Detection of hidden Damages in Fibre Laminates using low-quality Transmission X-ray Imaging, X-ray Data Augmentation by Simulation, and Machine Learning

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Detection and characterisation of hidden damages like cracks and delamination in layered composites like Fibre laminates, e.g., Fibre Metal Laminates (FML), is still a challenge. Detection of such kind of damages and defects by visual inspection is a challenge, even using 3D CT data, and moreover using single 2D transmission images. For damage characterisation, micro-focus CT X-ray scanner are used, providing a high resolution below 100 μm, but with the disadvantage of high scanning times (up to several hours) [4]. Anomaly detectors based on advanced data-driven Machine Learning methods can be used to mark Regions-of-Interest (ROI) in images automatically (feature selection process). ROI feature extraction is the first stage of an automated damage diagnostic system providing damage detection, classification, and localisation. But data-driven methods require typically a sufficient large set of training examples (with respect to diversity and generality), which cannot be provided commonly in engineering and damage diagnostics.

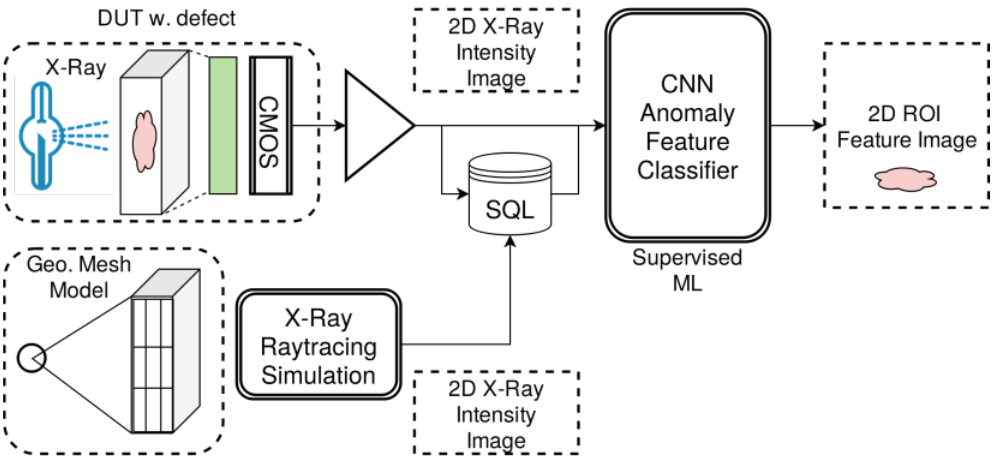

Figure 1. Overview of the automated and data-driven damage diagnostic and characterisation system combining measuring data and X-ray image simulation to augment the data base.

In this work, the challenges, limits, and detection accuracy of automated ROI damage feature detection from low-quality and low-resolution 2D X-ray image data using data-driven anomaly detectors are investigated and evaluated comparatively with high-quality and high-resolution 3D X-ray images obtained with a state-of-the-art X-ray microscope for advanced material characterization. In addition to experimental data, X-ray simulation is used to create an augmented training and test data set. Simulated and experimental X-ray data are compared (see Fig. 1). The simulation is carried out with the gvirtualxray [2] software. It is based on the Beer-Lambert law to compute the absorption of light (i.e. photons) by 3D objects (here polygon meshes). Additionally, X-ray-tracing by the x-ray projection simulator [3] software is used for comparison.

Suitable data-driven anomaly detectors estimating and marking the ROI candidates of damage areas are Convolutional Neural Networks trained supervised (i.e., using manually feature labelled data), either used as a pixel-based feature classifier (Point-Net) or as a region-based proposal network (Region-based CNN, R-CNN, Fast R-CNN, Region-proposal networks) [1].

References

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