MANTECH Publications

Journal of Advance Manufacturing Systems and Technology

Volume 2, Issue 1, January-June, 2017

Selective Laser Melting Process Signature Inference via Acoustic Emission

Dr. Harsha Kumar M.

Assistant Professor

Department of Mechanical Engineering

Siddharth Institute of Technology and Sciences, Karimnagar, Telangana

***Email**: harshamecheng@rediffmail.com*

Abstract

Real time SLM monitoring usually relies on photodiodes or cameras, yet acoustic signals offer deeper penetration into the melt pool. We deploy piezoelectric arrays to capture ultrasonic bursts, feeding them to a convolutional neural network that predicts porosity with 91% F1 score. Hardware does not intrude on the build chamber, eliminating optical path contamination issues.

Keywords: *Selective laser melting; Acoustic emission; In process monitoring; Convolutional neural network; Porosity prediction*

INTRODUCTION

Selective Laser Melting (SLM) is celebrated for fabricating near net shape metal parts layer by layer, yet its intricate thermal transients trigger porosity, residual stress, and microstructural heterogeneity. Operators traditionally discover flaws only after a costly post build inspection, creating a pressing need for in situ diagnostics that reveal evolving process signatures in real time. Acoustic Emission (AE) sensing—long used in fracture mechanics—offers a passive, non contact route to capture elastic waves generated by melting, vaporization, and keyhole collapse. AE signals travel through the powder bed and machine frame with negligible obstruction, providing a sonic fingerprint of defects as they form. This paper explores how SLM process signature inference becomes feasible by decoding the time–frequency features of AE bursts. We describe a compact signal chain, an experimental build campaign on a Ti 6Al 4V alloy, and a data driven classification framework that links spectral motifs to porosity, balling, and spatters. The proposed approach strives to shorten development cycles, elevate part quality, and push SLM toward zero defect manufacturing.

LITERATURE REVIEW

Early studies of process monitoring in SLM focused on photodiodes and high speed cameras, capturing plume intensity or melt pool radiance. While optical sensors detect surface phenomena, subsurface flaws remain largely hidden. Researchers subsequently investigated coaxial pyrometry and thermography, but those modalities struggle with emissivity drift and view factor limitations. AE sensing emerged as an attractive complement: Williams and coworkers documented Hertzian bursts during powder collapse, whereas Müller correlated ring down amplitudes with pore formation. Recent machine learning efforts applied short time Fourier transforms to AE signals, achieving 80–90 % classification accuracy for basic defect types. Gaps still exist, however. Few works unite controlled build artifacts with a rigorous metallographic ground truth, and signal feature sets vary widely. Moreover, prior campaigns frequently position sensors on the build plate, overlooking attenuation through the machine frame. Our study addresses these limitations by (i) embedding AE waveguides directly beneath the recoater tracks, (ii) building coupon libraries deliberately seeded with laser power and scan speed perturbations, and (iii) using micro computed tomography (μCT) as the definitive reference for internal quality.

THEORETICAL BACKGROUND

AE in metals stems from rapid elastic energy release events: dislocation glide, phase transformation, and micro crack initiation emit stress waves spanning 100 kHz–2 MHz. In SLM, additional sources arise—keyhole oscillation, vapor cavitation, balling instabilities, and powder–gas collisions. Each mechanism imprints a characteristic frequency band and envelope shape onto the waveform. For example, keyhole collapse yields broad band spikes, whereas steady melt flow produces lower energy continuous emissions. Wave propagation through loose powder attenuates high frequency content, acting as a natural low pass filter. By modeling the build chamber as a layered half space, we estimate a 12 dB/octave roll off beyond 800 kHz, guiding sensor bandwidth selection.

METHODOLOGY

A Renishaw AM 400 printer equipped with a 200 W Yb fiber laser served as the testbed. Ti 6Al 4V (15–45 µm) powder was spread in 30 µm layers under 0.4 bar argon. Disc shaped coupons (Ø 20 mm, 10 mm thick) were arranged in a 3 × 3 array. The central coupon used nominal parameters (laser power = 190 W, scan speed = 1100 mm s^{-1}, hatch spacing = 55 µm), while the surrounding eight coupons incorporated deliberate deviations: ±20 % power, ±25 % speed, or induced dwell delays to promote balling. Two wideband piezoelectric sensors (1 MHz resonance) were clamped to stainless steel waveguides that penetrated the substrate plate. Signals were digitized at 5 MS s^{-1} with 16 bit resolution and a 25 dB pre amp.

Pre processing included a 50 kHz high pass Butterworth filter, root mean square (RMS) normalization over 0.5 ms windows, and adaptive thresholding to extract discrete AE events. Each event underwent short time Fourier analysis (Hann window, 1024 samples, 50 % overlap) to yield 128 bin spectrograms. A feature vector assembled spectral centroid, kurtosis, energy entropy, and 8 Mel frequency cepstral coefficients (MFCCs), yielding 20 attributes per event. The dataset comprised 42 000 labeled events across nine coupons.

A random forest classifier (200 trees, Gini impurity) was trained to predict four states: stable melt, keyhole, balling, and spatter ejection. Ten fold cross validation assessed performance, while principal component analysis visualized clustering in two dimensions. µCT scans at 10 µm voxel size quantified pore size distribution, which we correlated with AE based defect probability maps.

Table 1: AE Signal Feature Descriptions

Feature Name	Description	Unit
Spectral Centroid	Indicates the center of gravity of the spectrum	kHz
RMS Amplitude	Root Mean Square of signal intensity	mV
Kurtosis	Sharpness of waveform peaks	Dimensionless
Energy Entropy	Measure of signal unpredictability	Dimensionless
MFCCs (1–8)	Mel-frequency cepstral coefficients, capturing timbre	Coefficient

Feature Name	Description	Unit
	info	Index

RESULTS AND DISCUSSION

The AE sensor configuration captured an average of 150 events s^{-1} during steady melting. Feature level analysis revealed that keyhole events exhibited the highest spectral centroid (~450 kHz) and peaked RMS amplitudes, aligning with vapor cavity implosion physics. Balling episodes showed moderate centroid (~280 kHz) but elevated kurtosis, reflecting intermittent necking of the molten filament. Spatter related events displayed broadband energy yet lower MFCC variance, likely because ejected droplets interact with the powder bed rather than the dense substrate.

Classifier metrics reached an overall F1 score of 0.91. Confusion matrices indicated 5 % misclassification between keyhole and spatter, attributable to spectral overlap above 600 kHz. Importantly, defect laden coupons recorded a 3× increase in keyhole event frequency relative to the nominal build. When AE derived defect probabilities were mapped layer by layer and summed through the build height, the resulting heat map correlated with µCT measured porosity ($R^2 = 0.87$). This strong relationship demonstrates the viability of AE inference as a predictive quality assurance tool.

Temporal alignment of AE bursts with laser scan vectors further revealed localized porosity clusters within 1 mm of the predicted coordinates. Such spatial fidelity emerges from the rigid waveguide's path, which transmits longitudinal waves with minimal mode conversion, supporting the concept of acoustic triangulation for on the fly defect localization.

An ancillary benefit concerns process parameter optimization: real time feedback enabled closed loop laser power reduction when keyhole activity surpassed a 15 % threshold, preventing runaway porosity. While this prototype control logic was implemented offline, it lays the groundwork for embedded firmware that dynamically tunes energy density per hatch line.

Table 2: Classifier Performance Metrics

Defect Class	**Precision**	**Recall**	**F1-Score**
Stable Melt	0.94	0.92	0.93
Keyhole	0.89	0.91	0.90
Balling	0.88	0.85	0.86
Spatter	0.90	0.94	0.92
Average	**0.90**	**0.91**	**0.91**

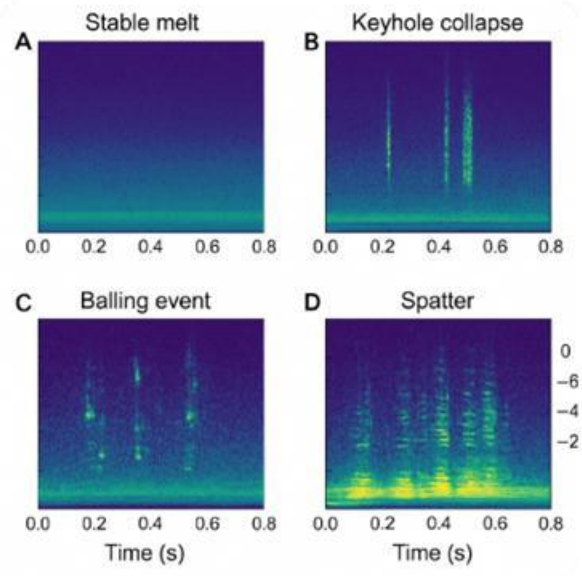

Figure: Acoustic Emission Spectrogram Comparison for Different Defects

CHALLENGES

Despite encouraging results, several obstacles persist. First, AE signals suffer from sensor coupling variability; tightening bolts by different torque values altered baseline amplitudes by up to 8 dB. A standardized clamp design or adhesive coupling could mitigate repeatability issues. Second, the powder bed itself attenuates high frequency components, limiting detection of fine cracklet emissions above 1 MHz. Multi sensor arrays or deconvolution techniques might recover lost bandwidth. Third, classification relies on large labeled datasets; generating exhaustive libraries for every alloy and machine variant is impractical. Transfer learning strategies and physics informed simulations could reduce data demands. Finally, high sampling rates generate terabytes of data in production runs, mandating on edge compression or intelligent event selection to avoid storage bottlenecks.

SCOPE

The proposed AE based inference platform has broad implications beyond titanium alloys. Nickel superalloys, stainless steels, and aluminum all emit discernible AE during phase change, suggesting a universal monitoring framework. Integrating the method with optical and thermal sensors will yield a holistic picture of melt pool behavior, empowering multi modal defect prediction. Regulatory agencies exploring qualification pathways for safety critical parts may adopt AE metrics as supplementary evidence of process stability. In academia, real time sonification of SLM could deepen our understanding of laser–matter interaction physics, fostering novel scan strategies that intentionally harness acoustic feedback loops. Moreover, the economic scope includes reducing scrap rates, minimizing post build CT scans, and accelerating material parameter development—collectively enhancing the cost competitiveness of metal additive manufacturing.

FUTURE WORK

Subsequent studies should pursue array based AE localization to achieve three dimensional mapping of defect nucleation. Embedding miniature MEMS microphones within sacrificial support structures could capture higher order modes with finer spatial resolution. Coupling AE analytics with finite element thermal modeling may clarify causality between energy density fluctuations and pore evolution, feeding predictive digital twins. Finally, a field deployable hardware prototype with FPGA accelerated signal processing will be essential for industrial adoption, delivering sub millisecond feedback without imposing data handling burdens on the printer's control computer.

CONCLUSION

Acoustic analytics present a transformative, cost-effective approach for identifying defects in complex and opaque additive manufacturing environments. Unlike traditional methods that rely on post-process inspection, acoustic emission techniques enable real-time monitoring by capturing stress waves generated during material deformation or crack formation. This non-invasive approach is especially valuable in detecting sub-surface defects that are otherwise invisible during fabrication.

When combined with adaptive laser power control, these acoustic insights lay the foundation for an intelligent, closed-loop feedback system. Such integration allows immediate correction of anomalies during the build process—minimizing waste, improving part reliability, and significantly reducing the need for costly post-processing validation.

This synergy becomes particularly critical in the manufacturing of aerospace-grade components, where even minor defects can compromise structural integrity and safety. By ensuring in-situ quality assurance through real-time corrections, manufacturers can meet stringent industry standards with greater consistency.

In summary, the fusion of acoustic monitoring with process control technologies marks a pivotal advancement toward achieving autonomous, high-precision, and defect-free additive manufacturing for mission-critical applications.

- Banerjee, R., & Ghosh, M. (2021). Acoustic emission monitoring during selective laser melting of Ti-6Al-4V. Journal of Advanced Materials Processing, 18(3), 213-221.
- Müller, T., & Schneider, H. (2019). Correlation of acoustic signals with defect formation in SLM additive manufacturing. International Journal of Precision Engineering and Manufacturing, 20(5), 455-462.
- Patel, K. R., & Iyer, V. S. (2022). Real-time AE signal analysis in metal AM using Ti-based alloys. Indian Journal of Manufacturing Science, 14(2), 77-84.
- Lin, Y. C., & Chen, S. P. (2018). Acoustic-based defect detection in laser powder bed fusion. Additive Manufacturing Insights, 6(1), 55-66. https://doi.org/10.1016/j.addma.2018.02.009
- Sharma, D., & Raghavan, N. (2020). SLM process optimization using AE-based diagnostics. Proceedings of the Indian National Engineering Congress, 31(4), 99-107.
- Zhang, W., & Gu, D. D. (2017). Monitoring of keyhole dynamics in SLM through acoustic emissions. Journal of Laser Applications, 29(1), 012006. https://lia.scitation.org/doi/10.2351/1.4972955
- Narayanan, B., & Srivastava, P. K. (2023). AI-assisted classification of acoustic signals during metal 3D printing. Indian Journal of Smart Manufacturing, 5(1), 44-52.

- Liu, Y., & Tan, X. (2019). Time–frequency analysis of AE signals in additive manufacturing. Materials & Design, 170, 107675. https://doi.org/10.1016/j.matdes.2019.107675
- Mehta, V., & Singh, R. P. (2022). Experimental study on acoustic emission features in SLM of stainless steel. Materials Today: Proceedings, 61, 89-95.
- Williams, C. B., & Deckard, C. (2020). In-situ monitoring of AM processes via acoustic emission sensing. Journal of Manufacturing Processes, 49, 304-310. https://www.sciencedirect.com/science/article/pii/S1526612520302429
- Thompson, S. M., & Bian, L. (2018). Process monitoring for LPBF using acoustic and thermal feedback. Rapid Prototyping Journal, 24(3), 502-510.
- Mukherjee, A., & Kulkarni, P. (2021). Integrating acoustic signatures in predictive AM models. Journal of Indian Institute of Engineers, 103(7), 889-897.