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Fully convolutional network-based ultrasonic inversion for multi-layered bonded composites

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Abstract. Ultrasonic methods are widely used for the detection and characterisation of defects in multi-layered bonded composites. However, quantitative reconstruction of defects, such as disbonds, which can affect adhesive bond integrity and severely reduce the strength of assemblies, remains challenging. In this work, a supervised full convolutional network (FCN)-based ultrasonic method is used to quantitatively reconstruct defects hidden in multi-layered bonded composites. This proposed method consists of a training process and a predicting process. In the training process, the FCN builds a non-linear mapping from the ultrasound data to the corresponding longitudinal (L-wave) velocity model. In the predicting process, the network obtained from the training process is used to directly reconstruct the L-wave velocity models from the new measured ultrasonic data of adhesively bonded composites. The simulation results show that the FCN-based ultrasonic inversion method has the ability to achieve the accurate quantitative reconstruction of ultrasonic L-wave velocity models of the high contrast defects, which has potential in online detection of multi-layered bonded composites.

Introduction

Multi-layered bonded composites are widely used in aerospace, marine, nuclear and offshore industries due to their advantages of easy assembly, low manufacturing cost, and uniform distribution of mechanical loads resulting in reduced stress concentration [1]. However, decreased bond strength or defects may occur in composite materials due to external loads, various harsh environmental conditions or natural ageing [2]. Therefore, an accurate and efficient assessment of the bond quality is critical for structural integrity and reliability. Ultrasonic non-destructive evaluation methods have proven to be useful for assessing the health status of multi-layered bonded composites [3].

The detection of deep defects can be provided by ultrasonic bulk wave testing, which can be broadly divided into techniques applied in the time domain and the frequency domain [4]. For example, through-transmission and analysis of pulse-echo signals in the time domain [5], as well as the fundamental through thickness resonance frequency [6] have been used for detecting disbonds, albeit at a degree of quantitative assessment of the multi-layer structures. Nevertheless, when extended to the quantitative detection of disbonds and other defects, little work has been carried out to achieve quantitative reconstructions of these high contrast defects in adhesively bonded structures by building accurate ultrasonic velocity models.

There are two major groups of velocity model building techniques: exploiting the focusing properties of migration and using information like traveltime extracted from the data [7]. Many techniques in these two major groups may require either repeated application of the migration or

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time-consuming picking of traveltime information from the measured data [8]. Therefore, there is a need for a method that can surpass the accuracy of these conventional methods based on all the information contained in the measured data while avoiding computational complexity and inversion constraints.

Deep learning is a subset area of machine learning that has demonstrated the potential to alleviate these restrictions [9]. Deep learning can exploit all signal content in the data for predicting models, can offer computational advantages over traditional inversion methods, and does not depend on the reliability of the initial model [10]. In deep learning, the convolutional neural network (CNN) is one of the most commonly used frameworks among deep neural networks, which is capable of approximating nonlinear mapping from input to output [11]. CNNs enable image and label recognition and different types of data association, especially for inverse problems such as model/image reconstruction and image super-resolution [12]. This development opens up new perspectives for signal inversion and velocity model reconstruction, where some work has already made progress [13]. However, when using standard multilayer perceptrons in CNNs, i.e. fully-connected layers, CNNs are computationally expensive because of the large number of dimensions involved, and too many parameters in fully-connected layers slow down the training speed of the network [14]. Besides, conventional CNNs cannot well identify highly complex settings containing different backgrounds and a lot of overlap [15]. To address these issues, a fully convolutional network (FCN) is proposed to replace the fully-connected layers with only convolutional layers, which can better preserve the neighbourhood information in the pixel-wise outputs [16]. Furthermore, a modified FCN with an encoder-decoder structure can yield more precise predictions. It contains a contracting path for capturing the useful features and a symmetric expanding path for enabling precise localization or reconstruction, showing good performance in velocity model reconstruction.

In this work, we propose a new FCN-based encoder-decoder network that can directly reconstruct the ultrasonic longitudinal wave (L-wave) velocity models of multi-layered bonded composites containing high contrast defects from raw ultrasonic data [17]. The proposed FCN-based network can be utilised to approximate a nonlinear mapping from the full matrix capture (FMC) data (input) to the corresponding ultrasound L-wave velocity model (output) in the training process. In the predicting process, the trained network can be used to predict the unknown multi-layered bonded structures using the new measured FMC data. The remainder of this work is organized as follows. The FCN-based ultrasonic inversion method is introduced. Then, numerical models and results of adhesively bonded structures with various defects are presented. Finally, the conclusions are summarized.

FCN-based ultrasonic inversion method

The purpose of this work is to directly use the FMC data (input in the data domain) to reconstruct a 2D ultrasound L-wave velocity model (output in the model domain), and therefore the FCN-based ultrasonic inversion method is proposed. The basic idea of this method is to establish the non-linear mapping between input and output, which can be expressed as

$$\hat{\mathbf{v}} = Net(\mathbf{d};\boldsymbol{\Theta}), \tag{1}$$

where $\hat{\mathbf{v}}$ denotes the 2D predicted L-wave velocity models, and $\mathbf{d}$ is the measured ultrasonic FMC data. This method includes a training process and a predicting process, as shown in Fig. 1. Before training, the true L-wave velocity models of adhesively bonded composites with different defects (e.g., location and length) are randomly created and then the measured ultrasonic FMC signals are obtained from simulations.

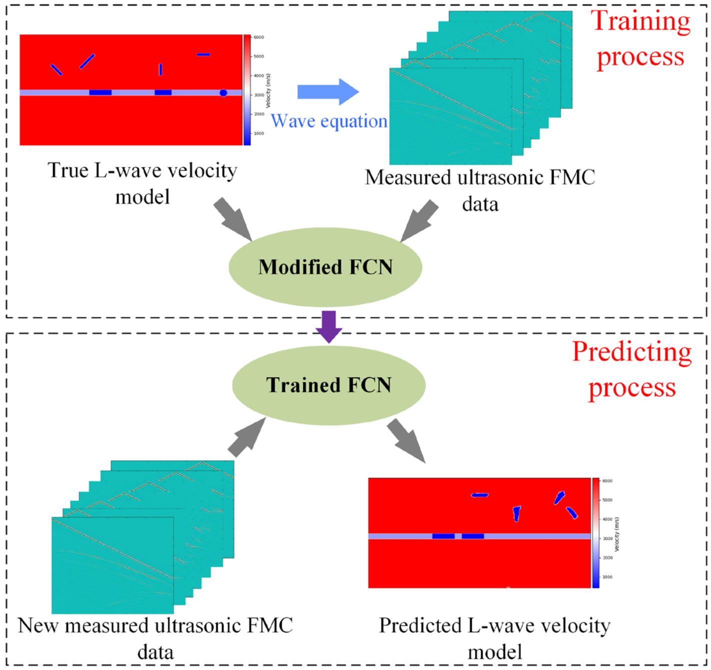

Figure 1. Structure of FCN-based ultrasonic inversion method.

To achieve the ultrasonic velocity model reconstruction directly from the measured ultrasonic FMC data, the proposed encoder-decoder architecture of the network has two major modifications compared to the conventional FCN architecture to match the linear phased array ultrasonic testing of multi-layered bonded composites. First, the ultrasonic FMC data instead of images is acquired as input, and the number of transmitters in each model is used as the number of channels for the input. Second, the input and output of traditional FCN are in the same image domain, while the proposed architecture is used to realize the domain transformation from the data domain to the model domain.

In the modified FCN structure, the process of extracting the feature maps from the input ultrasonic FMC data is a down-sampling process (encoder), as shown in Fig. 2. Taking the simulated FMC data of 2000×64×64 (sampling points × receivers × transmitters) as an example, the time step is $5e^{-9}$ s (i.e., the total time is $1e^{-5}$ s) in this work and this data contains 64 × 64 time traces. The feature map obtained by the convolutional operation has 64 channels and its dimension is 500 × 64 × 64. Then, the number of channels is doubled in each operation of the encoder path. After that, the feature map extracted by the encoder is enlarged by the corresponding decoder (up-sampling process). Finally, a cropping process is added after the last feature map to ensure that the output size is the same as the input size.

Materials Research Proceedings **27** (2023) 315-321
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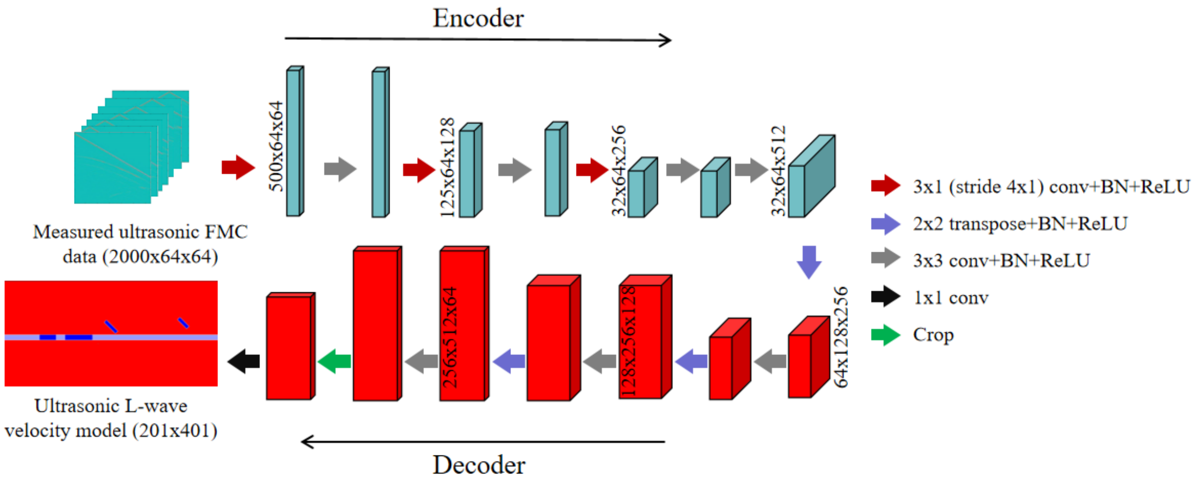

Figure 2. An illustration of the network architecture used in the FCN-based ultrasonic inversion method. Note that conv, BN and ReLU denote 2D convolution, batch normalization and Rectified Linear Unit, respectively; (2000×64×64) represents (sampling points × receivers × transmitters); (201×401) is the number of grids in the vertical and horizontal directions of the velocity models.

In the training process, the proposed network requires fitting a nonlinear function from the FMC data to the corresponding L-wave velocity model, so the network is constructed by solving an optimization problem:

$$\hat{\mathbf{\Theta}} = \arg\min_{\mathbf{\Theta}} \frac{1}{mN} \sum_{n=1}^{N} L(\mathbf{v}_{\mathrm{n}}, Net(\mathbf{d}_{\mathrm{n}};\mathbf{\Theta})), \tag{2}$$

where N is the number of training dataset and m represents the total number of pixels in one velocity model. The loss function L measures the difference between the predicted velocity models $\hat{\mathbf{v}}_{\mathrm{n}}$ and true velocity models $\mathbf{v}_{\mathrm{n}}$. In the modified FCN, L is set to $L(\mathbf{v}_{\mathrm{n}}, \hat{\mathbf{v}}_{\mathrm{n}}) = \sum(\beta \times (-\log(\mathbf{s})) \times |\mathbf{v}_{\mathrm{n}} - \hat{\mathbf{v}}_{\mathrm{n}}|)$, where $\mathbf{s}$ represents the matrix of pixel-wise probability. β is a user-defined weight matrix based on the matrix $\mathbf{s}$ to make a trade-off between different colours. $|\cdot|$ represents the absolute value. In this work, we use a small subset of the whole training dataset (i.e., the mini-batch size h) in each iteration to calculate L_h due to the relatively large number of the training dataset N. Then, Eq. (2) can be rewritten as

$$\hat{\mathbf{\Theta}} = \arg\min_{\mathbf{\Theta}} \frac{1}{mh} \sum_{n=1}^{h} L_h(\mathbf{v}_{\mathrm{n}}, Net(\mathbf{d}_{\mathrm{n}};\mathbf{\Theta})). \tag{3}$$

The small batches of the shuffled training data are sequentially processed to ensure one epoch e (i.e., single pass), which requires exactly one forward and one backward pass through all training data. In this work, the Adam algorithm is used to update learnable parameters to minimise the objective function:

$$\mathbf{\Theta}_{(\mathrm{e}+1)} = \mathbf{\Theta}_{(\mathrm{e})} - \alpha g(\frac{1}{mh} \nabla_{\mathbf{\Theta}} L_h(\mathbf{d}_{\mathrm{n}};\mathbf{\Theta};\mathbf{v}_{\mathrm{n}})), \tag{4}$$

where $g(\cdot)$ denotes a function and α is a positive learning rate. The gradient of L_h is calculated using the chain rule to find the derivative of the weights and biases of L_h.

Materials Research Proceedings **27** (2023) 315-321 https://doi.org/10.21741/9781644902455-41

In the predicting process, the unknown velocity models can be obtained from the new measured FMC data using the trained network. All computations described next are performed on a desktop workstation (GeForce GPU, Ubuntu operating system).

Numerical models and results

Data preparation. In this section, the data preparation, including ultrasonic L-wave velocity models of adhesively bonded composites, and modelling procedures for both training and testing datasets, is presented.

To train an efficient network for quantitatively reconstructing defects in multi-layered bonded composites, a relatively large number of ultrasonic velocity models are first randomly generated. The adhesively bonded models by bonding two metal layers with an epoxy resin adhesive layer are considered in this work. The configuration of the multi-layered composite is shown in Fig. 3. The dimensions of the top titanium layer, the bottom aluminum layer and the adhesive layer are 40 mm × 10 mm, 40 mm × 1 mm and 40 mm × 9 mm, respectively. Different notches are randomly generated in the top layer. Different sizes and locations of disbonds in the adhesive layer are also introduced. The simulated training dataset contains 3000 ultrasonic L-wave velocity models, and two typical velocity models are shown in Fig. 4. Ultrasonic L-wave velocities of aluminum, titanium, epoxy resin adhesive and air are 6235m/s, 6144m/s, 2100m/s, and 340m/s, respectively.

In this work, the implicit time-domain staggered-grid finite difference scheme using second-order in time and eighth-order in space is used to solve the acoustic wave equation. We use a grid spacing of 0.1 mm in both the x and z directions of the velocity model. This guarantees the calculation accuracy which requires at least four grid points per shortest wavelength. To avoid reflections coming from the left, right and bottom edges, the space domain is surrounded by perfectly matched layers. The input Ricker signal with a central frequency of 5 MHz is monitored by a linear phased array with 64 equally spaced elements (pitch of 0.6 mm) placed on the top surface of the model (see Fig. 3). Note that only the ultrasonic L-wave is excited and recorded, and shear-waves and mode conversions between L-waves and shear-waves are not considered here.

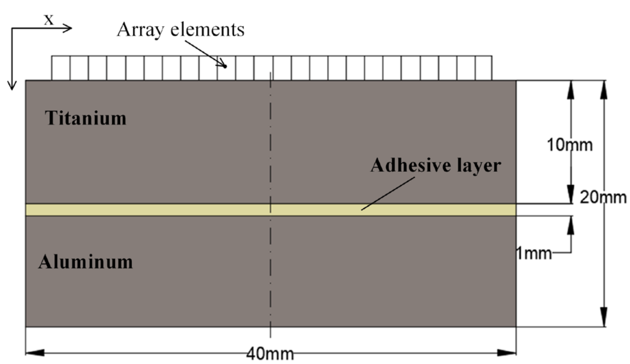

Figure 3. Configuration of multi-layered bonded composites.

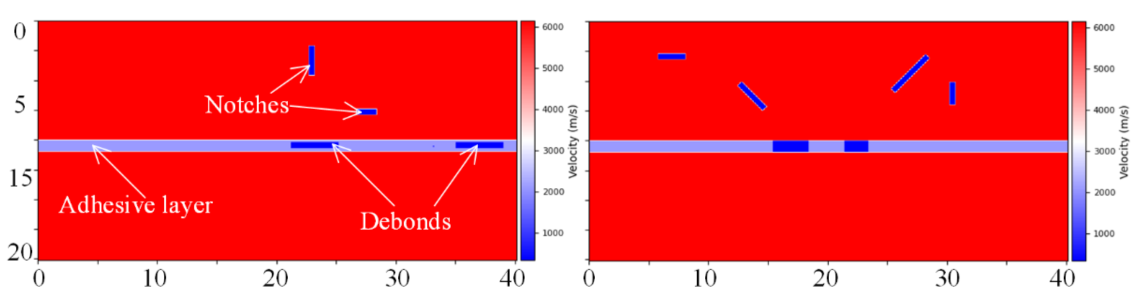

Figure 4. Representative ultrasonic L-wave velocity models. The unit in this figure is mm.

In the testing dataset, the ultrasonic L-wave velocity models have similar distributed structures as the examples in the training dataset because the FCN-based inversion method proposed in this work is a supervised learning method. Note that the test examples are not included in the training dataset and are therefore unknown in the predicting process. In this work, 10 examples are used to evaluate the proposed method.

Inversion results. In this section, the inversion is performed on the 1 mm-thick bonded composites. In the training process, the learning rate of the Adam is set as 10^{-3}, the number of epochs is chosen as 120, and the batch size is 10 [16,17]. After training, new ultrasonic FMC examples from the testing dataset are used to test the performance of the FCN-based ultrasonic inversion method.

Two representative true L-wave velocity models from the testing dataset are shown in Figs. 5(a) and 5(c), and Figs. 5(b) and 5(d) show the corresponding L-wave velocity reconstructions using the FCN-based ultrasonic inversion method. It is clear that high-quality quantitative images of the high velocity contrast are achieved with good reconstructions of the locations and the shapes of the defects. The sizes of notches and the disbond with a circular shape are slightly larger than the true velocity models. The possible reason could be that the spatial correspondence between features in the model domain and data domain is not considered in this work.

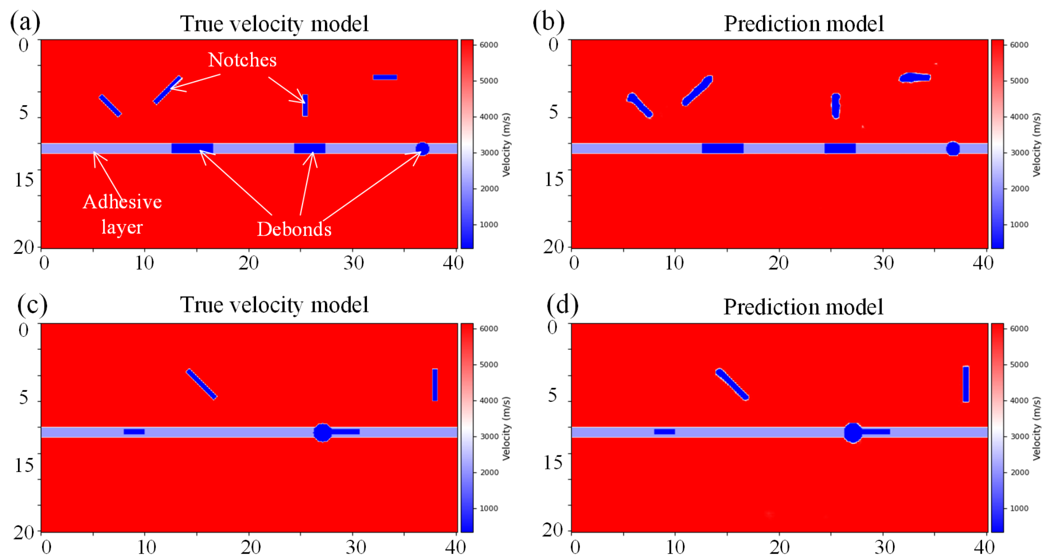

Figure 5. Reconstructions of L-wave velocity models based on the simulated data. Notches are contained in the top layer of titanium and the disbonds are hidden in the adhesive layer, as shown in the true L-wave velocity models of (a) and (c). (b) and (d) show the FCN-based ultrasonic inversion reconstruction. The unit in this figure is mm.

Conclusions

In this work, a supervised FCN-based ultrasonic inversion method is proposed for the quantitative reconstruction of multi-layered bonded composites. It utilises a network to directly transform ultrasonic FMC data into L-wave velocity reconstructions. The network obtained from the training process is then applied to reconstruct the L-wave velocity model of multilayer bonded composites from the test dataset. The performance of the proposed FCN-based inversion method is tested with the simulated data. The numerical results are in good agreement with the true velocity models.

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