Multi-Layer Thermal Feature Analysis for Defect Detection and Characterization in AlSi10Mg Parts Produced by Laser Powder Bed Fusion

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Abstract

An infrared thermography (IRT)-based monitoring framework based on the extraction of physics-informed thermal features was developed for in-situ detection and characterization of intentionally introduced defects in AlSi10Mg parts produced by Laser Powder Bed Fusion (L-PBF). Thermal image sequences acquired with an off-axis microbolometer infrared camera were processed to extract pixel-wise temperature histories. Event-based signal alignment enabled the computation of features describing local heating and cooling behavior.

Preliminary results with an unsupervised clustering using a Gaussian Mixture Model, enhanced through multi-layer feature aggregation, classify the presence of persistent anomalous regions corresponding to imposed defect geometries. Results demonstrate the potential of IRT and data-driven analysis for online defect detection and quality assurance in additive manufacturing.

1. Introduction

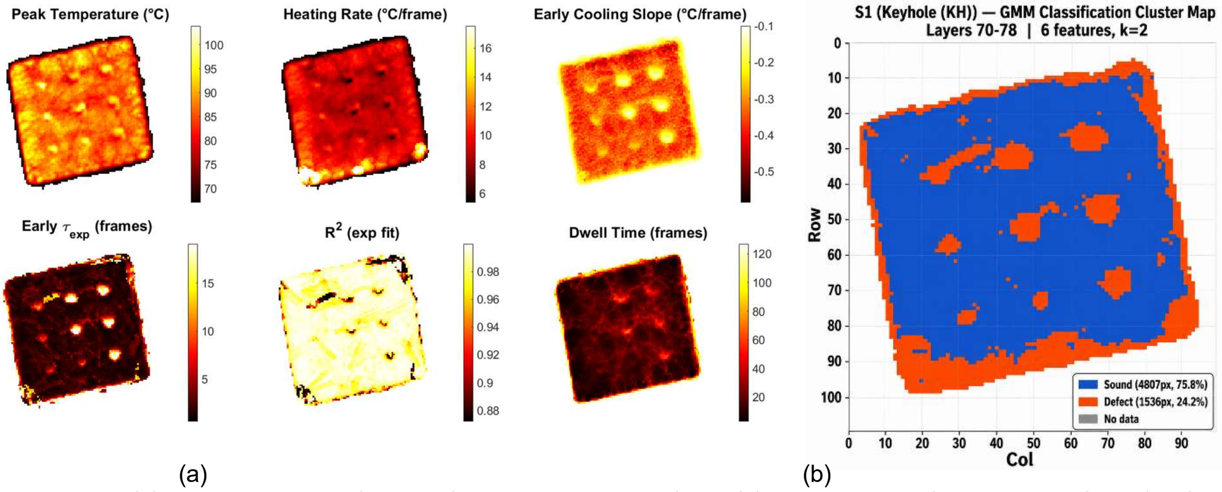
Laser Powder Bed Fusion (L-PBF) has emerged as one of the most advanced metal additive manufacturing (AM) technologies, enabling the production of complex components with high geometric accuracy and material efficiency [1-4]. Despite these advantages, the process is highly sensitive to local thermal conditions and process parameter variations, which may lead to defects such as lack of fusion, porosity, and gas entrapment. These defects can significantly compromise the mechanical performance and reliability of manufactured parts, limiting the adoption of L-PBF in safety-critical applications [1-4].

Conventional defect assessment is generally performed through post-process inspection techniques, such as X-ray computed tomography [1-4], which provide quantitative information on internal defects but are expensive, time-consuming, and unsuitable for real-time process control. Consequently, increasing research efforts have focused on the development of in-situ monitoring strategies capable of identifying defect formation during the manufacturing process. Among the available monitoring techniques, infrared thermography (IRT) has attracted significant attention due to its non-contact nature, real-time response, and its direct relationship with the thermal phenomena governing melt pool dynamics and defect formation [1-4]. Previous studies have demonstrated the potential of thermographic monitoring for detecting process instabilities and identifying thermal signatures associated with the presence of defects. However, many existing approaches rely mainly on qualitative analyses or require complex sensing systems and extensive calibration procedures, based on the emissivity estimation and the focused analysis of the melt pool, limiting their industrial applicability. Furthermore, the correlation between thermal signals, the real morphology and persistence of defects across multiple layers remains an open challenge.

In this context, the present work proposes an infrared thermography-based framework combined with physics-informed thermal analysis and preliminary machine learning approaches for the in-situ detection and characterization of typical additive manufacturing defects intentionally introduced into the CAD design of AlSi10Mg specimens produced by L-PBF. The aim is to identify defect-related thermal signatures directly during the build process, enabling online non-destructive evaluation without the need for post-process non-destructive inspection.

2. Methods, Procedure for Data Analysis and Results

The experimental setup was identical to that described in [4], including the EOS M290 L-PBF system and the FLIR A700 infrared camera. The only modification was the adoption of a 17 mm lens, resulting in an effective spatial resolution of approximately 0.4 mm/pixel. All specimens were manufactured in AlSi10Mg. This work focuses on the characterization of keyhole defects; therefore, only the keyhole-inducing process condition is considered. The reference (sound) condition was defined as 352 W laser power, 1344 mm/s scan speed, and 0.124 mm hatch spacing. The keyhole sample (S1) was produced using 370 W laser power, 700 mm/s scan speed, and 0.12 mm hatch spacing, corresponding to a volumetric energy density of 146.83 J/mm³, i.e., +98.1% relative to the reference condition. The specimen was fabricated including defects of cubic geometries and nominal sizes of 1 mm and 2 mm, with different depths as reported in [4]. The infrared image sequences were processed in MATLAB to reconstruct a quasi-static representation of the thermal history despite the continuous laser motion during the L-PBF process, following a similar procedure to the one reported in [4]. The temporal evolution of each activated pixel was then analyzed independently. From the heating and cooling stages of the thermal cycle, six physics-informed thermal features were extracted to characterize the local thermal behavior: peak temperature, heating rate, early cooling slope, early cooling time constant, cooling fit quality (R^2), and dwell time above a temperature threshold. These descriptors provide complementary information on local energy input, heat accumulation, and dissipation mechanisms. The presence of hatch-pattern of side-by-side laser passes shows a thermal signal very similar to the one related to the presence of a defect; for this reason and to exploit the persistence of defects through successive layers, the thermal features were aggregated across multiple layers. For each pixel, the mean and standard deviation of the six descriptors were computed, generating a 12-dimensional feature vector that captures both the average thermal response and its layer-to-layer variability. This strategy enhances defect-related signals while reducing random process noise. The resulting feature vectors were used with a preliminary approach as input for an unsupervised Artificial Intelligence framework based on Gaussian Mixture Models (GMM, [5]).



(a) (b)

Figure 1. (a) Extracted thermal features (average layers 70-78) and (b) corresponding Cluster Map – GMM (k=2).

Figure 1a presents the spatial distribution of the extracted features considering a part of the specimen where, nominally, all the simulated defects are present, after a moving average of 9 layers. The results show that defect signatures are not equally visible across all descriptors. In particular, the Early Cooling Slope and Early Time Constant exhibit the highest spatial contrast, highlighting defect regions more clearly than the remaining features. Peak Temperature and Heating Rate provide moderate sensitivity, whereas R^2 and Dwell Time display more homogeneous spatial distributions. The corresponding result reported in Figure 1b shows the classification defect (red) and sound (blue) after the application of GMM AI unsupervised model (k=2, where k represents the number of clusters).

Conclusions

This work presented a preliminary infrared thermography-based framework for in-situ defect detection in Laser Powder Bed Fusion of AlSi10Mg. The results demonstrate that multi-layer feature aggregation combined with unsupervised GMM clustering can identify persistent thermal anomalies associated with intentionally induced keyhole defects, highlighting its potential for online process monitoring and quality assurance.

References

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