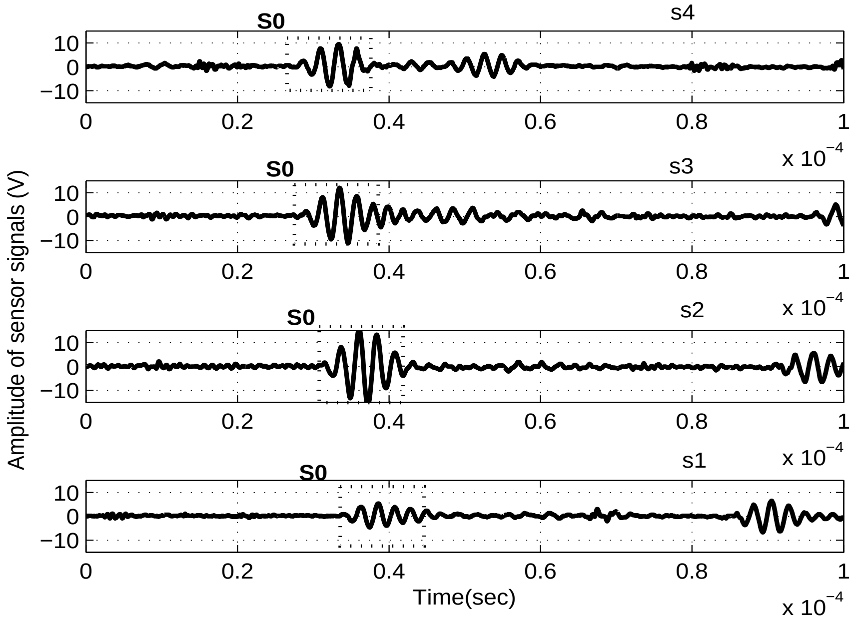

Fig. 4. Experimental sensor signals for the pristine plate.

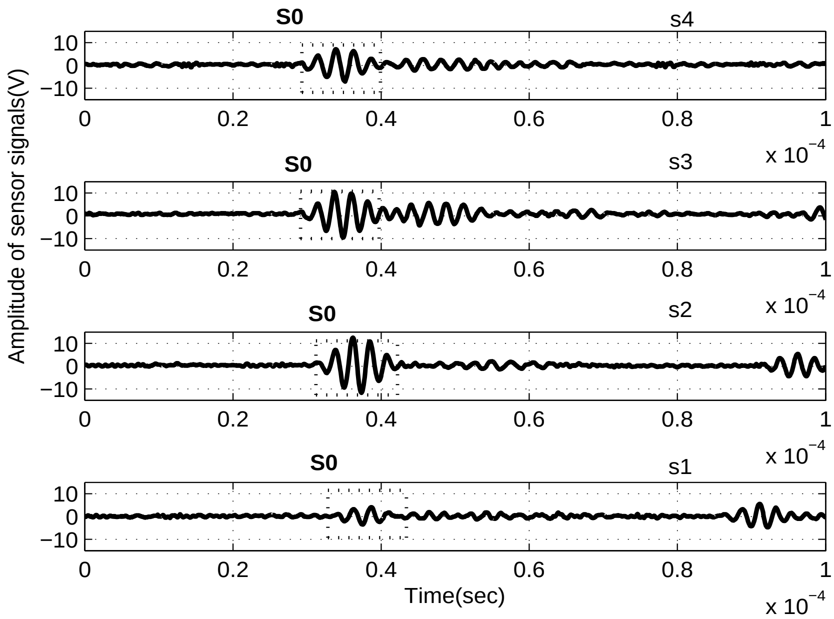

Fig. 5. Experimental sensor signals for the plate with cracks *l*=6mm at hole #4 and *l*=2mm at hole #1.

The classification architecture being used is shown in Fig. 6. The key steps involved in the methodology are 1) S0 wave extraction or feature extraction, 2) Estimation of principal components, 3) Structure condition classification using a neural network. 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. The traditional method of singular value decomposition is used. The last and the main step of classifying structure conditions are obtained from the methodology of neural network. The neural network is based on LVQ nets. The LVQ network is trained using Kohonen learning rule to classify structure conditions.

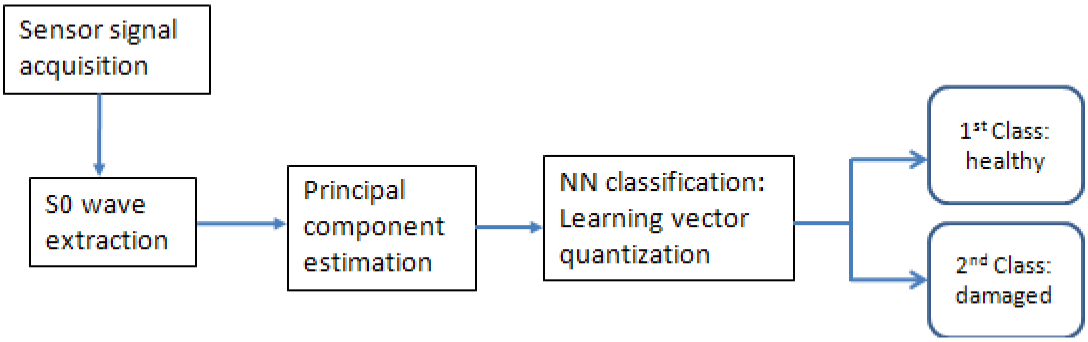

Fig. 6. Classification architecture.

3. Feature Extraction

To facilitate the NN training which needs sufficient sensor data, numerical data are desired to replace testing data from specimens in order to increase cost efficiency. For this purpose, verification of the numerical sensor signals is necessary to prove that they are reliable. Details about the simulation of the wave propagation for the system in Fig. 1 are seen in [15].

To normalize the simulation and the experiment data, a scaling is needed and can be determined according to the sensor data for the pristine plate. Fig. 7 shows the simulation result of sensor signals for the pristine plate. Similarly to the experimental result in Fig. 4, S0 wave is obviously fetched by the sensors. Also, for the plate with cracks *l* =6 mm at hole #4 and *l* =2 mm at hole #1, Fig. 8 shows its simulation results. It is noticed that S0 waves agree well in amplitude between the simulated and the experimental results, while a time shift is seen, which is due to the time shift of the excitation signals. Since the excitation signal is known, the time shift of the sensor signals is easily removed. After a thorough examination to 10 specimens, we believe that the FEM simulation can guarantee the reliability of S0 wave, which implies that the simulated S0 waves are believable and thus can be used to replace real testing data for the structure condition classification. So in the next section the features from the FEM results together with some of the experiment data will be used in the neural network training for damage classification.

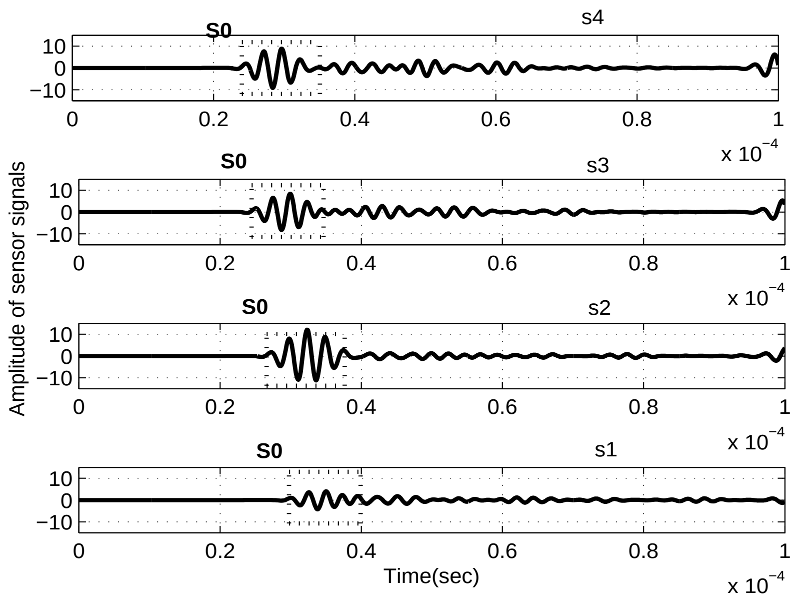

Fig. 7. Simulated sensor signals for the pristine plate.

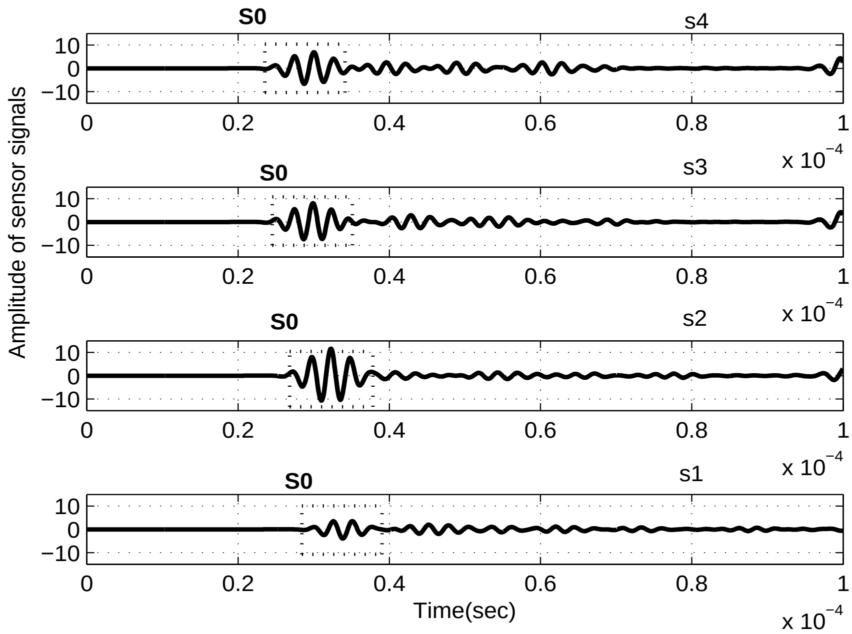

Fig. 8. Simulated sensor signals for the plate with cracks l=6 mm at hole #4 and l=2 mm at hole #1.

Next, we shall systematically analyze the relationship of the S0 wave with the crack length based on the simulated sensor data. With different crack lengths, the maximum amplitude of S0 wave of each sensor signal is plotted in Fig. 9. As expected, sensor s4 is most sensitive to crack at hole #4, which is seen from Fig. 9 as the curve corresponding to s4 drops most significantly even for a small crack l =2 mm. 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.

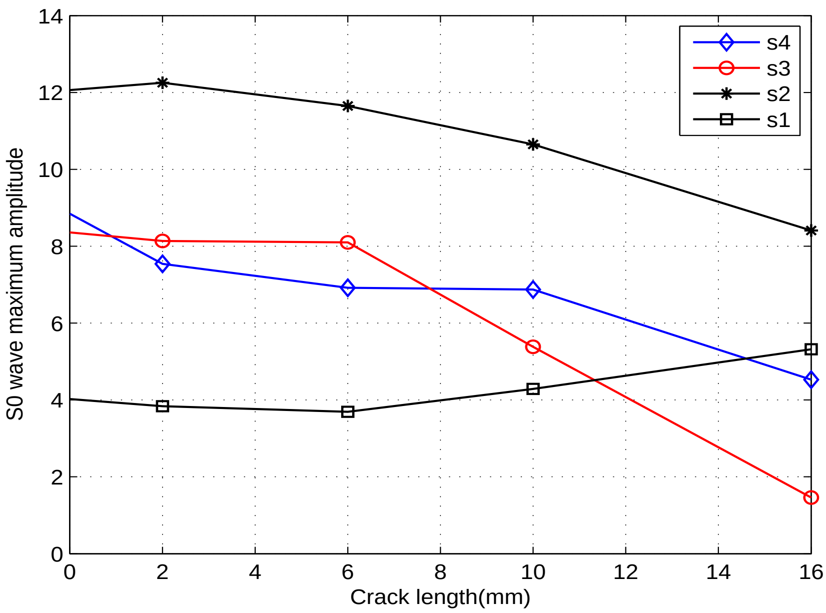

Fig. 9. Maximum amplitude of S0 wave versus crack length for crack at hole #4.

As for cracks located respectively at holes #3, #2 and #1, the S0 wave maximum amplitude versus different crack lengths is displayed in Figs. 10-12. In Fig. 10, s3 and s2 are most sensitive to cracks, and s1 is also possibly useful to detect crack. In Fig. 11 for the crack at hole #2, s1 and s2 are able to detect it. However, in Fig. 12 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.

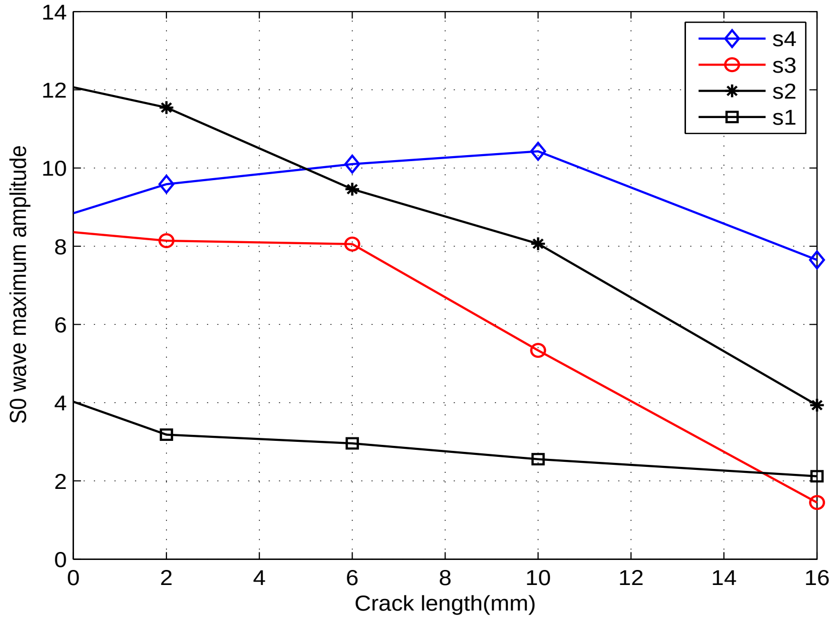

Fig. 10. Maximum amplitude of S0 wave versus crack length for crack at hole #3.

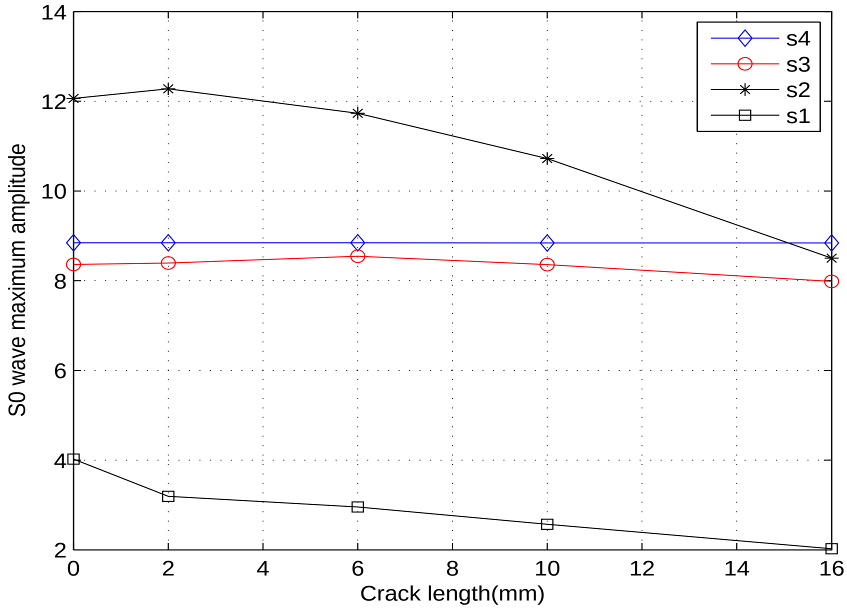

Fig. 11. Maximum amplitude of S0 wave versus crack length for crack at hole #2.

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 [11]) relative to actuator signal are sensitive to the crack. Therefore the time 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. 13.

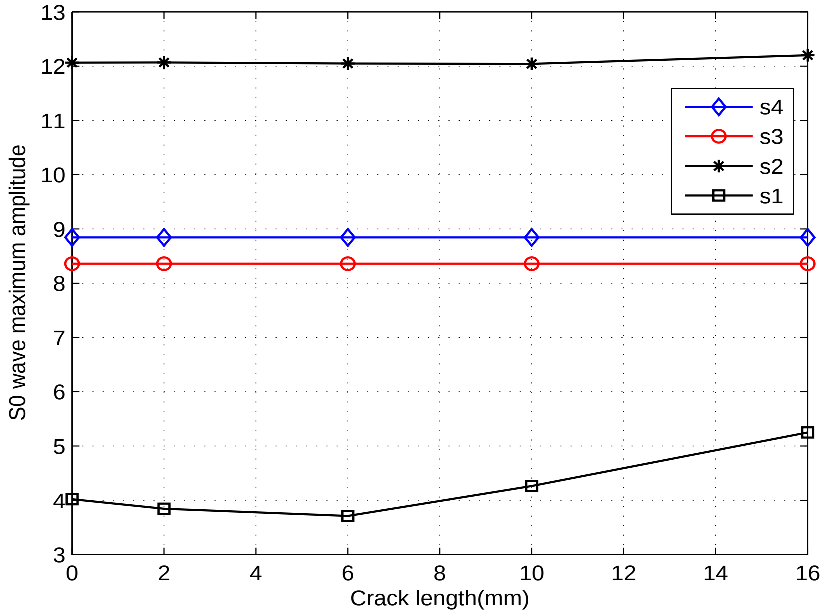

Fig. 12. Maximum amplitude of S0 wave versus crack length for crack at hole #1.

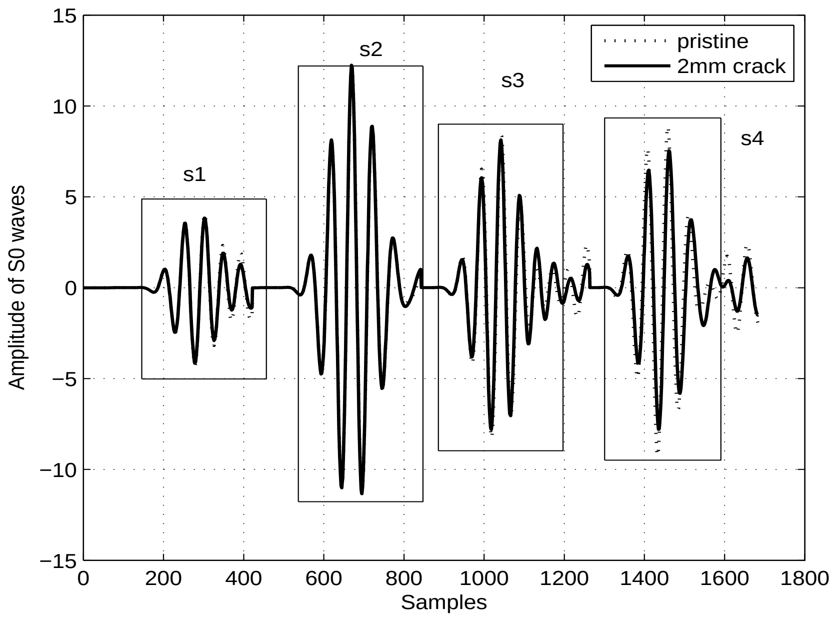

Fig. 13. S0 waves for crack at hole #4.

4. Principal Component Estimation

To make the damage classification simple, the time sequence of the S0 waves undergoes the principle component analysis so that the principal components are extracted. Principal component analysis (PCA) is a statistical technique used for data compression by determining a linear transformation matrix $W \in \mathrm{R}^{m \times n}$ ($m<n$). The data $X \in \mathrm{R}^{n \times 1}$ is compressed and a lower dimension data $y \in \mathrm{R}^{m \times 1}$ is yielded and given by

$$y = WX. \tag{1}$$

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*. A very brief introduction to the standard principal components computation is given as follows.

Let the time sequence of S0 wave from each sensor signal be denoted as $s_k \in R^{M\times 1}$, $k = 1, \cdots, N$. The total number of the sensors is *N*. All extracted S0 waves form a 1-D vector given by

$$c_i = \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{bmatrix}, \qquad c \in R^{Q=MN}, \qquad i = 1, \cdots, L, \tag{2}$$

where the total number of the specimens participating in the principal component estimation is *L*. The mean of the S0 waves for all specimens is obtained as

$$\tau = \frac{1}{L}\sum_{i=1}^{L} c_i . \tag{3}$$

Subtracting the mean from the original data c_i yields

$$\tilde{c}_i = c_i - \tau . \tag{4}$$

The covariance matrix for the different specimens is obtained as

$$C = \sum_{i=1}^{L} \tilde{c}_i \tilde{c}_i = \Gamma\Gamma^T , \tag{5}$$

$$\Gamma = [\tilde{c}_1 \quad \tilde{c}_2 \quad \cdots \quad \tilde{c}_L]. \tag{6}$$

The eigenvectors corresponding to the covariance matrix *C* in (5) are computed in order to form the basis for the construction of *W* matrix in (1). The number of possible eigenvectors that would yield the maximum information about the dataset, is equal to the number of specimens in the training set. Therefore, for a dataset with *L* specimens, *L* eigenvectors are reasonably taken into account to form the *W* matrix. Consider a new matrix given by

$$G = \Gamma^T \Gamma \in R^{L\times L} , \tag{7}$$

and let the eigenvalue-eigenvector pairs of *G* be (μ_k, θ_k) (k=1, ... , *L*). We have

$$G\theta_k = \mu_k \theta_k . \tag{8}$$

It is easily known that $\Gamma\theta_k$ are the eigenvectors of $C=\Gamma\Gamma^T$. Thus L eigenvectors are computed instead of computing Q eigenvectors. A transformation matrix *W* is then constructed for dimension reduction as follows.

$$W = \begin{bmatrix} (\Gamma\theta_1)^T \\ (\Gamma\theta_2)^T \\ \vdots \\ (\Gamma\theta_m)^T \end{bmatrix}, \qquad m < L, \tag{9}$$

and correspondingly $\mu_1 > \mu_2 > \cdots > \mu_m$. Therefore, $y=WX$ produces transformed input vectors y whose components are uncorrelated and ordered according to the magnitude of their variance. Those components that contribute only a small amount to the total variance in the data set are eliminated.

5. Damage Classification Using a Neural Network Method

In this section, a neural network is used to classify the structure conditions which are normal and abnormal. The output of the previously calculated principal components becomes the input to the neural network for training. The neural network is a learning vector quantization network which is shown in Fig. 14.

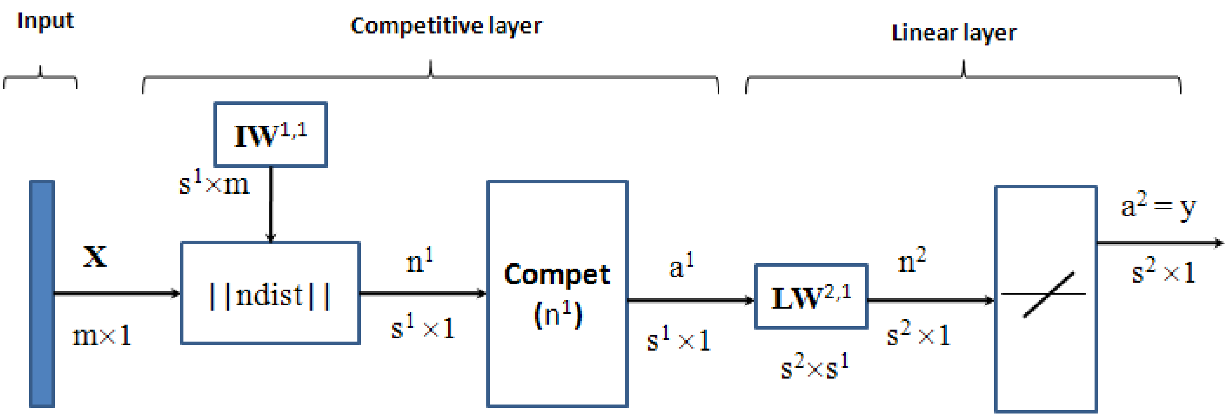

Fig. 14. LVQ network architecture.

5.1. LVQ Neural Network

The LVQ network is trained according to Kohonen learning rule [13]. The learning starts from a set of input and target pairs:

$$x_1,\ t_1;\ x_2,\ t_2;\cdots;\ x_K,\ t_K. \tag{10}$$

Each target vector has a single 1. For example, for input vectors to be assigned to four classes,

$$t_K = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \tag{11}$$

means the corresponding x_k belongs to the second of four classes.

When the network is in training, the distance from an input x to each row of the input weight matrix $IW^{1,1}$ is computed with the function *ndist*. The hidden neurons of layer 1 compete. If the i^{th} element of n^1 is most positive, and the neuron i wins the competition. Then the competitive transfer function produces a 1 as the i^{th} element of a^1, and all other elements of a^1 are zero. a^1 is then multiplied by the layer 2 weights $IW^{2,1}$, the single 1 in a^1 selects the class k^* associated with the input x. Thus the network has assigned the input vector x to class k^* and $a^2_{k^*}$ is 1. If the assignment is correct, the i^{th} row of $IW^{1,1}$ is adjusted in such a way to move this row closer to the input vector x, and if the assignment is not correct, the i^{th} row of $IW^{1,1}$ is adjusted to move the row away from x. Therefore, if x is classified correctly,

$$a^2_{k^*} = t_{k^*} = 1, \tag{12}$$

the new value of the i^{th} row of $IW^{1,1}$ is computed as

$${}_iIW^{1,1}(q) = {}_iIW^{1,1}(q-1) + \alpha(p(q) - {}_iIW^{1,1}(q-1)). \tag{13}$$

If x is classified incorrectly,

$$a^2_{k^*} = 1 \neq t_{k^*} = 0, \tag{14}$$

the new value of the i^{th} row of $IW^{1,1}$ is computed as

$${}_iIW^{1,1}(q) = {}_iIW^{1,1}(q-1) - \alpha(p(q) - {}_iIW^{1,1}(q-1)). \tag{15}$$

5.2. Classification Performance Analysis

In this section, we mainly would like to demonstrate the effectiveness of this kind of time-domain feature processed via principle component extraction in the crack detection with the implementation of neural network. As such, without loss of generality, cracks at holes #1 to #4 associated with sensors 1 to 4 are considered here. As is discussed in Section 3, the time domain data of S0 waves from sensors 1 to 4 are used as features to classify the plates 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 consideration. The data used for principal component estimation and neural network training mostly come 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 used for 1019 times with random noise (≤ 5 %) added, and the sensor data for each damaged case is used for 46 times and also coupled with the random noise. 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 LVQ neural network being used ('newlvq' function in Matlab) is 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 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 neural network leads to such a classification results for the tested specimens is acceptable and promising. It is also noticed that the trained neural network is potentially able to identify combined cracks, although the training is solely based on the single crack cases.

Table 1. Structure Condition classification results.

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

6. Conclusions

In this paper, the aluminum plates with the riveted holes and possible crack damage at these holes have been considered 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 the diagnostic signal and injected to the actuator and it propagates to sensors in order to detect the integrity of the plate. The combination of time-domain S0 waves from all sensitive sensor signals has been directly used as the feature to detect the crack damage. After the principal component estimation, the reduced-size data work as inputs for the LVQ neural network training. The neural network training has mainly relied on a number of FEM simulation results, since the simulated S0 wave agrees well with its experimental testing result on the real plate. The performance of the classification has been validated by using the testing results from 10 real plates, and it results in 8 plates classified correctly. The results imply that this time-domain feature processed with principle component extraction is straightforward and effective to identify the crack damage facilitated by the active sensing network.

References

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

[2]. K. Zgonc, and J. D. Achenbach, A neural network for crack sizing trained by finite element calculations, *NDT and E International*, Vol. 29, No. 3, 1996, pp. 147-155.

[3]. V. Lopes Jr. a, G. Park, H. H. Cudney, and D. J. Inman, Smart structures health monitoring using artificial neural network, in *Proceedings of the 2nd International Workshop on Structural Health Monitoring*, Stanford University, Stanford, CA, September 8-10, 1999, pp. 976-985.

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

[5]. V. Giurgiutiu, Tuned Lamb wave excitation and detection with piezoelectric wafer active sensors for structural health monitoring, *Journal of Intelligent Material Systems and Structures*, 16, 2005, pp. 291-305.

[6]. U. Bork, R. E. Challis, Artificial neural networks applied to Lamb wave testing of T-form adhered joints, In *Proc. of the Conference on the Inspection of Structural Composites*, 1994.

[7]. 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, 2003, pp. 403-412.

[8]. 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, 2003, pp. 97-111.

[9]. 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, 2006, pp. 224-233.

[10]. 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, 2004, pp. 609-620.

[11]. 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, 2004, pp. 621-630.

[12]. 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 and Automation*, Athens, Greece, 27-29 July, 2007.

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

[14]. 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, 2006, pp. 753-780.

[15]. J. Q. Mou, L. Martua, Y. Q. Yu, Z. M. He, C. L. Du, J. L. Zhang, and E. H. Ong, Structural health monitoring using PZT transducer network and Lamb waves, in *Proc. of the ASME 2010 International Mechanical Engineering Congress and Exposition, IMECE 2010*, Vancouver, British Columbia, Canada, 12-18 November 2010.

Guide for Contributors

Aims and Scope

Sensors & Transducers Journal (ISSN 1726-5479) provides an advanced forum for the science and technology of physical, chemical sensors and biosensors. It publishes state-of-the-art reviews, regular research and application specific papers, short notes, letters to Editor and sensors related books reviews as well as academic, practical and commercial information of interest to its readership. Because of it is a peer reviewed international journal, papers rapidly published in *Sensors & Transducers Journal* will receive a very high publicity. The journal is published monthly as twelve issues per year by International Frequency Sensor Association (IFSA). In additional, some special sponsored and conference issues published annually. *Sensors & Transducers Journal* is indexed and abstracted very quickly by Chemical Abstracts, IndexCopernicus Journals Master List, Open J-Gate, Google Scholar, etc. Since 2011 the journal is covered and indexed (including a Scopus, Embase, Engineering Village and Reaxys) in Elsevier products.

Topics Covered

Contributions are invited on all aspects of research, development and application of the science and technology of sensors, transducers and sensor instrumentations. Topics include, but are not restricted to:

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- Virtual instruments;
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- Technologies and materials;
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