Characterizing Digital Light Processing (DLP) 3D Printed Primitives

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Abstract. The resolution and repeatability of 3D printing processes depends on a number of factors including the software, hardware, and material used. When printing parts with features that are near or below the nominal printing resolution, it is important to understand how the printer works. For example, what is the smallest unit shape that can be produced? And what is the reproducibility of that process? This paper presents a method for automatically detecting and characterizing the height, width, and length of micro scale geometric primitives produced via a digital light processing (DLP) 3D printing process. An upper limit, lower limit, and best estimate for each dimension is reported for each primitive. Additionally, the roughness, rectangularity, and tilt of the top of each primitive is estimated. The uncertainty of the best estimate is indicated using standard deviations for a series of primitives. The method generalizes to unseen primitives, and the results illustrate that the dimension estimates converge as the size of the primitives increases. The primitives' rectangularity also increases as the size increases. Finally, the primitives specified with 5 to 68 μ m varying heights have been estimated to group into five different heights with fairly low variance of the best estimates of the heights. This reflects how the requested geometry is parsed and produced by the printer.

1 Introduction

Although the development of additive manufacturing technologies began in the mid-1980s [3], until recently they were limited mainly to models and prototypes. The direct manufacture of net shape parts is still relatively new and engineering applications that require high geometric precision and accuracy are still limited. This work is motivated by a desire to understand, improve, and control the resolution and repeatability of digital light processing (DLP) 3D printing to facilitate micro scale and precision production. DLP 3D printing uses light to solidify a liquid photopolymer. By changing the pattern of the light and incrementing the vertical position of the workpiece, the desired geometry is built up

layer by layer. One of the advantages of the DLP technique is that the workpiece is suspended upside down from the build platform. This allows for better control of the process and thus better layer thickness and uniformity [6].

This work proposes a method for characterizing micro scale cuboid primitives that were produced via DLP 3D printing. This task is challenging because primitives are produced using the same process as the surrounding bulk material. Therefore, they share the same surface characteristics. In addition, the printing process produces features with rounded edges and tapered sidewalls. Thus, there are often no clear edges to detect or constant dimensions to identify, unlike data used for previously proposed imaging processing techniques to characterise engineered surfaces in e.g. [8]. Finally, the printed features were imaged using a focus variation microscope. This introduces noise, holes, and other artifacts into the data set.

The method presented in this work detects features on 3D printed samples, determines which features are primitives for future analysis, deletes erroneous values in the data set to be analyzed, and characterizes the dimensions of the detected primitives. To address the challenges associated with the production and measurement, an inner and outer boundary for each primitive is defined. From this, an upper and lower boundary and a best estimate of the desired characteristics (height, width, and length) of the primitives can be obtained. In addition, the primitives are characterized based on their centroid, roughness, rectangularity, and tilt. We illustrate the measures on an unseen sample and look at how they vary over the workpiece in general and for varying heights.

The paper is structured as follows. First, we introduce the experimental setup, the printed data, and the digitalized data (Section 2). Next, we introduce the method for detecting the primitives (Section 3) and define the measures of characterization (Section 4). This includes pre-processing and other data manipulation. Finally, we present the results of the method and conclusions (Sections 5 and 6).

2 Data

Three pairs of samples were produced in RCP30 (a pinkish peach photopolymer) using an EnvisionTEC Perfactory 3 Mini Multi Lens 3D printer. With the lens and settings used, the printing process has a nominal resolution of $32\mu\text{m}$ in x and y and a $15\mu\text{m}$ layer thickness. Each sample is a $10\times 10\times 5\text{mm}$ block with a 20×20 grid of features. The features on each sample have two fixed dimensions that are large relative to the nominal resolution of the machine and one variable dimension that is not (table 1). All features in a given row have the same specified dimensions. Thus, each sample should represent a total of 20 feature geometries, each replicated 20 times.

Each block was designed with a $0.5\times 0.5\times 0.75\text{mm}$ border to protect the features from damage during handling and small rectangular channels on the top left and bottom right corners of the border to indicate the orientation of the part (figure 1). The geometries were designed in SolidWorks and exported as

STL files. The digital masks for the DLP process were automatically generated from the STL files using EnvisionTEC’s proprietary software Perfactory RP 2.6. This conversion means that the geometry requested in the STL file is known but the geometry specified by the masks is not. It is not guaranteed that all of the requested features were printed on any given part or that the features were printed with the specified dimensions.

Table 1. The printing specifications for the three pairs of workpieces

Pattern	Length (μm)	Width (μm)	Height (μm)
Tall and rectangular (X)	5-100	200	100
Tall and rectangular (Y)	200	5-100	100
Short and square (Z)	200	200	5-68

Fig. 1. CAD model for printing the primitives with changes in z (left) and an image of the printed primitives taken with a standard Leica camera (the Z_1 sample) (right). The heights of the primitives increase from top to bottom. Both images seen from the top. The workpiece is $1\text{cm} \times 1\text{cm}$.

The samples were imaged with an Alicona Infinite Focus microscope using a $5\times$ objective (x, y resolution: $1.75\mu\text{m}$). This microscope combines images taken at different vertical focus points to create a 3D height map, a color map, and a quality map. Like all optical metrology instruments, the Alicona is affected by the interaction of the light with the sample. Measurements are affected by the sample’s material properties, its geometry, and any dirt or debris that might be present on its surface. As a result, data sets often contain spikes that do not represent true measurements (Figure 2) and have holes where the reflected light was unable to return to the sensor. The Alicona is unable to measure very steep slopes. Thus, the primitive sidewall data is often incomplete. The Alicona measures heights relative to its reference coordinate system. If the surface of the sample is not perfectly horizontal to the Alicona’s system, a systematic planar tilt will be present in the data set. Finally, if the sample is rotated relative to the Alicona, the edges of the primitives will not be parallel to the measurement coordinate system.

Fig. 2. Illustration of the surface of a 3D printed plate as captured by the Alicona

3 Methods

This section describes the pre-processing of the raw data, the detection of the primitives, and the definitions of their top, edge, and sidewalls. On this basis, the length, width, and height of the primitives is defined, as well as the centroid, the roughness, the rectangularity, and the tilt. In the next two sections, we concentrate on characterizing the first Z workpiece (Z_1).

3.1 Pre-processing

The pre-processing uses frequency filters to remove the optical artifacts created by the Alicona. This is done in two steps: a spike detection step and a frequency separation step. For the spike detection, we used a Gaussian high-pass filter as described in [4,5]. A series of different bandwidths were examined to determine a bandwidth adequate to identify the high-frequency noise patterns in the images (Table 2). Subsequently, a simple thresholding is performed to obtain the mask for the valid data (Figure 3).

In the second step, the data is split into regions of different frequency. This is done according to Whitehouse's guidelines for the identification and separation of surface features [9]. The idea is to separate the roughness of the surface (high-frequency noise), the waviness of the surface (medium frequency noise often associated with the manufacturing process), the primary profile of the surface (the printed surface of interest), and the orientation of the surface (low-frequency process or measurement noise). Waviness was not observed and therefore omitted. The cut-off frequencies were chosen manually from a series of Gaussian filters with varying bandwidths (Table 2). Previous work [1] using the same measurement instrument used cutoff values of $2.5\mu\text{m}$ and $500\mu\text{m}$ for identifying the roughness. In comparison, the values chosen in this work are more conservative. The orientation and the roughness are then removed as illustrated in Figure 4. The most critical parameter is the orientation cut-off frequency which separates the background from the foreground. Based on investigations on the samples presented here this is however also the parameter with largest span in which the results are robust.

Fig. 3. The spike detection algorithm detects spikes using a high pass filter. This figure shows the data before reconstruction, the mask, and the data after the reconstruction. The mask includes data points that were marked as invalid by the Alicona.

Fig. 4. The raw data are illustrated to the left. The data after removing spikes, roughness, and orientation are illustrated to the right. Note, the different scales on the colorbars.

3.2 Primitive Detection

The first step in the primitive detection involves an initial guess of where the primitives are by simple thresholding. To remove some of the false positives associated with debris and the roughness of the surface, the mask is opened with a 25px radius disk before labeling. This segmentation and the initial labeling yields some false positives, which are removed automatically from the set at a later time. The result is seen in Figure 5. Each primitive is labeled for separation using connected components labeling [2].

3.3 Tilt Correction

Once the primitives have been detected, a linear plane is fitted to the background. The tilt (likely due to manufacturing error) is estimated and removed for both the background as well as primitives. This was done locally for each primitive as the above orientation removal could be improved this way. The correction is illustrated in Figure 6.

Table 2. The chosen cut-off frequencies for the separations calculated from a defined cut-off frequency as a 3dB attenuation and the given standard deviations of the Gaussian filters. Included is the cut-off frequency used in the spike detection.

	Standard deviation σ	Cut-off at -3dB [μm]
Orientation	>100	>933
Primary profile	50-100	466-933
Roughness	<1	<9
Spike detection	<50	<466

Fig. 5. The results from primitive detection after the morphological opening with the mask in black and the detected primitives in white. The centers of the primitives are marked with red crosses. Left: All primitives in the workpiece. Right: Detailed view of the lower right corner of the workpiece showing 25 detected primitives and one false positive.

3.4 Segmentation

For a given feature, the distributions of the heights (Figure 6, right) is generally bi-modal, with the larger lower peak coming from the surrounding surface and the smaller and higher peak belonging to the primitive. For generalisation purposes, a *K*-means algorithm is used to find the two cluster centers, and the midpoint between the two centers is used as a threshold on the height map. To ensure that there is only one object (the primitive) in the image, labeling is used and only the object with the largest area is kept for further analysis. Finally an erosion on the image is performed and subtracted from the original image to get the border of the object. Figure 7 illustrates the different steps in defining the boundary of the primitive.

After the border is found, each primitive is divided into four segments: the top, the sidewall, the floor, and invalid data. The invalid data is the part of the data where a spike has been detected. The sidewalls are defined as the parts of the primitive with an overall gradient. A normalised Sobel filter [7] is used to find the gradient row wise and column wise. The edges are found by using a threshold on the gradient image. In this case, everything with an angle greater than or equal to 30 degrees is classified as sidewall. To ensure that only pixels around the top pixels are used as sidewalls, morphological reconstruction is used [2], as illustrated in Figure 8. The top pixels and the floor are given from the detection of the primitives (Figure 5), combined with the sidewall (edge)

Fig. 6. Illustration of a primitive before and after the tilt correction (left). Histogram of tilt corrected height map (right).

Fig. 7. Illustration of the different steps used to find the border of the primitive

Fig. 8. Illustration of the effects of morphological reconstruction. Sidewalls are not always closed due to the pre-processing where invalid data are masked out.

detection and invalid data detection. Figure 9 (left) illustrates a primitive and its different segments.

4 Characterization

The definition of the top pixels together with the sidewalls of the primitives gives a starting point for characterizing the primitives. In the following subsections only valid data points are included in the estimations.

Fig. 9. Image of different segments (left). Different segments with bounding boxes (right).

4.1 Length and Width

We define the length (L) and width (W) as a best guess, an upper bound, and a lower bound. The upper and lower bound of the length and the width are determined by finding the smallest bounding box for the inner and outer boundary of the sidewalls. To account for the fact that the primitives may be rotated in the microscope, the primitive is rotated 90 degrees in steps of 2 degrees to find the smallest bounding box that encloses the pixels. The principle is shown in Figure 9 (right) with an angle of zero degrees.

The mean of the upper and lower bound is used as a measure of the best guess, i.e. $L_{best} = (L_{low} + L_{up})/2$ and $W_{best} = (W_{low} + W_{up})/2$. The upper and lower bound should not be considered uncertainties of the best guess, as we have no guarantee that the true estimate lies within our bounding boxes. The lower and upper bound can be interpreted as a measure of how broad the sidewalls are.

4.2 Height

The height (H) is defined as a best guess, an upper bound, and a lower bound. The median of all valid top pixels defines the best guess of the height ($H_{best} = median(z_i)$). The median is a robust measure in this context since it is not sensitive to local roughness or waviness of the primitive (see Figure 10). An

Fig. 10. Effects of calculating surface height as mean vs. median

upper and a lower bound are calculated as well, and the definition of these are the 2.5 percentile (lower bound, H_{low}) and the 97.5 percentile (upper bound, H_{up}) of pixels defined as top (example in Figure 11). There is still a chance that the true height is outside the upper and lower bound, but the 2.5 percentile and the 97.5 percentile are picked because of the possibility of noise in the data.

Fig. 11. Height estimates

4.3 Centroid

The centroid is calculated as the center of mass of the valid top pixels $[x_i, y_i]$ as $\mathbf{C}_{x,y} = \frac{1}{n} \sum_{i=1}^n [x_i, y_i]$, where n is the number of valid top pixels.

4.4 Roughness

The roughness measure indicates how rough the top of the primitive is. The roughness is defined as in [9] by $R_a = \frac{1}{n} \sum_{i=1}^n |z_i - \mu_z|$, where z_i is the height of the i^{th} top point, and μ_z is the mean of all the top heights.

4.5 Rectangularity

Rectangularity measures how rectangular each primitive is. It is defined as the area of the primitive (number of top pixels) divided by the area of the smallest bounding box for the top pixels? which is the same as the lower bound of the length and width $S = \frac{n}{L_{low} \cdot W_{low}}$.

4.6 Tilt

The tilt of the top of the primitive characterizes the overall asymmetry in the printed primitive. For this, it is assumed that the top pixels can be described by a plane. The tilt is defined as the angle between a plane, P , fitted to the top pixels and the $(x - y)$ -plane, O : $T = \angle(P, O)$.

5 Results

The sample Z_1 was used to calibrate the method and tune parameters (training), thus we will use sample Z_2 to test the performance of the proposed method (testing). Table 3 summarizes the number of detected primitives, together with the false and true negatives as compared to a manual detection by an expert. The results are similar in the training and in the testing sample after automatic post processing. We do not detect primitives that were not manually detected. And after post processing, we do not miss any of the primitives that were observed by visual inspection of the sample by an expert. The visual inspections found only 379 and 380 primitives in the samples as the smallest of the 20 rows was not visibly printed, and a single primitive in one row in the Z_1 sample was corrupted.

Table 3. Summary of the statistics on the detection of the primitives

Sample Type	Primitives detected manually	Detected in pre processing	False positives	After post processing	False positives
Sample Z_1	379	418	39	379	0
Sample Z_2	380	415	35	380	0

The characteristics of the primitives are summarized in Table 4 as means and standard deviations of all the primitives in the sample Z_2 . The estimated heights are presented as a plot in Figure 12 as we expect the primitives to vary in height. There seem to be five different heights in the sample Z_2 although the specifications increased in height for each of the 20 rows in the sample. These indicate the true vertical step height used by the printer. Additionally, we note that the best estimates of primitives with similar heights are very close, and thus their uncertainty small, whereas the estimated lower and upper bounds for the estimate give a much wider span. The lower and upper bounds give a conservative boundary for the definition of our best estimate, whereas the standard deviation of the best estimates gives an uncertainty of our estimated best height.

Table 4. Summaries of the estimates for the measures characterizing the primitives. The mean and standard deviation (std.) of each measure for all the detected primitives in the sample Z_2 are given.

Measure	Width	Length	Rectangularity	Roughness	Top tilt
Mean	238.9 μm	247.5 μm	87.4 %	1.74 μm	0.526°
Std.	20.89 μm	29.28 μm	4.98 %	0.359 μm	0.269°

Fig. 12. Height chart of the sample Z_2

We use the five estimated levels of heights to illustrate how the length, width, and rectangularity vary as a function of height (Figure 13). It is apparent that as the height of the primitives increases, it is easier for the algorithm to segment them. Thus, the best estimates of width and length decrease and become more consistent. Furthermore, it shows that the top becomes gradually smaller and more rectangular as the height increases. The standard deviations of the best estimates give us an uncertainty estimate of the estimated best values, whereas the upper and lower bounds on the best estimate are related to the uncertainty of our definition of the estimate.

Fig. 13. Mean and standard deviations for the best estimates of the length, width, and rectangularity as a function of the grouped heights for sample Z_2

6 Conclusion

We presented a method for automatically detecting and characterizing the dimensions of micro scale geometric primitives produced via a digital light processing (DLP) 3D printing process. We proposed the best estimate of the height of a primitive to be the median of the top pixels as this is a more robust estimate than the mean. This robustness is also seen in the small standard deviations of the estimated heights for primitives of the same height. The length and width were defined using the top and the sidewalls to define lower and upper bounds for the primitives, and taking into account any rotations of the primitives that may occur. Finally, estimates of centroid, roughness, rectangularity and tilt of the top of a primitive were defined. Standard deviations for these estimates were also relatively small. The method was shown to have high precision (no false positives nor false negatives) when compared to a visual inspection by an expert.

The features for the samples presented in this work had a nominal size of $200 \times 200 \times 5 - 68 \mu\text{m}$ in intervals of 1 or $5 \mu\text{m}$ for a total of 20 different heights. However, it was shown that primitives were produced in only five heights. This could be due to the printer's parsing of the specifications, due to the thickness of the layers it is capable of printing, or due to a combination of the two. We observed that the lengths and widths of the primitives were consistently estimated when

the primitives had a height of $50\mu\text{m}$ or more. Also the rectangularity of the primitives increased from 80% to 90% as the height increased. This is to be expected as the features were specified close to or below the minimum nominal resolution of the machine. We also showed that several characteristics of the printed primitives are worth taking into account, as they vary for primitives with varying size specifications.

In this work, we focused on the Z samples for clarity and because the Z primitives were generally better formed than the X and Y primitives. However, the method in this work was developed for and is applicable to cuboid primitives with variations in x , y , and z . Future work will include additional testing and tuning of the method for the more challenging variations in X and Y . It will also further address the repeatability and uncertainty of the defined characteristics. Alternative segmentation techniques using shape priors could also be of future interest both for more complex primitives as well as for implicit definitions of primitive characteristics.

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