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Melt-pool Defects Classification for Additive Manufactured Components in Aerospace Use-case

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Abstract—One of the crucial aspects of additive manufacturing is the monitoring of the welding process for quality assurance of components. A common way to analyse the welding process is through visual inspection of melt-pool images to identify possible defects in manufacturing. Recent literature studies showed the potential use of prediction models for defects classification to speed up the manual verification criteria since a huge data is generated from the additive manufacturing. Although a huge image data is available, the data needs to be labelled manually by experts which results in small sample datasets. Hence, to model small sample sizes and also to acquire the importance of parameters, we opted a traditional machine learning method, Random Forests (RF). For feature extraction, we opted for the Polar Transformation to explore its applicability using the melt-pool image dataset and a publicly available shape image dataset. The results show that RF models with Polar Transformation performed the best on our case study datasets and the second-best for the public dataset when compared to the Histogram of Oriented Gradients, HARALICK, XY-projections of an image, and Local Binary Patterns methods. As such, the Polar Transformation can be considered as a suitable compact shape descriptor.

Index Terms—Melt-pool defects classification, Polar Transformation, Random Forests, Additive Manufacturing, HOG, LBP.

I. INTRODUCTION

Additive Manufacturing (AM) is becoming more popular nowadays for producing light-weight customized products and for decreasing the cost and time of manufacturing [3]. One of the crucial aspects of AM is the monitoring of the welding process for a better quality of products. A common way to analyze the deviations in the welding process is through visual inspection of melt pool images which are captured by cameras [16]. However, this is a very time-consuming verification procedure if done manually since there is a large number of images generated from every built component, and it is also prone to human-inaccuracy due to the time consuming and tedious task. Another problem is that material and time are wasted because defect analysis is done after the component is manufactured (post-production). For instance, if larger defects are detected in the manufactured component, the product may be entirely discarded. Hence, process engineers need a support to automate the manual analysis for defects analysis of process data. Furthermore, Wang et al., stated that data modelling and analysis form an essential part in smart manufacturing

to support real-time data preprocessing, which is needed by most manufacturers [22].

To address this problem to some extent, prediction modelling with process data has been used to provide more efficient ways for quality assurance of manufactured components. For instance, Alessandra et al., have used deep convolutional neural network-based (CNN) model for detecting defects in selective laser melting (SLM) method [3]. SLM is one of the processes of AM methods. They showed the potential of prediction models, specifically, modelling with SLM process data for process control and part quality assurance in AM. Although prediction modelling has been shown as an efficient way, experts' manual labelling is needed to analyse images which result in fewer sample sizes. Consequently, there is a need to investigate methods to handle small sample sizes to get accurate models. Therefore, we aim to support process engineers in finding more efficient ways to model the available data for quality assurance of manufactured components.

Deep Learning (DL) has been applied in many domains for image classification and it has received increased attention from many researchers recently. However, in some domains where the number of labelled samples are few, it is difficult to construct accurate models because of the assumption that DL needs large size of datasets as discussed in Section II. Furthermore, despite the efforts on researching to understand CNN models, it is still an issue to understand which features contribute most to the built models. On the other hand, traditional Machine Learning (ML) techniques can handle small sample sizes and are less data dependent than DL techniques. This motivates us to explore the possibility of using the traditional ML methods, especially, Random Forests (RF) for image classification as it has been shown to perform well on high dimensions and small sample sizes [2] [6].

In contrast to DL techniques, feature extraction is needed to construct models using traditional ML techniques. For this, there have been a huge effort spent on feature extraction methods to automatically extract handcrafted features from images. These methods' applicability is shown in the literature exhibiting better performance, especially when there are limited labeled samples. Furthermore, in our domain, we integrate the compound of image data together with numerical side-information data (robot control parameters) to build prediction

models. The reason is that the robot control parameters' (or features) fine tuning cannot be done without knowing the influence and the impact of each parameter. Hence, the importance of robot control parameters is of a great help to domain experts to understand them better. This is also another reason to choose RF to build models as it can provide the importance of parameters.

For the feature extraction, we opted for Polar Transformation (PT). Our assumption is that PT is suitable for shaped object images as it extracts a salient signature of shapes. However, we have not found any studies which have investigated its applicability on shaped object image recognition especially in conjunction with the AM. Hence, the goal of the paper is to empirically investigate how PT affects the performance of RF models on melt-pool images (binary image classification tasks) in AM. In addition, we use a public binary shape image dataset to explore the potential use of PT on multi-class image classification tasks. For the performance comparison, we use three of the state-of-the-art handcrafted feature descriptors (i.e., the Histogram of Oriented Gradients (HOG), the HARALICK descriptors and the Local Binary Patterns (LBP)) and a naive XY-projections of images to build different RF models.

II. RELATED WORK

In this section, we discuss related work on defect classification tasks and their methods that have been used for these tasks.

For defect detection in steel surface images, traditional ML techniques have shown reliable results in many cases [17]. Due to the small size of datasets, Iker et al., have used traditional ML techniques which are k-Nearest Neighbors (kNN), Bayesian networks, Support Vector Machines (SVM) and decision trees for defects classification of surface of iron casting images [21]. For feature extraction from the images, the authors have used Fast Fourier Transformation (FFT) and Co-occurrence Matrix methods. The authors of this study concluded that FFT and SVM performed better compared to other methods. Domingo et al., have conducted a huge study for non-destructive test using X-ray images with defects and non-defects of automotive components [15]. The authors have compared 24 computer vision techniques using these X-ray images to evaluate their performance. The authors concluded that SVM has obtained the best accuracy, and stated that although CNN is fine-tuned, they could not improve the performance, most-likely due to overfitting. They also stated that handcrafted engineered descriptors showed to be sensitive to local textures which are the key for defect detection in X-ray images.

Due to the limited amount of training dataset (124 samples) and noisy environment to classify defects on surface of the tube in steel manufacturing, Chi-Tho et al., have proposed a method using feature vector and Artificial Neural Networks (ANN) [4]. They have compared the performance of kNN, SVM and ANN using the same descriptor, and concluded that,

on average, ANN outperformed than other methods. Furthermore, due to cost and time constraints of getting more data, Jens et al., have used eight traditional ML techniques—which are SVM, Decision Trees (DT), kNN, Logistic Regression, RF, ANN, Adaboost, and Discriminant Analyzer—for predicting cracks on inline images (camera images) of sheet metals to improve the monitoring in automotive industry [12]. The authors of this study concluded that DT has achieved the best accuracy to detect the cracks for quality inspection compared to other methods. For more literature, a recent study provided detailed review on surface defect detection using flat steel surface images [14].

Gao et al., have used Back Propagation Neural Networks (BPNN) and Radial Basis Function (RBF) to build prediction models using four features which are extracted from the shadow of molten pool images—which represent the morphology of molten pool—to characterize the weld quality. The authors investigated the effectiveness of these two models by analyzing different welding speeds and concluded that BPNN had better results compared to RBF [9]. Zhang et al., have used SVM and Fuzzy Neural Networks to build prediction models for weld defect classification using eight features extracted from a weld X-ray of weld image dataset of limited samples (84 samples). The authors of this study show that SVM has better performance on their costly and limited samples [24]. These aforementioned studies have focused on weld defect classification using mainly geometric features from images. A recent study provided more detailed literature on weld defect detection on radiography images [13].

DL techniques also have been used to classify defects for non-destructive testing. Daniel et al., have opted deep CNN for defects classification in industrial optical inspection [23]. The authors have used artificially generated huge dataset with more than a million samples for investigations and presented the hyper parameter analysis for their deep CNN architecture. They have showed that optical quality control could be developed with minimum knowledge of the problem domain by automated feature extraction using deep CNN. Alessandra et al., have used deep CNN based model for detecting defects in SLM process [3]. They have shown that their proposed model can be applied for adaptive SLM process control and part quality assurance in AM. Although DL techniques can extract features automatically, they require huge amount of training data [12]. This is not always feasible due to cost and time constraints of data labeling. Nevertheless, DL techniques can build accurate models in cases where sufficiently large number of datasets are available as shown in [23]. This was the reason for us to use traditional ML techniques which are vital for classifying defected surfaces.

As one can see from all aforementioned literature studies, the small sample sizes of data is one reason to investigate traditional ML techniques, and hence feature extraction techniques. However, we found very few studies that investigated melt-pool images for defect analysis using prediction modelling. Furthermore, there might be unknown patterns that need to be learned from these images and hence, there is a need

to focus on more features than geometrical features. It is also mentioned that previous studies are mainly focused on geometrical and texture features even though there are infinite unknown patterns and shapes for each type of weld defect [13]. Hence, we attempt to investigate different feature extraction techniques on melt-pool images to provide insights on these techniques to be able to model with the available data.

III. IN-SITU QUALITY CONTROL OF AM COMPONENT IN AEROSPACE USE-CASE

AM is "a process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies" [8]. One of the popular processes of AM is Laser Melt Deposition (LMD). In the LMD, a part is built by melting a surface with a laser beam and simultaneously applying metal wire or powder [7]. This process is captured with a camera, and it contains melt-pools which are created when the material is melting with a laser beam. The welding process is monitored by tuning robot control parameters, for instance, the distance of nozzle in relation to the substrate and the wire feed rate. The recorded video will be later used to analyze the deviations in welding process manually. The criteria to identify good from bad melt pool images are as follows: (1) Stubbing: If the distance of nozzle is too small or the wire feed is too high, this causes stubbing, and it is considered as bad welding (2) Dripping: Drops build up on the wire tip, if the height is too large or the wire feed is too low, since the wire melts very quickly. This is also considered as bad welding and (3) Smooth metal transfer: the process of melt pool is stable when the distance and wire feed speed are adjusted perfectly. This is considered as good welding.

By looking at images guided by the above criteria, process engineers check the defects in melt pool images (in-site quality control) visually to learn about input parameters to have better quality of manufacturing. However, the gained knowledge regarding defects or their potential causes is not often stored and re-used for future production pipeline. Furthermore, as explained in Section I, the visual inspection process is prone to human-inaccuracy due to the time consuming and the tedious task it requires. Therefore, we attempt to automate the manual inspection by reusing data to speed up and perform a continuous defect analysis while the welding robot is operating.

IV. METHODS

We use quantitative experimental research method to investigate the effect of PT for feature extraction on the performance of RF for melt-pool classification in AM. For the performance of PT comparison, we use XY projections, HOG, HARALICK and LBP feature extractors to build RF models to determine the applicability of PT. In the following, we describe all these methods and their setup briefly.

Polar Transformation: In the PT, the original image (in the cartesian coordinate system) is converted to polar image with polar coordinates. The contrast, calibration and pixel size are copied to the transformed images. The PT assumes that the

input image is in Cartesian space and uses the x values of the distance from the center (to calculate the radius r) and y-values to represent the angel (theta θ).

The PT requires specifying the center point in the original image [10]. Let us denote the original image dimensions as (M, N) with the coordinates (X, Y) , the center which the PT uses to calculate the distance to is $(\lceil \frac{M}{2} \rceil, \lceil \frac{N}{2} \rceil)$ for gray-scale images. In case, the image is binary and contains a single shape, as is the case in our datasets, then the sought center is in fact the center of the object $(\lceil \frac{X_{x \in object}}{|X_{x \in object}|} \rceil, \lceil \frac{Y_{y \in object}}{|Y_{y \in object}|} \rceil)$, where $\lceil \cdot \rceil$ denotes a ceiling operator and $|\cdot|$ denotes the length of a vector. The latter makes the Polar representation eventually invariant to translation. After identifying this center, the PT will operate on this new center treating it as the origin (0,0), and then we choose 360 degrees data—which assumes that x-values start from 0 to positive radius values—to extract data.

The PT always results in an image with the height of 360 (due to the circular scan) and the width is a variable corresponding to the largest distance (depending on the original image dimensions). To be able to extract descriptor vectors with the same length, the resulting Polar image is resized to (360, 256) where the height is kept unchanged. Subsequently, we extract the XY-projections of the polar image and concatenate them to form the final feature vector with a fixed length of 616 values. We believe that the PT is useful to extract features from images embodying round shaped objects. Since we have round shaped objects in our welding images, we opted for PT to investigate its applicability for feature extraction.

XY Projections: We create a feature vector profile by extracting horizontal (X-projection) and vertical (Y-projection) projections from the images to build a prediction model.

Histogram of Oriented Gradient: HOG is a feature descriptor that is used to extract features from images [18]. The HOG focuses on shapes or structure of objects and it is able to provide the edge directions by extracting the gradient (magnitude) and orientation (direction). First, the image is divided into smaller regions. Second, the gradients and magnitudes (x and y directions) are calculated for each of these regions. Third, it generates a histogram for each of these regions separately using the gradients and orientations. Forth, it uses normalization on these features because gradients of the image are very sensitive to overall lighting. Last, the algorithm combines all these regions of HOG features into one feature vector that represents the whole image.

HARALICK: In 1973, Robert M. Haralick, a computer scientist, introduced the gray scale co-occurrence matrix (GLCM) to extract texture features from images [11]. The GLCM uses adjacency concept that looks for pairs of adjacent pixel values in an image and then it keeps recording these values for the entire image. Once the GLCM matrix is constructed, texture features are computed as a global representation of a given image using the descriptive statistical equations from [11].

Local Binary Patterns: Unlike HARALICK, the LBP method computes the local representation of texture by com-

paring each pixel with its surrounding neighbouring pixels [19].

V. EXPERIMENTAL DESIGN

The aim of the experiment is to determine which feature extraction method gives the most accurate RF models for the studied classification of melt-pool defects and also for the publicly available image shape dataset. In this section, we describe our experimental design which includes datasets description, hyperparameter tuning and configuration selection, evaluation procedure and performance measures.

Datasets Description: We used three datasets for the experiments. The first dataset D1 contains 140 gray images and two classes (binary image classification). The second dataset D2 is an extension of D1 in which each image has four robot control parameters associated with each image. Both the D1 and D2 are aerospace use-case datasets (use-case description found in section III), and are generated from videos (15 images per second) supplied by our partner company. The labels of these images are either "good" or "bad" (the labeling criteria is explained in Section III). We removed the timestamps from images before we apply feature extraction techniques and build models with RF. The third dataset D3 is a public shape image dataset which contains 1400 binary images with 70 classes, each of which has 20 samples [1]. It is clear that the dataset D3 is not directly relevant to AM but it has shape image objects similar to D1 and D2. The reason of choosing the dataset D3 is to explore the applicability of PT for multi-class image classification and test the models' generalizability.

Hyperparameters and Configuration Selection: We selected the number of trees (*ntree* hyperparameter for RF. The reason is that in a previous study, it states that increasing the *ntree* can decrease the forest error rate [5] [20]. A threshold range is provided for *ntree* which are values between 10 and 130 for classification tasks. Hence, we choose 130 for *ntree*. For the feature extraction techniques, we use the default settings of MATLAB packages.

Evaluation Procedure and Measures: For all the datasets, we use 70% of data for training the models and 30% for testing. We run 10 experiments for each dataset and each method by randomly sampling the train and test datasets while keeping the same ratio. For the performance evaluation, we measure the classification accuracy (the number of correct predictions divided by the total number of predictions) and the F-score metrics (harmonic mean of precision and recall).

Experiments: We use MATLAB for the experiments. The specifications of the system are as follows: 64-bit Windows 10 operating system with 3.10GHz Intel XeonE3-1535M CPU processor and 32 GB RAM. We set the following steps to conduct the experiments: (1) Perform data preprocessing to eliminate the timestamps on the welding images (only for D1 and D2) (2) Apply the selected feature extraction techniques to extract the features (3) Build the classification models using RF with extracted features (4) Apply the evaluation procedure and evaluation measures and (5) Measure the accuracy and the F-score of models using each of the selected methods.

TABLE I
MEAN OF ACCURACY AND F-SCORE FOR ALL DATASETS

Method	Accuracy			F-score		
	D1	D2	D3	D1	D2	D3
XY proj	0.9333	0.9262	0.8183	0.9364	0.9297	0.8147
HOG	0.9357	0.9357	0.8276	0.9399	0.9404	0.8401
HARALICK	0.9238	0.9286	0.5229	0.9255	0.9323	0.5320
LBP	0.9357	0.9429	0.7600	0.9406	0.9463	0.7737
PT	0.9452	0.9405	0.8090	0.9475	0.9434	0.8248

VI. RESULTS AND ANALYSIS

In this section, we present results for our use-case study datasets (D1 and D2) and the public image shape dataset (D3) using the five feature extraction methods and the prediction models. Table I shows the mean classification accuracy on each of the test datasets (mean of accuracy of 10 experiments for each model). For the D1, the PT method yields the best accuracy. For the D2, both PT and LBP methods have better accuracy (we compare first two decimals of results) compared to other methods. For the dataset D3, HOG outperformed others. Also, we have measured the F-score for performance comparison as it gives a fairer comparison of the performance of feature extraction methods. As shown, the F-score in Table I, shows that both LBP and PT performed equally good for D1 and D2, the HOG also yielded a good result for D2. For the public shape dataset D3, the HOG method performed the best compared to other methods, with the PT being the second performer.

Analysis: Figure 1 shows bar plots for the F-scores which are shown in Table I. We observed that PT outperformed other methods for the binary image classification for D1 and D2, and is also the second-best for D3 for multi-class image classification (70 classes). Whereas the HOG performed the best for the D3, and the reason might be that the D3 dataset has 1400 samples which are ten times larger than D1 and D2. Hence, the HOG might perform better if we have more samples for D1 and D2. Nevertheless, the difference between PT and HOG are around one to two percent of accuracy for all three datasets. However, the extracted features from HOG (3780 features for D3) are higher compared to PT (616 features for D3) and hence HOG exhibits more time complexity in building models. Furthermore, although the PT has fewer features (616) compared to the XY projections (6462), the LBP (7076) and the HOG (3780), it outperformed other methods for melt-pool classification.

In general, we observed that the accuracy differences between all methods are one to two percent for both D1 and D2. However, it is not the case for the dataset D3 in which HARALICK and LBP have lower accuracy compared to other methods, and both are texture descriptors. The reason is that D3 comprises binary image shapes and hence some of the texture features are not contributing to the predictive performance which results in low accuracy.

Another observation is that, by adding the robot control parameters to dataset D2, the accuracy increases slightly from that of D1 in which we have only melt-pool images.

Fig. 1. Mean of F-score for All Datasets

Nevertheless, this is an attempt to investigate melt-pool images together with robot control parameters as they play a vital role in the manufacturing process. Hence, this investigation allows us to study more robot control parameters in the future to understand their effects on welding quality by extracting their importance from RF models. Furthermore, we observed that the accuracy of RF models shows that it has reasonable accuracy on small image samples (140 images) and high dimensions. However, we have not compared the performance of RF to any other classification methods because we focused on a classifier (RF) that is capable of producing parameters importance. Due to confidentiality of the use-case data, we are not allowed to provide more details of melt-pool images and robot control parameters. Nevertheless, the dataset D3 is publicly available [1] to reproduce the results.

VII. CONCLUSION AND FUTURE WORK

In this paper, we attempted to investigate the applicability of Polar Transformation (PT) on images with shaped objects to extract features to build melt-pool defects classification models using RF. To compare the performance of the PT method, we have opted for XY projection, HOG, HARALICK and LBT methods. The experimental investigations are conducted using our case study image datasets from additive manufacturing for binary image classification. Furthermore, we have used a public shape dataset for the multi image classification to investigate the applicability of PT. The results show the potential of using PT on the shaped object images as it performed the best for our case study datasets and the second-best for the public dataset. In future work, we will study more robot control parameters together with melt-pool images to understand their effects on welding quality for multi class image classification tasks.

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