

Explainable AI for precise fatigue crack detection

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Digital image correlation (DIC) data

- Training and validation data from AA2024-T3 MT-specimen ($w = 160$ mm, $t = 2.0$ and 4.8 mm) *fatigue crack propagation (fcp)* experiments **generated and labeled in [1]**
- Additional test data stems from large (950 mm) MT-specimen *fcp* experiments [2]

Neural network architectures U-Net and ParallelNets

- U-Net [3] with crack tip **segmentation** as output and **Dice loss** to deal with **class imbalance** of $\sim 1:50,000$
- additional **FCNN regressor arm** predicting the crack tip position in coordinates relative to the center of the image

Legend

- GAP: Global average pooling
- ✗: Crack tip position
- : Segmentation of crack tip

Methodology

- **Exhaustive data augmentation** (random crop & rotation) and **normalization** of input data
- Training and validation with independent full field displacement DIC data from *fcp* experiments
- Gradient-weighted class activation mapping adapted for semantic segmentation (**Seg-Grad-CAM** [4])
- Visualization of overall network attention using **internal features** from several U-Net blocks
- Features are weighted by the respective (average-pooled) gradients calculated during backpropagation

Attention heatmaps

- Top two examples (a,b) are from [1] and bottom one (c) from [2]
- First column shows a U-Net with inconsistent attention, the second is focussing on the crack path, and the third shows a *ParallelNets* model consistently focussing on the crack tip field

Results

- Models trained with the classical U-Net architecture systematically focus on parts of the crack path to predict the tip
- Using the crack paths to detect the tip seems reasonable but often fails in practice and produces large outliers (of up to 60 mm)
- With the **novel ParallelNets architecture** we were able to train models which **focus on the physical crack tip field**
- *ParallelNets* is **10% more accurate** than the best U-Net (U-Net-2)
- *ParallelNets* has **reliability of 98%** (U-Net-1: 77%, U-Net-2: 95%)
- *ParallelNets* is more **robust and stable** not producing any outliers on the considered datasets

Conclusions

- **Network architecture:** A combination of segmentation and regression of the crack tip in a parallel deep model leads to improved results.
- **Interpretability:** The Seg-Grad-CAM method produces high-level visual explanations for network decisions demystifying deep models and enabling human experts to understand their reasoning.
- **Model selection:** Our study found that models focusing on the physical crack tip field (like *ParallelNets*) are more accurate, reliable, and robust. These findings give rise to new model selection techniques (after or even during training).
- **Explainability:** These advances are a necessary prerequisite for the usage of deep models in safety relevant applications like the inspection of aircraft components during service [5].

[1] T. Strohmam, D. Starostin-Penner, E. Breitbarth, G. Requena. Automatic detection of fatigue crack paths using digital image correlation and convolutional neural networks. *Fatigue Fract Eng Mater Struct.* 2021; 44(5): 1336-1348

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

[3] O. Ronneberger, P. Fischer, T. Brox. U-Net: Convolutional Networks for Biomedical Image Segmentation. *Medical Image Computing and Computer-Assisted Intervention – MICCAI* (2015)

[4] K. Vinogradova, A. Dibrov, G. Myers. Towards Interpretable Semantic Segmentation via Gradient-Weighted Class Activation Mapping (Student Abstract). *AAAI* (2020)

[5] EASA Concept Paper: First usable guidance for Level 1 machine learning applications (<https://www.easa.europa.eu/easa-concept-paper-first-usable-guidance-level-1-machine-learning-applications-proposed-issue-01pdf>) (2021)