Rock Recognition from MWD Data: A Comparative Study of Boosting, Neural Networks and Fuzzy Logic

Ali Kadkhodaie-Ilkhchi, Sildomar T. Monteiro, *Member, IEEE,* Fabio Ramos, *Member, IEEE,* and Peter Hatherly

***Abstract*—Measurement-while-drilling (MWD) data recorded from drill rigs can provide a valuable estimation of the type and strength of the rocks being drilled. Typical MWD sensors include bit pressure, rotation pressure, pull-down pressure, pull-down rate and head speed. This paper presents an empirical comparison of the statistical performance, ease of implementation and computational efficiency associated with three machine learning techniques. A recently proposed method, Boosting, is compared with two well-established methods, Neural Networks and Fuzzy Logic, used as benchmarks. MWD data were acquired from blast holes at an iron ore mine in Western Australia. The boreholes intersected a number of rock types including shale, iron ore and banded iron formation. Boosting and neural networks presented the best performance overall. However, from the viewpoint of implementation simplicity and computational load, Boosting outperformed the other two methods.**

***Index Terms*—Pattern recognition, boosting, neural networks, fuzzy logic, measurement-while-drilling, geological modeling.**

I. Introduction

DRILL parameters recorded while drilling have the potential to provide information regarding the lithology and the strength properties of the rock formations being drilled. Some studies have tried to find relationships between drilling data and rock types [1]. However, few works have addressed the application of machine learning techniques to estimate geology from measurement-while-drilling (MWD) data. If the geology can be characterized reliably from MWD data this information can be used in many applications, from mining operations to tunnel excavation and petroleum exploration.

There has been considerable interest over the past decade in applying machine learning, artificial neural networks and fuzzy systems in the areas of geology and petrophysics. Techniques for petrophysical predictions and porosity estimation have been proposed using neural networks, e.g. [2]. Fuzzy neural networks have also been applied for permeability estimation from wireline logs, lithology discrimination from well logs and lithology identification [3]. A new and powerful technique which could be used for the estimation and analysis of geoscience data is the *boosting* algorithm [4]. We have investigated LogitBoost, a Boosting variant, which can handle multiclass problems and also provides class probability estimates as output. To the best of our knowledge, this is the first study reporting the applicability of LogitBoost for rock recognition from MWD data. This study also investigates two other methods: neural networks and fuzzy systems. Neural networks have been investigated for providing state-of-the-art solutions for many problems. Fuzzy systems present a coherent framework to handle uncertainty and noisy inputs which are appealing for the rock recognition problem. There are many factors that influence the classification accuracy based on sensor measurements. Since machine learning algorithms may behave differently on specific kinds of data, a comparative study of different approaches is necessary to provide a better understanding of the problem.

This paper investigates the application of boosting, neural network and fuzzy logic to analyze drill performance data acquired from blast holes in an iron ore mine located in Western Australia. The MWD data used as input was composed of 12 measurements which include: bit pressure, rotation pressure, pull-down pressure, pull-down rate, head speed; along with seven pressure transducers recording: feed down, feed up, reverse rotation, forward rotation, rotation relief, feed relief and hold back. Four rock types were considered as the target labels of the machine learning classifiers including: iron ore zones A and B, banded iron formation (BIF), and shale. The main objectives and contributions of this study are:

- To classify MWD data into rock categories autonomously,
- To investigate a recently proposed algorithm, LogitBoost,
- To evaluate the performance of different machine learning techniques.

II. Methodology

In this study, machine learning techniques are used for supervised learning of classifiers. The goal is to construct a classifier that can correctly predict a label sequence given a new input sequence. Here, the output classes are rock labels and inputs are drilling plant conditions. This section summarises the basic concepts of the classification algorithms tested.

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A. Boosting

Boosting has become popular because many empirical studies show that it tends to yield lower classification error rates and is more robust than competing methods when it comes to overfitting [10]. Boosting is a machine learning technique for supervised classification that employs a combination of "weak" simple classifiers to produce a powerful "committee" [5]. A weak learner is defined to be a classifier which is slightly better than random guess. The method consists of iteratively learning weak classifiers to produce a final strong classifier. Each weak classifier receives a weight representing its relative importance to the overall ensemble. The learning procedure is performed in a greedy manner by adding one weak classifier at the time, trained on misclassified data points from the previous iteration.

The resulting committee is a classifier that provides a non-linear combination of input features. Boosting is thus more powerful than conventional linear classifiers, e.g. linear discriminant analysis, and competitive with state-of-the-art non-linear classifiers, e.g. neural networks. In addition, boosting optimizes a criterion equivalent to the binomial log-likelihood instead of the more commonly used mean squared error.

The most commonly used version of boosting is *AdaBoost* (from adaptive boosting). AdaBoost is well suited to solve binary class problems. In this study, however, there are more than two rock classes. While there are several methods to extend AdaBoost to handle the multiclass case, we implemented a version of boosting named *LogitBoost* which can handle multiclass problems directly. LogitBoost fits additive logistic regression models by stagewise optimization of the maximum likelihood [6]. It optimizes the maximum likelihood through adaptive Newton steps.

B. Artificial Neural Networks

Among the several architectures of neural networks, the multilayer perceptron (MLP) network is the most popular due to the fact that it is capable of approximating any function to arbitrary accuracy, given a sufficient number of hidden units [7]. The MLP network can be trained using the back-propagation algorithm, which propagates the error backwards through the network and adjusts the weights during a number of epochs. Adding more hidden layers and neurons increases the non-linearity and complexity of the model and may lead to the overfitting, i.e., the model performs well on the training samples and poorly on the test samples.

The MLP training may be trapped in local minima depending on the weights' initialization conditions. Several MLP networks were trained and the one presenting best performance was retained. Unfortunately, the MLP network does not provide class probability estimates as LogitBoost does. The alternative architecture Probabilistic Neural Networks did not perform well in our experimental data set.

C. Fuzzy logic systems

The nature of geological data is not precise and there is always uncertainty and error. Fuzzy systems are well suited to deal with the uncertainty in data analysis. A fuzzy inference system (FIS) provides a formulation between input and output data using fuzzy logic. The Takagi-Sugeno and Mamdani methods are the two main types of FIS [8].

TABLE I
DEFINITIONS OF ACCURACY, PRECISION AND RECALL

Metric	Formula
Accuracy	(TP + TN) / (TP + TN + FP + FN)
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)

TP (True Positive); FN (False Negative); FP (False Positive); True Negative (TN)

The formulation between inputs and outputs is performed through a set of fuzzy if-then rules. Normally, fuzzy rules are extracted through a fuzzy clustering process. Subtractive clustering is one of the effective methods for constructing a fuzzy model. The effectiveness of a fuzzy model is related to the search for the optimal clustering radius which is a controlling parameter for determining the number of fuzzy if-then rules. Fewer clusters might not cover the entire domain, and more clusters (resulting in more rules) can complicate the system behavior and may lead to lower performance. It is necessary to optimize this parameter for construction of fuzzy model.

Depending on the case study and nature of the data set some of these techniques may present better performance than others. FIS and ANN have been applied successfully to solve many problems in geology and petrophysics. Nevertheless, their performance needs to be compared to more recently proposed algorithms, such as boosting, in order to decide which method produce the best model for specific data types, such as MWD data. Boosting has less parameters to tune and is thus faster to optimize, however its performance has not been tested as widely on real data sets. Moreover, boosting is designed for solving classification problems (outputs are discrete classes), whereas FIS and ANN can be easily applied for both classification and regression (outputs are continuous data) problems.

III. EXPERIMENTAL RESULTS

For measuring the performance of the algorithms on unseen data, the k-fold cross-validation method was applied using a "leave-one-borehole-out" approach, i.e., all sections from one borehole are left out during training. Evaluation metrics for the classifier performance were carried out through calculation of the accuracy, precision and recall (also called sensitivity). As described in Table I, precision is the percentage of positive predictions that are correct. Recall is the percentage of positive labeled instances that were predicted as positive. Accuracy is the percentage of predictions that are correctly classified.

In this study, we have used binary decision trees as weak learners. The only parameter of the LogitBoost algorithm that needs to be specified is the number of weak learners. The LogistBoost algorithm was run 300 times, progressively increasing the number of weak learners from 1 to 300. The variation of accuracy, recall and precision versus the number of weak learners for the first 100 trials is shown in Fig. 1. According to this experiment, running LogitBoost with 25

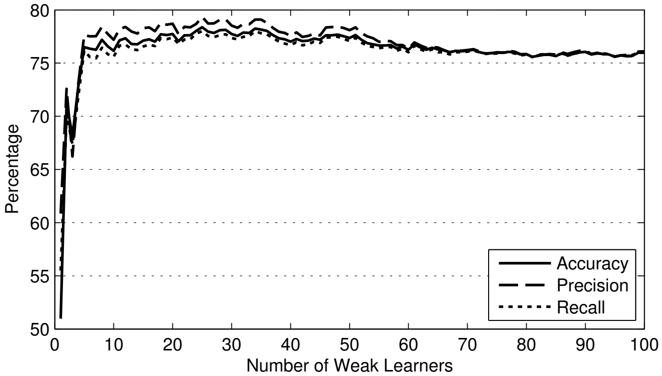

Fig. 1. Accuracy, recall and precision versus number of weak learners, optimizing LogitBoost model parameter. After adding more than 68 weak learners similar results are obtained

weak learners provides the highest overall accuracy (78.4%). It is noticeable that the overall accuracy of the estimation after 68 trials is similar and increasing the number of weak learners would result in a similar accuracy. This shows the resistance of boosting to overfitting. 25 weak learners were therefore considered to be the best solution. The running time is fast and the accuracy is the highest among 1 to 300 weak learners.

For the MLP, the parameters that need to be specified are the number of hidden layers, the number of neurons in the hidden layers, the transfer functions, the training function and the training epochs. Input data was normalized between -1 and 1. As with LogitBoost, cross-validation was employed to measure the performance. In order to prevent overfitting, the data (after omitting the cross-validation test hole) was divided into two parts including 80% for training and 20% for validation. This procedure is known as early stopping, because the training is stopped when the performance on the validation data set starts to deteriorate. This validation data set used for training should not be confused with the cross-validation data used to generate the statistical results. Constructing several MLP network models using trial and error showed that increasing the number of hidden layers and hidden layer neurons, increases the complexity of the model and affects its predictive performance. Moreover, there is a significant increase in computational time that does not occur with boosting. Thus, we used a network architecture with one hidden layer. Accuracy, recall and precision metrics versus number of neurons in the hidden layer is shown in Fig. 2.

For TS-FIS model a subtractive clustering method was used for extraction of clusters and fuzzy if-then rules [9]. Searching for the optimal clustering radius was done by performing the clustering process several times and gradually increasing the clustering radius from 0.005 to 1 (with 0.005 intervals). Thus, 200 fuzzy models with different numbers of if-then rules were established. The accuracy, precision and recall of the fuzzy models versus clustering radius are shown in Fig. 3. This shows that choosing the value of 0.155 for the clustering radius is associated with the highest accuracy (74.1%) and that this generates 13 fuzzy clusters for each of the 12 input drilling data types. The TS-FIS model's membership functions (clusters) constituted a 12 by 13 matrix, i.e., for each of the 12

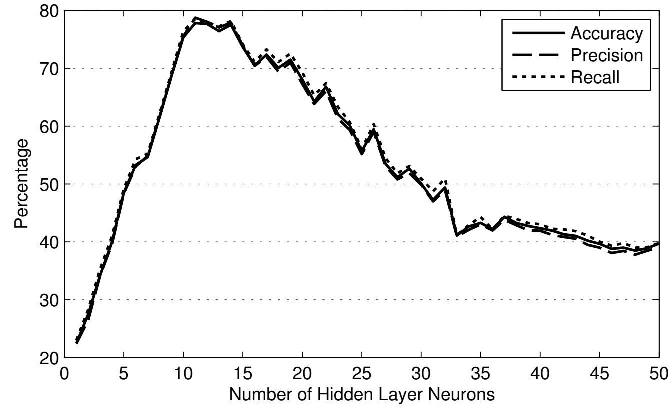

Fig. 2. Accuracy, precision and recall versus number of hidden layer neurons, optimizing neural network model parameter. Using 11 neurons in the hidden layer provides the highest accuracy

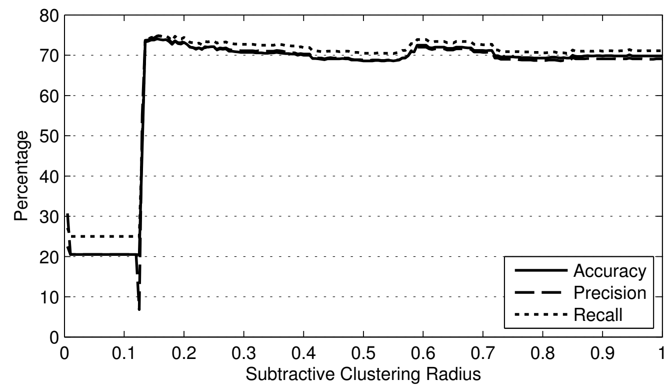

Fig. 3. Accuracy, recall and precision versus clustering radius, optimizing clustering radius of fuzzy logic system

MWD input data, 13 clusters were generated, resulting in 156 rules. Each cluster represents a fuzzy if-then rule and each rule has a partial impact on the output (rock classes). The closer a given input is to the "if" part of the rule the more the "then" part will be influenced. This implies that some ranges of the input MWD data have greater importance for the output rock class. By passing a row of the inputs MWD matrix from the FIS, its related MFs are affected by each rule. Because a rule's antecedent has more than one part, the fuzzy "and" operator is applied to obtain a rule that represents the result of the antecedent for that rule. Applying fuzzy operators gives a value to the antecedent of each rule and the output membership function is then truncated by this value. Then, outputs of each rule that fit into a fuzzy set are combined into a single fuzzy set (aggregation). Finally, FIS uses a weighted average method (defuzzify) for the resulting rock label which is discrete.

This study utilized data from blast holes in a Western Australian iron ore mine, Fig. 4. The site was chosen because down-hole geological conditions were expected to vary. 28 holes 12 m deep were drilled at 3 m spacings with the drill in percussion mode. The holes intersected a number of rock types including shale, zones of enriched iron ore and banded iron formation (BIF). A geological model through the holes 1 to 28 used to train the algorithms is shown in Fig. 5. The

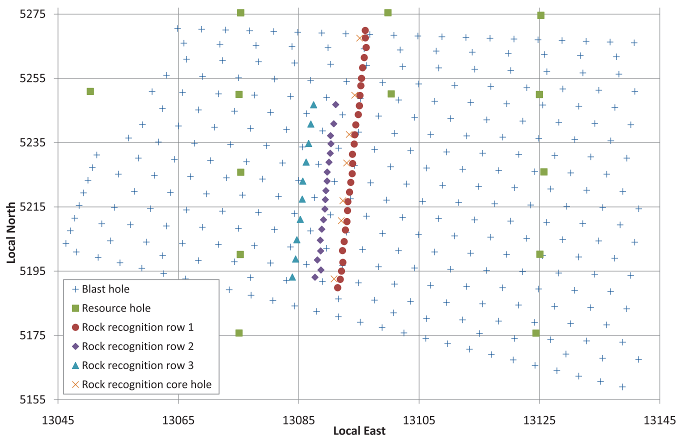

Fig. 4. Map showing location of the blast holes in the study area (brown round dots)

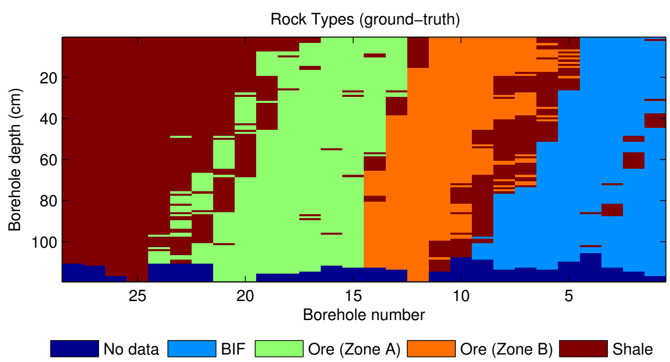

Fig. 5. A geological section through holes 1 to 28

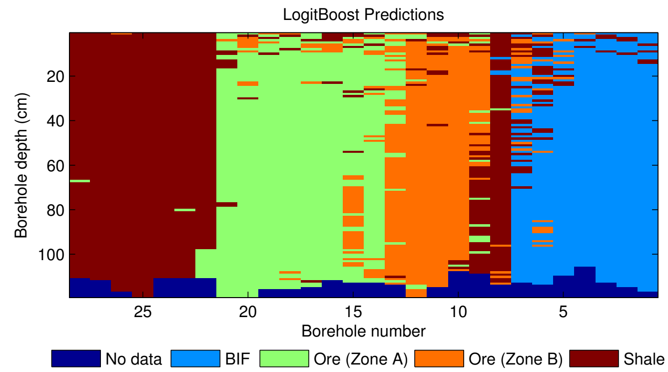

Fig. 6. Estimated rock types for 28 blast holes using LogitBoost

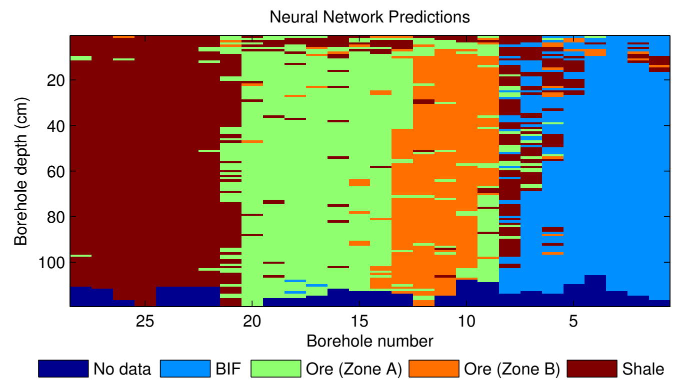

Fig. 7. Estimated rock types for 28 blast holes using neural network

geological interpretation is a challenging procedure involving geophysical, chip and core logging. The inherently subjective nature of this interpretation adds to the complexity of training a model to estimate the geology from MWD data.

Estimated rock types for the 28 blast holes using LogitBoost, MLP network and FIS are shown in Fig. 6, 7 and 8, respectively. The performance calculations for the estimated rock types using the three techniques are shown in Table II. In this experiment, the overall accuracy of LogitBoost model (78.4%) is better than that of the MLP network (77.8%) and the FIS (74.1%). Precision of the MLP network (78.7%) is higher than the LogitBoost (78.0%) and the FIS (74.8%). From the recall point of view, the LogitBoost model performs better than the MLP network and FIS models (79.3%, 78.5% and 74.9%, respectively).

IV. Discussion

The analysis of MWD parameters using machine learning techniques indicates that the mechanical measurements produce a response corresponding to changes in rock strength which can reveal changes in lithology. For example, the strength of the banded iron formation is greater than for the iron ore zones which in turn is greater than for the shales. It is also important to understand the relationship between a set of inputs and the resulting outputs of the machine learning algorithm. One approach is to rank the inputs in order of relevance to the classification; depending of the algorithm, a rank can be obtained directly from its parameters (weights). A different approach is provided by Boosting, which naturally perform feature selection as part of the learning procedure. It is also clear that drilling performance may not be the same for all holes, due to changes in drill characteristics and bit wear. These variations can add complexity to the analysis. However, the algorithms should be able to overcome those minor changes.

Neural networks are affected by overfitting. In our experiments, overfitting was avoided in the MLP network by using early stopping with a validation data set. In Boosting, this was

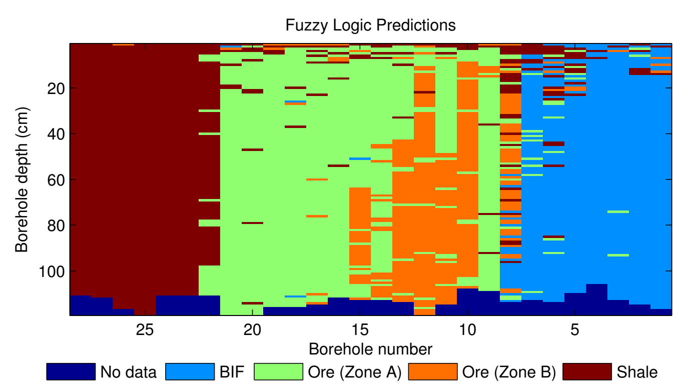

Fig. 8. Estimated rock types for 28 blast holes using fuzzy logic

TABLE II
COMPARISON OF RESULTS OF ROCK RECOGNITION USING LOGITBOOST, MULTILAYER PERCEPTRON NETWORK AND FUZZY INFERENCE SYSTEM

Method	Metric	BIF	Iron Ore (Zone A)	Iron Ore (Zone B)	Shale	Total†
LogitBoost	Acuracy	0.932	0.875	0.890	0.825	**0.784**
	Precision	0.836	**0.733**	0.730	0.821	0.780
	Recall	0.898	0.846	**0.717**	0.712	0.793
MLP	Acuracy	0.936	0.850	0.905	0.820	0.778
	Precision	**0.842**	0.682	**0.824**	0.800	0.787
	Recall	0.912	0.816	0.678	**0.724**	0.785
FIS	Accuracy	0.928	0.809	0.862	0.815	0.741
	Precision	0.817	0.600	0.704	**0.869**	0.748
	Recall	**0.926**	**0.849**	0.571	0.649	0.749

† Best total accuracy, and best precision and recall for each class are highlighted in bold

not necessary, even models using a higher number of weak learners did not degrade performance severely.

FIS results comparing to MLP and Logitboost show more noise in the estimations, see Fig. 6–8. There is a layer of shale in the boundary between BIF and iron ore Zone B in the ground reference. MLP network and LogitBoost have detected this layer even with over or under-estimations whereas the FIS method misses this layer especially at the depths below 2 m. The estimation results show maps of rock types having near-vertical boundaries with each other, whereas in the geological section the dip of the interfaces are between 45 and 70 degrees. This apparent "trend" affecting all methods is a consequence of the cross-validation approach and the characteristics of the data set utilized in this study. Instead of separating the cross-validation data randomly, we systematically selected one entire hole and left it out for validation. The process was repeated for each of the available holes. This approach was designed to simulate the real scenario of having to estimate the geology of new holes using models trained with previous holes. However, when performing cross-validation, the training data had few other holes for the algorithms to learn a correct model of the boundaries. This issue might be minimized by the acquisition of more training data involving boundaries.

The LogitBoost algorithm provided the highest statistical accuracy overall, as can be seen in the results summarized in Table 2. In addition, LogitBoost's predicted rock classes in contrast with the ground reference (Fig. 5) shows better qualitative results geologically compared to the other techniques. There is more noise in the MLP and FIS predictions which make it difficult to interpret the estimated lithology, especially in the iron ore Zones A and B. Moreover, some techniques are better than others for a particular rock type. This might be related to the statistical relationship between the input and output data and the nature of the specific method. In general, the model parameters for each technique are very sensitive to type and distribution of the input and output data sets. Again, the results are also deeply affected by the selection of cross-validation data. Validation data selected randomly from areas with similar distribution as used for training may show higher classification accuracies but might not have the same generalization performance on newly acquired data. In the case of MWD, the data will always be collected one borehole at a time, thus the proposed cross-validation analysis provide statistical results closer to what is expected of a deployed classification system.

V. CONCLUSION

We have demonstrated the applicability of Boosting, Neural Networks and Fuzzy Systems to predict rock types from MWD data. The methods were compared using blast-hole data from an iron mine in Western Australia. The different methods were analyzed on the basis of their accuracy, simplicity of implementation and computation time. In our experiments, all methods were able to classify all rock types with over 80% accuracy and the difference between the methods' performance was statistically small. Nevertheless, Boosting and neural networks presented slightly better overall performance followed by fuzzy logic. Boosting was the easiest method to implement and had the greatest computational efficiency.

Even though the implications of this study are specific to the type of data used in the experiments, a similar behavior can be expected when applying these methods to other data sets with similar characteristics, e.g., multiple sensor measurements from the same geology, noisy readings, and varying sampling rates. The use of MWD data provides a good estimate of the true physical parameters and has the potential to significantly improve subsurface characterization. The main requirement will be for training sets consisting of MWD data and corresponding labels. The method will also need to accommodate the use of different drills and changes in the geological conditions.

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