A Study of Online Melt Pool, Plume, and Spatter Tracking in Laser Powder Bed Fusion using DBSCAN

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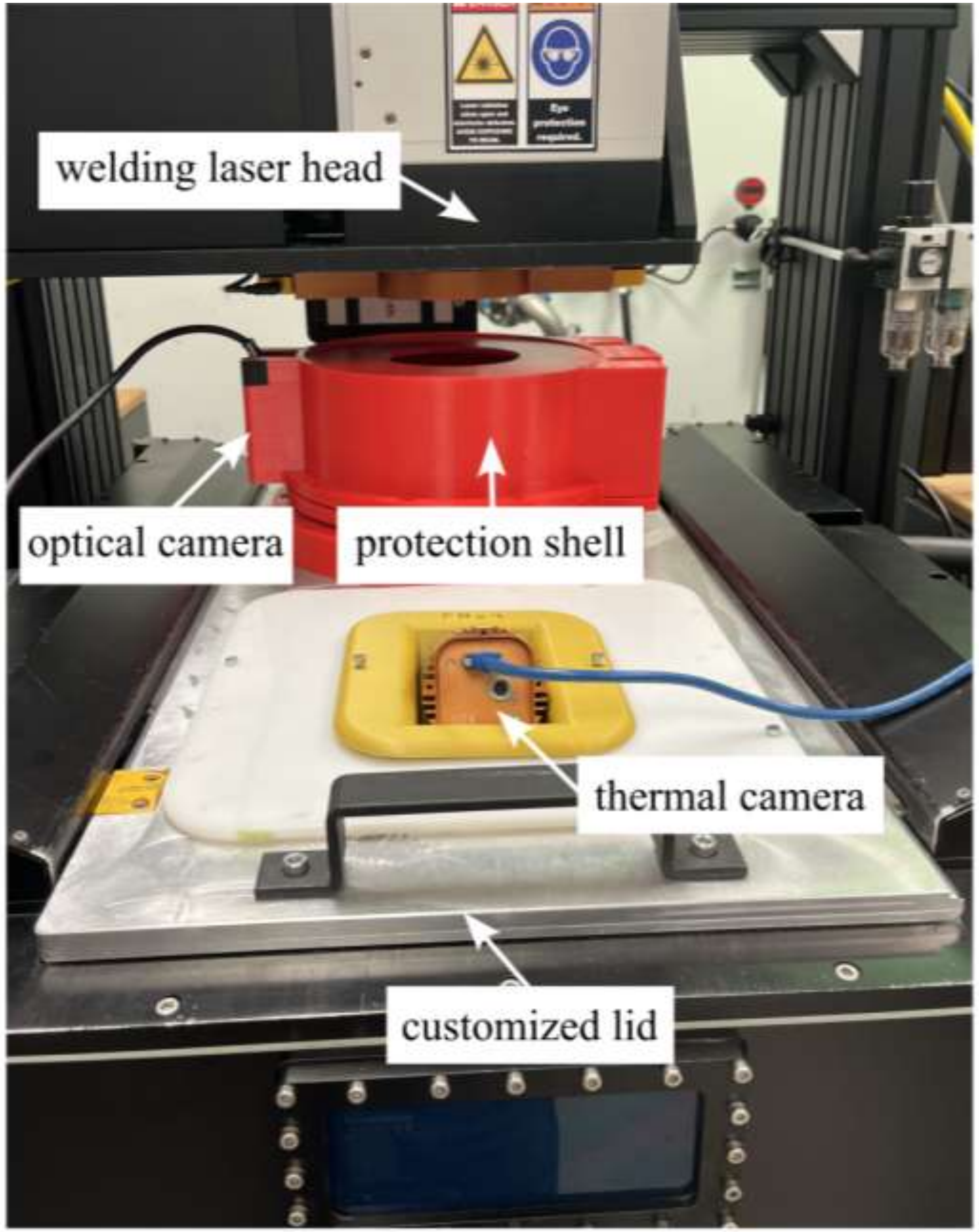
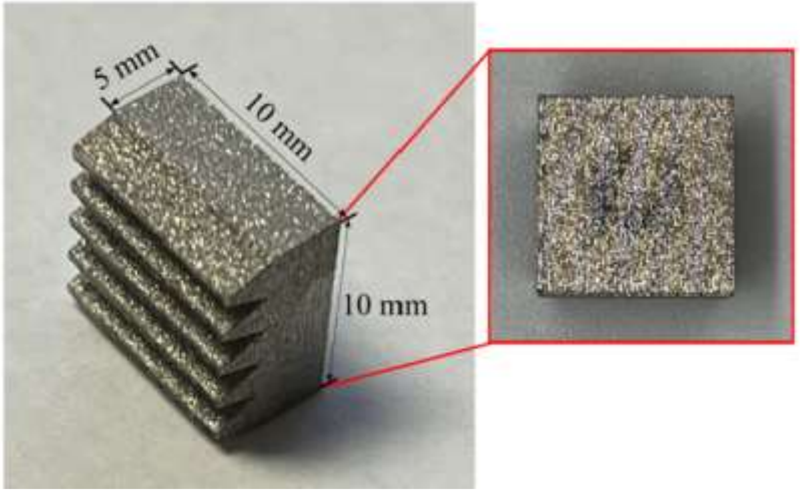


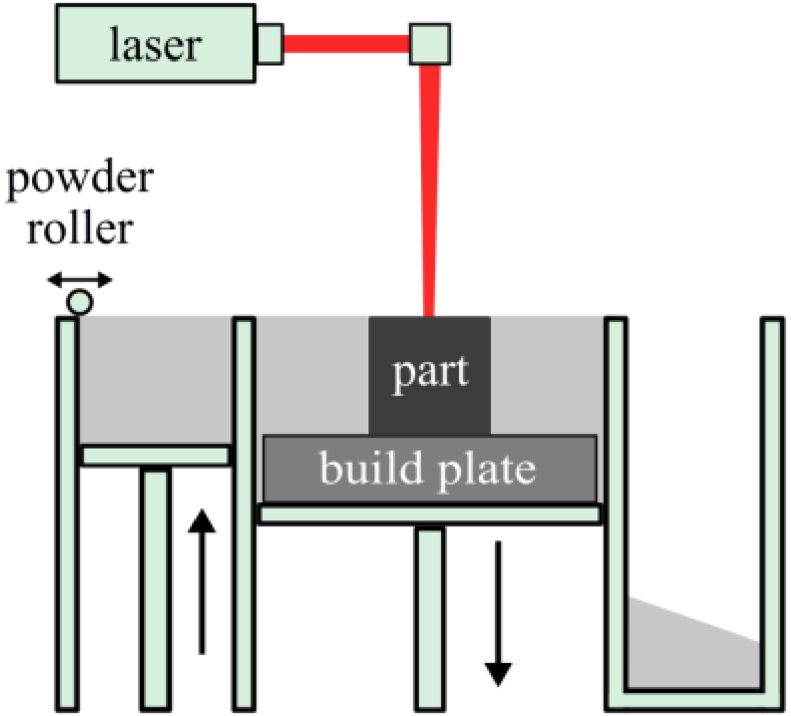
welding laser head
optical camera
protection shell
thermal camera
customized lid

LASER POWDER BED FUSION (LPBF)

Laser Powder Bed Fusion (LPBF)

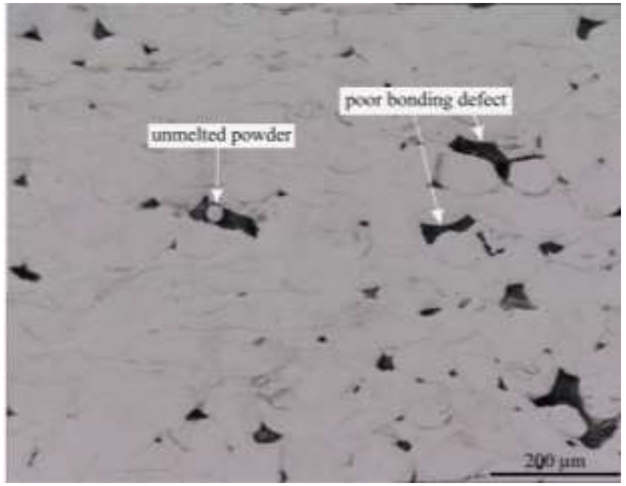
- Make complex parts
- High precision
- Material efficiency
- Wide materi



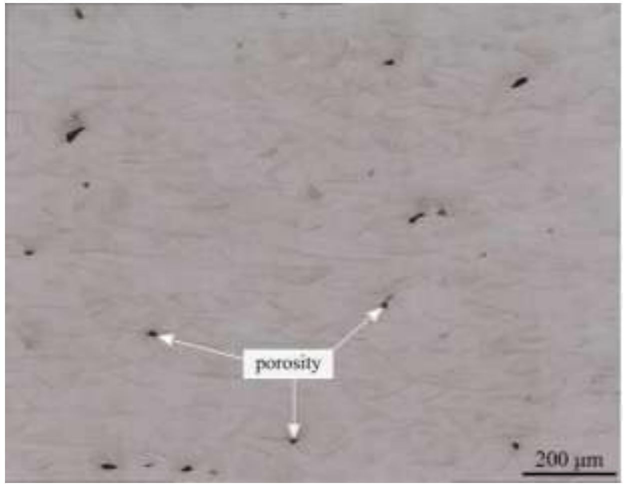


1. https://www.bcn3d.com/introduction-fff-3d-printing-technology-additive-manufacturing-basics/

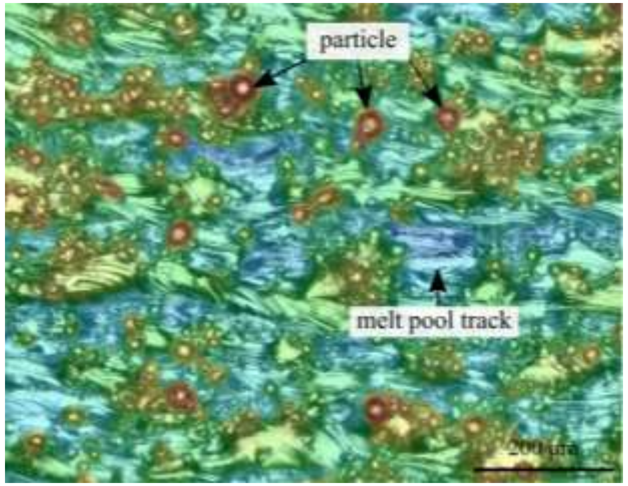
DEFECTS IN LPBF MANUFACTURING



Keyhole



Porosity



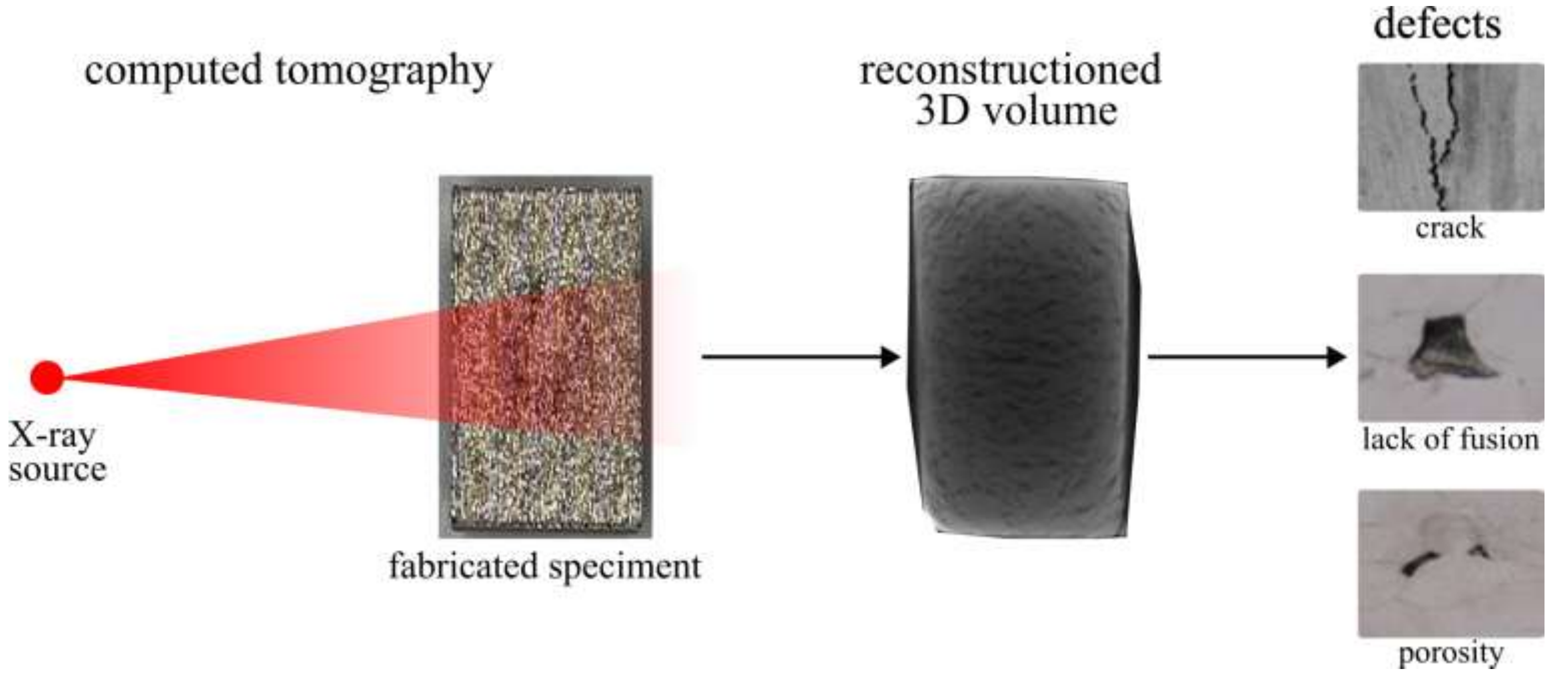
Surface roughness

Distortion

CHALLENGES IN LPBF MONITORING

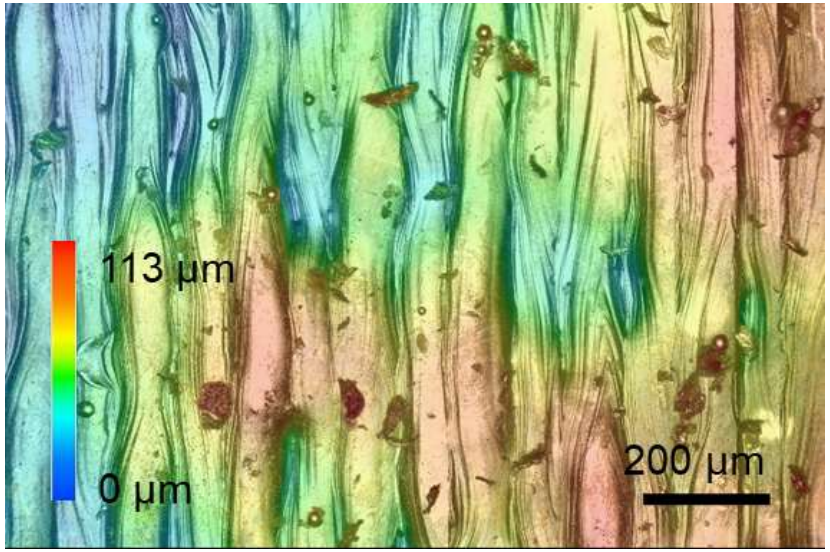
Drawbacks:

- Post-processing
- Lack of real time results
- Costly and time-consuming



Surface Roughness

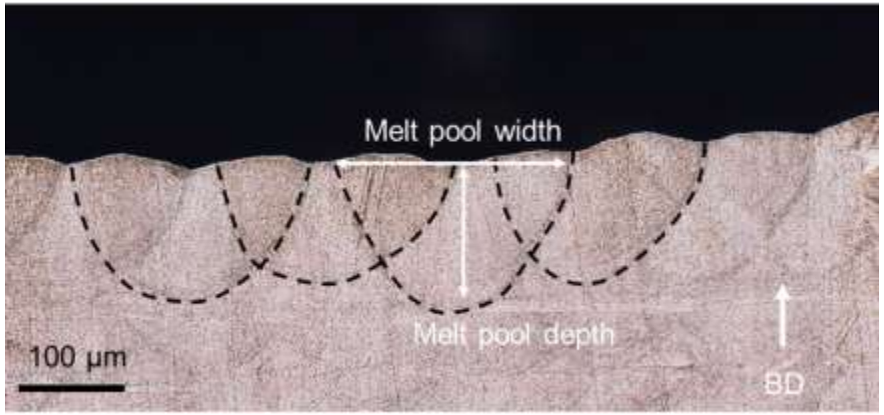
- Key indicator of LPBF part quality affecting mechanical performance
- Driven by melt pool instability and spatter formation
- Low power leads to discontinuities; high power causes humps and spatter
- Improved through real-time monitoring and optimized process parameters

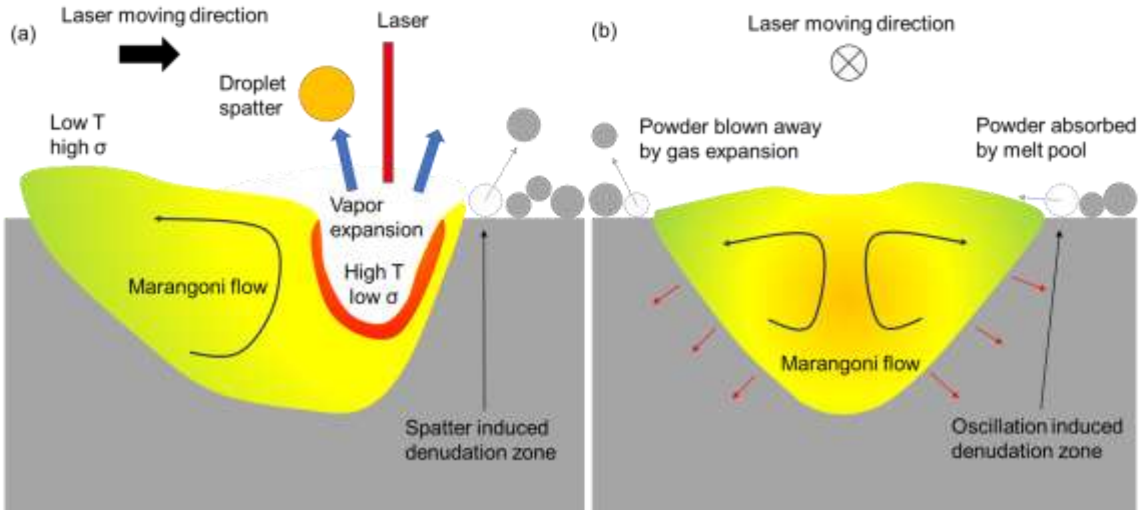


Melt Pool Stability and Spatter on Surface Quality

Smooth surface roughness challenge:

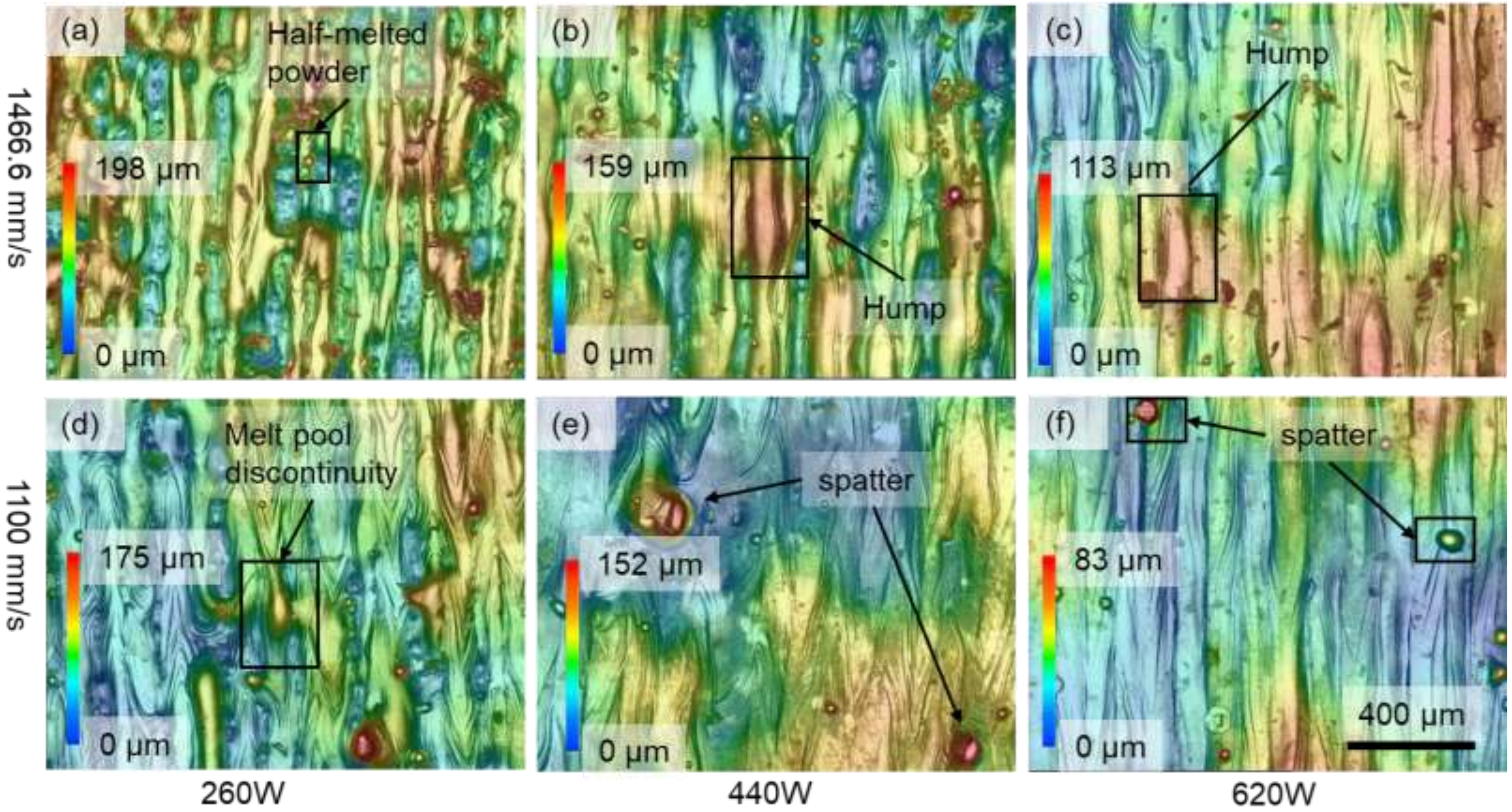
- Melt pool stability and spatter control are crucial for achieving a smooth surface roughness.
- Unstable melt pools and excessive spatter increase surface roughness.





Impact of Laser Power on Surface Roughness

- Top surface roughness is dominated by melt pool discontinuity and valleys between melt tracks at 260 W condition.
- With power increasing, the disappear of melt pool discontinuity and valley leads to the smoother top surface (lower Sa and Za).
- Top surface roughness is dominated by hump and spatter at 620 W condition.

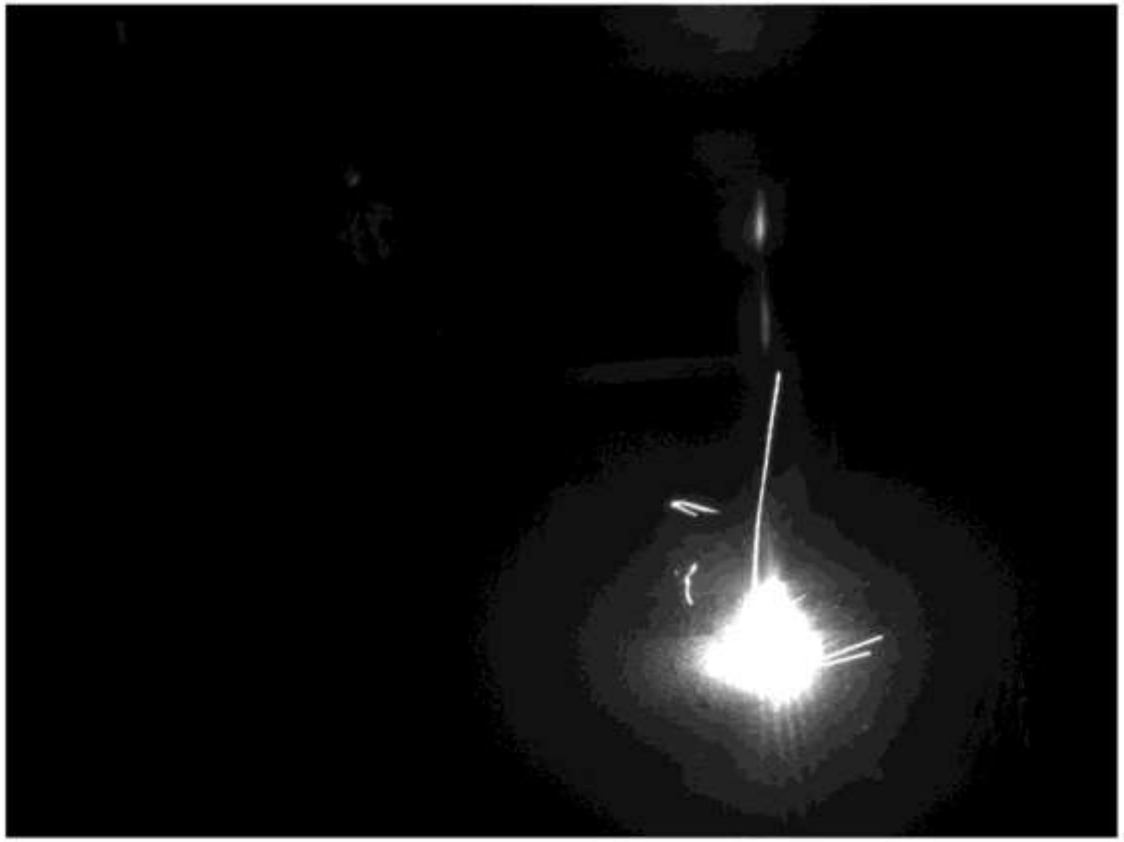


Eliminating melt pool discontinuities, valleys, and spatter improves the top surface quality.

Relationship Between Printing Defects and Process Conditions

Correlation between defect and printing information:

- Melt pool: too little causes porosity
  too big leads keyholing
- Plume: affects laser absorption, excessive formation causing unstable melting
- Spatter: redistributes molten particles, leading to roughness and porosity



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EXPERIMENTAL SETUP FOR LPBF PROCESS

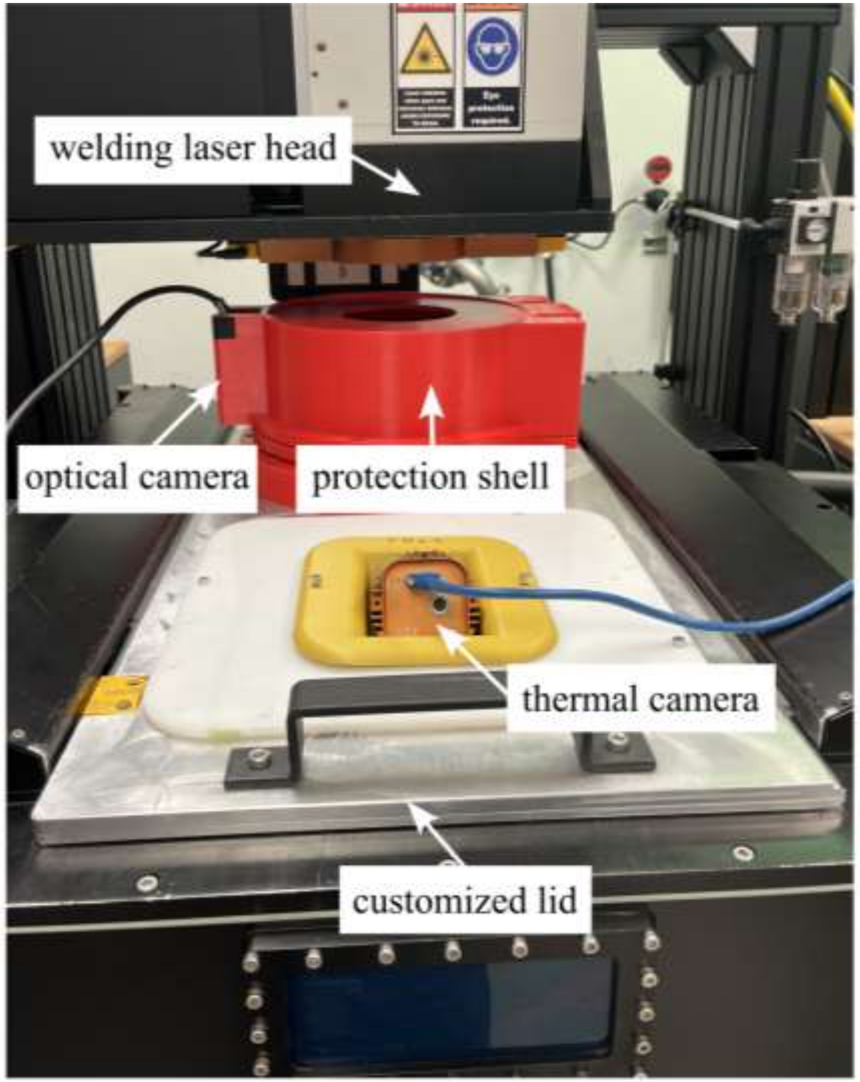
Experiment setup:

part: 10 mm x 10 mm

material: 316L stainless steel powder

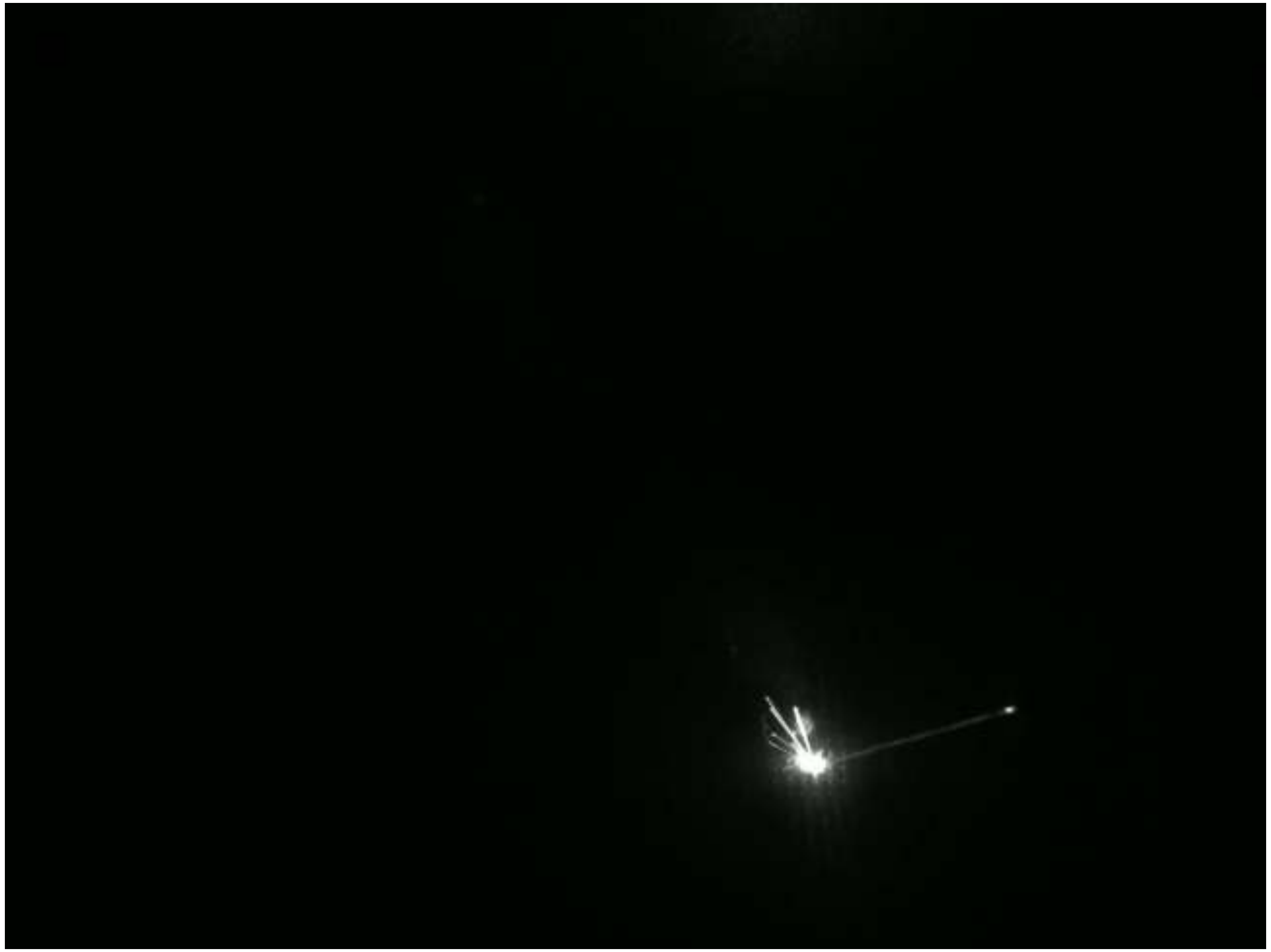
printing parameters:

- power: 200 W
- speed: 100 mm/s
- laser spot: 100 μm
- hatch distance:100 μm



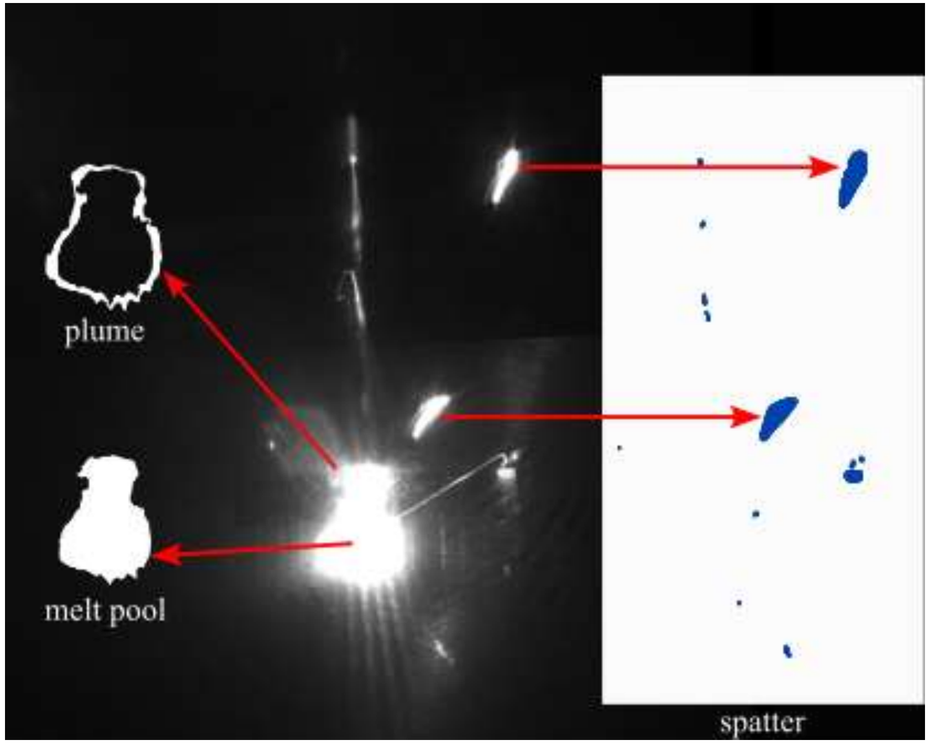
High-Speed Imaging of LPBF Welding Process

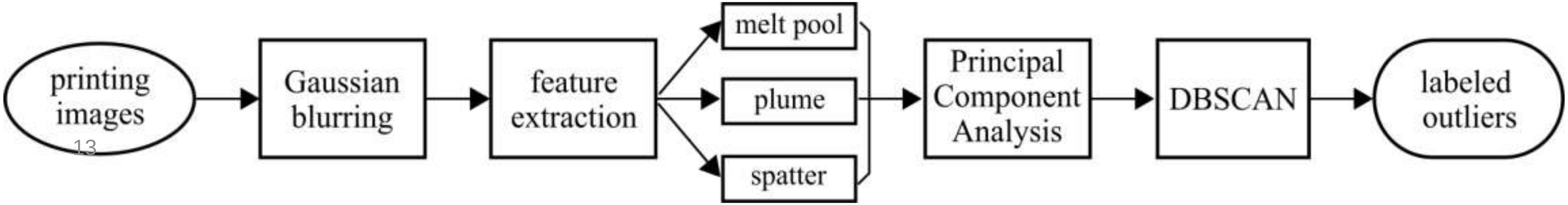
- Captured using a FLIR Blackfly USB optical camera (1440 × 1080 resolution, 100 fps).
- Tracks melt pool, plume, and spatter dynamics in real-time.
- MidOpt BP660 bandpass filter (640-680 nm) enhances imaging clarity.
- Provides critical insights into process stability and defect formation and abnormal printing conditions.



DATA PROCESSING WORKFLOW

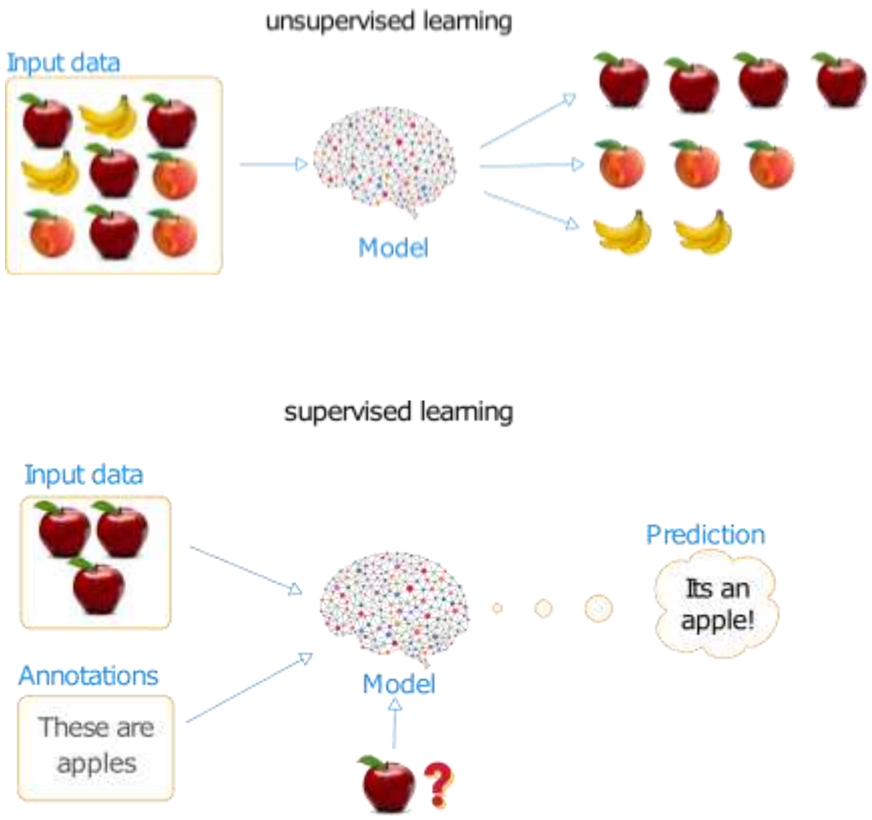
- Optical images captured during printing are pre-processed using Gaussian blurring.
- Key features—melt pool, plume, and spatter—are isolated through image segmentation.
- Principal Component Analysis (PCA) reduces feature dimensionality, highlighting essential process variations.
- DBSCAN clustering identifies anomalies without labeled training data, distinguishing normal and abnormal printing conditions.





Supervised vs Unsupervised learning

- Unsupervised Learning:
  - Learns from input data without labels.
  - Groups similar data together, identifying natural clusters.
- Supervised Learning:
  - Learns from labeled input data (annotations).
  - Makes predictions based on previously learned examples.
- Application in LPBF:
  - Unsupervised: Identifies defects without labeled examples (anomaly detection).
  - Supervised: Predicts specific defects when labeled training data is available.

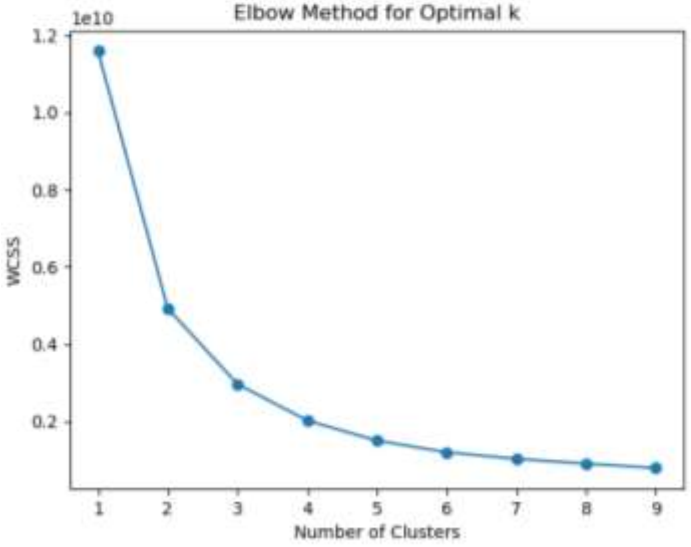


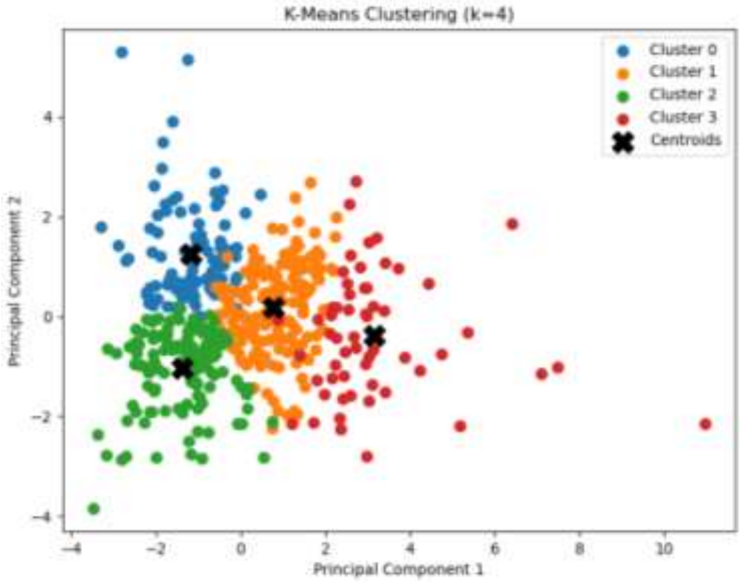
[1] Ma, Y., Liu, K., Guan, Z., Xu, X., Qian, X. and Bao, H., 2018. Background augmentation generative adversarial networks (BAGANs): Effective data generation based on GAN-augmented 3D synthesizing. Symmetry, 10(12), p.734.

K-MEANS CLUSTERING

***K*-means clustering disadvantages:**

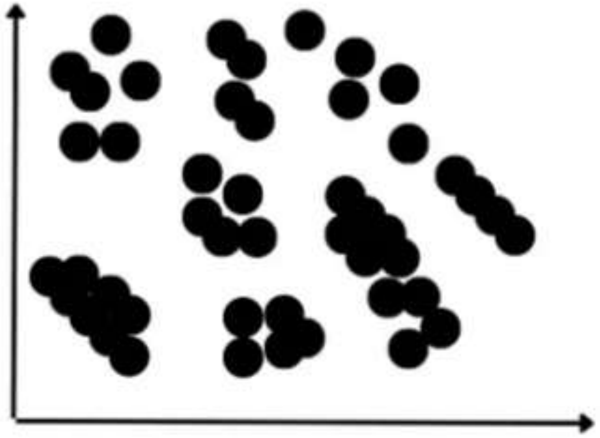
- K-Means is a common clustering algorithm that requires selecting the number of clusters (k).
- The Elbow Method helps determine the optimal k, but it assumes well-separated, spherical clusters.
- LPBF process data is highly irregular, with overlapping and non-uniform distributions.
- DBSCAN is preferred as it identifies arbitrary-shaped clusters and effectively isolates outliers.



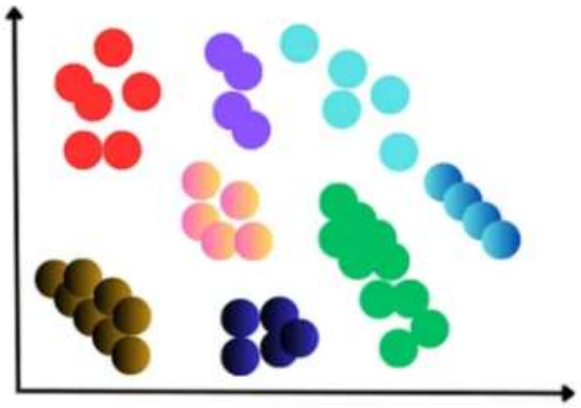


Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

- Unlike K-Means, DBSCAN does not require predefining the number of clusters and can identify arbitrarily shaped groups.
- It separates dense regions (clusters) from sparse points (outliers), making it ideal for detecting anomalies in LPBF data.
- This method is particularly useful for automated defect detection, as it isolates process instabilities without prior labeling.



Original Data



DBSCAN Clustering

[1] https://medium.com/@jayaramganesh238/dbscan-clustering-dea27873ed30

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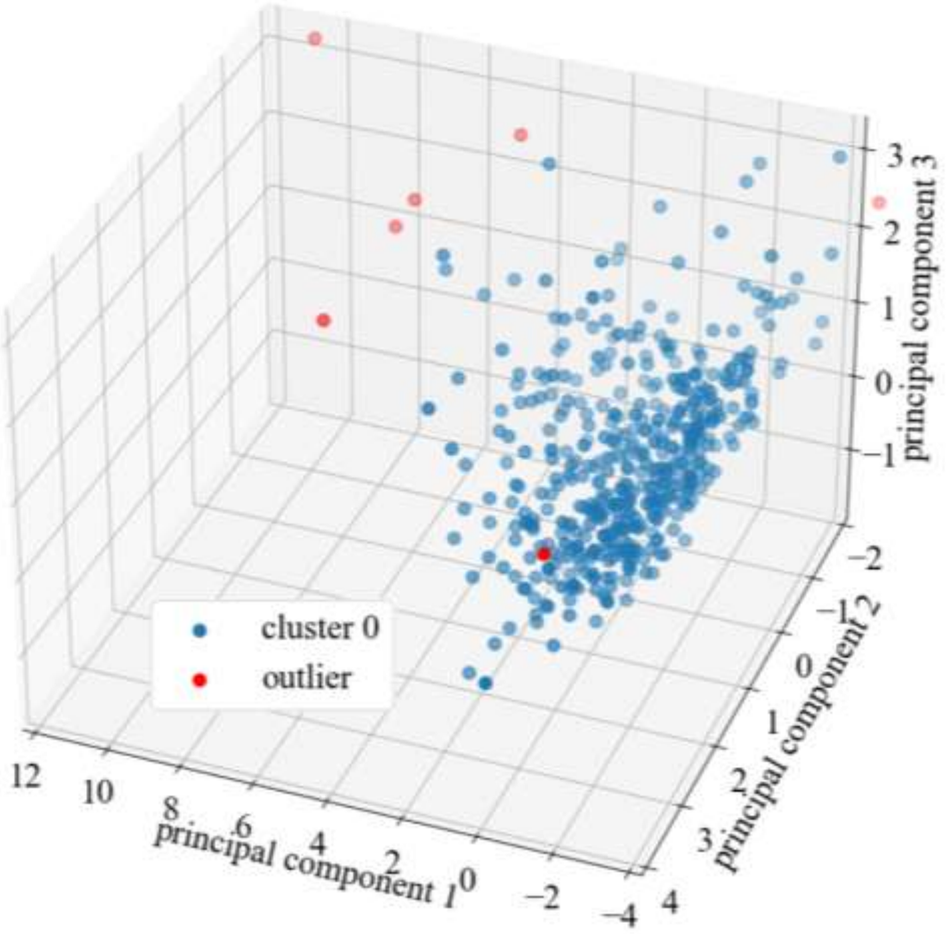
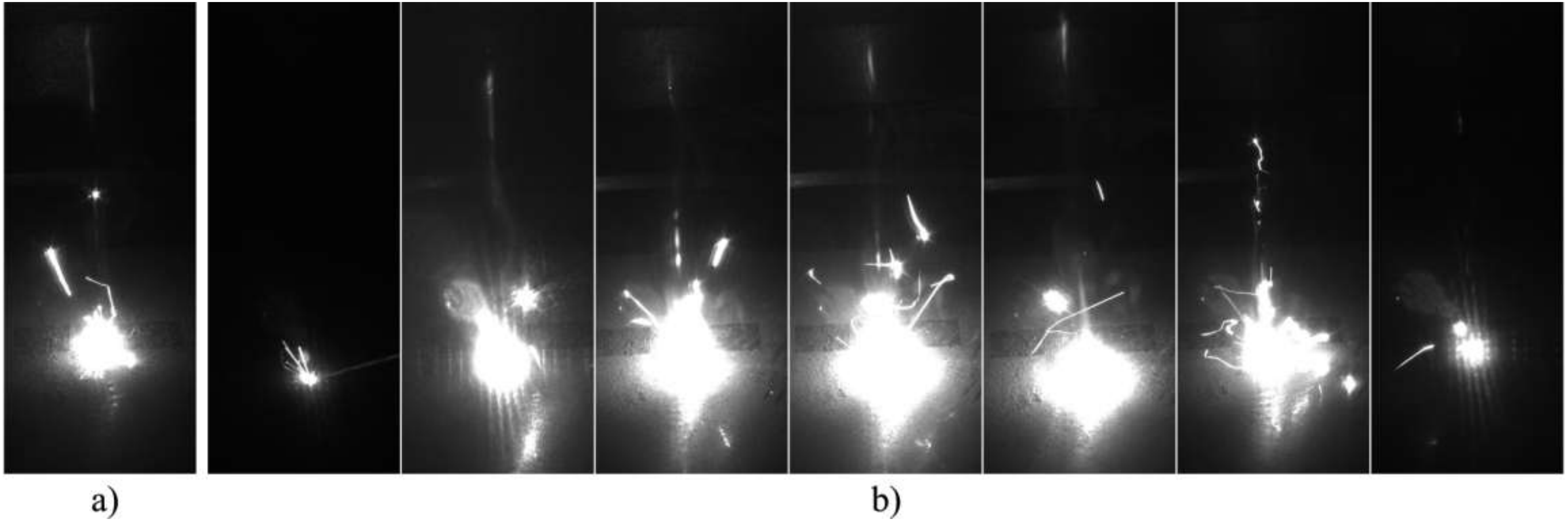
DD Visualization of DBSCAN Clustering in LPBF

- 445 frames analyzed from the last printed layer using DBSCAN clustering.
- Blue dots indicate normal printing conditions.
- Red dots represent detected outliers linked to potential defects.
- 2D and 3D visualizations clearly distinguish normal frames from anomalous ones.
- Key insight: Clustering identifies process instabilities, improving real-time defect detection.



Outliers Identified using DBSCAN



The clustering frames from DBSCAN: a) the normal printing frame and b) seven outliers from the DBSCAN.

Detailed Result

- Normal frames provide a baseline for comparison.
- Outliers 1 & 7: Smaller melt pool, plume, and spatter areas with lower intensity (insufficient energy).
- Outlier 4: Larger melt pool, plume, and spatter areas but similar intensity (excessive heat).

	melt pool area (pixel)	melt pool intensity	plume area (pixel)	plume intensity	spatter area (pixel)	spatter intensity
normal (averaged)	8184.54	250.71	3745.02	181.34	2030.80	193.68
outlier 1	789.5	246.50	141.0	175.02	39.0	191.75
outlier 2	15353.5	250.85	14554.0	177.97	7021.0	191.30
outlier 3	29273.0	251.48	13324.0	180.20	7358.5	192.95
outlier 4	38743.0	251.30	18507.0	180.21	10252.0	193.15
outlier 5	26556.0	251.23	13407.0	180.64	7493.0	193.03
outlier 6	22814.5	250.37	11211.0	182.52	6802.5	193.85
outlier 7	2054.5	248.95	1605.0	187.37	1084.5	196.04

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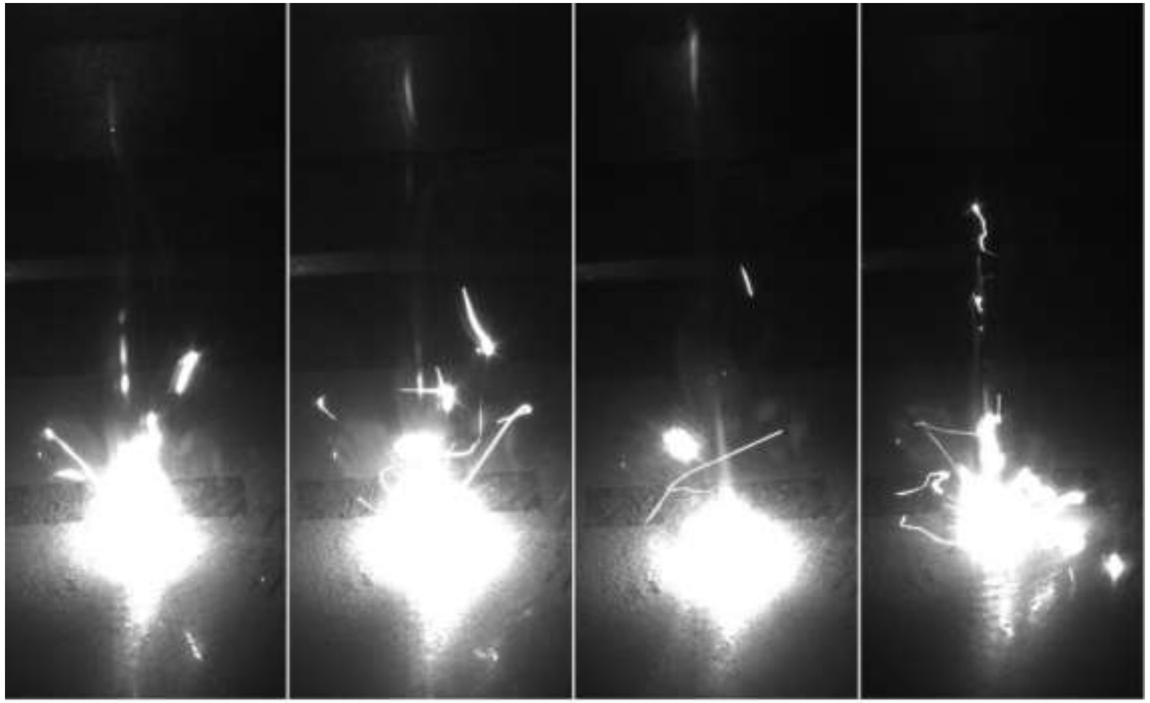
Conclusion and future work

1. This paper presented a study of online methodology of melt pool, plume, and spatter tracking.
2. The DBSCAN approach successfully identified process anomalies without requiring labeled training data.
3. These clustered outliers suggest unstable process conditions that may lead to porosity, lack of fusion, or surface irregularities.
4. A key next step is to validate clustered outliers using post-process like X-ray computed tomography to link internal defects directly to process anomalies.
5. Additionally, integrating multi-modal sensing, such as thermal imaging and acoustic monitoring, could improve defect prediction accuracy



Thank You

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