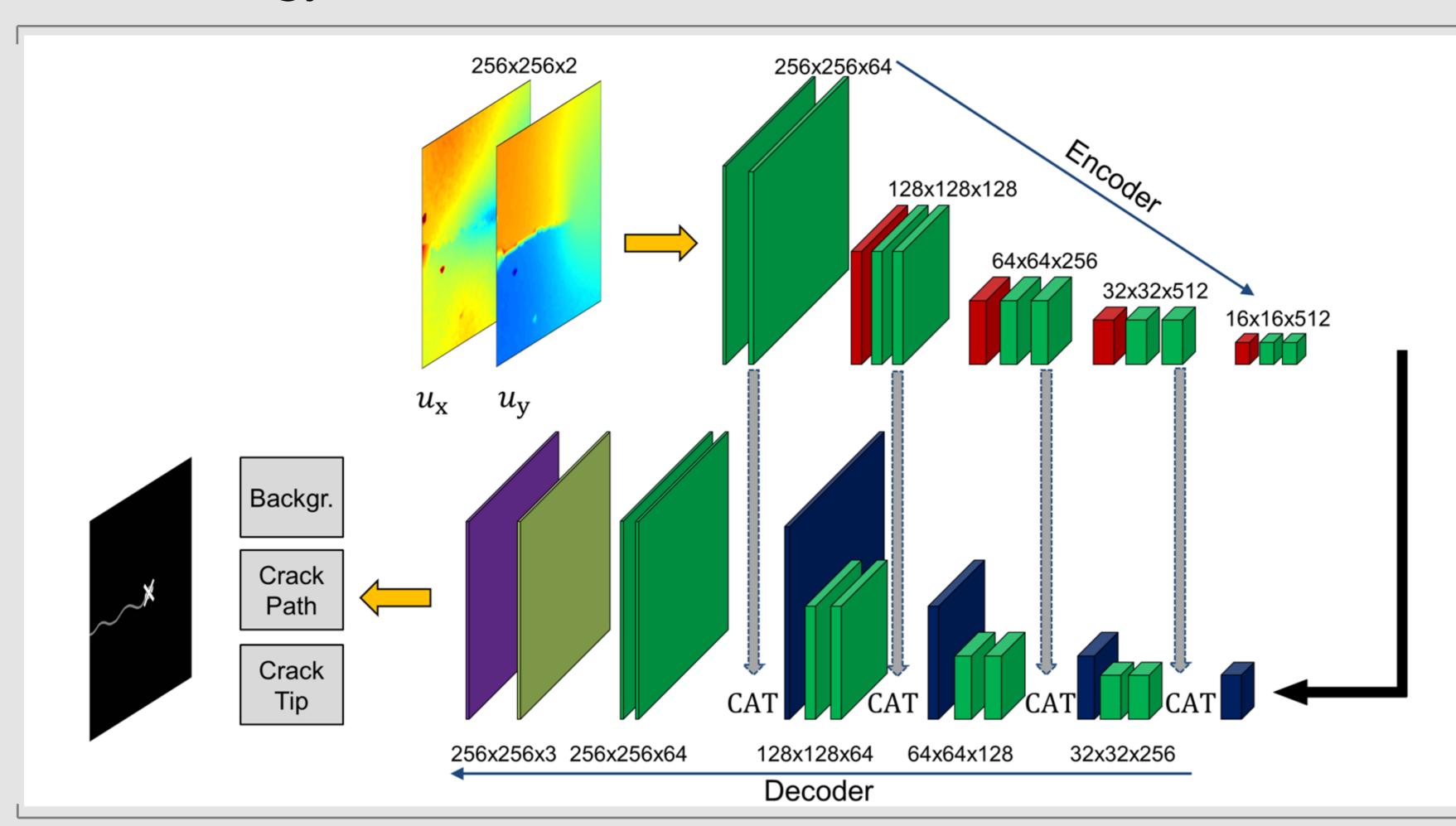
Automatic detection of fatigue crack paths using digital image correlation and deep neural networks

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Methodology



Deep convolutional neural network

- Using a U-Net architecture [1] for a segmentation of the crack path and crack tip
- The detection is done using displacement fields u_x and u_y measured experimentally by digital image correlation (DIC) [2].
- Conv2D + BatchNorm2D + Leaky ReLU (kernel=3, padding=1, stride=1)
- Max Pooling (kernel=2)
- Bilinear Interpolation (scale_factor=2)
- Conv2D (kernel=1, stride=1)
- Cross Entropy Loss
 (Log Softmax + NLL Loss)

Fig. 1 - U-Net architecture implemented in PyTorch to perform a segmentation of points that belong to a crack (path or tip)

Data set generation

- We capture images of the deformed specimen from both sides simultaneously (Fig 2).
- The front side was polished and images are captured via a Cannon 70D reflex camera (1) and a 90 mm macro lens. These images are used to identify the crack path manually (Fig. 3 a, c).
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Fig. 2 - Experimental setup for training data generation

- On the back side ② a GOM Aramis 12M System measures the displacement fields (see Fig. 3 b).
- We use the manual segmentation from the front side as ground truth for the back side (Fig 3 d).
- We capture images at different crack lengths and loads for high data variation.
- Data augmentation is performed by translation and mirroring.

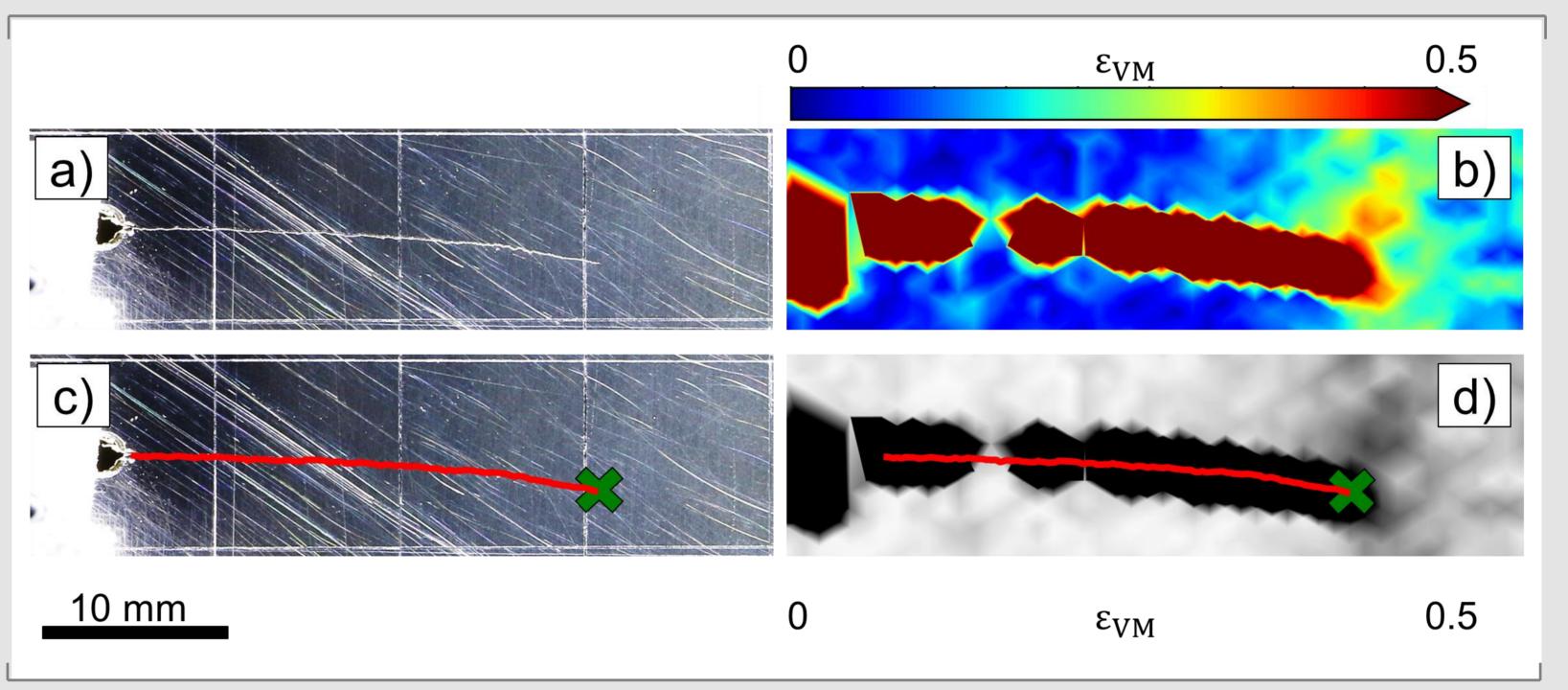


Fig. 3 – Polished specimen side used for ground truth generation (a, c). That ground truth is superimposed on the displacement data obtained from the DIC measurement (c, d).

Results

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[2]

- a-N diagrams are reproduced precisely for DIC results at maximum load (Figure 4).
- Higher scatter for minimum load

DCPD

Ground Truth

CNN_{FEA} (Ep. 5)

CNN_{W/O FEA} (Ep. 20)

- Using additional FEM data to make the network more robust
- Find detailed insights in our open access publication
 [3]

Application on large specimen

- We tested the trained network on a much larger specimen (950 mm width, [4]).
- To this purpose, we retrain the network based on FEM data with a respectively higher load spectrum.
- The a-N diagram could be reproduced also for the large specimen.

Outlook

- The method will be used for in-situ crack detection on different levels of magnification.
- To this purpose we use a global DIC system to detect fatigue cracks automatically. Using that information, a KUKA cobot carrying a light optical microscope and a reflex camera will follow the crack tip for local high resolution DIC.

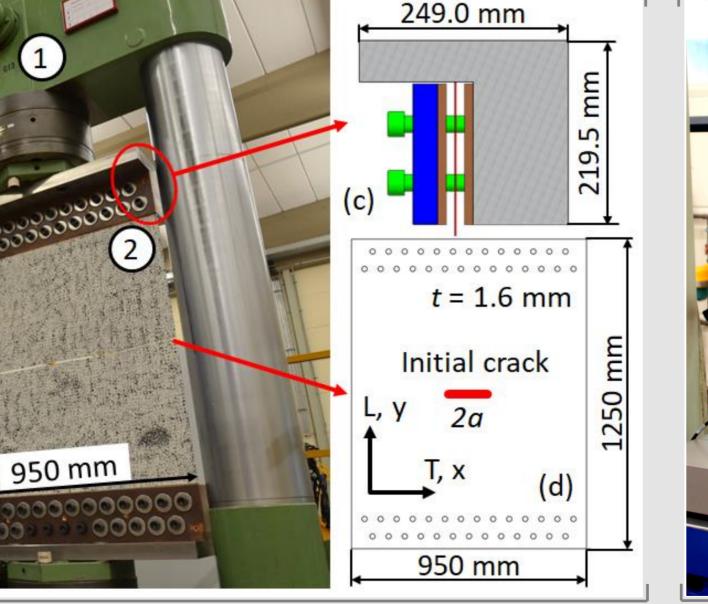


Fig. 4 – a-N-Diagram obtained from the CNN crack path detection

N [10⁵ cycles]

Fig 5. – Experimental setup at our 400 kN testing rig ① for larger test specimens (W = 950 mm ②) using the Aramis 12M system ③

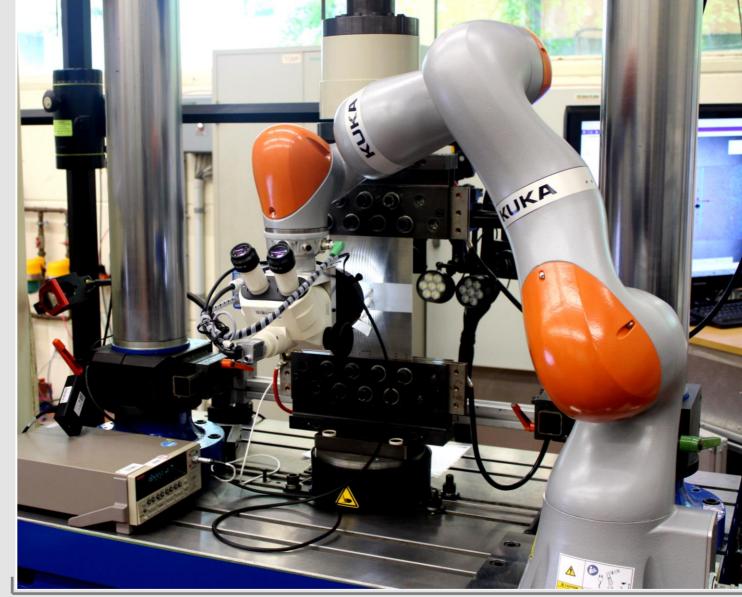


Fig. 6 – KUKA cobot equipped with a light optical microscope and a digital reflex camera, which automatically follows a fatigue crack tip

[1] O. Ronneberger, R. Fischer, T. Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI, Springer Vol. 9351: 234-241 (2015).

(a)

- B. Pan, Digital image correlation for surface deformation measurement: historical developments, recent advances and future goals, Meas. Sci. Technol. 29 082001 (2018)
- T. Strohmann, D. Starostin-Penner, E. Breitbarth, G. Requena, Automatic detection of fatigue crack paths using digital image correlation and convolutional neural networks, Fatigue Fract. Eng. Mat. Struct. 44(5): 1336-1348 (2021)

[4] E. Breitbarth, T. Strohmann, G. Requena, High-stress fatigue crack propagation in thin AA2024-T3 sheet material, Fatigue Fract. Eng. Mat. Struct. 43(11): 2683-2693 (2020)

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