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Simultaneous Monitoring of Impact Locations and Damages in Composite Laminates Using Piezoceramic Sensors

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SUMMARY: Low-velocity impact is a major concern in the design of structures made of advanced laminated composites, because it can cause extensive delaminations inside composites that can severely degrade the load-carrying capability. To develop the impact monitoring techniques providing on-line diagnostics of smart composite structures can be helpful in the health monitoring of structures susceptible to impacts. In this paper, we discuss the signal processing techniques for the simultaneous monitoring of impact locations and damages using piezoceramic sensors (PZT).

KEYWORDS: smart composite laminates, health monitoring, impact, damage detection, acoustic emission, neural networks, wavelet transform, PZT

INTRODUCTION

Until now, the routine nondestructive test must be performed over the entire surface of structures susceptible to low-velocity impact. Due to recent advances in sensor technology and information processing techniques, a new concept of damage diagnostics for monitoring the integrity of in-service structures has been proposed. This concept is generally known as the health monitoring of smart structures. The health monitoring system can estimate structural health by using all of the information provided by the various sensor measurements. The impact monitoring is especially involved in the tracking of impact load. The health monitoring of composite structures susceptible to impacts had two main research directions up to now. One was the impact identification and the other was the detection of impact damages such as delaminations after impact.

Recently, Chang et al. [1] proposed the techniques for the reconstruction of force history and the determination of impact location by minimizing the difference between the modeled response and the actual response from built-in piezoceramic sensors. The response comparator using an optimization algorithm was applied to compare the responses. However, these techniques are time-consuming process in many cases. Moreover, the response of real complex structures cannot be the same as the modeled one, because the result of this analytical method can be much 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 neural networks (Jones, Sirkis and Frebele) [2]. This method may be easily applied when a specific equation or algorithm is not applicable, but when adequate knowledge

or data exists to derive a knowledge-based solution. This approach uses 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 paradigm was used for an inverse problem solver.

The active sensing diagnosis (ASD) was proposed to detect impact damage in in-service composite structures using piezoceramic sensors/actuators to generate and receive diagnostic waves (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 wavelet transform (WT) method can provide the time-frequency localization of sensor signals. The WT itself is a more intuitive decomposition of data since it provides simultaneous time-frequency localization at multiple levels. 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 have shown 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 (Wang et al.) [4-5]. Though the WT has been applied to the diagnostics of transient vibration signals of machinery, this has been rarely used for the application to damage diagnostics of composite structures.

Sung et al. [6] studied on the integration and improvement for both the impact identification and the PSD techniques using PZT. 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 the AE waves. The event and location of an impact load can be identified by the acoustic waves. The procedures of the identification of impact locations using neural network paradigms will be presented. Simultaneously, the PSD of impact damages can be made to determine whether the incipient damage is initiated or not from the information of the acoustic emission (AE) waves.

SIMULTANEOUS IMPACT MONITORING

Impact Identification Using Neural Networks

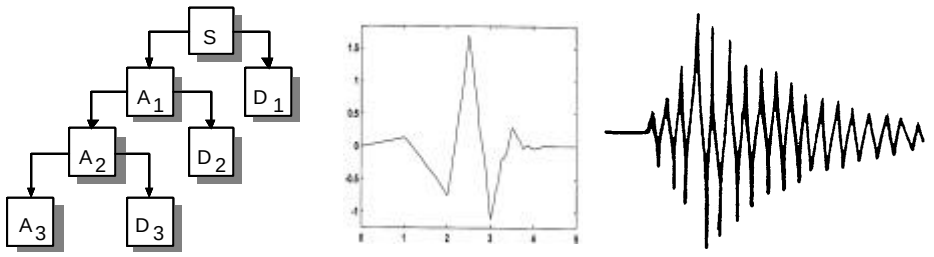
When a foreign object is incident upon a plate, both surface and bulk acoustic waves are generated. The sensors attached to a plate are used to determine the time at which the local superposition of these acoustic waves reaches the sensors. The acoustic wave velocity is dependent on the material property, 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 the fiber than the matrix. Then it is not adequate to apply the triangulation equation to composite laminates from the assumption based on the constant velocity of propagation.

Neural networks can be used as an inverse problem solver for the identification of a certain location of impact using the differential arrival times of the acoustic waves to the sensors. One inherent advantage in using neural networks is that their performance is independent of a particular system's complexities; the physics of boundary conditions, the velocity of surface acoustic waves, sensor contact and mounting, etc. The success of the neural network is more

dependent on the consistency of signal patterns. The method could be easily automated and implemented in a structural monitoring system. It was discovered that the back-propagation multi-layer perceptron (MLP) was adequate for the impact location detection. In this paper, the Levenberg-Marquardt (LM) algorithm for nonlinear least squares was incorporated into the backpropagation algorithm for training the MLP. 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 becomes 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. In the early stopping method, the available data is divided into three subsets. The first subset is the training set which is used for computing the gradient and updating the network weights. The second subset is the validation set. The error on the validation set is monitored during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights at the minimum of the validation error are returned.

Impact Damage Monitoring Using Wavelet Transform

It was found that the AE waves generated by impact damages are undistinguishable from each damage mode and the amount of damage by the conventional analysis methods in time or frequency domain. The Fourier transform decomposes a signal into its various frequency components. Because it uses the sinusoidal basis functions that are localized in frequency only, it loses the transient feature of the signal. Therefore, it is necessary to implement the time-frequency analysis for diagnostics of a transient signal such as damage-induced signals. 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. The WT can decompose the AE waves in time and wavelet scale domain and catch the differences of these waves. This makes it possible to distinguish the damage modes and size by the decomposed wavelet details.
The WT decomposes a signal into a set of basis functions that are localized in both time and



(a) wavelet decomposition tree (b) *db3* wavelet (c) acoustic emission waves

Fig. 1 Wavelet decomposition tree, *db3* wavelet function and AE waves

frequency. Each wavelet function $\Psi_{a,b}(t)$ is a stretched or narrowed version of a prototype wavelet $\Psi(t)$,

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \tag{1}$$

where $a \in R^{+}$ and $b \in R$ are scale and shift parameters, respectively.
The continuous wavelet transform (CWT) is defined as follow,

$$\begin{aligned} W_{\Psi_x}(a,b) &= \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\Psi^{*}\left(\frac{t-b}{a}\right)dt \\ &= \left\langle \Psi_{a,b}(t), x(t) \right\rangle \end{aligned} \tag{2}$$

That is, we measure the similarity between the signal $x(t)$ and the shifts, scales of an elementary function. Because the wavelet basis function is localized in both time and frequency, it can act as multi-scale band-pass filters when convoluted with the signal data. From the discrete wavelet transform (DWT), a signal can 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 level components, referred as the wavelet decomposition tree as shown in Figure 1(a). The high frequency AE waves of PZT signals can be decomposed into several details 'D_j'. As the selection of wavelet functions, these details can show detailed characteristics that could not be represented by the harmonic function based analysis.
In this analysis, the *Db3* wavelet was used. The *Db3* stands for the 3rd order Daubechies wavelet as shown in Figure 1(b). The general AE waves are shown in Figure 1(c). The Daubechies wavelets have the high regularity that is defined by the order of differentiability as compared with Meyer and Morlet wavelet that are the localized harmonic functions. The *Db3* is useful in the estimation of the local properties of signals such as breakdown points, and discontinuities in higher derivatives, because AE waves generally have these transient features.

Fundamental Studies

The fundamental studies have been carried out to identify the impact location of composite laminates. Moreover, the time-frequency characteristics of impact damages have been investigated by the WT. The MLP using the LM algorithm with the generalization methods was used for the identification of several kinds of laminates. For example, this predicted the location of impact below the error of about 6 *mm* on a 330 *mm*×330 *mm* $[0/45/-45/90]_{4S}$ Graphite/Epoxy laminates with a circular hole.
These techniques used the first arrived acoustic wave having the characteristic frequencies and duration. There is the smaller leading waveform before the larger prominent wave motion on the PZT output. The leading waves have the characteristic frequencies of 1~10 *kHz* for

composite laminates. The frequencies are dependent on the stiffness and damping ratio of a material. The acoustic wave motion is composed of the extensional and flexural modes. The extensional wave mode having faster and smaller amplitude dominantly makes the leading acoustic waves. We can detect the arrival times of acoustic waves by examining the leading waves. These leading waves were shown not be much influenced by boundary conditions from the previous studies (Sung et al.) [6]. This confirms that the leading waves are not affected by the reflection from boundaries. These are the advantage of this approach. In this paper, the effect of the impact energy level on the leading acoustic wave will be presented. Moreover, the identification accuracy will also be discussed after certain impact damage has occurred.

The characteristics of the PZT signals due to matrix cracks and the evolution of free-edge delamination were analyzed by the WT. Tension tests were performed to investigate the AE waves due to matrix cracks and free-edge delaminations using $[\pm 45_2/0_2/90_2]_S$ Gr/Ep specimens. The differences in the transient characteristics of the AE waves due to matrix cracks and delaminations can be identified by the time-frequency analysis. The WT can be used to characterize damage modes by measuring the transient signals decomposed into the wavelet details. The wavelet details are indicated by D_1^{1M} of which the subscript represents the level of decomposition and the superscript represents the sampling frequency. The details, D_1^{1M}, D_2^{1M} and D_3^{1M}, represent approximately 300~400 *kHz*, 140~240 *kHz*, 80~100 *kHz* signal range respectively from the calculation of approximate frequencies. Therefore, these details can represent the main characteristic frequencies of the AE signals. These results showed that the AE signals due to matrix cracks are dominantly composed of the detail D_1^{1M}. The AE signals due to delaminations are mainly composed of D_2^{1M} and D_3^{1M}. From these results, matrix cracks and delaminations known as the primary damage modes of low velocity impacts can be detected by observing the details $D_1^{1M} \sim D_3^{1M}$.

Experiments for the simultaneous impact monitoring

These procedures were implemented to the simultaneous impact monitoring of 330 *mm*×330 *mm* $[0_4/90_4]_S$ Graphite/Epoxy laminates. The experimental setups are shown in Figure 2. Four PZT sensors were attached on each corner of plate as shown in Figure 3. The PZT was chosen to detect not only the acoustic waves but also the AE waves. The PZT made by Fuji Ceramics Co. has a circular disk shape of 2 *mm* in thickness and 5 *mm* in diameter. The maximum measurable frequency is 370 *kHz*. The boundary conditions of the plates were clamped in all

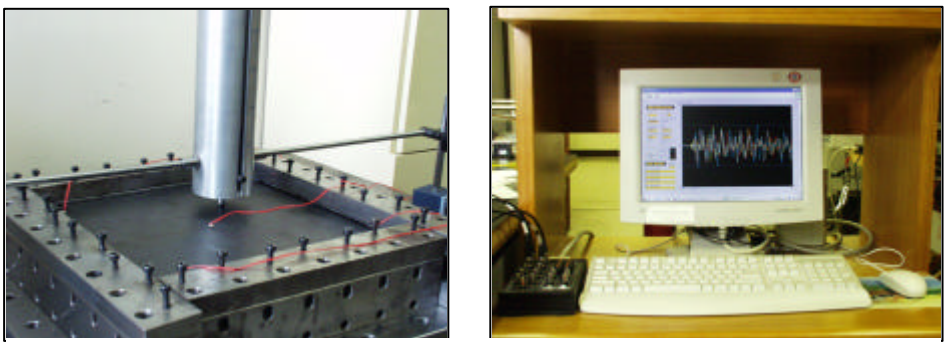


Fig. 2 Overall view of the experimental setup for the impact monitoring

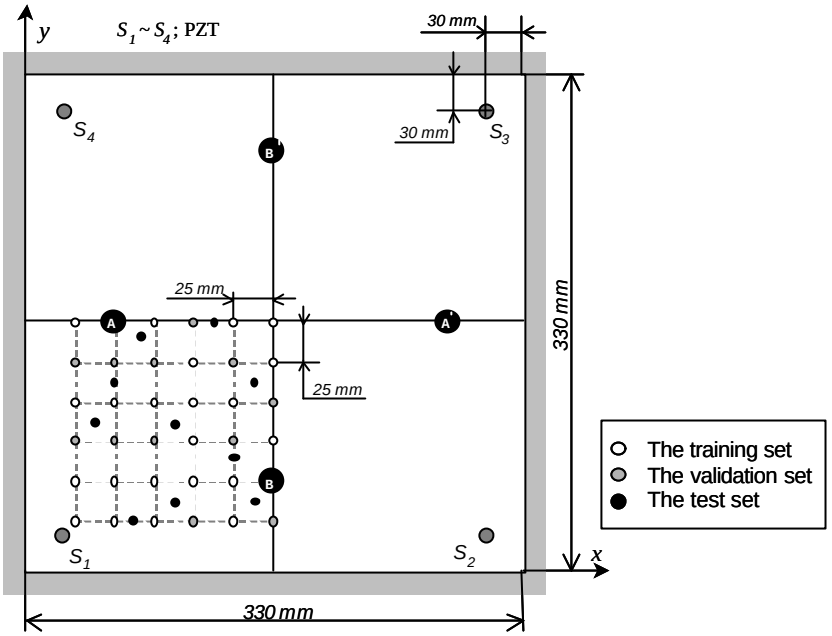


Fig. 3 Three subsets of impact locations for the training, validation and test of the MLP and the locations for the damaging impact

edges with steel frame system on the steel base-plate. The weight of steel impactor and the drop height can be adjusted. This can be dropped on the desired impact location precisely by the guiding column. The high-resolution data acquisition board PCI-6100E by National Instruments Co. was used to acquire the PZT signals. The sampling frequency was 1 *MHz*. Firstly, the MLP was trained using the arrival time differences in the leading acoustic waves of four sensors. The energy of impact was fixed to 0.3 *J*. After the training of the MLP, the low velocity impact test was carried out to make any damage. The *A*, *B*, *A′* and *B′* locations represent the test impact location as shown in Figure 3. Four kinds of impact energy level were 3 *J*, 5 *J*, 8 *J* and 11 *J* respectively. The PZT signals were used to obtain the arrival time differences in the leading acoustic waves and the AE waves.

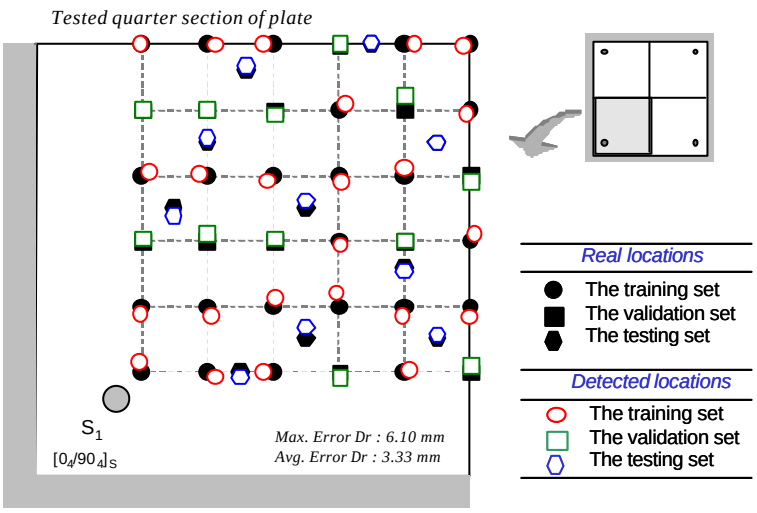
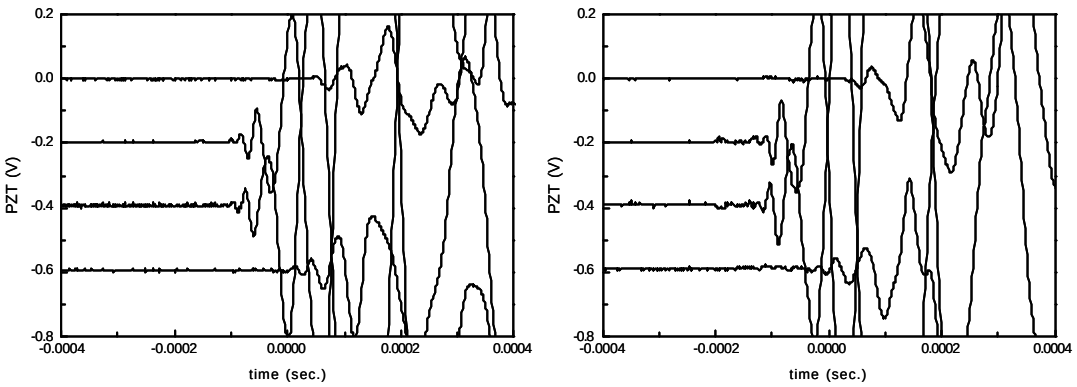


Fig. 4 Detected impact locations for the non-damaging impacts by the MLP using the LM algorithm with the generalization methods



(a) 0.3 J impact (b) 8.0 J impact

Fig. 5 Comparison of the leading acoustic wave signals at *A*¢; (a) 0.3 *J* impact and (b) 8.0 *J* impact

Results and Discussions

For the non-damaging impacts, the identification results are shown in Figure 4. The maximum error was 6.10 *mm* in the radial direction. The average error was 3.33 *mm*. Then, we investigated whether this trained MLP could be used for the damaging impacts. First of all, the effect of the impact energy level on the leading acoustic wave was investigated. Figure 5 shows the comparison of the leading acoustic waves for the case of 0.3 *J* and 8.0 *J* impact on the location *A*′. Because the leading waves are mainly composed of the extensional wave mode, the amount of the perpendicular impact load cannot much affect the extension wave mode. Then, the leading acoustic waves are not much influenced by the impact energy level. Therefore, we can use the trained MLP for the higher impact energy cases.

First, the plate was subjected to 3.0 *J* impact on the location *A*. After impact, delaminations having the planar dimension of about 20 *mm*×10 *mm* were detected by the C-Scan. After 5.0 *J* impact on *B*, the size of delaminations was about 35 *mm*×20 *mm*. After 8.0 *J* impact on *A*′, it

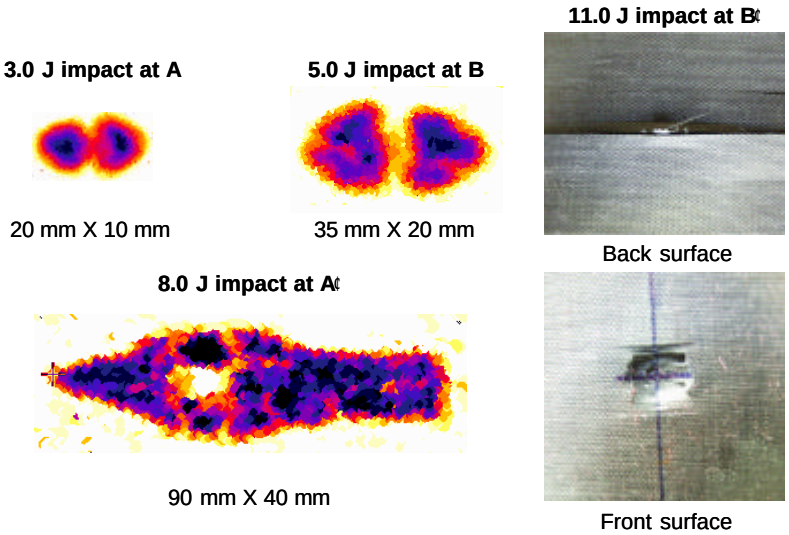
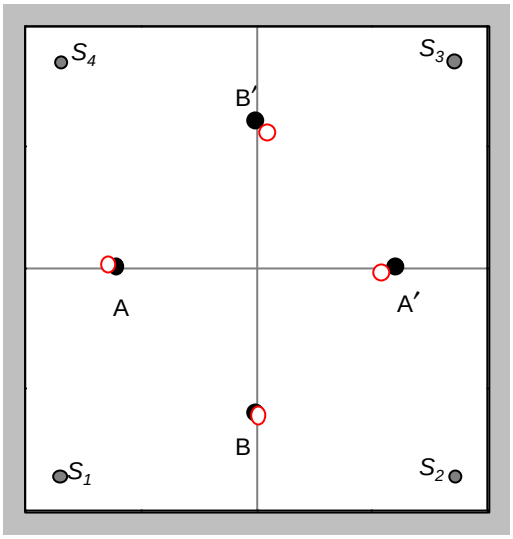


Fig. 6 Investigated delaminations of *A*, *A*¢, *B* and *B*¢ locations of $[0_4/90_4]_S$ laminates using C-Scan and the pictures of final failures



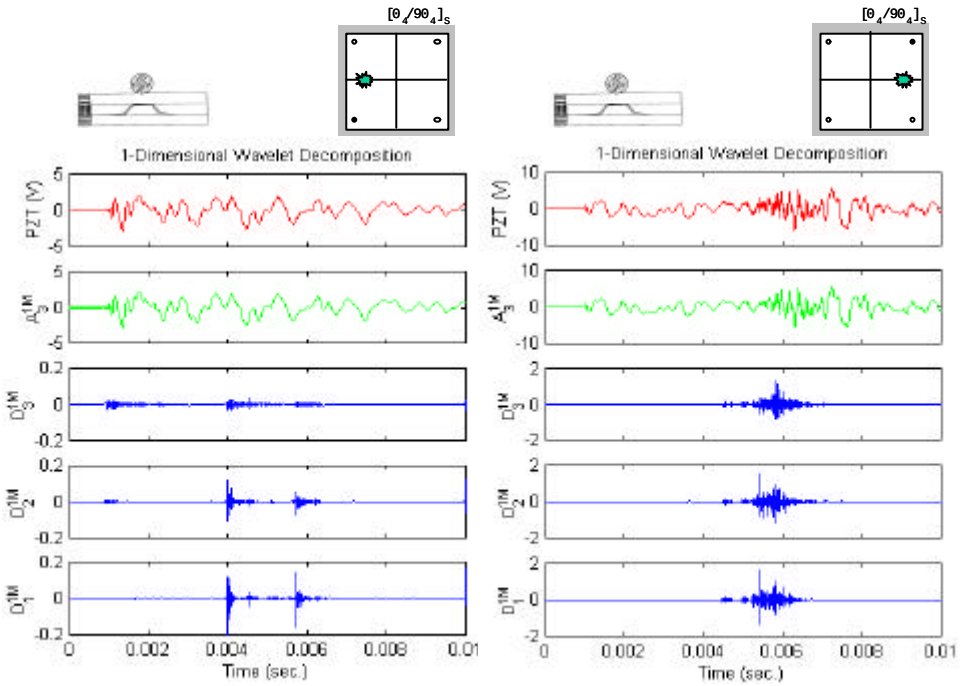
Actual Locations		*Detected Locations*	
x	*y*	*x*	*y*
65.00	165 .00	59.36	165.97
165 .00	65 .00	166.88	63.50
265 .00	165 .00	254.86	161.25
165 .00	265 .00	173.19	256.67

unit : *mm*

Fig. 7 Detected impact locations for *A*, *A*′, *B* and *B*′ locations by the trained MLP

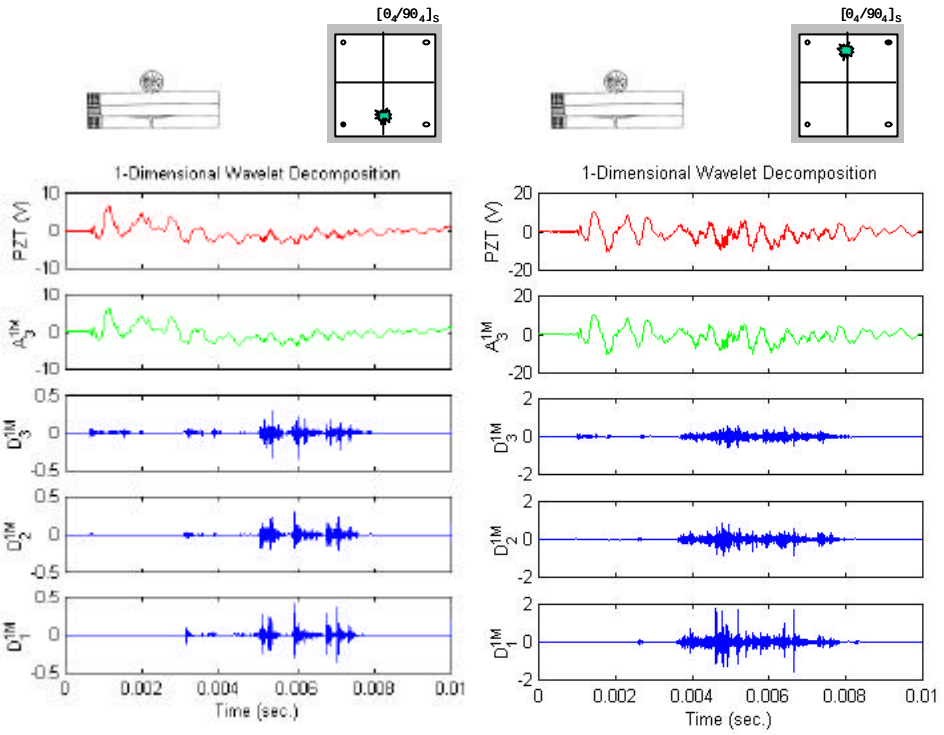
was about 90 *mm*×40 *mm*. After 11.0 *J* impact on *B*′, the final fracture mode with fiber failure and indent was observed. Figure 6 shows the investigated delaminations and final failures for each case. Figure 7 shows the results of identification for *A*, *B*, *A*′ and *B*′ locations by the trained MLP. For the case of *A*′ and *B*′, the error was much more than that of case *A* and *B*. Because the impacts on *A* and *B* made some delaminations, the propagation of acoustic waves from the impact on *A*′ and *B*′ was disturbed by the presence of delaminations due to the beforehand impact. The error in the radial direction for case *A*′ was 10.80 *mm* and that for case *B*′ was 11.68 *mm*.

After the impact location is identified by the trained MLP, the PZT signals can be analyzed to



(a) *A* (b) *A*′

Fig. 8 PZT signal *S*, the decomposed details D_1^{1M}~D_3^{1M} by DWT of case *A* and *A*′



(a) *B* (b) *B*¢

Fig. 9 PZT signal *S*, the decomposed details D_1^{1M}~D_3^{1M} by DWT of case *B* and *B*′

evaluate damages by decomposing the AE waves by the WT simultaneously. Figures 8 and 9 show the wavelet details D_1^{1M}~D_3^{1M} for each case. For the impacts on *A* and *A*′, the impacted region was dominantly shaped by the upper and lower 0° plies. On the other hand, for the case of *B* and *B*′, the upper and lower 90° plies make the lower flexural stiffness than that of *A* and *A*′. This yields the different damage mode. For the case of *A* and *A*′, the shear matrix cracks and delaminations are the dominant damage mode as shown in the upper diagram of Figure 8. For the case of *B* and *B*′, the bending matrix cracks and delaminations are dominant as shown in Figure 9. Comparing the AE signals, the impact durations of the cases, *B* and *B*′, are much longer due to the lower flexural stiffness. For the case *A*, the delamination is developing during the two main AE events. The higher D_1^{1M} means that the main damage mode is made by two large shear matrix cracks. The bell-shaped short duration of the AE waves denotes the sudden creation of delaminations and shear matrix cracks, as shown in Figure 8(b). The continual events of the AE waves in Figure 9(a) means the bending matrix cracks and the delamination propagations in many times. As shown in Figure 9(b), the high peaks in the band of D_1^{1M} means the occurrence of fiber failures. The long band of the details was involved in making an indent on the laminate. We can observe that the severity of damage is proportional to the amplitude of the wavelet details. Moreover, the wavelet details represent the damage mode and mechanism.

CONCLUSION

In this paper, the impact monitoring techniques for smart composite laminates were proposed. These make it possible to identify the location of impacts, determine the occurrence of

damage and estimate the severity of damage simultaneously. The MLP using the LM algorithm with the generalization methods can identify the location of impact below the error of about 6 *mm* in the radial direction for 330 *mm*×330 *mm* cross-ply laminates. Moreover, for the damaging impact case, the trained MLP using the leading acoustic wave could detect the location of impacts very well. The maximum detection error was about 12 *mm* in the radial direction for the case of the existing delaminations due to the beforehand impact. The PSD using the time-frequency analysis like the WT can provide the information of the occurrence of damage and the damage modes. The impact damage mode and severity can be estimated by the wavelet details. We confirmed that the WT could be the better tool for the analysis of the damage-induced transient signal. This makes it possible to examine the interested multi-band frequency range by adjusting wavelet function. Future works include the impact monitoring of a stiffened composite plate and the real-time data processing programming.

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