Meta-Transfer-Learning based Damage Detection of CFRP Composite Structures

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ABSTRACT

Applying data-driven approaches in damage detection of CFRP composites is becoming increasingly popular with the rapid development of deep learning methods. However, obtaining enough data for training these data-driven models is challenging, and the presence of imbalanced data can further exacerbate the problem. Moreover, due to the limited availability of CFRP data under various structural conditions, it is desirable to make the most use of the existing data or leverage the previously learned models. To handle these problems, we propose a transfer learning-based approach, which combines the benefits of transfer learning to overcome the challenges caused by limited data, and benefits of meta training to effectively train new models. Our experiments demonstrate the efficacy of this approach in identifying damage in CFRP.

INTRODUCTION

To automatically detect the localization of damage area, researchers have applied data-driven approaches [1,2,3,4] to identify the failure mode of inter-laminar delamination for Carbon Fiber Reinforced Plastics (CFRP). For instance, in a prior study [2], the path length across the damaged area was utilized as target. Then, damage area estimation was conducted using geometric relationships. The CWT-DCNN approach was developed [1] to facilitate damage localization in real-time. The proposed approach transforms Lamb wave signals into Continuous Wavelet Transform (CWT) representations. These representations are then inputted into a CNN for feature extraction and detection of potential damage along the corresponding path.

However, obtaining enough labeled data for model training can be a significant challenge. In machinery fault diagnosis, scholars employed deep generative adversarial networks (GAN) to produce new data and facilitate model training [5]. But training a

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GAN is notoriously hard and also requires sizeable data. To overcome this, in our study, few-shot transfer learning has been proposed [6], which enables models to learn new concepts from a few labeled data. It has been applied to various fields such as computer vision [7], natural language processing [8], and recommendation systems [9].

The integration of meta transfer learning into CWT-DCNN will be explored to localize the damage area and overcome those challenges mentioned above. We will focus primarily on the learning strategy and demonstrate its performances. The remainder of this paper starts with the Method of Approach. The details of combining few-shot meta transfer learning into CWT-DCNN is presented in Technical Details, and experimentally validated and investigated in the section of Experiment. We close the paper in the section of Conclusion.

METHOD OF APPROACH

This paper aims to train a model on an original dataset and then refine it using limited samples from a new dataset. This process leverages meta-learning, which can improve the efficiency of transfer learning by learning the hyperparameters.

Continuous Wavelet Transform (CWT)

Lamb wave damage detection is widely used for detecting structural failure by analyzing signals through feature extraction. However, the original wave signals are not suitable for deep learning. Therefore, we can turn to CWT, which is a multiresolution method that describes energy changes in images [10].

Residual Neural Network

To ensure the performance of basic model, we used a residual network [11].

Few-Shot Transfer Learning and Meta Learning

Few-shot transfer learning helps to adapt models to new tasks with limited data [12]. Meta-learning refers to the process of learning something that is typically not learned directly, like hyperparameters [13]. For instance, in training a neural network, we specify the number of layers, but does not know whether the selected hyperparameters are optimal. Thus, learning the hyperparameters is an instance of meta-learning.

Our approach leverages the benefits of transfer learning and meta-learning to enable neural networks to converge faster. "Transfer" means the ability to utilize the network's previously trained weights in new tasks through 2 operations: scaling and shifting (SS), i.e., $\alpha X + \beta$. "Meta" implies that SS can be observed as hyperparameters. This idea is the same as the MTL proposed by [14]. However, in contrast, our approach emphasizes binary classification rather than the identification of multiple classes.

Data Source

TABLE I. COUPON SPECIMENS

Layup type	Ply orientation	Coupon specimens
Layup 1	[02/904]	L1S11 L1S12 L1S18 and L1S19
Layup 2	[0/902/45/-45/90]	L2S11 L2S17 L2S18 and L2S20
Layup 3	[902/45/-45]2	L3S11 L3S13 L3S18 and L3S20

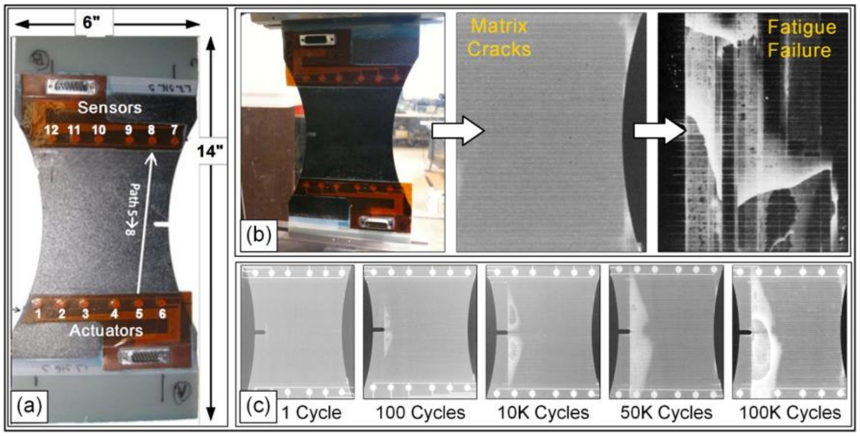

Figure 1. (a) Specimen with a PZT sensor array, (b) Investigation into the progression of fatigue damage resulting in fatigue failure, and (c) Increase in delamination as the number of cycles augmented [16].

The initial experiments were carried out by the SACL in partnership with the PCoE. To evaluate the material's endurance against fatigue-induced deterioration [15,16], accelerated aging tests were executed. And to examine the impact of the splint's orientation on the experimental outcomes, three ply structures were selected as Table I.

The setup for the experiment comprised of 36 transmission paths, with each specimen equipped with one actuation and one receiving PZT sensor array, as demonstrated in Figure 1. (a). The fatigue test applied cyclic load, resulting in the progressive development of damage, as illustrated in Figure 1. (b). Ground-truth data for the damage were acquired by conducting X-ray imaging on the specimen, as depicted in Figure 1. (c), and utilized to validate the analysis of measurement data.

The CWT-DCNN approach preprocesses the historical sensor signal data and converted them into CWT images in a unified format. Those labeled CWT graphs will be used directly in our approach.

TECHNICAL DETAILS

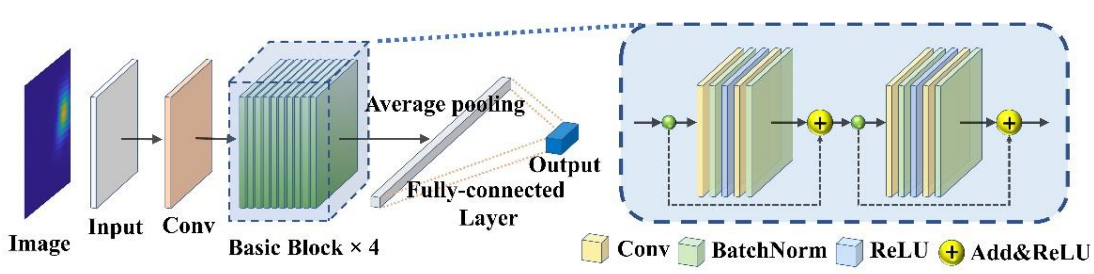

Figure 2. Structure of proposed neural network.

Our network consists of a feature extractor coupled with a meta-learner and a classifier, where Φ_{S1}(Scaling) and Φ_{S2}(Shifting) are used as hyperparameters for the meta-learner.

The network starts with a 3 × 3 kernel CONV layer, followed by 4 residual blocks and 4 CONV layers with 3 × 3 kernels in each block as shown in Figure 2. Following the completion of 4 blocks, the output feature maps undergo compression by using average pooling layer. The designs of Φ_{S1} and Φ_{S2} are based on the structure of Θ, which is the CONV core. Finally, the classifier θ is a fully connected FC layer that has the same structure as the pre-trained FC layer. To begin transfer learning, it is necessary to first train a basic model, also known as pre-training. We will initialize Θ and θ with random values and optimizing them through gradient descent.

$$[\Theta;\theta] =: [\Theta;\theta] - \alpha\nabla\mathcal{L}_{\mathcal{D}}([\Theta;\theta]) \tag{1}$$

$$\mathcal{L}_{\mathcal{D}}([\Theta;\theta]) = \frac{1}{|\mathcal{D}|}\sum_{(x,y)\in\mathcal{D}} l\left(f_{[\Theta;\theta]}(x), y\right) \tag{2}$$

which is cross-entropy loss, and α is learning rate. During pre-training, Θ will be learned and frozen in the following transfer learning as Figure 3. The classifier θ will be retained and not frozen. Meta-training and testing are sequential processes. Meta-training uses few-shot samples randomly selected from the target datasets, and meta-testing performs on the remaining samples.

Our approach is based on modifying the Scaling and Shifting (SS) meta operations introduced in previous research [14] rather than using the parameter-level Fine-Tuning (FT) employed by methods such as MAML [17]. Unlike FT, which updates all neuron parameters of CONV layers, SS reduces the parameters need to learn and avoid overfitting. Additionally, SS maintains the frozen large-scale trained parameters to prevent catastrophic forgetting [18,19]. Specifically, the SS operations Φ_{S1} and Φ_{S2} will not change the frozen neuron of Θ in learning, whereas FT updates the entire Θ. To elaborate on SS operations, we optimize classifier θ' with the loss of few-shot samples using gradient descent.

$$\theta' \leftarrow \theta - \beta\nabla_{\theta}\mathcal{L}_{\mathcal{T}(tr)}\left([\Theta;\theta], \Phi_{S_{1,2}}\right) \tag{3}$$

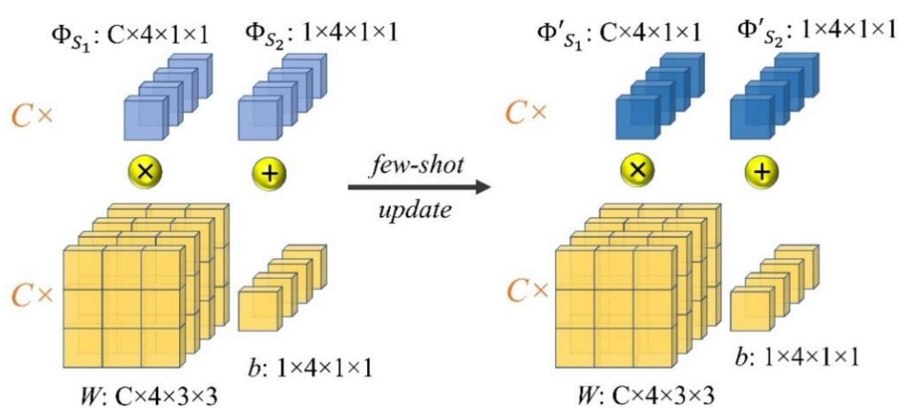

Figure 3. Difference between Fine-Tuning and Scaling & Shifting.

unlike Eq. (1), where Θ is not updated. We introduce θ' as a temporal classifier specifically designed for the current test after each learning. Its initialization is based on the optimized θ obtained during pre-training, which distinguishes it from the MTL method [14], where θ learned in the pre-training phase is forgotten. In our method, Φ_{S1} is initialized with values of 1, while Φ_{S1} is initialized with values of 0. Subsequently, they are optimized using the loss function.

$$\Phi'_{S_i} =: \Phi_{S_i} - \gamma \nabla_{\Phi_{S_i}} \mathcal{L}_{\mathcal{T}^{(te)}}\left([\Theta; \theta'], \Phi_{S_{1,2}}\right) \tag{4}$$

The application of $\Phi_{S\{1,2\}}$ to the frozen neurons is shown in Figure 3. The pre-trained parameter set, for a given layer, comprises K neurons. For a neuron, we have a pair of parameters consisting of weight and bias, represented as (Wi, bi), i=1,2. We apply the meta-learning process to learn K pairs of scalars, denoted as $\Phi_{S\{1,2\}}$, which are used to modify the parameters (W, b) given the input X.

$$SS\left(X; W, b; \Phi_{S_{1,2}}\right) = \left(W \odot \Phi_{S_1}\right)X + \left(b + \Phi_{S_2}\right) \tag{5}$$

where we use the symbol $\odot$ to represent element-wise multiplication. Figure 2 is an illustration performed on a 3 × 3 filter. Following SS operations, this filter undergoes scaling by Φ_{S1}. Additionally, the feature maps resulting from convolutions are shifted by Φ_{S2} in addition to the original bias b.

Moreover, the proposed approach offers more creative features compared to the MTL method: 1.the ratio of positive samples in each few-shot can be modified, and 2.the number of gradient descent iterations can be adjusted based on the sample's label in the few-shot. The experimental results suggest that these measures are effective.

EXPERIMENT

Overall Test Procedure

In experiments, we used the 3 datasets from loading experiments mentioned above. Because the Lamb wave data have already been transformed into CWT images, the "data" afterwards only refers to images.

Take Layup1 as an example, after the model being trained on Layp1, it was first be tested on data from other two Layups. Then, we selected few-shot samples from L2 and L3, and used the proposed method to meta-train the pre-trained model. Finally, we evaluated the meta-trained network's performance by using it to predict the label of the remaining data in L2 and L3, and recorded the results in confusion matrixes.

Data Selection and Parameter Setting

We selected specimen 11 from Layup1, specimen 18 from Layup2 and specimen 13 from Layup3 as our datasets. For base model learning, the dataset was divided into training, validation, and testing sets in a 7:1:2 ratio. The validation set was used to evaluate the model's accuracy and loss after each training epoch. We selected the model with the lowest loss as the final base model, and we used the testing set to evaluate its performance. The few-shot size was fixed to 18. The proportion of positive samples in the few-shot is adjustable, with experiments conducted using ratios of 1/3, 1/2, and 2/3. The experimental performances are presented by specimen as below.

Performances

MODEL TRAINED ON LAYUP1

Layup1specimen11 contains 957 records with 225 positive class data. The pre-testing results on L1S11 are as shown in Figure 1. (a).

For transfer to L2S18, the gradient descent cycle was 5 for both positive and negative samples. The ratio of positive few-shot samples is 1/3. Figure 1. (b) showed the performance tested before transfer on the same dataset as Figure 1. (c). The best performance obtained after repeating the transfer experiment 10 times is shown in Figure 1. (c).

The model showed decent performance on L2S18 even without transfer, indicating some similarity between L1S11 and L2S18. After transfer, the overall accuracy of the model increased by 8%, with positive class recognition accuracy increasing by 5% and negative by 10%. This result is satisfactory.

It is important to note that transfer learning heavily depends on the selection of few-shot data. Due to the unique characteristics of the dataset, particularly the lower data quality in L2 compared to other Layups, it is not always possible to obtain good and representative data by randomly selecting few-shot samples. Consequently, the model's performance on the new Layup may suffer from poor few-shot samples.

Next, we evaluate the transfer performance of L1S11 to L3S13 using the following configuration: 3 cycles of gradient descent for positive samples and 1 cycle for negative samples, with 1/2 positive samples in few-shot. After ten runs, the best result is obtained as Figure 1. (e). Figure 1. (d) showed the performance tested before transfer. Although the overall accuracy is acceptable, there are more incorrect identifications of positive samples than correct ones.

In comparison, the meta-trained model shows an overall accuracy improvement of 2%, with a 3% increase in accuracy for positive recognition and a 1% increase for negative. This improvement is not as significant as the transfer on L2S18, but it is still noteworthy. Further experiments or changes in parameters may yield better results.

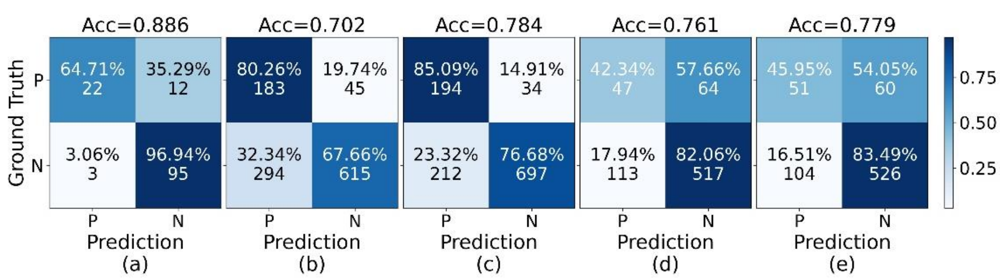

Figure 4. Performances of model pre-trained on L1.

MODEL TRAINED ON LAYUP2

The model trained on L2S18 and transferred to L1 or L3 produced unsatisfactory results that are not presented in this part, because L2 was incompletely recorded.

MODEL TRAINED ON LAYUP3

L3S13 contains 759 records with 120 positive class data. The pre-testing results on L3S13 are shown as Figure 4. (a).

For transfer to L1S11, the gradient descent cycle was set to 7 for positive samples and 4 for negative samples, respectively. The positive ratio of few-shot is 1/3. In Figure 4. (b), we can see that the performance before transfer is general, especially the base model is poor for the recognition of positive samples in L1S11. Then in Figure 4. (c), the accuracy of the model increased by about 7% after transfer, with a 23% increase in positive accuracy and a 3% increase in negative.

For transfer to L2S18, the gradient descent cycle was set to 5 for both positive and negative samples. The ratio of positive samples in few-shot is 1/3. After transfer, the obtained results reveal an overall accuracy improvement of approximately 7% as shown in Figure 4. (e). The recognition accuracy of positive samples increased by about 27% compared with the results before transfer as Figure 4. (d), while the accuracy of negative ones increased by 2%. These findings are considered satisfactory, particularly with the significant improvement in recognizing positive samples.

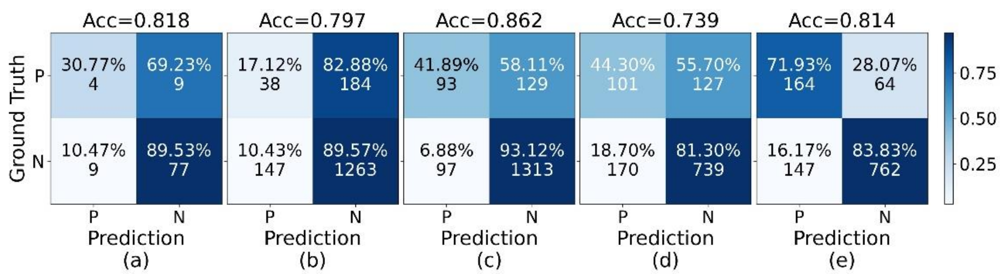

Figure 4. Performances of model pre-trained on L3.

CONCLUSION

In our experiments, we observed that using the better recorded L1 and L3 specimens as the base model training data yielded more satisfactory results, while training the base model with L2 did not perform well. This highlights the importance of having a suitable dataset for transfer learning, whether it is a general transfer learning scenario or our proposed few-shot meta transfer learning. The dataset must have enough samples, a relative balanced ratio of positive and negative samples, and be representative enough. In our context, L2 was incompletely recorded compared to L1S11 and L3S13, resulting in poor experimental results.

Our study successfully combined few-shot learning with meta transfer learning for damage detection of CFRP. While good randomly selected data is important for transfer learning, we demonstrated through experiments that our proposed method is effective.

In the future, we could explore more suitable datasets for transfer experiments and apply this method to damage monitoring of other materials and structures.

REFERENCE

1. Wu, Jun, et al. "Lamb wave-based damage detection of composite structures using deep convolutional neural network and continuous wavelet transform." *Composite Structures* 276 (2021): 114590.
2. Liu, Huan, et al. "Data-driven approaches for characterization of delamination damage in composite materials." *IEEE Transactions on Industrial Electronics* 68.3 (2020): 2532-2542.
3. Yue, Nan, and M. H. Aliabadi. "A scalable data-driven approach to temperature baseline reconstruction for guided wave structural health monitoring of anisotropic carbon-fibre-reinforced polymer structures." *Structural Health Monitoring* 19.5 (2020): 1487-1506.
4. Su, Chenhui, et al. "Improved damage localization and quantification of CFRP using Lamb waves and convolution neural network." *IEEE Sensors Journal* 19.14 (2019): 5784-5791.
5. Zhang, Wei, et al. "Machinery fault diagnosis with imbalanced data using deep generative adversarial networks." *Measurement* 152 (2020): 107377.
6. Wang, Yaqing, et al. "Generalizing from a few examples: A survey on few-shot learning." *ACM computing surveys (csur)* 53.3 (2020): 1-34.
7. Koch, Gregory, Richard Zemel, and Ruslan Salakhutdinov. "Siamese neural networks for one-shot image recognition." *ICML deep learning workshop*. Vol. 2. No. 1. 2015.
8. Bansal, Trapit, Rishikesh Jha, and Andrew McCallum. "Learning to few-shot learn across diverse natural language classification tasks." *arXiv preprint arXiv*:1911.03863 (2019).
9. Zhang, Yin, et al. "A model of two tales: Dual transfer learning framework for improved long-tail item recommendation." *Proceedings of the web conference 2021*. 2021.
10. Chen, Zuoyi, et al. "Sensor data-driven structural damage detection based on deep convolutional neural networks and continuous wavelet transform." *Applied Intelligence* 51 (2021): 5598-5609.
11. He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.
12. Zhang, Chuxu, et al. "Few-shot learning on graphs: A survey." *arXiv preprint arXiv*:2203.09308 (2022).
13. Zhou, Fengwei, Bin Wu, and Zhenguo Li. "Deep meta-learning: Learning to learn in the concept space." *arXiv preprint arXiv*:1802.03596 (2018).
14. Sun, Qianru, et al. "Meta-transfer learning for few-shot learning." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019.
15. Saxena A, Goebel K, Larrosa CC, Janapati V, Roy S, Chang F-K. Accelerated Aging Experiments for Prognostics of Damage Growth in Composite Materials. In Proceedings of the 8th International Workshop on Structural Health Monitoring. 2011;1:1139-1149.
16. Saxena A, Goebel K, Larrosa CC, Chang F-K. CFRP Composites Data Set. NASA Ames Prognostics Data Repository (https://ti.arc.nasa.gov/tech/dash/group s/pcoe/prognostic-data-repository/), NASA Ames Research Center, Moffett Field, CA. 2011.
17. Finn, Chelsea, Pieter Abbeel, and Sergey Levine. "Model-agnostic meta-learning for fast adaptation of deep networks." *International conference on machine learning*. PMLR, 2017.
18. Lopez-Paz, David, and Marc'Aurelio Ranzato. "Gradient episodic memory for continual learning." *Advances in neural information processing systems* 30 (2017).
19. McCloskey, Michael, and Neal J. Cohen. "Catastrophic interference in connectionist networks: The sequential learning problem." *Psychology of learning and motivation*. Vol. 24. Academic Press, 1989. 109-165.