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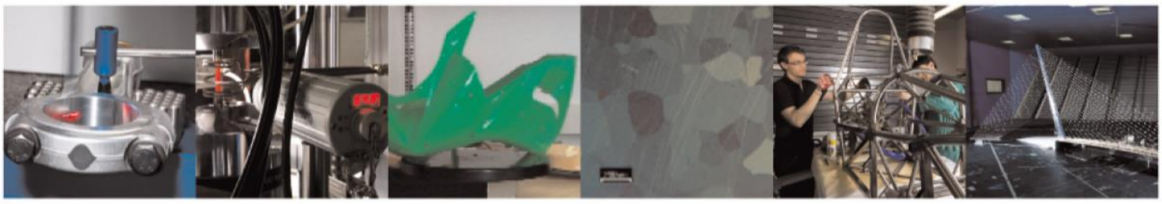

Quality Monitoring and Control in Additive Manufacturing

Bianca M. Colosimo

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http://www.mecc.polimi.it
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Quality monitoring and control in additive manufacturing

by *Bianca Maria Colosimo*

Keywords: *quality, statistical process monitoring, statistical process control, SPC, additive manufacturing, 3D printing, in-situ monitoring, quality control, machine learning, profile, image, video.*

Abstract: Additive manufacturing has a great potential for the development of innovative industrial applications in different domains, as it enables the production of complex shapes, topologically optimized structures and high-value-added components with novel embedded functionalities that are difficult or even impossible to produce with traditional technologies. However, stringent quality standards and qualification requirements impose defect-free and first-time-right capabilities that are still challenging to achieve with state-of-the-art AM systems. This chapter discusses existing solutions and open challenges for quality modelling, monitoring and control in AM.

1 Introduction

Additive Manufacturing (AM), also known as 3D printing, refers to an emerging class of manufacturing processes[1][2], which allows one to produce a novel generation of products characterized by complex shapes, topologically optimized structures and high-value-added components with novel embedded functionalities and mechanical properties, which are difficult or even impossible to produce with traditional technologies. Metal additive manufacturing (AM) has a great potential for the development of innovative industrial applications in different domains, e.g., aerospace, bio-medical, tooling and molding, automotive (Figure 1). Contrary to traditional processes, AM does not need any dedicated, part-specific tool or fixture and thus allows designers to enjoy an almost complete *design freedom*. Compared with traditional processes, where product complexity is always associated to expensive processes and complex set-ups, AM allows one to realize complex shapes without significant cost increase and this is why it is often considered as a viable solution to achieve "*complexity for free*".

Targeted applications of AM design freedom and digital manufacturing are: i) customized parts (in biomedical and dental applications); ii) lightweight designs (in the aerospace and the automotive industries); iii) functionally-enhanced parts (complex cooling in heat exchangers and molds in the oil and gas and machinery sectors). In all these applications, stringent quality standards and qualification requirements impose defect-free and first-time-right capabilities that are still challenging to achieve with state-of-the-art AM systems. Shape complexity and high customization of AM parts produce as side effect new challenges for quality inspection, measurement and control. On the other hand, the layerwise nature of the process (Figure 2) allows one to acquire big data streams during the process itself, to keep it under continuous control and provide the final product with a sort of digital ID card based on in-situ gathered information.

This article focuses on existing solutions and novel challenges for quality inspection, monitoring and control of AM products and processes.

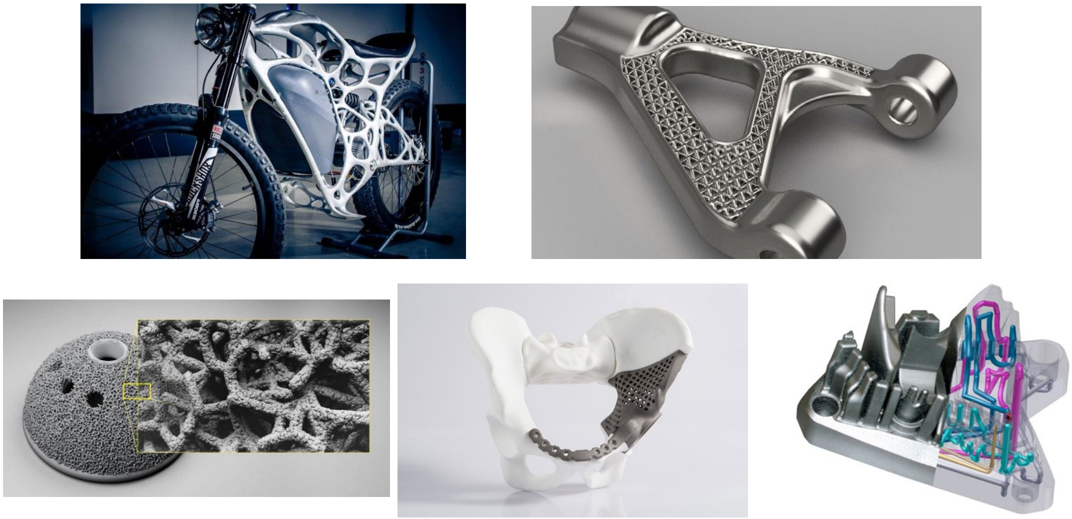

Figure 1 Examples of products obtained via AM (courtesy APWorks motorbike, EOS, Arcam, Renishaw) [3]

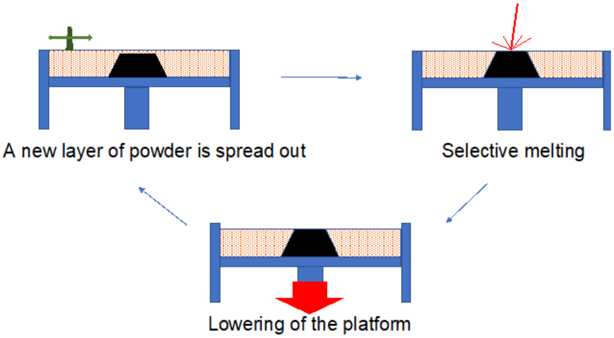

Figure 2 The layerwise production paradigm in AM processes.

2 Quality in AM: defects in AM products

The poor quality and high defective rates of AM processes represent one of the main barriers to the widespread adoption of this class of technologies in many industrial sectors. According to the National Institute for Standards and Technology (NIST)[4]

> *``the variability in part quality due to inadequate dimensional tolerances, surface roughness, and defects, limits the metal AM broader acceptance for high-value or mission-critical applications".*

Defects can be due to improper design choices (lack of supports, staircase effect, thin walls, abrupt changes of the product thickness); feedstock materials (chemical composition of the material, contaminants, wrong shape or density of the powder); equipment (e.g., powder coater, wire dispenser, inert gas atmosphere); process conditions (wrong parameters, unstable or unexpected changes of the energy source, atmosphere, etc.)[3]-[7].

Among defects, geometrical and/or dimensional errors can affect external or internal surfaces but inspection of complex, internal shapes can be very difficult, unless destructive testing is assumed.

A second class of defects known as *volumetric errors* (e.g., unwanted voids and pores, intrapped gas, cracks and inter-layer delamination) can often characterize additively manufactured products. This second class of defects is critical, as it adversely affects the mechanical properties (e.g., tensile and fatigue resistance).

3 Quality inspection in AM

Quality inspection of AM parts poses many different challenges **[8]**., as geometry complexity, which represents the main distinctive feature of many AM products, is negatively correlated with inspectability. In particular, inspection of complex internal cavities and detection of inner pores are the most complex tasks as traditional metrology systems, such as Coordinate Measurement Machines (CMMs) and non-contact systems (e.g., laser scanners, structured light), are mainly suitable for external, accessible surfaces.

X-Ray Computer Tomography (X-Ray CT) is recently representing the viable solution to inspect internal features of AM products[8]-[9]. One key feature of X-ray CT is that it produces reconstructions based on *voxels*, which are 3-dimensional extensions of pixels. Images based on pixels can be modeled as a greyscale map on a 2D grid. Similarly, voxel-based data can be represented as grey scale elements of a 3D volume grid (Figure 3). Surface reconstruction based on voxel-based data, uncertainty estimate and Repeatability and Reproducibility (R&R) studies are all interesting areas for future research [10]- [12].

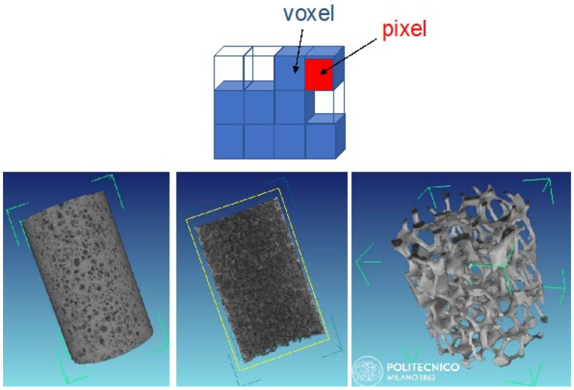

Figure 3 Voxel and vowel-based reconstruction of a sponge (courtesy Politecnico di Milano)

3 Statistical Quality monitoring or Statistical Process Control (SPC) for AM

When process stability is of interest, statistical quality monitoring (also known as statistical process monitoring or statistical process control – SPC [stat04039]) can be implemented. A first way to implement SPC is to check for stability of the quality features measured on the produced products. Unfortunately, this conventional approach to control charting can be hardly applied when small lots or one-of-a-kind, customized production is implemented, as in AM applications.

A second possibility for quality monitoring is to use process by-products (signals, images, video-images [stat00050]) acquired while the part is being built to detect unstable conditions and issue an alarm. This second solution, referred in the literature as *in-situ process monitoring*, is a very promising direction for future research in AM.

3.1 SPC applied to the final product Quality

Design freedom is one of the main advantage of AM and this is why additively manufactured products are usually characterized by complex shapes. In this context, approaches proposed in the literature for profile [13]-[18] and surface monitoring[19]-[23] can be applied as viable solution for quality control of 3D-printed parts. Profile and surface monitoring can be performed in two steps: first, a statistical model of the geometric profile or surface to be monitored is defined; then, all the estimated coefficients and the residual variance are monitored via multivariate and univariate control charts. In the context of AM applications, a main challenge is the lack of data to design control charts, i.e., to perform Phase I analysis. Phase I and Phase II are usually two different steps of control charting. In Phase II, the process distribution is assumed to be known. Before Phase II, Phase I has to be carried out to ensure that the process is statistically in control and to estimate the in-control distribution. When small lots are produced, one cannot wait for the accumulation of sufficiently large subgroups to perform Phase I analysis.

As AM is usually considered for high-value-added, customized products, design of the control chart can be very difficult or even an impossible task, as lot sizes are typically small. Even if *short run SPC* has been discussed in the literature for long time [24][25], no satisfying solutions are currently available in practice. The most common way for dealing with short run SPC [stat04056] consists of computing a control chart based on the “deviation from the nominal” values observed on many different products. In other words, quality indicators are measured on different products and *standardized* with respect to the target value before designing a joint control chart. Recently, *self-starting methods* have been proposed in the literature [26]-[28] to face situations when no large samples are available for Phase I analysis. In this case, the need of preliminary data is minimized to start monitoring in start-up stages.

3.2 In-situ process monitoring for AM processes

In-situ process monitoring represents an interesting opportunity to detect process changes and ensure product quality while the part is being built [3][31]. In fact, many features of the AM process can be observed in-situ and in-line: signals, images and video-images represent the process signature and can be directly related to the final quality of the printed products.

In-situ data for AM, can be mainly classified into three data types:

- Signal data, which can be modelled as time series or profile/functional data (e.g., melt-pool temperature, melt pool area, acoustic emission for crack detection);
- Image data, as the high-resolution picture (in the visible or infrared ranges) acquired at each layer or the surface texture observed before or after the printing step;
- Video-image data representing the melting process and/or the cooling phase.

Geometric deviation from the nominal shape can be foreseen by comparing the image of the melted zone to the nominal shape at each layer. All the information linked to the melt pool can be possibly used to predict volumetric errors, i.e., detecting local porosity. Thermal stresses and cracks can be linked to the cooling transient and to the acoustic emission.

While profile or functional data monitoring can be used for signal data [13]-[18] [stat04061], new solutions are required when images and video-images have to be statistically monitored with time [32]. In this case, a pre-processing step is usually needed to analyze each frame of the video or the image acquired in order to compute significant features to be monitored with time. For example, possible features to be computed for in-situ monitoring in powder-bed fusion processes are: the geometry of each printed layer [33]; the shape, area and mean temperature of the melt pool [6][7]; the area and the average temperature of the plume [34]; the number, area and average distance among spatters produced at each track during printing [35]. Then, multivariate control charting can be applied to the quality features of interest to detect process instability.

When more complex process dynamics are of interest, as for instance in *hot-spot* detection when unusual cooling transients have to be detected, more complex spatio-temporal models [32] have to be applied to speed up the out-of-control detection. Eventually, a recent and emerging stream of research combines computer vision to machine learning for in-situ process monitoring of AM processes [35]-[41].

4 Quality prediction and Quality control

One of the main sources of volumetric and dimensional error of AM products is due to *shrinkage*. As in all thermal processes, the solidification and cooling of the 3D printed volume bring volume contractions, which can cause thermal stresses that can be hardly predicted when complex geometries are produced. This is why some authors focused on *quality prediction*, i.e., predict the final geometry of AM products, starting from a limited number of test cases [42]-[45], using a transfer learning paradigm [46]-[48] or combining simulation and real data in a multi-stage calibration framework [49].

A second main direction of future research is quality control, i.e., compensate for product defects using a feedback/feedforward control [50]-[51] of process parameters or using a layerwise correction of defects with novel hybrid system solutions [48]. In this case, defects are not only detected in line and in-situ but also corrected while printing to achieve the ideal paradigm of defect-free or zero-defect manufacturing.

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Related Articles

stat04039 Control Charts, Overview; stat04056 Control Charts for Short Production Runs, stat04047 Hotelling's T2 Chart; stat00050 Image Processing; stat03109 Multivariate Quality Control; stat04061 Profile Monitoring

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