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MODULAR ARTIFICIAL NEURAL NETWORK FOR PREDICTION OF PETROPHYSICAL PROPERTIES FROM WELL LOG DATA

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ABSTRACT - This paper reports the application of Kohonen's Self-Organizing Map (SOM) and Learning Vector Quantization (LVQ) algorithms, and the commonly used Back Propagation Neural Network (BPNN) to the prediction of petrophysical properties from well log data. Recently, the use of artificial neural networks (ANN) in the field of petrophysical properties prediction has received increasing attentions. In this paper, a modular ANN comprises of a complex network made up of a number of sub-networks is introduced. In this approach, the SOM algorithm is first applied to classify the well log data into a pre-defined number of classes. This gives an indication of the lithology of the given well. The LVQ algorithm is then applied to train the network under supervised learning. A set of BPNN which corresponds to different classes is then developed for the prediction of petrophysical properties. Once the network is trained, it is then used as the classification and prediction model for subsequent input data. Results obtained from example studies using this proposed method have shown to be fast and accurate as compared to a single BPNN network.

I. INTRODUCTION

Two key issues in reservoir evaluation using well logs are the characterization of formation and the prediction of petrophysical properties. A large number of techniques have been introduced in order to establish an adequate interpretation model. However, the task is not simple because of the complexity of different factors which influence the log responses and the increasing amount of downhole measurements employed [1,2]. Derivation of such interpretation models normally falls into two main approaches: graphical crossplotting/statistical techniques, and, multivariate statistical methods such as principal component analysis and cluster analysis. Although both approaches are used extensively, they do have their inherent shortcomings. Most of the time, it is difficult to determine any theoretical or empirical formula for accurate reservoir analysis.

In recent years, neural network is an emerging technology which has been applied to many areas of log evaluation. This new technique has proved to be more successful than the classical statistical method [3,4]. Most of the neural network applications reported are based on Back Propagation Neural Networks (BPNN) [3,4,5,6] with the exception of some applications, which used Fuzzy ARTMAP [7], Self-Organizing Map [8] and Learning Vector Quantization (LVQ) [8]. When BPNN is used as the interpretation model, the input applied are data from various logging instruments such as gamma ray, resistivity, neutron porosity and bulk density. The outputs from BPNN are corresponding to different output parameters such as rock matrices, porosity and permeability. As BPNN is a supervised network, a set of input and output vectors is used to train the network. The most widely used learning algorithm is the error back-propagation algorithm [9]. Although this algorithm has been successful in many applications, the disadvantages such as long training time has caused inconvenience in practical use. This calls for improvement of the basic BPNN algorithm or other forms of network configurations.

In this paper, a proposed modular neural network using SOM, LVQ and BPNN is used to predict the petrophysical properties from well log data. As compared to the usual BPNN approach which uses only a single network, this modular network enables the division of a complex network into a number of sub-networks. This approach is similar to the 'genetic approach' [10] used for petrophysical properties prediction. The SOM and LVQ are used to classify the well log data which gives an indication of the lithology. Several BPNN corresponding to the number of classes
obtained from SOM are then developed for the purpose of petrophysical properties prediction. Since the number of data to be handled by each sub-network is reduced, the training time is therefore significantly shortened. Results obtained from example studies using this method have also shown to be more accurate as compared to a single BPNN approach.

II. ARTIFICIAL NEURAL NETWORK

A. Self-Organizing Map (SOM)

In 1980s, Teuvo Kohonen has developed an algorithm to simulate the brain’s ability to organize itself in response to external stimuli, known as Self-Organizing Map (SOM) [11, 12, 13]. As it has the ability to learn and organize information without being given correct outputs for the inputs, the SOM is considered to be performing unsupervised learning. The SOM network consists of two layers of nodes. Each output node is computed with the dot product of its weight vector and the input vector. The result will reflect the similarity between the two vectors. It should be noted that only the node with the maximum activation will produce an output. SOM network performs clustering through a competitive learning technique known as “winner-take-all”. The winner in this case is the node with largest activation level. Only the winning node and its neighbor nodes are the only nodes that are allowed to learn for the current input pattern. Kohonen uses lateral inhibition for learning which has the appearance of a Mexican sombrero. After a few iterations, only the winning node that is closest to the input vector is allowed to be reinforced. SOM network is faster than perceptron learning as it uses single-pass learning rather than multiple feedback [13].

B. Learning Vector Quantization (LVQ)

The Learning Vector Quantization (LVQ) is closely related to SOM [13, 14]. While SOM is an unsupervised learning network, LVQ uses supervised learning. Another difference between them is that LVQ has no defined neighborhoods around the “winner” during learning. LVQ makes use of competitive learning rule to define decision boundaries in the input space. It is supervised because they are given a set of input patterns along with correct class labels. Its main purpose is to define class regions in the input data space. LVQ is fast in learning and the classification accuracy is high.

C. Back Propagation Neural Network (BPNN)

Back Propagation Neural Network (BPNN) is the most widely used neural network system and the most well known supervised learning techniques [9,15]. BPNN is a systematic method for training multilayer artificial neural network. Although it has some limitations, it has generated many successful applications which clearly demonstrate its applicability in diverse areas.

BPNN has a number of layers: an input layer; an output layer; and a hidden layer. In some cases, more than one hidden layer may be used. Each layer consists of a number of neurons and each neuron is connected to all the neurons in the next layer. The connection between two neurons in different layers is represented by a weight factor. The objective of training the BPNN is to adjust the weights so that application of a set of inputs produces the desired set of outputs. A training set containing a number of desired input and output pairs is used in training. The input set is presented to the input layer of BPNN. A calculation is done to obtain the actual output set by proceeding in order from the input layer to the output layer. After this stage, feed forward propagation is completed. At the output, the total error which is the sum of the squares of the differences between the desired output and the computed output on each output neuron is calculated. This value is used in a learning algorithm to update the weights and the process is back propagated through the network. Once the modification of all the connection weights is done, a new set of output can be computed and subsequently a new total error will be obtained. This back propagated process repeats until the value of the total error is below some particular threshold. At this stage, the network is considered to be converged. As the network repeats the back propagated process, the learning speed is slow as compared to SOM and LVQ. Recent literature has reported different ways to accelerate the convergence process by modifying the basic BPNN algorithm [16].

III. MODULAR ARTIFICIAL NEURAL NETWORK

A typical application of BPNN in petrophysical properties prediction is shown in Fig. 1. Data from input logs such as spontaneous potential, uninvaded zone resistivity and gamma ray are normalised before applying to the input layer of the BPNN. For most applications, one hidden layer is chosen. The output neurons are assigned to correspond to the petrophysical properties such as sandstone, limestone and dolomite.
This paper proposes a modular neural network which makes use of SOM, LVQ and BPNN to perform the lithology classification and petrophysical properties prediction. The block diagram of the modular neural network is shown in Fig. 2. Further details of the proposed classification process in the block diagram, which comprises of SOM and LVQ, can be found in [8]. The unsupervised SOM is first used to classify the training input logs and output parameters into a number of predefined classes. The classification output from the SOM will give an indication of the lithology of the training well. The classes obtained from the SOM are then appended back to the training input logs for the training of the supervised LVQ. After training, the LVQ is then used to classify any unknown input logs, according to the training classes.

A number of BPNN networks corresponding to the number of classes obtained from SOM are developed and trained. After the classification process, the data that are fed into the different BPNN will resemble similar characteristics. In this way, training of the BPNN are expected to take a shorter time.

IV. CASE RESULTS AND DISCUSSIONS

A set of 127 data has been used for training. Another set of 127 testing data are used to examine the performance of the modular neural network. The results obtained are then used to compare with the traditional single BPNN network. The hardware platform used for this work is a PC Pentium-90 computer.

In this study, only three output rock matrices are used to demonstrate the prediction ability of the proposed network. The rock matrices are sandstone (MAT-1), limestone (MAT-2) and dolomite (MAT-3). The input logs used in this work are bulk density (RHOB), neutron (NPHI), uninvaded zone resistivity (RT), gamma ray (GR), sonic travel time (DT) and spontaneous potential (SP).

The BPNN configuration chosen for the single network consists of 6 input neurons, 5 hidden neurons and 3 output neurons. As for the modular network, the SOM is initially used to classify the training data into 9 different classes. Then, the obtained classes are attached to the input logs used for training of the LVQ network. The training data are also divided into the corresponding classes for development of individual BPNN networks. The BPNN configuration chosen for all the 9 sub-networks is the same as the single BPNN network.
Table 1 shows the results obtained from modular network as compared to the results from the single network approach. As expected, the training time for the modular network is very much shorter than the single network method. The overall accuracy of the modular network is also better based on the comparison between the mean square errors. The mean square error of the modular network is calculated by taking the average of the mean square errors from the sub-networks. Fig. 3 shows the graphical comparison of the output rock matrices predicted by each method. From Fig. 3, it can be observed that the modular network’s output follows closely to the desired output core data.

Fig. 3(a). Single BPNN output compared to core data

Fig. 3(b). Modular Network output compared to core data

Fig 3. Comparison of Single BPNN output and Modular Neural Network output. (Core Data are represented by dot in the plot)
TABLE I

<table>
<thead>
<tr>
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<th>Single Network</th>
<th>Modular Network</th>
</tr>
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<tbody>
<tr>
<td>BPNN Config</td>
<td>6-5-3</td>
<td>9 x (6-5-3)</td>
</tr>
<tr>
<td>Training Time</td>
<td>34 minutes</td>
<td>7 minutes</td>
</tr>
<tr>
<td>Mean Square Error</td>
<td>0.0297</td>
<td>0.00048</td>
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</table>

V. CONCLUSION

A petrophysical prediction method based on a modular artificial neural network is proposed in this paper. SOM and LVQ algorithms have been used to classify the lithology of a given well from the input log data. After the classification process, a number of BPNN are then used. This approach of petrophysical prediction has shown to be more accurate as compared to the traditional single BPNN approach. Results from the example case study have shown that the training time of this modular network is shorter. This reported approach can be used as an alternate method for petrophysical prediction in addition to the traditional approaches.

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