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Towards additive manufacturing process control using semi-supervised machine learning

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Executive Summary

Additive Manufacturing (AM) is revolutionising UK industry. It is a tool-less digital approach that produces highly customised parts on demand, anywhere in the product life cycle (from prototyping to maintenance and repair)[1]. Relative to conventional methods, AM can drastically improve component performance, reduce whole lifecycle waste[2] and create parts with superior mechanical properties[3].

To maximise its impact, the risks associated with deploying AM technology needs to be reduced. AM has the potential to transform healthcare (custom implants, prosthetics, drug delivery), aerospace (lightweight optimised components)[1] and automotive[4] sectors, but these disciplines are highly regulated and sensitive to failure. Uncertainties associated with the quality, reproducibility[3] and material properties[5] of AM parts inhibit significant adoption in these areas[6]. This is compounded by high machine-to-machine variability[2] and difficulties correcting manufacturing errors (which may occur internally to the part). While computational models can be used to predict build quality to a certain extent, they take a very long time to run and must be re-parameterised in response to new geometries and/or materials.

The overall aim of this project was to investigate whether, using machine learning methods, it would be possible to identify the quality of AM parts purely from build process measurements. The project specifically focused on analysing Laser Powder Bed Future (L-PBF) builds, conducted using a Renishaw RenAM 500M machine.

1. Research challenge

The algorithms developed during the project were designed to infer part quality, based on photodiode measurements of back reflected light that were obtained during laser powder bed fusion (L-PBF) builds. Before a machine learning algorithm can be applied it must be 'trained' on a set of data. In the current context, creation of this data typically involves the manufacture of many nominally identical parts, before each part is then labelled as being 'acceptable' or 'faulty'. Such labelling of AM builds can, however, be a difficult and time-consuming process (often involving CT scans). As a result of this limitation, many sets of process measurements remain unlabelled. The focus of the current project was to exploit information in both labelled and unlabelled builds, thus realising an efficient machine learning approach that is suitable for AM.

The research challenges can be summarised as follows:

1. Big data. Each build analysed in the project consisted of approximately 3600 layers. During each build the x-y coordinates of the laser were measured alongside readings from two photodiodes (focused on the visible and infrared spectrums). This lead to approximately 400 GB of data per build. The first major research challenge, therefore, concerned the analysis of such large datasets.

2. Feature extraction. Because of the size of data involved, training algorithms to identify build quality from the 'raw' sets of photodiode data was impractical. Rather, the algorithms had to be trained on specific *features* that were extracted from the data. Crucially, these features had to give a statistically significant indication of build quality. The identification and extraction of these features was the most challenging part of the project and involved the application of techniques from the field of Big Data analytics[7]. The hypothesis for this high-risk part of the project was that photodiode measurements would be closely related to properties of the melt pool[8] and, as a result, would correlate with build quality.

3. Machine learning. To be suitable for AM applications, the developed approach needed to be able to use data from both builds that had been labelled and those which had been left as unlabelled. Labelling AM builds is often expensive (involving CT scans, for example), making algorithms that can only use data from classified builds expensive to implement. The project aimed to circumvent this issue using a 'semi-supervised learning' approach, that could exploit both labelled and unlabelled data. A schematic representation of semi-supervised learning is shown in Figure 1.

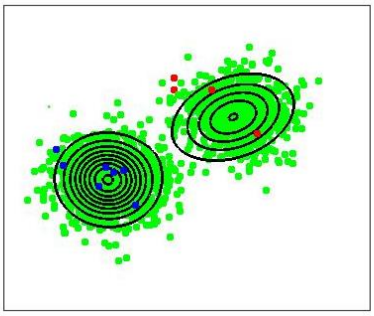


Figure 1. An illustration of semi-supervised learning. Finding clusters that separate points that have been labelled as blue or red, is aided by unlabelled data (green points).

2. Approach

Novelties of the proposed approach were as follows:

1. A methodology was used to extract key features of build quality from large sets of laser powder bed fusion (L-PBF) process measurements, using novel methods from the field of Big Data analytics.

2. The feasibility of using machine learning to detect unsuccessful L-PBF builds, from photodiode measurements, was investigated.

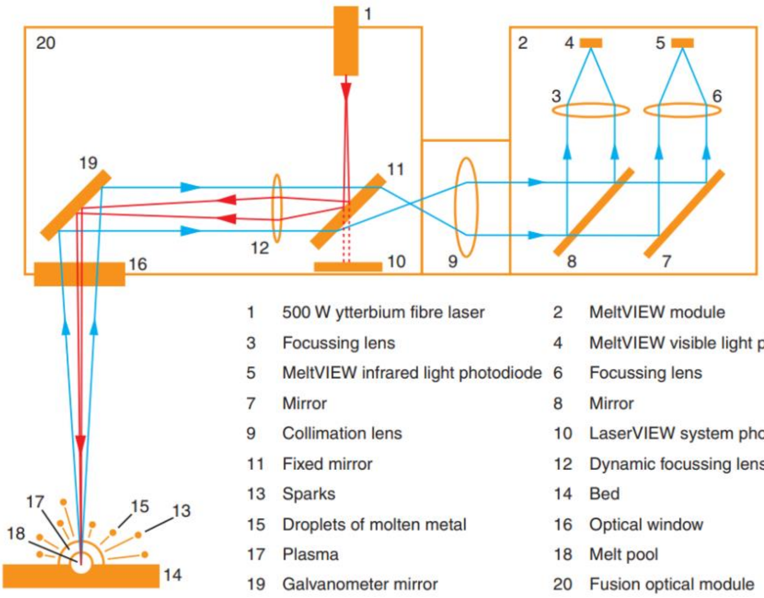
3. The ability of semi-supervised learning to reduce the number of costly certification experiments associated with applying machine learning in the context of AM was investigated for the first time. The approach utilised was *probabilistic*, and therefore able to quantify the uncertainties involved in classifying build quality.

3. Implementation

To create the data needed for the study, two builds were conducted using a Renishaw RenAM 500 L-PBF machine. Each build consisted of the construction of 25 individual tensile test bars (leading to 50 in total). All specimens used in the study were produced from a single batch of Inconel 398 718.

Figure 2 shows a schematic of the machine and optical system used to control the movement of the nominal 80µm diameter focused laser spot. Samples were built in a layer-wise fashion on a substrate plate. The plate was connected to an elevator which moved vertically downwards, allowing the controlled deposition of powder layers at 60 µm intervals. Laser position was

matrix using a randomised singular value decomposition[7] (RSVD). The RSVD allowed us to extract two features per specimen. Figure 3 shows each specimen in this two dimensional 'feature space' (where green and red colours indicate 'acceptable' and 'faulty' specimens respectively). Machine learning was applied in this feature space.



1	500 W ytterbium fibre laser	2	MeltVIEW module
3	Focussing lens	4	MeltVIEW visible light photodiode
5	MeltVIEW infrared light photodiode	6	Focussing lens
7	Mirror	8	Mirror
9	Collimation lens	10	LaserVIEW system photodiode
11	Fixed mirror	12	Dynamic focussing lens
13	Sparks	14	Bed
15	Droplets of molten metal	16	Optical window
17	Plasma	18	Melt pool
19	Galvanometer mirror	20	Fusion optical module

Figure 2. : Schematic of Renishaw RenAM 500M SLM machine and optical sensing system (image taken from the Renishaw Brochure 'InfiniAM Spectral', available at http://www. renishaw.com/en/infiniam-spectral--42310).

measured throughout each build. Using the laser position data it was possible to identify which sets of photodiode measurements corresponded to each individual test bar.

After construction, each specimen was tested using an Instron tensile test machine. The ultimate tensile strength (UTS) was then used to label each specimen as 'Acceptable' (UTS > 1400 MPa) or 'Faulty' (UTS < 1400MPa). Tensile tests were used to classify the specimens as they are relatively fast and cheap to implement (allowing us to classify every specimen). Having labelled every specimen, deliberately deleting some of the classification results allowed us to analyse the ability of the semi-supervised learning approach to analyse different ratios of labelled and unlabelled builds.

Time histories of the photodiode measurements corresponding to each specimen were arranged in a 'data matrix'. Each column of this matrix contained the photodiode measurements that corresponded to a particular specimen. The data matrix therefore had 50 columns (one per specimen) and approximately three million rows. Features were extracted from this

Specimen classification was conducted using a semi-supervised Gaussian Mixture Model, trained using the Expectation Maximisation algorithm. Repeated tests were conducted using different numbers of classified and unclassified specimens.

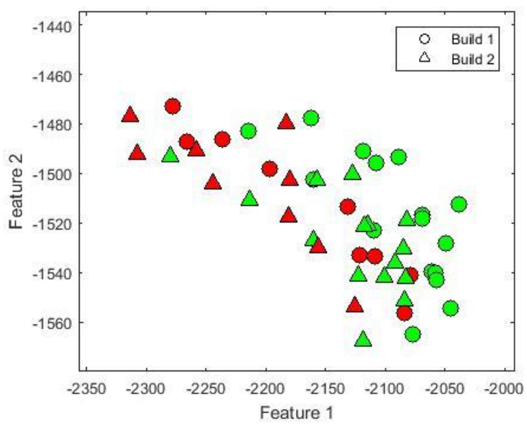


Figure 3. The position of each specimen in the feature space. The colour green represents 'acceptable' specimens and red represents 'faulty' specimens.

4. Results

Figure 4 shows the results obtained when half of the specimens are labelled and half are unlabelled (noting that the unlabelled and labelled specimens have been selected randomly). Green and red contours illustrate identified clusters that correspond to “acceptable” and “faulty” specimens respectively. The proposed approach was consistently able to correctly classified builds with a 77% success rate.

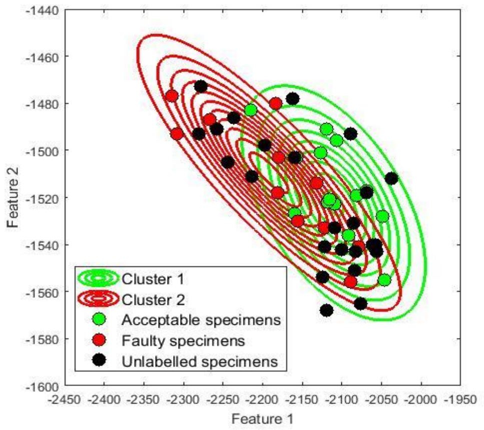


Figure 4. Semi-supervised learning results when half of the specimens are treated as unlabelled.

Repeating these tests for different numbers of unclassified builds it was found that similar algorithm performance could be achieved using as little as one third of the classified builds. This is particularly important when the cost of more thorough certification experiments are considered (CT scans, for example, often cost between £500 and £1000 per scanned component).

5. Wider applications

The project focused specifically on laser powder bed fusion applications. Currently it is being extended towards other forms of additive manufacturing, with a specific focus on inkjet printing (working in collaboration with Dr. Kate Black at the University of Liverpool). The aim is to predict optimum process parameters to produce higher quality parts. Stereolithography is another potential area of application.

6. Future Plans

For future work the goal is to implement *machine-learnt process control.* In such an approach, an algorithm would infer process windows within which parameters must remain to ensure part quality. By using the semi-supervised approach to reduce the number of certification experiments needed to infer such a control mechanism, it is expected that this work will greatly reduce the costs and time associated with new materials innovation in additive manufacturing.

The outcomes of the study are currently being developed into a graphical user interface for applications at Renishaw, UK. This work is being funded by an EPSRC impact acceleration account at the University of Liverpool.

An ultimate goal is to use real-time measurements to monitor the manufacturing process as it is carried out and allow only good products to reach the end-point of manufacture.

7. Conclusions

Additive Manufacturing (AM) is a digital approach for manufacturing highly customised components. However, uncertainty surrounding part quality hinders the adoption of AM technology in risk-averse sectors. This study investigated the application of a semi-supervised machine learning algorithm to the identification of faulty AM builds. Specifically, photodiode measurements from Laser Powder Bed Fusion (L-PBF) builds we used to automatically classify tensile test specimens, based on their ultimate tensile strength. Key outcomes were:

1. When using machine learning to infer build quality from L-PBF process measurements, the large quantity of available data can prevent the application of more conventional feature extraction methods. It was illustrated how this challenge can be overcome by using methods from the field of Big Data analytics.

2. By successfully classifying AM builds with a 77% success rate, the feasibility of identifying faulty L-PBF builds using a purely data-based analysis of photodiode measurements was shown.

3. It was demonstrated that, through a semi-supervised approach, the number of costly

certification experiments required in the implementation of automatic AM build classification can be significantly reduced.

8. References

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9. Feasibility study team members

The study was conducted by a team of researchers from the **University of Liverpool**

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Dr Kate Black, Inkjet Printing
Professor Chris Sutcliffe, Additive Manufacturing
Dr Ikenna Okaro, Data processing
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