Damage Classification in Composite Materials for UAVs Using FBG Sensors and Artificial Neural Networks

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ABSTRACT

The structural integrity of composite materials in unmanned aerial vehicles (UAVs) is critical for ensuring flight performance, safety, and durability under various operational conditions. These materials are subject to progressive damage accumulation due to external loads, fatigue cycles, and environmental factors, which can compromise their mechanical properties over time. This work proposes a damage classification system based on Fiber Bragg Grating (FBG) sensors and Artificial Neural Networks (ANN) to detect and classify structural damage in composite material parts of UAVs. The validation of the methodology is performed in data from a composite wing section representative of an unmanned aerial vehicle (UAV) structure. The system integrates thirty-two FBG sensors strategically placed to measure strain variations through wavelength shifts, capturing subtle deformations indicative of material degradation.

The sensor data collected are processed to classify the material conditions into five damage states ranging from undamaged to increasingly deteriorated structural responses. The neural network model, designed as a multilayer perceptron (MLP), receives wavelength shifts as input, leveraging supervised learning to achieve accurate damage classification. The model is trained on a diverse dataset generated from controlled experiments to enhance robustness, where composite UAV materials are subjected to various stress conditions to ensure that the ANN can generalize damage classification across different failure modes commonly observed in UAV structures. 210 labeled experiments were used for training and validation, providing the model with a broad representation of structural responses. The results demonstrate that the proposed ANN-based approach achieves high classification accuracy, effectively distinguishing different levels of material degradation based on the FBG sensor data.

INTRODUCTION

Structural Health Monitoring (SHM) systems are critical for aerospace structures

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like UAVs, enhancing safety and extending service life by detecting progressive damage from fatigue, overloading, and environmental exposure [1, 2]. Traditional inspection methods often identify damage only at advanced stages, leading to high maintenance costs [3].

Fiber Bragg Grating (FBG) sensors address these limitations with high sensitivity, multiplexing capability, and EMI immunity [4]. While FBGs have proven effective for aerospace applications [5, 6], their full potential is limited by the complexity of signal interpretation for damage classification. As noted by [7], this requires ”extracting meaningful features from time series data to determine damage states.”

This work presents a supervised learning framework combining 32 FBG sensors with a lightweight ANN to classify five damage levels in UAV composite structures. Our pipeline processes 210 experimental datasets through cleaning, normalization, and vectorization, demonstrating the viability of AI-driven optical sensing for autonomous structural monitoring. This paper includes a theoretical background, the experimental setup and data acquisition, data processing and the decsription of the machine learning model with the results. Finally, the concluding remarks are described in the final section.

THEORETICAL BACKGROUND AND METHODOLOGY

Composite materials are essential in aerospace due to their high strength-to-weight ratio, but their layered structure makes them susceptible to internal damage modes like delamination and matrix cracking that are often undetectable visually [8]. These defects typically originate from mechanical fatigue, environmental exposure, or design limitations [3].

Fiber Bragg Gratings (FBGs) address these challenges through their core sensitivity mechanism (Fig. 1): mechanical strain alters the grating period ($\Delta\lambda_B \approx 1\,\mathrm{pm}/\mu\varepsilon$) and refractive index, shifting the reflected wavelength [8]. This physical principle enables:

- Absolute wavelength measurements (immune to power fluctuations)
- Multiplexing of multiple sensors via WDM (Fig. 1)
- Embedding within composites without mechanical interference

For damage classification, multilayer perceptrons (MLPs) are theoretically well-suited due to:

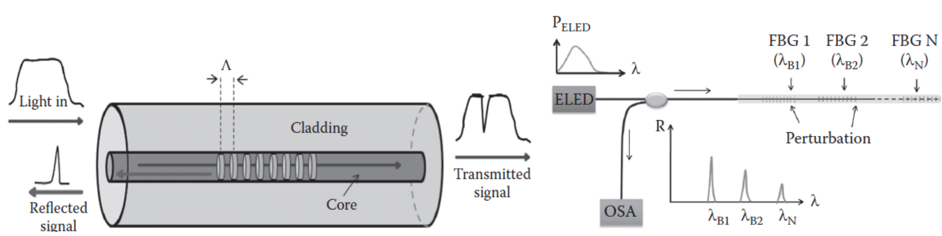

Figure 1. (left) Operating principle of FBG sensors: strain-induced wavelength shift. (right) Wavelength-division multiplexing (WDM) for quasi-distributed FBG sensing [8].

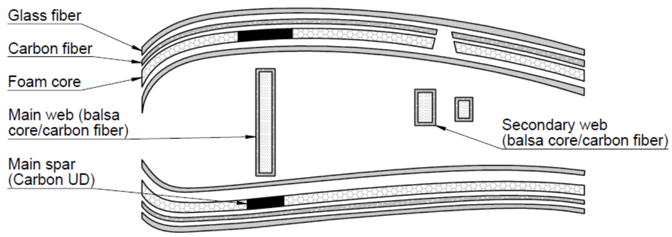

Figure 2. Internal structure and materials of the wing section [9].

- Nonlinear mapping between strain patterns and damage states [10]
- Hierarchical feature learning through dense layers [11]
- Regularization compatibility (e.g., dropout) for small datasets [12]

EXPERIMENTAL SETUP AND DATA ACQUISITION

The experimental campaign builds on work by Sierra-Pérez [13, 14] at Universidad Politécnica de Madrid, focusing on SHM systems for composite aeronautical structures using fiber-optic sensing. The test specimen was a UAV wing section comprising carbon fiber, glass fiber, PVC foam, and balsa [14], with its internal structure shown in Figure 2.

Thirty-two FBG sensors (2 mm long, wavelengths 1529.2-1562.4 nm) were strategically deployed across wing surfaces (Fig. 4) and interrogated at 10 Hz (0.2 pm resolution) using a Micron Optics Si425 system [14]. The wing was mounted to a test fixture (Fig. 3) and loaded statically at the tip with weights (3.25-7.25 kg).

Five progressive damage levels were introduced (Fig. 4):

- Longitudinal skin cut (3 cm)
- Transverse cuts (1-4 cm) with spar cap cuts (6.5-12 mm)

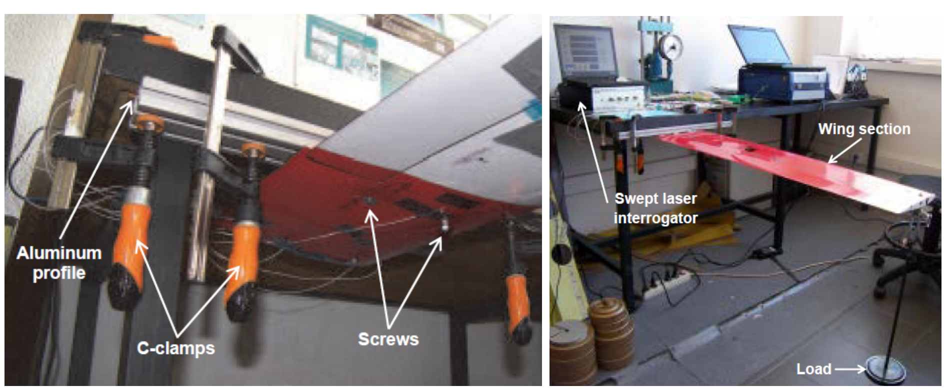

Figure 3. (a) Wing attachment detail (b) Complete test setup [14].

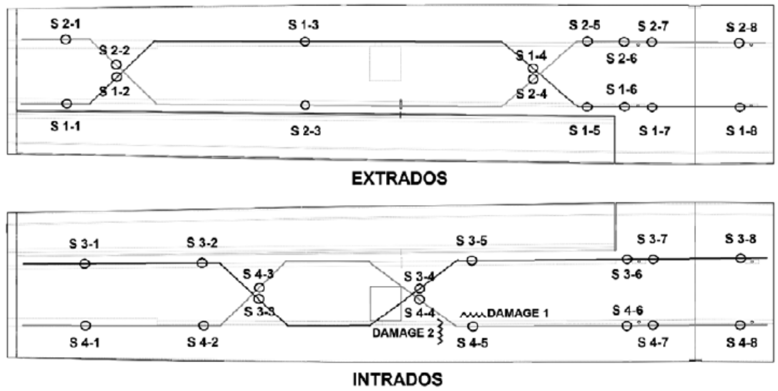

Figure 4. FBG sensor locations and induced damage zones [13].

Each damage state underwent 10 repetitions of loading protocols (zero load + 4 weights). FBG data was recorded as 32×277 matrices (truncated from 400 samples, Fig. 5), totaling 210 experiments. Representative sensor data is shown in Figure 5.

DATA PROCESSING

The raw 32 FBG signals (32 sensors $\times$ 277 samples) underwent a rigorous preprocessing pipeline as illustrated in Figure 6, an essential data cleaning and preparation phase was conducted on the raw experimental recordings. Initial inspections revealed corrupted sensor readings in several experiments - as corrupted data from sensors 28 and 30 were excluded - , particularly constant zero values caused by acquisition failures—an issue commonly observed in optical interrogation systems, especially at moderate sampling rates [4].

Sensor outputs exhibited two baseline ranges (0.000 nm and 1550 nm), necessitating normalization to unify the dataset. Baseline subtraction was selected over min-max normalization, as it preserved the physical meaning of strain variations relative to the unloaded state (Figure 7)

The normalized data was structured into a machine-learning-ready format through folding and unfolding operations. Each experiment was converted from a 32$\times$277 matrix

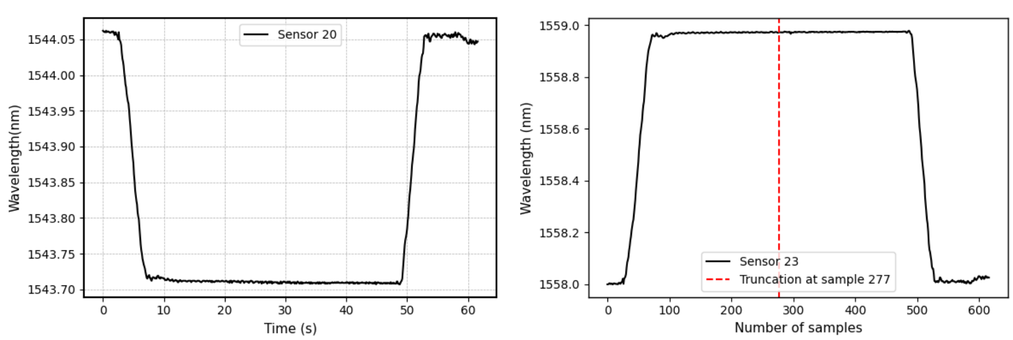

Figure 5. (left) Strain response from Sensor 20 during loading. (right) Truncated sensor sample.

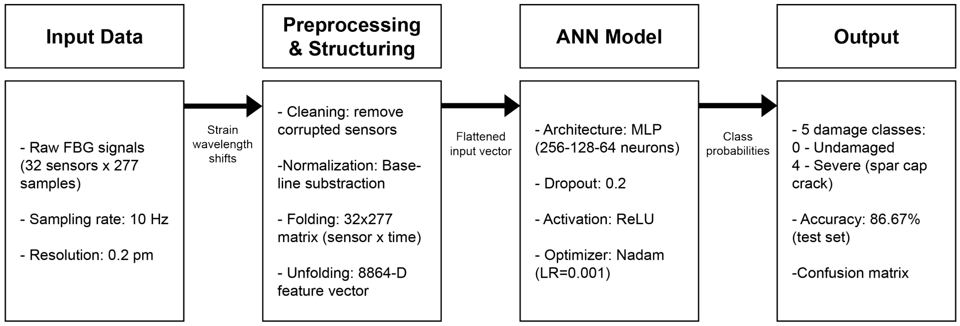

Figure 6. Damage Classification Pipeline

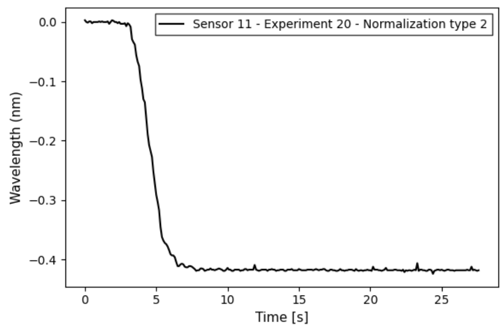

Figure 7. Baseline Substraction Normalization.

to an 8864-D vector, maintaining spatiotemporal relationships between sensors and time samples. This standardization enabled consistent training and evaluation of the ANN model across all 210 experiments.

Finally, the preprocessed dataset was validated by comparing strain responses across damage states. The baseline subtraction method proved critical for distinguishing subtle degradation patterns, as it eliminated sensor-specific offsets while preserving load-induced strain magnitudes. This approach aligned with the requirements of SHM systems, where physical interpretability is as essential as classification accuracy [7].

MACHINE LEARNING MODEL

The preprocessed 8864-D vectors were classified using a feedforward MLP, optimized for lightweight deployment in UAVs. The architecture comprised three hidden layers (256-128-64 neurons) with ReLU activation and dropout (0.2), trained via Nadam (LR = 0.001). Early stopping (patience = 20 epochs) prevented overfitting on the 80/20 train-test split.

From 200 random initializations, the best model (Seed 17) achieved 86.67% test accuracy, with misclassifications primarily between adjacent damage levels (Fig. 9). This balance between complexity and performance aligns with real-time SHM requirements.

RESULTS

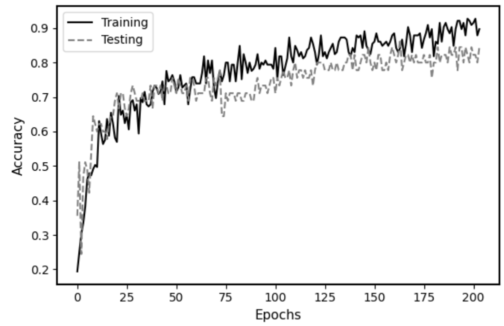

Figure 8. Training and testing accuracy across epochs for the selected model (seed 17).

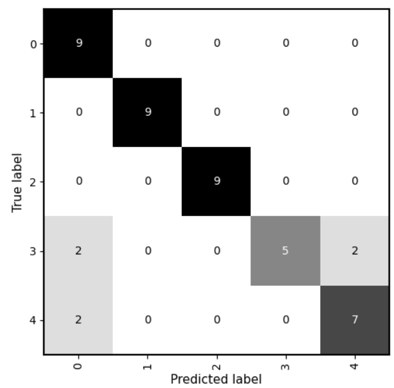

Figure 9. Confusion matrix showing classification performance across damage levels.

This final classification model achieved a test accuracy of 86.67%, effectively distinguishing between five progressive damage levels in the UAV wing structure. This level of performance reflects the model´s ability to generalize from experimental strain patterns obtained via FBG sensors, even under subtle degradation differences. Notabily, the classifier exhibited strong performance in identifying both undamaged and severely damage states, where the mechanical response differs clearly in magnitude and distribution.

The confusion matrix (Figure 9) shows that the majority of misclassifications occurred between adjacent damage classes - particularly between the 6.5 mm and 12 mm spar cap cut states - where the structural deformation patterns are naturally similar. These results align with the expected physical behaviour of composite materials under progressive damage accumulation.

To objectively assess the impact of the data preprocessing strategy, the baseline subtraction approach resulted in significantly higher test accuracy, confirming its suitability for preserving meaningful strain variations across the experiments. This difference was evident not only in final accuracy metrics but also in the training dynamics, as models trained on baseline-normalized data converged faster and more consistently.

Moreover, the training history of the final model (Figure 8) indicates stable learning with no overfitting, validating the choice of architecture and regularization strategies. This balance between computational efficiency and classification performance makes the proposed pipeline a suitable candidate for real-time onboard SHM applications in UAVs.

CONCLUDING REMARKS

This work presented a supervised learning framework for damage classification in UAV composite structures using FBG sensor data and a lightweight neural network model. A robust preprocessing pipeline—including folding, baseline normalization, and vectorization—was combined with a compact feedforward architecture trained on real experimental data from a progressively damaged wing section.

The proposed system achieved a test accuracy of 86.67%, with strong performance in identifying both undamaged and severely damaged states. Most misclassifications occurred between adjacent damage levels, which naturally exhibit similar strain patterns.

These results demonstrate the feasibility of integrating fiber-optic sensing with machine learning to enable automated, data-driven structural health monitoring in UAV components. Future work will explore temporal models, extend the dataset with additional damage modes, and evaluate real-time deployment scenarios to further improve generalization and adaptability.

ACKNOWLEDGMENT

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REFERENCES

1. Inman, D. J., C. R. Farrar, V. L. Junior, and V. S. Junior. 2005. "Damage Prognosis For Aerospace, Civil and Mechanical Systems," Tech. rep.
2. Glisic, B., D. Inaudi, and N. Casanova. 2010. "SHM process as perceived through 350 projects," in *Smart Sensor Phenomena, Technology, Networks, and Systems 2010*, ISBN 9780819480637, doi:10.1117/12.852340.
3. Mufti, A. A. and I. Canada. 2001. *Guidelines for Structural Health Monitoring*, ISIS Canada (Intelligent Sensing for Innovative Structures), ISBN 9780968900604.
4. López-Higuera, J. M., L. R. Cobo, A. Q. Incera, and A. Cobo. 2011. "Fiber optic sensors in structural health monitoring," *Journal of Lightwave Technology*, 29:587–608, ISSN 07338724, doi:10.1109/JLT.2011.2106479.
5. Mckenzie, I. and N. Karafolas. 2005. "Fiber optic sensing in space structures: the experience of the European Space Agency (Invited Paper)," *Proc SPIE*, 5855, doi:10.1117/12.623988.
6. ichi Takeda, S., Y. Aoki, T. Ishikawa, N. Takeda, and H. Kikukawa. 2007. "Structural health monitoring of composite wing structure during durability test," *Composite Structures*, 79:133–139, doi:10.1016/j.compstruct.2005.11.057.
7. Burgos, D. A. T. 2013. "Design and validation of a structural health monitoring system for aeronautical structures." *TDX (Tesis Doctorals en Xarxa)*.
8. Rajan, G. and B. Gangadhara. 2016. *Structural Health Monitoring of Composite Structures Using Fiber Optic Methods*, CRC Press, ISBN 9781498733205, doi: 10.1201/9781315369815.
9. Röbler, C. 2008. "Design of a fuel cell powered UAV, wing and Vtail building instruction," *Technical report, Institute of Aeronautical Engineering*, 1.

10. Worden, K. and G. Manson. 2007. "The application of machine learning to structural health monitoring," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 365:515–537, ISSN 1364-503X, doi:10.1098/rsta.2006.1938.
11. Nair, V. and G. E. Hinton. 2010. "Rectified linear units improve restricted boltzmann machines," in *Proceedings of the 27th International Conference on International Conference on Machine Learning*, Omnipress, ISBN 9781605589077, pp. 807–814.
12. Srivastava, N., G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. 2014. "Dropout: a simple way to prevent neural networks from overfitting," *J. Mach. Learn. Res.*, 15:1929–1958, ISSN 1532-4435.
13. Sierra-Pérez, J., A. Güemes, and L. E. Mujica. 2013. "Damage detection by using FBGs and strain field pattern recognition techniques," *Smart Materials and Structures*, 22, ISSN 09641726, doi:10.1088/0964-1726/22/2/025011.
14. Sierra-Pérez, J. 2014. *Smart Aeronautical Structures: Development and Experimental Validation of a Structural Health Monitoring System for Damage Detection.*, Ph.D. thesis, Universidad Politécnica de Madrid.