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Correlation of In-Process Monitoring Data and Defects in X-ray CT for Direct Metal Laser Sintering

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Direct Metal Laser Sintering (DMLS) is a type of Additive Manufacturing (AM) technique which is well suited for production of complex parts in low to medium volumes. The lack of quality assurance has been identified as a key barrier that reduces the speed of AM adoption by manufacturers for serial production. During AM serial production, random process instabilities can happen, and these can manifest to defects such as lack-of-fusion pores and cracks, which has a strong impact on fatigue performance and lead to early component failures.

In this study, an array of cutout coupons of an industrial swirler component was fabricated using the EOS M290 system. In-process monitoring using EOSTATE Exposure Optical Tomography (OT) was used to detect process instability during the production process. The Exposure OT is based on a camera collecting near-infrared emissions similar to that of a thermal imaging camera. Process instability was artificially generated by altering the inert gas flow at specific regions of the build platform. A poor inert gas flow condition can trigger smoke plume and splattering effect which can then lead to defocusing of the laser beam.

The process instability can be reflected as hotspots, which can be detected by the OT monitoring system. These hotspots can be correlated to porosity in X-ray CT scan. However, Exposure OT is sensitive and not all hotspots manifest into defects when compared to the CT results as some hotspots are unique process signature within the build part & support geometry. Comparative analysis of the data between OT and X-ray CT showed a series of conditions for which one can have strong correlation to defects. Firstly, hotspots with extreme mean grey values above a threshold of 80K have greater potential to manifest into porosities. Secondly, the overlap of hotspots in consecutive layers was observed to have greater potential to manifest into porosities. These conditions can be used to accelerate the decision-making process under a serial production scenario, where post inspection processes such as non-destructive and destructive testing can be reduced, lowering cost of quality assurance for parts.

NOMENCLATURE

DMLS = Direct Metal Laser Sintering
AM = Additive Manufacturing
OT = Optical Tomography
CT = Computed Tomography
GV = Grey Value

1. Introduction

Direct Metal Laser Sintering (DMLS) is a type of Additive Manufacturing (AM) technique which is well suited for production of complex parts in low to medium volumes. As AM technology shifts towards serial production, more demand is required for process reproducibility and traceability. The lack of quality assurance has been identified as a key barrier that reduces the speed of AM adoption by manufacturers for serial production [1].

During AM serial production, random process instabilities can happen due to lack of machine maintenance, statistical variances in gas flow, powder recoating or human error. These can manifest to defects such as lack-of-fusion pores and cracks, which has a strong impact on fatigue performance and lead to early component failures. Conventional part quality inspection includes non-destructive X-ray Computed Tomography (CT), which are often time-consuming and expensive.

The aim of this study is to correlate in-process monitoring data

and porosity in X-ray CT data, so as to accelerate the process of part validation and quality assurance.

In this study, an array of cutout coupons of an industrial swirler component was fabricated using the EOS M290 system. In-process monitoring using EOSTATE Exposure Optical Tomography (OT) was used to detect process instability during the production process. The Exposure OT is based on a camera collecting near-infrared emissions similar to that of a thermal imaging camera [2]. During printing, the camera captures 10 frames per second. At the end of each layer, the images are combined into a single image, as shown in Fig. 1.

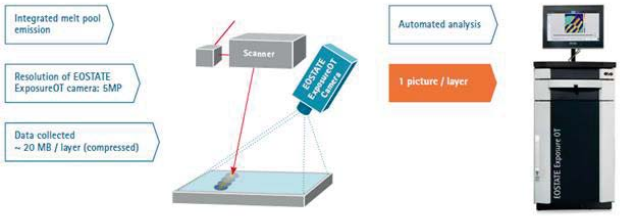

Fig. 1 The operating principle of EOSTATE Exposure OT for in-process monitoring [3]

2. Methodology for correlation of Exposure OT and X-ray CT scan

2.1 Experiment setup overview

A total of 21 coupons were distributed evenly on the build platform. The general workflow is shown in Fig. 2. To generate process instability, the inert gas flow was disrupted by partially blocking the outlet channel with aluminium foil. This created a zone of instabilities downstream of the blocked channel due to smoke plume and the signals can be strongly picked up in Exposure OT.

After the print job was completed, the effects of instability can then be studied using the OT signals and CT separately. Selected coupons in the instability zone were post-processed and evaluated using X-ray CT. The OT data and images for the corresponding coupons were evaluated to identify conditions for which defects can be detected.

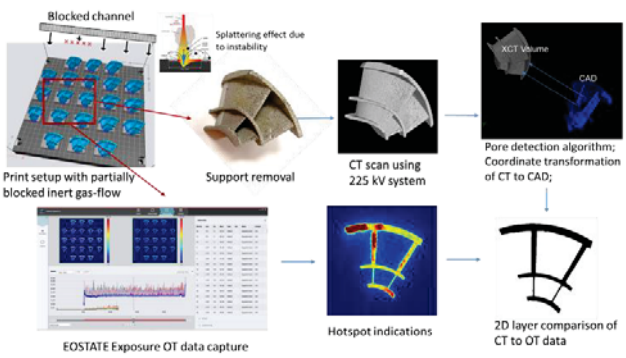

Fig. 2 Overall workflow for OT and CT evaluation

2.2 Exposure OT data capture

From the Exposure OT software, the OT raw images of every print layer can be exported for image analysis. The captured data contains the intensity in terms of Grey Value (GV) for each pixel. The software algorithm allows hotspots with extreme GV to be flagged out as indications for further analysis. These data were studied and later correlated to that of CT data.

2.3 X-ray CT scan and pore detection

The CT scan was conducted using Nikon XT H 225 ST equipment with reflection tube and flat panel detector. Voxel size of 25 µm is used. The projection data was processed with Nikon CT Pro software to build a reconstructed CT data and the quality of the scan was observed by rendering the volumetric CT data with VGStudio Max. Pore detection was conducted using a U-NET based deep learning algorithm developed by Bisma et al [4]. The Artificial Intelligence (AI) model used to segment this model was trained on 600 2D-dataset containing porosity of different shapes, and external geometry. The porosity detection of the rendered CT scan is shown in Fig. 3.

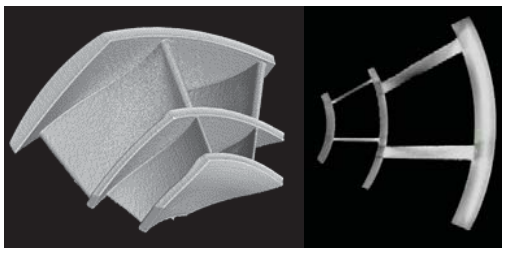

Fig. 3 CT reconstruction (left) and CT pore detection (right)

3. Results and discussions

The experiment with induced process instabilities yielded porosities which can be identified in CT scan. Most of these pores can be matched to OT hotspot indications. However, OT is more sensitive and not all indications manifest into defects according to the CT results. Based on the data analysis, two conditions were found to be highly correlated, namely hotspots of extreme mean values and overlapping hotspots in consecutive layers.

3.1 Hotspots with extreme mean GV

Firstly, hotspots with extreme mean GV have high potential to manifest into porosities. From the Exposure OT software, all the hotspots are tagged with the mean grey values. By arranging mean values of hotspots from highest to lowest, as shown in Fig. 4, there exists a small percentage of hotspots with very high mean values. Subsequently, by setting a threshold of 80K as grey value (~top 1%), the model narrowed down the characteristics of hotspots which may manifest into defects. It is to be noted that the specific values are material and process dependent.

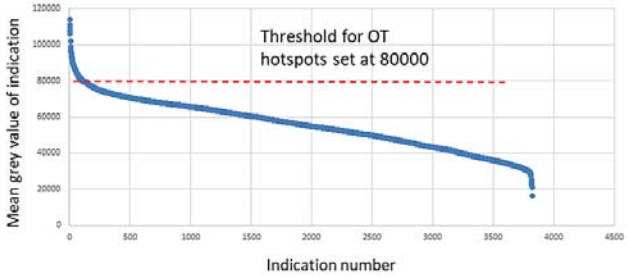

Fig. 4 Mean value of indication arranged in decreasing order

To illustrate the manifestation of defects due to extreme hotspot grey values, pictorial comparisons of the OT raw images and CT sliced data were conducted.

In Fig. 5, OT hotspot (GV~ 90K) at top left side was correlated to corresponding pores (circled in red, ~ 400 µm) detected in CT at layer of 14.36 mm height.

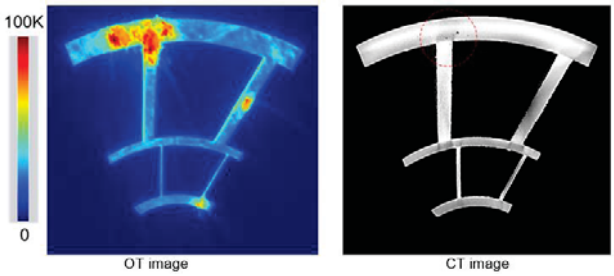

Fig. 5 Comparison of hotspots detected in OT to porosity in CT

In Fig. 6, OT hotspot (GV ~ 90K) on right side of fin was correlated to corresponding pores (circled in red, ~ 300 µm) detected in CT at layer of 12.04 mm height. Although a similar hotspot exist at the bottom right region, no pores were detected in CT. This showed that OT is sensitive to pick up instability and not all hotspots manifest into porosity.

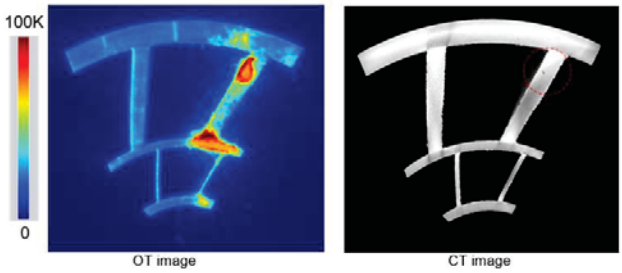

Fig. 6 Comparison of hotspots detected in OT to porosity in CT

3.2 Hotspots with overlap in consecutive layers

In the second condition, the overlap of hotspots in consecutive layers was observed to have greater potential to manifest into porosities. This condition requires greater scrutiny as the hotspots typically do not overlap fully, but only a small region for some of the overlapping hotspots. As the laser melting and solidification typically can penetrate more than one layer, single-layer instability has a high chance of healing, thus not all hotspots will become defects. However, instabilities occurring in consecutive layers can be stacked up and manifest into lack-of-fusion pores more readily.

In Fig. 7, OT hotspots (GV~ 80K) at upper left corner detected in consecutive layers were correlated to corresponding pores (circled in red, ~ 150 µm) detected in CT at 17.40 mm height.

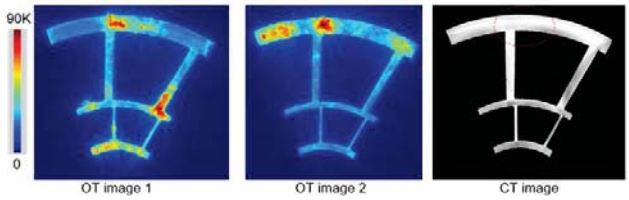

Fig. 7 Comparison of hotspots detected in OT in consecutive layers to porosity in CT

4. Conclusions

A first correlation between the OT data and pores detected in CT scan on an industrial swirler coupon was established. Two conditions of hotspot indications with extreme mean grey value and hotspot indications that overlap in consecutive layers were found to have higher probability of pore manifestation.

Using this information, the quality assurance engineer can quickly establish the part quality and minimize the costs from ordering additional non-destructive inspections, thereby lowering cost of quality assurance for parts.

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