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

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ABSTRACT

Additive manufacturing offers unmatched design flexibility, but this advantage comes with inherent process uncertainties that can lead to defects affecting mechanical properties. Ensuring consistent quality requires reducing part-to-part variations, yet traditional ex-situ characterizations, such as X-ray computed tomography, are time-consuming and constrained by part complexity. To address this challenge, we propose a low-cost, in-situ monitoring framework utilizing unsupervised learning to detect and classify defects in Laser Powder Bed Fusion (LPBF). Our approach leverages optical imaging data captured during printing to identify anomalies. In this study, image processing techniques, including contrast enhancement, normalization, and noise filtering, are applied to extract critical features such as melt pool, plume, and spatter behavior, which are key indicators of print stability. Principal Component Analysis (PCA) is then used to reduce dimensionality while preserving key process variations. Subsequently, unsupervised clustering techniques, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), are applied to classify printing conditions to detect outliers indicative of defect formation. This study provides valuable insights into the relationship between in-situ monitoring data and defect formation in LPBF, demonstrating the feasibility of machine learning-driven real-time quality assurance. By correlating detected outliers with actual porosity and defects, this approach has the potential to reduce reliance on post-processing inspections, improve defect prediction accuracy, and enhance the reliability of additive manufacturing processes.

Keywords: additive manufacturing, laser powder bed fusion, unsupervised learning, printing-related features extraction, defect detection

1. INTRODUCTION

Laser Powder Bed Fusion (LPBF) is a cutting-edge metal additive manufacturing technology that has revolutionized the manufacturing industry by offering unparalleled design and fabrication flexibility.[1] LPBF enables the precise construction of complex geometries layer by layer, which has been widely utilized in aerospace, medical, and automotive applications. During the process, a laser beam selectively scans and melts metal powder based on a predefined path from a CAD model, fusing particles into a solid layer. The build platform then lowers, fresh powder is recoated by a blade, and the process repeats until the final part is completed. Despite its advantages, LPBF is governed by complex physical phenomena, including laser energy absorption, material evaporation, remelting, solidification dynamics, and microstructural evolution through epitaxial growth and nucleation.[2] Additionally, multiple process parameters, such as laser power, scanning speed, and hatch spacing, directly influence defect formation, leading to issues like cracks, porosity, and lack of fusion, which compromise

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mechanical integrity.[3] To ensure high-quality prints, a robust defect detection system is essential for real-time monitoring and quality assurance in LPBF manufacturing.

Machine learning-based detection is a promising approach for ensuring print quality in LPBF. Recent advancements in defect detection for LPBF have leveraged machine learning and in-situ monitoring techniques. For instance, Gobert et al. applied supervised machine learning techniques to high-resolution imaging data for defect detection during metallic powder bed fusion additive manufacturing.[4] Their methodology demonstrated the potential of machine learning in identifying defects in real-time, thereby enhancing the quality control process in additive manufacturing. Additionally, Liu et al. proposed an innovative monitoring method that utilizes acoustic and thermal emission data to infer critical melt pool characteristics and detect lack-of-fusion defects in LPBF.[5] This approach offers a cost-effective solution for real-time monitoring and quality assurance in additive manufacturing. Incorporating sensor fusion, Snow et al. developed a system that integrates data from multiple sensors, including visible light and near-infrared cameras, to detect subsurface flaws in LPBF-produced parts.[6] This approach enhances the detection of defects that are not visible on the surface. Furthermore, Pak et al. introduced "ThermoPore," a deep learning framework that predicts part porosity based on in-situ thermal images, aiming to create real-time porosity maps to reduce reliance on post-build inspections.[7] This model assists in identifying regions within a part that are likely to contain porosity defects, allowing for targeted quality control measures.

Unsupervised learning has been explored for in-situ defect detection in LPBF, offering label-free anomaly identification. For instance, Scime and Beuth developed a methodology utilizing unsupervised machine learning and computer vision techniques to analyze melt pool morphology in real-time using high-speed visible-light imaging.[8] Their study constructed a scale-invariant representation of melt pool characteristics and employed clustering techniques to identify in-situ signatures indicative of defects such as keyhole porosity and balling instabilities. By linking these in-situ observations with ex-situ defect analysis, they demonstrated the potential for machine learning-driven classification of melt pool behaviors, which could improve real-time monitoring and reduce reliance on post-process inspections. This approach offers a promising pathway for detecting and predicting flaws in LPBF processes without requiring extensive labeled datasets, making it a viable alternative to supervised learning approaches.

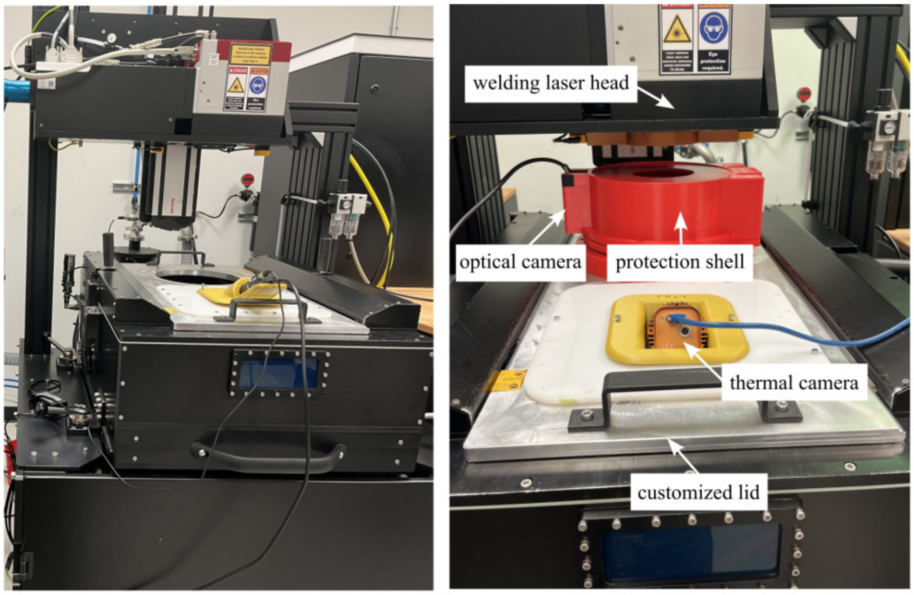
A major challenge in LPBF is obtaining accurate defect labels, which are essential for training machine learning models. These defects often require post-process validation, such as X-ray computed tomography (XCT), which is costly and time-consuming, limiting the creation of large, well-annotated datasets for supervised learning. Additionally, defect formation depends on multiple process parameters, making it difficult to develop models that generalize across different conditions. To address this, establishing strong correlations between real-time process signals and actual defects is crucial.[9] Unsupervised learning offers a solution by detecting anomalies in in-situ monitoring data. If a reliable correlation is found, this approach could enable real-time defect detection, reducing reliance on post-process inspections and improving LPBF quality control.

In LPBF, melt pool, plume, and spatter indicate process stability.[10] The melt pool controls fusion quality: too little causes porosity, too much leads to keyholing. The plume affects laser absorption, with excessive formation causing unstable melting. Spatter redistributes molten particles, leading to roughness and porosity. In this research, we propose an unsupervised learning approach that leverages melt pool, plume, and spatter from printing images to detect outliers that are directly correlated to surface roughness. To do this, we track features extract from melt pool, plume, and spatter that are obtained using our custom-built LPBF in situ motioning system. Then Principal Component Analysis (PCA) is performed on the features and unsupervised clustering is applied to identify outliers. For this work, we select Density-Based Spatial Clustering of Applications with Noise (DBSCAN) for unsupervised clustering.[11] DBSCAN is particularly well-suited for this task as it detects outliers and clusters data based on density rather than predefined categories. Unlike K-Means clustering,[12] which assumes clusters of similar size and requires a predefined number of clusters, DBSCAN identifies high-density regions while treating rare defects as noise, making it ideal for detecting anomalies in melt pool, plume, and spatter behavior. The contributions of this paper are twofold: (1) Unsupervised process state characterization using DBSCAN clustering to analyze melt pool, plume, and spatter behavior in LPBF. (2) Experimental validation of process feature clustering, demonstrating the ability to distinguish variations in printing conditions through data-driven analysis. Supplementary data and code are provided via a public repository.[13]

2. METHODOLOGY

This section describes the methodology undertaken in this work.

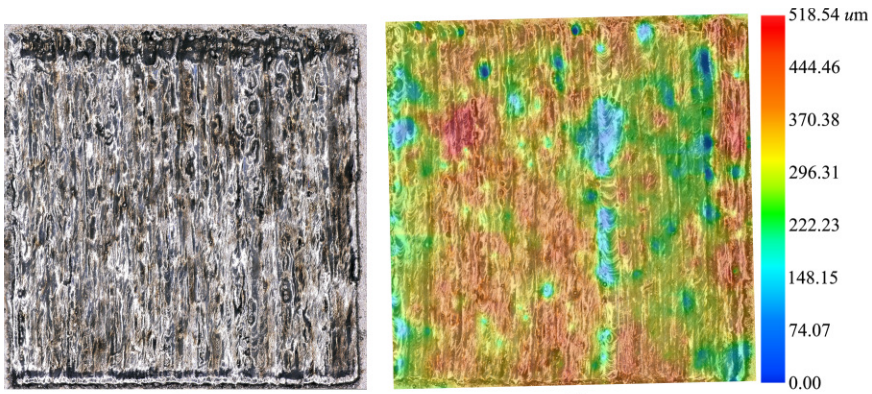
2.1 Experiment Setup



a) b)

Figure 1. Experimental data collection setup on the metal 3D printer: a) the printer with the customized cover and b) data collection setup with the optical and thermal cameras.

The AcontyMIDI LPBF printer is used to fabricate the part in this work, which is shown in Figure 1. A FLIR blackfly USB optical camera with a resolution of 1440 $\times$ 1080 and a Workswell Infrared Camera with a resolution of 640 $\times$ 512 are utilized on the customized printer cover to collect the printing process images with a frame rate of 100 and 60. A MidOpt bandpass filter BP660 is applied in front of the lens to get a clear printing image with a valid range of 640-680nm. In this research, a 10 $\times$ 10 mm specimen with 20 layers is fabricated using 316L stainless steel powder. Only the last layer's optical frames are used and extracted in this research, which makes it easier to check the surface quality by microscope. Figure 2a) shows the last layer's surface quality by microscope, and Figure 2b) shows the printed specimen surface height changes. The key printing parameters such as power, speed, laser spot, and hatch distance for specimen printing are 200 W, 100 mm/s, 100 µm, and 100 µm.



a) b)

Figure 2. The sample in the research: a) the last layer's surface quality and b) the printed specimen surface height.

2.2 Algorithm Development

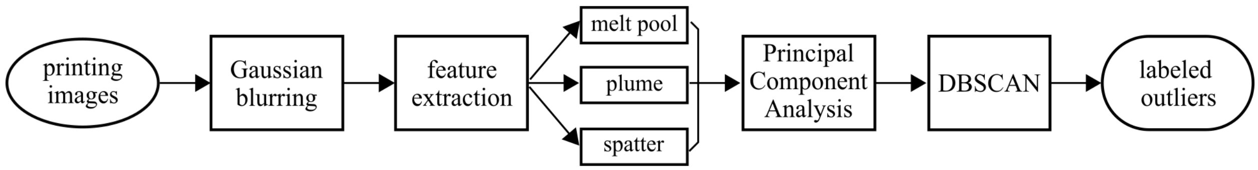


Figure 3. Flowchart for in-situ monitoring and unsupervised clustering analysis in laser powder bed fusion.

This study presents an unsupervised learning approach to identify anomalies in printing images without requiring labeled defect data. The methodology, as illustrated in Figure 3, begins with image preprocessing, where Gaussian blurring is applied to reduce noise and enhance feature clarity. Next, feature extraction isolates key process characteristics, melt pool, plume, and spatter, which serve as indicators of energy input, material ejection, and process stability. Following feature extraction, PCA is employed to reduce dimensionality while retaining the most critical variations in the dataset.[14] This step optimizes computational efficiency while preserving the key information necessary for defect detection. Finally, DBSCAN is used to categorize printing conditions, distinguishing between normal process behavior and potential defects. By leveraging this data-driven approach, the proposed method identifies real-time process instabilities, eliminating reliance on predefined defect labels.

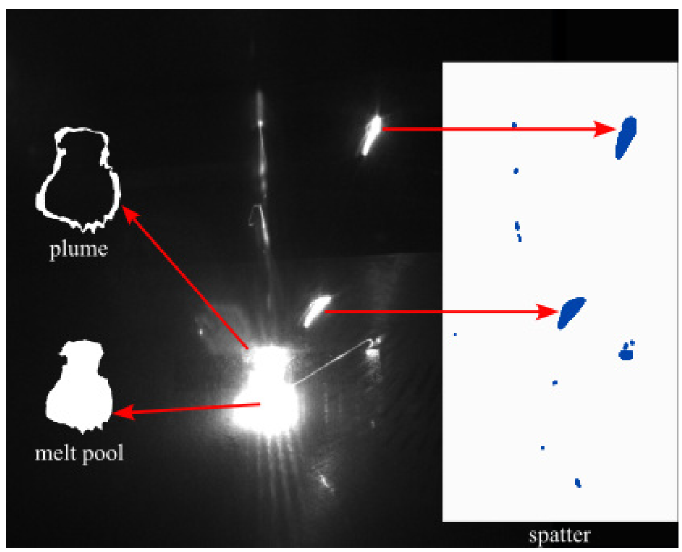


Figure 4. The extracted melt pool, plume, and spatter from the printing image.

The ultimate goal of outlier detection is to correlate the outliers' information with printing abnormality. Therefore, feature extraction is applied to the printing images to obtain key information. Figure 4 shows the three key features from one of the printing images, the are plume, melt pool, and spatter. For each, intensity and area are extracted, leading to six extracted features: melt pool intensity and area, plume intensity and area, and spatter intensity and area. The primary tool used for feature extraction in this work is OpenCV, an open-source computer vision library, which is a collection of programming functions mainly for real-time computer vision.

In this study, DBSCAN is applied to extracted process features to detect abnormal conditions. Establishing a correlation between detected outliers and actual defects enhances real-time process monitoring and reduces reliance on post-production inspections. Another advantage of DBSCAN is its ability to handle irregularly shaped clusters and effectively separate meaningful process variations from background noise. In LPBF, process conditions vary significantly, making traditional clustering techniques less reliable. DBSCAN's ability to dynamically classify process variations ensures that abnormal conditions can be detected without prior knowledge of the exact number of defect types.

3. RESULTS AND DISCUSSION

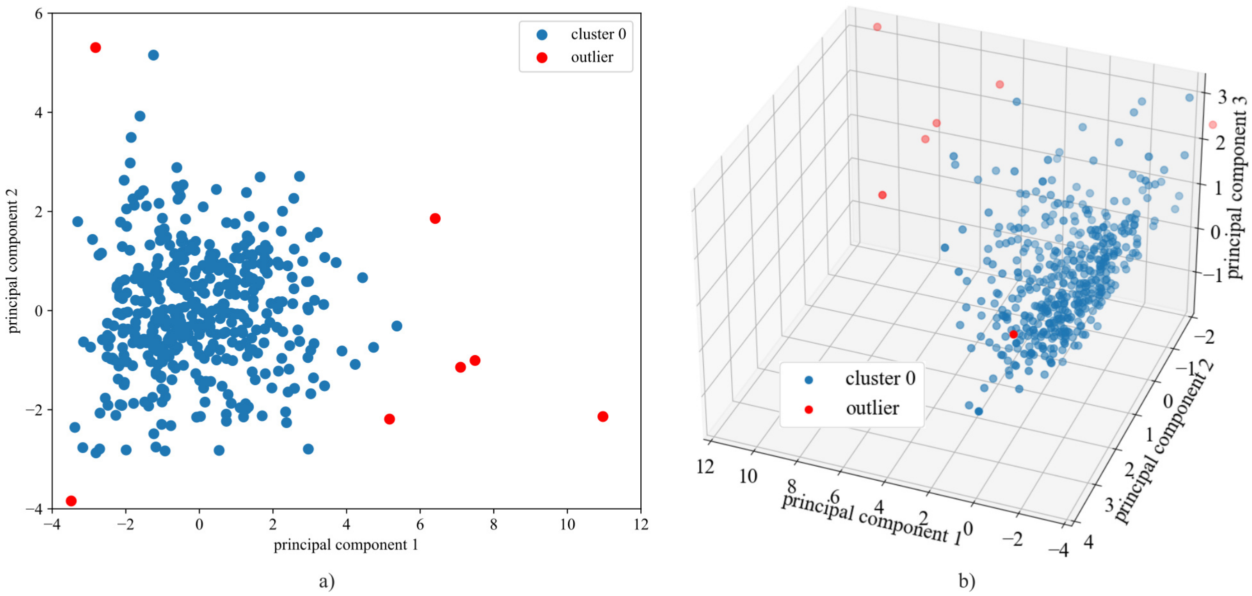


Figure 5. The clustering result visualization: a) 2D visualization for clustering and b) 3D visualization for clustering.

The clustering result from DBSCAN is shown in Figure 5, which provides valuable and promising insights into the correlation between in-situ monitoring features and defect formation in LPBF. DBSCAN clustering is applied to melt pool, plume, and spatter characteristics, effectively distinguishing normal process behavior from potential printing defects. The 2D and 3D visualization for the DBSCAN clustering results are shown in Figure 5 a) and b), separately. Each dot represents one frame. Since high-dimensional data visualization is inherently challenging beyond three dimensions, we primarily present 2D and 3D visualizations for interpretability. The 2D PCA scatter plot provides a simplified overview of clustering trends, while the 3D visualization adds an additional feature for a more comprehensive spatial representation. The normal printing frame with the other seven clustered frames is shown in Figure 6. Figure 6 a) is one of the normal printing frames, and Figure 6 b) are the seven outliers clustered out by DBSCAN.

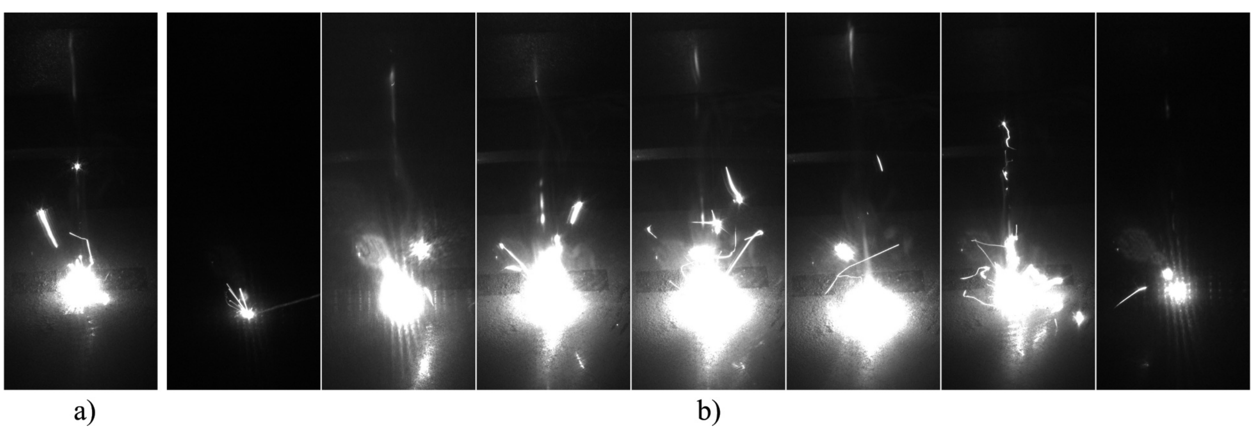


Figure 6. The clustering frames from unsupervised learning DBSCAN: a) the normal printing frame and b) seven outliers from the DBSCAN.

The total number of frames for the last layer printing is 445. From the clustering results, most frames were classified as normal, with only a small percentage (7 frames) identified as outliers. The averaged feature values for normal printing conditions provide a useful baseline for comparison. Normal prints exhibited a consistent melt pool area (8,184 pixels), plume area (3,745 pixels), and spatter area (2,030 pixels), indicating a relatively stable printing process. The intensity values remained within a controlled range across both normal and outlier conditions, suggesting that intensity alone may not be the best predictor of defects but could be useful when analyzed alongside spatial features. The outlier images displayed significant deviations in at least one key feature compared to the normal data. The feature comparison between the normal data with the outliers is displayed in Table 1. For example, certain outliers exhibited abnormally large melt pool areas (e.g., outlier 3 with 29,273 pixels and Outlier 4 with 38,743 pixels), which suggests excessive heat input, potentially leading to keyhole formation or unstable melt pool dynamics. Similarly, outliers with significantly high plume areas (e.g., Outliers 2 to 6) indicate excessive vaporization, which could scatter laser energy and contribute to defects such as porosity or surface irregularities.

Table 1. The feature comparison between the normal data and the outliers.

	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

Another important observation is that some outliers exhibited significantly lower spatter areas compared to normal printing conditions. Since spatter is often associated with recoil pressure and melt pool instability, a drastic reduction in spatter (e.g., outlier 1 with only 39 pixels) may indicate insufficient melting, which could lead to lack-of-fusion defects. Conversely, outliers with excessive spatter (e.g., outliers 2 to 6) suggest turbulent melt pool behavior, which may introduce inconsistencies in the powder bed and affect layer bonding.

4. CONCLUSION AND FUTURE WORK

This study explores the application of unsupervised learning for in-situ process state characterization in Laser Powder Bed Fusion (LPBF), focusing on the analysis of melt pool, plume, and spatter features using DBSCAN clustering. By applying density-based clustering to extracted features, it successfully identified process anomalies without requiring labeled training data, demonstrating the feasibility of machine learning-driven real-time quality monitoring. The results indicate that DBSCAN effectively distinguishes between normal printing conditions and potential defects, with outliers exhibiting significant deviations in melt pool size, plume expansion, and spatter distribution. These variations suggest unstable process conditions that may lead to porosity, lack of fusion, or surface irregularities. The clustering analysis provides valuable insights into LPBF process stability, reinforcing the potential of automated defect detection for additive manufacturing. Despite these promising results, further work is needed to enhance the robustness of process state characterization by establishing explicit correlations between tracked features and final part quality. A key next step is to validate clustered outliers using post-process X-ray computed tomography to link internal defects directly to process anomalies. Additionally, integrating multi-modal sensing, such as thermal imaging and acoustic monitoring, could improve defect prediction accuracy. Furthermore, machine learning-based classification of surface roughness can provide a stronger relationship between melt pool, plume, and spatter behavior and the final part's mechanical and surface properties. These advancements will help refine in-situ monitoring systems, enabling real-time adaptive process control and reducing reliance on post-processing inspections in LPBF.

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