Damage Location Detection of the CFRP Composite Plate Based on Neural Network Regression

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ABSTRACT

Damage localization takes an important part in the structural health monitoring (SHM) process for Carbon Fiber Reinforced Polymer (CFRP) composite materials, which can ensure the structure safety. Due to the anisotropy, it is of great challenge for the composite materials to obtain the accurate signal source position. Some methods, mainly based on specific machine learning algorithms, perform excellently in fitting non-linear relationships between input features and position tags. However, numerous data extracted from physical objects are required to ensure accuracy, which brings great inconvenience to practical application. This research presents a damage localization algorithm based on Neural Network regression to process signals obtained by Acoustic Emission (AE) sensors in CFRP composite SHM system to achieve the purpose of detecting the damage position. First of all, A method for acquiring training data is proposed, which prefer to obtain training data from a finite element analysis model, constructed in accordance with physical objects, rather than capture directly from real structure. Besides, two measures are performed to reduce the complexity of the algorithm, one is that feature combinations and selections are conducted, and the other is the hidden layer structure of the neural network is optimized. Finally, experiments are preformed on the composite structure to verify the proposed method, in which a minimal amount of data is extracted from the real object to adjust the positioning algorithm. The estimation of localization results are in good agreement with the actual sources of damage signals which shows that the algorithm effectively reduce the amount of data required for algorithm fitting, the generalization ability and application convenience are significantly improved.

1. Introduction

Composite materials are widely used due to their advantages of stiffness, strength, weight and excellent fatigue and corrosion resistance\textsuperscript{1-3}, whether in the military or civilian sector. However, damage to composite materials is difficult to detect and identify. When these conditions occur – (1) impact of a foreign object, (2) crack formation, and (3) structural element failure, acoustic waves are generated. The process of locating the source of these acoustic waves, by recording the propagating acoustic signals by various sensors and properly analyzing them, is commonly known as the acoustic source localization technique. It is an important step for structural health monitoring (SHM)\textsuperscript{4}. In recent years, with this
technique, numerous methods for locating the damage of composite structures have been proposed\cite{5-8}. Among these methods, there is a class of methods that rely on the theory of optimization and the idea of machine learning. The advantages of such methods are high accuracy and strong adaptability to complex structures\cite{9-12}. But they usually require a large amount of data to train the algorithm model, which makes the application in the actual scene very inconvenient.

In this article, a damage localization algorithm is proposed, which based on Neural Network regression to process signals obtained by Acoustic Emission (AE) sensors in CFRP composite SHM system. The finite element simulation technique is used to solve the problem of acquisition of training data, the technique can well describe the structural characteristics, material properties, and propagation of acoustic emission signals of the monitored object. To verify the effectiveness of this algorithm, we have applied it on an AE detection system.

The remainder of this paper is organized as follows. Section 2 discusses the construction of simulation model and the acquisition method of training data. Section 3 introduces the signal processing method used and data pretreatment. Section 4 explains the feature engineering and positioning algorithm in detail. Section 5 proposes the calibration algorithm and introduces the verification experiment. At last, conclusion and future work are given in section 6.

2. Finite element analysis model and data acquisition

In this section, a new method for acquiring training data is proposed, which prefer to obtain training data from a finite element analysis model, constructed in accordance with physical objects, rather than capture directly from real structure. Fig. 1 shows the structure of the proposed model. As illustrated in Fig 1, the model is established for CFRP composite plate.

![Figure 1. The structure of the finite element analysis model](image1)

The model is a square plate with a side length of 800 millimeters and a thickness of 3 millimeters. T800 carbon fiber is selected as the material. There are 12 layers in the model, and the fiber direction of the adjacent layer is 45 degrees.

![Figure 2. The location area on the model](image2)
As is shown in Fig. 2, a square region with a length of 500 millimeters is set to the location area. Signal output points are arranged at four vertexes of the square. When a damage happens in the composite structure, the AE signal will be generated. In order to carry out the simulation experiment, a simulated AE signal is employed. The simulation AE signal of damage can be expressed as follows:

\[ x(t) = A \left[ H(t) - H \left( t - \frac{N}{f_c} \right) \right] \left[ 1 - \cos \left( \frac{2\pi f_c t}{N} \right) \right] \sin(2\pi f_c t) \]

(1)

where \( A \) is the signal amplitude; \( f_c \) is the central frequency; \( t \) is the time; \( H(t) \) is the Heaviside step response; \( N \) is the wave numbers.

For example, when \( A = 5, N = 20, t = 1 \text{ms}, f_c = 40 \text{kHz} \), and the sample rate is \( 1 \text{MHz} \), the simulation AE signal is shown in Fig. 3.

![Figure 3. The simulation AE signal: (a) Waveform; (b) Spectrum.](image)

In order to obtain train data of the location algorithms, several simulation calculations need to be carried out. In the course of each experiment cycle, the input load signal is applied to different locations in the position area. A total of 361 sets of signals were collected.

### 3. Data pretreatment and signal processing

After a successful acquisition of original signals, some appropriate signal processing methods need to be carried out to extract more valuable features. Fig. 4 shows one of the 361 sets of original signals. The damage signals captured by different signal receiving points differs in the amplitude and arrival time.

![Figure 4. Four signals collected in one experimental cycle](image)

Take one of four signals recorded by four signal receiving points in an experiment cycle as an example. In order to accurately extract the arrival time and amplitude information contained in each signal waveform, signals are processed as follows: Firstly, the envelope of the original signal is obtained by Hilbert transform. After that, it is necessary to eliminate interference from echo signals.
Fig. 5 shows the extracted envelope and the superposition of the damage signal and the echo signal and there are two typical superpositions. In Figure a, the echo signal has less interference to the damage signal, and the amplitude and arrival time of the signal can be easily obtained by common threshold methods. The time and amplitude corresponding to the maximum point of the signal function is what we want. However, in the case shown in Figure b, the interference of the echo signal on the damage signal is very serious. In order to solve this problem, some improvements have been made to the general threshold method. First, solve the derivative of the envelope function of the signal, the threshold method is used for the derivative function, and the point at which the derivative function is close to zero is the arrival time point of the damage signal. The amplitude corresponding to this point on the envelope function is what we need.

![Figure 5](image)

**Figure 5.** Envelope extracted from the original signal

4. Feature engineering and localization algorithm

In this section, the input characteristics and the structure of the artificial neural network of the localization algorithm are determined.

![Figure 6](image)

**Figure 6.** Sensor placement position and coordinate system

Establish the coordinate system shown in Fig. 6, the final output of the algorithm is the coordinates of the point at which the damage signal is emitted. Taking the abscissa as an example, the process of proposing the algorithm is illustrated.

First, the input characteristics of the algorithm are determined. After signal processing, each set of signals is converted into a corresponding signal arrival time and amplitude. The arrival time of the signal received by the sensor $n$ is recorded as $t_n$, and the amplitude is recorded as $a_n$. 
In practical applications, the time when the damage signal reaches the sensor cannot be obtained, but the time difference of the signals received by different sensors can be easily obtained. Time difference of arrival of the signals collected by sensor 1 and sensor 4, recorded as \( t_{4-1} \), and that between sensor 2 and sensor 3, record as \( t_{3-2} \). In addition, the amplitude of the signal received by each sensor is also determined as the input characteristics of the algorithm.

**Figure 7.** Schematic diagram of neural network algorithm

BP neural network has arbitrarily complex pattern classification ability and excellent multi-dimensional function mapping ability[14]. Structurally speaking, the BP network has an input layer, a hidden layer and an output layer[15]; in essence, the BP algorithm uses the network error squared as the objective function and uses the gradient descent method to calculate the minimum value of the objective function. As shown in Fig. 7, in the input layer, there are six nodes, which are \( a_1, a_2, a_3, a_4, t_{4-1} \) and \( t_{3-2} \) as input features. The output layer contains only one node, representing the abscissa of the damage location.

Next is the most critical step to determine a suitable hidden layer structure. There is a significant nonlinear relationship between the location coordinates of the damage source and the input features. The neural network is selected as the prototype of the algorithm and its powerful nonlinear expression ability is explicitly valued. In addition, the algorithm can be flexibly adjusted by changing the number and structure of the neural nodes in the hidden layer. In this paper, extremely complex algorithm models are not pursued, which not only requires a large amount of training data to ensure the acquisition of low-error training results, but also limits the speed of the algorithm. These hidden layer structures as shown in Fig. 8 are available as an alternative.

<table>
<thead>
<tr>
<th>Type</th>
<th>Number of hidden layer nodes</th>
</tr>
</thead>
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<tr>
<td>Single layer</td>
<td>3, 4, 5, 6, 7, 8, 9</td>
</tr>
<tr>
<td>Double layer</td>
<td>5-3, 6-3, 7-3, 5-6, 4-7, 4-5, 5-6, 5-7, 5-5, 6-6, 6-7, 6-5, 7-7, 7-7</td>
</tr>
</tbody>
</table>

**Figure 8.** Hidden layer structures to be selected

In this paper, the data set is divided into two parts, about 10% of the total amount of data as a test data, which is used to evaluate the final model that is trained. The remaining data sets will be used as training and cross-validation data sets. Used to train the model and fit the parameters. In order to make full use of the training data as much as possible, a k-fold cross-validation method is adopted. This cross-validation method is used to evaluate the trained algorithm model and select the best performance hidden layer structure. Mean squared error regression loss is using as the error evaluation criterion.

\[
MSE(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=1}^{n_{samples}} (y_i - \hat{y}_i)^2.
\]

The mean of the 5 cross-validation results is the final training error. Fig. 9 shows the fitting results of the algorithm models of the different hidden layer structures mentioned above. After the training error...
drops to a certain extent, there will be no obvious downward trend. Continue to increase the number of hidden layers or the number of nodes in each layer is not significantly improved, but will increase the risk of over-fitting. The final neural network structure has two hidden layers, the first layer has 7 nodes, and the second layer has 5 nodes.

For the positioning algorithm in the ordinate direction, the input features \(t_{2,1}\) and \(t_{3,4}\) are used instead of \(t_{4,1}\) and \(t_{3,2}\), and the output \(y\) instead of \(x\). The algorithm obtained by applying the test data set is used for predictive calculation, the obtained result and error conditions are shown in Fig.10 and Fig.11.

In Fig.11, the error is calculated by the following formula:

\[
e = \frac{x' - x}{\text{range of } x} \times 100%. \tag{3}
\]

As is shown in Fig 11, the maximum value of the abscissa error of the predicted position and the actual position is only 5.00% and the ordinate error is 5.60%, which indicates that the selection of the neural network structure and input characteristics is reasonable.
5. Verification experiment

In order to verify the validity of the algorithm, the actual AE signal is captured by an AE detection system, the schematic diagram of the experimental system is displayed in Fig. 12. It consists of CFRP plate, AE sensor, pre-amplifier, data acquisition (DAQ) card and industrial computer. The carbon fiber used as the raw material of the plate is consistent with the material properties used in the simulation model. Furthermore, the geometry of the plate is the same as the simulation model’s. Besides, the plate is quasi-isotropic, but the specific layup direction and the number of layers are unknown. The AE sensor is mounted on the top surface of CFRP, and a total of 36 sets of AE signals are captured in the experiment.

![Figure 12. The schematic diagram of the experimental system](image1)

The location of the acquired damage signals are shown in Fig. 13. Calibration is required before applying the algorithm. In the actual system, since the simulation model can not fully describe the characteristics of the physical system, the calibration is used to make up for the difference between the simulation model and the physical model.

![Figure 13. Signal acquisition location used for calibration](image2)

One of the 36 sets of signals is shown in Fig. 14. The corresponding input characteristics are obtained by using the signal processing and feature extraction methods mentioned above. Taking the feature of...
as an example, the process of calibration is explained. In the red box area in Fig.15, a total of six sets of data are collected from the AE detection system, and a total of 19 sets of data were collected in the corresponding area on the simulation model.

![Figure 15. Signal acquisition point used to illustrate the calibration process](image)

A linear model with $l_2$-regular terms is used, and the eigenvalues extracted from the physical model are used as input. The eigenvalues in the simulation model are used as output results to fit the relationship between the two.

$$\hat{y}(w, x) = w_0 + w_1 x_1 + \ldots + w_p x_p.$$  \hspace{1cm} (4)

$$w^* = \arg \min_w \| Xw - y \|_2^2 + \alpha \| w \|_2^2.$$  \hspace{1cm} (5)

![Figure 16. Characteristics before and after processing by the calibration algorithm](image)

After calibration, the feature values extracted from the actual system can be mapped to the corresponding feature values on the simulation model. For testing the accuracy of the algorithm, 20 sets of signals are collected from the actual system. After the signal processing, feature extraction, and mapping of the calibration function mentioned above, the obtained feature values are brought into the positioning algorithm obtained in the previous chapter. Positioning results and error conditions are shown in Fig.17 and Fig.18.

![Figure 17. Comparison of the positioning result of the test data with the actual signal excitation point](image)
As is shown in Fig 18, the maximum value of the abscissa error of the predicted position and the actual position is 7.40% and the ordinate error is 9.40%, which indicates that the algorithm meets the requirements for accuracy.

<table>
<thead>
<tr>
<th>Damage location</th>
<th>Forecast position</th>
<th>Error of $x$</th>
<th>Error of $y$</th>
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<tbody>
<tr>
<td>X/mm</td>
<td>Y/mm</td>
<td>X/mm</td>
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<tr>
<td>50</td>
<td>50</td>
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Figure 18. The error between the positioning result of the test data and the actual signal excitation point.

6. Conclusion

The aim of this paper is to point out a damage localization algorithm based on Neural Network regression to process signals obtained by Acoustic Emission (AE) sensors in CFRP composite SHM system to achieve the purpose of detecting the damage position. The acquisition of training data restricts the further application of this type of algorithm. In order to solve this critical problem, a method for obtaining training data by means of finite element simulation model is proposed. In addition, the feature extraction and selection, and the optimization of the neural network structure are described in detail. The final verification experiment proves the effectiveness of the algorithm in practical use. In the actual application process, if the composite parts have irreparable damage and need to be replace with the new parts of the same pattern, only the recalibration is required according to the algorithm proposed in this paper.

The proposed algorithm has been proved applicability and effectivity for damage location problem of composite structures. The algorithm still has room for improvement in the following aspects. (1) Finding a way to build a simulation model that is more in line with the actual composite structure. (2) Applying better signal processing methods for feature extraction, especially to eliminate interference from echo signals. (3) The application of algorithms in more complex structures.

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References