Real-time Splatter Tracking in Laser Powder Bed Fusion Additive Manufacturing

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ABSTRACT

In additive manufacturing, laser powder bed fusion (LPBF) has unrivaled strengths due to its design and manufacturing freedom. The in situ validation of additively manufactured components would reduce or entirely remove the need for post-processed non-destructive evaluation. Potentially enabling the direct utilization of components from the print bed. However, typical approaches to in situ monitoring of the LPBF process utilize high-speed thermal and optical cameras coupled with advanced optics to enable co-axial imaging of the weld pool. The amount and quality of the data obtained through these systems necessitate the need for extensive post-processing of data. In contrast, this work provides a low-cost in situ monitoring and real-time computing alternative using industrial cameras and optical filters to track the splatter area of the welding process. To reduce the dimensionality of data retained for a given component, the proposed process tracks the brightness contours of the welding process in real-time and retains only a select number of features. In this introductory work, the prototype system is investigated using a variety of different image processing methods to optimize processing speed (measured in frames per second) versus the size of melting splatter for a test specimen of 10 mm $\times$ 10 mm $\times$ 5 mm. Defects in the specimen are quantified using computed tomography and linked to information extracted from tracking the splatter-related features in situ. Results show that the speed of the computational system, visibility of splatter, and the accurate translation of splatter brightness to contours with area and locations is critical to functionality. A discussion on the trade-offs between these constraints is provided.

Keywords: additive manufacturing, laser powder bed fusion, splatter tracking, splatter-related features extraction, defect detection

1. INTRODUCTION

Laser powder bed fusion (LPBF), one of the metal additive manufacturing technologies, has unrivaled strengths due to its design and manufacturing freedom, which has changed the whole manufacturing enterprise. LPBF has been widely applied to various fields, such as aerospace, medical, and automotive. In the LPBF printing process, the laser beam scans the metal powder based on the generated path from the designed CAD model to melt and fuse a thin layer of powder particles. Then, the building platform sinks, and the powder container rises at a specific height. The blade recoats a new layer of particle powder. This process repeats until the designed part is finished. Although LPBF has unique fabrication convenience, it is a complicated physics process, which includes laser energy absorption and transmission, material evaporation, remelting and solidification, melt pool fluid dynamics, and microstructure evolution via epitaxial growth and nucleation. In addition, many process parameters, such as laser power, scanning speed, and hatch spacing, are involved. These physical processes and factors affect defect formation, such as cracks, porosities, and lack of fusion, which impair the product's physical and mechanical properties. To guarantee the printing of products with good quality, a defect detection system should be developed for LPBF.

Numerous researchers have focused on defect detection for the LPBF printing process.[1,2] For example, Pandiyan et al. developed a combination deep learning algorithm by integrating a convolutional neural network

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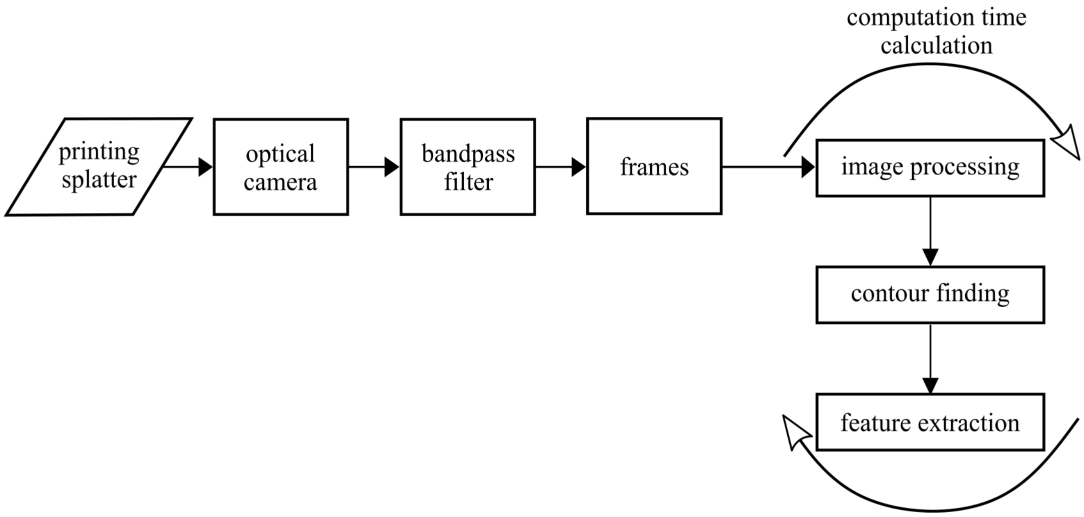

Figure 1. The methodology of splatter tracking.

with long-short term memory, which can classify the sensor signals into three classes (e.g., lack of fusion, conduction mode, and keyhole).[3] Zhao et al. achieved an in situ characterization for LPBF with high-speed X-ray imaging and diffraction approach.[4] Baumgartl et al. used a deep learning-based neural network to process the thermographic off-axis images for defect detection in LPBF.[5] The proposed approach has an accuracy of 96.8% for delamination and splatter recognition. Taherkhani et al. developed a porosity defect detection platform utilizing the light intensity emitted from the melt pool.[6] The results showed that porosities larger than 120 µm were recognizable with the obtained photo-diodes signals. The same author group presented a self-organizing map (SOM) approach for porosity prediction by analyzing the collected intensity signal.[7] The results showed that the deployed SOM algorithm has the capacity to detect defects with sizes from 100 to 320 µm with various geometry and distribution.

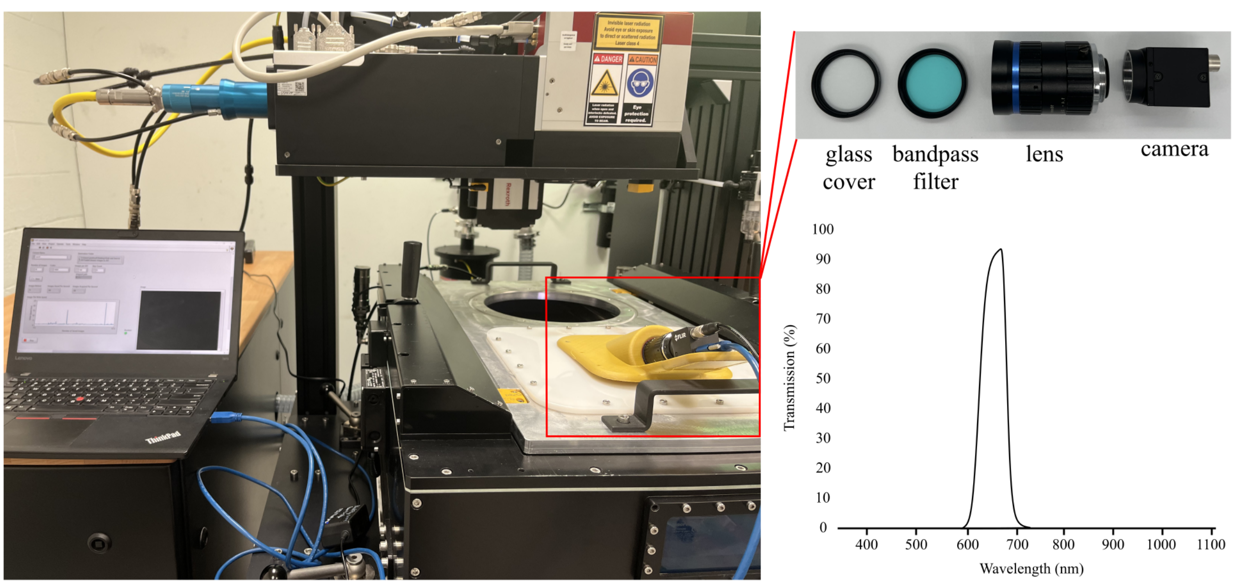

Figure 2. Splatter tracking setup on the metal 3D printer with the bandpass filter range.

Prior research has focused on finding defects with different approaches and achieved good results. However, the best way to guarantee product quality is by performing real-time defect detection during the printing process. In the LPBF printing process, splatter originates from the laser interaction with the metal powder, which not only reveals the melting and printing quality but also reflects the laser scanning path. Before real-time splatter tracking for defect detection in LPBF, some basic investigations, such as computation time, feature extraction, and defect correlation, must be done. Therefore, in this paper, a basic splatter tracking approach is investigated to provide a solid foundation for future real-time applications that is capable of correlating the defects with splatter information. The methodology of splatter tracking is shown in Figure 1, which contains image processing, contour finding, and feature extraction in three steps. Computation time for each step in the tracking process is calculated. In addition, the relationship between the splatter area with processing computation time is established. Various features are extracted from the splatter with contour, which can be used for reflecting the melting quality and referring to the laser moving path accuracy. Based on the time calculation and information extraction, splatter tracking has a promising potential to be the real-time defect detection approach for the LPBF technology.

2. METHODOLOGY

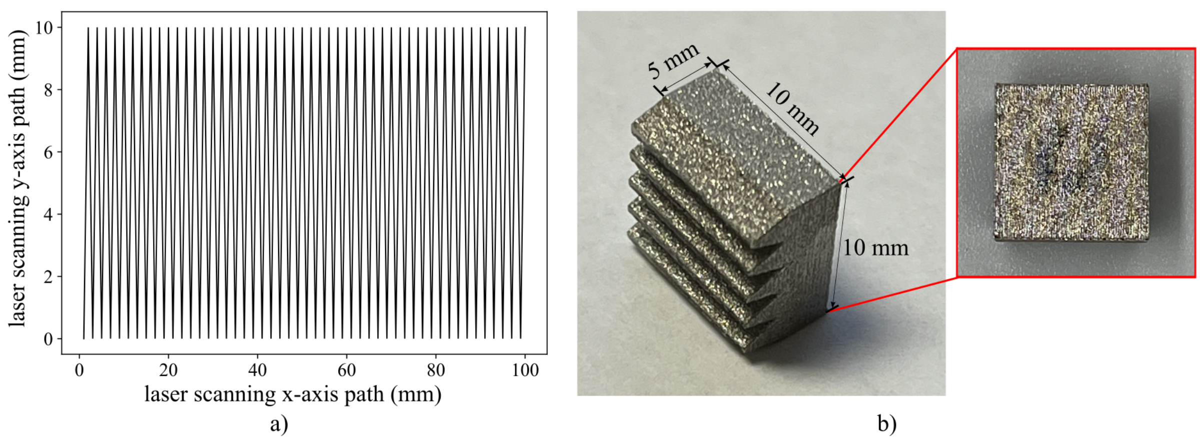

Figure 3. The sample in the research: a) laser scanning path from G-code and b) the printed specimen.

The AcontyMIDI LPBF printer used in this work is shown in Figure 2. A FLIR blackfly USB optical camera with a resolution of 1440 × 1080 is utilized to collect the splatter images with a frame rate of 100. A MidOpt bandpass filter BP660 is applied in front of the lens to get a clear splatter image with a useful range is 640-680nm. The splatter tracking setup on the customized printer cover is shown in Figure 2. The splatter images from the printing process are used to investigate the tracking. In this research, a 10 × 10 × 5 mm specimen is fabricated with 316L stainless steel powder. Figure 3a) shows the designed laser scanning path for the specimen and Figure 3b) shows the printed specimen. The key printing parameters such as power, speed, laser spot, and hatch distance for specimen printing are 200 W, 800 mm/s, 100 µm, and 100 µm.

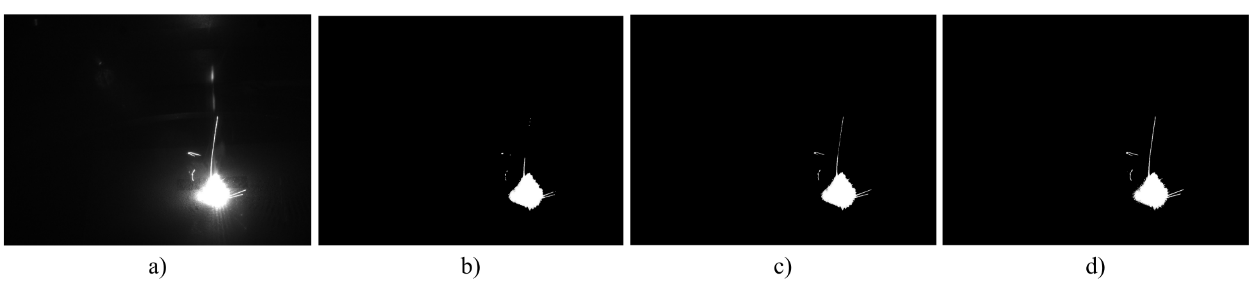

Figure 4. Splatter image processing showing: a) the raw splatter image; b) splatter with Gaussian blur, erode, dilate, and threshold filter; c) splatter with Gaussian blur and threshold filter; and d) splatter with threshold-only filter.

2.1 Splatter image processing approach and time calculation

In LPBF, splatter is stated as the ejection of molten metal droplets or hot but not fully melted particles that get away from the laser irradiation zone and then fall back on the powder bed.[8] There are various types of splatter based on the formation principles, such as droplet splatter, sideways splatter, and agglomerated splatter. In this research, the type of splatter is not considered. In order to remove the laser irradiation and splatter from the splatter contour, different filters are utilized to get a precise splatter. Those splatter image processing filters include Gaussian blur, erode, dilate, and threshold. Gaussian filter blurs an image using a specified Gaussian kernel. The erode filter erodes an image by using a specific structuring element that determines the shape of a pixel neighborhood over which the minimum is taken. Whereas the dilate filter dilates the source image using the maximum. The threshold filter applies a fixed-level thresholding to a multiple-channel array to get an image out of a grayscale image or to remove noises, that is, filtering out pixels with too small or too large values. For accurate splatter information, all the images after the implementation of filters are grayscale, not binary. The splatter images after processing with different filters are shown in Figure 4. Figure 4a) is the raw splatter image before processing. Figure 4b), c), and d) are the splatter images with the integration of Gaussian blur, erode, dilate, and threshold; with Gaussian blur and threshold filter; and threshold-only filter.

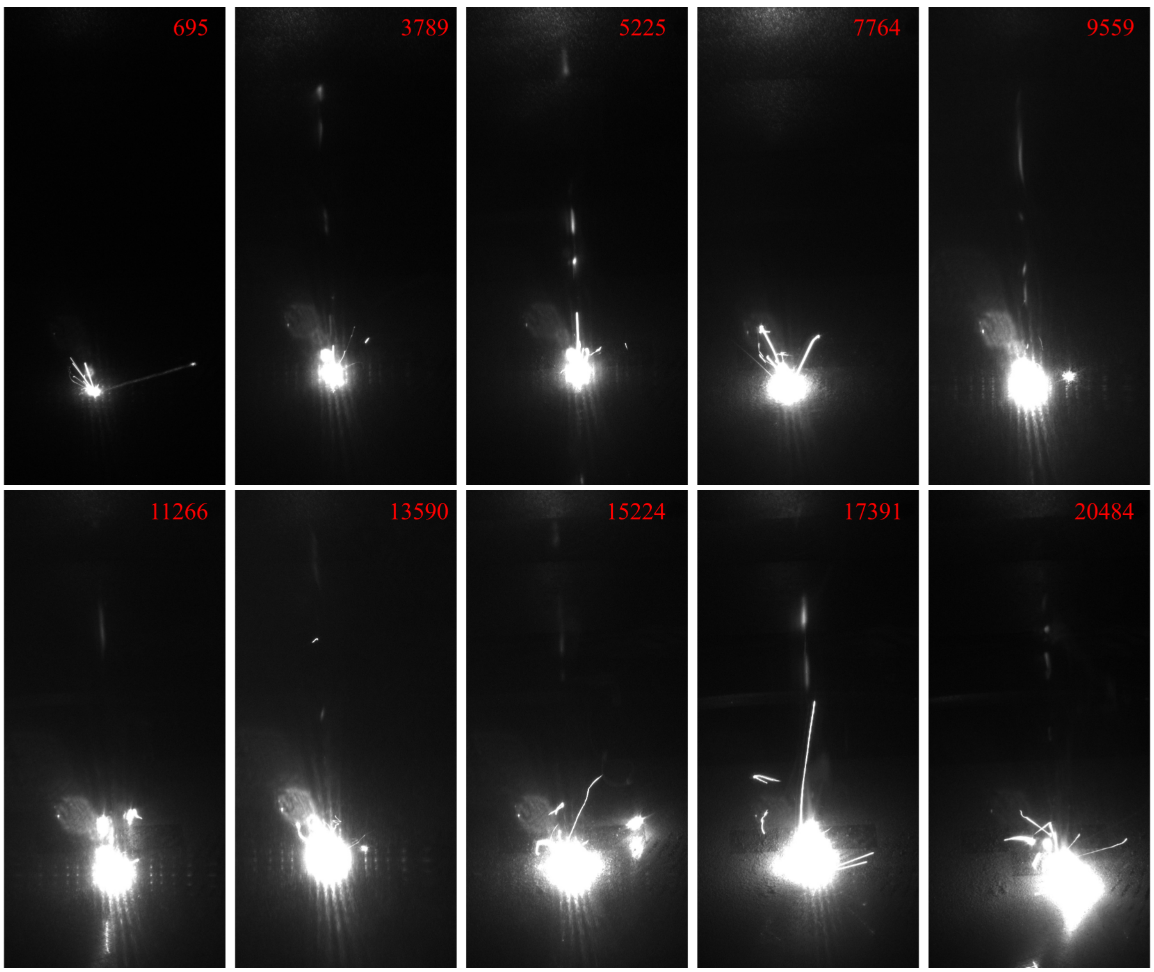

Figure 5. Splatter images with various splatter areas, measured in units of pixels.

To guarantee the proposed approach can meet the timing constraints for real-time splatter tracking, the algorithm's timing consumption for each step with different filters is calculated. In addition, the computation time versus splatter area is also established. The raw splatter images with diverse areas are shown in Figure 5. The splatter areas are counted by pixel from small to large, which are 695, 3789, 5225, 7764, 9559, 11357, 13590, 15224, 17391, and 20484. All cycle times are calculated on a personal computer with an i7-3770 CPU @ 3.40 GHz with 8 GB RAM.

2.2 Splatter information extraction

The ultimate goal of splatter tracking is to correlate the splatter information with printing abnormality. Therefore, after filter processing, feature extraction is applied to the splatter images. Those features include splatter area, splatter radius, splatter intensity, and splatter moving path. The main tool for feature extraction is open-source computer vision (OpenCV), which contains numerous computer vision libraries, tools, and hardware.[9] Splatter intensity, area, and radius can be utilized for tracking the powder melting conditions, which can further be associated with the defect.[10] The abrupt splatter changes can be indicators of defect formation. Splatter moving path can be taken as a laser scanning path evaluation reference.

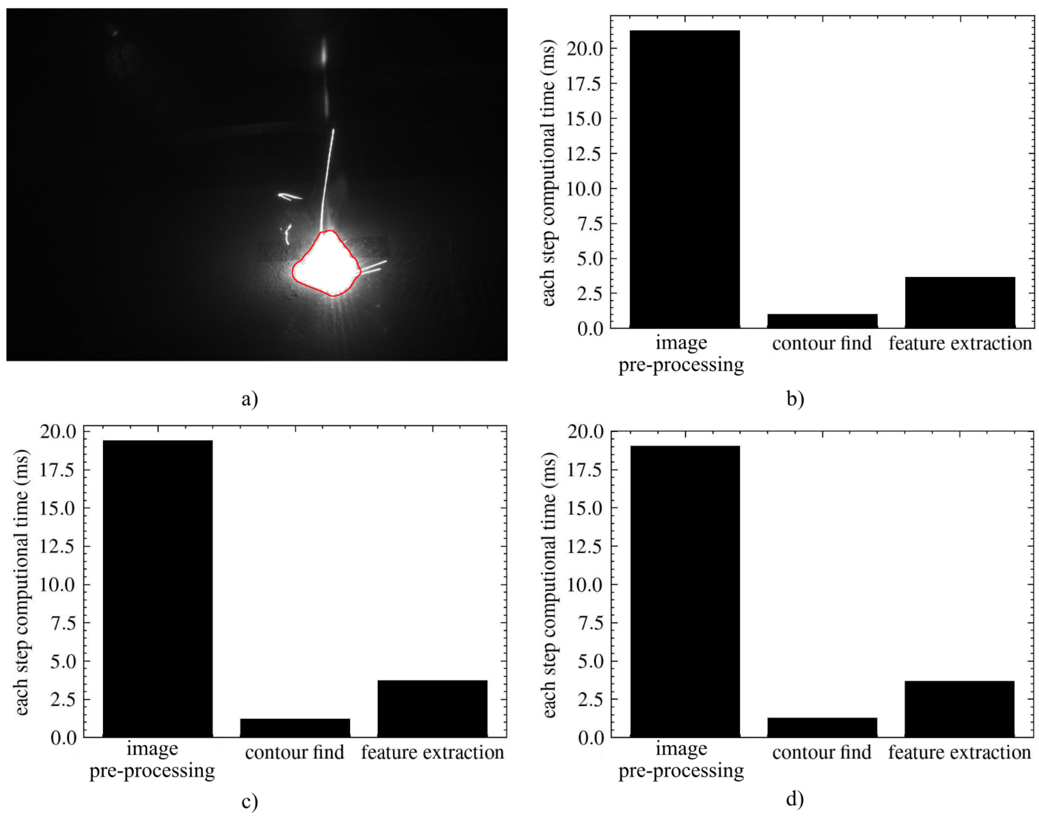

Figure 6. Splatter image processing for an image with 17391 pixels, showing: a) the image of splatter with contour; b) each step computation time with Gaussian blur, erode, dilate, and threshold filter; c) each step computation time with Gaussian blur and threshold filter; and d) each step computation time with threshold-only filter.

3. RESULTS AND DISCUSSION

For plotting the computation time in each step, the splatter image with 17391 pixels is chosen. The result is shown in Figure 6. An image of the splatter with a red contour line is shown in Figure 6a). Note that the red contour line is not necessarily needed for splatter tracking, as it takes time to plot the contour. However, the addition of the contour line here makes the concept of splatter tracking more clear. Each step's computation time for the splatter tracking methodologies with different filters is shown in Figure 6b), c), and d); which display the averaged recorded times for the twenty cycles. As reported in Figure 6, image pre-processing takes most of the time, and splatter contour finding occupies little time. Table 1 reports timing for a number of images with various pixel sizes. From Table 1, it can be seen the type and number of filters chosen only have a limited effect on the total computation time.

Figure 7 reports temporal results for the five features considered in this work. The features are plotted against 445 frames which are obtained from one layer of specimen printing. The features of splatter area, mean intensity, radius, and center moving path on the x and y-axis are reported here. As seen in Figure 7, there are

Table 1. Computation time (ms) for different filters processing splatter with various areas.

filters \ splatter area (pixel)	695	3789	5225	7764	9559	11266	13590	15224	17391	20484
Gaussian blur, erode, dialte, and threshold	24.15	25.21	25.00	25.45	26.03	26.02	25.92	25.72	25.61	25.45
Gaussian blur and threshold	22.48	23.49	24.02	24.29	24.62	24.37	24.69	24.50	24.38	24.41
threshold	21.81	23.29	23.23	23.59	23.85	24.08	24.04	24.39	24.42	23.55

some abrupt splatter changes during the printing process. The features extracted from the splatter can provide useful information about the printing process. However, these changes need further investigation to verify their relations with defect formation.

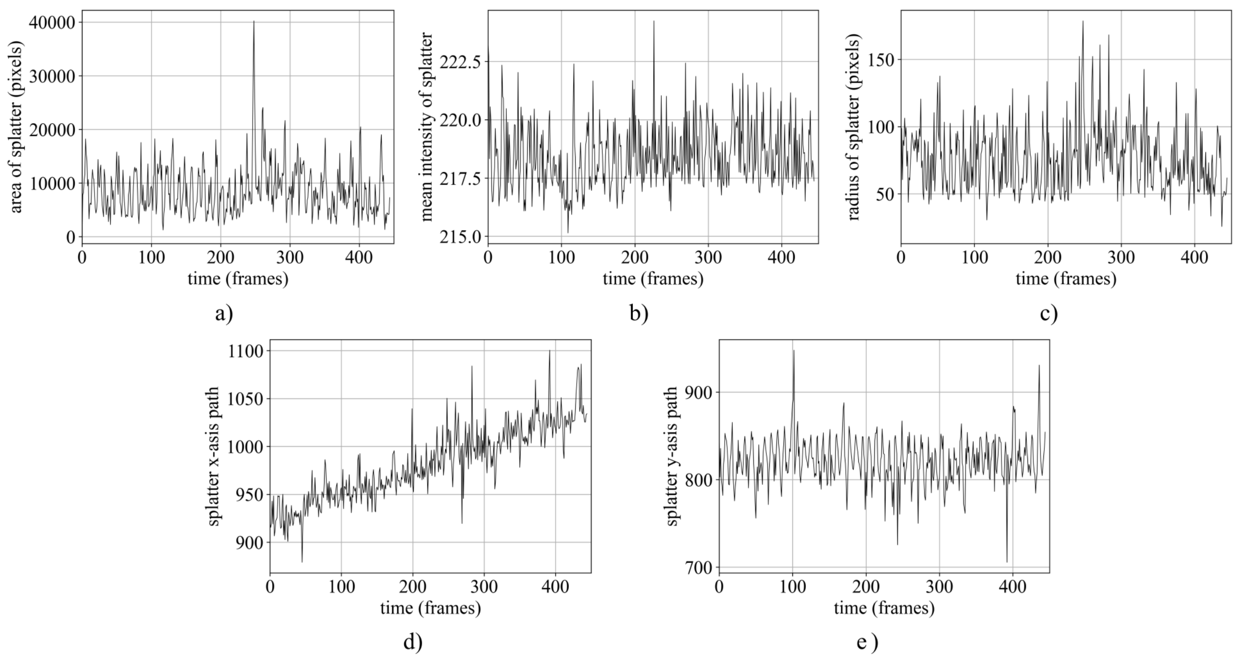

Figure 7. Splatter image processing: a) extracted area of splatter; b) extracted mean intensity of splatter; c) extracted radius of splatter; d) extracted x-axis moving path of splatter; and e) extracted y-axis moving path of splatter.

4. CONCLUSION AND FUTURE WORK

This paper presented a real-time splatter tracking approach for laser powder bed fusion (LPBF). The basic investigation on splatter tracking provides a foundation for future real-time splatter tracking implementation. First, various filters were applied for splatter image processing. The result shows that the integrated Gaussian blur, erode, dilate, and threshold filter has the best filtering result of noise, irradiation, and splatter, but requires the most computation time. In comparisons, the threshold-only filter has the shortest processing time; however, the splatter boundary is not clear. Second, the relationship between image processing time and splatter area was established. The result shows that the larger the splatter area, the greater the computation time. The required processing time is also affected by the splatter and irradiation-related noise in the image. Third, a series of temporally-tracked features were extracted from the splatter images. The extracted features can provide useful information about the printing process. Future work will investigate the correlation of printing defects with splatter features and develop hardware for real-time product quality monitoring for LPBF additive manufacturing.

ACKNOWLEDGMENTS

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