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Porosity prediction: Supervised-learning of thermal history for direct laser deposition

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ABSTRACT

The objective of this study is to investigate the relationship between the melt pool characteristics and the defect occurrence in an as-built additive manufacturing part. One of the major detrimental microstructure properties associated with additive manufacturing (AM) is porosity within final parts. State-of-the-art porosity detection methods focus primarily on post-manufacturing approaches that are susceptible to high cost of process, longer process time, and are incapable of characterizing pores during fabrication. A real-time porosity prediction method is developed using morphological characteristics of the melt pool boundary (i.e., features obtained via functional principal component analysis (FPCA)). A thermal monitoring system is used to capture the time-varying melt pool signal, which are labeled as either pores or normal melt pools by X-ray tomography. Supervised learning methods are utilized to identify the patterns of melt pool images and build a black-box model for the probability distribution of class labels (namely, porosity) based on data characteristics of predictors (e.g., melt pool characteristics). The resultant model does not depend on specific design of specimens with varying material properties; and can be effectively developed as long as thermal-porosity data can be obtained. In the current study, multiple supervised machine learning approaches are used to classify melt pools to predict porosity in a part. Two different accuracy measures are used and numerical experiments show that among the classification approaches used (i.e., Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA)), KNN results in the highest rate of accurately classifying melt pools (98.44%). However, DT results in the lowest rate for incorrectly identifying normal melt pools as pores (0.03%). A comparative study is conducted that compares the performance of supervised learning methods leveraging the proposed morphological model and simple metrics of the melt pool. Numerical experiments show that the morphological model combined with supervised learning techniques vastly outperform the simple melt pool metrics combined with supervised learning techniques (approximately 250% better performance for correctly predicting abnormal melt pools). Our approach may potentially be applied to other AM processes that share similar energy-material interactions (e.g., powder bed fusion, electron beam melting).

1. Introduction

The inadvertent defects of additive manufacturing (AM) parts result in low repeatability of AM products, which prevents wider adoption of AM technologies. One of the more detrimental microstructural properties associated with AM is porosity within final parts. The existing methods of defect detection/characterization mainly rely on *post-manufacturing* methods, such as X-ray computed tomography (CT), ultrasonic inspection, and many more [35,51]. However, these post-manufacturing techniques are extremely expensive and time-consuming. Hence, there is an imperative need to develop methods for online detection/control of defects during the build. Establishing a quantitative relationship between the characteristics of melt pools and the formation of porosity in the as-built parts during the fabrication provide a rational solution to this predicament.

The characteristics of melt pools are expected to be highly correlated to abnormalities of microstructure, and thus defects in the fabricated parts [5]. Finite element modeling (FEM) has been developed to

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characterize the underlying thermo-physical process of AM, and predict the evolution of microstructure [14,70]. These methods are mainly developed according to the specific part designs (e.g., cube, thin wall). Hence, tremendous efforts are needed to model the thermo-mechanical process while fabricating parts with complex geometries. Moreover, due to the deterministic nature of most FEMs, process uncertainty is not taken into consideration. The predicted microstructure and mechanical behaviors tend to deviate from the actual manufacturing. Last but not least, FEMs usually require high computational costs, which will be difficult to implement for real-time monitoring/control.

To circumvent the challenges of modeling the complex thermo-physical process, supervised machine learning can be utilized to identify the patterns of melt pool images and its relationship to porosity. Melt pool morphological characteristics play a crucial role in determining the thickness of deposited layers, the microstructure evolution, and the pore formation. This has been studied extensively in [11,13,61]. Supervised learning builds a *black-box* model for the probability distribution of class labels (namely, porosity) based on data characteristics of predictors (e.g., melt pool characteristics). The class labels are defined as binary random variables that give the value of 1 if the melt pool is identified as porosity, and 0 otherwise. The resultant model does not depend on the specific design of specimens of material properties and can be effectively developed as long as thermal-porosity data can be obtained. To establish an accurate supervised learning model, a major challenge must be addressed: melt pool signals are represented by high-resolution images with varying sizes and shifting centers due to the dynamic thermal process. Using such ill-structured melt pool signals as predictors directly causes issues such as co-linearity and curse-of-dimension, which affects the prediction accuracy. Hence, dimension reduction and feature extraction procedures are needed to develop a structural predictor that captures the critical characteristics of melt pools. To address this challenge, we develop a methodology based on functional principle component analysis (FPCA), which extracts key characteristics of melt pools and converts it to smooth functional curves. The first few principle components (PCs) of these curves represent the major sources of variation in the thermal history, and thus are used as the predictor of porosity. It is shown in Section 3 that principle components (PCs) of melt pool images can potentially distinguish normal melt pools from abnormal ones.

Once the melt pools are labeled via X-ray tomography, we apply multiple classification methods (i.e., Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA)) to establish the relationship between the PCs of melt pool images and the binary response that indicates the formation of porosity at the corresponding location. Cross validation is used for parameter tuning and model validation. In particular, the classification models are trained based on a randomly selected subset of the data and tested based on the remaining dataset. This procedure is repeated for multiple times to ensure that each data point is selected for both model training and testing. Fig. 1 accounts for overall machinery of the supervised learning methods for porosity prediction.

We compare the accuracy of the proposed method that utilizes comprehensive melt pool characteristics with simple metrics of the melt pool such as length, width, peak temperature, area, etc. [36,51]. Results show that porosity prediction using the simple metrics of the melt pool produces very poor accuracy measures compared to the morphological characteristics of the melt pool. In summary, the technical contributions of this study to the existing literature are as follows:

1. We develop a novel data processing method for reducing the dimension of the thermal image data and extracting features relevant to the generations of porosity in the as-built parts.
2. The proposed method is compared with the studies in the literature, which mainly use the simple characteristics for thermal monitoring and control. Although such characteristics provide general information about the stage of the process, our comparison shows that using such simple characteristics are not sufficient for porosity prediction.
3. The proposed machine learning method for porosity prediction results in high recall value (98.44%), which provides a means to circumvent time-consuming porosity characterization.
4. Five supervised learning classification methods (i.e., Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA)) have been investigated. The most suitable classification methods for thermal-porosity relation have been identified and recommended.

2. Literature review

In this section, we survey the papers that investigate the melt pool quantification and characterization as well as discuss the existing porosity detection techniques. This section is divided into two sub-sections, i.e., (1) existing porosity detection techniques and (2) quantifying and characterizing the time-varying melt pool.

2.1. Existing porosity detection techniques

The existing literature on porosity detection techniques can be broadly classified into three major areas: (1) porosity detection techniques based on post-manufacturing characterization, (2) visual based porosity detection techniques, and (3) simulation based porosity detection techniques.

2.1.1. X-ray computed tomography and ultrasonic

X-ray computed tomography or ultrasonic techniques have been the major mechanisms that are extensively used for post manufacturing characterization while detecting porosity. Many researchers have provided a higher level overview on the operations of the machine and how it can contribute to detect porosity in the parts. For instance, the benefits of using flash thermography against other approaches such as ultrasonic attenuation estimation have been investigated by Meola and Toscano [44], where the authors show that flash thermography is non-contact, cost-effective, and fast compared to other approaches. Through experiments, the authors have also found that by flash thermography, a part can be inspected while viewing the smooth or the rough side indifferently. For three-dimensional (3-D) defect characterization, analysis, and visualization, Wells has showed X-ray computed tomography modality using advanced Volume Graphics StudioMax (VGSM) voxel analysis and visualization software [68]. Porosity and some inclusions have been found in this study and the total defect level has been found to be 1.11% of the total casting volume. X-ray computed tomography method, involving image enhancement and ring artifact removal prior to image segmentation, has been proposed by Cai et al. [6], where the authors investigate the effect of process parameters on material porosity. The authors validate the superiority of X-ray computed tomography over other conventional methods through several experiments.

Ultrasonic methods are primarily used for analyzing the porous structure, mechanical strength, and to detect internal defects [39]. Kim et al. [36] have investigated the procedure for estimating the porosity content of composite materials, which relies on the decomposition of the original ultrasonic pulse-echo signal into a sum of elementary wavelet contributions. This results in the reduction of complicated functions into several simpler ones, which are studied separately later. Eren et al. [16] propose three different ultrasonic approaches for characterizing porosity as well as for detection and imaging of different type of defects in the ceramic materials. Among the three approaches, the A-scan analysis has been found to be better suited for the detection of different type of defects in the ceramic tiles with a contact high-frequency longitudinal wave transducer. Air-coupled ultrasound is suitable for non-contact detection and the imaging of defects in ceramic