An automated high-resolution digital image correlation system for capturing fatigue crack growth mechanisms

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Abstract. The virtual certification of aeroplane structures is becoming increasingly important and requires accurate models to predict service life and damage tolerance. Therefore, fatigue crack growth models that consider the interaction between local mechanical loads and microstructural features of the materials are needed. The crack tip field provides a lot of information, such as the plastic zone, mixed-mode loading conditions, crack closure mechanisms or the stress state. This work presents a fully-automatic robotic test stand to acquire high-resolution digital image correlation data. Intelligent algorithms evaluate a large amount of data, determine the crack tip position and compute the crack tip loadings. The enhanced da/dN-ΔK_{DIC} evaluation for 2-mm-thick aluminium AA2024-T3 sheet material explains the ~56 % higher crack propagation rate for the T-L in contrast to the L-T crack growth direction.

Introduction

The propagation of fatigue cracks in ductile materials is related to local mechanical crack tip loads and the damage mechanism of the material. Most of the promoting and retarding mechanisms such as plasticity or crack closure occur in the bulk of the material [1]. Therefore, they are difficult to access and are evaluated using indirect measurement techniques such as back-face strain gauges or crack-mouth clip gauges. Optical methods like digital image correlation (DIC), which capture the full-field displacements and strains, are becoming increasingly important in experimental mechanics and especially in fracture experiments. The crack tip field on the surface reveals a lot of information about the crack driving mechanisms. Stress intensity factors and the J-integral are determined by integral [2] or near-field fitting techniques. Additionally, the plastic zone on the surface provides information about local damage mechanisms such as plastic deformation [3, 4], crack closure, crack branching, or crack deflection, but is difficult to access due to its small extension.

Experimental framework

Our novel experimental setup extends classical fracture mechanics by combining robotics, 3D DIC, data storage algorithms, and explainable artificial intelligence (XAI). Fig. 1a shows the experimental setup of the servo-hydraulic testing rig (A). A 3D DIC system (B) on the back side captures the entire surface of the MT(160) sample. On the front side, a robot (D) moves a light optical microscope (C) to follow the crack tip. The machine controller organises the test sequence and TCP data streams communicate between the different systems. Here, fatigue crack propagation of 2-mm-thick AA2024-T3 aluminium specimens was investigated under constant load amplitudes parallel (T-L) and perpendicular (L-T) to the rolling direction. For each 0.2 mm crack extension, the robot scans the surface in a 30% overlapping checkerboard pattern. The data are stored in a database in a structured format together with all available meta-information and labels, which can be made available to project partners, customers, or the scientific community.

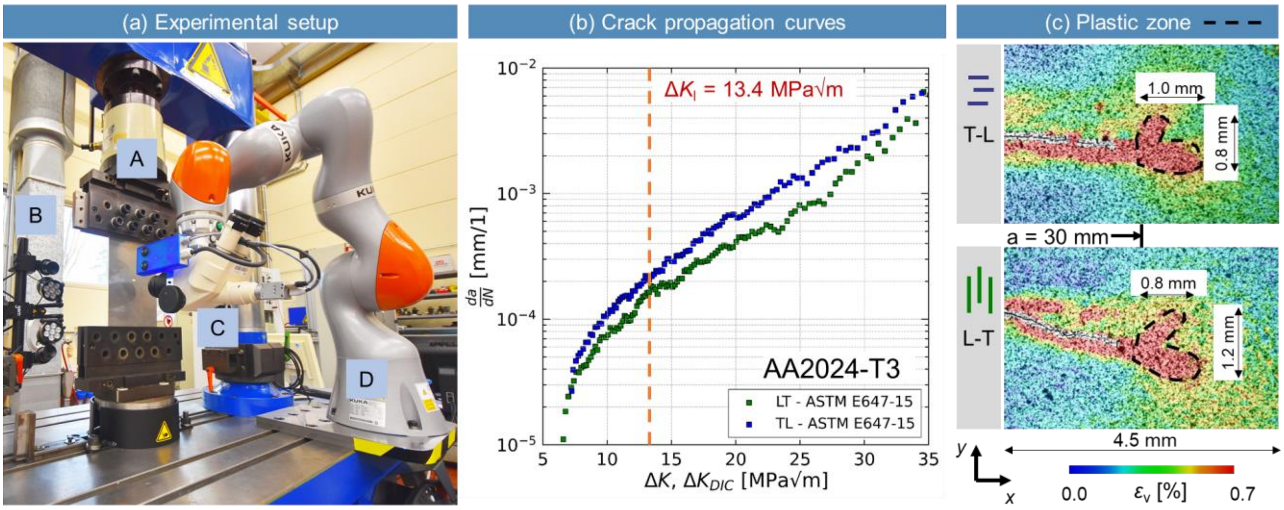

Figure 1: Servo-hydraulic testing machine (a), LT/TL crack propagation curves of AA2024-T3 sheet material (b) and crack tip plastic zones captured with the DIC microscope.

Digital framework

Smart algorithms automatically evaluate the large amount of data. 2D and 3D DIC data are automatically evaluated and stored in a neutral file format. A pre-trained machine learning model recognises and segments the crack tip and the crack path based on the displacement field in each DIC data set [5]. With the number of load cycles, the crack propagation rates d*a*/d*N* are calculated. Then, the crack tip loads K_I and K_{II} are calculated with the J-integral, interaction integral, or by fitting the CJP model or Williams field. The integration paths are defined automatically in the linear-elastic region outside the plastic zone at minimum and maximum loads. Finally, this digital framework provides d*a*/d*N*-ΔK_{DIC} data based on the DIC data incorporating crack closure, the fracture mode and the crack tip yielding conditions. The underlying algorithms for data acquisition and data analysis will be available in our open access gitlab repository “Toolkit for Mechanical Testing”.

Results and Discussion

First, the crack propagation data were evaluated using the standard ASTM E647 method with a linear elastic ΔK evaluation. Thereby, the crack propagation curves in Fig. 1b show the known characteristic of about 56 % faster crack growth in T-L than in L-T for the AA2024-T3 alloy. Moreover, 300 GB of data generated in each experiment are available for evaluation with our digital toolkit for mechanical testing. In particular, the microscopic 2D DIC data in the crack tip areas have a field of view of 4.5 x 3.1 mm² and a spatial resolution of 5 µm to reveal localized effects. In the case of L-T, a significant deviation from the ideal crack path is caused by the microstructural texture and the plastic zone is larger compared to TL (Fig. 1c). Additionally, its overall asymmetry is explained by local mixed-mode conditions because of crack front turning. The digital framework evaluates the data within several hours, compared to weeks of manual work.

Conclusion

The fully automated, multi-scale and time-resolved data acquisition during fatigue crack growth experiments provides high-quality data and enables new insights into crack propagation mechanisms. Machine learning-based crack tip detection in DIC data with subsequent evaluation algorithms enables the determination of crack tip loads, crack closures and plastic zone characterisation. Based on locally high-resolution displacement field data of the crack tip field, intrinsic and extrinsic fatigue crack effects are captured. Thus, the mechanisms underlying each data point are explainable in the generated crack propagation models. In addition to the high reliability of the data, the system can generate high-quality information and detailed knowledge in a shorter time than ever before.

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