Transfer learning for classification of experimental ultrasonic Non-Destructive Testing images from synthetic data

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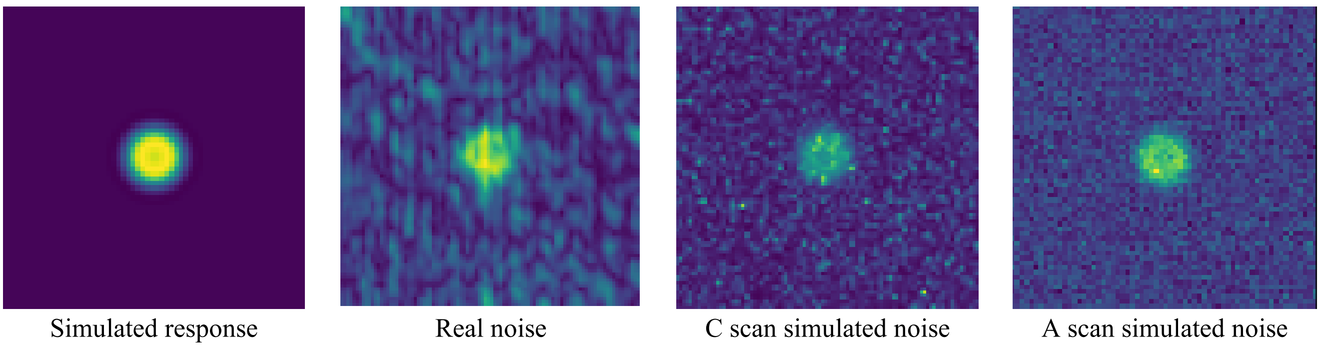
Lack of experimental training data is a significant challenge for the use of Deep Learning algorithms in Non-Destructive Testing. This work provides a Transfer Learning solution to the challenge of low training data volumes in Non-Destructive Ultrasonic Testing of carbon fibre reinforced polymer composites, which are known for their high structural ultrasonic noise.

The performance of Convolutional Neural Networks for classification was initially tested on experimental data when trained on simulated data. The results demonstrated that due to inaccurate noise production the simulated data domain was too far from the experimental test data to provide accurate classification. Different synthetic datasets were then generated using a variety of methods and their effect on classification performance was studied. The primary focus of these datasets were different methods of noise generation for more experimentally accurate simulated images.

To allow for the direct comparison of the different synthetic data generation methods, a standardized custom Convolutional Neural Network was developed. To make sure that the Neural Network was complex enough for the solution space hyperparameter optimization was performed on the network using a secondary experimental dataset. The hyperparameter optimization was a variant of Regularized Evolution [1] which was adapted for continuous and integer valued hyperparameters. The algorithm was initialized with a Population of 128 configurations generated via a random search. At each iteration of Regularized Evolution, a parent model was selected from a sample of configurations from the population, with the highest F1 score. A new child configuration was generated by mutating one of the parents hyperparameters. This child model was then trained and prepended to the population with the 'oldest' model discarded. The best performing model was then used for comparisons of classification accuracy for different synthetic datasets. The best performing synthetic dataset saw an F1 score increase of 0.34 (0.738-0.394) from the simulated dataset.

Figure 1: Examples showing the comparison between simulated data and the different types of synthetic data produced.



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[1] E. Real, A. Aggarwal, Y. Huang, and Q. V. Le, 'Regularized Evolution for Image Classifier Architecture Search'. arXiv, Feb. 16, 2019. doi: 10.48550/arXiv.1802.01548.

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