Delamination Damage Detection of CFRP Composite Structures Using DSAN-based Deep Transfer Learning Approach

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ABSTRACT

Carbon fiber reinforced plastics (CFRP) is a kind of lightweight composite material widely used in aerospace. Since the progressive development of fatigue damage is complex and leads to potential safety risks in CFRP structures, structural health monitoring based on Lamb wave has been developed to track the growth of fatigue damages using a sensor network attached to the surface, which is experimentally intensive and expensive. To overcome the above challenges, a composite fatigue damage diagnosis method based on deep transfer learning is proposed to transfer the physical mechanism provided by numerical models to the diagnosis of real monitoring data. Firstly, numerical models of the composite structures are built to indicate the accumulation of fatigue damage during the full life cycle by introducing delamination between three sub-structures of cross-ply laminates. Then simulation signals with high fidelity are generated by virtual sensors and input into a data-driven diagnostic model with monitoring data. By aligning the data distribution of corresponding categories in simulation and experiment datasets respectively, the sub-domain adaptation is implemented and the physical mechanism provided by digital models is thereby fused with monitoring data. In this situation, the diagnostic model can still achieve more than 81% accuracy on a smaller training set, which performs better than conventional methods and significantly reduces the number of aging experiments.

INTRODUCTION

Carbon fiber reinforced plastic (CFRP) is a lightweight composite material with excellent mechanical properties, which is therefore widely used in the aerospace industry in the form of laminates [1]. Since the in-plane anisotropy of laminates leads to complex fatigue damage modes in composite structures, structural health monitoring (SHM) is developed to monitor internal damage by Lamb wave technology. Although the low scatter energy in long-distance propagation makes Lamb wave well suited for plate detection, its inherent frequency dispersion and multi-mode make it still challeng-

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ing to extract effective information for fatigue damage from monitoring signals [2].

Conventional damage detection methods based on physics usually concentrate on the wave packet of the S_0 and A_0 mode [3] which are normally obtained at the cut-off frequency, and define features to quantify the influence of defects on guided wave propagation. These features include amplitude attenuation, power spectral density change (ΔPSD), scattered energy, time of flight (ToF), phase shift, and so on [4, 5]. Taking the quantitative indexes of fatigue damage and these features as independent variables and dependent variables respectively, the damage index models [6, 7] can be established by statistical methods and output diagnosis results based on physical laws. These physical models work effectively in the lab with a controlled environment, but obtaining pure S_0 or A_0 mode wave packets from real-world structures for feature extraction is usually not feasible. In addition, it is also difficult to define a general damage feature or combination that is suitable for most ply orientations.

With the miniaturization design and implementation of sensor technology for SHM, it is quite convenient to acquire monitoring data for intelligent damage diagnosis and location using data-driven methods. Through manual feature engineering or automatic feature extraction, data-driven methods including machine learning (ML) models [8] and deep learning (DL) methods [9] can easily learn information related to defects from massive training data, although they may not have interpretability in the real world. These features not only include the damage indexes with physical meanings but also statistics calculated in the time domain, frequency domain and time-frequency domain of raw signals in most research [10, 11], such as skewness, kurtosis, divergence and so on. To improve the usability of features, correlation analysis is also applied to screen more important items, such as the Pearson correlation coefficient [12]. Whether ML or DL methods, their excellent performance requires a huge amount of training data support. However, due to cost and labor considerations, monitoring data obtained through experiments is usually limited and insufficient to train well-generalized models, especially the paucity of damage-related data.

To solve the above challenges, a deep transfer learning-based method is proposed to generate life cycle monitoring data of composite structures using finite element methods, which provide diagnostic-related knowledge for the diagnosis of real monitoring data. According to actual damage areas in X-rays, delamination damage is injected into models by dividing laminates into three sub-structures, where the propagation of Lamb wave is captured by sensors and output as simulation signals. Then, data from simulations and experiments are regarded as source and target domains by converting them into images. By aligning the distribution of the subdomains corresponding to each category, the subdomain adaptation is implemented to learn diagnostic knowledge from the source domain and then transfer it to the target domain. Based on the monitoring data provided by the accelerated aging experiment, a case study was carried out to verify its effectiveness.

The rest of the article is organized as follows. Section "METHODOLOGY'' presents the framework of the proposed diagnostic method, including the strategy for generating high-fidelity signals in the source domain and the mathematical principle of building a deep subdomain adaptation network for fatigue damage diagnosis in the target domain. The validation of the proposed method is provided in the section "CASE STUDY" where the technical details are shown. Finally, the conclusion and future work are summarized in the section "CONCLUSION".

METHODOLOGY

Based on deep transfer learning, a diagnostic method for fatigue damage of composite structures is proposed in this study, which aims to improve the resistance of pure data-driven model to the performance degradation caused by the lack of damage samples. This method consists of three modules, which are responsible for numerical simulation, automatic feature extraction and defects diagnosis and location. For the numerical simulation model, finite element models of CFRP laminates are established to generate the simulation data under different damage conditions. By introducing delamination defects with different locations and contours into the model, the run-to-failure monitoring data of structures can be obtained by virtual sensors in the numerical model. Then, these simulation data and experiment data are regarded as source domain and target domain respectively. The continuous wavelet transform (CWT) is applied to convert signals into time-frequency graphs as input of feature extraction module and a backbone network based on convolutional neural network (CNN) is constructed to learn feature representation from input data. Due to the inevitable discrepancies between the simulation model and physical entity, the obtained features are regarded as two domains with different data distributions, but holding certain similarities. Therefore, a deep subdomain adaptation network (DSAN) is adopted to leverage the similarity by aligning the distributions of sub-domains corresponding to each category. After the physical mechanism provided by finite element models is fused with experiment data by subdomain adaptation, a discriminative classifier can be learned to generalize well from simulation data to target domain experiment data. Finally, the performance of the fatigue damage diagnosis model is improved when the damage data for training is lacking.

Numerical Simulation of Lamb Wave Propagation in Delaminated Laminates

As shown in Figure 1(a), the active sensing system for Lamb wave propagation consists of pairs of actuators and sensors attached to CFRP laminates, which induce Lamb waves propagating in the substrate material and then receive them as output signals. According to the equations of motion of domains defined in Figure 1(a) and Gauss's law for electricity, governing partial differential equations of Lamb wave propagation in an active Lamb monitoring system is determined. And finite element method (FEM) is adopted to provide the approximate solution for structures in the baseline condition. Then simulated delamination inside the CFRP plate is introduced into the FEM models. For the selected composite sample with ply orientation shown in Figure 1(b), interfaces between +45 and -45 layers are proven [5] to induce delamination defects. Hence, the

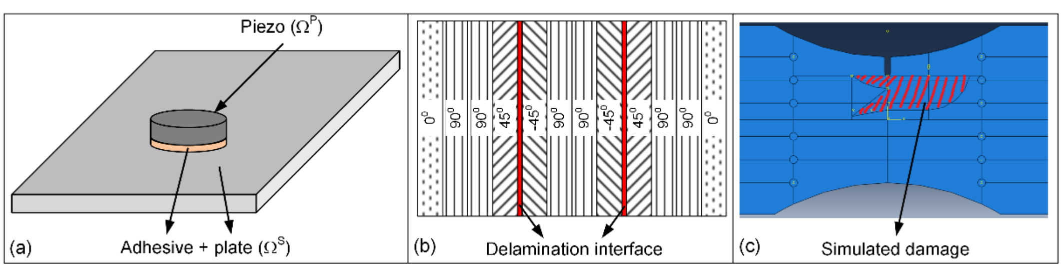

Figure 1. (a) Domain definition of the active sensing system. (b) The architecture of Layup 2 with delamination interface. (c) Simulated defects in the FEM model.

cross-ply structure simulated in the model is divided into three sub-structures by delamination interfaces, including the upper part [45/90$_2$/0], the mid part [-45/90$_2$/-45] and the bottom part [0/90$_2$/45]. In the baseline condition, these parts are bonded by tie constraint to form the entire laminate. Once a new delamination area is indicated in the X-ray images obtained with the experiment data, constraints on the corresponding interfaces in the model will be removed to simulate the growth of defects. By matching the simulated defects with experiment records, the finite element model can output simulation data containing any defect regions via virtual sensors and provide us with an additional simulation dataset containing sufficient monitoring data.

Fatigue Damage Diagnosis Based on Deep Transfer Learning

Since monitoring data from simulations and experiments are regarded as the source domain $= \{\mathbf{x}_i^s, y_i^s\}_{i=1}^{n_s}$ and target domain $= \{\mathbf{x}_j^t\}_{j=1}^{n_t}$ respectively, an end-to-end damage diagnosis model based on DSAN [13] is introduced to learn diagnostic knowledge from $\mathcal{D}_s$ and then transfer to $\mathcal{D}_t$. As shown in Figure 2, the feature extraction G_f and the defect classifier G_c form the DSAN. Raw signals are firstly converted into CWT graphs and then input into G_f using a backbone network based on ResNet-50 to indicate fatigue damages in $\mathcal{D}_s$ and $\mathcal{D}_t$, respectively. Then $G_f(x_i^s)$ and $G_f(x_j^t)$ are input into G_c made up of three fully connected layers to predict whether there are defects in sensor paths. The optimization goal for DSAN consists of the classification loss $Loss_{cls}^s$ and the domain adaptive loss $Loss_{DA}$, which can be formulated as:

$$\min_{G_f, G_c} \underbrace{\frac{1}{n_s}\sum_{i=1}^{n_s} J\left(G_f(\mathbf{x}_i^s), y_i^s\right)}_{Loss_{cls}^s} + \lambda \underbrace{\sum_{l\in L} \hat{d}_l(p,q)}_{Loss_{DA}} \tag{1}$$

where $J(\cdot,\cdot)$ is the classification error for $\mathcal{D}_s$ using a cross-entropy loss function and $\hat{d}_l(\cdot,\cdot)$ is the estimation of the discrepancy between distributions of $\mathcal{D}_s$ and $\mathcal{D}_t$ using the local maximum mean discrepancy (LMMD). λ denotes the trade-off hyperparameter tuned during the training. As a non-parametric distance estimate, LMMD further subdivides the global domain shift of $\mathcal{D}_s$ and $\mathcal{D}_t$ into the distribution discrepancy of

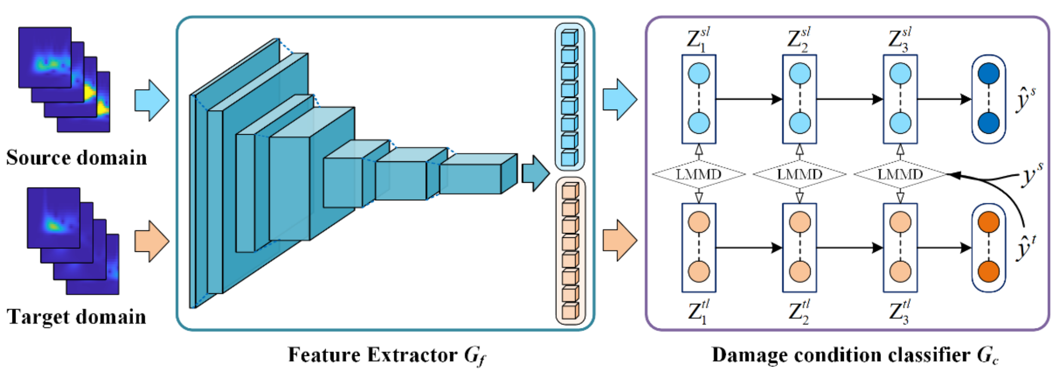

Figure 2. The architecture of the deep subdomain adaptation network.

corresponding subdomains to achieve more accurate domain adaptation. Specifically, given the input data sample $(\mathbf{x}_j, \mathbf{y}_j)$, its weight belonging to class c can be computed by$\omega_i^c = y_{ic}/\sum_{(\mathbf{x}_j,\mathbf{y}_j)\epsilon\mathcal{D}} y_{jc}$, where y_{ic} is the cth entry of label vector $\mathbf{y}_j$. Since training data of $\mathcal{D}_t$ is unlabeled, real labels $\mathbf{y}^s$ of $\mathcal{D}_s$ and prediction labels $\hat{\mathbf{y}}^t$of $\mathcal{D}_t$ are used to calculate ω_i^{sc} and ω_j^{tc}, respectively. Then the LMMD can be formulated as:

$$\begin{aligned}\hat{d}_l(p,q) = \quad & \frac{1}{C}\sum_{c=1}^{C}\left[\sum_{i=1}^{n_s}\sum_{j=1}^{n_s}\omega_i^{sc}\omega_j^{sc}k\left(\mathbf{z}_i^{sl},\mathbf{z}_j^{sl}\right)+\sum_{i=1}^{n_t}\sum_{j=1}^{n_t}\omega_i^{tc}\omega_j^{tc}k\left(\mathbf{z}_i^{tl},\mathbf{z}_j^{tl}\right)\right. \\ & \left.-2\sum_{i=1}^{n_s}\sum_{j=1}^{n_t}\omega_i^{sc}\omega_j^{tc}k\left(\mathbf{z}_i^{sl},\mathbf{z}_j^{tl}\right)\right]\end{aligned} \tag{2}$$

where $\mathbf{z}^l$ are the activations generated by lth layers in G_c and $k(\cdot,\cdot)$ is the inner product of vectors mapping raw samples to the reproducing kernel Hilbert space (RKHS).

CASE STUDY

The full-life monitoring data of CFRP laminates provided by accelerated aging experiments are leveraged to carry out a case study to validate the proposed approach [14]. Among the coupons laminated with three symmetric layup configurations, ply orientation of the Layup 2 ([0/90$_2$/45/-45/90]s) is the most complex and has been proven to reduce the diagnostic performance of pure data-driven methods. In addition, according to the experiment logs [14], sensors of some samples failed in the later stage of fatigue loading resulting in insufficient monitoring data for analysis, such as L2S18. Therefore, L2S18 was selected to discuss the generality of proposed method.

Run-to-Failure Simulation Data Generated by FEM

Based on the actuation frequency selected for data processing [9], actuators in FEM models use a 150kHz standard five-tone-burst signal as the electrical boundary conditions of top surfaces while the bottom of all PZT sensors is set to 0 V as the ground. To simulate the clamping constraint imposed by MTS on the coupons in experiments,

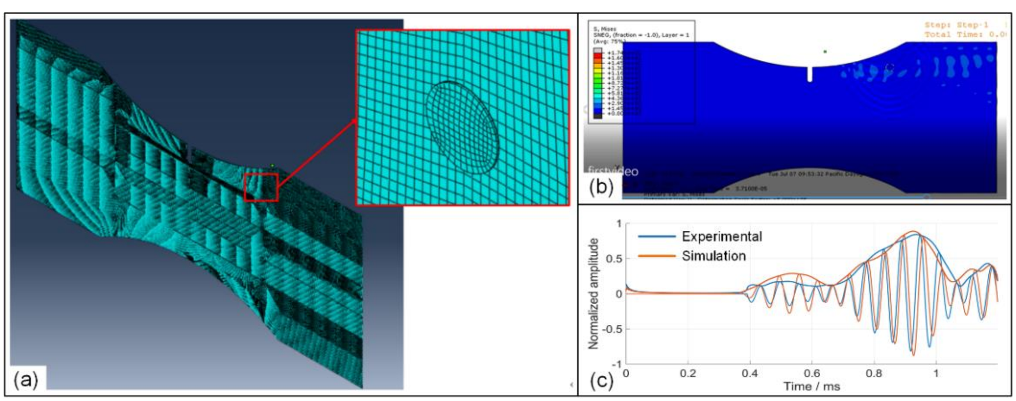

Figure 3. (a) The mesh in the FEM model. (b) Lamb wave propagation in CFRP laminates. (c) Comparison between simulation and experimental signals at the actuation frequency of 150 kHz.

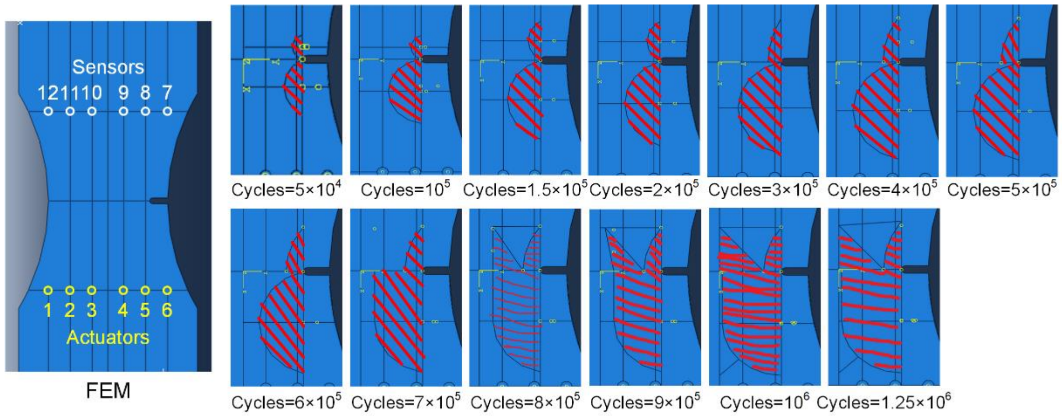

Figure 4. Simulated delamination area in laminates with the increase of loading cycles.

fixed mechanical boundary conditions were applied to both ends of laminates. As shown in Figure 3(a), the 4-node doubly curved thin shell elements, C3D8E elements and C3D8R elements were assigned to the laminates, PZT sensors and the adhesive layer, respectively. Since the wavelength of the fastest wave mode at an actuation frequency of 150 kHz is 0.03 m, the mesh size for the laminates, PZT sensors and adhesive layers were set to 0.8 mm, 0.5mm and 0.2 mm, respectively. Then, ABAQUS 6.12 is used to simulate the particle motion in the CFRP Laminate by providing a dynamic implicit analysis. As shown in Figure 3(b), Lamb waves are actuated at the location of the actuator and then propagate toward sensors. When these mechanical waves are captured by virtual sensors, they are converted into electrical signals through the converse piezoelectricity and output as a simulation result as shown in Figure 3(c). Compared with the real experimental signal, the simulation signal output by the FEM model matches well with the experiment data on the first wave packet representing the S_0 mode. In addition, their envelope lines can also be basically matched.

After matching FEM models with experimental signals in baseline condition, delamination is introduced to simulate the accumulation of fatigue defects under fatigue loadings. As shown in Figure 4, the fatigue delamination damage is induced at the notch and expands with the increase of loading cycles, whose outline is determined according to the ground truth in X-ray images. A total of 13 finite element models are built to generate simulation signals with loading cycles ranging from 5×10^4 to 1.25×10^6, which

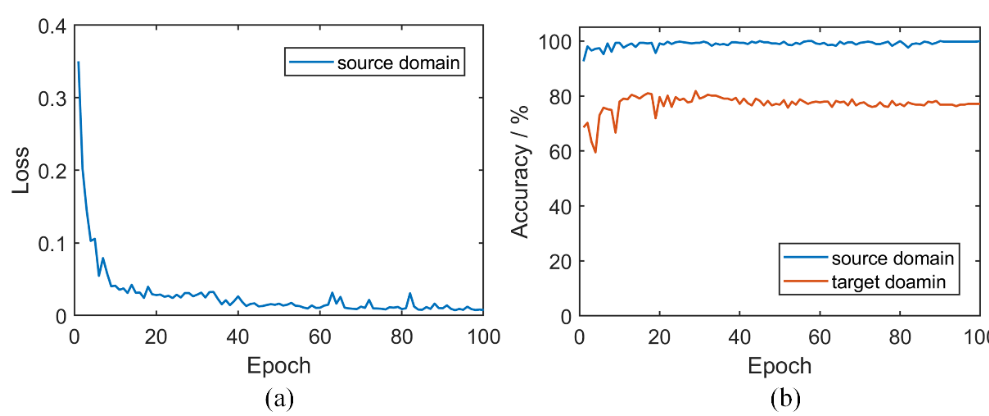

Figure 5. The training process of DSAN. (a) Training loss. (b) Accuracy curves.

provide us with new full life cycle monitoring data. Since sensor paths including path 5-7, 6-7, and 6-8 passing through the notch area, 33 Lamb signals were generated per model, except for channels 6-8.

Result of Fatigue Damage

Except for signals corresponding to path 5-7, 6-7 and 6-8 that pass through the notch area, all the Lamb signals obtained from experiments and simulation were converted into CWT images which constituted $\mathcal{D}_s$ and $\mathcal{D}_t$, respectively. To simulate the general process of using historical monitoring data in practical scenarios, transfer tasks based on existing experimental results were designed to diagnose fatigue delamination. Take T-C150k as an example, the training data includes all the labeled simulation data in $\mathcal{D}_s$ and 3×33 unlabeled signals in $\mathcal{D}_t$ corresponding to experiment data collected under 0, 5×10^4 and 10^5 cycles. Then, the remaining experiment data collected from 1.5×10^5 cycles are used to evaluate the diagnostic model as the testing set. The Resnet-50 was selected as the backbone to train the DSAN model shown in Figure 2 and the initial learning rate was set as 0.001 followed by a cosine decay strategy. As observed from Figure 5(b), the accuracy of the source domain is always close to 100% during the training process, which indicates the excellent feature extraction capability of the backbone network. As the decreasing of total loss, the accuracy of the target domain gradually increases and reaches its optimum at 30 epochs.

To further compare the conventional data-driven approach, DCNN was also trained with the same setup and their confusion matrixes for $\mathcal{D}_t$ is shown in Figure 6, where D indicates that sensor paths pass through the delamination area and are regarded as damage condition while H represents the opposite. Since the lack of training data, DCNN was unable to accurately classify data labeled as D, resulting in poor overall recognition performance. While DSAN learned better discriminant ability from a large amount of simulation data and transferred it to the classification of $\mathcal{D}_t$ by implementing subdomain adaptation. Hence, the proposed method achieves a performance improvement of more than 13% with limited training data. Finally, based on the condition of each sensor path output by DSAN, the localization method [9] that we have already proposed was used to identify the exact location of delamination defects. As shown in Figure 6(c), the area surrounded by white lines is the result of localization, which basically matches the real region of delamination shown in X-rays.

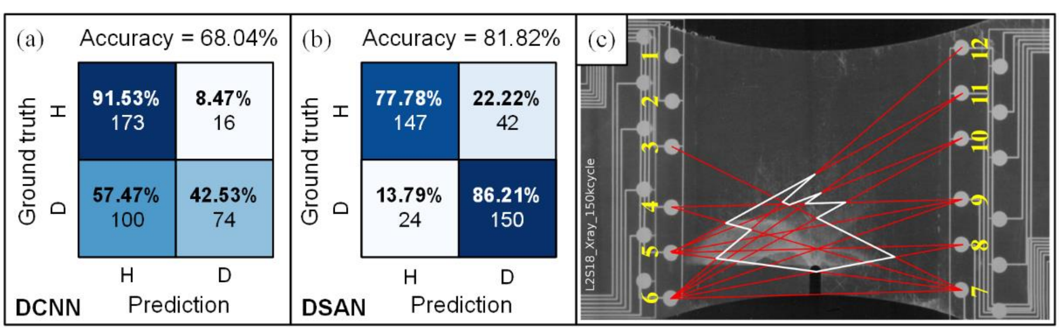

Figure 6. Confusion matrixes of transfer task T-C150k using (a) DCNN, (b) DSAN and (c) localization result of DSAN.

CONCLUSION

This study proposes a new fatigue damage diagnosis method using deep transfer learning, which requires only a small amount of unlabeled experiment data to achieve more than 81% accuracy. By dividing the laminated plate into three sub-structures, the delamination is introduced into the finite element model to simulate the accumulation of fatigue damage in CFRP laminates and generate the run-to-failure simulation data. Then, the DSAN model is constructed to learn diagnostic knowledge from large simulation data in volume and transfer it to the application of experiment data by aligning the distribution of subdomains. Monitoring data provided by accelerated aging experiments are used to implement the case study proving the proposed method to achieve a performance improvement of over 13% with limited training data. Future work will focus on improving the fidelity of simulation results and the accuracy of transfer learning models.

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