2021 QSR Data Challenge Competition

In-Situ Quality Process Monitoring in Additive Manufacturing

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Abstract: Additive manufacturing technologies entail a layer wise production paradigm that permits the collection of a large amount of information, both in-situ and in-line, during the manufacturing of parts. This information is in the form of, among others, sensor signals, images, and videos. Such information can be effectively used for quick detection of anomalies and in-line qualification of complex, highly customized shapes.

This QSR Data Challenge Competition is the result of a joint project on open science run by Politecnico di Milano and Trumpf. It consists of signals from two photodiodes acquired during a Laser Powder Bed Fusion (L-PBF) process, in which anomalies were purposively introduced by designing overhanging areas within bulk specimens. The task of the QSR Data Challenge is to develop a Statistical Process Monitoring procedure that is able to detect melting anomalies as soon as possible. Guidelines for using the data and method development are provided. The efficacy of a proposed method will be gauged based on the time to detect the anomaly as a function of the severity of the anomaly itself, and the number of false alarms.

Keywords: additive manufacturing, anomaly detection, in-situ monitoring, melt pool, photodiode.

1. Problem

Additive Manufacturing (AM) processes and technologies have experienced continuous growth in their adoption across a wide variety of industrial sectors. They have impacted, among other domains, the biomedical, aerospace, racing and automotive, oil and gas, tooling and molding, and creative industries. From a statistical process monitoring (SPM) perspective, the AM paradigm entails a layerwise production that enables the in-line and in-situ collection of a vast amount of signal data. These data can be used to determine process stability and to accelerate the detection of anomalies and defects during the manufacturing process.

The 2021 QSR Data Challenge Competition corresponds to an open data science project run by Politecnico di Milano (www.polimi.it) and Trumpf (www.trumpf.com). This project focuses on in-situ anomaly detection in Laser Powder Bed Fusion (L-PBF), which is a metal AM process in which a laser beam selectively melts thin layers of metal powder[1]. Among the diverse array of sensing configurations that are available for this process, a very effective and largely studied configuration consists of using the optical path of the laser to measure the radiation emitted by the melt pool and its surroundings (Fig. 1). The melt pool is the region where the laser beam exposure melts the material, and it is known to be a primary feature of interest in any process that involves a beam-material interaction aimed at achieving a local melting of the material.

The dataset in this competition includes signals acquired via one spatially-integrated sensor (an indium gallium arsenide (InGaAs) photodiode) mounted co-axially to the laser path that measures the integral radiation within a field of view centered in the melt pool in the near/short infrared range. The photodiode signal was acquired during the manufacturing of one AlSi10Mg (aluminium) specimen produced with fixed process parameters (specifically, a scan speed of 1500 mm/s, laser power of 4800 W, and laser spot diameter of 100 μm). The specimen was manufactured using a multi-laser L-PBF Trumpf system.

Within the specimen, anomalies were purposely introduced in specified layers by designing some unexposed blocks, i.e., inner regions of the specimen in which no laser scan occurred for a number of consecutive layers (ranging between 1 and 10). The first layer after an unexposed block has a large overhanging area with loose powder underneath. The heat exchange in this overhanging layer (and possibly in few of the layers that follow it) is altered by the fact that the loose powder has much less conductivity than the bulk material. Therefore, unexposed blocks tend to force heat conduction anomalies with increasing severity as the number of unexposed layers increases.

The objective of the QSR Data Challenge is **to develop an SPM procedure that can detect such anomalies as soon as possible while achieving the best compromise in terms of false positives and false negatives.**

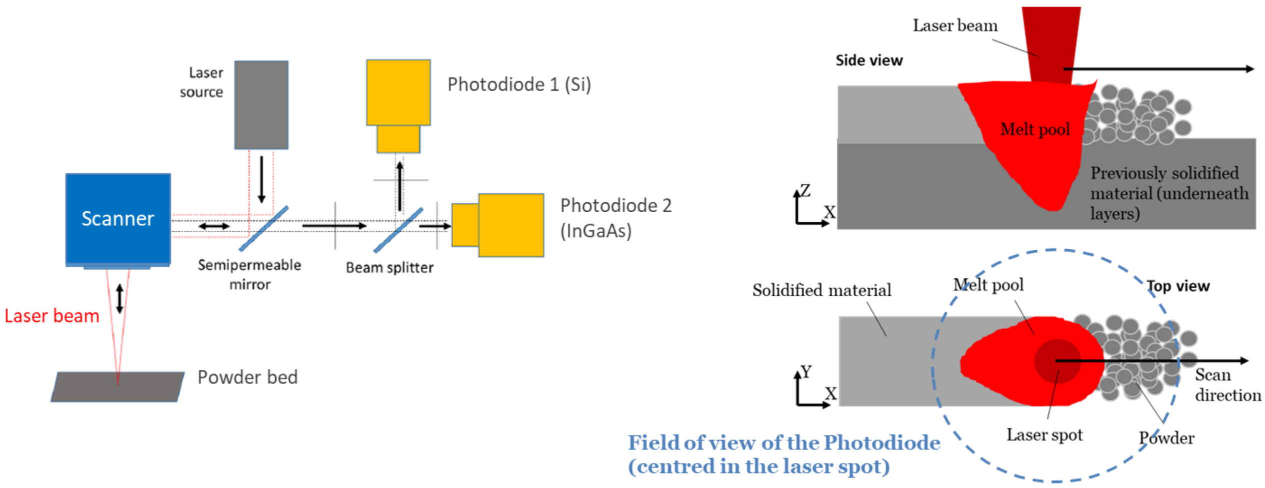

Fig. 1 –Left: The co-axial monitoring setup that utilizes two photodiodes aligned to the optical path of the laser. Only the InGaAs photodiode is considered for this challenge. Right: Schematic side and top views of the melt pool along the laser scan direction.

[1] An illustrative video of the L-PBF process can be viewed at https://www.youtube.com/watch?v=HaWEw2sH4Kk

2. Data

The specimen is a parallelepiped of size 10 × 10 × 25 mm. It was built vertically (i.e., the *z* direction is the build direction) in the L-PBF process (Fig. 2). In the bottom layers, corresponding to the tapered base area, the process was still not in its regime conditions, and so data collected during the production of such bottom layers are not included in the dataset. The number of unexposed layers within each unexposed block increased from 1 to 10 along the z direction.

The dataset is in HDF5 format, with one file per layer. For each layer, a data matrix is provided in which each row corresponds to one photodiode measurement and different columns correspond to the different variables described in Table 1.

The photodiode signal was initially acquired with a sampling rate of 100 kHz and then down-sampled in order to have one datapoint every 30 µm along the laser scan path. The orientation of the laser scan direction and the laser scan path were changed every layer, as is commonly done in L-PBF. The dataset includes the X and Y coordinates of the laser spot (i.e., the coordinates of the center of the photodiodes' field of view) recorded synchronously to the photodiode signals.

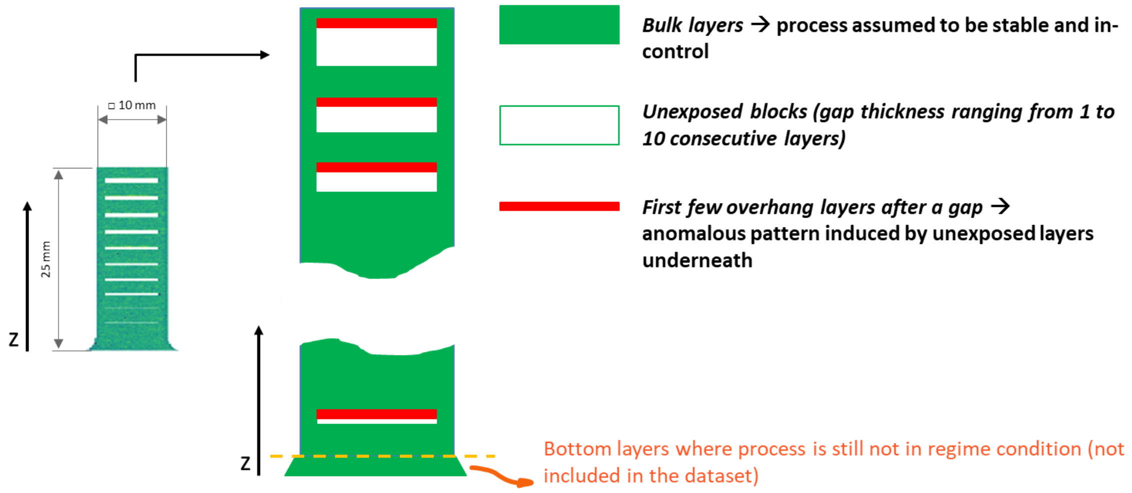

Fig. 2 – Schematic view of the additively manufactured specimens with unexposed blocks, which are purposely used to force heat exchange anomalies in overhanging layers.

Table 1 – Contents of the data associated with each layer.

Column of Data Matrix	Label	Description
1	X	Coordinate X of laser spot (in mm)
2	Y	Coordinate Y of laser spot (in mm)
3	NominalPower	Nominal power (in W)
4	NominalSpeed	Nominal scan speed (in mm/s)
5	NominalSpotDiameter	Nominal laser spot diameter (in µm)
6	LaserPowerCurrent	Measured laser power (in W)
7	SignalInGaAs	Photodiode signal (arbitrary unit, proxy of temperature)

8	IDbulkLayer	Indicator variable that identifies bulk layers (value = 1) and layers that belong to unexposed blocks (value = 0). Signals acquired during the production of bulk layers are assumed to be in-control.
9	IDoocLayer	Identifier of the layers affected by the anomaly (first overhang layer following an unexposed block and two following layers), with values consisting of the integers from 0 to 9.
10	c_1_cost	Cost for late detection (see Table 2). c_1_cost = 0 for all layers where no anomaly is present, i.e., bulk layers and unexposed layers
11	c_2_cost	Cost for false alarms (see Section 3). c_2_cost = 20 for all bulk layers (i.e., layers to be used for false alarm rate estimation), c_2_cost = 0 for all remaining layers.

The right panel of Fig. 3 provides a schematic representation of the link between the recorded laser spot locations (X and Y variables) and the corresponding photodiode measurement (SignalInGaAs variables). The left panel of Fig. 3 shows how anomalous layers are labeled in the IDoocLayer variable.

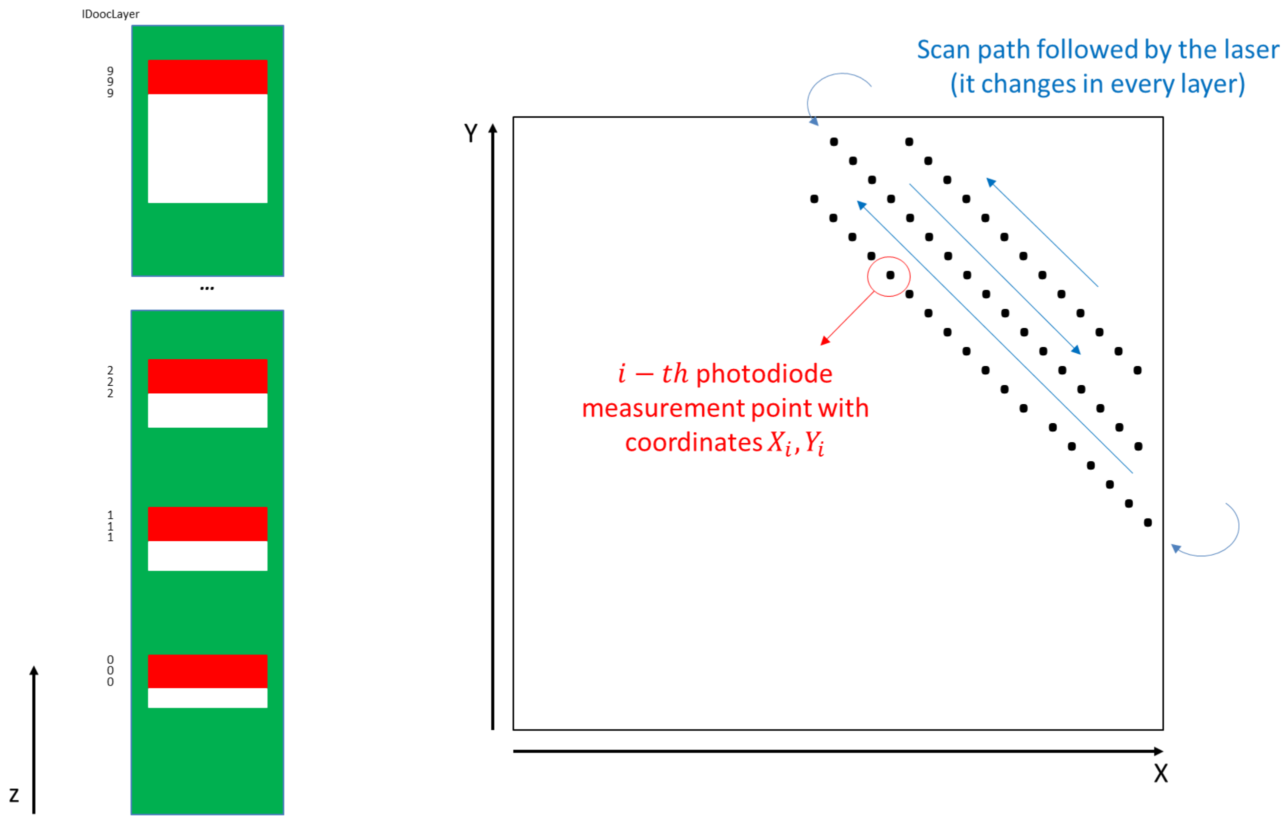

Fig. 3 – Left: Illustration of the labelling of the anomalous layers. The three layers following the first unexposed block that consists of only one layer are labelled as 0. This is because, similar to bulk (in-control) layers, no anomalies were observed in the three layers labelled as 0. Right: The link between laser spot locations (X and Y variables) and the photodiode measurements.

3. **Evaluation and Expected Output**

The task in the 2021 QSR Data Challenge Competition is to develop an SPM methodology that can detect the out-of-control states as soon as possible in the three layers following an unexposed layer while avoiding false alarms (i.e., alarms issued when the laser is scanning bulk in-control layers). A cost objective function is specified that considers the trade-off between the time to detect an out-of-control state (defined in terms of the number of points scanned in the out-of-control layers before the detection) and the number of false alarms that cause a cost due to diagnostic actions.

The SPM methodology shall be designed with a nominal false-alarm probability (Type I error) equal to 0.1%. Moreover, a set of in-control data for the SPM design phase (Phase I) can be considered available. These data consist of signals acquired in the first $m = 25$ layers of each specimen. Specimens produced with the same laser scanner can be assumed as replicates.

The SPM performance will be evaluated by means of an objective function that takes into account the cost for late detection of the anomaly and the cost for false alarms.

The cost associated to late or missed detection of an anomaly, labeled by $c_{1,k}$ $(k = 1 \ldots ,9)$, is based on the severity of porosity observed on the final specimen using X-ray Computed Tomography (CT). This cost ranges between 0 for no anomaly to 100 for high severity (Table 2). The greater defect severity, the greater the cost for late detection. All bulk layers not affected by anomalies have a cost $c_{1,k} = 0$, as they are assumed to be in-control.

The cost associated to each false alarm is $c_2 = 20$. This is based on the diagnostic procedure and the operator's time that is spent on looking for an assignable cause.

The objective function to be minimized is

$$\text{TOTAL COST} = \sum_{k=1}^{9} c_{1,k} T_k + c_2 FA$$

where T_k is the time (in terms of the number of measurement points) taken to signal the anomaly in the kth anomaly (i.e., in the kth group of three consecutive layers after an unexposed block), and FA is the total number of false alarms in bulk layers.

Table 2 – Cost for late or missed detection of each anomaly.

Anomaly ID (IDoocLayer)	**Cost for late detection**
1	10
2	20
3	40
4	80
5	100
6	100
7	100
8	100
9	100

The expected output shall consist of the following results.

- Time to signal for each anomaly. This will be counted as the number of measurement points that have been scanned since the start of the overmelting layer, i.e., the first overhang layer produced after one block of unexposed layers. If the anomaly is not detected, the time to signal shall be defined as the total number of measured points in the three layers affected by the anomaly (i.e., the three layers after the unexposed block).
- Number of false alarms: an alarm is considered to be false if it is issued in any bulk layer out of the first three layers after each unexposed block. False alarms are counted at the individual measured point level.
- Objective function value, defined as in the equation above.
- ID of locations (X's and Y's) and layers where the anomaly has been detected.

The best solution will be the one that minimizes the TOTAL COST.

4. Download link

The dataset can be downloaded at the following link: https://www.ic.polimi.it/open-challenge-QSR/

5. Submission

The link to the website where you can upload your code and your results will be provided at a later stage, together with specific instructions on how to format your submitted output.

You are encouraged to use open source codes.

References

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