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Development of a standalone in-situ monitoring system for defect detection in the direct metal laser sintering process.

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Abstract

Direct metal laser sintering (DMLS) is a powder bed fusion (PBF) additive manufacturing process commonly used within the medical device and aerospace industries where regulations drive the requirement for stringent quality control. Using in-situ monitoring, the identification of defects, as well as the geometric and dimensional measurement of the layers throughout the build allows for greater quality control, as well as a reduction in the requirement for ex-situ measurement. A standalone monitoring system for the EOS M280 is presented in this research, allowing for the build process to be monitored layer-by-layer. The system images the build area after powder deposition and after laser exposure allowing for the identification of inefficiencies in both the powder deposition and the laser exposure. The system has proven to be capable to identify in build defects and work is ongoing to develop an automated program to identify these defects and notify the operator in real time.

Keywords: Metal additive manufacturing, Powder bed fusion, in-situ process monitoring, defect detection

Introduction

Additive manufacturing (AM) allows for the manufacture of high-value complex components and as such has gained popularity in a range of industries. Due to this, research into the AM process has received increased attention. The AM process is a layer-by-layer process allowing for the production of high value, complex components in industries such as aerospace, automotive and medical device [1], [2]. The process presented in this research is a powder bed fusion (PBF) process called Direct Metal Laser Sintering (DMLS). The process selectively melts a powder bed, layer-by-layer to build a final part. The powder layer is deposited on the build platform by the re-coater blade. The laser then melts the powder layer and a new layer of powder is deposited, as depicted in Figure 1. The process repeats layer-by-layer until the part is complete.

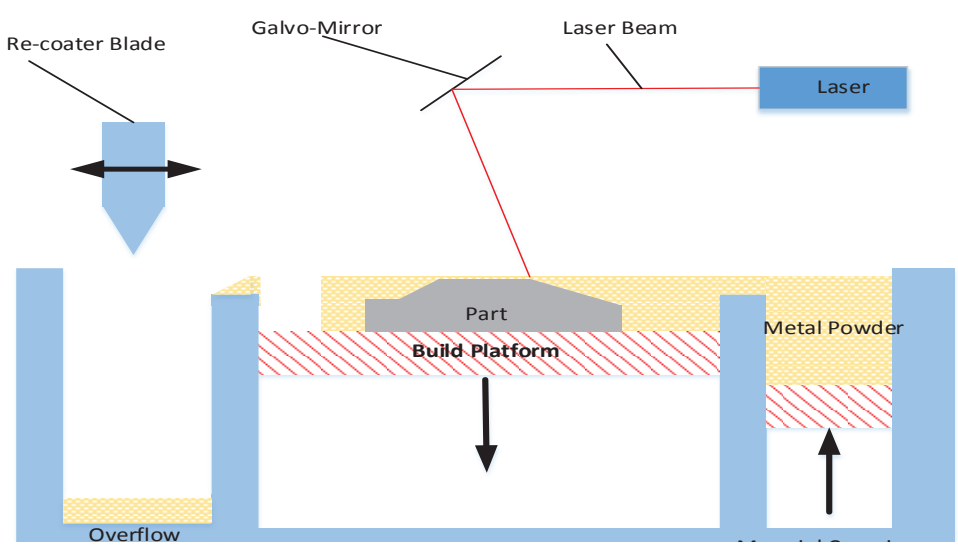


Figure 1: DMLS process, showing the powder dispenser, build platform, laser system and AM part

The ability to manufacture components while monitoring their quality throughout the process is a requirement for many of the highly regulated industries such as medical device, aerospace and automotive. This is pertinent to the quality assurance of the final AM part. This area of research has been identified as one requiring significant attention [3]. The use of in-situ monitoring allows for in-process defects to be identified and quantified during the build process eliminating costly post-process testing such as computed tomography (CT) [4]. Quantifying the defect will allow for a decision to be made on the impact of the defect on the final integrity of the part. The application of in-situ monitoring can also be used to observe the consistency of the powder deposition process in DMLS. Consistent and repeatable powder deposition is vital for the successful outcome of the powder bed fusion (PBF) process as it leads to consistent melting during laser exposure [5] [6].

The early work in the in-situ inspection of the powder bed fusion process utilized an in-line camera system [7]. Previous monitoring systems for the PBF process have utilized the application of some form of a digital camera mounted to the roof of the build chamber pointing at the build platform. This method is known as build platform monitoring which enables the build plate and distributed powder layer to be monitored throughout the build process. The camera images the build platform and the resulting powder bed allowing for defects and anomalies in the powder deposition and the laser scanning to be identified. Utilization of a high resolution digital single-lens reflex (DSLR) camera mounted within the chamber of a PBF machine enables images of the deposited powder bed to be captured, as well as the subsequent laser exposure. Abdelrahmn et al. [8] used this method to detect anomalies in the powder bed after re-coating and laser scanning. An algorithm was applied to the captured images in order to detect anomalies between layers. Land et al. [9] used a similar method; however, this paper proposed the use of multiple cameras in order to image the build platform from multiple angles. This multi-camera approach allows for the parts being produced to be captured at different angles permitting their features to be observed.

Jacobsmühlen et al. [10] used a charge coupled device (CCD) camera mounted on the outside of the chamber door of an EOS M270. Images were captured using various light sources after powder recoating. Areas which appear shiny in the images are those in which there is a lack of powder deposited. These areas were highlighted using an image analysis tool and the operator was notified. This method illustrated that the setup can identify areas where there is insufficient powder deposited [10].

Other in-situ monitoring methods have been applied to the PBF process which utilizes the use of thermal imaging to monitor process signatures. A process signature is a dynamic characteristic of the PBF process, for example the size, shape or temperature of the melt pool during laser interaction. These signatures can significantly affect the final quality of the parts produced [3]. Monitoring of the process signatures has been previously investigated in [11], [12] and [13]. Thermal imaging allows the process signature to be monitored and used to control the process parameters such as laser speed and power. The ability to adjust the process parameters, laser speed and power, enables the process signature to be controlled [14].

Defects in the PBF processes lead to the weakening of the mechanical properties which are critical in some of the industrial applications using metal AM processes [6]. The origin of the defects can be caused by the following [15]:

a. Powder feedstock or chosen processing parameters.
b. Ineffective build planning such as part geometry, support design and part orientation.
c. Uncalibrated or damaged equipment.

The objective of an in-situ monitoring system is to identify defects that originate from the list shown above. Some of the common defects in the PBF process have been previously classified into the following categories, defined by the way the defect affects the quality of the final manufactured part [6]:

1. Geometry and Dimension – Geometric and dimensional inaccuracy.
2. Surface Quality – Surface roughness, morphology and deformation.

3. Microstructure – Anisotropy, heterogeneity and poor density.
4. Mechanical Properties – Fracture, cracking, porosity and lack of interlayer bonding.

These defects originate from the reasons outlined above. For the PBF process the resulting part quality relies on a consistent and uniform deposition of powder across the build plate. This ensures that the laser interaction is repeatable for each layer of the build. Variations in the uniformity of the powder layer can lead to re-melting of previous layers or lack of fusion to the previous layers.

This research will utilize the methods of line segment and anomaly detection to identify defects in the build platform. Line segment detection is a machine learning technique that identifies locally straight contours known as line segments in digital grey-scale images. Anomaly detection is the identification of patterns in data that do not conform to typical behavior. Failure to detect anomalies can cause loss of revenue and business as well as reputation. In smart manufacturing, data is gathered using sensors that monitor processing conditions. Detecting anomalies as they occur in production can indicate tool wear [16] and tear and whether a product is deviating from specification, thus, reducing scrap rates and lowering energy consumption [17]. Other applications of anomaly detection are ubiquitous in our data rich world, for example, fraud detection [18], telecommunications [19], bio-surveillance [20] and infection control [21].

Research in anomaly detection abounds in the scientific literature. Reviews and/or experimental studies are presented in [22], [23] and [24] from the statistical, machine learning and computer science perspectives, respectively. Gupta [25] provides a thorough review, comparing classification based, clustering based, nearest neighbor based, statistical and information theoretic approaches for anomaly detection using examples from the diverse fields of fraud detection, image processing, sensor networks and textual anomaly detection.

Kandanaarachchi and Mu [26] discussed the algorithm selection problem for unsupervised anomaly detection. Alternatively, a combination of techniques may be applied. Talagala et al, [27] provide a useful framework to optimize anomaly detection performance in high frequency time-series data. The framework is a 10-step process to aid the identification of end-user needs, prioritizing anomaly types and selecting suitable methods of anomaly detection, assessing and comparing their performance and making recommendations. An example of the use of this framework in water-quality data is given in [28].

In this research a standalone in-situ monitoring system for defect detection in the PBF process is presented. The monitoring method presented is a standalone optical monitoring system for the PBF process allowing the powder deposition and laser exposure to be monitored. Despite the rapid developments and improvements in the PBF processes the range of defects are currently limiting the repeatability of the process [6]. In-situ monitoring of the process has been identified as an area in need of further research for the additive manufacturing process [3].

Development of the Monitoring System

The aim of the development of the monitoring system presented in this research is to provide a standalone platform allowing for the build plate to be monitored layer-by-layer throughout the PBF process of Direct Metal Laser Sintering (DMLS). The method presented in this paper allows for the identification of defects and inefficiencies in the powder deposition stage. These defects may include but are not limited to:

- Lack of powder deposition (short-feeding)
- Raised edges or lifting parts

The system has been installed in the chamber of the EOS M280 DMLS machine in the South Eastern Applied Materials (SEAM) Research Centre in Waterford Institute of Technology. As the monitoring system is standalone from the operation of the M280, there are some constraints in the selection of the required image acquisition equipment. The installation of the selected system is presented in the following section.

Installed System

The chosen system consists of a 21 MP complementary metal oxide semiconductor (CMOS) monochrome camera with a 16 mm lens attached. This is mounted in the chamber above the build platform, as shown in Figure 2, to capture images of the build platform during the AM process. The camera is triggered using two laser trigger sensors mounted behind the machine panels, as shown in Figure 2. These sensors utilize the motion and position of the re-coater blade to trigger the camera and capture the image. The images are then collected by the camera controller unit and stored to an external hard drive.

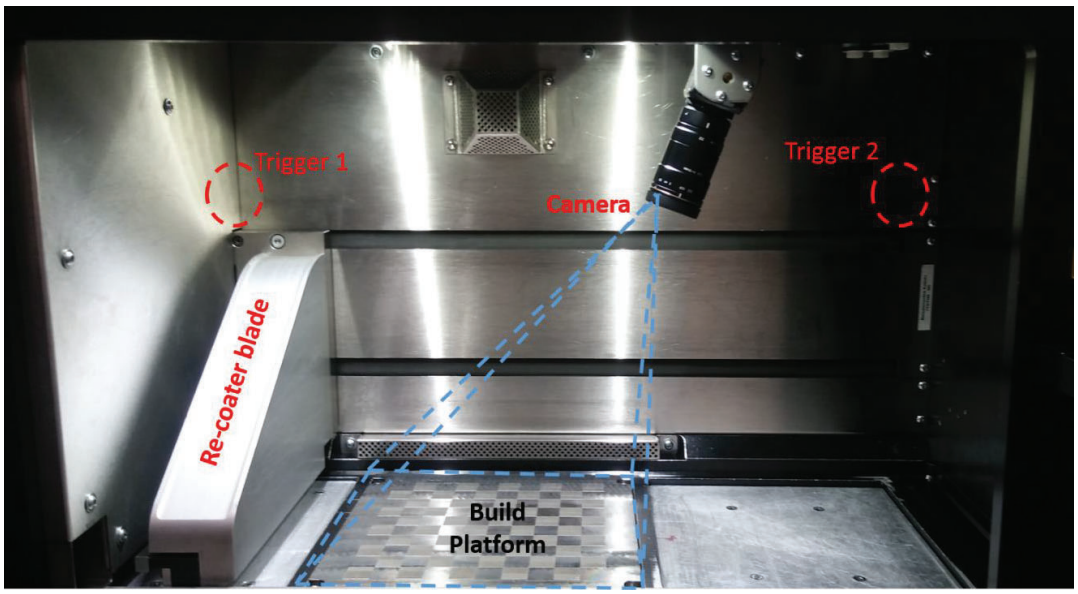


Figure 2: In-situ standalone monitoring system installed in the build chamber of the EOS M280 machine.

System Operation

The monitoring system captures two images per layer of the build process. An example of a pair of these images is shown in Figure 3 below. The first captured image, Figure 3(a), is the deposited powder layer, after re-coating, and the second image, Figure 3(b), is captured after the laser exposure. The first image enables the quality of the powder deposition to be assessed using the image analysis methods described in the next section.

(a) After Powder Deposition (b) After Laser Exposure

Figure 3: Captured images (a) after powder re-coated and (b) after laser exposure

Once the images have been captured they are sent to the camera controller unit which allows for image distortion correction due to the off-center location of the camera. The controller then stores the image onto the external hard drive allowing for the required image processing to be completed.

Image Processing

At present, the images are exported to a desktop PC for ex-situ analysis after the build process is completed. Future work will enable the acquired images to the analyzed in real-time during the AM process. Figure 4 shows a flowchart of the current operations carried out on the images acquired.

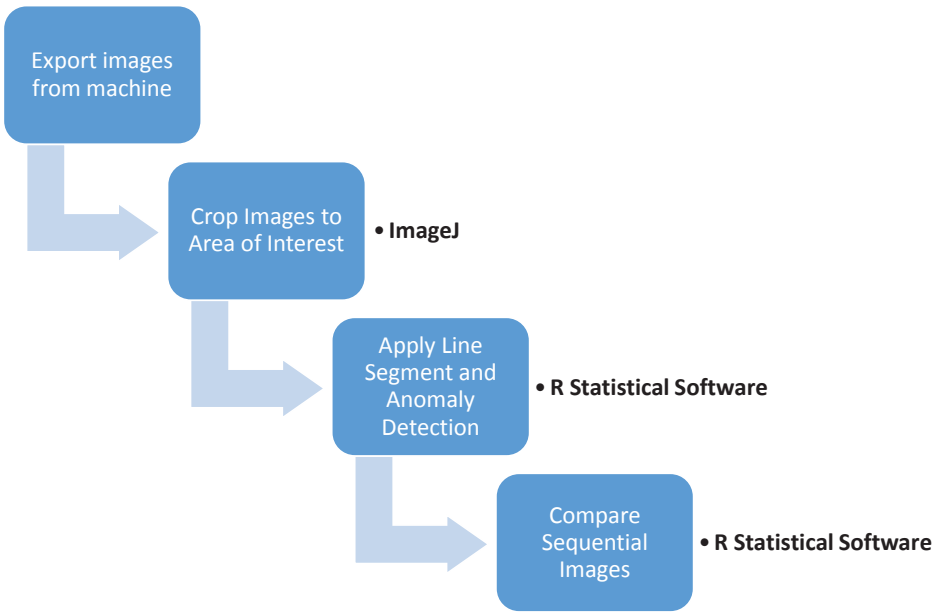


Figure 4: Flowchart of the image processing operations

Software packages ImageJ and R statistical are the used to process the images once they have been exported from the camera controller. ImageJ is an open source image analysis program [29]. A macro script is used to apply a batch crop on all of the images acquired from the camera. This allows for the regions of interest to be selected and the other areas to be removed. This is shown in Figure 5 below.

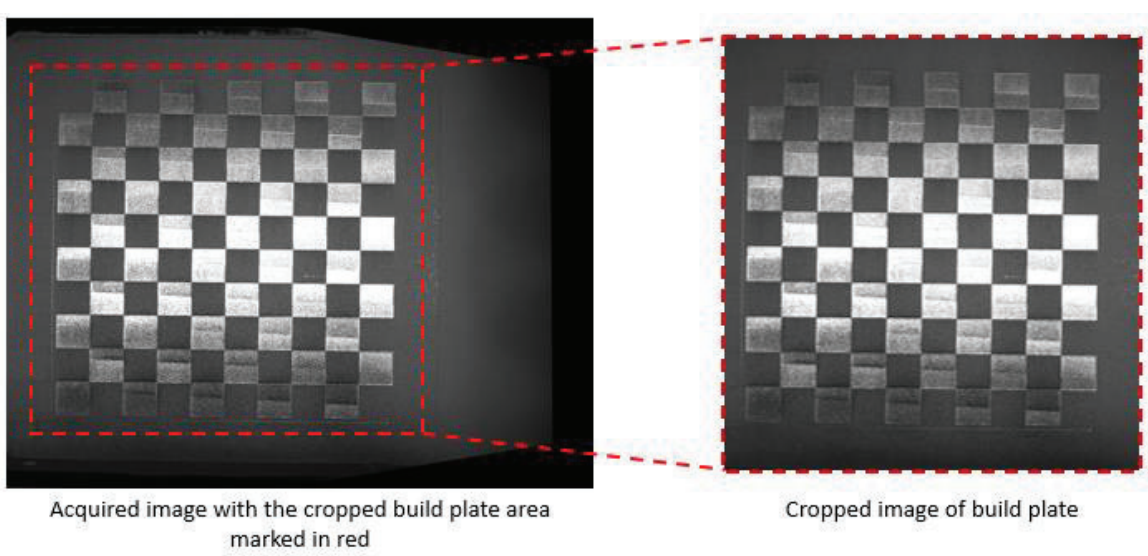


Figure 5: ImageJ cropping tool

Anomaly detection and line segment detection tools are applied to the cropped images using R Statistical Software [30]. In this paper we focus on the problem of detecting anomalous images of the powder bed pre-laser exposure. Study 1 in the following section discusses an example of the application of these image analysis tools in the PBF process. To aid the identification of process defects, line segment detection is applied, a machine learning technique which identifies locally straight contours known as line segments in digital grey-scale images. Each pixel of an image has an associated grey-level value and the contours or line segments that are detected by the algorithm are zones of the image where the grey-level is changing suddenly from dark to light or from light to dark [31]. The anomaly detection tool can then be used to detect anomalous counts of line segments in the images. The broader research challenge is to detect anomalous images of the entire build plate as they arrive in real-time and to alert the machine engineer in sufficient time to rectify the issue.

Study 1: Powder Short Feeding

The aim of this study is to evaluate the effectiveness of the installed monitoring system and of the newly developed image analysis methodology to identify instances of short feeding of powder, which leads to a lack of powder deposition on the parts being produced. In this study, multiple builds consisting of two sets of four 10mm^2 cubes were manufactured. The parts were positioned on the build plate in the locations shown in Figure 6. The two sets (Set 1 and Set 2 in Figure 6) of cubes were then cropped as shown in Figure 6, before being analyzed using the line segment detection and anomaly detection scripts.

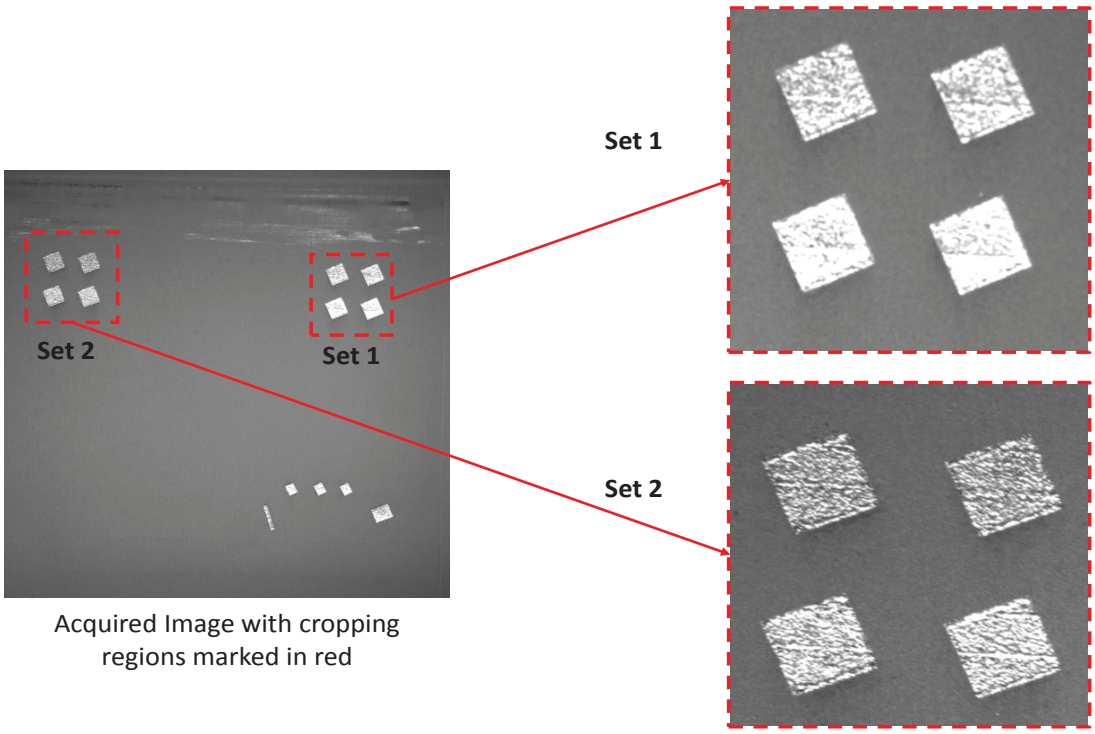


Figure 6: Cropping Regions for Set 1 and Set 2 of parts

Set 1 is the control set of samples and are built without any deliberate defects. Set 2 is deliberately subjected to some short-feeding of powder during the build between the build height of 4.5 mm and 6.5 mm. The short feeding will be induced by reducing the volume of powder that is fed to the re-coater blade before a new layer of powder is deposited. This will result in a region on the cubes in Set 2 with a shortage of powder deposited. This lack of deposited powder will result in the re-melting of previous layers causing voids and delamination in the part. The damage to the final part due to the short-feeding is presented in Figure 7. This type of damage can have a detrimental effect on a part, if not detected within two or three layers of the start of the short-feeding.

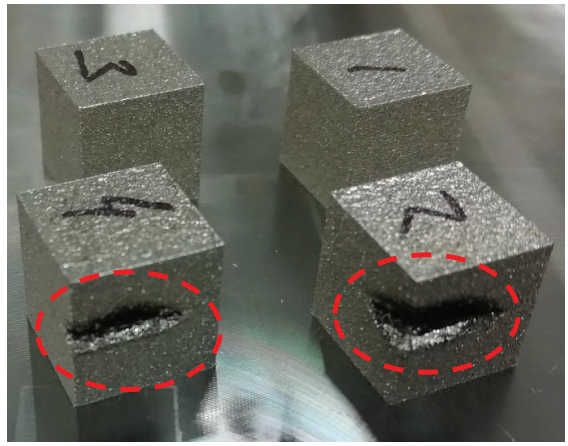
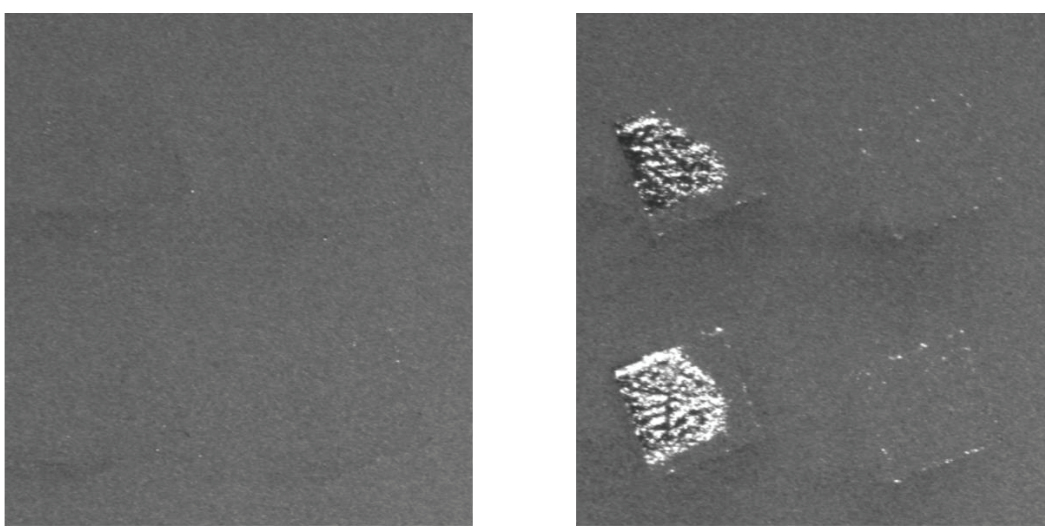


Figure 7: Set 2 parts - with damage due to short-feeding highlighted

The short-feeding was applied by reducing the amount of powder that is deposited on the build plate. This is controlled by the re-coating percentage, which can be explained as a percentage of the volume of the build area. Typical recoating parameters are 120%; meaning that 120% of the volume in the build area (i.e.120% layer thickness by the area of build platform) is re-coated. This ensures that the entire build plate is covered. The short-feeding of powder was created through the reduction of the re-coating parameters to 80%, for layers between the heights of 5 mm and 6 mm. This created an area on Set 2 of the cubes which received no powder during the recoating stage.

For example, images that capture unusual lines or patches of powder can be seen on the build plate. Figure 8(a) shows a typical image where a consistent layer of powder was deposited correctly on Set 2 parts prior to the introduction of short-feeding. Figure 8(b) shows and example of where short-feeding has occurred on these parts. This can be seen as an area on the part where there is no deposited powder, which exposes the previously melted layer. Typically, two to three problem layers can cause a defect in the built part.



(a) New Powder Layer – no short feeding

(b) New Powder Layer – short feeding

Figure 8: In-situ camera images showing (a) an example of correct powder distribution on the cubes in Set 2 after recoating and (b) an example of short-feeding resulting in insufficient powder being deposited on the cubes in Set 2.

The line segment detection tool has been used to identify this issue of short feeding, shown in Figure 8(b). When the short feeding of powder begins, the area with a lack of powder will show an increase in the number of line segments detected. This is indicated by a spike in the plot of the number of line segments per image, as shown in Figure 9. The anomaly detection tool is then used to track any deviation in the quantity of line segments detected and then inform the machine operator of the increase in the line segments detected.

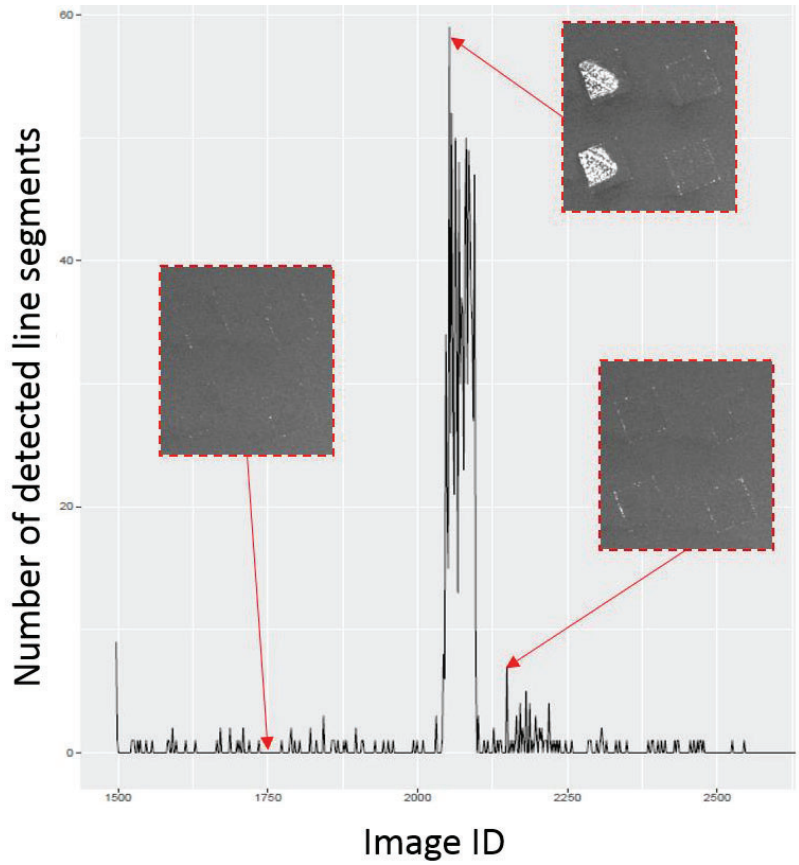


Figure 9: Line segment detection tool output with cooresponding Set 2 build images.

In Figure 9 it is clear from the number of line segments detected where a defect has begun to develop. The spike in the graph occurs 5.4 mm (Image ID 2041) into the build process. The deliberate short feeding of powder has reduced the quantity of powder deposited on the build plate, leaving an area on the parts without new powder. This exposes the previously melted layer which is then re-melted by the laser. This issue of short feeding can be rectified by operator intervention, if noticed in time. The operator can, once the defect has been identified, increase the quantity of powder fed to the re-coater blade. This intervention was applied in the study after 6.0 mm (Image ID 2101) of the build by increasing the amount of powder fed to the re-coater blade. This is shown in Figure 9 by a decrease in the line segments detected as the powder deposition recovers (Image ID 2130).

Conclusions

In this paper, a standalone monitoring system for the PBF process is presented. An accompanying image processing methodology has been developed, which can identify defects in the powder deposition stage of the DMLS process. The algorithm is computationally efficient and works well for the application presented. The images collected for Study 1 were analyzed post-build using R statistical software on a remote server. However, the method is efficient enough to use in real-time and work is ongoing to enable this process on site. With this facility an anomaly detection algorithm will be used to detect anomalous counts of line segments in the images.

Future work will expand the capability of the algorithm to enable defect detection in the images post-laser exposure, as well as enabling the defect detection to operate in real time with the process alerting the machine

operator of any identified defects. Thus, allowing the operator to alter the process as required to ensure the successful outcome of the AM build, reducing scrap costs for the process.

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