Improving Ecology and Economics of Aluminum High Pressure Die Casting Processes

A data-driven analytical characterization of hidden pores and defects using low-cost X-ray radiography images and advanced simulation methodologies

Priv.-Doz. Dr. Stefan Bosse, Dr.-Ing. Dirk Lehmhus

Summary

We address high pressure die casting processes and aim to reduce resources (water, energy, CO_2) by investigating material defects like gas and shrinkage-induced pores using X-ray radiography images and automated data-driven modeling[5]. We solve the missing ground truth issue by using advanced simulation and Monte Carlo methodologies to create synthetic measuring data used for the training of a data-driven pore analysis and feature marking model, which is finally applied to measured data.

Methods

The entire workflow [See Figure C] consists of a set of methods required for data processing, feature extraction and labeling, model training, and analysis:

X-ray Radiography and CT

- Measurement and simulation of X-ray attenuation
- Different measuring devices [See Figure A] differing in resolution and Signal-to-Noise (SNR) ratios, Micro-focus device (3) used only for reference data
- Computer Tomography (CT) by multi-projection imaging and filtered back-projection reconstruction
- Single projection images used for automated data-driven defect analysis

Semantic Pixel Classifier and DBSCAN

- Image pixel classifier creating a feature map image from an input image by classifying pixels[4]
- Divide-and-Conquer: Simple model applied to local data
- Pixel clustering with *DBSCAN* to group classified pixels to defects (pores) on global level

X-ray Simulation

- Pure absorption X-ray tracing based on Beer-Lambert law (no scattering, no reflection)
- GPU-driven computation, fast! 1 ms/Image (Rotation of objects for CT!), *gVirtualXray*[1]*xraysim*[3]
- Input: Multi-material triangular mesh grid
- Output: High resolution X-ray images

´CAD Modeling and Monte Carlo Simulation

- Materials, components, and defects are modeled using Constructive Solid Geometry (CSG)
- Defects are added to materials by Monte Carlo simulation using a core set of defect parameters from CT analysis (reference)
- An STL mesh model is created form the programmatically generated CAD model by *OpenSCAD*[2]
- *Automated ground truth annotation for training*

CT Reconstruction

- Sine filtered back-projection without post-filtering, applied to simulated and measured data
- Multi-threaded software fbp/xraysim[3]

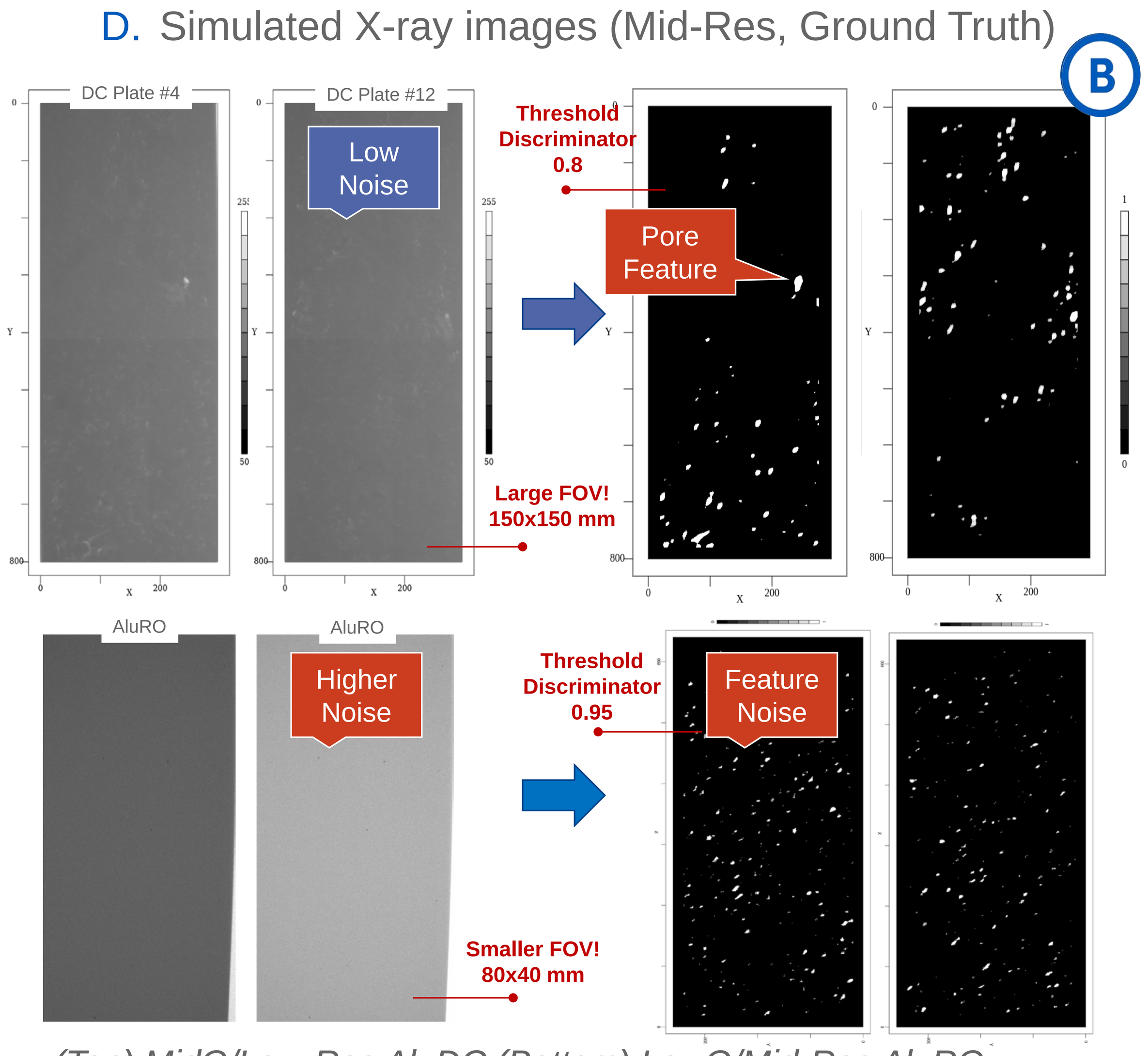
Measuring Instruments

(1) HighQ Zeiss Xradia 510 [1μm res., 10W, 5s/img, high SNR]
(2) MidQ IFAM [200μm res., 1kW, 100ms/img, high SNR]
(3) LowQ Bosse [40μm res., 50W, 5s/img, mid SNR]

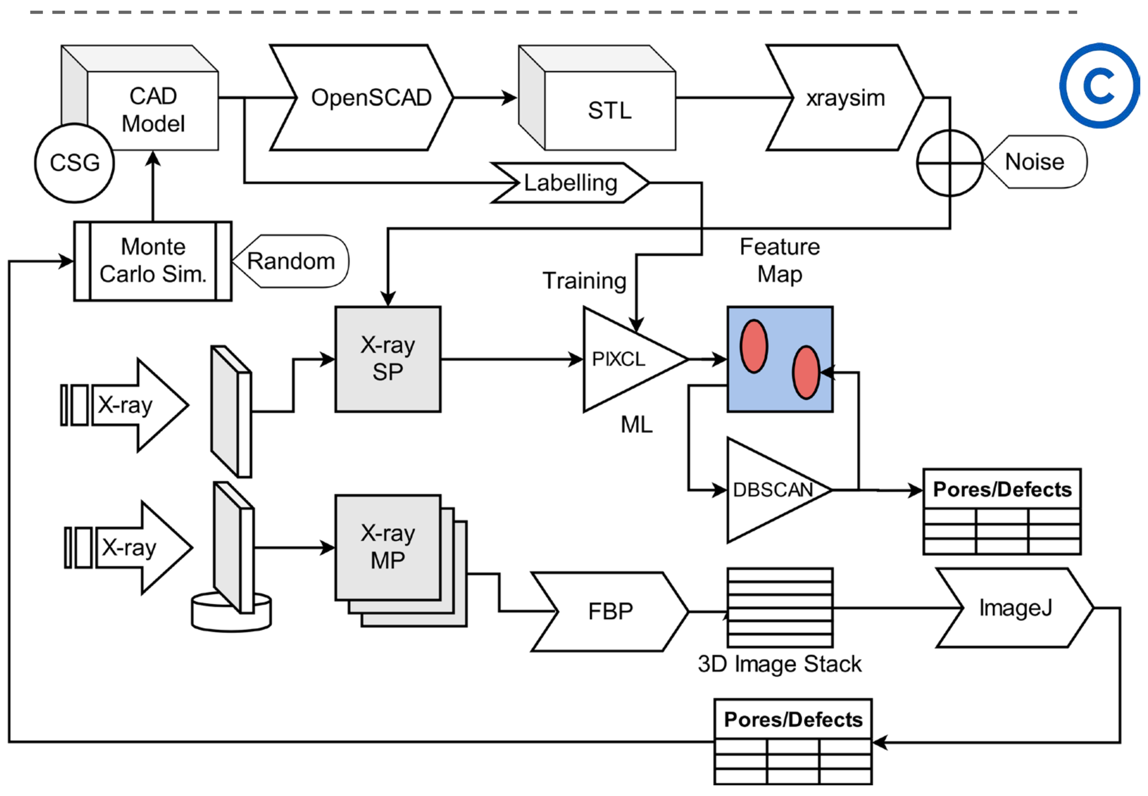
Experiments and Data Analysis

Experiments were made by using [See Figure B]:

A. **AluDC**: High-pressure die cast aluminum plates 150x40x3 mm with pores in the range of 10-1000 μm
B. **AluRO**: Rolled aluminum plates 100x40x2 mm without pores (base-line)
C. X-ray images from MidQ/Low-Res and LowQ/Mid-Res measuring devices (A-2,A-3), CT from MidQ
D. Simulated X-ray images (Mid-Res, Ground Truth)



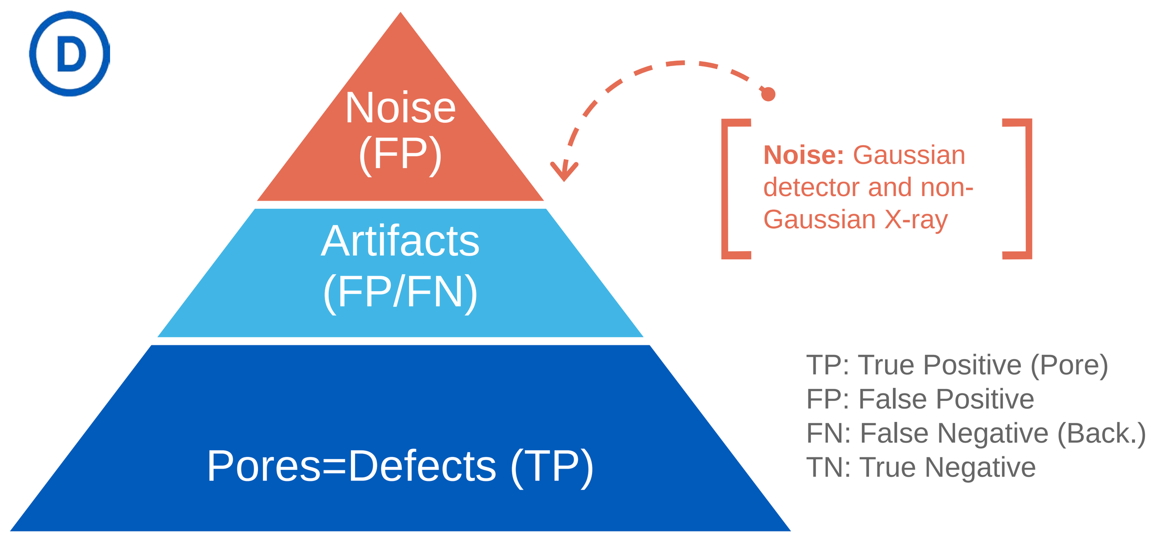
(Top) MidQ/Low-Res AluDC (Bottom) LowQ/Mid-Res AluRO
(Left) X-ray Image (Right) Feature Map / Semantic Pixel Classifier



Methods and Workflow Architecture (FBP: Filtered back-projection, SP: single projection, MP: Multi-projection)

Results

- **Synthetic X-ray images AluDC:** Ground truth accuracy TP > 90%, FN < 5%, FP < 5%
- **MidQ X-ray images AluDC:** Pore coverage > 70%
- **LowQ X-ray images AluDC:** Pore coverage > 90%
- **LowQ X-ray images AluRO:** Noise artifacts > 10%



Semantic pixel classifier is robust against Gaussian detector noise, but highly sensitive to non-Gaussian spatially correlated X-ray noise.

Conclusion

Reducing material defects requires robust automated feature detection. Low-cost measuring technologies like X-ray radiography with lowered SNR are preferred in manufacturing processes and quality control. But:

- **Defects (pores) are hard to identify by visual inspection in X-ray images**
- **Due to the missing ground truth in real world images, the feature marking model must be trained with synthetic images derived from CAD models**
- **Due to the missing ground truth in real world images, there is no statistical analysis and assessment of the results possible**
- **Artifacts (FP) were observed in feature maps of synthetic X-ray images independent of the CAD model!**
- **The classifier is sensitive to noise, therefore:**

Do not trust data-driven models!

Future Work

- Overlaying X-ray noise patterns on synthetic images
- Analysis of geometrical pore and size distributions
- STL → FEM transformation for damage simulation and pore metrics correlation with damage

References

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5. Chirag Shah, Stefan Bosse, and Axel von Hehl. Taxonomy of Damage Patterns in Composite Materials, Measuring Signals, and Methods for Automated Damage Diagnostics, Materials 15 (MDPI), no. 13 (2022): 4645

Universität Bremen
Fraunhofer IFAM
DFG FOR3022


Stefan Bosse
University of Bremen
sbosse@uni-bremen.de
www.edu-9.de


Dirk Lehmhus
Fraunhofer IFAM
dirk.lehmhus@ifam-fraunhofer.de

Department of Mathematics & Computer Science
University of Bremen, Germany
edu-9.de