Ultrasonic Guided Wave Damage Detection Method for Stiffened Plates Based on Deep Learning

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Abstract—In order to solve the problem of debonding damage detection commonly exists in stiffened plates, we propose an ultrasonic guided wave damage detection method based on deep learning and conduct a numerical study of the method. The guided wave signal get from a Finite-Element-Model (FEM) is pre-processed through wavelet transform to obtain the wavelet coefficient matrix (WCM), which is input into Convolutional Neural Network (CNN) in the form of gray image to obtain the neural weights. The detection accuracy of debonding damage in the stiffened plate has reached nearly 99%.

1. Introduction

In recent years, ultrasonic guided waves have been widely used in the structural health monitoring (SHM) of plate structure for the excellent performance of long propagation and less dissipation. With the development of guided wave detection technology, more and more researchers focus their attention on the complex structural plate, which is more suitable for practical application.

Stiffened panels are widely seen in industrial applications, however, it is difficult to analyze the propagation of waves. Fabrizio et al. [1] analyzed the propagation of guided waves in stiffened plate by simulation and experiment. By defining the stiffening factor, Li et al.[2] studied the gap between it and stiffened plate’s geometric shapes, which explains the influence of geometric shapes on the guided wave transmission characteristics. Based on the global local method, Steffen et al. [3] investigated the effects of multiple stiffeners on the guided wave propagation characteristics. They found that the guided wave has a strong sensitivity to the stiffened plate under appropriate excitation amplitude. They also proposed that the damage detection of stiffened plate structure can be carried out by abnormal wave packet in waveform diagram.

The above works are focused on the study of the propagation of guided waves in stiffened plates and the sensitive of guided waves to damage, but actually the damage detection of stiffened plates based on guided waves haven’t been solved yet. More importantly, with the huge demand for detection and massive
database generated by the Internet of things and Industry 4.0, a real-time and efficient ultrasonic guided wave detection method for stiffened plates is urgently needed.

Machine learning (ML) is a neural network algorithm for big data, which can learn the complex mapping relationship end-to-end through neural network model. Li et al.[4] extracted the damage features from different numerical methods, and then input the parameters into support vector machine (SVM) after fusion. Finally they realized the identification of different damage of engine stator. This method is a traditional ML method. Although the detection accuracy is improved, the process of extracting damage features manually is extremely time-consuming.

Compared with ML, deep learning (DL) has a deeper network structure, and can mine more complex mapping relations. Vincent et al.[5] proposed a self-learning model framework based on ultrasonic guided wave structural health monitoring, i.e., DeepSHM, and then realize the damage identification of different length. Yuan et al. [6] pointed out that most of the ML methods based on supervised learning are lack of robustness and universality, while the physical model and theoretical basis can make up for this deficiency.

The structure of this paper is as follows: The second section introduces the data-driven method based on physical model. The third section discusses the classification task, network framework and training process of DL model. The fourth section describes the test results and analysis of the convolutional neural network. The last is the summary and future work.

2. Data-driven Method Based on Physical Model
The proposed method consists of four steps. The first step is to analyze the propagation characteristics of Lamb waves in stiffened plate by numerical simulation, and obtain the transmission signal which contains damage information. Then, the abnormal packets in the waveform are transformed into two-dimensional image features including time-frequency information by numerical processing. Then the processed signal is expanded to establish a database. Finally, the neural network framework is trained and tested by database. The specific process is shown in Fig. 1.

![Fig. 1 Method framework flow chart.](image)

2.1. Excitation and Reception of Ultrasonic Guided Waves
In this section, FEM is used to simulate the transmission of guided wave in the stiffened plate. The geometric model of the stiffened plate is shown in Fig. 2. The base plate is an aluminum plate, the size is 360 mm*400 mm*2 mm, the Poisson's ratio is 0.33, the Young's modulus is 300 Gpa, and the density is 3900 kg/m³. The T-shaped stiffeners are uniformly distributed on the surface. T-stiffener is composed of two L-stiffener, with a size of 360 mm*25 mm*1 mm, as shown on the right side of Fig. 2.
In order to simplify the model, we only use the model of two stiffeners (A and B) for numerical study as a case, and consider the debonding damage in the stiffened plate as the detection object. The structure is shown in Fig. 2. During the simulation process, only the mechanical force is used for point excitation. The mechanical force is shown in Eq. (1). The excitation center frequency $f$ is 150 kHz, $t$ is the propagation time, $n = 5$ is the number of control wave peaks. The time-domain variation is shown on the left side of Fig. 3, and the frequency-domain variation after one-dimensional Fourier transform is shown on the right side of Fig. 3.

$$F(t) = \frac{a}{2} \left(1 - \frac{\cos(2\pi ft)}{n}\right)\sin(2\pi ft)(t \geq 0)(\frac{n}{f} \geq t)$$

Guided wave signals at different receiving points are various, the corresponding damage features are also inconsistent. Thus, a linear array method is used to receive the guided wave signals. The receiving methods of linear array mainly include horizontal and vertical, and the arrangement of specific receiving points is shown in Fig. 4. By taking 5 receiver points as examples, the guided wave signals obtained by the two receiving methods are compared, as shown in Fig. 5.
2.2. Preprocessing of Ultrasonic Guided Wave Signals

Continuous wavelet transform (CWT) method is selected to process the characteristics of the received signal intensively and efficiently, and then the wavelet coefficient matrix is derived in the form of gray image. The specific signal processing process is shown in Fig. 6.

![Fig. 6](image)

Fig. 6   Guided wave signal preprocessing process (a) Normalization; (b) Adding noise; (c) Wavelet transform; (d) Gray image of coefficient matrix.

2.3. Convolution Neural Network

Convolution neural network (CNN) is a typical deep learning network, which can be used to process data with grid topology (spatial sequence). Convolution is a linear commutative operation. For 2D signal (time-frequency 2D representation), convolution operation is shown in Eq. (2), while for 1D signal (Time Series), 1D-CNN output is shown in Eq. (3).

\[ S(i, j) = I * K = \sum_{m} \sum_{n} I(m, n)K(i - m, j - n) \]  

Where \( S(i, j) \) is the resulting feature graph, \( I(m, n) \) is the input image, and \( K(i - m, j - n) \) is the kernel.
\[
y_i' = f\left(b_i + \sum_{k=1}^{N} Conv1D\left(w_{ik}, S_i^{l-1}\right)\right)
\]  

(3)

Among these, \(y_i'\) is the input, \(b_i\) is the bias of the \(k\)-th neuron in the \(l\)-th layer, \(S_i^{l-1}\) is the output of the \(i\)-th neuron, and \(w_{ik}\) is the weight of the nuclear connection between the \(i\)-th neuron in the \(L-1\) layer and the \(k\)-th neuron in the \(L-1\) layer. \(f(\cdot)\) is the activation function, which can be ReLU, sigmoid, tanh, etc. The purpose of the training program is to find the best set of kernel functions and offsets to minimize the loss.

In this paper, the guided wave signal is one-dimensional time series signal, and the signal obtained by wavelet transform is a two-dimensional graphic signal containing time-frequency information. Therefore, a two-dimensional convolutional neural network is used for training.

3. Results And Discussion

3.1. Classification Tasks
For the case of two stiffeners, 5 groups of data were obtained through simulation, which were 0 mm (complete structure), B20 mm (debonding at B stiffener), A20 mm, A25 mm and A30 mm (debonding at A stiffener). Each set of data has 250 WCM images. On the basis of 5 sets of data, we design 3 tasks to realize guided wave damage detection of stiffened plates. The classification tasks and the composition of the data set are shown in Table 1.

| Table 1  | The classification TASK |
|----------|-------------------------|
| Task1    | 0 mm and 20 mm debonding |
| Task2    | 0 mm and 20 mm debonding(In A and B, respectively) |
| Task3    | 0 mm and 20 mm, 25 mm, 30 mm debonding(In A) |

3.2. Proposed CNN Architectures and Training Process
As is well known, CNN has two advantages: weight sharing and migration. In order to select and determine the applicable network framework, four network structures are established from simple to complex. The specific architecture is shown in Table 2.

| Table 2  | CNN Architecture |
|----------|-------------------|
| Net 1    | D(128)-D(16)-CL   |
| Net 2    | C(8)-MP-DO(0.5)-D(128)-DO(0.5)-CL |
| Net 3    | C(8)-MP-DO(0.5)-C(16)-MP-DO(0.5)-D(128)-DO(0.5)-CL |
| Net 4    | C(8)-MP-DO(0.5)-C(16)-MP-DO(0.5)-C(32)-MP-DO(0.5)-D(128)-DO(0.5)-D(16)-CL |

\(C(i)\): \(i\)-filter convolutional kernel; MP: MaxPooling layer; DO(\(j\)): dropout regularization with rate of \(j\); D(\(k\)): dense (fully-connected) layer with \(k\)-neurons, CL: Classification layer, typically a softmax function.

In order to prevent over fitting, the dropout technique is used to regularize each layer. 0.5 is chosen as default.

3.3. Training Process and Analysis for CNN
In this section, different data sets are used to train different neural networks. Before that, the dataset in each task is divided into training set and testing set according to the ratio of 7:3. Firstly, network 1 is trained by data sets of task 1 and task 2. Results show that the complex classification task requires a deeper network structure.

Next, network 3 and network 4 are used to learn the features of data sets in task 3, and the results are shown in Fig.7.
Both network 3 and network 4 perform well, but network 3 with fewer layers converges faster than network 4. So network 3 is more suitable for data sets in task 3 than network 4. So network 3 can realize the detection of damage degree, without the need of more complex structure.

3.4. Test Results and the Final CNN Framework

During the test, data representing different damage are randomly selected and input into the trained network. Results are shown in Fig. 8. It can be clearly seen that the trained network 3 can achieve nearly 99% damage detection, which shows that the network is applicable to the established dataset, and also proves that the proposed method can realize the detection of debonding in stiffened plates. Finally, the visual structure of the final network is shown in Fig. 9.
4. Summary and Prospect

In this paper, a method of ultrasonic guided wave damage detection for stiffened plates based on convolution neural network is proposed. We use database established by the gray images obtained by wavelet transform to train and test the CNN. Results show that the proposed method is feasible and efficient, which means the trained CNN can realize the damage detection of debonding in stiffened plates. This work overcomes some problems that are difficult to solve by traditional methods. Most importantly, it provides a feasible reference framework for the damage detection of composite materials.

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