Image analytics and machine learning for in-situ defects detection in Additive Manufacturing

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***Abstract*—In the context of Industry 4.0, metal Additive Manufacturing (AM) is considered a promising technology for medical, aerospace and automotive fields. However, the lack of assurance of the quality of the printed parts can be an obstacle for a larger diffusion in industry. To this date, AM is most of the times a trial-and-error process, where the faulty artefacts are detected only after the end of part production. This impacts on the processing time and overall costs of the process. A possible solution to this problem is the in-situ monitoring and detection of defects, taking advantage of the layer-by-layer nature of the build. In this paper, we describe a system for in-situ defects monitoring and detection for metal Powder Bed Fusion (PBF), that leverages an off-axis camera mounted on top of the machine. A set of fully automated algorithms based on Computer Vision and Machine Learning allow the timely detection of a number of powder bed defects and the monitoring of the object's profile for the entire duration of the build.**

***Index Terms*—Industry 4.0, Additive Manufacturing, Powder Bed Fusion, Computer Vision, Machine learning**

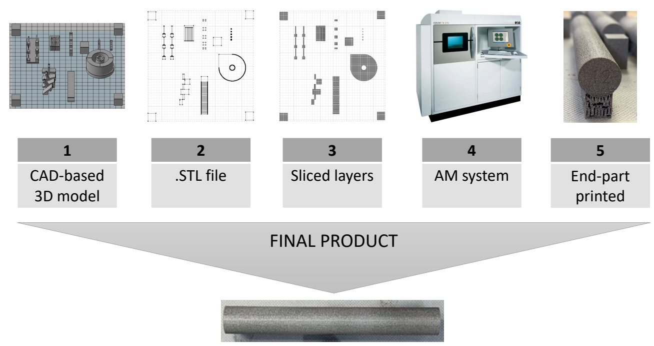


Fig. 1: AM process: main phases.

I. Introduction

Additive manufacturing (AM), also known as 3D printing, is the process of joining materials layer by layer to make objects, starting from a three-dimensional (3D) model. This process typically enables the creation of lighter and more durable parts and systems, with higher flexibility than traditional subtractive techniques. Thanks to these characteristics, AM is typically considered one of the pillars of the Industry 4.0 revolution.

Fig. 1 shows the main phases of a typical AM process. It starts from a 3D CAD model of the objects, then the 3D CAD model is converted into a stereolythography (STL) file format, which is a triangular mesh representation of CAD geometry. The STL is processed by a slicer, a software that converts the model into a series of thin layers and produces instructions tailored to a specific AM system. Finally, the manufactured object may undergo a subtractive finishing process to achieve the best resolutions.

Among metal AM technologies, Powder bed fusion (PBF) involves the spreading of powder material on top of the previous layers by means of a roller or recoater, with a reservoir providing fresh material supply. A heat source, either laser or electron beam, selectively melts together each layer of metal powder [1]. One of the most used PBF technologies in AM industry is Direct Metal Laser Sintering (DMLS), that allows to print parts with a 95% density without requiring any additional post-build sintering [2].

Metal AM is primarily used for manufacturing in industry fields such as aerospace, automotive and medical, where AM is pushing forward innovative designs and applications in a competitive market. In aerospace and automotive, AM is helping suppliers and companies to develop consolidated, lightweight components that lead to more efficient vehicles. In the medical industry, manufacturers are taking advantage of a wide range of high-strength and biocompatible 3D printing materials to customize designs and create functional prototypes, true-to-life anatomical models and surgical grade components [3].

Despite the many possibilities and advantages compared to traditional technologies, the widespread diffusion of AM in industry is limited by a lack of repeatability and quality assurance. To this date, many AM manufacturing systems do not have the capability to assess the quality of the products that they produce, if not with expensive and time-consuming post-process analysis. This majorly affects the overall costs and time of the production.

To address this issue, in recent years many companies are providing commercial software for real-time visualization and monitoring of several process parameters. Nonetheless, these commercial solutions are generally limited in their scope, as they do not develop a fully automated quality control strategy, and they fail to detect minor defects in the printed part that could be automatically corrected before another layer is built [4]. Moreover, monitoring tools are generally not available on older machine models that are currently used by manufacturers, or require expensive and complex set-up.

In the last few years, researchers are using more and more data analytics approaches to address the problem of AM monitoring, mostly combining off-line Machine Learning (ML) methods with other types of algorithms such as Computer Vision and signal processing. For example, recent works describe monitoring tools for AM machines and try to apply ML to different types of sensed data, to obtain automated detection of a number of defects [11]–[13]. Even though some of these works show interesting proofs-of-concept, their application to real industrial scenarios is very limited, due to lacks in the efficient collection, storage, annotation and integration of the data that are produced by the machines. Hence, the use of data-driven techniques to monitor and improve the AM process, even though very promising, is still at its very early stages.

In this paper, we describe a real-time fully-automated framework for layer-wise defects monitoring in DMLS Additive Manufacturing. The system exploits an off-axis low-cost camera to automatically acquire images of the powder bed and of the manufactured object during the layering process. Then, a set of fully-automated tools based on Computer Vision and Machine Learning allow a real-time detection of possible defects of the part, that are hard to spot by visual inspection. The prototype was designed in a real-world industrial scenario, and developed on top of a DMLS machine of an automotive company. By allowing the early stopping/correction of the faulty artefacts, this system is expected to improve process repeatability and majorly reduce human intervention, with major positive impacts on the production costs.

The outline of this paper is as follows. Section II provides an overview of the state of the art of the monitoring systems for AM. Section III describes our real-time AM monitoring system, along with the defects detection tools. In Section IV, case study results are shown to assess the system and the algorithms developed. The paper is concluded in Section V.

II. State of the Art

One of the major challenges in AM is developing in-situ sensing and feedback control capabilities to eliminate build errors and allow qualified part creation, avoiding the need for costly and destructive external testing. There is an industry pull for in-situ inspection and closed-loop control techniques for AM, which is not provided yet by commercial solutions [5]. Indeed, most of the available tools allow monitoring of AM processes but they do not allow robust in-process identification of material discontinuities [6].

Visual, camera-based methods have been used to identify processing errors mostly for PBF, such as powder bed condition and geometrical accuracy. However, the main limitation of such solutions is the lack of robustness, as they work only for specific machines and experimental set-ups [7].

In [8], the authors rely on the idea that the by-products of Laser Powder Bed Fusion (LPBF) can be used as process signatures to design and implement statistical monitoring methods. However, their solution is material and process dependent, and requires costly equipment that are usually not available in a standard industrial scenario.

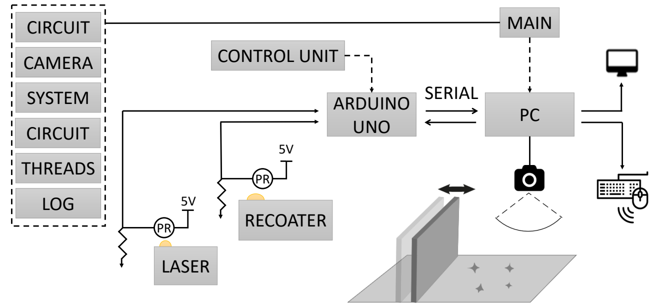


Fig. 2: In-situ monitoring infrastructure.

In [9], a low-cost thermal imaging solution is implemented, that allows relative temperature measurements for detecting unwanted process variability. Nonetheless, the proposed solution is not real-time and there is no control loop automation.

In [7], the authors propose an image processing method designed to extract features from the melt pool in a PBF process, using a high-speed camera to analyze the plumes during the process. Hence, the system is susceptible to the disturbance caused by vapour plume ejection.

To overcome these problems, we propose a low-cost and machine-independent monitoring system based on a standard visible range camera, that can be replicated on top of any industrial DMLS machine. The system includes a fully-automated image analysis suite to identify a number of defects in real-time during the layering process, without any a priori knowledge of the process characteristics.

III. Methods

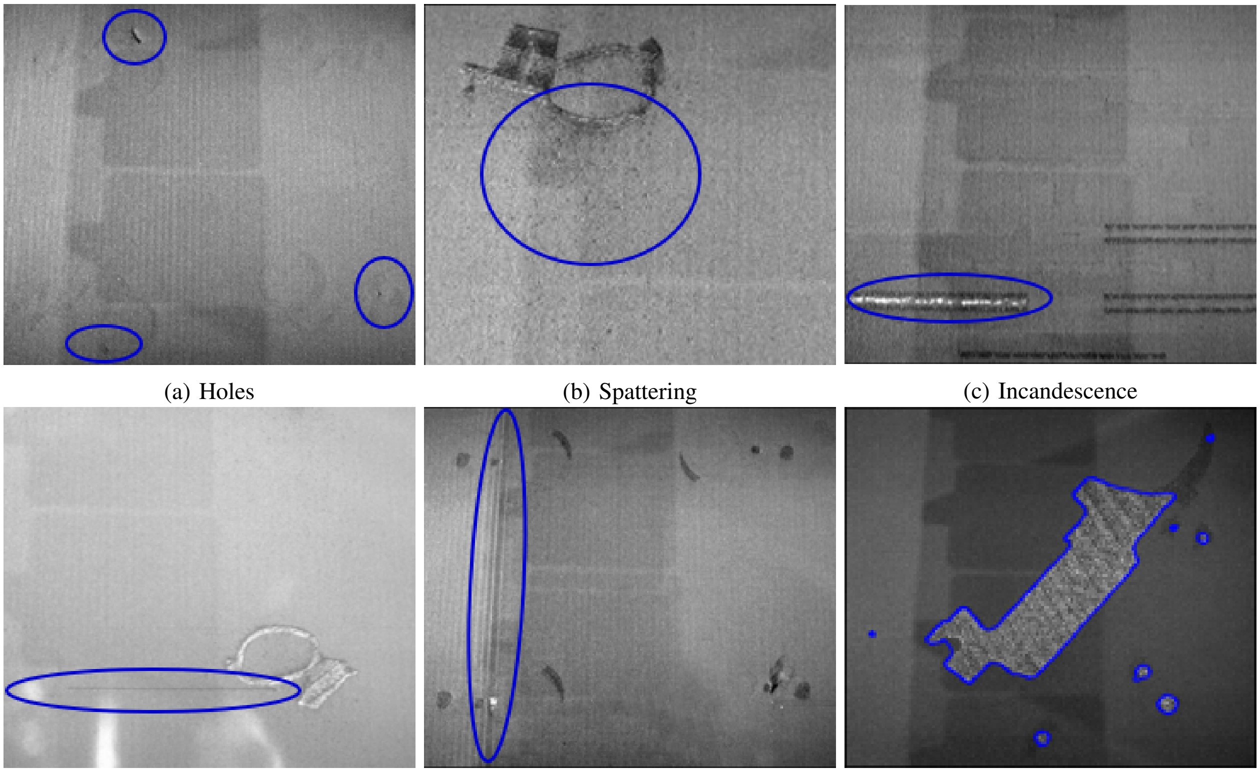
In this section we describe our in-situ imaging infrastructure for real-time layer-wise monitoring of powder bed defects and object profile.

A. *In-situ monitoring infrastructure*

Our prototype is built using low-cost hardware and camera on top of a EOS M290 DMLS printer in an automotive company (FCA Product Development AM Centre). As shown in Fig. 2, it includes:

- an Arduino Uno computing platform directly connected with the 3D printer, used to manage the system, trigger the camera and take images of the powder bed.
- an IDS UI-1540-SE 1.31Mpix camera (1280×1024 resolution). The camera is triggered through the Application Programming Interface (API) made available by the manufacturer. The acquisition is off-axis with respect to the optical path of the laser.
- A standard low-cost PC running Linux, to collect images and run the image analytics algorithms.

The image acquisition is automatically triggered by 3D printer states, exploiting the signals emitted respectively by the action of the laser and of the recoater, by means of photo-resistors. By



(a) Holes (b) Spattering (c) Incandescence

(d) Horizontal (e) Vertical (f) Profile monitoring

Fig. 3: (a)-(e) Examples of powder bed defects targeted by the system. (f) Profile monitoring example.

doing so, the system is able to acquire images of the powder bed before and after each layer is printed, without requiring any user interaction.

B. Defects detection

In the current version of our prototype, the system includes a set of real-time image analytics algorithms that allow the real-time detection of five different powder bed defects, as well as a continuous monitoring of the profile of the object that is being printed. The algorithms are based on image processing and Machine Learning and were developed in Python using OpenCV and Keras standard libraries, respectively.

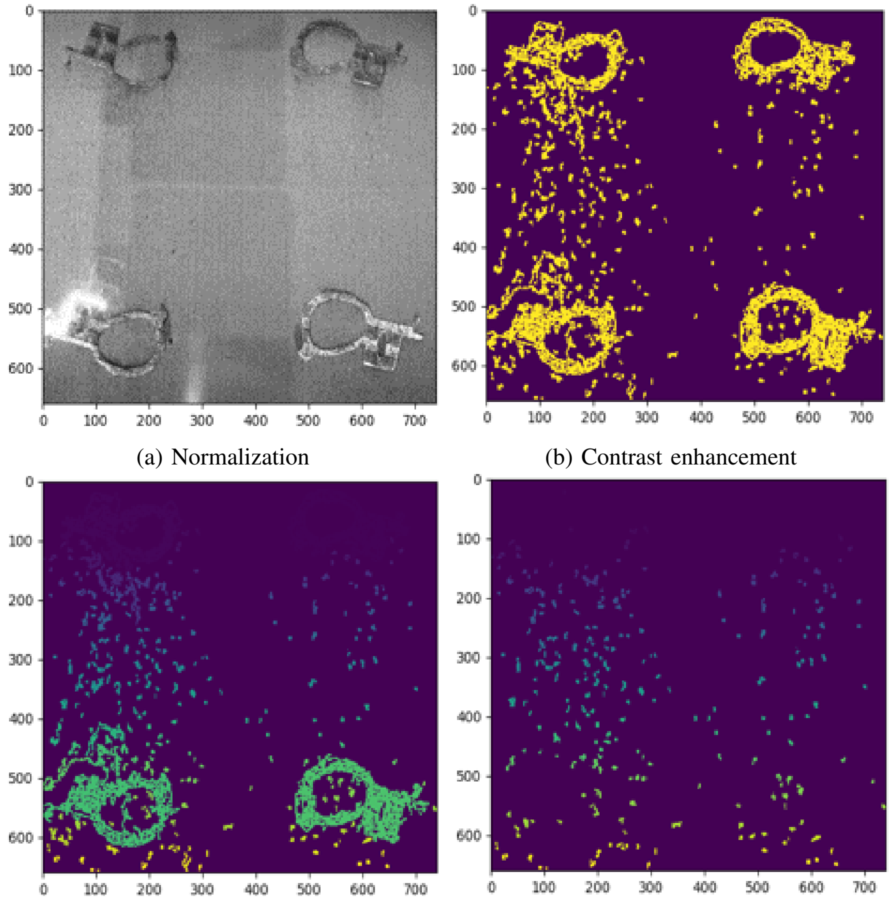
Fig. 3 (a)-(e) show five main categories of defects targeted by our system:

- *Holes*: localised lacks of metallic powder that create small dark areas in the powder bed image. The origin is a lack of powder due to bad regulation of the dosing factor.
- *Spattering*: droplets of melted metal ejected from the melt pool and landed in the surroundings.
- *Incandescence*: high-intensity areas in the completed layer image, resulting from excess of laser energy density and consequent inability by the melt pool to cool down correctly.
- *Horizontal* defects: dark horizontal lines in the powder bed caused by incorrect spreading of the powder, possibly because of geometric imperfection of the piece or of the metallic powder.
- *Vertical* defects: vertical undulation of the powder bed, consisting in alternated dark and light lines along the direction of the recoater's path. The origin is either a mechanical interference between the part and the recoater or a mechanical defect of the recoater's surface.

Each of these powder bed defects is known to cause either porosities or microstructural alterations in the printed parts, as well as lower mechanical characteristics.

The pipeline for real-time defects detection consists of several image processing steps.

- Normalization. The images are first normalised against a common reference frame, in order to correct uneven illumination problems. To do so, an image of the powder bed is acquired before the start of the layering process and used as a reference throughout.
- Contrast enhancement. A standard background subtraction algorithm is applied to make the objects more distinguishable from each other, as well as from the background [14].
- Objects identification. Intensity discontinuities are identified by means of automated intensity thresholding algorithm. This provides a rough identification of the different objects in the image.
- Morphological filtering. Specific objects are recognized based on their shape, exploiting morphological algorithms. More in detail, Watersheds and Hough transforms, followed by standard morphological regularization (i.e.,



(a) Normalization

(b) Contrast enhancement

(c) Objects identification

(d) Morphological filtering

Fig. 4: Example of spattering defects detection pipeline.

opening, closing, holes filling), are respectively applied to identify round-shaped and horizontal/vertical lines. Based on the specific shape and number of objects that are detected, the software identifies a specific category of defect and triggers a corresponding alarm

As an example, in Fig. 4 we show the outcome of each intermediate step of our pipeline, when applied to a spattering defect. Spattering is indeed one of the defects that most frequently happens during powder bed fusion: it involves tiny particles of liquid metal being ejected from the laser's path, which may contaminate the powder bed and create issues such as porosity, roughness, and lack of adhesion in the finished parts. At the end of the last step in Fig. 4(d) (i.e. morphological filtering), it is possible to see the most relevant spatters identified.

C. *Profile monitoring*

Besides powder bed defects detection, the system includes a fully automated *profile monitoring* suite, that is able to monitor the profile of the build on a layer-by-layer basis (see an example in Fig. 3(f)). This task has additional algorithmic and computational challenges compared to basic powder bed defects detection, because the printed parts may have very different shapes and dimensions.

In our solution, profile monitoring is addressed as a semantic segmentation problem. Semantic segmentation aims to cluster parts of an image together, which belong to the same object, using a pixel-level prediction to classify each pixel in an image according to a category. In other words, image segmentation becomes a binary classification task, where each pixel needs to be labeled as belonging to the object of interest (in our case, the printed part) or to the background. This is a task that can be effectively addressed by a supervised Machine Learning algorithm.

To achieve this purpose, we employ a U-Net architecture [10], a state-of-the-art deep learning algorithm that was initially designed for biomedical image segmentation and then successfully applied to many different Computer Vision applications. The network implements an end-to-end fully convolutional network (FCN) that is only composed of convolutional and pooling layers without any dense layer, which makes it is suitable for any image size. As shown in Fig. 5, the architecture is composed of two paths. The first path is the contraction path or encoder, which is used to capture the context in the image, and consists of a stack of various convolutional

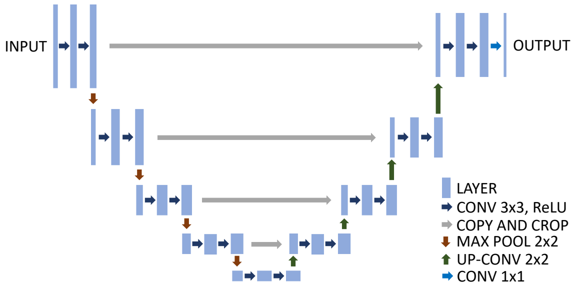


Fig. 5: U-Net architecture.

and max-pooling layers with gradually decreasing feature map dimension. The second path is a symmetric expanding path or decoder, which is used to enable precise localization using transposed convolutions.

In our approach, the U-Net is initialised as suggested by [10] and then fine-tuned on a representative PBF layer image, acquired by our system.

IV. Experimental results

To validate the algorithms, we used a set of images pre-annotated with all the defects targeted by our system. For the five main categories of defects, we run a statistical validation by analysing whether the algorithm identified the defect or not, using metrics that are widely accepted in descriptive statistics:

- Accuracy: it represents the number of correct classification with respect to the total cases.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Precision: it is the fraction of relevant cases among the retrieved instances.

$$Precision = \frac{TP}{TP + FP}$$

- Recall: it is the fraction of the total amount of relevant instances that were retrieved.

$$Recall = \frac{TP}{TP + FN}$$

In our work, True Positives (TP) represent the instances when the algorithms were able to detect a defect that was really present. True Negatives (TN) represent the instances when a given defect was not present, and the algorithm was right in not detecting it. False Positive (FP) and False Negative (FN) represent the possible errors of the algorithms, respectively in detecting a defect that was not present, or not being able to identify a defect that was present.

In Table I we report the results obtained on a test set of 24 images with different powder bed conditions and defects.

For all the five defects, the results of the metrics considered are $\geq$ 75% with the worst results for the Incandescence defects (Precision: 75%) and Vertical defects (Recall: 75%). According to our tests, Incandescence proved to be the most challenging defect to be recognized, probably due to the high variation of pixel luminosity. On the other hand, Spattering

TABLE I: Defects detection algorithms validation

	Holes	Spatt.	Incand.	Horizontal	Vertical
TP	14	22	15	11	6
TN	8	1	4	11	16
FP	2	1	5	1	0
FN	0	0	0	1	2
Accuracy	91.3%	95.8%	79.2%	91.6%	91.67%
Precision	87.5%	95.6%	75%	91.6%	100%
Recall	100%	100%	100%	91.6%	75%

defects are the easiest due to the high amount of spatters generated.

For the profile monitoring task, the validation exploits the Sørensen–Dice coefficient (DSC) to compare the profile segmentation obtained with our algorithm against a manually obtained ground truth. This metrics is used to gauge a 0 to 1 similarity of two binary images, as follows:

$$DSC = \frac{2|X \cap Y|}{|X| + |Y|}$$

where $|X|$ and $|Y|$ are the number of pixels of the two images (in our case, the automatic segmentation and the ground truth) and $|X \cap Y|$ the number of pixels that are common to both images. Fig. 6 shows and example of this procedure, with (a) the binary mask obtained by manual segmentation, used as the ground truth, and (b) the binary mask obtained by our profile monitoring suite.

In our tests, which involved 44 independent profiles from 4 different AM parts, we obtained a very good similarity between automated segmentation and manual ground truth: mean DSC value was equal to 0.878, when computed on each single segmented object, and to 0.911, when computed on each layer image taken as a whole.

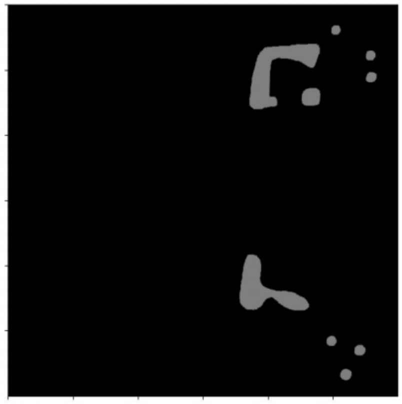
Finally, in TABLE II we report the execution time of all the tested algorithms. As it can be seen from the reported values, execution times are all below $2.5s$, which is well below the time elapsing between two subsequent layers. Profile monitoring is the algorithm taking the longest time ($2.461s$) because it involves running deep neural network. The other algorithms, which exploit standard image processing operations, are all below $1s$ of execution time.

TABLE II: Mean execution time of the algorithms.

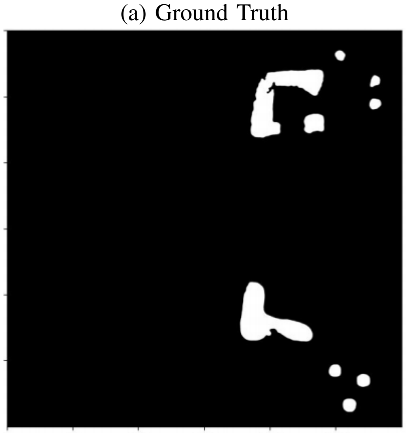
Operation	Time [s]	Operation	Time [s]
Holes	0.791	**Horizontal**	0.593
Spattering	0.574	**Vertical**	0.932
Incandescence	0.821	**Profile monitoring**	2.461

V. Conclusions and future work

Computer Vision and Machine learning have been proven to be promising approaches to the problem of in-situ monitoring of the AM process. Nonetheless, the actual use of these approaches in a real industrial scenario is still limited due to



(a) Ground Truth



(b) Automatic algorithm

Fig. 6: Profile monitoring: validation example.

a number of problems. First of all, the lack of effective data collection infrastructure specifically devoted to AM. Second, the necessity to train the models on large annotated datasets, which are typically costly and difficult to obtain in industrial environments. This paper presented a low-cost camera-based in-situ defects monitoring system for metal PBF. The preliminary prototype, developed and tested in a real industrial scenario of an automotive company (FCA Product Development AM Centre)), includes a set of real-time Computer Vision and Machine Learning algorithms to detect five different categories of powder bed defects, as well as the layer-wise monitoring of the profile of a printed part. Our preliminary results show that the algorithms have a good performance in terms of defect detection accuracy and profile segmentation and they are suitable for real-time execution with low-cost hardware. The framework is currently being extended to provide layer-by-layer comparisons between the profile of the printed part (as returned by the profile monitoring suite) and the desired profile as defined by the slicer. This will allow a real-time automated detection of any profile alterations during a build.

Future works will include further optimization of the algorithms, to allow even faster execution in a resource constrained environment.

Additional efforts are also being directed towards the well-known problem of the scarcity of annotated data, which currently limits the possibility of training and testing Machine Learning models. In this regard, we are currently investigating the use of Generative Adversarial Networks (GANs [15]) for the generation of synthetic images of powder bed defects, to train deep learning classifiers even more efficiently.

Acknowledgment

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