IMPACT MONITORING TECHNIQUES FOR SMART COMPOSITE LAMINATES

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SUMMARY: The impact monitoring techniques providing diagnostics of smart composite structures is proposed in this paper. We discuss the process for impact location detection in which the generated acoustic signals are detected by PZT using the improved neural network paradigm such as Levenberg-Marquardt algorithm and generalization methods. This paper describes a method of detecting the location of impacts for an aluminum rectangular plate and composite laminates subjected to transverse impacts. This study concentrates not only on the determination of the location of impacts, but also the implementation of time-frequency analysis such as the Short-Time Fourier Transform (STFT) and the Wavelet Transform (WT) on the determination of the occurrence and the estimation of damage.

KEYWORDS: smart structures, impact, delamination, PZT, neural networks, Levenberg-Marquardt algorithm, Short-Time Fourier Transform, Wavelet Transform

INTRODUCTION

Low-velocity impacts in composites have been found to be the primary cause of delaminations; such impacts also give rise to primary matrix cracks, delamination and fiber fracture. Therefore, it becomes necessary to detect impacts occurring on the surfaces in composite laminates. Due to recent advances in sensor technology, a new concept of damage diagnostics for monitoring the integrity of in-service structures has been proposed. This concept is generally known as a health monitoring of smart structures. The health monitoring system must estimate structural health by using all of the information provided by the various sensor measurements.

Recently, Chang et al. [1] proposed techniques for the reconstruction of force history and the determination of impact location by minimizing the difference between modeled response and actual response from built-in piezoceramic sensors. The response comparator using an optimization algorithm was applied to compare the responses. However, these techniques are in many cases a time consuming process. Moreover, the response of real complex structures cannot be the same as the modeled response, because the result of this analytical method can be more influenced by boundary conditions, noises, and vibrating conditions of structures. An alternate approach to identify the impact location of a composite structure is to use a neural network [2]. These approaches used several kinds of information as the input data such as the differential signal arrival times of propagating acoustic waves and the integrated real and imaginary parts of the FFT of four strain signals. In this study, neural network paradigms are used for an inverse problem solver. This method may be usually applied when a specific equation or algorithm is not applicable, but when adequate knowledge or data exists to derive a knowledge-based solution.

The active sensing diagnosis (ASD) was proposed to detect impact damage in in-service composite structures using piezoceramic sensors and actuators to generate and receive diagnostic waves by Chang [3]. The passive sensing diagnosis (PSD) without actuators may be simpler and more lightweight than the ASD system. Recently, the PSD method using the time-frequency analysis has been issued. The WT method can provide the time-frequency localization from sensor signals. The WT itself is a more intuitive decomposition of the data since it provides simultaneous time-frequency localization at multiple resolutions. Being a more flexible method of time-frequency decomposition, wavelets can describe signal characteristics in a much more precise manner and result in more accurate feature extraction. Several researches show that the WT can be a powerful tool for condition monitoring and fault diagnosis by using its ability to "zoom in" on short lived high frequency phenomena for the analysis of transients [4].

This paper mainly focuses on three ultimate goals to improve the impact identification and the PSD techniques. The first goal of this research is to improve the previous neural network based impact identification method using the fast learning algorithm such as Levenberg-Marquardt (LM) algorithm and the generalization methods such as regularization and early stopping methods. Secondly, this study focuses on the integrated approach for both two objects by one piezoceramic (PZT) sensor system. This paper proposed the simultaneous impact monitoring techniques to identify the impact location and to detect the impact damage using the propagation property of acoustic waves and acoustic emission waves. Though the WT has been applied to the diagnostics of transient vibration signals of machinery, this has been rarely used for damage diagnostic application to composite laminates. Thirdly, this paper proposes that the PSD method using the WT can be applied to monitor acoustic emission signals due to damage initiation of composite laminates during the low velocity impact.

IMPACT MONITORING TECHNIQUES

The impact monitoring process provides diagnostics of composite structures susceptible to the impact load. This process is composed of three major functions; impact identification, impact damage assessment and damage diagnostic. In this process, we can monitor the event of an impact load and identify the location of impact from the information processing of the sensor signal. After identifying the location of impact, the impact damage assessment is carried out to determine whether the incipient damage is initiated or not after the impact and to estimate the severity of incipient damage. Figure 1 shows the impact monitoring procedure with the detection of impact locations and the assessment of impact damage.

Impact Identification by Neural Networks

The acoustic wave velocity is dependent on the material property, the wave frequency and the type of waves. In the case of composite laminates, the acoustic wave velocity varies with the direction of propagation because the wave propagates faster along fiber rather than matrix. Neural networks can be applied to make a nonlinear modeling for the differential arrival time of acoustic waves at a certain location of impacts. One inherent advantage in using neural networks is that their performance is independent of a particular system's complexities; the physics of boundary conditions and the velocity of acoustic waves, etc.

It was discovered that the backpropagation Multi-Layer Perceptron (MLP) was adequate for the impact location detection. In this paper, the LM algorithm for nonlinear least squares was incorporated into the backpropagation algorithm for training the MLP. The algorithm was tested on many function approximation problems, and was compared with a conjugate gradient algorithm and a variable learning rate algorithm. In general, on networks that contain up to a few hundred weights the LM algorithm will have the fastest convergence. Another problem that occurs during the neural network training is called overfitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples but it has not learned to generalize to new situations. We used two methods for improving generalization: regularization and early stopping methods.

The PSD of Impact Damage by the Wavelet Transform

This research provides the real-time in-service damage monitoring techniques using the time-frequency analysis of PZT sensor signals. PZT sensors were utilized to monitor the impact events. These can be used as wide-band transducers of low-frequency vibrations and high-frequency acoustic emission waves. We chose PZT sensors suitable for detecting the frequency range from 20 *kHz* to 200 *kHz* that is known as the general frequency range of acoustic emission during the initiation of damage such as matrix cracks and delamination in composites laminates. These techniques present the simultaneous monitoring of damage at the time of impact events. Time-frequency analysis can be implemented by the STFT and the WT. The STFT cannot be a local spectral density because of the continuing nature of harmonic waves. Moreover, it is impossible to achieve high resolution in time and frequency simultaneously.

The WT decomposes a signal into a set of basis functions that are localized in both time and frequency. Each wavelet function in the basis set is a stretched or narrowed version of a prototype wavelet. Because the wavelet basis function is localized in both time and frequency, it can act as multiscale bandpass filters when convoluted with the signal data. From the DWT, a signal may be represented by its approximations and details. The approximations are the low frequency components of the signal decomposed by the high-scaled wavelet basis function. The details are the high frequency components of the signal decomposed by the low-scaled wavelet basis function. By selecting different dyadic scales, a signal can be broken into many lower-resolution components, referred as the wavelet decomposition tree.

Experiments and Results

The experimental setup used to test neural network-based impact location methodologies is shown in Figure 2. The tested plats are shown in Figure 3. In the case of using the general backpropagation algorithm, the detection error of the training set is much smaller than that of the test set. This means that the typical algorithm cannot be generalized for all input data. For the aluminum plate, the error of the training set is less than 2.0 *mm* - the following detection error is expressed in the radial direction. Then we defined the maximum error and the average error from the detection results of the test set. However, the maximum detection error of is 15.7 *mm* in radial direction. The average detection error is 10.5 *mm*. For the composite plate, the maximum detection error of is 26.0 *mm*. The average detection error is 15.2 *mm*.

In the case of using the Levenberg-Marquardt algorithm with the improving generalization methods, the training results are as follows. For the aluminum plate, the result of location identification of the training set, the validation set and the testing set using the trained neural network is shown in Figure 4. The maximum error of these results is 2.96 *mm*. The average location error for all sets is 0.92 *mm*. For the composite plate, it can be expected that the error of location detection be increased more than that of the aluminum plate because the acoustic wave velocity is dependent on the direction. The results of location detection of the training set, the validation set and the testing set are shown in Figure 5. The maximum error of these results is 5.04 *mm* in radial direction. The average location error for all sets is within 2.05 *mm* in radial direction. It would not require more than about one minute to run through 200 epochs. A typical backpropagation algorithm requires more than about twenty minutes to run through 4000 epochs for the same case.

The Graphite/Epoxy specimen for low-velocity impact test is shown in Figure 6. Firstly, the laminated plate was subjected to 0.1 *J* impact. We confirmed that any damages were not generated. Secondly, the plate was subjected to 3.7 *J* impact. Delamination with the dimension of 35 *mm* × 20 *mm* was investigated by the C-Scan as shown in Figure 6. Thirdly, after 6.0 *J* impact, it was observed that a final fracture mode with fiber breakage and delamination.

Figure 7~9 show the results of the STFT respectively at the three kinds of impact. Acoustic emission waves induced by the generation of delamination can be observed by the examining the 20 *kHz* to 200 *kHz* frequency range. The time of occurrence of delamination can be identified by this figure. Figure 11~13 show the results of the WT decomposition respectively at the three kinds of impact using *Db4* wavelet to the level 3. For 3.7 *J* impact, acoustic emission waves due to delamination can be observed in the detail components. For 6.0 *J* impact, the higher amplitudes of *D1~D3* coefficients are observed at the generation time of more severe damage such as fiber breakage.

CONCLUSION

The neural network using the LM algorithm with the generalization methods predicted the location of impact better than the general backpropagation algorithms. We also have presented the PSD using the time-frequency analysis such as the STFT, the WT on the determination of the occurrence of damage and the estimation of damage. It can be carried out simultaneously with the detection of impact locations using a PZT sensor system. The WT is regarded as the better tool for the analysis of the transient signals like damage-induced signals. This makes it possible to examine the interested frequency range by adjusting the wavelet functions.

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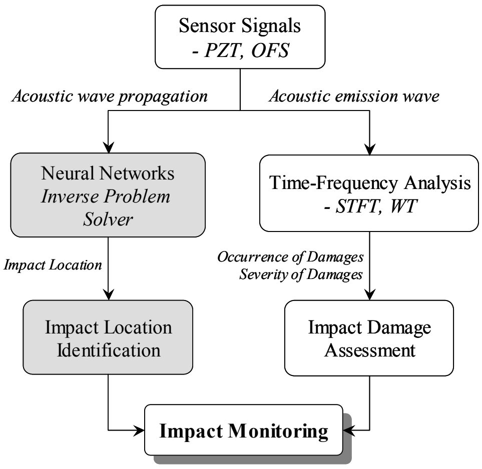

Fig. 1 Block diagram of the impact monitoring procedure.

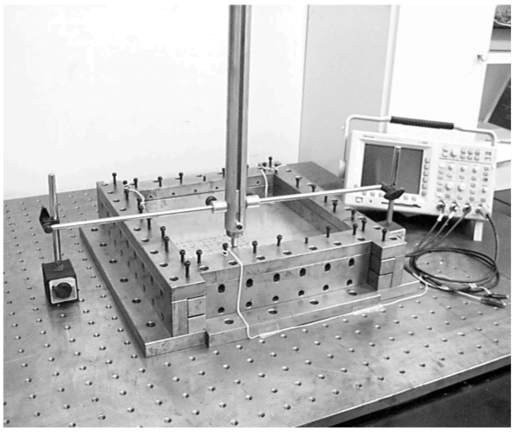

Fig. 2 Experimental setup for impact identification.

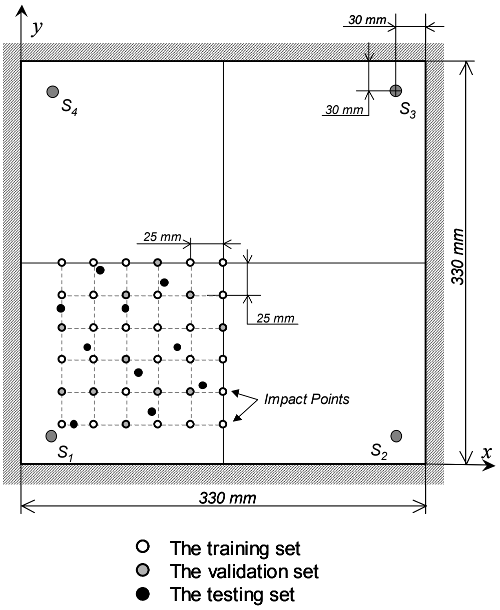

Fig. 3 Specimen for impact identification with four PZTs ; 3 sets of locations.

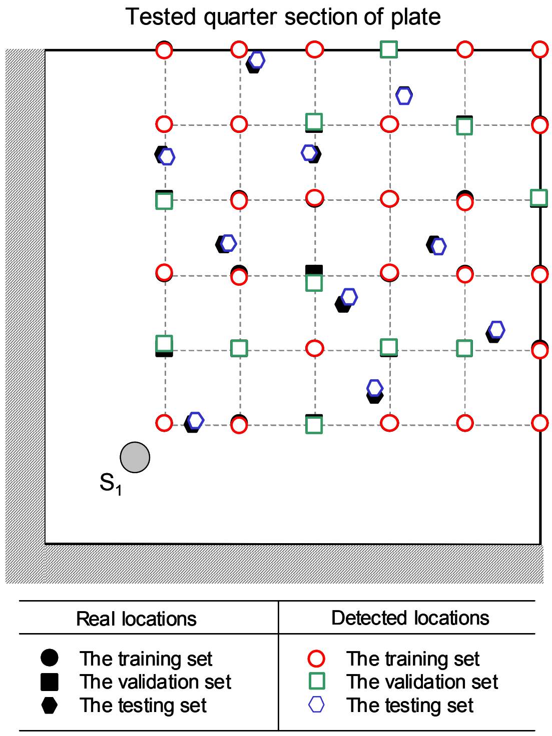

Fig. 4 Detected impact locations for the aluminum plate using the neural network with LM algorithm.

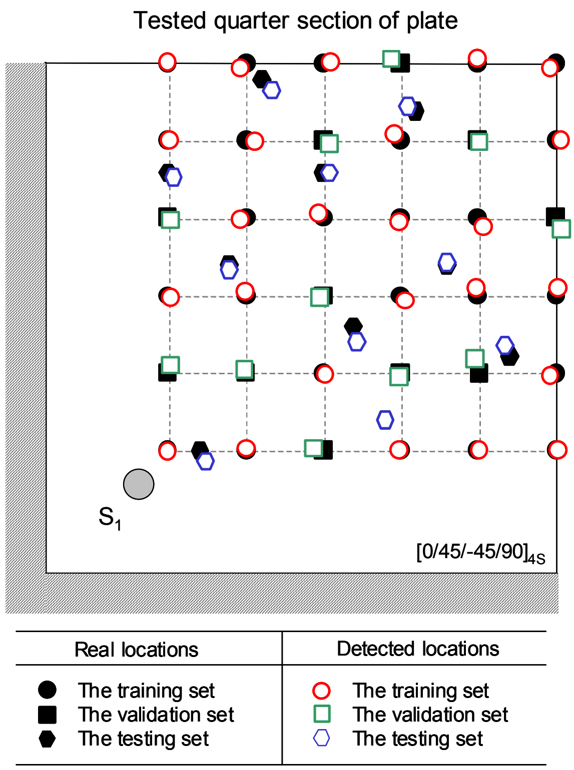

Fig. 5 Detected impact locations for the composite plate using the neural network with LM algorithm.

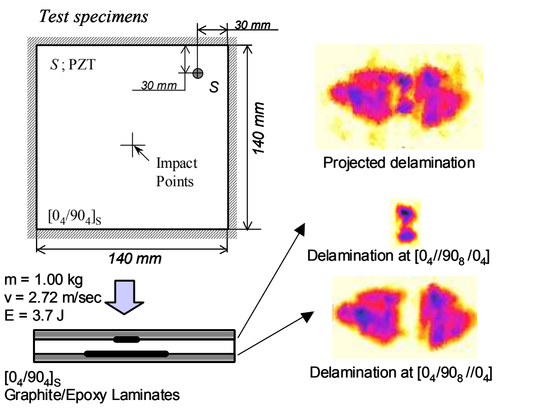

Fig. 6 Test specimens for low-velocity impact and the investigation of delaminations in 3.7 *J* impacted plates using C-Scan.

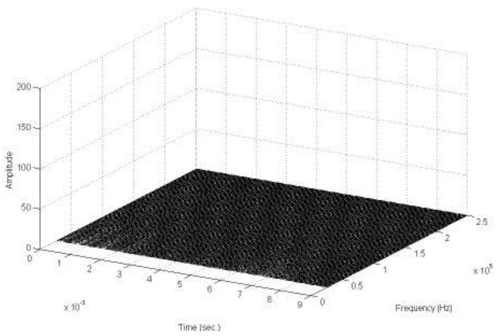

Fig. 7 STFT of PZT signal during 0.1 *J* impact in 3D view.

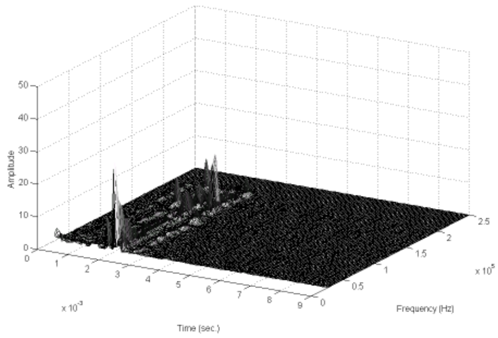

Fig. 8 STFT of PZT signal during 3.7 *J* impact in 3D view.

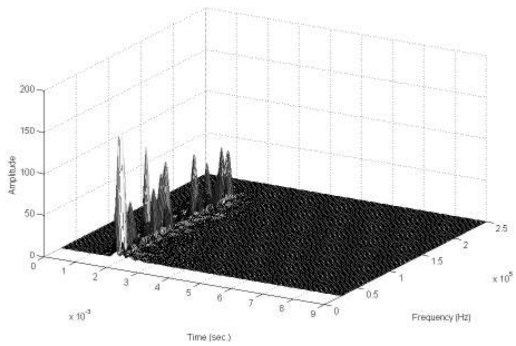

Fig. 9 STFT of PZT signal during 6.0 *J* impact in 3D view.

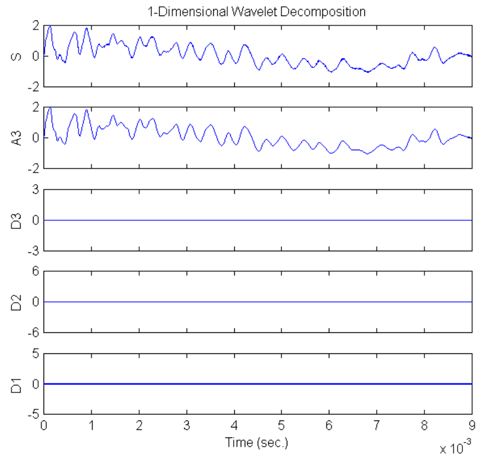

Fig. 10 PZT signal *S*, the detail signal *D1~D3*, the approximation signal *A3* by DWT during 0.1 *J* impact.

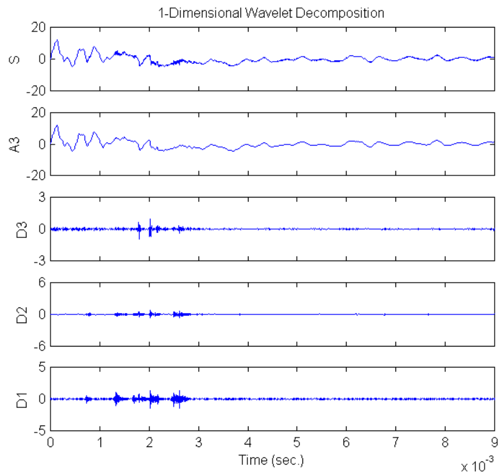

Fig. 11 PZT signal *S*, the detail signal *D1~D3*, the approximation signal *A3* by DWT during 3.7 *J* impact.

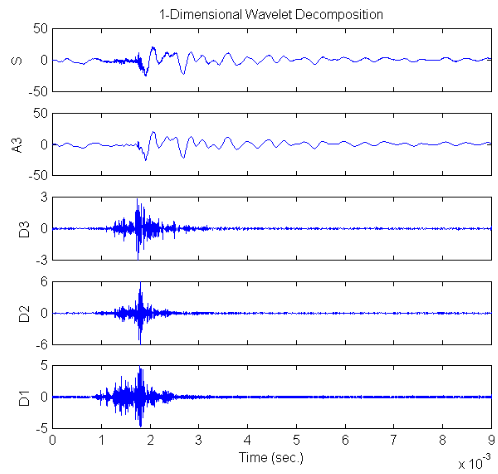

Fig. 12 PZT signal *S*, the detail signal *D1~D3*, the approximation signal *A3* by DWT during 6.0 *J* impact.