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Ground characterization and roof mapping: Online sensor signal-based change detection

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ABSTRACT

Measurement while drilling systems are becoming an important part of excavation operations for rock characterization and ground support design that require reliable information on rock strength and location & frequency of joints or voids. This paper focuses on improving rock characterization algorithms for instrumented roof-bolter systems. For this purpose, an improved void detection algorithm is proposed, where the underlying theory is built upon the concept of mean change detection based on the feed pressure signals. In addition, the application of acoustic sensing for void detection is examined and it is shown that the variance of the filtered acoustic signal is correlated to the strength of the material being drilled. The proposed algorithm has been validated on the data collected from full-scale drilling tests in various concrete and rock samples at the J. H. Fletcher facility.

1. Introduction

Application of rock bolts is standard practice in ground support due to the relatively easy installation, lightweight, convenient transportation, and high anchorage capacity (Fig. 1). Effectiveness of rock bolts is highly dependent on correct identification of the geological conditions, including discontinuities, because they tend to vary, even within a short distance [1]. Various drilling parameters are collected and processed when using roof bolters in underground construction and mining that can potentially be utilized to evaluate the geological conditions at the jobsite [2]. A series of studies has demonstrated the potential for analyzing drilling parameters from roof bolters to estimate rock properties and to identify discontinuities [3–8].

A portable pneumatic roof bolter with the ability to record torque, thrust, revolution, and stroke was utilized [3,4]. Torque and thrust were monitored by using strain gauges installed on the surface of the drilling rod, while penetration and rotation rate were kept constant during the tests. The manufactured blocks included sandstone, sandy shale, and coal samples with three different discontinuity angles of 0 degrees, 30 degrees, and 60 degrees and three types of discontinuities, namely cracks, boundary, and separation of layers. Cracks are discontinuities within a layer. Boundary and bed separation are discontinuities between the layers and often feature a small aperture between layers in the rock mass, often intersected by joints. The average value of torque and/or thrust was found to be an indicative index to allow for classification of the rock layers along the borehole. Furthermore, it has been proposed that patterns of thrust or torque along with neural network algorithms may be used to categorize the discontinuities, but the resulting error was rather large. The feasibility studies of rock mass characterization while drilling for roof bolts in an underground coal mine in Queensland, Australia were studied [6–8]. In these studies, 48 holes were drilled using the instrumented drill unit, and one hole was cored in the test area to provide core for rock strength testing. The system successfully showed the distribution of discontinuities and layer boundaries using the ratio of recorded parameters of torque and thrust.

In a similar approach, J. H. Fletcher & Co. developed a system that monitors drilling operations using instrumented roof bolters to monitor drilling parameters, including thrust (obtained from feed pressure), torque (obtained from rotation pressure), rotation rate, and bit position [1]. The data is processed on board to detect joints and voids as well as rock strength in a relative scale. This system has been successfully employed in various mining operations to detect different kinds of discontinuities including voids, fractures, and bed separations, and to estimate the relative hardness of the rock mass [9]. Variation of thrust or feed pressure has been found among the most suitable identifiers for detecting

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Fig. 1. J. H. Fletcher roof bolter.

discontinuities [1,2,9–14]. For example, a thrust valley concept was proposed by which the presence and the size of discontinuities, such as fractures, joints, and voids in the rock, can be evaluated [10]. Based on this concept, thrust decreases rapidly after reaching a void and increases rapidly again when it goes through the discontinuity to keep the preset level of penetration constant. A drop of more than 50% was then considered as an index to detect discontinuity. The distance between the two sides of the valley was also used to measure the discontinuity aperture. Two models were offered for estimating the size of discontinuity.

A secondary parameter of rotational acceleration was also proposed to detect beddings. This parameter could detect 70% of the interfaces designed in the experimental program using layered blocks. The location of 57% of these interfaces was predicted within 2 in. of the actual locations. This system was further developed [1,15] with the introduction of the drilling hardness (DH) parameter. The DH parameter considers the geometry of the drill bit and contact area between the drill bit and rock, the friction between the drill bit and rock, and the energy lost in kinetic energy, potential, and torsion energies. The slope of the drilling hardness curve and its peak values are used to determine the location of discontinuities and interfaces. Discontinuities are detected using threshold-based algorithms that need to be adjusted for different rock types. This limits the applicability of the system for deployment and utilization in different mining locations. For example, only 25.86% of the discontinuities were detected by DH method within an acceptable error window [1]. He explained that this failure was related to the rocks not being weak enough to be detected by the DH slope approach. A method is developed which is able to detect fractures with an aperture of 1/8 in. or larger [12]. However, this approach was found to be somewhat ineffective for discontinuities of 1/16-in. aperture or smaller.

The instrumented void detection system was subsequently improved to a great extent, but some inaccuracies in detecting the location and, especially, the size of discontinuities is reported from time to time. It is explained that some major voids could not initially be detected by the system during a series of field experiments in a limestone mine, mainly, because of the difference between the hardness of concrete used in the laboratory and the limestone at the roof of the mine [16]. In this situation, the parameters of the roof mapping algorithm in the onboard processing system need to be updated occasionally. Another observation was that unlike the usual pattern observed in the laboratory, in which both thrust and torque would drop simultaneously, a sudden rise in the rotation torque happened just before encountering the voids in the field. Meanwhile, the thrust did not have a consistent reaction when passing through the void in the field. Another issue was reported that the hairline and vertical cracks along with layers of the rocks could not be correctly identified [17].

In a more recent study, vibration and acoustic measurements were used to improve the accuracy of the void detection and rock characterization when using roof bolters [18]. The study concluded that valuable information can be extracted from the high frequency components of the vibration and acoustic signals, which was subsequently used for void detection. This allows for using secondary sensors for void detection and can provide a degree of redundancy in instrumentation and higher detection rate when using a combination of the standard instrumentation with the acoustic and vibration sensors.

This paper focuses on two new void detection algorithms using the standard and new instrumentation of the roof bolters. One is a mean change detection on the feed pressure signal and the other the other a variance change detection problem on appropriately filtered acoustic signal. The corresponding mean and variance change detection problems are then solved using the online CUSUM algorithms [19]. The experimental results suggest that the proposed algorithms can improve the performance and efficiency of the existing void detection algorithm. The new algorithm also enjoys an adaptive threshold that does not need readjusting or fine-tuning when dealing with different rock strengths and various drilling parameters such as desired penetration rates and rpm. Moreover, they can be efficiently implemented using recursive formulations and therefore are well suited for real-time monitoring of the roof condition. The proposed algorithm for mean change detection on the feed pressure is presented for a decrease in the mean value but it can be easily extended to be sensitive to both sudden decrease and increase in the mean of the feed pressure. This phenomenon was reported in literature, where both trends were observed [16]. Finally, it will be shown that the proposed variance change detection on the acoustic signal can be utilized for the relative rock strength estimation.

2. Instrumented roof bolt drilling system by JH Fletcher

J. H. Fletcher & Co. has developed the Fletcher Information Display System, which uses a programmable logic controller (PLC) to monitor drilling operations. This system features a drill control unit (DCU) to automate and optimize the cycle of drilling and bolting for safety and productivity reasons [17]. The DCU processes the drilling parameters including torque, thrust, rotation rate, and position, along with vacuum or water pressure used for flushing, bit breakage, or bending of the drill by controlling the drilling parameters without deteriorating the optimum drilling operation [17]. Several modifications have been made to improve the accuracy of measuring bit position and torque [1]. The software was modified to communicate with the DCU to display the information from four separate drill holes side-by-side so that trends could be easily observed in real time. These graphs can show the material hardness and can display the location of voids or other discontinuities in the mine roof structure. Also, rotation related events, like stalls, and water events, which may indicate that the drill steel is being plugged with soft material, are marked with colored lines and letters. The Information Display System features a rugged touch screen panel, a solid state flash memory for better durability, uninterrupted power supply, a virtual keyboard for entering additional information to the files, a back-up video display, and a print function [17]. The sampling interval in this system is usually 10 Hz or 0.1 s time interval which can be increased up to 100 Hz. In this study, the data were collected using sampling rate of 100 Hz.

2.1. Installation of new sensors

Vibration and acoustic sensors were added to the Fletcher drill unit to collect additional information from the drilling process

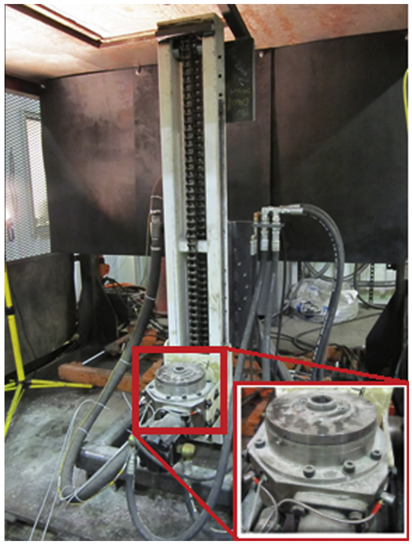

Fig. 2. J. H. Fletcher drill unit equipped with the acoustic and vibration sensors.

[18]. The Fletcher unit and the added instruments are shown in Fig. 1. An experienced operator can notice changes in vibration of the drill rod and noise amplitude when the rock strength changes. Previous studies have also examined the advantage of vibration and acoustic sensors for rock characterization drill [20,21]. Therefore, the drill unit was equipped with vibration and acoustic sensors to study the suitability of these sensors for ground characterization and roof mapping. The vibration sensor was a Piezo Star accelerometer with frequency range of 1–5 kHz with high sensitivity (50 mV/g). The acoustic sensor was a Piezo disc, also known as a contact microphone, which is a small ceramic wafer on a thin metal disc that can be used for acoustic measurements. As shown in the Fig. 2, the sensors were glued to the drilling unit to avoid additional machining and save time. The initial testing and calibration showed that this type of mounting did not impact the performance of the sensors, but, for field deployment, their location should be optimized, and a more permanent arrangement should be used to protect the sensors. The sensors, including the accelerometer and microphone, are monitored in parallel to the existing data acquisition device at a high sampling rate of 1 kHz. This is done by using a separate data acquisition system (DAQ). The wires from new sensors are directly connected to the new DAQ for excitation and sensor output channels. Also, data from the original sensors of the standard Fletcher instrumented drill void detection system were collected by the new DAQ as analog input from the wiring terminal of the existing Programmable Logic Controller (PLC) of the machine. The signals from the two data acquisition devises were further synchronized using a relay.

In this paper, the feed pressure and acoustic data are utilized for void detection purpose. While vibration sensor has similar signature to the acoustic signal and can also be used for void detection, it is empirically observed that acoustic signal is more reliable than the vibration sensor for void detection. Before presenting the void detection algorithms, typical feed pressure and acoustic signals during voids are presented.

2.2. Pattern of the feed pressure signal for void detection

Fig. 3 shows a typical sensory data collected while drilling into a stack of two concrete blocks with a void at the intersection of the two concrete blocks. The experimental setup will be discussed in more details in following sections. The measured attributes are rotation pressure, feed pressure, rpm, position, bite rate (penetration per revolution), and vacuum pressure. It is seen here that feed pressure, which can be converted to the corresponding thrust, is the most sensitive parameter to existence and encountering of a joint or void and rock strength. This pattern was observed in almost all the experiments performed in the current study as has been reported in the past [1]. The existing void detection algorithm on the Fletcher roof mapping software uses certain patterns in feed pressure line, in addition to the rotation pressure, position, and the signals related to the control unit, for void detection purpose by measuring the rate of change. The existing void detection program

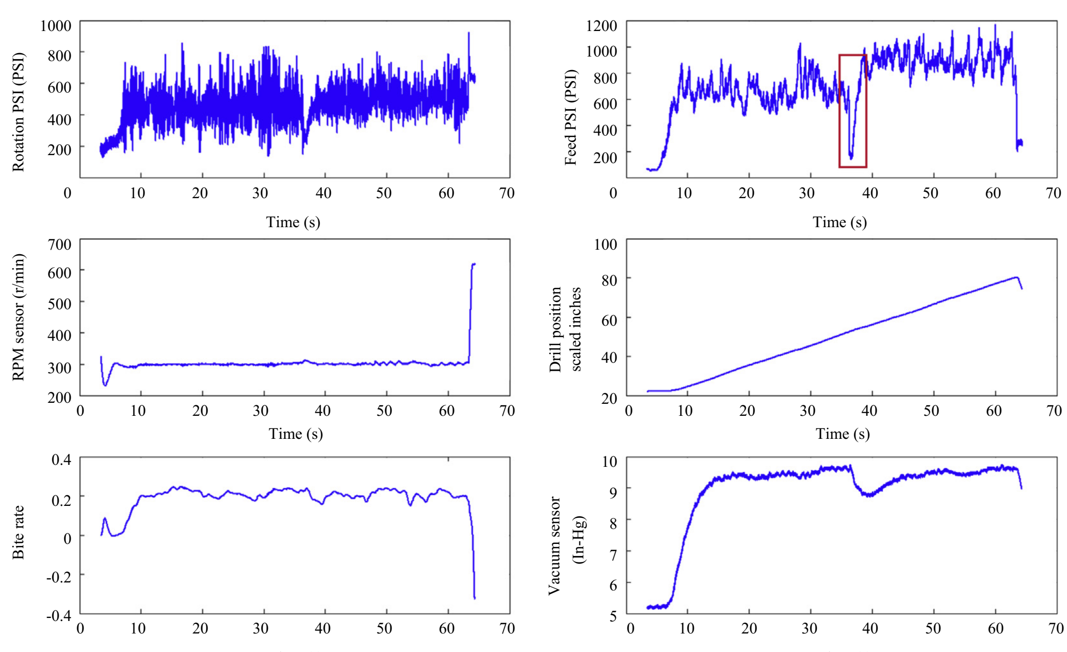

Fig. 3. Typical sensory data collected by the measurement while drilling system of J. H. Fletcher (The measurements correspond to drilling into a stack of two concrete blocks with a void at the intersection of the two concrete block. During the void, the feed pressure signal drops in response to the control unit which regulates the penetration rate).

does rely on observing certain drop level in feed pressure to recognize any joint or voids, and thus it requires some fine tuning from time to time to reflect some changes in ground and the equipment. In this study too, it is proposed to formulate the void detection problem using feed pressure data, but as a mean change detection problem which can be solved using wide range of tools from online change detection theory, also known as Quickest Change Detection Algorithms [19]. In this approach, it is assumed that the mean of the stochastic signal (feed pressure here) is almost constant when there is no void and it undergoes a change (decrease here) when a void appears. The goal is to detect the change as quickly as possible with high detection rate and small false alarm rate. For solving this problem, the CUMSUM algorithm, which is a well-known change detection algorithm was used, will be briefly discussed.

2.3. Pattern of the acoustic signal for void detection

Fig. 4 shows the plot acoustic signal obtained corresponding to the same experiment where the Fletcher data are shown in Fig. 3. The drill was set with penetration rate of 1 Inch per second at 400 r/min. In contrast to the feed pressure data, the amplitude of the acoustic signal does not appear to change significantly between the first 3 s, when no actual drilling is performed, and the rest of the test. The reason for this is that, even if drill bit is not moving forward, the drill bit is rotating and, therefore, generating noise. The acoustic signal is not a uniform periodic signal mainly because the concrete block is not a homogeneous material. Moreover, the raw acoustic signal does not reveal information about the void and it needs to be filtered appropriately [18].

A Short Windowed Fourier transformation is presented to filter the signal for void detection [18]. A more advanced signal processing tool, namely Wavelets analysis [22], was subsequently utilized to pre-process the acoustic data. Wavelet analysis provides a tool for time–frequency localization of the signal at different scales. Fig. 4 shows the three level decomposition of the acoustic signal using the Daubechies wavelet with 3 vanishing moments [22] on the acoustic signal. The figure shows the detailed part of the acoustic signal at level 1, 2, and 3. As shown, the detailed signal at level 1, corresponding to the high frequency components of the acoustic signal, has a clear change in its variance during a void. A pattern was also observed [18] that low frequency components of the acoustic signal were mainly affected by the RPM of the drill unit and its higher frequency components could be utilized for void detection. The detailed signal at level 1 is used here for void detection in which the void detection problem is formulated as a variance change detection problem using the detailed signal at level 1. Similar to void detection using feed pressure, a CUSUM algorithm was utilized for real time variance change detection. It should be noted that variance change detection is usually considered a more challenging task rather than the mean change detection [19]. It should be emphasized that high frequency components of the acoustic signals are more informative for the application of the void detection than the low frequency components, as discussed here. The acoustic signal used in this study was collected using sampling rate of 1 kHz while the feed pressure data was collected using sampling rate of 10 Hz.

3. Void detection using real time change detection algorithms

In this section, the void detection algorithms are presented by modeling the pattern observed on the feed pressure and acoustic signals, as mean and variance change detection problems [19].

3.1. Mean change detection on feed pressure

In this section, the CUSUM algorithm, which was first proposed [23] and has undergone several modifications [19], is briefly reviewed and the algorithm for void detection is discussed. Let $y_k, k = 1, 2, \ldots$ be a time series that can be approximated with a Gaussian random sequence with variance σ^2. Let also assume that time series has mean of μ till time step t_0 and mean of $\mu - \eta$ afterwards. The sufficient statistic s_k is defined as

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

and the CUMSUM decision function is defined as

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

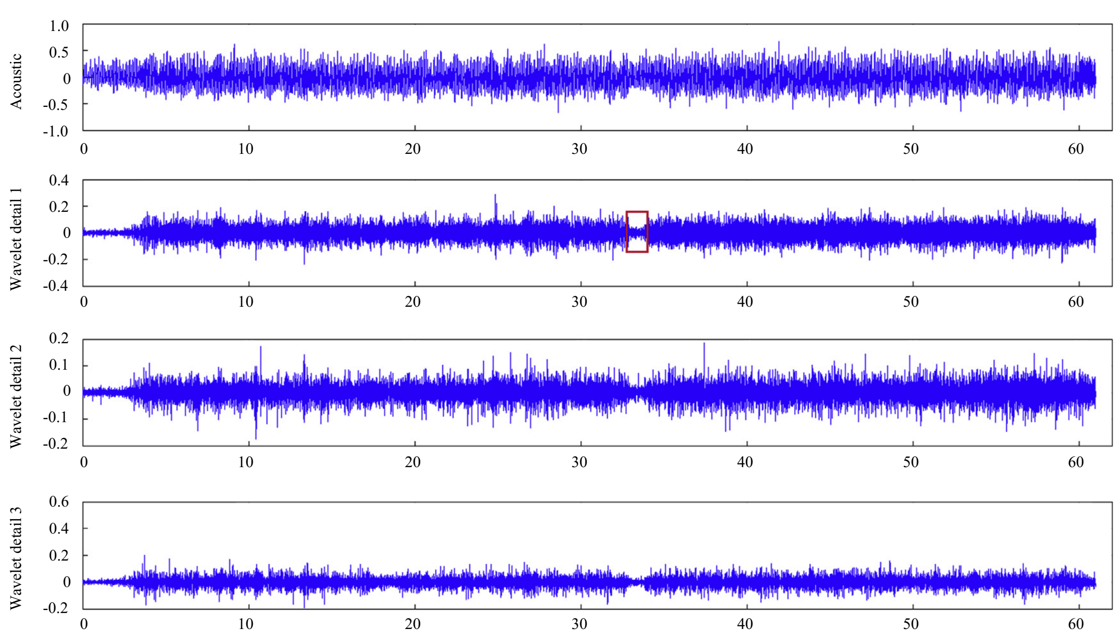

Fig. 4. Acoustic signal (top) and its detailed signals at different levels obtained using 3-level wavelet decomposition with the Daubechies wavelet db3.

In this algorithm, the resulting alarm time is calculated as

$$t_a = min\{k : g_k \geqslant h\} \quad (3)$$

where h is a pre-defined threshold and $g_0 = 0$. It can be shown that the above decision function is equivalent to the following stopping rule:

$$t_a = min\{k : S_k \geqslant m_k + h\} \quad (4)$$

With $S_k = \sum_{i=1}^{k} s_i$, and $m_k = min_{1 \leqslant i \leqslant k} S_i$. Therefore, it is clear that the discussed detection rule is in fact a comparison of the cumulative sum S_k with an adaptive threshold $m_k + h$ which carries information about the past observations and is modified on-line [19].

The proposed void detection algorithm uses the above algorithm on the feed pressure time series. In the above formulation, it is assumed that feed pressure drops when the drill bit approaches a void. The algorithm requires estimation of the mean μ, variance σ^2, and change amplitude η. For this purpose, the void detection algorithm makes observation of the measured values during the first 5 in. of the drilling and the initial time series is used to estimate mean and variance. Information about the magnitude change is usually not known a priori. One good choice is to replace η with minimum possible magnitude of the jump. In this paper, η is selected to be 40% of the mean μ. In other words, the algorithm would be sensitive to all change greater than 40% of the mean value of the time series. More sophisticated algorithms can be used to estimate the parameter η such as the generalized likelihood ratio method but this will significantly add the computational costs. In this study, the threshold h is selected to be 7000 for all the experiments. It should be noted that after a void is detected, the algorithm is restarted to detect new voids.

3.2. Variance change detection on the acoustic signals

As explained in the previous section, the variance of the filtered acoustic signal changes when a void is encountered. Therefore, one can use variance change detection algorithms to detect voids using acoustic signal. These algorithms are broadly categorized as non-additive change detection, or spectral change detection, algorithms. In this paper, we use auto-regressive (AR) model to represent the signal behavior. Autoregressive models have been successfully applied for segmentation of the acoustic signals.

Let the filtered acoustic signal be donated as $y_k, k = 1, 2, \ldots$, the AR model of order p can be written as

$$y_k = \sum_{i=1}^{p} a_i y_{k-i} + v_k, \quad (5)$$

where v_k is a random Gaussian noise with mean zero and variance σ^2. The associated change detection problem can be defined as finding changes in the parameter vector θ [19]

$$\theta_l^T = (a_1^l, \ldots, a_p^l, \sigma_l)^T, \quad l = 0, 1, \quad (6)$$

i.e., assuming the parameter vector is θ_0^T and θ_1^T before and after the change, respectively, the problem is to find the time t when the change occurs first. To implement the variance change detection algorithm, one needs to estimate the parameters of the regression model and the variances before and after the change, if it is not already known. Let the sufficient statistic S_j^k be defined as

$$S_j^k = \sum_{i=j}^{k} s_i, \quad (7)$$

where

$$s_k = \frac{1}{2} ln \frac{\sigma_0^2}{\sigma_1^2} + \frac{(\varepsilon_i^0)^2}{2\sigma_0^2} - \frac{(\varepsilon_i^1)^2}{2\sigma_1^2}, \quad (8)$$

and the residuals are defined as

$$\varepsilon_k^l = y_k - \sum_{i=1}^{p} a_i^l y_{k-i}, \quad l = 0, 1. \quad (9)$$

Then the CUSUM algorithm for online change detection is summarized as follows:

$$t_a = min\{k : g_k \geqslant h\}, \quad (10)$$

$$g_k = max(0, S_{k-N_k+1}^k), \quad (11)$$

$$N_k = \begin{cases} N_{k-1} + 1 & if\, g_{k-1} > 0 \\ 1 & Otherwise \end{cases}, \quad (12)$$

The parameter before change is estimated using a growing time window and the parameters after the change are estimated using a sliding fixed-size time window. The size of the sliding time window is chosen based on the penetration rate, i.e., for faster penetration rates, smaller windows are used. For more details about the CUSUM algorithm and the implementation details [19].

4. Full scale drilling tests

4.1. Experimental setup

This section presents the setting for the experiments performed at the Fletcher testing facility in Huntington, WV, on concrete blocks as well as composite sample of various rock types. For this purpose, a set of 16 concrete blocks with different predetermined strength levels were poured and allowed to cure for more than 28 days. The blocks were approximately 0.5 m × 0.5 m × 0.75 m (~20 in. × 20 in. × 30 in.), and the concrete mix was designed for strengths ranging from low (~20 MPa or 3000 psi), to medium (50 MPa or 7,500 psi), and high (70 MPa or 10,000 psi). Different combinations of concrete blocks were used to test robustness of the algorithm to deal with different setups. For examples, a hard (high-strength) concrete block on top of a soft (low-strength) concrete block or a hard concrete block on top of another hard concrete block etc. to represent various sequencing of rock layers that may be encountered in the field. There is a small gap of less than a couple of millimeters between each two concrete blocks that was considered to simulate a joint or "void" in this study. Fig. 5 shows samples photos of the voids between the concrete blocks obtained by bore-scoping.

In addition to void detection, the problem of interface change detection, where the strength or the rock type changes within a hole, is studied. For this purpose, interface change detection was performed on a composite sample or "sandwich" of rocks which consisted of soft rocks (shale) and hard rock (limestone), embedded in a concrete block as shown in Fig. 6. The drilled holes were surveyed by using borescope to identify the interface between the blocks and between various rock types. Samples of the concrete and rocks were also cored to obtain specimen for rock mechanic testing and measurement of strength. Several values of feed rates, rotational speeds, and bit diameters were used in the tests.

4.2. Void detection using feed pressure data

The existing void detection software utilizes the torque and thrust signals, which is obtained by appropriate conversion of the rotation and feed pressure data, as well as the position signal to estimate the voids in the roof-mapping software. The algorithm identifies the sudden changes in these signals through several inter-connected logics to identify different void events.

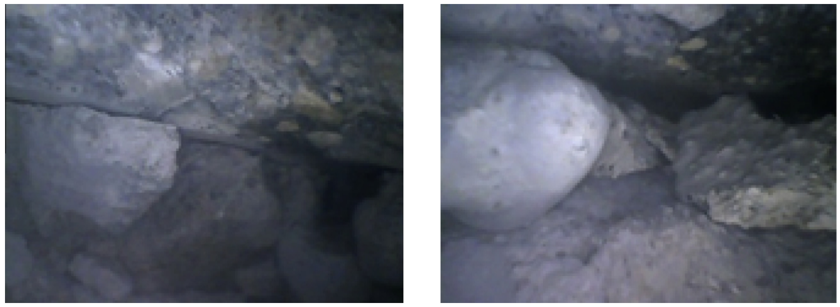

Fig. 5. Sample photos of borescoping showing the void positions within the concrete blocks.

Fig. 6. Rock samples embedded in a concrete to study the correlation of the drilling parameter with respect to the different rock types.

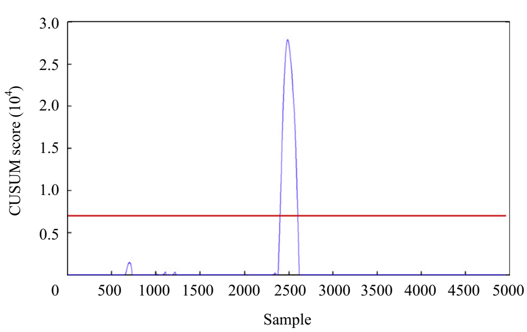

Fig. 7. CUMSU score generated by the mean change detection algorithm on the feed pressure signal and the corresponding threshold.

Fig. 7 shows the CUSUM score generated by the proposed void detection algorithm on the feed pressure signal. It is clear that the CUSUM score remains small when there are no significant mean changes and it increases when the mean change occurs and it crosses the threshold. This algorithm was used to analyze the data from full scale testing in various drilling scenarios to examine the sensitivity of the algorithm to variations in the sample setting.

Table 1 summarizes the results of the proposed mean change detection algorithm on the feed pressure signal and comparison with the existing void detection on the different concrete combinations. The table reports the number of holes drilled in each setup along with void detection rate and false alarm rate where 'S', 'M', and 'H' letters stand for soft, medium, and hard concrete, respectively. For example, H-S indicates that a soft concrete block is placed on top of a hard concrete block. Different values of penetration rate and rpm are used in the tests to evaluate the performance of the algorithm to various drilling parameters. As it can be seen, the proposed algorithm has resulted in improved performance than the threshold-based algorithm with high detection rate and a few false alarms. Overall, the detection rate of 96.0% (4% misses) was achieved with false alarm rate of 11.8% (15 joints were indicated by the program that did not exist) in 127 holes. It should be noted that these false alarms could be due to conditions within the concrete samples that could be conceived by the algorithm to be a void, but was not a pre-designated joint as the interface surface between the blocks.

It should be noted that the results of the existing algorithm is reported using the default parameters and threshold values which can be further adjusted for an improved performance. One advantage of the proposed algorithm is that it only requires two parameters to be selected as discussed in the previous section, i.e., one needs to only select a threshold and the sensitivity of the algorithm to the change of the mean. On the other hand, the existing algorithm uses five parameters for detection which makes it more difficult to fine tune if threshold adjustment is needed. Moreover, the proposed algorithm does not utilize the torque and position sensor and only used the thrust signal for the void detection. One disadvantage of the proposed algorithm, on the other hand, is that the algorithm is not able to detect voids in the first 125 mm of the drilling since it uses the initial data to estimate the required parameters in an adaptive fashion. Therefore, a combination of these two algorithms can be utilized for the real-time void detection.

Table 1
Results of the existing and the proposed void detection algorithm on different combinations of concrete soft (S), medium (M), and hard (H) blocks.

Concrete combinations	M–H	H–H	H–M	M–S	S–M	M–M	S–S
Number of holes	17	18	21	18	18	18	17
Detection rate (existing algorithm)[a] (%)	81.2	61.1	95.2	100	81.3	56.2	82.4
Detection rate (CUSUM) (%)	100	88.8	100	100	88.8	88.8	100
Number of false alarms (existing algorithm)[a]	>25	>30	>60	>60	>60	>55	>50
Number of false alarms (CUSUM)	0	1	2	2	3	4	3

Note:
[a] The detection rate and false alarm is based on a present threshold. In the field the system can be adjusted to reduce the false alarms as the thresholds are adjusted for various sites.

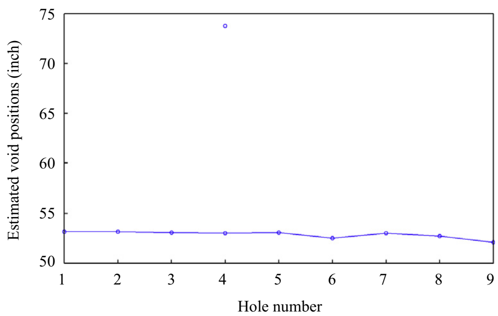

Fig. 8. Estimation of the voids in 9 nearby holes.

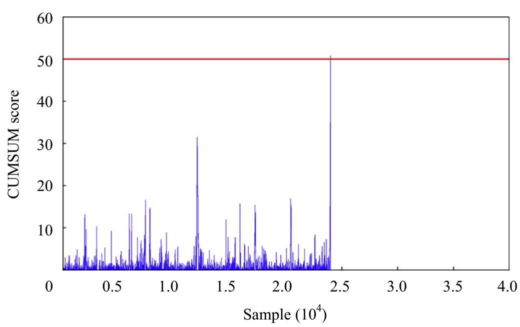

Fig. 9. CUMSU score generated by the variance change detection algorithm on the filtered acoustic signal and the corresponding threshold.

Moreover, with higher sampling rate, the initial window for estimating parameters can potentially be reduced.

It should be emphasized that the above algorithm used only feed pressure for detection of the voids. Using other sensory data such as vacuum pressure and rotation pressure can further improve the results which will be examined in more details in the future. Another obvious approach to reduce false alarms is to look at the continuum of the holes to find the voids and bed separations instead of deciding based on individual holes. Fig. 8 shows estimation of the voids in 9 nearby holes of the H–H scenario. The actual void is approximately located at 1330 mm as estimated by the void detection algorithm. The algorithm also generated one false alarm for the 4th hole. However, this false alarm can be easily removed in a post-processing step by simultaneously looking into predicted void positions in the nearby holes. This clearly demonstrates that the proposed algorithm can potentially be modified with simple post processing routines that can improve the detection performance by comparing the adjacent holes and making the data available to the operator on site.

4.3. Void detection using acoustic data

Fig. 9 shows the CUMSU score generated by the variance change detection algorithm on the filtered acoustic signal. It is seen that the CUSUM score remains small when there is no significant mean change and it started to increase when the mean change occurs and it crosses the threshold. The threshold is selected using a few of the drilled holes to minimize false alarm rate while keeping the detection rate reasonably high. Table 2 summarizes the results of the proposed variance change detection algorithm on the filtered acoustic signal on the different combinations of the concrete blocks. Compared to the results obtained using Feed pressure (Table 1), using acoustic signal results in better performance than the existing algorithm that is used in the DCU system. However, its performance is not as accurate as that of the proposed mean change detection algorithm on the feed pressure signal. One advantage of the new algorithm is that, similar to CUSUM algorithm in feed pressure, it only requires two parameters to be monitored and adjusted, i.e., threshold and the sensitivity Similarly, this algorithm is not able to detect voids in the first 5 in. of the drilling since it uses the initial data to estimate the required parameters for adaptive variance changes. Therefore, a combination of these two algorithms can be utilized for the real-time void detection.

The acoustic signal provides a measure that is directly correlated with existence of the void, and it is independent of the closed loop control unit of the drill machine. This is the main advantage of using the acoustic signal for void detection, rather than using a process-dependent signal such as feed pressure. In other words, although a drop of the feed pressure is usually observed at the location of the voids, as observed in the experiments in this paper, there exist cases in which feed pressure would increase when reaching a void based on the feedback loop installed on the machine for optimization. Therefore having other sensory information adds redundancy to the roof-mapping software to allow an independent set of measurements that is not grouped with or interdependent on drill's operational parameters.

4.4. Interface detection on sandwich of rocks

In this section, the result of the proposed variance change detection algorithm for the relative strength identification is presented. For this purpose, the composite rock sample (sandwich) discussed in previous Section was utilized and the boreholes crossing through various rocks and concrete were used as ground truth. Fig. 10 shows the filtered acoustic signal, which is obtained when drilling into the preset sequence of rocks. It is clear that the pattern of the signal changes when the strength of the medium changes. For the soft rock layers, which correspond to the segments of the acoustic signal approximately at 12–20 and 34–37 s, respectively, the variance of the acoustic signal is low. On the other hand, for the hard rock layer, which corresponds to the segment of the signal starting approximately at 49 to the end of the borehole, the variance of the signal is high. This shows that the proposed variance change detection algorithm can be utilized for identification of changes in the relative strength of the materials. Fig. 11 shows the corresponding CUSUM score and Fig. 12 shows the color-coded variance of each segment identified by the CUSUM algorithm. As can be seen, the color-coded variance follows the pattern of rock embedment in the composite sample, thus indicating the ability to use the algorithm for rock identification

Table 2
Results of the using variance change detection algorithm on the filtered acoustic signal using the different combinations of concrete soft (S), medium (M), and hard (H) blocks.

Concrete combinations	M–H	H–H	H–M	M–S	S–M	M–M	S–S
Number of holes	17	18	21	18	18	18	17
Detection rate (CUSUM) (%)	100	83.3	95.2	100	88.8	72.2	82.4
Number of false alarms (CUSUM)	4	0	3	9	3	1	4

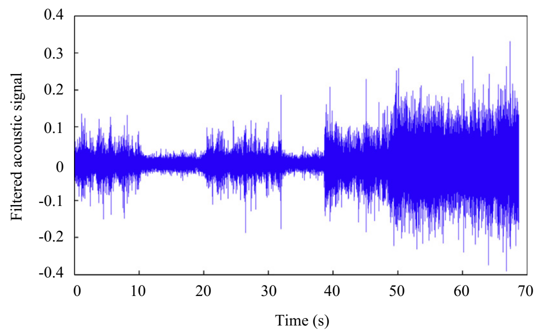

Fig. 10. Filtered acoustic signal when drilling into the sandwich of the rocks consisting. (The drill bit reaches concrete->soft rock->concrete->soft rock->concrete->hard rock consecutively.)

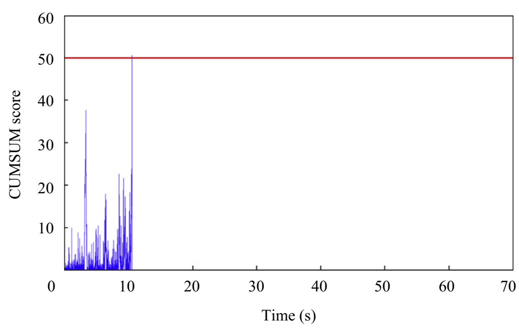

Fig. 11. CUMSU score generated by the variance change detection algorithm on the filtered acoustic signal and the corresponding threshold. (After a change in interface is detected, the algorithm restarts.)

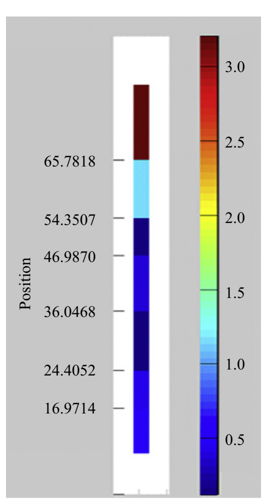

Fig. 12. Color-coded variance of each segment relative to the position of the drill bit. (Each segment is identified using the variance change detection algorithm on the filtered acoustic signal.)

and classification. This method combined with analysis of other parameters can be used to provide a preliminary and relative estimate on rock strength as well.

5. Conclusions and future research

In the context of excavation operations, this paper has addressed the following issues: characterization of the ground while installing roof bolts by a drill and subsequent roof mapping using drilling information. In particular, it is shown that void detection can be formulated as mean change detection based on the feed pressure signal which can be effectively solved by the cumulative sum (CUSUM) algorithm. Compared to the existing void detection algorithms, the proposed method incorporates an adaptive threshold that does not need frequent fine-tuning and has worked reasonably well in different test scenarios. Moreover, the algorithm has a recursive formulation that facilitates real-time computation. It is also shown that acoustic sensing can be used for void detection purpose provided that the signals are appropriately pre-processed. Tools of wavelet analysis have been applied to filter the acoustic signal in combination with variance change detection that, independent of drill's operating parameters, makes use of a different CUSUM algorithm for secondary void detection system. While the usage of the feed pressure signal resulted in higher detection and smaller false alarm rate compared to that of the acoustic signal, having additional information for void detection provides redundancy to the ground characterization software. It is also shown that acoustic signals can be used to identify changes in the rock types and (possibly) rock strength. Additional testing and analysis efforts are underway to improve the capability of drilling operation software for identification of various features in the ground; this is expected to yield an efficient and accurate rock strength classification tool by using the drilling parameters.

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References

[1] Gu Q. Geological mapping of entry roof in mines. WV: West Virginia University; 2003.
[2] Peng S, Tang D, Mirabile B, Luo Y, Wilson G. Mine roof geology information system. In: Proc 22nd international conference on ground control in mining. Morgantown; 2003. p. 127–35.
[3] Ichihara Y, Deguchi G, Itakura K. Development of roof logging system using bolt-setter. In: Proc of Asian Pacific workshop on coal mine safety. Tokyo; 1995. p. 31–40.
[4] Itakura K, Sato K, Ichihara Y, Deguchi G, Matsumoto H, Eguchi H. Development of a roof-logging system by rockbolt drilling. Trans Inst Mining Metall 1997;106:A118–23.
[5] Itakura K, Sato K, Deguchi G, Ichihara Y, Matsumoto H. Estimation of the 3-D geostructure of roof rock in mines using a mechanical data logging system for rock-bolt drilling. In: Proc 4th international symposium on mining mechanization and automation. Brisabane, Australia; 1997. p. 65–74.
[6] Itakura K, Sato K, Deguchi G, Ichihara Y, Matsumoto H. Estimation of roof structure by mechanical data logging system for a roof bolter. Coal Saf 1998;13:42–56.
[7] Itakura K, Sato K, Deguchi G, Ichihara Y, Matsumoto H. Visualization of geostructure by mechanical data logging of rockbolt drilling and its accuracy. In: Proc 20th international conference on ground control in mining. Morgantown; 2001. p. 184–90.
[8] Itakura K, Goto T, Yoshida Y, Tomita S, Iguchi S, Ichihara Y, Mastalir P. Portable intelligent drilling machine for visualizing roof-rock geostructure. In: Proc of the rockbolting in mining & injection technology and roadway support systems conference. Aachen; 2008. p. 597–609.
[9] Finfinger G, Peng S, Gu Q, Wilson G, Thomas B. An approach to identifying geological properties from roof bolter drilling parameters. In: Proc 19th international conference on ground control in mining. Morgantown; 2000. p. 1–12.
[10] Finfinger G. A methodology for determining the character of mine roof rocks. WV: West Virginia University; 2003.
[11] Mirabile B. Geologic features prediction using roof bolter drilling parameters. WV: West Virginia University; 2003.
[12] Tang X. Development of real time roof geology detection system using drilling parameters during roof bolting operation. WV: West Virginia University; 2006.
[13] Luo Y, Peng S, Mirabile B, Finfinger G, Wilson G. Estimating rock strengths using drilling parameters during roof bolting operations-progress report.

In: Proc 21st international conference on ground control in mining. Morgantown; 2002. p. 288–93.
[14] Luo Y, Peng S, Wilson G. Identification of lithologic changes using drilling parameters. Trans Soc Mining Metall Explor Incorporated 2003;314:6.
[15] Gu Q, Watson GA, Heasley KA. Detection of roof geology variation using recorded drilling parameters.In: Proc 32nd international symposium on the Application of Computers and Operations Research in the Mineral Industry (APCOM). Tuscon; 2005. p. 527–34.
[16] Collins C, Wilson G, Tang D, Peng S. Field testing of a real time roof mapping drilling display system in a limestone mine. In: Proc 23rd international conference on ground control in mining. Morgantown; 2004. p. 48–55.
[17] Anderson R, Prosser L. Improving the capability for real time assessment of roof conditions through intelligent roof bolt drilling operations. In: Proc 26th int conf on ground control in mining, Morgantown; 2007. p. 287–92.
[18] Bahrampour S, Rostami J, Naeimipour A, Collins CM. Field testing of a real time roof mapping drilling display system in a limestone mine. In: Proc 32nd int conf on ground control in mining, Morgantown; 2013.
[19] Basseville M, Nikiforov IV. Detection of abrupt changes: theory and application. Englewood Cliffs: Prentice Hall; 1993.
[20] Gradl C, EusteslII AW, Thonhauser G. An analysis of noise characteristics of drill bits. J Energy Resour Technol 2012;134:0131031–37.
[21] Celada B, Galera JM, Muñoz C, Tardáguila I. The use of the specific drilling energy for rock mass characterisation and TBM driving during tunnel construction. In: ITA-AITES world tunnel congress, Budapest; 2009. p. 1–13.
[22] Mallat S. A wavelet tour of signal processing. US: Academic Press; 1999.
[23] Page ES. Continuous inspection schemes. Biometrika 1954;41:100–15.