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ABSTRACT

PRESENTATION

PAPER

Mathias Kersemans obtained a PhD in engineering pysics from Ghent University on the topic of ultrasonic characterization of composite materials in 2014. He is currently an associate professor in the Mechanics of Materials and Structures research group (UGent-MMS) at Ghent University, where he is leading the research on non-destructive testing and structural health monitoring of advanced light-weight materials. His research team focuses on the development of novel and sensitive (nonlinear) inspection techniques for accurate monitoring and assessing the damage state in complex materials. This includes design of experimental methodology, optimization of excitation and acquisition strategy, advanced signal and image processing, prognostic damage evolution and estimation of remaining useful lifetime. He is author of more than 80 publications in SCI Web of Science.

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MODEL-BASED DEEP LEARNING FOR AUTOMATED DEFECT DETECTION IN COMPOSITES

The application of deep learning in thermographic inspection has seen an immense growth over the last years. One of the key challenges is the proper training of a learning model in order to achieve high inference performance as well as sufficient generalizability of the trained model.

This study introduces a model-based training approach for deep learning in optical infrared thermography. To this end, a parametrized 3D finite element method has been implemented in Fortran90 which allows to efficiently simulate the thermal response of multi-layer anisotropic composite plates. An interface element is introduced for the modelling of an imperfect thermal contact, allowing to simulate a variety of defect types. The flexibility of the interface element allows to simulate delaminations with different thickness using the same discretized model, leading to a computationally efficient model. A stochastic morphology generator is introduced for modelling realistic irregular defect geometries in the composite plates. In order to achieve realistic thermographic simulation data, non-uniform heating conditions are adopted from experiment, and temporal pink noise is added. A large-scale and diverse virtual dataset is generated by the simulation model, and is used to train a deep learning model which is based on Faster R-CNN with an attention-based feature fusion network. After training the deep learning model, it is tested on experimental thermographic data obtained on composite coupons as well as composite aircraft components with a range of defect types, sizes and depths. Good inference results are obtained (see below figures), illustrating the high performance, generalizability and reliability of the proposed model- based deep learning framework.