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Statistical Analysis of the Capabilities of Various Pattern Recognition Algorithms for Fracture Detection Based on Monitoring Drilling Parameters

Wenpeng Liu[1] · Jamal Rostami[1] · Asok Ray[2] · Derek Elsworth[3]

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Abstract

Ground conditions, including characteristics of fractures, joints, bed separations, and strengths of rock layers, are critical factors for proper design of openings in underground mining and construction projects. 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 evaluate 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. 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 data recorded in the full-scale drilling tests. To precisely locate joints, composite parameter was 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 · Fracture detection · Composite drilling parameters · Field penetration index (FPI) · Instrumented roof bolter · Pattern recognition algorithm

✉ Wenpeng Liu
wenpengliu@mines.edu

Jamal Rostami
rostami@mines.edu

Asok Ray
axr2@psu.edu

Derek Elsworth
elsworth@psu.edu

1 Department of Mining Engineering, Earth Mechanics Institute, Colorado School of Mines, Golden, CO 80401, USA

2 Department of Mechanical Engineering, The Pennsylvania State University, State College, PA 16802, USA

3 Department of Energy and Mineral Engineering, The Pennsylvania State University, State College, PA 16802, USA

1 Introduction

Any form of ground instability, particularly roof falls and wall failures, 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

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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 or estimated from the scan lines on the walls/outcrops 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 is often conducted which offers 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, 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 study reported in this paper 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 instantaneous updates to geological models describing ground conditions and can be used for quick reaction to variations in the ground that could require adjustments 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 roof bolter. This study is focused on the process of data collected from the roof-bolting units to evaluate rock strengths and locations of joints along the holes. Measured data from full-scale testing were used to train a pattern recognition program for assessment of the rock strength and detection and locating of 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 used in different operations with various degrees of success. Underground mining and tunnel construction projects have experimented smart drilling units for identifications of the various rock formations and tracking of the joints along the holes drilled for blasting or installation of rock bolts. Rostami et al. (2014) maintained that this concept can be introduced for application in tunneling and underground mining/construction for geological mapping of the ground. A key component of performing ground characterization while drilling is to record and analyze drilling parameters while drilling through various rock types to identify target geological features based on correlations between these features and certain patterns in the data and drilling parameters. For example, Fig. 1 presents typical behaviors of the drilling thrust force corresponding to various rock discontinuities, which are modified from the drilling torque in previous studies (Itakura et al. 1997).

One of the early studies on the MWD technology was conducted by Brown and Barr (1978; Barr 1984), they proposed the idea of using instrumented drilling for site investigations. In the early 1990s, the Spokane Research Center of the National Institute of Occupational Safety and Health (NIOSH, formerly known as USBM) performed a research project to develop the MWD technology in mining field. 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). A detection system, which was an instrumented roof-bolting unit to monitor drilling, was proposed by Parvus Corporation of Salt Lake City, Utah to monitor drilling parameters (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 needed 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

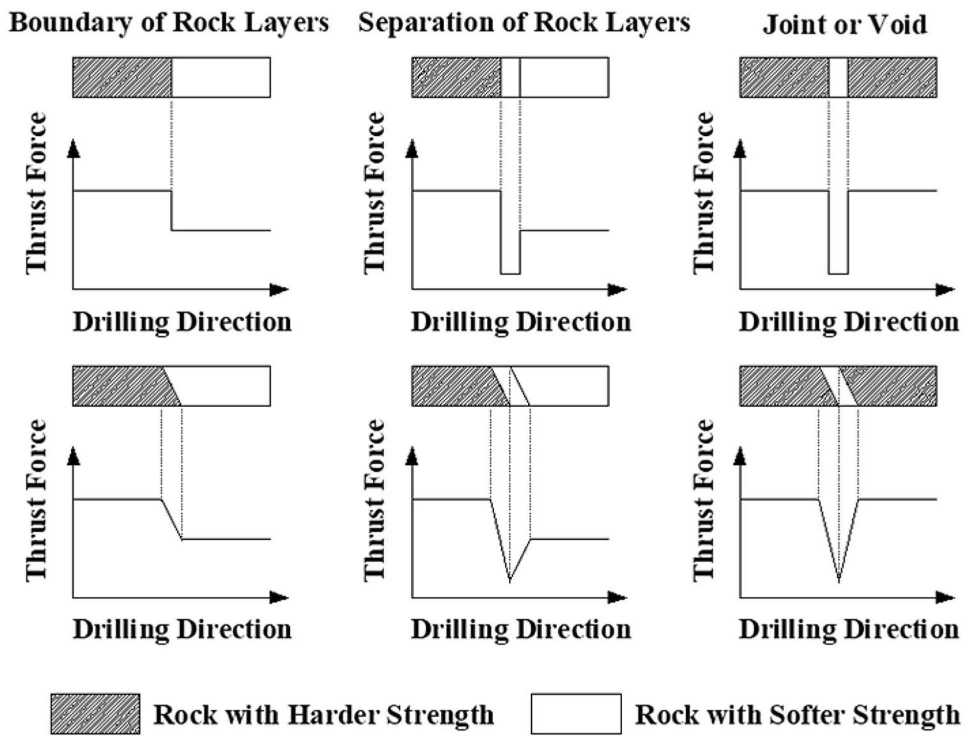


Fig. 1 Typical behaviors of the thrust force as drill encounters various rock discontinuities

Table 1 A summary of four intelligent drilling systems to instrument roof bolters for ground characterization (Kahraman et al. 2016; Liu et al. 2018)

System	Country	Parameters	Specification	Remarks
Parvus Corporation System	United States	Thrust, torque, RPM, penetration rate	The real-time specific energy of drill was calculated	Not currently applied
Muroran Institute of Technology System	Japan	Thrust, torque, RPM, penetration rate	The system could estimate roof rock 3-D geo-structure	No updates
Robotics Institute of Carnegie Mellon University System	United States	Thrust, torque, RPM, penetration rate	A neural network was used to classify rock lithology	No updates
J. H. Fletcher & Co. Feedback Control System	United States	Thrust, torque, RPM, penetration rate	Real-time detection of roof geology. Drilling parameters can be preset	Commercially available
Atlas Copco AB Boomer E3-C30 based MWD-systems	Sweden	Percussive pressure, feed pressure, dampener pressure, rotation pressure, RPM, penetration rate	The system could interpret rock strength include Schmidt Hammer, Point-Load, Indirect Brazilian Tensile, and Uniaxial Compressive Strengths	Commercially available

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 (false negative), many false alarms have been reported (false positive), identifying joints and/or voids that do not actually exist in the ground. Using the MWD technologies, such as the percussive drill or the rotary drill units, for rock characterizations were also studied in the past few years (Posiva 2010; Schunnesson and Kristoffersson 2011; Rai et al. 2015; Hatherly et al. 2015; Ghosh et al. 2017; Khorzoughi et al. 2018). However, the ability of these drills in sensing hairline joints was not discussed.

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, detection-programs development based on pattern recognition algorithm (Murphy 2012; Bishop 2006; Duda et al. 2012). These programs were used to examine their capability to maximize their detection rate, while minimizing the number of false alarms. 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 automatic control of the drilling cycle and collecting drilling data during the drilling process, was installed 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, and were used for joint detection in this study. The sampling interval

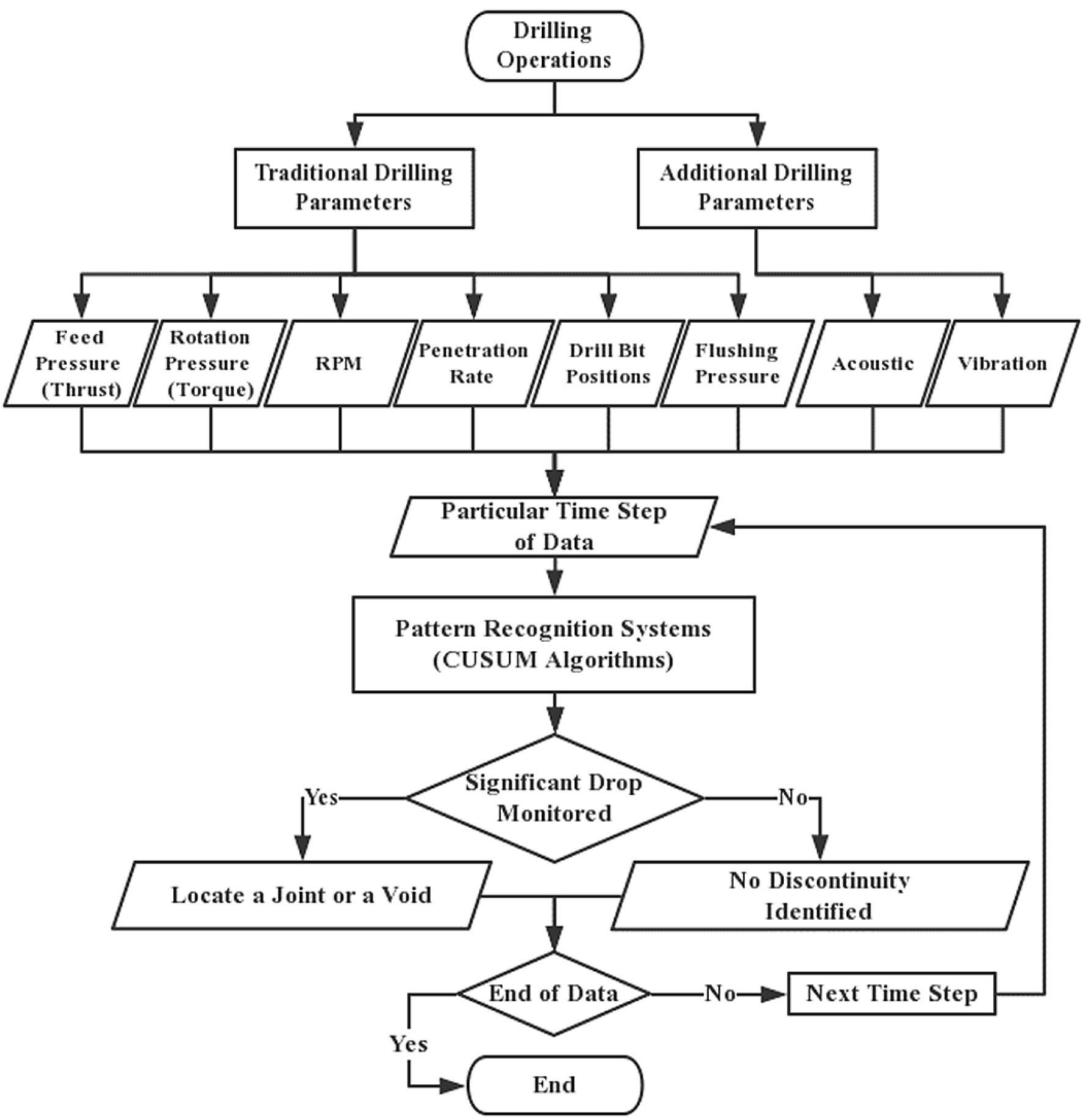


Fig. 2 The schematic of pattern recognition programs available/proposed for joint/void detection

of the DCU was preset at 100 Hz for data collection. In addition, vibration and acoustic sensors were added to the drilling unit drive system to generate related data as additional sources of information for improving the capabilities of the unit for characterizing the ground while drilling. 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, 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 × 0.9 m × 0.76 m, and 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 ~20 MPa, 50 MPa, and 70 MPa. 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. Table 2 shows the matrix for full-scale laboratory drilling tests for joint detection.

4 Analysis of Drilling Data for Joint Detection

Drilling parameters including feed pressure (thrust), rotation pressure (torque), rate of penetration (ROP), rotary speed (revolution per minute, RPM), acoustic, vibration, etc., were recorded while drilling into the test samples. Reviewing properties of the recorded drilling data indicate that

Fig. 3 The J.H. Fletcher roof bolter testing unit with the data-recording system

Fig. 4 An example of a cast concrete block and a testing sample

Table 2 Matrix of laboratory tests for joint detection

Order	Sample setup		Joint condition
	Bottom	Top	
1	S	S	A simulated "joint" with the aperture less than 3.175 mm (or 1/8-in) that located at the depth of about 76.2 cm (or 30-in)
2	S	M	
3	S	H	
4	M	S	
5	M	M	
6	M	H	
7	H	S	
8	H	M	
9	H	H	

Concrete Block Strength: S, soft strength (~20 MPa or ~2900 psi); M, medium strength (~50 MPa or ~7200 psi); H, hard strength (~70 MPa or ~10,000 psi)

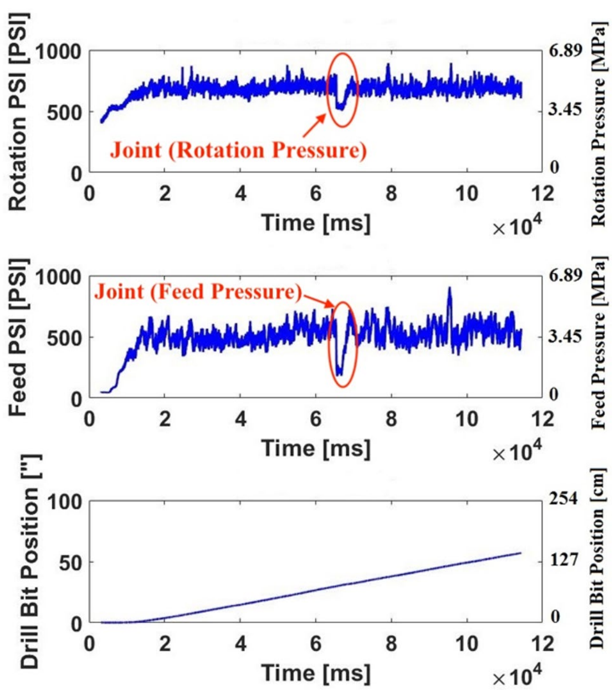


Fig. 5 Example of the drill bit position, feed pressure, and rotation pressure data collected while drilling

signature behaviors can be observed while drilling through the pre-designed joints. Given the objective and scope of the study, the test settings were designed to simulate various possible scenarios of encountering various rock strengths along the borehole. Some of the observed signature behaviors in the monitored drilling parameters were because of the drill control system of self-adjusting to keep the preset ROP and RPM, while the drill bit encountered a joint/void. In addition, the captured signature behavior was different from one drilling parameter to another. For example, mean changes in the feed pressure and rotation pressure were the signature of passing through a joint, while changes in the frequency and amplitude of signal were the signature of the same feature in the acoustic and vibration data. Therefore, the objective of statistical analysis of joint detection algorithms, in particular pattern recognition algorithm, was to examine the efficiency of the proposed methods to observe 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 Fig. 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 ~0.76 m.

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. The recorded acoustic and vibration signals tend to have a higher frequency than the "noise" while drilling through the block. Thus, high-pass filters were designed to filter out the low-frequency components for the recorded signals with objective of improving 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 assessment of the results of analyzing 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 due to the interference by the noises in the surround environment; in other words, it tends to be easily disrupted or interfered by various sound sources. As such, it is extremely difficult to filter out "noises" from the raw acoustic data. Therefore, the acoustic data were also excluded in further analysis.

A closer examination of the drilling parameters showed that 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 in the detection process.

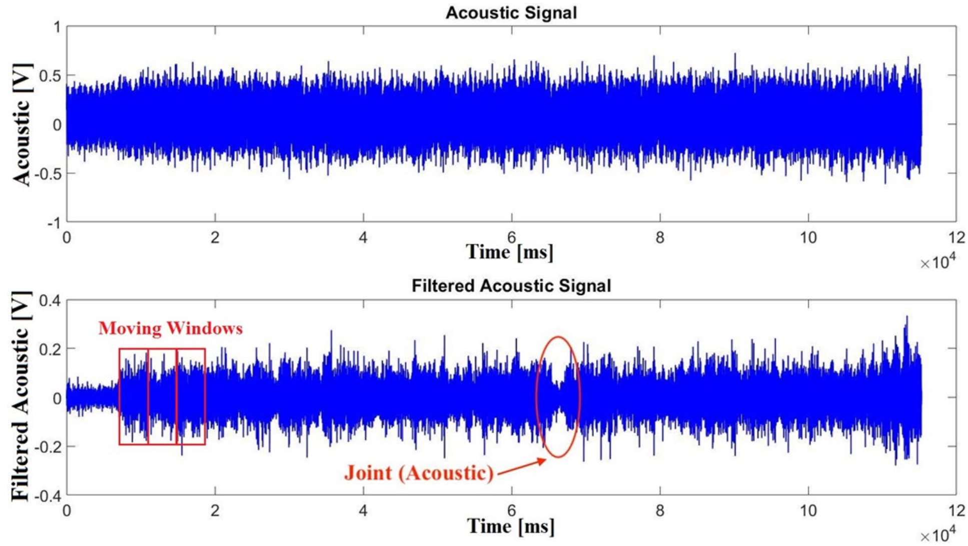


Fig. 6 An example of the raw and filtered acoustic data

5 Programs Development Based on Pattern Recognition Algorithms

The pattern recognition algorithms such as mean detection, CUSUM, etc. were designed based on the AI and machine learning routines that are used in various industries to identify and detect changes in data stream. The algorithm discussed in this section is one of the different algorithms used in this study that had better performance.

The cumulative sum (CUSUM) algorithm, which was initially presented by ES. Page (1954) and further refined by 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 incorporated in the updated CUSUM algorithm in which mean changes between two adjacent windows could be calculated, as presented in Fig. 6. This approach allows the detection algorithm to report a joint alarm once the change over the preset threshold was detected and continuously examine following windows. 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 σ^2. Supposing an unknown change exists in the data stream at time t_a, and y_k has a mean of μ_0 before t_a, the mean value of y_k becomes $\mu_1 = \mu_0 - v$ 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:

$$g_k = \max\left\{ g_{k-1} - y_k + \mu_0 - \frac{v}{2}, 0 \right\}. \tag{1}$$

The detection alarm time can be defined as:

$$t_{\text{alarm}} = \min\left\{ k : \left(g_k \geq h \right) \right\}, \tag{2}$$

where h is an adaptive threshold that can be pre-defined based on the property of the analyzed data, v 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). Figure 7 shows a plot of calculated g_k from a feed pressure signal. 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 for the detection algorithms were 50% of μ_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 detection of the pre-designed joints using the pattern recognition algorithms. Figure 8 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 in this sample. The data collected from the tests have subsequently been analyzed and the results are summarized in these 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 Fig. 8). All the joints were successfully identified at approximate location of the pre-designed joints. While, the potential errors and successes of analyzing different drilling parameters to sense joints in rock are not fully explored. The observations could provide suggestions for parameter selections and performance evaluations in field practices. The selection of viable algorithms was based on maximum detection rates and minimum errors, as indicated by statistical analysis of the results. 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 were detected (100% detection rate) but 17 false alarms were also 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 provide a detection rate of approximately 83% with 11 false alarms. Meanwhile, since the acoustic and vibration signals were recorded by a separate data acquisition system, there were some variations on the estimated joint locations compared to those recovered from the feed and rotation pressure data. Similar joint detection results were also achieved from another eight block samples by monitoring the drilling parameters.

Table 3 shows the summary statistics of the joint detection results from the 156 boreholes (drilled holes in nine block combinations) by monitoring the drilling parameters of feed pressure, rotation pressure, acoustic, and vibration data. Of these four drilling parameters, the feed pressure offered the best performance in joint detection in all nine concrete composite samples. This generated 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 was about 84% with 39 false alarms in all 156 boreholes. The average detection rate was ~68% with 92 false alarms when vibration data were used. The gravels used in the concrete blocks caused relatively large deviations in recorded drilling parameters compared to drilling through the rock. The signature of drilling through gravels could confuse the detection algorithms to locate pre-designed features and therefore caused 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. To mitigate this problem, all the follow-up tests were conducted in grout samples with a set target strength and excluding large size gravels in the mix.

Detection results reveal that drilling parameters have different capabilities and performances for joint detection. Analysis of the data shows that monitoring different parameters might result in different detection results. For example, a joint could be detected through analysis of one drilling parameter, but was missed when interrogating another parameter. Similarly, analyzing one drilling parameter might cause a false alarm that is not generated by monitoring another parameter. Therefore, the use of statistical

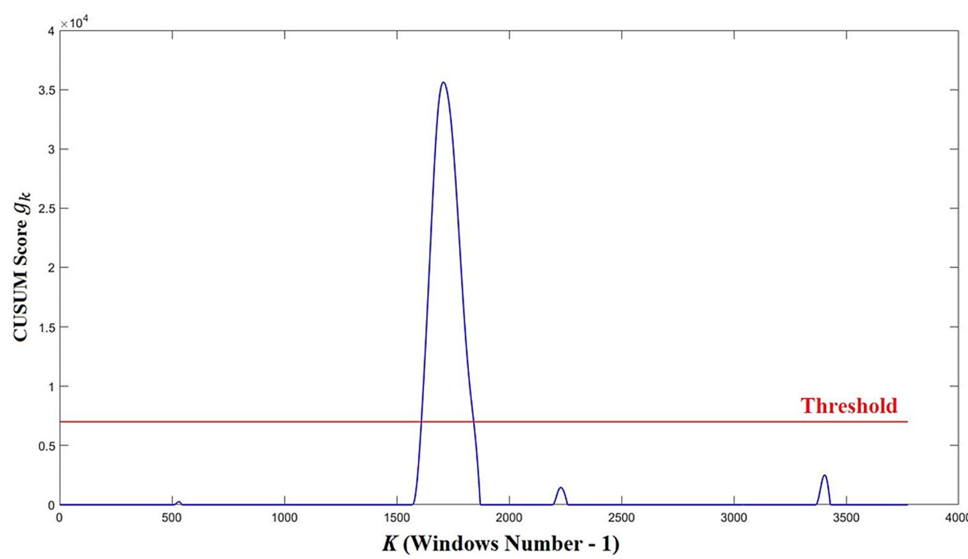


Fig. 7 A plot of calculated g_k from a feed pressure signal

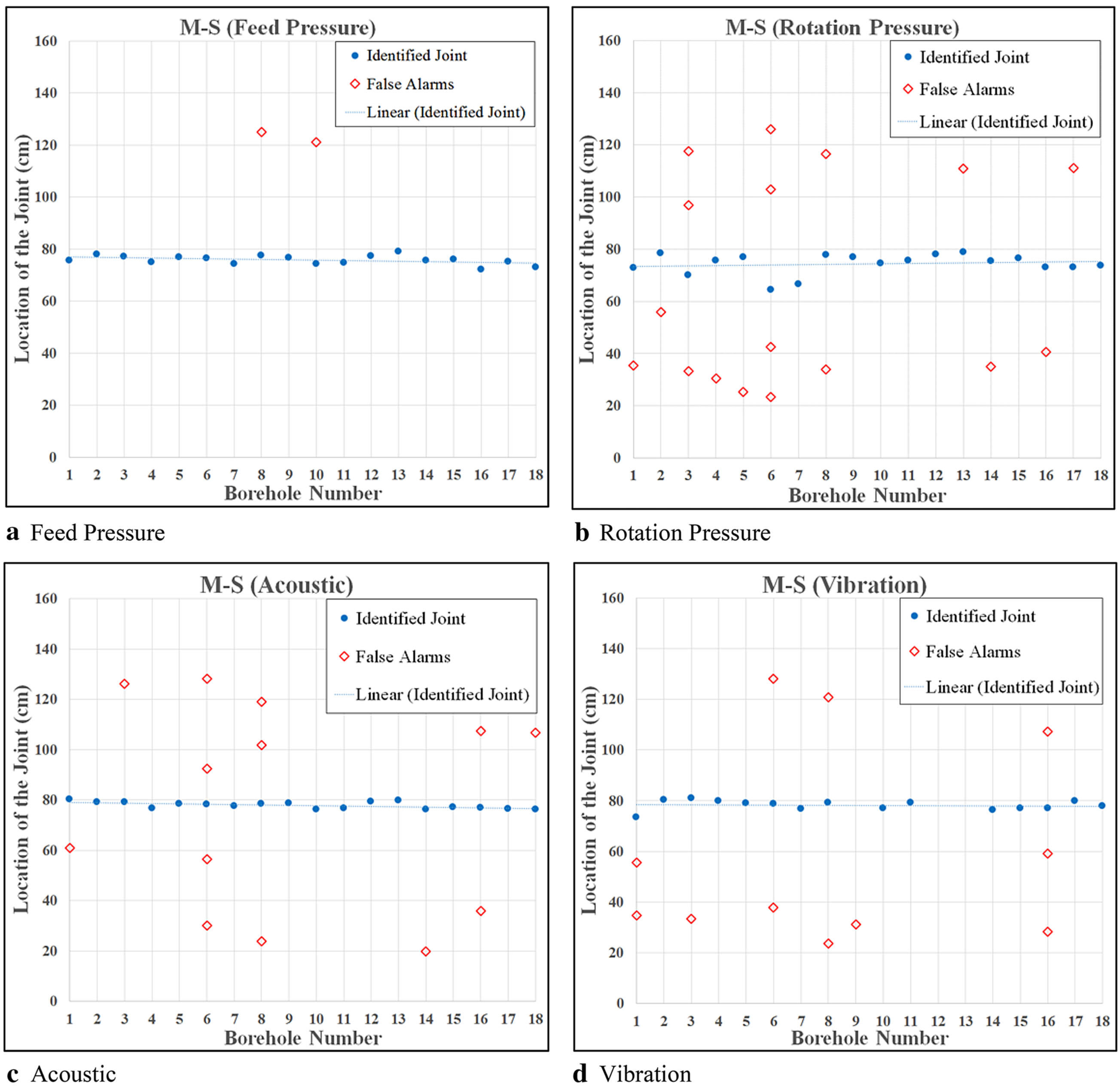


Fig. 8 An example of joint detection results on the M–S composite sample by analyzing the feed pressure, rotation pressure, acoustic, and vibration data. **a** Feed pressure. **b** Rotation pressure. **c** Acoustic. **d** Vibration

analysis methods is critical to evaluate performances of various detection algorithms using a certain drilling parameter and to make the proper selection of parameters or composite parameters to detect the target rock properties, in this case joints. 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 was missed. A Type II error only occurs when a false alarm was generated and a joint was suggested by the program where it did not exist. As for

Table 3 Statistics of joint detection results using the four drilling parameters in 156 boreholes

Concrete settings	Feed pressure		Rotation pressure		Acoustic		Vibration	
	Detection rate (%)	False alarms	Detection rate (%)	False alarms	Detection rate (%)	False alarms	Detection rate (%)	False alarms
S–H	93	1	86	8	64	4	43	4
H–S	88	1	76	4	82	3	53	2
M–H	100	0	94	6	100	4	76	9
H–H	94	1	83	1	83	0	72	3
H–M	100	2	95	16	95	4	62	11
M–S	100	2	100	17	100	13	83	11
S–M	89	2	83	20	83	3	56	18
M–M	82	1	76	13	71	1	82	17
S–S	100	2	94	24	81	7	81	17
Summary	94	12 (8%)	88	109 (70%)	84	39 (25%)	68	92 (59%)

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 a drilling parameter is the probability calculated using 1 min 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 hardnesses. 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 false alarms up to 109 in this study, 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.

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

7 Use of Composite Parameters

The capabilities of using pattern recognition algorithms to monitor individual drilling parameters for joint detection were examined but possibility of improving the detection rates with composite parameters was 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 identify 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

Table 4 Probabilities of the Type I and Type II errors and corresponding powers of using various drilling parameters

Drilling parameter	Probability (Type I error) (%)	Probability (Type II error) (%)	Power (%)
Feed pressure	6	8	92
Rotation pressure	12	70	30
Acoustic	16	25	75
Vibration	32	59	41

tunneling. It describes the boreability of the rock while operating a TBM in changing geological conditions (Tarkoy and Marconi 1991; Hassanpour et al. 2011). In tunneling, FPI is simply the rate of penetration normalized by thrust. It is calculated by dividing the thrust, in this case feed pressure, by the rate of penetration per revolution, expressed in "kN/(mm/rev)" (MPa.rev/cm in this case). In this study, recorded FPI (based on pertinent parameters during the drilling test) was also analyzed with the above-proposed pattern recognition algorithms for joint detection, and it can be defined as:

$$\mathrm{FPI} = \frac{\mathrm{FP}}{\mathrm{PR/RPM}},$$

where FP, feed pressure, MPa (or psi);

PR, penetration rate, cm/second (or inches/second);

RPM, rotary speed, rev/second;

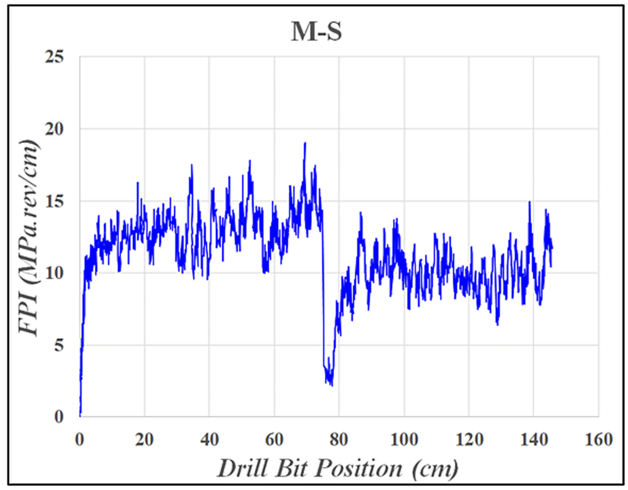
FPI, MPa.rev/cm (or psi.rev/in).

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 Fig. 9a. Figure 9b shows joint detection results on the M–S sample by monitoring the FPI data.

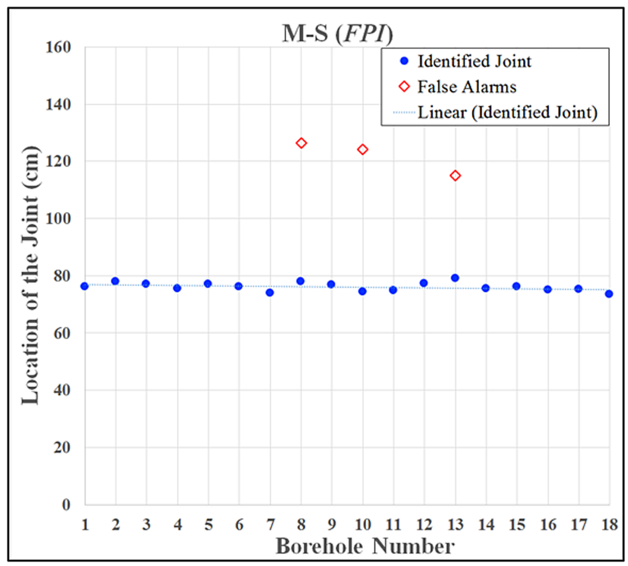
Table 5 summarizes performance of the FPI on joint detection for all concrete samples. The average detection rate was up to 96% in all 156 boreholes; in addition, a total number of 14 false alarms, or 9%, were generated while drilling through the nine concrete sample combinations. The probabilities of 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 10a shows the schematic diagram of inclined joints in the concrete sample. #A and #B refer to two different samples in



a The variations of *FPI*



b The joint detecion result

Fig. 9 An example of joint detection results on the M–S sample by monitoring the FPI. **a** The variations of FPI. **b** The joint detection result

Table 5 Performance of the FPI on joint detection from all concrete samples

Drilling parameter	Average detection rate (156 Holes)	False alarms (156 Holes)	Probability (Type I error)	Probability (Type II error)	Power
FPI	96%	14 (9%)	4%	9%	91%

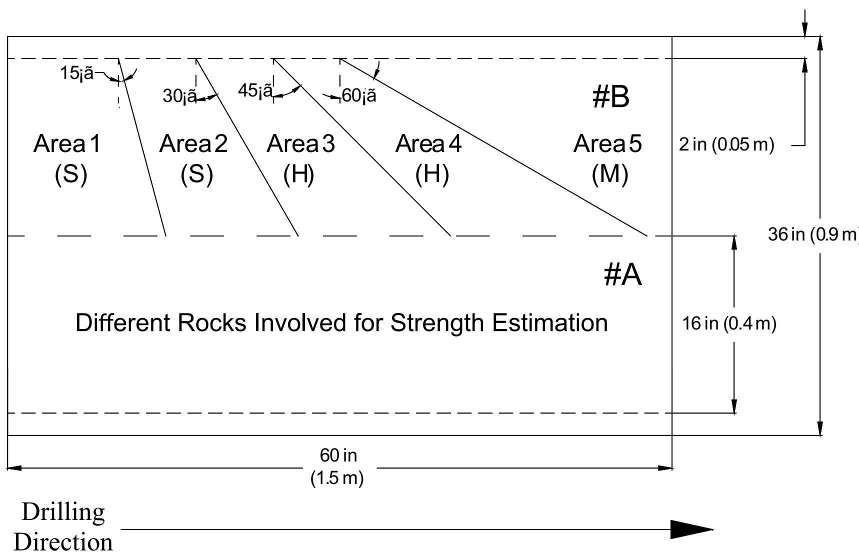
one test block, where the # B was cast on the top of #A after it had been cured for 2 days. The sample was made of pre-designed grout with three different strengths (UCS), including Low (L, ~ 20 MPa), Medium (M, ~ 50 MPa), and

High (H, ~ 70 MPa) strengths, were used to fill various areas of #B, to simulate different rock layers. Figure 10b shows a picture of four inclined joints simulated with the Teflon material. Figure 10c 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 11 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 vary 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 12 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.

Fig. 10 Distributions of inclined joints in the concrete sample



a The schematic diagram of inclined joints

b Simulate inclined joints with Teflon material **c** A simulated joint in boresocping

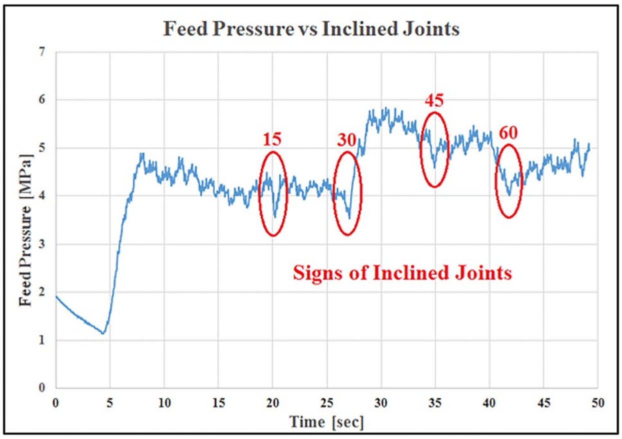


Fig. 11 The plot of recorded feed pressure data for drilling in the sample with inclined joints

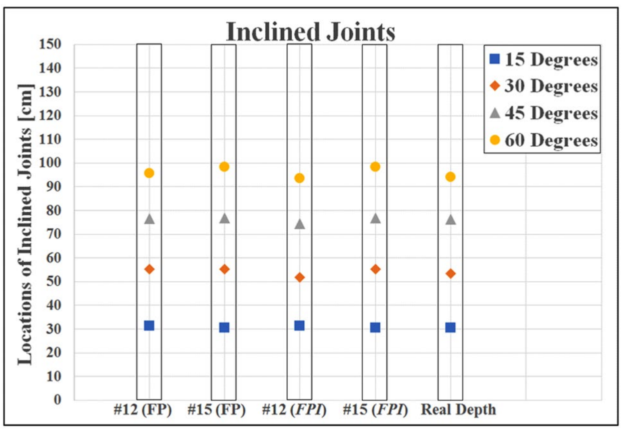


Fig. 12 Joint detection results for drilling through inclined joints

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 roof bolter drills indicated that joints and/or voids with an aperture of less than 3.175 mm (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, was 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 drilling parameters that were monitored in the full-scal tests, including feed pressure, rotation pressure, acoustic, and vibration, the feed pressure is the preferred parameter which offers the most reliable and precise performance in sensing joints with an aperture less than 3.175 mm (1/8-in), with a minimum number of false alarms in various combinations 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. Compared 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 1.588 mm or 1/16-in), also proved the possibility of using the modified algorithms for joint/fracture identification. This was based on 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 suitable to 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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