DEVELOPMENT OF IMPROVED ALGORITHMS FOR DETECTION OF JOINTS AND ESTIMATION OF ROCK STRENGTH IN ROCK STRUCTURES BY USING DRILLING PARAMETERS OF THE INSTRUMENTED ROOF BOLTER

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by
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ABSTRACT

Accurate understanding of geological features, including locations of joints, cracks, bed separations, and rock strength, allows for optimization of ground support measures and mitigation of ground instabilities in underground structures. The concept of using operational parameter data, collected by monitoring the work cycle of a roof bolting unit drilling into roof and ribs, to predict geological features of interest has been proposed in the past and studied in the last few decades. Some smart drilling systems have been developed to implement this concept, but despite their limited success on joint detection and/or rock classification, they fail to identify hairline joints, (aperture less than 3.175 mm) and discriminate between rocks with similar strengths.

This research aimed to advance the existing smart roof bolting systems to enhance their capabilities to sense geological features of interest along boreholes. To achieve this objective, full-scale laboratory tests were conducted involving a set of concrete blocks with various strength properties and small joints to simulate drilling from rocks of various strength properties into another. Some pattern recognition algorithms were developed to detect pre-designed joints. To improve capabilities of the existing algorithms, several composite parameters were introduced to provide collaborative decisions for locating the joints. Moreover, wavelet analysis was also employed to improve pattern recognition algorithms and therefore to enhance their capabilities for joint detection.

A set of additional holes were also drilled into a block that included joints at four different angles (15°, 30°, 45, and 60°) relative to the direction of drilling. The area between the joints were filled with grout having various strength. Also, a sample composed of blocks of various rocks were cast in grout to represent variation of rock strata while drilling. The rocks used in this composite block included soft shale, sandstone, limestone and shale with strength ranging from 3 to 130 MPa.
These tests allowed examination of the capabilities to identify angled joints, while generating data for the programs for estimating rock strength.

The result of the analysis of the drilling parameters proved that joints with smaller aperture (less than \(3 \text{ mm, } 1/8\text{th inch}\)) could be successfully detected at high rates, reaching 94% by using feed pressure. The algorithms have also resulted in generating various amounts of false alarms, but the improved algorithms have been able to reduce the false alarms down to 14 in a set of 156 drill holes tested. The use of composite parameter RP/FP/PR and the same algorithms could increase the detection rate to 97%, with false alarms reduced to 9. Use of wavelet and other noise filtering systems could also improve the detection rates and reduce false alarms compared to the straight use of single drilling parameters but could not substantially increase the detection rates. Therefore, it was concluded that the use of composite parameters was sufficient for the data set that is currently available. The same was true for detection of angled joints, but the available data in this setting was only on a few drill holes.

As for the estimation of rock strengths by monitoring drilling parameters, data from drilling into the composite sample showed very good correlation between Field Penetration Index (FPI), which is calculated from feed pressure and drilling rate, and rock strength values. This is especially true when a Wear Index (WI), based drilling distance on a given bit, was used to adjust the calculated values of FPI and account for the wear on the drill bit. Correlation coefficient for statistical analysis of rock strength data from drilling parameters in the limited full-scale drilling tests were around \(R^2 = 92\%\).
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Chapter 1
INTRODUCTION

1.1. Research Background

One of most frequent and serious hazards in the field of underground mining, tunneling, and underground construction is ground instability that including roof and rib failures. It leads to equipment damages, personnel physical injuries, and fatalities every year. The statistics, issued by Mine Safety and Health Administration (MSHA), indicates incidents of “Fall of Ground” were the most fatal accidents in underground coal mining between 2003 to 2012. These incidents caused 27% (the largest portion) of fatal accidents in the industry of coal mining, and were responsible for around 33% of fatal accidents in underground coal mining (NIOSH, 2015a). Review of statistics from the National Institute for Occupational Safety and Health (NIOSH) shows that ground fall incidents in underground mining cause 8 to 10 fatalities and more than 800 personnel injuries each year. These numbers of fatalities and injuries represent about 30% of fatal disasters and 15% of injuries in underground mines every year. Moreover, these statistics noted that approximately 2,000 reportable non-injury ground falls also occur each year (NIOSH, 2015b). Despite much advancement of techniques within the field to mitigating ground instability and reducing the number of related injuries in underground mining and tunneling operations, ground instability such as roof and/or rib failures has been fairly persistent issue and needs further improvement in these fields.

Typical geological features of interest, including the locations and characterizations of joints, voids, cracks, bed separations, rock type, rock strengths, and similar geotechnical features, and control the ground failures and accidents. To improve the underground mine safety and mitigate roof fall incidents, a suitable ground support design should be implemented, and
optimization of ground support measures is a function of rock mass and joint conditions. As such, ground characterization is essential for design of safe and cost effective ground support of the underground spaces.

Information of ground characteristics is usually provided by qualitative geological reports that issued from geotechnical borings. To obtain more accurate ground information, geotechnical borings such as core drilling are carried out at the surface of underground workings, such as the roof, ribs, and floor. However, this technique is very costly, and sometimes disruptive to the operations. Therefore, it may be impractical in many applications. In addition, cores of rock collected from coring operations are sent to rock mechanics laboratories to perform rock mechanics tests, including Uniaxial Compressive Strength (UCS), Brazilian Tensile Strength (BTS), Point Load Test (PLT), Punch Tests, etc. These tests offer information on a limited length of the sample or borehole, and insufficient for optimized design of ground support measures. Moreover, the geological conditions of the rock mass tend to be vary even within a short distance, many critically geological features will be missed for the design of ground support, and therefore lead to potential risks of ground instability (Debasis, 1994; Gu, 2003).

This project, with the title of “Instrumentation of Roof Bolt Drill for Ground Characterization, Mapping, and Support Design”, was funded by Centers for Disease Control and Prevention, National Institute of Occupational Safety and Health (NIOSH), Office of Mine Safety and Health Research. The contract (No. 211-2011-41138) was awarded to the Pennsylvania State University (PSU) in 2011 as part of a Broad Agency Announcement for Capacity Building in the field of Ground Control in Mining. There were three major objectives of this project, aim to: “(1) advance the existing smart roof bolting systems so that they can collect additional information, which can be used for estimating the rock strength and evaluating rock mass conditions, (2)
generate a 3-D geological, hazard map of the underground spacing, and, (3) incorporate the acquired data into ground support programs to evaluate the suitability of designed support system.”

Figure 1-1 shows overall review of this project. Figure 1-2 illustrates overall review of proposed systems in this project.

As part of a major project, this dissertation is titled as “Development of Improved Algorithms for Detection of Joints and Estimation of Rock Strength in Rock Structures by Using Drilling Parameters of Instrumented Roof Bolter,” and aims to provide reasonable geological information, including the location of joints, voids, cracks, bed separations, and strengths of rock layers, for ground characterization and 3-D geological roof mapping. Figure 1-3 briefly presents proposed detection systems in this project.

Figure 1-1. Overall review of this project
1.2. Problem Statements and Research Objectives

Roof characterization is essential for design and optimization of safe and effective ground support for the underground workings. As such, many methods and techniques, such as visual observation and geophysical loggings, bore scoping, rock mass systems, and instrumented roof
bolters, have been introduced and applied in underground environment. However, these methods and techniques are experiencing many shortcomings and limited capabilities, and are also facing many challenges. For example, they fail to provide sufficient information on roof conditions within the desired time frame, and cannot identify hairline joints or cracks (e.g. less than 3.175 mm or 1/8-in) and discriminate rock layers with similar strengths. Moreover, they seem to indicate joints that are not exist in the ground, in other words, generating false alarms.

This project was focused to improve the precision of drilling display system (DDS) joint detection system of the J.H. Fletcher & Co. as well as to increase its abilities to predict rock strengths as an attempt to complement the Mine Roof Geology Information System (MRGIS), and develop a 3D visualization of the ground conditions in the mine roof.

As a part of this project, the objectives of this research were to improve the sensitivity and precision of existing joint detection programs based on updated pattern recognition algorithms in sensing joints, cracks, and/or voids with the aperture smaller than 3.175 mm (1/8-in) while reducing the number of false alarms; in addition, to estimate strengths of rock layers by analyzing drilling data recorded from the instrumented roof bolter. There are also many uses for the data, for example, the data can be used to optimize supports since the geological conditions of the rock mass tend to be vary even within a short distance, and regular geological back mapping may miss many critical geological features. In addition, the data can be used to develop 3D mapping of geological conditions.

1.3. Research Methodology

To achieve aforementioned research objectives, this research has followed the steps outlined below:

1) Instrumentation of the J.H. Fletcher & Co. roof bolter
One of the initial steps in improving the detection system was to install new types of sensors to complement the existing instruments, and have a closer look at the data collection rate. This allowed for collecting additional drill data for data analysis in future steps. Moreover, with a proper data collection rate, additional joint information could be tagged in collected data. The instrumented roof bolter, located at a J.H. Fletcher & Co. testing facility, was employed to perform drilling tests for data collection and detection-system development.

2) Laboratory experiments at J.H. Fletcher & Co., Huntington, WV

The initial laboratory experiments were conducted at a J.H. Fletcher & Co. testing facility. Nine concrete blocks were cast with different prescribed strength. When cured, one sample could be placed on top of another sample to simulate a transition from one rock type to another. Each set of two concrete blocks made a drilling specimen which contained a simulated joint at the contact point with the aperture less than 3.175 mm (or 1/8-in). Drilling data, including the feed pressure, rotation pressure, RPM, penetration rate, acoustic, and vibration signals, were recorded during the drilling process.

In the following laboratory tests on concrete blocks, a composite sample was prepared where pieces of several different rocks were stacked and cast in a concrete jacket to represent a sandwich of various layers. Drilling into this sample generated data for estimation of rock strength as well as transition between the rock types where there was no joint. Furthermore, two grout blocks were poured where the layers were separated with membranes and each section contained grouts with different strength and contact surfaces with slanted joint surfaces. Simulated joints, with the aperture about 1.588 mm (or 1/16-in), were pre-designed at four different angles in one block, including 15°, 30°, 45°, and 60°, and grouts with three preset strengths were used to simulated various conditions with inclined joints and strata of different strength values. A second
composite block was also fabricated for rock classification where four common rock samples, including shale, sandstone, limestone, and coal, from mines around Pennsylvania, were cast in a block to simulate different rock layers. The instrumented roof bolter was employed for drilling all these fabricated samples, and data from various sensors were collected for analysis and development of new algorithms as will be discussed later.

In the laboratory tests included bore scoping of the samples to collect video images of the inside the boreholes for ground truth of preset geological structures along the boreholes. In other words, the real locations of preset joints and boundaries of the rock layers were controlled by the bore scoping to train the pattern recognition programs. Moreover, core samples were collected from preset grouts and four simulated rock layers and tested to characterize the material and measure related strength values. The testing followed the American Society for Testing and Materials (ASTM) standards. Concrete or grout samples were tested in the Civil Infrastructure Testing and Evaluation Laboratory (CITEL) and rock samples were tested in Geo-Mechanics Laboratory of the department of Energy and Mineral Engineering at the Pennsylvania State University. The testing measured mechanical properties of the core specimens, such as Uniaxial Compressive Strength (UCS), Point Load Tests (PLT) for the rock, and compressive tests for the grout samples.

3) Data analysis and algorithms development for joint detection

Given the objective of detecting joint and voids in the rock mass, drilling parameters, including the feed pressure, rotation pressure, RPM, penetration rate, composite parameters, etc., were analyzed and compared to the available information on the joint locations. In order to effectively and accurately extract geological features of interest, such as locations of joints, cracks,
voids, bed separations, pattern recognition algorithms or change detection algorithms were employed to analyze the measured drilling parameters.

4) Data analysis for estimation of rock strength

As for the goal of using recorded drilling data to predict rock strength, mathematical models have been developed to examine relationships between recorded drilling parameters and the strength properties of the rock layers. Moreover, a factor of Wear Index (WI), in terms of drilling distance, has been proposed to incorporate the effects of the wear of the drill bit on the recorded drilling parameters.

1.4. Dissertation Outline

This dissertation consists of nine chapters as outlined below:

- Chapter 1 briefly introduces the research background and research methodology.
- Chapter 2 reviews the available literature and discusses the status of presently available ground characterization techniques.
- Chapter 3 examines previous studies on ground characterization by using instrumented drills.
- Chapter 4 introduces an instrumented roof bolter utilized for testing and data collection in this study.
- Chapter 5 offers a discussion of the initial laboratory tests that were conducted in this study and data analysis by using updated pattern recognition algorithms to detect joints with the aperture smaller than 3.175 mm (or 1/8-in) in various conditions.
- Chapter 6 introduces three composite parameters that could be used to improve joint detection performances of updated algorithms.
• Chapter 7 focuses on using the wavelet analysis to further improve the pattern recognition algorithms and therefore improve their capabilities on joint detection.

• Chapter 8 introduces new laboratory tests that were implemented for joint detection and estimation of rock strength. Joints, with the aperture around 1.588 mm (1/16-in), were pre-designed at four particular angles relative to the direction of drilling. Moreover, mathematical models for prediction of the UCS properties of the rock samples will be discussed.

• Chapter 9 contains the conclusions and provides some recommendations for future research.
Chapter 2
REVIEW OF GROUND CHARACTERIZATION
TECHNIQUES

To obtain a more sufficient and accurate geological report of ground features for ongoing or future underground activities, various methods or techniques has been used. This includes geophysical logging, bore scoping, and physical sampling. These methods provide some of the critical inputs for ground characterization that could be used as input for rock mass classification systems, used in underground mining, tunneling, and underground construction. Following is a brief summary of the selected methods or techniques that represent the ongoing challenges and some of the deficiencies and shortcomings.

2.1. Geophysical Logging

In the past few decades, geophysical logging techniques, including resistivity, sonic, neutron, and gamma ray logs, were introduced and applied for rock mass characterization in underground mining by various researchers (Kahraman, et al., 2016). For example, Carroll (1966; 1968) worked on correlating UCS values to sonic velocity or interval transit. Elkington et al. (1982) and Halker et al. (1982) of the National Coal Board (NCB) of UK performed studies on relationships between rock strengths and N-N log responses, and they also proposed relationships between neutron porosity and strength indices of the rock, such as the Point Load Test (PLT). In Australia, geophysical logs were used to predict overburden strength at ten mines, and empirical relations were proposed to predict rock strength (UCS) by analyzing responses of the neutron and sonic log (McNally, 1987 and 1990).

Medhurst and Hatherly (2005) used borehole logs to estimate rock properties of rock layers in the field of coal mining. In their research, Geophysical Strata Rating (GSR) was introduced to
predict geological features of the intact rock mass, including porosity, cohesion, and quartz and clay content, based on geophysical logging. In the United States, Oyler et al. (2010) carried out many field tests in different states, including Illinois, Pennsylvania, Colorado, western Kentucky, and southern West Virginia, to establish relationships between sonic velocity logs and UCS values of the rock, and an exponential equation was introduced to describe relationships between the UCS values and the sonic travel time.

These methods require highly specialized equipment and well trained and experienced staff to perform the procedures. Meanwhile, they are relatively expensive methods to apply and therefore, they are typically used in very specific and mission critical applications. These systems cannot be used on a daily or regular basis in mining operations due to the cost associated with running them and the disruptive nature of the procedures which requires near complete stoppage of operation for performing these logs.

2.2. Bore Scoping

The technique of borescope, including borehole periscope and stratascope, is an optical instrument that is used to offer visual inspections of boreholes to observe geological features of interest, such as joints, voids, cracks, bed separations, rock layers, etc. This technique has been widely applied in field.

Thomas (1966) used a purpose-built type of periscope to inspect short boreholes in underground applications in British collieries. To collect geometry information of fractures, involving spacing, orientation, and aperture, Mahtab et al. (1973) at United States Bureau of Mines (USBM) used the technique of bore scoping to inspect boreholes in underground mines before 1970. Afterward, the fiberoptic flexible stratacope was developed by researchers at the USBM, and it was successfully examined in many metal mines and coal mines (Fitzsimmons et al., 1979).
However, through application of the technique of bore scoping at Martinka Mine of Southern Ohio Coal Company, Tennant (1982) stated that this technique is not a cure-all method to resolve all roof control problems. However, Shepherd et al. (1986) mentioned positive ideas on this technique. They carried out studies on bore scoping at Australian Coal Industry Research Laboratories, and noticed that the technique of bore scoping is useful for assessments of ground stabilities. Unrug (1994) stated that the technique of bore scoping played important roles on identification of certain rock layers and optimization of support measures. Comparing with applications of geophysical logging to recognize geological features, including rock types, fractures, and boundaries of rock layers, in roof boreholes, Ellenberger (2009) mentioned that the technique of borescope was relatively much easier to be operated.

For the time being two different levels of bore scoping can be applied. One is a rough method that is cheap and quick and involves simple devices that can look at the borehole walls and offer a visual record of the walls for further interpretation. Often these devices are used in tandem with voice recording of the depth as observed on a ruler or tape by the operator, to keep track of the depth. As such the accuracy of these systems are very limited and can only locate the joints and cannot offer additional information on the dip angle or bearing of the joints.

The other alternative is the use of borehole optical televiewer that can offer a 360-degree scan of the borehole walls. These systems are slightly more expensive, need trained operators, and are more delicate to handle. However, the information they provide is very comprehensive relative to the joints and various strata encountered by the system and can offer the direction of the joints. Either one of these systems are still disruptive to mining and tunneling operations. Also, despite the good information that they provide, they are not able to offer any indication of rock strength.
2.3. Rock Mass Rating Systems

In the past few decades, many rock mass rate systems were developed to assess rock mass behavior, and have been widely applied in the field of mining and tunneling. Example of rock mass classification system includes Deere’s Rock Quality Designation (RQD), Bieniawski’s Rock Mass Rating (RMR), Barton’s Q system, and Coal Mine Roof Rating (CMRR) developed by the USBM. (Deere and Miller, 1966; Bieniawski, 1973; Barton et al., 1974; Molinda et al., 2001). The information collected from the geophysical logging and bore scoping can be the input parameters for the rock mass classification systems. **Figure 2-1** shows the application of the CMRR system to evaluate the structural competency of a coal mine roof. The CMRR value of a coal mine roof can be computed by evaluating six geological parameters, including compressive strength of intact rock, discontinuity cohesion, discontinuity spacing, discontinuity roughness, discontinuity persistence, and moisture sensitivity (Mark et al., 1994; Molinda and Mark, 1994).

![CMRR Diagram](image)

**Figure 2-1.** The application of the CMRR (Molinda and Mark, 1994)

In 2002, Mark et al. (Mark et al., 2002) revised the system of CMRR, and limited the required field or core data to only three input parameters including UCS (strength) values, fracture
spacing (or RQD), and PLT of the diametral test to compute the CMRR. Currently, as a reliable and repeatable rating system to measure roof quality, the CMRR system has been world widely accepted in the field of coal mining (Mark and Molinda, 2005). The final computed rating of CMRR is in the range of 0-100. Table 2-1 lists the basic CMRR classes used in the United States, similar to the cumulative rating system of the RMR (Mark and Molinda, 2007). The quality of rock mass, such as weak, moderate, or strong, can be evaluated based on corresponding CMRR score region indicated in this table (Calleja, 2006). There are ground-support design methodologies that are linked to CMRR. This includes the methodology introduced by National Institute for Occupational Safety and Health (NIOSH) and related program called Analysis of Roof Bolt System (ARBS) and similar design procedures that use CMRR as an input to offer the required bolting pattern for support of the coal mine entries (Mark et al., 2001; Molinda et al., 2001).

Table 2-1. The basic CMRR classes used in the U.S. (Calleja, 2006)

<table>
<thead>
<tr>
<th>CMRR Class</th>
<th>CMRR Region</th>
<th>Geological Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weak</td>
<td>0 – 45</td>
<td>Claystones, Mudrocks, Shales</td>
</tr>
<tr>
<td>Moderate</td>
<td>45 – 65</td>
<td>Siltstones and Sandstones</td>
</tr>
<tr>
<td>Strong</td>
<td>65 – 100</td>
<td>Sandstones</td>
</tr>
</tbody>
</table>

In order to systematically predict roof fall incidents in mining, NIOSH proposed Roof Fall Risk Index (RFRI) (Iannacchione et al. 2006a; 2006b; 2007a; 2007b). Four categories, including geologic factors, mining-induced failures, roof profile, and ground water influx, were employed to compute the RFRI. To use RFRI or ARBS or similar design/assessment procedures requires a reasonable characterization of the ground and related classification by following an established method such as CMRR. This in turn requires several input parameters that can be obtained from various methods that were noted above. However, most of the existing methods for ground characterization could be unavailable or very disruptive. Thus, the possibility of obtaining the
required information for ground characterization from the roof bolter drilling unit while it is performing its duty during the normal operation could be very valuable. This means that there is no additional equipment needed and the unit that drills the roof/ribs in the normal work cycle can generate the necessary data to quantify the rock strength, and locate the joints, which is the necessary information for CMRR or similar classification method. The added advantage is that the suggested method does not impose any additional disruptions or delays in the operation. Following is a brief statement of the objective which outlines the goals of this study.

2.4. Problem Statement

Despite the introduction of some techniques which offer certain capabilities for ground characterization, and some of them being applied in mining and tunneling operations, there are some shortcomings and limitations associated with using these techniques. For example, over past decades, many studies were carried out on ground characterization by employing geophysical logging. The cost of equipment to perform logging methods is relatively high, and these techniques cannot offer all required information for classification. Moreover, the geophysical logging techniques require skilled operators for data collection and interpretation and sometimes, they produce inconsistent results.

Bore scoping technique, which provides abilities for visual inspection of boreholes in field, can be employed to identify geological features in rock mass. However, this technique is time consuming and disruptive, while it requires additional equipment and skilled operators to run the tests to interpret the result. Since these activities are usually performed after drilling, it causes delays in operation, and the results cannot be used for adjustments to bolting measures on real-time basis.
Reviewing various techniques for ground characterization and their limitations indicates the needs for development of a system that can be employed through drilling for roof and/or ribs bolting, to characterize the ground in real time and as part of the operating cycle. Consequently, the current study is focusing on development of a system for rock characterization while drilling for roof bolts or for other purposes in the mining and tunneling operations.
Chapter 3
GROUND CHARACTERIZATION BY INSTRUMENTED DRILLS

3.1. Introduction

All underground mines can suffer incidents of ground falls, and the statistics issued by NIOSH points that some forms of roof and/or ribs support are employed in over 90% of over 700 underground mines (NIOSH, 2015b). Roof bolting is the dominant method of ground support and widely employed in underground mining and tunneling applications, especially in underground coal mines as required by Law in the U.S. (30CRF75.204, 1990). Figure 3-1 shows a schematic drawing of typical roof and rib bolting pattern in a coal mine entry (LaBelle et al., 2000).

![Figure 3-1](image_url)

**Figure 3-1.** A schematic drawing of typical roof and rib bolting pattern in a coal mine entry (LaBelle et al., 2000)

Practical experience clearly shows that effectiveness of rock bolts is directly related to conditions of joints, cracks, and bed separations. These geological features trend to vary even
within a short distance (Gu, 2003), thus the design based on the actual condition at any given location is very difficult and as such ground support design for mine entries are based on the worst case scenarios in a given stretch of the mine. The concept of using drilling parameters from the bolter for ground characterization, involving joints detection and rock classification, has been studied for a few decades. Some studies have used drilling data obtained from roof/rib bolting for development of ground characterization. Moreover, drilling data is recorded, with no interruption to the operation during drilling cycle for general roof bolt installation in mining and tunneling (Peng et al, 2003).

3.2. Ground Characterization by Instrumented Roof Bolters

One of the early studies on the subject was a research project, which was performed at the Spokane Research Center of the United States Bureau of Mines (USBM) where the researchers analyzed drilling parameters of a roof bolter, including thrust, torque, penetration rate, and rotational speed, to predict roof strata information (Frizzell et al., 1992). Signer and King (1992) and King et al. (1993) updated an instrumented roof bolter with the unsupervised learning technique and the expert system to detect geological features, and therefore improved the support design which critically detected roof features. Besides, the system could calculate the Specific Energy of Drilling (SED) based on measured drilling parameters. Through immediately analyzing desired drilling parameters with a microcomputer, hazardous roof conditions could be alarmed to the operator. Field tests at an underground coal mine proved the capability of this system. They also stated several improvements of this system, such as sensory instruments for measuring the drilling parameters (torque, thrust, penetration rate, and rotation rate), and optimizing display method to show detections to operators (Frizzell et al., 1992). In addition, as part of this project, a new system, which was an instrumentation of a USBM model roof-bolting drill to monitor drilling,
was proposed by Parvus Corporation of Salt Lake City of Utah to monitor drilling (Takash et al., 1992; Hill et al., 1993).

Itakura et al. (1997) and Itakura (1998) instrumented a pneumatic rock bolt drill to monitor drilling parameters included torque, thrust, revolution, and stroke both in the laboratory and the field. In the laboratory tests, sandstone, sandy shale, and coal were embedded in a set of manufactured blocks to simulated three different discontinuity angles (0 degrees, 30 degrees, and 60 degrees) as well as three different discontinuity types (cracks, boundaries, and bed separations). Figure 3-2 represents typical patterns corresponding to various discontinuities. This instrumented drill could categorize the discontinuities with neural network algorithms, for example it could identify locations of discontinuities pre-positioned as boundary layers, boundary separation, and cracks in rock, but it also generated rather large errors in detection results. Fields tests at a coal mine showed that geological structures could be involved in mechanical data logs, and locations of discontinuities could be successfully identified by employing these algorithms and the adaptive theory. However, their instrumented drill could not distinguish cracks and layer boundaries.

Figure 3-2. Typical patterns corresponding to various discontinuities (Itakura, 1998)
Through analyzing torque, thrust, revolution and stroke data of the machine, Itakura et al. (2001) developed a Measurement While Drilling (MWD) System to locate discontinuities. From field tests, which they conducted in Taiheiyo Coal Mine in Japan, they stated that ratio of torque/thrust data could show geological structures. However, MWD system still could not detect discontinuities with small aperture, and Itakura indicated that it was hard to identify cracks with small size (hairline cracks) from drilling data. Itakura et al. (2008) continuously conducted field experiments to detection locations of discontinuities with the instrumented roof bolter that was equipped with the neural network techniques. They stated that, through drilling a certain pattern of boreholes, the instrumented roof bolter was able to estimate 3-D geological structures of various rock types and discontinuities in roof rock mass. To express relations between rock properties, bit shapes, and several drilling parameters including thrust, torque, rotary speed, and stroke, Li and Itakura (2011a; 2011b) introduced an analytical model. Using a portable smart drilling machine in field tests, they proposed some relationships between drilling parameters of torque and penetration rate and UCS of rocks. Afterward, Li and Itakura (2012) used specific energy to describe UCS values of rocks with an in-situ method. Results from the laboratory and field experiments represented the feasibility of using specific energy to evaluate UCS values of the rocks.

A research team at West Virginia University was working on the characterization of mine roof by using drilling parameters of an instrumented roof bolter. They completed many tests in the laboratory and in some underground mines. In their project, they used J.H. Fletcher HDDR Walk-thru type dual head roof bolter which was equipped with the intelligent drilling systems to detect the locations of voids, joints, bed separation, fractures and formation interfaces in many mining operations; meanwhile, they also estimated the relative rock hardness with this instrumented roof bolter. Drilling parameters, including thrust (feed pressure), torque (rotation pressure), penetration
rate, rotation rate, and bit position, were able to be recorded by the Fletcher instrumented roof bolter while drilling was in process. While they proved the feasibility of applying the specific energy of drilling (SED, an indicator which was converted by drilling parameters) for identifying rock types and fractures, SED showed a significant variation in same rock materials, and the variation of SED that caused by other factors, such as friction, could not be incorporated in the calculations. Their research also did not demonstrate the capability to identify joints and/or cracks with the aperture smaller than 3.175mm (1/8-inch) (Finfinger et al. 2000).

Luo et al. (2002) built a mathematical model to measure rock strengths by using drilling parameters collected from roof bolting operations. In this model, drilling operation was assumed to reach a state during the drilling and the thrust of the roof bolter was plotted against the compressive strength of the rock, while the torque was affected by the frictional resistance at the drill bit and drill steel as well as the shear strength. Hence, they believed that compressive and shear strength of rock could be estimated by using this systematic approach. In their research, they introduced empirical equations to calculate compressive strength and shear strength from drilling parameters. However, their research could not efficiently discriminate rock strengths, especially toward rocks with similar strength range.

In order to resolve the correlations between drilling parameters of the instrumented roof bolter and the rock properties at the locations of joints, voids, cracks, bed separations, fractures, rock layer boundaries, and rock strengths, Finfinger (2003) conducted a series of laboratory tests. A set of manufactured roof rock blocks, which simulated conditions of the mine roof strata, were built in the laboratory. He stated that four primary drilling parameters of the Fletcher instrumented roof bolter, including thrust, torque, rotational velocity, and penetration rate, could be affected by the physical properties of the rocks. Moreover, he assumed that geological features such as joints,
cracks, voids, and fractures could be detected through monitoring changes in the thrust when the penetration rate was kept constant, or alternatively monitoring changes in the penetration rate when the thrust was preset and kept constant. In the cases of keeping the penetration rate constant, Finfinger proposed a concept of “thrust valleys”, as shown in Figure 3-3, and the “thrust valley” was shown up at the time that the drill bit hit a joint or a void. Moreover, every “thrust valley” was appeared like a symmetrical “V” shape, and the drop of thrust value at each “thrust valley” was at least 50%. Therefore, in this scenario, joints, cracks, voids, bed separations, and fractures could be identified by monitoring “thrust valleys” in thrust.

![Figure 3-3. Thrust valleys corresponding to fractures in a concrete block (Finfinger, 2003)](image)

Finfinger also indicated that these four primary drilling parameters (thrust, torque, rotational velocity, and penetration rate) could not be applied to identify boundaries between two rock layers. Therefore, he introduced a set of parameters included rotational acceleration and axial acceleration. These two secondary parameters could be employed to identify joints and/or voids and discriminate boundaries between various rock types. He also concluded that the rotational acceleration had better correlations with boundaries between rock layers compared with the axial
acceleration. Figure 3-4 shows an example of the indicated locations in terms of the actual locations of rock boundaries (Finfinger, 2003).

![Graph showing indicated vs actual locations of rock boundaries](image)

**Figure 3-4.** An example of the indicated locations in terms of the actual locations of rock boundaries (Finfinger, 2003)

A new drilling parameter, namely the drilling hardness, was proposed to be represent geological features such as joints, cracks, voids, bed separations, boundaries between rock layers, and therefore to be used for geological roof mapping in real-time. Besides, the drill hardness could be assessed from the geometry and the contact area of the drill bit, the friction on drill bit, and kinetic and torsional energy losses. Figure 3-5 represents variations of drilling hardness while drilling into a concrete block with variable strengths of rock layers in a laboratory test. As shown in this figure, the locations of boundaries between rock layers and discontinuities in rock mass could be identified with related feature of the drilling hardness, and therefore achieving the objective of geological mapping (Gu, 2003; Gu et al., 2005). To assess the performance of the drilling hardness, they performed field tests at two different mines, and he stated that the average
errors between the predicted boundaries and the actual boundaries at two mines were 3.5 cm and 3.1 cm, respectively. However, he did not mention conclusions of locating discontinuities from field tests at these two mines in his publication.

![Graph showing variations of drilling hardness](image)

**Figure 3-5.** Variations of drilling hardness in a concrete block with variable strengths of rock layers (Gu, 2003)

The research team at West Virginia University developed a Real-Time Roof Geology Detection System and a Mine Roof Geology Information System (MRGIS) to monitor drilling parameters while the routine cycle of roof bolting operation (Peng et al., 2003; Tang et al., 2004; Peng et al., 2005a; Peng et al., 2005b; Tang, 2006). In their research, the J.H. Fletcher & Co. HDDR dual head roof bolter, which was equipped with a Drill Control Unit (DCU), was applied to control drilling and recorded drilling parameters for predicting roof geology. With respect to the objectives of their research, a series of laboratory and field tests were conducted on thirteen concrete and simulated blocks, and eight underground coal mines, respectively. **Figure 3-6** shows a fabricated concrete block with five layers that was built for laboratory test.
A Real-Time Drilling Display System, developed by J.H. Fletcher & Co., was equipped on the J.H. Fletcher & Co.’s HDDR dual head roof bolter. This advanced instrumented roof bolter applied a Programmable Logic Controller (PLC) to control roof bolting and monitor drilling operations. Field experiments in underground mines with this instrumented roof bolter proved that data from special sensor that is obtained while drilling can be used to identify the locations of geological features like voids, joints, cracks, bed separations, and fractures in the mine roof. Moreover, the geological information of local roof condition, determined along each borehole, could be immediately displayed to the operator on real-time basis. In order to assess the precision of detection of this instrumented roof bolter, bore scoping was also employed to examine the real depth of target features in the boreholes. Figure 3-7 shows an example of feed pressure plotted
against time and bore scoping results for the tests performed with the roof-rock condition of shale at a coal mine (Peng et al., 2003; Collins et al., 2004; Tang, 2006).

**Figure 3-7.** An example of feed pressure plot and bore scoping results (Tang, 2006)

The cited study was further continued with development of a software to analyze the data from the instrumented Fletcher roof bolter to optimize the drill parameters through a control unit and show the data on real-time basis via an information display system. With the updated system and instrumented Fletcher roof bolter, information of geological features of interest, including locations of joints, voids, cracks, bed separation, and fractures, along boreholes could be illustrated while the boreholes were being drilled. Furthermore, as shown in **Figure 3-8**, the maximum of four side-by-side columns could be illustrated, which included the detected “voids” information from four separate boreholes on the Fletcher Digital Screen. As such, the distributions and trends of those geological discontinuities could be simply predicted by comparing the information from adjacent holes and made available to the operator. The laboratory tests at J.H. Fletcher & Co., and field tests at several limestone mines and one underground coal mine, allowed the team to examine the capabilities of the developed joint detection system. They concluded that the size/aperture of a
“void” that can be detected was very limited even with the modifications on the updated system. In other words, the system offered a fairly high percentage of prediction on “voids” with the aperture larger than 3.2 mm (1/8-in). However, in condition where the size/aperture of “voids” was smaller than 3.2 mm (1/8-in), the system did not offer a good performance and missed many of the joints (Anderson and Prosser, 2007).

![Figure 3-8. “Voids” information displayed on the Fletcher Digital Screen](image)

3.3. Various Instrumentation Systems for Roof Bolt Drills and Critical Drilling Parameters for Monitoring

Over the past few decades, ground characterization, including locating of joints, voids, cracks, bed separations and bed separations, and discriminating rock strengths in rock mass, by employing instrumented drills has been studied. Moreover, several intelligent drilling systems, had been proposed and applied to monitor drill parameters to evaluate conditions of rock mass surrounding the underground space. Notably smart systems, as shown in Table 3-1 (Kahraman et
were presented by Parvus Corporation in United States, Muroran Institute of Technology in Japan, Robotics Institute of Carnegie Mellon University in United States, and J.H. Fletcher & Co. in United States, respectively. Following section briefly review these four intelligent drilling systems.

**Table 3-1.** Summary of four instrumented roof bolt drills (Kahraman et al., 2016)

<table>
<thead>
<tr>
<th>System</th>
<th>Parameters monitored</th>
<th>Specification</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>System by Parvus Corporation</td>
<td>Thrust, torque, RPM and penetration rate</td>
<td>The real time specific energy of drilling is calculated by the expert system.</td>
<td>The system is not currently used.</td>
</tr>
<tr>
<td>System by Muroran Institute of Technology</td>
<td>Thrust, torque, RPM and penetration rate</td>
<td>The system is able to estimate roof rock 3-D geostucture.</td>
<td>No updates are available.</td>
</tr>
<tr>
<td>System by Robotics Institute of Carnegie Mellon University</td>
<td>Thrust, torque, RPM and penetration rate</td>
<td>A neural network is used to classify lithology of geo-material.</td>
<td>No updates are available.</td>
</tr>
<tr>
<td>Feedback Control System by J. H. Fletcher &amp; Company</td>
<td>Thrust, torque, RPM and penetration rate</td>
<td>Real time detection roof geology is performed. Drilling parameters can be preset.</td>
<td>The system has been fully developed and is commercially available.</td>
</tr>
</tbody>
</table>

### 3.3.1. System Developed by Parvus Corporation

Parvus Corporation of Salt Lake City, Utah designed and fabricated a drill monitoring system in 1990. This system included a standard-size roof bolter drill mounted on a mast. A portable hydraulic power pack was used to power the drill, and a hydraulic cylinder was used to apply thrust to the drill head. Besides, the drill can be either automatically controlled by a personal computer or manually controlled by direction and flow control valves. The Parvus Corporation system had four data recorders, and four parameters to monitor, including revolutions per minute (RPM), position of the drill bit, thrust, and torque while drilling. As noted before, the system was designed with the objective to offer decisions to optimal roof support measures with varying roof
geology, but it showed unstable performances and had high requirements on the quality of recorded data (Takah et al., 1992; Hill et al., 1993).

3.3.2. System Developed by Muroran Institute of Technology

In 1993, a research team at Muroran Institute of Technology advanced a mine roof characterization system to measure drilling parameters of a rock bolter, included torque, thrust, revolution, and stroke, while drilling (Itakura et al., 1997). In laboratory tests and field tests, an Australian-made pneumatic portable roof bolter, Wombat L.P., was selected for this study. With a data acquisition system, which was developed for a pneumatic roof bolter, Itakura (1998) proposed a new logging system for hydraulic roof bolter, and this system could be typically employed on most hydraulic drills.

In order to identify cracks/fractures and strata changes in rock mass, Itakura et al. (2008) instrumented a portable pneumatic drilling machine, called Trussmaster 1 P/N TRUSS001-1828 (Rambor Ltd.), and applied it in an underground mine. In field tests, mechanical data, including torque, thrust, rotation speed, and stroke, were measured while drilling to detect distributions of discontinuities and changes of roof strata.

3.3.3. System Developed by Robotics Institute of Carnegie Mellon University

An intelligent instrumented drilling system was developed by Robotic Institute of Carnegie Mellon University (CMU). This smart unit was equipped with appropriate sensors, data acquisition system, and a laptop computer to collect data while drilling. Moreover, the electronic hardware was isolated from the instrumented drill, and the data acquisition system was protected by a waterproofing box with cables connected to the instrumented drill and the laptop. Therefore, it allowed operators to control this instrumented drill in a safe and supported underground environment. Drilling parameters, including torque, thrust, rotary speed, hydraulic pressures, and
drill bit position could be recorded while drilling. Additionally, to keep the drill hole clean, and reduce the consumption of mechanical energy, this instrumented drill used water as flushing medium to remove drill fines that were generated while drilling (LaBelle, 2001).

3.3.4. Feedback Control System Developed by J.H. Fletcher & Company

In 1998, Structured Mining System, Inc. and J.H. Fletcher & Co. initially developed a feedback control system for the roof bolter product line of Fletcher. This system was mainly developed to advance drilling reliability, drill-bit life, and offer the possibility of ground characterization while drilling. Moreover, it allowed the units to be controlled automatically with pre-set drilling parameters. Afterward, J.H. Fletcher & Co., in cooperation with West Virginia University, continued to advance this system with closed control loops for the control of feed and rotation. Several sensors were installed in this system to record drilling parameters, such as thrust (from feed pressure), torque (from rotation pressure), rotational rate, penetration rate (from drill bit position), with a sampling frequency of every 100 milliseconds (10 Hz) during drilling. An internal chip in the operator cabin was used to store recorded drilling parameters and allowed for downloading of the data at any time using a jump drive. Moreover, J.H. Fletcher & Co. developed a drill control unit, and machine parameters of penetration rate, rotation rate, and the maximum feed pressure could be preset before drilling operation. Figure 3-9 presents a J.H. Fletcher & Co. HDDR Walk-thru type dual head roof bolter (Finfinger, 2003; Tang, 2006).
3.4. Summary of the past experiences with instrumented roof bolt drills for rock characterization

According to a brief review of aforementioned instrumented drills and intelligent systems for ground characterization, their efforts for predicting rock/strata strengths and geological features, such as joints, voids, and bed separations, while drilling a borehole have achieved limited successes. However, the instrumented drills are also experiencing many shortcomings, and much additional work is needed to improve their performance. This refers to the precision and the sensitivity of system for detection of small joints and ability to estimate rock strength. For example,
the smart system developed by CMU was used for various laboratory and field tests at coal mines and achieved limited successes in controlled environments. However, this unit, which featured a neural network pattern recognition algorithm, could not properly recognize cracks and layer boundaries. Furthermore, it could not accurately classify coal and shale in most of the preliminary field experiments. The research team stated that an accurate classification of geological features would only be possible if sufficient datasets were available (LaBelle et al., 2000; LaBelle, 2001).

The Feedback Control System that was proposed by J.H. Fletcher & Co. is fully developed and commercially available. However, this system also has some limitations in the identifying required rock properties that is necessary rock mass characterization. A series of laboratory and field tests conducted at several underground coal mines showed that the instrumented roof bolter could detect certain voids or fractures, while missing some features, especially the joints with the aperture of about 3.175 mm (1/8-in) or smaller. Except for detecting voids with the opening larger than 12 mm (1/2-in), the precision of detecting result was also too low. Anderson and Prosser (2007) carried out many field tests by using the J.H. Fletcher & Co.’s HDDR dual head roof bolter that was equipped with the drill control unit. Despite their limited success in joints or fractures detection in field applications at one coal mine and three limestone mines, this system also had limited success in identify hairline and vertical cracks which were observed by bore scoping videos. Typically, many factors, including drill size, bit type, bit wear, type of rock, style of drill, RPM of the drill, type of cutting removal (vacuum or water), type of feed mechanism, etc., may affect the thrust, torque and other parameters that used to locate fractures within rock mass or used for estimation of the rock strength. As such, some adjustments of the software must be considered to detect joints or fractures with smaller opening and to be able to estimate rock strength using various drill types and site conditions.
Chapter 4
INSTRUMENTATION OF THE ROOF BOLT DRILL

4.1. Instrumentation of the Fletcher Drill Unit

A Fletcher Information Display System, which is equipped with a programmable logic controller (PLC), has been used by the J.H. Fletcher & Co. to monitor drilling operations for ground characterization. A drill control unit (DCU), which was developed by Fletcher and integrated into Information Display system, was used to automate and optimize the routine cycle of drilling operations. Drilling parameters, including thrust, torque, rotation rate, penetration rate, drill bit position and vacuum or water pressure used for flushing, can be observed during the process of drilling (Anderson and Prosser, 2007).

As an attempt to complement the Mine Roof Geology Information System (MRGIS) and proposed a 3D geological visualization of the ground in the mine roof, this study has been carried out to improve the precision and reliability of the Fletcher Information Display System to identify geological fractures of interest and enhance the machine’s ability to discriminate rock strengths. In order to improve the Fletcher Information Display System, one of the initial steps in this research was to install additional sensors on the drilling unit to complement the existing instruments, and to enhance the data collection rate as well as the ability to detect targeted geotechnical features.

4.2. Installation of Acoustic and Vibration Sensors

The acoustic sensor was a simple Piezoelectric disk, or piezo buzzer, which is also known as a contact microphone. It was selected and installed on the J.H. Fletcher & Co. roof bolter to collect audio signals. This acoustic sensor, which is a small ceramic wafer, can be mounted on a
thin metal disk to gather acoustic data that is generated while drilling into rock materials. Figure 4-1 shows a picture of the selected acoustic sensor.

![Figure 4-1. A picture of the selected acoustic sensor (Sparkfun Co., 2017)](image)

The vibration sensor, which was a PiezoStar accelerometer and is known as PCB 353B31 accelerometer, was selected to measure vibration signals while drilling into rock materials. The frequency range of this unit is 1 to 5k Hz, and its sensitivity is 50 mV/g. Figure 4-2 presents a picture of the selected vibration sensor.
With installation of acoustic and vibration sensors, drilling parameters, monitored by the modified configuration of the instrumented J.H. Fletcher & Co. roof bolter, included:

- Operation time
- Thrust or Feed Pressure
- Torque or Rotation Pressure
- Acoustic signals
- Vibration signals
- RPM of the bit (Rotation Rate)
- Penetration Rate (calculated from bit position)
- Drill bit position
- Vacuum pressure or water pressure of the flushing system

### 4.3. Data Acquisition Systems

In this study, there were two separate data-acquisition systems, including the machine PLC of J.H. Fletcher & Co. and a separate data-acquisition (DAQ) system. These systems have been
employed to record various drilling parameters at the same time while drilling a hole. Drilling data that was collected from these two data-acquisition systems were synchronized by using a relay. Drilling parameters, such as time, thrust or feed pressure, torque or rotation pressure, rotation rate or RPM of the bit, penetration rate, drill bit position, vacuum pressure or water pressure, etc., that was connected to the DAQ system by connecting it to the machine PLC. The sampling frequency of Fletcher roof bolter’s PLC system was 10 Hz (or 0.1 second time interval), and for this study was increased up to 100 Hz.

The parallel DAQ system was used to monitor acoustic and vibration signals while drilling the holes was a National Instruments data acquisition box, controlled by a PC and Labview software. A MATLAB code was developed interface the LabView program and thus the DAQ system to collect data from acoustic and vibration sensors. Wires from installed acoustic and vibrations sensors were directly connected to the new DAQ system. Moreover, this DAQ system allowed for better control of the data rate and the ability to enhance the sampling frequencies to facilitate detecting certainly geological features. The sampling frequency for the drilling tests was selected at 1000 Hz (or 0.001 second time interval) for acoustic and vibration signals. Figure 4-3 presents this new DAQ system and Figure 4-4 shows a screen shot of the input data recorded by a LabView code.
Figure 4-3. A picture of a DAQ system to record acoustic and vibration signals

Figure 4-4. A screen shot of the input data recorded by a LabView code
4.4. Data Analysis using Pattern Recognition Algorithms

In this study, joint detection algorithms were combined with pattern recognition with the objective of locating known joints. Drilling parameters, including feed and rotation pressure, as well as acoustic and vibration signals were analyzed by joint detection algorithms. According to different observed characteristics of various drilling parameters, mean change detection system was selected for data analysis and pattern recognition. The discussions, developed algorithms, and formulations used in this study are mainly based on the recommended concepts by the classic textbook in pattern recognition: “Detection of Abrupt Changes: Theory and Application” (Basseville and Nikiforov, 1993).

4.4.1. The Cumulative Sum (CUSUM) Algorithm

The CUSUM algorithm is a sequential analysis technique, which was first proposed by E.S. Page of the University of Cambridge. This concept is usually applied for detection of abrupt changes in streaming data (Page, 1945a). The CUSUM algorithm has been subject of several subsequent modifications (Basseville and Nikiforov, 1993).

According to a brief review of the CUSUM algorithm, assuming a time series $y_k, k=1,2, \ldots$ is an approximate Gaussian random sequence, and the variance of it is $\sigma^2$. In addition, assuming this time series has a mean of $\mu$ till step $t_0$, and a mean of $\mu-\eta$ after the step $t_0$.

Therefore, the sufficient statistic $s_k$ can be defined as:

$$s_k = \mu - \frac{\eta}{2} - y_k$$  \hspace{1cm} (1)

The CUSUM decision function can be defined as:

$$g_k = \max (g_{k-1} + s_k, 0)$$  \hspace{1cm} (2)

The alarm time of detection can be calculated as:

$$t_a = \min (k: g_k \geq h)$$  \hspace{1cm} (3)
where,

- \( h \): a pre-determined threshold to define changes;
- \( g_0 = 0 \).

As for the equation (3), it is equivalent to the following stopping rule:

\[
t_a = \min (k: S_k \geq m_k + h)
\]  

where,

- Cumulative sum: \( S_k = \sum_{i=1}^{k} S_i \);
- An adaptive threshold: \( m_k + h \), and \( m_k = \min_{1 \leq i \leq k} S_i \).

Thus, in fact, it is apparent that the adaptive threshold \( m_k + h \) carries information about the former observations, and it can be modified on-line. In addition, the discussed detection rule is a comparison of cumulative sum \( S_k \) with the adaptive threshold \( m_k + h \) (Basseville and Nikiforov, 1993).

### 4.4.2. Development of Algorithms for Mean Change Detection

According to the characteristic of recorded drilling parameters, pattern recognition algorithms have been developed for joint detection. Taking the recorded feed pressure and rotation pressure signals (an example is shown in Figure 4-5), a critical drop has been observed both in the feed pressure signal and the rotation pressure signal at around 76.2 cm (or around 30-in), which was the location that the drill bit encountered the joint in the specimen. In addition, the values of feed pressure and rotation pressure recover rapidly after the drill bit moves across the joint, and as noted before, a V type drop can be observed in the streaming data. This V type drop can be utilized as a basis for joint detection. Therefore, the joint detection algorithms, to monitor feed pressure signal as well as rotation pressure signal, can be created to evaluate mean changes of the streaming data to identify the information of the joint location. In this study, an updated two-side CUSUM
algorithm has been employed to develop joint detection algorithms which aim to identify the location of the joint in the specimen by monitoring feed and rotation pressure signals. In addition, to smooth out short-term fluctuations and highlight long-term trends of the recorded data, the statistical method of running average has also been applied on feed pressure and rotation pressure signals.

![Figure 4-5](image)

**Figure 4-5.** An example of feed pressure and rotation pressure signals indicate a significant change at the location that the drill bit encountered the joint in the specimen

As for the updated two-side CUSUM algorithm, assuming that time series $y_k$, $k=1,2,\ldots,$ which has been mentioned above, has a mean of $\mu_0$ till step $t_a$, and the mean value after step $t_a$ is either $\mu^+_1 = \mu_0 + \eta$ or $\mu^-_1 = \mu_0 - \eta$. In this case, the scenario of $\mu^+_1$ is applied for detecting the upward change in the mean, and the scenario of $\mu^-_1$ is applied for identifying the downward change in the mean, in other words, a drop in the time series. This mimic the concept of “Thrust valley” that was observed by Finfinger et. al. (2003).

Therefore, comparing with equations (1) and (2), the CUSUM decision function can be defined as:

For the upward change:
\[ g_k^+ = (g_{k-1}^+ + y_k - \mu_0 - \frac{\eta}{2})^+ \quad (5) \]

For the downward change:

\[ g_k^- = (g_{k-1}^- - y_k + \mu_0 - \frac{\eta}{2})^+ \quad (6) \]

Moreover, regarding to two different scenarios that include the upward change and the downward changes, respectively, the detecting alarm time can be defined as:

For the upward change:

\[ t_a = \min\{k: (g_k^+ \geq h)\} \quad (7) \]

For the downward change:

\[ t_a = \min\{k: (g_k^- \geq h)\} \quad (8) \]

where,

- \( h \): a pre-defined threshold;
- \( g_0^+ = g_0^- = 0 \).

These algorithms have been implemented in a MATLAB program that loads the drilling parameter data files and performs the subsequent analysis for identifying the joints or voids along the borehole. More detailed discussion of the results of these programs will follow.
5.1. Initial Laboratory Tests on Joint Detection

5.1.1. Test Sample Preparation

Given the objective of joint detection from drills, a series of laboratory tests have been carried out with the instrumented roof bolter testing unit at the J.H. Fletcher & Co. testing facility, Huntington, WV, USA. This refers to a series of full scale drilling tests in controlled environments, namely various pre-designed joints by pouring concrete blocks with prescribed strength that were stacked on top of each other to represent various drilling mediums and the contact surface between the blocks to represent a pre-planned joint. Figure 5-1 shows the instrumented Fletcher drill unit with mounted acoustic and vibration sensors.

Figure 5-1. The instrumented Fletcher drill unit with vibration and acoustic sensors
Preliminary laboratory drilling tests for joints and/or voids detection involved a set of 18 concrete blocks with various strengths that were cast to simulate various rock strength conditions, and these blocks were allowed to be cured for more than 28 days to reach their pre-designed strengths. The dimensions of each block were approximately of 0.91 x 0.91 (width) and 0.75 m in height (or 36 x 36 x 30-in). The concrete blocks were divided into three groups with 3 different strength classes of hard, medium and soft. **Figure 5-2** shows the process of purring of concrete blocks with various strength. **Table 5-1** demonstrates 3 groups of concrete blocks with three pre-designed strengths.

![Figure 5-2. Pouring of concrete blocks with various strength for testing](image)

**Table 5-1.** 18 concrete blocks with 3 different strengths

<table>
<thead>
<tr>
<th>Group</th>
<th>Number of Concrete Blocks</th>
<th>Strength of Concrete Blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soft (S)</td>
<td>6</td>
<td>~ 20 MPa (or ~2,900 psi)</td>
</tr>
<tr>
<td>Medium (M)</td>
<td>6</td>
<td>~ 50 MPa (or ~ 7,200 psi)</td>
</tr>
<tr>
<td>Hard (H)</td>
<td>6</td>
<td>~ 70 MPa (or ~10,000 psi)</td>
</tr>
</tbody>
</table>
The testing samples with pre-determined joints in this study was a combination of two concrete blocks that were stacked to build a testing sample, in other words, one concrete block was placed on the top of another concrete block. Besides, a small gap, which was less than 3.175 mm (or 1/8-in), was left to simulate a “joint”. As such, a set of 9 different types of testing specimens with a pre-determined location of joint in each were built for drilling tests, including S-M (Soft-Medium), S-H (Soft-Hard), S-S, M-S, M-M, M-H, H-S, H-M, and H-H. Moreover, the simulated joints were located at the depth of around 76.2 cm (30-in) within each testing specimen. Table 5-2 presents various combinations of concrete blocks for drilling tests. Figure 5-3 shows a poured concrete block and a model of testing sample with a simulated “joint” between two concrete blocks.

### Table 5-2. Various combinations of concrete blocks for drilling tests

<table>
<thead>
<tr>
<th>Order</th>
<th>Sample Setup</th>
<th>Joint Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bottom</td>
<td>Top</td>
</tr>
<tr>
<td>1</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>2</td>
<td>S</td>
<td>M</td>
</tr>
<tr>
<td>3</td>
<td>S</td>
<td>H</td>
</tr>
<tr>
<td>4</td>
<td>M</td>
<td>S</td>
</tr>
<tr>
<td>5</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td>6</td>
<td>M</td>
<td>H</td>
</tr>
<tr>
<td>7</td>
<td>H</td>
<td>S</td>
</tr>
<tr>
<td>8</td>
<td>H</td>
<td>M</td>
</tr>
<tr>
<td>9</td>
<td>H</td>
<td>H</td>
</tr>
</tbody>
</table>

*Concrete Block Strength:*
- S: Soft Strength (~ 20 MPa or ~2,900 psi)
- M: Medium Strength (~ 50 MPa or ~ 7,200 psi)
- H: Hard Strength (~70 MPa or ~ 10,000 psi)
Figure 5-3. A poured concrete block and a model of testing sample
5.1.2. Testing Process and Data Collection

For full-scale drilling tests on every concrete block settings, a pattern of boreholes (around 20 holes) were drilled by the instrumented roof bolter in each testing specimen. As mentioned in Chapter 4, in these preliminary laboratory tests, two separate data-acquisition systems, including the machine PLC of J.H. Fletcher and an additional DAQ system were employed to record data while drilling. Table 5-3 lists various drilling data and their unit that were recorded by these two data-acquisition systems. Figure 5-4 demonstrates an example of drilling parameters that were recorded by the machine PLC of J.H. Fletcher. Figure 5-5 shows an example of acoustic and vibration signals that were collected by the DAQ system.

Table 5-3. Various drilling parameter recorded from two data-acquisition systems

<table>
<thead>
<tr>
<th>Drilling Data</th>
<th>Data-acquisition Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operation Time [ms]</td>
<td>The machine PLC of J.H. Fletcher &amp; Co</td>
</tr>
<tr>
<td>Feed Pressure [psi]</td>
<td></td>
</tr>
<tr>
<td>Rotation Pressure [psi]</td>
<td></td>
</tr>
<tr>
<td>RPM (or Rotation Rate) [rev/min]</td>
<td></td>
</tr>
<tr>
<td>Penetration Rate [in/sec]</td>
<td></td>
</tr>
<tr>
<td>Drilling Bit Position [in]</td>
<td></td>
</tr>
<tr>
<td>Vacuum Pressure of the Flushing System [In-Hg]</td>
<td>A DAQ system</td>
</tr>
<tr>
<td>Acoustic Signals [dB]</td>
<td></td>
</tr>
<tr>
<td>Vibration Signals [mV/g]</td>
<td></td>
</tr>
</tbody>
</table>
Figure 5-4. An example of recorded drilling parameters

Figure 5-5. An example of collected acoustic and vibration signals

5.2. Joint Detection by Using Proposed Algorithms

In the initial analysis, joint detection programs, based on aforementioned updated CUSUM algorithms, were developed to analyze collected drilling parameters. Individual drilling parameters, including feed pressure, rotation pressure, acoustic, and vibration signal were recorded. In addition, briefly review of the feed and rotation pressure data, showed that the drilling machine did not reach
steady state at the beginning and end of the borehole. Therefore, to rectify the situation these stages, the data recorded within the first 12.7 cm (or 5-in) and last 12.7 cm (or 5-in) were not used in the analysis. Joint detection results by analyzing recorded drilling parameters on various concrete block setups will be discussed in following sections.

Reviewing the characteristics of recorded drilling parameters, recorded data varied within a limit while drilling through grout/rock, and the variation was much less than 40%; meanwhile, the sudden change or drop, which occurs while the drill bit goes through a joint/void, is larger than 40%, such as the thrust data. Therefore, the 40% of the mean was used as the threshold for joint detection in this study. In addition, the value of this threshold can be adjusted based on different geological conditions to achieve better detection results.

5.2.1. Soft - Hard (S-H) Concrete Combination

The S-H concrete specimen was formed by placing a hard-strength concrete block on the top of a soft-strength concrete block. A total of 14 boreholes were drilled by the instrumented roof bolter to collect aforementioned drilling parameters and identify the location of pre-designed joint. Joint detection programs generated joint alerts, as shown by red points in Figure 5-6, at certain positions along the boreholes. However, if there was no joint and/or void existed in these positions based on the initial design of testing samples, the “detected joints” were considered as false alarms generated during the processing of the data.

The four main drilling parameters had a distinctively different capability and sensitivity to locate the joints. The detection rates for analyzing the feed pressure, rotation pressure, acoustic, and vibration were about 93%, 86%, 64%, and 43%, respectively. Moreover, the programs generated 1, 8, 4, and 4 false alarms, for the four drilling parameters, respectively. Figure 5-6
shows the joint detection results achieved by monitoring drilling parameters of the feed and rotation pressure data in S-H concrete setup.

![Graphs showing feed and rotation pressure data](image)

**Figure 5-6.** Joint detection results by monitoring the feed and rotation pressure data in S-H concrete setup

### 5.2.2. Hard - Soft (H-S) Concrete Combination

The concrete-block setup of H-S, the combination of hard strength and soft strength concrete blocks, a total of 17 boreholes were drilled by the instrumented roof bolter. Joint was identified at the depth of approximately 76.2 cm (or 30-in) in majority of boreholes, while also generating several false alarms. The joint detection rates via monitoring the feed and rotation pressure, acoustic, and vibration were around 88%, 76%, 82%, and 53%, respectively, with accordingly 1, 4, 3, and 2 false alarms. **Figure 5-7** shows the joint detection results achieved by monitoring the feed pressure and rotation pressure data in H-S concrete setup.
5.2.3. Medium - Hard (M-H) Concrete Combination

The M-H testing specimen by combining the medium with the hard strength concrete block was tested and 17 boreholes were drilled in this specimen for data collection. As before, the joint was placed and identified at 76.2 cm (30-in) from the collar. The joint detection rates, achieved from monitoring the feed and rotation pressure, acoustic, and vibration, were 100%, 94%, 100%, and 76%, respectively. Moreover, the feed pressure did not generate false alarm during the process of data analysis, while the rotation pressure, acoustic, and vibration created 6, 4, and 9 false alarms, respectively. **Figure 5-8** demonstrates the joint detection results achieved by monitoring the feed pressure and rotation pressure data in M-H concrete setup.
5.2.4. Hard - Hard (H-H) Concrete Combination

To identify the simulated joint in high strength rocks, two hard strength concrete blocks were used to build the H-H specimen and 18 boreholes were drilled in this sample. The feed pressure offered the joint detection rate was up to 94% with 1 false alarm. The rotation pressure detected the joint in 83% of the cases with 1 false alarm. The joint detection rates were obtained from the acoustic and vibration were around 83%, and 72%, respectively, with 0 and 3 false alarms, respectively. Figure 5-9 demonstrates the joint detection from the feed and rotation pressure data in M-H concrete setup.
5.2.5. Hard - Medium (H-M) Concrete Combination

In the H-M concrete combination was used for drilling a total of 21 boreholes and the joint detection rates from the feed and rotation pressure were up to 100% and 95%, respectively. Corresponding number of false alarms were 2 and 16. In addition, the joint detection rates, obtained from the acoustic and vibration signals were 95% and 62%, respectively, while created 4 and 11 false alarms. Figure 5-10 represents the results for the feed and rotation pressure data in H-M concrete setup.
5.2.6. Medium - Soft (M-S) Concrete Combination

A M-S concrete testing specimen was set up and a total of 18 boreholes were drilled in this sample. Joint detection rates by using the feed and rotation pressure were both up to 100%. However, in this case, the feed pressure created 2 false alarms while the rotation pressure created 17 false alarms. Joint detection rates by analyzing the acoustic and vibration were 100% and 83%, respectively, with corresponding 13 and 11 false alarms. **Figure 5-11** shows the joint detection results obtained for feed and rotation pressure data in M-S concrete setup.
5.2.7. Soft - Medium (S-M) Concrete Combination

The S-M concrete combination was drilled 18 times but joints in 16 boreholes was successfully identified by the feed pressure, a detection rate of around 89% with 2 false alarms was achieved. The rotation pressure offered the joint detection rate of about 83% in this sample, and it created 20 false alarms from all 18 boreholes. The joint detection rates for the acoustic and vibration were 83% and 56%, respectively. Moreover, the acoustic and vibration also generated responding 3 false alarms and 18 false alarms. **Figure 5-12** shows the joint detection results in S-M setup.
**5.2.8. Medium - Medium (M-M) Concrete Combination**

In this combination, a set of 17 boreholes were drilled and detection rate of analyzing the feed pressure was about 82% with 1 false alarm was generated. The detection rate of about 76% with 13 false alarms were generated during the process of monitoring the rotation pressure data. The joint detection rate from the acoustic signal was around 71% with 1 false alarm and the analysis of vibration signal offered the detection rate of about 82% with 17 false alarms were created. **Figure 5-13** shows the joint detection results of the feed and rotation pressure data in M-M concrete setup.
5.2.9. Soft - Soft (S-S) Concrete Combination

The scenario of detecting the simulated joint existed in rock with low strength was also tested in the initial research by mounting two concrete blocks with soft strength in a sample. The joint detection rates from the feed and rotation pressure in this case were about 100% and 94%, respectively, with corresponding 2 and 24 false alarms for the 16 boreholes drilled in this sample. Both the acoustic and the vibration signals offered the joint detection rate of 81%, while corresponding 7 and 17 false alarms were created. Figure 5-14 shows the joint detection results obtained by monitoring the feed and rotation pressure data in S-S concrete setup.
5.3. Summary

In the initial full-scale drilling tests conducted to verify the ability of the joint/void detection algorithms to identify small fractures involved casting concrete samples with various strength, which allowed for a set of nine combination samples for drilling. The simulated joints with the apertures less than 3.175 mm (or 1/8-in) was located at the depth of approximately 76.2 cm (or 30-in). The existing void detection software (before this study) monitored drilling data for the torque (rotation pressure) and thrust (feed pressure) for joint detection. While its detection algorithm provided curtained capabilities to locate some joints, it offered relatively low detection rates and generated a notable number of false alarms. Table 5-4 summaries joint detection results by using the existing void detection software to monitor the feed pressure data in seven concrete setups (Bahrampour et al., 2015).
**Table 5-4.** Joint detection results by using the existing algorithm to monitor the feed pressure data in seven different concrete setups

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of holes</strong></td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>18</td>
<td>17</td>
</tr>
<tr>
<td><strong>Detection rate</strong></td>
<td>81%</td>
<td>61%</td>
<td>95%</td>
<td>100%</td>
<td>81%</td>
<td>56%</td>
<td>82%</td>
</tr>
<tr>
<td><strong>False alarms</strong></td>
<td>&gt;25</td>
<td>&gt;30</td>
<td>&gt;60</td>
<td>&gt;60</td>
<td>&gt;55</td>
<td>&gt;50</td>
<td></td>
</tr>
</tbody>
</table>

The improved CUSUM algorithms were applied with the objective of enhancing joint detection and reducing the false alarms in this study. By application of the modifications in the algorithm, pre-designed joints could successfully be identified by monitoring individual drilling parameters of the feed and rotation pressure, as well as acoustic, and vibration in many cases.

**Table 5-5** to **Table 5-8** summarize joint detection results in all nine concrete block setups.

**Table 5-5.** Joint detection results via monitoring the feed pressure data in all nine specimens

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of holes</strong></td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td><strong>Number of holes have identified joint</strong></td>
<td>13</td>
<td>15</td>
<td>17</td>
<td>17</td>
<td>21</td>
<td>18</td>
<td>16</td>
<td>14</td>
<td>16</td>
<td>147</td>
</tr>
<tr>
<td><strong>Detection rate</strong></td>
<td>93%</td>
<td>88%</td>
<td>100%</td>
<td>94%</td>
<td>100%</td>
<td>100%</td>
<td>89%</td>
<td>82%</td>
<td>100%</td>
<td>94%</td>
</tr>
<tr>
<td><strong>False alarms</strong></td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>12</td>
</tr>
</tbody>
</table>
Table 5-6. Joint detection results via monitoring the rotation pressure data in all specimens

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>12</td>
<td>13</td>
<td>16</td>
<td>15</td>
<td>20</td>
<td>18</td>
<td>15</td>
<td>13</td>
<td>15</td>
<td>137</td>
</tr>
<tr>
<td>Detection rate</td>
<td>86%</td>
<td>76%</td>
<td>94%</td>
<td>83%</td>
<td>95%</td>
<td>100%</td>
<td>83%</td>
<td>76%</td>
<td>94%</td>
<td>88%</td>
</tr>
<tr>
<td>False alarms</td>
<td>8</td>
<td>4</td>
<td>6</td>
<td>1</td>
<td>16</td>
<td>17</td>
<td>20</td>
<td>13</td>
<td>24</td>
<td>109</td>
</tr>
</tbody>
</table>

Table 5-7. Joint detection results by monitoring the acoustic signals in all specimens

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>9</td>
<td>14</td>
<td>17</td>
<td>15</td>
<td>20</td>
<td>18</td>
<td>15</td>
<td>12</td>
<td>13</td>
<td>133</td>
</tr>
<tr>
<td>Detection rate</td>
<td>64%</td>
<td>82%</td>
<td>100%</td>
<td>83%</td>
<td>95%</td>
<td>100%</td>
<td>83%</td>
<td>71%</td>
<td>81%</td>
<td>84%</td>
</tr>
<tr>
<td>False alarms</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>0</td>
<td>4</td>
<td>13</td>
<td>3</td>
<td>1</td>
<td>7</td>
<td>39</td>
</tr>
</tbody>
</table>

Table 5-8. Joint detection results by monitoring the vibration signals in all specimens

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>6</td>
<td>9</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>15</td>
<td>10</td>
<td>14</td>
<td>13</td>
<td>106</td>
</tr>
<tr>
<td>Detection rate</td>
<td>43%</td>
<td>53%</td>
<td>76%</td>
<td>72%</td>
<td>62%</td>
<td>83%</td>
<td>56%</td>
<td>82%</td>
<td>81%</td>
<td>68%</td>
</tr>
<tr>
<td>False alarms</td>
<td>4</td>
<td>2</td>
<td>9</td>
<td>3</td>
<td>11</td>
<td>11</td>
<td>18</td>
<td>17</td>
<td>17</td>
<td>92</td>
</tr>
</tbody>
</table>

Table 5-9 shows comparison of joint detection results by monitoring individual drilling parameters. Of these four individual drilling parameters used in this study, the feed pressure
offered the best performances on joint detection in all nine concrete sample setups. The average detection rate was about 94% with the number of 12 false alarms generated. The rotation pressure provided lower performances of joint detection using the same joint detection programs. The average detection rate achieved from the rotation pressure was about 88% with 109 false alarms.

The acoustic and vibration sensors were initially mounted on the instrumented roof bolter to record related data for classifying rock strata. While the recorded data also offered certain capabilities to identify joints and/or voids, the overall performance was not acceptable. The average detection rates obtained from various of nine concrete block settings were 84% and 68%, respectively. Moreover, using the acoustic and vibration to detect pre-designed joints generated more false alarms than the other parameters when processing data from all 156 boreholes.

Table 5-9. Comparison of joint detection results of various individual drilling parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Average detection rate (156 holes)</th>
<th>Number of false alarms (156 holes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feed Pressure</td>
<td>94%</td>
<td>12 (8%)</td>
</tr>
<tr>
<td>Rotation Pressure</td>
<td>88%</td>
<td>109 (70%)</td>
</tr>
<tr>
<td>Acoustic</td>
<td>84%</td>
<td>39 (25%)</td>
</tr>
<tr>
<td>Vibration</td>
<td>68%</td>
<td>92 (59%)</td>
</tr>
</tbody>
</table>

In the study of hypothesis testing, the notion of statistical errors, including type I and type II error, is an integral part of the evaluation process. A type I error, is also called false positive, occurs when the null hypothesis ($H_0$) is true but it is rejected; in other words, the type I error is the inappropriate rejection of a true null hypothesis ($H_0$). A type II error, which is also called false negative, occurs when the null hypothesis ($H_0$) is false but it is accepted. Namely, the type II error is the incorrect acceptance of a false null hypothesis ($H_0$). In this study, the null hypothesis $H_0$ was set as the exist of a void/joint (Neyman and Pearson, 1933; Sheskin, 2004; Peck and Devore, 2011).
Hence, as shown in **Table 5-9**, the type I error only occurs when the $H_0$ is true; namely, the low detection rate. The type II error only occurs when $H_0$ is false; namely, the false alarms. **Table 5-10** to **5-13** show a probability summary of examining joint detection results achieved from monitoring the feed pressure, rotation pressure, acoustic, and vibration, respectively.

**Table 5-10.** A probability summary of examining detection results obtained from the feed pressure

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accept $H_0$</strong></td>
<td>94% (correct decision)</td>
<td>8% (type II error)</td>
</tr>
<tr>
<td><strong>Reject $H_0$</strong></td>
<td>6% (type I error)</td>
<td>92% (correct decision)</td>
</tr>
</tbody>
</table>

**Table 5-11.** A probability summary of examining detection results obtained from the rotation pressure

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accept $H_0$</strong></td>
<td>88% (correct decision)</td>
<td>70% (type II error)</td>
</tr>
<tr>
<td><strong>Reject $H_0$</strong></td>
<td>12% (type I error)</td>
<td>30% (correct decision)</td>
</tr>
</tbody>
</table>

**Table 5-12.** A probability summary of examining detection results obtained from the acoustic

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accept $H_0$</strong></td>
<td>84% (correct decision)</td>
<td>25% (type II error)</td>
</tr>
<tr>
<td><strong>Reject $H_0$</strong></td>
<td>16% (type I error)</td>
<td>75% (correct decision)</td>
</tr>
</tbody>
</table>

**Table 5-13.** A probability summary of examining detection results obtained from the vibration

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accept $H_0$</strong></td>
<td>68% (correct decision)</td>
<td>59% (type II error)</td>
</tr>
<tr>
<td><strong>Reject $H_0$</strong></td>
<td>32% (type I error)</td>
<td>41% (correct decision)</td>
</tr>
</tbody>
</table>

The power of a test is the probability to reject an incorrect null hypothesis ($H_0$); thus, the powers of the feed pressure, rotation pressure, acoustic, and vibration is 92%, 30%, 75%, and 41%, respectively.
respectively. Table 5-14 contains the summaries corresponding to the probabilities of the type I and II errors and powers for using these four individual parameters.

Table 5-14. A probability and power summary of using individual parameters

<table>
<thead>
<tr>
<th></th>
<th>Probability (type I error)</th>
<th>Probability (type II error)</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feed Pressure</td>
<td>6%</td>
<td>8%</td>
<td>92%</td>
</tr>
<tr>
<td>Rotation Pressure</td>
<td>12%</td>
<td>70%</td>
<td>30%</td>
</tr>
<tr>
<td>Acoustic</td>
<td>16%</td>
<td>25%</td>
<td>75%</td>
</tr>
<tr>
<td>Vibration</td>
<td>32%</td>
<td>59%</td>
<td>41%</td>
</tr>
</tbody>
</table>

Of these four examined joint detection results by monitoring individual parameters, using the feed pressure offers the minimum probability of type I error as well as the smallest probability of the type II error, and it offers the most reliable performance. Meanwhile, using the rotation pressure provides the smaller probability of type I error, it yields a high number of 70% type II error. The probability of the type I error that is achieved from using the acoustic and vibration signals are 16% and 32%, respectively; and yield corresponding 25% and 59% type II error.

According to above statistical analysis, updated pattern recognition algorithms (or change detection algorithms) have provided improved capabilities in sensing joints with the aperture less than 3.175 cm (or 1/8-in). However, the sensitivity and precision of these joint detection programs were limited and prone to errors. There were still several issues that must be resolved to reduce the type I and II errors and to improve the detection rates and reduce the number of false alarms, and to discriminate joints and/or voids with smaller apertures.

As the above-mentioned analysis shows, two kinds of failures, including false negative (missed detections) and false positive (false alarms), were generated while analyzing collected drilling parameters for joint detection. Of these two sorts of failures, each one may lead to significant risk and safety issues in engineering applications. For example, the false negative,
namely missed detections, may be critical joints and therefore results in instability of ground support. As for the false positive, namely false alarms, it may generate many unnecessary detections and increase require additional supporting and impose unnecessary costs to the operation. Comparing to the previous studies and existing algorithms, reducing both false positive/negative is a laudable goal in this study.

Several reasons may lead to registration of a false alarm. This includes the quality of monitored data, precision of algorithms, and the capability of data acquisition system. The capability of detection sensors to sense joints while drilling and the accuracy of detection algorithms are two main focuses of the current study. Therefore, several composite parameters are introduced to enhance the capabilities of the system in identifying the joints or geological features. In addition, the wavelet analysis is also employed to improve the sensitivity of detection algorithms by reducing the noise in data stream. The details of studies on these two approaches will be discussed in the following chapters.
Chapter 6
APPLICATION OF COMPOSITE PARAMETERS TO IMPROVE JOINT DETECTION

6.1. Introduction

The results of using pattern recognition algorithms to monitor individual drilling parameters and identify locations of joints/voids in the rock mass, and evaluation of their corresponding performances and related deficiencies are discussed earlier. While analysis of individual drilling parameters offers certain capabilities in sensing joints with small apertures, they are also experiencing many limitations; therefore, affecting their sensitivities (detection rate) and precisions (false alarms) during the process of joint detection.

The limitations of joint detection algorithms using individual parameters could be due to various reasons. For example, the changes in feed pressure might be due to joints or voids, but could also be caused by the drill control system trying to adjust the drilling rate. However, using multiple parameters and combined / composite parameters could rectify the problems and offer a better means of detecting changes, which can be used to detect joints/voids more accurately. Such composite parameters would be more effective to increase the detection rate and to reduce the number of false alarms. It could also reduce the “noises” in drilling parameter signals that might confuse joint detection algorithms.

For this purpose, various combinations of input parameters and their algebraic relation have been examined to find the best composite indices for joint detection. Simultaneously, artificial intelligence systems such as PCA and Decision Tree systems are under evaluation to find the most suitable combination of input parameters for joint detection. In this chapter, three composite
parameters, including \( RP/FP/PR \), \( (RP/FP)/SED \), and Field Penetration Index \((FPI)\), will be introduced to provide collaborative decision on joint detection.

### 6.2. Use of \( RP/FP/PR \) for Joint Detection

#### 6.2.1. Introduction

One of the composite parameters that has offered a good performance is the ratio of rotation/feed pressure divided by penetration rate or \( RP/FP/PR \).

\[
RP/FP/PR = \text{Rotation Pressure/Feed Pressure/Penetration Rate}
\quad (6-1)
\]

Where, 
- \( RP \), Rotation Pressure, MPa (PSI);
- \( FP \), Feed Pressure, MPa (PSI);
- \( PR \), Penetration Rate, cm/second (inches/second);
- \( RP/FP/PR \), second/cm (second/inches).

**Figure 6-1** shows examples of the variation of \( RP/FP/PR \) composite parameters for combinations of nine different concrete block settings. A distinct change can be observed in each \( RP/FP/PR \) data at the location of pre-designed joint. The distinct change could be used for locating the joint and/or a void by pattern recognition algorithms to link the location with drill bit position data or borehole depth.

![Figure 6-1](image_url)

a. H-H  
b. H-M
Figure 6-1. Examples of the variation of RP/FP/PR for a set of nine concrete block settings
A close examination of the behavior and properties of RP/FP/PR data, shows that the value of RP/FP/PR in each concrete block setting varies approximately the same amount before and after the change. This was observed even when drilling into the samples with different strength. Moreover, to eliminate the noise generated by the drilling unit, the data collected within the first 12.7 cm (or 5-in) and last 12.7 cm (or 5-in) was not included in the analysis. Meanwhile, the input signal data was also pre-filtered to smooth out short-term fluctuations and noises by digital filtering which allows for higher contrast in the targeted features and highlight the trends. Therefore, the threshold was set up at 60% of the mean of entire effective RP/FP/PR data (excluding cut off data).

6.2.2. Statistical Analysis of Joint Detection Results from the RP/FP/PR

Using the drilling parameters recorded from drilling aforementioned nine concrete block setups, the updated joint detection programs were employed to analyze the RP/FP/PR data to identify the locations of pre-designed joints. Figure 6-2 represents an example of the plot of feed pressure, rotation pressure, and RP/FP/PR for drilling in an H-H concrete setup. Comparing these three parameters for joint detection, each of them shows an apparent change at the depth of approximately 76.2 cm (or 30-in) where the pre-designed joint was located. However, the change in the RP/FP/PR is more distinct than the individual parameters. Moreover, the rest of RP/FP/PR data shows less variations and noise compared to individual drilling parameters. Thus, monitoring RP/FP/PR may provide a more accurate result for joint detection, and allow for reduced number of false alarms.
Figure 6-2. Plot of feed pressure, rotation pressure, and RP/FP/PR for drilling in an H-H sample.

Figure 6-3 demonstrates joint detection results by analyzing the RP/FP/PR data while drilling into the S-M concrete block setting. In this test, a set of 18 boreholes were drilled. Typically, joint information, shown as blue points, was reflected as a void in each borehole. The joint detection rate on the S-M concrete setup was about 94%, and 1 false alarm (red point) was generated in borehole #12 during the detection process. Furthermore, in borehole #16, the programs failed to detect the joint. A trend line (the blue break line in this figure was drawn from joining the detected voids in the borehole) can be considered as a secondary measure for the estimation of the location of the joint by the detection programs.
Figure 6-3. An example of joint detection result by analyzing the RP/FP/PR data in the S-M concrete setup

As for the other eight concrete block settings, using the updated programs to monitor the corresponding RP/FP/PR data also achieve relatively better results. Figure 6-4 shows joint detection results using the RP/FP/PR data on the S-H, H-S, M-H, H-H, H-M, M-S, M-M, and S-S concrete block settings.
Table 6-1 summarizes joint detection results by analyzing the $RP/FP/PR$ on all concrete setups. Using the composite parameter of $RP/FP/PR$ which offers better joint detection results compared to individual drilling parameters. The average joint detection rate, obtained from 156 holes in all nine concrete settings, is up to around 97%, with only 9 false alarms are generated while monitoring the $RP/FP/PR$.

Table 6-1. Joint detection results by monitoring the $RP/FP/PR$ on all concrete setups

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of holes</strong></td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td><strong>Number of holes have identified joint</strong></td>
<td>13</td>
<td>15</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>16</td>
<td>151</td>
</tr>
<tr>
<td><strong>Detection rate</strong></td>
<td>93%</td>
<td>88%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>94%</td>
<td>94%</td>
<td>100%</td>
<td>97%</td>
</tr>
<tr>
<td><strong>False alarms</strong></td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>9</td>
</tr>
</tbody>
</table>
6.3. Use of (RP/FP)/SED for Joint Detection

6.3.1. Introduction of (RP/FP)/SED

A new composite parameter, (RP/FP)/SED, has also been considered in this study to improve performances of the joint detection algorithms. In addition to drilling parameters of rotation pressure and feed pressure, the specific energy of drilling (SED), representing required energy to fracture a unit volume of rocks (Teale, 1965), has also been added to this composite parameter. The SED and the (RP/FP)/SED can be defined as

\[ SED = \frac{(W_t + W_q)}{V} = \frac{(\tau \omega + F_u)}{(\pi r^2 u)} \]  

(6-2)

\[ \frac{(RP/FP)}{SED} = \frac{\text{Rotation Pressure}}{\text{Feed Pressure}} \times \frac{\pi r^2 u}{\tau \omega + F_u} \]  

(6-3)

Where, \(RP\), Rotation Pressure, MPa (PSI);

\(FP\), Feed Pressure, MPa (PSI);

\(\tau\), torque, N m;

\(\omega\), rotary speed, rad/second;

\(F\), thrust, N;

\(u\), penetration rate, m/second;

\(r\), the radius of the rotary drill string, m.

Figure 6-5 shows an example of a data stream for (RP/FP)/SED compared to corresponding feed pressure, rotation pressure, and drill bit position data recorded by drilling into the H-H concrete setup. Similar to the collected feed pressure as well as rotation pressure data, the (RP/FP)/SED also demonstrates a distinct change at the location of approximately 76.2 cm (30-in) where the pre-designed joint was located. Similar to the RP/FP/PR, the change observed in this new composite parameter is more apparent than individual parameters of the feed pressure and rotation pressure, and the (RP/FP)/SED data exclude at the change happened shows less variations
and noise. In other words, monitoring the \((RP/FP)/SED\) for the objective of joint detection, compared to individual parameters, may result in higher detection rate and lower number of false alarms.

**Figure 6-5.** Feed pressure, rotation pressure, and \((RP/FP)/SED\) associated with drill bit position

### 6.3.2. Statistical Analysis of Joint Detection Results from the \((RP/FP)/SED\)

**Figure 6-6** shows joint detection results for monitoring the \((RP/FP)/SED\) data, collected from drilling into the H-H concrete setup in 18 boreholes. The pre-designed joint is detected at the location of around 76.2 cm (or 30-in) within the specimen with no false alarms.
Figure 6-6. Example of joint detection result for analyzing (RP/FP)/SED data in the H-H sample

Figure 6-7 shows joint detection results in other combinations of concrete blocks. As shown in these plots, the majority of simulated joint information, represented as blue points, have been detected by the developed joint detection programs to monitor the (RP/FP)/SED data stream. The locations of joints, observed as the blue break lines, are predicted at the depth of approximately 76.2 cm (or 30-in) within various combinations of concrete blocks. Furthermore, several false alarms are generated during the process of these joint detections in some concrete specimens.
a. S-H

b. H-S

c. M-H

d. H-M

e. M-S

f. S-M
Table 6-2 offers a summary of joint detection results by analyzing the (RP/FP)/SED in all test setups. Of the total of 156 boreholes drilled in the nine concrete block combinations, simulated joint in 151 boreholes have been detected. The average detection rate, achieved from using the detection programs to monitor this composite parameter offers is up to 97%, and the total number of 9 false alarms are generated in all 156 boreholes.

### Table 6-2. Joint detection results by monitoring the (RP/FP)/SED in all test setups

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of holes</strong></td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
</tr>
<tr>
<td><strong>Number of holes have identified joint</strong></td>
<td>13</td>
<td>15</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td><strong>Detection rate</strong></td>
<td>93%</td>
<td>88%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>94%</td>
<td>94%</td>
<td>100%</td>
<td>97%</td>
</tr>
<tr>
<td><strong>False alarms</strong></td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>
6.4. Use of \textit{FPI} for Joint Detection

6.4.1. Introduction of \textit{FPI}

Field Penetration Index (\textit{FPI}) is widely used in the field of tunneling where hard rock tunnel boring machines (TBM) are used for rock excavation. It is commonly applied to describe the bore ability of the rock with conditions of changing geologies and/or geo-techniques (Mobarral et al., 2013). In this study, the FPI is employed as a new composite parameter to dispute machine data for the objective of joint detection, and it can be defined as

\[ FPI = \frac{FP}{(PR/RPM)} \]  \hspace{1cm} (6-4)

Where, \( FP \), Feed Pressure, MPa (PSI);

\( PR \), Penetration Rate, cm/second (or inches/second);

\( RPM \), rotary speed, rad/second;

\( FPI \), MPa/cutter/cm/rev (or PSI/cutter/in/rev).

Figure 6-8 shows a plot of a converted \textit{FPI} data and corresponding feed pressure, rotation pressure, and drill bit position data. Briefly reviewing the trend of the converted \textit{FPI} data, a distinct drop (or change) also can be observed when the drill bit encounters the pre-determined joint. This drop can be considered as a sign to identify the location of the joint while monitoring the \textit{FPI} data.
Figure 6-8. Plot of feed pressure, rotation pressure, and FPI versus time

6.4.2. Statistical Analysis of Joint Detection Results Using FPI

As shown in Figure 6-9, for the H-H specimen, the pre-designed joint is detected by analyzing the composite parameter of the FPI that was calculated from recorded machine data. All joint information in 18 boreholes have been predicted at approximately pre-determined location of the joint (76.2 cm or 30-in). The detection rate for using FPI was 100% with no false alarms.
Figure 6-9. Example of joint detection result using $FPI$ data on the H-H sample

Figure 6-10 shows joint detection results in other concrete block combinations. Similar to former two composite parameters, using updated detection algorithms to analyze the $FPI$ also offers improved capabilities to discriminate the location of joints. The analysis of data from all sample settings using $FPI$ index shows some improvement, compared to analysis of individual drilling parameters. Table 6-3 summarizes joint detection results for calculated $FPI$ on all concrete setups and overall, out of the total number of 156 boreholes, joints in 150 boreholes have been detected for the average detection rate of 96%. However, it also generated 14 false alarms.
Figure 6-10. Joint detection results by using the FPI in various concrete block settings

Table 6-3. Summary of the results of Joint detection by using the FPI on all concrete setups

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>13</td>
<td>15</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>151</td>
</tr>
<tr>
<td>Detection rate</td>
<td>93%</td>
<td>88%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>89%</td>
<td>94%</td>
<td>100%</td>
<td>96%</td>
</tr>
<tr>
<td>False alarms</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>14</td>
</tr>
</tbody>
</table>
6.5. Summary

Various drilling parameters such as feed and rotation pressure are recorded by drill control system. These parameters in addition to data from sensors including acoustic and vibration signals can be applied for joint detection while drilling by the roof bolter. However, the sensitivity and precision of the pattern recognition algorithms using individual drilling parameters to locate joints and/or voids in ground are limited and are prone to errors. Using composite parameters, including RP/FP/PR, (RP/FP)/SED, and FPI, to provide additional basis for joint detection can be one of the effective methods to improve detection rate and filter noises in the data stream which may otherwise confuse detection programs and cause false alarms. The preliminary analysis shows that the use of composite parameters can generate more reliable results than analyzing the signals from individual drilling parameter. The analysis of the composite parameters shows lower noise in the data and somewhat more distinct change at the location of the pre-determined joint.

Table 6-4 summaries comparison of performances of using individual parameters as well as composite parameters in locating pre-designed joints for nine different concrete block settings. The comparison of the results obtained by using composite parameters with those of the past analysis using individual parameters has indicated a better performance with the higher detect rate as well as lower number of false alarms can be expected when using composite indices.

Table 6-4. Comparison of Joint detection results obtained from various parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>The average detection rate (156 boreholes)</th>
<th>False alarms (156 boreholes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feed Pressure</td>
<td>94%</td>
<td>12 (8%)</td>
</tr>
<tr>
<td>Rotation Pressure</td>
<td>88%</td>
<td>109 (70%)</td>
</tr>
<tr>
<td>Acoustic</td>
<td>84%</td>
<td>39 (25%)</td>
</tr>
<tr>
<td>Vibration</td>
<td>68%</td>
<td>92 (59%)</td>
</tr>
<tr>
<td>Composite Parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RP/FP/PR</td>
<td>97%</td>
<td>9 (6%)</td>
</tr>
<tr>
<td>(RP/FP)/SED</td>
<td>97%</td>
<td>9 (6%)</td>
</tr>
<tr>
<td>FPI</td>
<td>96%</td>
<td>14 (9%)</td>
</tr>
</tbody>
</table>
Table 6-5 to 6-7 present probability summary of examining detection results achieved from monitoring the RP/FP/PR, (RP/FP)/SED, and FPI, respectively. In addition, the detection rate of using the RP/FP/PR, (RP/FP)/SED, and FPI is 91%, 91%, and 86%, respectively.

Table 6-5. A probability summary of examining detection results obtained from the RP/FP/PR

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept $H_0$</td>
<td>97% (correct decision)</td>
<td>9% (type II error)</td>
</tr>
<tr>
<td>Reject $H_0$</td>
<td>3% (type I error)</td>
<td>91% (correct decision)</td>
</tr>
</tbody>
</table>

Table 6-6. A probability summary of examining detection results obtained from the (RP/FP)/SED

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept $H_0$</td>
<td>97% (correct decision)</td>
<td>9% (type II error)</td>
</tr>
<tr>
<td>Reject $H_0$</td>
<td>3% (type I error)</td>
<td>91% (correct decision)</td>
</tr>
</tbody>
</table>

Table 6-7. A probability summary of examining detection results obtained from the FPI

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept $H_0$</td>
<td>96% (correct decision)</td>
<td>14% (type II error)</td>
</tr>
<tr>
<td>Reject $H_0$</td>
<td>4% (type I error)</td>
<td>86% (correct decision)</td>
</tr>
</tbody>
</table>

Table 6-8 summarizes the corresponding probabilities for using four individual drilling parameters and three composite parameters. The comparison of the probabilities of type I and II errors that are recorded by examining composite parameters with those of the former results using individual parameters has also proved that composite parameters offer better performances on joints and/or voids detection. The probability of type I error via examining results from monitoring the RP/FP/PR, (RP/FP)/SED, and FPI is 3%, 3%, and 4%, respectively. In addition, they are yielding corresponding 9%, 9%, and 14% type II errors.
<table>
<thead>
<tr>
<th></th>
<th>Probability (type I error)</th>
<th>Probability (type II error)</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feed Pressure</td>
<td>6%</td>
<td>8%</td>
<td>92%</td>
</tr>
<tr>
<td>Rotation Pressure</td>
<td>12%</td>
<td>70%</td>
<td>30%</td>
</tr>
<tr>
<td>Acoustic</td>
<td>16%</td>
<td>25%</td>
<td>75%</td>
</tr>
<tr>
<td>Vibration</td>
<td>32%</td>
<td>59%</td>
<td>41%</td>
</tr>
<tr>
<td>RP/FP/PR</td>
<td>3%</td>
<td>9%</td>
<td>91%</td>
</tr>
<tr>
<td>(RP/FP)/SED</td>
<td>3%</td>
<td>9%</td>
<td>91%</td>
</tr>
<tr>
<td>FPI</td>
<td>4%</td>
<td>14%</td>
<td>86%</td>
</tr>
</tbody>
</table>
Chapter 7
IMPROVEMENT OF ALGORITHMS TO ENHANCE CAPABILITIES OF JOINT DETECTION BY USING WAVELET ANALYSIS

7.1. Introduction of Wavelet Analysis

The wavelet transformation process is well-known and suited for time-frequency analysis of non-stationary signals corrupted by noise and spurious disturbances (Mallat, 2008; Sifuzzaman et al., 2009). Drilling parameters, collected from the monitoring unit while drilling into the test samples, are considered as non-stationary signals that can carry many geological information. Scaling parameters and time-translations that can be used to extract desired information (or details) from the signal. Thus, the signal as a function of "\( t \)" at some fixed scale value "\( s \)". A detail is contained in the collected signal \( f(t) \) (Kaiser, 1994). Note, that a signal \( f \) must belong to the Hilbert space, \( \mathbb{H} \), to be admissible for wavelet analysis. Furthermore, approximations of the original signal is possible by removing specified details, such as noise. The mother-wavelet, the function used in junction with the collected signal to perform the wavelet transform, is denoted by \( \psi_{0,0} \equiv \psi(u) \), which can be translated and scaled using the following equation

\[
\psi_{s,t} = |s|^{-p} \psi \left( \frac{u-t}{s} \right) \quad (7-1)
\]

Where, \( s \) is scale and \( t \) is central-time.

The collected signal is \( f(t) \), and the resulting signal after wavelet transformation is \( \tilde{f}(s, t) \). The equation to derive the resulting signal is:

\[
\tilde{f}(s, t) = \int_{-\infty}^{\infty} du \psi_{s,t}^{*}(u)f(u) = \langle \psi_{s,t}, f \rangle = \psi_{s,t}^{*}f \quad (7-2)
\]

Where \( \psi_{s,t}^{*} \) is the adjoint of \( \psi_{s,t} \).
Since the material being drilled through may contain changes in rock strength, joints, cracks, voids, etc., the signal can be decomposed into two parts; the parts of the signal that pertain to the joints or voids, and all other factors which will be considered noise. Then, $f$ can be expressed as

$$f = f_{\text{joint}} + f_{\text{noise}}$$  \hspace{1cm} (7-3)

Moreover, $\tilde{f}$ can be expressed as

$$\tilde{f} = \langle \psi_{s,t}, f_{\text{joint}} \rangle + \langle \psi_{s,t}, f_{\text{noise}} \rangle \equiv \tilde{f}_{\text{joint}} + \tilde{f}_{\text{noise}}.$$  \hspace{1cm} (7-4)

Thus, through appropriate scaling, it becomes possible to de-noise the signal by extracting all details related to noise and simply removing them from the signal.

### 7.2. Using Wavelet Analysis to Improve Joint Detection Algorithms

In this research, the wavelet analysis has been employed to further improve capabilities of joint detection algorithms. The choice of the wavelet basis function and wavelet scales depends on the time-frequency characteristics of individual signals. Few properties need to be considered when selecting a wavelet basis.

For time-frequency localization, the analyzing wavelet must be well localized either in time and/or frequency for the wavelet transform to exhibit locality. Note, another property to consider is the vanishing moments. This property is beneficial for detecting anomalies since if the incoming signal is smooth and the wavelet has enough vanishing moments, it results in small wavelet coefficients at smaller scales (finer anomaly detection). Lastly, there exists the property of support, which is proportional to the number of vanishing moments. An increase in vanishing moments may lead to enhanced anomaly detection, yet an increase in support leads to greater computational complexity. Therefore, Daubechies wavelets are optimal since they give minimal support for a
given number of vanishing moments (Ray, 2004; Rajagopalan and Ray, 2006; Samsi and Ray, 2008).

Daubechies wavelet db45 is the highest number of Daubechies wavelet that MATLAB can offer, and it mimics a sinusoidal wave well enough, which is desired since the collected signal from the drilling unit is non-stationary with sinusoidal characteristics. To confirm the frequency and bandwidth of the db45, the DWT: Wavelet Tree Mode was applied to found a level that can best removing “noise” from raw signal. For example, the level 5 was used to process the raw signals of feed pressure, rotation pressure, etc. In additional, the exact level of different signals might be varied based on the characteristic of the specific signal.

Figure 7-1 and Figure 7-2 show examples of using db45 to pre-process feed and rotation pressure signals, respectively. The three plots presented are the collected drill bit position data, raw signals for feed pressure (or rotation pressure), and processed signals of feed pressure (or rotation pressure) when using db45 wavelet digital filtering. In addition, as shown in the two figures, the majority of the noise have been removed for further data analysis. Thus, applying the wavelet analysis with a db45 wavelet could effectively improve joint detection rate and reduce the number of false alarms.
Figure 7-1. Example of using db45 to pre-process feed pressure signal

Figure 7-2. Example of using db45 to pre-process rotation pressure signal

7.3. Statistical Analysis of Joint Detection Results

7.3.1. Joint Detection Results from the Feed Pressure

The feed pressure data, recorded from drilling into various concrete sample settings has been used to evaluate performance of new joint detection algorithms to locate simulated joints. As
shown in Figure 7-3, pre-designed joint in various concrete specimens have been identified at the location of approximately 76.2 cm (or 30-in). However, there are still several joints that were missed by using the newly updated algorithms, and many false alarms were generated while analyzing the feed pressure.
Figure 7-3. Joint detection results by analyzing the filtered feed pressure using Wavelets
Table 7-1 summarizes joint detection results for using wavelet analysis of db45 wavelet to filter feed pressure. The average detection rate, obtained from all the total 156 boreholes in all nine specimens, is about 97%. However, a total number of 18 false alarms were generated during the process of detection which is slightly higher than the number of false alarms from the composite index analysis.

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>15</td>
<td>15</td>
<td>16</td>
<td>151</td>
</tr>
<tr>
<td>Detection rate</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>83%</td>
<td>88%</td>
<td>100%</td>
<td>97%</td>
<td></td>
</tr>
<tr>
<td>False alarms</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>4</td>
<td>2</td>
<td>4</td>
<td>18</td>
</tr>
</tbody>
</table>

7.3.2. Joint Detection Results from the Rotation Pressure

Wavelet analysis using the db45 wavelet, along with updated CUSUM algorithms, were used to analyze rotation pressure signal for joint detection in boreholes. Figure 7-4 shows joint detection results by using newly updated algorithms to analyze the filtered rotation pressure data. While all pre-determined joints were located at the correct depth, the rotation pressure offers inconsistent performance in different concrete specimens. For example, for some combinations including S-H, H-S, M-H, H-H, and M-M, the predicted joint (blue points) can be clearly observed in corresponding plots with small number of false alarms (red points). Yet the analysis of data for H-M, M-S, S-M, and S-S block combination lead to generation of many false alarms and missed joints in several boreholes.
a. S-H

b. H-S

c. M-H

d. H-H

e. H-M

f. M-S
Figure 7-4. Joint detection results by analyzing the filtered rotation pressure

Joint detection results using new algorithms to analyze the filtered rotation pressure signal in various concrete settings are shown in Table 7-2. Although the detection rate on the H-S sample is only about 76% by monitoring the filtered rotation pressure signal, relatively high detection rates in the other concrete setups has been achieved. The average detection rate in all concrete conditions is around 92%, with 62 false alarms in all 156 boreholes.
Table 7-2. Joint detection results by monitoring the filtered rotation pressure

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>14</td>
<td>13</td>
<td>17</td>
<td>15</td>
<td>21</td>
<td>16</td>
<td>17</td>
<td>15</td>
<td>16</td>
<td>144</td>
</tr>
<tr>
<td>Detection rate</td>
<td>100%</td>
<td>76%</td>
<td>100%</td>
<td>83%</td>
<td>100%</td>
<td>89%</td>
<td>94%</td>
<td>88%</td>
<td>100%</td>
<td>92%</td>
</tr>
<tr>
<td>False alarms</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>14</td>
<td>10</td>
<td>14</td>
<td>4</td>
<td>15</td>
<td>62</td>
</tr>
</tbody>
</table>

7.3.3. Joint Detection Results from the RP/FP/PR

Using aforementioned algorithms to monitor composite parameters, including the RP/FP/PR, (RP/FP)/SED, and FPI, has achieved reasonable performances on joint detection. In this chapter, the wavelet analysis of the db45 wavelet, along with the modified algorithms have also been used to analyze these composite parameters.

The RP/FP/PR index parameter calculated from recorded machine data was processed with the wavelet filters and the results are plotted in Figure 7-5. This figure shows that joint detection based on the filtered RP/FP/PR data offers fairly stable performances for joint detection. The simulated joints were located in the correct location. Yet, small number of false alarms (red points) were generated by the data analysis.
a. S-H

b. H-S

c. M-H

d. H-H

e. H-M

f. M-S
Figure 7-5. Joint detection results by analyzing the filtered $RP/FP/PR$ data using wavelets

Table 7-3 summaries joint detection results by monitoring the filtered $RP/FP/PR$ data in all nine concrete block settings. Despite the minimum detection rate, obtained from the concrete condition of M-M of about 88%, detection rates achieved from the other eight specimens were higher than 90%. The average joint detection rate based on these nine concrete setups is about 96%, with 18 false alarms for all 156 boreholes. This does not show major improvement over the normal analysis of the $RP/RP/PR$ data using the raw, unfiltered data.
7.3.4. Joint Detection Results from the \((RP/FP)/SED\)

Wavelet analysis of the db45 was used to pre-treat and filter data for \((RP/FP)/SED\) data for joint detection using modified pattern recognition algorithms. As shown in Figure 7-6, monitoring the filtered \((RP/FP)/SED\) also offers reliable detection results in various concrete sample combinations. Pre-determined joints have been detected at the right location in majority of the boreholes and some false alarms were generated. Table 7-4 is the summary of joint detection results by analyzing the filtered \((RP/FP)/SED\) data in various test setups. A detection rate of about 97% in 156 boreholes and only 9 false alarms was the result of this procedure and use of the composite parameter of the \((RP/FP)/SED\).

**Table 7-3. Joint detection results by monitoring the filtered \(RP/FP/PR\)**

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>13</td>
<td>16</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>17</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>Detection rate</td>
<td>93%</td>
<td>94%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>94%</td>
<td>88%</td>
<td>94%</td>
</tr>
<tr>
<td>False alarms</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>
a. S-H

b. H-S

c. M-H

d. H-H

e. H-M

f. M-S
Figure 7-6. Joint detection results by analyzing the filtered (RP/FP)/SED

Table 7-4. Summary of joint detection results by monitoring the filtered (RP/FP)/SED

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>13</td>
<td>15</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>15</td>
<td>150</td>
</tr>
<tr>
<td>Detection rate</td>
<td>93%</td>
<td>88%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>94%</td>
<td>94%</td>
<td>94%</td>
<td>96%</td>
</tr>
<tr>
<td>False alarms</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>10</td>
</tr>
</tbody>
</table>
7.3.5. Joint Detection Results from the $FPI$

The composite parameter, Field Penetration Index ($FPI$), was also calculated from the raw data and filtered by wavelet analysis of the db45 wavelet and analyzed by using the joint detection algorithm. Figure 7-7 shows corresponding joint detection results, where the most of the simulated joints have been identified at the right location. Some missing joints and false alarms were also observed in the process as anticipated. Table 7-5 is the summary of the results and shows the average detection rate of about 95% for all 156 boreholes and of 14 false alarms for using wavelet filters on $FPI$ data.

![Joint Detection Results](image.png)

- a. S-H
- b. H-S
- c. M-H
- d. H-H
Figure 7-7. Joint detection results by analyzing the filtered \textit{FPI} index
Table 7-5. Summary of joint detection results by monitoring the filtered $FPI$ data

<table>
<thead>
<tr>
<th>Concrete combinations</th>
<th>S-H</th>
<th>H-S</th>
<th>M-H</th>
<th>H-H</th>
<th>H-M</th>
<th>M-S</th>
<th>S-M</th>
<th>M-M</th>
<th>S-S</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of holes</td>
<td>14</td>
<td>17</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>18</td>
<td>17</td>
<td>16</td>
<td>156</td>
</tr>
<tr>
<td>Number of holes have identified joint</td>
<td>13</td>
<td>14</td>
<td>17</td>
<td>18</td>
<td>21</td>
<td>18</td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>150</td>
</tr>
<tr>
<td>Detection rate</td>
<td>93%</td>
<td>82%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>89%</td>
<td>94%</td>
<td>100%</td>
<td>95%</td>
</tr>
<tr>
<td>False alarms</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>14</td>
</tr>
</tbody>
</table>

7.4. Summary

In this chapter, wavelet analysis using the db45 wavelet, along with modified CUSUM algorithms were used to improve capabilities of pattern recognition algorithms to sense joints and/or voids while drilling for roof bolts using a rotary drill. This involves the use of wavelet to filter the noise in the data and enhanced CUSUM algorithms to improve the detection rate and reduce the number of false alarms. The analysis of modified detection algorithms for locating simulated joints in nine specimens with various strengths shows that detection results could be enhanced. This was based on analysis of feed and rotation pressure data. Moreover, the modified algorithms are self-adjusting to offer better performance in different conditions.

The modified algorithms also offer higher precision while sensing hairline joints when analyzing the composite parameters, including the $RP/FP/PR$, $RP/FP/SED$, and $FPI$. However, the algorithms have limited capabilities when analyzing the acoustic and vibration data. This is because the acoustic and vibration data exhibit different characteristics and require extensive digital filtering to eliminate the noise and allow for distinguishing special features such as a joint and/or void.
Table 7-6 shows comparison of joint detection results for modified algorithms without the wavelet analysis and updated algorithms with the wavelet analysis. Using updated algorithms with the wavelet analysis of the db45 wavelet, the detection results achieved from feed and rotation pressure have been clearly improved; namely offering higher average detection rates and lower number of false alarms. However, the new algorithms did not offer improved performance when analyzing the composite parameters. That is because many of the noises have been removed during the process of formulating corresponding composite parameters, and applying the wavelet analysis to additionally analyze the composite parameters may eliminate some important joint information or increase or introduce some noise in the signal and therefore lead to missing joints or generating more false alarms. Thus, for the purposed of joint detection, new algorithms based on the wavelet analysis of the db45 wavelet is best employed to monitor individual drilling parameters instead of composite parameters.

Table 7-6. Comparison of joint detection results obtained from detection algorithms with and without the wavelet data filtering.

<table>
<thead>
<tr>
<th>Drilling Parameters</th>
<th>Updated Algorithms Without Wavelet Analysis</th>
<th>Updated Algorithms with Wavelet Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Detection Rate</td>
<td>False Alarms (156 Boreholes)</td>
</tr>
<tr>
<td>Feed Pressure</td>
<td>94%</td>
<td>12 (8%)</td>
</tr>
<tr>
<td>Rotation Pressure</td>
<td>88%</td>
<td>109 (70%)</td>
</tr>
<tr>
<td>RP/FP/PR</td>
<td>97%</td>
<td>9 (6%)</td>
</tr>
<tr>
<td>(RP/FP)/SED</td>
<td>97%</td>
<td>9 (6%)</td>
</tr>
<tr>
<td>FPI</td>
<td>97%</td>
<td>14 (9%)</td>
</tr>
</tbody>
</table>

Table 7-7 to 7-11 is the summary of probabilities of type I and II errors via examining the detection results obtained from using newly developed algorithms to monitor the feed pressure, rotation pressure, RP/FP/PR, (RP/FP)/SED, and FPI, respectively.
Table 7-7. A probability summary of examining the feed pressure

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept $H_0$</td>
<td>97% (correct decision)</td>
<td>12% (type II error)</td>
</tr>
<tr>
<td>Reject $H_0$</td>
<td>3% (type I error)</td>
<td>88% (correct decision)</td>
</tr>
</tbody>
</table>

Table 7-8. A probability summary of examining the rotation pressure

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept $H_0$</td>
<td>92% (correct decision)</td>
<td>40% (type II error)</td>
</tr>
<tr>
<td>Reject $H_0$</td>
<td>8% (type I error)</td>
<td>60% (correct decision)</td>
</tr>
</tbody>
</table>

Table 7-9. A probability summary of examining the $RP/FP/PR$

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept $H_0$</td>
<td>96% (correct decision)</td>
<td>12% (type II error)</td>
</tr>
<tr>
<td>Reject $H_0$</td>
<td>4% (type I error)</td>
<td>88% (correct decision)</td>
</tr>
</tbody>
</table>

Table 7-10. A probability summary of examining the $(RP/FP)/SED$

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept $H_0$</td>
<td>96% (correct decision)</td>
<td>10% (type II error)</td>
</tr>
<tr>
<td>Reject $H_0$</td>
<td>4% (type I error)</td>
<td>90% (correct decision)</td>
</tr>
</tbody>
</table>

Table 7-11. A probability summary of examining the $FPI$

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accept $H_0$</td>
<td>95% (correct decision)</td>
<td>14% (type II error)</td>
</tr>
<tr>
<td>Reject $H_0$</td>
<td>5% (type I error)</td>
<td>86% (correct decision)</td>
</tr>
</tbody>
</table>

As shown in Table 7-12, the probability of the type I error generated from examining detection results by using the newly updated algorithms to analyze the feed pressure, rotation
pressure, $RP/FP/PR$, $RP/FP/SED$, and $FPI$ is 3%, 8%, 4%, 4%, and 5%, respectively. Furthermore, they yield 12%, 40%, 12%, 10%, and 14% probability of the type II error, for the same set of individual and composite indices, respectively. The detection rate of using these five parameters is account to corresponding 88%, 60%, 88%, 90%, and 86%, respectively. In comparison with the analyzed results discussed in chapter 6, updated algorithms based on the wavelet analysis db45 provide higher precision while sensing joints with smaller apertures. In addition, the detection results obtained from the feed pressure and rotation pressure have been clearly enhanced while almost no changes on the other three composite parameters is noted.

Table 7-12. A probability and power summary of various parameters

<table>
<thead>
<tr>
<th>Drilling Parameters</th>
<th>Probability (type I error)</th>
<th>Probability (type II error)</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feed Pressure</td>
<td>3%</td>
<td>12%</td>
<td>88%</td>
</tr>
<tr>
<td>Rotation Pressure</td>
<td>8%</td>
<td>40%</td>
<td>60%</td>
</tr>
<tr>
<td>$RP/FP/PR$</td>
<td>4%</td>
<td>12%</td>
<td>88%</td>
</tr>
<tr>
<td>$(RP/FP)/SED$</td>
<td>4%</td>
<td>10%</td>
<td>90%</td>
</tr>
<tr>
<td>$FPI$</td>
<td>5%</td>
<td>14%</td>
<td>86%</td>
</tr>
</tbody>
</table>
Chapter 8

TESTING OF ANGLED JOINTS AND ESTIMATION OF ROCK STRENGTH

To improve capabilities of the developed pattern recognition algorithms to sense joints that are not perpendicular to the borehole, additional laboratory tests have been performed at J.H. Fletcher & Co testing facility. As mentioned before, the initial testing in various concrete blocks were conducted with all joints being perpendicular to the direction of drilling. However, in field setting, orientations of many joints in rock mass may not necessarily be perpendicular to the direction of drilling. The objective of additional tests is to evaluate the possibility of sensing joints at an angle with in addition to joints that perpendicular relative to the direction of drilling. For this purpose, a new sample containing pieces of rock to simulate various conditions of rock layers, and a sample with various strength of grout was designed and cast for the part of the study.

8.1. Testing for Simulation of Inclined Joints

Joints in a rock mass could be at angles ranging from 0° to 90° relative to the axis of drilled boreholes (Gong et al., 2005), and many researchers have selected the joints with specific angle or orientation from this range for their studies (Liu et al., 2012; Xu et al., 2013; Bohaaddini et al., 2016). To observe the behavior of the drill and variations in drilling parameters, it was essential to design and fabricate a new sample with prescribed joint dip angles to train the joints detection algorithms. Given the size limitation of the sample block that could be mounted on the test unit in the Fletcher facility in Huntington, blocks with special geometry were designed to contain four joints preset angles of 15°, 30°, 45°, and 60°. Figure 8-1 shows the configuration of the blocks and pre-designed four angled joints in the block. This arrangement allowed for accommodating various
joint angles without exceeding the sample sizes. The sample could facilitate encountering different joint angles in the same borehole and also different areas could represent various sample strength by using grouts with variable strength properties.

Figure 8-1. The configuration of sample block with four angled joints

In the initial laboratory tests, concrete blocks with three preset strength values were used to simulate different scenarios that could impact conditions of joints. However, close examination of the drilling parameters (i.e. feed and rotation pressure) revealed large variations while drilling through the concrete compared to drilling through the rock. Therefore, it was decided to use grouts to replace concrete for casting the new blocks that would offer closer vibrations signatures to the rock drilling. Every block was poured by preparation and casting of the grout and was cured for
more than 18 days, the dimensions of each block was about 910x910x1520 mm (or 36x36x60-inch). Furthermore, to simulate joints with different conditions, the grouts were designed with three different strengths, including Soft (S, low strength, ~20 MPa, or ~3,000 psi), Medium (M, medium strength, ~50 MPa, or ~7,500 psi), and Hard (H, high strength, ~70 MPa, or ~10,000 psi), to fill various areas. Table 8-1 shows the setting of grouts in the block with angled joints.

**Table 8-1. Composition of the grout block used for drilling in sample with simulated angled joints**

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>A(1/16-in)</th>
<th>B(1/16-in)</th>
<th>* Grout Strength:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area 1</td>
<td>H</td>
<td>S</td>
<td>S, low strength;</td>
</tr>
<tr>
<td>Area 2</td>
<td>H</td>
<td>S</td>
<td>M, medium strength;</td>
</tr>
<tr>
<td>Area 3</td>
<td>S</td>
<td>M</td>
<td>H, high strength</td>
</tr>
<tr>
<td>Area 4</td>
<td>S</td>
<td>M</td>
<td></td>
</tr>
<tr>
<td>Area 5</td>
<td>M</td>
<td>H</td>
<td></td>
</tr>
</tbody>
</table>

The aperture of the joint in the initial laboratory tests was planned to be around 3.175 mm (or 1/8-in), and the pattern recognition algorithms were used to analyze various drilling parameters, (individual and composite parameters) to detect the joints. In order to further improve capabilities of detection algorithms to sense smaller joints, in the new laboratory tests, the aperture of the joint was preset at around 1.588 mm (or 1/16-in). To introduce the joints with small aperture, a Teflon sheet with the thickness of about 1.58 mm (or 1/16-in) was used between the areas of the sample that was filled with selected grout. **Figure 8-2** shows the layout of four angled joints and the poured block.

To perform new laboratory tests, Fletcher test unit was used to drill through the block as before. Patterns of boreholes were drilled both in sample block with area A and B, and drilling parameters were recorded. **Figure 8-3** represents the Fletcher drill unit and the patterns of boreholes in the block.
To verify the locations of inclined joints inside borehole, bore scoping was performed.

**Figure 8-4** shows screen shots of bore scoping to locate inclined joints.
8.2. Data Analysis for Detection of Angled Joints

During the laboratory tests for detection of various angled joints, drilling data from many boreholes were failed to be collected. This was because broken Teflon pieces plugged the hole and affected the normal operation of vacuum system that was applied for flushing of the borehole while drilling. However, the drilling data that was recorded from valid boreholes and part of the valid data from plugged boreholes, showed that the drilling parameters do exhibit distinct changes when the drill bit encountered inclined joints. Figure 8-5 shows an example of collected feed pressure data with corresponding distinct changes when passing through joints.
As discussed earlier, using pattern recognition algorithms to monitor individual drilling parameters and composite parameters have offered reasonable abilities to sense joints with small apertures (around 3.175 mm or 1/8-in). These programs were also used for analyzing the data from new laboratory tests with simulated joints at four different angles. This includes individual and composite parameters, including the feed pressure, $RP/FP/PR$, $(RP/FP)/SED$, and $FPI$.

As shown in Figure 8-6 and Figure 8-7, drilling data recorded from borehole #12 and #15 were analyzed by the modified algorithms, and correspondingly inclined joints in these two boreholes have been identified at pre-designed locations. Furthermore, for these two boreholes, no false alarms were generated while analyzing drilling parameters of the feed pressure, $RP/FP/PR$, $(RP/FP)/SED$, and $FPI$. Analyzing detection results achieved from the limited number of boreholes drilled, as compared to the 156 holes drilled in earlier set of tests, no false alarms and missing joints were generated. It is logical to anticipate that with larger number of boreholes, there are possibilities for encountering false alarms or missing joints in certain combination of the strata that the drills will go through.
**Figure 8-6.** Detection results of inclined joints by monitoring various drilling parameters in borehole #12

**Figure 8-7.** Detection results of inclined joints by monitoring various drilling parameters in borehole #15
8.3. Drilling Tests in Blocks with Different Rock Samples

In addition to joint detection, one of the objectives of this study was to develop a system that could estimate rock strengths based on the recorded drilling parameters. This requires drilling in different rock types with known strength and seeking relationships between rock properties and drilling parameters. For this purpose, a block with four pieces of rock was cast. The rock samples included shale, limestone, sandstone, and coal. Figure 8-8 shows the setting of the block with four rock samples before pouring grout. Moreover, the grout, with medium strength (~50 MPa, or ~7,500 psi) was used to cast the rock samples. Figure 8-9 is the screen shots of bore scoping, which shows a separation between two shale samples and a boundary between grout and shale are observed inside a borehole.

![Figure 8-8. Picture of setting of the rock samples in the test block](image)
Figure 8-9. Example of bore scoping screen shots, displaying conditions of rock layers inside a borehole

8.4. Data Analysis for Estimation of Rock Strength

To develop relationship between drilling parameters and rock strengths, drilling data and result of rock mechanical property tests has been used in this study. Various rock samples were cored, and the core specimens were tested for various rock strength properties according to the American Society for Testing and Materials (ASTM) standards at the Geo-Mechanics laboratory at the Pennsylvania State University. Laboratory tests included Uniaxial Compressive Strength (UCS) and Point Load Tests (PLT). Grout samples were also tested at the Penn State CITEL lab. Figure 8-10 shows the picture of prepared samples for UCS test. The coal samples, as shown in Figure 8-8, were also cast in the block but their locations were out of the maximum drilling distance, and no related drilling data was collected. Thus, no tests were performed on coal samples.
Figure 8-10. Picture of prepared rock and grout samples for laboratory strength tests
UCS is the most frequently used and an essential geotechnical property of the rock in many rock engineering applications and related analysis. Therefore, UCS, as an index of rock strength, was used as a target parameter for analyzing drilling data. Laboratory testing of core samples yielded the UCS for several rock types but it was difficult to obtain sufficient core length in shale to run UCS tests and alternatively, PLT test was used to estimate UCS values of shale samples. To estimate UCS of the shale samples, a conversion factor $K = 21.8$ was used in this study (Rusnak and Mark, 1999). The relationship between PLT results and UCS is expressed as

$$UCS = K \cdot I_{S50}$$

(8-1)

Where, $UCS$ is the value of UCS;

$K$ is conversion factor;

$I_{S50}$ is the value of point load index for core samples of 50mm (~2 inch) diameter.

Table 8-2 shows rock strengths for various rock types measured at the Geo-Mechanics laboratory and the UCS values of the shale are calculated based on the equation 8-1.
Table 8-2. Corresponding rock strengths for various rock types

<table>
<thead>
<tr>
<th>Rock Type</th>
<th>Order</th>
<th>PLT [MPa]</th>
<th>UCS [MPa]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shale</td>
<td>1</td>
<td>1.76</td>
<td>38.4</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.92</td>
<td>41.9</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.90</td>
<td>41.4</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1.79</td>
<td>39.0</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>1.73</td>
<td>37.7</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>1.82</td>
<td>39.7</td>
</tr>
<tr>
<td>Sandstone</td>
<td>1</td>
<td>112.0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>108.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>100.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>107.1</td>
<td></td>
</tr>
<tr>
<td>Limestone</td>
<td>1</td>
<td>139.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>150.0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>130.8</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>140.2</td>
<td></td>
</tr>
<tr>
<td>Grout</td>
<td>1</td>
<td>50.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>49.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>44.8</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>48.3</td>
<td></td>
</tr>
</tbody>
</table>

8.4.1. Wear Index of the Drill Bit

While drilling through the rock materials, the values of monitored drilling parameters were varied were not only because of the rock strength, but also due to wear on the bit tip or tip of the cutting edges. As such, drilling parameters for cutting the same rock are not necessarily at a constant level while drilling, and often feed pressure show an upward trend when drilling in the same rock at constant speed when plotted against time. Added to the complexity is that rock material or rock mass is not a homogeneous medium and sometimes it is difficult to track the variations and the impact of bit wear. Variation in drilling parameters, including the RPM and penetration rate that is preset to the unit control system, could also induce variation in data stream that could masque the wear of the drill bit. To develop a reliable relationship between drilling parameters and rock strength requires a closer look at the bit wear and making proper adjustment
for this parameter to account for its impact and to offer a more accurate model for estimation of rock strength from drilling parameters.

This section focuses on the effects of the wear of the drill bit on the changes of the values of drilling parameters. The application of the composite parameter, Field Penetration Index (FPI) is a proven approach to eliminate the effects of the RPM and penetration rate and to allow for isolating the parameters that are critical for correlating drilling parameters to rock strength and bit wear. To account for the wear of the drill bit which is a function of the drilling distance with the same bit, a Wear Index (WI) is proposed to quantify the wear of the drill bit and adjust the values of drilling parameters, such as the feed pressure and FPI.

In the laboratory test on the composite rock sample, six adjacent boreholes were drilled with the same drill bit at the preset conditions of RPM = 300 rev/min and penetration of 2.54 cm/sec (or 1 in/sec). The drilling parameters were monitored as in the previous testing, and average values of the feed pressure and FPI from these six adjacent boreholes were calculated and summarized, as shown in Table 8-3.
Table 8-3. The average values of the feed pressure and $FPI$ and corresponding ratios while drilling through various rock types.

<table>
<thead>
<tr>
<th>Rock Types</th>
<th>Hole #</th>
<th>Drilling Distance [mm]</th>
<th>Feed Pressure [MPa]</th>
<th>$FPI$ [MPa/cutter/cm/rev]</th>
<th>$FP_N/FP_1$</th>
<th>Standard Deviation ($FP_N/FP_1$)</th>
<th>$FPI_N/FPI_1$</th>
<th>Standard Deviation ($FPI_N/FPI_1$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grout</td>
<td>1</td>
<td>1270</td>
<td>5.44</td>
<td>10.72</td>
<td>1.00</td>
<td>0.03</td>
<td>1.00</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>990</td>
<td>5.73</td>
<td>11.28</td>
<td>1.05</td>
<td>0.03</td>
<td>1.01</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>970</td>
<td>6.12</td>
<td>12.04</td>
<td>1.12</td>
<td>0.02</td>
<td>1.11</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1020</td>
<td>6.53</td>
<td>12.85</td>
<td>1.20</td>
<td>0.02</td>
<td>1.20</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>740</td>
<td>6.83</td>
<td>13.45</td>
<td>1.25</td>
<td>0.04</td>
<td>1.25</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>940</td>
<td>7.32</td>
<td>14.42</td>
<td>1.35</td>
<td>0.05</td>
<td>1.35</td>
<td>0.05</td>
</tr>
<tr>
<td>Shale</td>
<td>1</td>
<td>1270</td>
<td>2.93</td>
<td>5.76</td>
<td>1.00</td>
<td>0.06</td>
<td>1.00</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>990</td>
<td>3.10</td>
<td>6.10</td>
<td>1.06</td>
<td>0.04</td>
<td>1.06</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>970</td>
<td>3.11</td>
<td>6.12</td>
<td>1.06</td>
<td>0.03</td>
<td>1.06</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>740</td>
<td>3.42</td>
<td>6.73</td>
<td>1.17</td>
<td>0.04</td>
<td>1.17</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>940</td>
<td>3.45</td>
<td>6.79</td>
<td>1.18</td>
<td>0.06</td>
<td>1.18</td>
<td>0.06</td>
</tr>
<tr>
<td>Limestone</td>
<td>1</td>
<td>1270</td>
<td>9.20</td>
<td>18.11</td>
<td>1.00</td>
<td>0.01</td>
<td>1.00</td>
<td>0.01</td>
</tr>
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<td></td>
<td>2</td>
<td>990</td>
<td>9.19</td>
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<td>1.00</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
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<td>970</td>
<td>9.17</td>
<td>18.03</td>
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<td>0.01</td>
<td>1.00</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1020</td>
<td>9.29</td>
<td>18.29</td>
<td>1.01</td>
<td>0.01</td>
<td>1.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>740</td>
<td>9.27</td>
<td>18.26</td>
<td>1.01</td>
<td>0.01</td>
<td>1.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>940</td>
<td>9.24</td>
<td>18.19</td>
<td>1.00</td>
<td>0.01</td>
<td>1.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Sandstone</td>
<td>1</td>
<td>1270</td>
<td>8.86</td>
<td>17.44</td>
<td>1.00</td>
<td>0.02</td>
<td>1.00</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>990</td>
<td>8.81</td>
<td>17.22</td>
<td>0.99</td>
<td>0.02</td>
<td>0.99</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>970</td>
<td>8.73</td>
<td>17.18</td>
<td>0.99</td>
<td>0.02</td>
<td>0.99</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
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<td>1020</td>
<td>8.82</td>
<td>17.37</td>
<td>1.00</td>
<td>0.02</td>
<td>1.00</td>
<td>0.02</td>
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<td>8.88</td>
<td>17.48</td>
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<td>0.02</td>
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</tbody>
</table>

As for the data recorded from six adjacent boreholes at the preset conditions of RPM = 300 rev/min and penetration of 2.54 cm/sec (or 1in/sec), Table 8-4 summarizes 95% confidence interval ranges of values while drilling through various rock types. This table also represents uncertainty of 95% data points for estimation of rock strength, and the uncertainty of 95% data points were less than 1.5% of the mean values.
Table 8-4. 95% confidence interval ranges of mean values while drilling through different rock types

<table>
<thead>
<tr>
<th>Rock Types</th>
<th>Hole #</th>
<th>( FP_N )</th>
<th>( FPI_N )</th>
<th>Lower Bound (95%)</th>
<th>Upper Bound (95%)</th>
<th>Lower Bound (95%)</th>
<th>Upper Bound (95%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grout</td>
<td>1</td>
<td>1.00</td>
<td>1.00</td>
<td>0.997</td>
<td>1.005</td>
<td>1.004</td>
<td>0.996</td>
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<tr>
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<td>1.05</td>
<td>1.050</td>
<td>1.058</td>
<td>1.057</td>
<td>1.049</td>
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<tr>
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<td>1.12</td>
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<td>1.126</td>
<td>1.121</td>
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<td>1.20</td>
<td>1.196</td>
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<td>1.202</td>
<td>1.195</td>
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<td>1.341</td>
<td>1.352</td>
<td>1.350</td>
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<tr>
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<td>1.006</td>
<td>1.003</td>
<td>0.992</td>
</tr>
<tr>
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<td>1.047</td>
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<td>1.068</td>
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<td>1.06</td>
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<td>0.999</td>
<td>1.001</td>
<td>1.003</td>
<td>0.999</td>
</tr>
<tr>
<td></td>
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<td>1.00</td>
<td>1.00</td>
<td>0.988</td>
<td>1.000</td>
<td>1.000</td>
<td>0.998</td>
</tr>
<tr>
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<td>0.997</td>
<td>0.996</td>
<td>0.995</td>
</tr>
<tr>
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<td>1.004</td>
<td>1.005</td>
<td>1.005</td>
<td>1.004</td>
</tr>
<tr>
<td>Sandstone</td>
<td>1</td>
<td>1.00</td>
<td>1.00</td>
<td>0.988</td>
<td>1.001</td>
<td>1.001</td>
<td>0.998</td>
</tr>
<tr>
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<td>0.993</td>
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<tr>
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<td>0.987</td>
<td>0.987</td>
<td>0.983</td>
</tr>
<tr>
<td></td>
<td>4</td>
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<td>1.00</td>
<td>0.994</td>
<td>0.998</td>
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<td>1.000</td>
<td>1.004</td>
<td>1.004</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Figure 8-11 shows changes of the ratio of feed pressure values in terms of the drilling distance (WI) while drilling through the grout, shale, limestone, and sandstone in six adjacent boreholes. The values of feed pressure (FP) and FPI are normalized with the initial values when the bit started as new to show the variations in their value relative to the initial setting, thus allowing for comparison of the changes based on drilling distance. As mentioned earlier, all six boreholes were drilled by a same drill bit and at the same preset conditions (RPM and penetration rate). As shown in these plots, the values of the feed pressure have the most significant increase while drilling through the grout, and the feed pressure values offer a relatively lower rate of
increase when cutting the shale samples. However, comparing with the grout and the shale, there are almost no noticeable change in feed pressure values while drilling through limestone and sandstone in these six adjacent boreholes. The 95% confidence interval for feed pressure values while drilling through the limestone is between 0.998 and 1.008. While the 95% confidence interval for feed pressure values while drilling through the sandstone is between 0.990 and 1.002.

Figure 8-11. Changes of the ratio of normalized feed pressure values with drilling distance (WI) in different rock samples
As can be observed in the Table 8-3 and Figure 8-11, the value of the feed pressure is apparently increasing by the wear of the drill bit while drilling. This is more pronounced in rock layers with lower strength, such as grout used in this test and shale. However, the change of feed pressure values caused by the wear of the drill bit is less clear and perhaps can be ignored while drilling through high strength rock strata such as the limestone and sandstone. The threshold for making adjustment for bit wear while analyzing the feed pressure, can be accurately determined from sufficient tests and field practices. Moreover, for the rock with relatively low strengths, the values of the feed pressure need to be adjusted based on corresponding equations while estimating rock strengths from the drilling parameter of the feed pressure. For example, in this test, the feed pressure can be adjusted by Equation 8-2 and 8-3 when drilling through the grout and shale, respectively.

\[
\frac{FP_N}{FP_1} = 0.00007I_{WI} + 0.9804 \quad (R^2=0.98) \quad (8-2)
\]

\[
\frac{FP_N}{FP_1} = 0.00004I_{WI} + 0.9999 \quad (R^2=0.97) \quad (8-3)
\]

Where, \( FP_1 \) is the value of the feed pressure collected from the 1\textsuperscript{st} borehole (new bit), MPa;

\( FP_N \) is the value of the feed pressure collected from the N\textsuperscript{th} borehole, MPa;

\( I_{WI} \) is the drilling distance (WI), mm.

To combine Equation 8-2 and 8-3 and offer an equation for the adjustment of the feed pressure values, changes of the normalized feed pressure values as a function of drilling distance while drilling through various rock layers in six adjacent boreholes were shown in Figure 8-12.
Therefore, the equation to adjust the feed pressure can be defined as

\[
\frac{F_P}{F_{P_1}} = 0.00005I_{W1} + 0.992 \quad (R^2=0.82) \quad (8-4)
\]

Where, \(F_{P_1}\) is the value of the feed pressure collected from the 1\(^{st}\) borehole (new bit), MPa;

\(F_{P_N}\) is the value of the feed pressure collected from the N\(^{th}\) borehole, MPa;

\(I_{W1}\) is the drilling distance (WI), mm.

**Figure 8-13** shows changes of the normalized \(FPI\) values as a function of drilling distance (WI) while drilling through the grout, shale, limestone, and sandstone in six adjacent boreholes. Similar to the feed pressure, at the same preset conditions of the RPM and penetration rate, the increase in \(FPI\) values is at higher rate while drilling through the grout. The rate of increase in normalized \(FPI\) is relatively lower. However, compared to the grout and shale, there is almost no rises in the \(FPI\) values while drilling through the limestone and sandstone in these six adjacent boreholes. The 95\% confidence interval for \(FPI\) values while drilling through the limestone is
between 0.998 and 1.008. While the 95% confidence interval for $FPI$ values while drilling through the sandstone is between 0.990 and 1.002.

![Grout - FPI](image1.png)
![Shale - FPI](image2.png)
![Limestone - FPI](image3.png)
![Sandstone - FPI](image4.png)

**Figure 8-13.** Changes of the values of normalized $FPI$ as a function of the drilling distance (WI) in different rock samples

Similar to the feed pressure, the value of the $FPI$ can be significantly affected by the wear of the drill bit while drilling through the rock with relatively low strength, including the grout used in this test and the shale; however, this effect can be insignificant for the rock with relatively high strength, such as the limestone and sandstone. In addition, to estimate rock strengths by monitoring
the $FPI$, the values of the $FPI$ need to be adjusted based on corresponding equations. For instance, in this test, the $FPI$ can be adjusted using **Equation 8-5 and 8-6** when drilling through the grout and shale, respectively.

$$\frac{FPI_N}{FPI_1} = 0.00007I_{W1} + 0.9804 \quad (R^2=0.98) \quad (8-5)$$

$$\frac{FPI_N}{FPI_1} = 0.00004I_{W1} + 0.9999 \quad (R^2=0.97) \quad (8-6)$$

Where, $FPI_1$ is the value of the $FPI$ collected from the 1st borehole, MPa/cutter/cm/rev;

$FPI_N$ is the value of the $FPI$ collected from the Nth borehole, MPa/cutter/cm/rev;

$I_{W1}$ is the value of the drilling distance (WI), mm.

To offer one equation for the adjustment of the $FPI$, changes of the normalized $FPI$ values as a function of drilling distance were shown in **Figure 8-14**.

![Figure 8-14](image)

**Figure 8-14.** Changes of the ratio of normalized $FPI$ values with drilling distance (WI)

Thus, the equation to adjust the $FPI$ can be defined as

$$\frac{FPI_N}{FPI_1} = 0.00005I_{W1} + 0.992 \quad (R^2=0.82) \quad (8-7)$$

Where, $FPI_1$ is the value of the $FPI$ collected from the 1st borehole, MPa/cutter/cm/rev;
$FPI_N$ is the value of the $FPI$ collected from the $N^{th}$ borehole, MPa/cutter/cm/rev;

$I_{WI}$ is the value of the drilling distance (WI), mm.

It should be noted that these results are preliminary and in practical application, the impact of bit wear should be calculated by accounting for the weighted sum of distances drilled in various rock types to keep track of the wear more accurately.

8.4.2. Estimation of Rock Strength via Monitoring Drilling Parameters

Strength of rock layers being drilled can be estimated by using drilling parameters, including the feed pressure and composite parameter such as $FPI$. For this purpose, drilling data, which was recorded by drilling through aforementioned six adjacent boreholes with preset drilling conditions of the RPM and the penetration rate were analyzed for the estimation of rock strength. Figure 8-15 shows an example of collected feed pressure and $FPI$ data while drilling through the block with various rock samples.

![Figure 8-15](image.png)

Figure 8-15. Example of record feed pressure and $FPI$ while drilling through various rock layers

The recorded values of the feed pressure and $FPI$ were adjusted for drilling distance based on Equation 8-4 and 8-7 to account for bit wear and the results are summarized in Table 8-5. The information in this table was used for estimation of rock strength from drilling parameters through
the use of statistical analysis and seeking correlations between the objective parameter, namely rock strength, and input parameters, which is primarily the drilling data.

Table 8-5. Various parameters and adjusted drilling parameters for the estimation of rock strength

<table>
<thead>
<tr>
<th>Rock Types</th>
<th>UCS [MPa]</th>
<th>Drilling Distance (WI) [mm]</th>
<th>Feed Pressure [MPa]</th>
<th>Adjusted Feed Pressure [MPa]</th>
<th>FPI [MPa/cutter/cm/rev]</th>
<th>Adjusted FPI [MPa/cutter/cm/rev]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grout</td>
<td>48.3</td>
<td>1270</td>
<td>5.44</td>
<td>5.44</td>
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<td></td>
<td>48.3</td>
<td>990</td>
<td>5.73</td>
<td>5.43</td>
<td>11.28</td>
<td>10.70</td>
</tr>
<tr>
<td></td>
<td>48.3</td>
<td>970</td>
<td>6.12</td>
<td>5.54</td>
<td>12.04</td>
<td>10.90</td>
</tr>
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<td>5.90</td>
<td>14.42</td>
<td>11.62</td>
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<td>5.76</td>
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<td>990</td>
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<td>8.88</td>
<td>17.48</td>
<td>17.48</td>
</tr>
</tbody>
</table>

As shown in Figure 8-16, the mathematical relationships can be expressed to relate UCS of the rock and feed pressure, while running the drill at preset RPM and feed rate. In addition, the adjustment of feed pressure for drill bit wear through drilling distance can further improve this mathematical relationship. This is reflected by the value of the $R^2$ that increased from 0.78 to 0.88. Therefore, the Equation 8-8 and 8-9 can be proposed for the estimation of rock strength by monitoring the feed pressure at present drilling conditions.
**Figure 8-16.** Mathematical relationships between UCS values of the rock and the feed pressure and the adjusted feed pressure

\[
FP_{adjusted} = 0.0558 I_{UCS} + 1.9691 \quad (R^2 = 0.86) \quad (8-8)
\]

\[
FP_{adjusted} = 4.597 \ln (I_{UCS}) - 13.087 \quad (R^2 = 0.92) \quad (8-9)
\]

Where, \( FP_{adjusted} \) is the value of adjusted feed pressure, MPa;

\( I_{UCS} \) is the UCS value of the rock, MPa.
Equation 8-8 and 8-9 represent linear and exponential regressions between the adjusted feed pressure and UCS value, and the exponential regression shows better correlations. According to Equation 8-4 and 8-9, the UCS as a function of raw feed pressure can be defined as

$$UCS_E = \exp\left(\frac{FP_N}{0.000231I_{WI} + 4.56} + 2.85\right)$$

(8-10)

Where, $FP_N$ is the value of $N^{th}$ feed pressure recorded while drilling borehole $N$, MPa;

$I_{WI}$ is the value of the drilling distance (WI), mm;

$UCS_E$ is the estimated UCS value of the rock, MPa.

It should be emphasized that this equation is very preliminary and just the proof of concept for relating rock strength and drilling parameters and is only applicable to the drill bit, drill unit, and the preset conditions that were used in the testing (RPM and feed rate).

To use the composite parameter $FPI$ for the estimation of rock strength, a mathematical relationship could also be proposed based on the data collected from the preliminary tests discussed earlier. Similar to the feed pressure, the proposed mathematical relationship can be adjusted to reflect the effects of bit wear and drilling distance, and the value of $R^2$ shows an increased from 0.7833 to 0.8797. Figure 8-17 shows mathematical relationships between UCS and the $FPI$ as well as the adjusted $FPI$. Therefore, the UCS values of the rock can be predicted by using Equation 8-11 and 8-12 to analyze the adjusted $FPI$ at current drilling conditions. The advantage of using $FPI$ instead of feed pressure is that this composite index can account for the changes in RPM and feed rate, thus make it more useful if the different drilling parameters are used. Again, the results are only valid for the drill bit used in the testing and the exact model of drilling unit used and cannot be expanded to other bits and machines. Therefore, the results are just the proof of the concept and shows the potential for the method, instead of offering a universal model for prediction of UCS from the drilling parameters in different conditions.
Figure 8-17. Mathematical relationships between UCS of the rock and FPI and adjusted FPI

\[
FPI_{adjusted} = 0.1098 I_{UCS} + 3.8772 \quad (R^2=0.86) \tag{8-11}
\]

\[
FPI_{adjusted} = 9.0413 \ln(I_{UCS}) - 25.733 \quad (R^2=0.92) \tag{8-12}
\]

Where, \(FPI_{adjusted}\) is the value of adjusted FPI, MPa/cutter/cm/rev;

\(I_{UCS}\) is the UCS value of the rock, MPa.

Equation 8-11 and 8-12 indicate linear and exponential regressions between the adjusted FPI and UCS value, and the exponential regression shows better correlations. Therefore, shown
as Equation 8-13, the UCS as a function of raw FPI can be defined based on Equation 8-7 and 8-12.

\[ UCS_E = \exp \left( \frac{FPI_N}{0.00045I_{WI} + 8.97} \right) + 2.85 \]  

(8-13)

Where, \( FPI_N \) is the value of \( N^{th} \) FPI recorded while drilling borehole \( #N \), MPa;

\( I_{WI} \) is the value of the drilling distance (WI), mm;

\( UCS_E \) is the estimated UCS value of the rock, MPa.

### 8.5. Summary

The results of additional testing in samples containing inclined joints at four different angles, including 15\(^\circ\), 30\(^\circ\), 45\(^\circ\), and 60\(^\circ\), relative to the direction of drilling and a smaller aperture (1.588 mm or 1/16-in), showed the potential for detection of the inclined joints by analysis of drilling data. The modified pattern recognition algorithms for joint detection was used by analyzing individual drilling parameters (feed pressure) and composite parameters (\(RP/FP/PR\), \((RP/FP)/SED\), and \(FPI\)) to detect inclined joints, and they have offered fairly accurate detection results.

In addition, the analysis of drilling data showed that feed pressure (thrust) and \(FPI\) can be used to estimate rock strength. The correlations between rock strength, thrust, and FPI index in the limited tests including six boreholes drilled in a composite sample, containing various rock types, showed the potential to estimate rock strength from these parameters. More accurate results can be obtained when bit wear is accounted for in the analysis, through a Wear Index (WI), which could simply be represented by cumulative length of boreholes drilled by the same bit. This is relatively easy issue to track by resetting the distance when bits are changed in the operation. Also, the new bit can be tagged by the program when comparing the input data with previous records to identify the use of new drill bits in the same formations. The preliminary analysis of data shows
that the drilling parameters, specially changes in feed pressure, shows more sensitivity to the distance drilled by the same bit in softer rocks. This could be due to the higher feed pressure to drill in high strength rocks to maintain the same feed rate and thus the variation or slight increase in the required feed pressure as the bit wears is more difficult to register.

To account for the effects of bit wear, the drilling parameters could be normalized and adjusted based on the distance drilled by a new bit. For this purpose, two equations were offered to adjust the values of the feed pressure and FPI to account for the bit wear. These equations should be further modified and updated based on additional data to be collected from more laboratory tests and field practices in the future.

The statistical analysis of drilling data collected from the limited testing shows the potential to estimate rock strength from adjusted feed pressure and adjusted FPI values. Two models are introduced in this study to predict UCS values from recorded feed pressure and FPI. Furthermore, the precision and reliability of those mathematical relationships can be further improved by collecting additional drilling data through full scale drilling tests in various rock types.
Chapter 9

CONCLUSION AND RECOMMENDATION

9.1. Conclusion

The objective of this study was to examine the possibility of detecting and recording geological features in the ground, including joints, voids, bed separations, as well as estimation of rock strengths in an underground opening by analyzing drilling parameters collected from an instrumented roof bolter.

Previous studies in this field have offered limited success to identify joints with smaller apertures, especially for joints with the aperture less than 3.175 mm (or 1/8-in). As mentioned earlier (Table 5-4), the existing system for joint detection offered relatively low capabilities to identify preset joints in the same data set that is used in this study. In other words, lower detection rates and higher number of false alarms were generated by the previous algorithm while analyzing the drilling parameters, including feed pressure that offered comparative better results.

To improve capabilities of joint detection system, new pattern recognition algorithms have been examined and used to analyze drilling data from a roof bolter. The proposed programs for enhancing the detection rate of the joints are based on the Cumulative Sum (CUSUM) algorithms as well as wavelet analysis of the db45 wavelet in this study. These algorithms were used to analyze the drilling parameters of interest, such as the feed pressure, rotation pressure, acoustic, vibration, RPM, and penetration rate, for the identification of target geological features. Moreover, composite parameters, including the $RP/FP/PR$, $RP/FP/SED$, and $FPI$ were introduced to provide improved precision in joint detection, and monitoring these composite parameters also offers more reliable results. Analyzing the drilling data collected in full-scale laboratory tests showed that the
proposed new algorithms can offer better performances in sensing joints with the aperture less than 3.175 mm (or 1/8-in); in addition to being self-adjusting and generating lower false alarms.

To develop pattern recognition algorithms for detecting joints with smaller aperture and at angles relative to the direction of drilling, new laboratory tests were carried out with inclined joints at 15°, 30°, 45°, and 60° from the plane that was perpendicular to the borehole. Individual drilling parameters such as the feed pressure and composite parameters \((RP/FP/PR, RP/FP/SED, \text{ and } FPI)\) were used in the data analysis. Despite limited number of boreholes, distinct changes could also be observed in drilling data that allowed for sensing preset inclined joints.

Moreover, the preliminary result of the analysis showed that the rock strength, UCS, could be estimated by using drilling data including feed pressure and \(FPI\) index. The statistical analysis of the data collected in the initial testing clearly shows that the bit wear leads to variation in the values of drilling parameters. This was more pronounced in low strength rocks such as grout and the shale. The impact was less noticeable in rock with higher strength, like the sandstone and the limestone. To incorporate the impact of bit wear on estimation of the rock strength, a Wear Index (WI) is proposed which is simply related the drilling distance with the same bit. Linear regression was used to determine the equations for adjustment of feed pressure and \(FPI\) to allow for calculation of rock strength. Two equations were introduced for estimation of the UCS from the feed pressure and \(FPI\).

The focus of the study at this stage has been the feasibility of using the drilling data to estimate the rock strength and the result of the study shows that it is feasible and the results could be reliable. However, the equations as indicated in the dissertation were not to be used as universal formulas to estimate rock strength since they are fully dependent on the bit type, machine type,
operational setting etc. Machine and bit specific studies are essential to develop strength formulas or by using AI for interpretation of the drilling data with known strength in a new setting

9.2. Recommendation

This study has proved the possibility of improving the algorithm and programs for identification of the joints and bed separation with small opening and aperture. The use of new algorithms for pattern recognition proved that very high detection rates with low false alarms could be achieved by using individual parameters, mainly feed pressure that represents drilling thrust, and composite indices. Use of data filtering for noise reduction such as wavelets could also improve the performance of the joint detection programs. Furthermore, the analysis shows that the drilling data can be used for estimation of the rock strength, especially when properly adjusted for the bit wear. Much additional work is also needed to utilize the finding of this study in developing a commercially available product that can be used for rock characterization while drilling with different drills, specially rotary drilling used for roof bolting. Following is a short list of items that can be considered for continuation of this study.

1) To study characteristics of drilling system and bits used in this study and perform additional test under different conditions, including various bit types, rock types, and joint apertures and angles. This could be done in laboratory setting under controlled conditions to generate additional data for verification of the capabilities or shortcoming of the existing algorithms and to seek possible improvement in the detection programs.

- In this study, the drill bit ProBore\textsuperscript{TM} for Roof Drilling, which was produced by Kennametal was used to perform drilling tests. Different drill bits use different mechanisms to break the rock and affect characteristics of drilling process and operating parameters. Therefore, additional testing with various drill types are
recommended for future tests to see the capabilities of the detection programs to offer reliable joint detection with different bit types.

- Study of various joint conditions, including joint apertures and angles, and rock types, are also suggested to simulate various joint settings for training of the program development of a self-adjusting joint detection algorithm.

2) Estimation of rock strength that proposed in this study was based only on limited samples and drilling conditions. To increase the capabilities and accuracy of the programs and offer formulas for rock strength estimation based on drilling parameters for application in different conditions, additional testing should be performed. The future tests should include different drilling settings, including different penetration rate, different RPM, and different drill bit types. Moreover, testing various rock types with different UCS strengths are necessary to expand the range of rock strength in the database and improve the precision of mathematical models that are proposed in this study.

The effects of the in-situ stresses are also not accounted in this study since cannot simulate this conditions with current facilities in the laboratory tests as well as no valid field data. Although the impact of in-situ stresses on the drilling parameters is rather minimal, as compared to other parameters and for the shallow holes we were drilling, they could be ignored for practical purposes, the effect of in-situ stresses can also be considered as a condition in future study. Moreover, the factor of stress can be involved, and a coefficient can be proposed in the mathematical relationships to get rid of the effects of the stress for estimation of rock strength.

3) If data from field trials and operations become available along with the geotechnical information for training of the pattern recognition programs, the proposed algorithms can
be further refined to include and incorporate field conditions and perhaps introduce the artificial intelligence programs to recognize change in conditions, repetitive actions, and similar behavior of drill that could indicate the same rock types.

4) Integration of the developed programs and algorithms into a 3D visualization of the data to show the formations around the opening, distribution of the various rock strength, joints/voids and their spatial relations, and rock mass conditions. Feedback from the 3D modeling of the joints and formation into the algorithms can allow for indicating the missing joints in the boreholes and keeping track of formations in the rock mass by the pattern recognition programs when analyzing the drilling data.
REFERENCE


on Ground Control in Mining, Morgantown, WV. 2004.


Gu, Q.: Geological mapping of entry roof in mines, West Virginia University. 2003


Control. Ausimm Illawarra Branch, Ground Movement and Control related to Coal Mining Symposium, pp. 32-42. 1986.


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