A Novel Method for In-process Inspection of Lattice Structures via In-situ Layerwise Imaging

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Abstract. Lattice structure are among most promising geometrical features to take full advantage of the design freedom enabled by additive manufacturing. However, their several benefits can be adversely affected by local defects and geometrical deviations, which can be hardly identified via ex-situ metrology. This paper is the first to prove that lattice structure inspection can be implemented in-situ, tackling the uncertainty of in-process imaging. The method combines powder bed image segmentation with robust statistical modelling to translate the in-line 3D geometry reconstruction into a 1D representation of unit cell's properties. Results demonstrate the agreement between in-situ modelling and ex-situ ground-truth inspections.

Keywords: powder bed fusion; lattice; geometry reconstruction; in-situ monitoring; powder bed camera.

1. Introduction

Thanks to the increasing industrial adoption of additive manufacturing technologies, a novel level of shape complexity is replacing traditional designs for a variety of high value-added products. Despite several enabled benefits, brand new challenges must be faced, including the need to rethink statistical quality modelling and monitoring methodologies. Indeed, traditional methods are conceived for simple geometrical and/or dimensional features, and they require a design (training) phase consisting of several copies of the same part. In a rapidly evolving discrete manufacturing scenario where products are more and more characterized by complex shapes and customization is pushed to unprecedented levels, these methods are not effective or even not applicable anymore.

A category of complex shapes enabled by additive manufacturing processes consists of lattice structures, i.e., geometries where a unit cell of given geometry regularly repeats in space within the part, enabling enhanced mechanical and functional properties [1]. Lattice structures are effectively adopted for a wide range of industrial applications, e.g., in automotive, aerospace, space, oil and gas, and bio-medical applications [2]. Various authors pointed out that geometrical and volumetric defects in lattice structures have detrimental effects on their functional performance [3 – 5]. Nevertheless, there is a lack of statistical quality modelling and monitoring methods for these structures. The common practice, discussed and adopted in previous studies [3 – 7] consists of using global and synthetic quality indexes, like the average distance between each pair of struts, called average pore size, or the ratio between the empty volume and the overall envelope volume of the unit cell. Relying on these descriptors entails a great information loss, which in turns limits the effectiveness of statistical inference applied to industrial quality control and the reliability of product qualification procedures.

A different perspective was proposed by Colosimo et al. [8]. They presented a quality modelling approach based on the seminal idea of translating the complex 3-D shape reconstructed via x-ray computed tomography (CT) into a 1-D model of deviations from the nominal shape of each unit cell. Colosimo et al. [8] showed that the method enabled the detection of geometrical errors and distortions affecting portions of the lattice structure within a statistical profile monitoring framework [9]. The present study inherits and extends this seminal idea by moving from *ex-situ* CT measurements to *in-situ* and in-line powder bed images of the solidified layers. The proposed methodology combines an image processing step, for the segmentation of solidified layers in powder bed images, with a statistical modelling step to translate layerwise computed properties into a 1-D profile representation, i.e., a quality signature in a functional format that maps the quantity of interest along the build direction at unit cell level. A primary aspect of the proposed approach regards the way in which the uncertainty resulting from in-situ measurements is tackled and embedded into the model. Indeed, the uncertainty affecting the layerwise geometry reconstruction inflates the variability of modelled features, possibly limiting the effectiveness in detecting anomalous deviations [10 - 11]. Starting from the preliminary results presented in [12], the present study presents a novel approach that, thanks to a weighted modelling framework, allows achieving not only an accurate in-line geometry characterization, but also a low prediction uncertainty that is needed to enhance anomaly detection capabilities. Our approach is specifically aimed at synthesizing and modelling quality metrics of lattice structures at unit cell level, by translating the 3D information into a 1D representation. The purpose is to enable the detection of local distortions and geometrical errors affecting one unit cell, or a small group of unit cells, compared to the rest of cells in the same part. The same approach can be used also to compare, at unit cell level, multiple copies of the same lattice structure, for process monitoring purposes in the presence of a series production.

This study presents the effectiveness of the proposed approach in laser powder bed fusion (L-PBF). Ex-situ x-ray CT inspection was used to determine the ground truth of as-built lattice structure geometries. The preliminary results here presented highlight the good agreement between in-situ and ex-situ reconstructions, opening to the development of novel process monitoring and product qualification solutions.

The paper is organized as follows: section 2 introduces the methodology, section 3 presents the results achieved in the L-PBF case study, section 4 concludes the paper.

2. Methodology

The scheme of the proposed approach is depicted in Fig. 1. It relies on high spatial resolution images of the powder bed acquired after the melting phase in each layer before the powder recoating in the following layer. All industrial L-PBF systems are equipped with powder bed cameras that can be used to this aim. The method consists of three main steps briefly described in the following.

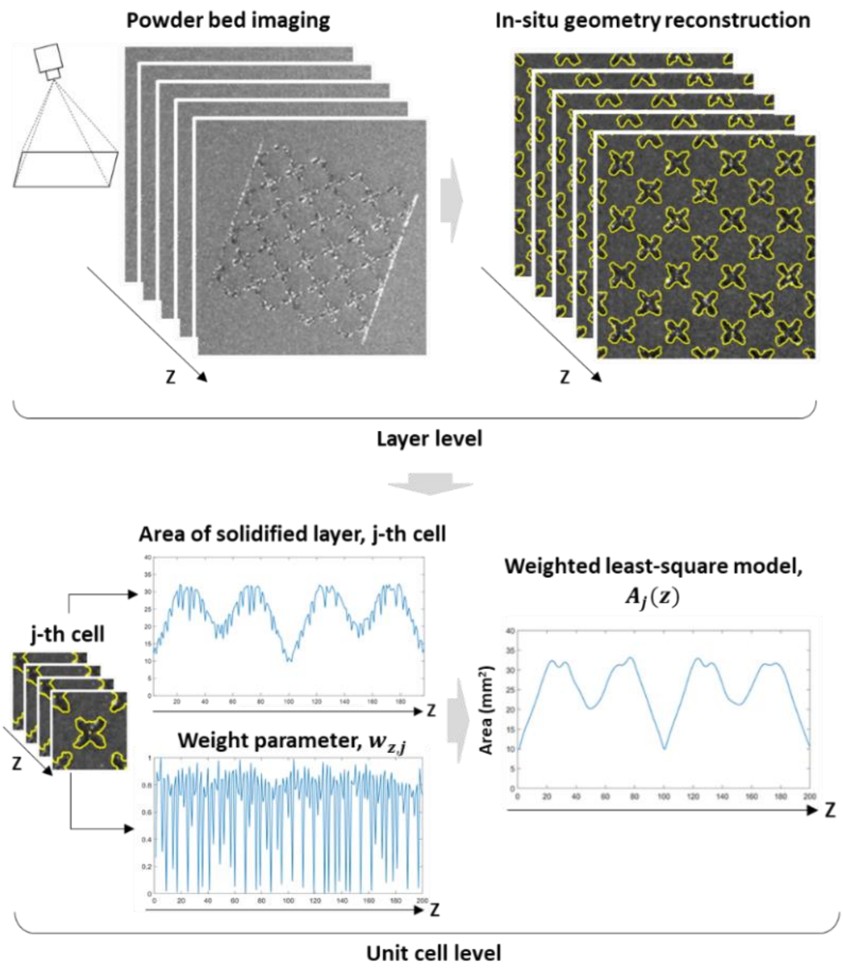

Fig. 1 – Scheme of the proposed approach

The first step involves the segmentation of the powder bed image to reconstruct the solidified layer geometry. To this aim, the active contours segmentation methodology presented in Pagani et al. [13] can be used. It involves an iterative level set procedure that starts from a first contour definition in the form of a closed curve (i.e., the nominal shape of the layer from the sliced CAD model) and iteratively modifies the contour by minimizing an energy functional that depends on both edge-based and region-based properties.

The second step consists of computing, layer by layer and cell by cell, any quantity of interest suitable to characterize the segmented region. In this paper, we use the area of the solidified layer as synthetic descriptor, but other quantities could be used as well. As an example, the deviation from the nominal shape can be computed if powder bed images are properly aligned to the slices of the originating CAD model. At this stage, another metric is computed, i.e., a metric representative of the uncertainty of layerwise geometry reconstruction. Indeed, layerwise variations of pixel intensity patterns in the foreground (i.e., the solidified layer) and the contrast between foreground and background (i.e., the loose powder) may affect the accuracy of image segmentation in different layers. Such variations are mainly associated to layerwise changing scan directions that affect the surface texture and directional light reflection properties. A variety of factors may influence the in-situ reconstruction accuracy. Among them, the reflectivity of the powder bed surface, due to material type and powder properties, together with the regularity of the powder bed topography play a major role. Thus, one key idea of the proposed approach consists of taking into account the in-line geometry reconstruction uncertainty to enhance the unit cell shape modelling. Based on previous studies in L-PBF [14], it is known that a dark field condition, i.e., when the majority of light is not reflected by the foreground surface towards the camera, allows enhancing the foreground contour identification. Thus, the proposed metric is a scalar weight, $w_{z,j}$, whose value is large when a dark field condition occurs in the z-th layer of the j-th unit cell, and small when the opposite condition, also call bright field, occurs. The lower is $w_{z,j}$, the higher is the uncertainty about the in-situ geometry reconstruction in the z-th layer of the j-th unit cell. The weight $w_{z,j}$ can be computed by identifying a region of interest consisting of a band of predefined width centered around the contour of the segmented solidified layer. It is such that one half of the band belongs to the foreground region (solidified layer), and the other half belongs to the background (loose powder surrounding the part). Such region is identified by means of morphological operations on the binary image resulting from the active contours segmentation. The weight $w_{z,j}$ is then defined as the inverse of the variance of pixel intensities within this region, for the j-th cell in the z-th layer. The rationale is that a high pixel variance around the contour of the solidified layer is in indication of a bright field condition, which implies a high reconstruction uncertainty and consequently a low weight in our proposed model. The opposite occurs in the presence of a dark field condition. The width of the band used as region of interest for the weight computation was 11 pixels in this study.

At the end of the former two steps, a discrete quantity, e.g., the area of the solidified layer, can be computed for each unit cell in all the layers the cell has been sliced into. In this study, we computed such area as $A_j(z) = r^2 Np_{j,z}$, where $Np_{j,z}$ is the number of pixels in the segmented solidified layer of the j-th unit cell in the z-the layer, and r is the spatial resolution of the powder bed camera (in mm/pixel). The last step of the method consists of passing from a discrete to a functional representation of the quantity of interest by fitting a model. In order to include the in-line reconstruction uncertainty information into this model, a weighted least-square estimation is advocated, where the weight matrix $\boldsymbol{W}$ is a diagonal matrix whose elements on the main diagonal are the weight $w_{z,j}$. Following the approach proposed in [8], we propose using a B-spline model formulation, where the number of basis functions and the knot sequence can be determined by looking at the salient features of the nominal unit cell geometry. The result is a 1-D curve $A_j(z)$ that captures the evolution of the j-th unit cell geometry along the build direction Z, where the z-th value measures the area of the in-line reconstructed cell in the z-th layer along the build direction[1]. By comparing the 1-D curves associated to different cells it is possible to make inference about the shape variability within one lattice structure and between copies of the same structure, enabling the detection of outlying patterns and possible geometrical defects.

3. Test case and results

The proposed approach was tested during the production of maraging steel lattice structures on an industrial L-PBF machine, namely a Trumpf TruPrint 3000. A gas-atomized 18Ni (300) maraging alloy powder with average particle size of 35 μm was used. The lattice structures were composed by 4 × 4 × 4 rhombic unit cells. Each cell had a size of 10 × 10 × 10 mm and a nominal strut diameter equal to 1.5 mm. The cubic lattice structures were produced with two lateral walls of 0.6 mm thickness, not considered in the analysis presented in this study. It is worth noticing that the minimum size of the geometrical features that can be reconstructed in-situ depends on the spatial resolution of the powder bed camera. In this study, the struct diameters was 15 times larger than the spatial resolution, enabling a reasonably accurate reconstruction. Much finer features would need the adoption of a much higher resolution. The lattice structures were produced with fixed process parameters (laser power 275 W, scan speed 1200 mm/s, hatch distance 0.09 mm and layer thickness 0.05 mm), with a meandering line scan strategy and rotation of the scan direction of 67° per layer. Fig. 2 shows an example of manufactured lattice structures together with the nominal geometry of the unit cell.

[1] To allow the comparison between cells printed at different heights of the build, the domain z is normalized in the range $[1\ n]$ for all cells, such that $z = 1$ refers to the first layer belonging to the unit cell, and n is the total number of layers within the cell, assumed equal for all unit cells.

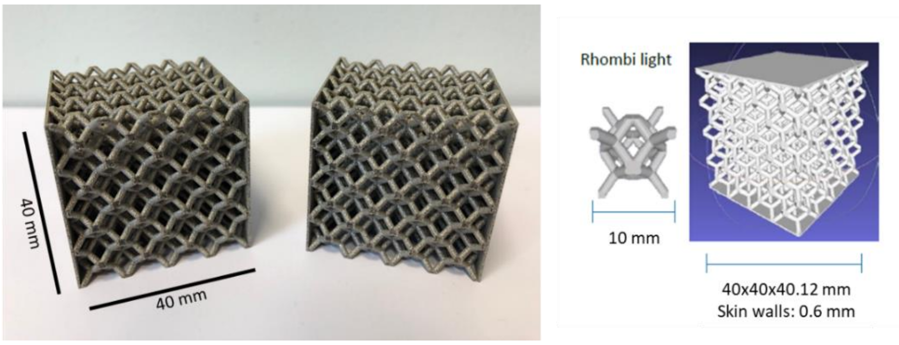

Fig. 2 – Example of two as-built lattice structures (left) and corresponding nominal geometry (right)

The Trumpf TruPrint 3000 is equipped with an embedded powder bed camera placed on the top of the build chamber. Powder bed images are captured with a spatial resolution of 100 μm/pixel exploiting a flashlight inclined at 60° with respect to the build plate.

A ground truth reference of the as-built geometry was obtained by means of x-ray CT using a North Star Imaging X25 X-ray CT scan system with a voxel size of 33 μm.

Fig. 3 shows an example of layerwise measurements of the solidified layer area in one unit cell with the corresponding weighted least-square B-spline fitting $A_j(z)$ and the ground truth reference based on ex-situ CT scan. Fig. 3 shows that the measured area profile exhibits spikes towards underestimated values that systematically repeats within the whole domain. Fig. 3 also shows an example of powder bed image corresponding to one of these spikes and a powder bed image where the agreement between the in-situ reconstructed model and the ex-situ CT reference is higher.

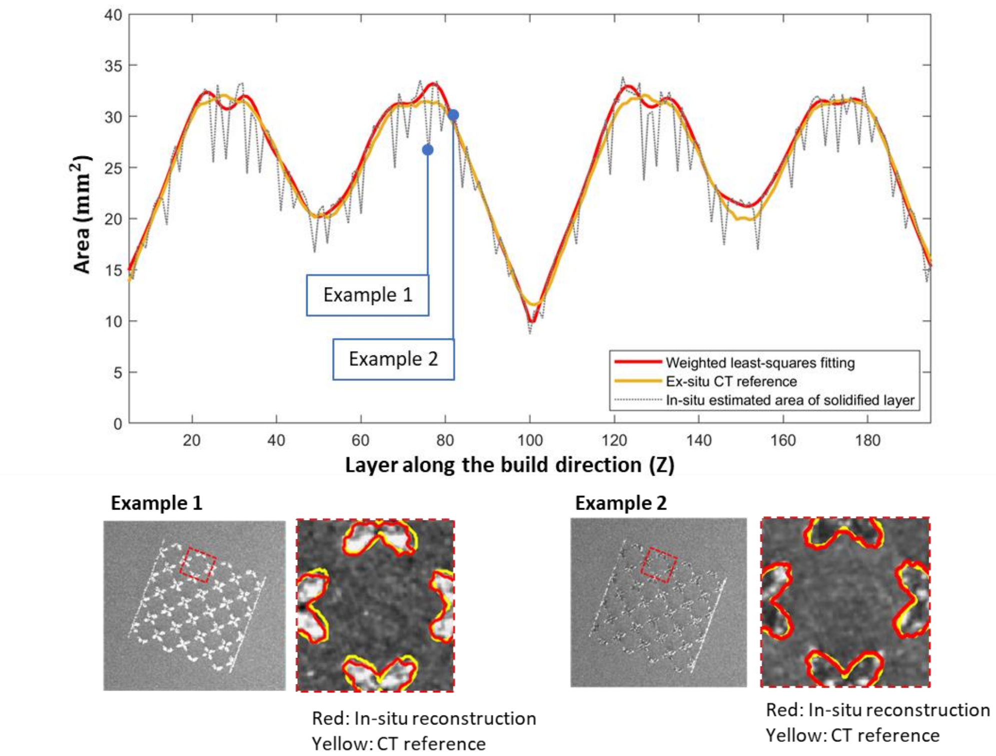

Fig. 3 – Example of example of layerwise measured solidified layer area in one unit cell with the corresponding weighted least-square B-spline fitting $A_j(z)$ and the ground truth reference based on ex-situ CT scan; bottom panels show a superimposition of in-situ reconstructed contours and CT-based ground truth contours in two layers characterized by a poor fidelity (example 1) and high fidelity (example 2) reconstruction

The underestimation of the solidified layer area occurred when the scan direction was such that a bright field condition was generated, causing a high intensity (and partially saturated) foreground area. Layers affected by this pattern are the ones with the lower value of the weight parameter. Because of this, the proposed weighted least-square modelling approach led to a robust and accurate reconstruction of the 1-D area profile along the build direction.

Fig. 4 shows the 95% prediction interval of the 1-D area profiles $A_j(z)$ of the same unit cell belonging to two copies of the same lattice structure manufactured within the same build. The prediction intervals are superimposed to the reference area profiles obtained via ex-situ CT scan for the same cells.

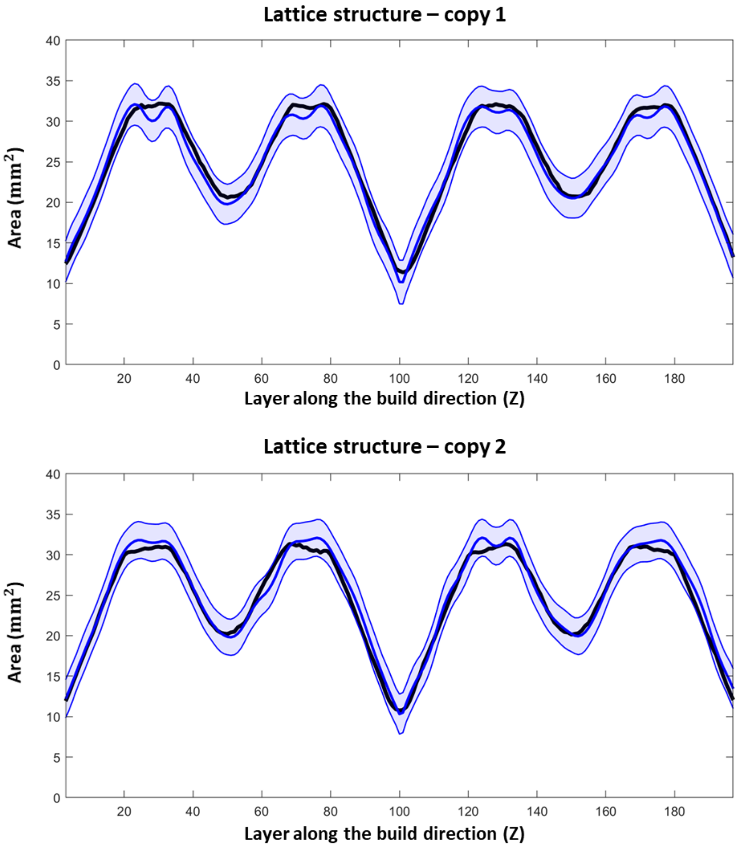

Fig. 4 - 95% prediction intervals for in-situ estimated area profiles $A_j(z)$ for one unit cell of two copies of the same lattice structure (blue band) compared to the ex-situ CT reference (black solid line)

Fig. 4 shows that, for both the structures, the prediction interval includes the reference profile, which indicates the statistically significant matching between the in-situ geometry model and the ground truth. The fidelity of in-situ geometry modelling is needed to anticipate, while the part is being produced and on a cell-by-cell scale, the detection of shape deviations that may correspond to actual defects and non-conformity. Such in-situ geometry reconstruction and modelling prediction enables the development of automated in-situ monitoring methods, to be possibly used in combination with in-line defect repair or removal solutions, as a step towards novel zero-defect additive manufacturing capabilities.

4. Conclusion

The industrial adoption of in-situ measurements combined with appropriate data modelling techniques can open to new product qualification and statistical quality monitoring solutions in additive manufacturing. The proposed method enables a quick in-line analysis of within-part and part-to-part variability. Moreover, thanks to the characterization of a quality signature at unit cell level, it allows the possible detection of geometrical errors and anomalies unless they originate after the current layer has been printed. Ongoing research is devoted to better characterize the benefits of the proposed weighted modelling approach against benchmark competitors. Future developments will also include the test and validation in the presence of 1) different lattice geometries, to support part-to-part and build-to-build variability analysis, and 2) defect-free and defective parts, to demonstrate the potential of the proposed approach for process monitoring and anomaly detection purposes. More extensive follow up studies could be also aimed at investigating the performance of the method in the presence of changes in process and material settings.

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