
Improving the capability of detecting joints and fractures in rock mass from roof bolt drilling data by using wavelet analysis

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Abstract: To optimise ground supporting and mitigate ground instability, a proper understanding of the ground conditions is critical. The concept of monitoring drilling parameters of a bolter for ground characterisation, which refers to identifying geological features included locations of joints and strengths of rock layers, has been studied in the past few decades. Several intelligent drilling units have been developed for joint detection but have limited capabilities. For instance, the existing systems fail to discriminate joints with the aperture of less than 3.175 mm and tend to generate false alarms. The objective of this research was to develop more efficient and sensitive detection programs for joint detection. To achieve this objective, a series of full-scale drilling tests with various simulated joint conditions have been conducted, and

new detection programs have been proposed based on pattern recognition algorithms. Moreover, wavelet analysis has been applied to pre-process data to further promote detection programs. [Received: July 15, 2017; Accepted: November 18, 2017]

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1 Introduction

Ground instability, including roof and rib failure, has been one of the persistent safety issues in tunnelling and underground mining (i.e., coal mining, industrial minerals) and construction. Despite much advances in the equipment and automation of various processes in underground mining, ground instability still causes damages to equipment, personnel injuries, and even fatalities every year. Especially in underground coal mining industry, 'fall of ground' is one of most fatal incidents (NIOSH, 2015a, 2015b). The existence and frequency of joints and voids are critical properties of rock masses that control ground instability. Accurately characterising the ground conditions, and developing a better understanding of the rock mass properties, is the key component to effectively optimise ground support design and mitigate the risk of ground instability.

Various techniques, including back mapping, bore scoping, and geophysical logging have been applied for generating the input parameters for rock mass classification as part of quantifying ground characteristic pertinent to the stability analysis. These techniques also experience various shortcomings and suffer different degrees of limitations that cannot be widely applied in the field. For instance, bore scoping where a camera is used to observe the borehole walls offers visual observation of geological features along a bore hole. However, skilled operators are required to run bore scoping to precisely recognise certain geological features. Given the restriction of working under the supported roof, bore scoping cannot be applied in unsupported areas where ground support is being installed and may need improvements. Other ground characterisation methods have also been found to suffer from similar issues (Rostami et al., 2015)

Drilling into the roof and/or ribs is a routine part of ground support installation in underground construction and mining such coal mines. As such it is an integral part of the operation cycle. Therefore, the possibility of real-time detection of joints by monitoring the drilling parameters collected during the routine drilling process is an intriguing and attractive feature to have on roof bolting units.

This paper reviews previous studies related to ground characterisation and the practical issues in their application, and presents modified programs used for pattern recognition to improve the joint detection rates and reduce false alarms. Here the basic theory for statistical analysis of data is similar to the cumulative sum (CUSUM) algorithm used in an earlier publication (Bahrapour et al., 2015; Liu et al., 2016, 2017). However, according to the characteristics of collected data, statistical methods, including running average and autoregressive model, are also applied to update this algorithm. Furthermore, latest modifications in the program involve the application of wavelet analysis for pre-processing of the data, which yields better detection results will be discussed. The result of applying the new program and performance of related joints detection algorithms for analysis of drilling parameters, specially feed and rotation pressures, will be reviewed.

It should be noted that all the tests for this study were performed at the manufacturer's testing facility with the real drilling units, with actual drill bits and rods in large samples of rock and concrete. The same system has been deployed in the field and the data stream is identical to what was measured in the lab, with the exception of the acoustic and vibration sensors. Thus the result of this study is fully adoptable to field applications by the machine manufacturer, when they switch the control system to a more computationally powerful system that can implement the calculations and use the AI programs for real time analysis of data.

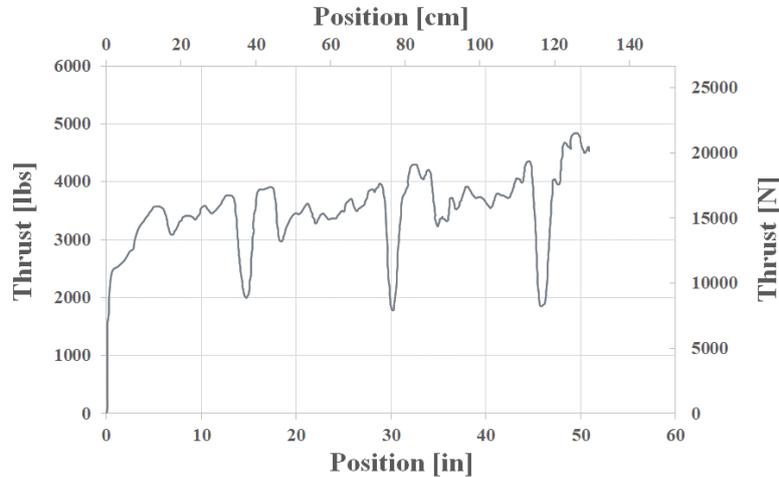
2 Background

The issue of characterising ground while drilling boreholes has been a subject of interest in mining, petroleum, and civil engineering for decades. The objective of these studies has been the identification of certain features in the ground relative to the performance of the underground workings. For example, in mining and civil engineering, the main goal has been to use this information for evaluation of the ground stability and optimisation of

ground support for improved safety. Researchers at the Spokane Research Center of the United States Bureau of Mines (USBM) conducted a research project to collect and analyse data from many drilling tests using a roof bolter. The drilling parameters used in their studies included thrust, torque, penetration rate, and rotational speed of the bit. King et al. (1993) updated an instrumented roof bolter with an unsupervised learning technique, as well as an expert system to detect critical geological features to improve support design. The updated system could calculate the specific energy of drilling (SED) based on measured drilling parameters. Field tests in an underground coal mine proved the capability of this updated system to identify the roof strata using SED values (Frizzell et al., 1992; Signer and King, 1992; King et al., 1993). As a part of their research project, a new drill monitoring system, which was proposed by Parvus Corporation of Salt Lake City of Utah, was installed on a Bureau model roof-bolting drill (Takach et al., 1992; Hill et al., 1993). While the findings of these studies have been critical, there is no operating unit using this system in the industry.

Itakura et al. (2001) instrumented a pneumatic rock bolt drill to detect locations of fractures in the ground by monitoring drilling parameters. In order to evaluate the capability of this instrumented drilling unit, laboratory tests were conducted with controlled geological conditions and field tests in a coal mine. Drilling parameters, including torque, thrust, rotational speed, and stroke were monitored by this instrumented drilling unit for joint detection. Despite the ability to identify location of discontinuities in rock mass, the system was unable to sense discontinuities of small size and aperture. In a follow-up study, a measurement while drilling (MWD) System was developed which could detect discontinuities in the rock mass along the borehole by analysing collected data including torque, thrust, revolution, and stroke. Field tests were also performed in Taiheiyo Coal Mine in Japan to evaluate the performance of the MWD system. This system also failed to detect discontinuities with small aperture. Thus, they concluded that discontinuities with small sizes (such as hairline cracks) were difficult to be identified by monitoring the drilling data (Itakura et al., 1997, 2001; Itakura, 1998).

A research team at West Virginia University (WVU) has worked on the characterisation of the roof strata in underground coal mines by monitoring drilling parameters of an instrumented roof bolter. In their research, a roof bolter, developed by the J.H. Fletcher & Co., was employed. Intelligent drilling systems were equipped on the roof bolter for the purpose of detecting geological features, such as locations of voids, joints, and bed separations. Drilling parameters including rotational speed, thrust, torque, and penetration rate, were recorded and analysed for mine roof characterisation. The SED, which is an indicator that can be calculated from drilling parameters, was applied toward identification of fractures as well as rock type/strength in rock mass. SED provided certain capabilities for joint detection, but it showed dramatic variations in the same material, and still could not identify joints with apertures smaller than 3.175 mm. Moreover, the WVU research team proposed the concept of 'thrust valley' through pattern analysis of recorded drilling parameters. The phenomenon of 'thrust valley' can be observed in the collected thrust (or feed pressure) data while the drill bit encounters a geological discontinuity during the drilling process. Figure 1 shows an example of 'thrust valleys' associated with simulated fractures in a concrete block (Finfinger et al., 2000; Finfinger, 2003).

Figure 1 An example of ‘thrust valleys’ associated with simulated fractures in a concrete block

The WVU research team continued their research by developing a Real-Time Detection System, and installed it on a J.H. Fletcher & Co. roof bolter for joint and/or void detection. This instrumented roof bolter was tried in many underground coal mines to monitor several drilling parameters. However, it still could not identify joints and/or voids with smaller apertures (Peng et al., 2003; Collins et al., 2004). This was followed by updating the system to detect anomalies in real-time while drilling. The updated system still could not detect joints with smaller apertures that were clearly shown in bore scoping images (Anderson and Prosser, 2007).

The research proposed in this paper is conducted with the objective of addressing the issue of joint and/or void detection by analysing drilling parameters recorded while drilling. A J.H. Fletcher drill unit was employed for full scale drilling tests for this study, but with the addition of vibration and acoustic sensors, mounted on the drill to monitor other parameters in addition to drilling data that was monitored in the past. New joint detection algorithms have been developed based on pattern recognition algorithms and have been discussed in previous publications (Bahrapour et al., 2013; Rostami et al., 2014, 2015; Kahraman et al., 2016; Liu et al., 2016, 2017). Additional laboratory tests have been conducted with simulated joints with various aperture and angles relative to the borehole axis. New joint detection algorithms developed in this study offers improved capabilities to identify joints with apertures less than 3.175 mm. These algorithms failed to identify all joints and/or voids along the borehole, and generated false alarms during the detection process. Therefore, the testing and development of new algorithms has been continued as part of this study to address the noted shortcomings, and new pattern recognition and artificial intelligent systems have been examined to address the issues. This includes using new algorithms, pre-processing of data using wavelets, and using composite indices where multiple drilling parameters have been combined to represent drilling behaviour. The main objective has been to improve the ability of the system for identify tighter joints and joints at various angles along the borehole. This paper discusses the recent changes in the pattern recognition programs and their results relative to accurate and reliable detection of the joints in the rock mass.

3 Laboratory testing setup

For this study, laboratory tests were carried out at a testing facility of J.H. Fletcher & Co. in Huntington, WV. A drill control unit (DCU) is installed on the smart drilling units by Fletcher and was used to monitor the drilling process and collect data from various sensory systems on the drill during laboratory tests. These tests included data from the additional vibration and acoustic sensors, in addition to the standard drilling parameters including feed pressure (controlling thrust), rotation pressure (representing torque), rotational speed or RPM, penetration rate, vacuum pressure (used to flush the hole while drilling), and drill bit position. Vibration data was monitored by a 3D accelerometer and acoustic signal was generated by a specialised piezoelectric – flat microphone to complement the drilling parameters. Figure 2 is the picture of the J.H. Fletcher full-scale roof-bolt drill unit as well as a tested concrete specimen with a pattern of drilled boreholes.

Table 1 Various combinations of concrete blocks to build different testing specimens

<i>Order</i>	<i>Combination of concrete blocks</i>	<i>Joint condition</i>	<i>Top</i>	<i>Bottom</i>
Testing specimens	1	S	S	A simulated joint with the size less than 3.175 mm located at the depth of 76.2 cm.
	2	S	M	
	3	S	H	
	4	M	S	
	5	M	M	
	6	M	H	
	7	H	S	
	8	H	M	
	9	H	H	

Notes: *strengths of concrete blocks.

*S, ~20 MPa; *M, ~50 MPa; *H, ~70 MPa.

In order to simulate joints in various conditions, a set of concrete blocks were poured and cured for more than 28 days. These concrete blocks had three different prescribed strengths; namely, low (S, ~20 MPa), medium (M, ~50 MPa), and high (H, ~70 MPa). The dimensions of each concrete block were around 0.5 m × 0.5 m × 0.75 m in height. To build a testing specimen, one concrete block was placed on top of another, and the gap simulated a joint with an aperture less than 3.175 mm. Thus, the simulated joint was the target of joint detection in each specimen which was at the depth of 76.2 cm. There were nine entirely different testing specimens, as shown in Table 1 (Liu et al., 2016, 2017). Additional details about the testing, block combinations, data collection and initial analysis can be found in Rostami et al. (2014), and Bahrapour et al. (2013, 2014).

4 Initial analysis of collected data and effectiveness of joint detection program

In the preliminary analysis of the testing data for joint detection, new joint detection algorithms were developed to effectively increase the precision of joint detection and

decrease the number of false alarms (Rostami et al., 2015; Bahrampour et al., 2013, 2014). According to the theory of ‘thrust valley’, the phenomenon of ‘valley’ was also observed in the recorded data of rotation pressure (or torque). Figure 3 illustrates an example of collected rotation pressure (torque) and feed pressure (thrust) data that demonstrate a ‘valley’ at the moment that the drill bit encountered the artificial joint. Thus, the CUSUM algorithm, which is a sequential analysis technique typically applied to monitoring changes in streaming data (Page, 1954; Basseville and Nikiforov, 1993), has been updated and used to develop new joint detection algorithm in this research.

Figure 2 The J.H. Fletcher & Co. drill control unit (top) and a tested concrete specimen (bottom) (see online version for colours)



In the initial analysis, individual drilling parameters, including feed pressure, rotation pressure, acoustic signals, and vibration signals, were processed for joint detection. A brief review of trends in recorded feed pressure and rotation pressure data showed that the drilling machine did not reach steady state at the beginning and ending stages of the drilling process. Therefore, to eliminate the noise generated in these stages, the data recorded within the first 12.7 cm and last 12.7 cm were cut out of the analysis. The improved (current) joint detection algorithms were further updated in the follow up studies to accurately identify tight joints. Table 2 lists the pertinent results of performance of joint detection programs, obtained by analysing drilling parameters for feed pressure and rotation pressure for all nine specimen combinations, Table 3 summarises the results of joint detection by using acoustic signals and vibration signals for all nine concrete block combinations.

Table 2 Summary of the joint detection results by monitoring feed pressure and rotation pressure data on all concrete settings

<i>Concrete settings</i>	<i>Feed pressure</i>		<i>Rotation pressure</i>	
	<i>Detection rate (%)</i>	<i>False alarms (157 holes)</i>	<i>Detection rate (%)</i>	<i>False alarms (157 holes)</i>
S-H	87	1	93	6
H-S	88	1	77	4
M-H	100	0	100	5
H-H	94	1	83	1
H-M	100	2	95	16
M-S	100	2	100	17
S-M	89	2	89	19
M-M	78	1	89	10
S-S	100	2	100	22
Overall	93	12	92	100

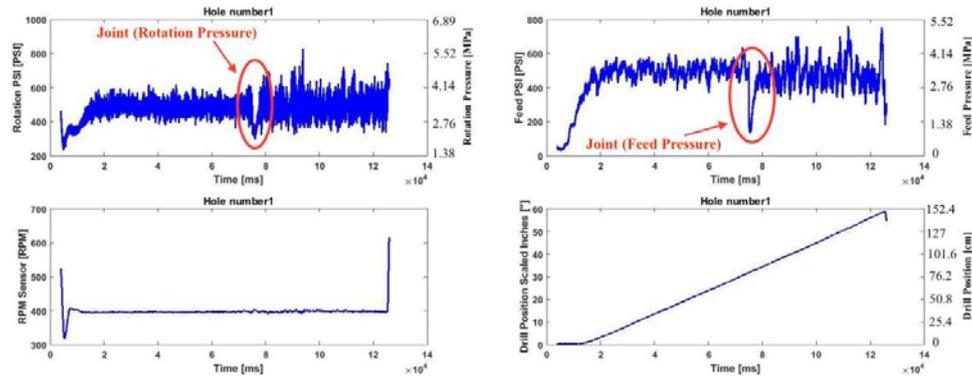
Table 3 Summary of joint detection results by monitoring acoustic and vibration signals on all concrete settings

<i>Concrete settings</i>	<i>Acoustic signal</i>		<i>Vibration signal</i>	
	<i>Detection rate (%)</i>	<i>False alarms (157 holes)</i>	<i>Detection rate (%)</i>	<i>False alarms (157 holes)</i>
S-H	60	4	40	4
H-S	82	3	53	2
M-H	100	4	77	9
H-H	83	0	78	2
H-M	95	4	81	7
M-S	100	13	89	10
S-M	89	2	67	14
M-M	72	0	83	16
S-S	81	7	88	16
Overall	85	37	73	80

As can be seen from these two tables, the performances of these four individual drilling parameters on joint detection show the superior performance of the feed pressure (or thrust) in the nine different concrete block combinations. The feed pressure offers the most accurate joint detection rate and the minimum number of false alarms with an average detection rate of 93% and 12 false alarms for the 157 holes drilled. As for rotation pressure, the average detection rate is 92%, but the total number of false alarms is 100 when the algorithm was used for all the specimen combinations. The acoustic and vibration signals were initially added to the system with the objective of improving the detection by independent sensory systems to complement the four major drilling parameters monitored in previous studies. However, they showed much inferior performances in comparison to the feed pressure and rotation pressure; with average detection rates of 85% and 73% for acoustic and vibration signals, respectively. Also,

they generated 37 and 80 false alarms, respectively. Some attempts were made to combine the drilling parameters and acoustic/vibration signals to improve the detection rate but the early trials did not yield notable improvements over the use of feed or rotation pressure.

Figure 3 An example of recorded rotation pressure (torque), feed pressure (thrust), RPM, and drill bit position data (see online version for colours)



The results shown in these tables suggest that the joint detection algorithms can detect joints with apertures smaller than 3.175 mm. However, the sensitivity and precision of the proposed joint detection programs still needed to be further enhanced to improve their detection rate and reduce the number of false alarms.

5 Use of wavelet analysis to improve joint detection algorithms

The wavelet transformation process is well-known and suited for time-frequency analysis of non-stationary signals corrupted by noise and spurious disturbances. As for the signals collected from the drilling unit, new degrees of freedom have been introduced; specifically, scaling parameters and time-translations that can be used to extract desired information (or *details*) from 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 become present 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

$$\psi_{s,t} = |s|^{-p} \psi\left(\frac{u-t}{s}\right) \tag{1}$$

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

$$\tilde{f}(s, t) = \int_{-\infty}^{\infty} du \bar{\psi}_{s,t}(u) f(u) = \langle \psi_{s,t} | f \rangle = \psi_{s,t}^* f \quad (2)$$

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

$$f = f_{joint} + f_{noise} \quad (3)$$

and \tilde{f} can be expressed as

$$\tilde{f}(s, t) = \int_{-\infty}^{\infty} du \bar{\psi}_{s,t}(u) f(u) = \langle \psi_{s,t} | f \rangle = \psi_{s,t}^* f \quad (4)$$

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.

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 localisation, the analysing wavelet must be well localised 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 fine 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). Furthermore, Daubechies wavelet db45 mimics a sinusoidal wave well enough, which is desired since the collected signal from the drilling unit is non-stationary with sinusoidal characteristics. According to aforementioned phenomenon of ‘thrust valley’, a sudden drop can be observed in the recorded feed pressure and rotation pressure data when the drill bit encountered the preset joint. However, the raw data also included a lot of noise that may confuse detection algorithms, and therefore generate more false alarms. For denoising of raw data, the db45 wavelet basis was used in this study, which would improve the performance of the detection algorithms. Figure 4 and Figure 5 show examples of using db45 to pre-process feed pressure and rotation pressure signals, respectively. The three sub-figures presented are the collected drill bit position data, raw signals of feed pressure or rotation pressure, and processed signals of feed pressure or rotation pressure while using db45. In addition, as shown in the two figures, the majority of the noise has been removed for further data analysis, and the phenomenon of valley became more apparent after using the wavelet analysis with a db45 wavelet. Thus, applying newly updated detection algorithms could effectively improve joint detection rate and reduce the number of false alarms.

Figure 4 An example of using db45 to pre-process feed pressure signal (see online version for colours)

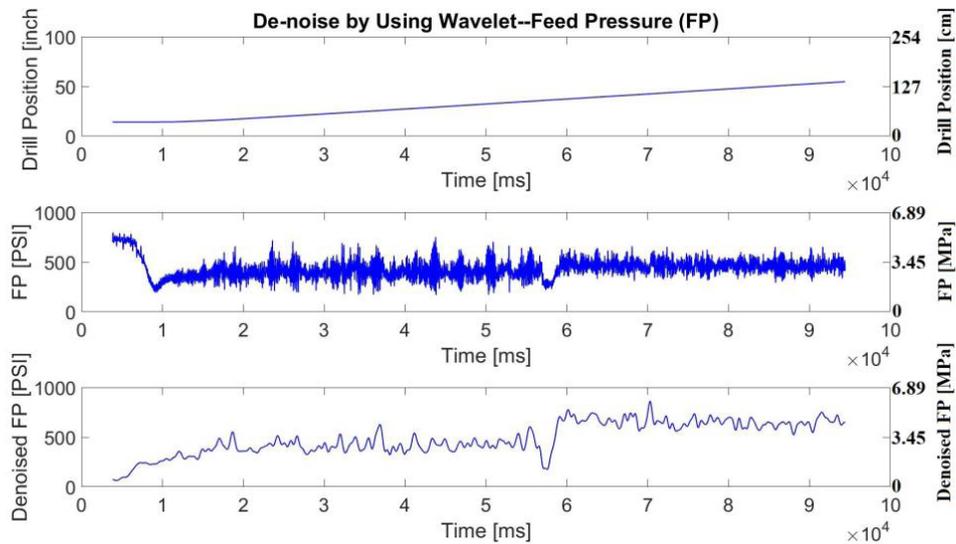
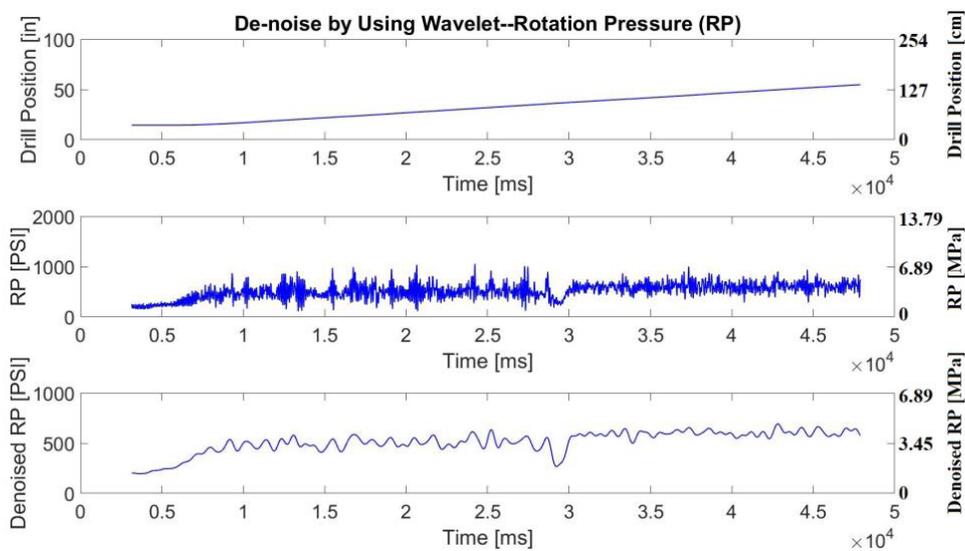


Figure 5 An example of using db45 to pre-process rotation pressure signal (see online version for colours)



6 Statistical analysis of joint detection results by using updated joint detection algorithms

The CUSUM algorithm is a sequential analysis technique, and it is usually applied for detection of abrupt changes in streaming data (Page, 1945). In this research, the

aforementioned sudden change can be considered as an abrupt change in collected drilling data, and an updated CUSUM algorithm has been used with the wavelet analysis using the db45 wavelet for joint detection in various conditions. The updated CUSUM algorithm is based on characteristics of de-noised feed pressure and rotation pressure signals. This assumes there is an unknown change at some time, t_a , in a time series, y_k ($k = 1, 2, \dots$), and the mean of y_k before time t_a is μ_0 , and the mean value after this change is $\mu_1 = \mu_0 - v$. Thus, the sufficient statistic, as shown as equation (5), is applied to process de-noised data, and therefore values of can be achieved along the data stream.

$$g_k = \max\left(g_{k-1} - y_k + \mu_0 - \frac{v}{2}, 0\right) \quad (5)$$

The detection alarm time can be defined as

$$t_a = \min\{k : (g_k \geq h)\} \quad (6)$$

where h is the threshold, μ_0 is the mean of time series, y_k , before the change, v is the difference of mean values before and after the change, and $g_0 = 0$.

Therefore, the detection alarm time t_a will be active once the value of g_k is equal to or larger than the threshold value h which is preset at 40% of mean μ_0 , and a joint or a void is assumed to be identified at time t_a .

Figure 6 shows an example of improvements on joint detection results in S-H specimen by analysing the rotation pressure data. In this sample matrix, a pattern of 14 boreholes were drilled, and blue points are identified joint information within the borehole; besides, red points represent false alarms that were generated while analysing the data. As can be observed, the detection results have been further improved with the lower number of false alarms.

Table 4 Summary of joint detection based on de-noised feed pressure

<i>Concrete combinations</i>	<i>S-H</i>	<i>H-S</i>	<i>M-H</i>	<i>H-H</i>	<i>H-M</i>	<i>M-S</i>	<i>S-M</i>	<i>M-M</i>	<i>S-S</i>	<i>Overall</i>
Valid holes	15	17	17	18	21	18	18	17	16	157
Holes missed joints	0	0	0	0	0	0	3	2	0	5
Detection rate	100%	100%	100%	100%	100%	100%	83%	88%	100%	97%
False alarms	0	1	0	0	3	4	4	2	4	18

Table 4 shows the result of analysis of the feed pressure using wavelet analysis and the updated CUSUM algorithm. As shown in this table, the precision and accuracy of the updated algorithm using a db45 wavelet notably enhanced. The resulting average detection rate has increased to 97% with 18 false alarms in all 157 boreholes. Despite the current joint detection algorithm generating six more false alarms (increasing from 12 to 18), the average detection rate has been increased by 4%. In addition, Table 5 shows the results of the rotation pressure data using the combination of wavelet analysis and the CUSUM algorithm. The average joint detection rate for the rotation pressure data remained at 92%. The total number of false alarms drops to from 100 to 62 in all 157 drilling holes.

Figure 6 An example of improvements on joint detection results in S-H specimen by analysing the rotation pressure data (see online version for colours)

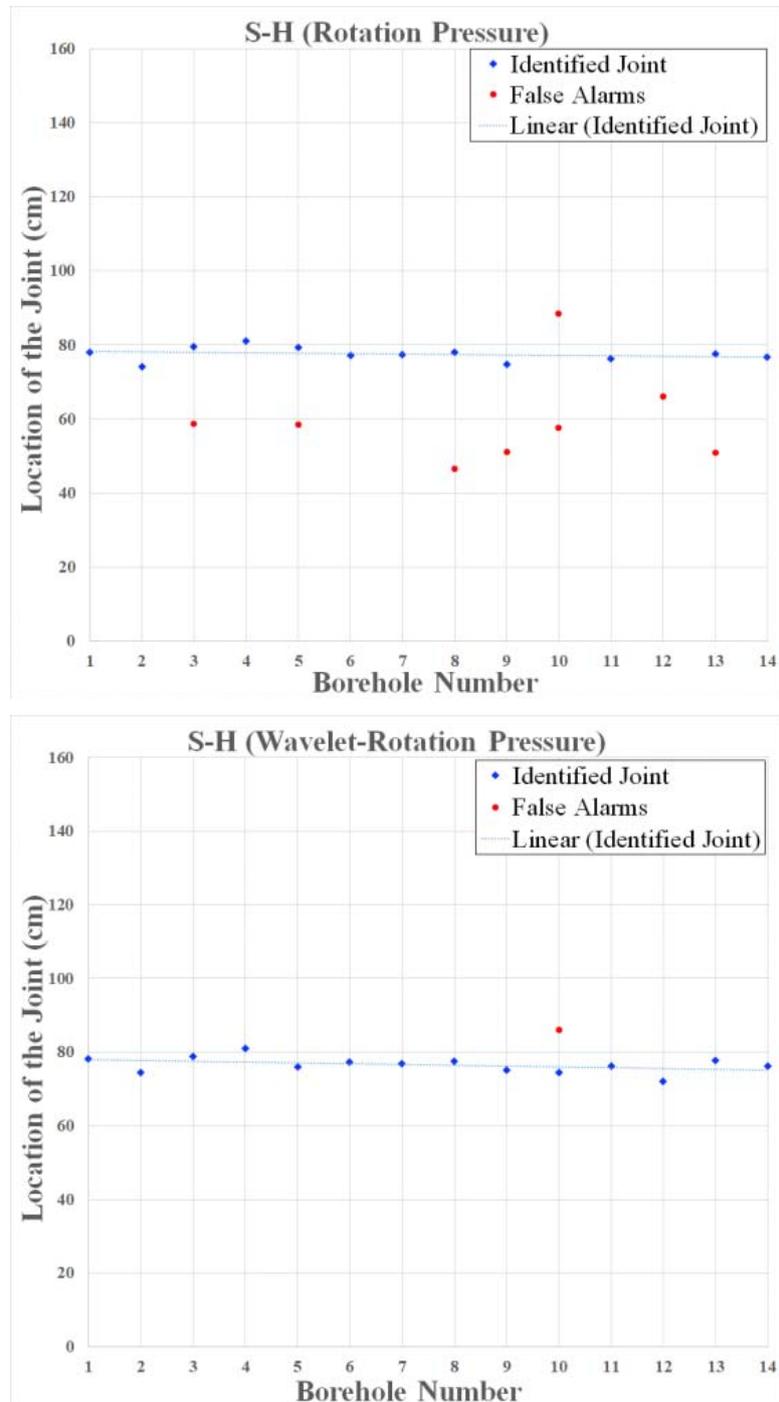


Table 5 Summary of joint detection based on de-noised rotation pressure

<i>Concrete combinations</i>	<i>S-H</i>	<i>H-S</i>	<i>M-H</i>	<i>H-H</i>	<i>H-M</i>	<i>M-S</i>	<i>S-M</i>	<i>M-M</i>	<i>S-S</i>	<i>Overall</i>
Valid holes	15	17	17	18	21	18	18	17	16	157
Holes missed joints	0	4	0	3	0	2	1	2	0	12
Detection rate	100%	76%	100%	83%	100%	89%	94%	88%	100%	92%
False alarms	1	3	1	0	14	10	14	4	15	62

7 Conclusions

Instrumented drilling units for ‘rock characterisation while drilling’ is an enabling technique to identify the location of geological discontinuities, including joints, voids, cracks, and bed separations, present in the ground surrounding an underground opening. Despite much advancement in this field, such as instrumented roof bolters, locating rock discontinuities with apertures less than 3.175 mm is still a challenge to the available smart drilling systems. Therefore, further research is necessary to improve the capability of available systems in identifying joints and/or voids with smaller apertures.

In this paper, wavelet analysis using the db45 wavelet, along with an updated CUSUM algorithm, were employed to improve capabilities of programs for detecting joints and/or voids with smaller sizes. This involves the use of wavelet to filter the noise in the data and enhanced CUSUM algorithm to improve the detection rate and reduce the false alarms. The analysis of updated detection programs for locating simulated joints with smaller aperture in combination of nine specimens with various strength shows that detection results have improved. This was based on analysis of feed pressure and rotation pressure data obtained during the drilling process. Moreover, the updated programs are self-adjusting to offer better performance in different conditions. However, the programs have limited capabilities when analysing acoustic and vibration data. This is because the acoustic and vibration data offered different characteristics and require extensive digital filtering to eliminate the noise and allow for distinguishing special features such as a joint and/or void.

Additional studies are underway to improve the capabilities of these programs in detecting joints with smaller apertures. Simultaneously, programs are being developed for rock classification and to offer estimated rock strength, while also looking at identification of inclined joints. Additional full-scale tests have been performed with these objectives in mind and data analysis is underway.

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