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Fast measurement of metal laser powder bed fusion layer surfaces using light scattering and principal component analysis

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Abstract
To address the future challenges in quality monitoring of metal laser powder bed fusion, a novel method is proposed to detect topographic anomalies on layer surfaces, which may appear during the manufacturing process. The method combines light scattering and principal component analysis. Scattering patterns, experimentally generated from real surfaces representative of in-control processes and encoded as digital images, are collected and used to build a reference set, which is then further populated by simulation. Principal component analysis is then applied to the set. A certain number of principal components is extracted and used to define a transform to map any scattering pattern to principal component space. Using the created transform, any new scattering pattern can be transformed to principal component space and then back into the original space (reconstruction), with some reconstruction error. The error is expected to be low if a pattern from the reference set is processed. However, if a different pattern is processed, e.g. generated by an out-of-control layer topography, then the reconstruction error is larger. In this work, a layer monitoring system is proposed, capable of detecting out-of-control topographies through observation of the reconstruction error. The system was implemented and experimentally validated through application to a selected test case.

Measurement, laser powder bed fusion, light scattering, principal component analysis

1. Introduction

With the rapid development of metal additive manufacturing (AM) techniques [1], topography measurement of layer surfaces has become increasingly important for in-process monitoring of the quality of fabricated parts [2]. Any problem discovered in the topographies of the layer surfaces may be indicative of problems in the manufacturing process and affect the final product. In metal AM processes, such as laser powder bed fusion (LPBF), non-intrusive methods to monitor layer topography are required, where the speed of measurement is essential to avoid slowing down the manufacturing process and possibly altering the physics of the process itself [3].

In previous work [4, 5], we have developed a method to measure grating surfaces combining light scattering and machine learning, which is suitable for fast and in-process surface measurement. We then further developed the method to monitor the quality of LPBF surfaces using an autoencoder [6]. In this paper, we present a fast method to measure topographical changes of LPBF layer surfaces, which combines light scattering and principal component analysis (PCA). In the proposed method, laser light is projected onto the layer surface and scattered light is captured by a camera. The scattering pattern is then processed by a PCA-based monitoring system which detects anomalous changes in the scattering pattern as an indication of possibly detrimental changes in layer topography.

Experiments performed using a prototype implementation based on the off-line measurement of test LPBF surfaces, show that the proposed monitoring solution can be used to discriminate between in-control and out-of-control LPBF topographies. Data processing in the prototype implementation is fast enough to warrant future in-process application without the need for slowing down or temporarily halting the fabrication process. Therefore, the proposed method has the potential to be integrated into a commercial LPBF machine for real-time, in-process quality monitoring.

2. Methodology

The schema of the proposed method is shown in Figure 1. Scattering patterns from reference surfaces (manufactured under in-control states using optimal parameters) are collected experimentally as digital images, and used to populate a reference dataset, which is then augmented by simulation (algorithmic shifts and rotations applied to the measured images). PCA is then applied to the reference dataset. The principal components represent the inherent multidimensional features of the scattering patterns from the reference surfaces. A PCA-based encoding and decoding system is then created using a certain number of principal components (the first 50% components). Using the encoding/decoding system, scattering images can be encoded into principal component space and then back into images, with a small reconstruction error. As the PCA-based encoding and decoding system has been tuned specifically for in-control surfaces (i.e. the reference dataset), any out-of-control scattering pattern processed through the

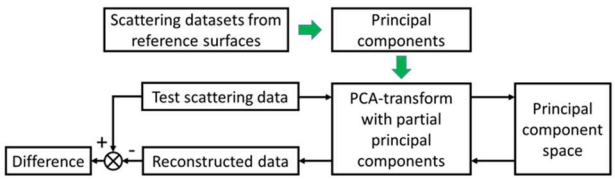

Figure 1. Schema of the proposed method

same system will result in a larger reconstruction error. Thus, reconstruction error itself can be used to detect out-of-control patterns.

Figure 2 shows the experiment setup to evaluate the proposed method. Collimated laser light with a wavelength of 633 nm and an approximate beam diameter of 0.8 mm is projected to a mirror and reflected onto the measured LPBF sample. The sample is mounted on a rotation stage, to simulate different surface orientations. Scattering light is reflected to a 150 mm × 150 mm screen. The scattering pattern can then be captured by a camera and further processed by a PC.

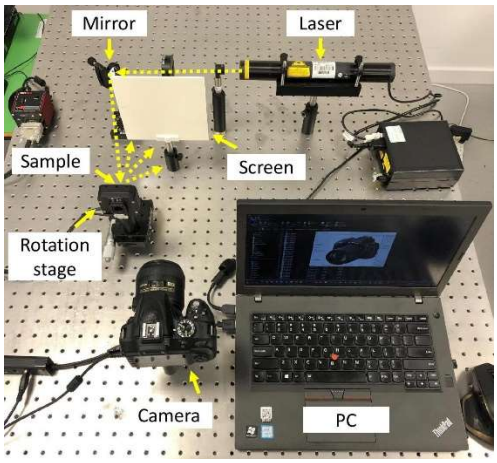

Figure 2. Experiment setup

3. Results and discussions

Two LPBF samples were used for the experiment; one was a reference surface produced by an in-control LPBF process, whilst another was representative of an out-of-control process. The topographies of the two surfaces are shown in Figure 3 and their manufacturing parameters are shown in Table 1. The reference surface was manufactured using optimal parameters, resulting in evenly distributed textures, as shown in Figure 3(a). The defective surface was manufactured using significantly lower energy density, which resulted in large humps on the surface (due to insufficient melting energy), as shown in Figure 3(b).

Both samples were used to perform the scattering experiment in the setup shown in Figure 2. For each sample, thirty-six scattering patterns were measured by rotating the surface every 10°. The scattering patterns were then further populated in simulation by algorithmically shifting the digital images by six steps in both the *x* and *y* directions and by rotating ten steps with 1° per step. As a result, there were 36 × 6 × 6 × 10 = 12960 datasets for each sample. A circular mask was applied for each dataset to make the effective area rotationally symmetric, eliminating the corner effect due to rotating the square-shaped dataset. The original pixel densities of the measured images were 6000 × 4000. The images were cropped according to the size of the screen and were eventually resized to 20 × 20 pixels. As a result, the data size was significantly reduced. The intensity values in the pixels of the reference set were then processed by mapping to the standard normal distribution (zero mean, unit variance) [7] and used to perform the PCA. In total, there were 20 × 20 = 400 principal components. In this study, we used the first half of the principal components, i.e., 200 principal components, to reduce the dimension of the datasets and establish the PCA-transform.

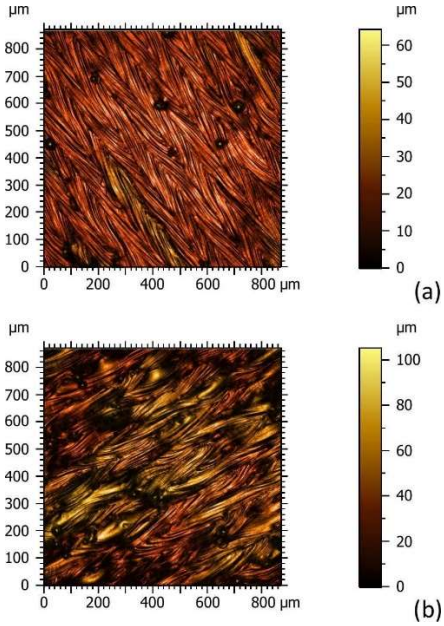

Figure 3. Topographies of LPBF samples, (a) reference surface, and (b) defective surface, measured by Zygo NexView NX2 with 20× objective lens

Table 1 Manufacturing parameters for the LPBF samples

Surface	Laser power/W	Scan speed/m s^{-1}	Energy density/J mm^{-2}
Reference	170	1.1	2.1
Defective	120	1.1	1.5

Figure 4 shows the results for one dataset from the reference surface. Figure 4(a), Figure 4(b) and Figure 4(c) are the input scattering pattern, reconstructed scattering pattern and the reconstruction error, respectively. The results show that the reconstructed scattering pattern is visually similar to the original one. The reconstruction error is determined by the deviations from the reconstructed scattering pattern to the input scattering pattern. The root mean square (RMS) value of the reconstruction error is 0.089, which is relatively small, indicating that the PCA-transform can efficiently transform and reconstruct the scattering pattern measured from the reference surface.

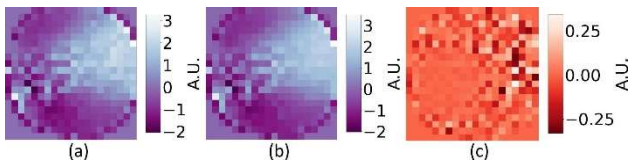

Figure 4. Results for the reference surface, (a) original scattering pattern, (b) reconstructed scattering pattern, and (c) reconstruction error. All subfigures are 20 × 20 pixels

The results for one dataset from the defective surface are shown in Figure 5. Comparing to the results for the reference surface, the RMS value of the reconstruction error is significantly larger, which is 0.214. The large reconstruction error is due to the low efficiency of the encoding/decoding process for the defective surface, whose datasets were not used to establish the PCA-transform. The results of the reconstruction errors for the reference surface and the defective surface are also summarised in Table 2.

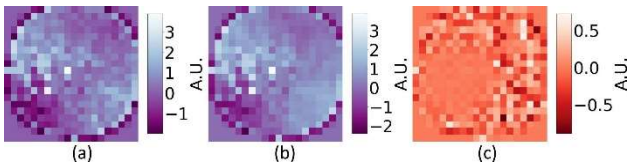

Figure 5. Results for the defective surface, (a) original scattering pattern, (b) reconstructed scattering pattern, and (c) reconstruction error. All subfigures are 20 × 20 pixels

Table 2 Reconstruction errors for the reference surface and defective surface

Surface	RMS of reconstruction error/A.U.
Reference	0.089
Defective	0.214

The RMS values for the reconstruction error for all datasets from both reference and defective surfaces are summarised in Figure 6. The mean value for those from the reference surface is 0.055 whilst it is 0.155 for the defective surface. These two types of surfaces can be easily discriminated by thresholding the reconstruction error. In this study, we set the threshold to be 0.1, i.e., if the RMS error is less than 0.1, the measured surface is classified as a non-defective surface, otherwise a defective surface. As a result, 12861 and 99 datasets from the reference surface were classified as non-defective and defective, respectively. On the other hand, 12938 and 22 datasets from the defective surface were classified as defective and non-defective surface, respectively. The confusion matrix can then be summarised as shown in Table 3. The overall accuracy of the classifier is 0.995, indicating that the proposed method has good performance.

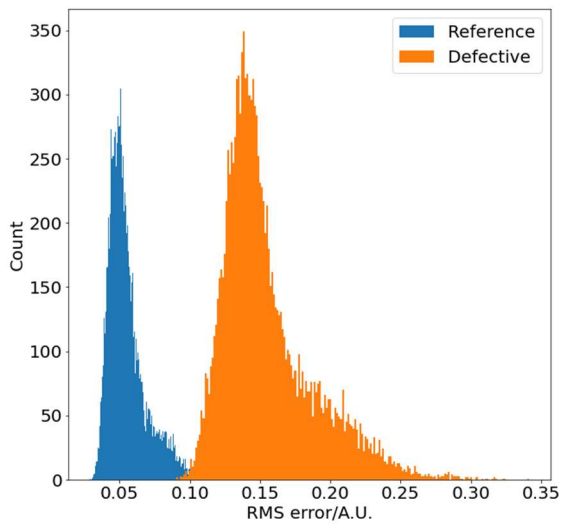

Figure 6. Histogram of results for all the datasets from the reference surface and defective surface

Table 3 Confusion matrix

	Predicted: Non-defective	Predicted: Defective
Actual: Non-defective	12861	99
Actual: Defective	22	12938

4. Conclusions

The paper presents a fast method to measure the LPBF layer surfaces combining light scattering and PCA. A PCA-based encoding/decoding system is developed and tuned on a reference dataset made of scattering patterns experimentally acquired from reference surfaces and further augmented by simulation. The PCA-based encoding/decoding system can then be used to convert scattering pattern images into the principal component space, and then back into images. The reconstruction error can be used to classify whether the measured surface has significantly different topography from the reference surfaces, possibly produced from an out-of-control process. The accuracy of the classifier was experimentally determined to be as high as 0.995, which indicates the good performance of the proposed method, although more and more diverse datasets are needed to obtain a more comprehensive assessment of performance. The computational burden of the PCA-based encoding/decoding process is relatively low, which makes the system able to achieve fast response times, an essential prerequisite for in-process utilisation. The relatively simple and low-cost design makes the proposed method potentially suitable for implementation in modern LPBF machines.

Acknowledgements

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