Detection of Over-melting Layers in Laser Powder Bed Fusion Process using Machine Learning

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***Abstract*— The laser powder bed fusion (L-PBF) process is the most widely used metal additive manufacturing (AM) process. L-PBF uses laser energy to melt powder particles in a bed, layer by layer, to create a metal component. In the L-PBF process, appropriate heat exchange during the melting of the metal powder is critical for producing defect-free parts. The layer-wise production capability of L-PBF allows the use of in-situ process monitoring using sensing modalities like optical, thermal, acoustic, etc. In this study, we investigate different machine learning based classification models for in-situ identification of over-melting layers using characteristic features extracted from a spatially integrated indium gallium arsenide (InGaAs) photodiode signal. The extreme gradient boosting (XGBoost) classifier displays the best out-of-sample performance among all the tested models with a recall score above 97%. The proposed model will open the possibilities for corrective measures upon detection of over-melting layers and thus can contribute to the reduction of scrap parts.**

Keywords—L-PBF, XGBoost, in-situ monitoring, over-melting layers

I. Introduction

In recent years, the increasing availability of low-cost machine vision systems and the advances in computational capabilities for image, video, and signal processing have pushed the adoption of these systems for anomaly detection and process monitoring. High spatial and temporal resolution data streams from machine vision systems have found their application also in the metal additive manufacturing (AM) process. The layer-by-layer manufacturing mechanism of AM allows to monitor the process at a very high detail level, i.e., during the production of each layer up to melt pool dynamics level (at thousands of fps). It 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 the quick identification of defects in a layer.

The laser powder bed fusion (L-PBF) process is the most widely used metal AM process. L-PBF uses laser energy to melt powder particles in a bed, layer by layer, to create a metal component. Compared to traditional subtractive manufacturing, L-PBF can offer manufacturing functional parts with complex geometries and free-form shapes with reasonable feature resolution. However, the major inhibiting factor of industrial adoption of L-PBF is the generation of different types of defects associated with the process. Inappropriate heat exchange during the melting of the metal powder in L-PBF may lead to a defective part. Grasso and Colosimo [1] have summarized the commonly seen defects (e.g., porosity, residual stresses and cracking, balling, geometric defects) and their root causes in LPBF processes, as well as available commercial sensing tools and process signatures for in-situ detection of each defect type. Several defects (e.g., surface deformation, residual stress, warping) may arise due to the over-melting of a layer ([2], [3]). Detection of over-melting of layers during the L-PBF process can open the possibilities for corrective measures upon detection and thus can contribute to the reduction of defective parts.

Due to the layer-wise nature of the process, the defects are not always visible once the part production is completed. By introducing an online process monitoring system, the part quality can be monitored during the build. Grasso and Colosimo [1] and Yadav et al. [4] summarized the available in-situ monitoring systems for LPBF processes. The two most common sensing approaches for in-situ quality monitoring are thermal imaging and optical imaging, as they provide direct information related to melting pool, geometric information, structural defects, etc. Machine Learning (ML) techniques can effectively and efficiently process the collected data and classify it into normal and abnormal conditions for anomaly detection and process control, which is considered a classification problem. Depending on the sensing data modality, different ML techniques such as support vector machines (SVM) ([5], [6], [7], [8]) and convolutional neural networks (CNN) ([9], [10], [11], [12], [13]) have been widely used for thermal imaging and optical imaging based monitoring systems.

However, to the best of our knowledge, no research work considered measuring the radiation emitted by the melt pool (the region where the laser beam exposure melts the material) and its surroundings and using those signal data for in-situ over-melting layer detection. For this study, signals are acquired via one spatially integrated 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 (Fig. 1). The objective of the study is to develop a machine learning model that will enable the in-situ detection of over-melting layers.

The rest of the paper is organized as follows. In Section II, we describe the dataset collection, data preprocessing, feature extraction from the raw signal data, and evaluation method of

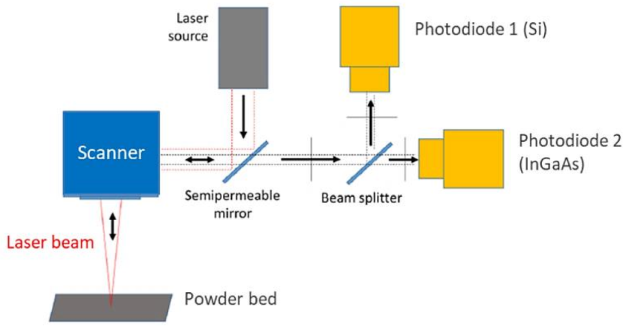

Fig. 1. The co-axial monitoring setup that utilizes two photodiodes aligned to the optical path of the laser [14].

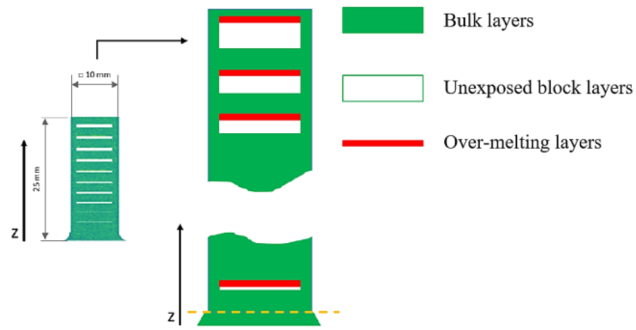

Fig. 2. Schematic view of the specimens with unexposed blocks, which are purposely used to force the creation of over-melting layers [14].

the investigated machine learning models. We discuss the results in Section III, and finally, in Section IV, we summarize our conclusions and posit some future directions.

II. METHOD

A. Data Collection

In this study, we have used a publicly available dataset that is part of an Open Data Science project between Trumpf GmbH and Politecnico di Milano and it is available at www.ic.polimi.it/open-data-challenge. The dataset contains signals acquired via spatially integrated indium gallium arsenide (InGaAs) photodiode sensor during the manufacturing of an AlSi10Mg (aluminum) specimen using a multi-laser L-PBF Trumpf system. The specimen was a parallelepiped of size 10×10×25 mm and it was produced with fixed process parameters (laser spot diameter of 100 µm, laser power of 4800 W, and a scan speed of 1500 mm/s). The labeled dataset was created by purposely introducing over-melting layers in a specified sequence by designing some unexposed blocks, i.e., no laser scan occurred for several consecutive layers (ranging from 1 to 10). The unexposed blocks tend to force the following layers to suffer from over-melting due to heat conduction anomalies with increasing severity as the number of unexposed layers increases. The rest of the layers in the specimen were nominally printed bulk layers. Thus, the specimen contains 3 classes of layers – bulk layers, unexposed block layers, and over-melting layers, as illustrated in Fig. 2.

B. Data Preprocessing

The specimen contains 379 layers among which there are 297 bulk layers, 55 unexposed block layers, and 27 over-melting layers. To ensure training on a balanced dataset, the minority classes (the unexposed block layers and over-melting layers) were over-sampled using the synthetic minority over-sampling technique (SMOTE) [15]. The balanced dataset was then randomly split into training (80%) and testing (20%) groups.

C. Feature extraction

The InGaAs photodiode signal array for the 379 layers varies depending on the geometry of the layers. The signal array ranges from 30339-31135 for the bulk layers, 9560-9726 for the unexposed block layers, and 30483-31102 for the over-melting layers. We extracted three sets of characteristic features from the signal array – (1) mean, standard deviation, and deciles (MSD); (2) mean, standard deviation, and quartiles (MSQ); (3) mean, standard deviation, median, maximum (MSMM). These three feature datasets will be used to train the ML models.

D. Evaluation Method

We have listed fifteen popular classifiers that will be trained on the three feature datasets (MSD, MSQ, and MSMM) and their performance score will be measured. The listed classifiers are logistic regression, support vector machines, *k*-nearest neighbors, decision tree, Gaussian Naïve Bayes, stochastic gradient descent, perceptron, nearest centroid, ridge, Nu-support vector, Bernoulli Naïve Bayes, random forest, AdaBoost, extreme gradient boosting, and passive-aggressive. We opt to use "Recall" (1) as the performance metric since detecting an over-melting layer is of utmost importance. In (1), "True Positives" refers to the number of correctly classified over-melting layers, and "False Negatives" refer to the number of over-melting layers misclassified as nominal layers.

Among the investigated fifteen classifiers, we will select the top three classifiers as baseline models depending on the performance over the three feature datasets. Next, we perform the hyperparameter tuning of the selected baseline models to improve the performance. To this end, we perform a 10-fold cross-validation using grid search.

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}} \tag{1}$$

III. RESULTS

As described in Section II, we extract features from the photodiode signals following three approaches and prepare three datasets (MSD, MSQ, and MSMM). For all three datasets, among the investigated fifteen classifiers, random forest (RF), extreme gradient boosting (XGBoost), and decision tree (DT) best fit the training data. The training recall scores of these algorithms are shown in Table I. The best values of the parameters for each algorithm obtained through hyperparameter tuning and 10-fold cross-validation are reported in Table II. The out-of-sample recall scores for each dataset after hyperparameter optimization are reported in Table III.

TABLE I. TRAINING RECALL SCORES OF BASELINE MODELS

Features	Algorithms		
	RF	XGBoost	DT
MSD	0.977653	0.972067	0.977653
MSQ	0.966480	0.955307	0.949720
MSMM	0.944134	0.960893	0.949720

TABLE II. HYPERPARAMETER OPTIMIZATION RESULTS

Algorithms	Parameters: Values (dataset)
RF	'n_estimators': 10(MSD), 100 (MSMM), 200 (MSQ) 'max_features': 'auto' (MSQ, MSMM), 'sqrt' (MSD) 'max_depth': 3 (MSD, MSMM, MSQ)
XGBoost	'learning_rate': 0.001 (MSMM, MSQ), 1 (MSD) 'n_estimators': 1000 (MSMM, MSQ), 500 (MSD) 'max_features': 'sqrt' (MSMM, MSQ), 'log2' (MSD) 'max_depth': 3 (MSMM, MSQ), 9 (MSD)
DT	'max_depth': 3 (MSMM), 2 (MSD, MSQ) 'min_samples_leaf': 5 (MSMM), 1 (MSQ, MSD) 'criterion': "gini" (MSQ, MSD), "entropy" (MSMM)

TABLE III. TESTING RECALL SCORES OF HYPERTUNED MODELS

Features	Algorithms		
	RF	XGBoost	DT
MSD	0.921787	0.977653	0.916201
MSQ	0.921787	0.927374	0.921787
MSMM	0.921787	0.932960	0.910614

Recall scores closer to 1 is desirable in the context of our classification problem. As we can observe from recall scores in Table III, XGBoost performs better than other algorithms on out-of-sample datasets although it shows mixed performance for training datasets. As we are mainly interested in out-of-sample performance, XGBoost has been selected as the best classification algorithm to identify over-melting layers in the L-PBF process. In practice, we opt to use the MSD features since the best classification performance is found with the selected XGBoost classifier, in both training and testing phases.

IV. CONCLUSIONS

The new radiation-based signal data analysis allows the implementation of an in-situ monitoring strategy to identify over-melting layers in L-PBF processes using machine learning model. The high computational efficiency of this approach enables fast processing of the signal data coming from a photodiode sensor and it opens new possibilities for the application of real-time monitoring and detection.

Features have been extracted from the layer-wise photodiode signal data following three approaches: mean, standard deviation, and deciles (MSD); mean, standard deviation, and quartiles (MSQ); mean, standard deviation, median, maximum (MSMM). Three machine learning classification techniques (random forest, XGBoost, decision tree) have been trained to identify intentionally introduced over-melting layers using the signal data extracted from different layers of the specimen of interest. An overall recall score between 92% and 97% was observed for all the 3 machine learning classification methods. However, XGBoost performed the best on out-of-sample data. Moreover, the largest recall value has been found when the mean, standard deviation, and deciles (MSD) have been used as the features of the dataset.

In conclusion, XGBoost has proved its efficacy in detection of over-melting layer and its real-time applicability will enable its application to in-situ process monitoring and, in the future, process control to correct the detected over-melting layers in the L-PBF process.

It should be noted that the geometry of the specimen considered in our study is simple, and the unexposed blocks with multiple layers exaggerated the over-melting effect in the following layers. Under this simplified scenario, we have found encouraging results in this study. In the future, this work can be extended to specimens with complex geometries including unexposed blocks with smaller size and varying shapes.

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