Powder Bed Fusion Laser Beam Metals Additive Manufacturing: Process Monitoring Approaches for Qualification and Certification

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All figures are credit NASA

Outline

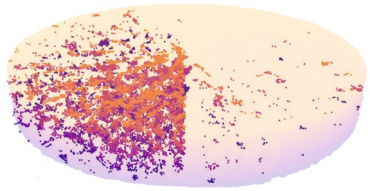
- Background and Big Picture
- Synchronized In-situ Monitoring Process Metrics
  - Melt Pool Imaging
  - Power Monitoring
- Additive Manufacturing Model-based Process Metrics (AM-PM)
  - Method
  - Mapping to Porosity

Computational Materials-Informed Qualification and Certification (Q&C) of Additively Manufactured (AM) Flight Hardware

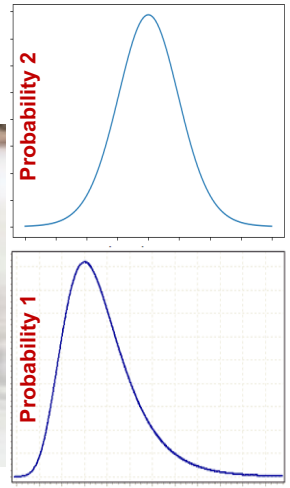
Photograph

5 [mm]

Porosity



AM Component



Process → **Structure** → **Property/Performance**

Small deviations in processing parameters may result in large differences in performance. Current approaches for Q&C of metallic materials (including AM) are entirely based on test data.

Change the Paradigm for Q&C

Develop a computational materials-informed ecosystem for quantifying sources of variability in fatigue performance of additively manufactured metallic materials through integrated multi-scale, multi-physics simulation, characterization and monitoring.

Computational Materials for Qualification and Certification (CM4QC) Steering Group

Formed through a NASA-FAA (Federal Aviation Administration) collaboration
Members: 10 industry, 8 government, 8 universities/labs

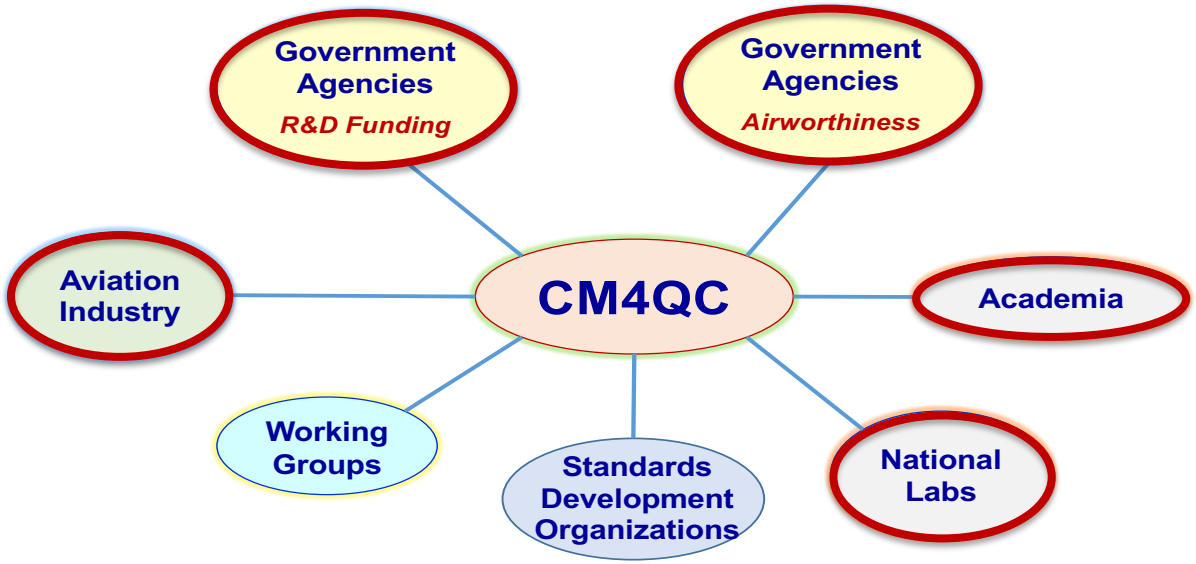
Primary goals

- Provide coordination for and focus to investments made by industry and government toward development of computational materials-based approaches (CM) for Q&C of process intensive metallic materials.
- Identify key considerations and enablers required to increase airworthiness / certifying authorities' acceptance of CM methods used for Q&C of structural or flight-critical parts.

Operation (TRL: technology readiness level)

- High TRL: Understanding industry priorities / timeline and key regulatory implications
- Mid TRL : Strategies for maturation and transition of Research to Engineering
- Low TRL : Development of required computational materials & measurement capabilities

Expected initial outcome –
Multi-year implementation plan



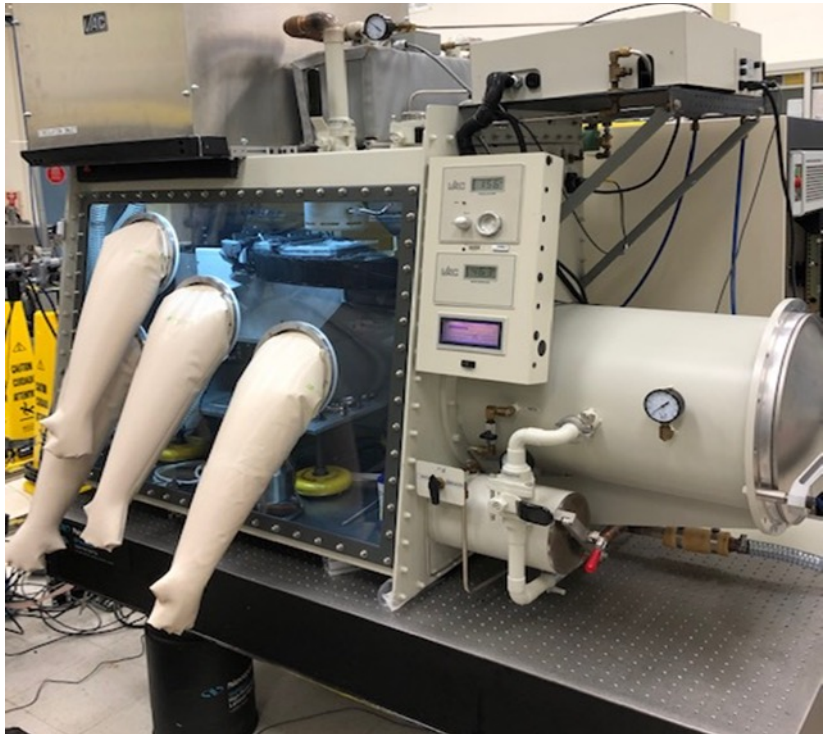
In-Situ Monitoring: Motivation

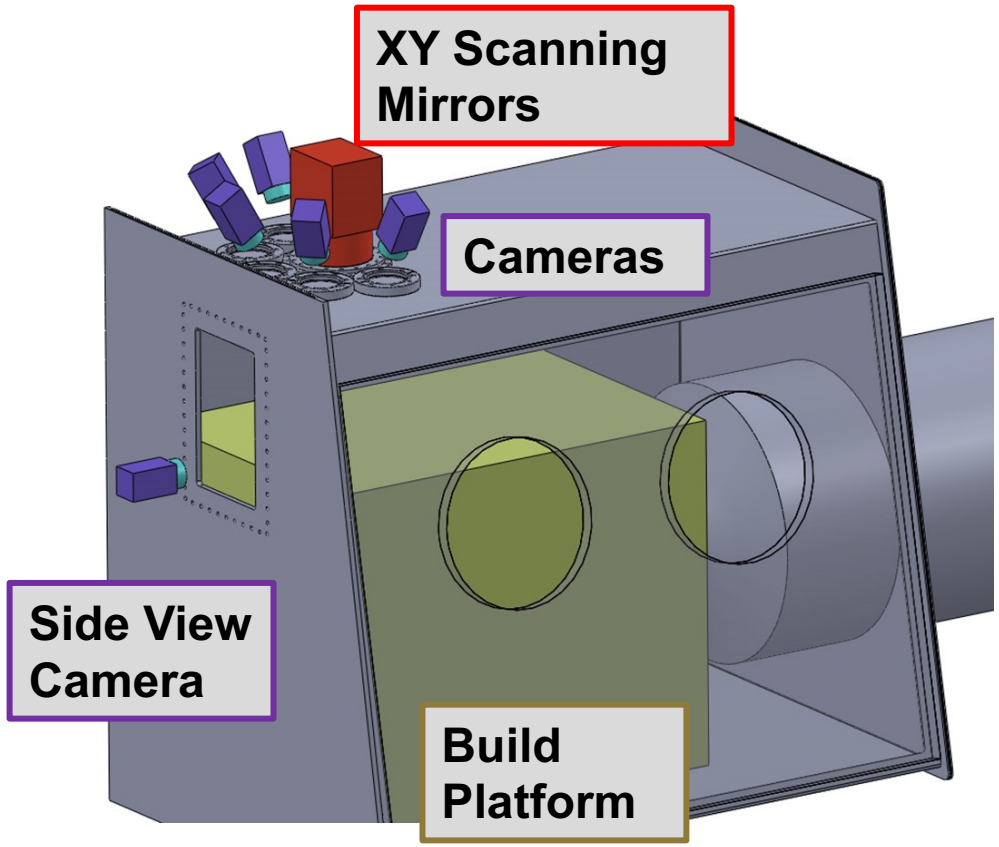
- Quality control of powder bed fusion laser beam metals (PBF-LB/M) AM flight hardware
  - Identification of process anomalies
- Reduce qualification and certification costs
  - Improve build designs
  - Discard builds based on the identification of anomalies

Complexity of PBF-LB/M AM

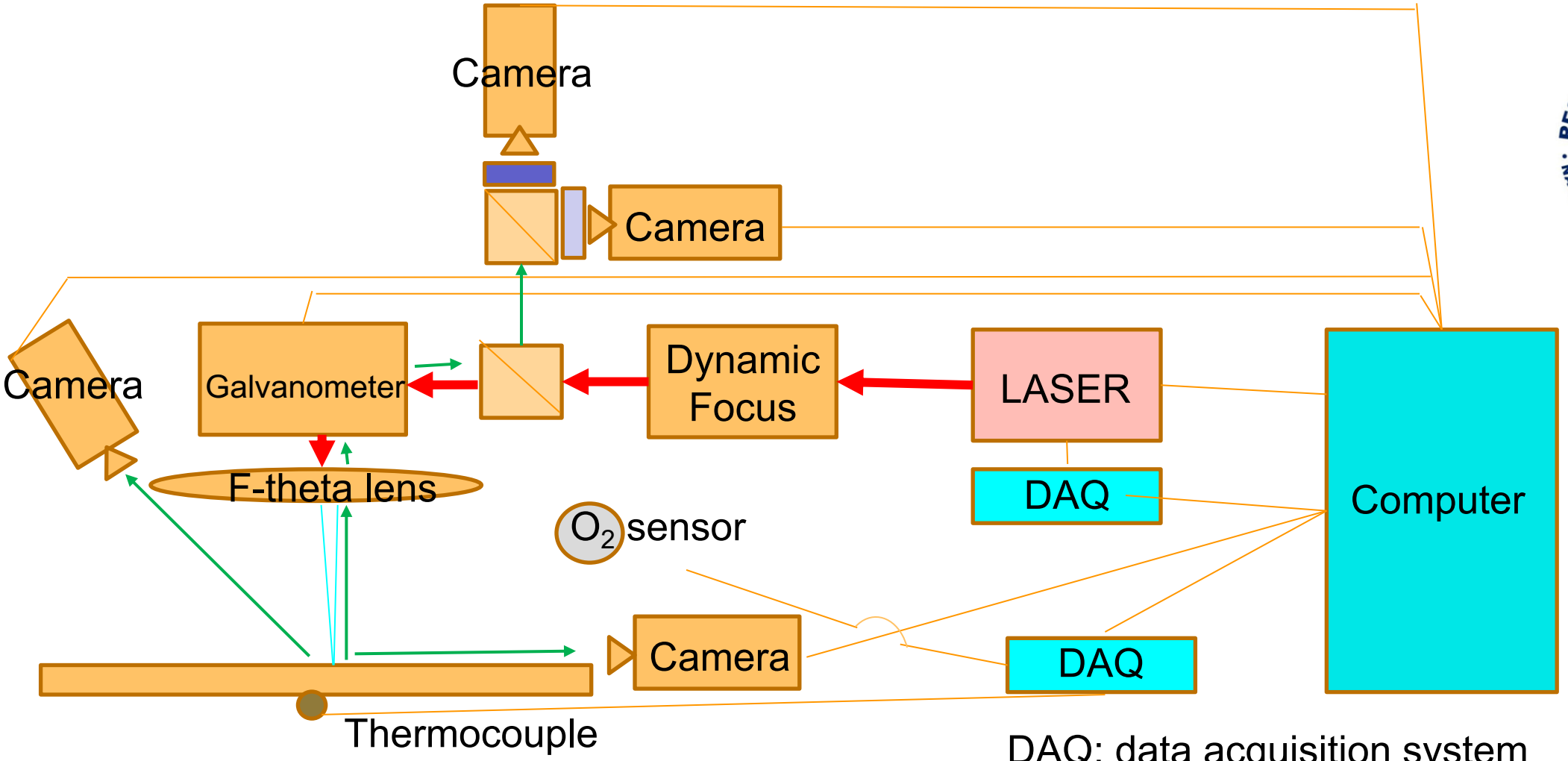
- Millions of ‘welds’ per part
- Sources of variability
  - machine-to-machine
  - day-to-day
  - hour-to-hour
- Utilize in-situ monitoring to develop qualification confidence in PBF-LB/M AM parts

Configurable Architecture Additive Testbed



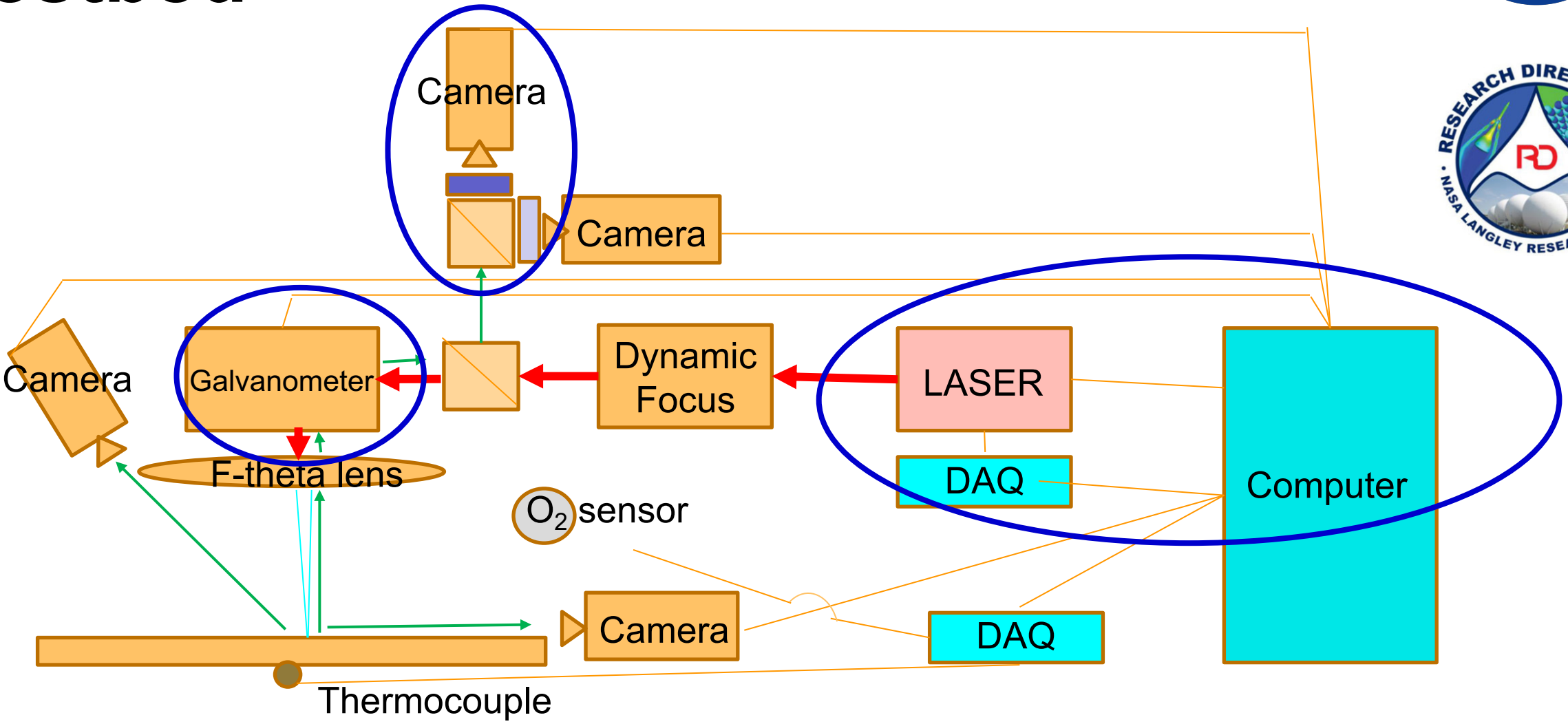


Configurable Architecture Additive Testbed

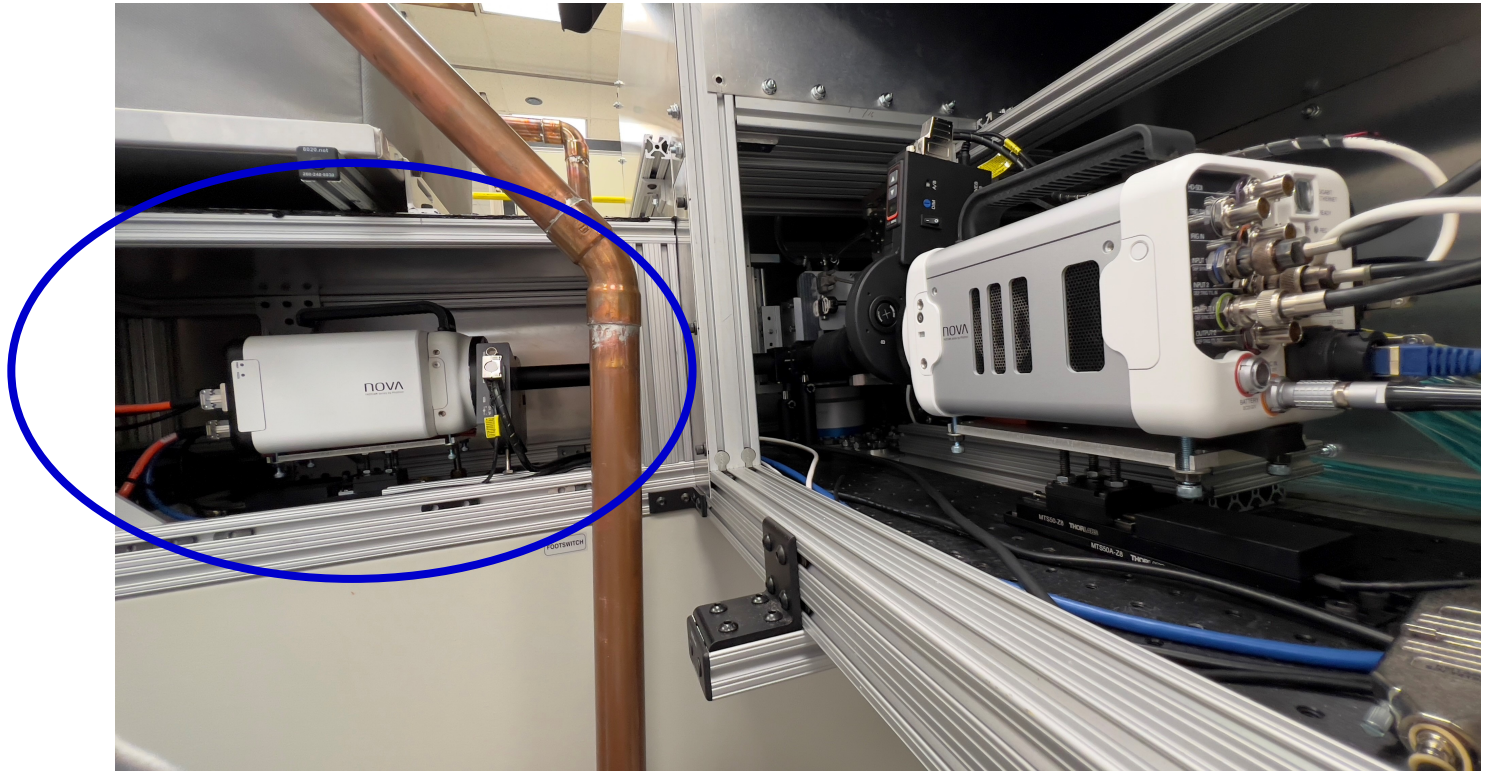


DAQ: data acquisition system

Configurable Architecture Additive Testbed

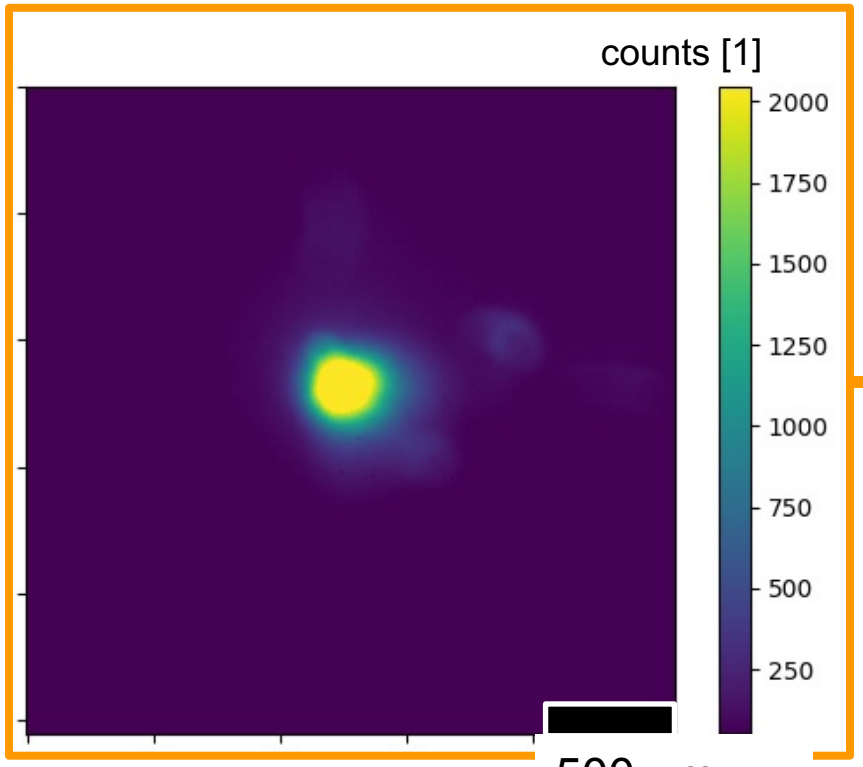


Melt Pool Imaging



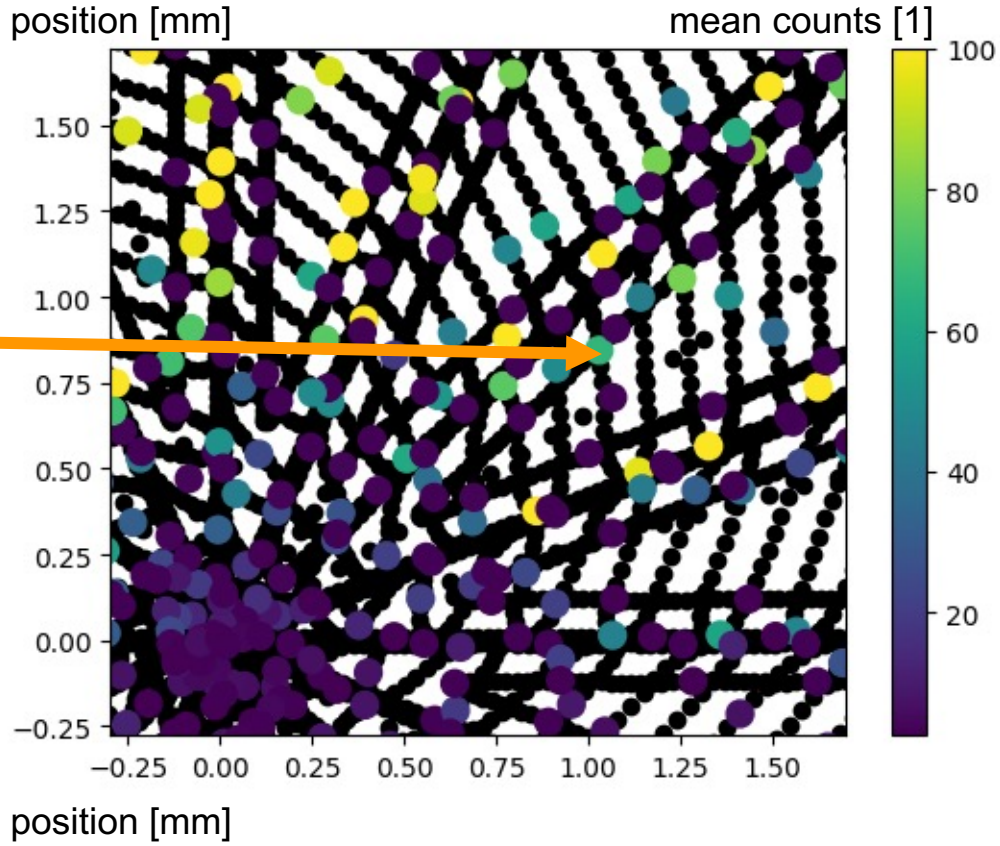
Dual-camera co-axial to laser melt-pool imaging, ~5 µm/pixel
Left camera: 730 nm bandpass filter and 333 µs exposure time

Synchronized Melt Pool Imaging: Mean Counts Metric



Melt pool image

Mean counts = 67



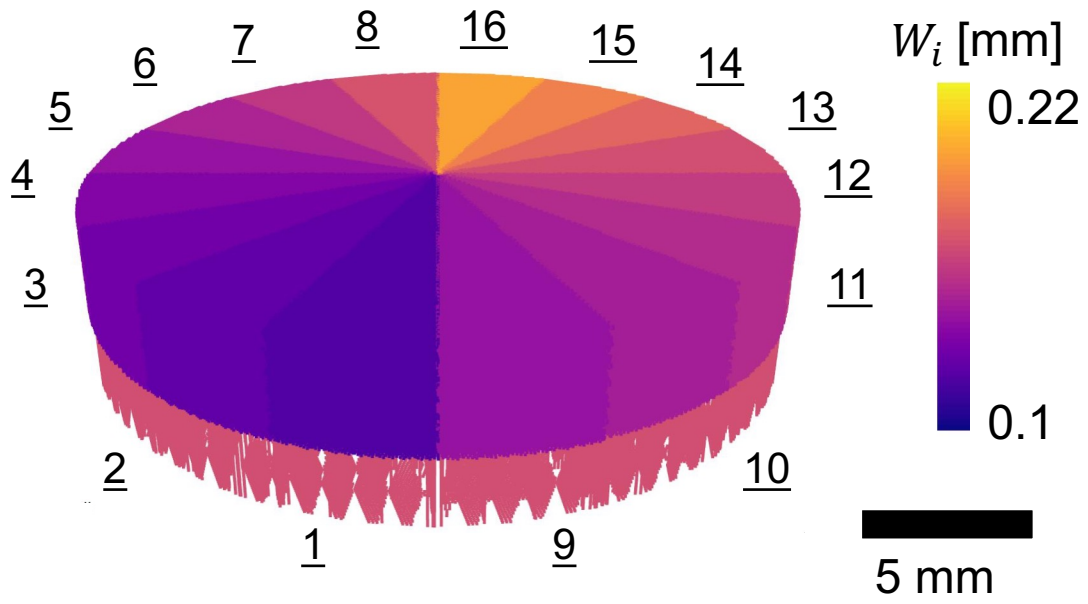
Test Article

- Material: Ti6Al4V
- 16 zones
- Power:
  - 221 W and 308 W
- Velocity:
  - 1176, 1092, 1008, 924, 840, 756, 672, 588 mm/s
- Calculated melt pool widths, W_i
  - 117 µm – 195 µm

$$W_i = 2\sqrt{\frac{2AP_i}{e\pi\rho c_p(T_m - T_0)V_{ij}}}$$

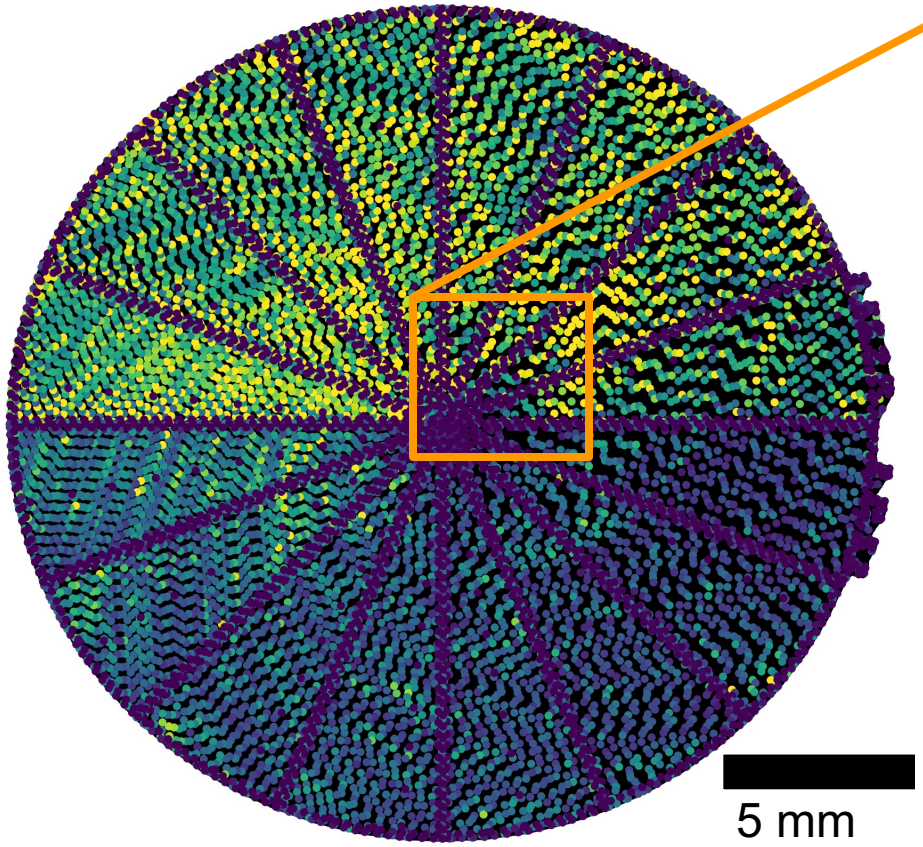
Power

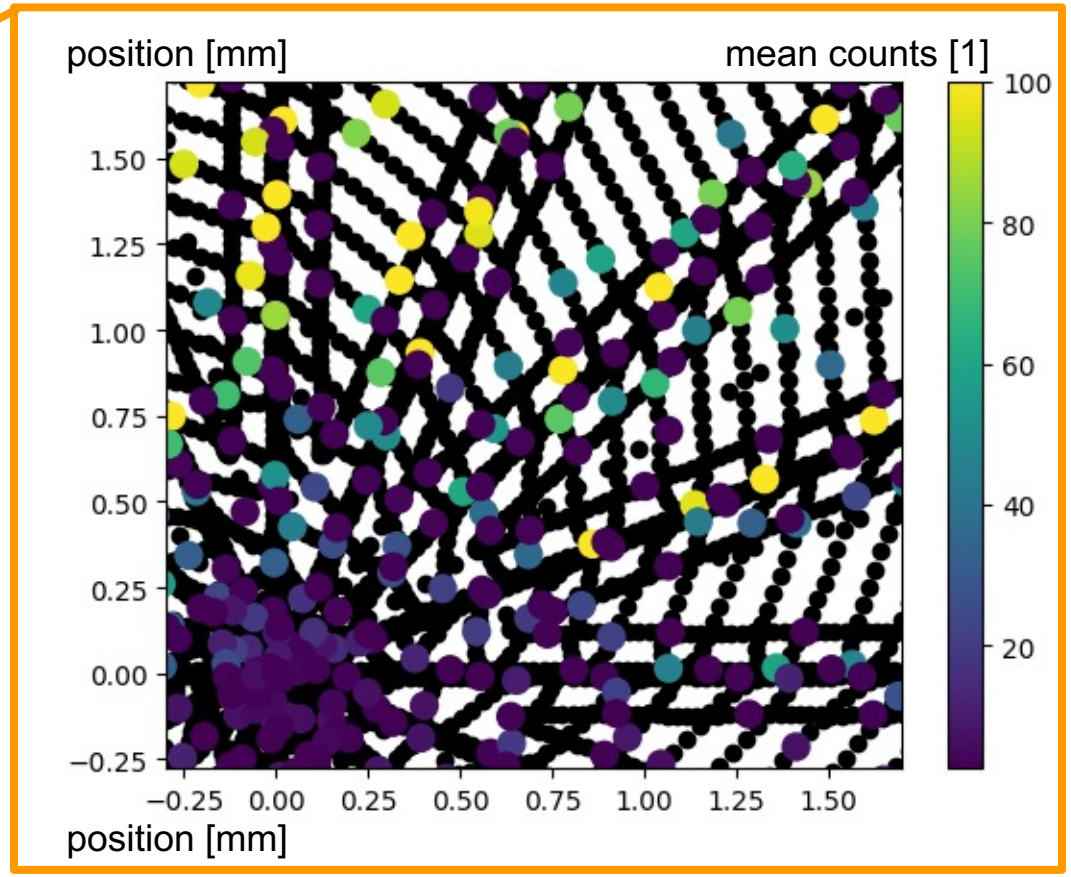
Velocity



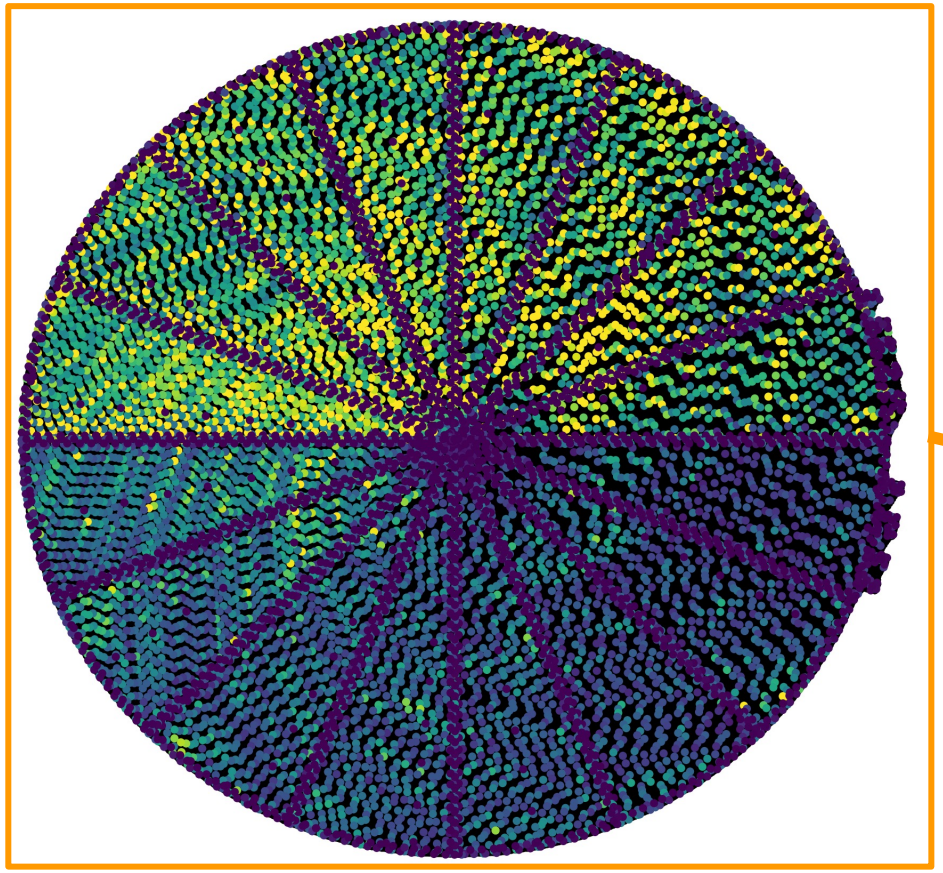
Rosenthal, Daniel. “Mathematical Theory of Heat Distribution during Welding and Cutting.” *Weld J* 20, no. 5 (1941): 220–34.

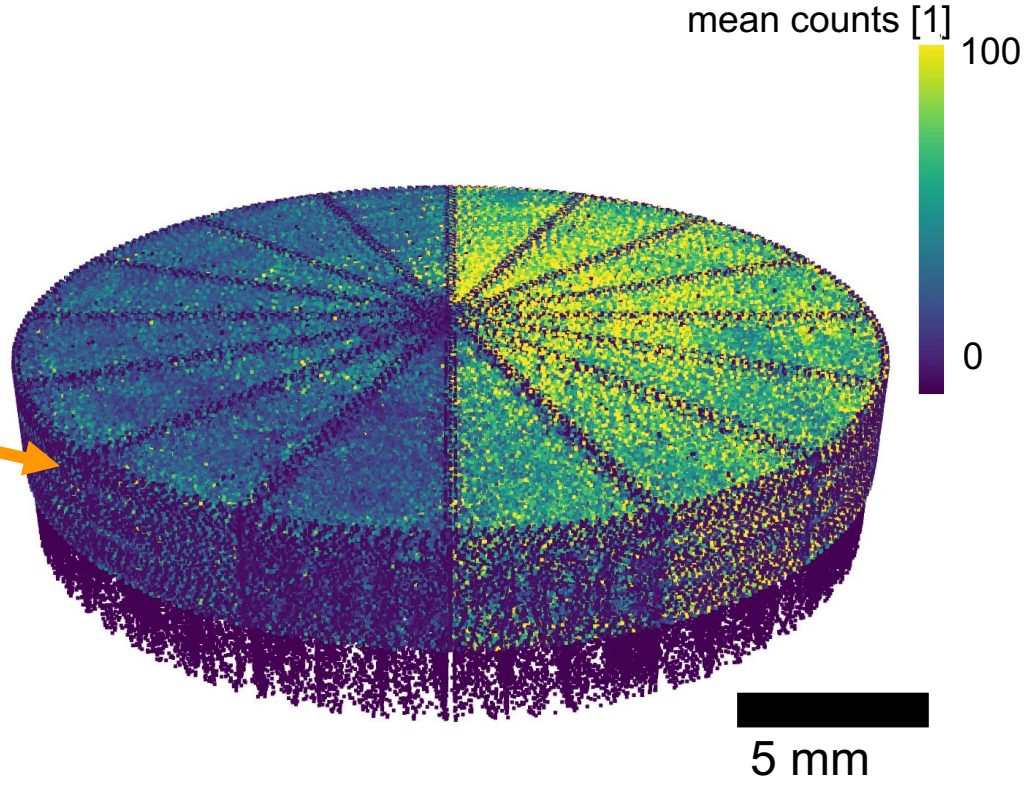
Synchronized Melt Pool Imaging: Mean Counts Metric





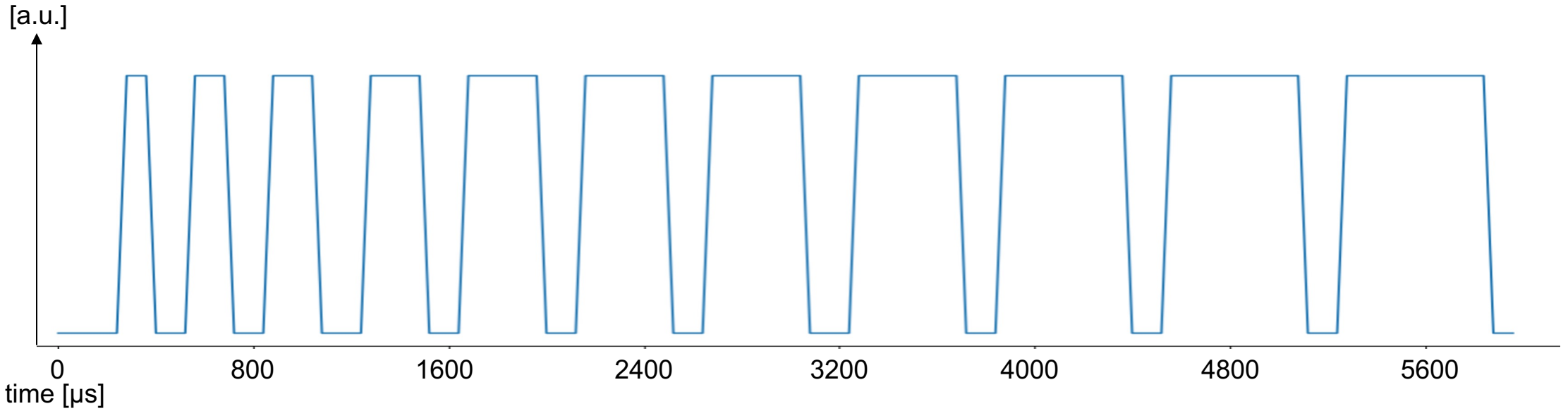
Synchronized Melt Pool Imaging: Mean Counts Metric





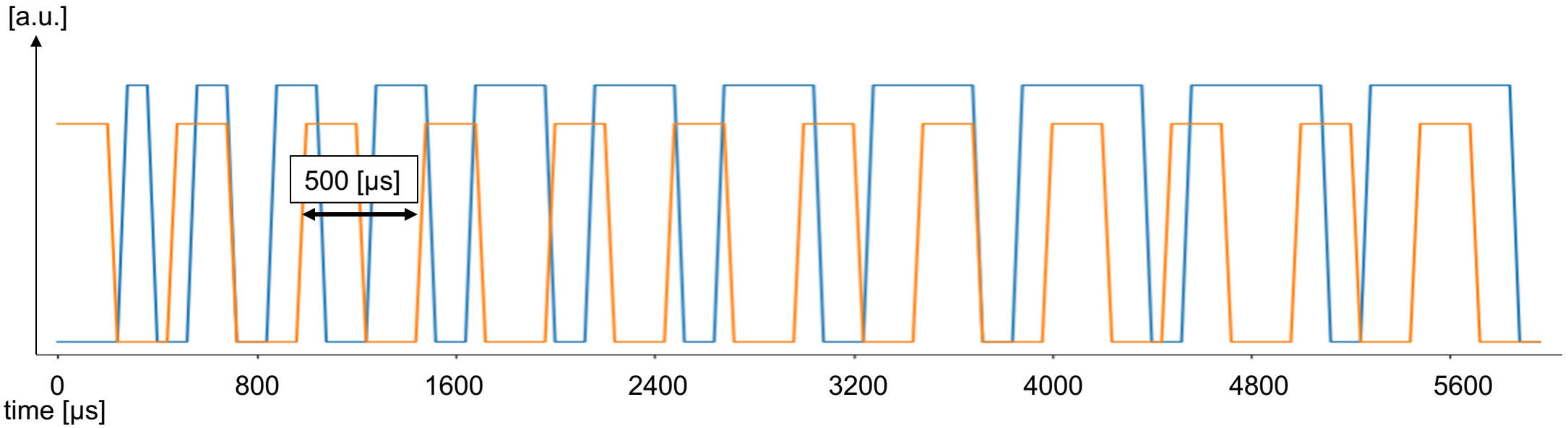
Real Time Clock Signals: Method

Laser modulation : Laser ON / OFF control



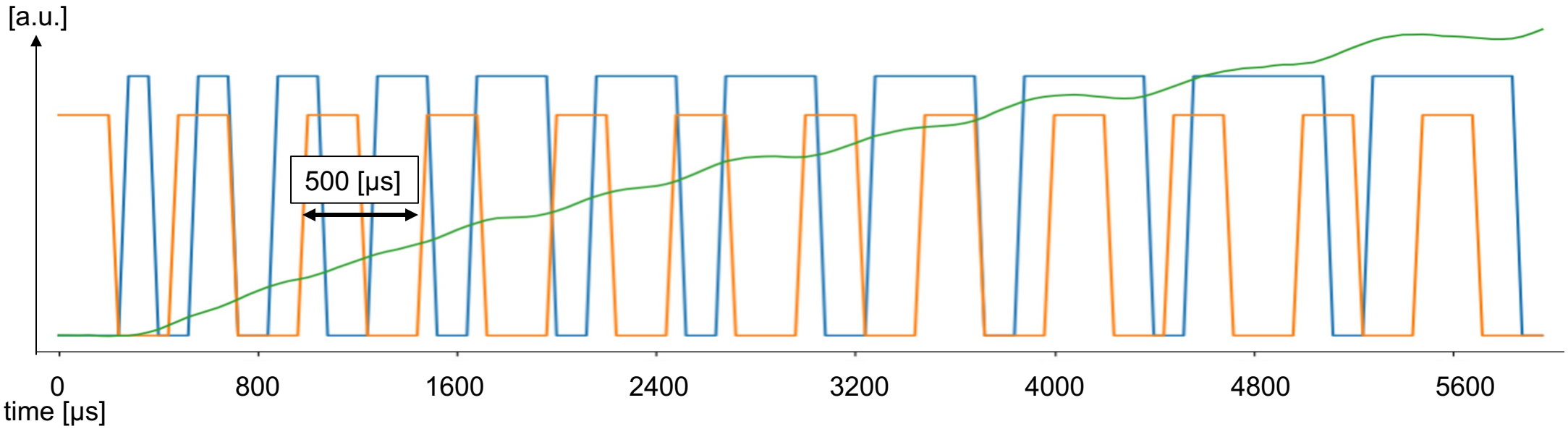
Real Time Clock Signals: Method

- Laser modulation
- **Synchronization signal, 500 µs : digital signal used to trigger sensors**



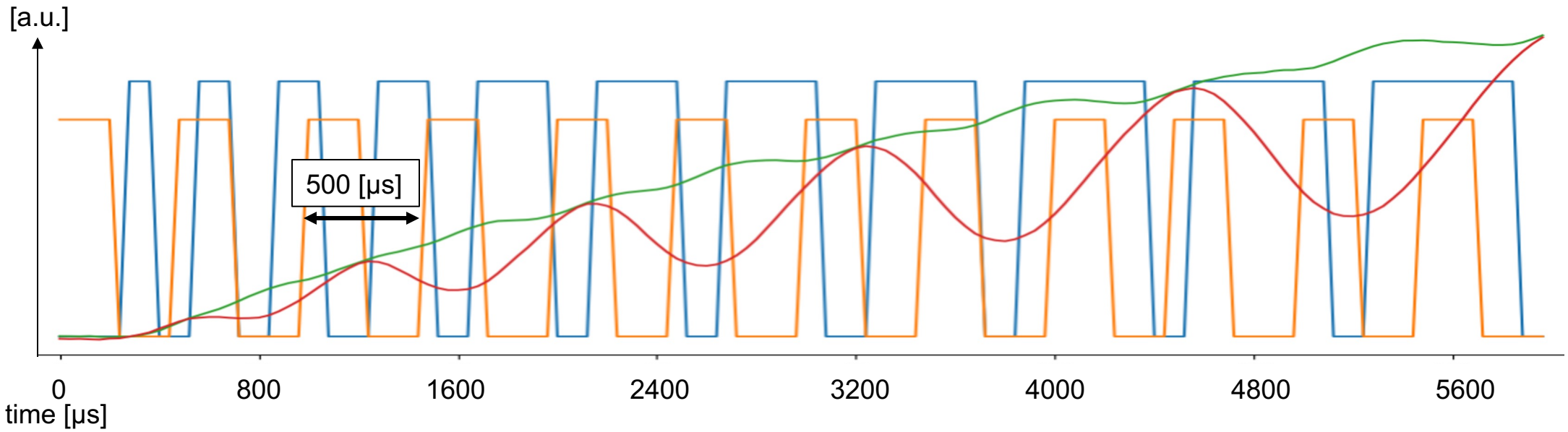
Real Time Clock Signals: Method

- Laser modulation
- Synchronization signal, 500 µs
- **X-position : the galvanometer reported digital position of the “x axis mirror”**

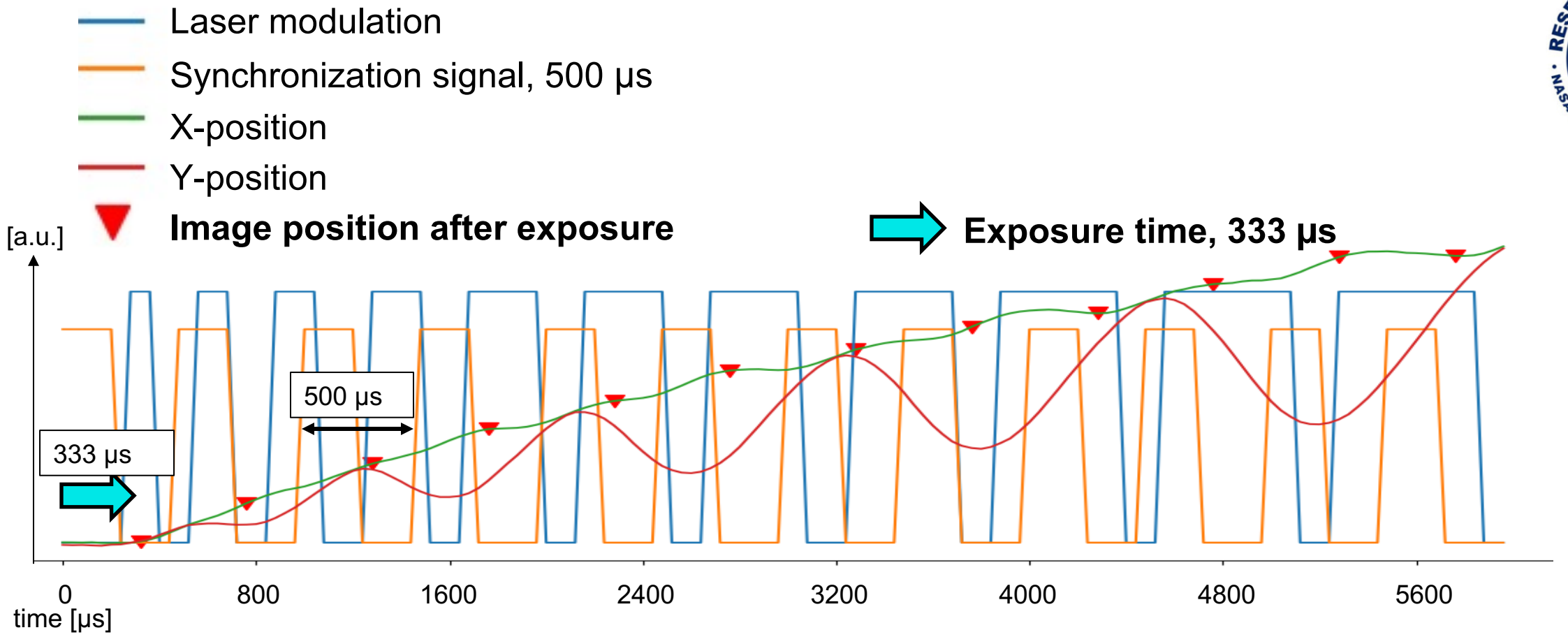


Real Time Clock Signals: Method

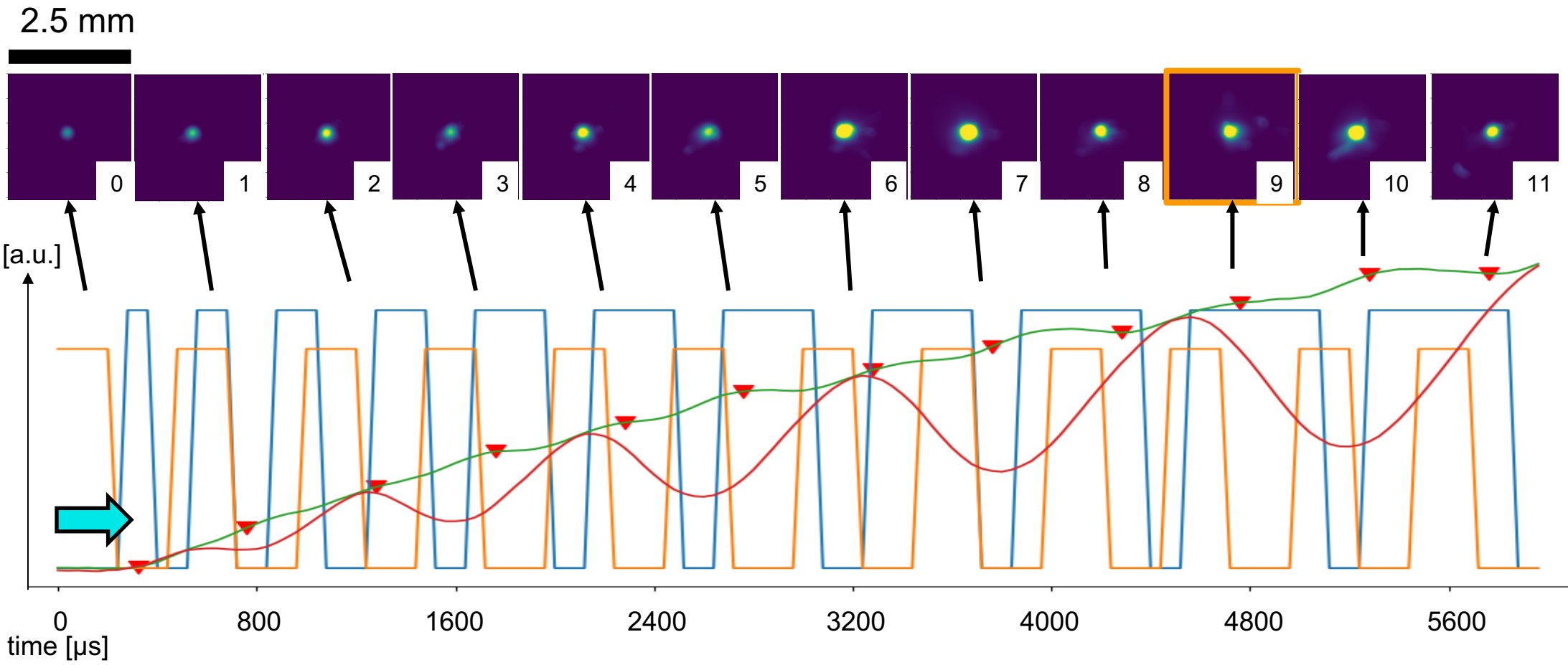
- Laser modulation
- Synchronization signal, 500 µs
- X-position
- **Y-position : the galvanometer reported digital position of the “y axis mirror”**



Real Time Clock Signals: Method

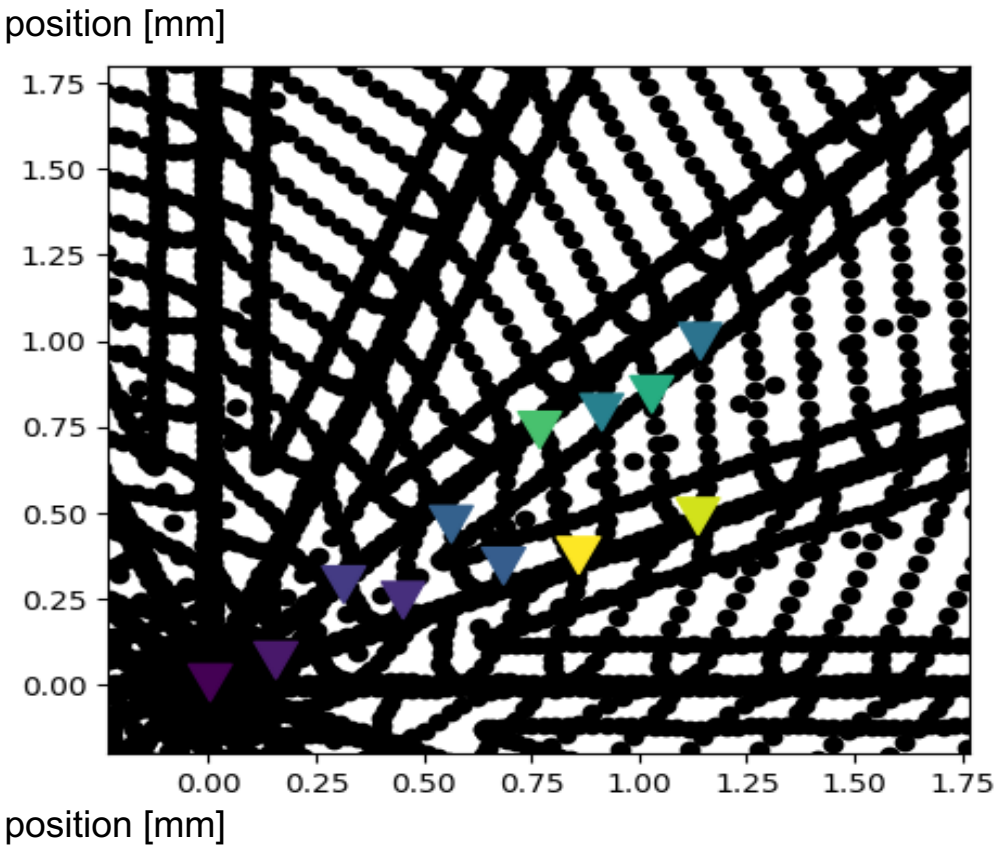


Synchronized Melt Pool Images



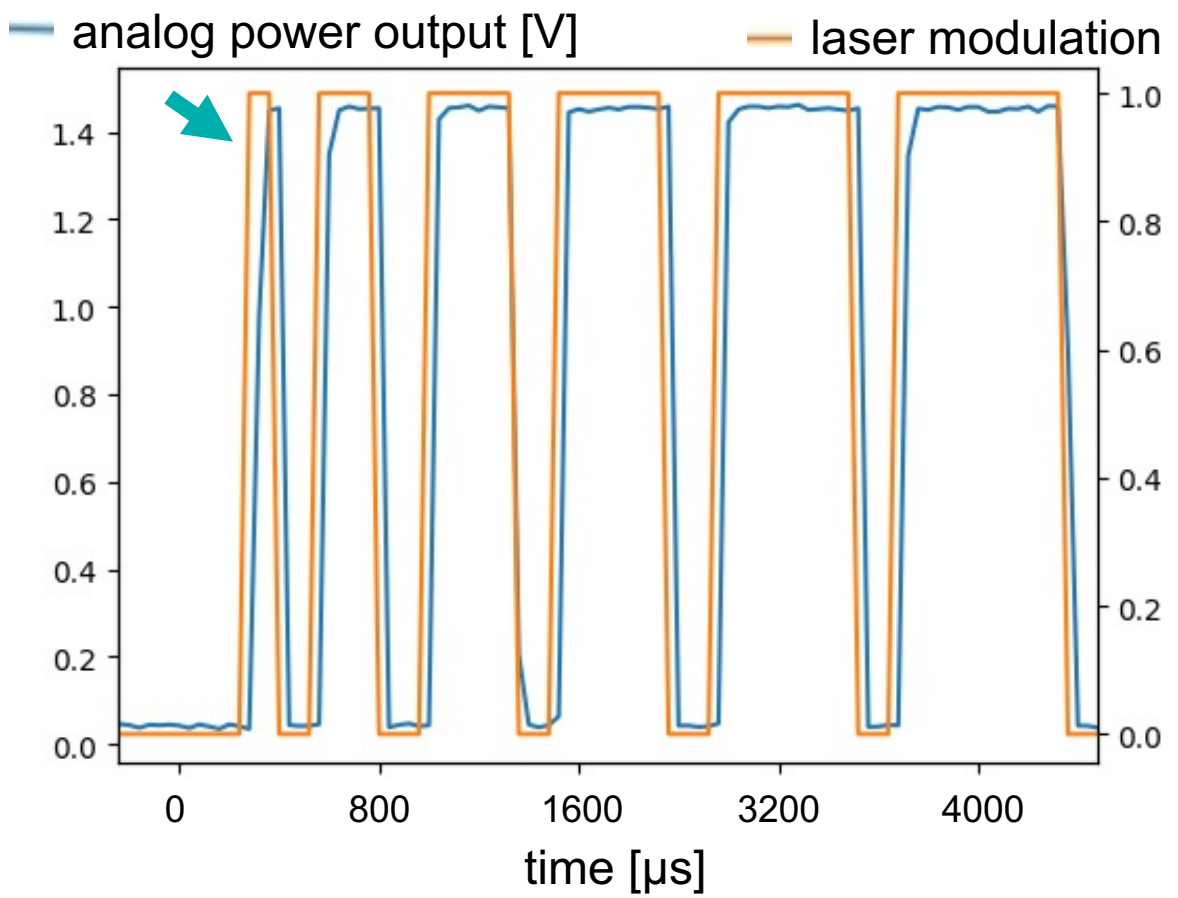
Melt Pool Image Locations

- Spatially resolved melt pool image locations enabled by time-synchronization
- Exposure time is added to synchronization trigger to find the nearest x/y position



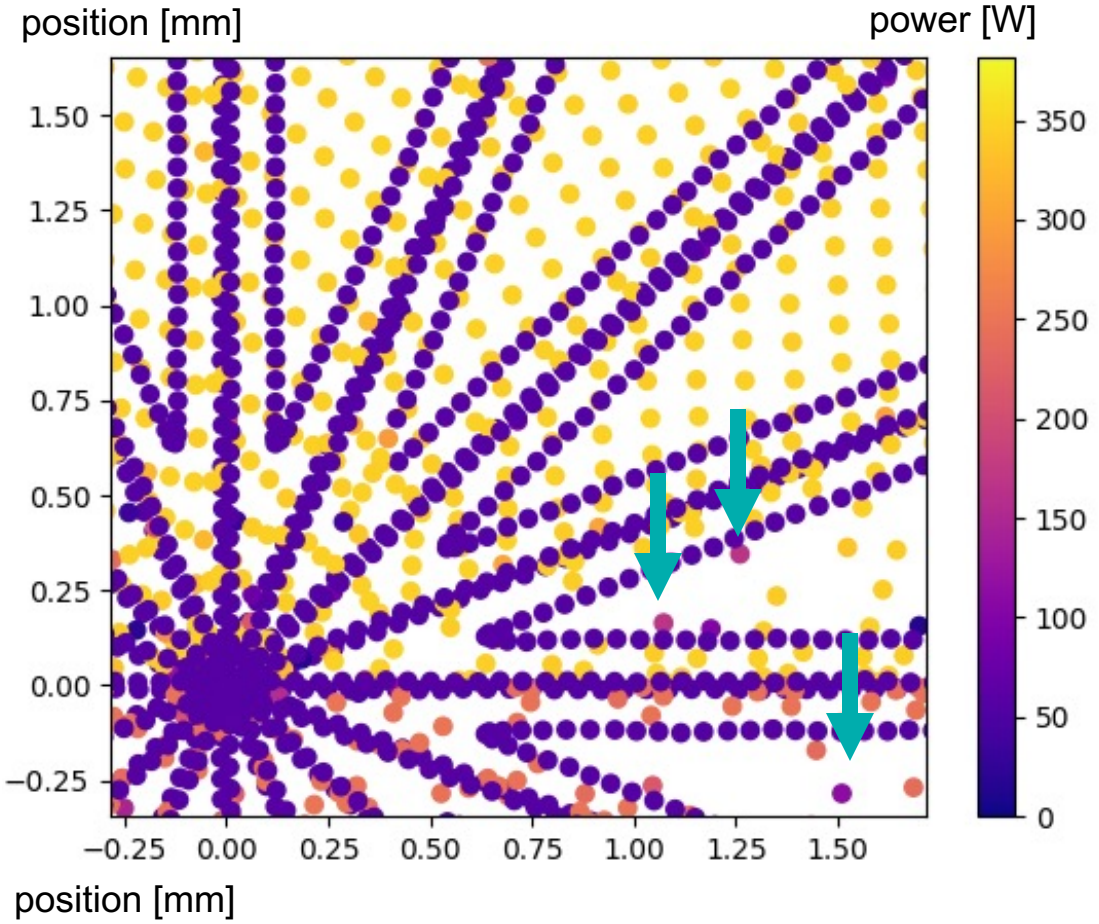
Laser Power Monitoring

- 25 [kHz] sampling rate
- Low cost
- Synchronized with position and time
  - Laser response timing is recorded



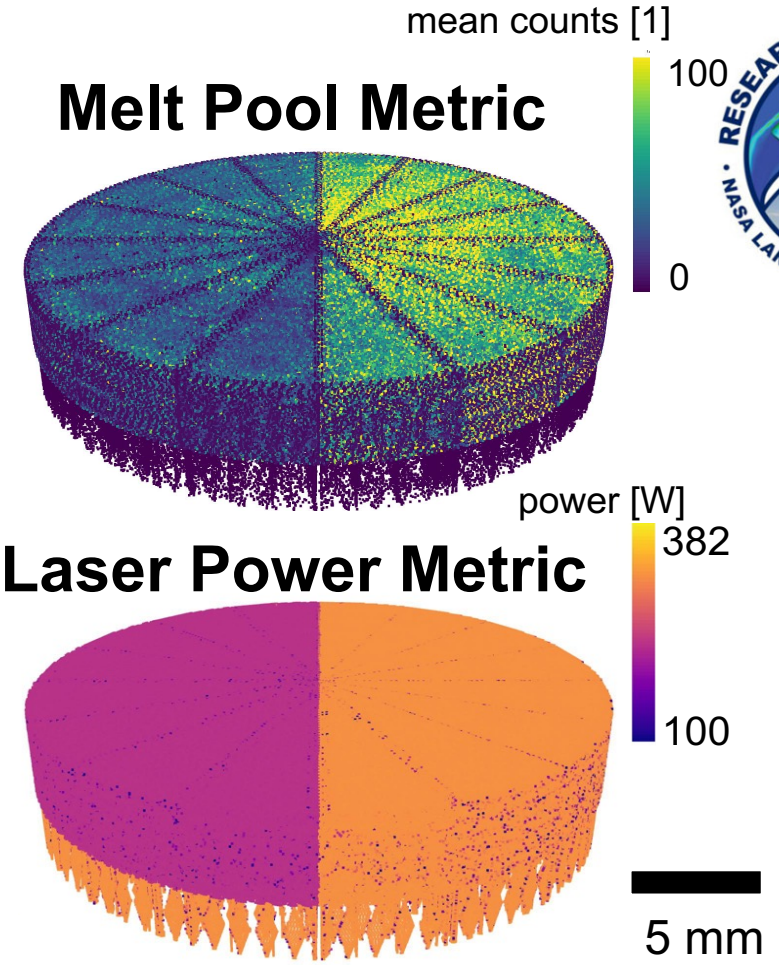
Laser Power Monitoring

- 25 kHz sampling rate
- Low cost
- Synchronized with position and time
- Point field of the process
  - ↓ – Laser response anomalies



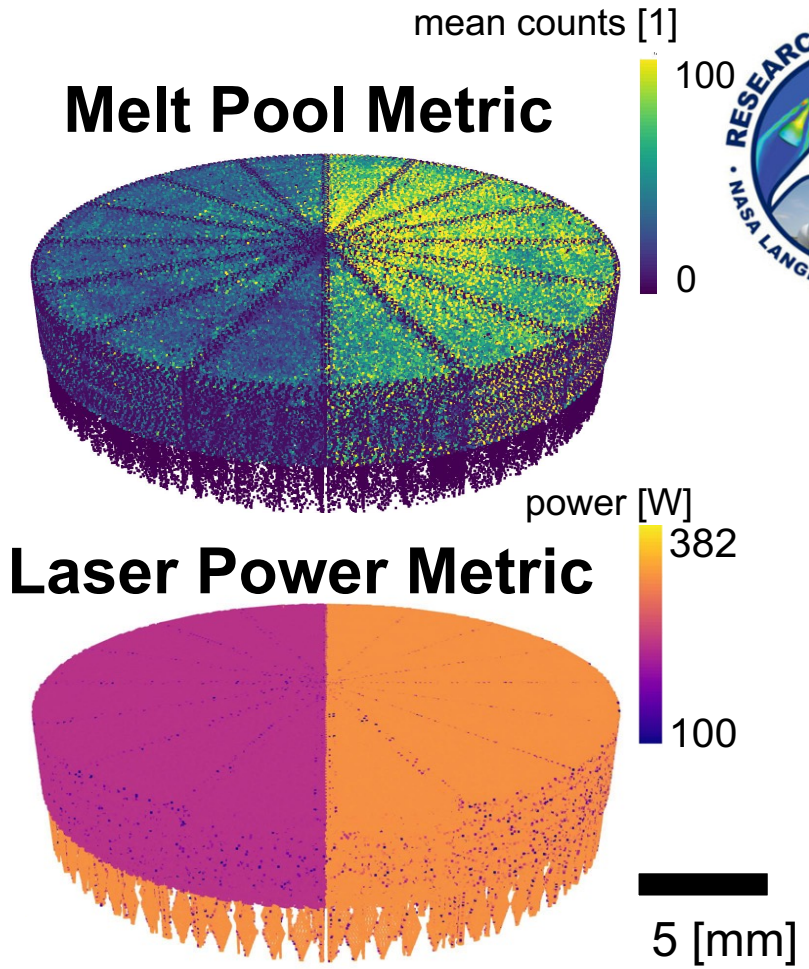
In-Situ Process Metric Summary

- Synchronization enables point-wise process metrics
- Melt pool imaging
  - Emission limits sampling rate
  - Tb data storage
  - Complex interpretation
  - High cost, rich data
- Laser power monitoring

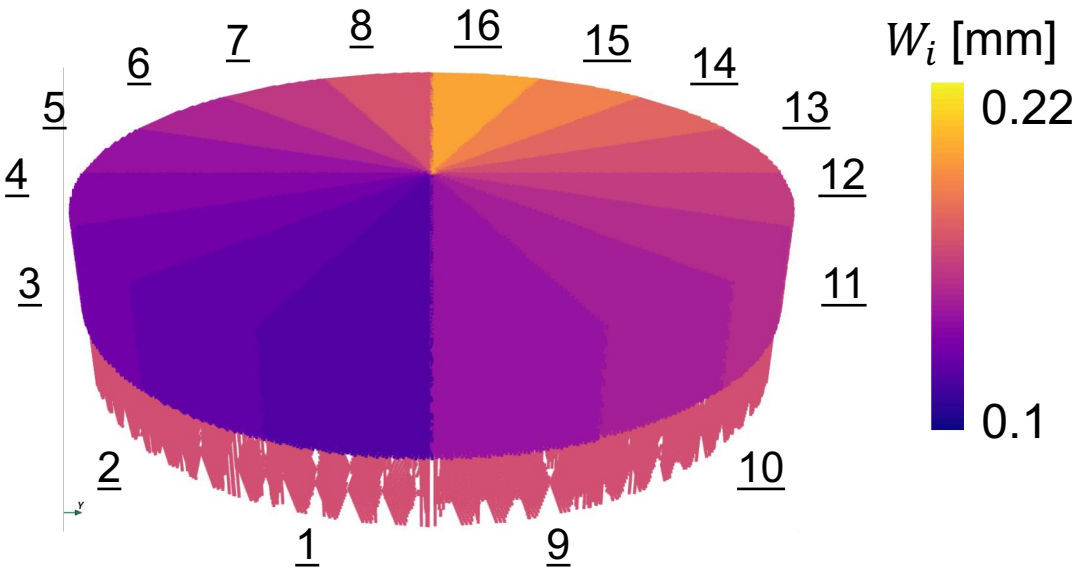


In-Situ Process Metric Summary

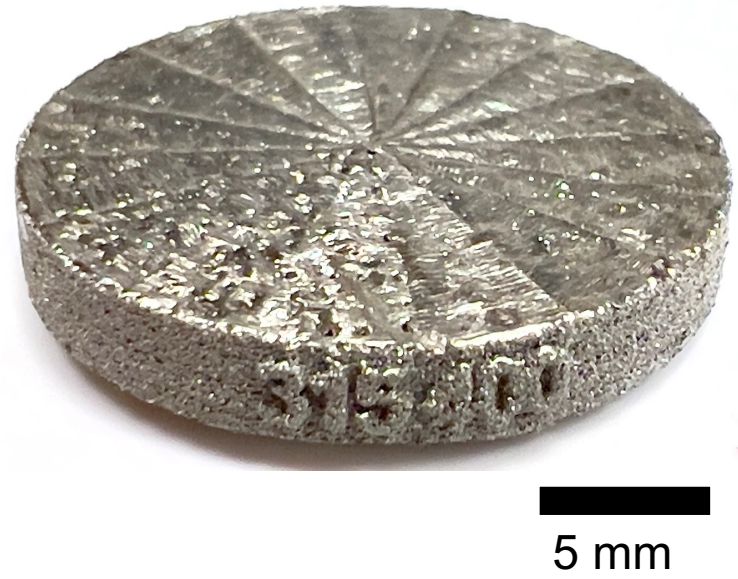
- Synchronization enables point-wise process metrics
- Coaxial imaging
- Laser power monitoring
  - Position synchronization limits sampling rate, ≤100 [kHz]
  - Point field of the process
  - Low cost, minimal data



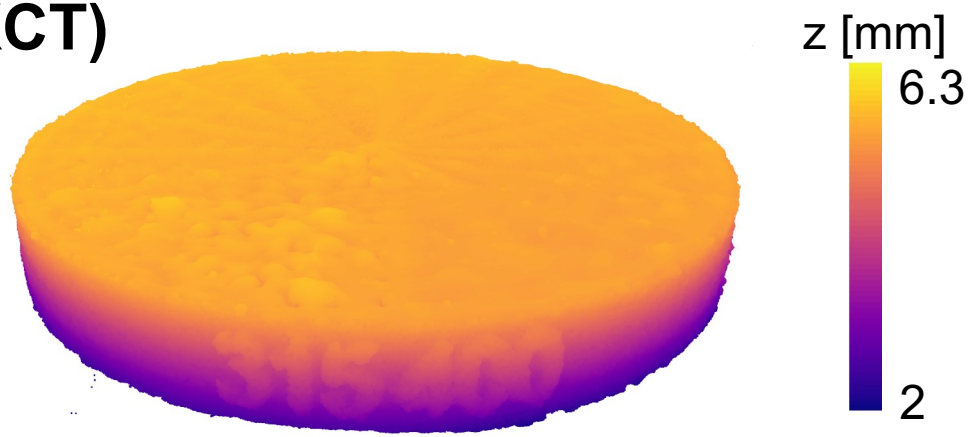
Melt Pool Width



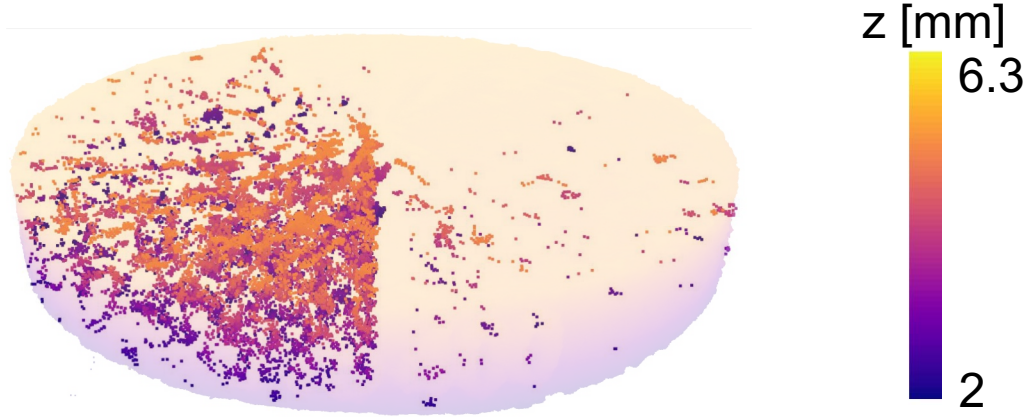
Photograph



X-ray Computed Tomography (XCT)

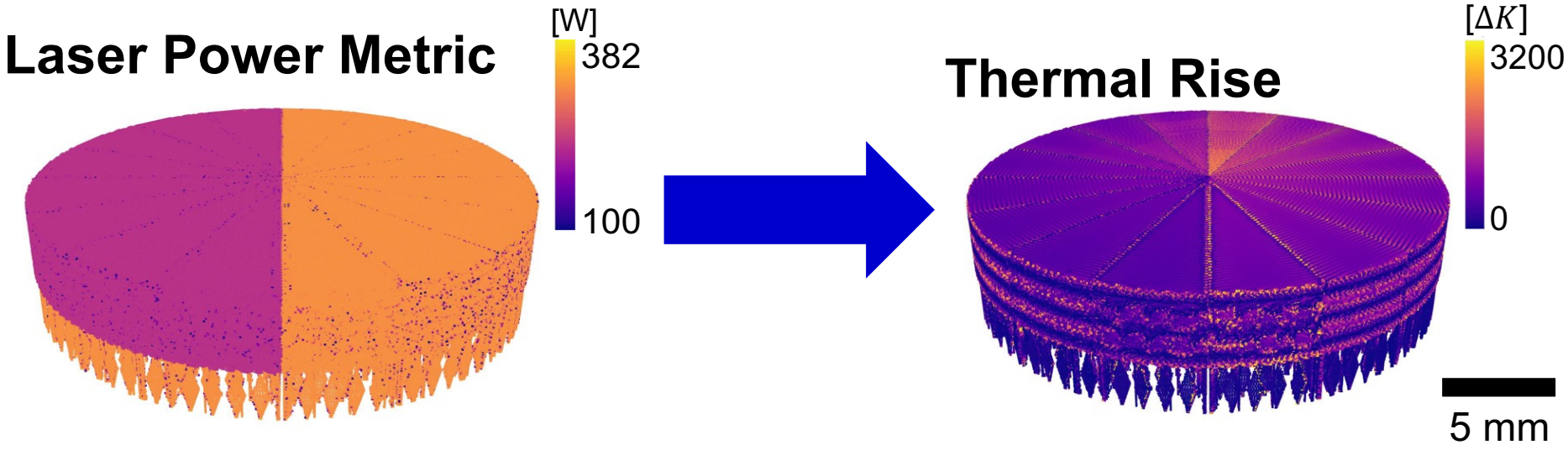


Porosity



Laser Power Point Field in Context

- Point-wise AM model based calculation
- **Laser power metric can be contextualized using AM process metric models**

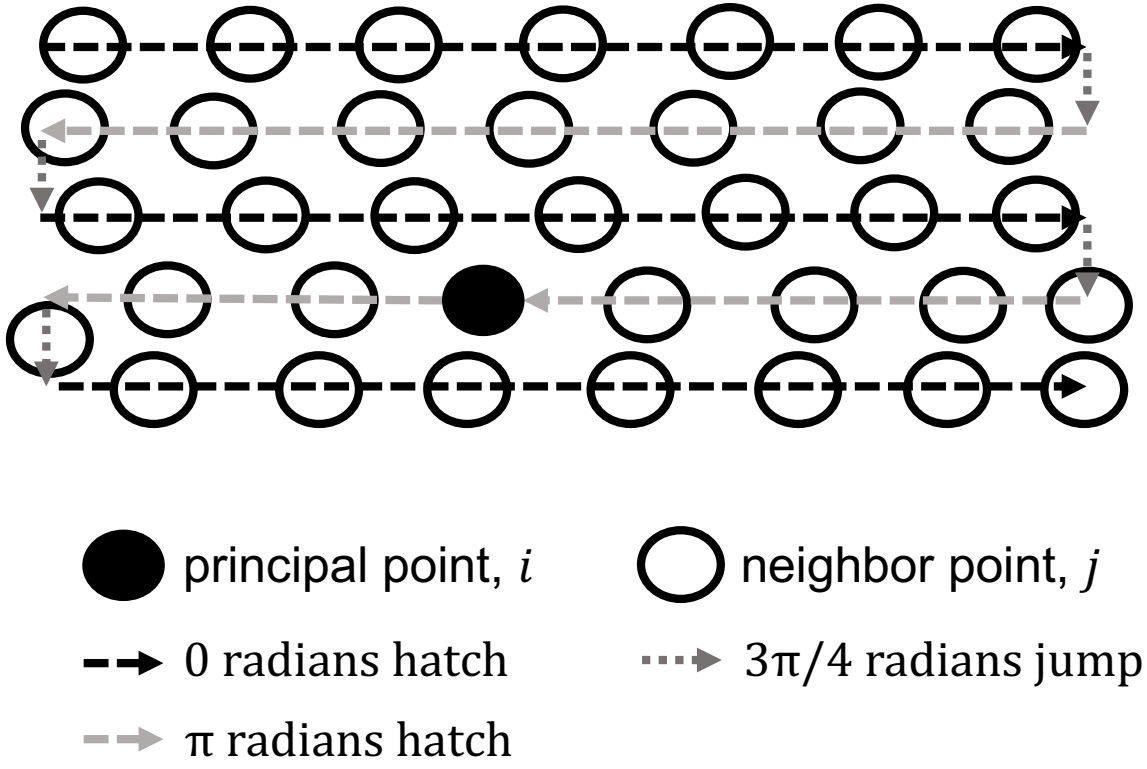


The Additive Manufacturing Model-based Process Metric (AM-PM) Method

- 2-Dimensional point field (PF)
- AM-PM at principal point
- Non-constant kernel correlation

2 parts

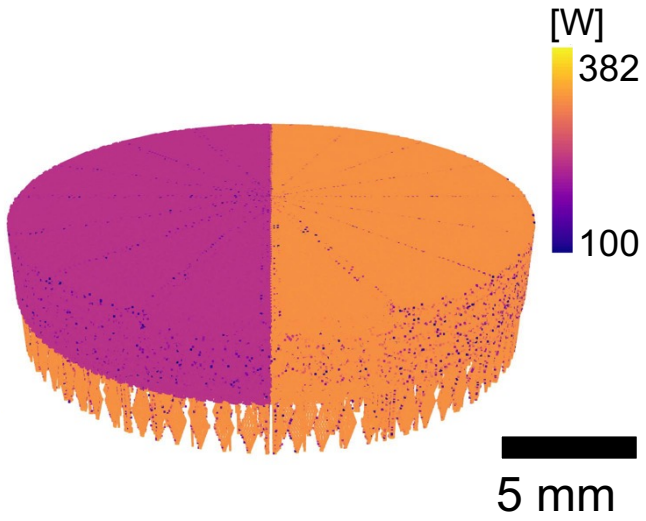
- Neighborhood search
- Kernel function



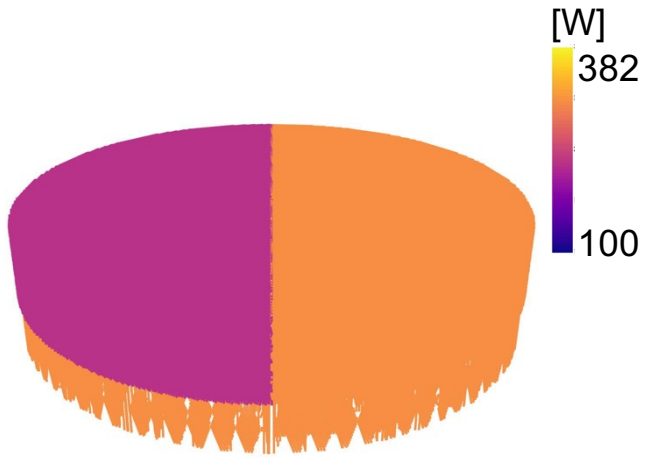
AM PM: Power

- Neighborhood: i, the principal point
- Kernel function: P_i, modeled or measured from the laser
- Deviations most prominent at interface of zones 1 and 9

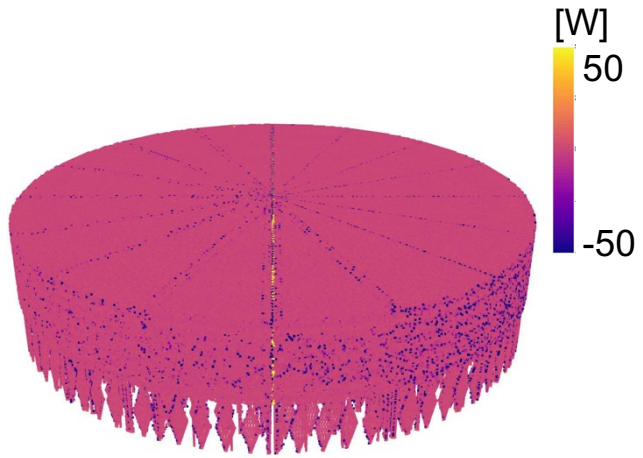
PF from in-situ measurements



PF generated from build file (model)



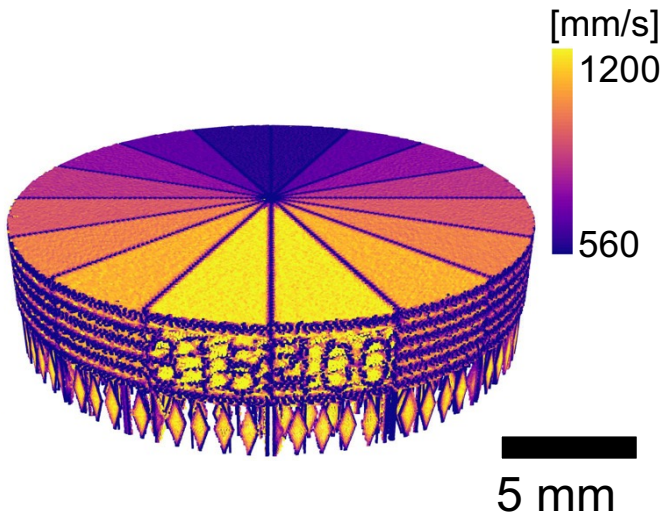
Difference



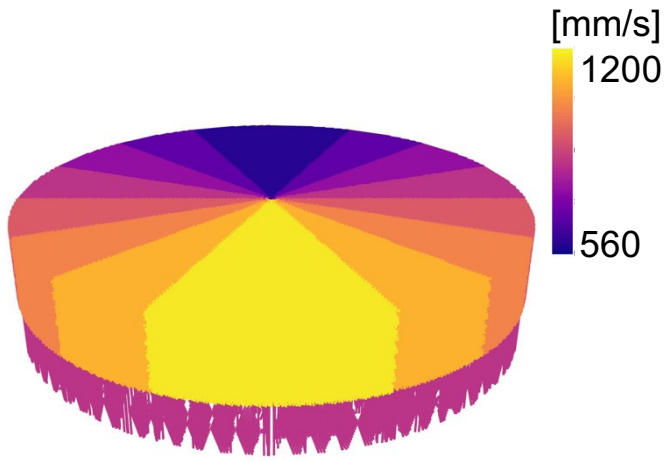
AM PM: Velocity

- Neighborhood: $i - 1$, the point preceding the principal point
- Kernel function: Δdistance / Δtime
- Deviations in speed at the turn-around regions

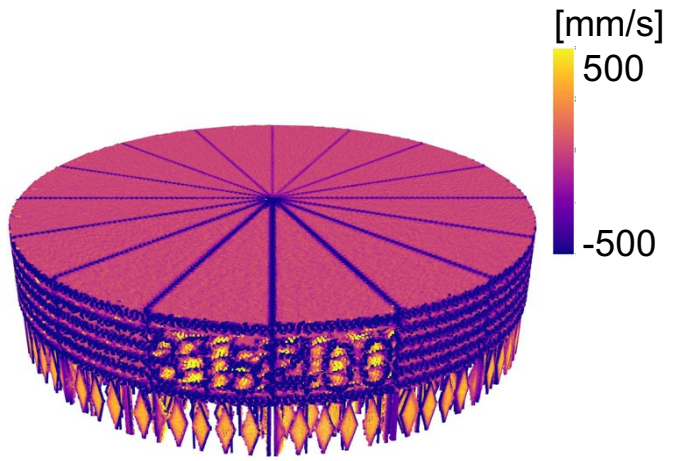
Measured PF



Modeled PF



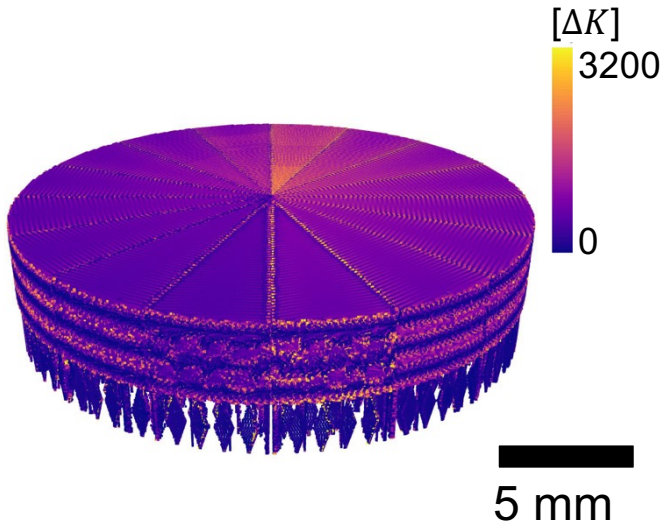
Difference



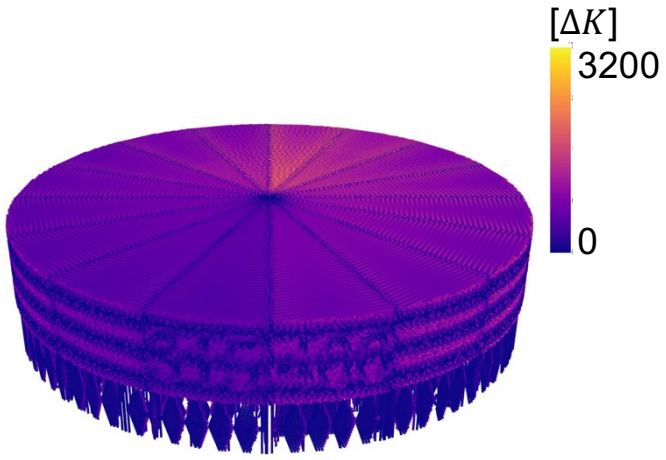
AM PM: Thermal Rise

- Neighborhood: 0.5 mm radius and time is past
- Kernel function: Green's function solution to the heat equation
- Hot near center and layer-wise banding: hatch pattern influence

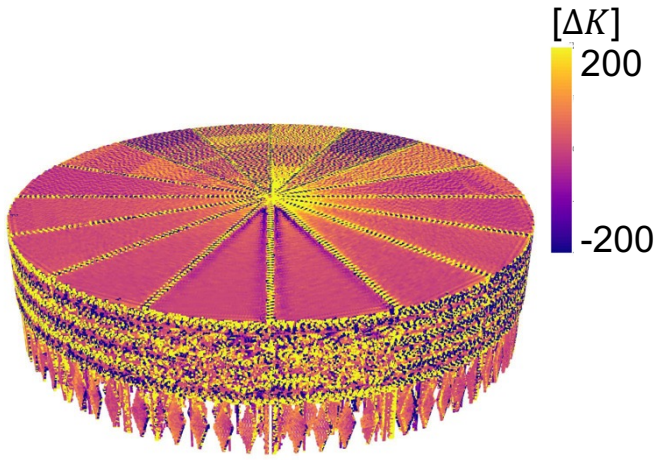
Measured PF



Modeled PF

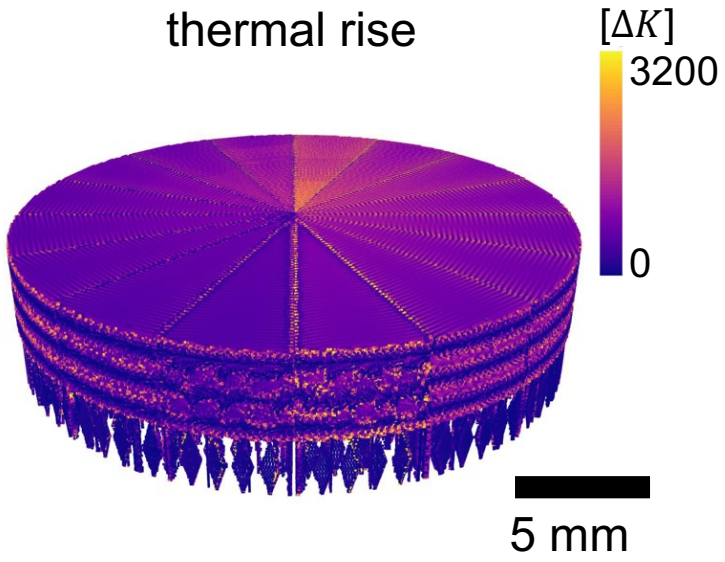


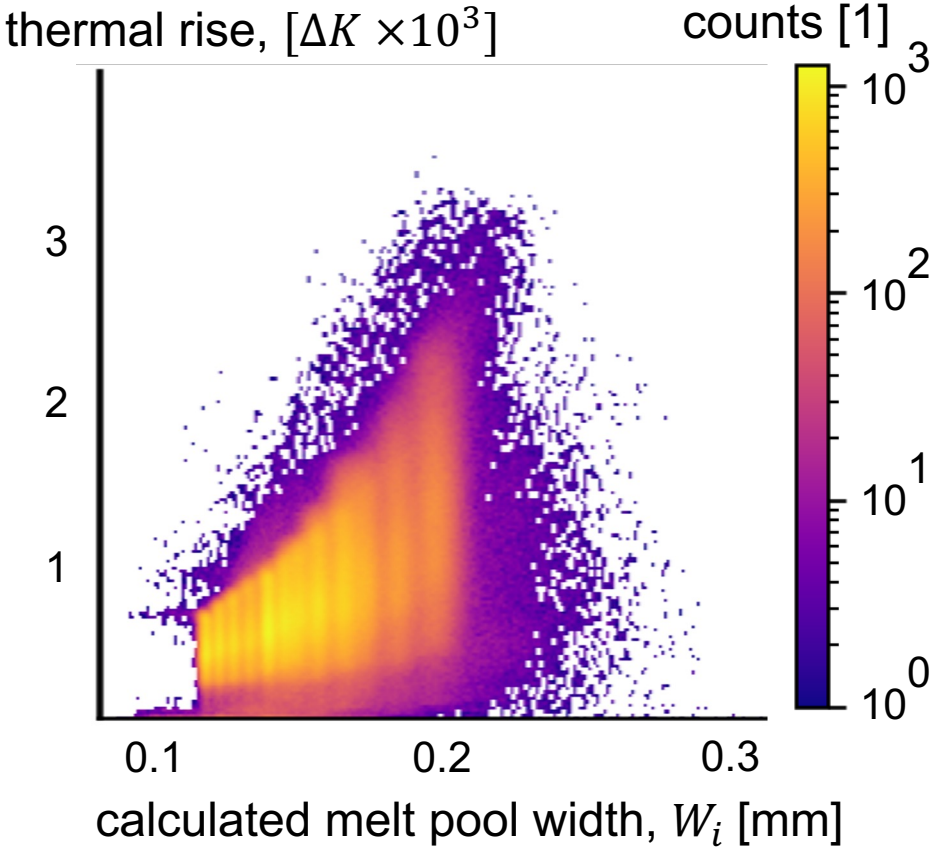
Difference



Mapping to Porosity

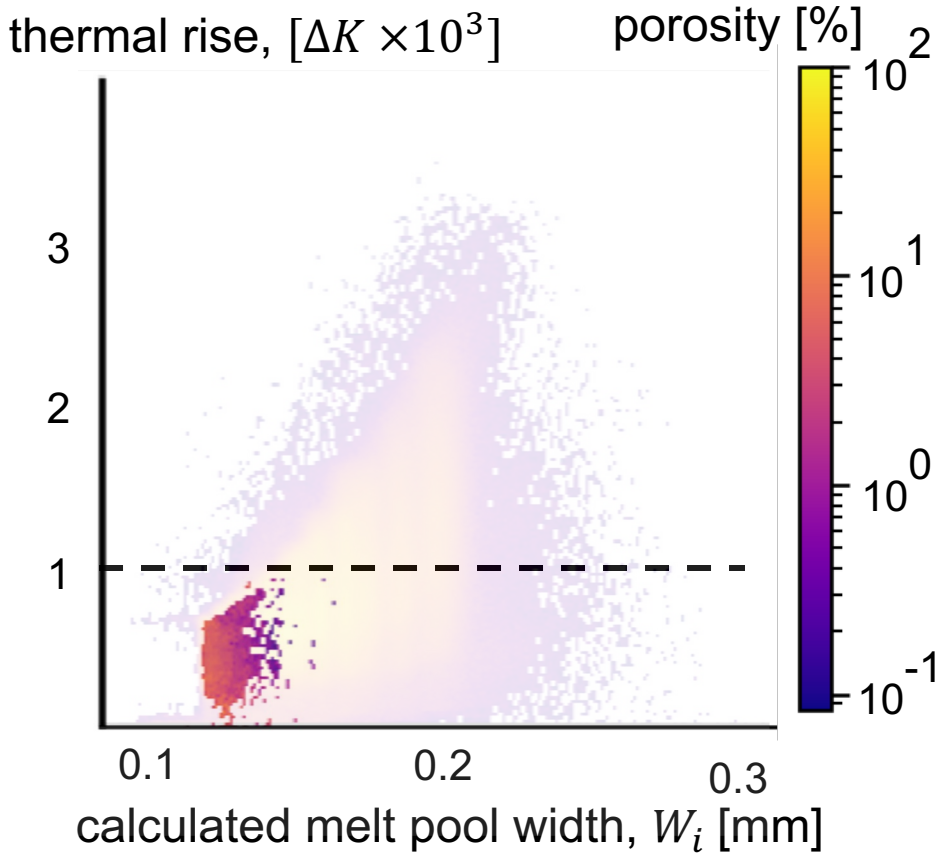
- Point-wise heat map analysis
- Thermal rise range increased with melt pool width



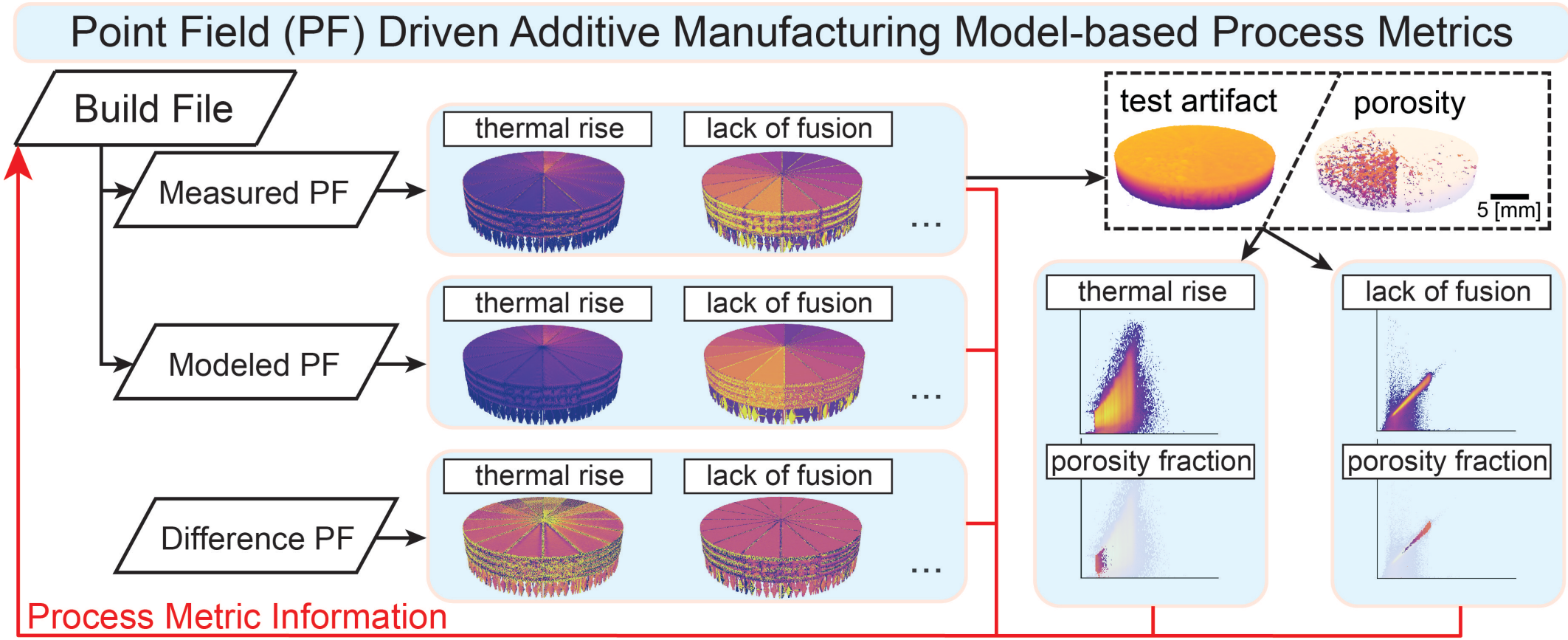


Mapping to Porosity

- Porosity fraction thermal rise heat map
- Porosity was not observed above 1000 ΔK.
- Porosity fraction can be used with a thermal rise metric towards development of predictions for the probability of porosity existence



Additive Manufacturing Process Metrics (AM-PM): Graphical Summary



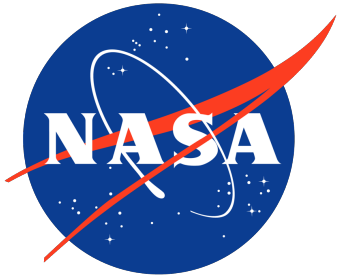
Summary

- PMs based on LPBF AM models
  - Contextualizes laser position and power
- High computational efficiency
  - Minutes to compute at part scale
- PM differences were demonstrated
  - Measured vs. Modeled PFs
- Useful approach for correlating precise process conditions with porosity

Acknowledgements

- NASA, Transformational Tools and Technologies project
- NASA Langley Research Center, Advanced Materials and Processing Branch
  - Joel Alexa, Peter Messick, James Thornton, Harold Claytor
    - Analytical Mechanics Associates, Hampton VA
- NASA Langley Research Center, Nondestructive Evaluation Sciences Branch
  - William Sommer
    - Analytical Services & Materials, Hampton VA

Questions



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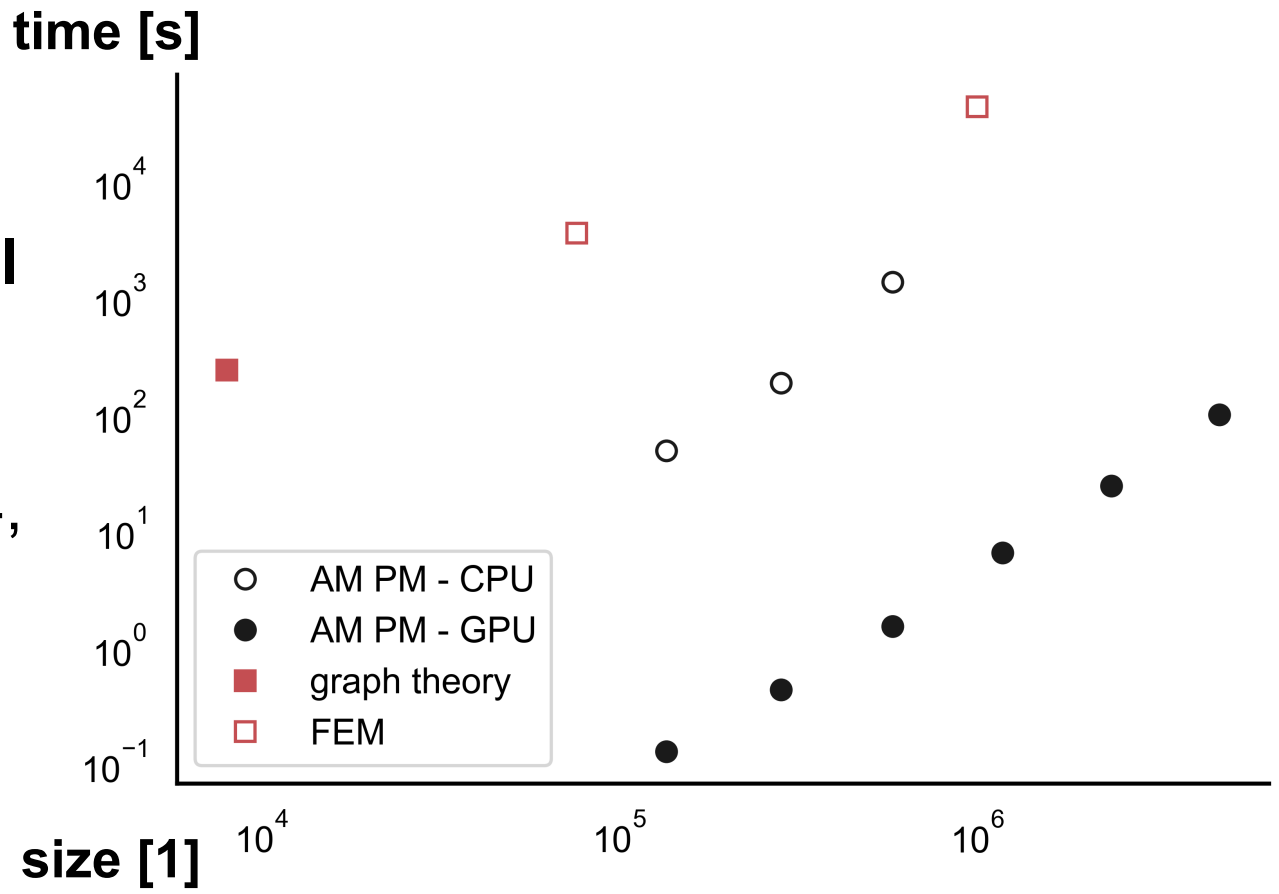
AM Model-Based PM (AM-PM)

- **GPU accelerated**
- **~650x faster than a finite element model (FEM)**
- **Single time step analytical models**
- CPU (Central Processing Unit): Intel Xeon E5-2667v4, 128 Gb memory
- GPU: Nvidia Titan V

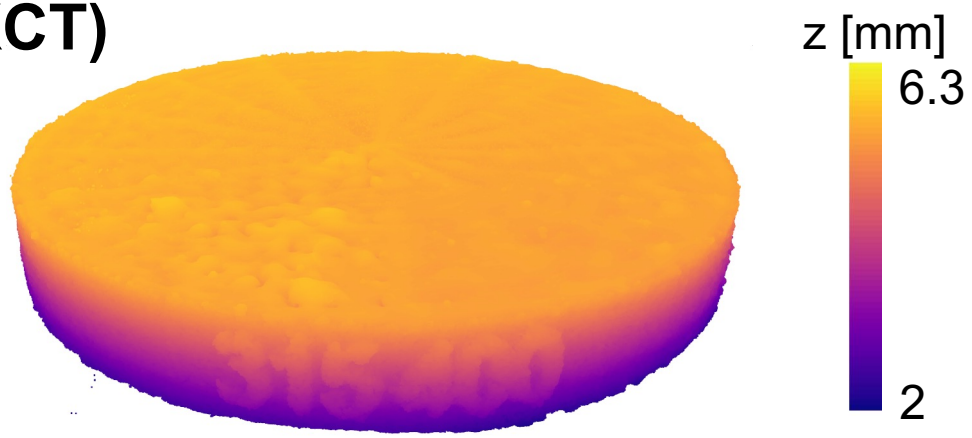


Yavari, M.R., Cole, K.D. and Rao, P., 2019. "Thermal modeling in metal additive manufacturing using graph theory." Journal of Manufacturing Science and Engineering, 141 (7). https://doi.org/10.1115/1.4043648

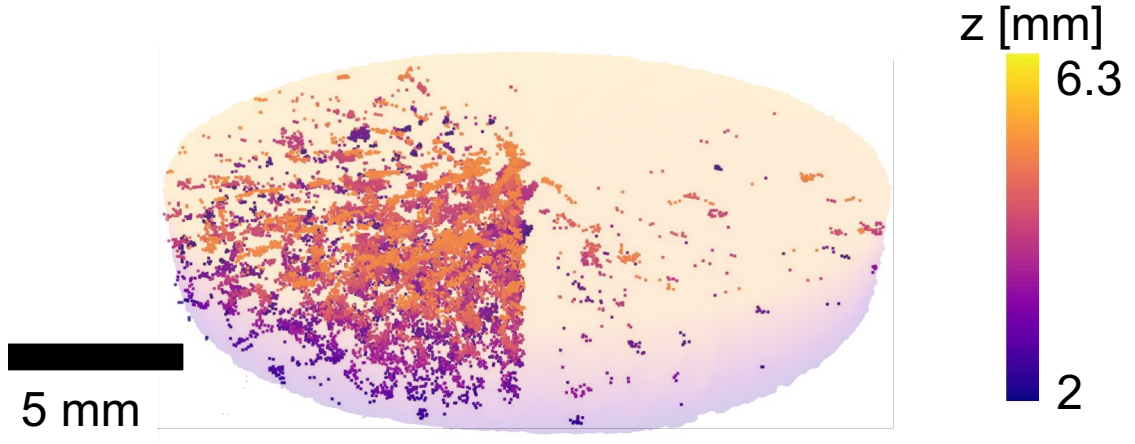
Preview of Ongoing Work

- **Determine statistical relationships between process metrics and porosity**

X-ray Computed Tomography (XCT)



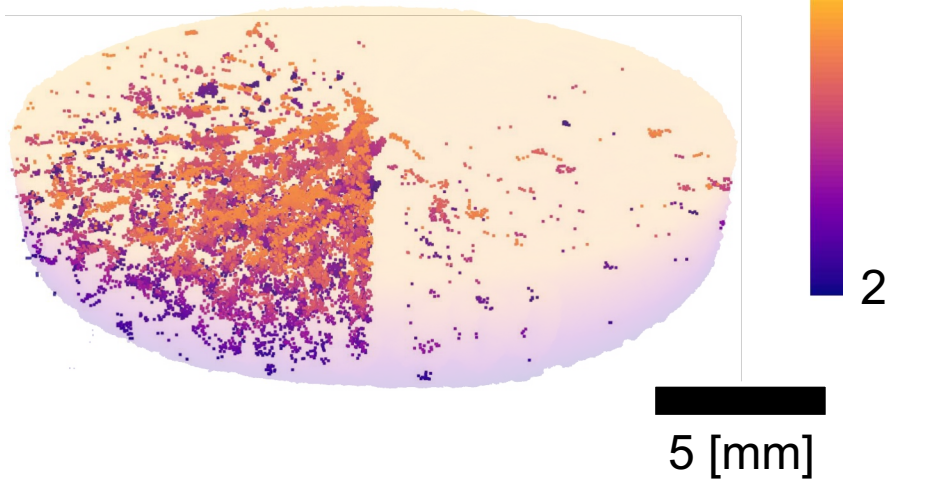
Porosity



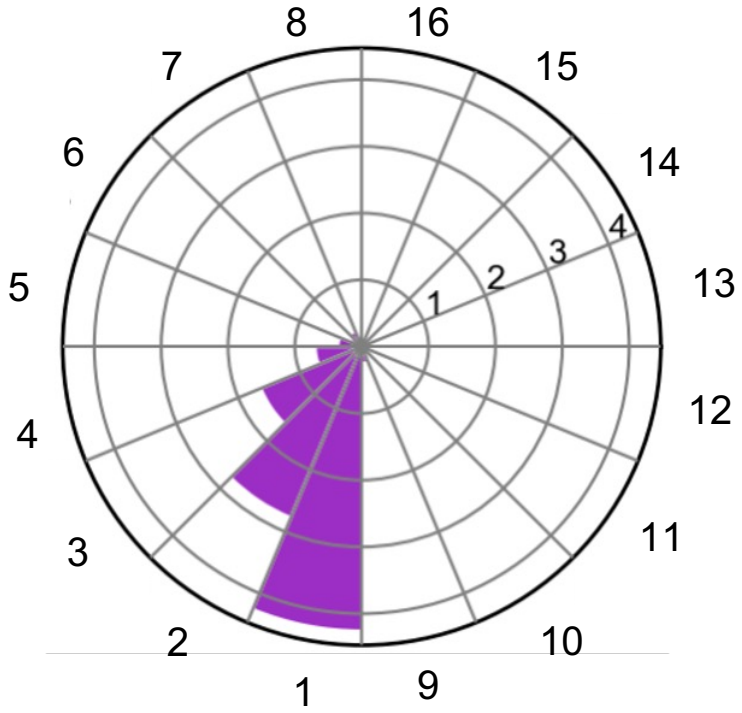
Point Field Mapped Porosity

- XCT porosity classified using Otsu's threshold
- Affine mapping for point-wise porosity
- **Zones 1 – 3 had >1% point-wise porosity**

Porosity



Point-wise [%] Porosity



AM Process Models

Many additive manufacturing process models

- **High fidelity models**
  - Khairallah et al., https://doi.org/10.1016/j.actamat.2016.02.014.
  - Martin et al., https://doi.org/10.1038/s41467-019-10009-2.
  - ….

  Physical accuracy
  Highest computational cost
  Part scales are not yet feasible
  part scales: 1 cm^3 – 100 cm^3

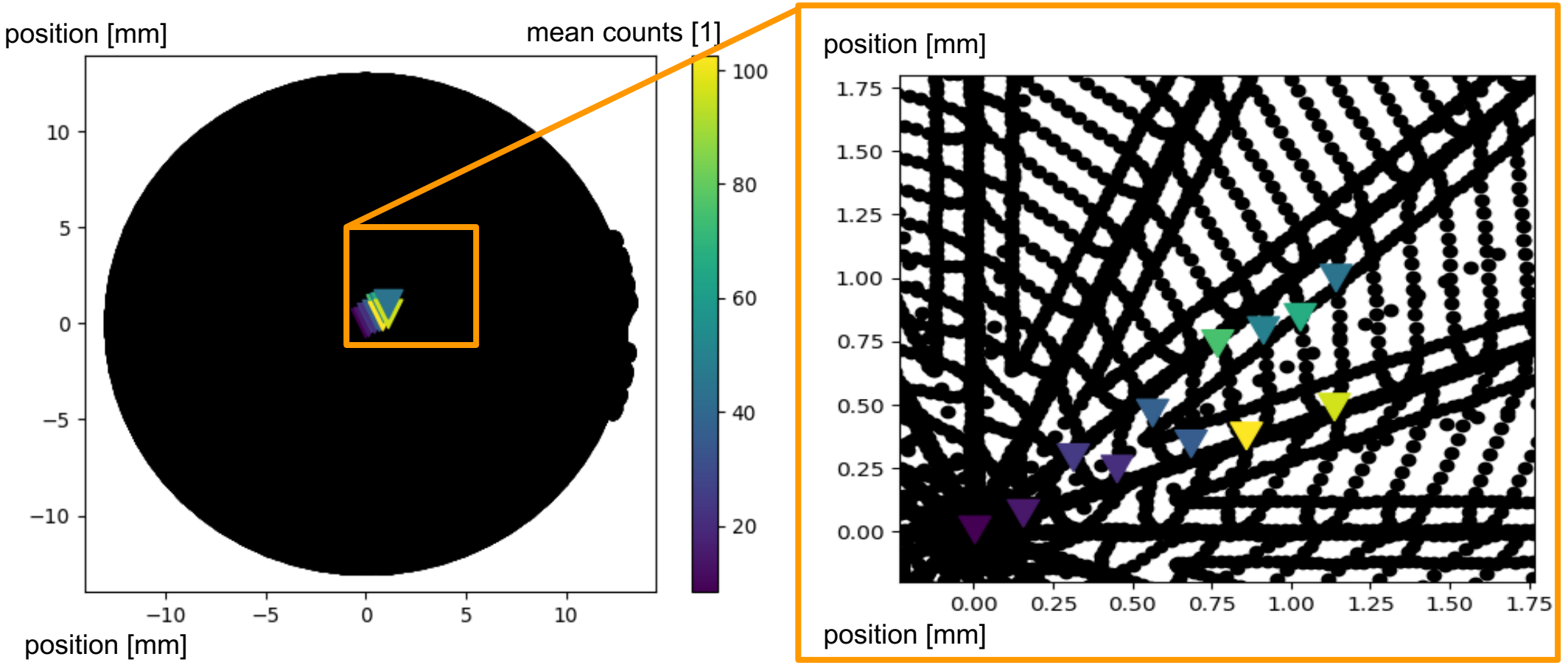
- **Analytical and semi-analytical models**
  - Tapia et al. https://doi.org/10.1007/s00170-017-1045-z.
  - Groeber et al., https://doi.org/10.1088/1757-899x/219/1/012002.
  - Tang et al., https://doi.org/10.1016/j.addma.2016.12.001
  - Promoppatum et al., https://doi.org/10.1016/J.ENG.2017.05.023
  - Zagade et al., https://doi.org/10.1016/j.addma.2021.102222
  - …

  Lower computational costs
  thermal history
  Mesh generation and optimization
  Time-step approach
  Localized build conditions:
  - Not addressed, or
  - Memory limited scales

- **Graph theory-based thermal models**
  - Rao et al., https://doi.org/10.1115/msec2016-8516.
  - Cole et al., https://doi.org/10.1016/j.ijthermalsci.2020.106383.
  - Yavari et al., https://doi.org/10.1115/1.4043648
  - …

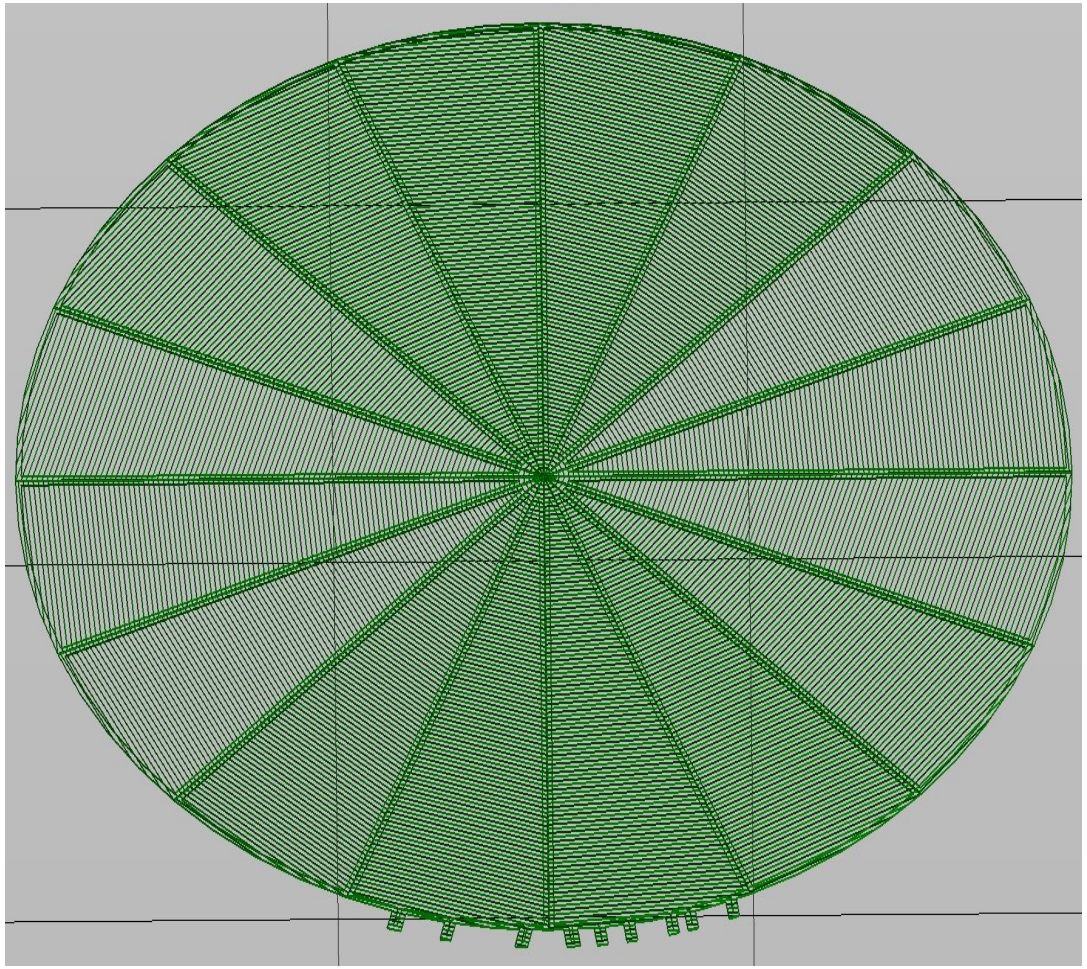
  Point-wise approach
  Layer-wise thermal history
  Time step approach
  Memory bounded for part scales

Melt Pool Image Locations



Build Instructions

- Layer-wise hatch patterns
- Hatch patterns combine with geometry
- Used to generate a model PF



Abstract

The use of in-situ process monitoring is of interest to lower the cost of inspection for the qualification of powder bed fusion laser beam metal (PBF-LB/M) additively manufactured (AM) parts. Precise monitoring of the PBF-LB/M AM build process constitutes a multi-scale and multi-discipline task. There are several significant challenges to the in-situ approach: the synchronization of sensor signals to process steps; the physical interpretation and classification of sensor signals; managing very large datasets; and comparing the inputs with the observed monitoring signals. At NASA Langley Research Center, a configurable architecture additive testbed has been developed to monitor the build process with synchronized sensors. The philosophy and method adopted for the synchronization of the cameras with laser power and position throughout a complex PBF-LB/M AM build will be described. The synchronized in-situ monitoring signals are compared with ex-situ nondestructive inspection, x-ray computed tomography (XCT). Such comparisons permit a better understanding of how the sequential process actions of LPBF-AM can affect build quality.

The multi-scale and complex process of printing additively manufactured (AM) parts can have unexpected, but predictable, build conditions that result in material microstructure variability. This presentation will describe an additive manufacturing model-based process metric (AM-PM) computational method that is a fully parallel reduced order modeling approach developed to evaluate the evolution of AM processes. This method couples the known sequence of the AM process with a physically informed nearest neighbors' calculation to map the conditions of a part-scale build. The result is a map of the build that is derived directly from build files or in-situ process monitoring sensors. The methodology of the approach will be described and mapped to the porosity observed from XCT for a complex PBF-LB/M build. Such comparative results develop understanding of how the sequential process actions can affect the PBF-LB/M AM build quality and microstructure variability.