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QUALITY MONITORING FOR FUSED FILAMENT FABRICATION PRODUCT: A REVIEW

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Abstract- Additive Manufacturing (AM) is the process of creating products from three-dimensional (3D) model data by combining materials and building them up, frequently layer by layer. Material efficiency, resource efficiency, production flexibility, and part flexibility are four main environmental advantages of AM over traditional or subtractive manufacturing. There are a lot of different ways to manufacture products with additive manufacturing now but, the focus of this review is on Fused Filament Fabrication (FFF). FFF has a low production cost and the ability to construct complex geometries and shapes. However, this 3D printer needs to be manually stopped by the user if any of the defects or abnormalities are detected. Therefore, many studies have been done on monitoring the 3D printer to spot any defects in the products. This paper summarizes the monitoring based on the defects that are categorized into (1) geometrical defect, (2) layer defect, and (3) surface defect. Based on the reviews, the common sensor used in the monitoring system has been concluded, and some of the limitations are listed.

Keywords – additive manufacturing, 3D printing, fused filament fabrication, monitoring, artificial intelligence.

I. INTRODUCTION

Additive manufacturing (AM) is the process of combining materials to produce items from 3-dimensional (3D) model data, usually layer-by-layer [1]. Material efficiency, resource efficiency, production flexibility, and part flexibility are four main environmental advantages of AM over traditional or subtractive manufacturing [2]. During the COVID-19 pandemic, additive manufacturing has emerged as a critical technology [3]. There are many different additive manufacturing processes available presently; they differ in how layers are deposited to produce parts, the working principle, and the materials that can be employed. However, this manuscript focuses on Fused Filament Fabrication (FFF) since it has been used in the automotive, aerospace, industrial and medical domains. When the FFF printer starts to print, the raw material comes out of the heated nozzle as a very thin filament. It is deposited at the bottom of the printer platform to make a first layer. Then it hardens and forms the next layer. The next extruded layer fuses with the previous one, layer by layer constructing the object. A lot of FFF printers start with the outside edges, then the inside edges, and then the inside of the layer, which can be a solid layer or a fill-in matrix. So, the most crucial part in this printing process is to fuse successive layers before they solidify. If solidification before the layer fuse together, it might have a significant impact on the building part properties [4]. Residual stress and part deformation caused by thermal effects are still significant difficulties that impede the technology's development [5]. So, the user needs to monitor the printing process from the beginning until end to make sure no materials and time are wasted. In 3D printing, quality control remains a significant difficulty. There is a lot of research has been done in monitoring the 3D printer to detect any defect at the products. Defect detection early in the printing process may trigger an alarm to pause or stop the print process so that corrective actions can be done.

This paper summarizes and makes a systematics review on some methods used in monitoring the quality of the 3D printed, in particular to FDM products. This review is not meant to be an exhaustive investigation of literature, but a selective representation from the view point of the author. The review is presented in sections where section II describes methods to monitor the geometrical defect while in Section III for the layer-by-layer defect. In Section IV, there are some monitoring methods for surface defect. The conclusion for this review article is present in the Section V.

II. GEOMETRICAL DEFECT MONITORING

When the printed product differs in shape and dimension from the 3D model or the completed printed output, this is referred to as a geometrical fault. These abnormalities are easily detectable with the naked eye, and numerous studies have been conducted to develop technology capable of monitoring these types of defects in place of humans.

Felix Baumann et al. proposed a camera-based error detection technique with a web-based interface for remote monitoring and early defect detection of the printed product's quality [6]. This study applies an auxiliary thresholding approach to detect errors categorized as Detachment and Deformed Object. Using this approach, the digital image is divided into binary images with a clean separation between the object and the background. Then, to detect missing material flow from the extruder, the blob detection method is employed and modified. The item's upper bounding box is used as a reference line (yellow line). As seen in Fig 1, this object reference line is compared to the print-head reference line (green circle). One limitation to the approach consistent error detection is camera pixel errors. The second issue is that the lighting on the object will vary, making it difficult to detect.

Additionally, Siranee Nuchitprasitchai et al. released two articles on the subject of monitoring geometrical defects in 3D printing items. There are methods for comparing single-camera to dual-camera setups [7] and for comparing rescaled to non-rescaled images [8]. To rebuild 3D images from merging 2D intensity values, the approach depends on a relaxed camera orientation constraint. The Scale Invariant Feature Transform (SIFT) and the Random Sample Consensus (RANSAC) models are used to achieve scaling and rectification. The camera takes the image and calculates the region of interest (ROI) to identify the object of interest in the single camera arrangement. By contrast, the two-camera configuration collects one picture from each camera (LeftImage and RightImage) and removes the background to calculate distortion and ROI. They then test image pre-processing and error detection in the two tests in the following paper. For image pre-processing, two approaches are used: SIFT and RANSAC for rescale and rectification, and non-rescale and rectification [8]. For all models, the non-rescale and rectification strategy is more exact in detecting an error than the SIFT and RANSAC rescale and rectification methods. To evaluate error detection, two methods are used: horizontal magnitude and horizontal and vertical magnitude. In terms of percentage of error and calculation time in the normal state, the non-rescale and rectification technique surpasses the SIFT and RANSAC rescale and rectification methods. To avoid the error of removing a facet, it is necessary to investigate the slicing stl model approach. To remove all noise, the background removal method must be more effective.

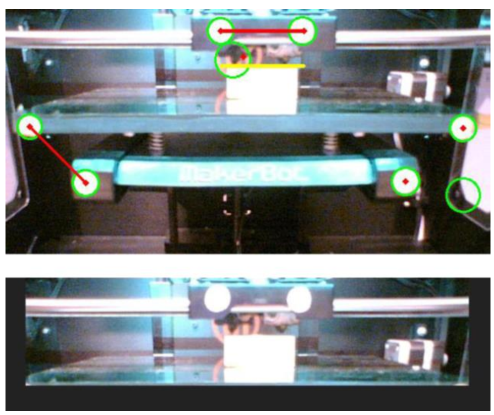

Figure 1. (top) Visual markers and control points (bottom) cropped area of interest [6]

The 3D printed parts are monitored in the following article by capturing them at various checkpoints with the use of a camera [9]. Support vector machine (SVM) is offered as a machine learning technique for identifying parts as 'good' or 'defective'. The biggest issue of the suggested method is that it requires interrupting the printing process to acquire images of a partially completed product. On the other hand, Mihiretie et al. suggested a monitoring approach based on hot disc sensors for detecting any internal geometrical defects in the printed product [10]. Thermal conductivity is then calculated using the temperature evolution of the sensor, whereas probing depth is proportional to the product of measurement duration and thermal diffusivity. The graph of thermal conductivity as a function of probe depth shows that the structure is not uniform. Such the plot produces an essentially constant value for homogeneous materials. To detect inhomogeneities, calculate deviations from the homogeneity curve caused by structural defects. However, it requires an understanding of the volumetric specific heat capacity of the material.

III. LAYER DEFECT MONITORING

3D printing is a layer-by-layer process. Thus, it is possible that the fault will occur itself during the process as a result of particular conditions, such as temperature changes that can cause warping. With regards to the first layer of the process, the material peels away from the build platform due to the weak connection between the layer and the build platform, scratching the nozzle and the distorted material. The quality of the interfacial bonding has a significant effect on the mechanical properties of the product. Delamination is a common type of printing failure caused by insufficient fusion between the preceding and new layers. While this is a little error, it has the ability to affect the entire printed output. In the majority of the cases, the first layer defect has a direct effect on the quality of the printing product, as illustrated in Fig. 2.

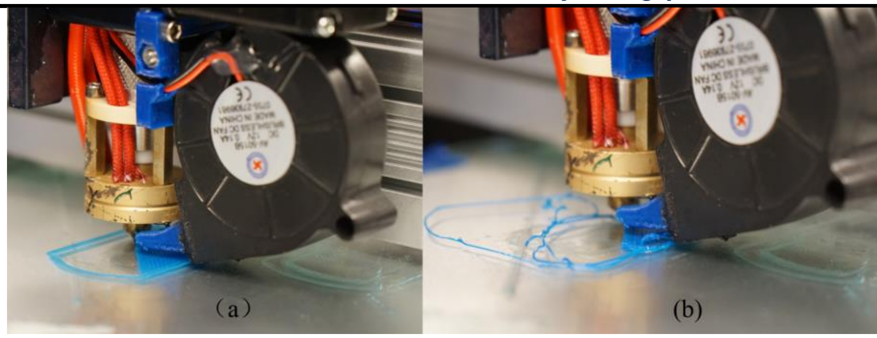

Figure 2. (a) The normal FFF printing status (b) The abnormal (first layer defect) printing status [11]

Haixi Wu et al. have carried out the research on the method for monitoring the first layer of the 3D printer (FFF) product using Acoustic Emission (AE) sensor [11]. Process AE hits faster than raw signal data. Each AE hit corresponds to an AE event that has been detected. The research demonstrates that the K-means clustering technique may be used to automatically detect differences in printing process status and identify failure modes. Additional research is required to ascertain the relationship between failure modes and dominant frequency. To acquire integrated process information while removing background noise, certain critical AE system parameters must first be set.

Next, the method developed by Charalampos Kopsacheilis et al. utilizes an RGB-Depth camera to collect both the RGB image of the scene and the Per-Pixel-Depth data [12]. The three-dimensional CAD model has been sliced into G-code, which provides instructions for moving the print head and build platform to certain X, Y, and Z coordinates in order to generate the three-dimensional model. This is then processed with a modified version of gcode2vtk, which simulates the planar-layered trajectories of the printer's 3D printer. The reconstruction technique for the point cloud is simplified in Fig. 3. Finally, these trajectories are evenly sampled, resulting in a theoretical 3D model point cloud. However, before combining the collected point clouds of every printed layer, preprocessing was required to improvise this method.

Other approach proposed by Huaqing Hu et al. is monitoring using thermal camera [13]. The established multi-classes classification approach seeks to diagnose FFF printing problems in two stages. As a result of temperature field fluctuations, the FFF component may be in one of four states: insufficient filling, warping, serious fault printing, or printing failure, which will be further diagnosed in the second step. Using Spearman rank correlation, a quantitative correlation between the four temperature parameters and the FFF printing states is calculated. According to the results of the Spearman rank correlation analysis, there are high relationships between four temperature parameters and four FFF printing states. Four relative temperature parameters are used to train the SVM-based multi-class classification model, which also serves as a means of identifying FFF printing difficulties using Spearman rank correlation analysis. The acquired data is subsequently preprocessed, which contributes to the Multi-classes Classification Model's generalization capability by virtually eliminating the influence of random interference.

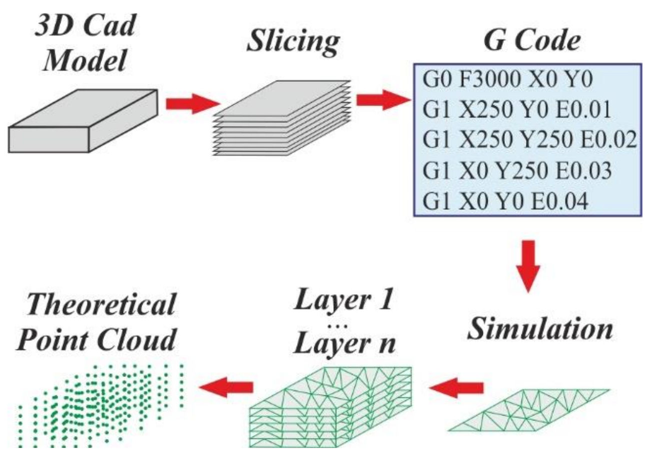

Figure 3. Theoretical point cloud reconstruction [13]

Yaser Banadaki et al. offer an automated quality monitoring system based on a deep convolutional neural network (DCNN) model [14]. Fig. 4 illustrates about using data-driven predictive modelling to train a deep convolutional adjacent neural network to detect and categorize AM process defects. The DCNN model of the additive manufacturing process accurately predicts printing quality at low speeds (50-100 mm/s), regardless of the temperature of the additive manufacturing process. In the future, a smarter control system may be a closed-loop machine that continuously learns and adapts important parameters during the operation of an AM machine.

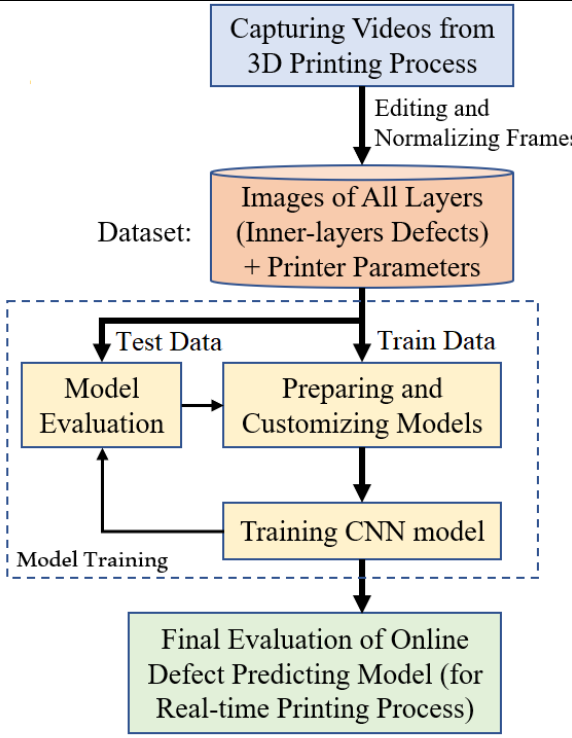

Figure 4. The overview of the technique [14]

Next article which has done by Zeqing Jin et al. examines interlayer defects [15]. One of the defects is delamination, which is generated mostly by an incorrect gap between the present nozzle height and the print, resulting in a weak link between layers. They built a system that, through the use of deep learning, replicates hand calibration. Offset nozzle heights are rated as "High+", "High", "Good", and "Low". Following the definition of the conditions for each of the four situations, image data is collected during the printing process. In order to train a convolutional neural network (CNN) model, the training data set is used. This is done after all the necessary image data sets have been prepared. A pretrained residual network (ResNet) model with a little change at the final layer is used in this case. It is because the output has four elements, so it needs two layers of fully connected layer. Warping is another layering issue in AM. This article also proposed the approach for predicting warping which is demonstrated using a strain gauge setup on the print bed as shown in Figure 5. In this situation, the strain gauge will detect any minor expansion of the plastic film due to printing sample deformation. Due to the extremely tiny elongation of the thin film, a sensitive measurement and signal amplification system is required. Throughout the printing process, an Arduino microcontroller board collects the voltage signal to calculate and plots the relevant strain curve versus time in real time. Future work will include developing an autocorrection first-layer calibration system based on classification findings, as well as adapting other sensors, such as an infrared camera, for in situ assessment.

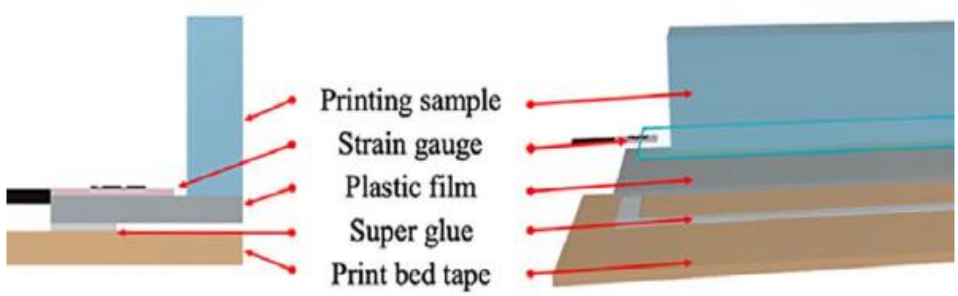

Figure 5. The section and exploded view of strain gauge setup [15]

The research of Aditya Saluja et al. utilizes deep learning to develop a warping detection system using Convolutional Neural Networks (CNN) [16]. A pipeline for real-time data collection and processing was designed. To allow for good visibility of the specimen corners, the G-Code was modified to pause the printer after each layer and resume after two seconds. When the camera was triggered by a script, the extruder slid out of view. The extracted region was then automatically extracted, shrunk, and grayscaled from the raw image using the CNN model. Layer by layer, the system captures the print while removing the component's corners. It is then sent into a CNN to ascertain the probability of a corner being twisted. The print is suspended if a warp is detected, establishing a closed-loop detection method. In an experimental arrangement, the underlying model obtained a mean accuracy of 99.3 percent. However, the current CNN classification model was manually developed by tuning the hyperparameters through trial and error. Additionally, the training images were taken in a well-lit environment to aid the underlying categorization system.

The monitoring system proposed by M. Moretti et al. is validated using a sensorized hardware prototype and trials involving the production of test parts [17]. The results demonstrate that a relatively inexpensive, rapid, and non-destructive sensing solution (that is, measuring the repulsive force acting on the extruder) can be used to detect part warpage with 92.9 percent accuracy, 91.5 percent specificity, and 95.7 percent sensitivity, demonstrating that it is possible to detect part warpage using a relatively inexpensive, rapid, and non-destructive sensing solution (that is, measuring the repulsive force acting on the extruder). In theory, reaction forces pushing the extruder upward during layer extrusion might be utilized to monitor the distance between the extruder nozzle and the surface below indirectly. Due to the fact that upward warpage is one of the reasons of gap shifts, force monitoring may be a more cost-effective solution than computer vision in some cases (e.g., complex geometries). However, it appears as though effective use of force to monitor warpage is only feasible in a limited number of situations.

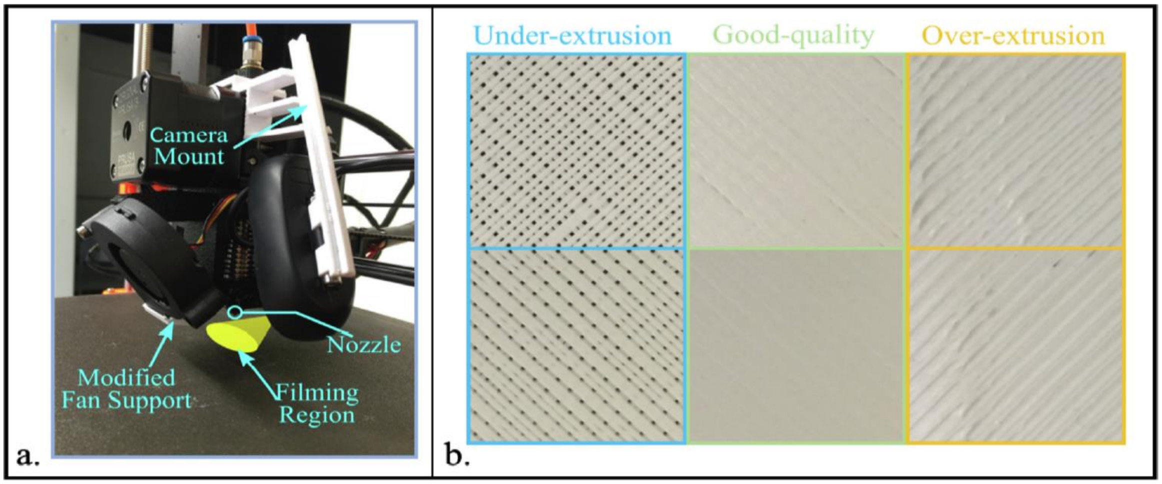

Figure 6. (a) The experiment setup (b) Different printing qualities categories zoomed-in images [18]

IV. SURFACE DEFECT MONITORING

While the surface roughness can be determined manually during the printing process with the aid of human eyes, this is not practical for such a lengthy printing procedure. As a result, numerous researchers proposed a monitoring system that would utilise a fairly common sensor in place of a human eye, a camera. However, it must be accompanied by an Artificial Intelligence (AI) algorithm capable of learning and determining when a defect occurs.

In an article published by Zeqing Jin et al., a machine learning technique is used to monitor the surface quality of a printed object [18]. As illustrated in Fig 6(a), a customized design of the 3D-printed camera mount is mounted to the extruder cap's top, supporting the camera and providing a static monitoring view during the printing process. Fig 6(b) depicts the varied quality of the product. In the first phase, a CNN classification model is trained using a ResNet 50 architecture. Following the training phase, real-time photos are continuously fed into the model and identified in order to determine the current state of printing. The system will be enhanced by expanding the training data set, increasing the degrees of printing quality, and developing new models for the images of border.

Next, a deep neural network (Single Shot detector) was trained on pictures of 3D printed products that had developed stringing faults and then deployed in a real-world context to detect stringing defects [19]. The model could detect defects and inform the printer handler when events with a high probability of defect occurred. The model identified faults that were equivalent to the training data, indicating the potential and utility of Deep Learning for detecting 3D printing issues (training accuracy). The primary advantages of this approach are real-time detection (59 frames per second) and the absence of camera or equipment calibration. According to the study, defect-specific detection modules can be developed and refined independently. For the Single Shot Detector, a training dataset of pictures with stringing was produced (Deep Neural Network). Following data collection, many data augmentation procedures were applied to enhance the number of training examples. The term "Data Augmentation" refers to a collection of approaches for generating new synthetic data from existing datasets. They used half-size scaling, horizontal flipping, random cropping, 90-degree rotation, and brightness alteration to each image in the base training set (randomly). This research uses an open-source annotation tool, LabelImg, to provide the ground truth (the true classes contained inside an image, as well as their positioning within the image). By manually annotating all the photographs with this tool, an XML file in the Pascal Visual Object Classes (PASCAL VOC) format was generated for each training image. Additionally, it has been demonstrated that data augmentation improves classification metrics in benchmark datasets. However, when applied to external data sets, it was unable to generalize well.

Next method is using another sensor, digital microscope. Using the texture analysis-based image diagnosis (TA-ID) method, a system for defect recognition has been built [20]. The system processes surface photos obtained with a digital microscope and recognized defects. Because of closed-loop feedback control, the system may even be able to change the corresponding printing parameters in real time in order to mitigate printing failures. In spite of the fact that there are just two microscopes, there may still be blind spots in the existing online monitoring device coverage, which could have an impact on the outcome of the diagnosis.

On the other hand, another research employs laser scanning technology to develop an online quality monitoring system for defect detection and feedback control during the material extrusion process [21]. During the material extrusion process, a laser scanner is utilized to build a three-dimensional point cloud of the deposited portion's upper surface. Additionally, the shape and location of manufacturing mistakes can be extracted by comparing the produced point cloud to the pre-sliced stereolithography (STL) model. The process's flow can be shown in Fig 7. Using laser scanning technology, this research develops an online quality monitoring system for fault identification and feedback control during the material extrusion process. The scanning system acquires a point cloud of the deposited part using a 2D laser scanner during the material extrusion process, and the scanning point cloud is then preprocessed in the control software. Simultaneously, the ideal contour of the currently depositing layer is retrieved and filled from the pre-sliced STL model of the part to create the reference point cloud. After converting the scanning and reference point clouds to depth images, an image processing technique is utilized to detect and extract the contour and position of defects. Finally, the three-dimensional model of the defect is created from the defect contour to provide quantitative information for the feedback control.

Besides, the goal of the next research is to offer printing technologies that utilize a sourcemeter and conductive filament to acquire an electrical signal during a print [22]. The goal of this research is to introduce printing methods that use a sourcemeter and conductive filament to allow for the acquisition of an electrical signal during the course of a print. Two points must be clarified before the data can be displayed. The first is concerned with how the data was normalized, while the second is concerned with how the data was mapped. Because of vibration or user interference, the electrical signal at initial contact, or the point at which the positive node hot end made contact with the negative node copper tape on the print bed, varied from run to run as data was collected.

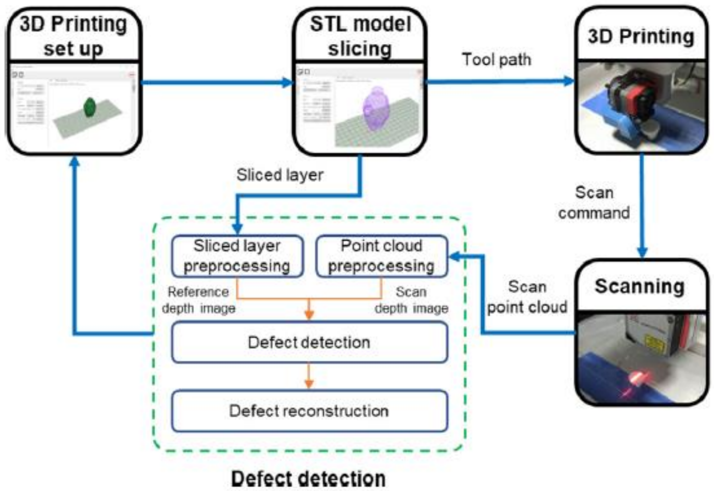

Figure 7. The flow of Weiyi Lin et al. research methodology [21]

The contact voltage, which is presumably the dataset's minimum value (Vmin), and the peak voltage were used to normalize the data (Vmax). As a result of normalization, all data provided is between 0 and 1. On the left, the reader will see various heatmap paths, while on the right, the reader will see reaction vs. time graphs. The heatmap paths are made by precisely plotting the voltage response value at the x and y coordinates provided by the machine at the time of the event. While the coordinates are correct, the road width is not. The road's width is the same as the thickness of the extruded line. This is because scaling the width would result in lines obscuring earlier ones in runs with any overlap. As a result, compared to the actual road width of 2 mm, the road width is limited to what is visible at 95 percent overlap, which is around 1.05 mm. These signal responses are especially useful for detecting flaws in prints. If the answer begins to vary, grow significantly larger, or jump suddenly, the operator or code can be alerted that a print error or defect has most likely occurred. mm. This is depicted in Fig 8.

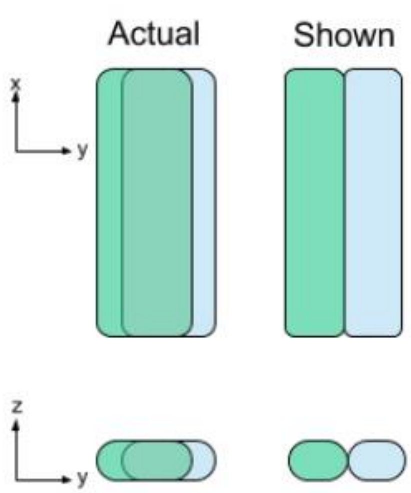

Figure 8. Visualization of actual overlap versus road width presented in heatmaps [22]

These signal responses are very valuable for detecting defects in printing. If the answer begins to vary, get much larger, or jump unexpectedly, the operator or code can be alerted that a print error or flaw has most likely occurred. Future research should look at manipulating different infill styles, percentages, and other space filling methods, as well as investigating the method's characterization and repeatability in multilayer.

V. CONCLUSION

FFF is the most popular 3D printing process due to its low cost and ability to create complicated geometries and shapes. However, due to its low reliability, much effort has been put into improving the FFF process control. Deficiencies are classified as geometrical, layer, or surface defects in this article. A camera with various detection algorithms is the most commonly used sensor for detecting these issues. However, it has some drawbacks, such as: In order to take an image of a printed object, the printing process must be interrupted for a few seconds and the quality of the image is determined by the camera setup and lighting.

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