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Optimization of Non-destructive Damage Detection of Hidden Damages in Fiber Metal Laminates Using X-ray Tomography and Machine Learning Algorithms

Chirag Shah[1], Stefan Bosse[2](✉), Carolin Zinn[1], and Axel von Hehl[1]

[1] Institute for Materials Engineering, Chair of Materials Science and Testing, University of Siegen, Paul-Bonatz-Straße 9-11, 57076 Siegen, Germany
[2] Department of Mathematics and Computer Science, University of Bremen, 28359 Bremen, Germany
sbosse@uni-bremen.de

Abstract. Detection of hidden damages in Fibre Metal Laminates (FML) is a challenge. Damage detection, classification, and localization is a part of the lower levels of Structural Health Monitoring (SHM) and is critical for damage diagnosis. SHM is an extremely useful tool for ensuring integrity and safety, detecting the evolution. Early damage detection and understanding of damage creation can avoid situations that can be catastrophic. X-ray tomography is a powerful tool for research as well as damage diagnostics. But high-resolution tomography results in high measuring and computational times up to 10 h for one specimen. The paper presents an early method of accessing the sections of the FML for identifying internal damages using X-ray imaging by optimized and adaptive zooming and scanning using automatic Region-of-Interest extraction with Machine Learning methods. The generated knowledge and the image data collected would further accelerate the development in the field of autonomous SHM of the composite and hybrid structures like fibre metal laminates which would further reduce the safety risks and total time associated with structural integrity assessment. A comprehensive image-based data set is collected by means of X-ray CT images containing micro-scale damage mechanisms (fibre breakage, metal cracks etc.) and macro-scale damages like delaminations. Starting point is an image sets were measured with two different X-ray CT devices with a static parameter set (set in advance and a-priori) and posing many limitations and issues that make damage diagnostics difficult. The adaptive and iterative measuring process should increase the quality of the images and decrease the measuring time significantly.

Keywords: Process optimization · Structural Health Monitoring (SHM) · Machine Learning (ML) · X-ray computer tomography (X-ray CT) · Fibre metal laminates (FML)

1 Introduction

Automated detection of hidden damages in laminate materials is still a challenge. Commonly, imaging techniques require the intervention and analysis by experts. X-ray CT

imaging techniques allow the inspection of hidden damages. Major limitations are image resolution, noise, contrast, intensity inhomogeneity, and X-ray diffraction and reflection effects. Beside algorithms for damage detection, measuring time is finally a major limitation of tomography. The measuring time typically increases with the image resolution. In [1], a rigorous taxonomy of damage patterns were investigated and applied to X-ray CT data for automated damage detection. Although, automated damage detection could not be validated with the proposed data processing algorithms, suitable intermediate features could be derived that can be used to define Regions-of-Interest (ROI). One reason that prevents robust and generalized automated damage detection was the low quality of the X-ray images with all limitations mentioned above. The measuring time for one sample was about one hour. In this work, we try to optimize the measuring process with respect to measuring time and image quality proposing a ROI-based adaptive measuring process that provides full CT images with coarse resolution and zoomed images of spatially bound ROIs with high resolution. The ROI prediction is performed at measuring time and provides measuring parameters at real-time.

Structural Health Monitoring has become a significantly vast area of research due to the increasing need of implementing a viable solution for non-destructive health monitoring. The SMH includes sensing technology, data acquisition, transmission and management, and health diagnostics [2]. SHM has led to a breakthrough by integrating the aspects of computer science and technology to make the structure have self-sensing and self-diagnostic abilities.

For a civil infrastructure to be in an operational status, it is very important to identify and detect the internal damages which could be detrimental to the overall performance of the structure and could potentially lead to a catastrophic failure. One step in this direction could be facilitated through the X-ray CT investigations of these structures leading to damage detection. X-ray computer tomography is becoming increasingly important among the non-destructive inspection techniques for applications where the three-dimensional (3D) nature of the phenomenon is important, or where the evolution of critical feature is of interest, either during manufacturing or under in-service conditions. Unique insights can be gained from the X-ray CT investigation revealing the damage patterns and in-service degradation. Although the capabilities of the X-ray systems have evolved over a period of time, specifically the laboratory-based equipment, its application in analyzing composites and hybrid structures still remains to be challenging [3]. This could be attributed to the thin cross-section of the composites as compared to the length or width of the specimens (non-isometric). A variety of these internal damages could be classified on the basis of certain consistent physical damage characteristics (such as type, location, size etc.) structured on different hierarchical levels with different differentiation. These damage patterns could further be utilized for GUW measurements. GUW propagation changes with the changes in the in-state characteristics of the specimens. A change in propagation pattern can be recorded with the corresponding unique damage pattern. This would allow comprehensive damage identification as these damage levels could be further correlated with the sensor response of the ultrasonic guided waves in order to enable differentiated damage identification and finally a class assignment of sensor responses leading to damage diagnosis.

A prerequisite for classification of these damages is the detectability and in addition, the identification of the specific damage characteristics. The identification of these damages is also dependent on the resolution limit. The detection and resolution limits are influenced both by the magnitude of the damage involved and the ability of the method used. Therefore, the paper highlights the findings from the X-ray CT investigations of different fibre metal laminates with artificially created defects to understand and determine the detection and resolution limits. In this paper, it is an attempt to develop the sensing technology for the monitoring of damage patterns that are unable to be detected with visual inspection or naked eyes using X-Ray CT derived 3D image volume sets. These 3D image volume sets are further utilized by the ML algorithms to identify and detect any anomalies when compared with the baseline undamaged specimens to optimize the measuring process. Figure 1 shows the schematic description of the research work highlighting the relation between detection and resolution limits, damage classification, and damage class identification using GUW signals which is a later goal of the research work.

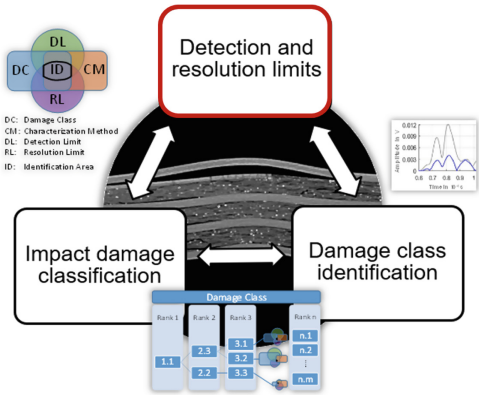


Fig. 1. Schematic description of the research work.

The research work also highlights a use-case study of automated damage detection using ML algorithms by investigating GLARE specimens with artificial defects. Glass-reinforced aluminium, known as GLARE, is a fibre metal laminate (FML) consisting of alternating S2-glass/FM94-epoxy composite plies and 2024-T3 aluminium layers. It is extensively used in the aerospace sector, where this detection technique can help to identify the damages and optimize the maintenance of aircraft. Aluminium materials under tensile loads are sensitive to the level of load and the type of variation of the load level. For this reason, crack growth rate, as well as residual strength (when the crack has developed), guides the selection of an appropriate alternative material candidate for aluminium structures [4]. GLARE offers higher intrinsic fatigue crack growth resistance [5] which has been a major driver for its selection as upper fuselage panels and skins by Airbus [4, 6]. The fatigue crack growth rates in GLARE are considerably lower in comparison to monolithic aluminium under identical loading conditions and are approximately constant for the major part of the loading [7]. GLARE has a shorter

crack initiation life but a remarkably longer crack propagation life in contrast to the monolithic aluminium where the fatigue life consists mainly of a long crack initiation phase and a small crack propagation phase. The laminated layout of FML also creates a material with good impact and damage tolerance characteristics [8]. The inner metallic layers are protected from corrosion by the fibre/epoxy layers whereas the fibre/epoxy layers are protected by the metal layers from picking up moisture [9].

2 X-Ray CT Investigations of Fibre Metal Laminates

2.1 Principle of X-ray Analysis

With the emergence of X-ray tomography for inspection of defects in parts, it became possible to inspect final parts and reject them based on defect size or location, according to some criteria. This has become routine for industrial inspection of castings, injection mouldings and composites as summarized in the review of industrial applications of X-ray tomography [10]. The non-destructive nature of the method allows the investigation of internal defects such as porosity and cracks in parts along with the internal details of the samples [11]. FML specimens with a variety of artificially created damages were fabricated to understand their detection using X-Ray CT methods. For this purpose, FML GLARE specimens were suitable for the study due to their relatively smaller density when compared to steel laminates allowing a better transmissivity of the X-rays through the specimens enabling better exploitation of the penetrating power of the high-density focused X-rays.

Feature detection (damage) using X-ray CT methods is highly dependent on the differences in contrast between the constituting elements within the specimen being investigated. For composite and hybrid materials it is related to differences between matrix, fibres, the constituting metal plies and the defects from the manufacturing (such as embedment of the foreign particle). In absorption mode X-ray CT, the contrast arises from the differences in linear attenuation coefficients (μ) of these constituting elements. In the range of X-ray energies used for the composite materials, the attenuation coefficients for a specific point (*x, y, z*) within the material, is given by [12, 13]:

$$\mu(x,y,z) = K\rho\frac{Z^4}{E^3} \tag{1}$$

where K is a constant, ρ is the density, Z is the material atomic number and E is the energy of the incident photons.

Consequently (directly proportional),

$$\mu(x,y,z) \propto K\rho\frac{Z^4}{E^3} \tag{2}$$

This means that materials with low atomic numbers exhibit low X-ray attenuation. This could be advantageous as X-rays can be transmitted through large composite materials but could also result in a poor contrast between fibres and matrix. It also limits the detectability of narrow matrix cracks. However, as a non-destructive tool, X-ray CT can provide 3D information to assess the quality of the manufactured components despite issues regarding the achievable spatial resolution specially in the examination of large components [3]. Figure 2 shows the schematic of X-ray computer tomography process.

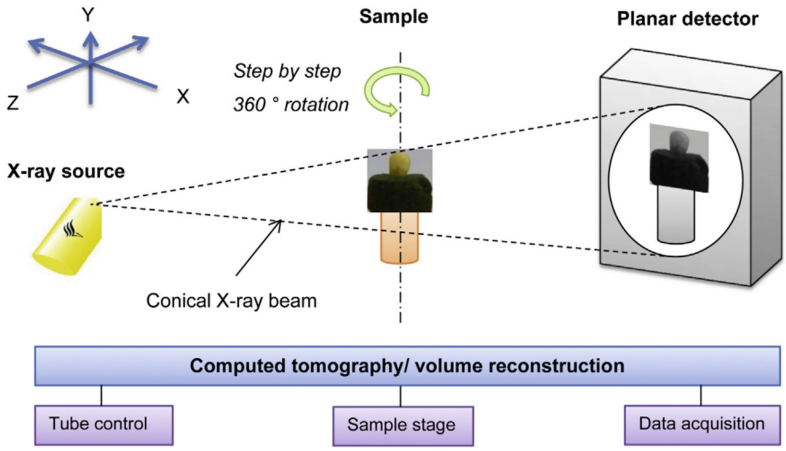


Fig. 2. Schematic of the X-ray micro-computed tomography process, taken from [14]

2.2 Experimental Procedure of X-ray CT Analysis

Detection and resolution limits of the X-ray CT method as a suitable characterization method are the prerequisite for accurate damage classification. These limits are determined by scans with various artificially induced damages. Since the characteristics and the exact location of the artificially induced damage are known inside the specimens, a manual finding of the damage and the analysis of the recorded CT images is ensured. To understand the detectability of a variety of damage patterns, various artificial damages were created to replicate the real case damage patterns occurring inside fibre metal laminates. These damages include:

- Disbonded laminate layers (i.e., delamination, kissing bonds) and weak bonds.
- Fibre breakage,
- Metal cracking and
- Sensors and sensor nodes (initially dummy sensors).

A 15 × 50 cm^2 GLARE 3-3/2 plate was fabricated consisting of 15 regions embedded with a variety of different artificial defects to replicate cracks in metal layer, fibre breakage, and delamination. Figure 3 shows the fabricated FML plate with different artificial defects. These regions with defects were cut into smaller 5 × 5 cm^2 specimens for evaluation in X-ray CT. The total thickness of the fabricated plate was 1.72 mm with a metal volume fraction of 70%.

Fig. 3. Fabricated GLARE plate (left) and specimens cut out from the plate to be investigated using X-Ray CT (centre) and a schematic figure of the layup configuration (right).

GFRP refers to Glass Fibre Reinforced Plastic prepreg consisting of FM 94-27%-S2-Glass-187-460. 0° and 90° refer to the layers of unidirectional glass epoxy oriented in a cross-ply configuration. Figure 4 shows the X, Y and Z planes for reference in an FML specimen. XY plane refers to the top and bottom face of the specimen and the Z plane refers to the thickness of the specimen. The X-ray CT investigations of these specimens were carried out using the General Electric Phoenix v|tome|x M system located at the Fibre Institute, University of Bremen. The specimens were stacked together for the CT investigations to overcome the limitations posed by the thin specimens. Thin specimens or plate-like structures, in general, are not well suited for X-ray CT investigations as the reconstruction algorithms rely heavily on the specimens being scanned to be of isometric shape.

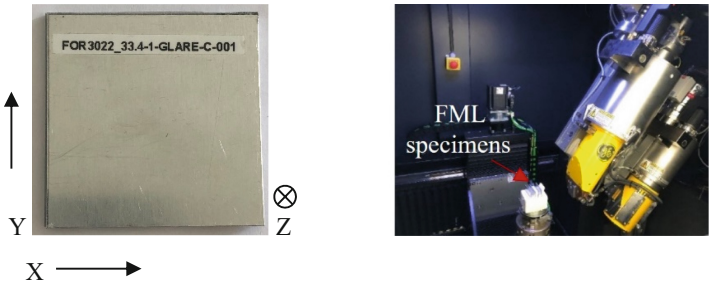


Fig. 4. A cut out FML specimen to be investigated using X-Ray CT (left) and the placement of the specimens inside the chamber for the investigations (right).

This ensures uniformity in terms of the absorption of X-rays through various sides and faces of the specimens. With plate-like structures, the penetration of X-rays varies based on the side of the plate being exposed to the X-ray source. The top face (XY plane in Fig. 4) of the specimen being scanned while facing the X-ray source would involve the scan through the thickness (X-ray penetrating through-thickness; Z-plane) which is usually quite smaller in comparison to the length and width of the specimen.

This means X-rays have a smaller path to travel to penetrate through the thickness whereas this is not the case when the specimen is being scanned through the width or the length. This creates ambiguity in terms of the X-ray intensities detected at the detector screen. Due to this, the final reconstruction of the specimen is irregular and could lead to inappropriate and irrelevant results.

2.3 Results of X-ray CT Analysis

A challenge with the X-ray CT analysis of the FMLs is associated with the energy required to fully penetrate the metal layers while obtaining the required contrast between the different density materials [15]. Defects related to cracks in the aluminium layer, foreign object embedment, resin fraction inhomogeneities and delamination were detected which are the key defects related to different failure modes encountered in FMLs. These CT investigations were carried out to assess its ability to provide information in 3D, qualitatively or quantitatively in a non-destructive fashion. The figures below illustrate the types of defects that can be imagined non-destructively by X-ray CT (Figs. 5, 6, 7, 8, 9 and 10).

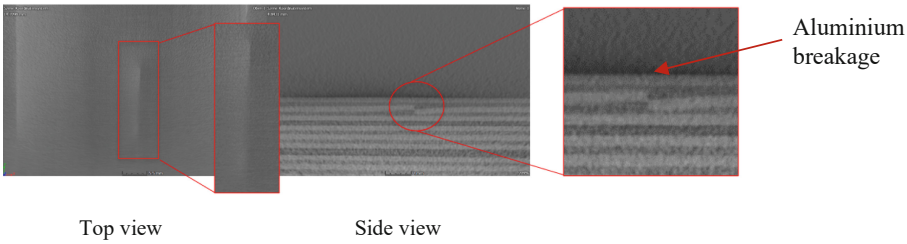


Fig. 5. X-ray CT image of the specimen with an artificially created crack in aluminium layers

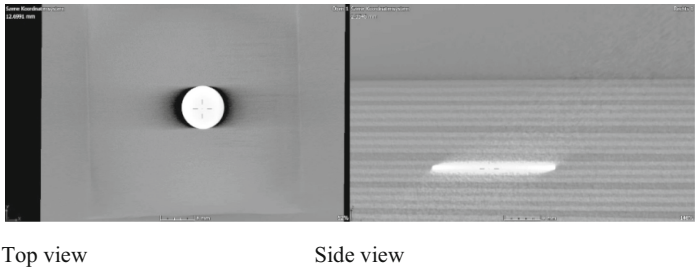


Fig. 6. X-Ray CT image of the specimen with embedded dummy sensor.

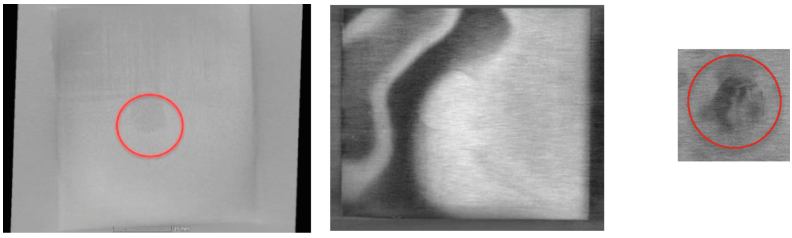
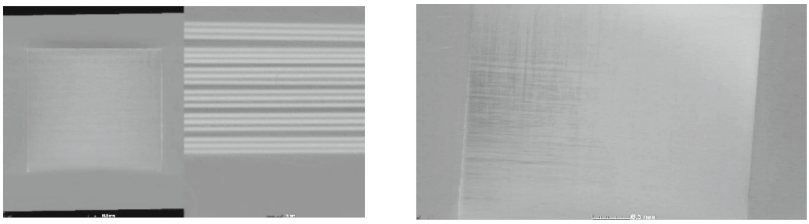


Fig. 7. X-ray CT image of the specimen with Teflon foil in a red circle (left), delamination (dark regions) due to Teflon (centre) resulting from Teflon foil and resin inhomogeneities (dark patches; in the right image) in top view [1].

The detectability of prepreg curing defects, fibre breakage, and defects resulting from liquid entrapments are challenging. Since such defects do not relate to any change in the



Top view Side view

Fig. 8. X-ray CT image of the specimen with water inclusion (left) and universal ballistol oil inclusion (right) in top view.

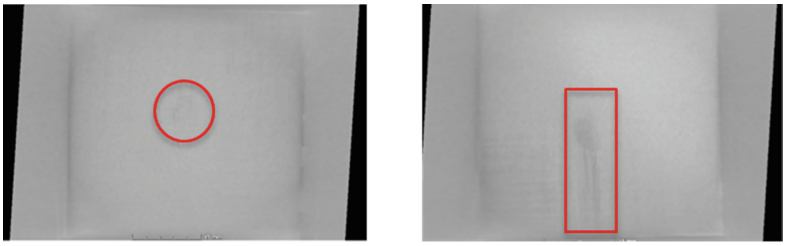
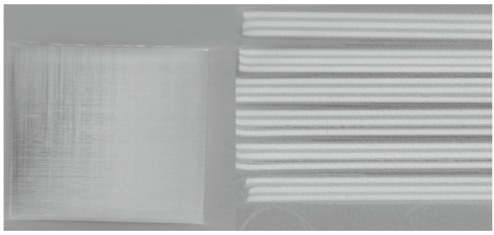


Fig. 9. X-ray CT image of the specimens with localized contact prepreg heating in top view.



Top view Side view

Fig. 10. X-ray CT image of a specimen with Loctite Frekote (mould release agent) inclusion.

density of the local region of interest, their detectability with the X-Ray CT methods is quite difficult. An automated X-ray CT image analysis using ML methods is further performed to investigate if the actual region of interest (ROI) is detected by means of non-monitored incremental learning or clustering (in Sect. 3).

3 Optimization of X-ray CT Measurements with ML Methods

The previous section gave an overview of specimens with different damage patterns and the challenges to identify them robustly in the CT images. To optimize the measuring process with respect to measuring time and image quality, we propose a ROI-based

adaptive and zooming measuring process that provides full CT images with coarse resolution and zoomed images of spatially bound ROIs with high resolution.

The X-ray CT image data quality is defined by:

1. Resolution ρ (spatially averaged) in lines/mm and sharpness ζ;
2. Homogeneity of image intensity distribution $I_{\text{avg}}(x, y, z)$ over the entire spatial volume (3D), i.e., material with same density and physical X-ray interaction properties should deliver the same intensity;
3. High contrast $C = I_{\text{max}}/I_{\text{min}}$ for the minimum and maximum material density;
4. Low diffraction and reflection artefacts A;
5. Low noise I_{noise}.

Beside these quality properties, the image quality is defined by a set of statistical and aggregate variables like mean, maximum/minimum, sharpness, contrast, spatial deviation, frequency spectra and MTF properties, intensity distribution, and most important texture features with specific geometric constraints (lines, points). These aggregate variables are closely related to the measuring parameters that should be optimized. In [16] the authors conclude, that "sharpness, contrast and noise were determined as a function of the number of projections. The number of projections was found to affect the contrast and the noise most, and had much less influence on resolution". The resolution of a CT imaging system can be specified by the Modulation Transfer Function (MTF) [17].

The X-ray CT measuring process is characterized by a static and a dynamic parameter set, P_{s} and P_{d}, respectively. The static parameter set defines the limitations of the imaging device itself, i.e., of the X-ray source (e.g., spot size) and the detector (sensitivity, converters, number of pixels and resolution), e.g., influencing the quality of the X-ray collimation. The dynamic parameter set includes the size if the specimen with respect to the field of view angle, the specimen rotation interval ($\alpha \in [0, 360]°$) and rotation increment $\Delta\alpha$ defining the projections, and the X-ray intensity and energy. In [1], three different ML-based algorithms were introduced and evaluated to find damage indicator features all applied to Z-profile CT image data (i.e., Z-axis slices of the image volume with respect to the specimen surface):

1. Variational Auto-encoder (VAE) delivering a 2D feature image indicating an anomaly if the reconstruction error is high and therefore providing a damage indication (used primarily for ROI selection and will be introduced in the next section);
2. Convolutional Neural Network (CNN) delivering a 2D binary damage classification image;
3. Self-organizing Kohonen maps (SOM) delivering a 2D similarity image, i.e., marking regions that pose some z-signal correlation.

A damage feature can be directly related to a damage pattern (probability) or just being an indicator for an anomaly that indicates there is maybe a damage nearby the spatial position and require further analysis either by data processing algorithms (ML) or by experts. A damage indicator correlates closely to the output of the anomaly detector.

The objective of the proposed ML-based measuring process optimization is two-folded:

1. Real-time adaptation of the dynamic measuring parameters to improve the image quality (max C, max ζ min I_{noise}, min A);
2. Reduction of measuring time and improving image resolution by performing an iterative zooming scan process by changing the rotation and translation with respect to identified ROIs, finally adapting the field of view angle and specimen position with respect to the X-ray beam.

3.1 Anomaly Detector as a Feature Marking Function

An anomalies detector is proposed to be a suitable feature marking function for damage and defect diagnosis. Input data for the proposed anomaly detector is three-dimensional CT image data of a layered material structure (here: FML plate). This anomaly detector is trained by unsupervised ML methods with baseline data (non-damaged specimen or an undamaged part of a specimen). The detector function should mark image regions where the Z-profile differs highlighting the region of interest (Anomalies Region-of-Interest, AROI), used for the following adaptive and iterative measurement process. These marked features can (but need not) identify damages or material defects. This detector is implemented with an auto-encoder architecture that reconstructs an encoded version of a signal to its original signal. Figure 11 shows the pre-processing workflow of the original raw CT image data with image transformation, image cropping, creating of a 3D Image data matrix cube, and finally Z-profiling with cylinders cutting z-signals from the image layer.

The variational auto-encoder (VAE) is implemented with a recurrent state-based Long-short Term Memory (LSTM) network. In this work, the first prototype consists of two LSTM layers with each consisting of about 7–9 LSTM neuron cells, and three dense layers with one neuron left and right from the LSTM layers.

The Z-Profile signals should contain local damage or defect information of any kind as a difference to a baseline signal. A Z-Profile signal is an average over a cylinder of

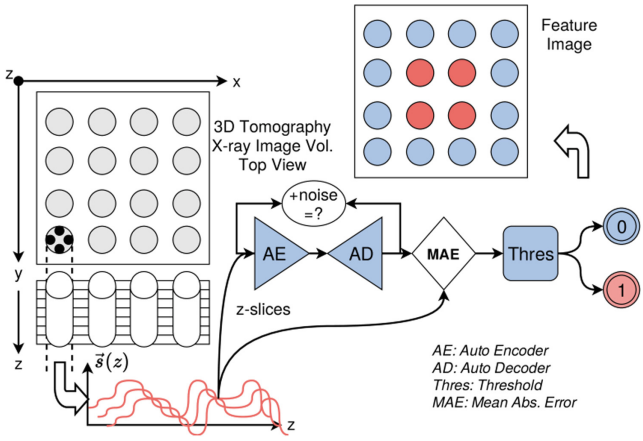


Fig. 11. Schematic representation of the slicing and Z-profiling of the 3D volumetric X-ray CT image sets and a variational auto-encoder with LSTM neural network architecture [details in [1]).

radius R. Samples of Z-signals from two images A0 (baseline) and A1 (defect; pseudo delamination) at various (X, Y) positions are shown in Fig. 12.

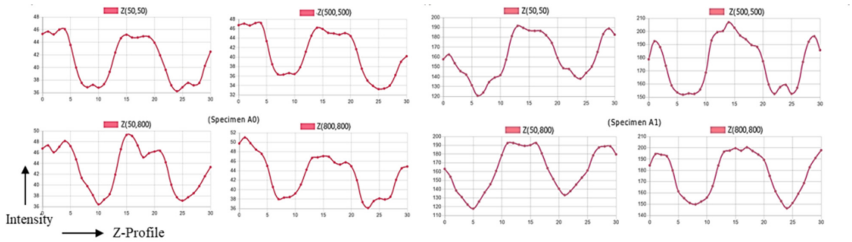


Fig. 12. Examples of z-signals of the baseline and specimen with defect at identical locations.

Some results of the anomaly detector are shown in Fig. 13. The AE was trained with all Z-signals over the circle-R-segmented (x, y) space of the image data cube of the baseline image. This trained AE was then applied to all Z-signals over the circle-R-segmented (x, y) space of the image data cube of the defect image consisting of pseudo delamination which could not be viewed manually. The delamination damage of the plate results in a large feature marking area. In [1] a rigorous evaluation showed that the VAE approach could not be used stand-alone without the correlation and comparison of the output of other methods delivering additional feature information, discussed in the next section. One major issue with the training of VAE is a spatial inhomogeneous intensity distribution and image artefacts (based on X-ray diffraction and reflection), which should be minimized by the following adaptive and optimized measuring process.

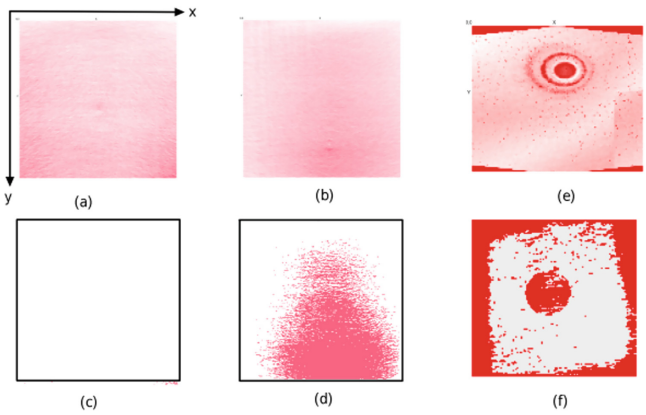


Fig. 13. Feature marking results of the anomaly detector with visible difference in image intensity scaling of both the baseline and defected specimens (a, b) with a delamination damage, results after threshold filtering (c, d), for an impact damaged specimen (e), and for a resin wash-out damaged specimen (f)

3.2 Adaptive and Iterative Measuring Process

The acquisition time for the specimens showed in the previous sections scanned at Fibre Institute in Bremen with GE Phoenix device was about 30 min. The one specimen with a higher resolution was scanned at MAPEX with a Zeiss X-radia system and had an acquisition time of around 6 h. This high measuring time is a major issue and challenge in any scanned X-ray NDT.

There are two types of magnification that can be varied: Mechanical magnification and Optical magnification. Mechanical magnification (GE Pheonix) works on the principle of the distance between the source and the object being examined. Here the magnification is controlled based on the principle of the distance between the source and the object. This is controlled manually. Optical magnification (Zeiss Xradia) is basically dependent on the use of a scintillator which converts the X-ray image into visible light which is then magnified using an optical lens.

For the reconstruction, the sample needs to be fully placed in the field of view. The number of projections has impact on the spatial resolution and the measuring time [16]. The reconstruction only considers the area which is being investigated and if the entire sample is not placed in the field of view, you will not get the complete reconstruction of the specimen being investigated. Field of view is also directly related to the resolution of the final results. Higher the field of view, lower the resolution and lower the field of view, higher is the resolution.

In general, flat surfaces and plates like structures like fibre metal laminates are not considered to be good enough for the X-ray CT because parallel surfaces are not properly penetrated by the X-rays which leads to image artefacts and lack of detail in the data set, particularly in the plane of the flat surface parallel to the beam. This can be seen in the CT results that we already have. This was the reason why we had to stack up the specimens altogether to be investigated.

The adaptive and iterative measuring process algorithm consists basically of alternated scanning and numerical processing steps, relying on a variable zoom technique proposed in [18]:

```
1. Perform a fast 2D transmission X-ray measurement ⇒
   α=0 with specimen surface orthogonal to the X-ray beam;
2. Perform statistical and texture analysis to optimize
   measuring parameters;
3. Apply damage feature marking algorithms (like semantic fully
   convolutional networks FCN) to the root 2D image to extract
   ROis by dividing the image in small segments and applying a
   supervised trained anomaly predictor to the segments (CNN) or
   apply a FCN on pixel-level; add ROIs to a ROI data base;
4. Perform a fast 2D transmission X-ray measurement ⇒
   α=90 with specimen surface parallel to the X-ray beam;
5. Repeat step 2, add ROIs to data base;
6. Perform an iterative fast coarse-grained 3D CT scan with
   Δα=10° with dynamic parameter adaptation optimizing
   the image quality in real-time;
7. Perform statistical and texture analysis to optimize
   measuring parameter;
8. Apply VAE, CNN, and SOM algorithms to z-profiled CT data
   (see [SHA22] for details);
9. Fusion of (VAE, CNN, SOM) output to extract ROIs and
   add ROIs to ROI data base;
10. Perform high-resolution scanning of selected ROIs by
   choosing appropriate field of view angels and rotation
   settings (increment and interval of α).
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Alg. 1. Basic iterative and zooming scan algorithm

3D Z-profiled CT image volumes can be processed by any kind of damage classificator (VAE, CNN, SOM, DT) using the z-signals as input and applying the predictor to each pixel in the x-y plane. 2D CT images can be processed by an image segmentation (using image segment as input data for CNN) or by using image transforming algorithms like FCN using the entire image as input and delivering the entire feature map image as output.

The control of the measuring process M adapting the measuring parameters is an optimization problem considering a quality function $Q(I)$ that should be maximized and the measuring time $T(M)$ that should be minimized by segmenting the entire specimen volume in smallest segment volumes given by the ROI selection process:

$$\begin{aligned} &\arg\max_{p} \; Q\left(\hat{I}(M)\right) \\ &\arg\min_{p} \; T(M) \end{aligned} \tag{3}$$

The overall measuring process and data processing chain is shown in Fig. 14. The output of the 3D CT image feature marking process is an intermediate 2D damage feature indicator image (spatially orientated parallel to the specimen surface). A point clustering algorithm (e.g., DBSCAN) is finally applied to the fusioned feature image to get relevant ROIs updating the ROI data base.

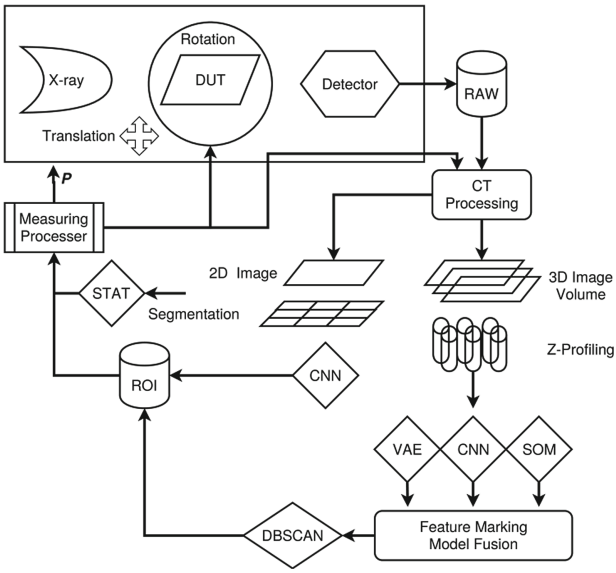

Fig. 14. Overview of the adaptive and iterative X-ray CT measuring process

Typical damages investigated in [1] were either locally bound (impact or resin wash-out damages) and therefore well suited for the ROI approach, or pose an extended large area (delamination) without clearly detectable geometric bounds. The measuring time can be reduced by ROI selection by at least 50% in the first case. If only one major damage pattern should be identified, delaminations can be detected fastly with low-resolution images by an anomaly detector. Therefore, an ordered set of damage patterns (with respect to geometrical features and expected size) should be analyzed iteratively with different resolutions and hence measuring times. The measuring and analysis process can be stopped if one damage pattern can be identified, modifying the above processing flow:

```
1. Perform 2D X-ray measurement (one projection);
2. Search damages that are extended in x-y and z-axis direction;
   if found go to end;
3. Perform first ROI selection; if ROis found go to 6;
4. Perform 3D X-ray measurement with low resolution of
   entire specimen;
5. Perform second ROI selection; if ROIs found go to 6;
   else go to 8;
6. Perform 3D X-ray measurement with high resolution of
   selected ROIs;
7. Perform damage analysis; if damage found go to end;
8. Perform 3D X-ray measurement with high resolution
   of entire specimen;
9. Perform global damage analysis.
```

Alg. 2. Advanced iterative scanning algorithm using an ordered set of damage patterns to be searched

4 Summary and Outlook

The detectability of certain damage patterns such as curing defects, disbonds and delamination due to liquid ingression visually using X-ray CT methods remains challenging. Image quality and measuring times of several hours are limiting factors for the deployment of X-ray CT damage diagnostics in FML materials. A ROI-based adaptive zooming iterative scanning process was proposed to improve the quality of the CT images and to reduce the measuring time significantly. The investigations of different composites and hybrid materials with a variety of damage patterns require advanced multi-level predictor models, starting with anomaly detection on the lowest level (for ROI selection), damage classification on mid-level, and damage localization on upper levels, furthermore, increasing its overall accuracy and consistency in identifying different damage patterns using selected ROI image volumes. The proposed measuring process optimization has to be investigated and evaluated rigorously with a broad range of specimens posing different damage patterns at different spatial locations.

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