Multi-Task Damage Identification Method for Composite Stiffened Plate Based on Lamb Wave and Multi-Task Deep Learning

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ABSTRACT

With the rapid growth of the demand for structural health monitoring in the aerospace field, especially under complex and changeable structural and damage cases, damage detection methods are facing the challenges of insufficient detection accuracy. To solve this problem, this paper proposes a detection method of damage location of composite stiffened plates based on Lamb wave and multi-task deep learning. In this paper, experiments are carried out on a composite stiffened plate with two stiffeners. Firstly, the damage monitoring area is divided into four sub-areas, each sub-area is further subdivided into nine grids, and five damage signals with different damage sizes are collected at the center of each grid. Through the differential operation between the baseline signal and the damaged signal, the damage scattering signal is extracted as the input of the deep learning model. The model training is only based on the data of the first sub-area, and its generalization ability is evaluated through two test sets: one test set contains the random signals of the non-center location of the first sub-area, and the other test set comes from the random signals of the other three sub-areas. Then, the Inception module and BiLSTM is used to extract the multi-level and multi-scale features of the damage signal, which effectively captures the features of the signal, thus significantly improving the accuracy of damage location. Finally, two output branches are designed to realize the multi-task learning target model, which can predict the x and y coordinates of the damage location at the same time. The experimental results show that this method can accurately identify the damage at any location in the monitoring area. In the tests of different sub-areas, the model still shows good robustness and generalization ability, showing a certain application potential.

INTRODUCTION

Composite materials have been widely used in aerospace, transportation and other high-end equipment fields because of their excellent specific strength, specific stiffness and corrosion resistance. However, the laminated structure and anisotropic

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characteristics of composite materials make it easier to produce complex damage forms in the service process, such as delamination, interfacial debonding and impact damage, which seriously affects the safety and service life of the structure [1]. Especially in complex structures, the diversity of damage locations and sizes significantly increases the difficulty of damage detection. The distributed sensing damage detection based on Lamb wave has shown excellent long-distance propagation and multi-modal excitation ability in the health monitoring of composite structures, and has become a research hotspot in the field of nondestructive testing [2]. When Lamb wave propagates in the structure, it will show obvious scattering characteristics in the received signal [3,4]. However, in complex structures such as composite stiffened plates, due to the non-uniformity and anisotropy of ribs and the influence of boundary reflection effect, which brings great challenges to traditional signal processing methods [5,6].

In recent years, data-driven machine learning methods have been gradually applied to composite damage detection. Azad et al. [7] used Lamb wave and several deep learning models to simultaneously locate the damage and evaluate the severity of composite structures. Sikdar et al. [8] designed CNN architecture and used nonlinear ultrasonic signals to automatically evaluate breathing-like debonds in lightweight breathing-like deboning. Zhang et al. [9] used dense convolutional sparse encoded network to locate the damage in composite materials. Shang et al. [10] use CNN-LSTM hybrid model to decode ultrasonic guided waves used for damage detection and classify different types of defects in metal pipelines. Xu et al. [11] proposed a data-driven transfer learning model for locating damaged areas in plate structures.

In previous studies, there are often problems such as complex damage signal characteristics and limited model generalization ability in composite stiffened plates. Therefore, this paper proposes a damage location method based on Lamb wave and deep learning. The method is tested on a composite stiffened plate with two ribs. Firstly, the monitoring area is divided into four sub-areas, each sub-area is further subdivided into nine grids, and five kinds of signals with different damage sizes are collected at the center of each grid. Then, the difference between the baseline signal and the damaged signal is used to extract the damage scattering signal to highlight the damage characteristics. In the aspect of deep learning model, this paper adopts the multi-scale convolution network in the Inception module to realize the multi-scale and multi-level feature extraction of Lamb wave signals and fully mine the complex features of the signals. At the same time, the BiLSTM is introduced to strengthen the model's ability to improve the model's feature representation ability and modeling ability of complex scattered signals. To meet the needs of multi-task learning, the model designed two output branches to realize the synchronous prediction of x and y coordinates, respectively. The experimental results show that the proposed method can accurately identify the damage at any location in the monitoring area under the condition of training only based on the data of the first sub-area. Moreover, even in the test of non-training area, the model still shows good robustness and generalization ability, which fully proves the engineering application potential of this method in complex structural health monitoring.

METHODOLOGY

Experimental signal acquisition

The experimental object is a typical composite stiffened plate with a size of 500 mm × 500 mm and a thickness of 2 mm. There are two ribs (40 mm in width) on the back of the plate to simulate the common stiffened structure in engineering. The structure has obvious anisotropic characteristics, which easily leads to differences in the propagation characteristics of Lamb wave signals in different areas. Nine PZTs, numbered 1-9, are arranged on the surface of the composite stiffened plate, and the distance between the sensors is 13 mm. All PZTs are Φ8 mm×0.38 mm in size. In the experiment, there are six sensing paths (1-2, 1-3, 1-4, 2-3, 2-4, 3-4). The xperimental schematic diagram is shown in Figuer1. In order to explore the generalization ability of the proposed method in different areas and its adaptability to complex structures, two areas formed by ribs are selected from composite stiffened plates and divided into four sub-areas. Each sub-area is further subdivided into 9 small grids (36 grids in total). Taking area-1 as an example, the damage of different sizes is simulated by putty paste in each grid, and five different damage sizes are set, which are 15mm, 20mm, 25mm, 30mm and 35mm, respectively. In the experiment, a five-period sinusoidal pulse with a central frequency of 80 kHz is used as the excitation signal. The sampling frequency and number of points for data acquisition are set to 6 MHz and 2000, respectively. The time domain signal of each signal path is combined into a time series with the size of 12,000× 1 through six acquisition paths. Baseline signals and damage signals are collected at each damage location and then the damage scattering signal is obtained by differential operation, which will be used as the input of the subsequent neural network model.

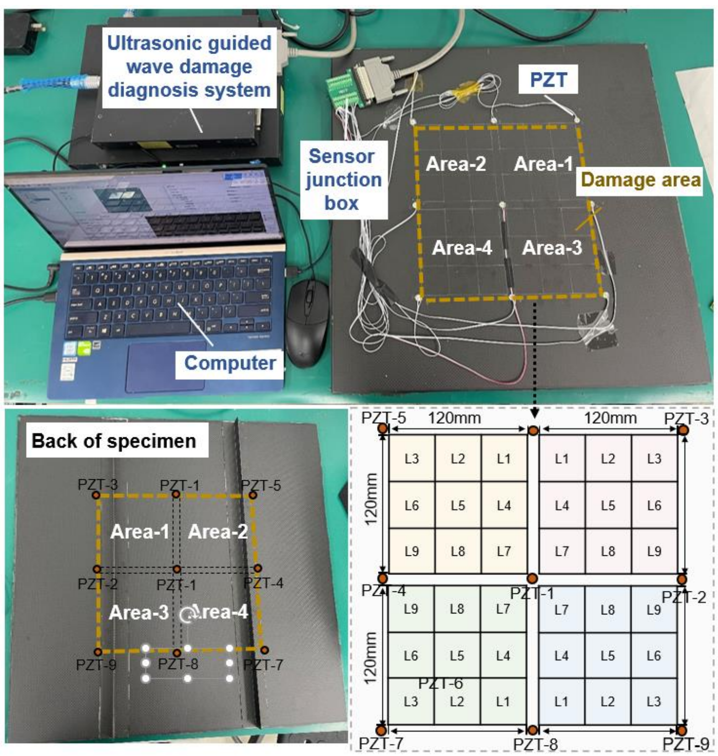
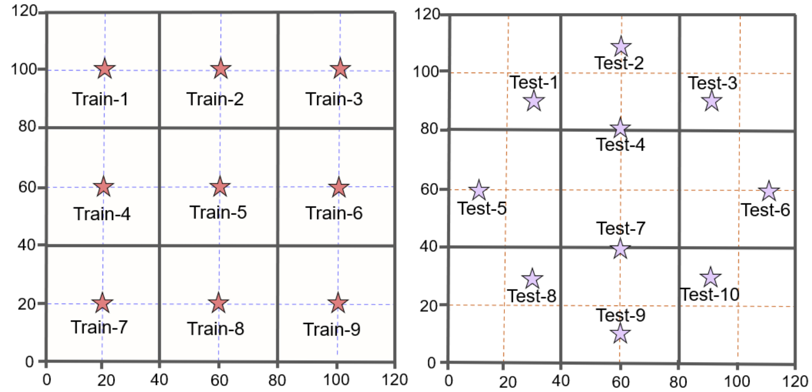


Figure1. Experimental schematic diagram.



(a) (b)

Figure2. Training and test set locations. (a) train set, (b) test set 1 and 2.

Data set construction

To verify the effectiveness and generalization performance of the proposed method, the experimental data are divided into a training set and two test sets.

1. Training set: 10 groups of signals are collected at each center location in the area-1, which covers all signals of 9 grids in the area under 5 damage sizes, and 450 samples are used for model training.

2. Test set 1: 10 non-center signal samples are randomly selected from the first sub-area as test set 1 to verify the generalization ability of the model in the known training area, and a total of 50 samples are used for model test.

3. Test set 2: 10 non-center signal samples are randomly selected from the other three sub-areas as test set 2 to evaluate the adaptability of the model in unknown areas, and each sub-area has 50 samples for model test.

Damage quantification based on deep learning

In this paper, a deep learning model combining the Inception module and BiLSTM model is constructed to predict the damage location, as shown in the Figure3. The model takes one-dimensional damage scattering signal (12,000×1) as input, and after a series of feature extraction and fully connected network, the *x* and *y* coordinate are output respectively. Firstly, the input signal passes through the Inception module to extract multi-scale features. Inception module extracts features of different scales through parallel convolution kernels (such as 1×1, 3×3 and 5×5), which can effectively capture possible local abrupt changes, high-frequency noise and large trend changes in Lamb wave signals [12]. After the Inception module, the model continues to introduce a convolution layer and max pooling layer, which parameter is (3,64) and 3, respectivly. The BiLSTM is especially suitable for capturing long-time dependent modes that may exist in Lamb wave signals [13], and its parameter is 16. After going through the flatten layer and the dropout layer (the parameter is 0.2), the model realizes the damage prediction of *x* and *y* coordinate through two independent fully connected branch networks. Each branch contains two layers of fully connected networks, the first layer is 32 neurons, and the second layer is 16 neurons, so as to fully extract features. Finally,

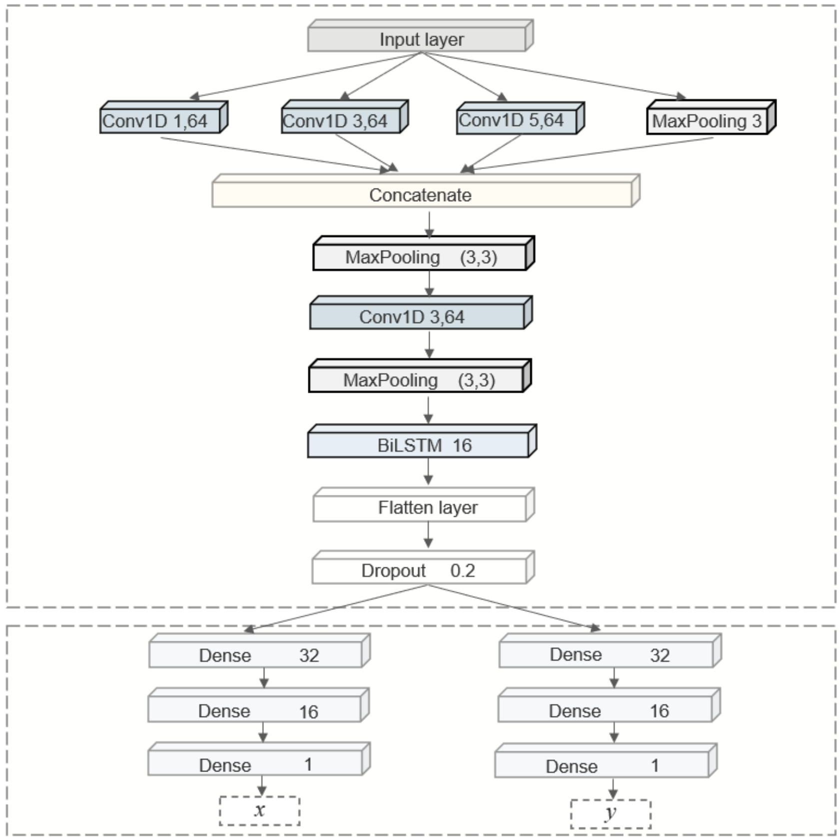


Figure3. Schematic diagram of deep learning model.

the output layer of each branch is a single neuron to output the corresponding damage parameters, namely *x* and *y* coordinate values.

RESULTS AND DISCUSSION

The prediction performance of the model is verified by test set 1. The waveform shape, time delay characteristics and amplitude distribution of the signal at the non-center location are different from the training data. This difference can effectively evaluate the spatial adaptability and robustness of the model.

The prediction results of test set 1 are shown in Table I. It can be seen that the average errors of *x* and *y* are 4.174mm and 4.911mm, the max errors of *x* and *y* are 15.464 mm and 13.738 mm. Considering that the training process only involves the data of the center location, this prediction accuracy shows that the model can be well generalized to the unknown location in the same area without serious prediction deviation.

Figure 4 shows the prediction results of test set 1. From box diagram on the left, the RMSE values of *x* and *y* at random locations are 5.15mm and 6.11mm. From the histogram on the right, the prediction error is approximately normal with 0 as the center. Therefore, for unknown samples different from the training set, the error level is within the acceptable range, indicating that the model still has good prediction performance in the random location scene.

TABLE I. PREDICTION ERROR OF TEST SET 1

Test set 2	**Prediction error**	***x*(mm)**	***y*(mm)**
Random location	Average error	4.174	4.911
	Max error	15.464	13.738

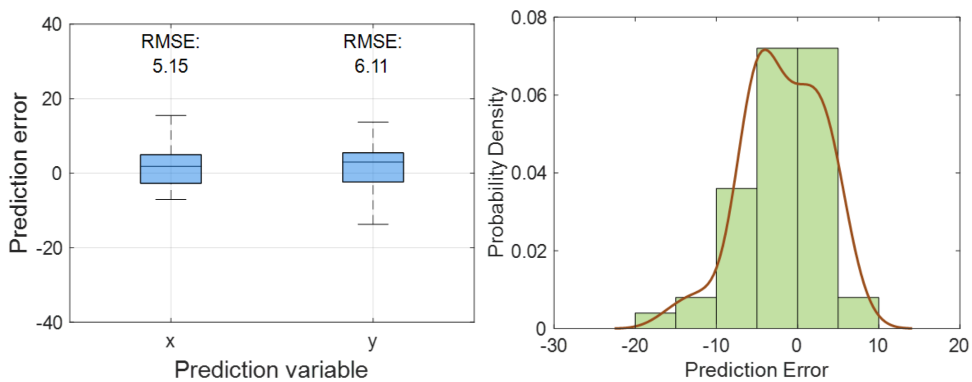


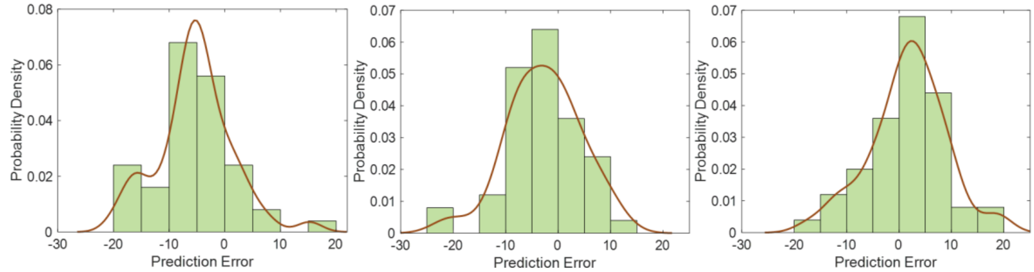
Figure4. The prediction results of test set 1.

The signal samples of test set 2 come from the random location in the other three sub-areas (area-2, area-3 and area-4) Therefore, the test set 2 examines the cross-area generalization ability of the model, especially whether the model can maintain high prediction accuracy when facing new signals that are quite different from the distribution of training data.

The prediction error of test set 2 at random location is shown in Table II. For random locations, the average errors of x and y are between 5.783-6.394 mm and 7.033-7.491 mm, respectively. The max error of x and y are 20.664 mm, 24.635 mm respectively. This shows that the prediction accuracy of the model is affected to some extent due to the change of signal mode in the random location of the new region, but this phenomenon conforms to the characteristics of training data distribution (only including the center location sample) and remains relatively stable in different regions, indicating that the model has certain cross-area adaptability.

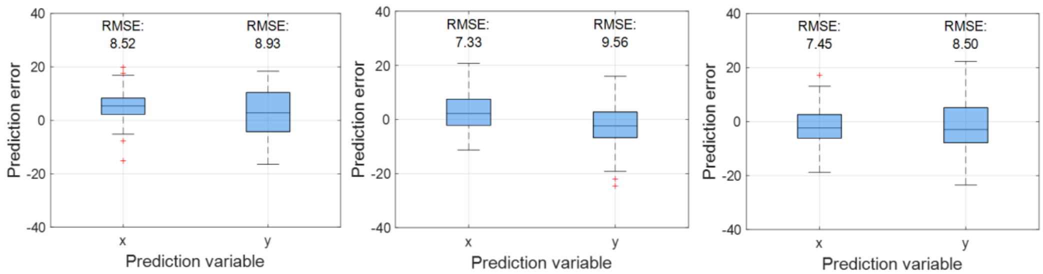
TABLE II. PREDICTION ERROR OF TEST SET 2

Test set 2	**Prediction error**	***x*(mm)**	***y*(mm)**
Area-2	Average error	6.934	7.491
	Max error	19.817	18.361
Area-3	Average error	5.783	7.342
	Max error	20.664	24.635
Area-4	Average error	5.787	7.033
	Max error	18.859	23.471



(a) (b) (c)

Figure5. The prediction results of test set 2. (a) area-2, (b) area-3, area-4.



(a) (b) (c)

Figure6. The prediction results of test set 2. (a) area-2, (b) area-3, area-4.

Figure 5 and Figure 6 show the prediction results of test set 2. The RMSE of x and y is within 10mm, and most of the damage prediction histogram display errors are still concentrated around 0, indicating that the deviation between most predicted values and real values is controllable. Therefore, the prediction error of the model is still at an acceptable level for the random location samples in the sub-area not covered by the training set, which verifies the generalization performance of the model in the multi-quadrant scene in the unknown area. Although the prediction difficulty increases, it has certain reliability.

CONCLUSION

A damage detection method of composite stiffened plate based on Lamb wave and deep learning is proposed, which can accurately locate the damage at any location in composite structure. The monitoring area is divided into several sub-areas, and the grid is further subdivided in each area to collect Lamb wave signals at multiple damage locations. Two different test sets are designed to comprehensively evaluate the prediction ability of the model. The multi-scale and multi-level feature extraction of Lamb wave signal by combining the Inception model and BiLSTM network can fully capture the time-frequency features of the signal, effectively improve the feature expression ability of complex scattered signals, and predict the x and y coordinate values of the damage location. The results show that the model can still maintain good prediction accuracy under the condition of different signal distributions in different domains, which shows that it has strong cross-area adaptability. It can adapt to the signal change of complex structure and maintain stable prediction performance.

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