Porosity Localisation in Metal Laser Powder Bed Fusion via Machine Learning

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I. Project scope

Additive manufacturing (AM) has gained academic and industrial interest for its competitiveness in meeting the increasing demand for rapid, flexible, and cost-effective manufacturing. An essential feature of the AM process is the resultant mechanical properties of the manufactured parts. In-situ monitoring and controlling the defect formations in AM is necessary as it dictates the mechanical properties of the sintered parts. To date, several studies have investigated the in-situ detection, localisation, and mitigation of porosities in metal additive manufacturing to control the mechanical properties of the sintered parts. Much of the current literature on in-situ porosity localisation relies on data-dense melt pool imaging and often suffers from poor experimental and model validation.

II. Industry objectives

The task is to build a fully-validated machine learning model for localising porosities in metal laser powder bed fusion via photodiode sensory data. You can use any model, but automatic modelling tools, such as the Matlab neural network fitting tool, are not permitted. You must demonstrate and report an understanding of developing a model-building strategy.

Main Objectives:

- Review the literature on additive manufacturing porosity detection and localisation [1–5].
- Review the industry (AMRC) data and sensing system to understand the input and target values and perform any necessary data treatment (repeated data, data imbalance, missing data, etc.).
- Identify and add features to the input data to improve the data set for a machine learning problem.
- Propose a suitable method, and apply, validate, and test a supervised machine learning algorithm for localising the porosities (binary classification problem).

Advanced Objectives:

- Convert the porosity volumes (trainRegressionTarget in itpAmCaseStudyData5.mat) from mm^3 to a spherical equivalent diameters (SED) in μm.
- Bin the porosity SED values into three classes where class 0 represents $SED \leq 50.00\mu m$, class 1 represents $50.00 < SED \leq 100.00\mu m$, and class 2 represents $SED > 100.00\mu m$.
- Apply, validate, and test a supervised machine learning algorithm to predict the porosity binned classes (multi-class classification problem).

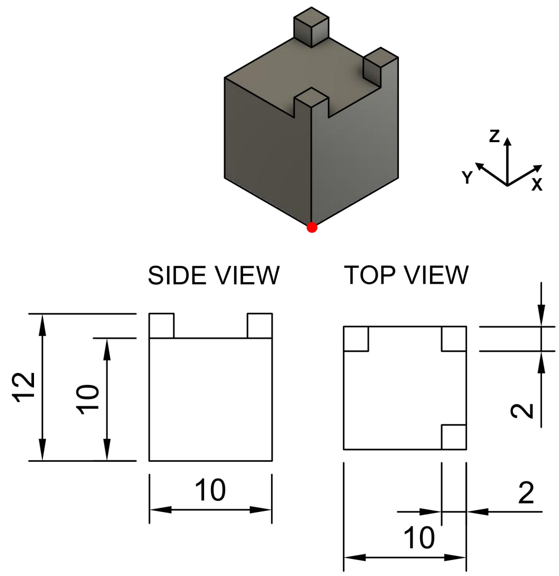

Figure 1: The part design and dimensions (mm unit) examined in this work.The red dot corresponds to the coordinates [0, 0, 0].

III. Case Study & Data

Three-dimensional parts (Fig. 1) were sintered in aluminium A20X using the RenishawTM AM 500M laser powder bed fusion (PBF) machine. The RenishawTM AM 500M uses a 500 W ytterbium fibre laser and a spectral emissions system for monitoring the process (Renishaw InfiniAM). The InfiniAM system includes three high-precision co-axial single-channel photodiodes. The LaserVIEW system photodiode monitors the laser power. The MeltVIEW infrared light photodiode (1080 to 1700 nm) and the MeltVIEW visible light photodiode (700 to 1050 nm) monitor the melt-pool plume characteristics.

A total of 44 cubes were sintered using high-strength aluminium A205. The hatch spacing and layer thickness are constant at 0.05 mm across the cubes. The border power, speed, and hatch offset varied following a randomised Box Behnken design with three factors and three replicates:

- Border Power: 100, 300, and 500 W
- Border hatch Offset: 0.00, 0.05, and 0.10 mm
- Border Speed: 50, 175, 300 mm/s

The data set available is provided in the mat-file, itpAmCaseStudyData5.mat. The mat-file contains the following matrices and vectors:

- Matrix, trainDataMatrix, contains 19 columns corresponding to the inputs.
- Matrix, trainCubeCoordData, contains 4 columns corresponding to the cube number and sample coordinates (mm) for each sample in the matrix, trainDataMatrix.
- Vector, trainClassifactionTarget, contains 1 column corresponding to the nominal dichotomous classification target (1 for Porosity and 0 for porosity free).
- Vector, trainRegressionTarget, contains 1 column corresponding to the regression target (porosity volume in mm^3).

- Matrix, trainDataMatrixPrior, contains 19 columns corresponding to the inputs of a prior data set.
- Matrix, trainCubeCoordPrior, contains 4 columns corresponding to the cube number and sample coordinates (mm) for each sample in the matrix, trainDataMatrixPrior.
- Vector, trainOutputPrior, contains 1 column corresponding to the nominal dichotomous classification target (1 for Porosity and 0 for porosity free).

The input data in matrices trainDataMatrix and trainDataMatrixPrior correspond to:

- Column 1: cube number
- Column 2: border label (1 for border and 0 for core)
- Column 3: Sintering Duration sum (us)
- Column 4: Sintering Duration mean (us)
- Columns 5 to 7: L1 Laserview, M1 MeltView Plasma, and M2 MeltView Melt Pool mean, respectively
- Columns 8 to 10: L1 Laserview, M1 MeltView Plasma, and M2 MeltView Melt Pool variance, respectively
- Columns 11 to 13: L1 Laserview, M1 MeltView Plasma, and M2 MeltView Melt Pool skewness, respectively
- Columns 14 to 16: laser speed (m/s), hatch spacing (m), and energy density mean, respectively
- Columns 17 to 19: laser speed, hatch spacing, and energy density variance, respectively

The prior data will be discussed in the technical briefing session and the seminar sessions. You do not need to use the prior data, but if it is used appropriately, it can improve a model's classification performance.

IV. Industrial Adoption

An industry partner needs to test and trust that your model works to deploy it. The industry partner achieved the classification performance in Table 1 via machine learning and expected your methods to outperform their results. You must rigorously test the validity and reliability of your methods and ensure that an industry partner can confidently deploy and rely on your model. The industry partner has withheld an out-of-sample (OOS) test data set of 4733 samples to test the performance of your proposed methods. The industrial partner has provided the inputs of the OOS data in the shared drive under the name itpAmCaseStudyTestData5.mat. During the submission of your final reports, please perform your data pre-processing steps on the test data and send via email (1) the classification predictions and (2) the regression predictions in Matlab's '.mat' format. One member of your team can send the predictions to mohamed.atwya@sheffield.ac.uk. In the email please provide the group name and two .mat files with clear names (e.g. 'classificationPredictions.mat' and 'regressionPredictions.mat'). Producing the predictions should take each team at most 30 minutes.

Note the following (OOS test data refers to the data in itpAmCaseStudyTestData5.mat):

- The OOS test data has the same column order as the train data.
- **Do not change the order (row-wise) of the OOS test data when you are computing your predictions.**

Table 1: Table 1. Reference classification performance metrics on the OOS test data. The average values are provided with a standard deviation and the median values are provided with the interquartile ranges.

	Metric	Value
Average	Classification accuracy (%)	70.45 ± 0.62
	Log loss error	0.58 ± 0.01
	Area under the curve	0.79 ± 0.00
Median	F-score	$0.74[0.73, 0.74]$
	Precision	$0.68[0.67, 0.68]$
	Recall	$0.80[0.80, 0.81]$
	True Positive	$1955.00[1951.50, 1965.50]$
	False Positive	$931.00[916.50, 950.00]$
	True Negative	$1373.00[1354.00, 1387.50]$
	Flase Negative	$474.00[463.50, 477.50]$

- If you have transformed each feature in the training data (e.g. z-score), you will need to transform the OOS test data using the mean and standard deviation of each feature from the training data.
- **The OOS test targets ('true values') are not provided**, so you cannot compute the performance metrics for the OOS test data. You are only expected to send the classification and regression predictions.
- The performance metrics will be computed by the industry partner using the withheld target values and the results will be emailed to each team.
- You can choose only to send the binary classification predictions if you have not completed the advanced multi-class classification objective.

REFERENCES

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