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Anomaly detection and classification in a laser powder bed additive manufacturing process using a trained computer vision algorithm

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ABSTRACT

Despite the rapid adoption of laser powder bed fusion (LPBF) Additive Manufacturing by industry, current processes remain largely open-loop, with limited real-time monitoring capabilities. While some machines offer powder bed visualization during builds, they lack automated analysis capability. This work presents an approach for in-situ monitoring and analysis of powder bed images with the potential to become a component of a real-time control system in an LPBF machine. Specifically, a computer vision algorithm is used to automatically detect and classify anomalies that occur during the powder spreading stage of the process. Anomaly detection and classification are implemented using an unsupervised machine learning algorithm, operating on a moderately-sized training database of image patches. The performance of the final algorithm is evaluated, and its usefulness as a standalone software package is demonstrated with several case studies.

1. Introduction

In recent years, Additive Manufacturing, colloquially known as 3D-printing, has experienced immense growth as an industry; this is particularly true for machines and processes producing net-shape metal parts [1]. Additive Manufacturing promises to be well-suited for aerospace and medical applications [2] as well as for producing mission-critical parts, on-site, at remote locations [3]. However, these applications require a degree of part quality assurance and process reliability that are difficult to achieve with the systems currently on the market [1]. It is commonly recognized that implementation of in-situ process monitoring and closed-loop control is necessary to meet the stringent requirements of these applications [1].

Laser Powder Bed Fusion (LPBF) machines operate by spreading a thin layer (typically 20 µm–60 µm thick) of metal powder over a build plate using a recoater blade. After powder spreading, a laser beam is used to selectively melt the powder in locations corresponding to a 2D slice of a 3D part. After the lasing is complete, the build plate is lowered, another layer of powder is spread (now over an existing powder bed, Fig. 1), and the process repeats until the part is finished. The entire process of creating a part is often referred to as a build. There has been extensive work performed on monitoring builds in-situ [4–6], with a particular focus on tracking both the size of the melt pool produced by the laser beam [7–9] as well as the powder bed temperature [10]. Many of the flaws in a final part, as well as the overall reliability of the build process, are directly related to interactions between the recoater blade and the powder bed. As a result, several groups have begun paying special attention to this stage of both the LPBF and Electron Beam PBF processes [7,11–17]. The focus of the presented work is to monitor the powder bed for indications of flaws in final parts, as well as anomalies that may impact the stability of the process as a whole.

For this work, six types of anomalies (not including the anomaly-free case), summarized in Table 1, were identified. These anomalies range in severity from recoater hopping which may only indicate the onset of a more severe problem, to super-elevation which can be quite serious. Some anomalies (such as part failure) may indicate flaws in the final part, while others, such as recoater streaking, suggest damage to the machine itself; further description of the anomalies is provided in Section 2.2. Detection of recoater streaking has been explored by Craeghs et al. [7] and various methods for detecting super-elevation (albeit at a different size scale) have been proposed by Jacobsmühlen et al. [12]. Recent work by Abdelrahman et al. [13] demonstrates layer-wise detection of general flaws via comparison of post-fusion optical images with the CAD model. Little work has been done to comprehensively address all of these anomaly types simultaneously, particularly over the entire build volume and using only hardware directly available from an AM machine manufacturer. Furthermore, much of the exist-

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Table 1
Brief description of anomaly classifications and their respective color codes used throughout this document. Additional descriptions can be found in Section 2.2.

Anomaly	Description	Color Code
Anomaly-Free/Okay	No significant anomalies in the powder bed.	Green (3D figures) Clear (overlays)
Recoater Hopping	Caused by the recoater blade striking a part, characterized by repeated vertical (perpendicular to the recoater spreading direction, Fig. 1) lines.	Teal/Light Blue
Recoater Streaking	Caused either by the recoater blade dragging a contaminant across the powder bed or by damage to the blade. Characterized by horizontal (parallel to the recoater spreading direction, Fig. 1) lines.	Dark Blue
Debris	Debris or other small to mid-sized discrepancies located in the powder bed but not directly over any parts.	Black (plots) White (overlays)
Super-Elevation	Occurs when a part warps or curls upwards out of the powder layer. Typically the result of a buildup of residual thermal stresses.	Red
Part Failure	General classification for any significant damage to a part. Characterized by a variety of signatures.	Magenta/Purple
Incomplete Spreading	Occurs when an insufficient amount of powder is repeatedly fetched from the powder dispenser (Fig. 1). Results in a lack of powder, the severity of which is highest nearest the powder collector (Fig. 1).	Yellow

ing work relies on human-created detectors for specific anomalies, e.g. line profiles [7] and segmentation [13], while the presented methodology makes use of contemporary machine learning techniques to construct the anomaly detectors. It is worth noting that LPBF machine manufactures (including EOS GmbH [18]) are now releasing process monitoring solutions that include analyses of the powder bed. Unfortunately, many of the details about the methodologies used by these systems are currently unavailable.

To accomplish the goal of comprehensive powder bed monitoring, this work presents an algorithm that implements contemporary machine learning and computer vision techniques to detect and classify the enumerated anomalies using only hardware provided by the LPBF machine manufacturer. In the computer vision community, machine learning has become immensely popular, though many of the methods are typically applied to entire images [19]. This presents a challenge as each powder bed image may contain hundreds of uniquely-identifiable anomalies; to compensate, this work modifies a standard approach (Section 3) to allow for classification of multiple objects within a single image, an approach also pursued by Winn et al. [20]. Even as stand-alone software (e.g. not integrated with the LPBF machine control system), this algorithm has proven valuable in analyzing build failures and in analyzing final part quality.

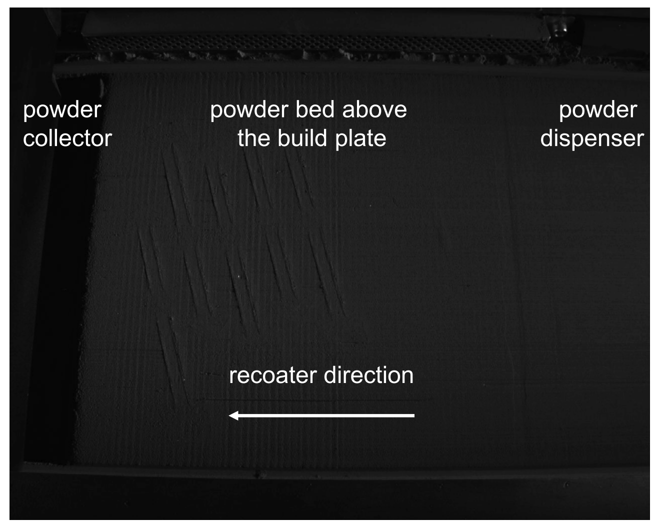

Fig. 1. Raw powder bed image collected by the EOS M290.

2. Experimental procedure and methods

All of the work presented herein is performed on an EOS M290 LPBF machine (EOS GmbH, Germany). No modifications are made to the EOS hardware, e.g. only the stock camera and lighting configurations are used. Images of the build plate and powder bed are taken through a viewport located (almost) directly above the build chamber. Grayscale images with a resolution of 1280 pixels $\times$ 1024 pixels are automatically captured immediately after a new powder layer is spread. All software was developed in the MATLAB R2015a and R2016a programing environments.

2.1. Image pre-processing

The raw images (Fig. 1) captured by the EOS M290 present several difficulties that prevent their direct usage in a machine learning-based algorithm. Fortunately, the camera mounting and lighting conditions remain consistent throughout a build as well as between different builds, so many of the required image enhancements can be greatly simplified.

Out of the necessity of avoiding the laser optic train, the camera is mounted such that its axis is not parallel to the normal vector of the build plate. This distortion is corrected using a fully-constrained Homography matrix [21] which warps and scales the raw image such that a square build plate in the image will appear square. Because the camera positioning and orientation are fixed, manual measurements of a powder-free build plate (within the camera's field of view) were taken and no fiducial (e.g. corner) detection was implemented to inform the Homography matrix. The image is then cropped to include only the region of the powder bed directly above the build plate. The spatial resolution (not synonymous with resolving power [22]) of the camera setup is between 290 μm/pixel and 340 μm/pixel (the existence of a range of resolutions is the result of the misalignment between the camera axis and the normal vector of the build plate). After the described warping and cropping, each pixel represents a 290 μm $\times$ 290 μm field of view; note that no anomalies with a dimension less than 2.9 mm are reported by the algorithm (Section 3.3).

During printing, the powder bed is lit by a single bank of white LEDs on the right side of the build chamber. This side lighting increases (compared to top lighting) the contrast of any 3D features (e.g. hills and valleys), but it also results in uneven lighting conditions. The uneven lighting causes a haloing effect in the images that is detrimental to the training process. To remedy this, an anomaly-free powder bed image was used to generate a baseline intensity mask. Stochastic noise present in the mask was reduced using a Gaussian filter. This mask is applied to each future powder bed image to levelize the lighting across the powder bed.