Proceedings of the ASME 2026
Annual Review of Progress in Quantitative Nondestructive Evaluation
QNDE2026
September 13–16, 2026, Albuquerque, NM

QNDE2026-191357

IN-SITU LAYER-WISE GEOMETRY EXTRACTION OF THIN-WALL 316L STRUCTURES FABRICATED BY LASER POWDER BED FUSION

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ABSTRACT

Thin-wall structures fabricated by laser powder bed fusion (LPBF) are highly susceptible to cumulative geometric deviations arising from steep thermal gradients, repeated reheating, and process-induced instability. Despite this sensitivity, many in-situ monitoring approaches remain focused on defect detection rather than direct measurement of geometric evolution during fabrication. This study presents an image-based geometric monitoring framework as a step towards the in-situ development of digital twins of thin-wall constructed via LPBF. 316L stainless steel thin walls with a nominal thickness of up to 1 mm are fabricated under controlled LPBF conditions, while a fixed optical camera recorded the top surface after each deposited layer. A computer vision-based edge-tracking algorithm was used to extract the visible wall boundary and compute cumulative drift relative to the first layer, generating midline curves that reveal progressive distortion accumulation and the onset of geometric instability at wall thicknesses approaching 1 mm. The wall segmentation against the surrounding powder bed and rectangle-based tracking were employed to quantify layer-wise wall thickness and shift relative to the nominal wall center. The result shows that layer-wise optical imaging can be transformed into quantitative geometric observables that describe dimensional evolution throughout the build. The proposed algorithm in the current study accurately detects and measures the designed wall thickness and tracks the changes in it layer by layer. Overall, the mean shift in the center lines of the thin walls is observed to be around 0.01 mm to 0.05 mm. The wall shift is also observed to be thickness-dependent and increases as the thickness increases till 1 mm. The proposed framework provides a practical basis for data-driven monitoring and future digital twin development for LPBF thin-wall fabrication of 316L stainless steel.

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Keywords: Additive manufacturing; model updating; LPBF, sensors, computer vision

1. INTRODUCTION

Accurate in-situ geometric measurement enables better understanding and control of fabrication quality in thin-wall structures produced by laser powder bed fusion (LPBF) [1]. Thin walls are widely used in lightweight load-bearing components, thermal management systems, lattice-supported architectures, and biomedical devices because they offer low mass and high geometric flexibility. However, their small cross-section, low bending stiffness, and repeated thermal cycling during layer-wise fabrication make them especially susceptible to dimensional variation, local distortion, and process-induced instability. In LPBF of 316L stainless steel, even small geometric deviations can accumulate from one layer to the next and significantly influence the final wall shape, effective thickness, and structural integrity.

In situ image-based reconstruction of thin-wall geometry provides a practical pathway for converting raw process observations into physically meaningful dimensional measurements. Rather than treating optical data only as qualitative records of the build, geometric reconstruction enables direct estimation of wall boundaries, wall thickness, and lateral shift throughout fabrication. Such measurements are valuable because they describe the actual evolving part geometry, which is more directly related to dimensional quality than many indirect process indicators [2]. For thin-wall structures, this capability is particularly important because localized geometric changes can serve as early signatures of instability, nonuniform heat accumulation, or process drift [3].

Existing in-situ monitoring approaches in LPBF have attracted substantial attention [4] because the process is governed by highly localized and rapidly evolving thermal phenomena that are difficult to infer from post-build inspection alone [1]. Many existing in-situ monitoring approaches have focused on process-

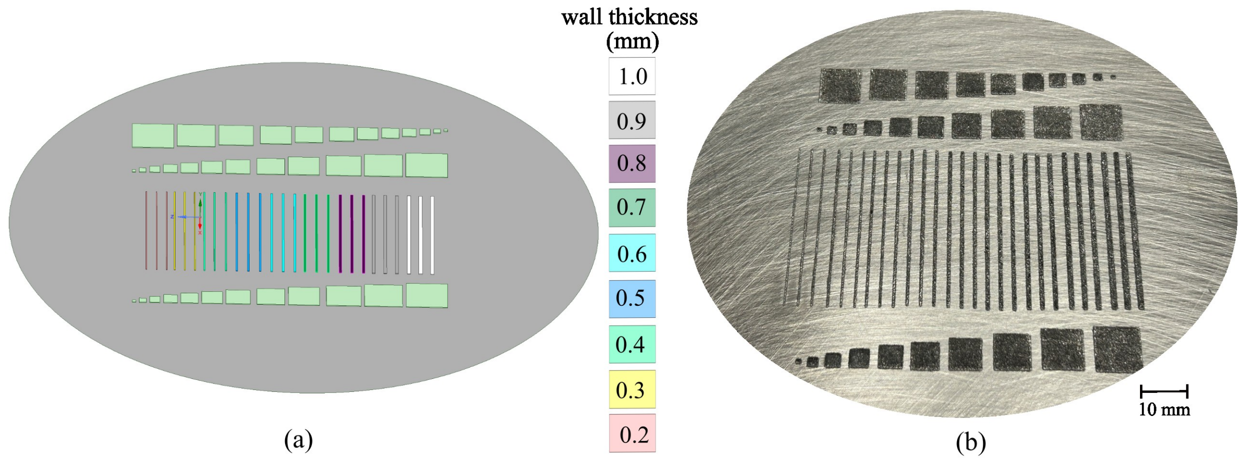

FIGURE 1: Details of thin wall design, showing: (a) 3D CAD design and; (b) LPBF printed design of thin-wall.

zone observables such as melt-pool behavior, thermal signatures, spatter, and anomaly detection [5]. Optical sensing methods are especially attractive because they are non-contact, relatively easy to integrate into manufacturing systems, and capable of capturing build-surface information at high spatial resolution [6]. Layer-wise optical and optical-tomography-based studies have further shown the potential of imaging systems for observing powder-bed condition, surface variation, and quality-relevant anomalies during metal additive manufacturing [7]. Contour-based geometric measurement is a prominent research direction in LPBF monitoring. In thin-wall LPBF builds, the final geometry is strongly influenced by repeated reheating and melt-pool spreading [8]. Edge effects and local process variability can further alter the apparent wall boundary during fabrication [9]. As a result, even when a wall is nominally designed with constant thickness, the measured contour can vary from layer to layer because of distortion, roughness, or apparent widening and narrowing of the visible boundary [10]. These observations motivate the use of image-processing methods capable of identifying wall edges, estimating wall center position, and tracking geometric evolution relative to a reference state. These contour-based metrics provide more direct information as they can be interpreted in relation to the actual part geometry. Edge detection and image-based feature extraction have been used to identify defect-related signatures such as porosity and surface irregularity [11]. Vision-based analysis has also been explored for assessing build quality in thin-wall or geometry-sensitive additive manufacturing scenarios [12].

Digital-twin concepts have gained attention in additive manufacturing because they seek to integrate sensing, data interpretation, and predictive modeling within a unified framework [13]. A digital twin is defined as a virtual representation of a physical system that remains dynamically linked to its real-world counterpart, enabling continuous state estimation and prediction [14]. These frameworks are increasingly being explored for real-time monitoring and adaptive control in manufacturing systems [15]. Recent advances in artificial intelligence-augmented additive manufacturing further highlight the role of data-driven approaches in enabling intelligent, adaptive process monitoring and control [16]. In parallel, prior work by the authors has explored simulation-in-the-loop approaches to construct evolving virtual representations within a digital twin framework by incrementally updating physics-based finite element models in real-time using in-situ data during the layer-by-layer build process [17] and demonstrated the relevance of this approach for thin wall structures [3].

In this work, we present an in-situ image-based framework for full-contour geometric reconstruction of LPBF-fabricated 316L thin-wall structures using layer-wise optical images. A fixed optical camera records the build surface after successive deposited layers, and a reference-guided computer vision workflow is used to identify wall boundaries and extract geometric descriptors from each observed layer. The proposed approach extracts wall boundaries, wall thickness, and lateral shift from each observed layer, enabling the image sequence to be interpreted as a history of geometric states. This is valuable not only for direct dimensional monitoring but also for future linkage with reduced-order learning models and digital-twin-enabled monitoring frameworks. The contributions of this work are:(1) a practical vision-based methodology for reconstructing thin-wall boundaries from in-situ optical data; (2) direct extraction of wall thickness and lateral geometric shift as quantitative layer-wise observables; and (3) an experimental analysis showing how these reconstructed measurements reveal thickness-dependent geometric trends in LPBF-fabricated 316L thin walls. This framework provides a foundation for future physics-based monitoring and digital-twin-enabled process control in metal additive manufacturing.

2. METHODOLOGY

2.1. Experimental Setup

Thin-wall specimens with nominal thicknesses ranging from 0.2 mm to 1 mm were fabricated and monitored using an in-situ optical imaging setup integrated with the manufacturing system, as shown in Fig. 2. The specimens were manufactured using a laser powder bed fusion (LPBF) system (Aconity MIDI, Aconity3D GmbH, Germany). Gas-atomized SS316L powder (Carpenter Technology, Germany) was used as the feedstock, and its chemical composition is listed in Table 1. The powder exhibited a particle size distribution in the range of 15–45 µm, with

TABLE 1: Nominal chemical composition of stainless steel 316L, expressed in weight percent (%).

Element	Iron	Ni	Cr	O	Si	S	P	N	C	Mo	Mg	Cu
Weight percent (%)	Bal.	12.7	17.7	0.03	0.62	0.01	0.01	0.10	0.02	2.36	0.65	0.02

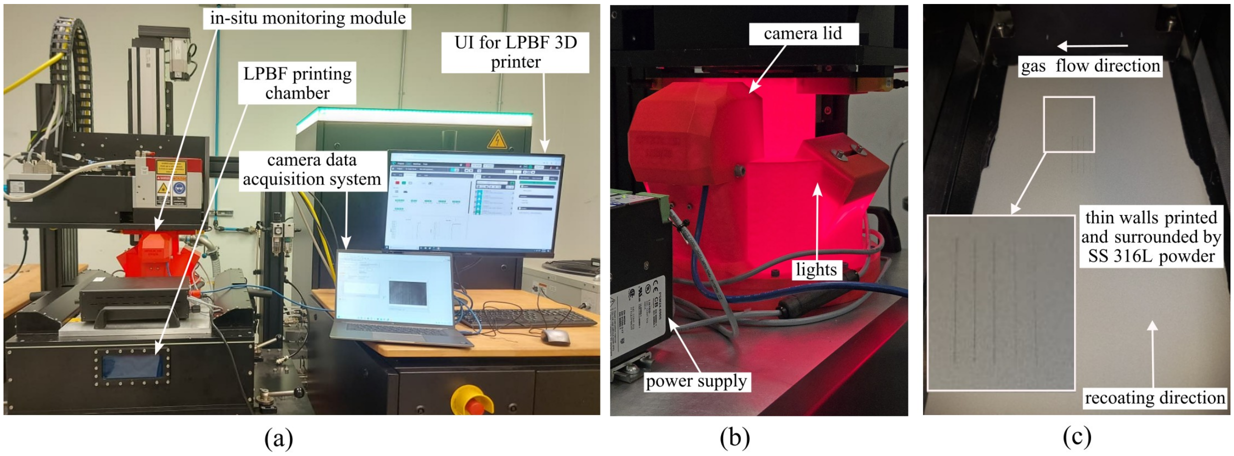

FIGURE 2: Experimental setup for LPBF thin-wall fabrication and in-situ monitoring, showing: (a) 3D printer along with data acquisition system; (b) side view of in-situ monitoring module and; (c) SS 316L powder spread on the print bed.

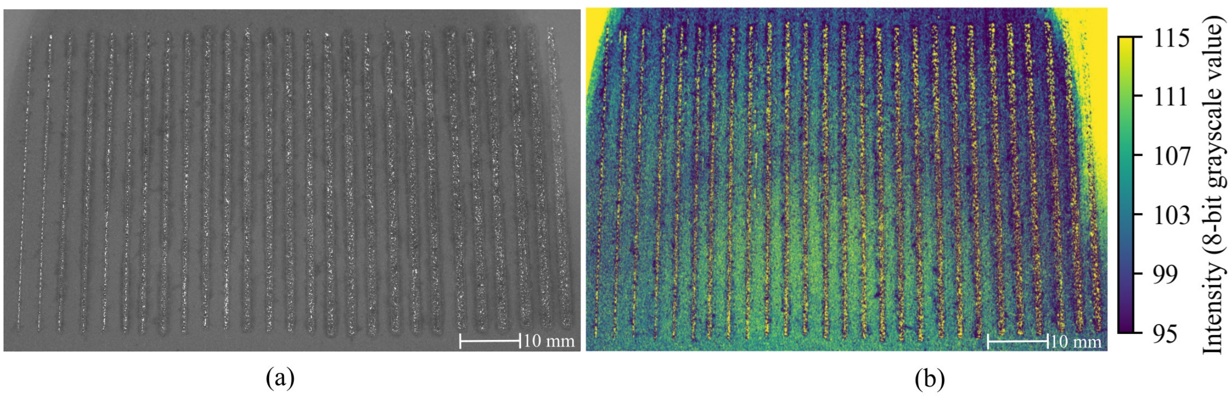

FIGURE 3: Representative in-situ optical images of the LPBF build surface, showing: (a) a monochrome, uncropped raw image of the printed walls on the build plate and; (b) a viridis colormap representation of the printed walls.

an average particle size of 30 µm. All samples were produced using constant processing parameters, including a laser power of 250 W, scanning speed of 1000 mm/s, hatch spacing of 100 µm, layer thickness of 30 µm, laser spot size of 100 µm, and scanning rotation angle of 90°. During fabrication, an argon atmosphere with oxygen levels below 100 ppm was maintained.

A dedicated enclosure is developed for mounting the optical camera inside the chamber and detailed in Adhami et al. [18]. The build process was observed inside this machine chamber using a camera-based imaging arrangement. Optical imaging was conducted using a FLIR Blackfly USB 3.0 camera (BFS-200S6M-C Teledyne FLIR) equipped with a 20 MP monochrome, 1-inch sensor (Sony IMX183), an Edmund Optics fixed lens (86573, 35 mm/F1.8, C-Series), a pair of Advanced Illumination 2×3 LED spot lights (AL143-625IC), and a Midwest Optical Systems bandpass filter (BP635-37). The separate computer workstation was used for real-time image acquisition, visualization, and post-processing. LabVIEW interface is developed for data acquisition. The imaging system provided layer-wise grayscale views of the printed walls periodically in sync with the 3D printer, which were subsequently used to quantify geometric variation during the build. Also, during image capturing, the parameters were adjusted to get high-definition, clear images by avoiding the flash of the laser and other image noise.

A computer vision-based analysis framework was developed to study the layer-wise evolution of an LPBF thin wall of SS 316L. The framework combinedly studies image-based geometric tracking of wall thickness and lateral drift; the objective was not only to quantify visible wall deformation, but also to connect morphological changes and midline shift evolution.

2.2. Computer Vision Pipeline for Geometry Estimation

The objective of the image-processing routine was to detect the left and right wall boundaries in each layer and to track the wall center across the build. The method used a reference-guided, layer-by-layer edge-detection strategy in which the wall position

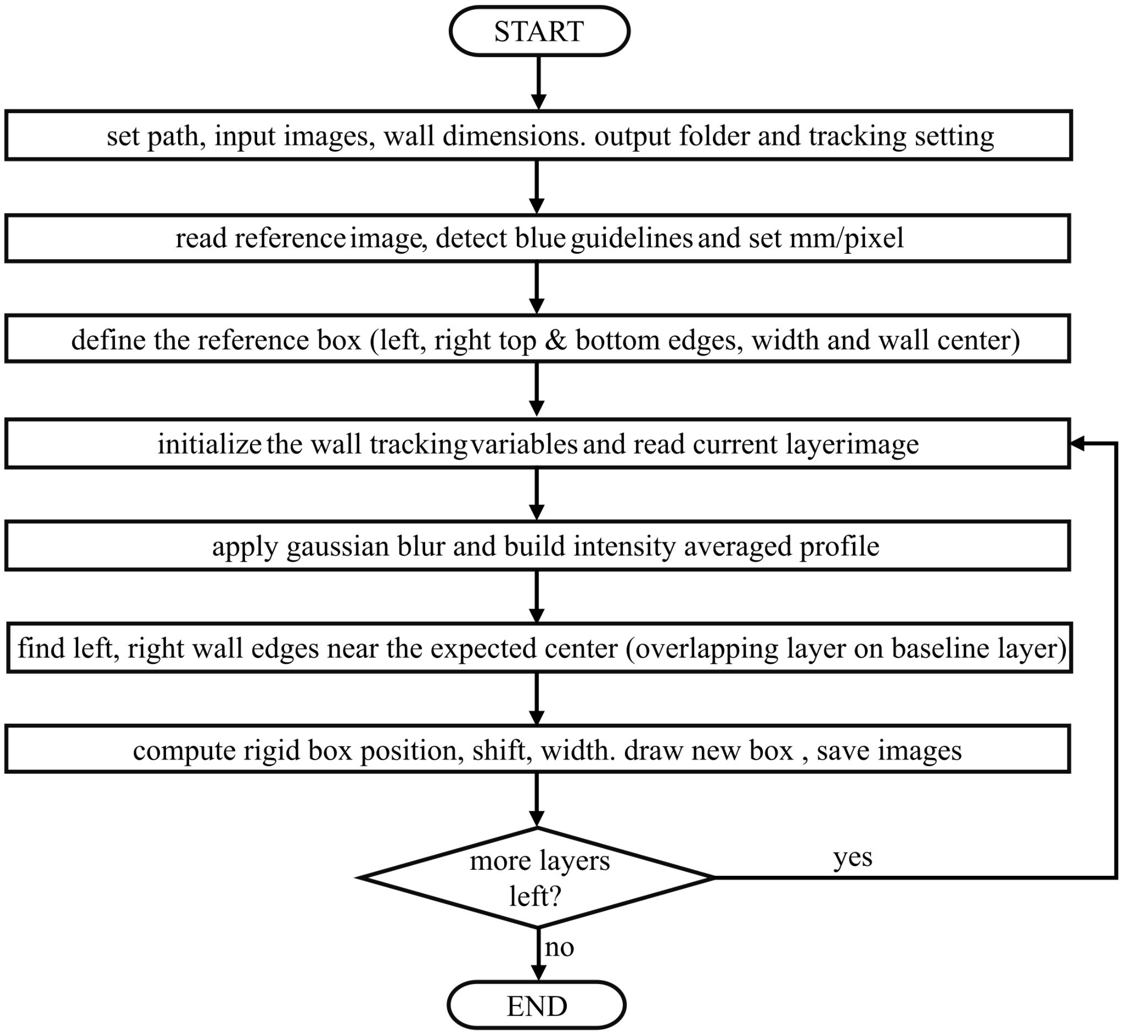

FIGURE 4: Flowchart of wall thickness and shift detection algorithm.

in each new layer was estimated using the previous layer as a prior. This improved robustness against brightness variation, local texture noise, and small frame-to-frame fluctuations.

As shown in the flowchart in Fig. 4, a reference image containing marked blue lines around the wall was used to initialize the tracking procedure. The inner edges of the two blue guide lines were detected automatically, and their separation defined the reference wall thickness in pixels. The extent of this reference box was then retained for all subsequent layer images. For each layer, the image was converted to grayscale and smoothed using a Gaussian filter to reduce pixel-level noise while preserving the dominant wall boundaries. The analysis was restricted to the region corresponding to the wall height in the reference image, while small margins near the top and bottom were excluded to minimize end effects and boundary noise. Within this selected region, grayscale intensities were averaged along the height direction to obtain a one-dimensional horizontal intensity profile for each layer. This averaging suppressed localized disturbances such as spatter, isolated bright pixels, or small powder-bed irregularities near the wall edges, since such features typically do not persist over the full wall height. As a result, the detected profile was governed primarily by the continuous wall contour rather than by local image artifacts. The smoothed horizontal intensity profile was then differentiated with respect to the horizontal coordinate. The left wall edge was identified as the strongest positive gradient near the expected location, and the right wall edge was identified as the strongest negative gradient. To further improve robustness, the detected wall center from the previous layer was used as a prior to define a narrow search window for the next layer. This constrained the detection to physically reasonable positions and reduced false identification caused by internal texture, background variation, or localized spatter near the wall boundary.

Once the left and right wall boundaries were identified, the wall thickness and center for layer i were calculated as

$$w_i = x_{\mathrm{R},i} - x_{\mathrm{L},i} \tag{1}$$

and

$$c_i = \frac{x_{\mathrm{L},i} + x_{\mathrm{R},i}}{2}, \tag{2}$$

where $x_{\mathrm{L},i}$ and $x_{\mathrm{R},i}$ denote the detected left and right wall edges, respectively. A rigid bounding box was then reconstructed for

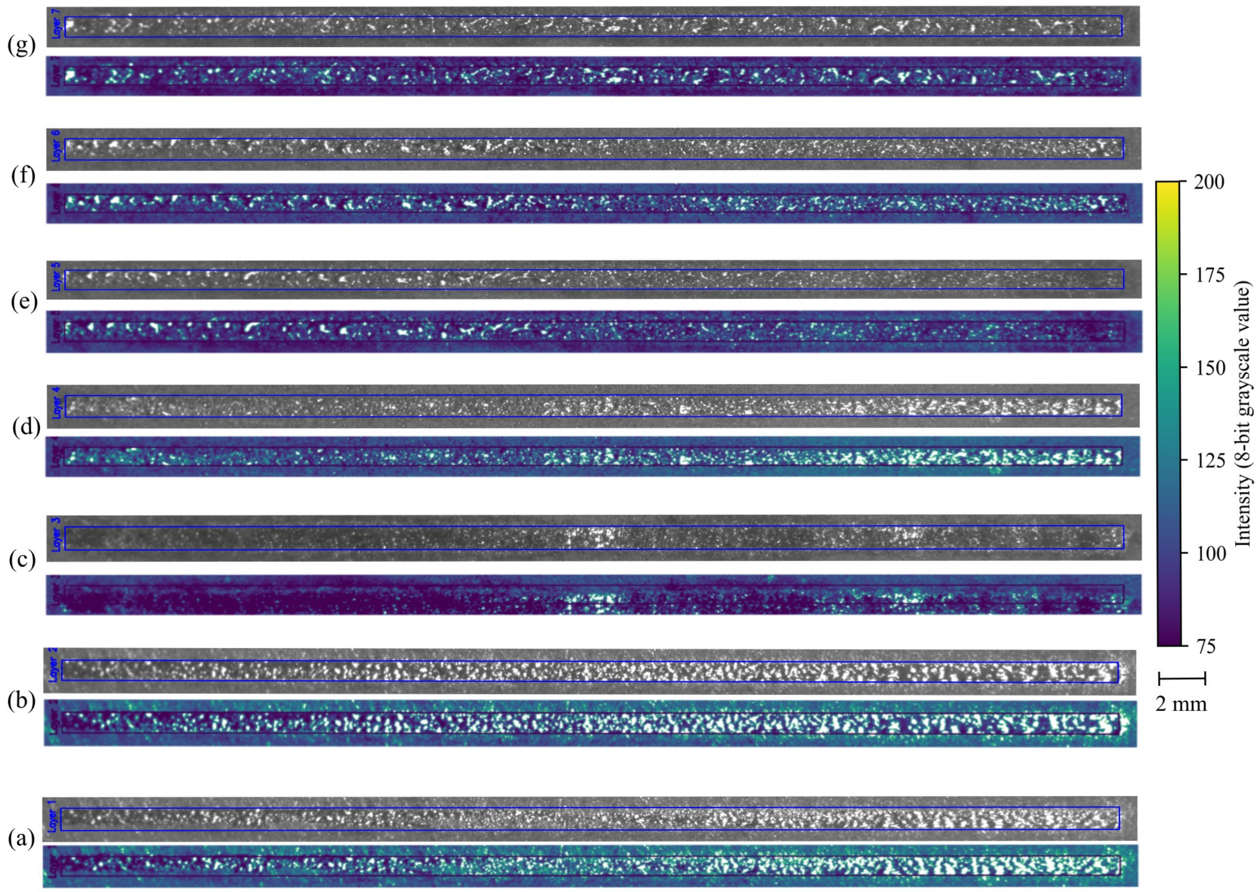

FIGURE 5: Wall and edge detection for layer 1 to layer 7 for a 0.6 mm thick wall design reported in gray scale and viridis for each layer, showing: (a) layer-1; (b) layer-2; (c) layer-3; (d) layer-4; (e) layer-5; (f) layer-6 and; (g) layer-7.

each layer using the reference thickness and the detected center position so that the box thickness remained fixed while allowing horizontal motion of the wall from layer to layer. Finally, the horizontal drift of each layer relative to Layer 1 was computed as

$$\Delta c_i = c_i - c_1, \tag{3}$$

and the measured shift was converted from pixels to millimeters using the reference calibration.

3. RESULTS AND DISCUSSION

The wall-detection results demonstrate that the proposed reference-guided computer-vision pipeline can consistently track the visible contour of the thin wall across successive LPBF layers. In the representative 0.6 mm case as shown in Fig. 5, the rigid tracking box remains well aligned with the wall region from Layer 1 through Layer 7, indicating that the combined use of grayscale preprocessing, restricted vertical-region analysis, gradient-based edge localization using Gaussian blur filters, and prior-guided search-window updating is sufficiently robust for the present in-situ images. Although the wall remains continuously detectable throughout the build, the middle and later layers exhibit visibly stronger local texture fluctuations and slight contour irregularity, especially around Layers 4 to 6. This suggests that the method is sensitive not only to the nominal wall boundary but also to evolving local geometric non-uniformity during fabrication. In other words, the tracking framework does not artificially force geometric constancy; instead, it preserves a stable reference frame while still allowing the detected wall center and apparent thickness to vary naturally from layer to layer.

The thickness comparison plot shown in Fig. 6 (a) further shows that the extracted wall thickness follows the nominal wall-thickness trend in a clear monotonic manner. Thicker-designed walls produce larger detected thicknesses, confirming that the image-based metric retains meaningful geometric information and can distinguish the wall classes reliably. At the same time, the data do not lie exactly on the one-to-one line, which indicates that the measured thickness is different than the actual or designed thickness. The deviation from the ideal line is likely influenced by local roughness of the physically visible contour, optical contrast, boundary blur, and perspective-related effects in the captured imagery. Generally, the edges of LPBF printed walls are not as sharp as machined components, and this is what the computer vision model is also predicting here. Thus, the present thickness metric is most valuable as a comparative in-situ monitoring indicator, going from layer to layer, more than just a standalone absolute thickness measurement. The average wall shift results shown in Fig. 6 (b) show that, for most of the investigated thickness

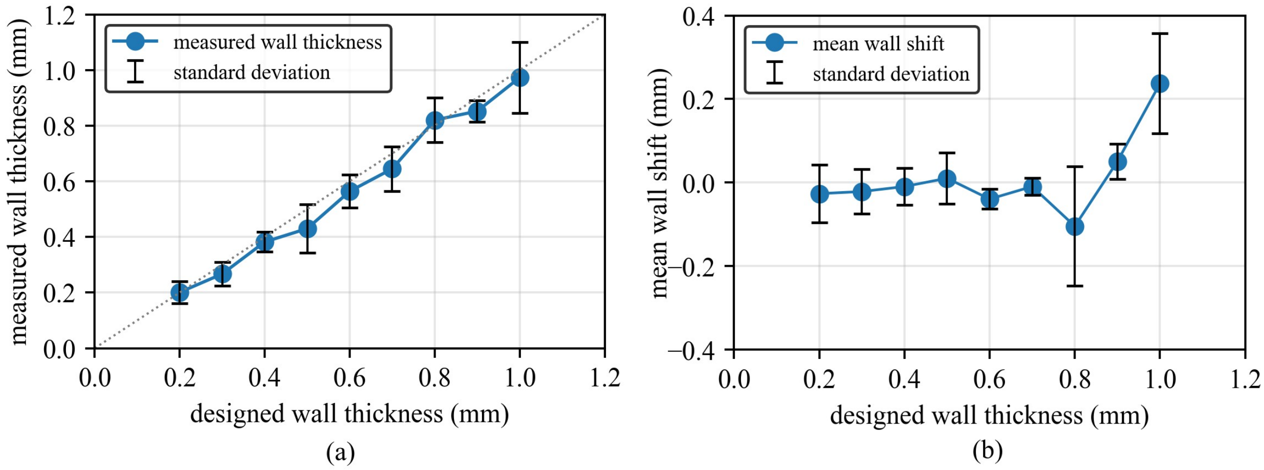

FIGURE 6: Comparison of layer-wise geometric metrics for LPBF-fabricated thin walls, showing: (a) measured wall thickness against designed wall thickness and; (b) mean wall shift of the wall center relative to the first layer, plotted against designed wall thickness.

range, the mean horizontal displacement remains small. This indicates that the wall center remains relatively stable for these cases, with only modest positive or negative midline shift relative to the Layer-1 reference of each of these walls. However, the shift becomes positive at the larger thicknesses and increases markedly for the 1.0 mm case. This rise suggests that the midline shift metric is sensitive to thickness-dependent geometric evolution, but it should be interpreted carefully, as the data analyzed here is a small number of layers with short height samples. The trend we observed here definitely shows that the wall drifts during layer-by-layer printing in LPBF for thin-walled structures. Nonetheless, a larger average shift does not necessarily imply structural instability alone; it may also reflect asymmetric contour development, brightness-induced boundary bias, or a slight systematic offset in the detected wall center. Accordingly, the shift metric should be considered complementary to the thickness metric, with both together providing a more complete description of layerwise geometric behavior.

The observations from the present images can be physically interpreted using the mechanisms of LPBF. The LPBF thin walls experience strong thermal gradients and complex melt-pool dynamics, and the thinner regions are especially vulnerable because their narrow cross-section limits lateral and downward heat conduction. As a result, heat must dissipate more through the surrounding powder bed, promoting heat accumulation, reduced melt-pool stability, and eventual balling or humping when the wall becomes too thin. It is also observed that during powder spreading, the recoater can impose lateral shear forces; if local protrusions have already formed, the recoater may strike the wall and induce elastic bending, plastic deformation in subsequent layers. The shifting of the box used in this study for fitting around the wall thickness supports this observation. This physical interpretation helps explain why the current 0.6 mm wall images shown in Fig. 5 do not show catastrophic breakup, but still exhibit evolving local irregularity. The wall images and predicted wall box around the wall thickness suggest that Layers 1 to 3 are often stabilized by rapid conductive cooling into the build plate, while the onset of stronger deformation tends to appear in Layers 4 and 5, followed by possible fragmentation and lack-of-fusion porosity in Layers 6 and 7. Hence, as shown in Fig. 5, the wall remains continuous across all seven layers, but the contour becomes visually less uniform in the intermediate-to-late layers, which may indicate the onset of localized thermal or morphological disturbance without complete structural breakdown.

Overall, the present results show that the proposed image-processing framework is capable of reliably tracking thin-wall geometry in LPBF and extracting physically meaningful thickness and midline shift indicators from in-situ image data. The representative 0.6 mm wall in Fig. 5 remains continuously trackable from Layer 1 to Layer 7, with only moderate local contour irregularity. The thickness results shown in Fig. 6 confirm correct geometric ordering across the wall set, while the shift results reveal additional thickness-dependent positional behavior. Also, although the present study focuses on geometric reconstruction rather than physics-based simulation, the extracted wall thickness and shift measurements already provide a compact set of interpretable observables for future physics-based monitoring trend analysis, anomaly detection, reduced-order learning, and future latent-state inference. In this sense, the present work establishes a measurement layer that can support future digital-twin development without requiring a full thermo-mechanical model in the current study.

4. CONCLUSION

This work presented an in-situ full-contour geometric reconstruction framework for thin-wall 316L structures fabricated by LPBF. Using a fixed optical imaging setup and a reference-guided computer vision pipeline, the method identified wall boundaries, estimated apparent wall thickness, and tracked wall-center movement in a layer-wise manner from grayscale build-surface images. The study demonstrates that raw in-situ optical images can be converted into quantitative geometric observables that are directly useful for process monitoring. The results showed that the detected wall thickness follows the expected overall trend with nominal wall thickness, confirming that the proposed method captures meaningful geometric differences among the wall designs. At the same time, deviations from ideal one-to-one agreement indicate that image-based thickness estimation is influenced by optical contrast, edge definition, and local morphology. The average midline shift provided complementary information by showing that positional behavior changes with wall thickness and should be evaluated alongside thickness. Layer-wise analysis revealed distinct geometric responses across the tested wall thicknesses. These results indicate that thin-wall LPBF behavior is governed not only by nominal geometry but also by cumulative layer-wise effects that influence contour formation and dimensional stability. Overall, the study establishes a practical experimental framework for in-situ geometric monitoring of thin-wall LPBF fabrication. The proposed approach is computationally simple, physically interpretable, and compatible with future extensions involving digital-twin-enabled monitoring. Future work can build on this foundation by linking the measured geometric histories to latent process-state inference and predictive quality assessment.

ACKNOWLEDGMENTS

This research was supported by the United States' National Science Foundation (NSF), USA, Grants Nos.CCF-2503055, and CPS-2237696. This work is also partially supported by the National Institute of Standards & Technology, United States, under grant number 70NANB23H030, as well as the South Carolina Space Grant Consortium under grants 21-117-RID RGP-SC-009, 25-073-REAP-SC-001, and 25-073-BTC-SC-001. Additional support is provided by the United States' National Science Foundation (NSF) through the NSF ASEE Fellowship. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation, the South Carolina Space Grant Consortium, or the National Institute of Standards & Technology.

REFERENCES

[1] Sames, W. J., List, F. A., Pannala, S., Dehoff, R. R. and Babu, S. S. "The metallurgy and processing science of metal additive manufacturing." *International Materials Reviews* Vol. 61 No. 5 (2016): pp. 315–360. DOI 10.1080/09506608.2015.1116649.

[2] McCann, Ronan, Obeidi, Muhannad A., Hughes, Cian, McCarthy, Éanna, Egan, Darragh S., Vijayaraghavan, Rajani K., Joshi, Ajey M., Acinas Garzon, Victor, Dowling, Denis P., McNally, Patrick J. and Brabazon, Dermot. "In-situ sensing, process monitoring and machine control in Laser Powder Bed Fusion: A review." *Additive Manufacturing* Vol. 45 (2021): p. 102058. DOI 10.1016/j.addma.2021.102058.

[3] Killedar, Digambar, Ogunniyi, Emmanuel, Fu, Yanzhou, Downey, Austin R. J., Yuan, Lang and Folsome, Matthew D. "In-Situ Monitoring of Geometric Drift and Thermo-Mechanical Modeling Toward a Digital Twin for Thin-Wall Fused Filament Fabrication." *Proceedings of SPIE 13947, Digital Twins, AI, and NDE for Industry Applications and Energy Systems 2026* (2026)DOI 10.1117/12.3090447.

[4] Fu, Yanzhou, Downey, Austin R.J., Yuan, Lang, Zhang, Tianyu, Pratt, Avery and Balogun, Yunusa. "Machine learning algorithms for defect detection in metal laser-based additive manufacturing: A review." *Journal of Manufacturing Processes* Vol. 75 (2022): pp. 693–710. DOI 10.1016/j.jmapro.2021.12.061.

[5] Fu, Yanzhou, Whetham, Matthew, Downey, Austin R. J., Yuan, Lang and Comert, Gurcan. "A study of online melt pool, plume, and spatter tracking in laser powder bed fusion using DBSCAN." Niezrecki, Christopher and Farhangdoust, Saman (eds.). *Digital Twins, AI, and NDE for Industry Applications and Energy Systems 2025*: p. 21. 2025. SPIE. DOI 10.1117/12.3051110.

[6] Fischer, Felix Gabriel, Birk, Niklas, Rooney, Leroy, Jauer, Lucas and Schleifenbaum, Johannes Henrich. "Optical process monitoring in Laser Powder Bed Fusion using a recoater-based line camera." *Additive Manufacturing* Vol. 47 (2021): p. 102218. DOI 10.1016/j.addma.2021.102218.

[7] Guerra, Maria Grazia, Errico, Vito, Fusco, Andrea, Lavecchia, Fulvio, Campanelli, Sabina Luisa and Galantucci, Luigi Maria. "High resolution-optical tomography for in-process layerwise monitoring of a laser-powder bed fusion technology." *Additive Manufacturing* Vol. 55 (2022): p. 102850. DOI 10.1016/j.addma.2022.102850.

[8] Tomas, Josef, Hitzler, Leonhard, Köller, Marco, von Kobylinski, Jonas, Sedlmajer, Michael, Werner, Ewald and Merkel, Markus. "The Dimensional Accuracy of Thin-Walled Parts Manufactured by Laser-Powder Bed Fusion Process." *Journal of Manufacturing and Materials Processing* Vol. 4 No. 3 (2020): p. 91. DOI 10.3390/jmmp4030091.

[9] Wu, Ziheng, Narra, Sneha Prabha and Rollett, Anthony. "Exploring the fabrication limits of thin-wall structures in a laser powder bed fusion process." *The International Journal of Advanced Manufacturing Technology* Vol. 110 No. 1-2 (2020): pp. 191–207. DOI 10.1007/s00170-020-05827-4.

[10] Veetil, Jithin Kozhuthala, Khorasani, Mahyar, Ghasemi, AmirHossein, Rolfe, Bernard, Vrooijink, Ivo, Van Beurden, Karin, Moes, Sebastiaan and Gibson, Ian. "Build position-based dimensional deviations of laser powder-bed fusion of stainless steel 316L." *Precision Engineering* Vol. 67 (2021): pp. 58–68. DOI 10.1016/j.precisioneng.2020.09.024.

[11] Imani, Farhad, Gaikwad, Aniruddha, Montazeri, Mohammad, Rao, Prahalada, Yang, Hui and Reutzel, Edward. "Process Mapping and In-Process Monitoring of Porosity in Laser Powder Bed Fusion Using Layerwise Optical Imaging." *Journal of Manufacturing Science and Engineering* Vol. 140 No. 10 (2018). DOI 10.1115/1.4040615.

[12] Gaikwad, Aniruddha, Imani, Farhad, Yang, Hui, Reutzel, Edward and Rao, Prahalada. "In Situ Monitoring of Thin-Wall Build Quality in Laser Powder Bed Fusion Using Deep Learning." *Smart and Sustainable Manufacturing Systems* Vol. 3 No. 1 (2019): pp. 98–121. DOI 10.1520/ssms20190027.

[13] Zhang, Li, Chen, Xiaoqi, Zhou, Wei, Cheng, Taobo, Chen, Lijia, Guo, Zhen, Han, Bing and Lu, Longxing. "Digital Twins for Additive Manufacturing: A State-of-the-Art Review." *Applied Sciences* Vol. 10 No. 23 (2020): p. 8350. DOI 10.3390/app10238350.

[14] *Foundational Research Gaps and Future Directions for Digital Twins*. National Academies Press (2024). DOI 10.17226/26894.

[15] Jyeniskhan, Nursultan, Shomenov, Kemel, Ali, Md Hazrat and Shehab, Essam. "Exploring the integration of digital twin and additive manufacturing technologies." *International Journal of Lightweight Materials and Manufacture* Vol. 7 No. 6 (2024): pp. 860–881. DOI 10.1016/j.ijlmm.2024.06.004.

[16] Zolfagharian, Ali, Jin, Liuchao, Ge, Qi, Liao, Wei-Hsin, Díaz Lantada, Andrés, Franco Martínez, Francisco, Zhang, Tianyu, Liu, Tao, Wang, Charlie C. L., Mosallanejad, Mohammad Hossein, Ghanavati, Reza, Saboori, Abdollah, De Blas De Miguel, Alejandro, Solórzano-Requejo, William, Cai, Yi, Dong, Xiangyang, Qu, Huangyi, Samadiani, Najmeh, Huang, Guangyan, Downey, Austin, Fu, Yanzhou, Yuan, Lang, Lee, Tsz-Kwan (Glory), Baniya, Arbind Agrahari, Waseem, Eisha, Sani, Abdul Rahman, Kouzani, Abbas Z., Wu, Yijia, Nemitz, Markus P., Shirzad, Masoud, Oh, Dageon, Nam, Seung Yun, Bonatti, Amedeo Franco, Chiesa, Irene, Fortunato, Gabriele Maria, Vozzi, Giovanni, De Maria, Carmelo and Bodaghi, Mahdi. "Roadmap on Artificial Intelligence-Augmented Additive Manufacturing." *Advanced Intelligent Systems* Vol. 8 No. 4 (2026). DOI 10.1002/aisy.202500484.

[17] Fu, Yanzhou, Downey, Austin R.J., Yuan, Lang, Huang, Hung-Tien and Ogunniyi, Emmanuel A. "Simulation-in-the-loop additive manufacturing for real-time structural validation and digital twin development." *Additive Manufacturing* Vol. 98 (2025): p. 104631. DOI 10.1016/j.addma.2024.104631.

[18] Adhami, Mumin, Garcia-Sandoval, Mateo, Hoang, Thienan, Whetham, Matthew, Sun, Can, Downey, Austin R. J., Fu, Yanzhou and Yuan, Lang. "Design of vacuum- and pressure-compatible optical and thermal camera modules for laser powder bed fusion." *Proceedings of SPIE Smart Structures + Nondestructive Evaluation (SPIE SHM)* (2026).