Rock Characterization using Time-Series Classification Algorithms

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Abstract

Development of the measurement while drilling systems for the ground control applications in mining applications has recently been an active research topic. The main goal is to utilize the drilling information for characterizing the ground condition. Such characterization is the key to the accurate and efficient mapping of the hazards and proper planning of the ground support. However, most of the existing drilling units and the measurement while drilling systems are mainly developed for joints and voids detection and much less research is done to estimate rock strength. This paper focuses on rock classification based on estimated strength from the drilling data. For this purpose, data from Fletcher roof bolters instrumented with the vibration and acoustic sensors as well as torque, thrust, penetration rate, rpm, and position signals is used. All the available data was utilized for rock classification using pattern recognition algorithms. The algorithms were developed based on data from drilling into three different rock types. The classification is performed using simple feature extraction algorithm with a well-known pattern recognition algorithm. The results demonstrate the suitability of the proposed algorithms in identifying the rock types based on their strength properties, which can be adopted in the measurement while drilling systems.

Introduction

The applications of rock bolts have become a standard part of the ground support in mining and tunneling operations due to their effectiveness in reinforcing the ground and allowing the use of the ultimate strength of rock. Effective design and application of rock bolts depends on correct mapping of the geological conditions, including identification of discontinuities and rock strength, as they tend to vary, even within a short distance (Gu, 2003). Currently, many drilling parameters, including thrust, torque, penetration rate, and drill revolutions are being collected that can be utilized to estimate the location of the joints and discontinuities as well as rock strength for evaluation of ground conditions (Peng, 2003). A series of studies has demonstrated the potential for analyzing drilling parameters from roof bolters to estimate rock properties and to identify discontinuities (Itakura et al., 2001; Itakura et al., 2008).

Among early attempts for analyzing the drilling parameters to characterize the rock, also known as measurement while drilling systems, Signer and King (1992) and King et al. (1993) proposed an unsupervised learning technique as an expert system which could interface with the
instrumented roof bolter to determine geological features. The system could identify the significant roof features in relation to the support parameters, and suggest improvements to the support design. The system could measure the drilling parameters and calculate the specific energy of drilling as an indicator of the type of rock being drilled. This system was successfully tested in an underground coal mine (Frizzell et al., 1992). Hoffman (1994) proposed an integration of the roof mapping with the control units and added vibration analysis to increase the safety of roof bolting in underground coal mines. An attempt for application of pattern recognition algorithms such as neural networks for classification of mine roof strata in terms of relative strength was proposed by Utt et al. (2002). LaBelle et al. (2000). LaBelle (2001) also studied neural networks for rock strata classification of a five layers of concrete using a portable hydraulic powered coal mine roof bolter. Some preliminary field experiments were also performed with the hand-labeled data and their algorithm was unable to correctly classify coal and shale mainly due to the limited training samples.

Luo et al. (2002) proposed a systematic approach for estimating the rock strengths using the acquired drilling parameters in roof bolting operations. The mathematical model developed based on this approach was able to take into consideration several factors including bit geometry and bit wear that have rarely been considered previously. The sensitivity analysis was performed, however, only with simulations. They found that both the bit geometry and the drilling operating parameters were important factors in determination of the thrust and torque required in the drilling process. Bit geometry was used for quantitative evaluation of the effects of bit wear on the drilling performance. More recently, Li and Itakura (2011a, 2011b) proposed a model to relate rock properties to bit shapes and drilling parameters. In this approach, the drilling process is divided into successive cycles where each cycle includes two motions of feed and cutting. According to the model, drilling torque consists of four components which are generated from cutting, friction, feed, and idle running. It was shown that the first three components are all proportional to the uniaxial compressive strength (UCS) when the penetration rate is kept constant. Their field experiments suggested that UCS is correlated with the torque and penetration rate. The proposed model and equations indicate the possibility of eliminating useless components of cutting forces when investigating the relation between mechanical data and physical properties of rocks. More recent study also confirms that UCS of rocks can be estimated using specific energy generated by the model extracted from regression analysis (Li and Itakura, 2012).

In addition, it was shown in Mirable (2003) and Mirable et al. (2004) that torque thrust ratio and also shear stress normal stress ratio are indicative features in distinguishing hard rocks from soft rocks. In a similar studies using J.H. Fletcher& Co.’s HDDR dual head roof bolter. Extensive experiments demonstrated that the magnitude of feed pressure is also another descriptive variable among the drilling parameters to estimate the strength of the rock due to its high correlation with the penetration rate and the rpm (Collins et al., 2004, Peng et al., 2005a; Peng et al., 2005b; Tang, 2006). Their algorithm estimates the location of the interface between different rock layers based on the observed trend in data sets from different rocks strength groups.

In this paper, a time-series classification algorithm is used to address the problem of rock classification using drilling information. The data are collected using a drilling unit at J.H. Fletcher facility (Bahrampour et al., 2013). The drilling unit is equipped with vibration and
acoustic sensors. For the rock strength classification, the time series data such as feed pressure, rotation pressure, and penetration rate as well as the vibration and acoustic signals are utilized. Also specific energy and torque thrust ratio are estimated from the measurements and are considered in this study. A set of statistical parameters and features are extracted from these time-series which are then fed into a pattern recognition algorithm. The use of support vector machine (SVM) is proposed to efficiently classify the time-series data. The proposed algorithm is evaluated on drilling data collected by drilling into three different rocks which are embedded within the concrete blocks.

**Overview of Fletcher roof mapping system and data collection**

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 the cycle of drilling and bolting for safety and productivity reasons (Anderson and Prosser, 2007). 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. Several modifications have been made to improve the accuracy of measuring bit position and torque (Gu, 2003). 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 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 (Anderson and Prosser, 2007). Fig. 1 shows the recent J. H. Fletcher & Co. instrumented roof bolter along with the new vibration and acoustic sensors installed on the rig. Bahrampour et al, 2013 have discussed how vibration and acoustic signals can be used for void detection (). As such data from these sensors are also monitored to provide additional information for rock strength classifications.
Figure 2. Rock samples are casted in concrete block which forma “sandwich” of rocks.

Figure 3. Bore-scoping of the drilled holes to identify the positions of different rock layers.

Rock characterization is performed on three types of rocks collected from different mines in Pennsylvania. Rock types include shale, sandy shale, and limestone. The rock samples were embedded within a concrete block as shown in Figure 2. This forms a “sandwich” of rocks which facilitates comparison of the drilling parameters when different types of the rocks are drilled in one hole. Overall, three blocks were drilled with different combinations of the rocks. To correlate the drilling parameters with the rock types, each drilled hole is bore-scoped and positions of the different layers are marked (Figure 3).

**Time-series classification for rock characterization**

In this section, a time-series classification algorithm proposed for real-time rock characterization is discussed. Feed pressure, rotation pressure, penetration rate, acoustic and vibration signals are utilized in conjunction with the time series classification algorithm to identify various rock types. Sample of time-series data for drilling a hole in composite sample, consisting of two shale and one limestone rock embedded in a concrete block, is shown in Fig. 4. An estimated strength of
the different layers of the block is also shown in the figure which is obtained from rock mechanics tests on core samples from each rock type. The figure shows clear correlation between the rock strength and the drilling signals. For example, it is seen that higher feed pressure is required to drill the limestone compared to the shale if the rpm and feed rate is fixed. Moreover, feed pressure data is less variable during drilling of the shale samples compared to relatively higher variability while drilling (non-homogeneous) concrete. In this paper, the time-series is classified into three different classes of shale, limestone, and concrete. The shale samples have the lowest strength in these experiments and are labeled as class 1. Concert has the relatively higher strength compared to shale and is labeled as class 2. Finally, limestone is the strongest type of the rocks in our experiments and is labeled as class 3.

The time-series are analyzed in a series of windows of one second length, where the consecutive windows have 50% overlap. For each window, a set of simple statistical features are obtained which are then fed into the classification algorithm. The feed pressure and rotation pressure signals are low-pass filtered before the feature extraction. The specific energy of the drilling (Teale, 1965) and scaled torque-thrust ratio have also been calculated. These parameters have been shown to be strongly correlated to the strength of the rock. The torque and thrust values have been estimated from the rotation pressure and feed pressure signals, respectively. In other words, ratio between the rotation pressure and feed pressure is used as an estimation of torque thrust ratio. Therefore, the rock strength classification is performed using the filtered feed pressure and rotation pressure, and their ratios in addition to the specific energy, acoustic, and vibration signals. For each signal, in each window of one second data, mean, variance, and kurtosis are calculated as features. Therefore, in the feature extraction step, total of 18 features are extracted for each window. Some of the calculated features are demonstrated in Figure 5. These features correspond to the data shown in Figure 4. The ground-truth label for each window is also shown in this figure. Note that each window is labeled based on the bore-scoped measurement of the middle sample.

For classifying each window, different pattern recognition algorithms can be utilized. In this paper, support vector machines (SVM), which is a state-of-the-art pattern recognition algorithm, is utilized. SVM is a binary classification algorithm which finds an optimal separating hyperplane, represented by \( w \in \mathcal{R}^n \) where \( n \) is the dimension of the feature vector, to classify the training samples from two different classes as depicted in Figure 6. The new test sample, represented by a feature vector \( x \), can then be classified into one of the two classes by finding the sign of \( w^T x \). To use SVM for our multiclass classification problem, a one-vs-all setting is utilized in which a separate SVM classifier is trained for each class which learns a hyper-plan that separates each class of the data from the rest of training data. The test sample is then evaluated by all the classifiers and the probabilities of it belonging to different classes are calculated. The label of the test sample is assigned as the class with the highest probability. For a detailed description of the SVM algorithm, please refer to (Bishop, 2006). It should be noted that
Figure 4. Samples time-series data obtained by drilling into a sandwich of rocks consists of three layers of rocks embedded in a concrete block.

Figure 5. Some of the features that are used for rock-strength classification. The ground-truth label for each window is also shown.
Classification Results and Discussions

This section discusses the results of rock strength classification which is obtained using the drilling data collected from 65 tests. Each test consists of drilling into different layers of rock and concrete as discussed before. The data is randomly split into training and test sets where the training portion consists of 45 drilling tests and the rest of the data is used as test data. The support vector machines (SVM) are trained using only the training data and the performance of the classification is reported on test data. Figure 7 shows sample probabilities generated by the SVM classifiers in a drilling test. The drilling starts with a concrete layer and, as drilling progress, it drills shale $\rightarrow$ concrete$\rightarrow$ shale$ightarrow$ concrete$ightarrow$ and limestone, respectively. These layers are correctly identified by the proposed classification algorithm. Each window is classified as the class with the highest probability. Figure 8 compares the predicted labels with the ground truth and, as shown, the algorithm successfully identified the different layers. There are some oscillations in the predicted label which mostly appeared at the interface between the different layers. It should be noted that SVMs classify each window of time-series independent of the other windows. To reduce the oscillations and also utilize the information carried by the consecutive windows, a simple post-processing step is utilized. In this step, the assigned label for each window is compared with its adjutant windows and a majority voting procedure is used to predict the class. While a more advanced tool such as Kalman filtering can also be used for this post-processing step, it is observed that this simple post-processing is still efficient in reducing the oscillations of the predicted class as shown in Figure 8. Table 1 summarizes the correct classification rates obtained on the test data. It is seen that the algorithms result in high correct classification rate, even without using the acoustic and vibration sensors. This demonstrates that the proposed algorithm can be readily utilized within the framework of the existing roof-mapping systems (without adding instruments) for a relatively accurate rock characterization. It should be noted that for the vibration and acoustic signals, the feature extraction is applied on the raw data. It is envisioned that using signal processing tools to preprocess these signals can further improve the classification performance which is a topic for future research.
Figure 7. Probabilities of a given window of the data belonging to the different classes as calculated by the SVM classifiers.

Figure 8. Ground truth and the predicted labels generated on a drilling test into a sandwich of rocks.

Table 1. Correct classification rates obtained on the test data.

<table>
<thead>
<tr>
<th>Correct classification rates</th>
<th>Without post-processing step</th>
<th>With post-processing step</th>
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<tbody>
<tr>
<td>Without acoustic and vibration</td>
<td>85.56%</td>
<td>85.69%</td>
</tr>
<tr>
<td>All sensors</td>
<td>86.35%</td>
<td><strong>87.46%</strong></td>
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Conclusions and Future Works

The problem of estimating rock strength using the drilling information was the focus of this study. To solve this problem a time-series classification is proposed by using a pattern recognition algorithm. This algorithm uses simple and yet efficient statistical features extracted from the time-series data. The proposed algorithm was tested using data collected at the J.H.
Fletcher facility by drilling into soft and hard rocks which are embedded in concrete blocks. The results suggest that the proposed algorithms can be efficiently used for real-time rock classification within the framework of the measurement while drilling system. Testing the algorithm on filed data from different mines as well as finding more discriminative features are among the topics for future research. Also, while the current study has focused on classification of various rock types in a known series of strata, additional emphasis will be placed on the estimation of rock strength in future steps. This allows the rock strength estimated from drilling parameters to be used in rock mass classification system and evaluation of ground support measures.

References


