Title:
Layering Defects Detection in Laser Powder Bed Fusion using Embedded Vision System

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Introduction:

AM technology is also known as 3D printing, rapid prototyping, or freeform fabrication. The process allows manufacture of a physical part by adding materials layer upon layer. Therefore, complex geometries and customized parts can be built directly from a 3D CAD model without using any tooling and additional resources as for conventional manufacturing processes. Due to its performance, AM is widely used in many areas, such as aerospace, biomedical, tooling, molding and defense industry [1]. Among available AM technologies in the market, LPBF is one of the most common AM technology that uses laser beam as a heat source to melt metallic powder layer by layer in a powder bed and forms final parts. One of the most significant prevents to the broad adoption of AM is the qualification of final AM parts [1]. Some defects can be explained by the interaction between the layering system and the powder bed in the layering stage (keyhole induced by a lack of powder), by non-well melted areas during the melting stage (porosity or keyhole) [2], or by part distortions in the solidification and cooling stages (cracking, warpage, base plate separation,...) [3], and so on.

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 [4]. Thus, in-situ monitoring in AM is major cause for concern to its industrialization. Recently, some papers related to this cause for concern were published. Luke Scime and Jack Beuth et al. [4, 5] focused on analyzing powder bed images using a computer vision algorithm and a multi-scale convolutional neural network to automatically detect and classify anomalies that occur during the layering stage. Christian Gobert and his colleagues applied supervised machine learning for defect detection during metallic LPBF AM using high resolution imaging [6]. M. Abdelrahman studied flaw detection in LPBF using optical imaging [7]. Defects in AM processes are mostly not detected before post-processing inspection and testing. AM parts are evaluated on their porosity and inclusion defects through the Archimedes method or destructive testing method. Although these methods are effective for estimating density and porosity, the evaluation processes are less efficient. It is also hard to exhibit the defect shape and actual location inside an AM part [8].

In order to clearly display part defects, CT method is also used. CT is also known as a non-destructive testing method that applied for geometrical reconstruction and analyzing defects of AM parts. However,

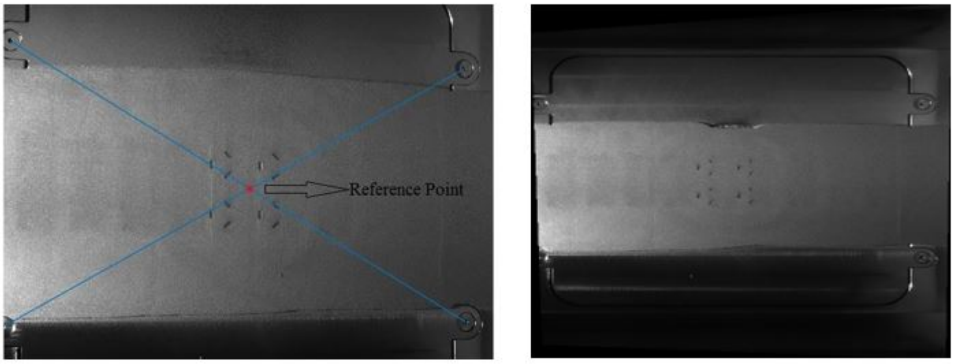

Fig. 1: Left: Reference points detection; Right: after applying Homography transformation

these conventional inspection methods also present some drawbacks that may be listed further: they are mainly both time-consuming and resources-consuming and may sometimes initiate unexpected defects. Contrary to CT scans inspection method, in-situ defect detection, such as layer wise visual inspection, enables the potential for in-process adjustments and thus facilitates in-process part qualification [6].

There are few approaches for linking powder bed measurements during production with internal defects in LBPF parts. This paper proposes a method that may almost provide real-time monitoring, allowing defects to be predicted, and potentially corrected before the build ends, saving time and resources. More especially, it is to monitor the powder bed to detect defects in AM part that may impact on the stability of the process as a whole [4]. It can be considered as an in-situ monitoring process and it is also potential to become a component of a real-time control system in the LPBF process. In particular, some image processing algorithms are developed to automatically detect defects that occur during the layering stage of the printing process from post-layering and post-melting images of all layers. After that, it is possible to obtain a 3D Voxel-based model of manufactured parts including potential defect areas in the parts. This model is also compared to a corresponding 3D model of the build that was achieved by X-ray Computed Tomography (CT) scan data using Fiji software. This allows evaluating the relevance of the proposed method. The results obtained in this study demonstrate that the proposed method can be used for in-situ monitoring of LPBF process.

Procedure and Methods:

Homography correction and edge detection process for all images:

In this paper, results and data are obtained from an AddUp FormUp 350 LPBF machine. The visible powder bed images are taken through a viewpoint located directly above the build chamber by using a camera and lighting configurations. Images with a resolution of 2448 x 2050 pixels are automatically captured after the layering and the melting stage of each layer. Thus n*2 images are considered, here n is the number of layers of the build: the studied build presents 462*2=924 pictures. All programs were developed in the MATLAB R2016a programming environments. This work is based on the following hypothesis, an important part of the porosity defects can come from the layering. Indeed, we regularly observe areas where the layering process does not deposit material. These areas of lack of powder are analyzed and linked to porosity.

The raw images were captured by the visible camera that causes several difficulties preventing direct computation in image processing. The camera mounting and lighting conditions remain consistent throughout a build as well as between different builds. So it is necessary to have image enhancements that are used to improve the accuracy of image processing, especially in edge detection stages. These adjustments include perspective distortion correction using a fully constrained Homography (H) matrix and noise reduction process. The camera is mounted such that its axis is not parallel to the printer Z axis (the powder bed is on a (X;Y) plane). It warps and scales the shape of a rectangle on a (X;Y) plane which can be defined by 4-reference points. In our case these 4 points are visible on the images. Please notice that these points are visible only in the first layers of the build, due to powder spreading that recover them during the process. Hence, the hypothesis of the camera mounting consistency is essential. By measuring these four points on the powder bed the homography and the associated matrix H can be computed, then this H matrix is applied to all images. The result of applying H matrix for the image is illustrated in the Fig. 1. This perspective distortion correction may be called as homography correction process.

During printing, the lighting conditions cause a haloing effect in the images that is detrimental to the image processing. Random noise present in the images was reduced mainly by using a Gaussian filter. This Gaussian filter is also applied to each powder bed image to levelize the lighting across the powder bed. The authors also used a suitable adaptive threshold value to convert the gray scale images into binary images. In particular, the noise reduction is also applied in the previous step (finding H matrix) to detect more exactly the edges of the different area. The result of edge detection of the melting images represents the manufactured part. The result of edge detection of layering images can be related to non-well recovered areas that may engender keyhole during the next melting step, and thus can be called as potential defect areas. In this process, the authors used a Sobel filter with the adaptive threshold value in each image for the edge detection task for the melting images group. After that, only keep the potential defects regions that are entirely on manufactured part and eliminate the remaining ones. This work is done for 2 images in both types respectively with the same slice of the manufactured part. These achieved results as in the Fig. 2 is used for constructing 3D volume that represents defects on the powder bed.

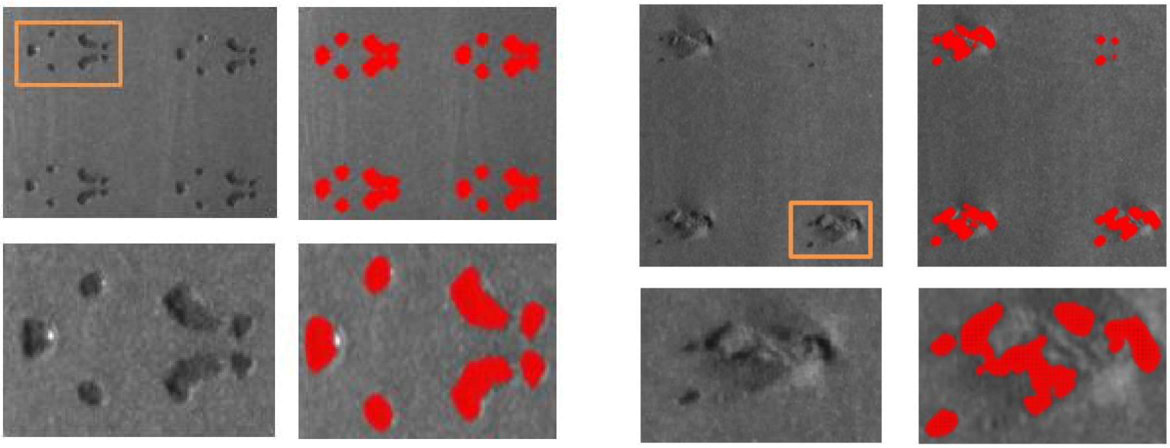

Fig. 2: Edge detection process for some images and detail of one area of each image: (a) Melting image (247) (b) Layering image (398)

Building 3D volume objects from images:

Voxel-based modelling is based on the use of a collection of voxels to model 3D objects. Compared to traditional solid modelling techniques, voxel-based modelling has several advantages, such as offers

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simple, intuitive, unambiguous, and unique representation, has identical complexity for all objects, and easily incorporates heterogeneity and anisotropy of models into analysis [9]. Thus, voxel-based modelling is suitable to use in the field of layered manufacturing. In particular, voxel-based method is applied to geometric modelling for layered manufacturing technologies for its advantages. For each image, we

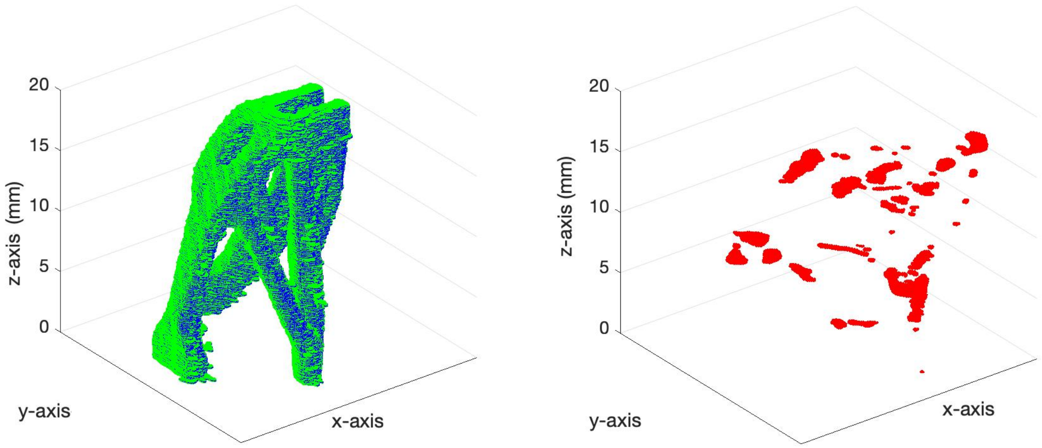

Fig. 3: Voxel map : (a) Printing 3D volume object (b) Potential defects 3D volume object

perform an edge detection. This allows us to detect the areas of fusion and therefore of the future part on the melting stage images (figure 3a), and to detect the lack of powder area on the layering stage images which potentially presents risks of porosity (figure 3b). Then, all achieved pixels of all images in each group (post-layering and post-melting) are regrouped by using an algorithm developed on MATLAB. Two voxel maps including the pixels identified on the set of image pairs for each layer can be built. One represents potential defect areas achieved from post-layering images and the second one represents manufactured parts achieved from post-melting images (Fig. 3). The first object will be used to compare and evaluate the porosity in the manufactured part built from CT scan data. The second object is close to the manufactured part that will be built from the CT scan data by using Fiji software mentioned in the next step. Besides, the separate manufactured voxel map and the corresponding defect voxel map is also built to identify only the potential defect located inside the studied part.

Porosity Analysis:

A ratio is determined by the division between the volume of the voxel map of the defect and volume of the voxel map of the part, this ratio is close to 0.77 percents for the 4 parts studied. This ratio represents the potential defect ratio achieved by image processing algorithms. In order to analyse the results, a CT scan of the four studied parts is performed. The input data of CT scan is a voxel map with a $20\mu m$ voxel size. Volume object is built after using a suitable process in Fiji. The porosity analysis is conducted using analyse particles function in Fiji. The ratio of defects for the four parts are between 0.11 percents and 0.13 percents. Our results on porosity prediction overestimate the value of porosity. These differences in results may be mainly due to two factors. The first one concerns the measurement of tomography, the resolution used may not be small enough to identify all porosity. The second is that we consider that porosity problems occur in all the area where there is a lack of powder, whereas in the construction of the next layer there is potentially an additional supply of powder that the laser can fuse.

Conclusion:

This study was conducted to detect potential defect areas in parts obtained by a powder bed based 3D printer, using a method that can be considered as an in-situ monitoring in the printing process of a LPBF AM machine. An algorithm using image processing in MATLAB was developed to build 3D Voxel-based model of manufactured parts with defects from post-layering and post-melting images. The achieved model was also compared to 3D model of manufactured part that was built from CT scan data by using Fiji software. This comparison process allows evaluating the performance of the proposed method. The results obtained in this study demonstrate that the proposed method could be a feasible solution in terms of idea and implementation method. Therefore, it can be used for in-situ monitoring of LPBF process. Future work by the authors will focus on some important targets such as improving the accuracy of edge detection process (especially, for the melting images), to compare and evaluate the accuracy the reconstruction. We will also work on a better understanding of porosity phenomena in relation to the detection of observed defect areas.

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