Automated X-ray-based damage detection and characterisation in composite materials by data-driven anomaly predictor models trained by a fusion of real and simulated X-ray data

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It is still difficult to identify and detect hidden faults in multi-layered composites like fiber-metal laminates (FML). To find hidden damages, guided ultrasonic waves (GUW) or X-ray imaging are frequently utilized. Using reconstruction algorithms to create a three-dimensional view from slice images, three-dimensional multi-projection tomography imaging is superior over X-ray imaging with two-dimensional single projection images. Layer delaminations, prolonged cracks, microcracks (in solid material layers and fibers), deformations, and manufacturing impurities are roughly the different types of damages or flaws. Even with 3D CT data and, additionally, with single projection 2D pictures, finding these kinds of damages and defects through visual inspection is difficult. Micro-focus CT X-ray scanners are utilized for damage characterization since they offer great resolution below 100 m yet with the disadvantage of high scanning times (up to several hours) [5] and limitation to laboratory deployment.

Regions-of-Interest (ROI) in images can be automatically marked using anomaly detectors built on cutting-edge data-driven machine learning techniques (feature selection process). An automated damage diagnostic system that provides damage detection, classification, and localization begins with the extraction of ROI features. However, engineering and damage diagnostics frequently lack appropriate large sets of training examples (with respect to diversity and generality); for instance, an impact damage can only be "created" once and is irreversible.

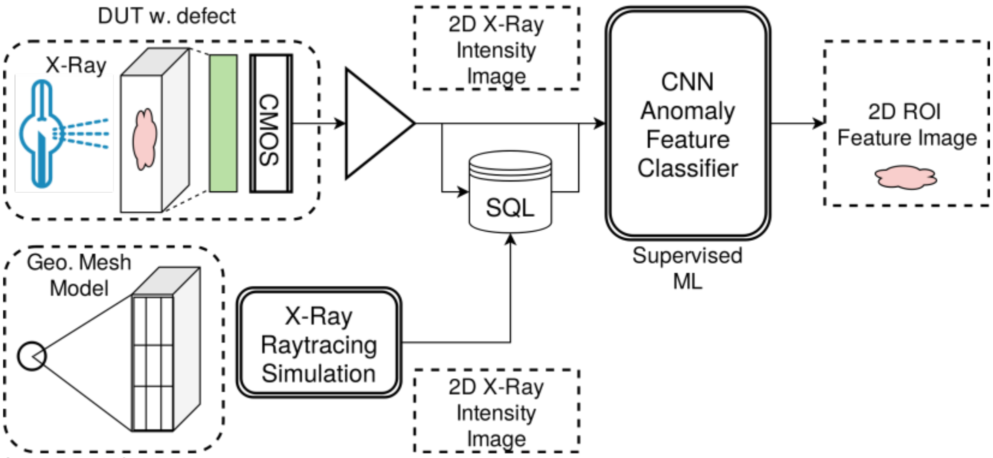

Figure 1. Overview of the automated and data-driven damage diagnostic and characterisation system combining measuring data and X-ray image simulation to augment the data base.

This study investigates and assesses the difficulties, restrictions, and detection accuracy of automated ROI damage feature recognition from low-quality and low-resolution 2D X-ray image data. An enhanced training and test data set is produced using X-ray simulation in addition to experimental data. Data from experimental and simulated X-rays are contrasted. The simulation is run using the program gvirtualxray [2;3]. The Beer-Lambert law is used to calculate how much light (or photons) is absorbed by 3D objects, in this case polygon meshes. Additionally, the x-ray projection simulator [4] software's ray-tracing of X-rays is employed for comparison.

Convolutional Neural Networks trained supervised (i.e., using manually feature labelled data) can be 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) to estimate and mark the ROI candidates of damage areas [1]. Ranked feature-vector decision trees are also assessed.

The acquired knowledge and the picture data gathered would speed up the development of autonomous SHM of composite structures, lowering safety concerns and shortening the overall time required for structural integrity assessment.

References

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