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Machine Vision-Based Detection of Surface Defects of 3D-Printed Objects

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Abstract

Due to advances in 3D printing technologies, 3D object manufacturing has attracted significant attention nowadays. The market size of 3D printing is increasing exponentially, ranging from tiny toys to nuclear reactors. The significant advantage of this 3D print manufacturing over conventional manufacturing tools is that it can produce a complex object within a short period with a flexible but precise design. On the other hand, this tool has shown disadvantages as well. One of the main disadvantages is forming irregularities and defects within the 3D objects, which cost a significant amount of time and resources. Now the main challenge is to detect the defects on time and find a suitable solution, which might save a lot of time and money. In this study, a machine learning (ML) technique with a 3D vision camera is employed to detect and classify the defects of 3D objects. First, images collected from a depth (3D) camera are utilized for training the model. Then, the trained model is tested on a large set of real objects to detect defects. With the application of this technique, it is possible to detect defects while printing. As surface defects are a serious issue for 3D printed products and many other types of manufacturing methodologies, we hope the research outcome can be applied in different manufacturing areas to maintain the pavement to the advanced inspection on time with high-quality accuracy.

Introduction

During the last years, there has been a revolution in applying three-dimensional (3D) printing/additive manufacturing (AM). AM is a type of manufacturing process where materials are added either layer-by-layer or point by point gradually, providing increased freedom of designing the model of the complex structure, rapid customization, lower production waste, rapid prototyping, and the use of materials for printing which includes metal alloys, composite of polymers, concrete, and ceramics. Due to the widening of the horizon of the uses of 3D printing, machine learning (ML)-based technologies have been used to improve 3D printing processes. 3D printing technologies have been widely applied in many fields, including aerospace, medicine, industry, and beautification. Also, additive manufacturing has been used in biological technologies, known as 3D bioprinting, which will be widely used for medical or daily purposes [1],[2].

In-situ defect detection is essential for AM, related to the waste resources, i.e., time and material. The standard procedure of additive manufacturing is that its prints continue until the final layer. So, detecting the defects is necessary for different states, whether in person or remotely [3]. With the recent developments in robotics, autonomous driving, and augmented/mixed reality, 3D sensing has become a significant research trend in computer vision. Conversely to RGB cameras, 3D capture sensors can provide rich geometric structure [4].

Access to large, diverse RGB-D datasets is critical for training RGB-D scene understanding algorithms [5] and to meet the future demand and expectation for developing the large structure and reduce the defects, which is the primary source of waste of time as well as materials, intensive research needs to be done. This study has tried to find the 3D printing defects using 3D images and Machine Learning.

Background

The additive manufacturing process has added benefits by reducing the manufacturing time, cost and increasing the quality of the product; ML can be added as an extra tool to increase the efficiency of all these measures [2]. Ahmad, et al. [6] presented a new approach of Real-time object detection, YOLO4D. They incorporate a 3D spatial dimension with a time dimension, together making 4D dimension. Using the publicly open data set, input as a point cloud data and the output are the classification of five objects with a confidence level (F1 score). The experiment results show a better result than the spatial dimension. Garfo, et al. [7] also showed crack and 3D printer defect detection with ML and 2D image processing.

Konstantinos, et al. [8] introduced a novel approach for detecting one type of 3D printing defect by using AI and computer vision. They have used a Deep Convolutional Neural Network for Machine Learning for capturing that type of defect during the Video Recording. Also, in that approach, they could terminate the printing process. Hermann, et al. [9] showed a combination of thermographic images and a neural network based on deep learning to detect 3D printing defects. They used a PYROVIEW thermographic camera for taking pictures.

Hammod, et al. [10] presented a paper for in situ defect detection of AM. They compared the computer-aided model (CAD) with the captured geometry using the 3D digital image correlation to detect the error in the printing process. Point clouds have been used to find the error between the CAD and printed object.

Sometimes 3D manufacturing has been done by combining two domains, the Cyber domain and the Physical domain. There has a high risk of attaching to the cyber domain known as cyber-attack that causes the error or defects of 3D print. Straub [11] published an article by describing an approach to protect from this unique type of defect.

Ugandhar and Shing proposed automatic defect detection for the 3D printed model. They used a supervised Machine Learning technique known as support vector machine (SVM) and image processing to classify the object as good or defective. Their method has some drawbacks, firstly, printing need to be paused for taking the picture and secondly, only one side view has been taken, that means it cannot detect the area which is out of the scope of the camera frame [3]. As we are using the 3D images, this problem will be solved.

Methodology

a. Machine Learning

ML is mainly a branch of an Artificial tree. Different algorithms and artificial neural networks have been used to train the different models to predict the desired texture from the previous data or experience, like the human brain. An artificial Neural Network can make a model which can predict the new date from the previous date (Figure 1). Supervised and unsupervised ML are mainly used.

Figure 1: Flowchart of ML.

The main difference between supervised and unsupervised ML is input date. In supervised learning, input data are labeled before the algorithm works, for example, for a set of images labeled as rough surface and smooth surface. In contrast, an unsupervised learning algorithm does the jobs, which means input data remain unlabeled. In this study, supervised ML has been used with the PointNet Neural Network [12]**.**

b. Defect detection with pointnet neural network [12]

Researchers are transforming the 3D images into the Point cloud, a widely used data structure with some problems while pre and post-processing. However, a novel type of neural network called PointNet which can read point clouds directly. This network is used for object classification or part segmentation. Moreover, PointNet is highly efficient and effective. This study used this network after some modification as per the following pipeline (Figure2).

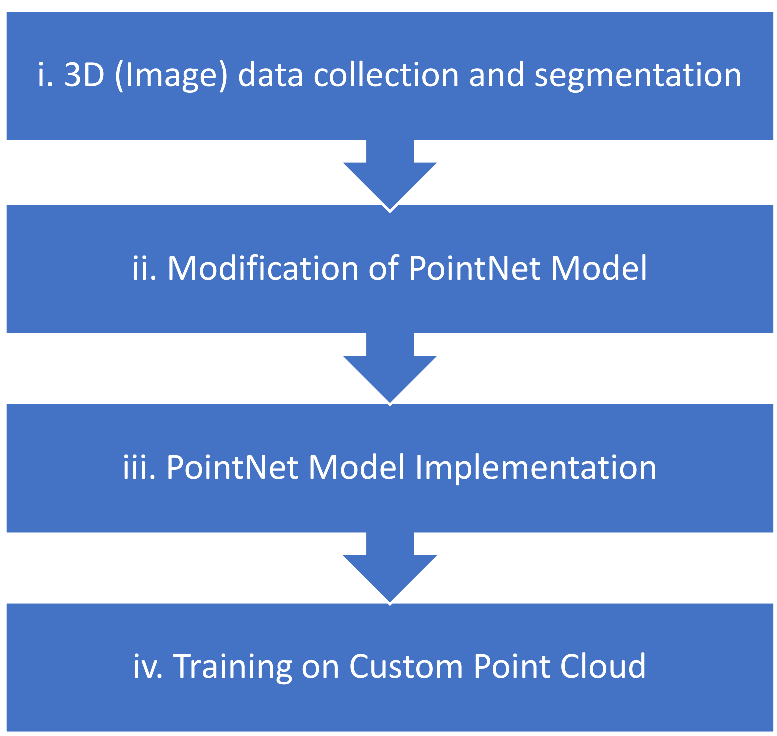

Figure 2: Pipeline of proposed defect detection.

i. 3D data collection and segmentation

In this study, two sources have been used for input data, CAD model and 3D scanner model, and two types of data (Defect & Normal) have been used for ML where 80% data have been used to train the model & and the rest of 20% data to test the model.

The first step was to convert the 3D data into a specific format (.off) format to segment raw mesh using the cloud compare software[13]. The dataset has been divided into two sections, “train” & “test.”

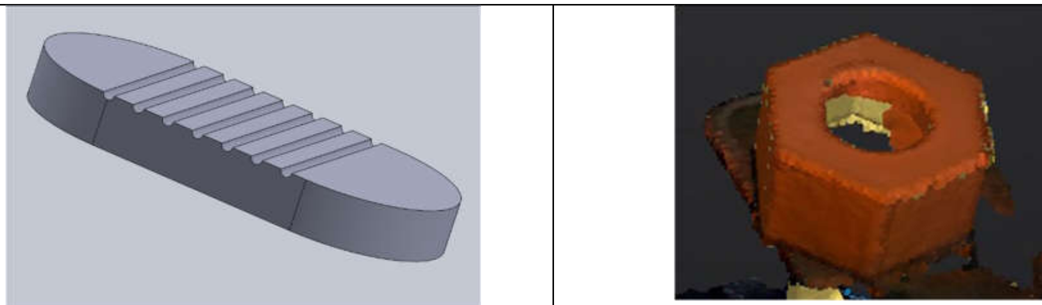

Figure 3: Sample (3D) images (Left- CAD software Model, Right- 3D scanner Model).

ii. modification of pointnet model

Some modification has been made in PointNet Mode. To load as the point cloud and converted it into the numpy array, all 3D “.off” format data have been parsed through the custom data folder. Some parameters have been set, i.e., the number of points, batch size, and classes to parse the dataset. An augmentation function has been created for augmentation and shuffles the training dataset. The primary parameter modification is as follows.

```
NUM_POINTS = 2048
NUM_CLASSES = 10
BATCH_SIZE = 32
```

iii. implementation of pointnet model

PointNet is a deep neural network (DNN), a feedforward network in which data flows only one way, from the input layer to the output layer. There have many layers for connection between the input and output layer.

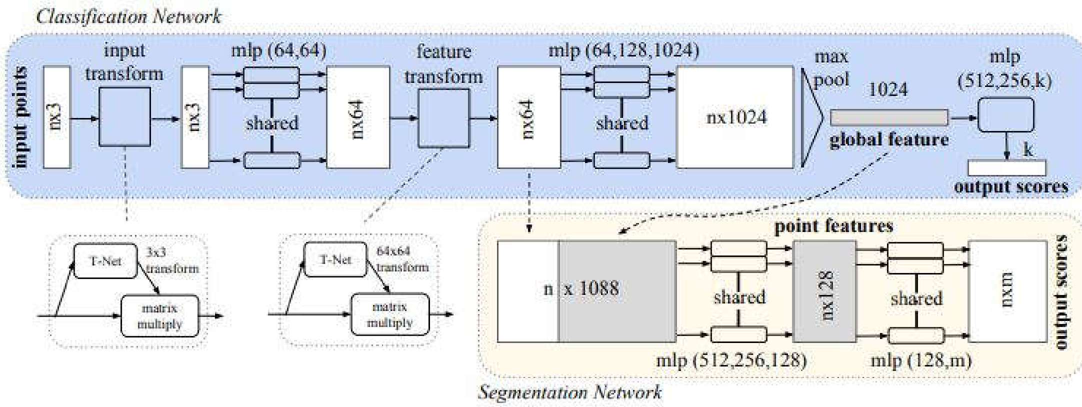

Figure 4: The Architecture of PointNet Neural Network [12].

The classification network (Figure 4) takes n number of points as input. After applying the input transformation and feature transformation, it aggerates the point features by max pooling. The output is classification scores for k classes where the segmentation network works as an extension. Multi-layer perceptron (MLP) works in between different layers [12].

iv. training on custom point cloud

Pointnet architecture has been used to build a custom model. We have completed our experiment with our 3d image dataset for the environment setup. The experiment has been implemented with PointNet using Keras framework on Google Colab environment with GPU Services [14].

PointNet architecture has two major components: the transformation net (T-net) and Multi-layer perception network. T-net is used two times for learning an affine transformation matrix, and this study used two class Custom datasets instead of the ModelNet folder [12],[14].

Training parameters

Hyperparameters	Values
Epochs	100
Learning Rate	0.001
Batch Size	32
No. of Points	2048

Results, Discussion, and Future Work

During the Training & Testing process, the entire program has been run several times for different combinations of samples. After completing the ML model, the test data set have been tested. As the input data are a combination of CAD and Scan 3D objects, we have tested two types of data (Figure-5).

From the test, we found the accuracy is 87.5%. Number 5 in Figure 5 are the defects scanned with the 3D scanner.

We have faced some difficulties; the major one was the raw 3D images. As 3D imaging is still new for capturing, another one is time, and it is time-consuming to take a 3D picture. Finally, the lack of large data sets dramatically impacts the results. The accuracy will be higher if we can use more data.

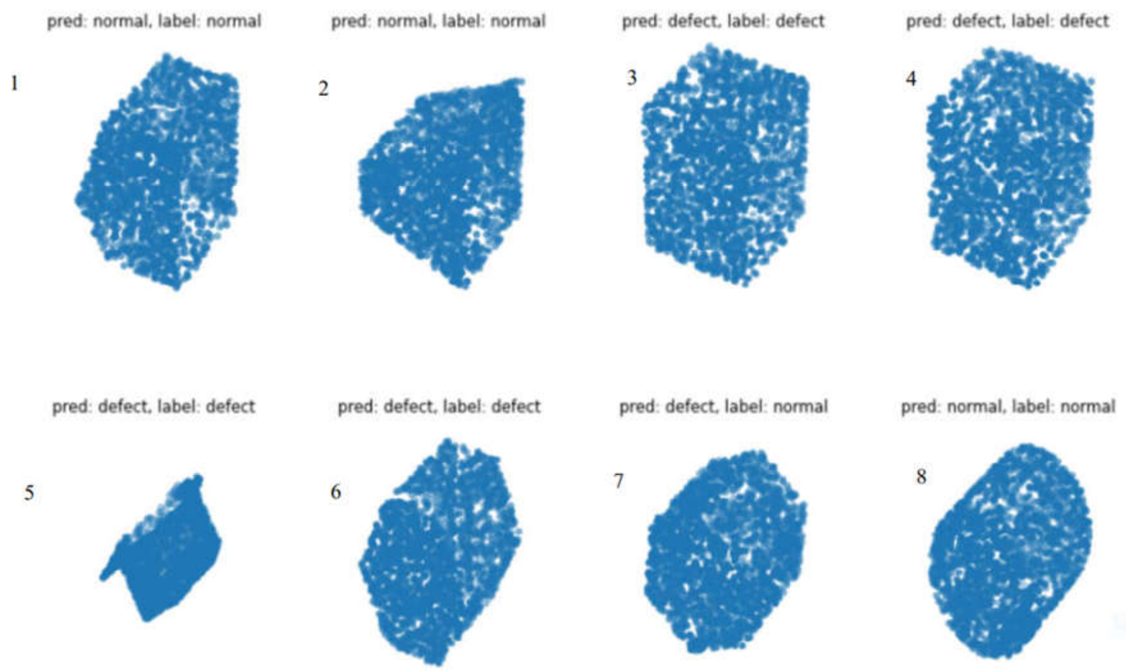

Figure 5: Tested result.

In the future, we will try to get better accuracy by taking the large data set and have a plan to mark the different types of defects, as the printed object has different types of defects. Also, we will try to implement this model directly with a 3D camera to detect the defects and set the camera on a robot for doing the same job where human presence is dangerous and time-consuming.

Conclusion

The demand for 3D printing is increasing day by day. According to Wohlers Associates [15], also referred to as the bible of 3D printing, there have more than 250 areas of production and development of AM. Recently, Italian firm Isinnova has manufactured respirator valves in just two days to support COVID-19 patients. Ten patients were able to breathe with the aid of a machine that included the 3D-printed valve. It also has a tremendous economic impact; if we consider one decade, from 2009 to 2019, money spent for AM production shows an exponentially increasing trend. In 2009 it was about 0.20 billion dollars, and in 2019 it was 1.45 billion dollars [15].

Researchers worldwide are researching to develop the process to be smooth without defects. This research work's purpose was the same though it has some limitations. As every technology has drawbacks, 3D printing is not different. Some drawbacks require further research and technological development to reduce production costs, increase applications, and produce large structures.

The outcomes of this research will be included in a multidisciplinary graduate-level course that may offer in industrial, mechanical, or electrical departments. The topics mainly cover digital image processing, machine learning (ML), and the implementation of autonomous systems. Students will learn digital image fundamentals for object classification/detection/quantification, image modification, segmentation, analysis, noise handling, and how to develop and implement algorithms, application of image processing, the introduction of ML, how to train a model with 2D and 3D images, and the application of ML in the areas of the autonomous systems and additive manufacturing.

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