



Task 4.3 – Defect-free metal additive manufacturing

Kurt De Grave, Cyril Blanc, Ayyoub Ahar, Emma van Doren (Flanders Make)

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Task 4.3 – Defect-free metal additive manufacturing



Laser powder bed fusion (LPBF) is the main industrial 3D printing process for metal parts

Major bottleneck: quality control

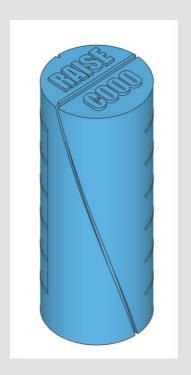


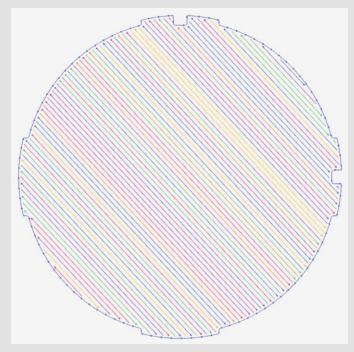


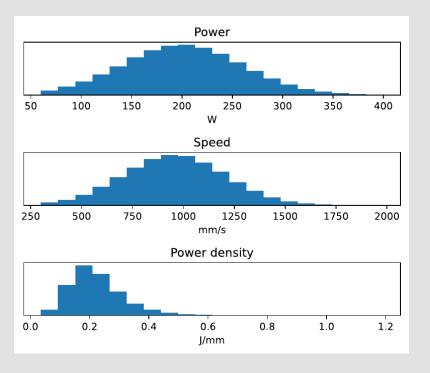
Dataset



Fuse powder using randomized laser parameters



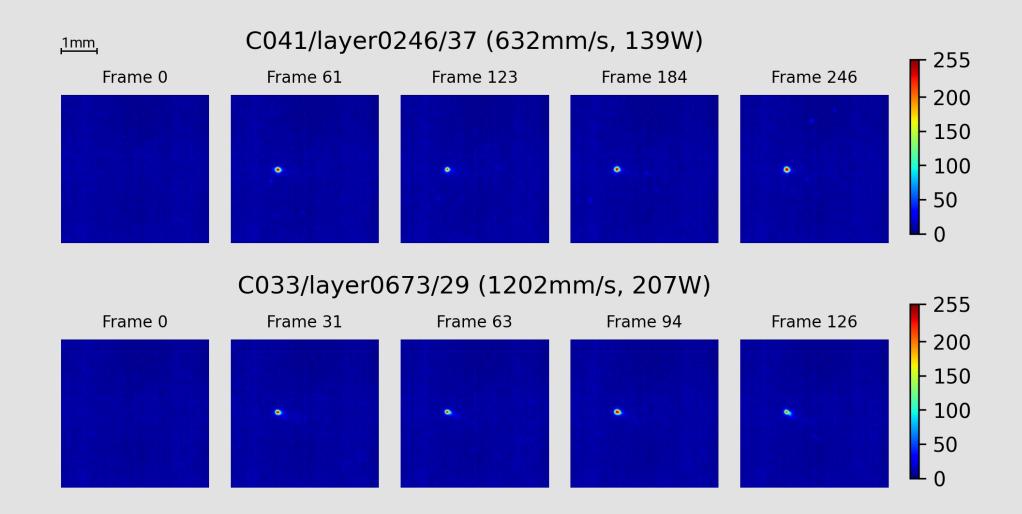






Dataset





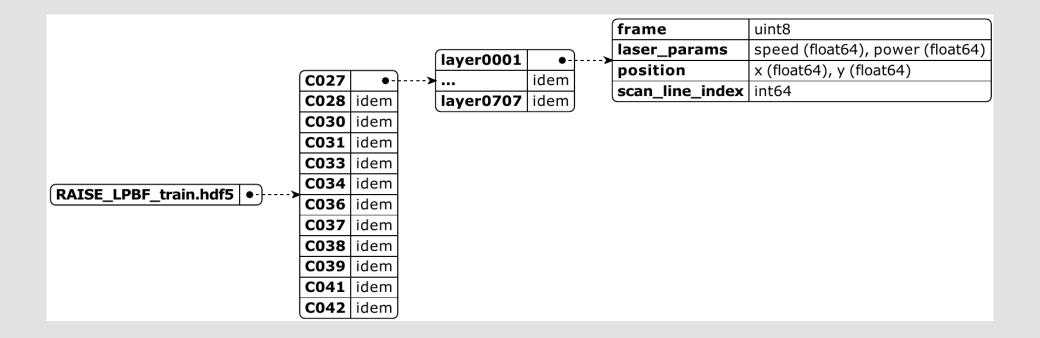


Dataset



Compiled to a simple HDF5 structure

1TB



Baseline models



KISS principle!

Baseline models simplified as much as possible:

- Only essential preprocessing
 - No cropping
 - No camera calibration
- Default hyperparameters
- Using only a few (equidistant) frames

Results: baselines



Model	Frames used	RMSE Speed	RMSE Power	RMSE Energy density
SlowFast	32	67.6	11.1	0.0290
3D ResNet	8	157.8	19.5	0.0520
MViT	16	191.9	24.9	0.0623
Swin3D	16	205.0	25.3	0.0568

Results: short journal paper



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Reference dataset and benchmark for reconstructing laser parameters from on-axis video in powder bed fusion of bulk stainless steel



Cyril Blanc, Ayyoub Ahar, Kurt De Grave*

Flanders Make vzw, Oude Diestersebaan 133, Lommel, 3920, Belgium

ARTICLE INFO

Keywords: Selective laser melting Stainless steel On-axis camera Machine learning Monitoring

ABSTRACT

We present RAISE-LPBF, a large dataset on the effect of laser power and laser dot speed in powder bed fusion (LPBF) of 316L stainless steel bulk material, monitored by on-axis 20k FPS video. Both process parameters are independently sampled for each scan line from a continuous distribution, so interactions of different parameter choices can be investigated. The data can be used to derive statistical properties of LPBF, as well as to build anomaly detectors. We provide example source code for loading the data, baseline machine learning models and results, and a public benchmark to evaluate predictive models.

1. Introduction

Powder Bed Fusion (PBF) is the most common Additive Manufacturing (AM) method where the powder of the chosen material (e.g., nylon, or various types of metal powder) is heated to construct the product. an heat sources are laser beam (LPBF, sometimes writsolution, the monitoring system observes the meltpool and monitors a set of print parameters to predict whether the current trajectory of the printing is expected to end up in generating pores. Consequently, the control unit may generate corrective control measures to prevent the generation of defects in the first place, or compensate for it by remelting

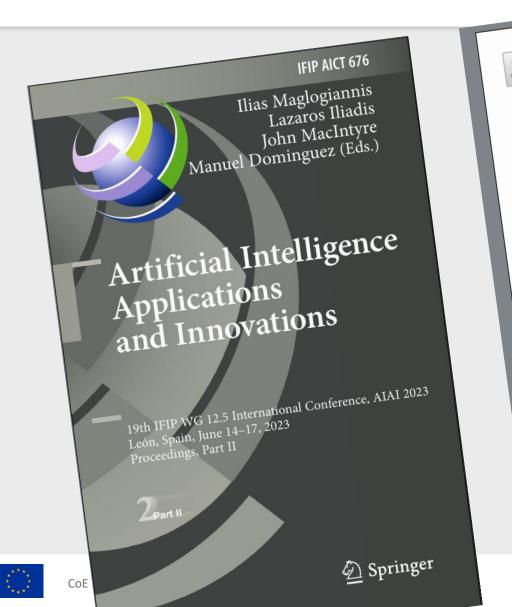
The very fast movements of the melting laser, i.e., laser dot speeds

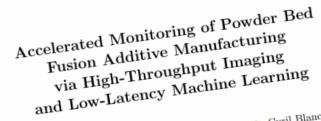


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Side result: AIAI conference paper







Ayyoub Ahar^(⊠), Rob Heylen, Dries Verhees, Cyril Blanc,

Flanders Make, 3920 Lommel, Belgium ayyoub.ahar@flandersmake.be

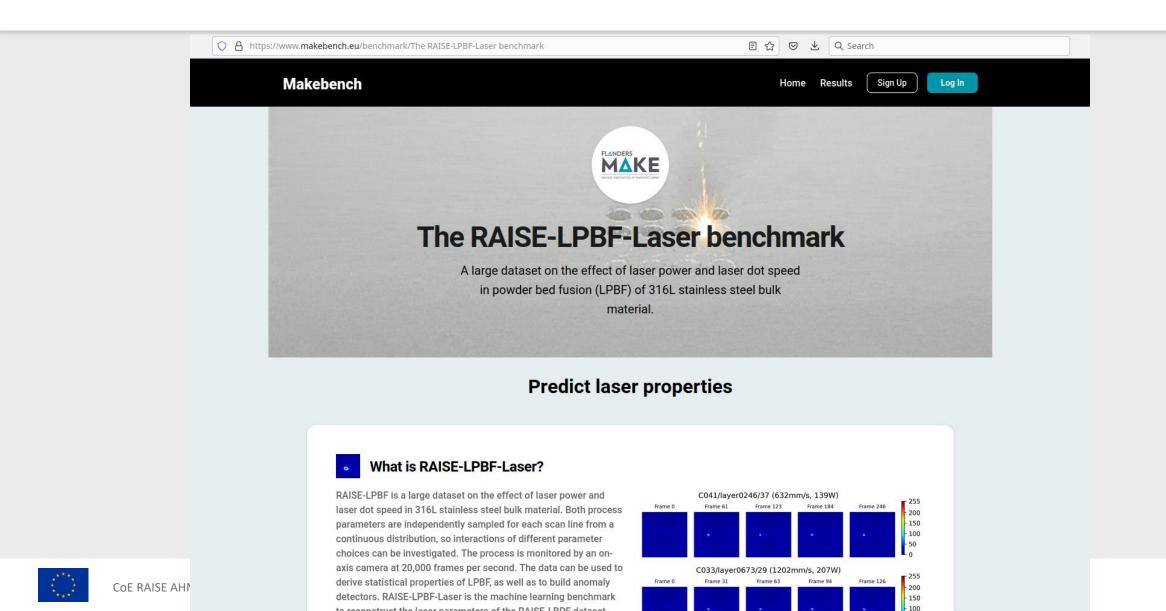
Abstract. Metal 3D printing in particular laser powder bed fusion is in the forefront of product manufacturing with complex geometries. However, these printed products are susceptible to several printing defects mainly due to complexities of utilizing high-power, ultra-fast laser for melting the metal powder. Accurate defect prediction methods to monitor the printing process are of high demand. More critically, such solutions must maintain a very low computational cost to enable feedback control signals for future low-latency laser parameter correction loops, preventing creation of defects in the first place. In this research, first we design an experiment to explore impact of several laser settings on creation of the most common defect called "keyhole porosity". We print an object while recording the laser meltpool with an externally installed high-speed visual camera. After extracting keyhole pore densities, we annotate the meltpool recordings and use it to evaluate performance of a simple but fast CNN model as a low-latency defect detector.

Keywords: pore density \cdot melt-pool monitoring \cdot keyhole pores \cdot defect detection · additive manufacturing · laser powder bed fusion

Layer by layer 3D printing of objects with high-complex geometries has been possible in a process called Additive Manufacturing (AM) [12]. Its advantages over other traditional manufacturing methods among others are: on-demand production of uniquely designed objects in limited quantities, substantial cost reduction via shorter supply chain and less storage [3], reduced parts counts, fortar and loss complicated assembling and decreased time and complexity for Various printing materials like polymers and metals

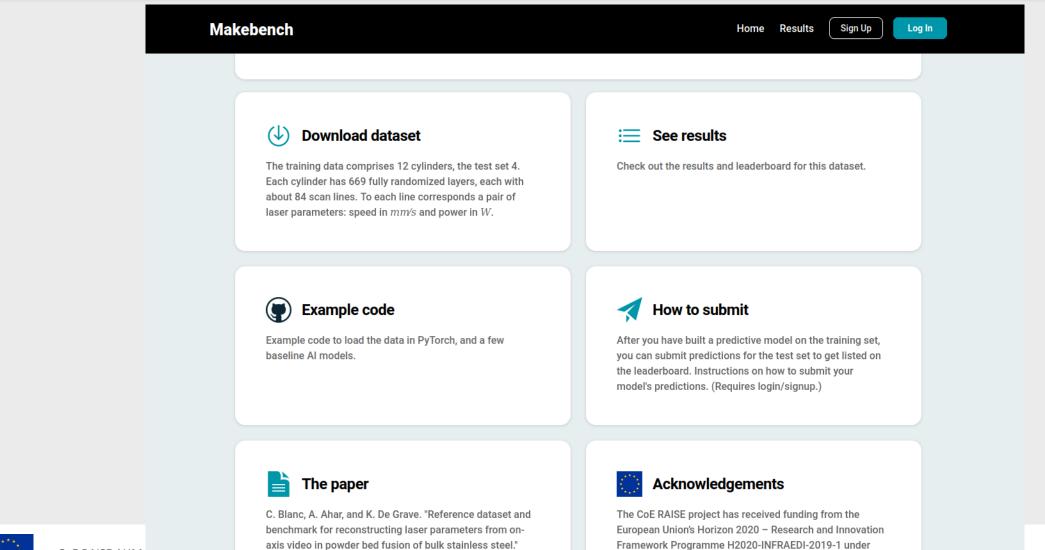
Results: makebench.eu





Results: makebench.eu (ctd.)



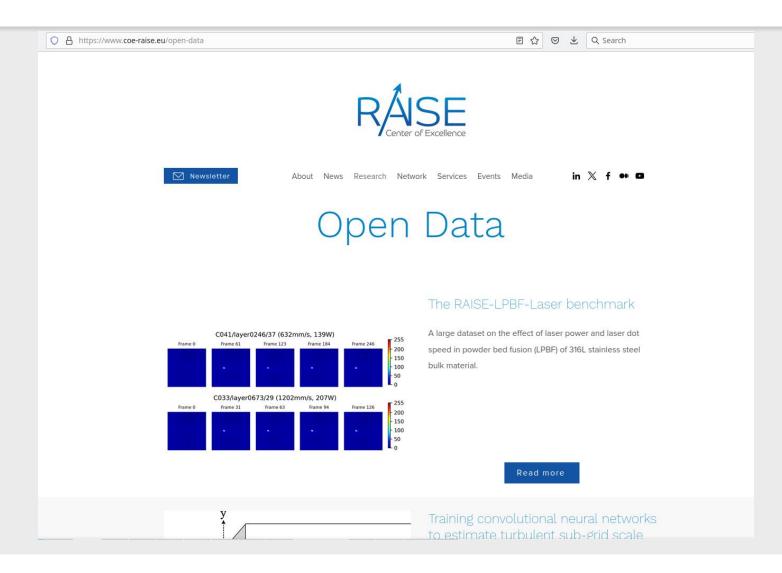


Additive Manufacturing Letters (2023): 100161.

Open data



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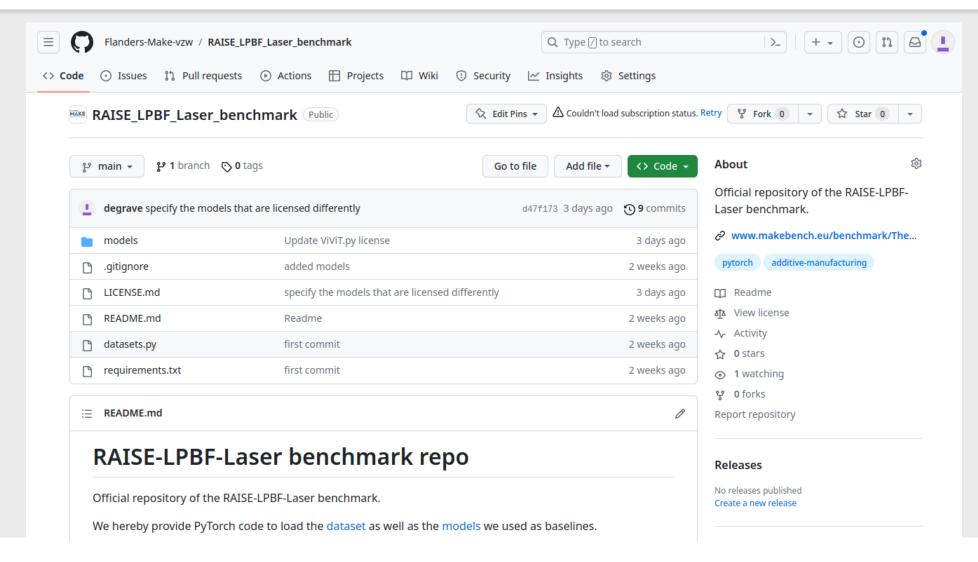


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Supporting public repo



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Misc.



- Master Thesis postponed to H2 2023.
- > Experimented with ClearML Agent in VSC cloud
 - Read-only git access (granted in advance)
 - Job isolation: OpenStack VM + Docker + non-privileged container
 - Various caches are necessary for performance but break isolation
 - Still GPU-accelerated
 - Data access still TBD

Next Steps



- > Beating the baseline
- > Helping others beat the baseline
- > Bigger Transformers and other foundational models
 - However, industry prefers small models and cheap sensors
- Mass density model







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