Lithofacies Prediction from Well Logs Data using Different Neural Network Models

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Abstract: The main objective of this work is to predict lithofacies from well-logs data using different artificial neural network (ANN) models. The proposed technique is based on three classifiers types of ANN which are the self-organizing map (SOM), multilayer Perceptron (MLP) and radial basis function (RBF). The data set as an input of the neural network machines are the eight borehole measurements which are the total natural gamma ray; the three concentrations of the radioactive elements Thorium, Potassium and Uranium; the slowness of the P wave, the bulk density, the neutron porosity and the photoelectric absorption coefficient of two boreholes located in Algerian Sahara. Hence, the outputs of three neuronal kinds are the different lithological classes of clayey reservoir. These classes are obtained by supervised and unsupervised learning. The output results compared with basic stratigraphy show that the Kohonen map gives the best lithofacies classification where the thin beds intercalated in the reservoir, are identified. Consequently, the neural network technique is a powerful method which provides an automatic classification of the lithofacies reservoir.

1 INTRODUCTION

Recently, pattern recognition context became a popular interest in geosciences by neural network techniques. In petrophysics, these last can be used for classification (Aliouane et al., 2011); (Ouadfeul and Aliouane, 2012) and approximation (Lim, 2005); (Amenian, 2005) and (Aminzadah, 1999); (Aliouane et al., 2012) in reservoir characterization by well log-data where the lithofacies prediction is an important step in crossed formations, mainly, in a reservoir.

Neural network as a nonlinear and non-parametric tool is becoming increasingly popular in well log analysis. Neural network is a computer model that attempts to mimic simple biological learning processes and simulate specific functions of human nervous system. The main objective of this work is to predict lithofacies from well-logs data using different artificial neural network (ANN) models. The proposed technique is based on three classifiers types of ANN which are the self-organizing map (SOM), multilayer Perceptron (MLP) and radial basis function (RBF) in order to choose the best lithological classifier.

The well-logs of the clayey reservoirs of two boreholes located in Algerian Sahara are exploited. One of them is selected as pilot well for training networks and the second is used for generalization.

In the present study, we start by basic concepts of principles of different neural network models such as SOM, MLP and RBF and their training model. Different learning parameters will be discussed to improve the network's architectures. At the end, the results will be compared to a basic stratigraphy.

2 DATA ANALYSIS OF THE CLAYEY RESERVOIR

The clayey reservoirs are, generally, radioactive. Their radioactivity is due to the presence of the three nuclear elements such as Thorium, Potassium and Uranium. The Cambrian reservoirs of two boreholes located in Algerian Sahara present the geological model constituted by sandstone and clay (Shonatrach and Shlumberger, 2007). Thus, this kind

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of reservoir is easily identified by the total natural gamma ray and its radioactive elements spectra (Ellis and Singer, 2008). This analysis is confirmed using other petrophysical parameters recordings sensitive to clays. These are the slowness of the P wave, the bulk density, the neutron porosity and the photoelectric absorption coefficient. (figure 1 and 2).

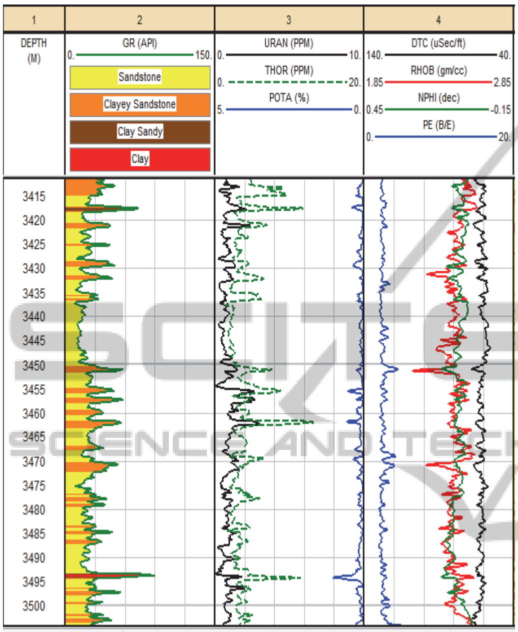

Figure 1: Petrophysical parameters recordings of well-1.

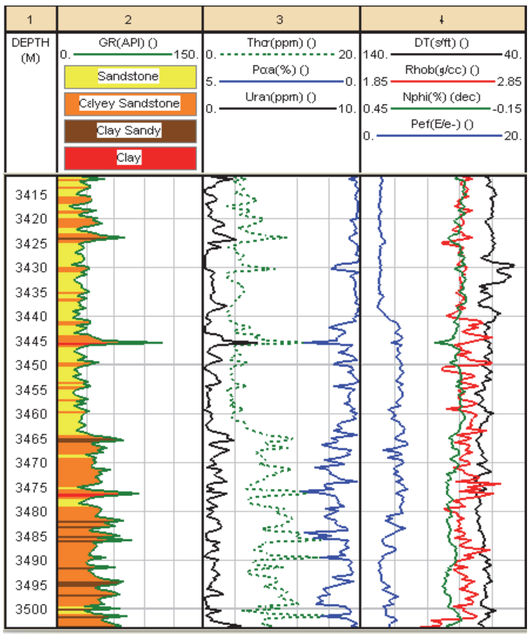

Figure 2: Petrophysical parameters recordings of a well-2.

The data set as an input of the neural network machines are the eight borehole measurements which are the total natural gamma ray; the three concentrations of the radioactive elements Thorium, Potassium and Uranium; the slowness of the P wave, the bulk density, the neutron porosity and the photoelectric absorption coefficient of two boreholes located in Algerian Sahara. Hence, the outputs of three neuronal kinds are the different lithological classes of clayey reservoir. These classes are obtained by supervised and unsupervised learning and constituted by 04 classes: sandstone, clay, clayey sandstone and sandy clay (Figure 3).

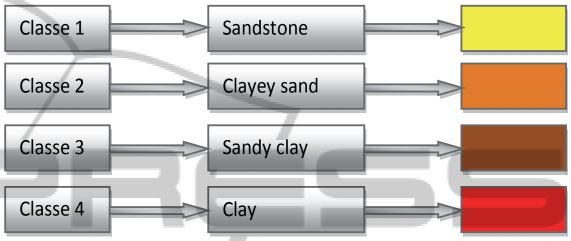

Figure 3: Lithological classes of the clayey reservoir.

Data of well-1 are exploited for training and the data of well-2 are used for generalization.

3 SELF ORGANIZING MAP

Self-organizing maps are different than other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space (figure 4).

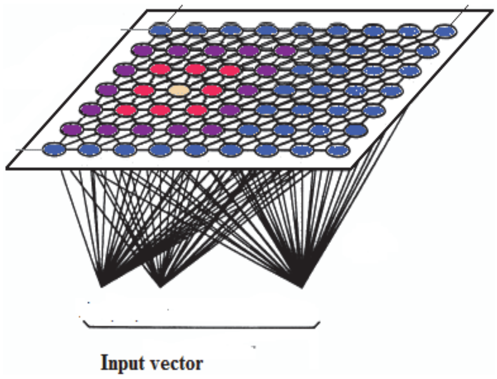

Figure 4: Kohonen's map principle.

This makes SOM useful for visualizing low-dimensional views of high-dimensional data, similar to multidimensional scaling. The model was first described as an artificial neural network by the Finnish professor Teuvo Kohonen (Kohonen, 1982), and is sometimes called a Kohonen map. Like most artificial neural networks, SOMs operate in two modes: training and mapping. Training builds the map using input examples. It is a competitive process, also called vector quantization. Mapping automatically classifies a new input vector.

The goal of learning in the self-organizing map is to cause different parts of the network to respond similarly to certain input patterns. This is partly motivated by how visual, auditory or other sensory information is handled in separate parts of the cerebral cortex in the human brain (Kohonen, 1982; 2000).

The training utilizes competitive learning. When a training example is fed to the network, its Euclidean distance to all weight vectors is computed. The neuron with weight vector most similar to the input is called the best matching unit (BMU). The weights of the BMU and neurons close to it in the SOM lattice are adjusted towards the input vector. The magnitude of the change decreases with time and with distance from the BMU. The update formula for a neuron with weight vector **Wv**(t) is:

$$\mathbf{Wv}(t+1) = \mathbf{Wv}(t) + \Theta(v,t)*\alpha(t)*(\mathbf{D}(t) - \mathbf{Wv}(t))$$

where $\alpha(t)$ is a monotonically decreasing learning coefficient and **D**(t) is the input vector. The neighborhood function $\Theta(v, t)$ depends on the lattice distance between the BMU and neuron *v*. In the simplest form it is one for all neurons close enough to BMU and zero for others, but a gaussian function is a common choice, too. Regardless of the functional form, the neighborhood function shrinks with time. At the beginning when the neighborhood is broad, the self-organizing takes place on the global scale. When the neighborhood has shrunk to just a couple of neurons the weights are converging to local estimates.

This process is repeated for each input vector for a (usually large) number of cycles **λ**. The network winds up associating output nodes with groups or patterns in the input data set. If these patterns can be named, the names can be attached to the associated nodes in the trained net.

During mapping, there will be one single winning neuron: the neuron whose weight vector lies closest to the input vector. This can be simply determined by calculating the Euclidean distance between input vector and weight vector.

While representing input data as vectors has been emphasized in this article, it should be noted that any kind of object which can be represented digitally and which has an appropriate distance measure associated with it and in which the necessary operations for training are possible can be used to construct a self-organizing map. This includes matrices, continuous functions or even other self-organizing maps.

The obtained lithofacies classification is presented in figure 7b.

4 MULTILAYER PERCEPTRON

The employed Neural Network type is a standard layered Neural Network type with a linear accumulation and a sigmoid transfer function, called multi-layer perceptron. Usually the network consists of an input layer, receiving the measurement vector x, a hidden layer and an output layer of units (neurons). In this configuration each unit of the hidden layer realizes a hyperplane dividing the input space into two semi-spaces. By combining such semispaces the units of the output layer are able to construct any polygonal partition of the input space. For that reason it is theoretically possible to design for each (consistent) fixed sample a correct Neural Network classifier by constructing a sufficiently fine partition of the input space. This may necessitate a large number of neurons in the hidden layer. The model parameters consist of the weights connecting two units of successive layers. In the training phase the sample is used to evaluate an error measure and a gradient descent algorithm can be employed to minimize this net error. The problem of getting stuck in local minima is called training problem.

The structure is constituted of one layer for inputs, one hidden layer and one layer for outputs (figure 5).

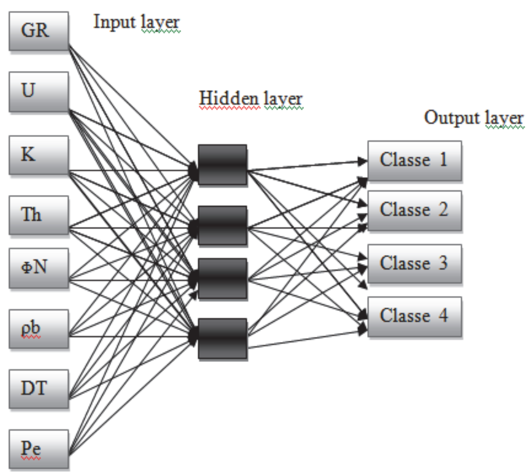

Figure 5: Architecture of MLP network.

Obtained lithological classification by the MLP is presented in figure 7c.

5 RADIAL BASIS FUNCTION

Powell (1985) surveyed the early work on RBF neural networks, which presently is one of the main fields of research in numerical analysis. With respect to this network, learning is equivalent to finding a surface in a multidimensional space that provides a best fit to the Learning data. Correspondingly, generalization is equivalent to the use of this multidimensional surface to interpolate the test data. The construction of a RBF network in its most basic form involves three entirely different layers. The input layer is made up of input nodes. The second layer is a hidden layer of high enough dimensions, which serves a different purpose from that in the multilayer perceptron. The output layer supplies the response of the network to the activation patterns applied to the input layer. In contrast to the multilayer perceptron, the transformation from the input space to the hidden layer space is non-linear, whereas the transformation from the hidden layer space to the output space is linear (figure 6).

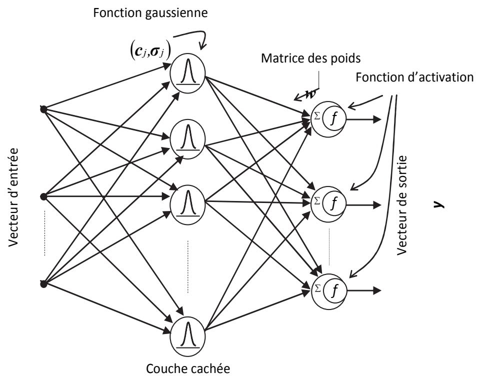

Figure 6: RBF principle.

The neurone number of the input layer is the same for the RBF and for the MLP, corresponding to the eight petrophysical measurements. The Obtained lithological classification by the RBF is presented in figure 7d.

6 RESULTS DISCUSSION AND CONCLUSIONS

By analyzing figure 7, one can remark that the Self Organizing neural network machine (figure 7b) gives more lithological details than the MLP (figure 07c) and RBF (figure 7d) networks.

By implementing our analysis, we have demonstrated that it is possible to provide an accurate geological interpretation within a short time in order to take immediate drilling and completion decisions, but also, in a longer-term purpose, to update the reservoir model.

Reservoir model based on the self organizing map neural network machine with the raw data as input gives a detailed information.

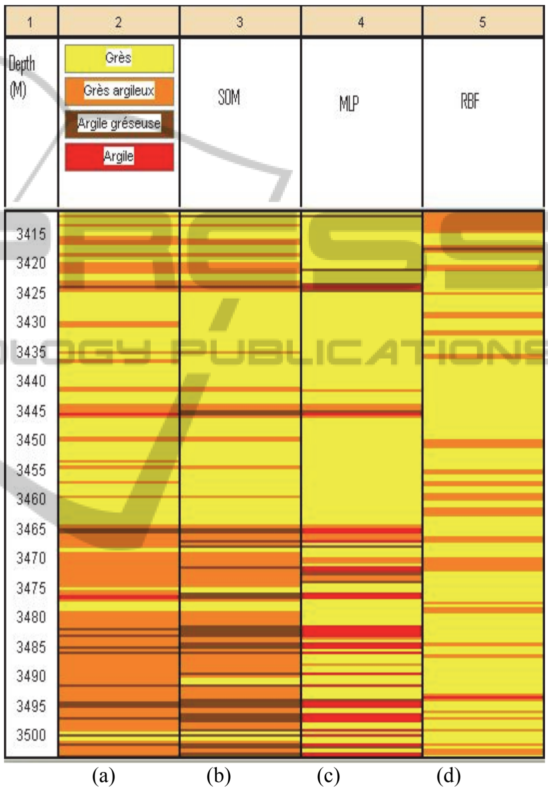

Figure 7: Lithofacies classification of a reservoir of Well-2. (a) basic stratigraphy; (b) by SOM; (c) by MLP; (d) by RBF.

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