3DP-FAS: An Intelligent Quality Assurance System for 3D Printer

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***Abstract*—3D printing or Additive Manufacturing is one among the key technologies of the decade, mainly used for rapid prototyping and experimental learning. Apart from its traditional usage, now 3D printing has be adapted by the Industry 4.0 for real time production. Hence, the future scope of 3D printing lies in industrial environments, where industrial manufacturing tools are replaced by 3D printers. Identifying the quality of the printed object and detecting the failures during printing are essential needs in industrial environments as well as in rapid prototyping. This paper proposes an architecture named 3D Printer Failure Analysis System(3DP-FAS) for remotely control, monitor and analyze 3D printing process. 3DP-FAS monitor the printing process with the help of a camera module and analyze the the 3D printing process with the fine-tuned models available in the model library. 3DP-FAS is also capable of controlling the 3D printer as well as making intelligent decisions based on the analysis. It also provides a web-based monitoring interface for a remote user to monitor the printing process. The system and experiments are implemented in IoT Cloud Research Laboratory of IIIT Kottayam.**

***Index Terms*—Industry 4.0, IoT, 3D Printing, IoT 3DP Ecology**

I. Introduction

3D printing or Additive Manufacturing creates 3D shapes from a 3D model with the help of 3D printers. 3D printers turned out to be extremely well known in the most recent years, in light of a few reasons like lapse of key licenses, simplicity of production, and the availability of moderate machines and materials. The 3D object is printed by additive procedures in which objects are fabricated layer by layer. Every one of these layers can be expected as a thinly cut flat cross-segment of the inevitable object. 3D slicing software is used to produce thin layers from a 3D model and the number of layers for each model differs based on the quality of the print.

One of the main advantages of 3D printing is that it uses less material consumption as compared to traditional material fabrication techniques. Everything begins with a 3D model, which can be made by ourselves or download it from a 3D store. 3D printing utilizes numerous types of advances and materials as 3D printing is being utilized in practically all businesses. The application area and research space of 3D printing includes, but not limited to: 3D Drug Delivery Systems [1]–[4], 3D Food manufacturing [5]–[7], 3D Concrete Structure Manufacturing [8], [9], Electrochemical Energy Device(EES) Manufacturing [10], [11], Bioink Development [12]–[15], Power Consumption Analysis [16]–[18] and so on. 3D printing is well known for its traditional usage:rapid prototyping, but it is now used in industrial sectors for rapid manufacturing. In rapid manufacturing, a large number 3D printers are used to run the production in an industry. 3D printers also eliminate the cost of industry-related specific tools since any complex designs can be printed with 3D printers. The new IOT 3DP Ecology, in which 3D printers are available remotely through a web interface, is helping 3D printing technologies to be popular with normal users who do not own a 3D printer.

In this emerging 3D printing era, assuring the quality of the printed 3D model and predicting the possible failures during printing are key factors to be monitored closely. In an industrial environment, where mass production is done using 3D printers, automatic quality assurance systems are vital. When users are remotely printing the 3D models through a web interface, an assurance should be given about their final printed model to get customer satisfaction. In both industrial and remote 3D printing scenarios, manual by-hand quality checking is a hectic task. A recent open source ecology, named IoT 3DP proposes Internet of Things enabled remote 3D printing using web bases tools. In this ecology, a remote user can execute printing jobs as well as monitor its status with the help of a web cam.

Extending the IoT 3DP open source ecology, this paper proposes a new architecture named 3D Printer Failure Analysis System(3DP-FAS) to monitor, control, and analyze the 3D printing process through the internet with help of IoT devices, camera modules and Web APIs. 3DP-FAS is also capable of making intelligent decisions upon different scenarios like filament damage, out-of filament, power failure, improper printer configurations etc. The rest of the paper is organized as follows: Section II presents a wide survey on the topic of 3D printer-related quality assurance systems. Section III explains the proposed 3DP-FAS architecture: its components, functionalities and working. And, finally, Section IV presents a few conclusions.

II. Related Work

Assuring the quality of the 3D printed object is one of the challenging areas in 3D printer-related research. Most of the existing research in this area uses Image Analysis and Deep Learning. [19] proposed Automated Testing and Quality Assurance of 3D Printing using a hardware setup. They compare the projected(CAD object in printing software) and sensored(using camera) objects for identifying defects in the 3d printed objects. Both internal and external defects are identified and they have developed an expert system taking decisions based on the the result of comparison during the print process. [20] suggested the requirement of video feedback with texture based image analysis to monitor the quality of 3D printing process to stop the printing upon decreased quality to save the filament and time. The proposed method uses the Gray-Level Co-occurrence Matrix (GLCM) and chosen Haralick features to determine the defects. One drawback of this method is that it depends on the availability of light. [21] developed a Convolutional and Artificial Neural Network for Additive Manufacturing Prediction using Big Data (CAMP-BD) for the analysis of thermal images captured during 3D printing. The model is well suited for the newly emerged Industry 4.0 focused additive manufacturing. Model contains a Convolutional Neural Network (CNN) for analyzing the thermal images with a concatenated Artificial Neural Network (ANN) at the end for including relevant process/design parameters as well as the final point wise distortion prediction. [22] introduces a deep learning framework for real time stress prediction for bottom-up SLA printing using labelled CAD 3D model database. Their framework consist of 3 convolutional layers and 2 fully connected layers which forms a 2-stream CNN.

[23] proposed a monitoring system for the detection of interlayer imperfections which causes delamination and warping in FDM printing process. The extent of delamination of printed parts is classified using real-time camera images and Convolutional Neural Network Model. The proposed system also does strain gauge measurements which determines the extent and tendency of warping before it actually occurs in the printing process. In the case of delamination, the focus is on the calibration of the nozzle height and the model achieves an accuracy of 91.0% testing accuracy. [24] presents a user-friendly and cost-effective maintenance framework for partially damaged parts using 3D printing, without having complex manufacturing processes and expert technical support. The proposed framework has three systems which consists of 3D scanning, maintenance support system, and 3D printing. A system for automatic error compensation in 3D printing based on Deep Neural Network is proposed in [25]. One of the methods for error compensation proposed here trains a prediction network with nominal models as input and deformed models as output. The model approximates the deformation function and gives error prediction results. In this system the deformation is approximated by the combination of translation, rotation and scaling operations.

A system for the prediction and compensation of errors in 3D printed objects using Convolutional-Auto Encoder architecture is proposed in [26]. There are two ways for error compensation. In the first method, a prediction network is trained by taking nominal models as input and printed models are taken as output. The second way is to train the compensation network by giving the printed models as input and nominal models are taken as output. The proposed system tests for four linear deformations and two nonlinear deformations using the CAE architecture which consists of an encoder and decoder part. [27] proposed a lightweight 3D Convolutional Neural Network which is proposed for real-time 3D object recognition by multitask learning. LightNet has less training parameters compared to various existing models like FusionNet, VoxNet etc. Different types of auxiliary learning tasks are combined into a network to handle large and small data sets without over fitting. [28] a colour independent visual quality assessment method based on the assumption of increase in image entropy for irregular surfaces. The method is useful in detecting and identifying quality problems visible on the surfaces of objects manufactured by additive manufacturing. Instead of direct usage of entropy, a combination of local image entropy and its variance is used in the proposed system.

A Decision support system for identifying parts or assemblies in a repository which are eligible for AM, based on Machine Learning and suitable candidacy criteria is proposed in [29]. The system consists of three main sections which are candidacy criteria, data acquisition, and decision model. The candidacy criteria on which the system focused are geometric analysis, model analysis, economic analysis, and design potential analysis. Decision model which aims at predicting AM models are created using various ML models and analysed, of which Boosted Decision Tree Regression gave the best result. [30] presents a method for analysis of layer-wise 3D printing process to monitor manufacturing errors, and it also generates suitable printer actions to repair and improve the process. The Process is based on multiple stage monocular image examination which checks both global and local deviations in the printed models. The proposed method utilizes side-view height validation, an iterative closest point algorithm for analysing the virtual top view of outer layer, Gaussian Mixture Model for inner layer texture analysis and agglomerative hierarchical clustering algorithm for identifying structural anomalies. The proposed technique can be considered as a good printing suspension tool which saves time and material rather than a complete failure correction system. All the above mentioned works lack a well-defined working environment which is proposed in this paper. Suitable related works mentioned can be added to the Model Library of the proposed architecture and can be used upon needs.

III. 3DP-FAS Architecture

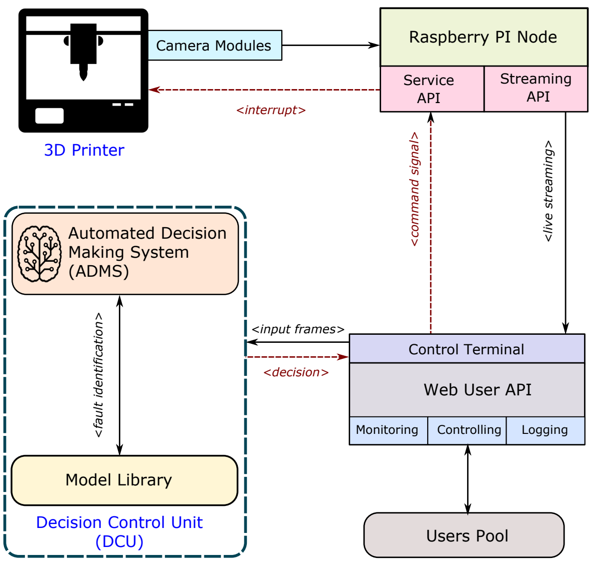

Fig. 1. 3DP-FAS Architecture

3DP-FAS in an automated decision control system to monitor and analyse 3D printers with the help of Machine Learning based tools. Figure 1 shows the architecture of 3D Printer Failure Analysis System(3DP-FAS) which can be attached to any 3D printer. The main components, functionality, and working of the 3DP-FAS is described below:

A. Components

Main components of 3DP-FAS architecture are the 3D Printer with an attached camera module(s), Raspberry Pi Node, Web User API, Decision Control Unit(DCU) and a User Pool. The camera modules are attached to 3D printer and are capable to monitor the printing process. Both the 3D printer and camera modules are connected to a Raspberry Pi Node which contains two Application Programming Interfaces(API) named Service API and Streaming API. Service API is used to control the 3D printer and Streaming API is used to monitor the 3D printer with the camera modules attached. Web User API is a programmable interface which is used to control the 3D Printer by a remote user as well as the Decision Control Unit(DCU). Decision Control Unit(DCU) receives inputs in the form of images and videos, processes it using the fine tuned machine learning models from the Model Library and based on the inputs, automated decisions are made. User Pool contains N number of online users who submits and monitors the printing jobs on 3D printer.

B. Functionalities

Functional usage of each components in the architecture is described below.

1) Camera Modules: Camera modules are attached to the 3D printer, captures images/videos and send it to Raspberry Pi. There can be N number of cameras depending up on the use cases. For example, there can be four primary cameras from all four directions of the bed as well as a fifth camera on the top.

2) Raspberry PI Node: Raspberry Pi node mainly provides two functionalities: through its service API, it controls the 3D printer and through its Streaming API, it provides a live image/video stream of all attached cameras. Stream API streams live recording of printing from Raspberry Pi with a unique URL and authentication token. Raspberry Pi node runs a media server like Plex to stream camera output to external worlds. The service API is built on OctoPrint to control the 3D printer from a remote interface. It allows the remote users to submit their 3D printing jobs as well as to monitor the status of currently printing jobs. Service API send and receive control commands like stop printing, start printing, preheat PLA and Bed, Move Nozzle, Printer information etc. with the help of Web User API.

3) Web User API: Web User API is used to manage user interactions, monitoring of jobs in the remote 3D printer, assigning and controlling jobs, logging, printing related incidents(faulty printing, low bed temperature, out of PLA, power failure, energy consumption etc.) in communication with Decision Control Unit(DCU). A Control Terminal in the Web User API is responsible for sending and receiving control signals from the service and streaming API as well as handling live streaming data.

4) Decision Control Unit: The main functionality of Decision Control Unit is to make automated decisions with the help of the machine learning models available in the Model Library. Automated Decision Making System(ADMS) in DCU makes automated decisions based on the output of machine learning model using streaming data as input and sends the necessary control signals to implement the decisions to the control terminal. Decision Control Unit contains a Model Library which contains fine tuned machine learning models to detect various quality related parameters. Different models are available in the Model Library for different use cases like detecting faulty prints, detecting filament shortage, identifying damaged filaments, estimating energy consumption, etc.

C. Working:

During 3D Printing, the camera module(s) records the printing process and passed to Raspberry Pi Node. Raspberry Pi node streams this live recordings through it Streaming API to the outside world. A Web User API reads this streaming through a unique URL and application key provided by the Streaming Server. Web User API pass each frames obtained from the live streaming to the Decision Control Unit which uses the Model Library to detect various events like faulty print, filament shortage, damaged filaments, improper layer height, energy consumption etc. Based on the machine learning model output, Automated Decision Making System generates decision commands like stop printing in case fault print and send to Web User API. Control terminal in the web user API send this command signal to the Raspberry Pi Node which has a dedicated Service API to handle such commands. Finally, Service API sends the interrupt signal to the 3D printer to stop the printing and sends the status back to the Web User API which indicates this action through notifications to the users whoever authorized to control the current printing job.

IV. Conclusion

Industry 4.0 has been adapted 3D printing as a key technology for modern manufacturing process. The new IoT-3DP ecology mixes the IoT with 3D printing through the internet which makes 3D printers more suitable for industrial sector. Assuring the quality of a 3D printed object and detecting the failures during the printing process without any human intervention is a challenging research topic, especially for industrial sector. This paper proposes a new architecture named 3DP-FAS, for detecting failures as well as assuring the quality of 3D printing. This architecture is built upon the IoT-3DP ecology of remote 3D printers connected through the internet, camera modules and Web APIs. Machine learning models and decision control system are integrated on the back end of this architecture to detect failures and to assure the quality. This architecture can be considered as a base for researchers and industrialists to build more complex systems. Numerous fine-tuned models can be added to the Model Library of the proposed architecture to extend the analysis capabilities.

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