3D imaging of geological scenes

By

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Abstract

The miniature structured-light sensor outputs a 3D image as a triangular mesh. The mesh was uploaded into software tools that calculated the strike and dip of each triangle, and stereonet. Results from the stereonet of specific areas showed that the strikes and dips derived from images were within 10° of the Brunton compass measurements. Twenty geological hand samples were ordered from smoothest to roughest by 10 people using their sense of touch. The samples were then imaged by a laser digitizer. As the surface became increasingly rougher, the standard deviation of the distance of individual points from the image to a best-fit plane calculated using principal component analysis (PCA) increased. Lidar data from the Canadian Wollastonite mine was uploaded into a program that separates point cloud data into cubes and calculated the PCA of each cube. Visual inspection showed that rough areas are either protruding or receding.

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1. **Chapter 1: Introduction**

1.1: Applications of 3D Imaging of Geological Scenes

In the last decade, 3D imaging of geological scenes emerged as part of the tool kit of geological and mining engineers. This growth in the number and variety of applications exploits mainly the fact that 3D imaging allows to make exact distance measurements at a small scale ranging from a few millimeters to a few centimeters (shotcrete thickness, tunnel wall deformation, etc.) and at a larger scale ranging from 10cm-10m (volumetric measurements of rock piles, “as-build” comparisons between planned and actual open pit mines, etc.). For example, terrestrial laser scanning (TLS) was used to image a drill blast tunnel the Sandvika-Asker Railway Project near Oslo, Norway, and two other tunnels in Oslo, to calculate the shotcrete thickness, as-built bolt spacing, and regions of potential leakage (Fekete et al., 2010). A similar study by Zhao et al. (2014) show that the TLS technique can be used for detecting geological features in tunnels, monitoring the geometry of tunnels during excavation, making deformation measurements, and extracting geological features (Zhao et al., 2014). The use of 3D imaging has been increasing in open-pit mines because TLS allows non-contact, rapid scanning of large scale areas with high accuracy (Zhao et al., 2014).

In geology and natural hazard management, it is becoming more common to use TLS to track the evolution of natural surfaces in 3D (Lague et al., 2013). Some examples of recent applications include: landslide and rock fall dynamics (Wawrzyniec et al., 2007; Teza et al., 2008; Abellan et al., 2009, 2010), coastal cliff erosion (Rosser et al., 2005;

Olsen et al., 2011), evolution of braided rivers (Milan et al., 2007), river bank erosion (O’Neal and Pizzuto, 2011) or debris flow impacts (Schurch et al., 2011).

3D imaging can provide added value in comparison to 2D imaging because 3D images can be processed to derive properties of surfaces. Two properties in particular that have peaked the interest of researchers are planar orientation (strike/dip) and surface roughness. For example, (Yeh et al., 2014) used TLS to capture the finer details of sedimentary terrain they were exploring and determined where the 3D strata boundaries were located. This helped them create their 2D geological maps and cross sections. 3D imaging can also be used to estimate surface roughness. In a study by Bizak and co-workers (2010) 10 samples of tuff were imaged and the results were compared with the corresponding Joint Roughness Coefficient (JRC) values. JRC is used as a part of the rock mass rating system (RMR) in mining engineering. It is a parameter used to evaluate the condition of rocks for drilling and tunnelling. If the condition is not suitable no drilling will take place to ensure the safety of the miners. Joint networks can also create roughness in rocks, if there are many pervasive networks of fractures in rocks this could create a rough surface. TLS has also been used to determine grain roughness in gravel-bed rivers (Heritage, G., and Milan, D., 2009).

Research on 3D imaging of large geological scenes has been ongoing at Carleton for a few years. It was initiated by McLeod et al. (2013) who used structure-from-motion software to convert video images acquired using an unmanned aerial vehicle into point clouds, and derived strike/dip information from rock walls along an exploration trench.

Subsequent research projects used point clouds directly acquired using TLS. Joint orientation from triangulated meshes were determined using the 3D pole density contouring method and directly from point clouds (Mah et al., 2013). They also estimated the joint roughness coefficient from point clouds. Lai et al. (2014) introduced different methodologies to reduce the size of point clouds of geological scenes (e.g. epsilon-nets) and to create realistic surface meshes (e.g. Poisson surface reconstruction). In addition, they proposed different methods to measure surface roughness from point clouds by using the curvature geometric property (Lai, P., 2014).

1.2: Objectives

In this research project I sought to make advances on two fronts:

1. Demonstrate the potential of miniature structured-light sensor for imaging geological scenes.
2. Estimate surface roughness from point clouds at different scales, from hand samples to rock walls.

Research involved using three different instruments, a miniature structure-light sensor, a triangulation-based non-contact laser digitizer, and a tripod-mounted Lidar. Image acquisition was done at small scale using hand samples in the laboratory, and at large scale in the field in an open pit mine.

This research is a contribution towards the overarching goal of computing geological maps automatically from images. It follows previous work done by: Sharif et al. (2013), Lai et al. (2013), Olson et al. (2013), and Mah et al. (2012).

1.3: Structure of Thesis

Chapter 1: this chapter presents a literature review of current applications for 3D imaging of geological scenes, and articulates the objectives of the research project described in the thesis.

Chapter 2: this chapter describes how principal component analysis can be used to estimate roughness of hand samples of 3D point clouds, and the following experiments that were performed in the laboratory to determine if principle component analysis is valid approach of estimating roughness.

Chapter 3: this chapter describes the strengths and weaknesses of the miniature structured-light sensor for imaging geological scenes.

Chapter 4: this chapter integrates several elements from Chapter 2 and 3 into a case study featuring field work done at the Canadian Wollastonite, Kingston open pit mine using both the miniature structured-light sensor and the Faro laser scanner Focus 3D Lidar. The methods for fracture orientation determination and color coding of the models are also discussed. Finally, the methods and results of estimating roughness from the Lidar data are described.

Chapter 5: this chapter summarizes the results of all three imaging systems and describes ideas for future work.

2. Chapter 2: Estimating Surface Roughness of Hand Samples from 3D Point Clouds

2.1: Theory

The theoretical framework used to derive surface roughness from 3D point clouds is Principal Component Analysis (PCA). PCA uses a least-squares method that determines the best fitting plane to a point cloud. The perpendicular distance between each point and the best fitting plane can then be calculated. Assuming that the distance data is normally distributed, the standard deviation of the distance data indicates the extent of deviation from the best fitting plane. Assuming perfectly flat surfaces and no instrument error, the predicted outcome is that high standard deviation values will correspond to the roughest samples because rough samples will have points that deviate further from the best fitting plane, and conversely, low standard deviation values will correspond to the smoothest samples because their points will deviate much less from the best fitting plane.

2.2: Instrument and Laboratory Setup

Point clouds of samples exhibiting a wide range of surface roughness were acquired with a Konica Minolta VIVID 9i non-contact laser digitizer inside the Geophysical Laboratory (HP 1150) at Carleton University. The digitizer uses a light-stripe method to acquire point clouds. A laser beam is emitted through a cylindrical lens onto a mirror whose movement is controlled by a galvanometer (Konica Minolta VIVID 9i non-contact laser digitizer user manual, 2004). The mirror then begins to move across the target from top to bottom and the reflected light is focused by the receiving lens, and captured by the charge-coupled device (CCD) detector (Olson, 2013). Finally, the data received by the

CCD is converted into Cartesian coordinates by triangulation which generates a point cloud (Olson, 2013). Some highlighted specifications of the camera include a maximum laser power of 30mW and in image resolution of 640 x 460 voxels (Table 2.1). The lens that was used to acquire all images was the tele lens whose specifications are included in Table 2.1.

Table 2.1: Specifications for Konica Minolta VIVID 9i non-contact laser digitizer.

Width x Height x Depth	221mm x 412mm x 282mm
Mass	15kg
Laser Wavelength	690nm
Maximum Laser Power	30mW
Laser Class	1
Image Resolution	640 x 460 voxels
Acquisition Time Per Image	10s
Focal Distance	25mm
Accuracy (Distance 0.6 m/1.0 m)	± 0.05 mm/ ± 0.10 mm
Price	~50, 000\$

The digitizer was placed approximately 700mm away from the target object. The digitizer head was inclined slightly down (20°) to face the object which sits on top of a table so that the laser beam projected from the digitizer illuminates the object approximately at normal incidence (Figure 2.1). This setup is similar to that used in a previous imaging study of hand samples (see Figure 1 in McCausland et. al., 2011).

Figure 2.1: Lab setup of Konica Minolta VIVID 9i non-contact laser digitizer imaging basalt hand sample on top of table. Coordinate system of the digitizer is included.

2.3: Description of Lab Experiments

In the first experiment, I imaged a calibration plate (Figure 2.2) the plate is made of plastic and has two sides attached at the middle like an open book. One side measures 28cm in length and 12cm in width. This object is perfectly flat and smooth so the deviation from the PCA plane is not roughness or change in shape, it is instrument error. This experiment is similar to what was done by Chris Fry (Fry, 2013) to determine the accuracy of the laser digitizer.

Figure 2.2: Calibration plate

For the second experiment a series of flat man-made objects were imaged (9 pieces of sandpaper and one welding object (Figure 2.3)). These objects are flat so the deviation from the PCA plane is a combination of roughness and instrument error. Nine pieces of sandpaper were imaged with increasing roughness each 22.5cm width and 28cm length. From smoothest to roughest the pieces of sandpaper are listed in the following order: 600 grit, 400 grit, 320 grit, 220 grit, 180 grit, 150 grit, 120 grit, 80 grit, and 50 grit. Grit refers to the size of particles on the rough side of the sandpaper. The roughest sandpaper (50 grit) has the largest particles (0.3mm) and the smoothest sandpaper (600 Grit) has the smallest particles (0.012mm). The welding object was also imaged. It is made out of metal and has a ripple texture on its surface. It measures 14.5cm width and 15cm length.

Figure 2.3: Welding Object

For the third experiment a suite of 20 rocks were borrowed from the collection of the Dept. of Earth Sciences at Carleton University, under the guidance of curator BethMcLarty Halfkenny and imaged using the Konica Minolta VIVID 9i non-contact laser digitizer. The three types of rocks (igneous, metamorphic or sedimentary) were represented in the suite. The rocks cover a wide range of roughness. Each rock was given an identification number from 1-20 and this number was chosen at random. Each rock is described in Table 2.2.

Table 2.2: Rock descriptions

Rock Identification Number	Rock Type	Rock Name	Figure Number	Description
1	Sedimentary	Fossiliferous limestone	2.4	Comes from a marine setting and contains many different kinds of fossils. Some are as large as 3cm and some as small as 0.5cm. These fossils are roundish in shape and create a “bumpy” surface on the rock.
2	Igneous	Basalt	2.5	This is a volcanic rock that contains few vesicles. The vesicles create cavities in the rock and the edges of the cavities are sharp. There are also areas of small sharp bumps (1mm) and areas that are smoother to touch. The surface is very variable.
3	Igneous	Pegmatite	2.6	This intrusive igneous rock is a pegmatite which contains large

				interlocking phaneritic pyroxene crystals that are greater than 5cm in size. The crystals themselves are smooth to touch but the large interlocking crystals create a variable surface of concave and convex areas.
4	Igneous	Basalt	2.7	This is a volcanic rock which contains no vesicles. The surface of the rock is generally smooth to touch but it also contains small smooth bumps on its surface (1cm).
5	Igneous	Basalt	2.8	This basalt has a “ropey” texture which is called paheohoe. The ropes are stuck together in rows and are approximately 1cm in length. Where the ropes are attached are concave areas and the ropes themselves are convex areas.
6	Igneous	Basalt	2.9	This volcanic basalt is filled with vesicles, some as small as 1mm and some as large as 1cm. The vesicles create concave areas on the surface. In between the vesicles are convex areas. The edges of the vesicles are sharp to touch.
7	Igneous	Basalt	2.10	This is a volcanic basalt which contains no vesicles. The edges of the rock are very sharp to touch but the surface of the rock is smooth to touch.

				This rock in particular has large concave areas and large convex areas on the surface. For example, on cavity in the rock is approximately 3cm in length and 2cm deep.
8	Sedimentary	Sandy Limestone	2.11	Surface contains sand and limestone which is smooth to touch, however the surface contains many bumps some as large as 2cm which creates a very variable surface.
9	Igneous	Basalt	2.12	This is a volcanic basalt whose surface is filled with large vesicles. Majority of the vesicles are approximately 0.5cm in length and the largest one is 2cm. The vesicles create concave areas on the rock which a very variable surface. The areas in between the vesicles are smooth to touch.
10	Sedimentary	Conglomerate	2.13	This is a clastic sedimentary rock that contains large rounded particles that are greater than 2mm in diameter and in between the large particles there is a matrix of much smaller particles (1mm) holding the rock together like cement. Both the large rounded particles and the cement are smooth to touch but the large rounded particles

				are protruding which creates a variable surface.
11	Sedimentary	Shale	2.14	This rock is very smooth to touch and contains dark mud which comes from a marine setting. There is almost no variability on the surface.
12	Sedimentary	Sandstone	2.15	This sandstone contains bands of 2 different types of sand. The particles are less than 1mm in size and the surface is smooth to touch. There are a couple of concave and convex areas on the rock but generally overall there is not much variability on the surface.
13	Sedimentary	Sandstone	2.16	This sandstone is very smooth to touch and contains almost no concave or convex areas. There is almost no variability on the surface.
14	Sedimentary	Claystone	2.17	This rock contains clay which is very smooth to touch. There are some concave and convex areas on the rock which creates a variable surface.
15	Sedimentary	Sandstone	2.18	This sandstone is very smooth to touch and contains almost no concave or convex areas on its surface.
16	Sedimentary	Sandstone	2.19	The particles contained in this sandstone are larger (1mm) which creates a rougher surface. There are also some bumps and concave areas

				on the rock which creates a variable surface.
17	Metamorphic	Granite	2.20	Granite contains potassium feldspar, quartz, and amphibole. The larger grains of quartz and amphibole create bumps across the surface of the rock. Some of the bumps are as large as 0.5cm.
18	Metamorphic	Gneiss	2.21	This metamorphic rock contains gneissic banding with large garnet crystals on its surface. The garnet crystals are protruding which creates a bumpy surface and some of the crystals are as large as 0.5cm.
19	Sedimentary	Sandstone	2.22	This sandstone is smooth to touch but also contains concave and convex areas which creates a variable surface on the rock.
20	Sedimentary	Shale	2.23	This rock comes from a marine setting and contains dark coloured mud. The surface is extremely smooth since there are no grains visible on its surface.

Figure 2.4: Rock 1 – Fossiliferous limestone, divisions of ruler are in centimeters.

Figure 2.5: Rock 2 - Basalt

Figure 2.6: Rock 3 - Pegmatite

Figure 2.7: Rock 4 - Basalt

Figure 2.8: Rock 5 - Basalt

Figure 2.9: Rock 6 - Basalt

Figure 2.10: Rock 7 – Basalt

Figure 2.11: Rock 8 – Sandy Limestone

Figure 2.12: Rock 9 - Basalt

Figure 2.13: Rock 10 - Conglomerate

Figure 2.14: Rock 11 - Shale

Figure 2.15: Rock 12 - Sandstone

Figure 2.16: Rock 13 - Sandstone

Figure 2.17: Rock 14 - Claystone

Figure 2.18: Rock 15 - Sandstone

Figure 2.19: Rock 16 - Sandstone

Figure 2.20: Rock 17 - Granite

Figure 2.21: Rock 18 - Gneiss

Figure 2.22: Rock 19 - Sandstone

Figure 2.23: Rock 20 – Shale

For the third experiment 10 people were asked to use their sense of touch to order the rocks from smoothest to roughest (Table 2.4). Using these results the rocks were grouped into 3 categories (the 7 samples with the smoothest surface, the 7 samples with the roughest surface, and the 6 samples with intermediate roughness). These three categories were named “smooth”, “rough”, and “in between smooth and rough” respectfully. After the touch experiment was complete the rocks were then imaged using the Konica Minolta VIVID 9i non-contact laser digitizer 10 times (Table 2.5) and PCA analysis was done on each image to investigate if the PCA roughness results matched the sense of touch results.

2.4: Data Processing

Each image that was taken with the Konica Minolta VIVID 9i non-contact laser digitizer was saved as an ASCII file and then uploaded into a program written in Matlab by Jason Mah (Mah et al., 2013) to perform PCA. For example, the smoothest rock that was imaged was Rock 20. This ASCII file was uploaded into the program for PCA calculations (Figure 2.24).

Figure 2.24: Print screen of Rock 20 point cloud uploaded into the PCA program (Mah et al., 2013). Red circle indicates PCA radius. The center point of the radius is determined by selecting the X, Y, and Z coordinate in the center of the image and inputting these coordinates into the X, Y, and Z coordinate of the input section. Once the PCA is calculated the red circle of the radius appears on the image.

The PCA program requires that the input section must be completed to indicate where on the image PCA will be conducted (which is indicated by the Step 1 button in Figure 2.24). In Figure 2.24 there are 5 buttons at the top left hand corner. The button on the very left is used for clicking and rotating the image however the user wishes, the second button to the right of it is used for rotating the image, the third button to the right is used for selecting a certain data point in the image, the fourth button is for zooming in on the image, and the fifth button is for zooming out. Step 2 located on Figure 2.24 is for uploading the point cloud ASCII file to the program. Once uploaded the point cloud will appear to the right of the input section with a coordinate system surrounding it. Using the “data cursor tool” which is the middle button at the top left of Figure 2.24 an X,Y, Z coordinate can be selected on the uploaded image and inputted into the X coordinate, Y coordinate, and Z coordinate of the input section of Figure 2.24. For this step a point is selected at the very center of the point cloud. The data cursor tool is used to select a point in the center and then the X, Y, and Z coordinates pop up in a little window which then can manually be entered in the X coordinate, Y coordinate, and Z coordinate spaces on Figure 2.24. In addition, a selected radius (in mm) and the strike and dip of the digitizer enclosure must be inputted manually. In this case a 25mm radius was chosen and the strike and dip of the scanner were kept constant at 0 degrees because we were only interested in the standard deviation which does not require these parameters. Once the input section is complete and the ASCII file is uploaded the user can then click on the “Step 3: Calculate PCA” button and the output results will be the strike and dip of the plane defined by the center point and radius, the standard deviation of the perpendicular distance between each point and the best fitting plane, the sum of squared errors and the

number of points within the selected radius. The PCA program is also capable of producing a figure which shows the plane of best fit and the points that are above and below the plane (Figure 2.25). The points that are above the plane are indicated in red and the points that are below the plane are indicated in green. A histogram can be created in Excel using this data (Figure 2.26). The histogram typically exhibits normal distribution. The majority of the points will be in the center of the histogram because they are part of the plane of best fit, and the points that are above (at a distance shorter than the distance to the plane of best fit) and below (at a distance larger than the distance to the plane of best fit) the plane will be to the right and left of the center bin respectively.

Figure 2.25: Print screen of Rock 20 point cloud showing points that are above the plane of best fit (green) and below (red). The points displayed are the red circle centered at 10.08, 5.827, and -808.4 and with a radius of 25mm shown in Figure 2.24. There were 34613 points in the circle in Figure 2.24 that are displayed in Figure 2.25.

Figure 2.26: Histogram of Rock 20 point cloud data. The histogram shows the distance from the plane of best fit or each point plotted in Figure 2.25.

For comparison, we examined the same series of displays for Rock 4 which was one of the roughest hand samples derived from images (Figures 2.27, 2.28. and 2.29). When performing PCA, the circular plane of interest (red circle) has to be as flat as possible so that curvature does not affect the roughness results.

Figure 2.27: Print screen of Rock 4 point cloud uploaded into Jason Mah's Matlab program (Mah et al., 2013). Red circle indicates PCA radius. The center point of the radius is determined by selecting the X, Y, and Z coordinate in the center of the image and inputting these coordinates into the X, Y, and Z coordinate of the input section. Once the PCA is calculated the red circle of the radius appears on the image.

Figure 2.28: Print screen shot of Rock 4 point cloud showing points that are above the plane of best fit (green) and below (red). The points displayed are the red circle centered at 8.458, -6.235, and -662.6 with a radius of 25mm shown in Figure 2.27. There were 42235 points in the circle in Figure 2.27 that are displayed in Figure 2.28.

Figure 2.29: Histogram of Rock 4 point cloud data. In Figure 2.29 the distance from the plane of best fit or each point plotted in Figure 2.28 is now presented as a histogram.

2.5: Results and Discussion

The calibration object is perfectly flat and smooth. The standard deviation of the perpendicular distance between each point within the radius of interest and the best fitting plane for this object was 0.016mm and was measured at a distance of ~ 0.7 m which corresponds to instrument error. These results are consistent with those of Fry (2013) and with the manufacturer's specifications (Table 2.1). The standard deviation needs to be greater than 0.016mm for a surface to be considered rough.

The standard deviations of the perpendicular distance between each point within the radius of interest and the PCA plane for each piece of sandpaper are presented in Table 2.3 and Figure 2.30. The standard deviations were calculated for 10 different images of the same sample, and the average of these ten standard deviations and its associated standard deviation are reported. One sample that was not included in Table 2.3 was the welding object; it was also scanned 10 times and had an average standard deviation of 0.33.

Table 2.3: Standard deviations (in millimeters) of the perpendicular distance between each point within the radius of interest (25mm) and the PCA plane for sandpaper samples of increasing roughness.

Grit	Std Dev 1	Std Dev 2	Std Dev 3	Std Dev 4	Std Dev 5	Std Dev 6	Std Dev 7	Std Dev 8	Std Dev 9	Std Dev 10	Average standard deviation	Std Dev of the average standard deviation	Number of points within radius of interest used to calculate Std Dev
600	0.32	0.34	0.34	0.33	0.33	0.34	0.33	0.33	0.33	0.35	0.33	0.01	40302
400	0.39	0.41	0.42	0.42	0.42	0.44	0.45	0.43	0.47	0.52	0.44	0.04	40337
320	0.11	0.11	0.11	0.12	0.12	0.12	0.13	0.14	0.14	0.14	0.12	0.01	40406
220	0.52	0.57	0.60	0.62	0.65	0.66	0.67	0.68	0.69	0.70	0.64	0.06	39442
180	0.28	0.30	0.32	0.29	0.30	0.30	0.32	0.32	0.33	0.33	0.31	0.02	40327
150	0.14	0.14	0.14	0.14	0.14	0.15	0.14	0.15	0.15	0.15	0.14	0.00	40243
120	0.37	0.38	0.39	0.39	0.40	0.41	0.41	0.42	0.44	0.45	0.41	0.03	40230
80	0.31	0.30	0.31	0.31	0.33	0.34	0.34	0.34	0.35	0.36	0.33	0.02	40037
50	0.17	0.17	0.17	0.17	0.16	0.17	0.18	0.17	0.18	0.17	0.17	0.00	40340

Figure 2.30: Standard deviations (in millimeters) of the perpendicular distance between each point within the radius of interest (25mm) and the PCA plane versus sandpaper roughness. Roughness is increasing from left to right.

Figure 2.30 displays a trend line that is slightly decreasing from 600 grit to 50 grit. This trend is the opposite of our prediction which was that the standard deviation would be higher for rougher objects because the points deviate further from the plane of best fit and the standard deviation for smoother objects would be lower because the points would deviate less from the plane of best fit. We have concluded that this statistical approach (i.e. standard deviation of the distance to the best-fit plane) might not be sensitive enough to distinguish roughness at this scale. Alternate statistical approaches should be tested in the future.

Results from the touch experiment for Rocks 1-20 are found in Table 2.4, and the standard deviations of the perpendicular distance between each point within the radius of interest and the PCA plane for Rocks 1-20 are presented in Table 2.5. Using the average standard deviations from Table 2.5 Rocks 1-20 were ordered from smoothest to roughest and then grouped into 3 groups: smooth (7 samples), in between smooth and rough (6 samples), and rough (7 samples). The average standard deviation values were then colour coded according to their groups: smooth (yellow), in between smooth and rough (green), and rough (blue) (Table 2.6). Finally, Table 2.5 was colour coded according to which category Rocks 1-20 fell into (Table 2.7).

Using the results from Table 2.7 these values were input into a confusion matrix for further analysis (Tables 2.8 and 2.9).

Table 2.4: Twenty hand samples listed in order of increasing roughness (from left to right) by 10 different people using the sense of touch.

	Smoothest							In Between Smooth and Rough							Roughest						
Person 1	20	11	14	15	13	16	12	19	17	18	8	10	5	3	1	6	2	4	9	7	
Person 2	20	11	19	15	14	18	13	16	12	17	10	3	5	1	8	9	4	2	7	6	
Person 3	20	11	15	14	19	18	12	13	16	1	17	10	8	3	5	9	6	2	4	7	
Person 4	20	11	14	15	19	18	12	16	17	10	1	13	8	9	5	3	6	2	7	4	
Person 5	20	11	14	15	19	13	16	18	10	12	1	10	8	3	9	6	5	2	4	7	
Person 6	20	11	14	15	17	19	16	18	13	3	10	1	12	8	9	5	6	2	4	7	
Person 7	20	11	14	13	15	3	19	18	16	1	12	17	2	10	9	8	7	4	6	5	
Person 8	20	13	11	16	15	12	14	18	17	19	10	1	8	3	2	9	5	4	6	7	
Person 9	20	14	11	19	15	13	18	17	16	12	10	8	1	9	3	4	6	5	2	7	
Person 10	20	3	2	13	14	15	9	11	1	10	16	19	17	18	8	12	7	5	6	4	

Table 2.5: PCA Results for 20 hand samples.

Hand Sample	St Dev 1	St Dev 2	St Dev 3	St Dev 4	St Dev 5	St Dev 6	St Dev 7	St Dev 8	St Dev 9	St Dev 10	Average standard deviation	St Dev of the average standard deviation
Rock 1	0.96	0.92	0.91	0.90	0.89	0.91	0.92	0.91	0.94	0.91	0.92	0.02
Rock 2	3.77	3.89	3.97	4.30	3.58	3.04	3.08	3.92	4.09	3.71	3.74	0.41
Rock 3	3.42	3.55	3.49	3.34	3.30	3.62	3.50	3.36	3.52	3.38	3.45	0.10
Rock 4	5.28	5.15	5.14	4.55	5.31	4.96	5.61	5.08	5.33	4.96	5.14	0.28
Rock 5	2.43	2.54	2.62	2.55	2.50	2.54	2.51	2.62	2.48	2.53	2.53	0.06
Rock 6	2.37	2.35	2.35	2.36	2.36	2.34	2.35	2.35	2.37	2.37	2.36	0.01
Rock 7	3.75	3.62	3.91	3.56	3.59	3.77	3.71	3.56	3.62	3.63	3.67	0.11
Rock 8	1.57	1.56	1.65	1.55	1.56	1.58	1.60	1.51	1.59	1.55	1.57	0.04
Rock 9	2.08	2.08	2.09	2.08	2.08	2.08	2.10	2.09	2.09	2.08	2.09	0.01
Rock 10	1.33	1.32	1.35	1.33	1.37	1.41	1.35	1.37	1.31	1.46	1.36	0.05
Rock 11	0.56	0.58	0.37	0.57	0.46	0.51	0.34	0.35	0.45	0.50	0.47	0.09
Rock 12	0.84	1.01	0.74	0.79	1.27	1.07	0.54	0.81	0.97	0.59	0.86	0.22
Rock 13	0.47	0.48	0.50	0.50	0.50	0.50	0.45	0.49	0.49	0.49	0.49	0.02
Rock 14	1.40	1.45	1.45	1.41	1.44	1.40	1.44	1.46	1.49	1.42	1.44	0.03
Rock 15	0.64	0.63	0.63	0.63	0.62	0.60	0.61	0.59	0.59	0.59	0.62	0.02
Rock 16	0.66	0.66	0.66	0.65	0.65	0.61	0.65	0.66	0.66	0.66	0.65	0.02
Rock 17	1.01	1.01	1.15	1.15	0.85	1.13	1.13	1.11	1.11	1.11	1.08	0.09
Rock 18	0.86	0.86	0.76	0.76	0.78	0.78	0.82	0.82	0.78	0.77	0.80	0.04
Rock 19	0.81	0.81	0.80	0.90	0.77	0.77	0.76	0.75	0.76	0.75	0.79	0.05
Rock 20	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.00

PCA results from hand samples indicated that the roughest hand sample was Rock 4 and the smoothest hand sample was Rock 20 which each had an average standard deviation of 5.13826 and 0.06668 respectively.

Table 2.6: Color coded average standard deviations.

Object	Average Standard Deviation (mm)	Category
Rock 20	0.07	Smooth
Rock 11	0.47	
Rock 13	0.49	
Rock 15	0.62	
Rock 16	0.65	
Rock 19	0.79	
Rock 18	0.80	
Rock 12	0.86	In Between Smooth and Rough
Rock 1	0.92	
Rock 17	1.08	
Rock 10	1.36	
Rock 14	1.44	
Rock 8	1.57	
Rock 9	2.09	Rough
Rock 6	2.36	
Rock 5	2.53	
Rock 3	3.45	
Rock 7	3.67	
Rock 2	3.74	
Rock 4	5.14	

Table 2.7: Table 2.5 colour coded according to Table 2.6.

	Smooth							In Between Smooth and Rough							Rough						
Person 1	20	11	14	15	13	16	12	19	17	18	8	10	5	3	1	6	2	4	9	7	
Person 2	20	11	19	15	14	18	13	16	12	17	10	3	5	1	8	9	4	2	7	6	
Person 3	20	11	15	14	19	18	12	13	16	1	17	10	8	3	5	9	6	2	4	7	
Person 4	20	11	14	15	19	18	12	16	17	10	1	13	8	9	5	3	6	2	7	4	
Person 5	20	11	14	15	19	13	16	18	10	12	1	10	8	3	9	6	5	2	4	7	
Person 6	20	11	14	15	17	19	16	18	13	3	10	1	12	8	9	5	6	2	4	7	
Person 7	20	11	14	13	15	3	19	18	16	1	12	17	2	10	9	8	7	4	6	5	
Person 8	20	13	11	16	15	12	14	18	17	19	10	1	8	3	2	9	5	4	6	7	
Person 9	20	14	11	19	15	13	18	17	16	12	10	8	1	9	3	4	6	5	2	7	
Person 10	20	3	2	13	14	15	9	11	1	10	16	19	17	18	8	12	7	5	6	4	

Table 2.7 shows at a glance that the roughness results from the touch experiment and those from PCA are generally consistent. Smooth rocks that were colour coded in yellow were generally located on the left side of Table 2.7 (which is categorized as smooth), rocks that were colour coded in blue were generally located in the middle of the table (which is categorized as rocks that fall in between smooth and rough), and rocks that were colour coded in green were generally located on the right side of Table 2.7 (which is categorized as rough). These results were as predicted: the general trend for the geological hand samples is that as the surface becomes increasingly rougher, the standard deviation of the distance to the PCA plane increases.

Table 2.8: Confusion Matrix of touch and PCA results.

		<u>Predicted From Images</u>		
		Smooth	In Between Smooth and Rough	Rough
<u>Actual Touch</u>	Smooth	51	18	1
	In Between Smooth and Rough	15	37	8
	Rough	4	5	61

Table 2.9: Confusion Matrix of touch and PCA results (in %).

		<u>Predicted From Images</u>		
		Smooth	In Between Smooth and Rough	Rough
<u>Actual Touch</u>	Smooth	25.5	9	0.5
	In Between Smooth and Rough	7.5	18.5	4
	Rough	2	2.5	30.5

Both Tables 2.8 and 2.9 provide alternative methods of analyzing the data. In total we have 200 results in Table 2.8 (20 rock samples X 10 people). The results for smooth rocks were consistent for both the touch experiment and the PCA experiment 51 times (which represents 25.5% of the dataset). The results for rocks in between smooth and rough were consistent for the touch experiment and the PCA experiment 37 times (which represents 18.5% of the dataset). And the results for the rough rocks were consistent for both the touch experiment and the PCA experiment 61 times (which represents 30.5% of the dataset). For the two extreme categories (smooth and rough rocks) the smooth rocks only had 1 result that fell within the rough category, and the rough rocks only had 4 results that fell within the smooth category. As for the in between smooth and rough category 8 of these rocks fell within the rough category and 15 fell in the smooth category which is to be expected because the instrument and the people will have a tougher time deciding what category these rocks fit into. These tables show that the results from the touch experiment were generally consistent with the PCA experiment.

3. **Chapter 3: Using a miniature structured-light sensor to image geological scenes**

3.1: Miniature structured-light sensor

Triangular meshes were acquired using the miniature structured-light sensor inside the Geophysical Laboratory (HP 1150) at Carleton University, the Canadian Wollastonite mine near Kingston, ON and the rock wall outside Staacie building at Carleton University. The sensor uses a method of 3D scanning where a known pattern of light is projected onto a surface with an unknown pattern. By analyzing the deformation of the known pattern the surface can mathematically be reconstructed into a virtual 3D model¹. The acquired data is saved as a mesh and can be uploaded to the open-source software Meshlab for analysis and editing. The scanner is also capable of taking 2D color photographs and draping it over the mesh. The resulting meshes are highly detailed and coloured 3D models of the scanned area. The “Structure Sensor” is a miniature structured-light sensor developed and commercialized by Occipital² as a device that people could use to rapidly scan objects, people, and create 3D maps of interior spaces. The sensor was chosen for this project because it is a relatively inexpensive instrument (approximately \$500) and attaches to a computer tablet (Figure 3.1). Key specifications (Table 3.1) of the miniature structured-light sensor include an acquisition rate of 30 frames per second, an image resolution of 320 x 240 voxels, and an accuracy of 30mm at 3m.

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¹ http://fab.cba.mit.edu/content/processes/structured_light/

² <https://occipital.com/> : The Spatial Computing Company

Figure 3.1: Miniature structured-light sensor attached to I-Pad tablet.

Table 3.1: Specifications of the Occipital “Structure Sensor”.

Length x Width x Height	119.2mm x 27.9mm x 29mm
Mass	95g
Acquisition Rate	30 frames per second
Image Resolution	320 x 240 voxels
Field of View	Horizontal: 58° Vertical: 45°
Range Accuracy	30mm at 3m
Laser Class	1
Laser Wavelength	830nm
Battery Life	3-4 hours

3.2: Imaging a landscape rock wall with the miniature structured-light sensor

The first test executed with the miniature structured-light sensor was to scan a small landscape rock wall just outside of Steacie Building (Figure 3.2) at Carleton University.

The purpose of this test was to learn how to use the image acquisition software and to become familiar with the sensor.

Figure 3.2: Sara McPeak imaging rock wall using the miniature structured-light sensor.

The coordinate system of the sensor is indicated with red arrows.

Before the sensor is attached to the tablet the Structure App and the Room Capture App must be downloaded from the App Store which will allow the user to begin scanning. Once these have been downloaded the user can then open the Room Capture App and follow the instructions that are prompted on the screen (Figure 3.3). The simple step by step instructions that the app provides for the user allows capturing a geological scene to be an easy task for a first time user of the software.

Figure 3.3: Print Screen of the user interface when the Room Capture App is open on a tablet. The sensor performs well surfaces which are mostly perpendicular to the Z axis. This image is almost parallel to the Z axis which is why the sensor has trouble imaging it.

Once the user opens the Room Capture App the next step is to adjust the size of the room using the size adjustment button on the bottom right corner of the screen. The smallest room size that the software is capable of capturing is 1.5m x 1.5m x 1.5m, the medium room size is 3m x 2m x 3m and the largest room size is 5m x 3.35m x 5m. If the user uses the smallest room size the software will build a mesh of many small triangles (Figure 3.4) which will capture higher detail. If the user decides to choose the medium room size (Figure 3.5) or the largest room size (Figure 3.6) the image will become coarser.

Figure 3.4: Mesh of the rock wall shown in Figure 3.2 build using the Room Capture App and a room size of 1.5m x 1.5m x 1.5m. Color photo is overlain onto the mesh. Number of triangles is 24218. Average surface area of triangles is 0.03cm².

Figure 3.5: Mesh of rock wall shown in Figure 3.2 built using the Room Capture App and a room size of 3m x 2m x 3m. Color photo is overlain onto the mesh. Number of triangles is 19275. Average surface area of triangles is 0.12cm^2 .

Figure 3.6: Mesh of the rock wall shown in Figure 3.2 built using the Room Capture App and a room size of 5m x 3.35m x 5m. Color photo is overlain onto the mesh. Number of triangles is 5397. Average surface area of triangles is 0.35cm^2 .

To begin scanning the user needs to press the “scan” button and the software will begin building a mesh (Figure 3.7). Any areas where the software is unable to capture data will be seen as a “black area”. The reason why this happens is either because the area that the user is trying to capture is occluded, its surface is at a grazing angle with respect to the sensor, or the size of the room needs to be adjusted to a larger size. Once the mesh starts being generated, the user moves the tablet to scan the entire scene of the size of the room specified. The sensor processes the raw data points internally and outputs a 3D image as a triangular mesh. The sensor builds the mesh continuously over time from the original position. The tablet must be moved slowly to ensure the mesh is built properly. If the user moves too fast the built scene will look irregular (Figure 3.8). As the user moves the tablet the screen will prompt messages to the user if he/she is moving too fast or if he/she is moving too far away from their original position.

Figure 3.7: Print Screen shot of the Room Capture App building a mesh once the scan button has been pressed by the user.

Figure 3.8: Print screen shot of an example of a “choppy” mesh built by the Room Capture App due to the user either moving the tablet too fast.

After the user has scanned a scene the mesh can be viewed using the “X-ray view” button on the Room Capture App (Figure 3.9). This feature is very useful because it allows the user to see the built mesh in detail and will help determine if the mesh was built satisfactorily or if scanning needs to be redone.

Figure 3.9: Print screen of the X-ray view of the mesh built by the Room Capture App.

The X-ray view button can be turned on by pushing the button next to the word “X-Ray View” and once it is green that indicates it is on.

Once the user is satisfied with the mesh, the Room Capture App allows files to be saved to disk. The files are then compressed into a zip file and saved. When the user goes to retrieve the files, the zip folder name indicates the file number, and the size of the room in meters. The zip file includes three files: the first is a .jpg file, the second is a .mtl file, and the third is an .obj file. A compressed zip file of the smallest room size is approximately 103KB and the largest size is approximately 268KB. Once the files have been extracted from the zip file the .obj file can be opened in the open source program Meshlab³.

³ <http://meshlab.sourceforge.net/>

It is important to note that the miniature structure-light sensor outputs a mesh directly, not a point cloud like most imaging sensors. Meshlab allows the user to view the mesh, rotate the mesh, and clip the data if there are any outliers. After editing, the vertices of the mesh can be exported as a point cloud in an ASCII file and uploaded into Excel. The ASCII file has three columns, corresponding to the X, Y, and Z coordinates of the point cloud in meters. The coordinate system of the miniature structured-light sensor is defined when the user sets the volume of the room to image. The origin coordinates 0,0,0 is set at the center of the room that is defined by the user before the scanning begins and as the user changes position while scanning the origin will stay at the center of the room (Figure 3.2).

3.3: Accuracy of the miniature structured-light sensor

To test the performance of the miniature structured-light sensor in controlled conditions, a flat indoor wall was scanned at the smallest room size ten times at increasing distance (in meters) (1.0, 1.5, 2.0, 3.0, and 4.0). Normally the sensor takes 30 frames per second but for this test only a single frame was taken each time. For each scan a PCA was conducted and the standard deviation was calculated and a radius of 200mm was used (Mah et al., 2013) (Table 3.2). The standard deviation represents the accuracy of the sensor.

Table 3.2: Average and standard deviation of the accuracy of the miniature structured-light sensor versus distance in millimeters for ten different tests.

Distance (m)	Radius used for PCA	Std Dev 1	Std Dev 2	Std Dev 3	Std Dev 4	Std Dev 5	Std Dev 6	Std Dev 7	Std Dev 8	Std Dev 9	Std Dev 10	Average Range Accuracy	Std Dev (1-10) of the Average Range accuracy
1.0	200mm	2.02	1.95	1.96	1.97	2.06	2.01	1.99	1.97	1.98	1.99	1.99	0.03
1.5	200mm	4.00	4.12	4.08	4.20	4.21	4.23	3.93	4.50	4.34	4.31	4.19	0.17
2.0	200mm	7.00	6.31	6.57	6.30	6.55	6.40	6.20	6.03	6.26	6.88	6.45	0.30
3.0	200mm	11.76	19.50	20.02	17.14	19.05	17.87	20.14	19.34	17.57	20.06	18.24	2.52
4.0	200mm	20.03	17.83	18.90	21.59	20.22	18.10	20.01	22.44	24.79	25.93	20.99	2.72

Results of this experiment concluded that range accuracy increases linearly with distance (Figure 3.10). The manufacturer quoted that the accuracy of the instrument was 30mm at 3m. After scanning the flat wall 10 times at 3m, our average standard deviation was 18.24 mm which is slightly smaller. This confirmed that the instrument was working within specifications.

Figure 3.10: Range accuracy of the miniature structured-light sensor versus distance.

4. **Chapter 4: Imaging Rock Walls in an Open-Pit Mine**

On December 8th, 2015 both the miniature structured-light sensor and a Faro Laser Scanner Focus 3D Lidar were taken to the Canadian Wollastonite mine to image two large freshly-blasted gneiss rock walls and measure fracture orientation from point clouds.

4.1: Previous Work

Previous studies have been conducted at the Canadian Wollastonite mine to measure fracture orientation using an unmanned aerial vehicle (UAV). In a study done by McLeod et al. (2013), one of the objectives was to see if the software that was used to determine joint orientation could be applied to point clouds that were generated from video images using structure-from-motion software. Using a UAV, flights were conducted in a trench that was oriented approximately north-south and was bordered by east and west walls on either side (Figure 4.1) (McLeod et al., 2013). All of the flights were flown at less than 15m altitude with the camera dipping approximately 10°. The walls that were imaged were benched and were covered with vegetation in places. In total, 86 manual compass measurements (42 on east wall and 44 on west wall) were taken and revealed 3 joint sets (strike/dip in degrees): 329/85 (joint set #1), 183/08 (joint set #2), and 32/78 (joint set #3).

Using the method developed by Mah et al. (2013), PCA was used to determine strike and dip from point clouds. Overall, joint orientations derived from compass measurements

and point clouds were found to differ approximately 10 degrees. Which validated the methodology of using images to measure strike and dip.

Figure 4.1: Study area of McLeod et al. and thesis study area, photo courtesy of Bob Vasily.

4.2: Description of Study Area

The Canadian Wollastonite mine (Figure 4.1) is located in Steeley’s Bay which is approximately 26km north of the city of Kingston, Ontario.

The Canadian Wollastonite mine is located in a “portion of the Precambrian Grenville geologic province known as the Frontenac Arch⁴”. Due to the uplift which resulted in the formation of the arch, this area has experienced granulite facies metamorphism and is

⁴ <http://www.canadianwollastonite.com/DepositRegional.htm>

dominated by two main rock units: the ‘Leeds Marble Belt’ and the Taylor syenitic pluton. The Leeds Marble Belt is a deposition of interbedded sandstones and impure limestones in a small oceanic or inter-arc basin and covers a 300km area. During the Orogens period the area was subjected to regional metamorphism which the pluton emplaced during Taylor syenitic pluton⁴. The marble belt contains narrow alternating layers of marble and siliclastic rocks (quartzite, paragneiss and calc-silicates) and the metasedimentary rocks within the belt strikes northeast and dip steeply southwest. Our study area was located within the marble belt where two large blasted rock walls were imaged as part of mining operations. One wall strikes north and is 10m long and 3m high and the other was striking east and was 6m long and 3m high. These two walls contained siliclastic rocks (quartzite, paragneiss and calc-silicates) whose grains were smaller than 5mm in size. The north striking wall contained large fractures which were striking north-west and south east and contained pink quartzite. The east striking wall has large vertical and horizontal fractures as well and is made up of calc-silicates.

4.3: Instruments and Field Work

Three different instruments were used to obtain point cloud data on December 8th, 2015 at the Canadian Wollastonite mine. The first was the miniature structured-light sensor. Using the sensor, both the north striking wall and the east striking wall were imaged. The Room Capture App was used at the largest room size (5m x 3.35m x 5m) to capture the data. A total of 95 scans were taken using the sensor which took approximately 3-4 hours. Since I was holding the instrument in my hands I could not reach pass a certain height to scan the entire rock wall (Figure 4.2).

Figure 4.2: Sara McPeak scanning the rock wall using the miniature structured-light sensor.

It was noted that the sensor operated best under shaded conditions because direct sunlight created areas of occlusion in the data. Therefore, had to wait until the afternoon when our study area was shaded to complete the dataset.

The 95 scans were later brought back to the lab and uploaded into a program called Meshlab and stitched together to create a model of the two rock walls. The miniature structured-light sensor does not know where it is in space therefore to solve this problem we uploaded the Lidar dataset (which is already georeferenced) as a separate layer and used it as a guideline to stitch the miniature structured-light sensor scans together so that the sensor's scans were georeferenced according to the Lidar data by visual inspection using common features.

To double check the strike directions of both the north wall and the east wall I rotated the complete model of the two rock walls so that it was in the direction of a "bird's eye view". I inserted a correct north arrow onto the figure and then inserted a line of best fit for the direction of the north striking wall and the east striking wall. I extended the north arrow and then measured both angles starting from north to the line of best fit of both the north and east striking wall. My measurements indicated that the strike direction of the north wall is approximately 345° and the strike direction of the east wall is approximately 50° (Figure 4.3)

Figure 4.3: Bird's eye view of rock wall model to check for strike direction.

The Lidar that was used at the Canadian Wollastonite mine is called the Faro laser scanner focus 3D Lidar. This instrument is designed for indoor and outdoor 3D laser imaging. It can capture 976,000 points per second, has a distance accuracy of $\pm 2\text{mm}$ and has an effective distance range from 0.6-30m⁵. High resolution 2D coloured photographs are also acquired simultaneously and can be “draped” over the point cloud (e.g. see Figure 4.5 and 4.6). The Lidar requires an experienced user to operate, (Figure 4.4) it is capable of scanning 360° images and each scan takes 30 minutes to complete¹. The set-up of the survey targets (for georeferencing) on the wall and on the ground also take approximately 30 minutes to set up and the resulting images are a point cloud. The cost of the instrument is approximately 40,000\$⁵. The Lidar uses High Dynamic Range imaging (HDR). The camera captures images with multiple exposure rates and then merges them into a single HDR layer. “This HDR provides additional details in dark or bright areas which would have otherwise been listed in a standard image. These images are then mapped onto the point cloud data generated by the scanner⁵.” The resulting output is a highly detailed and coloured point cloud file. The specifications for the Faro Laser Scanner Focus 3D Lidar are found in Table 4.1.

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⁵ <http://www.faro.com/en-us/products/3d-surveying/faro-focus3d/features#main>

Figure 4.4: Davide Mezzino operating the Faro Laser Scanner Focus 3D Lidar. Targets and white balls are used for georeferencing.

Table 4.1: Specifications for the Faro Laser Scanner Focus 3D Lidar.

	Units	Values
Enclosure Dimensions	mm	240 x 200 x 100
Mass	kg	5.2
Range	m	0.6-330
Range Error	mm	± 2
Laser Class	-	1
Integrated Color camera	Millions of pixels	Up to 70
Acquisition rate	Points/s	976,000

The third instrument that was used in the field was a Brunton compass. A total of 26 measurements were taken by Erin Bethell across the north striking wall and the east striking wall ensuring even coverage (Table 4.2). Measurements were taken at prominent features and planar 2D surfaces (Figure 4.5 and 4.6, both these figures are 2D color photographs taken from the Lidar and draped over the point cloud). Finally, field notes and pictures were taken at most measurement locations where the Brunton compass was used (Appendix A).

Table 4.2: Compass strike and dip measurements of fracture planes from the Canadian Wollastonite mine.

Measurement Location	Strike (degree from North)	Dip (degree)
1	57	81
2	333	67
3	325	63
4	334	66
5	118	90
6	123	89
7	50	83
8	49	82
9	64	76
10	77	65
11	59	69

12	55	74
13	92	67
14	58	62
15	103	76
16	349	38
17	330	20
18	320	50
19	335	81
20	335	86
21	102	84
22	88	75
23	256	24
24	333	77
25	310	76
26	316	76

Figure 4.5: Brunton compass measurement locations on north striking wall. The figure is a 2D color photograph taken by the miniature structured-light sensor that has been draped over the mesh acquired by this instrument.

Figure 4.6: Brunton compass measurement locations on east striking rock wall. The figure is a 2D color photograph taken by the miniature structured-light sensor that has been draped over the mesh acquired by this instrument.

4.4: Visualization

To enhance the visual aspect of the scene with respect to fracture orientation the mesh acquired with the Miniature structured-light sensor was uploaded into a program written by Lai et al (2014). This program calculated the strike and dip of every single triangle of the mesh and colour coded triangles according to strike and dip. Strike and dip are two angles describing the spatial orientation of mesh elements (Figure 4.7). Strike is the angle

between the North and the direction parallel to the surface of the triangle. The dip angle is the angle between the horizontal cutting plane of the triangle and the plane being measured.

Figure 4.7: Sketch of strike and dip angles, the angles alpha and beta are referred to as dip and strike, respectively.

“When the normal vector that is parallel to the z-axis α is equal to 0° , and when the normal vector that is perpendicular to the z-axis α is equal to 90° , this means that the angle α measures a normal vectors deviation with respect to the z-axis” (Lai, 2013). The second angle β is measured by projecting the normal vector onto the xy plane which means β ranges between $0-360^\circ$. “Together the angles α and β (Figure 4.7) represent the orientation of any normal vector $N = (n_x, n_y, n_z)$ and the two equations for α and β are defined below” (Lai, 2013).

$$\alpha = \arctan2(\sqrt{nx^2 + ny^2}, nz) \times 180/\pi$$

$$\beta = \arctan2(nx, nz) \times 180/\pi$$

In geology, the angles alpha and beta are referred to as dip and strike respectively.

Figure 4.7: An illustration of α and β . The X-axis is pointing North.

The use of different color wheels (Figures 4.9(a) and 4.10(a)) can help to visualize different aspects of a scene. Compare Figures 4.9(c) and 4.10(c). In Figure 4.9(c), the “right hand rule” is not applied (a strike angle of θ is assigned the same color as a strike angle of $\theta+180^\circ$). In Figure 4.10(c), the “right hand rule” is applied (there is a different color for angle values from 0° to 360°). In Figure 4.9(c), the scene is easy to interpret: the vertical fractures are very prominent (in light blue) against neighbouring planar surfaces (in purple). In Figure 4.10(c), the scene is more complicated to interpret but includes additional information. Depending if small features on the planar surfaces are protruding

($0^\circ < \theta < 180^\circ$, according to the right-hand rule) or receding ($180^\circ < \theta < 360^\circ$, according to the right-hand rule), they are assigned a red or a light blue color.

Figure 4.9(a): Color wheel used for when the “right hand rule” is not applied.

Figure 4.9(b): Photograph of measurement point 18.

Figure 4.9(c): Color coded mesh from the miniature structured-light sensor of site 18 using color wheel with no “right hand rule” applied. Black square box is the location of measurement 18.

Figure 4.10(a): Color wheel used for when the “right hand rule” is applied.

Figure 4.10(b): Color coded mesh from the miniature structured-light sensor of site 18 using color wheel with the “right hand rule” applied. Black square box is the location of measurement 18.

Using the same visualization techniques (Lai et al., 2014), it is possible to view the color-coded strike of the entire mesh of the rock wall. Figure 4.11 and 4.12 show the scene without and with the right-hand rule being applied respectively. As noted for Figures 4.9(c) and 4.10(c) above, 4.11 for which the right-hand rule is not applied shows less features and is easier to interpret. Figure 4.12 for which the right-hand rule is applied shows several small features color-coded in complementary colours (green and red, and yellow and blue) which might be distractive to the interpreter.

Figure 4.11: Rock wall color coded not according to the “right hand rule”.

Figure 4.12: Rock wall color coded according to “right hand rule”.

Dip can also be color-coded. Figure 4.13 show both. The dip is on a grey scale. On the dip image, a flat ledge where the compass measurement was made is easy to recognize on the dip image because it has a dip near zero and is white, while the rest of the surface are sub-vertical and therefore dark.

Figure 4.13: Specific site color coded to strike (color scale) and dip (grey scale).

4.5: Fracture Orientation

Fracture orientations were determined for the entire rock wall by uploading the strike and dip data determined from the program written by Lai et al. (2014) into another program called DIPS⁶ which allows users to visualize structural data by creating stereonet. This program generated stereonet of the strike and dip data and color coded the stereonet according to concentration of data in percentage. Three stereonet were generated from DIPS: one for the Miniature Structured-Light Sensor, one for the Lidar data (this data set

⁶ <https://www.rocscience.com/rocscience/products/dips>

had to be decimated by a factor of 100000 because it was too large to work with the program), and one more for the Brunton compass (Figure 4.14). The type of stereonet is equal area and lower hemisphere. Results from the stereonet show that strike and dip measurements derived from the Miniature Structured-Light Sensor data, the Faro Laser Scanner Focus 3D Lidar data and the Brunton compass are consistent within 10° which is the acceptable range of error in practice (Palstrom, 1995).

Figure 4.14: Equal area, lower-hemisphere stereonet created from the program DIPS.

Another observation made from the three stereonet is that there are two general orientations of strike which are highlighted areas of colour seen in Figure 4.15. The first orientation is approximately 050° which corresponds to the East striking wall and the second orientation is approximately 330° which corresponds to the North striking wall (Figure 4.3).

Figure 4.15: Rock wall loaded into program written by Lai et al. (2014) where strike ranges selected are highlighted in pink.

To check if the same approach could be used at smaller scale, I clipped a specific area in the rock mesh model (Figure 4.16(a), (b), (c)), computed and color coded the strike, and created a stereonet in the program DIPS (Figure 4.17). Two measurements were taken with a Brunton compass in this specific area. Measurement points 7 and 8 were both measured here and had strikes and dips of 050/83 and 049/82 respectively. These measurements were validated using the DIPS program where the highest contour corresponds to 040-045 degrees. This range falls within 10° of those of the Brunton compass which is within the acceptable range (Palstrom, 1995).

Figure 4.16(a): Photograph of the rock wall near measurement points 7 and 8. The approximately 1m x 1m area within the red box was selected on the mesh model to compute a stereonet.

Figure 4.16 (b): Color coded mesh from the miniature structured-light sensor data near measurement point 7 and 8 with “no right hand rule” applied. Black square box is the location of the area shown in (a).

Figure 4.16(c): Color coded mesh from the miniature structured-light sensor data near measurement point 7 and 8 with “right hand rule” applied. Black square box is the location of the area shown in (a).

Figure 4.17: Stereonet of the specific area shown in Figure 4.16. Contains 43064 strike and dip measurements.

At specific locations, the results of the imaging approach to strike and dip estimation were validated with conventional compass measurements. For example, in Figure 4.9(b) shows measurement point 18. The strike the measurement at this location was 320° . In Figure 4.9(c) and 4.10(c) the color coded miniature structured-light sensor data corresponded to a pink color in the area where she took her measurement. The pink color corresponds to a strike value of approximately 315° which is within 10° of the compass measurement, which considered acceptable. Another example is in Figure 4.18(a) where Erin took measurement point 25. The strike of her measurement at this location was 310° . In Figure 4.18(b) and 4.18(c) the color coded miniature structured-light sensor data corresponded to a pink color in the area where she took her measurement. The pink color corresponds to a strike value of approximately 315° which is within 10° of the compass measurement which is an acceptable result. These two examples confirm that the strike measurements based on meshes from the miniature structured-light sensor are consistent with the compass measurements.

Figure 4.18(a): Photograph of measurement point 25.

Figure 4.18(b): Color coded mesh from the miniature structured-light sensor of site 25 using color wheel with no “right hand rule” applied. Black square box is the location of measurement 25.

Figure 4.18(c): Color coded mesh from the miniature structured-light sensor of site 25 with “right hand rule” applied. Black square box is the location of measurement 25.

Figure 4.19: Stereonet of the specific area shown in Figure 4.1. Contains 4057 strike and dip measurements.

4.5: Roughness

Using the same theoretical framework used for estimating the roughness of hand samples (see Section 2.1: for each point in a point cloud the “roughness” value is “equal to the standard deviation of the distances between each point in the point cloud and the best fitting plane”), I attempted to measure the roughness of the two rock walls at the Canadian Wollasonite mine using data taken using the Faro Laser Scanner Focus 3D Lidar. Using epsilon nets (Lai et al., 2014), the Lidar data was decimated from 173 million points to 1 million points for practicality. The point cloud had had to be first reduced before inputting the data into the program so that the program could run smoothly. The epsilon net method requires the user to set the desired number of points and obtain the required

value for the parameter epsilon. After the decimation was complete the data was also “cleaned” in order to remove points that were not of interest (mostly the part of the image at the base of the rock walls where loose rocks are found). The data was uploaded to a program which allows the point cloud data to be separated into cubes (P. Lai, personal communication). The dimensions of the cubes are set by the user. The smallest cube size that the program is capable of producing is 0.5m x 0.5m x 0.5m (Figure 4.20).

Figure 4.20: Roughness mapping for 0.5m x 0.5m x 0.5m cubes. The standard deviation of distance between each point and from the plane of best fit is color coded from 0.00-0.12m.

To test if this approach can identify areas that are rough three different red sections were isolated from Figure 4.20 to check if they were rougher than the blue areas (Figure 4.21).

Figure 4.21: Three rough areas of interest from Figure 4.20 chosen for detailed visual inspection are circled in red.

The rough area 1 shows a small cavity in the rock wall (Figure 4.22). Rough areas 2 and 3 show “bumpy rocks” that are sticking out of the wall (Figures 4.23). This shows that, at a scale of half a meter, roughness estimation via PCA is mostly sensitive to small structural irregularities.

Figure 4.22: Area of interest 1 (Left) color-coded roughness map; (right) original point cloud.

Figure 4.23: Area of interest 2 and 3 (Left) color-coded roughness map; (right) original point cloud.

Roughness mapping was performed using different cube sizes (1.0m and 2.0m) to investigate how roughness varies with scale (Figures 4.23 and 4.24). For cube sizes of 1.0m and 2.0m, standard deviation values ranged between 0.00-0.20m and between 0.00-0.48m, respectively.

Figure 4.24: Roughness mapping for 1.0m x 1.0m x 1.0m cubes. The standard deviation of distance between each point and from the plane of best fit is color coded, and ranges from 0.00-0.20m.

Figure 4.25: Roughness mapping for 2.0m x 2.0m x 2.0m cubes. The standard deviation of distance between each point and from the plane of best fit is color coded, and ranges from 0.00-0.48m.

Three histograms were also created from the roughness analysis results of each cube size to visually compare trends (Figures 4.25, 4.26, and 4.27).

Figure 2.26: Histogram of roughness analysis results for the 0.5m cube size.

Figure 2.27: Histogram of roughness analysis results for the 1.0m cube size.

Figure 2.28: Histogram of roughness analysis results for the 2.0m cube size.

Figures 2.24 and 2.25 have a similar distribution (counts decrease gradually from lowest to highest standard deviation values) and Figure 2.23 has a different distribution (counts are mostly flat and then decrease abruptly for the highest standard deviation values). For a 0.5m cube size, the window of data analyzed follows the topology of the rock wall surface equally well everywhere. It is insensitive to protruding or receding features because they are approximately 0.5m or smaller. For the larger 1m and 2m cube sizes, the window of data analyzed captures more structural variations in the rock wall. There are therefore more cubes that have a higher standard deviation. Overall, the results show that at the scale of a rock wall, the PCA approach to roughness estimation is mostly sensitive to the presence or not of protruding or receding features; it does not capture roughness as experienced by the sense of touch as was the case at much smaller scale.

5. Conclusions

The original objectives of this thesis were to explore applications of 3D imaging of geological scenes, more specifically to demonstrate the potential of the miniature structured-light sensor and to estimate surface roughness from point clouds at different scales.

The miniature structured-light sensor shows great potential for imaging geological scenes. It is a relatively inexpensive instrument (~500\$) that is capable of producing highly detailed color images. The application that is downloaded on the tablet which is attached to the sensor provides a first time user with a step by step process on how to acquire scans which makes it very easy for everyone to use. As the user begins scanning the instrument is capable of processing raw data points internally and outputs a 3D image as a triangular mesh. It also takes 2D color photographs of the area being imaged and is able to drape the photographs over the point cloud resulting in a detailed colored 3D image. In operational conditions, I determined the accuracy of the instrument to be 18mm at 1.5m which is acceptable for imaging large geological scenes such as rock walls. A few weaknesses of this instrument are that it does not output georeferenced data (future versions of the Occipital might have an integrated GPS but this feature is not available at present) and it does not perform well in sunlight. To orient the data in space, I used the georeferenced Lidar dataset as a guide to create my complete rock wall mesh using the open-source software called Meshlab. The mesh is then input in a program to determine fracture orientations (Lai et al., 2014). This program is capable of calculating the strike and dip of every single triangle in the mesh and color code them according to strike and dip. These strikes and dips can then be uploaded into a program called DIPS which

generates stereonet from the uploaded strike and dip data and determines preferential orientations. On the stereonet the main orientations of the two rock walls were prominent. Additional results from the stereonet of specific areas of interest created in DIPS showed that the strike and dip measurements from the miniature structured-light sensor are within 10° of the Brunton compass which is within the acceptable range of error (Palstrom, 1995).

We used two different instruments to estimate surface roughness from point clouds at different scales. Roughness is a difficult concept to grasp and measure because it has multiple definitions and its properties have not been thoroughly explored. For example, in mining engineering, they call roughness joint roughness coefficient (JRC) or in remote sensing they call roughness terrain ruggedness. In this study, we defined roughness as deviation from a perfectly smooth surface.

The instruments used were the Konica Minolta VIVID 9i non-contact laser digitizer (for hand samples) and the Faro Laser Scanner Focus 3D Lidar (for the Canadian Wollastonite mine rock walls). Using PCA, I determined that the digitizer has an error 0.016mm at a distance of ~ 0.7 m which is consistent with earlier experimental results and with the manufacturer's specifications. Roughness was determined for 9 pieces of sand paper and 20 geological hand samples of varying roughness. The roughness of each object scanned was determined from the standard deviations calculated from PCA. I predicted that standard deviations would be higher for rougher samples (as their surface would deviate further from the plane of best fit) and standard deviations would be closer to 0 for smoother objects as their surface does not deviate much from the plane of best fit. Results of the roughness experiment for the 9 pieces of sandpaper were opposite of this

prediction. I conclude that, using the standard deviation from the best-fit plane to quantify roughness, the Minolta VIVID 9i non-contact laser digitizer is unable to distinguish the granularity of the different sandpapers. For the geological hand samples, I first asked 10 people to use their sense of touch to order the 20 hand samples from smoothest to roughest and then I compared these results to the PCA results to see if they matched. Results showed that the roughness results from the touch experiment and those from the PCA are generally consistent. These results were as predicted: the general trend for the geological hand samples is that as the surface becomes increasingly rougher as determined by touch, the standard deviation of the distance to the PCA plane increases. Taking into account its accuracy, this study has not identified at what level of roughness (somewhere between the roughness of the most granular sandpapers and the smoothest rocks) did Konica Minolta VIVID 9i non-contact laser digitizer start to deliver reliable roughness data using the PCA approach. This investigation is hampered by: (1) the lack of an independent quantitative roughness metrics against which I could compare my imaging results, and (2) the lack of a suite of artificial objects with surfaces rougher than the 50-grit sandpaper.

For my last experiment, I wanted to see if I could use the data from the Faro Laser Scanner Focus 3D Lidar to estimate the roughness of the rock walls at the Canadian Wollastonite mine. The data was uploaded to a program that separates point cloud data into cubes, calculates the PCA of each cube, and color code the point cloud data (Lai, personal communication). The smoothest and roughest areas on the rock walls were color coded blue and red, respectively. After visual inspection, it was observed that the rough areas are either protruding from the wall or receding which gives it a higher PCA value

because the points deviate further from the plane of best fit. This shows that roughness and geological “undulations” (e.g. due to fracture style, bedding, etc.) are difficult to distinguish from one another. Roughness might simply be defined as “departure from a flat plane” at any scale the user is interested to consider. Other than the PCA approach, there are other measures of roughness based on curvature. Future work would be to compare different approaches to roughness measurement using the Faro Laser Scanner Focus 3D Lidar data from the Canadian Wollastonite Mine.

Roughness is a property that is not well understood or explored. It would be a good idea to test other algorithms and compare different methods for measuring roughness as it is an interesting property to study and can be beneficial to understand in geological studies such as the study in networks of fractures, rock identification, and identifying different levels in weathering.

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Appendix A: Field Photos

Measurement Point 2

Measurement Point 3

Measurement Point 4

Measurement Point 5

Measurement Point 6

Measurement Point 13

Measurement Point 14

Measurement Point 15

Measurement Point 16

Measurement Point 17

Measurement Point 18

Measurement Point 23

Measurement Point 24

Measurement Point 25

Measurement Point 26