Evaluation of LIDAR systems for rock mass discontinuity identification in underground stone mines from 3D point cloud data

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Evaluation of LIDAR systems for rock mass discontinuity identification in underground stone mines from 3D point cloud data

Mario Alejandro Bendezu de la Cruz

Thesis submitted to the Benjamin M. Statler College of Engineering and Mineral Resources at West Virginia University

in partial fulfillment of the requirements for the degree of

Master of Science

in

Mining Engineering

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National Institute for Occupational Safety and Health

Morgantown, West Virginia
2021

Keywords: laser scanning, underground mines, point cloud, UAV

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ABSTRACT

Evaluation of LIDAR systems for rock mass discontinuity identification in underground stone mines from 3D point cloud data

Bendezu de la Cruz, Mario Alejandro

According to the National Institute for Occupational Safety and Health (NIOSH), ground control hazards (i.e., roof, rib, and face falls) are still one of the most frequent causes of injury and death in the U.S. underground mines (NIOSH, 2021). Underground stone mines in the United States use the room-and-pillar method for mining bedded limestone formations, and in general, these mines have inherently strong rock and experience good ground stability. Also, modern pillar design guidelines developed by NIOSH have improved the design of stable layouts for modern limestone mines. However, recent massive pillar collapse in an old section of the Whitney mine and frequent reports of pillar sloughing and roof falls in older sections of other mines highlight the potential safety impact on the miners in underground stone mines from unstable abandoned areas. Furthermore, these serious safety hazards highlighted the importance of identifying the discontinuity factors (location, orientation and spacing) in an underground stone mine and assessing their impact on pillar stability.

Brady and Brown (2005) explain some of the most widely used methods in the mining sector for mapping discontinuities such as scanline and windows mapping which are exclusively performed through field surveys and could be highly time-consuming. The development of new technologies like photogrammetry and remote sensing along with software programs that can process the large amount of sensor data, have been gradually adapted to the geotechnical fields and have been proven to be very efficient compared to conventional geological mapping methods.

The goal of this thesis is to compare the accuracy and precision of the discontinuity identification results obtained by three active remote sensing technologies along with a point cloud processing program, and the results obtained by conventional methods. For this research, the active remote
sensing devices were terrestrial LIDAR, mobile LiDAR with Simultaneous localization, and mapping (SLAM), and LIDAR/Camera on an autonomous UAV. The open-source point cloud data processing programs Discontinuity Set Extractor (DSE) and the Cloud Compare were used to process point cloud data.

The results of this research found that it is possible to identify certain geological structures such as bedding planes with even a point cloud density of 0.5 points per cm square, from the point intensity. However, identifying joint sets require higher point densities and needs detailed analysis of the 3D maps and expert interpretation. Therefore, this thesis couldn’t conclude if only LIDAR measurements, without expert interpretation, would be enough to identify geological structures even with high point densities. However, point intensity together with the high point density will allow a more accurate identification of the geological structures. Hence, LIDAR camera used on the autonomous robotic system can provide both accurate point coordinates with LIDAR measurement, but it requires necessary illumination to obtain clear pictures with the camera to perform an appropriate identification of the geological structures from dense 3D maps possible.
DEDICATION

This work is dedicated to my precious family, my parents Leonor de la Cruz Meneses and Mario Bendezu Vila whom I owe everything in life. Dora Bendezu de la Cruz, my sister whom I admire, my aunts and my grandparents.
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Chapter 1. Introduction

The rapid growth of population around the world has boosted the demand per capita for aggregate minerals due to the continuous development of infrastructure, only in 2019 the global aggregates market was valued at USD 463.3 billion and is expected to grow at a compound annual growth rate of 3.3% from 2020 to 2027 (Grand View Research, 2020). In the United States, stone mining is an essential sector for the construction industry, and aggregate mining is the largest mining industry sector in the country based on production and number of active operations (Robinson and Brown, 2002). In 2020, the United States has produced 1.46 billion tons of crushed stone produced by an estimated 1.410 companies operating 3,440 quarries for mainly construction aggregate (U.S. Geological Survey, 2020).

Although, majority of industrial minerals supply come from massive and extensive surface mining operations, there are several underground stone mines operating due to the better feasibility of underground mining method (Willet, 2017). Underground mining can be classified as the one of the riskier occupational sectors in general (ILO, 2018), but essential for modern life, for this reason, mining companies, private organizations like Alpha Foundation, and federal agencies put major effort for reducing and ultimately eliminating hazards and risks inherent to this activity. Incidents related to Ground control are still one of the top causes of injuries and fatalities in United Stated (NIOSH, 2021), for this reason effective rock mass characterization practices in underground mines are crucial to prevent fatalities and injuries by preventing ground falls, rib failures, massive pillar, and roof collapses.

1.1 Problem Statement

Between the 2010 and 2019, four fatalities and twenty-two nonfatal lost-time injuries due to fall of ground are reported in underground stone mines (NIOSH, 2021). The National Institute for Occupational Safety and Health (NIOSH) and Alpha Foundation for the Improvement of Mine Safety and Health have made several efforts in the development of ground control tools and design guidelines to help the mine workers recognize, create, and keep a safe and healthy workplace. Among these guidelines, it can be found the “Pillar and Roof Span Design Guidelines for Underground Stone Mines” published by NIOSH (Esterhuizen et al., 2011). These empirical design guidelines have helped to identify critical aspects of pillar and roof instability. However
recent massive collapse in Whitney mine and frequent reports of pillar sloughing and roof falls in older sections of other mines highlight the potential safety impact on the miners in underground stone mines generally from the older workings. These older working were designed before the development of the current NIOSH guidelines. Esterhuizen et al. (2019) studied the Whitney mine collapse and demonstrated that accounting for the impact of large through-going discontinuities in pillar design would have provided a clear indication of the critical stability condition of the pillars at this mine. Therefore, the successful application of the NIOSH design guidelines and other design methods highly depend on the accurate identification of the geological structures in the underground stone mines.

Rock mass classification indexes also demonstrates the importance of accurate identification of discontinuities on the response and stability of the rock mass and hard rock pillars. One of the most widely applied indexes is the Rock Mass Rating Index (RMR) (Bieniawski, 1989), where 40% of the total score given to the quality of the rock mass depends on the discontinuities. This score can go up to 60% if the hypothesis of Lowson et al. (2013) that states a direct correlation between the presence of discontinuities and the Rock Quality Designation (RQD) Index, is applied.

However, difficulties in surveying, recognizing, and assessing the geological structures or hazards in a dark underground stone mine environment are still a major problem. Terrestrial LIDAR and Photogrammetry applications have proven to be very effective in measurement and identification of the geological structures, however, surveying a mine with these methods is labor-intensive, and in the older workings of the mine it might not be even safe. Recent technological developments in Simultaneous Localization and Mapping (SLAM) and smaller mobile LIDAR technologies make it possible to survey large areas efficiently. Point clouds generated from these methods can also be used to assess the geological structures of the rock mass in underground operations. Given the importance of the discontinuities on the rock mass quality and mine stability, safety of stone mine workers would be improved with safe and efficient way to map geological structures and inspect pillars.

To realize this, WVU Mining Engineering and Robotic teams are developing a methodology for an enhanced monitoring and warning system for old workings in underground stone mines using an autonomous robotic system that is comprised of an Unmanned Aerial Vehicle (UAV) tethered to an Unmanned Ground Vehicle (UGV). This combination of remote vehicles can optimally
provide high-resolution 3D maps, which are then used as input for mapping geological structures on the pillars and assessment of pillar stability. However, it is crucial to ensure that sensors mounted on robotic system can capture the necessary resolution so that mine engineers or geologists can identify the geological structures from the 3D point cloud maps generated by the system.

1.2 Objective of the Thesis
The main objective of this thesis is to identify necessary resolution of mobile LIDAR technology that would be integrated to the autonomous robotic systems to characterize the geomechanical conditions in an underground mine efficiently. In addition, there are available algorithms that can extract the discontinuities from the point cloud data automatically, integration of such an application to robotic system can further improve the efficiency of the system. However, these algorithms are generally developed from specific surface mining applications. Evaluating the performance of these algorithms using the data collected from underground stone mines and identifying the weaknesses of these algorithms for the future development of an improved method are also the objectives of this thesis.

For meeting the goals of this research, latest active remote sensing technologies, terrestrial LiDAR scanner, a mobile LiDAR scanner with SLAM and a Depth Camera L1515 airborne LiDAR are utilized for executing the task of surveying in different underground stone mines. Along with application of these new data-collector technologies, open-source data-processing programs Cloud Compare, and Discontinuity SET Extractor (Riquelme et al., 2014) were used to process the data gathered by the LIDAR.

1.3 Work Statement
This research will follow the following tasks:

- Task 1: Map and collect data from stone mine pillars with the mobile LIDAR system, terrestrial LiDAR, and airborne LiDAR mounted on an autonomous Unmanned Aerial Vehicle (UAV).
- Task 2: Process the data in the Cloud Compare and Discontinuity Set Extractor (Riquelme et al., 2014) programs to characterize the rock mass of the underground stone-mine pillars.
• Task 3: Perform a sensitivity analysis with the Discontinuity Set Extractor program to
determine the precision and accuracy of the results obtained.
• Task 4: Compare the performance of different methods and identify necessary resolution
and the operational parameters for the sensor that would be integrated on the UAV for
autonomous scanning.

1.4 Thesis Outline
The thesis consists of 5 chapter. The chapter are the following:

• Chapter 1: Introduction chapter.
• Chapter 2: Literature Review of the history of the different methodologies for
characterizing a rock mass with active remote sensing technology.
• Chapter 3: Methodology followed for analyzing underground stone mine pillars.
• Chapter 4: Rock mass characterization case studies and analysis using LiDAR technology
and point cloud processing programs.
• Chapter 5: Conclusions reached after analysis.
Chapter 2. Literature Review

The continuous developments in new technologies have turned mine surveying and mapping into a more accurate, precise, effective, faster, and safer practice. These new technologies have also been used to map geological structures, necessary in the characterization of rock masses. In this chapter, chronological review of the most relevant mapping techniques, technologies and rock mass classification indexes that has been utilized up to date to analyze the geotechnical characteristics of a rock mass are presented. This review makes a special emphasis on the active remote sensing approaches and the software programs used for processing the data gathered by this method, as well as the most widely applied rock mass classification indexes to quantify the impact of geological structures on the rock mass stability. Finally, literature on the case studies where remote sensing technologies had been applied in underground mining with encouraging results and software programs used in the processing of the point cloud data are presented.


Brady and Brown (2005) indicated that an engineering understanding of the rock mass structure is necessary for successful mine design, and mine geology and the major geological structures present in the mine are essential information for ground control design, and mapping of surface and underground exposures and logging of boreholes are necessary applications to gather this vital information.

Brady and Brown (2005) describe scanline mapping and window surveying as the two most common traditional mapping methods (Figure 1). As shown in Figure 1, a scanline is a line set on the surface of the rock mass on a pillar or face, and the survey consists of recording data for all discontinuities that intersect the scanline along its length (Brady and Brown, 2005). They stated that an alternative approach is to measure all discontinuities within a defined area on the rock face, but they indicated that this approach is more difficult to control and map systematically than scanline surveys.
Window and scan line mapping methods do not require special equipment or devices, geological clino-compasses (Figure 2) and measuring tape are generally enough to map with these methods. Brady and Brown (2005) defined the scanline survey as a basic technique for mapping surface and underground exposures and consists in setting up a line along the rock mass for registering all the discontinuities that intersect the line. They also indicated that a combination of the scanline and an alternative method for characterizing the discontinuities within a specific area can be used for underground excavations where discontinuities are extrapolated to intersect the scanline. For applying the scanline method, a measuring tape which represents the scanline has to be as straight as possible and fixed to the rock mass by hammered nails, these nails should be spaced at approximately 3 m intervals along the tape. After the scanline is established, photographs must be
taken and location, data, rock type, face orientation, scanline orientation must be recorded by the surveyors on a logging sheet (Brady and Brown, 2005).

Applying a scanline survey in a stone mine pillar can be a challenging process due to height of tall pillars, illumination, position, and orientation of the scanline which might result in not registering accurately the discontinuities present in the rock mass.

2.2 Rock Mass Characterization

The ground control design of a mine to sustain its’ geomechanical stability relies on the geotechnical characteristics, such as the quality of the rock mass of the formation that mining takes place. The quality of the rock mass depends on physical and chemical properties of the rock matrix and characteristics of the geological structures of the formation. Geological structures like bedding planes and joint sets, or discontinuities, have been extensively studied because their presence in a rock mass influences the mechanical behavior of the rock mass, and design of the support system. Maintaining the global and local stability of a mine requires a proper assessment of the rock mass and without a detailed characterization of the discontinuities this assessment isn’t possible.

Discontinuity is defined as an inherent characteristic of the rock mass that has a structural change resulting in zero or low tensile strength, and it is a collective term for referring to joints, weak bedding planes, weak schistosity planes, weak zones, and faults (Zhang, 2006). There exist various forms of classifications for the discontinuities that goes from geometric classification, scale size, origins, among others that are used depending on the purpose of evaluation or the field of the professional evaluating. For examples, structural geologists classify discontinuities according to their spacing and orientation patterns (Hobbs, 1993), on the other hand geotechnical engineers by size of the discontinuity (Cruden, 1977).

The International Society of Rock Mechanics (ISRM, 1978) proposed a suggested method for the quantitative description of geometrical, mechanical, and hydraulic features of discontinuities consisting of the following ten parameters: orientation, spacing, persistence (trace length), roughness, apertures, wall strength, filling, seepage, number of sets and block size. From this method, several guides have been created for attempting to describe rock mass and the parameters that impact in its stability as effective as possible. Figure 3 shows, two additional parameters such as rock type and wall strength besides the ten discontinuity parameters already mentioned.
Figure 3. Diagram Illustrating rock mass properties (Wyllie, 1999)

Figure 4 shows the discontinuity survey data sheet that is published by IRSM (1978). According to ISRM (1978) procedures parameters such as persistence, aperture, nature of filling, compressive strength of infilling, water flow, termination, surface shape, surface roughness and spacing receive a quantitative score.

Figure 4. Discontinuity Data Survey Sheet (Wyllie and Mah, 2004)
Therefore, there are several discontinuity factors that impact the rock mass stability, but since photogrammetry and remote sensing can only identify the external visible features in a specific point of time, this research focuses on features such as the spacing and persistence of the discontinuities, and its conditions.

2.2.1 Discontinuity Intensity
Discontinuity intensity is defined as one of the most important parameters for describing discontinuities in a rock mass, and it can be expressed as linear, areal, and volumetric discontinuity spacing frequency, Rock Quality Designation (RQD), discontinuity trace length per unit area of rock exposure, and discontinuity area per unit volume or rock mass (Zhang, 2006).

2.2.1.1 Discontinuity spacing and linear frequency
Discontinuity spacing is defined as the distance between the visible sides of two or more adjacent discontinuity planes along a line of a specified location and orientation, however since discontinuities are not identical one to another, they are classified in three different categories depending on how the distance was measured between them. According to Priest (1993) it is useful to distinguish the different types of discontinuity spacing measurements classified as total spacing, set spacing, normal set spacing. Discontinuity spacing is an important parameter to evaluate the quality of the rock mass since it can be used to estimate the dimensions of the intact rock blocks forming the rock mass. Likewise, discontinuity spacing is linked to the reciprocal of discontinuity frequency which is a factor widely used in several rock mass classification indexes (Priest and Hudson, 1976). Discontinuity frequency is commonly expressed in terms of linear frequency, and it is defined as the number of discontinuities intersected by a unit length of sampling line and the frequency will vary depending on the direction of the sampling line.

The spacing between discontinuities vary along the rock mass but due to its importance on the rock mass stability, several studies about their frequency of occurrence have been performed such as a statistical distribution to identify a pattern and correlation between these two variables (spacing vs frequency) (Figure.5).
Figure 5. Discontinuity spacing histogram for all scanlines in the first 85 tunnels, Chinnor UK (Priest and Hudson, 1976)

Frequency that is represented by $f(s)$ can be calculated by the following equation:

$$f(s) = \lambda e^{-\lambda s}$$  \hspace{1cm} (1)

Where; $\lambda = 1/\bar{s}$ is the mean discontinuity frequency of a large discontinuity population and $\bar{s}$ is the mean spacing. Brady and Brown (2005) pointed out the basic sampling problem to be considered when assessing the mapping of the discontinuities. They indicated that there isn’t a clear answer to what portion of the mine should be surveyed to obtain satisfactory results. Statistical techniques used by Priest and Hudson (1976, 1981) to quantify the spacing frequency distribution provide valuable guidance as indicated by Brady and Brown (2005). Spacing distribution has been extensively studied and the negative exponential and lognormal distributions found to represent discontinuity spacing frequencies observed in the field satisfactorily (Rives et al. 1992; Brady and Brown, 2005). Discontinuity spacing data collected in United Kingdom for Lower Chalk, Chinnor and Oxfordshire (Figure 5) showed a probability density distribution close to a negative exponential distribution (Priest and Hudson, 1976). Same conclusion was reached for different formations such as igneous, sedimentary, and metamorphic origins (Wallis and King, 1980; Baecher, 1983).

2.2.1.2 Rock Quality Designation (RQD)

The RQD method proposed by Deere (1964) was created with the objective to quantify discontinuity spacing and consists in calculating the ratio of the total length sound core pieces that are at least 0.1 meters to the total length (Equation 2) (Figure 6).
\[ RQD = \frac{100 \sum x_i}{L} \]  

**Figure 6. Calculation of RQD (Deere, 1989)**

RQD determination has to meet some conditions such as a certain core size, form of measurement, fully circular lengths of core, the barrel used for drilling, the omission of artificial fractures among others determined by the ISRM Commission (1978). Priest and Hudson (1976) derived from experimental data a relation between RQD value and mean discontinuity frequency given by the average number of discontinuities per meter (\( \lambda \)) (Figure 7).
Figure 7. Relation between RQD and mean discontinuity frequency (Brady and Brown, 2005)

Figure 7 shows the relation between measured values of RQD, explained by the Equation 3 and the RQD theoretical curve (Equation 4) against $\lambda$.

\[
RQD = -3.68\lambda + 110.4 \quad (3)
\]

\[
RQD = 100e^{-\lambda t} (\lambda t + 1) \quad (4)
\]

However, RQD value from drill cores can be unreliable predictors of discontinuity frequency because it is required to identify natural fractures from artificial ones (blasting or drilling), strength of rock can change after drilling activity, core recovery, drilling orientation (when rock mass is anisotropic) (Brady and Brown, 2005).

### 2.2.1.3 Discontinuity Persistence and Roughness

The discontinuity persistence is considered to be one of the most important rock mass parameters as the shear strength is impacted in the plane of the discontinuity and on the fragmentation characteristics, cavability, and permeability of the rock mass. Discontinuity persistence is classified in 5 different categories depending on their most common or modal trace lengths (Table 1) (Brady and Brown, 2005).
Table 1. Discontinuity Persistence Classification

<table>
<thead>
<tr>
<th>Discontinuity Persistence</th>
<th>Modal trace length (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very low persistence</td>
<td>&lt;1</td>
</tr>
<tr>
<td>Low persistence</td>
<td>1-3</td>
</tr>
<tr>
<td>Medium persistence</td>
<td>3-10</td>
</tr>
<tr>
<td>High persistence</td>
<td>10-20</td>
</tr>
<tr>
<td>Very high persistence</td>
<td>20</td>
</tr>
</tbody>
</table>

However, persistence can be very difficult to determine since they are roughly quantified by observing the trace length of discontinuities on exposed surfaces. On the other hand, roughness is the surface characteristic that describes the unevenness and waviness of a discontinuity compared to the mean plane. The factors that are considered to have a potential impact by the roughness of a discontinuity are the shear strength and the displaced and interlocked features such as unfilled joints. ISRM Commission (1978) suggests the utilization of nine class of roughness (Table 2) which can be used to describe roughness on two scales, small scales (several centimeters) and intermediate scale (meters).

Table 2. Discontinuity Roughness Classification

<table>
<thead>
<tr>
<th>Roughness</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>Description</td>
</tr>
<tr>
<td>I</td>
<td>rough or irregular, stepped</td>
</tr>
<tr>
<td>II</td>
<td>smooth, stepped</td>
</tr>
<tr>
<td>III</td>
<td>slickensided, stepped</td>
</tr>
<tr>
<td>IV</td>
<td>rough or irregular, undulating</td>
</tr>
<tr>
<td>V</td>
<td>smooth, undulating</td>
</tr>
<tr>
<td>VI</td>
<td>slickensided, undulating</td>
</tr>
<tr>
<td>VII</td>
<td>rough or irregular, planar</td>
</tr>
<tr>
<td>VIII</td>
<td>smooth, planar</td>
</tr>
<tr>
<td>IX</td>
<td>slickensided, planar</td>
</tr>
</tbody>
</table>

The impact that roughness has on a discontinuity is inversely proportional to the increase of aperture, filling thickness or previous shear displacement.

2.3 Rock Mass Classification

The goal of the rock mass classification systems is to guide on the application of the best engineering principles or practices by understanding the nature of the mechanical behavior of the
rock mass in relationship to the properties or characteristics of the rock. However, analyzing rock masses is a difficult and complex task since they do not possess consistent features along its dimension and for this reason a thorough analysis approach is necessary to best estimate the impact of these features into its stability. Since the properties of rock mass changes from one location to another, and even with in the same formation in the same mine, empirical information collected from numerous case studies to identify the parameters that determine the rock mass behavior to develop rock mass classification systems, to ultimately extrapolate application of these systems to new and different design scenarios. In classification systems or schemes, parameters or features used to compute overall rock mass index are quantified depending on the correlation of its impact on the rock mass. The most widely known classification system are Rock Mass Rating (Bieniawski, 1976), Mining Rock Mass Rating (Laubscher, 1977; Laubscher, 1990), the Q index by Barton et al. (1974), and GSI system introduced by Hoek (1994) and developed further by Marinos and Hoek (2000).

2.3.1 RMR Index

The Rock Mass Rating (RMR) system was proposed by Bieniawski (1973), and it was developed at South African Council of Scientific and Industrial Research (CSIR) based on experiences in shallow tunnels in sedimentary rocks (Singh, 2011). The RMR evaluates 5 parameters to quantify the total RMR index: strength of the intact rock material, RQD, spacing of joints, condition of joints and groundwater conditions (Table 3).

- **Strength of intact rock material:** The uniaxial compressive strength of the intact rock may be measured on cores and accounts for 15% of the RMR score.

- **RQD:** Described in section 2.2.1.2 and it accounts for 20% of the RMR score.

- **Spacing of joints:** Described in section 2.2.1.1 and it accounts for 20% of the RMR score.

- **Condition of joint:** Separation or aperture of discontinuities, their continuity or persistence, their surface roughness, the wall condition (hard or soft) and the nature of any in-filling materials present. Accounts for 30% of the RMR score.

- **Groundwater conditions:** Influence of groundwater pressure or flow on the stability of underground excavations in terms of the observed rate of flow into the excavation accounts for 15% of the RMR score.
Certain conditions have been defined for each parameter as shown in Table 3 and if the studied parameter meets one of these conditions, the rock mass analyzed is given a rating value that overall rating can go from 8 to 100.

**Table 3. Rock Mass Classification Index (Bieniawski, 1989)**

<table>
<thead>
<tr>
<th>A</th>
<th>Classification Parameters and Their Ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Strength of Intact Rock Material</td>
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<tr>
<td></td>
<td>Point Load Index</td>
</tr>
<tr>
<td></td>
<td>&gt; 10 MPa</td>
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<td>4 - 10 MPa</td>
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</tr>
<tr>
<td></td>
<td>1 - 2 MPa</td>
</tr>
<tr>
<td></td>
<td>Uniaxial Comp. Strength</td>
</tr>
<tr>
<td></td>
<td>&gt; 250 MPa</td>
</tr>
<tr>
<td></td>
<td>100 - 250 MPa</td>
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<tr>
<td></td>
<td>50 - 100 MPa</td>
</tr>
<tr>
<td></td>
<td>25 - 50 MPa</td>
</tr>
<tr>
<td></td>
<td>For This Low Range - Uniaxial Compress. Test is Preferred</td>
</tr>
<tr>
<td></td>
<td>Rating</td>
</tr>
<tr>
<td></td>
<td>15</td>
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</tr>
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</tr>
<tr>
<td>2</td>
<td>RQD</td>
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<td>Rating</td>
</tr>
<tr>
<td></td>
<td>90% - 100%</td>
</tr>
<tr>
<td></td>
<td>75% - 90%</td>
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<tr>
<td></td>
<td>50% - 75%</td>
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<tr>
<td></td>
<td>25% - 50%</td>
</tr>
<tr>
<td></td>
<td>&lt; 25%</td>
</tr>
<tr>
<td>3</td>
<td>Discontinuity Spacing</td>
</tr>
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<td>Rating</td>
</tr>
<tr>
<td></td>
<td>&lt; 2 m</td>
</tr>
<tr>
<td></td>
<td>0.6 - 2 m</td>
</tr>
<tr>
<td></td>
<td>0.2 - 0.6 m</td>
</tr>
<tr>
<td></td>
<td>0.06 - 0.2 m</td>
</tr>
<tr>
<td></td>
<td>&lt; 0.06 m</td>
</tr>
<tr>
<td>4</td>
<td>Condition of Discontinuities</td>
</tr>
<tr>
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<tr>
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<td>Very Rough</td>
</tr>
<tr>
<td></td>
<td>Uncontinuous</td>
</tr>
<tr>
<td></td>
<td>No Separation</td>
</tr>
<tr>
<td></td>
<td>Unweathered Rock</td>
</tr>
<tr>
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<td>Rock</td>
</tr>
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<td>Slightly Rough</td>
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<tr>
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<td>Separation &lt; 1 mm</td>
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<tr>
<td></td>
<td>Slightly Weathered</td>
</tr>
<tr>
<td></td>
<td>Slickenside or</td>
</tr>
<tr>
<td></td>
<td>Slicken &lt; 5 mm Thick or</td>
</tr>
<tr>
<td></td>
<td>Separation 1 - 5 mm Continuous</td>
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</tr>
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<td>Strike and Dip Orientations</td>
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<td>100 - 81</td>
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<td>80 - 61</td>
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<tr>
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<td>1 week for 5 m span</td>
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<td>3 - 10 m</td>
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<tr>
<td></td>
<td>10 - 20 m</td>
</tr>
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<td>&gt; 20 m</td>
</tr>
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</tr>
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<td>6</td>
</tr>
<tr>
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<td>4</td>
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<tr>
<td></td>
<td>Separation (Aperture)</td>
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<td>&lt; 0.1</td>
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<td>0.1 - 1.0 mm</td>
</tr>
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<td>&lt; 5 mm</td>
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<tr>
<td></td>
<td>Rating</td>
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<td>6</td>
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<tr>
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<td>Rough</td>
</tr>
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<td>Roughly Slight</td>
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<tr>
<td></td>
<td>Smooth</td>
</tr>
<tr>
<td></td>
<td>Slickenside</td>
</tr>
<tr>
<td></td>
<td>Rating</td>
</tr>
<tr>
<td></td>
<td>6</td>
</tr>
<tr>
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<tr>
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<tr>
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<td>Infilling (Gauge)</td>
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<tr>
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<td>Hard Filling &lt; 5 mm</td>
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<td></td>
<td>Hard Filling &gt; 5 mm</td>
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<td>Soft Filling &lt; 5 mm</td>
</tr>
<tr>
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<td>Soft Filling &gt; 5 mm</td>
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<td>Rating</td>
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<td>Weathering</td>
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<tr>
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<td>Slightly Weathered</td>
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<td>Decomposed</td>
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<td>5</td>
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<tr>
<td></td>
<td>3</td>
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<tr>
<td></td>
<td>1</td>
</tr>
<tr>
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<td>0</td>
</tr>
<tr>
<td>F</td>
<td>Effect of Discontinuity Strike and Dip Orientation in Tunneling</td>
</tr>
<tr>
<td></td>
<td>Strike Perpendicular to Tunnel Axis</td>
</tr>
<tr>
<td></td>
<td>Strike Parallel to Tunnel Axis</td>
</tr>
<tr>
<td></td>
<td>Drive with Dip 45° - 90°</td>
</tr>
<tr>
<td></td>
<td>Drive with Dip 20° - 45°</td>
</tr>
<tr>
<td></td>
<td>Dip 45° - 90°</td>
</tr>
<tr>
<td></td>
<td>Dip 20° - 45°</td>
</tr>
<tr>
<td></td>
<td>Very Favourable</td>
</tr>
<tr>
<td></td>
<td>Favourable</td>
</tr>
<tr>
<td></td>
<td>Very Unfavourable</td>
</tr>
<tr>
<td></td>
<td>Fair</td>
</tr>
<tr>
<td></td>
<td>Drive Against Dip 45° - 90°</td>
</tr>
<tr>
<td></td>
<td>Drive Against Dip 20° - 45°</td>
</tr>
<tr>
<td></td>
<td>Dip 0° - 20° - Irrespective of Strike</td>
</tr>
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<td>Fair</td>
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<td>Unfavourable</td>
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<tr>
<td></td>
<td>Fair</td>
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</table>
2.3.2 GSI Index
As part of the continuing development and practical application of the Hoek-Brown empirical rock mass strength criterion, Hoek (1994) and Hoek et al. (1995) introduced a new rock mass classification scheme known as the Geological Strength Index (GSI). The GSI was developed to overcome some of the limitations in Bieniawski's RMR classification scheme for very poor-quality rock masses and for unrealistic rating adjustments for discontinuity orientation in slopes which have necessitated some significant changes in the criterion (Sonmez and Ulusay, 1999).

GSI Index was created for hard and weak rock masses, and it was accepted by experienced field engineers and geologists due to its simple, fast, and reliable classification that can be obtained by simple visual inspection (Zhang, 2017). The GSI rock mass classification index by Hoek and Brown (1997) introduces five main qualitative classifications of rock mass structure:

- Intact/Massive,
- Blocky,
- Very Blocky,
- Blocky/Disturbed,
- Disintegrated.

Likewise, discontinuities are classified into five surface conditions which are similar to discontinuity conditions in RMR (Table 4):

- Very good,
- Good,
- Fair,
- Poor,
- Very poor.
Table 4. GSI Index (Hoek and Brown, 1997)

<table>
<thead>
<tr>
<th>Geological Strength Index (GSI)</th>
<th>Surface Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>From the description of structure and surface conditions of the rock mass, pick an appropriate box in this chart. Estimate the average value of GSI from the contours. Do not attempt to be too precise. Quoting a range of GSI from 36 to 42 is more realistic than stating that GSI = 38.</td>
<td></td>
</tr>
</tbody>
</table>

2.3.3 Q-system

Barton et al. (1974) of the Norwegian Geotechnical Institute (NGI) originally proposed the Q-system as a rock mass classification based on several case histories of tunnels and caverns for making a preliminary characterization of the rock mass and determining a design of the support.
The Q-system is specifically recommended for tunnels and caverns with an arched roof and analyze six parameters (Equation 5).

\[ Q = \frac{RQD}{J_n} \times \frac{J_r}{J_a} \times \frac{J_w}{SRF} \]  

(Q5)

Q-system parameters are:

- RQD = Rock Quality Designation Index,
- Jn = joint set number,
- Jr = joint roughness number for critically oriented joint set,
- Ja = joint alteration number for critically oriented joint set,
- Jw = joint water reduction factor,
- SRF= stress reduction factor to consider in situ stresses and according to the observed tunneling conditions.

These six parameters of the Q-system are determined during geological mapping, but when paired, they represent the three main factors that describes the stability of the rock mass.

- \( \frac{RQD}{J_n} \), is the degree of jointing or block size,
- \( \frac{J_r}{J_a} \), is the joint friction,
- \( \frac{J_w}{SRF} \), is the active stress.

The Q-index values vary from 0.001 to 1000 and its classification is represented in table 5.
Table 5. Q Index Classification (Barton et al., 1974)

<table>
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<th>Q Value</th>
<th>Group</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
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<td>0.001-0.01</td>
<td>Exceptionally poor</td>
<td></td>
</tr>
<tr>
<td>0.01-0.1</td>
<td>3</td>
<td>Extremely poor</td>
</tr>
<tr>
<td>0.1-1</td>
<td>2</td>
<td>Very poor</td>
</tr>
<tr>
<td>1-4</td>
<td>2</td>
<td>Poor</td>
</tr>
<tr>
<td>4-10</td>
<td>1</td>
<td>Fair</td>
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<tr>
<td>10-40</td>
<td></td>
<td>Good</td>
</tr>
<tr>
<td>40-100</td>
<td>1</td>
<td>Very good</td>
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<td>100-400</td>
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<td>Extremely good</td>
</tr>
<tr>
<td>400-1000</td>
<td></td>
<td>Exceptionally good</td>
</tr>
</tbody>
</table>

2.4 Contactless Mapping Techniques

Buyer A. et al (2017) mention that scan lines and mapping windows are limited in terms of accessibility to the location, geological or geotechnical knowledge, time and scale which can produce subjective and not reproducible results. Contactless mapping techniques such as photogrammetry and active remote sensing applied to mining have become a well-established rock mass mapping method and have started to replace gradually the traditional methods due to the several advantages they can deliver. Remote sensing and photogrammetry techniques can provide the following advantages: fast and precise data collection, large data storage and employable on inaccessible areas with the help of drones and robotic systems.

2.4.1 Photogrammetry

Photogrammetry and remote sensing in the geotechnical and rock mechanics fields started as a complement of the traditional mapping methods which helped to provide a more comprehensive information of the rock mass (Sturzenegger and Stead, 2009). In the case of photogrammetry, this technique is much older than laser scanning and it is used to extract the information of three-dimensional figures from a series of two-dimensional photographs. Photogrammetry technique was widely used to obtain topographic maps (Slama, 1980; Wolf, 1983), but also has been used on the fields of geology and geomechanics for assessing the stability of excavated slopes (Wickens & Barton, 1971) and coastal cliff instability (Grainger & Kalauger, 1987). Traditional photogrammetric data collection and processing were performed by using complex and expensive
equipment such as metric cameras and stereo-plotters (Figure 8) to recreate the spatial relationships between the photographs and the ground.

![Figure 8. Galileo Santoni model III analog stereoplottter. Photo by W. Mayo](image)

Later, analytical photogrammetry replaced these stereo-plotters with computerized mathematical models by calculating distances and scale, introducing a photo-coordinate system (Chandler and Moore, 1989). Digital cameras allowed storage and sharing of large amount of digital image data possible since the data could be stored digitally and can be shared among unlimited users electronically. This also represented an advantage for the geotechnical field. Digital imaging and digital image processing offered the possibility to gather and process large datasets of information of fractures and associated properties from digital images of fracture traces (Figure 9). Digital image processing and mathematical algorithms developed to extract three-dimensional fracture properties could identity information such as orientation, length, spacing, large-scale roughness, among others (Kemeny and Post, 2003; Assali et al, 2014).

![Figure 9. Digital Photos used for delineation of fracture traces (Kemeny and Post,2003)](image)
Kemeny et al (2003) developed a new a rock mass classification index introduced for estimating the rock mass rating from digital images of rock faces, the name of this index was Digital Rock Mass Rating (DRMR), and it can be computed using the Equation 6.

\[ DRMR = F_1 + F_2 + F_3 + F_4 + F_5 + F_6 + F_7 \]  

where:

- \( F_1 \): number of joint sets,
- \( F_2 \): distribution of joint lengths,
- \( F_3 \): distribution of joint spacings,
- \( F_4 \): distribution of large-scale roughness,
- \( F_5 \): rock block size distribution,
- \( F_6 \): rock bridge size distribution,
- \( F_7 \): rock texture classification.

Methods mentioned above were still complex for users not related to photogrammetry (non-photogrammetrist) but with the development in computer technology and software programs for building three-dimensional models were allowing photogrammetry approach accessible for anyone (Sturzenegger and Stead, 2009).

Digital photogrammetry is preferred technique since it could be executed with inexpensive devices and minimal operator training, where fine details of the rock mass could be capture, these details could be paint markings, corrosion evidence, water intrusion, and damage to ground support (Figure 10) (Benton et al, 2017). Photogrammetry requires external lighting which could vary depending on the distance or environment for capturing true colors or any fine detail, for this reason this method has no problem when applied in open pit mines during the day.
In the case of underground mines, photogrammetry applications require an auxiliary lighting system. For example, Benton et al (2017) performed a rock mass displacement test where lighting devices that produced 3,000 and 6,000 lumens in different occasions were used. Slaker et al (2015) carry out a test to determine the volumetric change of underground stone mine pillars using photogrammetry as a tool, and seven different pillars were supervised for a 63-day period with four visits during this interval (Figure 11). The instruments employed in this investigation were a Digital Single-Lens Reflex (DSLR) Nikon D70S camera with a picture resolution of 3008x2000, and the image processing programs such as Agisoft Photoscan, Coloud Compare and Maptek iSite.

All pillars studied in this experiment presented signs of significant damage prior to the photos and after the field study, three geometrical changes were captured and were classified as weak band failure, spalling and expansion. Almost all the pillars, except for Pillar 1 and 4, presented spalling behavior that went from 0.39 to 0.52 m$^3$ of material being displaced from the rib, while pillar 5
presented the largest spalling away from the corner with a 4.03m$^3$ displacement. There were difficulties in processing the Pillar 1 images because photos were blurry, and Pillar 4 had no detectable change during the monitoring period.

As a result, the trial gave good results detecting material movements, absence of movement and rib changes that were modeled and were appropriately quantified, however some anomalies were also identified as for example false displacement due to poor quality of photos.

2.4.2 Laser Scanning
Laser scanning and its applications are relatively new compared to photogrammetry and were considered more suitable for geotechnical purposes in underground mines since measurements can go up to hundreds of meters (The FARO X330 can scan to ranges greater than 330 meters, Lidarusa), dark underground environment won’t affect the measurements and the point clouds that come out from the scan can be used to construct a high-detailed-three-dimensional model (Glaser and Doolin, 2000). The point clouds are composed of points that possess three-dimensional space information (x, y and z coordinates) obtained by the laser scanner that contains valuable information about the fractures in the rock mass such as orientation, size, shape, spacing and roughness (Kemeny et al., 2003). Extracting the information of a discontinuity from a point cloud can be performed manually using hand editing features in a point cloud software or using an automated software (Slob et al, 2002).

2.4.2.1 Terrestrial LiDAR
Fisher et al. (2014) mention how Terrestrial LiDAR is a method capable to model rock outcrops, and the output obtained after the scanning process can be utilized to build virtual 3D computer model from which geologic and geomechanical information can be derived (Fisher et al, 2014). Examples of these 3D models build with Terrestrial LiDAR can be found in the rock outcrop stratigraphic modeling test performed by Bellian et al. (2005), the study of the scale effect on the rock joint surface roughness by Fardin et al. (2004) and the visualization of structural features in rock outcrops by Rosser et al. (2005). Likewise, other uses for this technology can be achieved, monitoring geometric changes in time is one of them and can be applied for monitoring the erosion of a hard rock cliff (Rosser et al., 2005), visualizing structural features in rock outcrops (McCaffrey et al., 2008), monitoring unstable slopes (Jones, 2006), and kinematic analysis of slopes (Gischig et al., 2011). Slaker et al. (2015) performed a test to quantify volumetric change in an underground
coal mine where two scans were performed from the center of an entry, the first scan would establish initial condition and the second one the removal of the coal from the ribs (Figure 12).

![Figure 12. Study area and locations of removed coal (Brent Slaker et al., 2015)](image)

A LiDAR scanner FARO Focus 3D was used for this test, where six areas were studied giving a volumetric change that went from 57 cm$^3$ to 57,549 cm$^3$ (Figure 13).

![Figure 13. Surface change from coal removal at locations A, B and C (Slaker et al., 2015)](image)

However, one of the main disadvantages of Terrestrial LiDAR application is that the scanner is mounted in a stationary tripod when mapping, so depending on the height or orientation of the rock mass face to be analyzed, there could be occlusions or not visible spots for the scanner. Gallant et al. (2016) in their research talk about how these occlusions can be avoided by moving...
and reorienting the terrestrial LiDAR scanner but this cannot always be done efficiently in enclosed or inaccessible spaces like underground mines.

### 2.4.2.2 Mobile Lidar

Ground based LiDAR was an accepted technology for characterizing exposed rock face, however there were some challenges about this technique when it came to scanning long areas such as corridors or for avoiding occlusions in underground mines. Lato et al (2009) in his paper tested a mobile terrestrial Lidar as a data collection technique capable of generating accurate fully three-dimensional virtual models while traveling to a speed up to 30km/h, the mobile terrestrial system can be visualized in Figure 14.

![Multi-LiDAR scanner mounted on a truck](image)

*Figure 14. Multi-LiDAR scanner mounted on a truck Lato et al (2009)*

However, underground mines are very different from corridors because they are GPS denied environments, coordinates are not georeferenced, and the presence of ground control issues make the place dangerous for personnel and equipment. Recent advances in the use Unmanned aerial vehicles (UAV) transform these devices into useful mobile platform that could fly into unsupported underground excavations and obtain enough information to generate a 3D point cloud to interpret the geological structure of the mine (Turner et al. 2020). Flying manually an UAV equipped with a LiDAR scanner would become a tough task in an underground mine since most of the spaces are enclosed areas with limited illumination which could result in collision of the equipped drone with the walls or roof. For overcoming this problem, Simultaneous Localization and Mapping (SLAM) was introduced in the scanning process which allows the UAV to navigate through unknow environments while estimating its’ location relative to entry walls and at the same time plotting a map, an example of an UAV equipped with SLAM can be seen in Figure 15.
2.4.2.3 What is SLAM?

SLAM is a complex program created for constructing or updating a map of an unknown environment while keeping track of the sensor device localization and its relationship between itself and the surroundings (GeoSLAM, 2021). SLAM is a challenging problem for autonomous robots such as the one putting to work by the WVU Robotics and Mining Engineering teams as the robot needs an intelligent system that can navigate through an unknown, dark, GPS-denied environment without human interference. During the history of evolution of SLAM algorithms several type of sensors such as ultrasonic sensors, laser scanners, Red Green Blue (RGB) cameras among others have been employed for estimating the position of the sensor and simultaneously build 2D or 3D maps. Odometry in robotic refers to the result of motion integration provided by the robot’s motion sensors such as wheel encoders, to estimate the robot’s motion over time. The improvement on the results of the mapping process depends on the odometry and mapping is essential in SLAM because generating a map is the main goal for obtaining a path planning, obstacle avoidance, and the accuracy of location depends on the mapping accuracy. Loop closure is one of the most essential compounds of mapping that makes the sensor be able to recognize a visited place and therefore being capable of optimizing its estimated position (GeoSLAM, 2021). The loop closure reduces the drifts dramatically and lets the sensor to correct its odometry errors. Positioning is an essential concern of SLAM. The techniques for solving the positioning difficulties are classified into the probabilistic and non-probabilistic approaches. Approaches relying on probabilistic methods are the mainstream classification. The probability methods are based on the Bayesian estimation method where mainly Particle Filters (PF) and Kalman Filters
(KF) methods are used. A SLAM system can be broken down into two parts, the frontend, and back-end (Figure 16). The front-end takes the sensory raw data and does some preprocessing on data such as feature extraction, short and long-term data association, i.e., feature tracking and loop closure respectively to be able to transform the geometric information to the mathematical models and send it to the back end (Taheri and Xia, 2021).

![Figure 16. SLAM architecture (Taheri and Xia, 2021)](image)

### 2.4.3 Point Cloud Processing

The creation of several point-clouds reconstruction and processing programs solved one of the biggest challenges when these methods were started to be used frequently, and it was the significant knowledge that the user should have in data collection, processing, and analysis. For this reason, several software programs that could read the data collected by laser scanners were created that any user with limited knowledge of these methods could use them efficiently. Among the software written, it can be found programs such as DIPS, ShapeMetrix 3D (3GSM GmbH), Sirovision (Datamine and CSIRO), Split-FX (Slob, 2010), Coltop-3D (Jaboyedoff et al., 2009), Plane Detect (Vöge et al., 2013), Discontinuity Set Extractor (DSE, Riquelme et al., 2014) and RockScan (Ferrero et al., 2009), etc. These programs made this technology easily operable by any user which derived in a rapid growth in the efficiency of data collection on the field.

Point clouds are datasets that contain geometric coordinates of the surface of an object or space and are generally generated by LiDAR and Photogrammetry sensors and techniques. Point clouds can be used to reconstruct and model 3D objects in appropriate software programs but they can be used to obtain even more information derived from coordinates. Mining industry has found plenty of uses to this technology since point clouds software processing programs execute commands that can identify geomechanical features of the rock mass. There exists a great variety of programs that
can process point clouds but most of them follow similar computations for delivering the requested result.

2.4.3.1 Normal Vector Calculation

The calculation of normal vector has been up to the present time a very heavily used method for segmentation range data of LiDAR scanner (Hoover et al., 1996, Geibel and Stilla, 2000, Wang et al. 2013) because this type of calculation has become a fundamental step in the point cloud data processing. Surface normal is essential property of a geometric surface and can determine the orientation of the plane they belong to. Programs such as Discontinuity Set Extractor and Cloud Compare calculates the normal vector of each point to allocate groups of points to the best-fitting planes (Figure 17).

![Figure 17. Normal Calculation of Point cloud subsets (Riquelme et al., 2014)]

2.4.3.2 Registration

Registration points cloud solution is an algorithm that permits to reconcile several scans of the same object taken from different positions or angles, and there are several methods to find overlapping parts in the data which depend on the type of feature. Among the methods for matching coordinates between different scans, it can be found Brute force matching, kd-tree nearest neighbor search, iterative closes point algorithm, etc. This type of algorithm is applied by programs such as Cloud Compare (Figure 18).
2.4.3.3 K-nearest neighbors (KNN) algorithm

The k-nearest neighbor (KNN) algorithm is a classical non-parametric classification method that has been widely used in many fields such as pattern recognition, feature detection, outlier detection, etc. due to its simplicity, effectiveness, and intuitiveness (Pan et al., 2020). This algorithm is employed for the search of the points’ neighbors by using parameters such as fixed distance or fixed number of points. Octree and Kd-tree algorithms are some of the alternatives available for the fixed distance method, however, Lato et al. (2010) explain how some error may arise due to the heterogeneity of the density of points. The method of the fixed number of points is utilized in the program Discontinuity Set Extractor as one of the first parameters for the coplanarity test calibration which is employed by a MATLAB function called knnsearch (Riquelme et al., 2014).
Chapter 3. Methodology

Figure 19 shows the conceptual drawing of the robotic system that is currently under development. This system is designed to autonomously navigate in an underground stone mine and scan the pillars. During the scanning process, ground robot will stop, UAV will take off, move towards to pillar wall, and stop at a certain distance from the wall. Then it will start scanning the pillar wall by flying parallel to the width of the pillar until it reaches to the pillar corner. Next, UAV increase its altitude, and at this higher altitude, it will repeat the parallel flight in the opposite direction. UAV will repeat these series of parallel and vertical flights until it completely scans the whole pillar wall. Autonomous navigation of the system and scanning of the UAV are not in the scope of this thesis, WVU robotics team is working on these subjects. However, quantifying the necessary scan resolution to be able to identify the geological structures (discontinuities, bedding planes etc.) from the 3D point cloud data is the main objective of this thesis. Results of this study will help evaluation of the current sensor on the UAV, and if it is necessary, to select a new one. Results of this study will also help research team to decide how far the UAV should fly from the pillar wall since this distance also effect the resolution of the 3D maps.

![Conceptual drawing of the robotic system.](image)

In the introduction chapter, additional to the main objective of this thesis, to identifying necessary resolution of point clouds, following additional objectives of the thesis are listed as: (i) evaluating the performance of available open-source algorithms to extract discontinuities automatically from
the point cloud data collected from underground stone mines and (ii) identifying the weaknesses of these algorithms for the future development of an improved method.

In the second chapter of this thesis, relevant literature on the research studies where application of terrestrial, mobile, and airborne sensor devices for 3D mapping for different engineering purposes were summarized. Literature review demonstrated that there are many different LIDAR system available, and accuracy of the results could vary drastically depending on the type of the system used and the application. In addition, error of LIDAR measurements in the field applications specifically in the underground applications are much larger than the ones listed in the specification sheets provided by the manufacturer. Therefore, in this study to account for the effect of different LIDAR systems and the environmental conditions on the results, (i) three different LIDAR system were used and (ii) point cloud data collected from different field studies performed in two different mines where different systems were used. In addition, when assessing the visibility of discontinuities from different 3D point cloud maps, pictures taken during the field tests and in one instance, geological mapping performed by experienced geologist were used as a reference. Finally, performance of the automatic discontinuity extractor algorithm from point cloud data collected from the field tests were assessed relative the results of the manual methods.

In the following sections, details of each of these tasks were summarized in the following order: First, type of LIDAR systems used in this research are introduced. Then, open-source point cloud data processing software and algorithm for extracting the discontinuities are introduced. Finally, field studies performed during this research are summarized.

3.1 LIDAR Systems Used in the Research:
For this study, three different LiDAR scanners were evaluated: a I-site 8200 terrestrial LiDAR scanner, a ZEB horizon mobile LiDAR scanner and a Depth Camera L1515 airborne LiDAR.

3.1.1 Terrestrial LiDAR I-site 8200
I-site 8200 is a short-range laser scanner (Figure 20). designed for underground survey application, it has a size of 415mm x 216mm x 378mm, a weight of 11.9 kg, a battery duration of 2.5 hours and it is suitable for underground surveys mounted on tripods or moving vehicles. According to its technical specifications I-site 8200 can map objects from an interval distance of 1 meter to 500 meters, has a range accuracy of 6 mm and a repeatability of ±6 mm. The laser scanner possesses
an 80° Field of View (FOV) which allows to obtain a close-range wall imaging and a scan window of 125° vertically, and 360° horizontally to capture roofs and walls. It also has an automatic levelling capability.

![Field of View (FOV)](image)

**Figure 20. I-site 8200 LiDAR scanner (Maptek, 2021)**

The I-site 8200 was tested on the field, and fourteen different scans were taken, an average of 4.5 million-point clouds per scan were collected, and a mean time per scan was 6 minutes and 10 seconds. This result indicated that 12,000 points/second were scanned by the I-site 8200 LiDAR on the KY mine (Equation 7).

\[
\frac{\sum \text{Avg. Point Clouds per scan}}{\text{Avg. Time per scan (s)}}
\]  

(7)

### 3.1.2 GeoSLAM ZEB Horizon

ZEB horizon is a Hand-held personal LiDAR that is equipped with a Velodyne Puck (VLP-16) laser scanner that possess a Field of View of 360°x270°, uses 16 lasers channels which map in total 300,000 points clouds per second (Figure 21). The scanner has a maximum range of 100 meters and only the scanning head with the handle weights 1.49kg and for the datalogger and battery are external, they need to be wired during the whole scanning process, so the total weight is 4.2 kg. The ZEB Horizon consists of a D time-of-flight laser range scanner rigidly coupled to an internal measurement unit (IMU) mounted on a motor drive, the motion of the scanning head on the motor drive proved the third dimension required to generate the 3D information. The Lidar scanner uses a Simultaneous Localization and Mapping (SLAM) algorithm to combine the 2D laser scan data with the IMU data to generate 3D point clouds, for this reason it is recommended perform as many loops as possible to minimize error and improve the accuracy of the result point cloud. The SLAM algorithm used to process the raw laser scan data into a 3D point cloud relies
on there being features in the scanned environment that are repeatedly scanned as the operator passes through the scanned environment. For a feature to be significant, the ratio of its size to its range must be approximately 1:10, e.g., at 5m range for a feature to be significant it must be >0.5m in size. It is necessary to process the raw data collected by the ZEB-HORIZON using GeoSLAM’s 3D SLAM algorithm to generate a homogenous 3D point cloud of the environment that has been mapped. This is done using the GeoSLAM Hub processing software (GEOSLAM, 2020).

Figure 21. ZEB HORIZON LiDAR scanner (GEOSLAM, 2021)

3.1.3 GeoSLAM Hub

The ZEB HORIZON system generates an output file (geoslam file). The geoslam file must be loaded into GeoSLAM HUB to provide full access to the available data. Among the info displayed it can be found the time taken for scan and the number of points within the point cloud. When exporting the point clouds, the output file format can be e57, las, laz, ply, or txt (ASCII), and the characteristics of the point cloud, such as the percentage of point cloud, the spatial decimation, normals and the RGB color which depend on the time, height, shape, etc, to be exported can be decided. The GeoSLAM HUB has reprocessing options which are useful for data that contains drift or slip. Drift and slip can be caused due to an inconsistent scanning method, or if the scanned area does not contain any features, for example smooth tunnels or a large plain field. Using reprocessing helps to solve data inconsistency in most cases. There are two different options to use when reprocessing the data: Local and Global. Local parameters define the local SLAM processing options, and when increased, solves 80% of drift cases. Global parameters are used for global SLAM reprocessing and usually solves issues when the data capture method was inconsistent and
when start and finish of the scan was in different places. The GeoSLAM allows to merge scans and to view, interrogate and note the data straight after processing (GEOSLAM, 2021).

![Figure 22. GEOSLAM Hub viewer (GEOSLAM, 2021)](image)

### 3.1.4 RealSense L515 Lidar Camera 1515

RealSense L515 depth camera is a small LiDAR camera that enables highly accurate depth sensing in a small form factor. The short exposure time of less than 100 nanoseconds (ns) that the camera has permits to captures rapidly moving objects with minimal motion blur. The camera that weights approximately 100 grams, is 61mm in diameter and 26mm in height which makes it easy to carry on a drone. This device according to its specification can process 23 million points per second, has a scan range of 0.25 m to 9 m, possess a 2MP RGB Camera, Inertial Measurement Unit and has three available streams depth, infrared and confidence (Figure 23). Two resolutions are available to choose from: 640x480 (VGA) and 1024x768 (XGA). In order to achieve longer range detection, VGA resolution is the one recommended by the fabricator, while for achieving a higher lateral resolution (better edge fidelity) the XGA resolution is preferred. The L515 offers one fixed frame rate of 30 frames per second (fps). When enabled, the camera uses information from the onboard IMU to determine if the camera is falling. When a fall is detected, the MEMS stops moving which is the better state for surviving high impact (Intel RealSense, 2021).
3.2 Point Cloud data processing:
For working and processing the data gathered by the previous scanners, point cloud conversion and processing software are required in order to process and visualize the collected data in this thesis.

3.2.1 Cloud Compare:
Cloud Compare (2015) is a program for managing and comparing 3D point clouds among its several functions, it can calculate local distances, subsample, or segment dense point clouds, measure the spacing between points, and display the point cloud in 3D views. The essential input that the program requires for modelling the point cloud is the position of the points which have to uploaded in the form of coordinates (x,y,z), the format can be e57, las, laz, ply, txt, etc. Cloud Compare also accepts RGB colors which has different scales of how colors are displayed e.g., grey, HSV angle, Blue>Green>Yellow>Red among others. The point picking functions allows to obtain information of any point and between points like position, distance, and angle. When the point cloud desired to be analyzed is part of a bigger cloud, it can be pulled out with the function segment which allows to extract the points chosen by using a polygonal or rectangular selection. Likewise, if the point cloud to analyze has a high point cloud density, the file would be too large and difficult to manage or process, for this reason there has to be a trade-off between level of detailed required and dimension of the file. For this issue, Cloud Compare has the sub sample function which reduces the number of points according to three different methods such as space, random and octree method where the inputs used for each method are remaining points, minimum space between points and subdivision level respectively. When there are two or more scans of the same object but from different positions, the point clouds of these scans can be combined to create a more thorough point cloud by using a process called registration or scan matching in Cloud Compare.
Between the methods for matching two-point clouds, there are match bounding-box center, match scales, align by picking point pairs and Iterative Closes Point (ICP). Cloud Compare also give the chance to compute the normals, which is necessary to estimate the local surface represented by a point and its neighbors, and choose a local surface model e.g., best fit plane, 2D triangulation or quadric surface. The program has a facet/fracture detection where the facets can extract using kd-tree or fast marching algorithm, the facets are classified by orientation and can be visualized with a stereogram, however this was not used for this investigation.

![Figure 24. Point clouds in Cloud Compare (2015)](image)

### 3.2.2 Discontinuity Set Extractor

Discontinuity Set Extractor is a program developed by Adrian Riquelme (Riquelme et al., 2014) that uses as input point clouds to extract discontinuity sets and its geometrical properties from a rock mass. DSE calculates the orientation of the principal planes extracted from the point cloud data as well as the spacing and persistence of the discontinuities.

#### 3.2.2.1 Coplanarity Test

The DSE program asks for three inputs before coplanarity test, the first one is the coordinates of the point clouds, a fixed number of closest point neighbors and a coplanar tolerance percentage obtained by applying a Principal Component Analysis (PCA). This mentioned tolerance represents the maximum allowable deviation of a subset of points, such that the subset can be considered reasonably as a plane (Riquelme et al., 2014).
Rencher (2002) explains that PCA is a one-sample technique that seeks to maximize the variance of a linear combination of variables that is applied to data with no groupings among the observations, therefore none of the variables are designated as dependent. The linear combination with maximal variance is called the first principal component and the linear combination with maximal variance in an orthogonal direction to the first principal component is called the second principal component, and so on (Figure 27).

![Figure 25. Calculation of principal component from linear combinations of variables](image)

In the coplanarity test applied in the DSE program, it is only required the first two principal components which will compound a plane, and the third principal component would be the error. It is suggested that the variance of the principal components account for 80%, which is one of the guidelines proposed by A. Rencher (2002) for accepting the main principal components. This means that the DSE program recommends considering coplanar a subset of points that has maximum allowable deviation or variance of the third component of up to 20%. Equation 8, shows $z_i$ that represents the matrixes of the principal components that depend on the matrix of coordinates represented by $y_i$ that is rotated by an orthogonal matrix $A$.

$$z_i = Ay_i$$ (8)

PCA is applied in the DSE program by using the MATLAB function called “princomp” that calculates the eigenvalues and eigenvectors of the coordinate’s matrix. In Equation 9, the variance of the principal components is represented by $\lambda$, which is also the eigenvalue of the calculated component.

$$S_{z_i}^2 = \lambda_i$$ (9)

Equation 10 represents the calculation for obtaining the eigenvector represented by $\tilde{v}$:
\[(A - \lambda I)\vec{v} = 0\]  \(10\)

Where \(I\) is an identity matrix which is a square matrix of \(n \times n\) size with ones on the main diagonal and zeros elsewhere. For example, an identity matrix where \(n\) is 3 would be represented by Equation 11.

\[I_{n=3} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.\]  \(11\)

Equation 12 shows the proportion of variance by the third principal component, where \(n\) represents the error threshold for considering a group of points as a plane in DSE.

\[n = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}\]  \(12\)

### 3.2.2.2 Coplanar plane orientation calculation

After identifying all the groups of points that were considered coplanar between each other, the orientation of the new planes is calculated by obtaining the normal vector of each coplanar point. The normal vectors are already calculated by the PCA when the eigenvector of the third principal component was found in Equation 10.

\[\vec{v}_3 = (A, B, C)\]  \(13\)

\(\vec{v}_3\) stands for the eigenvector of the third principal component which serve as the unit normal vector for each coplanar point (Equation 13).

### 3.2.2.3 Best fitting plane statistical analysis

Parallelism of normal vectors is the key for this process, if the normal vector of different group of points possesses certain degree of parallelism between each other, it is expected that the orientation of the planes formed by those groups have similar orientation. For performing this analysis, normal vectors are calculated for each coplanar group of points, and they are converted into stereographic projection (Ramsay & Lisle, 2000). This process of stereographic projection consists in transforming the normal vectors of the coplanar points into dip and dip directions vectors.
In figure 26, \( \hat{n} \) represents the normal vector of the plane to be analyzed which can be obtained with the dip angle \((\delta)\) and the strike angle \((\phi_f)\) (Equation 14).

\[
\hat{n} = \begin{bmatrix} A \\ B \\ B \end{bmatrix} = \begin{bmatrix} -\sin(\delta) \sin(\phi_f) \\ -\sin(\delta) \cos(\phi_f) \\ \cos(\delta) \end{bmatrix}
\] (14)

Since the normal vector is already calculated with the eigenvector of the third principal component by the PCA, the dip angle and strike angle can be found by comparing them in Equation 14. A stereonet pole projection requires the dip and dip direction, therefore with the strike value, the dip direction can be known (Equation 15).

\[
\text{Dip Direction} = \text{Strike} + 90^\circ
\] (15)

Once generated the dip and dip direction of every single point clouds, they can be represented in the stereonet, however since the amount of point clouds are vast, drawing lines on the stereonet can result messy. For this reason, it is better to draw poles that is the projection of the line that passes perpendicular to the plane analyzed (Figure 27).
3.2.2.4 Kernel Density Estimation

Plotting a plane as a pole in a stereonet is more efficient than drawing lines, however a stereonet will not be able to represent clearly all the planes of a geometrically heterogeneous area such as an underground stone mine pillar that is composed of several planes with different and similar orientation (Figure 28).

Therefore, for representing the principal poles from a considerable number of poles like the one showed in Figure 28, it is used the algorithm Kernel density estimation (KDE) which allows to represent the density distribution of all the poles in the stereonet (Figure 29).
KDE is a non-parametric technique that permits to estimate the probability density function of random variables, in this study, these variables are the dip and dip direction of the pole’s projection. Equation 16 shows the function that represent KDE.

\[
\hat{f}_h(x) = \frac{1}{n} \sum_{i=1}^{n} K_h(x - x_i)
\]  

(16)

Where \( h \) represents the bandwidth that is the smoothing parameter for plotting the distribution curve that represents the data, \( x \) is the independent and identically distributed samples of \( n \) observations and \( f \) is the unknown probability density function at any given point \( x \). There are several types of kernel functions such as symmetric kernels and asymmetric ones, but DSE uses the Gaussian DSE function which is symmetric (Equation 17).

\[
K(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}
\]  

(17)

KDE is applied in DSE with the MATLAB command kde2d where the normal vector poles are clustered in distribution curves and the peaks represent the main orientations of the planes represented by \( J_n \) (Figure 30).
3.2.2.5 Semi-automatic set identification

In this step of the process, the number of principal poles is defined by two input factors that the DSE program requires; these factors are the minimum angle formed by two principal vectors called cone filters and the other one is the maximum number of principal poles represented in the stereonet called the pole filter. When the pole filter is applied, only the principal poles with the highest density are considered for further analysis (Figure 31).

When cone filter is applied, some of the poles are not assigned to any principal pole so they do not receive any orientation and are discarded, eliminating the noise in the stereonet allowing to have a clearer image of the principal planes or discontinuities (Figure 32).
Finally, the principal poles are registered as the main planes (or discontinuities) that the rock mass has, and it can be visualized in the program Cloud Compare for a better understanding. Figure 33 shows how the pillar was classified in 3 principal planes according to their orientation.

Figure 33. Pillar classified by planes orientations in Cloud Compare

3.3 Data Collection from field studies

The importance of identifying as much information as possible with a reasonable accuracy and precision is vital to perform a good characterization of the geological structures on the pillars. For this reason, the resources used for this study were digital cameras, external flashlights when there was no illumination, and Lidar scanners which were enough for obtaining the required data. The
digital cameras used for the case studies were phone cameras with 16 megapixels, the external illumination of one scenario came from lights already placed in the mine and on the other scenario the lights came only from hands-free cap lamps Wise Lite that provide 8500 lux which were necessary to identify visible geomechanical features present in the rock mass.

3.3.1 Field Study #1

The first case study was carried out in a KY stone mine in a location where the pillars were partially benched, and the only illumination used for the data compilation was the lights coming from the hands-free cap lamps (Figure 34).

![Figure 34. First Case of Study](image)

In this location at least 10 pictures from different angles of rock mass analyzed were taken, a visual assessment report was done by a geologist and fourteen scans with the Maptek I-site 8200 Lidar were performed. The I-site 8200 scanner was mounted in a tripod with a height over 5 feet and 18 feet away from the rock mass analyzed, and each scan took approximately six minutes. The objective for this field study with the data gathered were:

I. Compare manual mapping of discontinuities from 3D point clouds to mapping results of the geologist.

II. Compare manual mapping of discontinuities from 3D point clouds to automatic mapping with Discontinuity extractor.

III. Photographs from the phone are used to help you to visualize the structures not as a photogrammetry application.
3.3.2 Field Study #2

For the second field study, the area analyzed was one of the sides of a stone mine pillar located in the intersection of a main pass and a crosscut, this intersection was illuminated by the mine. The data gathered for this case study were around twenty pictures from different angles and the device used was a ZEB horizon LiDAR scanner. The ZEB-HORIZON is a 2D time-of-flight range Velodyne Puck VLP-16 scanner which for the collection of cloud points the user carried the scanner wired to an external battery and data logger device during all the scanning process (Figure 35).

![Figure 35. LiDAR scanner ZEB HORIZON](image)

For an efficient point cloud data collection with the ZEB HORIZON, the station where the scanning process starts must also be the last one. The scanner works with a SLAM algorithm that process the raw scan data into point cloud by applying a method analogous to the Traverse technique, where a known position is used to determine its current position. This survey practice is called loop closure and it is explicitly suggested by the manufacturer to close the loop as often as possible to minimize error and improve the accuracy of the resulting point clouds (Figure 36).
The objectives in this field study were:

I. Manually extract the discontinuities from the 3D point clouds. Photos from the phone used to verify if your assessment from pcs analysis.

II. Compare discontinuity extractor results with manual analysis.

3.3.3 Field Study # 3

The third field study was at the same location as the second one, therefore all the information gathered from the previous test helped for doing a comparison with the information gathered in this case. Autonomous scanning of the UAV was tested, the scanner used for this test was a RealSense L515 depth camera that was mounted on a drone and the mapping was performed from 2 meters away from the stone mine (Figure 37).
The objective was to identify the important operational parameters during this test to guide robotics team to set autonomous operational parameters (closeness to rib and necessary point cloud density) using the results obtained in field test #1 and #2.

Photos taken for field test #2 served as reference for making a preliminary identification of the discontinuities and features expected to be found after processing the data gathered by the Lidar scanner (Figure 38).
3.4 Processing of the Data

As mentioned before, the programs chosen for this research are GEOSLAM Hub, Cloud Compare, and Discontinuity Set Extractor (DSE) program for processing the point clouds obtained from the LiDAR. Cloud Compare and DSE are free open-source programs which code is publicly available for everyone.

3.4.1 Extraction of the Data

When using a LiDAR scanner, the mapping process obtains information from the whole environment where the scanner is used and not only from the area of interest, which can cause the scan files generated to be very large, noisy, difficult, and time-consuming to process by the software programs. For this reason, it is important to extract exclusively the point clouds necessary for the analysis, and this can be done by using the function segment of the Cloud Compare program. Figure 39 (left) shows a point cloud with 2,651,396 points but the only area in the green square is desired to be analyzed, so Cloud Compare can extract that area (Figure 39-right) that now
has 627,791 points, which is easier to evaluate and process due to it has a smaller size.

*Figure 39. Raw Point Cloud(left) and Segmented Point Cloud(right)*
Chapter 4. Discontinuity Mapping

In the previous chapter, research tasks performed during this study, objective of each task and methods used to reach the objectives were summarized. Three field tests were performed in this research. In the first field test, terrestrial LIDAR scanner, I-site 8200, was used to scan the stone mine face, and conventional geological mapping of the face was performed by an experienced geologist. Point cloud data collected in this test were processed with Cloud Compare, and discontinuities are mapped from the 3D map and compared with the conventional mapping performed during the field test by the geologist. In the second field test, SLAM based LIDAR system, GeoSLAM, was used to scan the stone mine pillar. Data from this test is also processed with Cloud Compare and discontinuities are mapped and compared with the discontinuities identified on the photographs taken during the field experiment. In the third field test, pillar wall was scanned by the UAV autonomously. During this test, the autonomous flight trajectory of the UAV and the LiDAR scanning were observed to identify the operational parameters necessary to reach desired high resolution 3D maps.

Point clouds data collected from the first two field tests were also processed using open-source DSE software algorithms to evaluate performance of automatic discontinuity extraction and identify weaknesses to improve these methods further. In addition, a sensitivity analysis is performed to evaluate the influence on the input parameters (KNN, tolerance, etc) of the program on the results of automatic discontinuity extraction.

In this chapter, first results of each field test are presented. Then automatic discontinuity extraction results are presented and compared with the results from manual methods. Finally, overall analyses of the results are summarized.

4.1 Field study #1 results

In the literature review section, applications of terrestrial LIDAR to map the discontinuities are presented, and most of these studies were performed in the surface operations (Fisher et al., 2014; Kemeny et al., 2003; Lato et al., 2009; Rosser et al. 2005; Sturzengger and Stead, 2009). Some authors presented that point cloud data gathered from the terrestrial LiDAR in underground mines can also be used to visualize and identify the geological structures on rock mass (Slaker, 2015; Chen et al., 2018; Idrees & Pradhan, 2018). These publications demonstrated that geometric properties of the discontinuities, size, shape, and orientation of structures can be extracted from
the LIDAR data. Monsalve et al. (2019) considered that a density between that 4 points per cm$^2$ and 16 points per cm$^2$ is acceptable to visualize discontinuity mapping in view of previous work regarding this topic (Lato et al., 2009; Cacciari & Futai, 2017). The point cloud density range used by Monsalve et al. (2019) must only be considered as a reference since the investigation aimed for structural mapping and not finding the ideal point cloud density (points/cm$^2$). Another important knowledge missing in the literature is how to perform field tests to get desired resolution to identify discontinuities from the point cloud data. To increase the resolution, scanner can be set up closer to the face, but such a practice might not be efficient since the number of scans to cover an area with a terrestrial LIDAR would increase. In addition, identifying joints or bedding planes might require consideration of different properties of the point cloud data than just resolution. For this case study, I-site 8200 LiDAR was used to map the discontinuities on the rock face, and conventional geological mapping of the face was also performed by an experienced geologist. Scanner used in this study was operated by Dr. Brent Slaker from Pittsburgh Mining Research Division of NIOSH.

4.1.1 Field test location

The investigation took place in main pass N-9 of an underground limestone mine where the pillars were partially benched. The zone analyzed was an area subjacent to two partially benched pillars and beneath a crosscut of an upper level (Figure 40). For this case study, I-site 8200 LiDAR scanner was used and according to manufacturer specifications, I-site 8200 can provide a range accuracy of $\pm 6$ mm. The scanner was placed approximately 18 feet away from the rock face.

![Image](image_url)

*Figure 40. I-site 8200 LiDAR scanner (Maptek, 2021)*
Fourteen scans were taken with the LiDAR scanner along the main pass N-9. Figure 41 shows the plan view of the mapped section from point clouds generated from those scans, and Figure 42 shows the plan view of the mine plan and location of each scan along the section.

Figure 41. Location of area scanned  

Figure 42. Plan View of KY Stone-Mine Point cloud

Figure 43 shows the area on the rock face that is selected for the mapping of the discontinuities. Area studied presents visually clear details of the bedding planes in the rock mass and have the dimensions of 35 ft of height and 52 ft of width represented by the green square.
There are total of 583,594 data points in this area, however, figure 44 reveals that there were several considerable voids in the point cloud represented by the yellow circles (Figure 45). Causes for data voids can be due to several factors such as water absorption, type of material, uniformity of the point density, among others. However, for this specific case it seems that probable causes for the gaps in the point cloud can be related to terrain conditions, location from the scanner and orientation of the rock mass. The first considerable void appears at a height of approximately 24 feet from the floor (Figure 45), the tripod height was 6 feet, and it was 18 feet away from the rock mass.

- \( H = \text{Height of first cloud point void from the floor} \),
- \( h = \text{Height of tripod from the floor} \),
- \( D = \text{Distance from} \),
- \( \alpha = \text{angle of scanner to point cloud void} \).

\[
\alpha = \tan^{-1}\left(\frac{H - h}{D}\right)
\]

The angle where the first point cloud gap appears is closely 45\(^\circ\) (Equation 18), this angle does not seem to be a problem for not scanning that part of the rock mass, so it seems that the orientation...
of that section of rock mass was the main cause of it. Therefore, it was decided to select a smaller portion of the face where the point cloud was denser and more homogeneous. Green square in figure 44 show a point cloud with fewer and smaller void spacings.

![Figure 44. Height of first point cloud void](image)

![Figure 45. Point cloud with voids spaces](image)
4.1.2 Conventional mapping of the discontinuities by the geologist

Conventional geological mapping of the rock face (Figure 43) was performed by a geologist during the field test. Figure 46 shows the results of mapping the total height of the partially benched pillar, the height and condition of the upper level crosscut, the type of material and discontinuities found, and the distribution of the roof supports of the cross-section in figure 43. According to the report, the height of the partially benched pillar is 66 feet, the height of the crosscut is 30 feet, the roof is a shaley limestone bedding plane, the floor of the upper level is fracture with an apparent heave or lamination, and the distribution of the bolts are 5 feet and 6 feet at the crosscut and main pass respectively. The four bedding planes identified in this section possess the following material characteristics and thickness dimension:

- Light gray and blocky with 2 feet,
- Medium gray and massive 1.5 feet,
- Light gray and blocky with 2 feet,
- Medium gray and massive with 1.5 feet.

Due to the lack of illumination of the place, no discontinuity joints were perceived by sight.

Figure 46. Geologist Visualization Assessment report
Digital photographs were also taken to help visualization of the section studied, the material looks very blocky, and 3 bedding planes were identified easily however faults or joints were not easily identified due to the lack of illumination (Figure 47).

![Figure 47. Picture of the area analyzed, and bedding planes visualized](image)

4.1.3 Discontinuity mapping from point cloud evaluation

The point cloud of the rock mass section in figure 43 is evaluated in the software program Cloud Compare to assess if the features and dimensions identified in the field can be seen in the point cloud. The height of the section is 65.5 feet, and the roof supports are visible and were measured resulting in a distance between bolts in the crosscut of nearly 6 feet (Equation 19) and in the main pass of closely 5 feet (Equation 20) (Figure 48).

\[
\text{Crosscut supports distance} = \frac{\sum \text{Spacing between bolts along the crosscut}}{\text{Number of bolts}} \quad (19)
\]

\[
\text{Main pass supports distance} = \frac{\sum \text{Spacing between bolts along the Main pass}}{\text{Number of bolts}} \quad (20)
\]
Due to abovementioned voids in the point cloud in Figure 45, a smaller portion with dimensions of 7.3 feet of height by 10.8 feet of width was selected (Figure 49), with the purpose to extract the as much detail as possible from the discontinuity joints. It is important to mention that this point cloud has RGB colors enabled which allows to see a difference of grays and identify the different rock bands. Four bedding planes were identified during the visual characterization. The uniformity and better density of the point cloud (Figure 49) depends on the position of the LiDAR scanner, terrain conditions (orientation) and height of the rock mass.
The 4 bedding planes were identified and have the following dimensions and characteristics (Figure 49):

- 2.0 feet and light gray,
- 1.7 feet and dark gray,
- 1.5 feet and light gray,
- 1.8 feet and dark gray.

The point cloud for the analysis has an area of $7.3 \, m^2$ and it is composed of 37,805-cloud points, resulting in a point cloud density of 0.5-cloud points per centimeter square (Equation 21):

$$\text{Cloud point density} = \frac{\text{Cloud points}}{\text{Area}}$$  \hspace{1cm} (21)

Joint sets were not easy to identify using this point cloud data (Figure 50), and the possible causes of this can be the low point cloud density or the blocky and massive nature of the rock mass. Although, some rock mass planes orientation could be identified as probable joints.

![Figure 50. Point Cloud Visual Characterization](image)

Analyzing the raw point cloud, it was found:

- A possible discontinuity with an approximate vertical orientation (yellow line),
- A possible discontinuity with a positive inclination from left right (red line).

The apparent discontinuities (Figure 50) were not explained in the geologist mapping and it will be discussed in detail later in the thesis.
4.1.4 Automatic discontinuity extraction analysis with DSE

Point cloud data used in the previous section to visually identify the discontinuities were processed using the open-source DSE software algorithms. In order to assess the effect of parameters on classification of the discontinuities, a sensitivity analysis was performed. DSE algorithms and parameters were explained in chapter 3 of this thesis. Figure 50 shows the point cloud used in the sensitivity analysis to understand how the nearest neighbors search with K-Nearest Neighbors Algorithm (KNN), the third principal component variance and the minimum angle between principal pole planes impacts on the results of classifying the principal pole planes. For KNN analysis, six different values of 5, 10, 20, 30, 50, 100 were taken, being 30 the number of point neighbors and the following input values recommended by A. Riquelme (2014):

- Third principal component variance = 20%
- Angle minimum between principal poles = 30°
Point clouds of figure 51 (1-3) with KNN of 5, 10 and 20 respectively, do not seem to classify efficiently the principal pole planes and as it can be observed, it is difficult to make a discrimination between the limits or boundaries between different planes. On the other hand, point clouds of figure 51(4-6) with KNN of 30, 50 and 100 respectively, provide better visualization of the planes classified by their orientation, the greater the number of KNN the better the classification. A test about the time taken to calculate the local curvature of the point cloud with the different KNN was performed and it was found that for KNN from 5 to 30 takes 77 seconds, being KNN = 30 the one that provides a better classification, while using a greater number such as 50 or 100 represents an increment of the time by 6% and 20% in time respectively. KNN of 50 and 100 delivers better but minimal improvements of classification compared to the results when using KNN of 30, however, time can be a problem when analyzing more than one side of a pillar where each side is mapped with 2 million points for example, therefore the value of 30 for KNN is the most efficient in terms of classification and time and was used for further analysis.

Figure 51. Comparison of principal pole planes with different KNN

(5) KNN = 50
(6) KNN = 100
For the analysis of the third principal component variance, 5 different percentages were chosen 5%, 10%, 20%, 30% and 40%, being 20% the maximum tolerance, while setting the input of KNN to 30 since in the previous analysis its efficiency was shown and the angle between principal pole planes was still set to 30° as suggested by Riquelme (2014).

All the point cloud models in Figure 52 (2-5) identify 8 principal pole planes, the total points visualized are approximately 28,000 and the principal pole planes can be easily identified in Cloud Compare. On the other hand, a tolerance of 5% (Figure 52.1) yielded a point cloud with considerable gaps with a total number of points of nearly 17,000 which made difficult to identify.

Figure 52. Comparison of principal pole planes with different tolerance values (third principal component variance)
the principal pole planes. Using a tolerance of 10% or higher (up to 40%) didn’t make any significant difference in the results, so further analysis will be done with 30% as suggested by A. Riquelme (2014).

For the analysis of the angle between principal pole planes, 5 different angles were chosen 10°, 20°, 30°, 40° and 50°, and the other parameters such as KNN and tolerance were set to 30 and 20% respectively according to the results found in the previous analysis.

(1) Angle = 10°

(2) Angle = 20°

(3) Angle = 30°

(4) Angle = 40°
The point cloud with the angle of 10° in figure 53(1) shows the calculation of 18 principal pole planes and several voids which makes it difficult to identify the principal pole planes. The point clouds with the angle of 20° and 30° in figure 53(2, 3) yields 9 and 8 principal poles planes respectively, and in both cases the principal pole planes agree more with the ones observed in figure 50. Finally, the results with the angles of 40° and 50° in figure 53 (4, 5) presents 6 and 5 principal poles planes respectively, however these angles discriminate several points, and the planes are not clearly appreciated. Hence, the angles 20° and 30° brings better results, for further analysis the angle 30° was used.

After the performing the visual evaluation of the point cloud with Cloud Compare and the sensitivity analysis with DSE, this point cloud is uploaded to the program Discontinuity Set Extractor for identifying the principal planes and their geometrical characteristics. Six principal plane sets along with their orientation (Dip and Dip Direction), Kernel density estimation values (Density) and point-cloud percentage (%) were calculated in the point cloud analyzed (Table 6). The point-cloud percentage shown in table 6 is the proportion of the points assigned to a plane divided by the total points that went through the coplanar calculation.

Table 6. Principal pole planes orientation

<table>
<thead>
<tr>
<th>Legend</th>
<th>Joint Set</th>
<th>Dip Direction</th>
<th>Dip</th>
<th>Density</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>117.44</td>
<td>79.48</td>
<td>2.52</td>
<td>53.47</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>332.72</td>
<td>82.86</td>
<td>0.4928</td>
<td>12.89</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>66.08</td>
<td>52.65</td>
<td>0.0184</td>
<td>1.27</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>226.59</td>
<td>78.63</td>
<td>0.017</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>262.55</td>
<td>90.00</td>
<td>8.04E-04</td>
<td>24.97</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>168.08</td>
<td>38.14</td>
<td>2.59E-04</td>
<td>0.95</td>
</tr>
</tbody>
</table>
DSE plots the principal plane sets in a stereonet, and it can be seen how Joint Set 1, Joint Set 2 and Joint Set 5 are the ones that have the highest local maximums (Figure 54); therefore, they are the most likely to be discontinuity joint sets.

![Figure 54. Plot of Principal planes in a stereonet](image)

The point clouds are colored according to their orientation and then grouped back again to visualize the new classified cluster of this data set; this point cloud is classified in 6 different colors (Figure 55).

![Figure 55. Cloud points classified by orientation](image)

Analyzing visually the processed point cloud with six different principal planes set, it can be said that:

- Joint set 1: not a discontinuity, it is the orientation of the nearly vertical rock face.
- Joint set 2: Possible discontinuity, with orientation nearly vertical going inside the rock mass.
- Joint set 3: not likely discontinuity, orientation of a neglectable small portion of rock mass.
• Joint set 4: not likely discontinuity, orientation of a neglectable small portion of rock mass.
• Joint set 5: Possible discontinuity, with orientation vertical going inside the rock mass.
• Joint set 6: not likely discontinuity, orientation of a neglectable small portion of rock mass.

It must be mentioned that the bedding planes were not calculated in the DSE analysis.

4.2 Field study #2 results
In the literature review section, mobile LiDAR technologies with SLAM approach are discussed. This new technology has the advantage to perform a more efficient and wide-ranging survey of the mine compared to static scanners. However, accuracy of these scanners would expect to be lower, but structural mapping by applying multi-view data collection due to their maneuverability reduce blind spots (Singh et al., 2021). In order to assess 3D resolution that can be gathered from this new technology, GeoSLAM ZEB Horizon was used in the second field study.

4.2.1 Field test location
The site of this second case study is located in an underground mine located in southwestern Pennsylvania, where the predominant geologic composition is Loyalhanna Limestone, major source of crushed stone. The subject of study was a development pillar with dimensions of 27 feet in height and 45 feet by 45 feet in length and width respectively, located in the intersection of main pass number 10 (M-10) and crosscut number 3 (C-3).

Figure 56. Location map of Pilar

Due to the operational activities of the underground stone mine, the location of the pillar analyzed was illuminated, allowing to make a preliminary identification of the visible discontinuities present on the surface of the rock mass. Likewise, the location of the pillar was not a transited area which
made it easy for the mapping with the mobile LIDAR. Several scans were performed over the same area to make sure sufficient data was recorded.

4.2.2 Preliminary visual characterization

- The pillar analyzed did not show any signs of failure such as major fractures, spalling, sloughing or other instability conditions that might represent a geomechanical issue or condition causing a hazard or risk. Two main discontinuity sets were identified in this step, the first one was an incline discontinuity set that has a negative slope from left to right of the pillar, the other one was a vertical joint on the right of the pillar. A bedding plane was also observed on the top middle that has a dark-brown coloration (Figure 57). Discontinuity 1: This joint set is represented by four yellow lines with a negative incline orientation from left to right,
- Discontinuity 2: This joint set is represented by the three blue lines located on the right side of the pillar with an orientation approximately vertical,
- Bedding plane: Bedding plane is represented by the brown line; the bedding plane has darker brown color which is located on the upper side of the pillar.

![Figure 57. Underground stone mine pillar and highlighted discontinuities](image-url)
4.2.3 Discontinuity mapping from point cloud evaluation

For this case study, the ZEB-HORIZON LiDAR scanner was used, and three loops were traversed around the pillar to obtain as much detail as possible from the section where the pillar to analyze is located, the information was uploaded to GEOSLAM Hub and the result can be visualized in Figure 58.

![Location of Pillar](image)

*Figure 58. Vertical sight of point clouds in GEOSLAM Hub*

GEOSLAM Hub allows the user to just visually inspect the point cloud and it can be found a purple line which represent that the estimated localization of the scanner during the mapping (Figure 59). GEOSLAM Hub program also transforms 3D data into point cloud data files readable by other point cloud processing programs such Cloud Compare.

![Point cloud analyzed in GEOSLAM Hub](image)

*Figure 59. Point cloud analyzed in GEOSLAM Hub*
After converting the point cloud of the mine section (Figure 54) in a readable file, this was uploaded to Cloud Compare in order to the segment the pillar of interest to perform discontinuity mapping analysis.

![Image of Stone mine pillar in Cloud Compare](image)

*Figure 60. Stone mine pillar in Cloud Compare*

After extracting the pillar from the mine section (Figure 54) the dimensions of the pillar were measured and it was calculated that the point clouds for the analysis have an area of 122.7 $m^2$ and it is composed of 1,602,314-cloud points, resulting in a cloud point density of 1.3-cloud points per centimeter square.

$$\text{Cloud point density} = \frac{\text{Cloud points}}{\text{Area}}$$

The point cloud of the pillar was visually assessed in GEOSLAM Hub and Cloud Compare, and although the pillar was shown with great detail in both programs it was not possible to visualize the discontinuities in any of them. The difficulty of observing the discontinuities that were identified in the field could be because the rock mass that compose the pillar seems to be massive, the traces of the discontinuities are not well represented in the point cloud.
4.2.4 DSE Point cloud processing

After the performing the visual evaluation of the point cloud (Figure 60) with Cloud Compare, this point cloud is uploaded to the program Discontinuity Set Extractor for identifying the principal planes and their geometrical characteristics. Three principal plane sets along with their orientation, density and point-cloud percentage were found in the point cloud analyzed (Table 7).

Table 7. Principal pole planes classification

<table>
<thead>
<tr>
<th>Legend</th>
<th>Joint Set</th>
<th>Dip Direction</th>
<th>Dip</th>
<th>Density</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>271.73</td>
<td>76.34</td>
<td>1.19</td>
<td>43.9</td>
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<td>2</td>
<td>44.99</td>
<td>3.85</td>
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<td>6.46</td>
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<td></td>
<td>3</td>
<td>24.45</td>
<td>81.57</td>
<td>0.22</td>
<td>11.04</td>
</tr>
</tbody>
</table>

DSE plots the principal plane sets in a stereonet, and it can be seen that Joint Set 1, Joint Set 2 are the ones that have the highest local maximums (Figure 61), there they are likely to be the main discontinuity joints, but interpretation is still required.

Figure 61. Plot of Principal planes in a stereonet

The cloud-points are colored according to their orientation and then grouped back again to visualize the new classified cluster of this points, and it can be seen that in this case of study there are only three different colors (Figure 62).
Analyzing visually the processed point cloud with six different principal planes set, it can be said that:

- Joint set 1: it is not a discontinuity; it is the orientation of the nearly vertical rock face of the pillar,
- Joint set 2: most of the points describe the roof and floor that have a nearly horizontal orientation and only a small portion of the discontinuity set that was identified visually is classified in the program.
- Joint set 3: likely discontinuity, with orientation nearly vertical going inside the rock mass.

4.3 **Field study #3 results**

The Unmanned Aerial Vehicle (UAV) build by the WVU Robotic department performed a test run to find the parameters required that would allow to obtain the best output for later discontinuity mapping analysis. The UAV equipped with a LiDAR Depth Camera L1515 was set up to execute a trajectory planning algorithm which consisted of flying and scanning the pillar wall by flying parallel to the width of the pillar and going higher each time it reached the limit of the pillar until the top (Figure 63).
The UAV did the trajectory two meters away from the pillar wall obtaining a field of view approximately of $6m^2$ per frame, however, the main goal of the test was to accomplish the autonomous flying of the drone, for this reason the vertical movement ($h$) for the scanning process was not taken into consideration. The result of the discontinuity mapping with the UAV was a 45-million-RGB point cloud that shows true colors of the pillars (Figure 64).
However, the point cloud generated did not match correctly with pillar scanned which it noticeable by checking the two characteristics of the pillar were taken as reference. The green circle marks the word “Exit” written with an orange color and the blue circle marks the sign “M-10” written in white that can be found in Figure 64. The main reason why the point cloud did not match correctly to the pillar was that the frames generated by the LiDAR camera did not overlap the previous frames specially the ones created when the drone would fly vertically. Taken as reference the overlap between photos where it is suggested a 50-60% of overlapping between them (Hernandez & Lemaire, 2017), it is possible that a lower overlap must have occurred in this test.

![Figure 65. Vertical sight of Point cloud model showing duplicate points](image)

The point cloud was uploaded to the Cloud Compare program to visualize the pillar model and several noise points were found and a portion of rock face had been duplicated showing a model with what apparently looked like a second layer. (Figure 65). Therefore, performing a point cloud analysis of this model would not have accurate results.

### 4.3.1 Point cloud collection and processing

The Intel RealSense L515 LiDAR camera used for this case study has a more restricted scanning range than the other scanners used, since it is a camera, the dimensions of the area to be scanned vary depending on the Field of View (FOV) of the camera and the distance of the device from the object to be mapped (Figure 66).
Field of view (FOV) is the maximum area of a sample that a camera or sensor can image. It is related to two things, the focal length of the lens and the sensor size (Teledyne, 2021). The Intel RealSense L515 LiDAR camera possess a field of view of $70^\circ \times 55^\circ$, and the camera was 2 m away from the pillar, therefore for obtaining the area that can be mapped from a certain distance, this can be calculated using the following equations:

\[
x = 2d \times \tan(H.FOV/2)
\]

\[
y = 2d \times \tan(H.FOV/2)
\]

\[
FOV\ Area = x \times y
\]

Where,

- H.FOV = Horizontal Angle of the Field of View,
- V.FOV = Vertical Angle of the Field of View,
- $d =$ distance from the object mapped to the camera,
- $x =$ maximum horizontal dimension camera can map,
- $y =$ maximum vertical dimension camera can map,

\[
Point\ Cloud\ density: \frac{Point\ cloud\ per\ frame}{Area\ FOV\ (cm^2)}
\]

The FOV areas obtained for the Intel RealSense L515 LiDAR camera vary depending on the distance of the UAV from the stone pillar and consequently this will impact in the point cloud density as it can be observed in the following chart (Figure 67).
Figure 67. Point Cloud Density VS Distance Chart

The point cloud density obtained for a distance of 2 meters in an area of 5.8 square meters was 396 points clouds per centime square.

4.4 Analysis of the results

This section presents the results found in the three field studies.

4.4.1 Field study #1

Visual assessment from digital images was not very effective since the illumination only permitted identify three bedding planes which were not very clear on the photos, likewise, it was not possible to identify any discontinuity joint.

Discontinuity mapping with Cloud Compare gave good results when comparing the geological visual assessment report, it was possible to identify the four bedding planes, the height of the not-fully benched pillar, the height of the crosscut and the distances between bolts very accurately. However, it was difficult to identify the discontinuity joints present in the rock mass, this could be due to the point cloud density or the detail of visibility that the point cloud or the Cloud Compare program permits. For this reason, the discontinuity joints observed were categorized as apparent discontinuities (Figure 68).
DSE Characterization calculates six principal pole planes from which the ones that appear to be the more relevant in the rock mass are Joint Set 2 Joint Set 5. Joint Set matches the apparent discontinuity 1 found in cloud compare. DSE also identifies another small pole plane under the name of Joint Set 6 which matches the apparent discontinuity 2 in cloud compare, however, the continuity and the trace length do not match accurately. DSE can help to confirm if there is a discontinuity or not.

4.4.2 Field study #2

The Visual characterization on field and the digital imaging assessment can identify the presence of two discontinuities joint sets and one bedding plane. On the other hand, it wasn’t possible to identify these discontinuities from point clouds scanned with Zeb Horizon LiDAR scanner uploaded to Cloud Compare and processed by GEOSLAM Hub. (Figure 70).
Discontinuity Joint sets characterization using DSE program found three discontinuity joint sets, from which only Joint set 3 (Figure 71) matched Discontinuity 2 (Figure 70). Discontinuity 2 (Figure 70) was not correctly identified by the DSE program, only a small portion matched with Joint set 2 (Figure 71), this could be because Discontinuity 2 is identified visually by its trace length while DSE only calculates plane orientations. Bedding planes could not be identified in this process.

Figure 70. Bedding Planes and Dimensions Comparison.

Figure 71. Discontinuity Joints Comparison characterization approaches
4.4.3 Field study #3

Airborne LiDAR output was a point cloud which dimensions did not match accurately the stone mine pillar due to the several frames scanned did not overlapped accordingly resulting in a model where it can be appreciated a repetition of the pillar surface like a double layer and noisy points as well. Intel RealSense L515 LiDAR camera, according to its specification sheets, can map 23 million point per second, and since its’ Field of View is 70° x 55°, high resolution 3D point cloud maps can be generated. Field Study #1 and #2 have shown a reference of the point cloud density required (0.5 and 1.3 pc/cm²) to visualize the desired discontinuities which is significantly lower than the density obtained in Field Study #3 (396 pc/cm²). For this, it is recommended to scan the pillar from a greater distance, e.g., 4 meters which will have a FOV area of 23 m², it is also recommended that for a good match of the point clouds there has to be at least 50% of overlap between frames, for this case an 80% of overlap was chosen. The path that the drone did for scanning the pillar is shown in figure 72, since the problem with matching the frames was vertical, it is necessary to know how high(h) the drone should go up for matching the lower scans.

![Drone path for scanning pillar](image)

\[ h = \frac{0.8 \times \text{FOV Area}}{x} \]  

(26)

For a distance of 4 meters the drone should go up by approximately 0.8 meters for matching 80% of the lower frames, this method can provide sufficient point cloud density (100 pc/cm²) and accuracy (matching) for recognizing the superficial discontinuities.
Chapter 5. Conclusions and Future Studies

5.1 Summary

In the United States, the room-and-pillar method is generally applied for mining bedded limestone formations in underground stone mines, which inherently possess strong rock and experience good ground stability. In addition, NIOSH have improved the design of stable layout for modern limestones by developing the modern pillar design guidelines. Unfortunately, a recent massive pillar collapse in an old section of the Whitney mine and frequent reports of pillar sloughing and roof falls in older sections of other mines highlight the potential safety impact on the miners in underground stone mines from unstable abandoned areas. Consequently, the goal of this thesis is to identify the necessary resolution and operational parameters of mobile LIDAR with SLAM technology that would be integrated to the autonomous robotic systems to characterize the geomechanical conditions in an underground mine efficiently.

In this research, the active remote sensing devices used for each case study were terrestrial LIDAR, mobile LiDAR with simultaneous localization and mapping (SLAM), and LIDAR/Camera on an autonomous UAV. Following research tasks were performed to reach the objective of this thesis:

- Map and collect the data from stone mines with the mobile LIDAR system, terrestrial LiDAR, and autonomous Unmanned Aerial Vehicle (UAV),
- process the data collected in the Cloud Compare, GEOSLAM Hub and Discontinuity Set Extractor (Riquelme et al., 2014) programs to characterize the rock mass of the underground stone-mine pillars,
- evaluate the functioning of the programs and perform a sensitivity analysis with the Discontinuity Set Extractor program to determine the precision and accuracy of the results obtained,
- compare the performance of different methods and identify necessary resolution and the operational parameters for the sensor that would be integrated on the UAV for autonomous scanning.
5.2 Conclusions

In the first field study, geologist identified four bedding planes, and these bedding planes can also be identified from discontinuity mapping from 3D point cloud data. Difference in the intensity (RGB colors) of the points that belong to each bedding pane, made this identification possible. Therefore, point cloud with RGB colors and a density of 0.5 points per square centimeter is capable to clearly represent the bedding planes of a rock mass in scale of greys in this field study. However, it was difficult to identify the joints present in the rock mass, and it was thought that the reason of this was because of a low point cloud density. A higher point cloud density is desired for obtaining a better visualization of the rock mass. The program DSE identified six joint sets for this point cloud data. However, only two of these sets might be considered as joint sets if the point cloud data is inspected carefully. It is also important to consider that geologist didn’t not provide detail information about the joint sets during the geological mapping for making an accurate comparison.

In the second field study, two discontinuities and one bedding plane were observed during the visual characterization in the field, and same discontinuities were identified during the visual analysis of the digital images. On the other hand, it wasn’t possible to identify these discontinuities from point clouds scanned with Zeb Horizon LiDAR scanner when they were uploaded to Cloud Compare and processed by GEOSLAM Hub, although the pillar was shown with great detail in both programs. The point cloud data consisted of 1,602,314-cloud points, resulting in a cloud point density of 1.3-cloud points per centimeter square, which was much higher than density in the first field of study. Discontinuities were identified in the field and from digital images but couldn’t from the 3D maps because the traces of the discontinuities are not well represented in the point cloud. Discontinuity joint sets characterization using DSE program found three discontinuity joint sets in this data. Only one discontinuity (vertical orientation) matches accurately with the one observed in the field and from the digital images, while the second discontinuity represent mostly the floor and roof, and the third one, the main rock face of the pillar. Bedding plane could not be identified in this process.

Results of these two field studies provided following valuable information. It is possible to identify the certain geological structures, in this study bedding planes, from the point intensity. However, identifying joints require very high point densities and needs detailed analysis of the 3D maps and expert interpretation. Therefore, this thesis couldn’t conclude if only the LIDAR measurements
would be enough to identify geological structures even with high point densities. However, point intensity together with the high point density will allow identification of the geological structures. Therefore, LIDAR camera that can provide both accurate point coordinates with LIDAR measurement and clear picture with the camera will make identification of the geological structures from dense 3D maps possible.

The UAV with the Intel RealSense L515 LiDAR camera provided a point cloud with a high degree of detail and RGB colors, however, objective of the third test was to try the autonomy of the UAV. The distance of the drone to the pillar and vertical flight path chosen were the cause of inaccurate images from the system. For this reason, it is recommended to fly the UAV from 4 meters to the pillar so the area of FOV would be large enough to get high density point clouds. When UAV completes flight path parallel to the width of the pillar, it is recommended to move vertically 0.8 meters each time and start next parallel flight in opposite direction to have 80% overlap in FOV areas during the scan. However, the big challenge continues being the illumination since quality of the camera images depends on it. Previous research demonstrated the difficulty of installing a powering light to give necessary illumination. System that is under development also has an unmanned ground vehicle (UGV) component. UGV can carry multiple high lumen lights on it and has a large enough battery to provide necessary power.

5.3 Suggestions for Futures Studies

Airborne LiDAR and camera technology has the potential to become one of the most efficient methods to perform discontinuity mapping in underground stone mines as the scanning process can be autonomous, the output can possess a better cloud point density and significantly fewer voids. The efficiency of LIDAR camera scanning with an UAV depends if challenges such as overlap between point clouds and illumination can be overcome. Field study # 1 and # 2 have shown that for a good discontinuity characterization, it is required to have a light system that provides enough lumen that discontinuities can be recognized visually. Therefore, to solve the issue of illumination it is recommended that the UGV will be equipped with a lighting tool. It is necessary to test this system in underground to evaluate the potential success, and WVU Mining and Robotic teams will perform these tests in near future.

For the overlap matter, some literature reviews recommend a 50% or higher of match between all the frames scanned, for assuring a good output of the point cloud this thesis has used the percentage
of 80%. Consequently, for obtaining this percentage of overlap between all the frames, it is essential to calculate the vertical distance the UAV should fly, which depends on the distance to the pillar and can be obtained by using Equation 26. Using these parameters for next trials with the autonomous UAV definitely would result in an improvement in the collection and match of the point clouds.

DSE does an efficient job by calculating the principal poles planes and grouping them back together by their orientation, this very same principle can be applied to identifying bedding planes since they depend on the intensity of the point clouds. By using K-nearest neighbor approach (KNN) the DSE program could recognize points that share similar color or intensity between a specific radius and calculate the clusters that could belong to a certain bedding plane. This method could also help to calculate the limits and the thickness of the bedding planes, giving, as a result, a more accurate characterization of the visible discontinuities of a stone-mine pillar.
References


Zekkos, D., Greenwood, W., Lynch, J., Manousakis, J., Athanasopoulos-Zekkos, A., Clark, M., & Saroglou, C. (2018). Lessons learned from the application of UAV-enabled structure-from-


