Loading Localization by Small-Diameter Optical Fiber Sensors

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Abstract: Structural health monitoring (SHM) in service has attracted increasing attention for years. Load localization on a structure is studied hereby. Two algorithms, i. e., support vector machine (SVM) method and back propagation neural network (BPNN) algorithm, are proposed to identify the loading positions individually. The feasibility of the suggested methods is evaluated through an experimental program on a carbon fiber reinforced plastic laminate. The experimental tests involve in application of four optical fiber-based sensors for strain measurement at discrete points. The sensors are specially designed fiber Bragg grating (FBG) in small diameter. The small-diameter FBG sensors are arrayed in 2-D on the laminate surface. The testing results indicate that the loading position could be detected by the proposed method. Using SVM method, the 2-D FBG sensors can approximate the loading location with maximum error less than 14 mm. However, the maximum localization error could be limited to about 1 mm by applying the BPNN algorithm. It is mainly because the convergence conditions (mean square error) can be set in advance, while SVM cannot.

Key words: small-diameter optical fiber sensor; structural health monitoring; loading localization; back propagation neural network; support vector machine

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0 Introduction

In many industrial structures applied in aerospace and renewable energy (wind turbines), longer service life and lower costs are among major concerns[1]. Replacing critical parts and high stress members by composite materials is a solution. Because of their higher specific strength and stiffness, composite structures are widely used[2-4]. However, the damage mechanism of composite materials is much more complex compared with traditional isotropic metal materials. Furthermore, the mechanical properties of composite materials can be rapidly degraded when internal damage occurs[4]. For composite structures, like those for aircraft, low velocity impacts can result in structural failure[5-6]. Therefore, structural health monitoring (SHM) of structures needs to be performed in order to detect load, especially dynamic load[7-8].

Among the developed technologies, optical fiber sensors have attracted considerable attention because they are lightweight, and immune to electromagnetism. Furthermore, they are flexible with sufficient strength and can be embedded into composite laminates[9-10]. Fiber optic sensors have played a major role in smart structure applications. Because of their characters of low-cost and wavelength-encoded linear response to the measured physical parameter, fiber Bragg grating (FBG) sensors have been extensively utilized in SHM[11-13].

FBG sensors have been utilized in impact localization. Shrestha[5] studied localizing impact points on composite wing by analyzing signal acquired by FBG sensors. They trained data from 121 points. The maximum localization error was 35 mm. After they improved the algorithm, the

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maximum error was decreased to 28 mm[6]. Chan et al.[14] studied the bird strike in a composite UAV wing using FBG sensors. The average error was 33.6 mm for the strike location estimate. Zhu[15] studied impact localization algorithm on an aluminum alloy structure by using a four-FBG sensing network. The maximum impact ordinate localization error was 9 mm. Small-diameter FBG sensors are preferred since they affect less on mechanical performance of host structures[16-18].

In this paper, load localization based on small-diameter FBG sensors is proposed. Two algorithms for load localization are discussed hereby. Feasibility of the proposed approach is evaluated through an experiment involving application of a 2-D FBG sensor array. An FBG interrogator is used to measure strain on the plate. The detected strain data are trained by the two different algorithm methods. The testing results are compared.

1 Methodology

Two different algorithms are proposed to recognize the load position on a structure.

1.1 Sensing principle

Small-diameter fiber Bragg grating (SDFBG) sensors are applied to structural strain monitoring here. The core diameter of the above-mentioned fiber sensor is 7 μm, and the cladding is 80 μm.

A schematic of FBG sensor is presented in Fig. 1. As a kind of reflective sensor, FBG perceives the change of parameters through the movement of resonant wavelength. When a broadband light transmits through the grating,

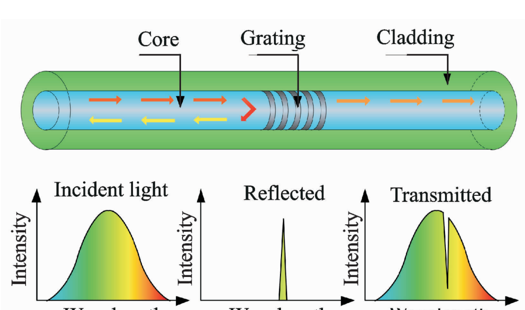

Fig. 1 Schematic of FBG sensing

the wavelength λ_B that satisfies the condition of Eq. (1) will be reflected

$$\lambda_B = 2n_{\mathrm{eff}}\Lambda \tag{1}$$

where n_{eff} is the effective refractive index of FBG and Λ the period of grating.

With the assumption of no temperature change, the Bragg wavelength will change with axial strain on optical fiber. The relative change in FBG wavelength $\Delta\lambda$ with axial strain ε_z can be expressed as[19]

$$\frac{\Delta\lambda_B}{\lambda_B} = S_\varepsilon \varepsilon_z \tag{2}$$

where S_ε is the relative strain sensitivity of a FBG sensor. For a common FBG, whose core is made of silicon oxide, the sensitivity S_ε is 0.784.

1.2 Support vector machine theory

Support vector machine (SVM) is a learning method based on statistical learning theory[20-21]. It is successfully used in prediction, pattern detection and classification.

Given a set of training data, i.e. $\{(x_1, y_1), \cdots, (x_n, y_n)\}, x_i \in X \subseteq \mathbf{R}^n, y_i \in Y \subseteq \mathbf{R}, x_i$ is the input data and y_i the corresponding target value. The SVM tries to estimate target values by using the following linear equation[22]

$$f(x) = \boldsymbol{w}^{\mathrm{T}} \boldsymbol{x}_i + b \tag{3}$$

where $f(x)$ is the output, $\boldsymbol{w}$ the n-dimensional vector and b a scalar.

By using a Vapnik ε-insensitive loss function, the optimal linear regression function can be obtained as a solution to the following optimization[23]

$$\min\left[\frac{1}{2}\boldsymbol{w}^2 + C\sum_{i=1}^{n}(\xi_i^+ + \xi_i^-)\right] \tag{4}$$

The following condition is to be satisfied

$$\begin{cases} \varepsilon + \xi_i^- \leqslant y_i - \boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_i - b \leqslant \varepsilon + \xi_i^+ & i = 1, \cdots, n \\ \xi_i^- \geqslant 0, \xi_i^+ \geqslant 0 & i = 1, \cdots, n \end{cases} \tag{5}$$

The calculation can be simplified by converting the problem into the equivalent Lagrangian dual problem[22].

With a kernel function as $K(\boldsymbol{x}_i, \boldsymbol{x}) = \varphi(\boldsymbol{x}_i) \cdot \varphi(\boldsymbol{x})$, the estimation of the SVM is obtained byEq. (6)[24]

$$f(\boldsymbol{x}) = \sum_{i=1}^{l} (a_i - a_i^*) K(\boldsymbol{x}_i, \boldsymbol{x}) + b \qquad (6)$$

where a_i, a_i^* are the Lagrange multipliers.

1.3 Back propagation neural network algorithm

BP neutral network has been one of the most widely used algorithms[25]. The network contains at least three parts: One input layer, at least one hidden layer, and one output layer. The input layer receives and distributes the input pattern. The hidden layers capture the nonlinearities of the input/output relationship. The output layer produces the output pattern. The structure of the BP neural network is shown in Fig. 2.

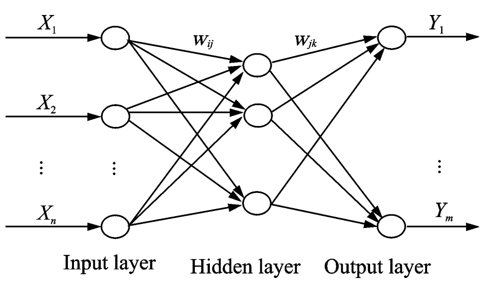

Fig. 2 Structure of a BP neural network

In the network, every neuron in each layer receives total input from all of the neurons in the previous layer. The relation is shown[24]

$$p_j = \sum_{j=0}^{N} w_{ij} x_i + b_j \qquad (7)$$

where p_j is the total input and N the number of inputs to the unit j in next layers, w_{ij} the weight coefficient, b_j threshold value, and x_i the input from unit i in the preceding layer. Then the output O_j of unit j can be calculated by processing the input through a transfer function $f(x)$ as

$$O_j = f(p_j) \qquad (8)$$

Hereby the function $f(x)$ is optional and selected as

$$f(x) = \frac{1}{1 + \mathrm{e}^{-x}} \qquad (9)$$

Based on BP neutral network, the data are trained by a series of input/output pattern sets, which are repeatedly presented to the network. The error between the actual data and the predicted output is used to adjust the weight. The network will gradually learn the relationship between the input and the output by adjusting the weights. When the error of the test set reaches its minimum, network training completes and the weights are fixed.

1.4 Load orientation

As a load is applied to a structure, the structure deforms. SDFBG sensors on the structure will detect the deformation. Load positions are changed during the test. Sensors will record the deformation changes. Therefore, historical database is built on the basis of recorded data. Afterwards, the data will be trained by algorithm till the loading discriminate is accomplished. Consequently, the orientation is achieved. As the structure is loaded, the captured data is denoted as real-time data. After the real-time data are input, the load would be located.

The discriminate procedure is sketched in Fig. 3.

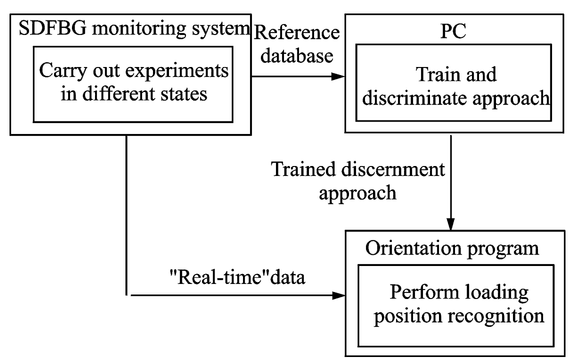

Fig. 3 Process of load orientation

In training and discrimination procedures, SVM and BP algorithms are applied, respectively. Therefore, two orientation programs are set. The feasibility of the proposed methods is evaluated experimentally.

2 Experiment

Optical fiber-based sensors were applied to monitoring a designed carbon fiber reinforced plastic (CFRP) laminate. The size of the laminate is 600 mm × 600 mm × 2.16 mm. The laminate is clamped on edges by specially designed clamps with a width of 30 mm.

Four small-diameter FBG sensors were glued on the back of the laminate, as shown in Fig. 4. The working length of the used Bragg is 10 mm. A local coordinate is set as shown in Fig. 4. The positions and the original central wavelengths of the sensors are listed in Table 1.

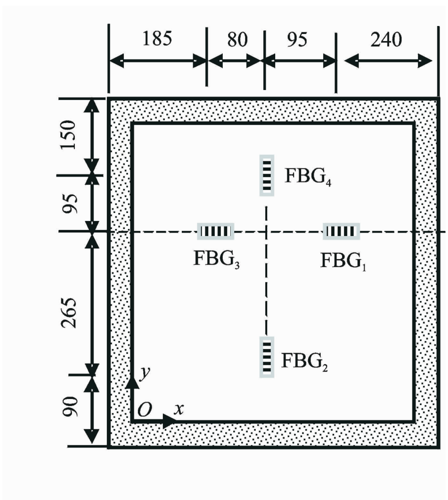

Fig. 4 Schematic of sensors on the monitored laminate

Table 1 Details of FBG sensors

Sensor	Central wavelength / nm	Location / mm
FBG_1	1 527.111	(330,325)
FBG_2	1 527.970	(235,60)
FBG_3	1 528.435	(155,325)
FBG_4	1 526.953	(235,420)

A FBG demodulator SI425 from Micron Optics Inc was used to capture the central wavelength of the sensor array. The experimental setup is shown in Fig. 5. The work area of the plate is 540 mm × 540 mm, which is divided into 12 parts on each side.

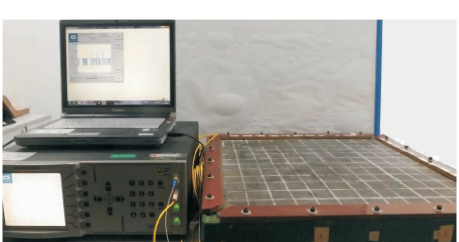

Fig. 5 Experimental setup

As the temperature is constant, a weight of 3 kg is slowly put on the surface of the plate. The weight stands at different grids. The wavelengths of four sensors are recorded every time. Together 65 signals are acquired. Among the detected data, 58 are taken as reference data at random. The left data, i. e. , seven data are chosen as tested ones.

3 Results and Discussions

The reference database is trained by using SVM and BP neutral network separately. The seven load localizations are predicted. The results are shown in Fig. 6.

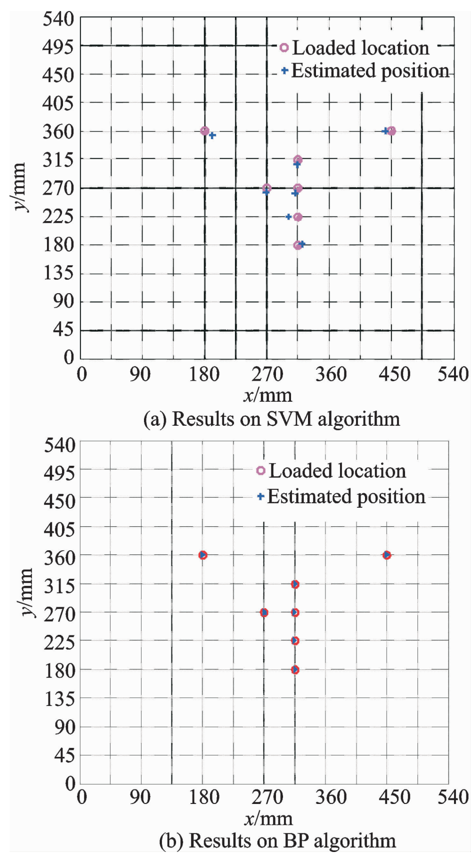

Fig. 6 Estimated load positions

The details of the tested load positions are illustrated in Table 2. According to SVM results, the maximum location error are 13. 669 mm and 9. 248 mm in x and y directions, respectively. However, the maximum error is 1. 124 mm in x direction, and 0. 015 mm in y direction based on the BP algorithm.

Table 2 Tested load positions

No.	Loaded position / mm		SVM estimated position / mm		BP estimated position /mm	
	x-coordinate	y-coordinate	x-coordinate	y-coordinate	x-coordinate	y-coordinate
1	180	360	191.163	352.813	180.003	360.003
2	270	270	269.293	263.080	270.056	270.000
3	315	180	321.393	181.039	315.898	179.991
4	315	225	301.331	223.827	313.876	225.015
5	315	270	311.231	262.036	314.496	269.998
6	315	315	313.165	305.752	315.676	314.997
7	450	360	440.755	359.296	449.998	360.000

Obviously, the predictive position is closer to the actual location according to the results by the BP algorithm. The reason may lies in difference between the two training methods. When the data are trained by means of BP procedure, a neural network which has marvelous approximation would be built. The network is trained to calculate the weights which minimize the mean square error (MSE) between network prediction and training data. The weights are updated until it converges to a certain value.

The training performance by BP is shown in Fig. 7, where the best training performances are 0.040 0307 and 0.001 989 8 at 539 and 897 epoches, respectively. In our study, MSE of the training data is set to 0.002. It can be observed that MSE gradient descend till it approaches the set value. Training process takes about 4 s for 897 iterations.

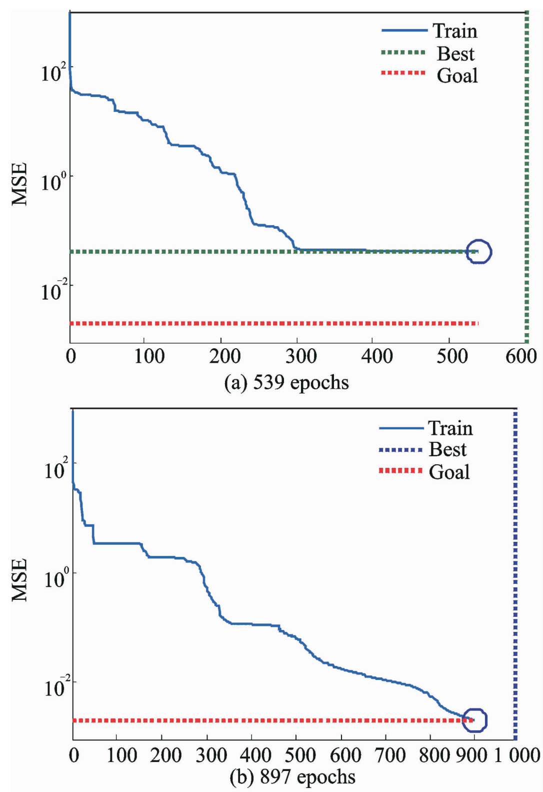

Fig. 7 Training performance by BP procedure

4 Conclusions

Loading position detective methods based on discrete strain have been proposed. The strain measurements are implemented by four small-diameter FBG sensors arranged in 2-D array. Development of the methods involves use of reference database by two different training techniques, namely SVM and BP neural network. The methods are evaluated experimentally on a 540 mm × 540 mm CFRP laminate.

Experimental results indicate that the 2-D small-diameter FBG sensors can estimate the planar loading location even with less data. The maximum error is less than 14 mm by using SVM method and could be limited to about 1 mm by the BP neural network algorithm. The testing error difference between the two methods is due to the difference in the training.

If the loading amplitudes are changed besides the loading positions, the predictive method is similar. However, more complicated algorithms are needed to predict both the loading positions and the loading amplitudes.

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