

Data processing I: objects tracking challenge

Looking into predictive single-particle tracking techniques

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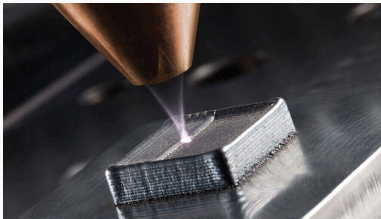
ITT9, 28.01.2019

Diamond Light Source



What is additive manufacturing

- **Additive manufacturing (AM)** is a transformative approach to industrial production that enables the creation of lighter, stronger parts and systems¹.
- Additive manufacturing uses data computer-aided-design (CAD) software or 3D object scanners to direct hardware to deposit material, layer upon layer, in precise geometric shapes².
- The terms '3D printing' and 'rapid prototyping' are the subsets of additive manufacturing.

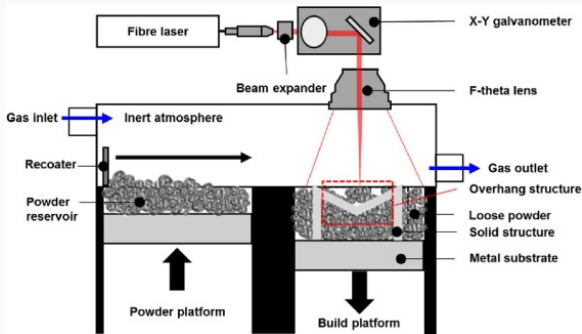


¹<https://www.ge.com/additive/additive-manufacturing>

²https://www.youtube.com/watch?time_continue=71&v=kKQ5KwFwW_s

How the data have been collected

- I12 beamline³ of DLS is used for very fast radiographic and tomographic imaging



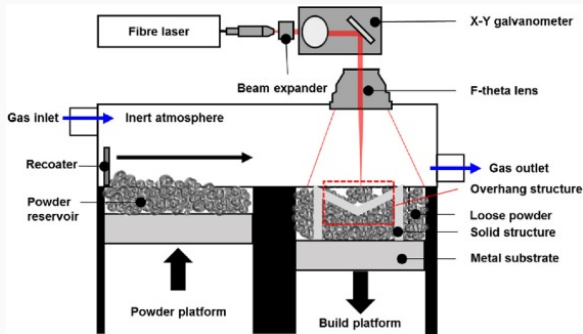
³<https://www.diamond.ac.uk/Instruments/Imaging-and-Microscopy/I12.html>

⁴<https://www.diamond.ac.uk/Science/Research/Highlights/2018/laser-additive-manufacturing.html>

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- I12 beamline³ of DLS is used for very fast radiographic and tomographic imaging
- The series of radiographs were collected resulting in a 3D dataset (x,y + time), i.e. 3D process captured in 2D⁴

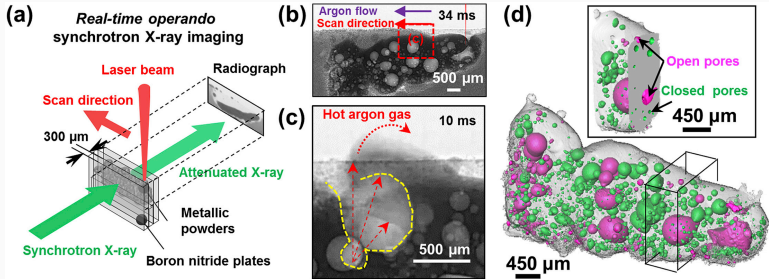


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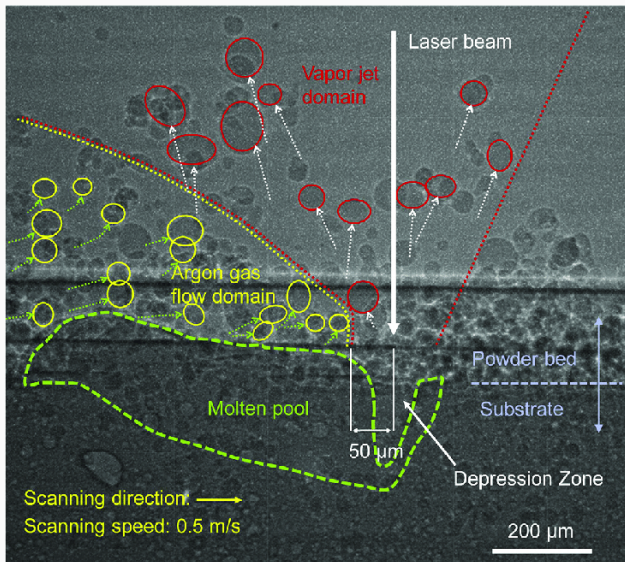
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Laser melting process in details



See videos here: <https://www.sciencedirect.com/science/article/pii/S1359645418309698>

Laser melting process in details



One data analysis pipeline

The following image processing pipeline was performed by Dr. *Alex Leung* et al. (UCL) [1, 3, 2] and it contained the following steps:

1. **Denoising** of time-series (radiographs) using state-of-the-art collaborative video block matching algorithm⁵.

⁵<http://www.cs.tut.fi/~foi/GCF-BM3D/>

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2. Custom background **subtraction** and image **thresholding** techniques to extract the evolution of melt features, which enables the quantification of the molten pool geometries over time, including the length, width, and area.

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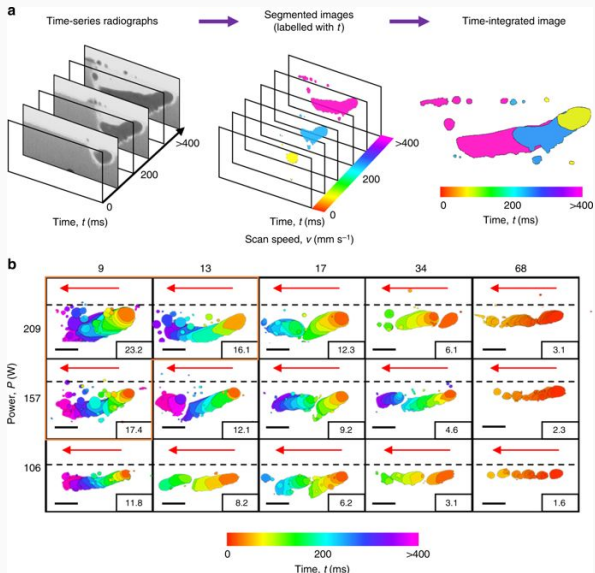
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3. Manual **tracking** with ImageJ⁶ and also the use of TrackMate software[4] (also available in ImageJ).

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Some data processing stages



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1. Better video denoising algorithms
2. Better background subtraction and segmentation methods
3. Objects classification and smarter tracking
4. Predictive models robustly estimating the path of a particle

Access to the data and software dependencies

- The raw I12 data are accessible at
`ITT_BATH_DLS/DataP_I_AdditiveManufact_tracking/rawdata`
- Python script to read data (stack of tiffs) into Numpy 3D array
`ITT_BATH_DLS/DataP_I_AdditiveManufact_tracking/ITT_AM.py`
- Python wrapper for Block-Matching denoiser
<https://github.com/ericmjonas/pybm3d>
- Regularisation (denoising) package
<https://github.com/vais-ral/CCPI-Regularisation-Toolkit>

All data have been kindly provided by Dr. **A. Leung**
alex.leung@ucl.ac.uk and Prof. **P. D. Lee** peter.lee@ucl.ac.uk



C. L. A. Leung, S. Marussi, R. C. Atwood, M. Towrie, P. J. Withers, and P. D. Lee.

In situ x-ray imaging of defect and molten pool dynamics in laser additive manufacturing.

Nature communications, 9(1):1355, 2018.



C. L. A. Leung, S. Marussi, M. Towrie, R. C. Atwood, P. J. Withers, and P. D. Lee.

The effect of powder oxidation on defect formation in laser additive manufacturing.

Acta Materialia, 2018.



C. L. A. Leung, S. Marussi, M. Towrie, J. del Val Garcia, R. C. Atwood, A. J. Bodey, J. R. Jones, P. J. Withers, and P. D. Lee.

Laser-matter interactions in additive manufacturing of stainless steel ss316l and 13-93 bioactive glass revealed by in situ x-ray imaging.

Additive Manufacturing, 24:647–657, 2018.



J.-Y. Tinevez, N. Perry, J. Schindelin, G. M. Hoopes, G. D. Reynolds, E. Laplantine, S. Y. Bednarek, S. L. Shorte, and K. W. Eliceiri.

Trackmate: An open and extensible platform for single-particle tracking.

Methods, 115:80–90, 2017.