doi:10.1017/S1431927622003828
Microsc. Microanal. 28 (Suppl 1), 2022

Merging Machine Learning and TriBeam Tomography for 3D Defect Detection in an AM CoNi-Based Superalloy

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Energy efficiency is a strong driving force for development of 3D printing processes for geometrically complex high temperature superalloy components. However, defects in additively manufactured (AM) multicomponent materials are currently a significant barrier. Superalloys have diverse chemistries that can result in complex solidification paths, heat affected zones, and liquation cracking [1,2]. It is well understood that selective laser melting (SLM) induces steep thermal gradients during printing that impose large thermal strains on the material [3]. These strains, in addition to chemical segregation during solidification, lead to significant cracking during AM, limiting mechanical performance. In addition to cracks, defects such as pores, voids, and inclusion phases can form during manufacturing due to either print parameters or material chemistry [4].

The effects of two different SLM print strategies are investigated in a new CoNi-based superalloy. Millimeter-scaled multimodal 3D datasets were collected using the TriBeam, a serial sectioning technique utilizing a femtosecond pulsed laser in a FIB-SEM. Electron backscatter diffraction (EBSD) maps and backscatter electron (BSE) images at each slice provide structural and orientational data of the entire dataset volume [5]. To reduce the already long collection time of these datasets, chemical information was not collected during serial sectioning. However, a combined high resolution EBSD and energy-dispersive X-ray spectroscopy (EDS) scan was captured at the final slice, providing training data for machine learning models to learn to identify cracks and inclusions. The nonlinearity of the classification problem required the use of neural network models to accurately classify features of interest in the dataset [7]. The EDS data provided over 6 million voxels to train the model on with the goal of classifying almost 3 billion voxels (a 3D volume of stacked BSE images). To train the network, each voxel was given three features: in-plane coordinates, and the BSE electron signal. By mapping the EDS data onto the BSE images via the Thin Plate Spline algorithm [6], alumina inclusions were identified and projected into the bulk dataset with the assistance of machine learning models.

From the combined data aided by the machine learning projections, regions previously identified as pores or other defects were correctly identified as alumina inclusions. In addition, void and pore surfaces were found to exhibit oxidation. Quantitative merging of the data modalities enabled analysis of the spatial distribution of the defects, inclusions, and microstructure and their correlation with parameters in the printing process.

Step	Time
Laser Cut	00:05:29
FIB Cleanup	00:13:11
SEM Imaging	00:01:38
EBSD Map	00:14:45
Stage moves	00:02:19
AF/ACB	00:00:08
TOTAL	00:37:30

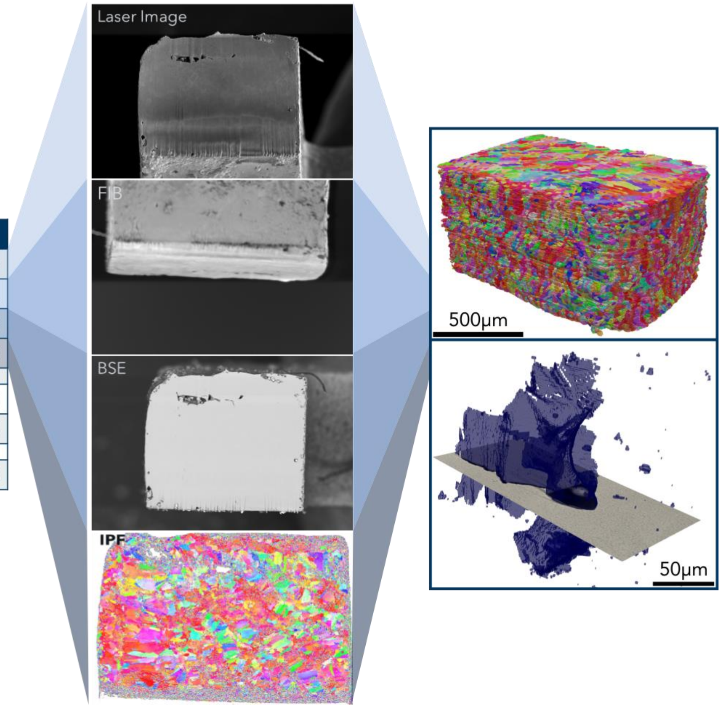

Figure 1. From data collection to volumetric analysis and defect identification. TriBeam experiment steps and approximate durations (left), various data modalities collected (center), 3D reconstructions of the bulk and a defect (right).

References:

[1] NJ Harrison et al., Acta Materialia **94** (2015), p.59-68. doi:10.1016/j.actamat.2015.04.035
[2] B Zhang, Y Li, and Q Bai, Chinese Journal of Mechanical Engineering **30** (2017), p.515–527.doi:10.1007/s10033-017-0121-5
[3] P Bian, X Shao, and J Du, Applied Sciences **9** (2019), p.2231. doi:10.3390/app9112231
[4] C Qiu, H Chen, Q Liu, S Yuea, H Wang, Materials Characterization **148** (2019), p.330-344. doi:10.1016/j.matchar.2018.12.032
[5] MP Echlin et al., Rev. of Sci. Instrum. **83** (2012), p.023701, doi:10.1063/1.3680111
[6] YB Zhang , A Elbrønd, and FX Lin, Materials Characterization **96** (2014), p.158–165. doi:10.1016/j.matchar.2014.08.003
[7] A Landi, P Piaggi, M Laurino, and D Menicucci, Proc. 2010 10th Int. Conf. Intell. Syst. Des. Appl. Proceedings (2010), p.115–120. doi:10.1109/ISDA.2010.5687280.