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Review Article

Pattern Recognition Approach (PRA) Expert Model for Identifying Lithofacies Aspects of Reservoir Rocks-Gamaal Oil Field, Yemen

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ABSTRACT

The accurate determination of reservoir lithology remains a challenge in petroleum engineering. There are some conventional techniques available to determine the lithology. However, the application of those techniques has been long and complex. So, the main goal of this study is to simplify identification of reservoir lithology.

This paper presents a Pattern Recognition Approach (PRA) to identify the reservoir lithology. Four wells from the Camaal field were chosen to develop this approach. Around of 32400 data points from the previous wells were digitized by Neuralog program (2015). The PRA approach used depth, gamma ray, lithology, sonic, neutron and density logs as inputs. Data were classified into three portions: 70% as training data and 15% as testing data and 15% as validating data.

The results show that the proposed approach provides better prediction of lithology with higher accuracy. The accuracy of this model predicts correctly for more than 97% of the test data points.

Keywords: Pattern recognition approach; Reservoir lithology rock types; Gamaal oil field

INTRODUCTION

In the exploration and production of petroleum, lithology must be determined from well log data. The quantitative examination of logging data can be used to build the lithology model of a reservoir. The amount of logging data is constrained due to the high expense of drilling cores. The distributions of logging data from various lithologies overlap as a result of the complexity of lithology, which broadens the range of identification options. Therefore, it is necessary to employ techniques that offer precise ways to make lithology forecasts.

Identification of formation lithology essentially depends namely on neutron, density and sonic porosities as well as formation radioactivity. The physical properties of sediments like natural radioactivity, resistivity, density, compressional/shear sonic travel time, neutron porosity commonly measured through geophysical logging, are used for identification the lithology of hydrocarbon bearing reservoir.

A quick look or cross plotting technique will be tedious and time consuming for identifying lithology using conventional well log responses.

Estimation of lithology from well logs in heterogeneous formation is difficult to solve by the quick look interpretation method [1]. However, many Artificial Neural Network (ANN) tools have been successfully utilized for the determination of lithology using the transformation between well logs [2-4]

The study is demonstrated using logs data analyses of different wells to distinguish different rock types along the field (shale, sand, sandstone, limestone and dolomite).

Therefore, the aim of this study is to develop the pattern recognition approach for identification the lithology of hydrocarbon bearing zones simply and accurately. The proposed approach is helpful to improve the performance of lithology identification taking less time.

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LITERATURE REVIEW

In recent years, lithology has been extensively identified using artificial intelligence based on well logs and much research has been done in this area.

Rogers [5], first determined lithology from well logs using a back-propagation artificial neural network. Cvetkovi [6], proposed artificial neural networks model to predict lithology using two wells in the Klotar field. Mohammad Ali proposed artificial neural networks model to identify the kind of lithology of a layer as it was being drilled using neighbor well data, and real-time drilling data from 12 wells in the South Pars gas field (in southern Iran). Zhang, introduced a novel machine learning-based methodology that incorporates seismic and well-log data to determine the lithology using thin-section photos in a deep marine clastic setting offshore West Africa. Gong, developed conventional single classification algorithms such decision trees, support vector machines and Bayes to determine the lithology of the Longqian region of China using three wells in the daan section. Zhong Johnson, predicted coal pay zones using a variety of machine learning algorithms using six wells in the Surat Basin of Australia. Mohamed, proposed the supervised learning algorithms, the unsupervised learning algorithms and a neural network machine learning algorithm in order to categorize and predict the geological facies using well log data in the Anadarko Basin, Kansas. Maia Ramos Lopes [7], presented fuzzy artificial intelligence to detect lithologies using wireline logs and core data from a specific drill in the Campo de Namorado (Bacia de Campos, Rio de Janeiro). Inoue Tanaka, developed machine learning techniques to forecast the lithology for surface drilling data and lithology information from core samples obtained during previous scientific drilling operations. Nanjo and Tanaka, showed how to use generative adversarial networks to recreate thin section images and identify carbonate lithology. Sun [8], proposed extreme gradient boosting and Bayesian optimization classifier for identifying the lithology of Daniudui and Hangjinqi gas fields. Sun [9], presented three machine learning algorithms models to determine the lithology while drilling. Xie [10], suggested a coarse-to-fine architecture that incorporates outlier detection, multi-class classification and a tree-based classifier to identify the lithology using two actual well logging data sets. Liu [11], proposed Artificial Neural Networks and Hidden Markov Models (ANN-HMM) hybrid framework to classify the lithological sequence. Hossain [12], suggested a novel and effective RST-based granular computing approach using well log features to categorize the ten lithology classes. Zeng [13], proposed a deep learning-based technique for mineral identification to integrate image and hardness minerals. Faria [14], developed a method for automatically classifying carbonate thin sections derived from plane-polarized and cross-polarized microscope images similar to natural rocks found in the Brazilian pre-salt reservoir. Liu [15] proposed a set of techniques and processes for the identification of complicated lithologies from log data in the Permian Longtan formation by analyzing the log response characteristics of various lithologies based on conventional log curves. Sun [16], presented a cross-domain lithology detection approach to integrate the geological data and domain adaption.

From the previous studies, identification of lithology required method to predict it accurately. So, pattern recognition approach will be proposed to identify the lithology of Camaal oil fields.

Data description

Around of 32400 data points were collected from four wells of Camal oil fields in Yemen. 9440 data points are from well A, 10000 data points from well B, 2000 core points from well C and 10950 core points from well D. These data were generated by digitizing their logs by Neuralog program. The digitized data are depth, gamma ray, lithology, density, neutron and sonic porosities. The main lithologies of these wells are shale, sand, sandstone, shale, dolomite and limestone. In this study, 70%, 15% and 15% of the studied data was used for training, validating and testing respectively. Table 1 describes the total data points with their different ranges [17,18].

Table 1: The ranges of the total data points.

	Min	Max
Gamma Ray, api	7.87	146.91
Density Logs, g/cc	1.93	2.95
Neuron Logs, v/v	-0.01	0.45
Sonic Logs, us/ft	2.87	141.76
Depth, ft	520	6179

Pattern recognition approach

Pattern recognition tool is type of artificial neural network. It used to classify input data regarding to how they are come together in the input space. The pattern recognition tool in networks is one of the most attractive topics in the ANN field.

Before using pattern recognition method, the first step is to define the problem by selecting a data set.

The pattern recognition problem is defined by arranging a set of input vectors as columns in a matrix and another set of target vectors for indicating the classes to which the input vectors are assigned. The target data has only two classes; we set each scalar target value to either 1 or 0, indicating which class the corresponding input belongs to.

The standard network that is used for pattern recognition is a two-layer feed forward network, with sigmoid transfer functions in both the hidden layer and the output layer. The hidden layer and number of input/output are shown in Figure 1. You might want to come back and increase this number if the network does not perform as well as you expect. The number of output neurons is equal to the number of elements in the target vector (the number of categories).

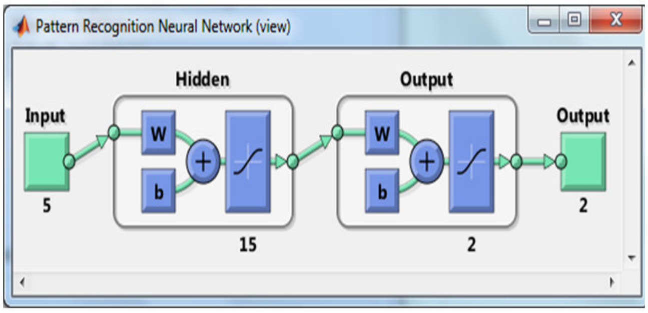

Figure 1: Depicts the structure of neural network.

DISCUSSION

In this study, the pattern recognition approach is applied four times as shown in Figure 2. Firstly, the proposed approach used all data to identify the lithology of permeable and unpermeable (Shale) rocks. The confusion matrices are shown in Figure 3 for training, testing and validation and the three kinds of data combined. The network outputs are very precise, as you can see by the high numbers of correct responses in the green squares and the low numbers of incorrect responses in the red squares. The lower right blue squares illustrate the overall accuracies about 76.2%. Figure 4 shows the first error histogram.

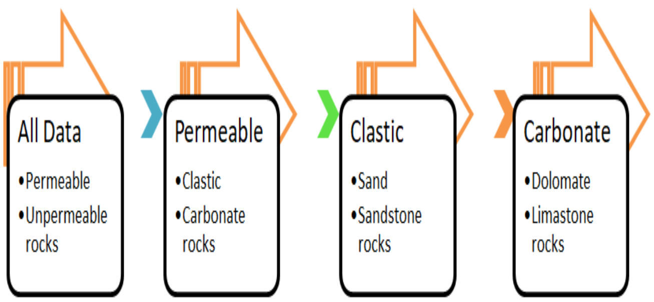

Figure 2: The expert procedure of pattern recognition approach.

Figure 3: Displays the confusion matrices of permeable/ unpermeable (shale) rocks.

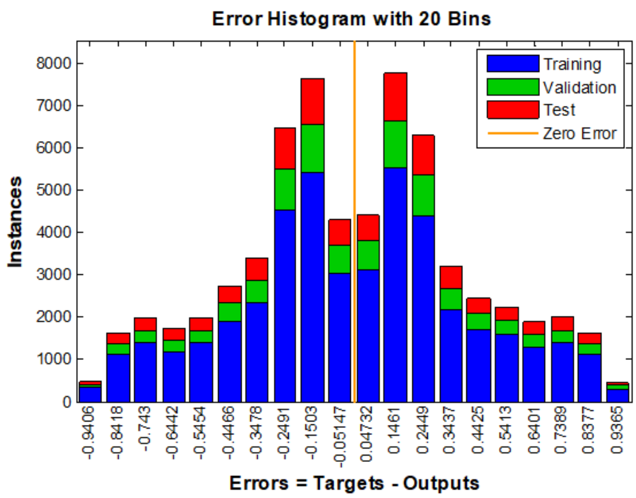

Figure 4: The first error histogram.

Secondly, the approach used only permeable rocks to identify the lithology of clastic rocks (sand and sandstone) from carbonate rocks. Figure 5 illustrates confusion matrices with overall accuracy about 95%. Figure 6 shows also their error histogram.

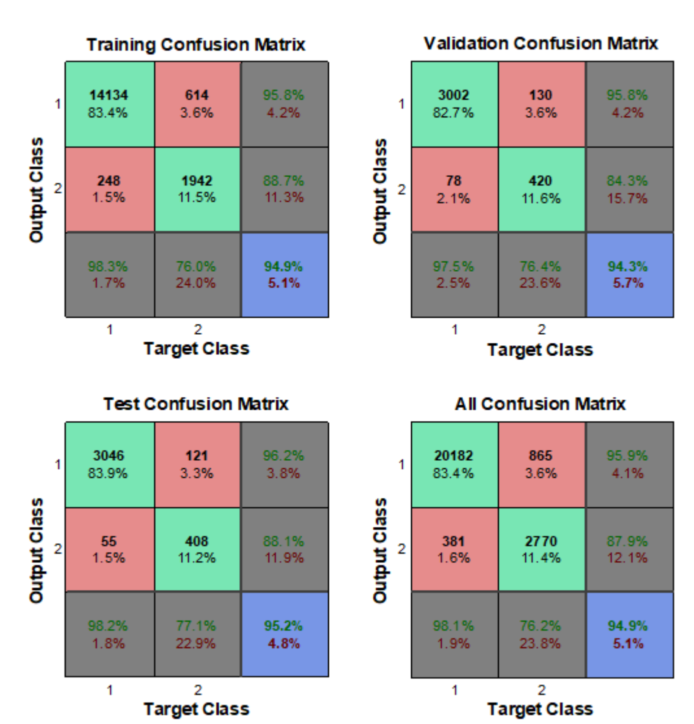

Figure 5: Displays the confusion matrices of clastic and carbonate rocks.

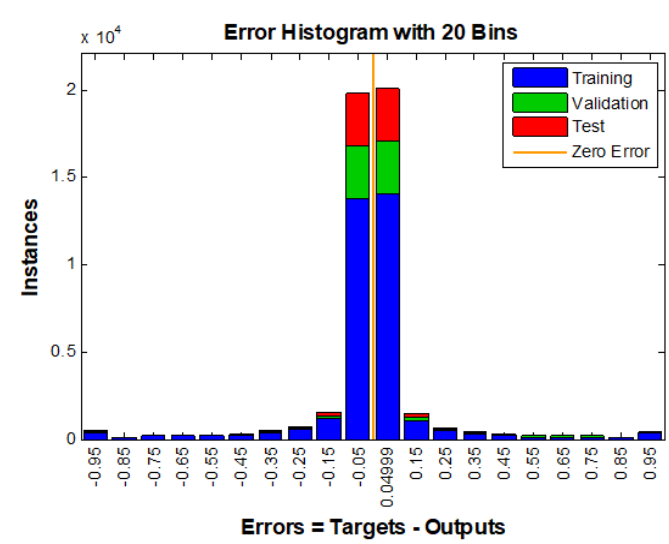

Figure 6: The second error histogram.

Thirdly, the pattern recognition tool applied the clastic data to categorize the lithology of sand and sandstone. Figure 7 shows confusion matrices with overall accuracy about 86.2%. Figure 8 shows also their error histogram.

Figure 7: Confusion matrices of sand and sandstone.

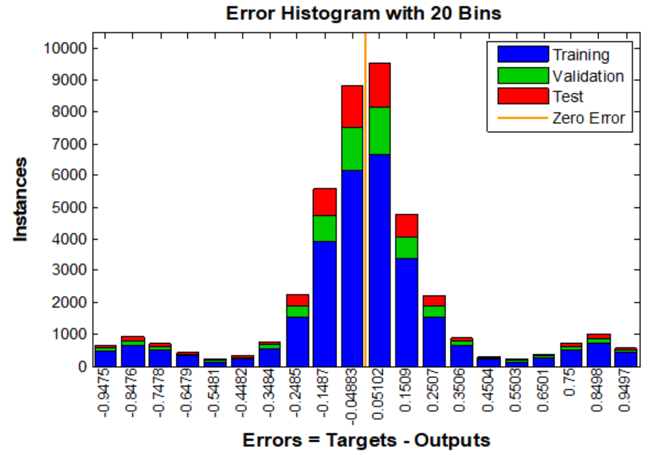

Figure 8: The third error histogram.

Finaly, the pattern recognition approach used carbonate data to identify the lithology of dolomate and limastone rocks. Figure 9 shows confusion matrices with overall accuracy about 93%. Figure 10 shows also their error histogram.

Figure 9: Confusion matrices of dolimate and limestone.

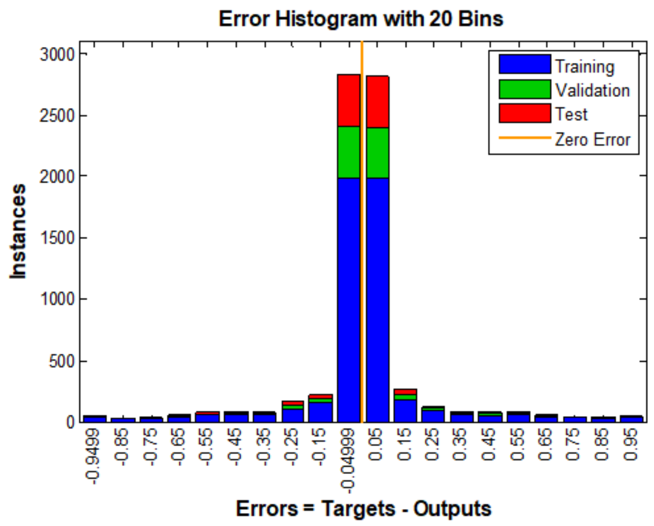

Figure 10: The fourth error histogram.

CONCLUSION

- The pattern recognition model performs well for prediction the lithology of Camaal oil field and it can be applied in another carbonate reservoir fields.
- The proposed model is more accurate and reliable for prediction than conventional log interpretation and can be used in wide range.
- This approach taking little time comparing with conventional method. The accuracy of pattern recognition approach decreases with increasing input data.

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