In Situ Visual Quality Control in 3D Printing

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Abstract: In the past decade, additive manufacturing technology has gained an immense attention in numerous research areas and has already been adopted in a wide range of industries relevant to transportation, healthcare, electronics and energy. However, the presence of defects and dimensional deviations that occur during the process hinder the broad exploitation of 3D printing. In order to enhance the capabilities of this emerging technology, online quality control methodologies and verifications of the manufacturing process are necessary to be developed. In the present article, a low cost in-situ vision-based monitoring technique applied in Fused Deposition Modeling (FDM) 3D printing technology is introduced. An optical scanning system was integrated in a commercial 3D Printer in order to scan and validate the performance of the procedure. The proposed methodology monitors the FDM process and correlates the theoretical 3D model with the manufactured one. This technique can be utilized in various additive manufacturing technologies providing integrity and reliability of the process, high quality standards and reduced production costs.

1 INTRODUCTION

Additive Manufacturing (AM), which is known to the public as three-dimensional (3D) printing, is a manufacturing process where the product is built incrementally and vertically to the build platform of the 3D printer, i.e. layer-by-layer (Gibson, 2014). Industries around the world utilize AM in order to decrease the cost of parts manufacturing and reduce the time-to-market. Products created using AM procedures have the potential to possess complex geometric characteristics and lightweight structure, challenges which are difficult be to addressed via traditional subtractive manufacturing procedures like turning and milling. 3D printing has undergone a rapid growth and there are various AM processes based on different physical principles (e.g. material extrusion, photopolymerization, sintering, material jetting, etc.) which are now available and allow the manufacturing industry to reduce lead times on the production. Depending on the applied AM technology, there is a wide range of materials which can be used such as plastics, ceramics and metals. From an application perspective, polymer-based AM methods are employed in various scientific fields like automotive engineering, medical and bioengineering. The most popular and rapidly-growing AM process using polymers as feedstock material is the extrusion based deposition process known as Fused Deposition Modeling (FDM). FDM is an AM technology representing the largest installed base of 3D printers in the world and is primary used for modelling, production and rapid prototyping. The abovementioned process a continuous filament of a thermoplastic material through a moving, heated extrusion print head. Once the nozzle of the print head has reached the desired temperature, the feedstock material is fed to the print head where it melts locally. The print head is connected with a computer numerical control system that allows it to move in two dimensions (on the horizontal plane), one layer at a time, depositing the feedstock material in

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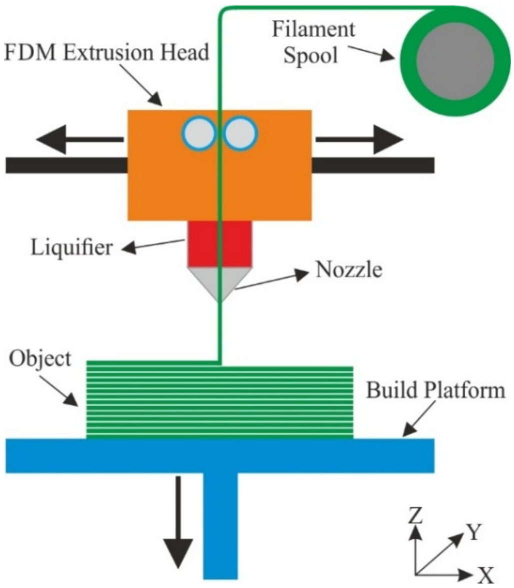

Figure 1: Principal of FDM process.

predetermined locations as illustrated schematically in Figure 1. The deposited melted material on the build platform cools and solidifies immediately after its extrusion from the print head's nozzle. When the layer is fully created, the build platform moves vertically down and a new layer is deposited. This procedure is repeated until the 3D geometry of the product has been printed.

In general, the quality of a product manufactured via the FDM procedure can be characterized by various aspects, such as dimensional accuracy, surface quality, mechanical properties and conformance to specifications. More specifically, the geometrical accuracy of the physical printed model consists one of the biggest concerns in AM and the utilization of non-destructive quality control methods constitutes a must in order to exploit the full capabilities of this state of the art technology (Dimitrov, 2006). In the scope of optimizing the FDM process via the reduction of dimensional deviations between the theoretical and the printed product, online monitoring of the procedure is considered to be mandatory. Real time monitoring of the AM procedure composes an essential phase but is frequently neglected; hence dimensional deviations from the printed model are unknown until the end of the process. Additionally, in situ visual monitoring of the 3D printing process could reduce material resources and production time, as the manufacturing process can be aborted if an error is detected. Therefore, semi-built parts which do not comply with the technical standards of the product can be interrupted prior to the prescribed process termination. Optical methods are appropriate for low cost, non-destructive and high resolution monitoring of AM procedures (Nuchitprasitchai, 2017). Moreover, monitoring of the manufacturing process could aid in predicting the performance of the operation and detecting possible failures beforehand.

The objective of the present work is to investigate and develop real-time optical monitoring techniques during the FDM process in order to perform in situ non-destructive quality control. Hereupon, an integration of an optical scanning system on a commercial FDM 3D printer has been established in order to exhibit real time monitoring of the AM process. The rest of the paper is organized as follows: Section 2 outlines the existing monitoring and error detection methods utilized in AM technology and more specifically in FDM procedures. Next in Section 3, the applied experimental setup and the pre-processing data of the employed methodology are discussed, while Section 4 explicitly presents the experimental assessment of the introduced optical monitoring technique. Finally, conclusions and future work are drawn in Section 5.

2 LITERATURE REVIEW

Taking into account the fact that 3D printing is a relatively new manufacturing technology, the research on available real time monitoring systems of extrusion based AM processes is currently limited. Up to now, commercial FDM 3D printers have developed and integrated some types of sensor solutions detecting lack of the feedstock material or malefactions on the nozzle. However, these methods investigate only a single form of a failure mechanism. In order to develop a fully functional monitoring system, which can be applied for real time error detection, more sophisticated methodologies have to be developed. Recent studies with applications in online monitoring of the FDM 3D printing process are documented in the next paragraphs.

An in situ monitoring method for evaluating the surface quality of parts manufactured via a FDM 3D printer was developed in (Fang, 2003). Grayscale images of the deposited layers were captured and analyzed during the process. Alterations in the grayscale values on the deposited surfaces allowed the detection of overfills and underfills of the printed parts. The authors in (Dinwiddie, 2013) utilized an extended range IR camera in order to measure the developed temperatures during the process correlating their effect on the mechanical properties and the quality of parts manufactured through a FDM

3D printer. The authors in (Faes, 2014) a modular 2D laser triangulation scanner has been utilized in order to analyze feedback signals during the process and to identify the source of the printing errors. Moreover, in the work presented in (Holzmond, 2017) the utilization of a three-dimensional digital image correlation (3D-DIC) system as an online measurement method has been introduced, in order to monitor and quantify the quality of the printed part surface. In particular, stereoscopic images were captured and spatially correlated using 3D Digital Image Correlation in order to extract the surface characteristics and produce the 3D geometry of the part during the process.

The authors in (Straub, 2015) developed a technique to detect failure defects during the 3D printing manufacturing procedure. In this study, the evaluation of the product quality was accomplished via a multi-camera system consisted of five monitor features (each feature consisted of a Raspberry Pi camera) and image processing analysis using Dot Net framework and C#. Images were captured during the process from eight predefined locations by each of the five cameras located at five different angles in order to compare the results with the final 3D printed part. The correlation was performed on a pixel-wise manner. The types of the failures which can be detected using this experimental procedure are either an early termination of the process resulting to an incomplete product or a failure on the injection of the filament into the printer's nozzle. The proposed technique cannot evaluate geometrical characteristics or structural defects, which are the most common errors in FDM process. However, in (Malik, 2019) a 3D reconstruction method was introduced requiring only one camera integrated on the top of the build platform avoiding the need for moving the camera around the printed part or employing multiple static cameras. Moreover, the isolation of the printed part was feasible by cropping the background and the unwanted information from the acquired images. The 3D model is reconstructed layer by layer; hence an online monitoring and error detection technique was developed. Finally, Augmented Reality (AR) methods were used to evaluate the procedure utilizing the reconstructed 3D model of the printed product. Recently, image-sensing systems combined with Artificial Intelligence (AI) algorithms have been reported for the characterization and the quantification of the geometric accuracy of 3D printed parts. The authors in (Delli, 2018) presented an in process quality control methodology for an FDM 3D printer utilizing the supervised machine learning algorithm support vector machine (SVM) and a single camera. In this work, the state of the printing process was classified as 'defective' or 'good' employing the machine learning model and the image captured during the building procedure.

3 EXPERIMENTAL METHOD

3.1 3D Printer Setup

The experimental setup utilized in this work comprises the commercial 3D Printer 'Ultimaker 3 Extended', an ADXL345 accelerometer and the RGB-Depth camera 'Asus Xtion Pro Live'. The Ultimaker 3 Extended applies the FDM 3D printing technology process providing a maximum build volume of (215x215x300) mm, a layer resolution from 20 to 200 microns and a XYZ print accuracy of (12.5, 12.5, 2.5) micrometers respectively. Polylactic acid (PLA) was used as an eco-friendly feedstock material in the experimental procedures. The process parameters were selected as documented in Table 1 and remained constant throughout the courses of the experiments. The accelerometer has been exploited in order to send a signal to the optical monitoring system during the FDM process for capturing images when the print head reaches a checkpoint, as it will be discussed in Section 3.2.

Table 1: 3D printing process parameters during the experimental tests.

Process Parameters	Value	Units
Nozzle diameter	0.4	mm
Layer height	200	μm
Printing speed	70	mm/sec
Printing temperature	205	°C
Wall thickness	1	mm
Top thickness	1	mm
Bottom thickness	1	mm
Infill density	25	%
Infill pattern	triangles	
Build plate temperature	70	°C
Overhang angle	45	degree

The Asus Xtion Pro Live sensor provides color images and Per-Pixel-Depth information. Depth data of the scene are provided from the integrated IR depth sensor of the camera and the RGB sensor implements the colored image on the captured scene. After the registration of these sources of data, an RGB image of the scene along with a Per-Pixel-Depth information is obtained. In the present article, only the depth sensing capabilities of the camera will be exploited. The 3D printed objects are monitored by capturing images during the process with the aid of the above-

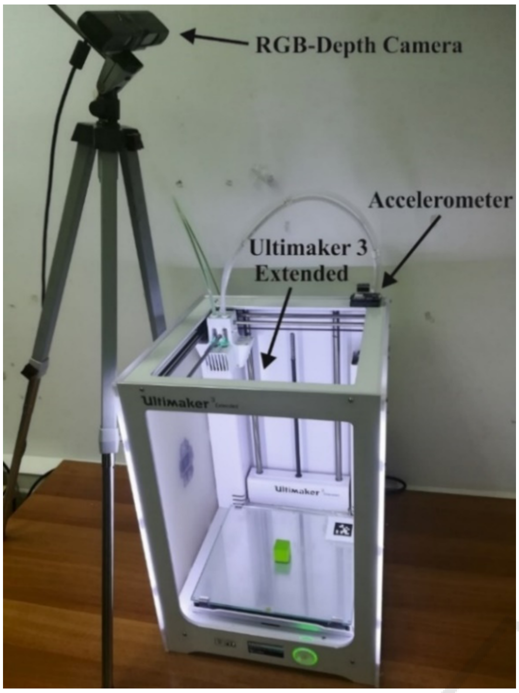

Figure 2: Experimental setup.

mentioned laboratory equipment, as shown in Fig. 2. It has to be noted, that the proposed experimental setup can easily be implemented in any type of 3D Printer and several AM technologies. The developed software was in C++, while also Point Cloud Library (PCL) (Rusu, 2011) has been used to for handling the 3D points; developing thus a pipeline which automates the in situ monitoring process of the FDM 3D printing procedure. Finally, taking into account the effect of variation in lighting conditions, numerous experiments in different light conditions have been performed in order to capture images using the RGB-D camera. Since the alterations in the lighting conditions influence the quality of the image, a constant lighting angle throughout the course of the experimental procedures was kept facilitating image analysis and comparison feasibility.

3.2 Data Pre-processing

One of the major advantages of AM is the ability to create a complex physical object utilizing only a digital 3D CAD (Computer Aided Design) model and a 3D printer. The executable commands of the 3D printer are derived from the digital 3D model and by employing a software called slicer; machine commands are generated representing the trajectories of the print head (Gcode). Gcode is a machine code which is utilized in various manufacturing procedures, like CNC milling, turning and 3D printing. These code structures contain the instructions for the printer in order to control and move its actuators, the build platform and the print head, which extrudes the semi-molten feedstock material. However, there is no control or guarantee that the commands of the Gcode will be accurately executed by the 3D printer resulting to inaccuracies of the manufactured product. Dimensional deviations of the physical printed part compared to the 3D CAD model is hard to be detected during the FDM process due to the fact that the printing object does not exhibit any obvious defects and the manufacturing process is successfully finished. This type of errors could occur in case of malefactions of the 3D printer during the process or in situations where the user applies unsuitable printing conditions. Therefore, in order to detect dimensional deviation errors, the physical printed part has to be monitored and compared to the theoretical model while the process is still ongoing.

In AM technologies and especially in FDM procedures, the conversion of a CAD model into a Standard Triangulation Language (STL) format is necessary in order for the slicer software to generate the Gcode for the manufacturing of the model (Gibson, 2014). STL format contains data that correspond to sets of surface normal vectors and triangle vertices, hence STL describe only the external surface geometry of the part without any representation of the internal structure (lattice structure) or the necessary support structures of the printed part. In some AM processes, like FDM, the physical objects are not printed as solids due to the high amount of the required feedstock material and the total duration of the procedure. The lattice structure (filling pattern) is the internal structure of a part created using the FDM technology. Additionally, as FDM 3D printing models are constructed layer by layer, a previous layer is necessary to build upon it. Hereupon, depending on the complexity of the 3D model and the overhang angle of the new layer compared to the previous one, support structures may be required (Volpato, 2014). These types of structures are exhibited in Fig. 3. For this reason, the comparison between the STL data and the printed part is not directly applicable, since the STL format does not contain information regarding the abovementioned structures.

In order to overcome such issues, a more holistic approach had to be developed. The employed methodology for the reconstruction of the digital model taking into account the internal and the support structures is presented schematically in Fig. 4. The proposed method is based on the generated Gcode

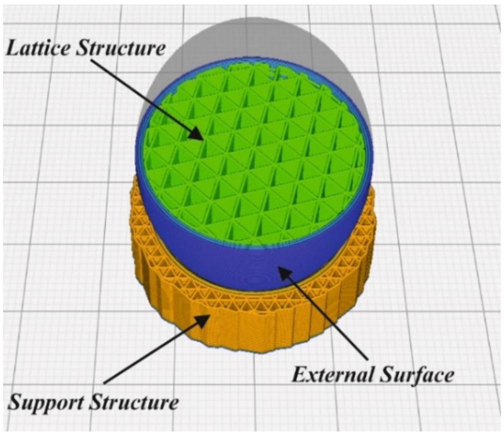

Figure 3: Lattice and support structures in FDM process.

from the slicer software and simulates the exact movements of the print head in order to create the theoretical point cloud of the digital 3D model. In the first step, the 3D CAD model is imported on the CuraEngine, which is a fast and robust engine for translating 3D models into 3D printing commands (Kocisko, 2017). The outcome of this step is the Gcode that contains certain instructions about the X,Y and Z coordinates to which the print head and the build platform have to move in order to build the 3D model. In the next stage, a simulation of the 3D printing process utilizing the Gcode takes place. The generated Gcode has been further processed using a modified version of gcode2vtk (Kubicek, 2011), emulating the functionality of the 3D printer by parsing the Gcode to extract the planar-layered trajectories of the print head. In the next phase, a structure containing every path of the 3D printer is created. It has to be noted that only the Gcode commands, which contain information about the extruded material and the movements of the print head (that ultimately builds the physical model) are taken into consideration. Finally, these trajectories are uniformly sampled generating a theoretical point cloud of the 3D model. An example of the developed technique is illustrated in Fig. 5, where a 3D model created in the slicer software and the corresponding theoretical point cloud are displayed.

In the last step of the preprocessing data module, some further parameters are passed to the 3D Printer. The print head has to move to the zero position (X=0 and Y=0) of the 3D printer in order for the monitoring system to capture a clear image of the printed part during the FDM process. That was accomplished through the modification of the Gcode sending the print head in the zero position of the 3D printer every 'n' deposited layers and with an accelerometer placed upon the 3D printer. In more detail, during the AM

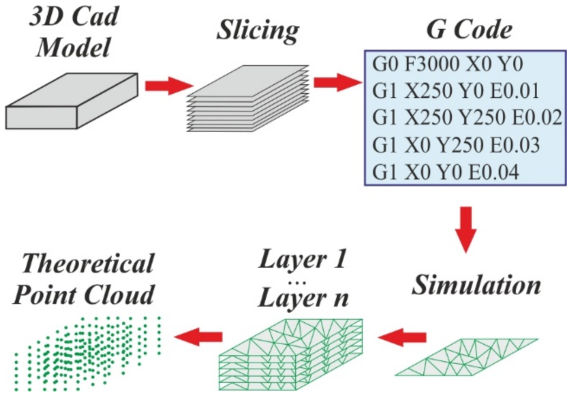

Figure 4: Theoretical point cloud reconstruction.

process the print head commanded to move towards the zero position and pauses for time t_w. During t_w, the accelerometer sends a signal to the monitoring system in order to capture an image of the printed part, which is clearly visible by the RGB-D sensor, without the printing head to occlude the visibility of the building plate. After this operation, the printing head moves back to its previous position and re-initializes the printing process again. In this way, the real-time point cloud from the printed part is captured during the FDM process; hence the monitoring of the process and the correlation with the theoretical point cloud is feasible.

4 EXPERIMENTAL ASSESSMENT

In this section, the experimental assessment of the present work is presented. The experimental procedure has been conducted on a 3D printed part which has been exploited as a test specimen of basic geometry, namely a spur gear, utilizing PLA filament of 2.85 mm diameter (see Fig.5).

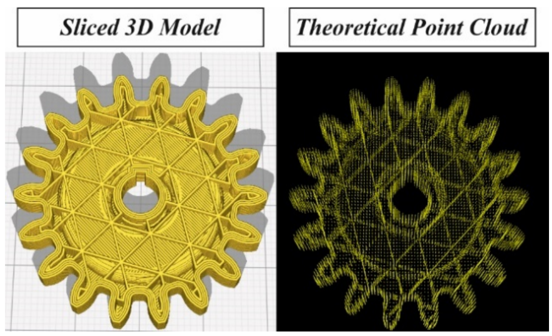

Figure 5: Sliced 3D model and the corresponding theoretical point cloud.

Figure 6 demonstrates a brief overview of the applied optical monitoring process. As it was described in the previous section, the print head moves to the zero position of the 3D printer every '*N*' layers, so the employed camera can capture a clear point cloud of the printed part during the FDM procedure. Due to the low resolution and broad field of view of the acquired point cloud by the Asus Xtion sensor, a fiducial marker was used to filter out the background and determine the area of interest to crop. The AprilTag visual fiducial system has been applied, which is widely used for a variety of tasks including augmented reality, robotics and camera calibration (Olson, 2011). Targets can be printed in any size on a simple piece of paper, thus allowing a low cost and accessible integration of the marker with the employed experimental setup. By placing a small AprilTag on the build platform of the 3D printer, the calculation of an orthogonal region of interest and filtering out any outliers from the initial point cloud is accomplished. The orthogonal region consists of the build platform, the AprilTag and the 3D printed model as shown in Fig. 7. This technique allows a fast filtering of the noise; hence focus on a small region of interest where the model is printed was ultimately achieved.

Once the original point cloud has been cropped down to the region of interest, consisting of the printed part, build platform and AprilTag, the next step comprises their separation acquiring only the printed layer in order to reconstruct the model and evaluate its quality. This issue boils down to a plane detection and segmentation problem. There is a variety of methods targeting towards plane segmentation of 3D point cloud data in literature. Ransac algorithm has been selected and applied in the present study, which is easily implemented in PCL providing accurate results. Ransac is relatively slow when provided with big data sets, however the crop of the original point cloud reduced the overall size heavily and thus applying it did not influence the performance of the introduced optical monitoring system. Using the algorithm on the cropped point cloud resulted in a fairly accurate segmentation of the build platform, although there were still some areas with a small concentration of outlier points (namely the area where the AprilTag was placed upon) as exhibited in the left part of Fig. 8. In order to tackle this issue, a technique has been developed in accordance to which a point cloud representation is obtained that retain only the inlier points belonging to the constructed model, excluding thus the outliers. Increasing the distance threshold, which Ransac applies to extract the points on the detected plane,

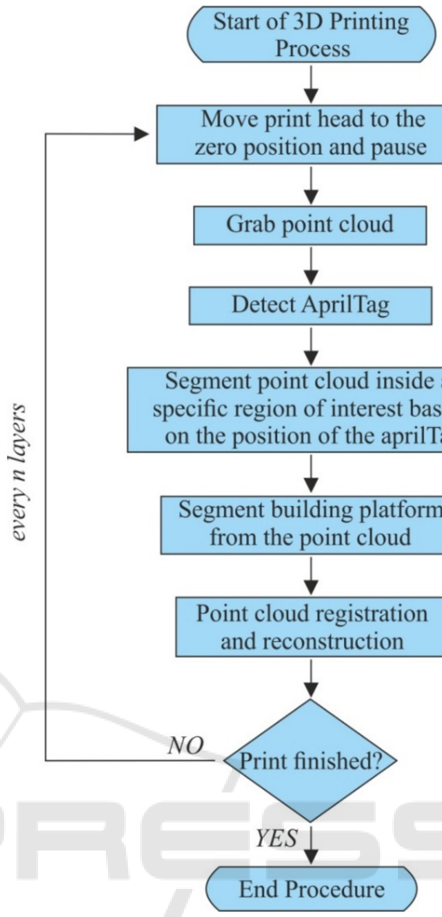

Figure 6: Flowchart of the monitoring procedure.

resulted in segmenting away points originally belonging on the printed model. The issue has been solved by applying a distance–based clustering algorithm to the remaining point cloud and segmenting the biggest cluster, which resulted in a point cloud consisting only from points belonging to

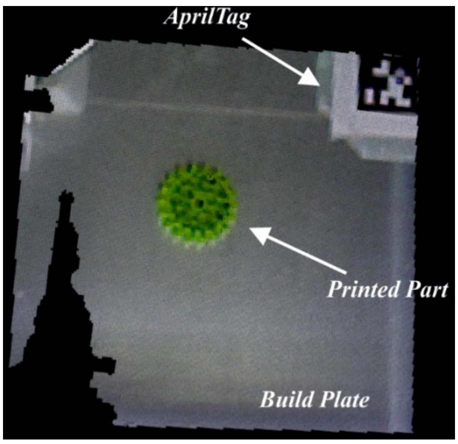

Figure 7: Region of interest.

the printed layer of the part. To this end, a Euclidean distance clustering algorithm has been utilized which clusters the remaining points based on the 3D Euclidean distance from their neighbors. Due to the sparsity of the outlier points, clustering the point cloud using distance between points as a metric leaded in a successfully filtering of the printed model as exhibited in the right part of Fig. 8.

Having successfully implemented a method for locating and segmenting each printed layer, the final step was to reconstruct the printed model and correlate it with the theoretical point cloud of the 3Dmodel. In situations where the build platform of the 3D printer was stationary, the reconstruction of the model using the methodology presented in this work would be as simple as concatenated all the obtained point clouds from each individual deposited layer. However, on the employed 3D printer (Ultimaker 3 Extended), the print head is stationary in the vertical direction and the build platform moves during the process. Therefore, preprocessing of the acquired point clouds of each printed layer before their concatenating was imperative. In the first step, the transformation between two subsequent layers was computed by aligning their build platforms. The alignment was conducted utilizing the Iterative Closest Point (ICP) algorithm (Bellekens, 2014), which is usually deployed in order to minimize the difference between two point clouds. Thus, the ICP algorithm was applied between two subsequent point clouds before the segmentation of the build platform. Due to the high concentration of points on the build platform, it was feasible to match the individual build platforms of two subsequent point clouds, acquiring ultimately their transformation. Hence, the segmentation of the build platform as well as the transformation of the extracted layers have been accomplished, enabling the representation of the physical printed object. Finally, it is a matter of concatenating the printed layers into a single point cloud to reconstruct the 3D model as illustrated in the left part of Fig. 9.

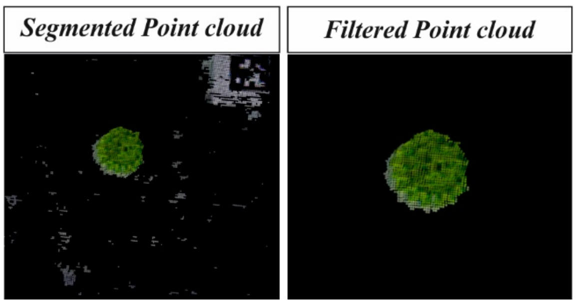

Figure 8: Segmentation of the build platform using Ransac and the filtered point cloud.

Results of the employed optical monitoring system are displayed also in Fig. 9, where in the middle the theoretical point cloud of the test specimen, which was obtained through the introduced methodology described in Section 3.2, is presented. Additionally, in the right part of Fig. 9 the correlation between the theoretical and the actual reconstructed point cloud of the examined model is exhibited. As it can be observed qualitatively, the reconstructed model is in decent agreement with the theoretical one. For the qualitative comparison, a point cloud spatial change detection method based on octrees has been employed to compare the reconstructed point cloud to its theoretical counterpart. An octree is a tree data structure in which each internal node has exactly eight children and is often used to partition a 3D space by recursively subdividing it into octants (Tang, 2016). By calculating both point clouds octrees, it was feasible to retrieve points that are stored at voxels of one octree structure but do not exist in the other. Using the abovementioned method on the generated point clouds with a voxel size of 0.5 mm, the differential point cloud representing the spatial change between the theoretical and reconstructed model was calculated and amounts to 9.6%. One reason for the deviation between the examined point clouds is a result of poor resolution of the employed low cost optical sensor. Nevertheless, the proposed optical monitoring system composes an efficient method for real time monitoring of the FDM process and in case of utilizing a more accurate optical sensor; the introduced methodology could be efficiently applied for any real time error detection in AM procedures.

5 CONCLUSIONS AND FUTURE WORK

In the present study, a low cost solution for online monitoring of the FDM process has been introduced through the integration of sensors on the 3D printer and the implementation of image analysis algorithms. In this sense, an optical scanning system was integrated to a commercial FDM type 3D printer using a low cost RGB-Depth camera and performed initial experiments. The suggested system provides an automatic optical monitoring system with no human oversight. Taking into account the generated Gcode for the manufacture of the product, a theoretical point cloud of the 3D model has been obtained. This digital representation of the part is in the most suitable form in order to evaluate the accuracy of the 3D printing

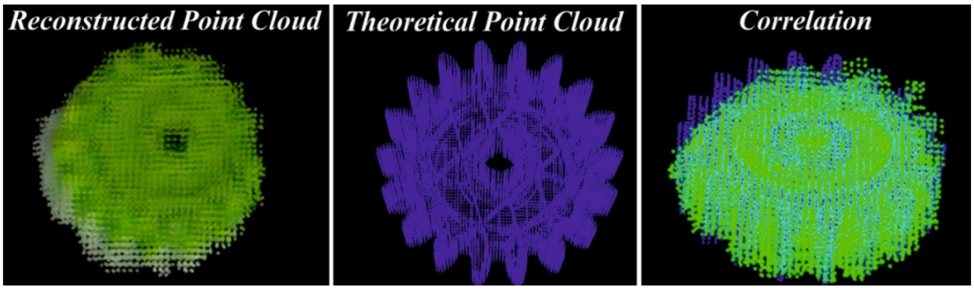

Figure 9: The reconstructed and theoretical point cloud of the test specimen and their correlation.

process, as it contains both the lattice and the support structures of the examined model. Albeit the fact that the resolution of the optical sensor is relatively low, the developed algorithms by means of computer vision and the obtained results exhibit that the suggested method is a promising tool in real time monitoring and detecting errors in 3D printing technology.

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