



Deep Semi-supervised Learning of Dynamics for 3D Defect Mapping in Laser Powder Bed Fusion

IBSim-4i conference

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Presentation overview

Part 1: Defect sources



Part 2: Defect detection



Part 3: Defect mapping



Part 1: Defect sources



L-PBF process





[1] – DebRoy et al. (2017) - Additive manufacturing of metallic components – Process, structure and properties

[2] - Fraunhofer Institute

[3] – Dall'Ava et al. (2019) - Comparative analysis of current 3D

printed acetabular titanium implants

[4] Tan et al. (2020) - Design and additive manufacturing of novel conformal cooling molds

Why do defects occur?



Laser Powder Bed Fusion process (Franhofer)



Process window showing varying types of defects. Section images: Gong H et al. (2013) "Defect morphology in Ti–6Al–4V parts fabricated by selective laser melting and electron beam melting"



Geometric induced (pre-build)



Laser Powder Bed Fusion process (Franhofer)



Grasso M et al. (2016) "In-process monitoring of selective laser melting: spatial detection of defects via image data analysis"

Variability induced (in-situ)



Video credits: Khairallah et al. (2020) "Controlling interdependent mesonanosecond dynamics and defect generation in metal 3D printing"

Part 2: Defect detection

Larsen & Hooper (2021) - <u>Deep semi-supervised</u> learning of dynamics for anomaly detection in laser powder bed fusion



Melt pool monitoring





Camera 1





The challange of False Positives (FP)

- False positive rate, $FPR = \frac{FP}{FP+TN}$
- 10x10 grid
- 0.01 FPR = 1 FP/layer
- 100x100 grid
- 0.001 FPR = 10 FP/layer
- One 25 mm² layer may have in the region of 10,000 measurements at 100 kHz.
- 100s of layers results in many FPs

Example of a component layer

Autocorrelation

- One cause of high FP: sequential data often has correlations
- This can cause defects to be obscured in the process
- Results in large amounts of false positives (FP)
- Hence modelling the process allows defects to be detected by reduced FP

Imperial College London Melt pool monitoring with FlawNet

(a) Dimensionality reduction

Input: high speed image data Output: extracted features

(b) Latent dynamics model

Input: melt pool state at time, t Output: melt pool state at time, t+1

(c) Data fusion of dynamics

Measure dynamic signature Combine local correlations

(d) Linear classification and regression

Local prediction of defect Layerwise porosity

Case study: detecting part-wide porosity

- 3 builds:
- 9x Ø5 mm cylinders9x focus heights
- -20 to 12 mm

Focus height vs. porosity indicating process window

Build plate with cylinder setup

Results 1: Correlating with global porosity

Porosity vs mean dynamic signature over one layer.

Focus height vs. porosity and dynamic signature.

Results 2: Localised defect detection (9 frames)

- Optimal vs. unstable
 - 14 samples
 - ROC AUC = 0.999 ± 0.001
 - Porosity = $8.93 \pm 8.73\%$
- Optimal vs. marginal
 - 4 samples
 - ROC AUC = 0.944 ± 0.013
 - Porosity = $0.14 \pm 0.07\%$
- Worst case:
 - ROC AUC = 0.935
 - Porosity = 0.07%

Receiver operating characteristic (ROC) for optimal (0,4mm) vs. rest of focus heights

> Part 3: Defect mapping

Part of an ongoing study

Machine inputs

Data representation

Part 3 summary

Thanks to our collaborators

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 - Research group including Harry de Winton and Dr. Richard Williams
 - Supervisor, Dr. Paul A. Hooper
 - MoM and Department of Mechanical Engineering at Imperial College London

Part 1: Part 2: Questions? **Defect Defect**

Thanks for your attention!

700, 950 nm

filters

- Laser

-Powder

Melt pool

High speed

camera

Part 3: **Defect** mapping

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