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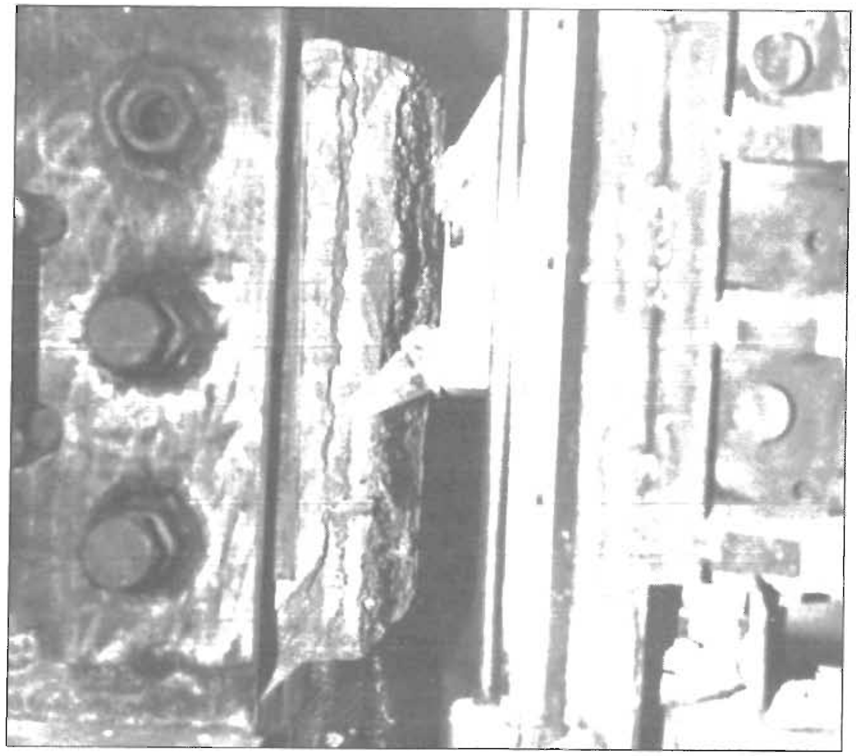

UNITED STATES DEPARTMENT OF THE INTERIOR

BUREAU OF MINES

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Cover: Conical bit cutting into coal block on linear-cutting apparatus. USBM researchers used this apparatus to collect data as part of a study on developing a method to distinguish between coal cutting and rock cutting in computer-assisted mining. Photo by G. L. Mowrey, Pittsburgh Research Center, U.S. Bureau of Mines.

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UNIT OF MEASURE ABBREVIATIONS USED IN THIS REPORT

Hz	hertz	lb	pound
in	inch	pct	percent
in/s	inch per second	s	second
kHz	kilohertz		

RECENT PROGRESS IN DISCRIMINATING BETWEEN COAL CUTTING AND ROCK CUTTING WITH ADAPTIVE SIGNAL PROCESSING TECHNIQUES

By Michael J. Pazuchanics[1] and Gary L. Mowrey[1]

ABSTRACT

This report documents the current status of the U.S. Bureau of Mines ongoing investigation of the use of adaptive signal discrimination (ASD) systems to distinguish between cutting coal and cutting rock. Cutting-tool forces and vibrations were measured in the laboratory using both conical bits and roller cutters in a linear-cutting apparatus for several material samples and two cutting directions. A number of ASD systems consisting of one or more signal classifiers were trained and tested to study how data window size, type of signal feature, and combining (polling) of classifier results influence system performance. The results show that ASD system recognition rates can be improved by increasing data window size, removing air-cutting portions from the signal data, overlapping data windows, and combining (fusing) information at various levels of ASD system operation.

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INTRODUCTION

For a number of years, the U.S. Bureau of Mines has been engaged in developing technology to permit the teleoperation and computer-assisted operation of mining machines in underground coal mining. This work is done in support of the Bureau's goal to reduce production costs and improve methods of recovering coal while enhancing the safety of the Nation's miners. One thrust of that effort deals with the problem of in-seam guidance, i.e., positioning the cutter head of a mining machine within the desired boundaries of a coal seam. An important element necessary for in-seam guidance is a coal interface detector (CID) system.

In recent years, most CID improvements have come about through extensive use of signal processing, which was made possible by the dramatic increase in computational power of ever-smaller computers. There are several examples. Sensor work is being conducted in the United Kingdom on pick force, using real-time correlation of cutting force signals with a reference cutting force signature (*1*).[2] In Germany, research has been done on machine vibration, using fast Fourier transformation of incoming vibration data every 0.1 s (*2*). In the United States, the Bureau has studied radar [automatic removal of undesired reflections (*3*)] and cutter tool force and vibration (application of adaptive signal techniques). The latter is the subject of this report.

The basis of force and vibrational CID is that cutting-tool force and induced-vibration signals (mechanical, acoustical, and seismic) are related to the mechanics of the cutting process—mechanical properties of the geologic material being cut, mining-machine type, cutting-tool condition, and the manner in which the coal is being cut (e.g., how each operator cuts the coal). Evidence exists from both the field and laboratory to support this hypothesis. Machine operators have reported that when sitting in the cab of continuous miners they were able to feel the difference between the machine cutting coal, top (roof), and bottom (floor).[3] General Electric performed a series of laboratory investigations and established that the vibrations of cutting tools and tool holders are related to the mechanics of the cutting process.[4] Furthermore, they showed that the basic character of vibrations induced by cutting of coal appeared different from those induced by the cutting of shale or sandstone.

A major problem with cutting-tool force and vibration signals obtained from the machines is their complex nature due to the variability of the geology, mining-machine types, and operational considerations. The Bureau proceeded to reduce the sources of variability by first acquiring less complex cutting data, i.e., data collected in the laboratory under controlled conditions. Cutting-tool force and vibration signals were measured as a linear-cutting apparatus (LCA) made constant-depth cuts in specially prepared specimens of coal and mine rock. The cutting of a specimen by a conical bit is shown schematically in figure 1. The Bureau then began to investigate the use of ASD systems to help classify these signals.

In 1990, Bureau work on adaptive signal discrimination (ASD) systems using LCA data provided the following observations (*4*):

- Of the four conventional classifiers investigated for use in ASD systems (linear discriminant, K-nearest neighbor, empirical Bayesian, minimum distance), no single classifier consistently performed better than the others.
- In most cases, system recognition rates were seen to improve as the number of signal features used by the system increased from one to five features. Also, the most significant improvement usually occurred within the first three features.
- Classifiers using cut force or normal force performed better than those using the horizontal-force component.
- The problem of discriminating between coal cutting and shale cutting was more difficult than discriminating between coal cutting and sandstone cutting.
- Best ASD system performance was accomplished by voting among the best three classifiers, followed by voting among the three force components.
- For the coal-shale case, a reduction in data window size, i.e., length of signal examined—4.16 to 0.51 in—resulted in a decrease in system recognition rate from 93 pct to 73 pct. This decrease was attributed to cutting brittle, nonhomogeneous materials which frequently have irregular surfaces with depressions or voids whose dimensions equal or exceed short data windows. Signals corresponding to intervals during which the bit lost contact with the sample (cutting air) appeared in both coal and shale data sets, thereby resulting in poor ASD system training and recognition rates.

The objective of the latest investigation was to first confirm the Bureau's findings of 1990 mentioned above, and then to explore means of improving ASD system performance. Additional data sets were acquired by measuring cutting-tool forces and vibrations in the laboratory for

[2]Italic numbers in parentheses refer to items in the list of references at the end of this report.

[3]Bendix Corp. Sensory Feedback for Remote Control of a Continuous Miner. Contract DOE DE-AC22-76ET-12458, formerly BuMines contract HO366057.

[4]General Electric Co. A Vibration Sensor for Horizon Control in Automated Longwall Mining. Contract DOE ET-75-C-01-9015, formerly BuMines HO155120.

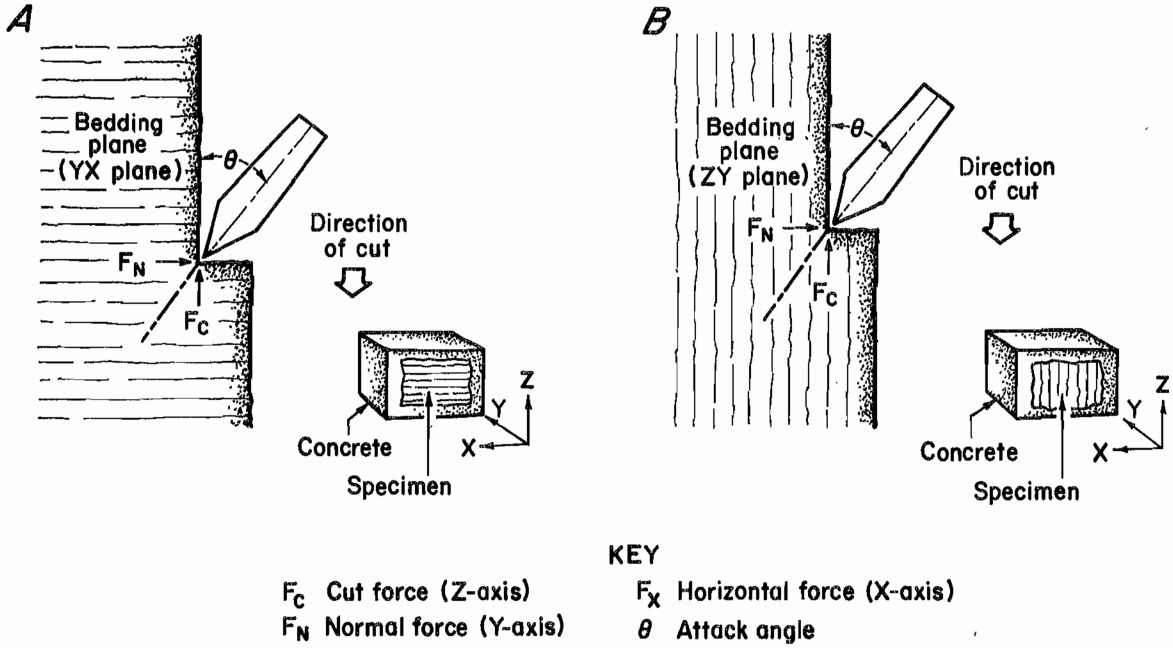

Figure 1.—Schematic of conical bit cutting specimen. *A*, Cutting perpendicular to the bedding plane; *B*, cutting parallel to the bedding plane.

several coal and rock samples for both conical and roller cutters on the LCA. Cuts were made in two directions, perpendicular and parallel to the bedding plane of the materials. A number of ASD systems were trained and tested to study how data window size (number of consecutive data points being examined), type of signal feature, combining or fusing cutting information, and cutter-tool type influence system performance. Both conventional and neural-network classifiers were investigated. Since a Bureau study (*5*) found that a coal-shale combination is the most likely to be encountered underground, emphasis was placed on working with those materials.

This report documents the status of the Bureau's CID sensor program in the area of tool cutting forces and tool cutting vibrations. In particular, it presents results from the Bureau's ongoing investigation of the use of ASD systems to distinguish between cutting coal and cutting mine rock.

ADAPTIVE SIGNAL DISCRIMINATION SYSTEM

The term "adaptive signal discrimination system" as used in this report denotes any system that extracts relevant features from sensor signals and provides signal trace classification capability. The term "adaptive" refers to the system having the capability of "changing," via training, to a given situation (not necessarily in real time). The ASD system is initially trained on a set of data originating from known conditions (e.g., class 1: "cutting coal" and class 2: "cutting rock"). It extracts a number of features from the data and then trains one or more signal classifiers. The classifier(s) are then used to identify unknown signals and can be used until the mining lithology changes significantly.

The recognition rates obtained for a given situation depend upon the nature of the problem (inherent separability of the classes being examined), the quality of signals, the quantity of signals, the subset of features used to represent the signals, and the type of classifiers used (based on sample size and probability distribution).

As in prior Bureau work, the software package ICEPAK[5] was used to implement the basic ASD system tasks: signal feature extraction, classifier training, and classification of unknown signals using conventional classifiers (*6*). The features automatically extracted by ICEPAK included various parameters in the time, frequency, phase, cepstral,[6] and autocorrelation domains (e.g., counting the number of peaks above different thresholds,

[5]Reference to specific products does not imply endorsement by the U.S. Bureau of Mines.

[6]The term "cepstral" is associated with the term "cepstrum," which is the inverse Fourier transform of the log of the power spectrum of a time-series signal.

bands of power spectra, and peak rise and/or fall times). Conventional classifiers used in the ASD's included the linear discriminant function, K-nearest neighbor, empirical Bayesian, and minimum distance. Each classifier is based on a different mathematical approach, and each is specially suited to particular situations. During the training mode, signal features that best differentiate the classes are obtained and are ranked in order of significance. The user selects a number of the highest ranked features and type of classifier to be used. To obtain reasonable classifier recognition rates, the data used for training must have a minimum of 10 signals per feature extracted per class.

In addition to the ASD systems that used conventional classifiers, a number of ASD systems utilized neural-network classifiers. As stated by Aziz and Wong (*7*) the neural-network model consists of layers of neurons connected by internal connections that are associated with weight matrices. The input and output layers serve as the communication link to the outside world.

Neural networks exhibit several attributes that offer the potential for better performing ASD systems. The advantage of the neural-network approach, with respect to the current applications, is its ability to generalize patterns through its associative memory. The associative memory of the network is the result of the correct weight matrices between the layers of neurons. With the associative memory, the network can retrieve a complete fact given a partial fact. A fact here refers to an input-output pattern. The presence of a second or third layer creates additional weight matrices that improve the ability of the network to generalize patterns.

The network is trained to become a pattern-matching engine through a supervised learning scheme known as back-propagation (*8*). This training process includes presenting input-output pairs to the network repeatedly, propagating the error signals backward through the network, and modifying the network's internal connections to reduce the errors. The objective of reducing the error by updating the weight matrices is achieved through the steepest descent-minimization method. The training is complete when the network reaches stochastic equilibrium within a specified tolerance. The tolerance parameter is the measure that quantifies the congruence between the network output and the training patterns.

TEST HARDWARE AND PROCEDURE

The Bureau's LCA was used to acquire cutting signals on coal and mine-rock materials under controlled conditions. A complete description of the LCA along with its instrumentation can be found in the literature (*4*). The data from these tests, which simulate ideal cutting conditions, helped determine the range of performance that may be expected from an ASD system and to give some insight into how its performance can be improved.

The test materials were made up from coal and mine-rock samples from three different sites—the Bureau's mine (Bruceton, PA), a coal yard (southern Pennsylvania), and Eastern Mingo Mine, Marrowbone Development Co. (southern West Virginia). Each sample, typically measuring 16 by 10 by 10 in, was cast in an 18-in-cube mold of concrete for mounting in the LCA. The sample was held in place on the fixture by steel plates and large set screws. During the tests, researchers did not attempt to simulate in situ stresses, but only ensured sufficient confinement to prevent block movement during cutting.

Prior to actual tests, the front surface of the block was "squared" by taking one row of cuts (0.5 in deep, 1 in apart) across the sample face. Test cuts were made using either a Kennametal U70 conical bit or a custom-made roller-disk cutter. Tests were run under the following conditions:

1. Constant depth of cut.
2. Constant 1-in intergroove (cut) spacing.
3. Repeated cuts made in the furrows of prior cuts.
4. Cuts made across (perpendicular) or along (parallel) the bedding plane of the sample.
5. Angle of attack of 37.5° (conical bit).
6. Cutter tool speed of approximately 100 in/s.

Data acquisition was initiated just prior to cutter contact with the block. All data were recorded on magnetic tape while cutting the encapsulating material and coal sample.

DATA ANALYSIS

A number of cases representing different operating conditions were run to study their effects on ASD system performance. The parameters being varied were as follows:

- Type of geologic material: three coals, two shales, one soapstone.
- Type of cutting tool: conical bit, roller-disk cutter.
- Type of cutting bit signal: force, vibration.
- Data window size: 0.25 to 1.0 in bit travel.
- Depth of cut: 0.125, 0.25, 0.5 in.
- Cut direction across or along bedding plane of sample.

It was not possible to collect data for all combinations of the above parameters for a number of reasons, including a damaged test block, too thin material specimen to ensure quality cutting data, and cutting forces sometimes beyond the range of the dynamometer.

For each case, ASD system training and testing proceeded in the same manner. Force or vibration data associated with a number of adjacent cuts made over several layers of test block were selected for processing. The signals comprising the data set were extracted from the innermost portion of each cutting pass across the test block and did not include any concrete material.[7]

Training for the ASD system consisted of defining the two classes of signals, namely "cutting coal" and "cutting rock." Then all digitized data were analyzed using ICEPAK for grouping into these two classes. Next, ICEPAK performed a feature extraction analysis based on these two classes. ICEPAK extracted a total of 108 features during the analysis and created a feature file for each class. These two feature files were then normalized via zero mean unit variance mapping (*6*). In order to provide a large feature set for training, the normalized files were not split into two independent sets, one for training and one for evaluation, as was the usual procedure by ICEPAK. The program then rank-ordered the features in terms of the best feature for classification. The best features, up to five, were used to train the ASD signal classifiers.

In the next step, the ASD classifier was tested with a set of unknown signals for cuts beyond that portion of the test block where training data were collected. Prior to testing, the same features as those used to train the classifier were extracted from the unknown signals. ASD system performance was expressed in terms of a recognition rate, i.e., the percentage of test signals that were identified correctly.

DISCUSSION

COMBINING CLASSIFIER RESULTS (VOTING)

Since current and prior work (*4*) demonstrated that no single classifier consistently performed better than the others, an improvement in ASD system performance was sought by combining or pooling results from several signal classifiers. Figure 2 illustrates the structure of an ASD system employing multiple signal classifiers. After each classifier was trained, as described above, features from test signals were extracted, then introduced at level 1. At each subsequent level, outputs were combined through majority voting to get a final decision at level 3. Note that at level 2 each classifier was assigned a voting weight corresponding to its performance during training, whereas at level 3 each axis was given a voting weight of 1. Twenty-two cases were performed as shown in figure 2, using six data sets. The data sets were associated with cutting across the bedding plane of different coal and mine-rock specimens. Training and test sets typically corresponded to 75 and 25 in of tool travel, respectively. The effects of combining information through majority voting can be seen in tables 1 and 2. Table 1 presents statistics for the 22 cases at each level of ASD system operation—level 1 before voting, level 2 after voting by classifiers, and level 3 after voting by axis. Table 2 shows individual ASD system performance, level 3, for all cases. Results of this exercise were as follows:

- For all three force or vibration axes, overall level 2 mean performance was greater and dispersion was less than at level 1.
- Overall level 3 performance was better, in terms of high mean performance and lowest dispersion, than level 2 performance.
- At levels 1 and 2, X-axis (horizontal axis) performance was lowest.

[7]Because of an upgrade in data acquisition equipment during cutting tests, initial conical bit cutting data were digitized at 11,200 samples per second versus 20,000 samples per second for subsequent conical and roller cutter data. The net result of using the new equipment with its higher sampling rate was a larger number of data points per inch of tool travel.

Table 1.—Overall performance (percent) at each level of ASD operation (22 cases)

	Mean	Variance	Standard deviation
Level 1: all classifiers:			
Z	77.5	165.4	12.8
Y	73.4	114.6	10.7
X	67.9	137.0	11.7
Level 2: vote by classifier:			
Z	82.1	136.4	11.6
Y	76.7	88.9	9.4
X	72.4	123.2	11.1
Level 3: vote by axis	81.3	84.5	9.1

DATA WINDOW SIZE

The influence of data window size on ASD system performance can be seen in table 2. Note that the results in table 2 were taken from level 3 of figure 2; however, level 1 and 2 results reflected the same window size effects.

There were 11 instances in which data window size was doubled—from 32 to 64 points for the conical tool and from 64 to 128 points for the roller cutter tool. For either tool, these windows corresponded to tool travel paths of 0.25 in and 0.5 in, respectively. On 10 occasions, ASD system recognition rates improved as data window size increased and in one instance the recognition rate decreased.

Table 2.—ASD system performance using conical and roller tool data (voting, five features, four classifiers, three axes)

Tool and data set	Material	Depth of cut, in	Location	Force, pct		Vibration, pct	
				32-point window[1]	64-point window[2]	32-point window[1]	64-point window[2]
Conical bit:							
1	Coal-shale	0.5	Coal yard . .	70.8	81.2	68.7	70.8
2	. . do. . . .	.25	. . do.	100.0	95.0	92.5	97.5
3	. . do. . . .	.25	PRC	65.9	77.2	NA	NA
Roller cutter:							
4	. . do. . .	.25	Coal yard . .	75.0	83.6	75.8	80.3
5	Soapstone	.25	Marrowbone	87.5	89.2	75.8	83.9
6	. . do. . . .	.125	. . do.	78.5	85.7	78.5	80.3

NA Not available.
PRC Pittsburgh Research Center.
[1]0.25-in tool travel.
[2]0.5-in tool travel.

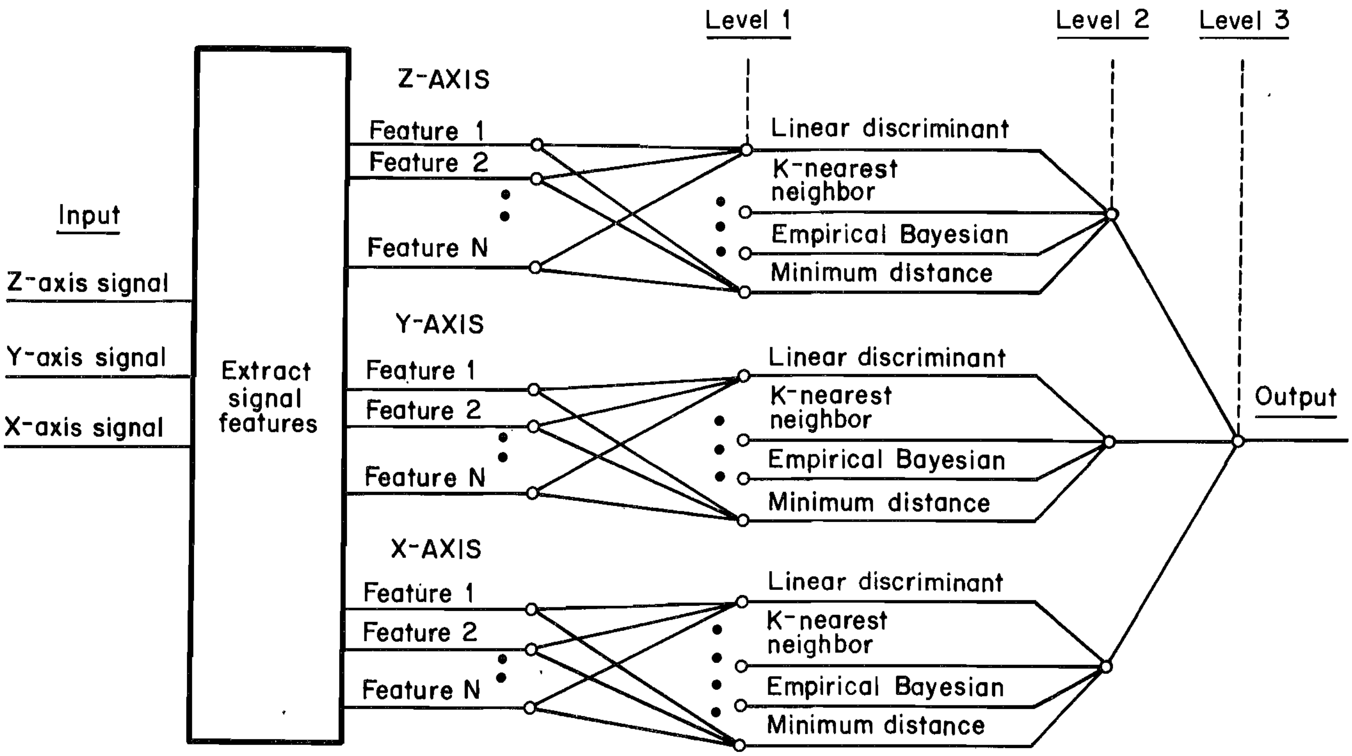

Figure 2.—Architecture of ASD system with conventional classifiers.

SIGNAL TRACES WITHOUT "AIR CUTTING"

In prior Bureau work (*4*), poor ASD system performance using short signal durations (representing only 0.25 to 0.5 in of cutter-tool travel) was attributed to "cutting air," i.e., the cutter tool passing through surface cavities or voids. Signals corresponding to intervals during which the bit lost contact with the sample (cutting air) appeared in both classes, thus resulting in poor classification accuracy. At that time it was suggested that the problem might be resolved by either improving data quality (i.e., remove "cutting air" segments from signal traces) or operating as a three-class classification problem (coal-rock-air). In effect, both solutions were different implementations of the same solution in that success was dependent upon the system's ability to identify and remove cutting air portions of a signal.

One attempt at improving data quality concluded with positive results. A computer program was written to remove four or more consecutive data points associated with air cutting (based upon a user-defined amplitude threshold value) from a signal and then to extract, from the remaining signal, only those data blocks (32 consecutive points that corresponded to 0.25 in of continuous tool travel) associated with material cutting. An example of preprocessing effects on a coal-cutting signal can be seen in figure 3. Table 3 shows the results for two cases of ASD system testing with preprocessed data using force data sets 1 and 3 (32-point window). One negative aspect of this approach to the problem is that a large percentage of the original signal may be removed (50 to 60 pct for the two cases run). This in itself is not a problem if the cutting air portions consist of many short "pieces" (0.25 to 0.50 in) interdispersed among a series of coal or rock classifications, since they can be assigned to the same classes (adjacent coal-cutting or rock-cutting designated classes) with a reasonable degree of confidence. On the other hand, if the removed portions are large "pieces" (1.0 in or more) then the probability of classifying them correctly, using the same procedure, will be low.

Table 3.—Effect of preprocessed data on ASD system performance, (percent) (voting, five features, four classifiers, three axes)

Data set	1	3
Processed data (without air cutting)	86.9	73.0
Unprocessed data (with air cutting)	70.8	65.9
Improvement	16.1	7.1

NEURAL-NETWORK CLASSIFIER

Whereas ASD systems using conventional classifiers, figure 2, combined information at two discrete levels (majority voting by classifiers at level 2, majority voting by axis at level 3), ASD systems consisting of neural-network classifiers permitted a more intricate fusing of information, i.e., because of structure, each input is fed to every other node at every level. A neural-network-based ASD system that was investigated is illustrated in figure 4. It consisted of three levels and was implemented as a back-propagation network with three layers—input, hidden, and output.

Neural-network ASD systems were trained and tested for three cases using force data sets 1, 3, and 4 (32-point window). In this exercise, input to the systems consisted of the first three highest ranked signal features from Z-axis (cut) and Y-axis (normal) data. Note that the features selected were based upon earlier findings relative to best features (*4*) and best cutting-tool forces (table 1). Table 4 shows that for all cases, the ASD systems using neural-network classifiers outperformed those using conventional classifiers. Although the results were positive, a large portion of the improvement in performance was attributed to not using horizontal force data.

Table 4.—ASD system performance (percent) using neural-network classifiers versus conventional classifiers

Data set	1	3	4
Neural-network classifiers	83.3	72.4	85.0
Conventional classifiers[1]	70.8	65.9	75.0
Improvement	12.5	5.5	10.0

[1]Performance results extracted from table 2 (force data, 32-point window).

At this point, a decision was made to continue the investigation with neural-network ASD systems because they (1) appeared to perform as well or better than ASD systems with conventional classifiers, (2) allowed more complex logic structures, and (3) were easier to implement.

MULTIPLE MOVING WINDOWS

As an alternative to removing "air cutting" portions of the signal trace to improve ASD system performance, the use of multiple moving windows was explored. The benefits resulting from their use included

1. Higher performance derived from large window size (0.5 to 1.0 in) since air cutting constituted a smaller proportion of the window.
2. System decision at each 0.25 in of tool travel.

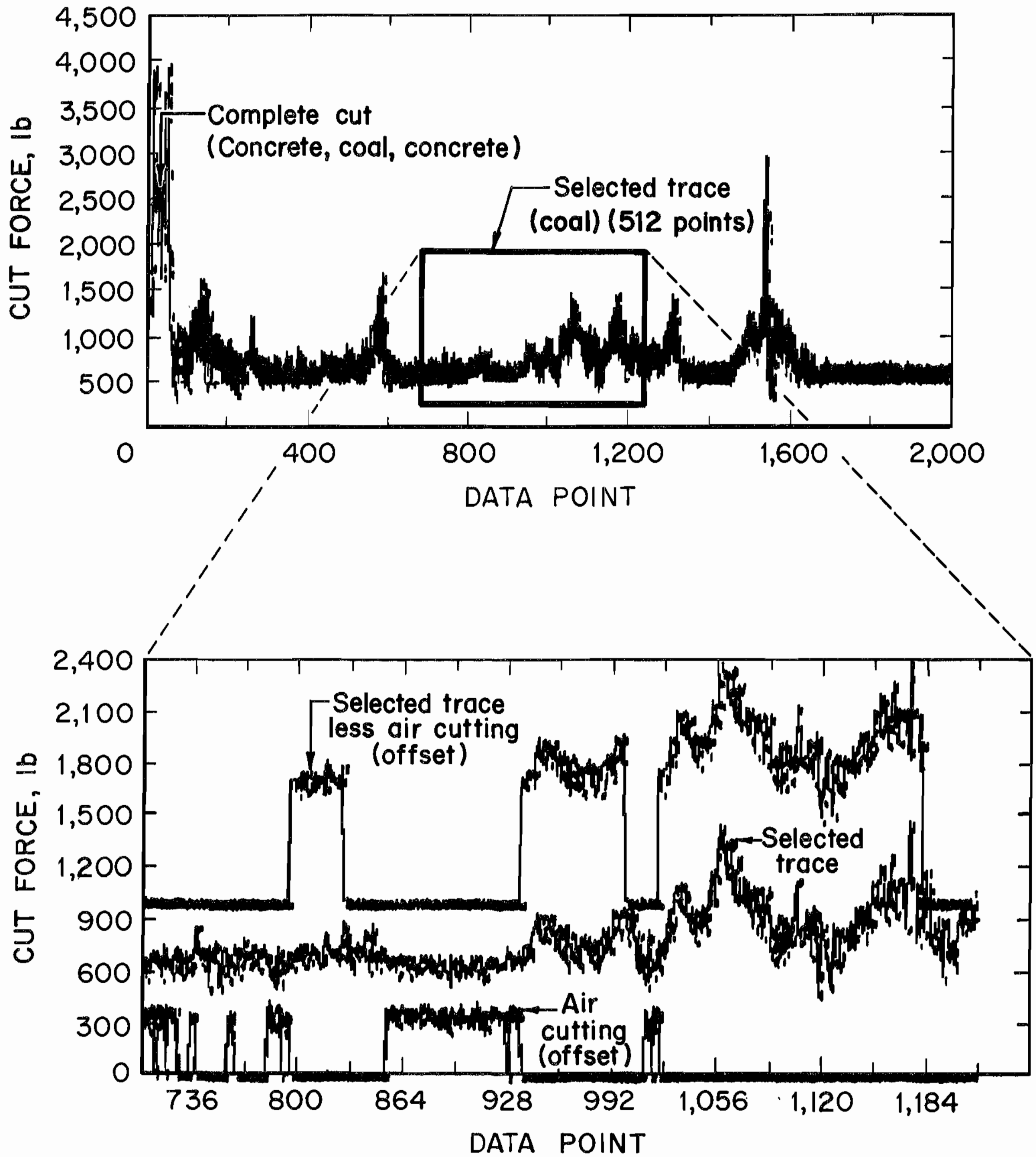

Figure 3.—Example of preprocessed force-cutting signal (conical bit, coal).

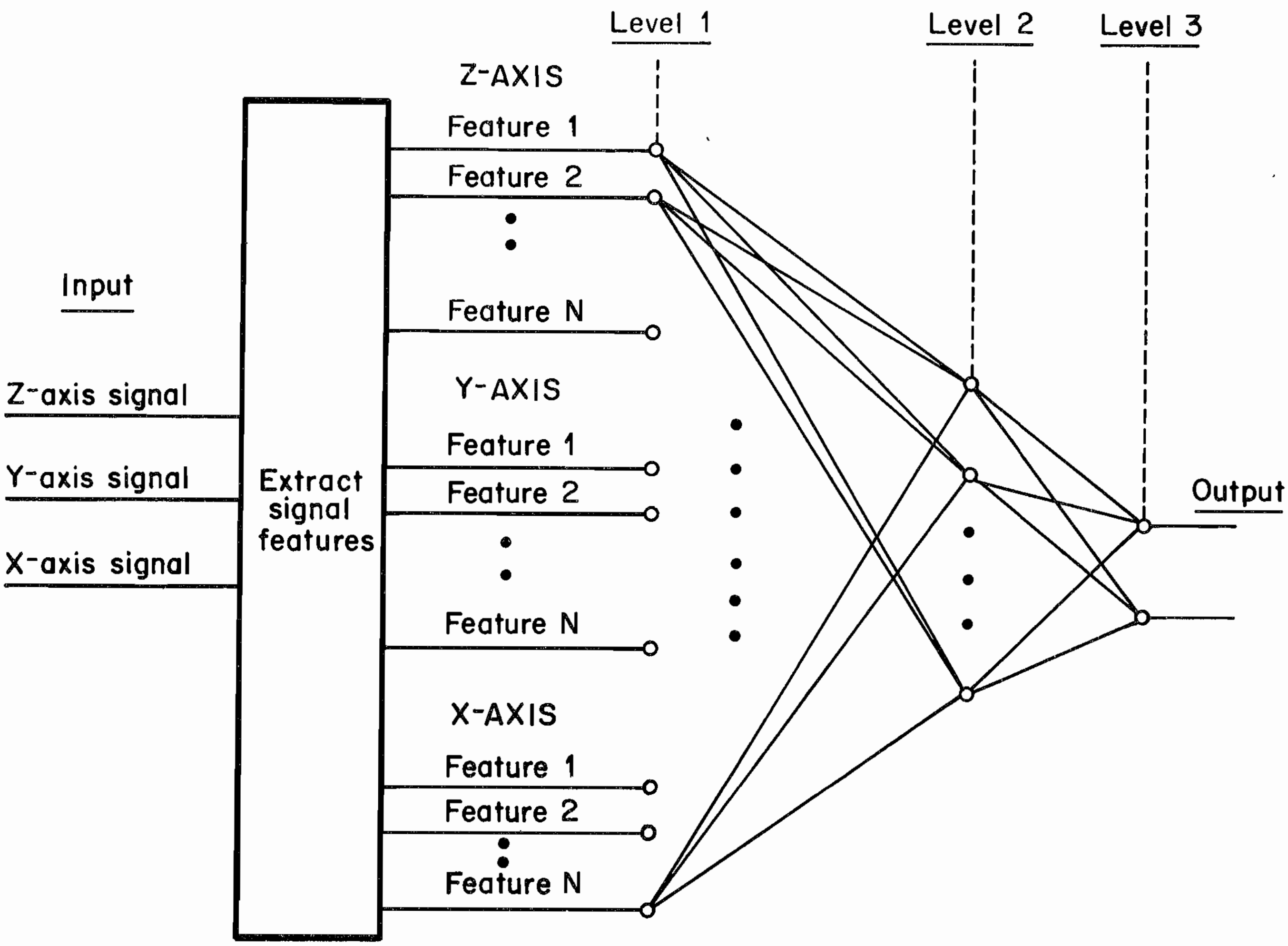

Figure 4.—Architecture of ASD system with neural-network classifier.

The term multiple moving window as used in this report is illustrated in figure 5.[8] Each signal was divided into "n" data blocks with a data block equal to data window 1. The data windows, corresponding to 0.25 in (window 1), 0.50 in (window 2), and 1.0 in (window 3) of tool travel, and the manner in which they overlap, are shown in figure 5. Each digitized signal was then transformed into three distinct data files, corresponding to three window sizes, the

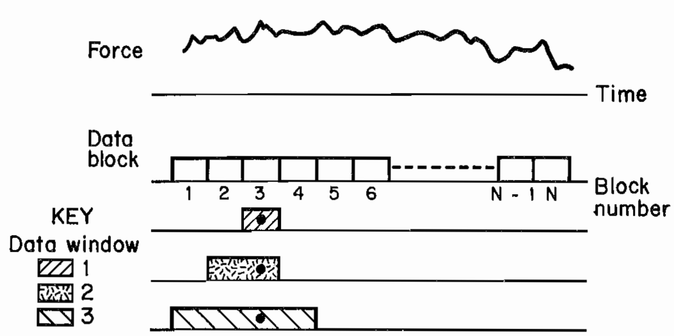

Figure 5.—Location of multiple moving data windows.

[8]Note that for the data sets used, window 1 was either 32 points or 64 points depending on the sampling frequency with which the signal data were acquired. The explanation given here is for window 1 containing 32 points.

second being double the first and the third double the second. Each window was advanced through the original signal at increments of 32 points. That is, file 1, associated with window 1 (32 data points), started with data block 3 in the original and ended with data block "n -1". File 2, associated with window 2, started with data block 2, and ended with data block "n -1". File 3, associated with window 3, started with block 1 and ended with data block "n".

ASD systems with a structure as shown in figure 4 were trained and tested for three cases using the signals from bit forces in data sets 1, 3, and 4. Data files based upon window size were assembled as described above and signal features were extracted. From the total feature sets, a set of 18 features were picked consisting of the first three features, as ranked by ICEPAK, from each window for the forces along the Z and Y axes. In addition to the case of three moving data windows, other variations were also tried (one and two moving windows) in order to determine the optimum window combination. Table 5 and figure 6 show how ASD system performance is influenced by different moving window combinations. Figure 6 discloses the following points:

- ASD system performance increased with increasing window size.
- The ASD system using data windows 2 and 3 (64 points and 128 points, respectively) resulted in the highest performance in two out of three cases.
- In an ASD system using three moving windows, window 1 (32 points corresponding to 0.25 in of tool travel) contributed least to ASD performance.
- ASD systems performed better when using multiple moving windows than when using preprocessed data (data with air cutting removed, table 3).

Table 5.—ASD system performance (percent) for different window sizes and window combinations (force data, neural-network classifiers)

Data window	1	2	3	2,3	1,2,3
Data set:					
1	83.3	85.4	88.5	93.7	92.7
3	72.4	77.5	85.7	83.6	82.6
4	85.0	86.0	89.0	90.0	91.0
Tool travel . . in . .	0.25	0.50	1.00	(1)	(2)

[1]0.50 and 1.00 in of tool travel data, combined.
[2]0.25, 0.50, and 1.00 in of tool travel data, combined.

ASD SYSTEM PERFORMANCE USING CUTTING FORCE AND VIBRATION

The effect of combining both force and vibration data on ASD system performance was explored using data set 1. Two moving data windows (windows 2 and 3 as defined in the previous section) were used to generate a total of 24 signal features (3 features from each of 2 parameters (force, vibration) and 2 axes (Z, Y). The ASD system structure was a derivative of that shown in figure 4. Results shown in figure 7 indicate that data from two sensors (which in this case can be viewed as two simultaneous measurements from the same type of sensor, since force and vibration are related) result in higher system performance than from a single sensor or single measurement. Note that the term "single sensor" used here refers to sensor type, i.e., force or vibration; however, it does include two axes of force or two axes of vibration.

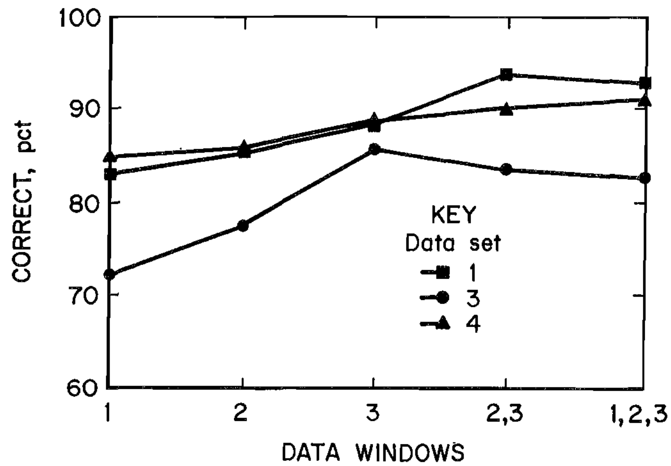

Figure 6.—Effect of multiple moving windows on ASD system performance (force data, neural-network classifiers).

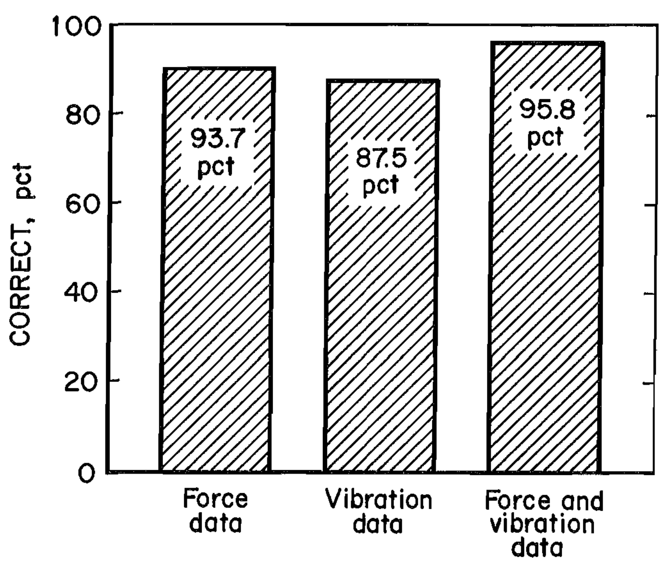

Figure 7.—ASD system performance using both force and vibration data [multiple moving windows (2 and 3), neural-network classifiers].

ASD SYSTEM PERFORMANCE WHEN CROSSING AN IDEAL INTERFACE

The performance of an ASD system using multiple data windows was examined for the case of a conical bit traversing an ideal coal-shale boundary. Since a real specimen containing both coal and rock was not available, Bureau personnel decided to proceed with an ideal interface. A number of ideal or pseudo interfaces were constructed by appending signals associated with cutting coal to signals associated with cutting shale (force data set 1). In effect, the resultant signals represented tool travel across 1 in of coal followed by 1 in of shale. Classifier training and testing were conducted with signal features from multiple moving windows corresponding to 0.25, 0.5, and 1.0 in of tool travel. Figure 8 identifies the classes used in training and testing. The signal feature set, which totaled 18 features, consisted of the first 3 features, as ranked by ICEPAK, for each window for both the Z and Y force components. When given an unknown interface and prompted to identify the material just cut as the conical bit moved from 0.5 in on the coal side of the interface to 0.75 in on the rock side, the ASD system responded correctly 86 pct of the time. As anticipated, the system was wrong most frequently only when the larger data windows (0.5 and 1.0 in) straddled the interface, i.e., contained both coal and shale signals (71.4 pct of the time the system was incorrect).

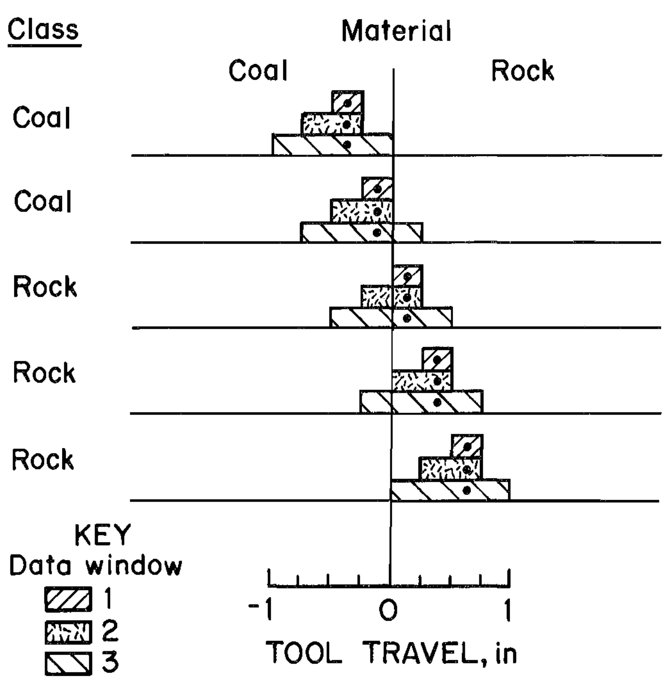

Figure 8.—Multiple moving data windows crossing coal-rock interface.

CONICAL BIT VERSUS ROLLER DISK

The use of roller-disk cutters was investigated as a means of obtaining better cutting (signal) data. Earlier tests indicated that roller disks[9] produced coal-cutting and rock-cutting signals that were more distinctly different than those produced by conical bits. In order to better ascertain the merits of roller cutters for CID, the earlier study was continued to develop a larger data base—one that included other materials and another cutting direction. The criteria for comparing the two cutting tools were (1) the degree of separation between the amplitude distribution of coal-cutting signals and the amplitude distribution of rock-cutting signals and (2) actual ASD system performance.

The first part of the investigation consisted of comparing appropriate data sets by overlaying the amplitude distribution plot of shale-cutting data on the amplitude distribution plot of coal-cutting data. A number of data subsets were first assembled from data set 7 based upon tool type (conical, roller), material cut (coal, shale), cut component [cut (Z-axis), normal (Y-axis)], and cutting direction (perpendicular or parallel to the specimen's bedding plane). Each data set corresponded to 48 in of cutting-tool travel, and the same coal and shale blocks were used to obtain perpendicular and parallel cutting data. Each composite plot was then examined for the degree of distribution overlap in order to judge how well the coal-cutting and shale-cutting classes were separated. That is, the greater the separation between distributions, the higher the chances of distinguishing between cutting classes. The results of this exercise, which are illustrated in figure 9, show the following with regard to cutting-tool force data:

- The roller cutter was clearly better than the conical bit at separating into classes the type of material being cut in both cut (Z-axis) and normal (Y-axis) components when the cutting tool traveled perpendicular (90°) to the bedding plane of the material.
- The roller cutter was moderately better than the conical bit for cut (Z-axis) and normal (Y-axis) components when the cutting tool traveled parallel (0°) to the bedding plane of the material.

In the second part of the investigation, a neural-network ASD system, as illustrated in figure 4, was trained and evaluated to show, in a quantitative manner, how well each tool performed. Because of specimen size and the loss of material when preparing the shale block for each cutting scenario, selected data sets for all scenarios were limited to a standard 40.5 in of cutting. Furthermore, as the result of short signal trace lengths, only a single moving data window was available, window 1 (64 data points, 0.25 in of tool travel). Thus, the six system inputs consisted of the

[9]SSI Services, Inc. Cutter Edge Profiles for Coal Interface Detection. BuMines contract S0398000.

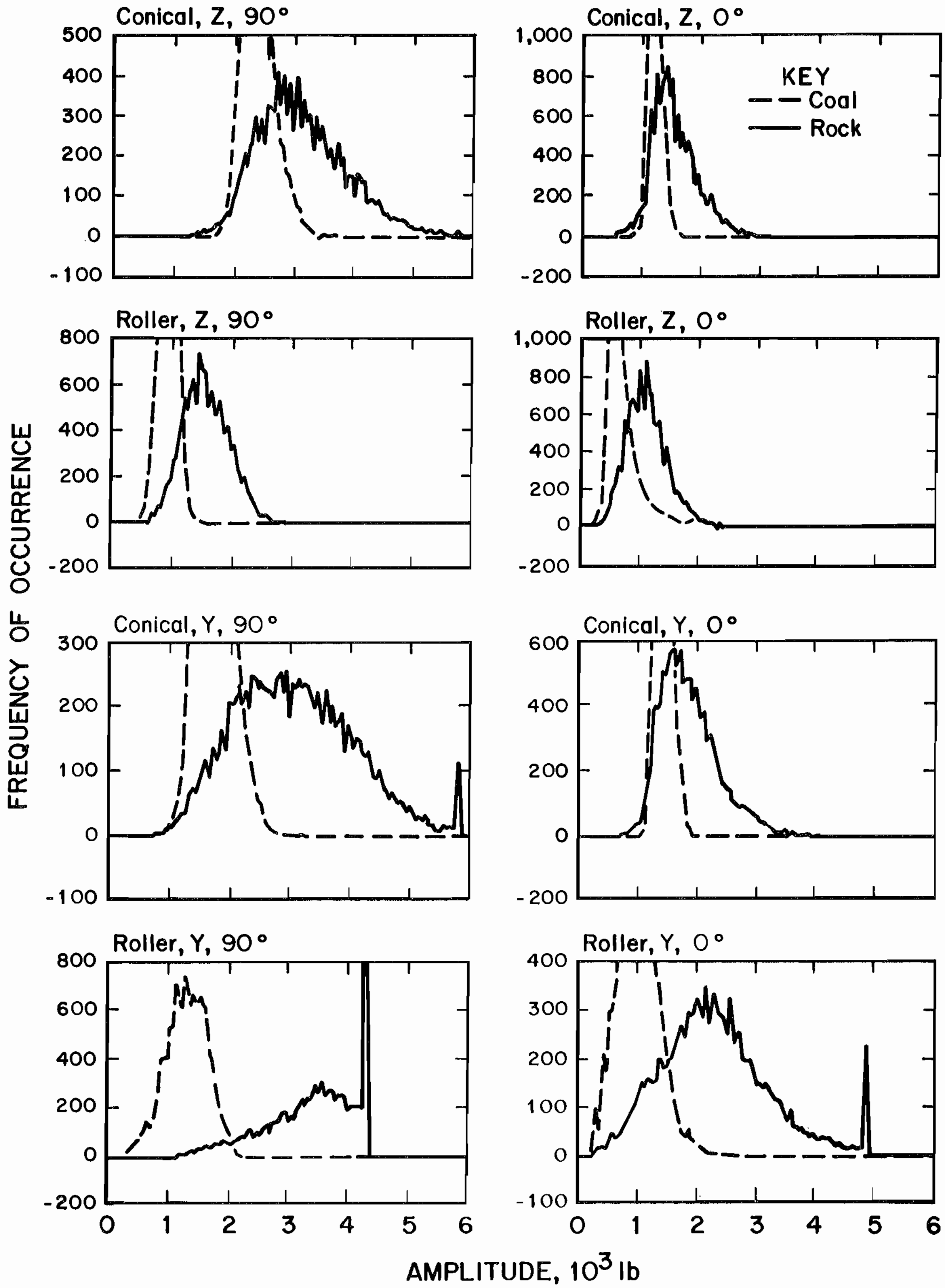

Figure 9.—Amplitude distribution plots of cutting-tool data [force data (Z-axis, Y-axis) for conical bit and roller cutter].

three highest ranked signal features from the Z-axis (cut) and Y-axis (normal) signal data. Because of the small data sets available, Bureau personnel decided that ASD evaluation results obtained during ASD training were a better indicator of performance than ASD results obtained with a very small test set after training. Results, which are given in table 6, indicate that ASD systems perform better with roller cutter data than with conical bit data regardless of signal type (force, vibration) or cutting direction (90°, 0°). In retrospect, ASD system performance appears to be a better criterion than the distribution of signal amplitude for comparing cutting tools because system performance is a function of multiple signal features (the best three in this case) versus one signal feature which may not be among the best three.

Table 6.—ASD system performance (percent) for two cutting tools (neural-network classifiers, three features, two axes, data window 1)

(Data set 7; coal-shale; blocks R, E; 0.25-in depth of cut; Marrowbone)

Signal type and cut angle	Conical bit	Roller cutter
Force:		
90°	69.1	95.0
0°	78.7	92.5
Vibration:		
90°	60.9	79.2
0°	67.0	90.8

SIGNAL FEATURES

An examination of the 3 highest ranked signal features for 22 cases (table 2) did not reveal any single repeatable feature set but did tend to show a grouping by domain (time, power) that could be associated with sampling frequency or cutting-tool type (table 7). For the conical bit data sampled at 11 kHz, the highest ranked features for each case, regardless of cutting tool, cutting axis, signal type, or material cut, were from the time domain more often than any other domain. For the roller cutter data sampled at 20 kHz, the best features were most often from the power domain.

Data set 7 (table 6), which was sampled at 20 kHz and whose best features were most often from the power domain, indicates an association between cutting-tool type and power-domain features. An examination of the frequency of occurrence of the three highest ranked features revealed a feature set associated with the roller cutter. Table 8 shows that for roller cutters the best feature set for either force or vibration signals consists of the percent partial power in three frequency bands—0 to 625 Hz, 1,875 to 2,500 Hz, and 2,500 to 3,125 Hz; for conical cutters the best set is not well defined and ranges over a larger number of features.

Table 7.—Signal features[1] associated with force and vibration data selected for cases 1 to 21 (table 2)

Axis	Ranked feature	Conical bit, 11-kHz sampling frequency									Roller cutter, 20-kHz sampling frequency											
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Z	1st	T	A	T	T	A	T	A	T	A	P	P	P	P	P	P	P	P	P	P	P	P
	2d	A	A	A	A	A	A	A	A	A	P	P	P	P	P	P	P	P	P	P	P	P
	3d	A	A	C	A	A	A	T	A	A	P	P	P	P	P	P	P	C	A	P	P	P
Y	1st	T	T	T	T	A	T	C	T	T	P	P	A	P	C	C	P	P	P	P	P	P
	2d	A	A	A	A	A	A	A	A	T	P	P	P	P	S	P	P	P	P	P	P	P
	3d	A	A	C	A	A	A	A	A	T	P	C	P	P	P	P	P	P	S	P	P	P
X	1st	T	P	T	S	C	T	A	T	T	P	P	P	P	P	P	P	P	P	P	P	P
	2d	A	P	A	P	S	A	C	A	A	P	P	C	P	P	P	P	P	P	P	P	P
	3d	A	S	A	S	C	A	T	A	A	P	P	P	C	P	P	P	P	P	P	P	P

[1]Domains: A = autocorrelation
C = cepstral
P = power
S = phase
T = time

Table 8.—Frequency of occurrence of best signal feature sets

Feature	Signal type: Force	Signal type: Vibration
CONICAL BIT		
TIME DOMAIN		
Greatest peak amplitude	0	1
POWER DOMAIN		
Number of peaks above 25-pct maximum signal amplitude	0	1
2d greatest peak amplitude	1	2
Percent partial power at—		
625 to 1,250 Hz	2	1
1,250 to 1,875 Hz	0	1
2,500 to 3,125 Hz	3	0
3,125 to 3,750 Hz	2	2
3,750 to 4,275 Hz	2	2
AUTOCORRELATION DOMAIN		
Number of peaks above—		
Signal base line	1	0
10-pct maximum signal amplitude	1	0
Percent partial power at—		
1,875 to 2,500 Hz	0	1
2,500 to 3,125 Hz	0	1
ROLLER CUTTER		
TIME DOMAIN		
Number of peaks above—		
10-pct maximum signal amplitude	1	0
25-pct maximum signal amplitude	1	0
2d greatest peak amplitude	1	0
POWER DOMAIN		
2d greatest peak amplitude	1	0
Percent partial power at—		
0 to 625 Hz	0	1
625 to 1,250 Hz	1	4
1,875 to 2,500 Hz	3	3
2,500 to 3,125 Hz	3	4
PHASE DOMAIN		
Percent partial power at 625 to 1,250 Hz	1	0

SUMMARY AND CONCLUSIONS

The objective was to train and test ASD systems on a range of coals and mine rocks in order to explore different means of improving system performance in distinguishing between the cutting of coal or rock. Cutting tool force and vibration sensor signals along three axes were recorded and digitized as the LCA made constant-depth cuts in coal, shale, and soapstone test specimens. ASD systems were trained and tested with various feature sets obtained from signals associated with two types of cutting tools (conical bit, roller disk cutter), two cutting directions (perpendicular, parallel), and three sets of coal and mine-rock samples. A number of cases were studied to observe the influence of signal features, data window size, combining or polling of information, and data preprocessing on ASD system performance. Results from this investigation include the following:

- ASD system performance improved with increasing data window size for both force and vibration signals and for both conical and roller cutters (table 2).
- An ASD system that used processed data (i.e., signal traces with "air cutting" segments removed) outperformed an ASD system that used unprocessed data (table 3).
- ASD systems using neural-network classifiers performed as well as or better than ASD systems using conventional classifiers (table 4).
- ASD systems performed better when using multiple moving windows than when using preprocessed data (data with "air cutting" removed) (table 5 versus table 3).

- An ASD system using two moving data windows corresponding to cut lengths of 0.5 and 1.0 in resulted in highest performance in two out of three cases (table 5).
- In an ASD system using three moving data windows, the largest window (1.0 in of tool travel) contributed most, and the smallest window (0.25 in of tool travel) contributed least to ASD performance (table 5).
- ASD systems performed better with roller cutter data than with conical bit data from both force and vibration signals and both cutting directions (90°, 0°) (table 6).
- The best feature set for roller cutters (based on 0.25 in of tool travel, 64 data-point window) for both force and vibration signals, consisted of the percent partial power in three frequency bands—0 to 625 Hz, 1,875 to 2,500 Hz, and 2,500 to 3,125 Hz (table 8).
- Signal features were seen to depend upon sampling frequency and cutting tool type. A sampling frequency of 11 kHz resulted in time and autocorrelation domain features whereas 20 kHz produced power domain features. For roller-cutter data acquired at a 20-kHz sampling frequency, a three-feature set was identified as best regardless of cut component or cut direction (table 8).

Based on the above results it is concluded that an ASD system that incorporates the following items has the potential of correctly classifying material being cut with a high degree of confidence.

- Uses a roller-disk cutter.
- Uses cutting force and/or vibration signals.
- Uses normal and cut components of data.
- Uses multiple moving windows corresponding to 0.5 and 1.0 in of cutter tool travel.
- Uses three signal features from the power domain (percent partial power) per axis of cutting.
- Uses back-propagation neural networks to classify signals and to fuse information.

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