Smart optical fiber sensor for impact localization on planar structures

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***Abstract*— This work shows a method to determine, in real time, external impact location on planar structures based on responses of optical fiber strain sensors. In order to demonstrate experimentally the sensing approach, four fibre Bragg gratings were attached to a polymeric board for detecting the disturbance caused by a drop weight impact. An artificial neural network was used to process the sensor responses and to identify the quadrant location of the impact on the structure. The results demonstrate that such location can be predicted with correct classification rate of approximately 85.0% in validation step.**

***Keywords*— optical fiber sensor; fiber Bragg grating; artificial neural network; structural health monitoring.**

I. Introduction

Mechanical impacts can affect structures compromising its integrity, operation performance and lifetime. An accurate characterization of the impact can prevent problems related to structural damages in naval, aerospace and civil structures. The development of techniques able to provide information about the magnitude and location of the impact forces, as well as its influence on the structural health, has been extensively investigated. The location and history of impact force acting on a panel were identified by measuring strain response with strain gauges attached on the panel surface. The method employs an experimental transform matrix relating the force history to the strain response [1]. The dynamic response of resins using plate impact experiments was studied in the impact velocity range from 80 to 960 m/s. The orthogonal components of stress were analyzed both during and after the shock arrival [2]. Global and local post-impact strain measurements were employed to determine the low velocity impact and quasi-static failure of polymethylmethacrylate (PMMA). Fiber Bragg Grating (FBG) sensors and finite-element analyses were applied to obtain information about the time behavior of the produced failure [3].

Conventional methods employed in structural health monitoring to investigate and locate damages are based on the detection of changes in the natural resonance frequencies of the structure. These methods rely on the previous modeling of the structure and become difficult to apply as the complexity of geometry increases. Therefore, the study and development of experimental techniques to identify the external impacts location and force, even in complex structures with unknown characteristics, is an interesting field of research.

In the field of structural health monitoring, fiber Bragg gratings (FBG) have emerged in the last past years as substitutes to conventional electrical transducers [4-6]. These optical fiber transducers show high sensitivity, immunity to electromagnetic interference and to the optical source intensity instabilities when wavelength coded. Besides, a large number of sensors can be multiplexed in the same optical link performing a quasi-distributed monitoring in real time.

Recently, some works have reported that the features of optical fiber sensors can be improved when their responses are supervised by artificial neural networks (ANN) [7-10]. This features results from the ANN ability to provide mathematical models to learn and generalize non-linear and complex behaviors by mean of an implicit mapping between input and output values [11]. Once ANN has adaptive learning ability, parallel processing capability and good generalization property for unseen data, ANN models have been used as an efficient technique to data-driven modeling. Particularly in applications where industrial fault detection is an important issue, neural network model can be used to combine information provided by sensors at different points in order to identify defects. Within this scenario, ANN can be used to perform both pattern classification and recognition in structural health monitoring.

In this paper, a method to identify the impact location is presented. Four FBG were used as strain transducers to detect disturbances propagating on a polymeric board as a result of a drop weight impact. Preliminary results show that the use of an ANN can supply, in real time, the quadrant location of the impact on the structure.

II. Methodology

A. Experimental Set-up

A square 60 cm side and 5 mm thick board of polymethyl methacrylate (PMMA) was employed as test structure, with four FBG attached to its corners. The FBGs presenting resonances wavelengths at 1534, 1538, 1540 and 1543 nm at (20.0 ± 0.5) ºC were bonded at the corners of each quadrant with cyanoacrylate, angled at 45° from the sides. Until the cure

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of the adhesive, FBGs were kept under constant dilational stress. A bi-dimensional matrix (50 cm x 50 cm) of points 5 cm apart was drawn on the board surface to provide the impact location.

Fig. 1 shows the geometry of the test board employed in the experiments, with a Cartesian coordinate system whose origin is the center of the plate. Cartesian coordinates (x_i,y_i) with i=1 to 4 of the four transducers (FBG1, FBG2, FBG3 and FBG4) in centimeters are respectively (-27.5,-27.0); (+26.0,-26.6); (+27.0,+26.6) and (-26.5,+26.5). Impact is depicted by the smaller red circle in quadrant Q3, while the wave-front associated with the perturbation is represented by the bigger red circumference.

A cylindrical hollow tube (8 cm length) kept in the vertical position was employed to guide a free falling metallic ball (34g weight) responsible by the impact. The impact was produced on each quadrant of the test board at (20.0 ± 0.5) ºC. When the disturbance produced by the impact reach each FBG, a dilational/compressional stress associated with the time evolution of the disturbance is detected by the gratings as positive/negative time shifts in their resonance wavelengths. Impacts were measured 20 times under reproducibility conditions for each quadrant of the test board.

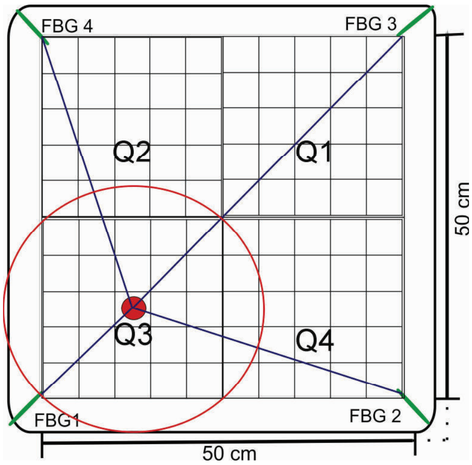

Fig. 1. Geometry of the PMMA test board instumented with FBGs for detect impact locations.

FBG1, FBG2, FBG3 and FBG4 were connected in series to a LED (Superlum PILOT 2) with wavelength range from 1520 to 1570 nm. Light back reflected from the FBGs at the resonant wavelengths is measured by an optical interrogation monitor (IBSEN PHOTONICS IMON-512E, 970 Hz maximum sampling rate, resolution < 0.5 pm), operating with a dispersion grating and a diode array. The IMON is used to measure simultaneously the wavelength shifts of the four FBG resonances ($\delta\lambda_{FBG1}(t)$, $\delta\lambda_{FBG2}(t)$, $\delta\lambda_{FBG3}(t)$ and $\delta\lambda_{FBG4}(t)$) along approximately 0.3 seconds. The beginning of this time window was selected by taking the time the FBG closest to the impact location first detects the disturbance, acting as a trigger for the data acquisition. Data of each grating sensor were used as inputs for an artificial neural network model. This architecture was successfully trained and tested to identify the quadrant of impact, without the need for physical modeling.

B. *Artificial Neural Network Model*

The ANN shown in Fig. 2 was implemented in proprietary software Matlab® version 2011 by means of functions available in Neural Network Toolbox™.

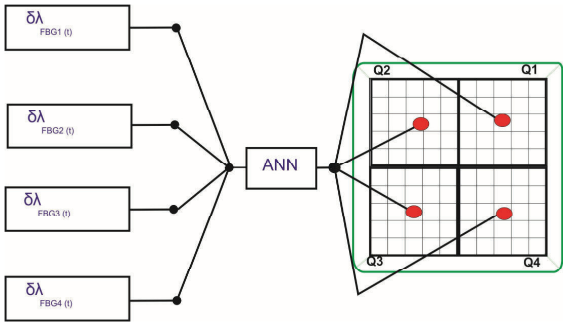

Fig. 2. Schematic diagram of the ANN used to supply the quadrant location of the impact produced on PMMA test board.

It was built an ANN of type Multilayer Perceptron with four neurons in the input layer (associated with FBG time responses), twenty neurons in the first hidden layer, thirty neurons in the second hidden layer, twenty neurons in the third hidden layer and one neuron in the output layer (associated with quadrant location of impact). The number of hidden layers and the number of neurons of each hidden layer were only determined after consecutive simulations which were realized in order to obtain the model with the minimal root mean square error and the best predictive capability.

The ANN was trained during 40 epochs according to Levenberg-Marquardt back-propagation algorithm with initial learning rate of 0.10 and mean squared error goal of 0.01%. Hyperbolic tangent sigmoid transfer functions were used in hidden layers. On the other hand, a linear transfer function was employed in output layer.

From the set of data obtained with 20 impacts measured at each quadrant, a sub-set randomly chosen corresponding to15 measurements was used as input data to train the ANN. The remaining set of 5 experimental measurements for each quadrant was employed to test the ANN. The ANN was validated with experimental data not used in the training step, allowing evaluating its generalization capability. The ANN output values used as target were 1, 2, 3 and 4, which were associated with the quadrants Q1, Q2, Q3 and Q4, respectively.

The ANN performance was evaluated in terms of correct classification rates for both training and validation steps. These rates were computed by the ratio between the number of correct classifications regarding the respective targets and the total number of targets. The classification provided by ANN was considered correct if its response is within the interval of ± 0.3 established around the output target.

III. Results and Discussions

Fig. 3 shows a typical four-FBG wavelength time response when an impact was produced at coordinates $x_0 = y_0 = -20.0$ cm. Similar set of data were used as inputs for the ANN, resulting from the other produced impacts, with the IMON frequency set at 948.8 Hz. The comparison between the target values and the values provided by ANN model for training and validation data are presented in Fig. 4 and 5, respectively.

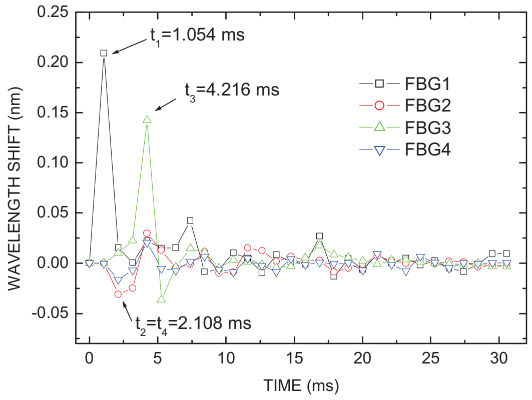

Fig. 3. Wavelength shift time response of FBGs when an impact was produced at coordinates $x_0 = y_0 = -20.0$ cm.

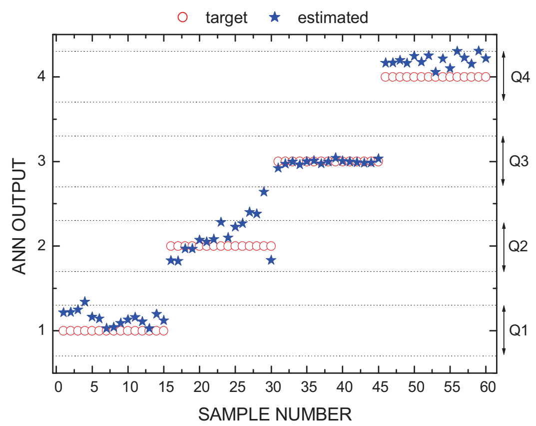

Fig. 4. ANN responses and target values for training data.

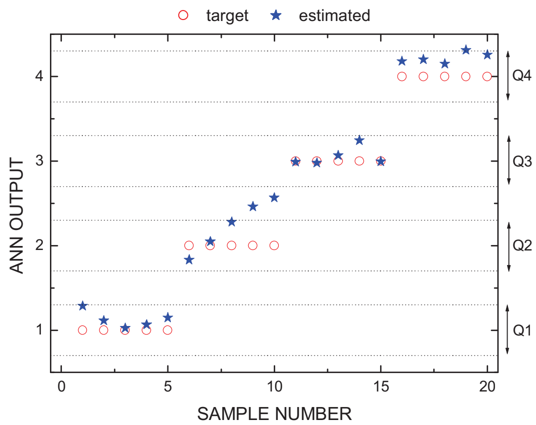

Fig. 5. ANN responses and target values for validation data.

The correct classification rates for both training and validation steps were respectively 90.0 and 85.0%. The mean squared error obtained in training and validation steps were 3.5% and 5.5%, respectively. These results prove the good learning and generalization capability of the ANN model.

IV. CONCLUSION

The results obtained in this work show that FBG strain sensors can be used to identify external impact location on structures in real time, despite of events are complex and fast. FBG must be properly attached to the structure and the time shifts of their wavelength resonances need to be simultaneously measured. The ANN model showed to be able to determine the quadrant of the impact on the structure without the need for physical modeling. ANN showed a good learning and generalization capability and its correct classification rate was 85.0% in validation step.

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