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in-situ laser-based process monitoring and In-plane surface anomaly identification for additive manufacturing using point cloud and machine learning

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Abstract

*Additive Manufacturing (AM) is a trending technology with great potential in manufacturing. In-situ process monitoring is a critical part of quality assurance for AM process. This paper presents an in-situ laser-based process monitoring and anomaly identification system to assure fabrication quality of Fused Filament Fabrication (FFF) machine. The proposed data processing and communication architecture of the monitoring system establishes the data transformation between workstation, FFF machine and laser scanner control system. The data processing performs calibration, filtering, segmentation for point cloud of each layer acquired from 3D laser scanner during the fabrication process. The point cloud dataset with in-plane surface depth information is transferred into 2D depth image. Using the image dataset, four Machine Learning (ML) classification model are trained and compared, namely Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Convolutional Neural Network (CNN), and Hybrid Convolution AutoEncoder (HCAE). The HCAE classification model shows the best performance to effectively classify the in-plane anomalies into four categories, namely empty region, normal region, bulge region, and dent region.*

Keywords: Additive Manufacturing, Anomaly Detection, Point Cloud Processing, Process Monitoring

1. INTRODUCTION

Additive Manufacturing (AM), also known as 3D printing, is one of the most promising manufacturing technologies. It shows excellent potential in cost and energy reduction compared with other manufacturing techniques [1]. It has an incomparable advantage in fabricating parts with complex structures. However, the process robustness, repeatability, and stability restrict the development of AM technologies. Therefore, the process monitoring, and anomaly detection become the pre-requisite of quality assurances for AM technologies.

Several in-situ process monitoring solutions have been presented to improve the part quality [2-6]. Due to the characteristics of AM parts and in-situ monitoring requirements, the non-contact and non-destructive sensors, like vision-based monitoring technologies, are widely utilized for AM systems. Yi et al. [4] used a single camera on the top of a Fused Filament Fabrication (FFF) machine. The upper surface of each layer was captured by the camera and analyzed using machine vision and statistical process to detect the contour profile defects. The single camera cannot capture the depth information accurately of fabricated parts. Li et al. [5] applied two camera stereovision system to obtain the surface topography of fabricated parts in Powder Bed Fusion system. With the structure light method, they could identify the big valley of parts. But the monitoring system is fixed on the top of the chamber. The robustness and reliability of the monitoring system highly rely on the environmental light intensity. The light condition could significantly change the parameters in the machine vision algorithm. The laser-based 3D scanner shows the better capability in obtaining comprehensive and accurate information of the target. The laser scanner operates typically with a laser stripe emitter and a camera according to the principle of optical triangulation. Jorge et al. [6] implemented a laser scanner on a Laser Metal Deposition (LMD) machine to obtain the point cloud data of fabricated part surface. Since the camera only receives the known laser line, the laser scanner has better repeatability on the fine-detailed shape measurements.

Different methods have been applied in laser-based sensor data processing for surface quality. Machine Learning (ML) algorithms assistant researchers to analyze the sensor data and identify the surface anomalies of fabrication process. Scime and Beuth [7] proposed a defect classification model for Laser Powder Bed Fusion (L-PBF) machine. The captured images of powder bed process were used as training data for a Convolutional Neural Network (CNN) model. The algorithm can extract the key features from the raw data and classify them accordingly. The classification model showed 84% classification accuracy. Most of the proposed deep network models relies on a significant number of labeled data for training to get a satisfactory accuracy. Huang et al. [8] proposed a Hybrid Convolution AutoEncoder (HCAE) network to extract meaningful information from limited number of labeled images and perform a generalized classification over unlabeled data. This method not only showed an acceptable accuracy in prediction of labels, but also by removing the barrier of training set size, it enabled researchers to step further in other subjects with more efficiency and flexibility.

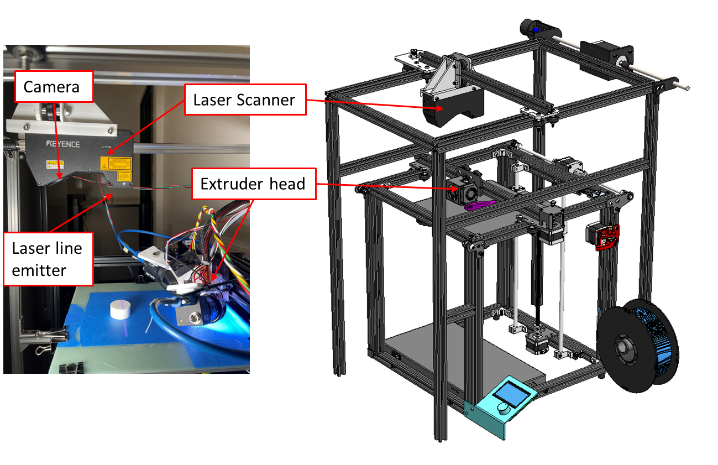
In this study, to promote quality assurance of AM process, an in-situ laser-based process monitoring and anomaly identification system is developed for FFF-type machine. During the FFF fabrication process, the non-optimal process parameters and accumulation of process uncertainties could cause the bad interior structure of parts, leading to weak mechanical properties or even fabrication failures. By monitoring the layer in-plane surface, the anomalies can be identified in the first place. Further controlling actions can be taken to operate the machine accordingly. To find the best anomalies classification model, several ML models are compared, and the classification results are validated.

1. **METHODOLOGY**

The proposed in-situ laser-based process monitoring and anomaly identification system is designed for the FFF machine. Equipping with non-contact laser scanner, the top surface profile of each layer can be captured during the FFF fabrication process. With the integrated ML algorithm, the anomalies of top surface can be identified.

**2.1 System Setup**

The monitoring system is built on a modified Creality Ender 5, which is an open-source FFF printer, shown in Fig. 1. The main board of the machine is using Marlin firmware and has bootloader install. The workstation could realize real time communication through serial communication. The laser scanner system used in this study is a KEYENCE high-speed Laser Profiler LJ-V7000 series. The sensor is mounted on the extra frame which is rigidly connected to the FFF printer. The sensor can move in a plane that is parallel with the FFF printer plane. The distance (in direction) between sensor and target surface is calculated with a resolution of 1 µm based on the laser-based 3D triangulation principle. The communication between the workstation and laser scanner is established via TCP/IP.



**FIGURE** **1**: THE HARDWARE SETUP OF MONITORING SYSTEM FOR FFF

**2.2** **Data Processing and Communication Architecture**

The data processing and communication architecture for the in-situ laser-based process monitoring and anomaly identification system is demonstrated in Fig. 2. The application is established using the Python programming language. The slicer algorithm slices the CAD model based on the fabrication requirement in the workstation. After generating the g-code, the multiprocessing software initializes the communication between the workstation, and FFF printer, and laser scanner. The g-code is sent to the buffer memory of the FFF printer line by line. During the fabrication process, the extruder head needs to move aside to clean the nozzle after each layer. Simultaneously, the scanner frame motion mechanism drives the sensor to move above the fabricating layer. The laser controller continuously triggers the laser emitter and built-in camera. When the predefined batch size is reached, the 2D laser line profiles are combined and published as a raw point cloud dataset. Then Three subprocesses of point cloud processing are executed successively. The raw point cloud dataset is pre-processed by noise removing algorithms and transforms from sensor local coordinate to printer Tool Centre Point (TCP). Then the upper surface is segmented from the pre-processed dataset and converted to a 2D depth image. Finally, the image is fed to an integrated pre-trained classification model and the anomalies can be identified.

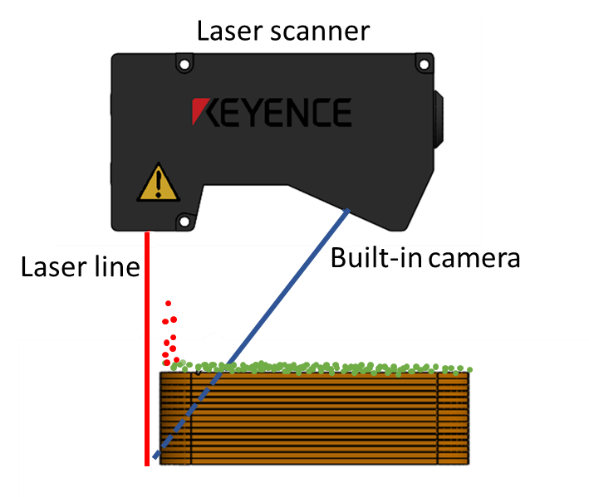


**FIGURE 2**. DATA PROCESSING AND COMMUNICATION ARCHITECTURE DIAGRAM

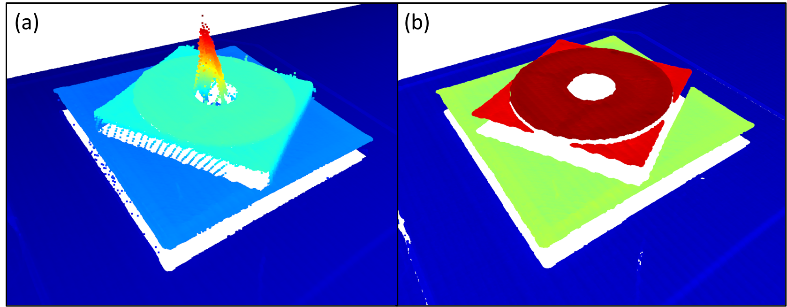
**2.3 Point Cloud Processing**

The raw point cloud dataset subscribed from the laser scanner includes noise which is commonly caused by the mechanical vibration and the shadow effect characteristics of optical scanning sensor. To obtain a clean dataset, replacing the missing measurement values and removing the outliers are necessary.

A batch of raw point cloud acquired from the sensor is formed as a 2D depth matrix. During the scanning process, if the target is out of the scanning range (in direction) or the built-in camera cannot capture sufficient laser line information, the corresponding pixels are flagged as missing measurement, as NaN in this paper. The median interpolation operator with a window is used to replace the missing measurements which show better performance for step-like features[9]. The laser scanner calculates the distance from the target based on the 3D triangulation method. Therefore, the shadow effect causes the sensor to be sensitive to the abrupt change of height, as shown in Fig. 3. The boundary area of the target could be recognized as outliers algorithmically. The statistical outlier removal method modified from the point cloud library (PCL) [10] is used to remove the noise. The neighbor points whose distance from the center point is over the threshold are eliminated. The comparison between raw point cloud dataset and cleaned dataset is shown in Fig. 4.

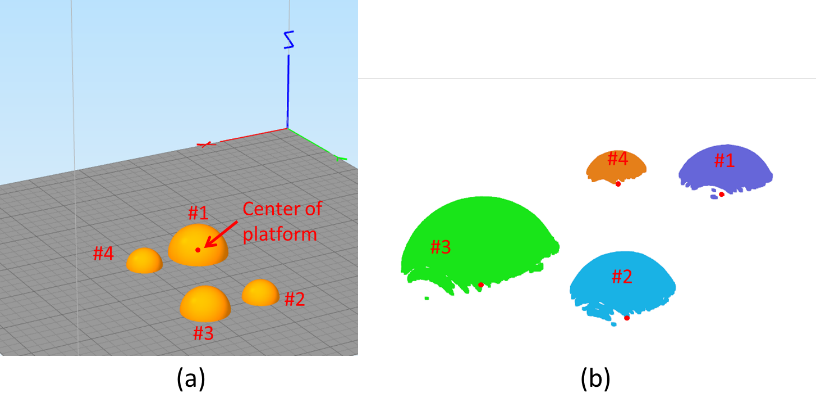


**FIGURE 3**. NOISE CAUSED BY SHADOW EFFECT (GREEN DOTS REPRESENT NORMAL POINT CLOUD AND RED DOTS REPRESENT NOISE)



**FIGURE 4**. EFFECTS OF FILTERING FOR RAW POINT CLOUD DATASET

After removing the noise from the dataset, it is necessary to perform calibration to find the spatial relationship between the FFF printer and laser scanner. In this paper, the fabricated spherical target is used for calibration. Compared with the conventional referencing marker, the fabricated target has a determined position on the platform of 3D printer. Meanwhile, the point cloud of the spherical target can be identified accurately and robustly by segmentation algorithms [11]. The spherical segmentation algorithm is modified from PCL to obtain the center coordinates. As shown in Fig. 5., Four hemispheres are designed and fabricated. The transformation matrix from laser scanner coordinate to printer TCP can be represented as 3D affine geometric transformation. For registering two coordinates, the iterative closest point (ICP) algorithm is widely used to minimize the difference between two point clouds. To reduce the computational burden, only the centers of four hemispheres are selected as key points of two coordinates. The point cloud of the platform needs to be removed first using random sample consensus (RANSAC) to reduce the consequences on sphere segmentation. After setting the spherical model parameters, the four hemispheres can be segmented. Then the center coordinates of scan data and designed position are used to calculate the transformation matrix using ICP algorithm.

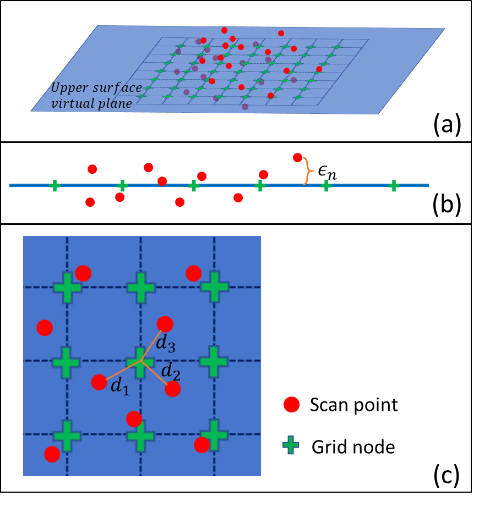


**FIGURE 5.** HEMISPHERE CALIBRATION TARGET

**2.4 Upper Surface Depth Image Generation**

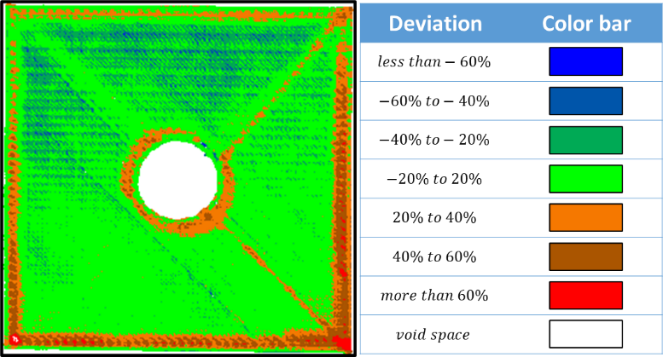
After pre-processing the raw dataset, the point cloud dataset needs to be segmented. To identify the upper surface in-plane anomalies, the 2D depth images are used as training data for ML classification algorithms. The 2D depth image shows better computational efficiency than the 3D point cloud in the classification process. The rasterization method is used to project the 3D point cloud onto a 2D image as shown in Fig. 6. Using the RANSAC algorithm, the inliers of the upper surface can be segmented, and the upper surface virtual plane is obtained, shown in Fig. 6(a). Then the inliers are projected on the virtual plane. Every projected point finds the nearest grid node using the K-dimensional tree (Kd-Tree) method and calculates the distance between them, shown as Fig. 6(c). The grid node has projected points around. The depth of the grid node is calculated by the depth between point cloud to virtual plane, shown in Fig. 6(b). The depth is weighted by the distance . The accumulated depth of the grid node is calculated by,

where .



**FIGURE 6.** POINT CLOUD RASTERIZATION METHOD (A) 3D VIEW (B) SIDE VIEW (C) TOP VIEW

Subsequently, the colors of the depth image are mapped based on the grid depth . To represent the bulge anomaly caused by over extrusion, and dent anomaly, and gaps caused by under extrusion, the RGB color space is selected to show both depth information and empty area. One point that needs to be emphasized is the color mapping standard must be constant to ensure an accurate classification result. The ratio of depth to designed layer thickness (which is 0.3mm in this paper) is mapped to the color space. To further improve the computation speed, the only six levels of color are selected and shown in Fig. 7.



**FIGURE 7**. RGB DEPTH IMAGE MAPPING RULE

**2.5 Classification algorithms**

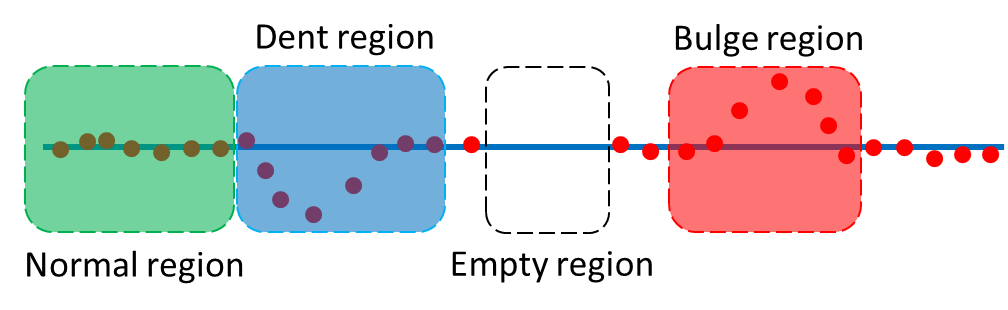
In this research, four different classification algorithms are trained and compared for accuracies in surface anomaly identification. The Support Vector Machine (SVM), K-Nearest Neighbors (KNN), CNN, and HCAE. The open-source TensorFlow 2.1.0 [12] and Scikit-learn 0.22.1 [13] libraries are used to implement these algorithms. The hyperparameter tuning for SVM and KNN is conducted by grid search which is an exhaustive method to compare all the possible combinations of hyperparameters. It takes longer computational time than the alternative random search method but ensures the optimal hyperparameters can be identified [14]. During the grid search, each classifier candidate is trained, and the performance is evaluated by k-fold cross-validation to avoid overfitting. The deep learning algorithm shows superiority for image processing and classification. CNNs, as one of the most popular deep learning algorithms, have been demonstrated the expertise in optimal feature extraction. [Say something about HCAE]

The F-score metric with range 0-1 is used to quantify the accuracy of each classification algorithm. The F-score is a way to combine the precision and recall of a model, and it is defined as the harmonic mean of the model’s precision and recall. The precision measures the proportion of true positives among test outcome positives and recall measures the fraction of samples classified as positive among the total number of positive samples. The F-score is calculated by,

where means true positive, false positive, and false negative, respectively. The most accurate classification model can be selected to perform the surface anomaly identification as the third subprocess of the point cloud process, as illustrated in Fig. 2.

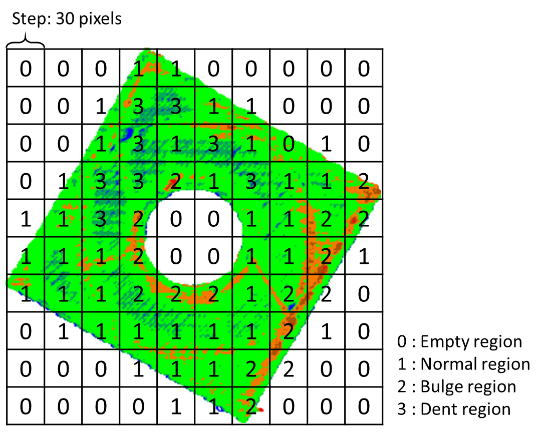
1. **RESULTS AND DISCUSSION**

The experimental verification of the proposed in-site laser-based process monitoring and anomaly identification system has been conducted. In order to train the classifiers of the in-plane surface anomaly classification model, the 73 test artifacts in different sizes, shapes, and process parameters are fabricated by the FFF machine to manipulate possible in-plane surface anomalies. Based on operation experience, the feed rate and extruder temperature are modified from 50% to 150% and 180°C to 250°C, respectively. The layer thickness is set as 0.3mm and infill density is set as 100%. All other process parameters are kept constant. During the fabrication process, the in-situ monitoring system captures the in-plane surface of each layer and convert the point cloud into a depth image of size . Judging on the rendering of the depth image, the in-plane surface identification results are classified into four classes, namely empty region, normal region, bulge region, and dent region, as illustrated in Fig. 8.



**FIGURE 8**. FOUR CLASSES OF IN-PLANE SURFACE IDENTIFICATION RESULTS

In order to identify the anomalies in a surface, the depth image is segmented into 100 sections with , as shown in Fig. 9. The images are labeled by a designed Graphical User Interface (GUI). Half of the images are labeled manually, and the rest are auto labeled by the HCAE which are checked by humans and reclassified if necessary.



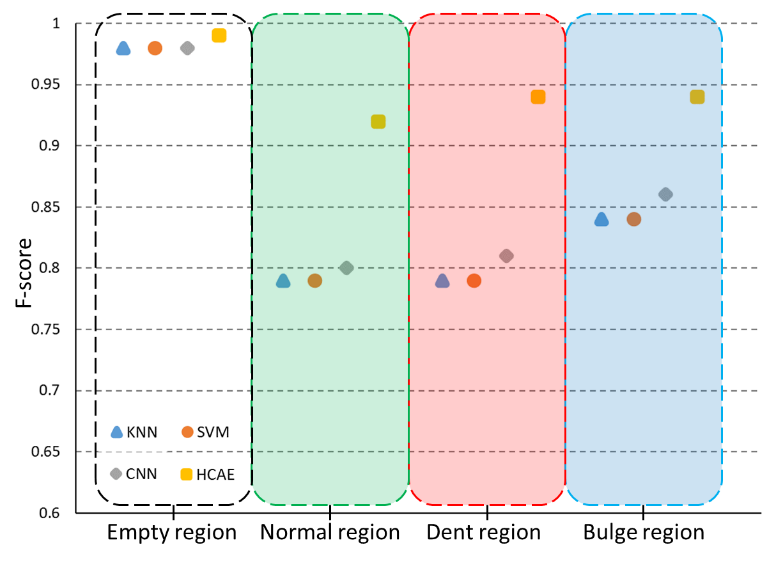
**FIGURE 9.** EXAMPLE OF DEPTH IMAGE LABELING

The four classifiers are trained and their hyperparameters are fine tuned to obtain the optimal classification results. The key hyperparameters of KNN and SVM are shown in the Table 1. The kernel of SVM is using Radial basis function (RBF). It is widely used in multi-class classification. The RBF kernel SVM also has the advantages of KNN and overcomes the space complexity problem. The CNN is constructed with four convolutional layers with kernel size and ReLU as activation function. The Max Pooling layer is attached after every two convolutional layers. The flatten layer is connected to the second Max Pooling layer. A dropout layer is between the flatten layer and two fully-connected layers. The softmax layer is added at the top of the CNN architecture. To improve the robustness of the learned features and alleviate the overfitting, the batch normalization is executed after every convolutional layer. [Add more details about HCAE]

**TABLE 1**. HYPERPARAMETERS FOR KNN AND SVM

|  |  |  |
| --- | --- | --- |
| Classifier | Hyperparameters | Values |
| KNN | Number of neighbors | 3 |
| Metric | Cityblock |
| Weights | Uniform |
| SVM | Kernel | RBF |
| Kernel coefficient | 0.001 |
| Regularization parameter (C) | 5 |

Each of the trained classifiers is evaluated by the testing data and their classification performances of each in-plane surface identification class are compared in terms of F-score. As shown in Fig. 10, in the four classification algorithms, the KNN and SVM show the similar classification accuracy. SVM only shows better results than KNN in the bulge region. The CNN shows better results than both SVM and KNN. CNN has a more complex architecture which helps the algorithm to extract more feature from the image dataset. The HCAE shows the best classification performance among all the classifiers. With the help of the concept of Google Inception model, the HCAE demonstrates a significant improvement of classification accuracy. Due to the high accuracy found through experiments, the HCAE is chosen as the classification algorithm that is added to the third subprocess of the point cloud process.



**FIGURE 10**. COMPARISON OF F-SCORES FOR THE FOUR IN-PLANE SURFACE IDENTIFICATION WITH FOUR CLASSIFICATION ALGORITHMS

To validate the performance of the in-situ laser-based process monitoring and anomaly identification system, a gear with size is fabricated by the FFF machine. The point cloud of the whole part is shown in Fig.11.

1. **CONCLUSION**

The in-situ laser-based process monitoring and anomaly identification system for the FFF process is presented in this study. This approach is developed to monitor the in-plane surface quality of FFF fabricated parts. The point cloud of each layer acquired from 3D laser scanner is utilized to generate 2D depth image. The proposed HCAE classification model shows the best classification accuracy using depth images among four ML algorithms. With the help of HCAE classification model, the anomalies of in-plane surface can be successfully identified.

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