Detection of impacts in composite materials using piezoceramic sensors and neural networks

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Detection of impacts in composite materials using piezoceramic sensors and neural networks

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ABSTRACT

The problem of detecting impacts in composite panels before and after damage is addressed in this paper. The data is taken from a simple impact experiment in which piezoceramic sensors are used to collect the impulse strain response. The data are subsequently analysed using neural networks to predict the impact location and energy on the basis of features extracted by various pre-processing algorithms. One of the main aims of the paper is to establish if the impact location and quantification results are affected by damage to the structure.

Keywords: Impact detection, damage detection, neural networks, piezoceramic sensors

1. INTRODUCTION

The continual ageing of aircraft fleets, new safety requirements and the introduction of new composite materials challenge the existing maintenance technologies in relation to damage detection. The ultimate objective of much current reasearch is to develop the technologies and signal processing techniques for integrated on-line damage detection systems for aerospace structures.

Statistics show that the major cause of in-service damage to composites is impact with ground support equipment. Any significant impact on composites can introduce hidden damage such as delamination. Thus impact detection on composite plates has direct relevance to the problem of damage detection in aerospace structures. Examples of impact detection on structures include: FE modelling analysis[1], experimental studies of metallic[2,3] and composite[4,5,6,7] plates and neural network analysis[1,2,6,7,8].

The previous work by the current authors[9] was concerned with determining neural networks which could locate and quantify damage on the basis of features taken from strain time-histories during the impact event. The problem of optimal design of the sensor network was also addressed. The current work seeks to extend the previous study by examining the effect on the neural netrwork of damage to the structure.

2. IMPACT DETECTION USING NEURAL NETWORKS

It is assumed here that an accurate method of locating and quantifying impacts essentially solves the impact damage problem. There is strong evidence that damage extent can be correlated with impact energy, with no damage occurring below a certain energy threshold. The diagnostic system proposed here is therefore based on two neural networks, which separately predict the impact location and energy.

The neural network paradigm used for this study was the standard Multi-Layer Perceptron (MLP) trained with the backpropagation learning rule. The particular implementation is described in some detail in the software manual[10]. The first problem in establishing the diagnostic networks analysis was to determine the appropriate structure i.e. the number of layers and number of neurons per layer. There is very little guidance available regarding the optimum dimensions for neural networks so a trial and error approach was adopted and numerous structures were assessed. Note that the input and output layers of the network are fixed by the number of measurement features and diagnostic outputs respectively. In the first case, the network was required to signal the location of damage and two outputs were required, namely the r and θ coordinates of the impact site (polar coordinates are the natural choice for the circular specimen). In the second case, the network was required to estimate the impact magnitude and therefore only needed one output.

The basic training data were obtained by experiment as described in the next section. As the number of training vectors was low, the training set was expanded by making multiple copies of the measured patterns and corrupting

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them with different Gaussian noise vectors. This strategy is commonly used to improve the generalisation capacity of neural networks.

The MLP used hyperbolic tangent activation functions and a bias neuron was connected to all neurons. In all cases, the number of data presentations during training was equal to 100000; this was sufficient to obtain convergence. The network weights were updated following each presentation i.e. there was one cycle per epoch. A learning schedule was adopted which allowed time-varying learning and momentum coefficients; these were high in the initial stages of learning to allow fast adaption, and low in the later stages to allow fine-tuning.

The network was validated using an independent testing set.

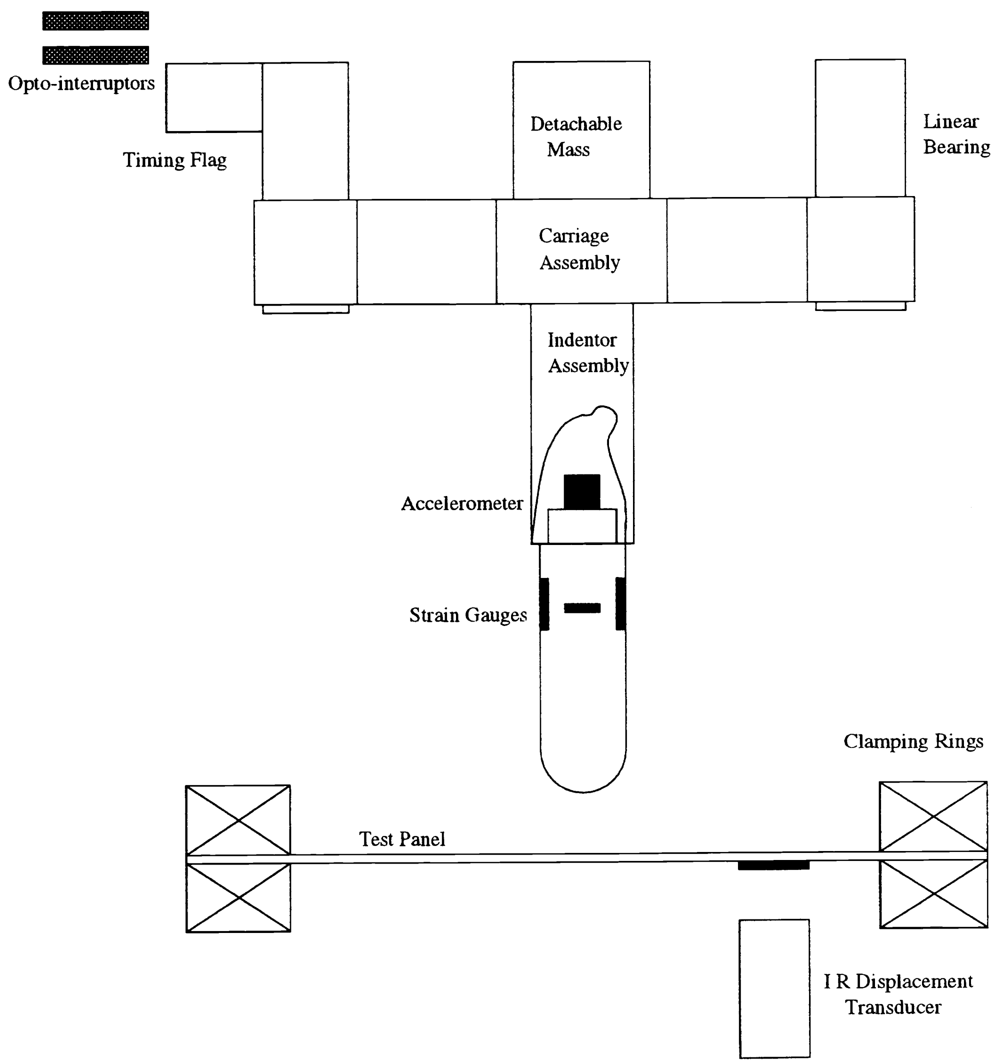

Figure 1. Schematic arrangement of indentor assembly.

3. IMPACT TEST OF THE COMPOSITE PANEL

An instrumented dropweight impact rig, briefly described in[11]., was used for conducting the impact tests under circularly clamped loading conditions. The test rig has recently been modified to permit clamping of larger panels and stiffened sections and further details are given in[12]. The impact rig is equipped with an accelerometer, a strain-gauged load cell, a displacement transducer and opto-electronic triggering and timing sensors which are located as shown in Figure 1. The instrumented indentor is released from a predetermined height by an electromagnetic switch and the data acquisition system is triggered when an aluminium flag, attached to the indentor assembly, passes the first opto-interrupter.

The test panel measured 340 x 340 x 2.5 mm and was cut from a laminate consisting of a carbon fibre fabric and a toughened epoxy resin. The laminate comprised of eight plies of preimpregnated material to give a quasi-isotropic lay-up [0/90,±45, 0/90, ±45]s which was autoclave moulded by Hurel-Dubois UK. Four piezoceramic transducer elements measuring 27 mm diameter were adhesively bonded to the backface of the panel, at locations identified in Figure 2, in order to monitor the impact strain response.

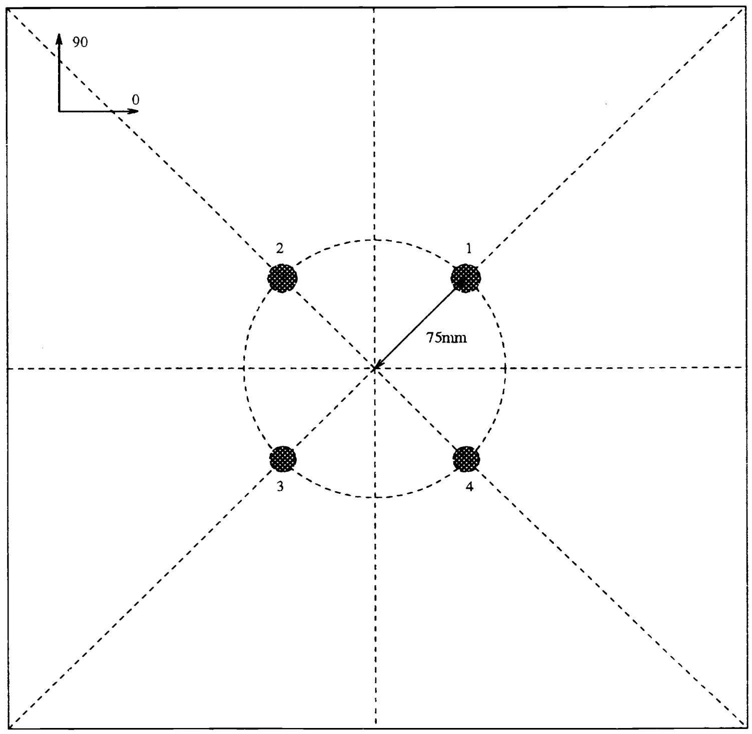

Figure 2. Backface of panel (sensor locations).

Some preliminary impact tests were undertaken in order to ascertain the signal response from the piezoceramic sensors and to ensure that there was minimum crosstalk between the channels of the data acquisition system. Given that the initial output from the sensors was greatly in excess of that of the other transducers a simple voltage divider was incorporated into each of the piezoceramic sensors. The best results were obtained by using three resistors of 1 MΩ, 100 kΩ and 10 kΩ in series across each of the sensors to produce voltage reductions of 9 or 110. In addition some impact tests were undertaken on a separate panel, without sensors, in order to ascertain a level of impact energy to produce damage between that which is barely visible and perforation.

A series of four different sets of impact tests were conducted on the instrumented test panel using hydraulically clamped rings of 300 mm internal diameter. Initially, one hundred impacts were performed at equally spaced sites to cover most of the panel and to train a neural network to recognise the location and magnitude of the signals. The impact sites were are the intersection of ten diametral lines and five concentric circles and were marked as a guide on the frontface of the panel as shown in Figure 3. The impact tests were undertaken at an incident kinetic energy of 0.3 J which was much below that to induce damage. A second set of thirty impacts was performed at randomly selected sites on the grid at the same energy as the initial tests. Next a single impact test was undertaken at a random site by increasing the mass at the indentor to produce an incident kinetic energy of 10 J which induced indentation on the frontface of the panel, backface cracking and internal delaminations between the plies. Finally another set of thirty impacts was performed at the same energy value and at the same site as those previously randomly selected for the second set of tests. All the unfiltered test data were analysed to see if the impact damage site could be accurately located and to identify if the piezoceramic sensor signals were affected by the prior structural damage.

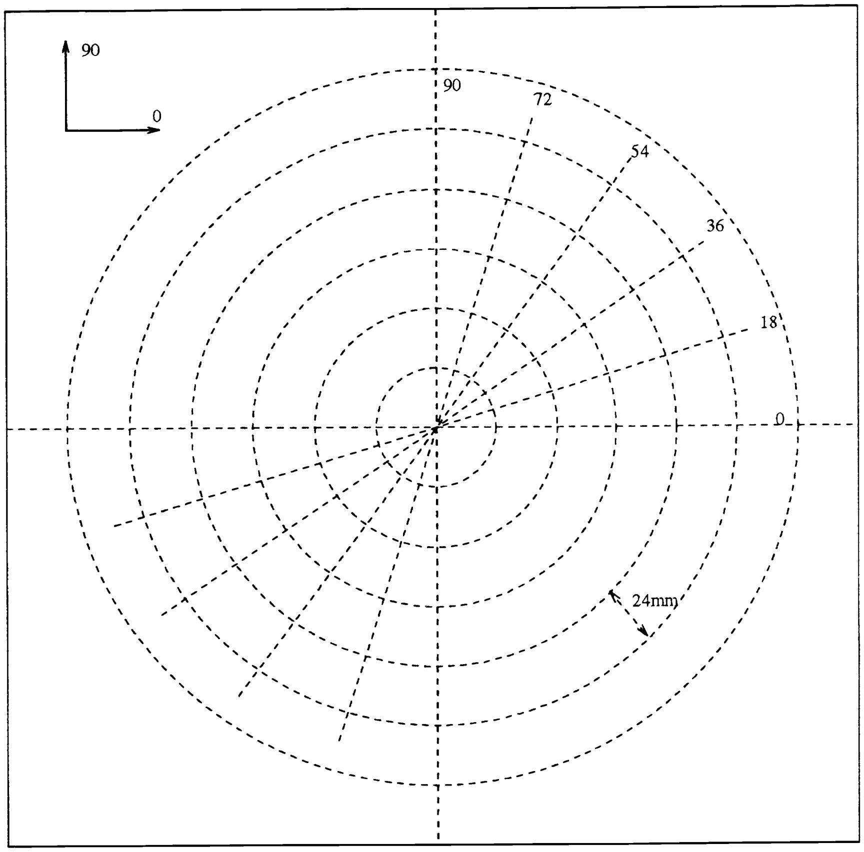

Figure 3. Front face of plate (impact locations).

4. NEURAL NETWORK RESULTS

It is clear that for each sensor location, the amount of strain data available for network training was unrealistically large; a feature extraction was therefore performed. The analysis considered several time and frequency domain features, namely: (A) time after impact of maximum response, (B) magnitude of maximum response, (C) peak-to-trough range of the response and (D) real and imaginary parts of the response *spectrum*, integrated over frequency. The input patterns to the network which proved most useful were (A) and (B), so the networks required 8 inputs, i.e. 2 values per sensor.

Figure 4 shows the impulse response from sensor 2 (Figure 2) after an impact at (24mm,18°).

4.1. Detection of Impact Positions

For the location problem, the level of noise introduced into the training data was 8% of the RMS of the measured strains. As discussed above, the network was required to return the r and θ coordinates of the impact position. Trial and error established a five-layer network structure 8:7:6:4:2 (in an obvious notation) for training with two features.

The network was trained and tested using the strategy described in the previous section. The mean errors on the testing set for the r and θ coordinates were $\pm 16.4mm$ and $\pm 22.2°$ respectively. Figure 5a shows the comparison between the actual and desired network output over the 30-impact testing set for the *theta* coordinate. The solid line shows the measured coordinate, the dashed lines show the network predictions before and after the plate was damaged. Figure 5b shows the corresponding comparisons for the r coordinate. The mean error on the location for the damaged plate was $\pm 17mm$ in r and $\pm 25.6°$, indicating very little degeneration in the network diagnostic.

4.2. Detection of Impact Force Amplitude

A different network structure was used to predict the impact force amplitude. The analysis used the same features (A and B); however, in this case, the added noise constituted only 8% of the *RMS* of the strain data. The network was required to predict the impact force amplitude, and trial and error yielded a structure 8:7:6:3:1. After training, the mean percentage error over the testing data for the undamaged plate was 16.7%. Figure 5c shows the comparison between the actual and desired network outputs. The network follows the amplitude trend; however, the higher the amplitude, the greater the error. When the network was used to quantify impacts on the damage plate, the percentage error rose only to 17.5%, again indicating no significant degradation.

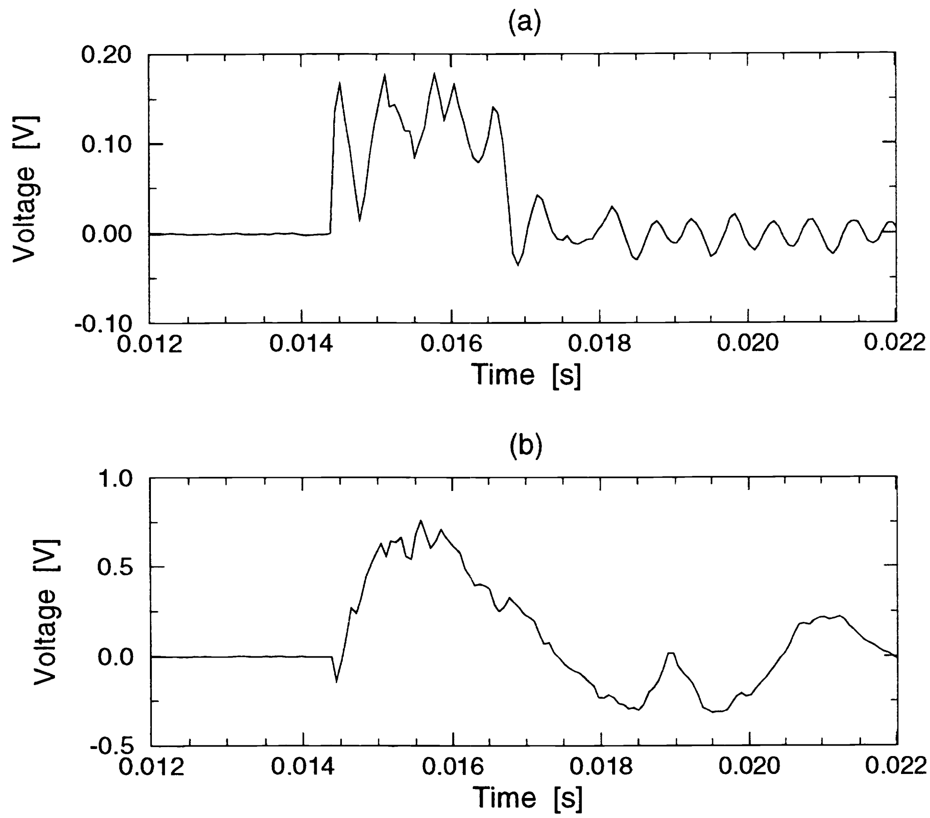

Figure 4. (a) Impactor acceleration signal (b) Strain measurement at sensor 2.

5. CONCLUSIONS

This study represents an incremental improvement on the previous study. An instrumented dropweight impactor rig was used which was specifically designed for the purpose of producing impacts on a composite panel which could be specified precisely in position and energy. Neural networks were obtained which could locate and quantify impact events with acceptable accuracy, on the basis of data obtained from strain time-histories recorded at piezoceramic sensors on the plate. It was shown that the network diagnostics still functioned with very little degradation of performance after the plate was damaged. The implications for on-line health monitoring systems are clear. Further studies are being undertaken to reduce the neural network errors of the impact detection system.

6. ACKNOWLEDGEMENTS

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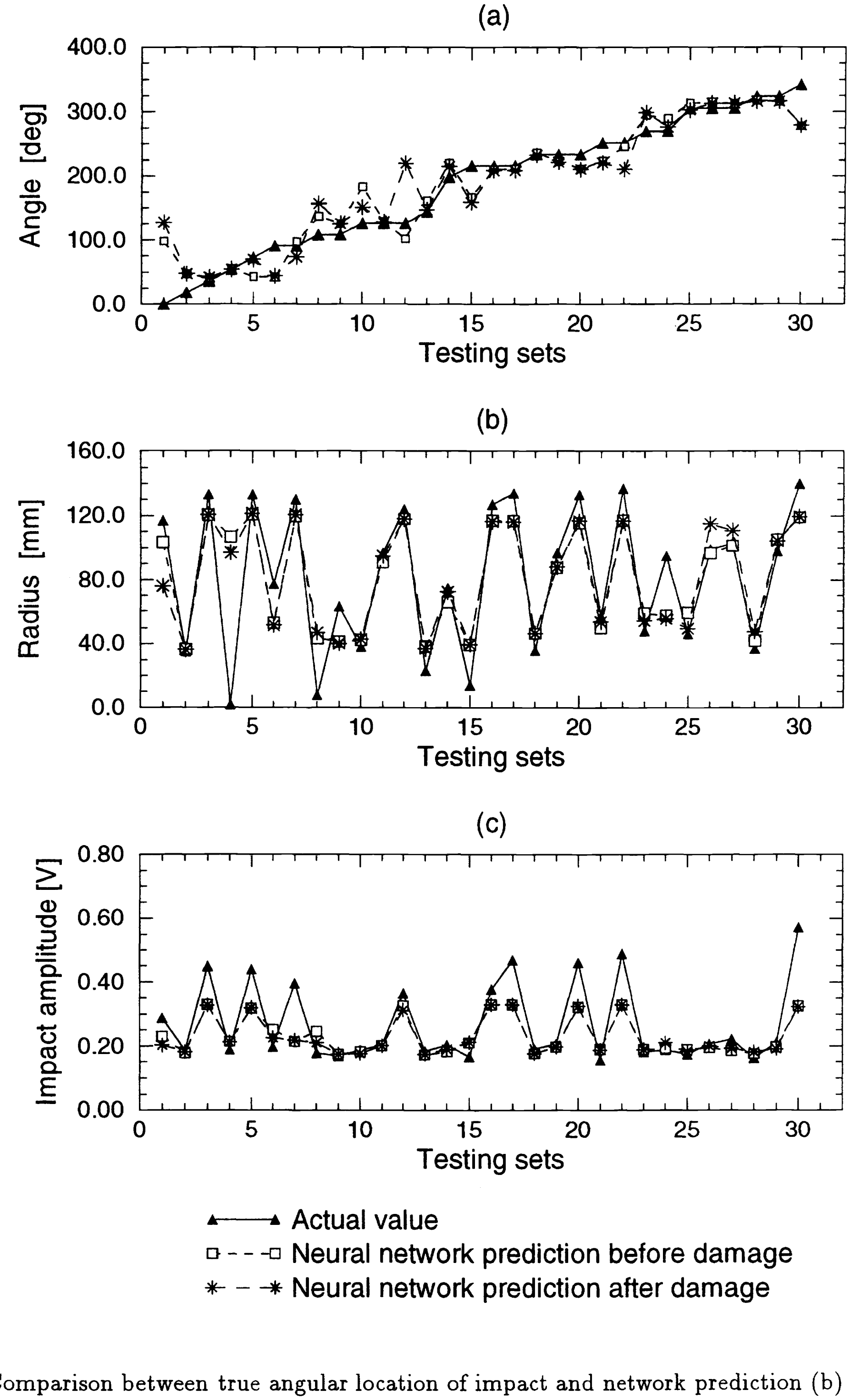

Figure 5. (a) Comparison between true angular location of impact and network prediction (b) Comparison between true radial location of impact and network prediction (c) Comparison between measured impact energy and network prediction.

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