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In-situ defect detection and material property evaluation in additive manufacturing using acoustic signal and machine learning

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Abstract

In-situ monitoring is crucial for detecting defects and estimating material properties to ensure the quality of printed parts in additive manufacturing. Acoustic signals produced during the interaction between the laser and material contain critical information about complex physical mechanisms such as crack formation. However, acoustic-based monitoring in laser powder bed fusion (L-PBF) has received little attention due to the noisy environment. This study presents an acoustic-based real time process monitoring method integrated with machine learning for L-PBF process. The key contribution lies in developing a feature extraction approach that utilize machine learning models such as random forests and k-nearest neighbors (KNN), and wavelet transform for defect detection and material property classification. Microphone data collected during L-PBF experiments capture both laser-material interaction signals and environmental noise, including contributions from the laser, fan, and powder flow. A bandpass filter is applied to isolate relevant signals, followed by wavelet transform in time- and frequency-domains to obtain representation of the laser-material interaction. The results show that the machine learning models achieve an average material property estimation accuracy of 94%, highlighting its effectiveness in enhancing the monitoring process parameters.

Keywords: Additive manufacturing, Acoustic, Machine learning, Real-time monitoring, Defect

Introduction

Laser powder bed fusion (L-PBF) is an increasingly popular metal additive manufacturing (AM) process due to its ability to produce geometrically complex parts [1]. This technique offers unique advantages in fabricating irregular and, with promising applications across biomedicine, aerospace, and other industrial sectors [2]. However, printed parts frequently exhibit defects such as cracks owing to material discontinuities, affecting reproducibility and part performance [3]. Thus, it is crucial to monitor part quality during the manufacturing process to promptly address any issues that may arise.

The real-time monitoring of the L-PBF process poses a significant challenge due to the intricate interactions between the laser and matter. While various sensing methods, including pyrometers, high-speed cameras, photodiodes, and thermography cameras, have been integrated into L-PBF. Acoustic Emission (AE) analysis has emerged as a particularly promising technique for process monitoring in AM [4]. AE arises from the release of elastic waves generated by localized stress changes within a material, e.g., crack formation [5]. This method is particularly effective in detecting cracks and is widely utilized in materials science and industrial monitoring, including AM operations [6]. Researchers typically employ AE sensors, such as microphones, to detect defects within a frequency range of 0 – 100 kHz [7]. Numerous studies have demonstrated the feasibility of in-situ defect detection using low-frequency microphones across various materials such as stainless steel and titanium alloys [8] [8-9].

The aim of this research is to evaluate material properties and identify defects within the acoustic spectrum of L-PBF. Although some studies have explored the use of acoustic sensors to identify defects and evaluate process parameter quality, there is still limited literature on L-PBF acoustic data analysis, its relationship with process parameters, and the identification of defects and material property assessment during part production. This study investigates the basic features of the AE signal associated with laser melting using machine learning.

Materials and methods

The experiments were conducted on an EOS M290 machine. This system utilizes a Continuous Wave (CW) fiber laser with a wavelength of 1064 nm. The laser powers investigated were 196 W, 280 W, and 364 W. The laser spot size in the processing zone was 80 µm. A C45 steel base plate was selected as the substrate material for building the parts. Ti64 powder was employed for the experiments, with a particle size distribution of 15–45 µm. The continuous energy release during the AM process generates stress waves, which are the underlying cause of AE. An acoustic sensor can record acoustic energy and couple with a data acquisition system to convert that energy into an electrical signal suitable for further analysis. The amplitude and other characteristics of the emitted acoustic waves change depending on process conditions and any defects forming during operation. So by using signal processing techniques like a bandpass filter, we can extract useful information about process quality.

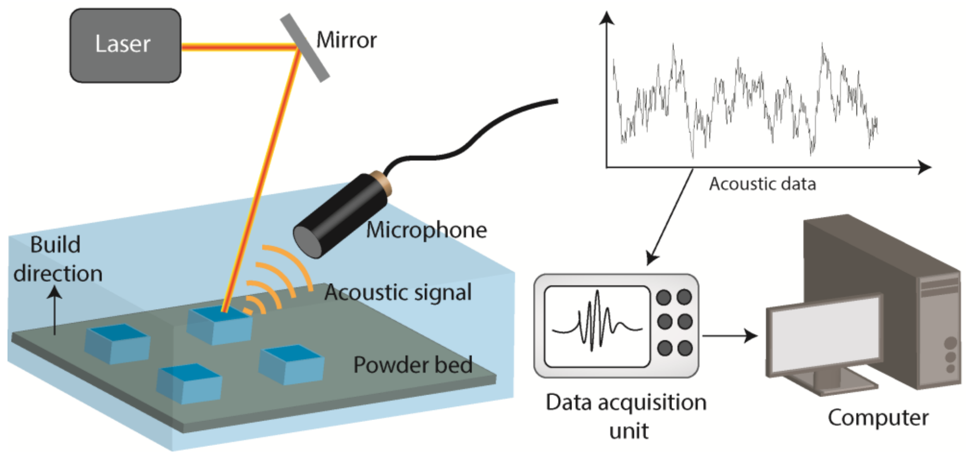


Figure 1. In-situ monitoring of L-PBF.

Table 1. L-PBF process parameters.

Coupon	Laser power (W)	Laser speed (mm/s)	Energy density (%)
1	280	1200	100
2	196	1200	70
3	280	840	142
4	364	1020	153

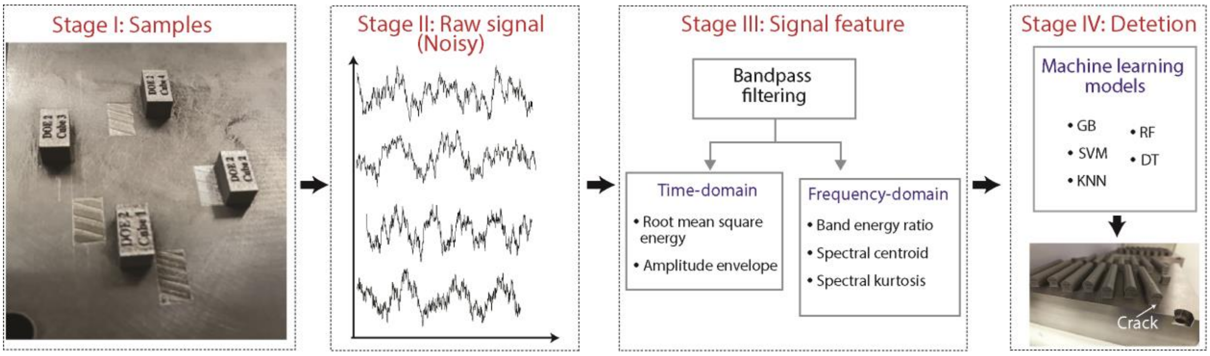


Figure 2. Schematic of the proposed defect detection flowchart through signal processing and machine learning.

Figure 2 presents an overview for acoustic-based evaluation of material properties and defect detection. The workflow comprises data collection during the printing process, signal denoising, feature extraction, and material property classification. Initially, a bandpass filter is utilized on the noisy L-PBF sound to decrease noise. Afterward, key acoustic signatures in the time and frequency domains are extricated from the denoised acoustic signal. Finally, various traditional machine learning models are trained to classify the L-PBF sound into two categories, including crack and material property samples.

Results and discussion

Acoustic signals can be greatly affected by environmental factors such as background noise, fan noise etc., thus noise emitted by the machinery can markedly influence acoustic data acquisition. Therefore, before conducting the analysis of the AE signals, we first eliminated the noise and examined the AE signals within the time- and frequency-domain using filtering approach. AE signals recorded during the three experiments belonged to background noise, fan noise and printing signals (including laser noise and laser-material integration) (Figure 3). The AE signals amplitude is very low when background noise alone exist, around ±1 mV. Although significant changes in processing conditions may lead to visible differences in the AE signature, identifying variations in material properties can be challenging due to external noise in the AE signal. Therefore, this study employs filters to examine the AE signals in both the time-domain and frequency-domain. The amplitude near zero in the denoised AE signals signifies the “background noise and fan noise” phase during the L-PBF process.

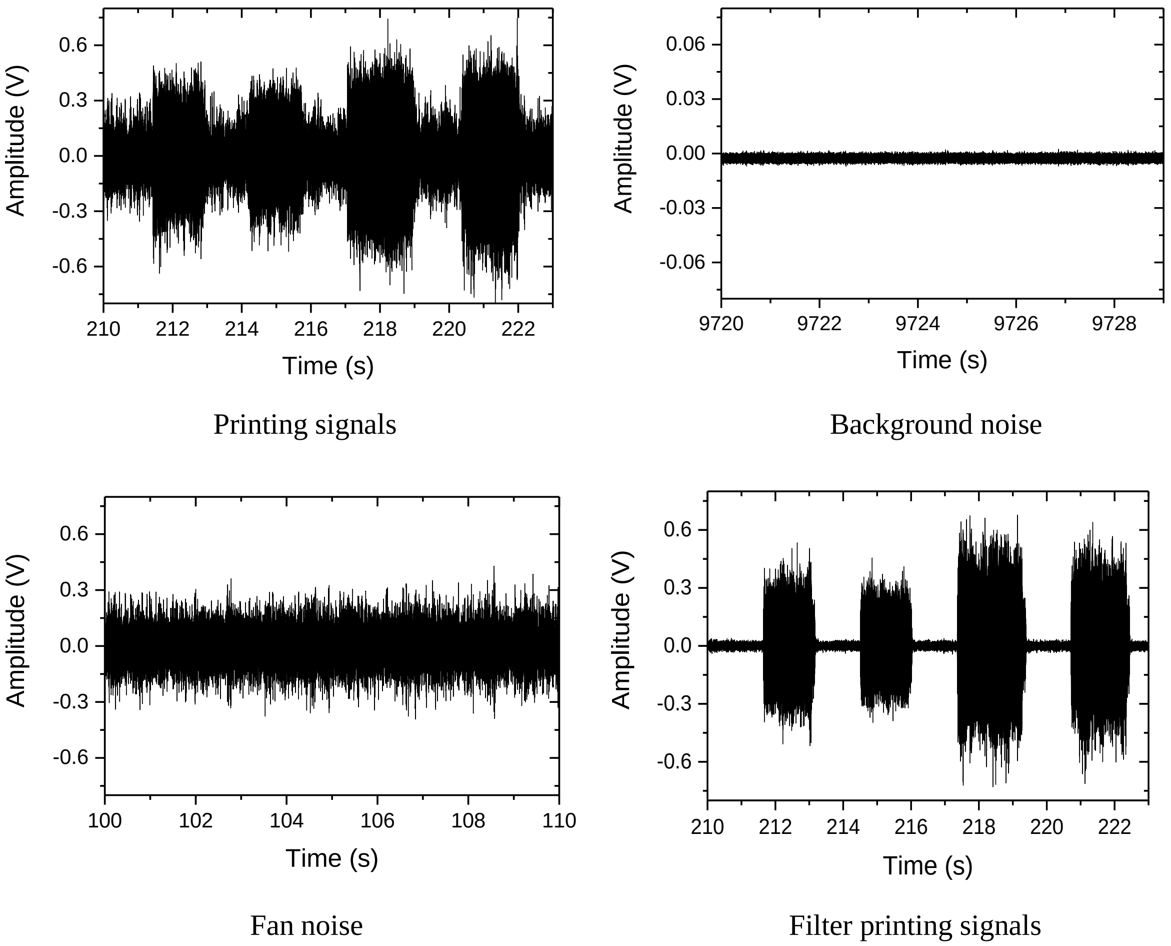
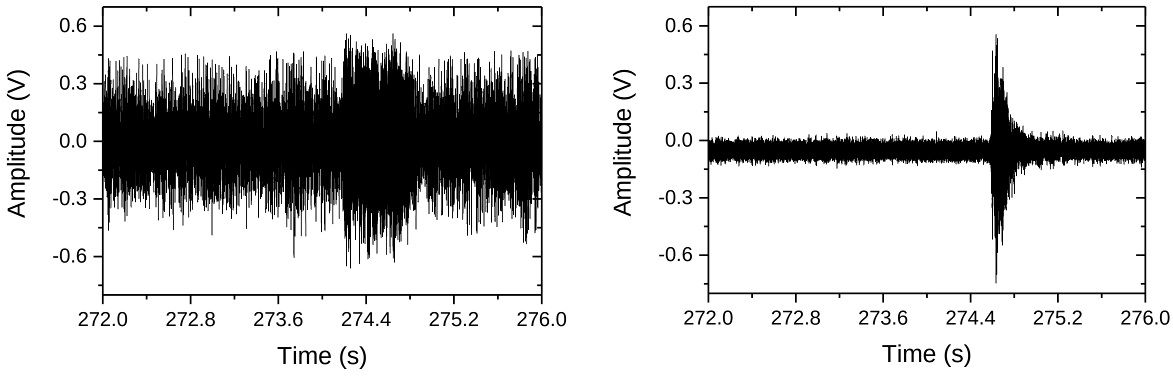


Figure 3. AE signals captured when laser printing on and off.



(a) (b)

Figure 4. Visualization of AE signal. (a) raw signal and (b) denoised signal.

In Figure 5, the AE signals from different cube coupons are analyzed using Fast Fourier Transform (FFT), revealing that ambient noise predominantly occupies the low-frequency spectrum. Interestingly, frequencies exceeding 17.5kHz are observed in the AE signals from varying coupons, indicating the impact of material properties on the signal. Notably, a noticeable high amplitude below 200 Hz may be attributed to background and fan noise interference.

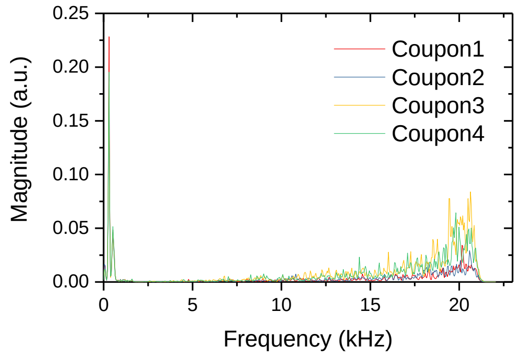


Figure 5. Frequency spectra for various coupon AE signals.

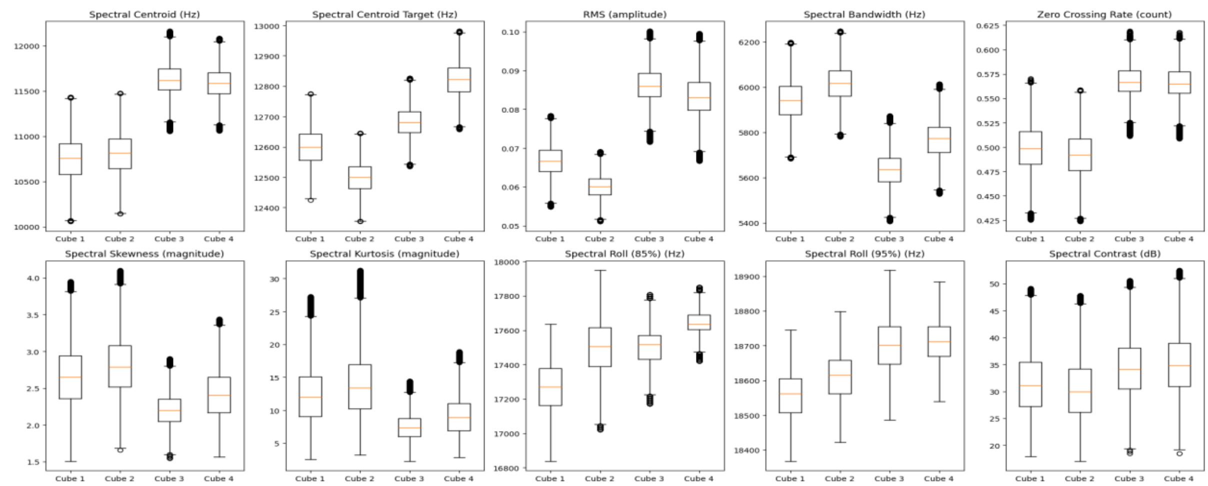


Figure 6. Performance evaluation for acoustic-based material property evaluation in L-PBF.

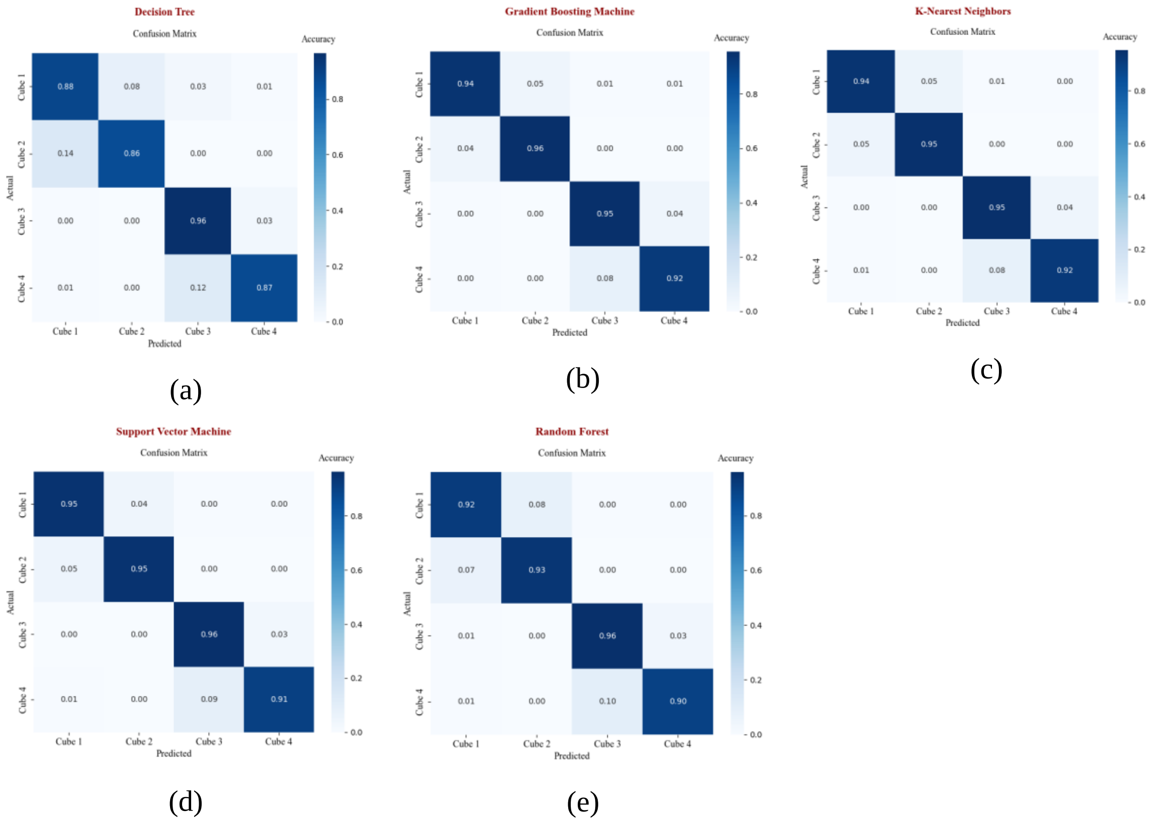


Figure 7. Confusion matrix for the classification task for ‘Decision Tree', ‘Gradient Boosting’, ‘K Nearest Neighbour’, ‘Gradient Boosting’, 'Support Vector Machine’, and 'Random Forest' trained on the denoised AE dataset.

Figure 6 shows the classification accuracy of various evaluation parameters such as RMS, spectral centroid, spectral bandwidth, Skewness, zero crossing rate and Kurtosis. Overall, there is a noticeable enhancement in accuracy following each denoising step. The confusion matrix generated from training a K-Nearest Neighbour model on denoised data displays remarkably high classification accuracy across multiple classes (Figure 7). Specifically, the accuracy for 'cube coupon 1' was 94%, 'cube coupon 2' was 95%, 'cube coupon 3' was 95%, and 'cube coupon 4' was 92%. Overall, the model achieved an impressive accuracy rate of 92.8%.

Conclusion

In this study, acoustic measurements were utilized during the Laser Powder Bed Fusion (LPBF) process to detect cracks and evaluate material properties in real-time. Ti64 powder was the material of choice for the experiments. The recorded acoustic signals were analyzed to correlate them with process parameters and assess the quality of the samples. Results showed statistically significant differences in the acoustic signatures between different material properties. Various machine learning models including Decision Tree, Gradient Boosting, K-Nearest Neighbor, Support Vector Machine, and Random Forest were employed to classify the sound produced during LPBF and predict material properties with an average accuracy of 94%. Notably, filtering the Acoustic Emission (AE) signals led to improved accuracy and reduced false positive rates in classifying the sounds. This research suggests that acoustic-based crack detection and material property evaluation have the potential to optimize additive manufacturing processes.

Conflicts of Interest

The authors declare no conflicts of interest.

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References

[1] G. Gong, J. Ye, Y. Chi, Z. Zhao, Z. Wang, G. Xia, X. Du, H. Tian, H. Yu, C. Chen, *Journal of Materials Research and Technology* **2021**, 15, 855.
[2] B. Zhang, Y. Li, Q. Bai, *Chinese Journal of Mechanical Engineering* **2017**, 30, 515.
[3] S. Chowdhury, N. Yadaiah, C. Prakash, S. Ramakrishna, S. Dixit, L. R. Gupta, D. Buddhi, *Journal of Materials Research and Technology* **2022**, 20, 2109.
[4] M. S. Hossain, H. Taheri, *Journal of Materials Engineering and Performance* **2020**, 29, 6249.
[5] P. Becker, C. Roth, A. Roennau, R. Dillmann, presented at 2020 IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA) **2020**.
[6] A. Ramalho, T. G. Santos, B. Bevans, Z. Smoqi, P. Rao, J. Oliveira, *Additive Manufacturing* **2022**, 51, 102585.
[7] J. R. Tempelman, A. J. Wachtor, E. B. Flynn, P. J. Depond, J.-B. Forien, G. M. Guss, N. P. Calta, M. J. Matthews, *Additive Manufacturing* **2022**, 55, 102735.
[8] K. Wasmer, T. Le-Quang, B. Meylan, S. A. Shevchik, *Journal of Materials Engineering and Performance* **2019**, 28, 666.
[9] R. Drissi-Daoudi, V. Pandiyan, R. Logé, S. Shevchik, G. Masinelli, H. Ghasemi-Tabasi, A. Parrilli, K. Wasmer, *Virtual and Physical Prototyping* **2022**, 17, 181.