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Computer Vision-Based Deep Learning Approach for Automated Delamination Detection and Classification in Carbon Fiber-Reinforced Polymer Composites

Paulo Monteiro Carvalho Monson[a], Pedro Oliveira Conceição Junior[a,*], Alessandro Roger Rodrigues[b], Fabio Romano Lofrano Dotto[a]

[a] *Department of Electrical and Computer Engineering, São Carlos School of Engineering, EESC/USP, Av. Trabalhador São Carlense 400, São Carlos, 13566-590, SP, Brazil*

[b] *Department of Mechanical Engineering, São Carlos School of Engineering, EESC/USP, Av. Trabalhador São Carlense 400, São Carlos, 13566-590, SP, Brazil*

* Corresponding author. *E-mail address:* pedro.oliveiracjr@usp.br

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Abstract

To ensure the structural reliability and safety of carbon fiber-reinforced polymer (CFRP) materials, the detection and classification of delamination are crucial. Therefore, this study proposes a novel approach for classifying delamination areas in CFRP samples based on computer vision-based deep learning algorithms. The proposed approach utilized signals acquired by piezoelectric transducers fixed in the inspected structure using the Lamb wave transmission-reception method. The methodology involved detecting delamination induced by fatigue loading in CFRP samples and classifying it through segmented regions. The dataset was divided into two classes based on damage levels: D1 (up to 10 cm²) and D2 (above 10 cm²). Time-frequency representations were generated the class imbalance was addressed with random oversampling. The EfficientNet architecture was employed for classifier development, achieving an accuracy of 83.33% and an area under curve (AUC) of 0.94, demonstrating feasibility in CFRP damage classification.

Keywords: CFRP, composite materials; computer vision; convolutional neural networks; damage detection; pattern recognition;

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1. Introduction

Detecting and classifying delamination in carbon fiber-reinforced polymer (CFRP) is crucial for ensuring structural reliability and safety. Non-destructive testing (NDT) methods based on acoustic emission (AE) offer valuable means for monitoring composite structures for damage. Likewise, recent advancements in computer vision and artificial intelligence have opened new possibilities for mitigating potential failures in CFRP. Deep learning algorithms, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in image recognition tasks, making them promising for delamination detection and classification. A delamination detection framework for an imbalanced dataset in laminated composites using a Wasserstein Generative Adversarial Network (WGAN) is presented in the study [1]. The framework combines adaptive synthetic sampling, system identification, and a one-dimensional convolutional neural network (1D-CNN) to diagnose faults in composite materials. Moreover, the reference [2] proposes the use of the Inception Time model, in combination with AE data to classify delamination in composite materials. The model achieves high classification accuracy for both raw AE time series and frequency-domain sequence data.

Furthermore, the study proposed by Deng et al. [3] focuses on the classification of barely visible impact damage (BVID) in composite laminates through a tailored deep-learning approach to characterize impact damage in CFRP laminates and pulsed thermographic inspections. The framework aims to learn features automatically for better classification accuracy and to

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improve the transparency of the produced models. Similarly, Wei et al. [4] discuss a deep learning method for the impact damage segmentation of curve-shaped CFRP specimens inspected by infrared thermography. Satisfactory results are achieved using a deep neural network trained for each wavelength. In addition, Cristiani et al. [5] present a strain-based delamination prediction in fatigue-loaded CFRP coupons using a deep-learning neural network, demonstrating the potential of structural vibration-based classification and prediction of delamination in smart composite laminates. On the other hand, Biagini et al. [6] integrate echo-pulse and through-thickness transmission ultrasonic scan inspections with acoustic emission monitoring to challenge the notion of a plateau phase and highlight the progressive nature of damage accumulation in fatigue tests in CFPR composites. Lastly, Batista et al. [7] contribute insights into the reduction of delamination in CFRP during drilling processes through the application of cryogenic cooling, which minimizes delamination at hole exits.

Despite the progress made in delamination detection techniques, several gaps and challenges remain in the field, especially in real-world scenarios with complex damage patterns and environmental variations regarding detection but also classify different levels of delamination based on its growth or segmented area. In a comprehensive study conducted by Paixao et al [8], for instance, the authors proposed an approach employing Gaussian Process Regression (GPR) for interpolation of global damage indices and Autoregressive (AR) model identification of Lamb wave signals for feature extraction, thereby enabling delamination area classification. In light of the previous study, this research is an initial and feasibility study that aims to integrate a time-frequency representation based on the Wigner-Ville distribution (WVD) with a computer vision-based deep learning approach for identifying and classifying delamination regions in CFRP composites. The study employed a CNN based on the EfficientNet architecture, fine-tuned on time-series images derived from a comprehensive dataset of fatigue tests conducted on CFRP samples with varying delamination sizes thus contributing to the advancement of damage detection and classification in composite materials.

2. Experimental Analysis

a) *Experimental tests*

An experimental analysis was conducted to investigate the classification of delamination areas in carbon fiber-reinforced polymer (CFRP) samples. Piezoelectric signals for CFRP test specimens were obtained from the NASA Ames prognostics data repository, as detailed in Saxena et al [9]. Torayca T700G uni-directional carbon-prepreg material was utilized for the specimens. PZT-sensor SMART Layer® systems from Acellent Technologies, Inc., were employed for monitoring wave propagation through the samples. Specimens with a layer configuration referred to as Layup 1 were utilized. A total of 48 X-ray images from three different CFRP specimens (L1S11, L1S12, and L1S19) were analyzed to assess delamination progression as a function of fatigue cycles. Using ImageJ software, damaged regions were segmented, and the delamination area of each sample was calculated (Figure 1).

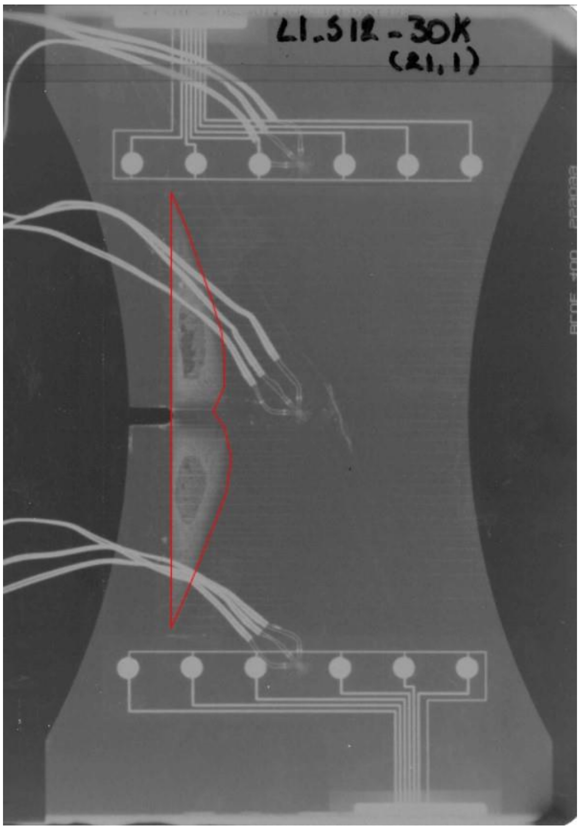

Fig. 1. Delaminated region segmentation
Adapted from "CFRP composites dataset" (Saxena et al. [9])

b) *Proposed methodology for delamination area classification*

The dataset was divided into two classes based on the levels of delamination: D1 (up to 10 cm^2) and D2 (above 10 cm^2). The time-domain signals from the damage inspection using Lamb waves to generate the time-frequency representations are shown in Figure 2. The proposed study lies in the integration of time-frequency analysis with deep learning techniques for delamination detection in CFRP composites. The signals in time-domain Time-frequency representations of the signals were generated using the WVD, which is a powerful signal processing technique that provides time-frequency representations, offering a more comprehensive insight into its spectral content over time [10],[11].

The proposed approach involves integrating the time-frequency information provided by the WVD into computer vision-based techniques for delamination detection. This integration enables the extraction of representative features from signals acquired by piezoelectric sensors, allowing the detection of variations in frequency and amplitude associated with delamination events, and providing valuable insights into the structural integrity of CFRP composites.

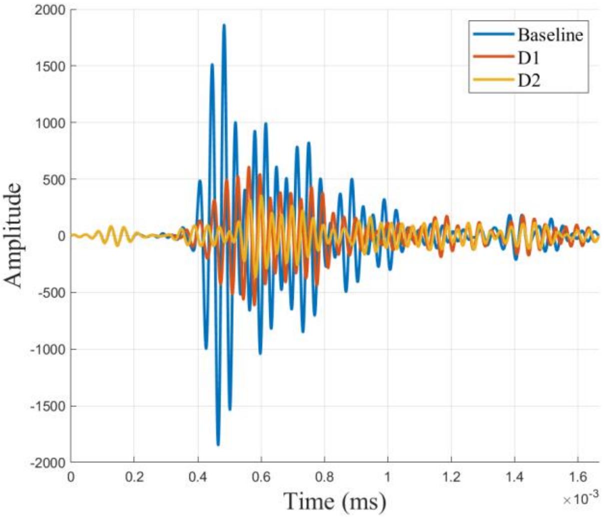

Fig 2. Time-domain signal for D1 and D2 conditions

The samples were then partitioned into different sets for model training and testing. A computational vision model was trained using the EfficientNet architecture available in the MATLAB R2022b Deep Learning toolbox. The employment of deep learning, specifically the EfficientNet architecture, is supported by the literature, which highlights the effectiveness of deep learning techniques in balancing the capability of extracting features from different levels and the computational cost [12]. The training was conducted using an NVIDIA RTX 3060 GPU, with a training time of approximately 15 minutes. The performance of the trained classifier was evaluated using metrics such as accuracy, precision, and the ROC curve. The ROC curve represents the measures of the false positive rate and true positive rate. The performance of a binary classifier can be plotted on this curve, equivalent to a point in two-dimensional space, where the diagonal line represents classifiers that make random predictions, and any result below this line can be considered worse than a random classification. When the value approaches 1 for the area on the curve, it represents an optimal classifier.

3. Results and Discussions

Figure 3 illustrates the key results of the proposed study. The EfficientNet architecture was employed for classifier development, trained using the generated time-frequency representations. The trained classifier achieved an accuracy of 83.33% on a test set comprising 12 samples from each class. Additionally, the classifier exhibited an AUC of 0.94, with a macro-average precision of 0.86.

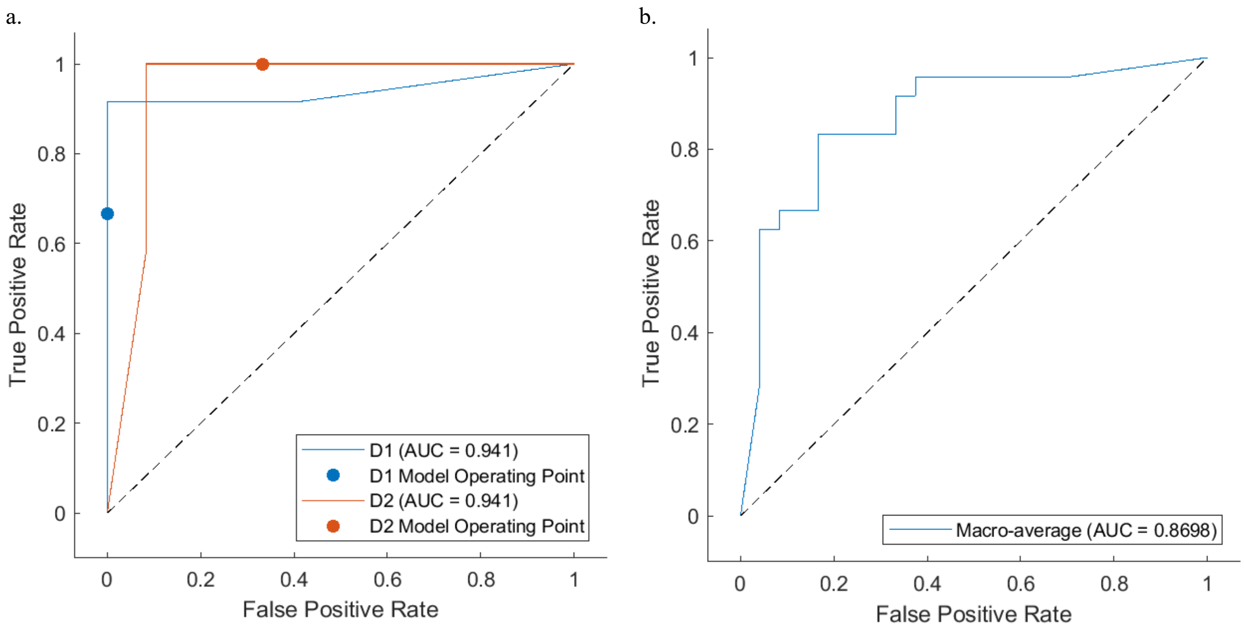

Fig. 3. ROC curves of the classifier.

In Figure 3a, the Receiver Operating Characteristic (ROC) curves illustrate the performance of a classification model in identifying delamination in the D1 and D2 damage regions. The steep rise of the ROC curve towards the upper-left corner indicates a high true positive rate for a relatively low false positive rate for both damage conditions D1 and D2. The results indicate that the model has accurate capability to identify and classify delamination, further supported by an AUC of 0.94 with few cases mistakenly classified (false positives). Figure 3b represents the macro-average AUC for both damage regions (D1 and D2), the curve reflects the average true positive and false positive rates for the entire classification model. The macro-average AUC provides a general measure of the model's ability to distinguish between classes across the entire dataset. A macro-average AUC of 0.86 suggests that the model has a robust performance in classifying damage regions, which indicates that the model can effectively distinguish between different classes of delamination in composite materials, with a generally low rate of misclassifications. These findings are crucial for assessing the effectiveness of the classification model in practical applications related to damage detection and classification.

4. Conclusions

The detection and classification of carbon fiber-reinforced composites using NDT techniques are of great importance, emphasizing the need for advancements in this area. In light of this, the present work was an initial and feasibility study that aimed to enhance delamination detection and classification in CFRP composites by integrating time-frequency analysis with deep learning techniques. The methodology involved monitoring CFRP specimens with piezoelectric sensors and assessing delamination induced by fatigue loading. The dataset was divided into two classes based on delamination levels through time-frequency representations. A computational vision model, employing the EfficientNet architecture, achieved an accuracy of 83.33% and an AUC of 0.94, demonstrating promising results for delamination detection and classification. Future research should focus on expanding the dataset to include a broader range of delamination sizes and configurations to enhance the model's robustness and generalization capability. Moreover, integrating real-time monitoring capabilities into the developed framework would facilitate practical applications in structural health monitoring systems.

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