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DETECTION OF HIDDEN DAMAGES IN FIBRE LAMINATES USING LOW-QUALITY TRANSMISSION X-RAY IMAGING, X-RAY DATA AUGMENTATION BY SIMULATION, AND MACHINE LEARNING

Stefan Bosse

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INTRODUCTION

- Spatially resolved Inspection and Testing of structures requires **image-based measuring methods**
- **Non-destructive testing** (NDT) of metal-based structures can exploit different imaging methods, mainly:
  - X-ray Radiography (single projection) and Computer Tomography (CT, multi-projection)
  - Guided **Ultrasonic Waves** (GUW) and Ultrasonic Sonography
- Homogeneous as well as Composite Materials can be tested, but reflection and diffraction can have a significant impact on image quality!
- Detection of hidden damages, defects, and impurities (e.g., pores) is still a challenge!

**Primary Goal.** Automated Damage, Defect, and Impurity Detection in materials and structures including composites using single X-ray projection images (from LowQ/MidQ devices) and data-driven feature marking models (Convolutional Neural Networks).
INTRODUCTION

Different specimens, structure geometries, materials, and defects are considered in this work! They pose different coincidence between material and image features.

1. Homogeneous aluminum die casting plates (150x40 mm) with gas pore defects
2. Composite Fibre Metal Laminate plates (FML, aluminum and PREG layers, 50 x 50 mm) with impact damages posing layer delaminations, deformation, cracks, and kissing bond defects.

Secondary Goal. Migration from laboratory (HighQ/MidQ) to in-field (LowQ) measuring techniques and devices.
INTRODUCTION

- Feature detection and marking in measuring images can occur on different levels:
  - Region-of-Interest Search
  - Feature Maps
  - Damage and defect classification
  - Damage and defect localisation
  - Global statistical aggregates (e.g., pore density, distribution)
- Either classical numerical and model-based algorithms (e.g., edge detection using a Sobel filter or Canny detectors) or data-driven models are used for feature marking ("Machine Learning")

Data-driven models require data! Data must contain a sufficient statistical variance and distribution of features to be detected. That's the first issue with most engineering data! Additionally, supervised data modelling requires accurately labelled strong feature examples, commonly not available, and being the second issue and downfall in data-driven modelling.
TAXONOMY OF NDT MEASURING TECHNIQUES

- Ultrasonic Wave Interaction: Material Density Variation
- Dispersion, Reflection, Mode Conversion

- X-ray Wave Interaction: Material Density Variation
- Transmission, Absorption

**GUW / US Air Scan**
- Reflection
- Time-of-Flight
- Sonogram

**US Sonography**
- Transmission, Absorption
- Multiple Projections
- Reconstruction + Filtering

**X-ray Radiography**

**X-ray Computer Tomo.**
GUW/US VERSA X-RAY RADIOGRAPHY/CT

- X-ray images can be simulated with high accuracy with respect to real measured images\(^1\)
- X-ray images enable direct interpretation and feature* detection (e.g., damages), but, not all features are directly visible and need to be intensified (contrast/SNR by algorithms)
- Ultrasonic signals cannot be simulated with high accuracy with respect to real measured images; there is a large reality gap!
- Features* are hard to be detected directly, advanced filtering and complex feature extraction models are required.

* Feature Classes: Damages, Defects, Inhomogenities, Pores, Delamination, Cracks
\(^1\) Simulation of X-ray projections on GPU: Benchmarking gVirtualXray with clinically realistic phantoms, Jamie Lea Pointon, Tianci Wen, Jenna Tugwell-Allsup, Aaron Sújar, Jean Michel Létang, and Franck Patrick Vidal Computer Methods and Programs in Biomedicine, 2023.....
DATA-DRIVEN NDT FRAMEWORK

**Radiography**
- One Projection
  - Transmission
  - MidQ and LowQ Devices
  - Input data for inference with data-driven predictor models

**CT**
- Multiple Projections
  - MidQ and HighQ Devices
  - Used for detailed material and defect characterisation
  - Input for CAD models and simulation

**ML**
- Data-driven Modelling
  - Feature/ROI Marking
  - Pore Analysis
  - Damage Detection
  - Anomaly Detection
  - Supervised / Unsupervised

**Semi CT**
- Some Projections
  - LowQ Devices
  - Reconstruction or Feature Extraction by data-driven CNN ML models

**Simulation**
- 2D/3D Raytracing
  - Transmission
  - (Reflection and Diffraction neglected)
  - Input data for training of data-driven predictor models

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**Data and Meth. Fusion**
PRINCIPLE CONCEPT

STEFAN BOSSE - DETECTION OF HIDDEN DAMAGES IN FIBRE LAMINATES USING LOW-QUALITY TRANSMISSION X-RAY IMAGING, X-RAY DATA AUGMENTATION BY SIMULATION, AND MACHINE LEARNING
ADVANCED CONCEPT

STEVEN BOSSE - DETECTION OF HIDDEN DAMAGES IN FIBRE LAMINATES USING LOW-QUALITY TRANSMISSION X-RAY IMAGING, X-RAY DATA AUGMENTATION BY SIMULATION, AND MACHINE LEARNING
### DEVICE CLASSES

<table>
<thead>
<tr>
<th></th>
<th>HighQ</th>
<th>MidQ</th>
<th>LowQ</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Single Projection</strong></td>
<td>✅</td>
<td>✅</td>
<td>✅</td>
</tr>
<tr>
<td><strong>Mult-Projection (Rotation)</strong></td>
<td>✅</td>
<td>✅</td>
<td>✅</td>
</tr>
<tr>
<td><strong>X-ray Tube Focal Diameter</strong></td>
<td>5μm</td>
<td>0.8mm</td>
<td>0.8mm</td>
</tr>
<tr>
<td><strong>X-ray Voltage/Current</strong></td>
<td>-120 kV/2 mA</td>
<td>-120 kV/10 mA</td>
<td>-70 kV/1 mA</td>
</tr>
<tr>
<td><strong>Detector</strong></td>
<td>2000x2000 Direct Sci./Imag.</td>
<td>1000x1000 Direct Sci.</td>
<td>2000x1000 Screen/Imaging</td>
</tr>
<tr>
<td><strong>Digital Resolution [Bits]</strong></td>
<td>16</td>
<td>16</td>
<td>12</td>
</tr>
<tr>
<td><strong>Sampling Time</strong></td>
<td>100 ms-5 s</td>
<td>10 ms-1 s</td>
<td>5 s</td>
</tr>
<tr>
<td><strong>Distance Object/Source</strong></td>
<td>5-10 cm</td>
<td>10-50 cm</td>
<td>20 cm</td>
</tr>
<tr>
<td><strong>Costs</strong></td>
<td>500 k€ (Zeiss)</td>
<td>100 k€ (IFAM)</td>
<td>1 k€ (Bosse)</td>
</tr>
</tbody>
</table>
DATA AND DATA SETS

- Micrographs
- Simulation SP/MP
- HighQ+Artificial Noise
- Ground Truth
- Reference
- Models
- LowQ/MidQ
- MidQ/HighQ
- Radiography
- X-ray CT

SP: Single Projection
MP: Multiple Projections

ML

SP: Single Projection
MP: Multiple Projections
KEY RESULTS AND CHALLENGES

Specimens:
1. Aluminum die casted plates with pores, Fraunhofer IFAM Bremen (Dirk Lehmhus)
2. GLARE Fibre Metal Laminate plates (5 layers) with impact damages, DFG research group 3022 (Bremen, Hamburg, Braunschweig, Siegen)

Objectives (Hypothesis: Can the goal be reached with the proposed method and data?)
1. Pore detection (feature marking) from single frontal LowQ X-ray projections using a Convolutional Neural Network
2. Damage or anomaly feature marking in 3D CT reconstructed HighQ image volumes using a Convolutional Neural Network

Measurements
1. MidQ X-ray (IFAM), single and multi-projection images (CT, 400/800 projections) 60 kV, 2 mA, 1000 x 1000 pix. SSD, 200μm
   LowQ X-ray (Bosse), single projection images, 55 kV, 1mA, 1920 x 1080 pix, Imaging detector with CMOS sensor, 40 μm
2. HighQ X-ray (Zeiss Xradia μCT) multi-projection images (CT, 800 projections), 110 kV, 1 mA, 2000 x 2000 pix. SSD, 20 μm
SPECIMENS

1. Aluminum Die Casting Plate (IFAM)  
   - Dimensions: 40 mm x 3 mm x 150 mm
   - Features: Pores, Impact Damage

2. GLARE FML Plate (DFG FOR 3022)  
   - Dimensions: 50 mm x 4 mm
   - Features: A|P|A|P|A|P|A|P|A|P|A
In this work a semantic pixel classifier is used for feature marking. From the model point of view, each pixel (and neighbour pixels) of an X-ray image is a sample instance!
COMPARISON RECONSTRUCTED MIDQ 3D CT AND 2D CNN PORE FEATURE MARKING

- Left: Volume projection of reconstructed CT images with data from a MidQ device (400/800 projections, rec. with classical fbp alg.)
- Right: CNN Pixel Classifier Feature Marking image predicted from single projection image (MidQ), trained with real images [8-8]

Large FOV! 150x150 mm

Trained w Real Images and hand-made manual ROI labelling

Feature Labelling: Second Challenge

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COMPARISON MIDQ RADIOGRAPHY AND CNN PORE FEATURE MARKING (R)

- Left: Single projection X-ray radiography images from a MidQ device (M=2, pixel size 200μm 1000x1000 pixels, cropped)
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image (MidQ), trained with real images [8-4]

- Large FOV! 150x150 mm

Trained w Real Images

[Images of DC Plate #4 and DC Plate #12]
COMPARISON MIDQ RADIOGRAPHY AND CNN PORE FEATURE MARKING (S)

- Left: Single projection X-ray radiography images from a MidQ device (M=2, pixel size 200μm 1000x1000 pixels, cropped)
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image (MidQ), trained with synthetic images [8-8-4]

- Threshold Discriminator 0.8
- Large FOV! 150x150 mm

Trained w Synthetic Images and CAD model-based automated ROI labelling
COMPARISON LOWQ RADIOGRAPHY AND CNN PORE FEATURE MARKING (S)

- Left: Single projection X-ray radiography images from an Imaging LowQ device (M=1, eff. pixel size 40μm 1920x1080 pixels)
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image (LowQ), trained with synthetic images [8-8-4]

- Smaller FOV! 80x40 mm
- Noise or Pores?

Trained with Synthetic Images and CAD model-based automated ROI labelling

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COMPARISON LOWQ RADIOGRAPHY AND CNN PORE FEATURE MARKING (S)

- Left: Single projection X-ray radiography images from an Imaging LowQ device // Extruded aluminum plates (d = 2 mm)
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image (LowQ), trained with synthetic images [8-8-4]

Threshold Discriminator 0.95

Smaller FOV! 80x40 mm

Noise!

Trained w Synthetic Images and CAD model-based automated ROI labelling

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COMPARISON SIMULATED RADIOGRAPHY AND CNN PORE FEATURE MARKING (GROUND TRUTH)

- Left: Single projection X-ray radiography images from XraySim (M=2, pixel size 150μm 1000x1000 pixels, cropped) // Synthetic Plate
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image [8-8-4]

Trained with Synthetic Images and CAD model-based automated ROI labelling

Large FOV! 150x150 mm
COMPARISON SIMULATED RADIOGRAPHY AND CNN PORE FEATURE MARKING (GROUND TRUTH)

- Left: Single projection X-ray radiography images from XraySim (M=2, pixel size 150μm 1000x1000 pixels, cropped) // Synthetic Plate
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image [8-8-4]

Large FOV! 150x150 mm

Two independent plates and images with different pore distributions, different gauss. pixel noise, produce same artifacts!
It is a challenge to estimate pore shapes (geometry, size), density, spatial distribution, and to distinguish reconstructed pores from image artifacts and noise!

- Manual measuring of shape parameters of selected pores (e.g., using ImageJ analysis software) with ellipse approximation
- Automated pore analysis by point clustering methods and ellipsoid approximation
It is a challenge to estimate pore shapes (geometry, size), density, spatial distribution, and to distinguish reconstructed pores from image artifacts and noise!

- Manual measuring of shape parameters of selected pores (e.g., using ImageJ analysis software) with ellipse approximation
- Automated pore analysis by point clustering methods and ellipsoid approximation
A **LSTM Autoencoder** is used as an anomaly detector. Shown is the feature marking of the AE (top view of the X-ray CT volume).

- Specimen: FML plate with impact damage. A.E: Different AE model configurations and trainings // Data from **HighQ** device.
HighQ single projection image data from μCT measuring devices are not always better than image data from LowQ devices for ROI and anomaly detection!

- **a)** HighQ μCT Zeiss Xradia
  - High Intensity Grad.
  - No Impact Damage Peak

- **b)** LowQ X-ray Bosse
  - Low Intensity Grad.
ANOMALY DETECTION IN FML CT DATA (POSITIVE TRAIN.)

- A **CNN** is used to detect anomalies in a CT volume (feature marking of damage candidates) // Data from **HighQ** device
- Specimen: FML plate with different damages: A: foil pseudo defect, B: Resin washout B, C: Baseline, D: Layer delamination:

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METHODS AND ALGORITHMS

- 3D CAD modelling using automated model code generators, Monte Carlo simulation, and openSCAD
- X-ray simulation using own simulation software based on proven and accurate gvxr/gVirtualXray library
- 3D CT reconstruction with Filtered Back Projection (using sine filters)
- Convolutional Neural Networks in different flavors
- Anomaly detectors applied to images and CT volume data
X-RAY SIMULATION

- **Input**: Polygon mesh grid (STL, Stereolithography file format) model
  - An STL file describes a raw, unstructured triangulated surface
  - Decomposition of multi-material structures in single density parts (finally merged in simulator)
  - 3D Model design: Constructive Solid Geometry (CSG)

- **Output**: X-ray intensity image with a specific detector resolution (number of pixels) and pixel size, floating point or integer data format (at least 16 Bits)

- Spatial source, object, and detector geometries can be fully parametrized including rotated planes

- **Core software library**: gvxr / gVirtualXray using GPU computations and the OpenGL Shading Language (faster than 1ms / image)
  - [https://gvirtualxray.fpvidal.net/](https://gvirtualxray.fpvidal.net/)
  - Based on the Beer-Lambert law to compute the absorption of light (i.e. photons) by 3D objects (here polygon meshes).
X-RAY SIMULATION: CAD MODEL

rotate ([90,90,90])
difference () {
  rotate ([90,0,0]) cube([100,4,40],true);
  union () {
    translate([3.17,6.14,0.67])
    rotate ([0,0,-1.43])
    scale([1.15,1.12,0.31])
    sphere(r=0.5,$fn=20);
    translate([-16.66,-4.05,0.39])
    rotate ([0,0,40.14])
    scale([0.89,2.21,1.46])
    sphere(r=0.5,$fn=20);
  }
  ...
}

Constructive Solid Geometry Model
X-RAY SIMULATION

- C++ simulation library gvxr/gVirtualXray
- Integrated in own simulator program XraySim: https://github.com/bslab/xraysim
- GPU/OpenGL Ray tracing using Beer-Lambert law
- Attenuation along direct transmission path from source to detector – no scattering and reflection

"I(x,y) is the integrated energy in eV received by pixel (x,y). In the polychromatic case, the beam spectrum is discretised in several energy channels. E_i corresponds to the energy in eV of the i-th energy channel. D(E_i) is the number of photons emitted by the source at that energy E_i. The detector response R(E_i) mimics the use of a scintillator by replacing the incident energy E_i with a smaller value, i.e. R(E_i) < E_i. μ_j(E_i) is the linear attenuation coefficient of the j-th material at energy E_i. d_j(x,y) is the path length."

\[ I(x, y) = \sum_i R(E_i) D(E_i) \exp \left( - \sum_j \mu_j(E_i) d_j(x, y) \right) \]

1 Simulation of X-ray projections on GPU: Benchmarking gVirtualXray with clinically realistic phantoms, Jamie Lea Pointon, Tianci Wen, Jenna Tugwell-Allsup, Aaron Sújar, Jean Michel Létang, and Franck Patrick Vidal Computer Methods and Programs in Biomedicine, 2023.....
WORKFLOW

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SEMANTIC CNN PIXEL CLASSIFIER

- **Input**: A sub-window of an X-ray image
- **Output**: The object class to which the central pixel of the window belongs
- The CNN classifier is applied to all pixels of an input image and produces an equally sized feature marking output image
- Point clustering (e.g., using DBSCAN) can be used to extract list of geometric objects (pores, damages, …)
- Supervised positive training (classification of known features classes)
ANOMALY DETECTION IN FML CT DATA

- Goal: Find (mark) damages (deformation, cracks, delaminations) in 3D CT volumes
- Method: Z-Slicing of 3D CT volumes and application of an anomaly detector to z-profiled slices
ANOMALY DETECTION IN FML CT DATA: NEGATIVE TRAIN.

- An anomaly detector is build with a Autoencoder, either using a CNN or a LSTM-ANN
- The AE is trained with z-profile slices without defects or damages (base-line, ground truth data)
- The AE „learns“ the z-profile structure of the FML plates and outputs a simplified representation (neg. Train.)
- If there is a damage/defect, the AE is not able to reconstruct the base-line structure, and an error occurs
ANOMALY DETECTION IN FML CT DATA: NEGATIVE TRAIN.

- A CNN is trained with damaged z-profiles to classify damaged versus undamaged z-profile slices.
ANOMALY DETECTION IN FML CT DATA: SIMULATION

- A typical sample set contains less than 10 different specimens, each with a distinct and unique impact damage (and base-line = no damage)
- **Data augmentation by simulation is required to increase feature and data variance!**
- But in contrast to mechanical pore modelling in homogeneous materials, modelling of impact damages in FML is much more complicated reaching high accuracy (wrt. real structures and images)
- Hand-made layer boundary point-marking using image tools
- Functional approximation → 3D CAD model → X-ray simulation
ANOMALY DETECTION IN FML CT DATA: SIMULATION

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CONCLUSIONS

Data

- Single- and Multi-Proj. X-ray Images
  - Data and feature variance is always limited!
    - CT scans require high measuring time and produce big data volumes
    - Noise (LowQ)
- Supervised Learning: Hand-made labelling is a challenge and inaccurate
  - Relation between image and target features can be very low (contrast)
- CT data cannot be used directly for labelling due to geometrical distortions (wrt. single projection input data)

Methods

- 3D CT reconstruction using Filtered Back Projection (sine wave filters)
- Convolutional Neural Networks for pore and damage feature marking (data-driven negative training) and LSTM anomaly detectors (positive training)
- X-ray simulation based on Beer-Lambert law and multi-material polygon mesh models
- Monte Carlo simulation of materials with defects and damages (openSCAD, Constructive Solid Geometry)
- Measuring devices: LowQ, MidQ, HighQ

Results

- A pure data-driven feature marking model (semantic image pixel classifier) trained with synthetic images only can be applied to real images
- The semantic pixel feature marking model is capable to highlight low-contrast features (e.g., hidden pores)
- X-ray noise has significant impact on feature prediction results
- Accurate and representative training examples (labelling, simulation models) are a prerequisite for robust data-driven models and a challenge!

Don’t trust data-driven models!
THANK YOU

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