

Anomaly Detection During Additive Processes for DLP 3D Printing

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Abstract—Additive manufacturing is gaining attention in various fields such as medical applications, aerospace, defense, and complicated manufacturing industries. This is due to the advantages of additive manufacturing including reduced logistical constraints and the ability to produce customized products. However, the materials used in additive manufacturing are generally expensive and highly sensitive to changes in external conditions. For these reasons, it is crucial from a productivity standpoint to monitor the additive manufacturing process closely to detect any anomalies early on and decide whether to continue with the layering process.

In this paper, we developed an algorithm that takes camera footage as input to determine the quality of the additive manufacturing output. We achieved an accuracy rate of 99.65%. Additionally, to simulate rare abnormal conditions, we used computer graphics to define nine different abnormal states and generated data for these conditions.

Index Terms—Additive manufacturing, DLP(Digital Light Processing), Anomaly Detection, Image, Anomaly Monitoring

I. INTRODUCTION

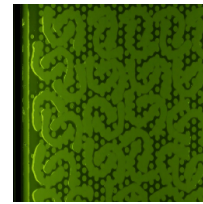
Additive manufacturing has gained attention as a future digital manufacturing tool, especially when all manufacturing processes are connected via IoT. It is also considered a solution for the decline in skilled low-wage labor. One of the greatest advantages of additive manufacturing is its ability to overcome spatial constraints. That is, it allows for remote control of the manufacturing process, eliminating the need for 'supply chain' logistics and 'inventory management.' This makes it highly promising for applications in space. Additionally, it holds promise in sectors that require complex part geometries, high precision, design flexibility, and a high demand for customized production. However, additive manufacturing is sensitive to external factors such as vibration of the 3D printing equipment and temperature changes. Also, the infiltration of fine particles into the machine can cause issues in the layering process. This process has a high likelihood of defects occurring during the printing process. Not only is the process slow, but the materials are also expensive. Therefore, it is crucial to determine the quality of the output during the additive manufacturing process. This allows for decisions to be made on whether to continue the output or make corrections to the defects.

In [1], a dataset for anomaly detection in Fused Deposition Modeling (FDM) additive manufacturing has been released. There has also been research on anomaly detection based on UNet for metal powder bed additive manufacturing citemeta-anomaly. This paper proposes an anomaly detection method

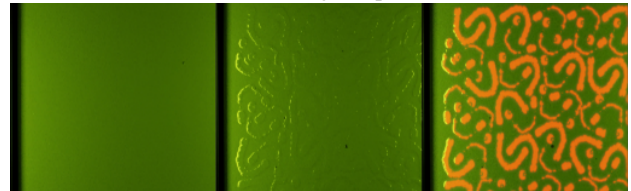
for the additive manufacturing process in the field of liquid material-based additive manufacturing.

II. METHODS

Our research purpose is to detection anomalies during additive processing, especially for DLP additive manufacturing device. The main material for DLP is liquid type. The additive process requires three steps: the baseplate moving upward, the baseplate descending to the correct position, and exposure to UV light. Between each DLP printing step, the slave moves to remove excess residue.



(a) A single input



(b) Three consecutive inputs

Fig. 1: Comparison between single input and consecutive inputs

In general, anomalies seldom appear during manufacturing process. Therefore, supervised approach is hard to apply to solve in this setting. So, to make our data closely resemble real-world data, we used Computer Graphics to generate synthetic data. At first, we thought generating the Ground Truth for CG would be a straightforward task. In the normal state, it was a matter of creating pixel-wise mask data when making CG for abnormal points. However, working with CG turned out to be not as simple as expected. When designating areas affected by abnormal light reflections in the CG as abnormal state areas, approximately one-third of the entire image was marked as abnormal, while in reality, the abnormal areas were much smaller. Because the abnormal area was too large, it was reduced in size, and the newly created mask image took the form of occupying a smaller area than the

actual abnormal region. Since the Ground Truth based on the mask image was not accurate, it was challenging to use the information about the occupied area for training. Because the abnormal area was too large, it was reduced in size, and the newly created mask image took the form of occupying a smaller area than the actual abnormal region. So, we attempted to solve this problem using the simplest classification method. Typically, when analyzing image sequences, it has been common to combine Convolution and LSTM. For early detecting anomalies, we attempt to design two networks: time-aware prediction network and CNN-based neural network. To reflect the three stages in the stacking process, we collected one image at each stage and combined them into a single input, resulting in three images as shown in Fig. 1.

III. EXPERIMENTAL RESULTS

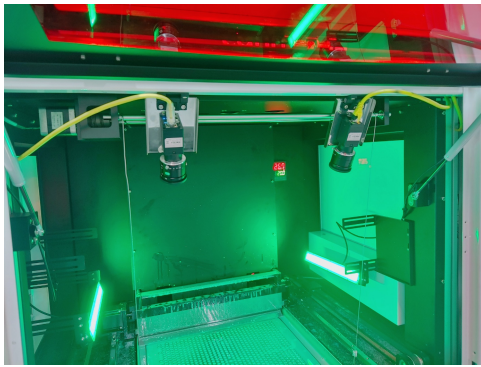
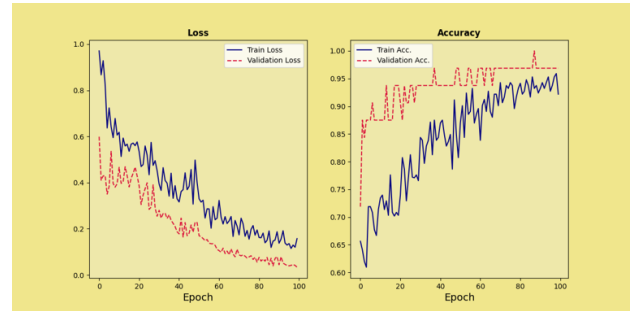


Fig. 2: The system of DLP Anomaly Monitoring System

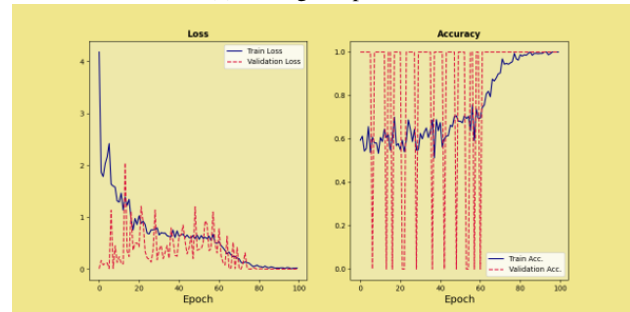
We have installed two cameras and two green lights on the DLP 3D printing machine. We have set up a system where the camera device and the DLP device communicate over TCP/IP, allowing central PC control and the ability to receive and store image sequence data on the PC as shown in Fig. 2. The build size of this 3D printer is $400 \times 330 \times 500 \text{ mm}^3$, offering a wide printing area. For Dental models, it can print up to 60 pieces at once. To cover this entire area, two cameras and two green lights have been installed. Particularly, since the resin's color is gray, and texture changes in the image are not well captured in low light, two green lights were installed on both walls. Each camera is a machine vision camera, initially mounted vertically to precisely detect the size of defect areas. However, due to the UV light being scattered vertically within the resin, there was a significant issue of light reflection observed in the cameras. To avoid this phenomenon, the camera's position was adjusted to an inclined direction rather than vertical. Our device initially targeted ivory-colored resin. However, after the purchase of the lighting equipment, the color suddenly changed to gray resin. Due to the gray color of the resin, making the texture less visible, we used jigs to mount the lighting closer to the resin, allowing the light to shine near the resin.

We have configured the system to receive signals for slave movement and stoppage via TCP/IP, allowing the camera to capture video only when the slave comes to a halt. The

captured video is then transmitted to the central PC, where a program for anomaly detection receives this video. Continuous monitoring for anomalies is performed while printing is in progress to detect any abnormal situations.



(a) A single input case



(b) Three consecutive input case

Fig. 3: Loss and Accuracy Comparison Graph



Fig. 4: An Error Sample

We construct additive manufacturing image sequence database consisting of five normal case image sequences and five abnormal cases using blender software [4]. A single sequence consists of 427 images. In the case of our proposed method, the length of input becomes 142 with a single last output image. To obtain UV output information, we included slicing images as inputs, resulting in a total of four images being used as input. However, experimental results showed similar performance even when excluding the slicing information, so we omitted the slicing information in the final proposed method.

To compare the performance of the model with three inputs and the model with one input, we compared the results in terms of loss and validation accuracy (see Fig. 3). The three concatenated input case in Fig. 3(b) obtains better performance than the single input case shown in Fig. 3 (a). Fig. 4 is an example of an error image evaluated using the proposed method.

IV. CONCLUSION

This proposed method has not yet been applied to real data and remains based on synthetic data. This is because the state of the DLP device for acquiring real data has been continuously changing. The initial version of the DLP equipment did not have a red-colored glass window. Therefore, initially, we generated CG data that closely resembled the acquired real data. However, upon acquiring actual data after the completion of the equipment, the red color of the glass window caused a transformation to a color closer to yellow rather than green. Furthermore, it was observed that this color was not consistent but changed continuously depending on the position of the slave, as the red glass window color was repeatedly reflected. The uniqueness of real data due to these red artifacts differs from synthetic data, and it is expected that there may be a performance degradation in real data.

V. ACKNOWLEDGEMENT

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