DOI 10.5162/SMSI2023/C5.4

From Thermographic In-situ Monitoring to Porosity Detection – A Deep Learning Framework for Quality Control in Laser Powder Bed Fusion

Simon Oster[1], Nils Scheuschner[1], Keerthana Chand[1], Philipp P. Breese[1], Tina Becker[1], Frank Heinrichsdorff[2], Simon J. Altenburg[1]
[1] Bundesanstalt für Materialforschung und -prüfung, Unter den Eichen 87, 12205 Berlin, Germany
[2] Siemens AG, Siemensdamm 50, 13629 Berlin, Germany
Simon.Oster@bam.de

Summary:
In this study, we present an enhanced deep learning framework for the prediction of porosity based on thermographic in-situ monitoring data of laser powder bed fusion processes. The manufacturing of two cuboid specimens from Haynes 282 (Ni-based alloy) powder was monitored by a short-wave infrared camera. We use thermogram feature data and x-ray computed tomography data to train a convolutional neural network classifier. The classifier is used to perform a multi-class prediction of the spatially resolved porosity level in small sub-volumes of the specimen bulk.

Keywords: Laser powder bed fusion, In-situ monitoring, Thermography, Machine Learning, Porosity

Introduction

Porosity in laser powder bed fusion (PBF-LB/M) is a major detrimental factor for the mechanical strength of safety-critical components. Thermography as an in-situ monitoring method can be used to monitor the thermal history of the component (Fig. 1). Deviations in the thermal history were shown to be an indicator for increased probability of porosity formation [1]. Thermographic in-situ monitoring of PBF-LB/M processes results in complex thermogram data of comprehensive size. The reduction to physically interpretable thermogram features can reduce the amount of data significantly. However, the layer-by-layer manufacturing increases the complexity of porosity prediction tasks due to phenomena such as remelting of subsequent layers. Machine Learning (ML) algorithms can be applied to overcome these issues. In this study, we use a convolutional neural network (CNN) to perform a spatially resolved multi-class classification of the porosity level based on thermogram feature data.

Experiments & Methods

We manufactured two cuboid specimens with identical process parametrization from Haynes 282 (Ni-based alloy) in separate build jobs using a commercial 3D printer. Laser power and scan velocity were varied in different component sections to force the formation of lack-of-fusion and keyhole porosity (Fig. 1). We monitored the manufacturing process using a short-wave infrared (SWIR) camera with a framerate of 2193 Hz and a spatial resolution of approx. 38 µm/pixel. From the resulting thermograms, we extracted features regarding the melt pool geometry and temperature, process spatter, and cooling of the solidified material. After manufacturing, both specimens were scanned using X-ray Computed Tomography (XCT) with a voxel resolution of (3x3x3) μm^3. The XCT data was segmented into material and voids. We registered both datasets based on our registration methodology presented in [2]. Thermogram feature data and XCT data were used to produce a dataset for the training of the CNN model.

Enhanced prediction model

We aim to extend our prediction framework by the following aspects: Firstly, at the current state of work, we already expanded the portfolio of thermogram features by spatter features (*e.g.*, *number of ejected spatter particles*) and further cooling features (*e.g.*, *cooling rate*). These new features are considered to provide additional valuable information about the local process condition which could further improve the performance of the classifier. Secondly, we aim to use natural neighbor interpolation to produce geometrically smooth feature layer data and calculate the respective interpolation uncertainty [3]. A main motivation behind this is the spatial aliasing inherent to the thermogram feature data. Aliasing occurs since the maximum acquisition frequency of the SWIR camera limits the sampling rate in which the melt pool can be monitored. The interpolation uncertainty will be incorporated into the CNN to weight the training samples. Thirdly, we intend to expand the model from binary classification to a multi-class classifier to predict different levels of porosity and the primal void class.

Preliminary results

The sensitivity of thermogram features to changes of the Volumetric Energy Density (VED) provides first indications about their potential for void prediction. In Fig. 2, the sensitivity of a selection of features to VED changes is shown. For better comparison between features, all data points were normalized using the results for nominal VED (57.95 J/mm³). All melt pool geometry features showed significantly decreased values for decreased VED and vice versa. In terms of spatter features, an increased *Number of ejected Particles* was present for decreased VED. For high VEDs, the feature showed very low values (< 0.25). The remaining spatter features showed overall low sensitivity to VED changes. *Time over threshold* (*TOT*) and *Sum of temperatures over threshold* (*SOTemOT*) showed comparable behavior and high sensitivity to increased VED. In contrast, the *Cooling rate* (CR) is increased for decreased VED and vice versa. The presented results indicate that especially *Number of Particles* and *Cooling rate* might include valuable information for defect prediction.

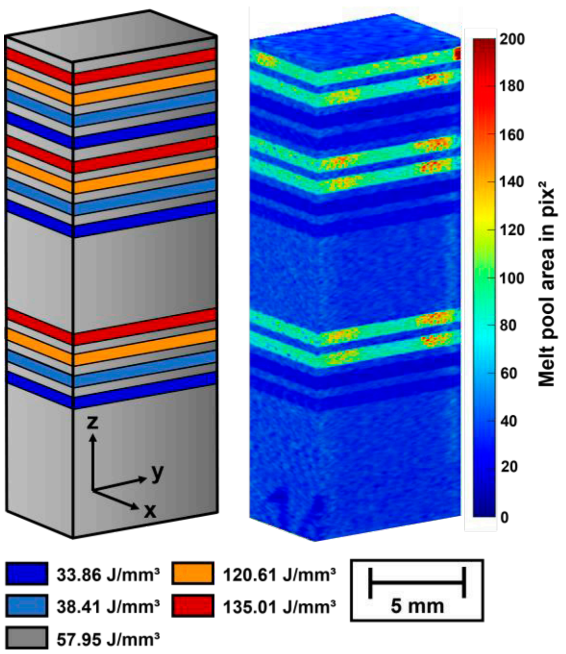

Fig. 1. Left side: Sliced representation of specimen design. Sections of changed VED are indicated by color and consist of 15 layers each. Right side: Sliced representation of thermal history indicated by melt pool area feature. Natural neighbor interpolation was used to produce the shown 3D volume.

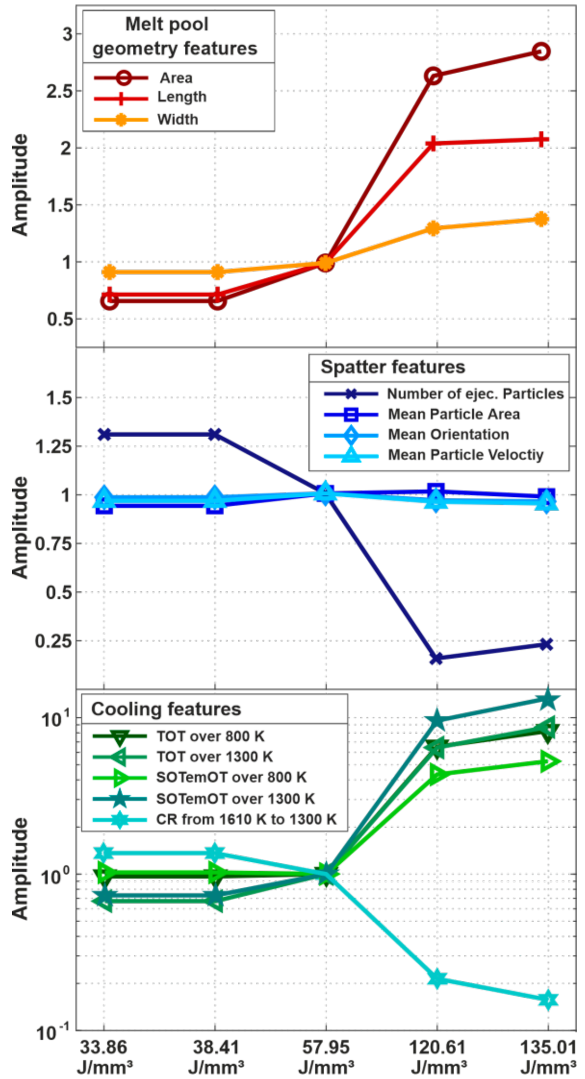

Fig. 2. Normalized mean feature response to VED changes. The abscissa shows the used VED settings, and the ordinate shows the normalized feature responses. The shown data points depict the normalized mean feature responses measured when using the given VED.

References

[1] C. S. Lough, T. Liu, X. Wang, B. Brown, R. G. Landers, D. A. Bristow, J. A. Drallmeier, E. C. Kinzel, Local prediction of Laser Powder Bed Fusion porosity by short-wave infrared imaging thermal feature porosity probability maps. *Journal of Material Processing Tech.*, 302 (2022); doi: 10.1016/j.jmatprotec.2021.117473

[2] S. Oster, T. Fritsch, A. Ulbricht, G. Mohr, G. Bruno, C. Maierhofer, S. J. Altenburg, On the Registration of Thermographic In Situ Monitoring Data and Computed Tomography Reference Data in the Scope of Defect Prediction in Laser Powder Bed Fusion, *Metals*, 12, 947 (2022); doi: 10.3390/met12060947

[3] T. R. Etherington, Discrete natural neighbour interpolation with uncertainty using cross-validation error-distance fields, *PeerJ Comput. Sci.*, 6:e282, (2020); doi: 10.7717/peerj-cs.282