Abstract

Ground conditions, including characteristics of joints, bed separations, and strengths of rock layers, are critical factors for underground mining and construction activities. Correct understanding of geologic conditions allows for improvement and optimization of ground support design and minimizing incidents of ground failure and instabilities in underground workings. Rock bolts have been widely accepted as the preferred method of ground support in almost all forms of rock excavation applications. The concept of monitoring drilling data to predict characteristics of geological features of interest in the rock surrounding the underground opening is a very attractive option for developing the geological model of the ground on real time basis. This includes information on distributions of joints and bed separations, locations of voids, and strengths of rock layers, which enables the automated and rapid evaluation of ground conditions while drilling is in progress. Several smart drilling systems have been developed and proposed to detect joints; however, they offer limited capabilities and have exhibited difficulties in identifying joints with small apertures (less than 3.175mm or 1/8-in). The current study was focused on developing a more sensitive method to locate joints with smaller apertures along the hole being drilled with an instrumented roof bolter. A series of full-scale drilling tests were carried out in samples which contained simulated joints with different inclined angles in controlled laboratory conditions. New joint detection programs, with improved capabilities based on various pattern recognition algorithms, have been developed and used for analysis of the full sale drilling tests. To precisely locate joints, composite parameter were also used to offer more accurate detection. This paper reviews the laboratory testing program, data analysis, logic/algorithms used in the programs, statistical analysis of the detection results, and comparison of the various algorithms for this application.

Keywords: inclined joints, joint detection, composite drilling parameters, Field Penetration Index (FPI), instrumented roof bolter, pattern recognition algorithm

1. Introduction

Ground instability may cause damage to equipment, delays and loss of production, and in some cases injuries or even fatalities in underground mining and construction activities. Proper design of rock support is the key for mitigating ground instability, and creating a safe work environment. Geotechnical investigations are routinely performed to evaluate ground conditions. This includes the recording of joint distributions, locating voids, and tracking discontinuities, as well as measuring rock strength which determines rock mass conditions and related ground support requirements. Core holes are typically drilled in various projects for geotechnical investigation, and rock samples are collected for additional laboratory testing to determine rock properties of
interest, such as the uniaxial compressive, tensile, and shear strengths. At the site, rock quantity designation (RQD) is measured on the core samples to determine rock mass classification (using RMR, Q, GSI etc.), when combined by laboratory testing. In addition, borehole logging in the form of optical or sonic logs are often conducted which offer visual inspections of boreholes to observe geological features of interest in ground, including joints, voids, bed separations, rock layers, etc. (Mahtab et al. 1973; Fitzsimmons et al. 1979; Unrug 1994; Tang and Doug 2005; Williams and Johnson 2004).

In many mining and tunneling projects, only limited geotechnical borings are drilled and even fewer borings are used for rock coring or borehole logging. As such, many critical geological features may be missed, while the geologic conditions in the subsurface might undergo considerable variations even over a short distance. In addition, measurements of rock properties require laboratory tests as well as specialized borehole logging in field that are time consuming and thus interject a time lag between drilling operation to the time when these results are available for interpretation. This can lead to delays in design and construction of the projects. Meanwhile, during construction and underground mining activities, the delayed availability of information does not facilitate timely adjustment of ground support measures.

The main premise of the reported study is to allow for analysis of the information from the drilling operation in real time to offer pertinent information on rock strengths, joints, and other forms of discontinuities. Such system offers instant updates to ground models describing ground conditions and can be used for quick reaction to variations in the ground that could require changes in ground support. One of the main forms of ground support in any underground application is the use of rock bolts which are installed in the boreholes drilled by a roofbolter. This study is focused on the process of data collection from the roof-bolting units to evaluate rock strengths and locations of joints along the holes. Measured data from full-scale testing was used to train a pattern recognition program for assessment of the rock strength and detection and locating open joints along the borehole. The results of using different joint detection algorithms and statistical analysis of the various programs used to track the joints in rock are presented in this paper. Comparison of the results allows for selection of the more versatile and accurate algorithm with higher potential for field applications.

2. Background

Many studies have focused on the material characterization while drilling in different applications. This includes oil well drilling, mining, and tunneling constructions, where systems known as Monitoring While Drilling (MWD) have been developed and deployed in different operations with various degrees of success. Underground mining and tunneling constructions have also experimented smart drilling units on identifications of the various rock formations and tracking of the joints along the holes. Measured data from full-scale testing was used to train a pattern recognition program for assessment of the rock strength and detection and locating open joints along the borehole. The results of using different joint detection algorithms and statistical analysis of the various programs used to track the joints in rock are presented in this paper. Comparison of the results allows for selection of the more versatile and accurate algorithm with higher potential for field applications.
One of the early studies on this topic was a research project at the Spokane Research Center of the National Institute of Occupational Safety and Health (NIOSH, formerly known as USBM) in the early 1990s. An instrumented roof bolter was developed to monitor drilling parameters, including thrust, torque, penetration rate, and rotational rate, to predict geological features in roof strata (Frizzell and Howie, 1990; Frizzell et al. 1992; Signer and King 1992, King et al. 1993). Moreover, a detection system, which was an instrumentation of a roof-bolting unit to monitor drilling, was proposed by Parvus Corporation of Salt Lake City, Utah to monitor drills (Takach et al. 1992; Hill et al. 1993). In addition, four more intelligent drilling systems, or instrumented roof bolters, have been offered by the Muroran Institute of Technology in Japan, the Robotics Institute of Carnegie Mellon University in the United States, J.H. Fletcher & Co. in United States, and Atlas Copco AB in Sweden. Table 1 shows a summary of these four smart drilling systems based on instrumented roof bolters for ground characterization (Kahraman et al. 2016, Liu et al. 2018).

Over the years, intelligent drilling systems have been advanced for ground characterization, such as joint detection and rock strength estimation, by monitoring various drilling parameters. However, these systems typically had limited accuracy relative to varying ground conditions and therefore need further improvement to be widely employed in field applications. For example, one of the remarkable studies in this field was conducted by a research team at West Virginia University (WVU). The WVU team, collaborating with J.H. Fletcher & Co., developed a smart drilling system that was focused on a roof bolter to monitor drilling processes for ground characterization; however, this intelligent system had limited success in detecting joints and/or voids with an aperture less than 3.175 mm (1/8-in) in many laboratory and field tests (Finfinger et al., 2000; Peng et al., 2003; Collins et al., 2004; Anderson and Prosser, 2007). The other three drilling systems have also had similar limitations. In addition to missing certain joints, many false alarms have been reported, identifying joints and/or voids that do not actually exist in the ground.

The research work reported in this paper mainly focuses on improving the precision and sensitivity of the joint detection system to identify joints and/or voids with an aperture less than 3.175 mm (1/8-in) by monitoring drilling parameters that are recorded while drilling. A J.H. Fletcher & Co. roof bolter was employed in full scale drilling tests in this research to refine capabilities of joint detection models and related data analysis programs. A set of new sensors, including acoustic and vibration sensors, were mounted on the drilling unit to record additional drilling parameters for further data analysis. This paper will briefly review procedures for laboratory testing, development of detection programs based on pattern recognition algorithms, updated detection results, and statistical analysis of the result of joint detection by various algorithms that were developed in this study. Figure 2 presents a flowchart summarizing the pattern recognition programs for joint/void detection.

3. Full Scale Laboratory Drilling Tests

A series of laboratory tests were planned and carried out with a J.H. Fletcher & Co. developed rotary-drilling roof bolter at the J.H. Fletcher & Co. testing facility in Huntington, WV, United States. A drill control unit (DCU), which allows for automatically controlling the drilling cycle and collecting drilling data during the drilling process, was equipped on the drill. Drilling parameters, including feed pressure (thrust), rotation pressure (torque), penetration rate, RPM, drill bit position in the borehole, and vacuum or water pressure, were monitored by the DCU while drilling. The sampling interval of the DCU was preset at 100 Hz for data collection. In addition,
new sensors, including acoustic sensors and vibration sensors, were mounted on the drilling unit to record additional drilling parameters for further analysis. The acoustic sensor was a simple Piezoelectric disk, or piezo buzzer, which is also known as a contact microphone. The vibration sensor, which was a PiezoStar accelerometer and is known as PCB 353B31 accelerometer. In this study, both the acoustic and vibration data were collected using sampling rate of 1000 Hz. (Anderson and Prosser, 2007; Bahrampour et al. 2015; Liu et al. 2017; Rostami et al. 2014 & 2015). Figure 3 shows the J.H. Fletcher roof bolter testing unit with the data-recording system.

In laboratory testing, a set of concrete blocks were cast, following by curing for more than 28 days. The dimensions of each block were approximately 0.9 m x 0.9 m x 0.76 m, with these blocks were arranged into three groups representing soft (S), medium (M), and hard (H) roof-rocks, respectively. Corresponding UCS strengths of samples in S, M, and H groups were ~20MPa, 50MPa, and 70MPa. Test samples were made by stacking one block on the top of another, leaving a gap with a clearance of approximately 2 mm between adjacent blocks to simulate a joint for detection. Figure 4 is an example of a cast concrete block and testing sample. The location of the planned joint was therefore at a depth of ~0.76 m within each testing sample. Furthermore, various combinations of the above-mentioned blocks allowed for simulations of different existing conditions of the joints in nine combinations of concrete blocks. This included soft-soft (S-S), S-M, S-H, M-S, M-M, M-H, H-S, H-M, and H-H. Table 2 is the matrix for full scale laboratory drilling tests for joint detection.

4. Analysis of Drilling Data for Joint Detection

Drilling parameters including as feed pressure (thrust), rotation pressure (torque), rate of penetration (ROP), rotary speed (rotary per minute, RPM), acoustic, and vibration, etc., were recorded while drilling into the testing samples. Reviewing properties of the recorded drilling data indicates that signature behaviors can be observed while drilling through the pre-designed joints. The appearances of the signature behaviors in the monitored drilling parameters were because of the drill needed to be self-adjusting to keep the preset ROP and RPM while the drill bit encountered a joint/void. In addition, the captured signature behaviors were varied from various drilling parameters. For example, mean changes in the feed pressure and rotation pressure as well as deviation changes in the acoustic and vibration data. Therefore, with the objective of joint detection while drilling, particular pattern recognition algorithm needed to be designed according to the observed signature behavior of each drilling parameter. Figure 5 is an example of the drill bit position, feed pressure, and rotation pressure data that were recorded while drilling into the M-M test sample. As circled in Figure 5, a clear change/drop was observed both in the data stream of feed pressure and rotation pressure when the drill bit reached the pre-designated joint at a depth of ~0.76m.

A preliminary analysis of properties of the collected acoustic data as well as the vibration data has also demonstrated the feasibility of using these drilling parameters towards locating of joints. Observing from the data collecting process in the laboratory tests, the recorded acoustic signal while drilling through the block tends to have a higher frequency than the “noise”. Thus, a high-pass filter was designed to filter out the low frequency components for the objective of joint detection. Figure 6 shows an example of the raw and filtered acoustic data. A clear gap was captured in the filtered acoustic data when the drill bit encountered the pre-designated joint. Similar features were also observed when analyzing the recorded vibration data. However,
subsequent statistical analysis of the results achieved from the vibration data showed that the
detection rates and number of false alarms were far inferior to those detected using measured feed
and rotation pressures and as such further work on the vibration data was suspended. In addition,
the acoustic data has strict limits on the surround environment; in other words, it tends to be easily
interrupted by various sound sources, and it is extremely difficult to filter out “noises” from the
raw acoustic data. Therefore, the acoustic data was also took out in further works.

According to aforementioned features of the drilling parameters, a sudden change in feed and
rotation pressures can be captured in the data stream when the pre-arranged joint was encountered
during the full-scale drilling tests. Thus, occurrence of these sudden changes in a certain direction
has been considered to be a signature for the detection of joints in this research. The research team
has focused on these signatures when developing new pattern recognition algorithms to achieve
higher accuracy and precision to detect joints while drilling. Higher accuracy is defined as an
increased detection rate (%) combined with a reduced occurrence of false alarms, or what some
can consider to be false negatives and false positives in the detection process.

5. Programs Development Based on Pattern Recognition Algorithms

The cumulative sum (CUSUM) algorithm, which was initially presented by E.S. Page (Page 1954)
and further refined by Basseville and Nikiforov (Basseville and Nikiforov 1993), is typically
applied to identify abrupt changes in streaming data. To develop pattern recognition systems for
joint detection, the CUSUM algorithm has been employed and fine-tuned for developing joint
detection algorithms in this research. As noted before, monitored drilling parameters, including
the feed pressure and rotation pressure signals were used in the analysis of mean change detection
to identify the joint signatures. In addition, the “moving windows” statistical technique was
involved in the updated CUSUM algorithm in which mean changes between two adjacent windows
can be calculated. The window scale can be defined according to the property of the monitored
drilling data.

To implement the updated CUSUM algorithm, a time series \( y_k \) \((k = 1, 2, 3 \ldots)\) was assumed to be
a time Gaussian random sequence with a variation of \( \sigma^2 \). Supposing an unknown change exists in
the data stream at time \( t_a \), and \( y_k \) has a mean of \( \mu_0 \) before \( t_a \), the mean value of \( y_k \) becomes \( \mu_1 = \mu_0 - \nu \) after time \( t_a \). Therefore, the variable \( g_k \) is used to process this time series and identify a
changed feature as expressed in the following formula:

\[
g_k = \max \left\{ g_{k-1} - y_k + \mu_0 - \frac{\nu}{2}, 0 \right\}
\]

The detection alarm time can be defined as:

\[
t_{alarm} = \min \{ k : (g_k \geq h) \}
\]

where \( h \) is an adaptive threshold that can be pre-defined based on the property of the analyzed data,
\( \nu \) is the difference of mean values of the time series, \( y_k \), before and after the change, and \( g_0 = 0 \)
(Basseville and Nikiforov 1993). Thus, when the value of \( g_k \) is equal to or larger than the threshold
value \( h \), the detection alarm will be activated, in this case, a joint is assumed to be identified. This
algorithm has been implemented in the detection program and data from various tests have been
analyzed using the suggested algorithm to measure the success of the program in the detection of
joints using changing threshold values. The threshold values used 50% of \( \mu_0 \) values to allow for self-adjusting of the detection program while drilling through different rocks.

6. Statistical Analysis on Joint Detection Results

In the laboratory tests, a pattern of boreholes was drilled in each set of test samples for pattern recognition of the pre-designed joints. Figure 7 represents an example of the joint detection results by analyzing the feed pressure, rotation pressure, acoustic, and vibration data on the M-S composite sample. A total of 18 boreholes were drilled for data collection in this sample. The data collected from the tests has subsequently been analyzed and the results are summarized in graphs where detection of the joint in the correct location is marked and the false alarm or detected joints where they did not exist was also marked (see Figure 7). All of joints that have been successfully identified at approximately the same location as the pre-designed joints are marked. Due to different capabilities of the monitored drilling parameters to sense the pre-designed joint in the blocks, monitoring various parameters led to varied detection results, meaning different detection rates and false alarms. This observation could provide suggestions on parameter selections and performance evaluations in field practices of this technique. A detection rate of 100% was achieved in the analysis of the feed pressure in this scenario. But two false alarms (red diamonds) were also generated during the detection process in sample M-S. When analyzing the rotation pressure data, all of the 18 joints are detected (100% detection rate) but 17 false alarms were generated. Performing pattern recognition on the acoustic and vibration data also provides reasonable joint detection results. The detection rate by analyzing the acoustic data was 100% with 13 false alarms and the vibration data provides a detection rate of approximately 83% with 11 false alarms. In addition, since the acoustic and vibration signals were recorded from a separate data acquisition system, there are some variations on the estimated joint locations compared to those recovered from the feed and rotation pressure data. Similar joint detection results are also achieved from another eight block samples by monitoring the drilling parameters.

Table 3 shows the statistics of the joint detection results from the 156 boreholes (drilled holes in 9 sample combinations) by monitoring the drilling parameters of feed pressure, rotation pressure, acoustic, and vibration data. Of these four drilling parameters, the feed pressure offers the best performance in joint detection in all nine concrete composite samples. This generates an average detection rate of ~94% with 12 false alarms. Compared to the feed pressure, the rotation pressure provides a slightly lower performance in joint detection as it generates a higher number of false alarms. Analyzing the rotation pressure using the current algorithm offers a detection rate of approximately 88% with a total of 109 false alarms. The acoustic and vibration sensors were initially mounted on the instrumented roof bolter to record related data for rock-strata classification. The recorded data also offered certain capabilities to identify joints and/or voids. The average detection rate obtained by analyzing the acoustic data is about 84% with 39 false alarms in all 156 boreholes. In addition, the average detection rate was ~68% with 92 false alarms for the vibration data. The gravels existed in the concrete blocks caused relatively large deviations in recorded drilling parameters compared with drilling through the rock. This could confuse the detection algorithms to locate pre-designed features and therefore cause different detection rates and errors in different concrete settings. However, the performances of the monitored parameters in various concrete settings were aligned with their performances in the overall analysis.
Detection results reveal that drilling parameters have different capabilities and performances in the objective of joint detection. In addition, monitoring different parameters may result in different detection results. For example, a joint was reported through examining a drilling parameter but failed in another parameter, and analyzing one drilling parameter might cause a false alarm but not in another parameter. Therefore, it would be critical to use statistical analysis methods to evaluate performances of various drilling parameters and give best suggestions on parameter selections as well as detection result judgments in future applications. In statistical hypothesis testing, the notion of Type I and Type II errors is an integral part of the evaluation process. A Type I error, also referred to as a false positive error, commonly occurs when incorrectly rejecting a true condition of the null hypothesis ($H_0$). Typically, a Type I error causes a conclusion that a supposed condition exists while in fact it does not. A Type II error, also referred to as a false negative error, happens when improperly accepting a false null hypothesis ($H_0$). Usually, a Type II error leads one to reject a true alternative hypothesis (Neyman and Pearson, 1933; Sheskin, 2004; Peck and Devore, 2011).

In this study, the null hypothesis ($H_0$) was set as the existence of a void/joint in real. Therefore, a Type I error only occurs when a joint information is missed. A Type II error only occurs when a false alarm is generated and a joint is suggested by the program where it does not exist. As for the statistical hypothesis testing of Type I and Type II errors, the power of a hypothesis test is typically applied to reject an incorrect null hypothesis ($H_0$) and therefore make the right decision. The power of the test is the probability calculated by using 1 minus the probability of the Type II error. Table 4 indicates probability and power summaries in evaluating joint detection results achieved from the monitoring of feed pressure, rotation pressure, and acoustics and vibrations.

According to the statistical analysis of the joint detection results, the feasibility of monitoring these four drilling parameters towards joint detection have been presented, but differences in their sensitivities and precisions are observed. Of these four drilling parameters, monitoring the feed pressure offers the best performance in joint detection in all nine scenarios for the various sequences of rock hardmesses. It generates the smallest probabilities of both Type I (6%) and Type II errors (8%); in other words, the feed pressure provides the highest sensitivity and precision in identifying joints and makes the minimum number of false alarms. Thus, the power of using the feed pressure is up to 92%.

Although the rotation pressure offers a slightly lower detection rate in joint detection (88%), it yields a low power number which is 30%. This is because the rotation pressure leads to large number of false alarms that up to 109, meaning a probability of 70% for the Type II error. Therefore, it is possible to analyze the rotation pressure for the objective of joint detection but it tends to cause much higher false alarms and have much lower power.

For the acoustic data, notable differences in performance are observed where relatively low probabilities of the Type I and Type II errors (16% and 25%, respectively) were achieved. Thus, the acoustic could be considered as an alternative parameter in terms of joint detection; however, it offered a relatively low number of power of only 75%. The vibration data is prone to miss the joints altogether and tends to issue more false alarms towards the objective of joint detection. The Type I error, the Type II error, and the power of the vibration as a joint-detection index are 32%, 59%, and 41%, respectively.

7. Use of Composite Parameters
The capabilities of using pattern recognition algorithms to monitor individual drilling parameters for joint detection was examined but possibility of improving the detection rates with composite parameters were also explored. This was due to different sensitivities of individual drilling parameters on joints or voids, which were marked as changes in recorded data. Using composite parameters which are combinations of multiple individual drilling parameters offered higher accuracy in identifying joints or voids, as will be discussed here.

Field Penetration Index (FPI) is widely applied on tunnel boring machines (TBMs) for rock excavation in the field of tunneling. It describes the bore ability of the rock while operating a TBM in changing geological conditions (Tarkoy and Marconi, 1991; Hassanpour et al., 2011). In this study, with the above proposed pattern recognition algorithms, the composite parameter FPI was employed to analyze recorded machine data for joint detection, and it can be defined as:

\[
FPI = \frac{FP}{PR/RPM}
\]

Where,
- \(FP\), Feed Pressure, MPa (or psi);
- \(PR\), Penetration Rate, cm/second (or inches/second);
- \(RPM\), Rotary Speed, rev/second;
- \(FPI\), MPa.rev/cm (or psi.rev/in).

Variations of FPI values while drilling through concrete blocks with different strengths as well as the pre-designed joint in the M-S sample can be clearly observed in Figure 8a. Figure 8b shows joint detection results on the M-S sample by monitoring the FPI data.

Table 5 summarizes performance of the FPI on joint detection from all concrete samples. The average detection rate was up to 96% in all 156 boreholes; in addition, a total number of 14 false alarms, which refers to a rate of 9%, were generated while drilling through the nine concrete sample combinations. The probabilities of causing Type I error and Type II error were 4%, and 9%, respectively. Therefore, a power of 91% was achieved by monitoring the FPI towards joint detection. Comparing to the feed pressure, which has the best performance on joint detection in above analysis, the composite parameter FPI offers slightly higher detection rate (2% higher). Since using the FPI causes two more false alarms are generated, the FPI provides 1% lower power than the feed pressure.

8. Identification of Inclined Joints

As described above, the concrete samples had one simulated joint perpendicular to the drilling direction. In real rock mass, the orientation of joints relative to the axis of drilled boreholes could be at angles ranging from 0° to 90° (Gong et al., 2005). Therefore, a set of new tests were performed in a specially designed and casted grout sample with multiple inclined joints. To simulate inclined joints, the soft strength Teflon material with the thickness of around 1.588 mm (or ~1/16 in) was placed in the concrete sample with pre-designed angles, including inclined angles of 15°, 30°, 45°, and 60° relative to the horizontally drilling face. Figure 9a shows the schematic diagram of distributions of inclined joints in the concrete sample. #A and #B refer to two different samples in one block, and the #B was cast on the top of #A after it had been cured for two days. The grouts with three different strengths (UCS), including Low (L, ~20 MPa), Medium (M, ~50 MPa), and
High (H, ~ 70 MPa), were used to fill various areas of #B to simulate different rock layers. Figure 9b shows a picture of four inclined joints simulated with the Teflon material. Figure 9c demonstrates an inclined joint along a borehole observed from bore scoping.

As noted before, the individual parameter feed pressure and the composite parameter $FPI$ offer most reliable performances on joint detection; therefore, these two parameters are employed as the main parameters for detections of inclined joints. Figure 10 displays the plot of recorded feed pressure data for drilling in the sample with inclined joints. As can be observed, the values of the recorded feed pressure are varying while drilling through grouts with various strength values. Moreover, four distinct changes on the feed pressure data are observed at the location of four inclined joints. Similar apparent changes are also observed in the computed $FPI$ data.

Drilling data from two nearby boreholes in which all four sets of inclined joints were located at similar depths were used in the analysis. Recorded feed pressure data from these two boreholes were analyzed by the modified algorithms, and correspondingly inclined joints in these two boreholes were identified at around expected locations, while no false alarms were observed. In addition, to evaluate the capability of the modified algorithms to locate inclined joints, bore-scoping was also performed to look at the real depth in the boreholes. Figure 11 shows joint detection results achieved from analyzing the feed pressure data (FP) and the $FPI$ data for drilling through inclined joints. The results show that perhaps detection of inclined joints could be easier since the drill bit spends more time in the joints within the borehole as compared to the joints that were perpendicular to the holes. This is due to the projected length of the inclined joints in the boreholes. At this time the algorithms are incapable of identifying the angle of inclination of the joints along the borehole. This could be an interesting topic for further studies on this topic.

9. Conclusions

In this research, new pattern recognition algorithms were proposed based on an updated CUSUM algorithm to precisely discriminate joints and/or voids with small apertures. The analysis of data collected from full-scale testing of roofbolter drills indicated that joints and/or voids with an aperture of less than 3.175mm (1/8-in) can be effectively recognized by employing newly developed algorithms to monitor drilling parameters. Statistical hypothesis testing, including quantifying false positive and false negative errors and corresponding powers of using four individual drilling parameters, were performed to assess their rationality and reliability for joint detection using a rotary drilling system. Statistical analysis verified the precision and sensitivity of the proposed pattern recognition algorithms to sense joints with small apertures. The results show that among the four individual drilling parameters, the feed pressure is the preferred parameter which offers the most reliable and precise performance in sensing joints with an aperture less than 3.175mm (1/8-in), with a minimum number of false alarms in various combination of rock strengths on opposite sides of the joint.

The feasibility of using the composite parameters to provide more accurate joint detection has been examined in this study. Compare to the four drilling parameters, the composite parameter $FPI$ offers better performance on joint detection. Subsequent laboratory drilling tests on samples containing four sets of inclined joints, with different orientation angles and smaller apertures (around 1.588mm or 1/16-in), also proved the possibility of using the modified algorithms for joint
identification. This was based using the detection program for analysis of recorded individual and composite drilling parameters.

Additional studies are essential to further improve the capabilities of the proposed pattern recognition algorithms to identify joints with more complex geometries and conditions, such as joints with even smaller apertures, joints at various angles of inclination to drilling, and the simultaneous presence of multiple joints. Moreover, to mitigate negative effects of “noises” which are also involved in data for operational and natural reasons, particular filters in terms of the properties of monitored parameters are also necessary to initially clean up the data before analysis. Additional full-scale laboratory tests have been carried out with these objectives in mind and data analysis is underway.

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