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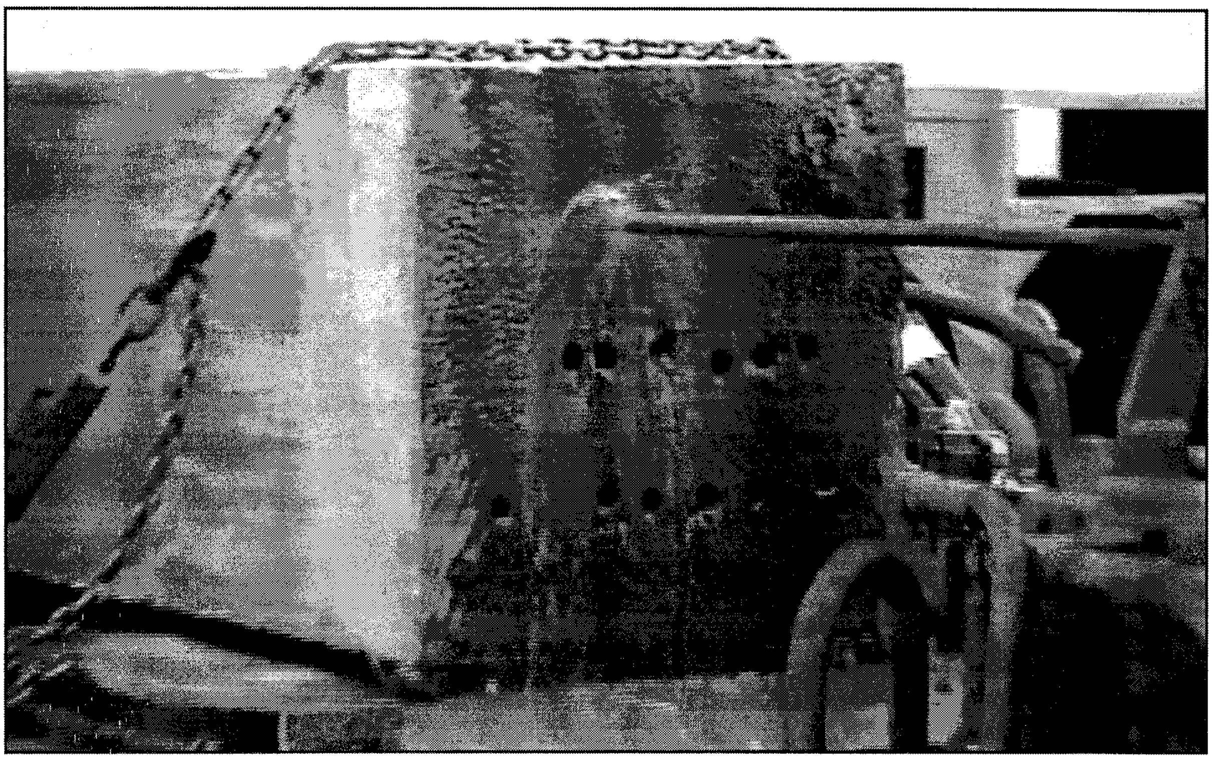
Drill Monitor With Strata Strength Classification in Near-Real Time



Department of Health and Human Services
Centers for Disease Control and Prevention
National Institute for Occupational Safety and Health

NIOSH

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Drill Monitor With Strata Strength Classification in Near-Real Time

Walter K. Utt, Gregory G. Miller, Wayne L. Howie, and Chelsea C. Woodward

U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES
Public Health Service
Centers for Disease Control and Prevention
National Institute for Occupational Safety and Health
Spokane Research Laboratory
Spokane, WA

July 2002

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CONTENTS

	Page
Abstract	1
Introduction	2
Theoretical background	2
Description of drill	3
Data acquisition instruments	4
Program organization	7
Neural networks	7
Neural network packages	7
Neural network training	7
Rock strength	9
Laboratory tests	10
Applications and extensions	12
Conclusions	13
References	14

ILLUSTRATIONS

1.	Accidents during roof bolting	2
2.	Drilling data flow	3
3.	Laboratory roof drill	3
4.	Overview of data collection process	5
5.	Preprocessing of individual channel signals	6
6.	LabView graphics display screen	7
7.	Example of artificial neuron	9
8.	Neural network training	9
9.	Neural network classification	9
10.	Mine roof strata characterization	9
11.	Strength index versus depth	10
12.	Test block 7 in form box	11
13.	Block with layers of differing strengths	11
14.	Detection of inclusion from change in strength	11
15.	Specific energy versus depth	11
16.	SED with detrending	12
17.	Penetration rate versus depth	12
18.	Tele-robotic roof drilling	13
19.	Tele-robotic core drilling	13
20.	Supervisory remote control	13

TABLES

1.	Calibration coefficients	6
2.	Training data set	8
3.	Training parameters for network	8
4.	Alternative parameter sets	10

UNIT OF MEASURE ABBREVIATIONS USED IN THIS REPORT

cm	centimeter	mA	milliampere
Hz	hertz	ms	millisecond
kbyte	kilobyte	N	newton
kg	kilogram	N·m	newton-meter
kPa	kilopascal	Pa	pascal
m	meter	sec	second
m^2	square meter	V	volt
m/min	meter per minute	dc	direct current
MHz	megahertz	rpm	revolution per minute

DRILL MONITOR WITH STRATA STRENGTH CLASSIFICATION IN NEAR-REAL TIME

By Walter K. Utt,[1] Gregory G. Miller,[2] Wayne L. Howie,[3] and Chelsea C. Woodward[4]

ABSTRACT

The process of drilling and bolting the roof is currently one of the most dangerous jobs in underground mining, resulting in about 1,000 accidents with injuries each year in the United States. Researchers from the Spokane Research Laboratory of the National Institute for Occupational Safety and Health are studying the use of a drill monitoring system to estimate the strength of successive layers of rock and assess the integrity of a mine roof so that roof drill operators can be warned when a weak layer is being drilled. Measurements taken during drilling can be converted to suitably scaled features so that a neural network can classify mine roof strata in terms of relative strength. The feasibility of this concept has been demonstrated in the laboratory. The research project was undertaken in order to increase the safety of underground miners, especially those involved in roof bolting. The system should be applicable to the mobile drills used in underground mining and would likely find wider application as well.

[1]Electrical engineer.
[2]Mechanical engineer.
[3]Electronics technician.
[4]Engineering technician, Spokane Research Laboratory, National Institute for Occupational Safety and Health, Spokane, WA.

INTRODUCTION

Roof falls in underground mines have caused many fatalities in the past. To reduce the risk of deaths and injuries from roof falls, roof bolts are used to reinforce the rock. However, the process of drilling and bolting the roof is one of the most dangerous jobs in underground mining, resulting in about 1,000 accidents with injuries each year in the United States (figure 1), according to data compiled from Mine Safety and Health Administration (MSHA) statistics. By using a monitoring system on a roof drill to assess the integrity of a mine roof, a roof drill operator could be warned when a weak stratum is encountered while drilling. Such a warning could make the difference between life and death for the operator.

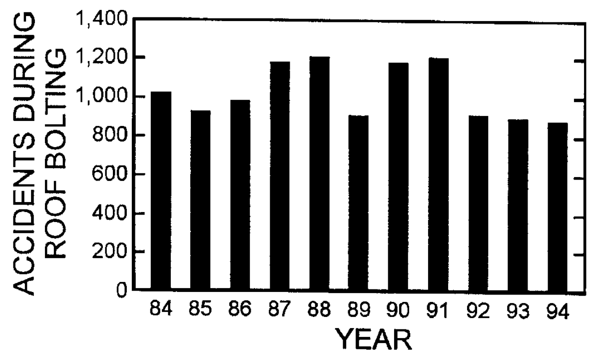

Figure 1.–Accidents during roof bolting.

The Spokane Research Laboratory (SRL) of the National Institute for Occupational Safety and Health (NIOSH) conducts research to improve the safety of miners. Building on prior research at the former U.S. Bureau of Mines' Spokane Research Center, the feasibility of a prototype strata strength classification and warning system was demonstrated on a full-scale commercial drill customized in the laboratory.

It is necessary to measure basic drilling parameters—torque, rotation rate, thrust, penetration rate, and depth of penetration of the drill tip—to establish the strength of the rock layer being drilled. To obtain maximum benefit from the information and provide a timely warning to a bolting machine operator, it is desirable that the computation of strength be completed within a few seconds of the measurement. The earlier the warning, the more time the operator has to move to safety.

Neural network technology was developed to classify strata according to their estimated strength. In this system, torque, rotation rate, thrust, penetration rate, and depth of the drill tip are measured and converted to electrical signals by transducers. This information flows through interface boards to a computer with a custom data acquisition program that includes a graphics display (see the section on "Neural Networks"). The data are smoothed by averaging or other means, and the specific energy of drilling (SED) is computed. Teale discovered a useful, approximate relationship between SED and the compressive strength of a layer of rock (Teale 1965). This relationship allows the use of a neural network to provide a satisfactory classification of mine roof strata according to relative strength. Using this relationship is a new development in mining, as is achieving such a classification in near-real time.

THEORETICAL BACKGROUND

SED is calculated as energy input during drilling or the work done per unit volume of rock excavated (Teale 1965), as indicated in the following equation.

$$e = \frac{F}{A} + \frac{2\pi(WT)}{Au} \qquad (1)$$

where e = specific energy, N/m^2 or Pa,

F = thrust, N,

A = area of drill hole, m^2,

W = rotation rate, rpm,

T = torque, N·m

and u = penetration rate, m/min.

SED includes both translational and rotational energy. Rotational energy input is usually much greater than translational energy. However, if thrust is zero, there will be no significant penetration of the rock, even if rotational energy input is high. During normal drilling operations, SED is usually greater than the compressive strength of the material being drilled and is a useful feature for strength classification, assuming drilling parameters are within a normal operating range. Consequently, at each individual mine, it would be advisable to monitor drilling parameters to be certain they are within the normal range of operation.

SED can be used in combination with penetration rate to provide a minimum set of features for a classifier. SED represents the energy input to drill the rock, and penetration rate represents the resulting output. The other measurements can be used as supplementary features, if desired. The full set of six parameters (that is, the five measurements plus calculated SED) may yield a more robust classifier, but the neural network would be significantly larger. The data processing program consists of three major parts: data acquisition, conversion to features, and the classifier, as shown in figure 2.

Since strength is to be evaluated while drilling is still underway, it is necessary to process a subset of data corresponding to each layer. Such a subset can be converted to suitably scaled features for a neural network classifier. A pipeline processing system is an appropriate concept for processing the data while drilling through successive layers because the data can be regarded as flowing past a window, with the computations being performed on the subarray of data in the window. The maximum processing speed would be obtained with each successive stage processing the subarray in its own window, but this is yet to be done. However, the laboratory version was designed to be consistent with anticipated pipeline processing. Graphics displays, especially the display of estimated strength class versus depth, result in a significant delay that will require attention when designing a prototype suitable for field use.

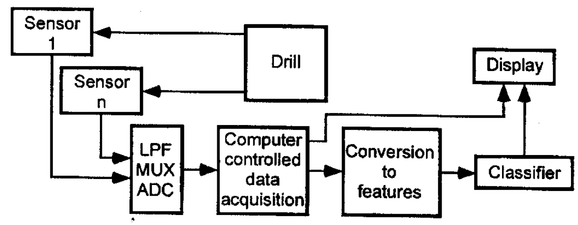

Figure 2.–Drilling data flow.

DESCRIPTION OF DRILL

A full-scale roof drill (figure 3) was customized in the laboratory at SRL to test intelligent drilling systems that could automatically determine the condition of the anchorage strata and optimize drilling efficiency. To accomplish this, the basic design of the roof drill was extensively modified to satisfy several objectives: the capability to sense drilling parameters, allow for remote control, and hold specific parameters constant to reduce drilling variability, as well as drill linearly and reduce machine vibration. The ability to flush cuttings with either water or a vacuum was also desired.

Features of the customized drill are listed below.

1. Sensors were installed to monitor torque, thrust, rotation rate, penetration rate, and position.
2. The drill could be put under automatic control using an industry-standard programmable logic controller (PLC) to hold operator-selected drilling parameters constant.
3. The drill was operated remotely by manual electronic joysticks or by the PLC. A remote-control pendant housed the joysticks and an electronic operator display of drilling parameters.
4. Machine noise was reduced by removing the gear-style drill head and gear pumps and replacing them with a smoothly operating rotor-vane drill head and hydrostatic pump. The hydrostatic pump gave exceptionally good drill head and mast control and had the additional benefit of not building up excessive heat.
5. A mast-type drill was selected to reduce the energy lost when the drill steel rubbed on the sides of the drill hole. (In contrast, arm-type drills result in high energy losses because of rubbing.)
6. The drill was built with intrinsically safe sensors, proportional valves, and wire routing with the expectation that it could be approved by MSHA with just the addition of explosion-proof boxes.
7. A combination drill head allowed rock cuttings produced during drilling to be removed from the hole using either standard water flushing or vacuuming. This allowed the selection and simulation of the different flushing procedures used in the field.

The drill was designed with the mast in a horizontal position so that a 2-m-long concrete block could be drilled by just elevating the block a half-meter or so off the ground into the fixture. (See the section on "Test Results.") Thus, the operator and laboratory equipment were not exposed to the dangers of spalling concrete associated with traditional overhead drilling.

Once the drill was developed, the sensors were calibrated with specially designed linear and rotary dynamometers. When completed, the laboratory drill (figure 3) was used as the testbed for the neural net strata characterization techniques discussed in the section on "Neural Networks."

Standard 2.54- or 3.49-cm-diameter, fluted, vacuum or water-flushed carbide bits can be used, as well as 2.54-cm-diameter, rounded, water-flushed diamond bits. Carbide bits are thought to cut rock by a breaking action, whereas diamond bits cut rock by a smoother grinding action. Diamond bits produce less vibration and have significantly increased bit life and should be selected if vibration and long bit life are concerns. Some research has been conducted earlier on diamond bit types by Sundae et al. (1995).

Carbide bits were chosen because they are the most popular bit used in the field. In the laboratory tests, a standard 2.54-cm-diameter, water-flushed carbide drill bit was mounted on a 1.52-m-long drill rod. To alleviate concerns about decreasing bit sharpness during drilling, a new bit was used for each hole drilled.

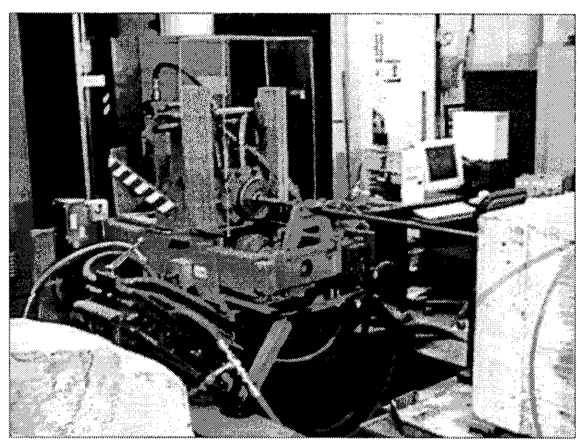
Figure 3.–Laboratory roof drill

A combination locking chuck and drill steel was selected to aid in removing a stuck drill steel. Rod rubbing, although reduced by the linear feed of the mast drill, was not totally eliminated. Incremental errors caused by rod rubbing as the drill steel penetrated the concrete block were further reduced by a detrending algorithm discussed in the section on "Test Results."

DATA ACQUISITION INSTRUMENTS

A laboratory test system was developed to test the strata classification concept. The data flow in through the transducers to the computerized data acquisition system. Some custom routines have been programmed to convert the data into appropriate groups of features for use in the neural network classifier. The data acquisition system will record raw data and data that have been scaled to the desired units. A second mode of operation converts the data to features, which can then be used to evaluate some of the alternative neural network classification techniques.

The system was designed to collect and process sensor data as a test block was being drilled. The raw sensor signals were preprocessed, then delivered to a differential amplifier card. The backplane that hosted the amplifier card was connected to a National Instruments[5,6] AT-MIO-16E-1 input/output (I/O) board mounted in an IBM-compatible computer.

The computer was built with a ASUS[7] P3V4X motherboard and an Intel Pentium III central processing unit (CPU) that operates at 866 MHz. The front-side bus speed of this motherboard is133 MHz. The I/O board uses the Industry Standard Architecture (ISA) interface to the motherboard and a SCXI (signal conditioning extension for instrumentation) bus connector to a National Instruments SCXI-1000 backplane chassis that hosts an eight-channel, simultaneously sampling differential amplifier. A National Instruments SCXI-1301 break-out box was used as the interface to the differential amplifier card (figure 4).

The I/O board collects the following signals into eight channels: torque, thrust, revolutions per minute (rpm), rate of penetration, position, void detection, remote data acquisition pulse, and drill motor rotation pulse. Depending on the channel, the preprocessing flow and sensor type are specified differently. Each measurement channel specification is described below and is shown in figure 5.

- Channel 0 was used for the torque input. From two NOSHOK[8] (model 100.3000.2.1.2.7) pressure transducers positioned before and after the hydraulic drill motor, two signals ranging from 4 to 20 mA were passed through a resistance and then subtracted from each other using a Burr-Brown INA114 integrated circuit. The output voltage approximated the torque on the drill motor.
- Channel 1 was used for the thrust signal. Initially, thrust was approximated with a pressure transducer in the hydraulic line of the thrust cylinder. The inaccuracy of this approximation suggested that another sensing method was needed. A 4,536-kg load cell was then installed in line with the hydraulic thrust cylinder to increase resolution. The current output from the Transducer Techniques[9] (model LBO-10K) load cell current output was converted to voltage, then passed to the differential amplifier card.

Measurements of rpm were acquired using a BEI[10] (model H25) incremental encoder. The quadrature square-wave output signal was sent through a Red Lion[11] bidirectional motion decoder (model BDMD 1000) then through a Red Lion frequency-to-analog voltage converter (model IFMA). The range used was 10 ms (100 Hz) for the minimum response time setting and 50 ms (20 Hz) for the maximum response time setting. The voltage output signals from the converter were then sent through a dual-pole, low-pass filter and voltage divider, then out to channel 2 of the SCXI 1140 I/O board. The corner frequency of the filter was set to 10 Hz and was adjustable to 20 Hz. The I/O board was configured to reference the external ground for this channel and provide a direct current (dc) path for the input bias current to avoid signal drift.

- The rate of penetration signal was delivered to channel 3 of the I/O board. Rate of penetration was determined using a Celesco[12] (model PT9600) cable extension position encoder. The raw quadrature output signal was first sent to a Red Lion bidirectional motion decoder (BDMD 1000) to reduce signal jitter. The signal was then processed by a Red Lion frequency-to-analog voltage converter. The range used was 5 ms (200 Hz) for the minimum response time setting and 20 ms (50 Hz) for the maximum response time setting. The output signals from the converter were then passed through another two-pole, low-pass filter and voltage divider, then onto the SCXI 1140 I/O board. The corner frequency of this low-pass filter was also set to 10 Hz. The SCXI-1140 board configuration was again modified for input from channel 3 after stray capacitances caused saturation, and the signal was lost. After board jumpers were changed to reference the ground, signal response improved.

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[5]Mention of specific products and manufacturers does not imply endorsement by the National Institute for Occupational Safety and Health.
[6]National Instruments, Inc., Austin, TX.
[7]AsusTek Computer, Inc., Newark, CA.
[8]NOSHOK, Inc., Berea, OH.
[9]Transducer Techniques, Inc., Temecula, CA.
[10]BEI Industrial Encoder Division, Goleta, CA.
[11]Red Lion Controls, York, PA.
[12]Celesco Transducer Products, Inc., Canoga Park, PA.

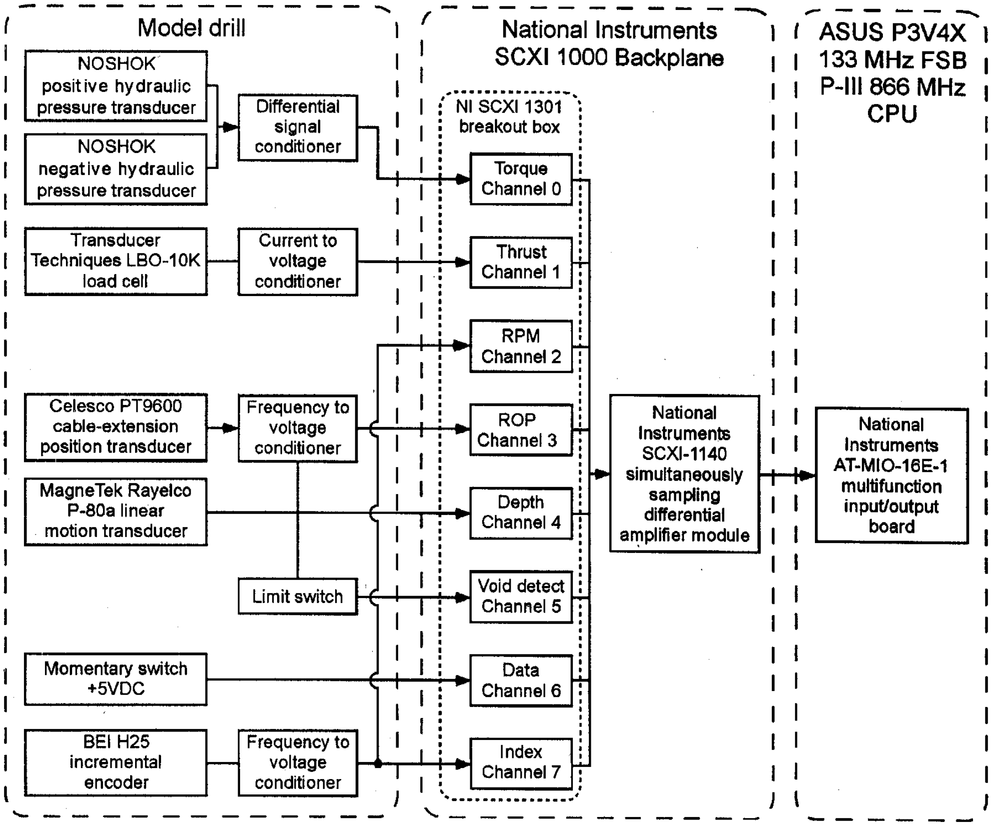

Figure 4.–Overview of data collection process.

• Channel 4 was reserved for the depth of the drilled hole. This position was attained by using the voltage output from a MagneTek Rayelco[13] (model P-80a) linear motion transducer. The cable was attached to the drill head and the instrument to the stationary frame. Output signal was proportional to the relative position of the drill head to the frame.

• Channel 5 was used to indicate a void in the drilled material. If a void is encountered during drilling, the rate of penetration should suddenly increase as resistance to forward motion is removed. The output of the Red Lion bidirectional motion decoder was also routed through a Red Lion limit switch when a signal frequency above the threshold was detected. When normally closed (NC setting), the switch terminals were tied to the supply power "common" terminal and then to the SCXI-1140, channel 5 positive input. This configuration prevents the SCXI-1140 input from floating.

• Provisions were made to send a momentary +5-V dc signal through channel 6 to provide an optional remote trigger for the strata-classifying application software to start recording drilling data. When the "data" switch is in the NC setting, the terminals are tied to the supply power "common" and to the SCXI-1140 channel 6 positive input. This configuration is similar to the "void detect" scheme and also prohibits the SCXI-1140 channel 6 input from floating.

• Channel 7 was used as an index reference to rotation of the drill motor. The BEI H25 incremental encoder used in measuring rpm produces an index signal that is gated at a half-cycle wide. This index signal is brought directly into the SCXI 1140 board, positive channel 7. The encoder provides one +5-V dc, square-wave pulse for every rotation.

Signal calibration of all channels involved an auxiliary test program that used the same data acquisition methods as the strata classifier application written in the graphics program LabView.[14] Signal levels were monitored in the test program and compared graphically to data experimentally collected through each iteration. Polynomials were used to approximate curves in the active range. The polynomial coefficients were then entered into the program software to translate the conditioned signal levels to meaningful values. The calibration of torque, thrust, and rpm were determined by developing signal-

[13]MagneTec, Inc., Los Angeles, CA.

[14]National Instruments, Austin, TX.

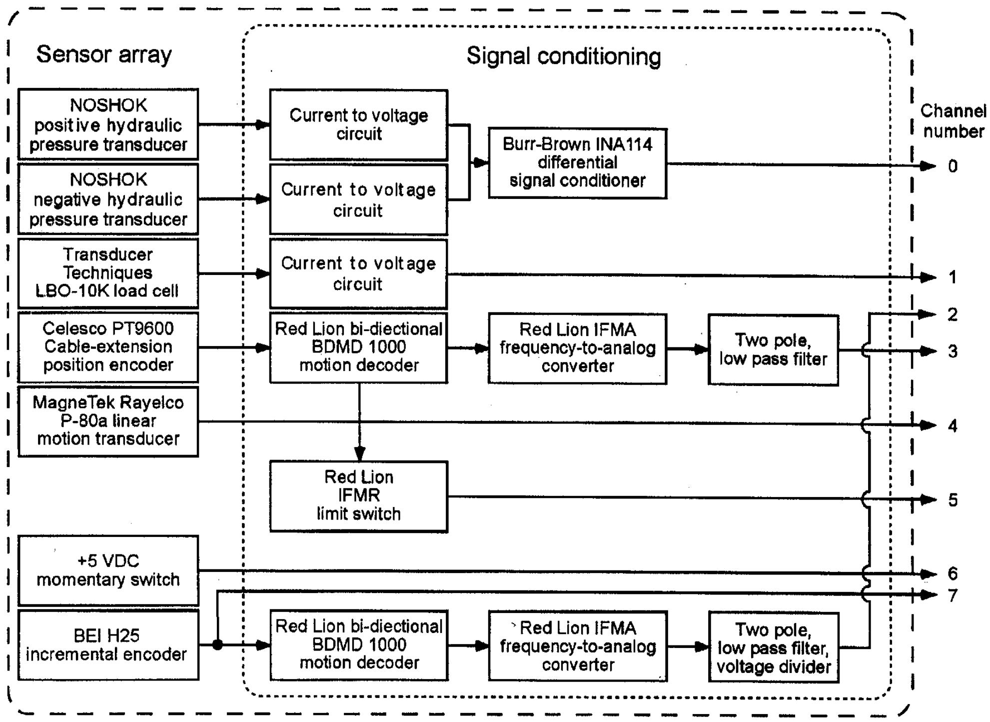

Figure 5.–Preprocessing of individual channel signals.

to-value curves. The reference values were read from a LeBow Products[15] (model 6446-104) thrust torque sensor. The rate of penetration was calibrated by measuring signal outputs as indicated in the test program and comparing them to actual distance traveled per minute. The position signal was linear to the actual distance the drill head traveled. The void-detect frequency was adjusted to compensate for the hysteresis caused by the trip and release points set too close together. The data switch and rpm reference tick signals did not require calibration. Calibration curves for the basic measurements are presented in table 1.

Table 1.—Calibration coefficients

	Torque, N·m	Thrust, N	Rotation rate, rpm	Penetration rate, m/min	Depth of bit, cm
Intercept	10.27	-250.4	0	0.0057	7.3098
Slope	116	3,569	125	0.8719	17.268

PROGRAM ORGANIZATION

An overview of the program structure, emphasizing data flow, is presented in figure 2. The software for the drilling application consisted of three parts.

1. A program to control the data acquisition process and display information, written in LabView.
2. A program to perform the necessary preliminary processing and convert the data into features, written in C language.
3. The classifier, a neural network created from the Data Engine[16] software package, which was compatible with LabView.

Some additional routines separate from the main program were created from Data Engine for training and labeling the neural network. A display panel from LabView is shown in figure 6. The data acquisition process is monitored by means of a graph displayed in the upper left portion of the panel. Eight channels of input data can be displayed as a function of time. The estimate of strength as a function of depth is presented in the lower graph. A few of the input parameter selections are depicted in the upper portion of the panel. A message box that informs the operator when a parameter is out of the normal bounds of operation is in the lower right portion of the panel.

[15]LeBow Products, Troy, MI.
[16]MIT GmbH, Achen, Germany.

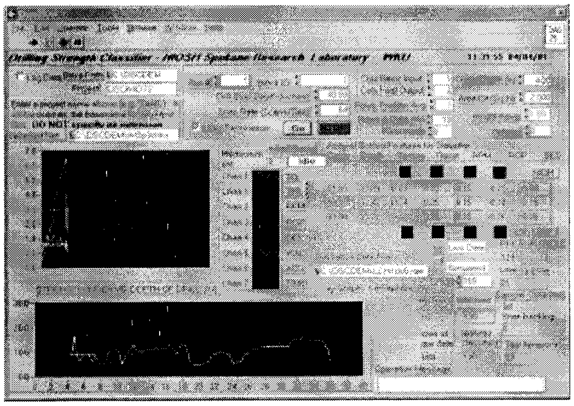

Figure 6.–LabView graphics display screen.

That part of the program coded in the LabView graphics language is rather extensive, requiring over 620 kbyte of memory. The program for preliminary processing, written in C, requires only 68 kbyte in the dynamically linked library (dll) version, which is called from the data acquisition program as a set of call library functions.

The integration of the classifier, based on Data Engine, with the data acquisition program, based on LabView, was completed successfully. However, calling the C language functions from the data acquisition program turned out to be more complicated than expected. The C language functions had been checked out in a console version with a C language driver. However, it was necessary to use several global variables with different names in so-called "exportable wrapper functions" to integrate the C functions with the data acquisition calling program. The attempt to develop a multithreaded version of the program with critical sections to avoid conflicting calls encountered such difficulties that it was abandoned. A functional laboratory program that interfaced with the transducers on the laboratory drill was then used to evaluate and refine the program.

NEURAL NETWORKS

NEURAL NETWORK PACKAGES

Two commercial neural network packages (EZ-1 [Pryor Knowledge Systems 1995] and Data Engine [MIT GmbH 1996a, 1996b]) were evaluated. The EZ-1 is a package of supervised neural network techniques with an accelerator board. The package contains three alternative software programs: (1) a probabilistic neural network (Specht 1988); (2) the RCE neural network (Reilly et al. 1982; Reilly and Cooper 1990), patented as the Self Organizing General Pattern Class Separator and Identifier (Cooper et al. 1982); and (3) PRCE, which is a combination of the probabilistic and the RCE methods.

Data Engine is a package of unsupervised neural network techniques that contains two alternative software programs: (4) Kohonen's self-organizing feature mapping algorithm (Kohonen 1995) and (5) fuzzy cluster means combined with Kohonen's algorithm (Tsao et al. 1994).

All five alternatives were tested to classify geologic strata and appeared to perform satisfactorily, which is an indication of the significant advances in neural network technology in recent years.

The unsupervised learning algorithm of Kohonen (MIT GmbH 1996a; Kohonen 1995) was selected for the crisp classification of layer strength in one of 32 classes. The Data Engine software package was compatible with the LabView software. The competing EZ-1 product, with the NESTOR accelerator board, processes data rapidly, but the software had not been upgraded for newer 32-bit address spaces now used in personal computers.

NEURAL NETWORK TRAINING

A supervised neural network architecture must be trained with known classifications prior to being used to classify new measurements. In the training or learning phase, classification output is compared to known classifications. The error in the output layer must be propagated back through the network in order to adjust weighting. The use of back-propagation of error in the manner of a steepest descent as described in Rumelhart et al. (1986) was a major step forward in neural network technology. However, there have been several subsequent modifications and variations on the iterative procedure, and this procedure can now be done off-line and need not affect the computational time required for classifying in near-real time. Note that linear independence is not essential in most neural network techniques, which would be the case in other mathematical representations.

The drill bit used in training must be of the same type as the bit used in subsequent drilling. Sharpness of the bit should also be monitored. Truth values should be obtained to compare measured parameters to known rock types and strengths. The training set of features required 32 cases for the 32 classes of strength, so interpolation and extrapolation were required. Although it is more common to scale to a specified range of values, the Kohonen method in Data Engine uses normalized input features. The input features, such as penetration rate and SED, are normalized using the following equation.

$$xp = \frac{(x - \mu)}{\sigma} \tag{2}$$

where xp = normalized value,

x = input value,

μ = mean or expected value,

and σ = standard deviation.

The normalized training data set is presented in table 2. The input parameter values for training the Kohonen network on the field data are presented in table 3. A generic artificial neuron is shown in figure 7. Most of the neural network techniques use an activation function, usually sigmoidal, as well as a weighted sum of the several inputs. The Kohonen algorithms are based upon competitive learning and do not require the activation function. The weight for each input to a neuron in the artificial neural network is fixed at the conclusion of the training or learning phase, as indicated in figure 8. It is recommended that a validation test be performed to demonstrate that the classifications are correct. The neural network can then be used to classify the new input data according to the rules frozen into the network, as indicated in figure 9. Only the classification process contributes to the computational time of primary concern during drilling.

Table 2.—Training data set

Strength class	Class mean strength, kPa	Rate of penetration, training 2, m/min	SED, training 2, kPa	Normalized rate of penetration	Normalized SED
0	3,447.4	3.048	6,894.8	3.4000	-1.6393
1	10,342.2	2.5908	20,684.4	2.6987	-1.5340
2	17,237	2.1336	34,474	1.9973	-1.4286
3	24,131.8	1.6764	48,263.6	1.2960	-1.3233
4	31,026.6	1.3716	62,053.2	0.8285	-1.2180
5	37,921.4	1.18872	75,842.8	0.5479	-1.1126
6	44,816.2	0.9144	89,632.4	0.1271	-1.0073
7	51,711	0.73152	103,422	-0.1534	-0.9019
8	58,605.8	0.71628	117,211.6	-0.1768	-0.7966
9	65,500.6	0.70104	131,001.2	-0.2002	-0.6913
10	72,395.4	0.6858	144,790.8	-0.2235	-0.5859
11	79,290.2	0.67056	158,580.4	-0.2469	-0.4806
12	86,185	0.65532	172,370	-0.2703	-0.3753
13	93,079.6	0.64008	186,159.6	-0.2937	-0.2699
14	99,974.6	0.62484	199,949.2	-0.3170	-0.1646
15	106,869.4	0.6096	213,738.8	-0.3404	-0.0593
16	113,764.2	0.59436	227,528.4	-0.3638	0.0461
17	120,659	0.57912	241,318	-0.3872	0.1514
18	127,553.8	0.56388	255,107.6	-0.4106	0.2568
19	134,448.6	0.54864	268,897.2	-0.4339	0.3621
20	141,343.4	0.5334	282,686.8	-0.4573	0.4674
21	148,238.2	0.51816	296,476.4	-0.4807	0.5728
22	155,133	0.50292	310,266	-0.5041	0.6781
23	162,027.8	0.48768	324,055.6	-0.5274	0.7834
24	168,922.6	0.47244	337,845.2	-0.5508	0.8888
25	175,817.4	0.4572	351,634.8	-0.5742	0.9941
26	182,712.2	0.44196	365,424.4	-0.5976	1.0994
27	189,607	0.42672	379,214	-0.6210	1.2048
28	196,501.8	0.41148	393,003.6	-0.6443	1.3101
29	203,396.6	0.39624	406,793.2	-0.6677	1.4155
30	210,291.4	0.381	420,582.8	-0.6911	1.5208
31	230,975.8	0.33528	461,951.6	-0.7612	1.8368
Mean		0.8315	221,495		
Stand. dev.		0.6519	130,910		

Table 3.—Training parameters for network

Input parameter	Input value	Comment
Kohonen parameters:		
No. of features	2	
No. of dimensions	3	
Neurons, 1st dimension	2	Initial, input layer
Neurons, 1st dimension	6	Initial, auto release
Neurons, 3rd dimension	32	Initial, outer layer
Training parameters 1:		
Initial learning rate	0.999	
Initial learning radius	4	
Learning rate factor	0.99	
Learning radius factor	0.995	
Presentation order	0	Sequential
Training parameters 2:		
Cycles	200	
Presentation order	1	Random
Training mode	0	Initial, new parameters

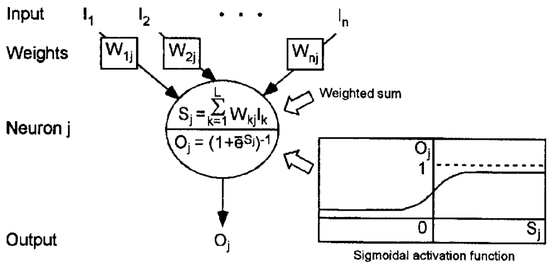

Figure 7.–Example of artificial neuron.

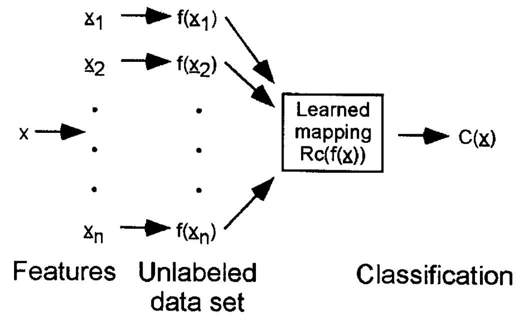

Figure 9.–Neural network classification.

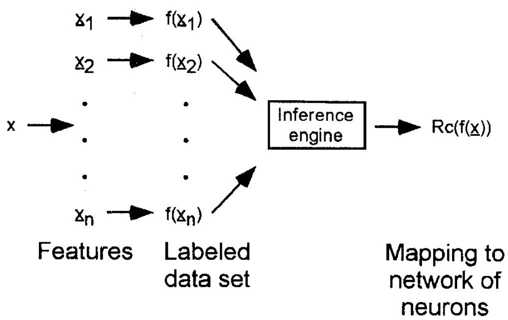

Figure 8.–Neural network training.

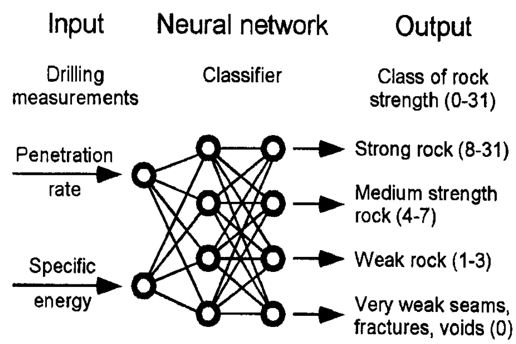

Figure 10.–Mine roof strata characterization.

The conceptual artificial neural network for strata characterization is shown in figure 10. The actual network would have many more neurons, from 64 up to 384 or more, depending on the choice of training parameters. Very strong rock would require a different drilling technique, that is, percussive drilling rather than rotary drilling. Roller cone bits are regarded as percussive. Consequently, the "very strong" rock category is not depicted. For a warning, classifications for the laboratory system were grouped into three color categories— red for weak, yellow for medium, and green for strong.

A brief investigation of alternate feature vectors was conducted early in the project using data from prior research at SRL and geological classes as described by King and Signer (1994) and King et al. (1993). After a neural network was trained on four of the existing data files, it was used to classify data from another file and was found to be successful in discriminating layers. The two features, SED and penetration rate, were found to be satisfactory for classifying different layers into the proper geologic classes. The SED input can vary from one operator to another, but penetration rate can help reduce the effect of that variation on the classification. The full set of features—SED, torque, rotation rate, thrust, and penetration rate, in addition to depth as an independent variable—gave comparable performances at discriminating layers to the set of SED and penetration rate.

The Kohonen approach combined with fuzzy clustering algorithm (alternative 5) automatically identified a start-in class that corresponded to observations made of the drill entering the rock, as indicated in table 4. The rock layers were arbitrarily labeled to compare the patterns of layer classifications in the preliminary analysis. When a drill bit first enters the rock, a lot of visible and audible chatter is observed, and noise in the data is high. When the drill tip is at a depth sufficient to quell the start-in chatter, it is said to have established a collar. In fact, the data obtained prior to reaching the collar depth should not be used in the strength classification, since these data would be misleading. Although the class must still be labeled, that the algorithm could automatically select an appropriate class is impressive.

ROCK STRENGTH

Naturally occurring rock varies considerably in both composition and strength. Rock strength is often classified in 32 classes (Carmichael 1982). Field strength values tend to be lower than laboratory values (Heuze 1980) because a larger volume of rock is likely to have more fractures or joint sets than a laboratory sample (Brady and Brown 1985:86-90). The presence of moisture also can degrade the strength of the rock. Bit geometry and bit sharpness have a significant influence on the strength estimate. Thus, an approximation of rock strength is the best that one can do under these circumstances.

The network was trained on data for which strength was known and labeled. Data from a typical borehole were placed

Table 4.—Alternative parameter sets

Parameter set	From line	To line	Cluster output	Layer label	Classification entropy	Partition coefficient	Proportion exponent
6, all scaled, 4 clusters,	0	2	3	Start in	0.6	0.68	337.4
exponent = 2	3	34	1	A			
	35	49	2	B			
	50	51	4	C			
	52	60	2	B			
	61	79	4	C			
3, depth not scaled, 4 clusters,	0	19	2	Start in	0.43	0.77	556
exponent = 2	20	40	4	A			
	41	64	1	B			
	65	79	3	C			
3, all scaled, 4 clusters,	0	9	3	Start in	0.6	0.69	359.2
exponent = 2	10	34	2	A			
	35	49	1	B			
	50	51	4	C			
	52	60	1	B			
	61	79	4	C			

NOTE: Six-parameter set = depth, torque, thrust, rotation rate, penetration rate, SED. Three-parameter set = depth, penetration rate, SED.

into one of 32 classes of compressive strength. The resultant strength index, or class, is presented as a function of depth in figure 11. There are three layers where the strength index drops below 4, indicating that these layers are weak and not suitable for anchoring. The deeper layers have a strength index greater than 8, which means they are strong enough to provide a good anchor.

If an estimate of compressive strength is required, it can be obtained. However, the strength class was adequate for the purposes of this project. The strength classification is both feasible and useful.

Computational time is a significant consideration for practical implementation. An autoregressive integrated moving average (ARIMA) process (Gelb 1974:92-96) with full overlap of the data window was used in the preliminary smoothing or noise reduction phase of computation, producing a relatively smooth plot. Although the ARIMA computation worked rather well, as indicated in the smooth plot of strength index versus depth in figure 11, it was too slow, requiring about 40 sec to process each window of data. Therefore, it was necessary to replace that approach with a much simpler averaging computation in a preliminary filter. The optional trend evaluation from the first to the current data window was retained.

An autoregressive moving average (ARMA) process could also be used if the trend were removed so that the statistical data would be stationary. The ARMA process was retained as an option, with no overlap of the data window, so that computational speed could be maintained. The software changes increased the speed of the computation. An additional speed increase by a factor of 4 was obtained by an upgrade of the computer hardware, resulting in a net increase in speed by approximately a factor of 10.

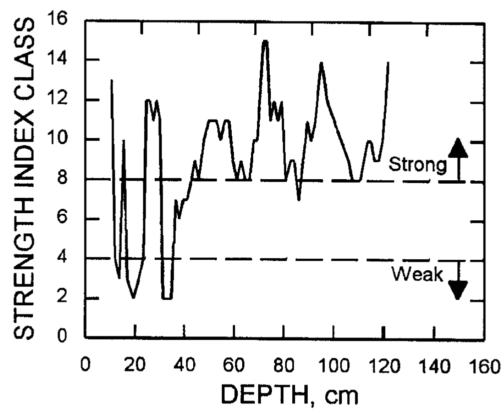

Figure 11.–Strength index versus depth.

LABORATORY TESTS

Concrete blocks containing various types of rock inclusions were constructed to simulate changing mine roof conditions. Plywood form boxes were built in the desired shape, and rebar racks were placed inside to elevate the rock inclusions to the center of the box (figure 12). Each rock inclusion was attached to the rebar with metal bands to hold it in place while the concrete was being poured. A brass rod was inserted along each side of the inclusion in the box to mark the position of the inclusion. Rebar was placed from each corner of the end of the box to the corner at the other end to give the block additional strength. Wire ropes were also placed at each end of the block to enable the block to be picked up easily. Six bags of cement (335 kg) per cubic meter of concrete were used. Samples of the concrete were taken for subsequent strength tests, and slump tests were conducted as well. A sketch of a block with layers of differing strength is shown in figure 13.

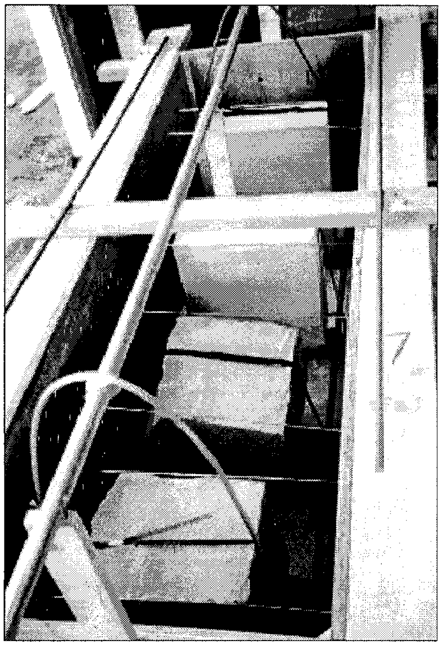

Figure 12.–Test block 7 in form box.

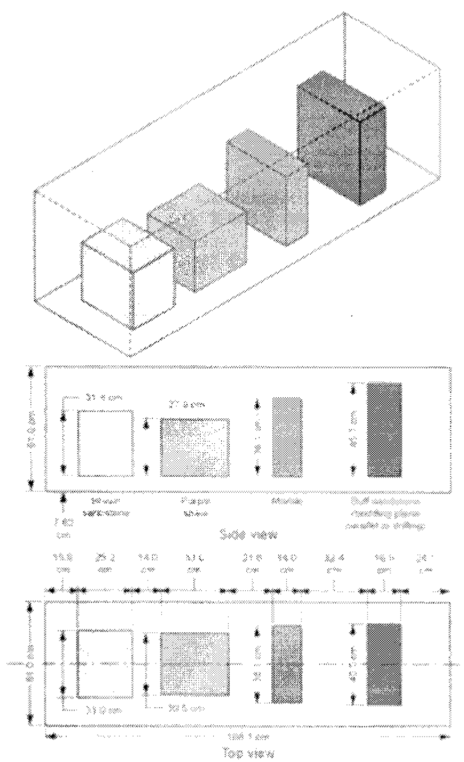

Figure 13.–Block with layers of differing strengths.

A laboratory test demonstrated the capability to detect an inclusion. The results of the test are presented in figure 14. A small change in strength is indicated at a depth of about 20 cm and a larger change at a depth of about 42 cm. The detection of an inclusion from a change in the strength was, to the best of our knowledge, the first successful demonstration of this capability.

Typical drilling data from a borehole were processed. Figure 15 presents SED as a function of the depth of the drill tip. The spurious peak would not be used in estimating rock strength, nor would the data collected before the collar depth is reached (10 cm). A linear upward trend in SED is probably caused by friction as the steel drill shaft bends under thrust and rubs in the borehole. Such trends should be removed from the data before classification (Masters 1993), and that has been done. The effect of removing the trend is shown in figure 16. The control limit lines shown enable a researcher to distinguish random noise between the control lines from significant differences in rock strength.

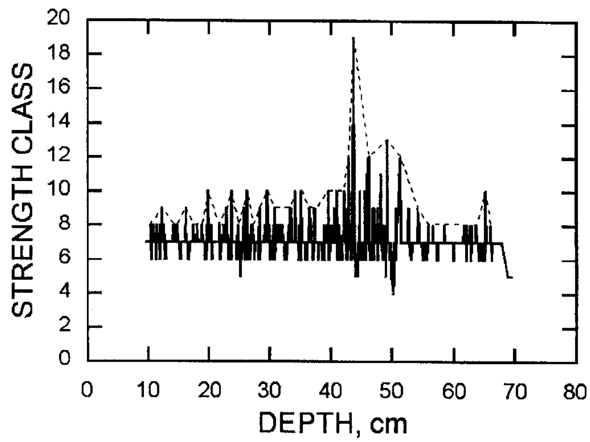

Figure 14.–Detection of inclusion from change in strength.

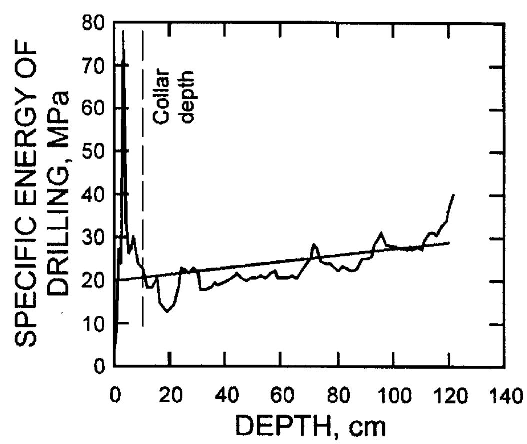

Figure 15.–Specific energy versus depth.

Penetration rate is presented as a function of depth in figure 17. Penetration rate indicates results of drilling, while specific energy represents the work put into the rock. The specific energy input can vary according to the manner of drill operation, but penetration rate should reduce the influence of that variability on estimated strength. Neither feature is without shortcomings, but together they provide a reliable basis for estimating the strength of the rock.

The presence of cracks or voids would indicate a weak layer, which would be dangerous in a mine roof. A strata depth resolution of 2.5 mm is desired to detect fractures.

A record of the strength estimate for rock layers as a function of depth should be retained for viewing after a hole has been drilled. Such a strength estimate will be useful in selecting appropriate bolt lengths and patterns for roof bolting and may also be useful for a preliminary description of the layer being drilled. Informing the operator when one of the measured variables is out of the normal band of operation would also be desirable, since variations would affect the validity of the estimate of the strength of the layer.

There are two problems to be addressed in a subsequent phase of development. The first is the time required to plot the graph of strength class versus depth of drill tip. The integration of the buffered results into the graphing software proved awkward, with the graphing software waiting for data from the buffer. This delayed output of the graph.

The other problem is noise. The drilling process introduces significant amounts of vibrational noise in the frequency band from 1 to 20 Hz. The use of a differential pressure transducer for torque measurement also contributes some oscillatory noise. One partial solution is to reduce the corner frequency of the low-pass filter, which is used to prevent aliasing, to reduce higher frequency noise. In the past, corner frequency has been reduced from 10 to 1 Hz. However, such a reduction could adversely affect performance in terms of response rate and detection of thin layers. The trade-off would be between noise reduction and execution speed and should probably be revisited during the design of a field prototype.

We expect the subsequent development of a field prototype to include the use of a real-time operating system and an appropriate set of accurate, reliable, and robust transducers. The software would be rewritten for a real-time operating system. A second microprocessor could be used to process the buffered output for the graph, which would free the main microprocessor for the rest of the calculations and speed up overall processing.

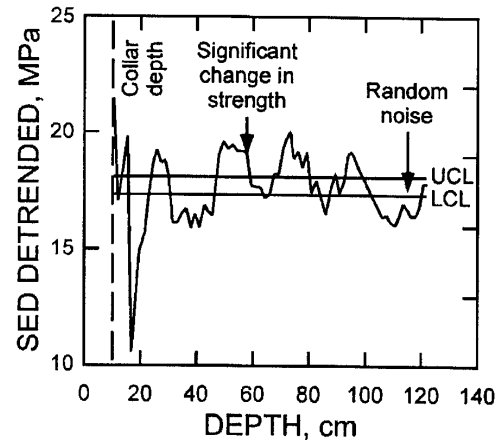

Figure 16.–SED with detrending.

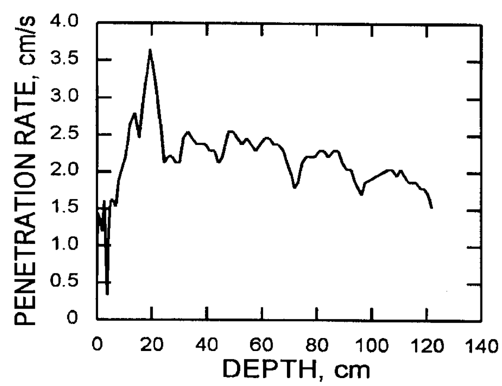

Figure 17.–Penetration rate versus depth.

In the future, a flat-faced, wear-resistant, diamond bit should improve detection of the interface between rock types, especially if that interface is perpendicular to the bit. In the field, the interface is unlikely to be perfectly horizontal.

APPLICATIONS AND EXTENSIONS

The technology described above has other drilling applications and could be used in other engineering research projects. Drilling holes for blasting in mining and construction is a possible application, since rock strength is an important consideration in efficient blasting (Hemphill 1981). The benefits of using microprocessor-based systems to monitor blast hole drilling have been described by Peck et al. (1988). Drilling exploration core is another likely area of application.

Drilling for oil is a feasible application, although additional measurements, such as resistivity, may be needed for geological analysis (McCormick 1991). A roller cone bit is used in drilling for oil. The vibrations of the drill string have been utilized, via a wireless transmission system, to refine control of the drilling process (Henneuse 1992).

In the future, it is expected that a remote-control system will be developed that would allow a drill operator to be positioned in a safer location (figure 18) and less likely to be under a roof fall. Tele-robotic core drilling is expected to develop along a parallel path (figure 19). Both remote-control tasks could serve as research projects.

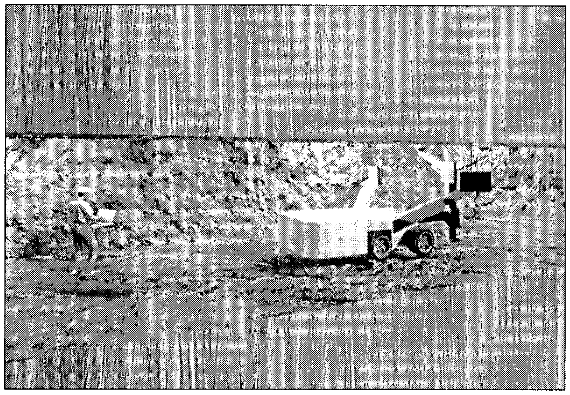

Figure 18.–Tele-robotic roof drilling.

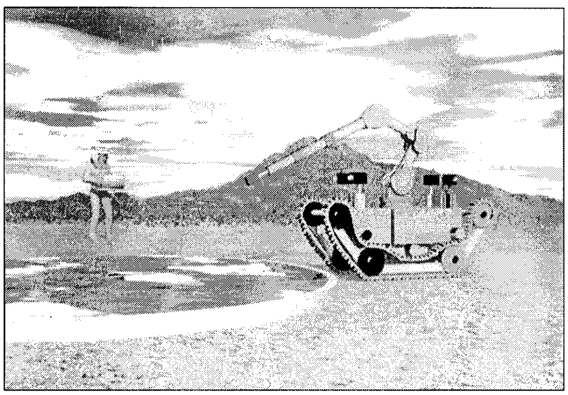

Figure 19.–Tele-robotic core drilling.

Detecting drill steel chatter would be very helpful because the chatter could warn of trouble. The chatter associated with a misaligned or damaged drill bit is of particular interest to a drill operator, especially a remote operator. An accelerometer at the chuck or the base of the drill could be used to measure vibrational accelerations, and either statistical or neural network techniques could be used to distinguish between tolerable and intolerable chatter. Geologists may be interested in measuring resistivity and electric potential to aid in the identification of strata. The temperature of the drill bit and drill bit wear might also be monitored (Choi and Ly 1992).

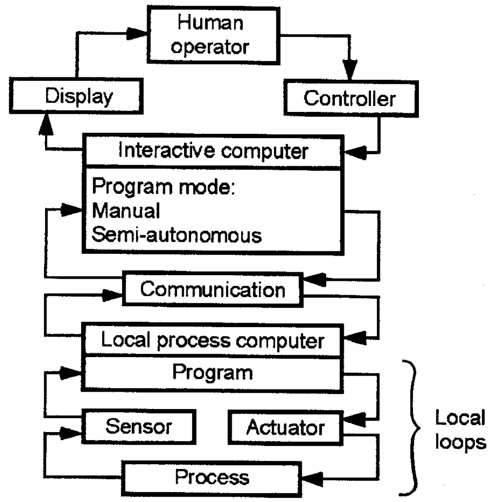

Figure 20.–Supervisory remote control.

Better measurements of the ultimate compressive strength of rock in the field should enable researchers to retrain the classifier for better performance. Type of drill, bit geometry, bit sharpness, rock stiffness, and the amount of fracturing in the rock are also important factors. The borehole penetrometer, described in Unrug et al. (2001), appears to be appropriate for testing rock strength in a mine. Rock material under the indenter of the penetrometer fails in shear because of triaxial conditions of loading. Some rock mass index properties may be useful. The number of fractures or joint sets in a drill hole could be used to determine rock quality (Franklin et al. 1971). A preliminary calculation of rock quality was included in this drill monitoring program, but was not validated before the project ended.

Supervisory remote control might be of interest where continuous remote control is not entirely satisfactory (Sheridan 1992:86-90). In the supervisory remote control paradigm, some necessary and routine control functions could be automated at a remote drill, but the capability to modify the task schedule, monitor progress, and interrupt in an emergency would be retained by the operator (figure 20).

A group of university researchers has expressed an interest in continuing the development of the drill monitoring system for use in mining, while another university research group has expressed interest in the feasibility of the system for extraterrestrial remote control applications using percussive drilling (Eustes et al. 1999).

CONCLUSIONS

A prototype drill monitoring system with a strata strength classifier was developed and demonstrated at SRL. The goal was to characterize the strength of the strata in a timely fashion so that the information can be used in the field, preferably while drilling is still underway. Drilling measurements for each roof bolt hole can be processed and the essential information displayed for the operator to monitor in near-real time. To do this, it is necessary to measure drilling parameters—torque, rotation rate, thrust, penetration rate, and the depth of drill tip penetration—and estimate the strength of the layers being drilled. Neural network technology can classify strata according to its estimated strength.

The Committee on Advanced Drilling Technologies of the National Research Council regards sensing and evaluating rock properties while drilling as a revolutionary improvement (National Research Council 1994). Detecting a different layer by the change in rock strength was, to the best of our knowledge, the first successful demonstration of this capability. The application of neural network technology to strength classification of the material being drilled is new, as is estimating the strength of rock layers in near-real time. The concept has been proven in principle, and a patent is pending (Utt 2000).

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