Automatic lithology identification from GR-M-N cross-plot.

Alexandre Silva Santos*,Anna Ilcéa Fischetti, André Andrade. Universidade Federal do Pará.

Copyright 2003, SBGf - Sociedade Brasileira de Geofísica
This paper was prepared for presentation at the 8th International Congress of The Brazilian Geophysical Society held in Rio de Janeiro, Brazil, 14-18 September 2003.
Contents of this paper was reviewed by The Technical Committee of The 8th International Congress of The Brazilian Geophysical Society and does not necessarily represents any position of the SBGf, its officers or members. Electronic reproduction, or storage of any part of this paper for commercial purposes without the written consent of The Brazilian Geophysical Society is prohibited.

Abstract

Lithology identification may be the most important activity performed by a geologist. In a borehole environment in two circumstances this task can be full completed, the first one is the case where there are cores and the second, the uncored borehole cross homogeneous rock, like evaporites – the conventional density log can identify it. In practices, these situations are rare. Nowadays there are some tools that can identify minerals in a borehole, but its use still is not common. We need some methods to identify lithologies, mostly direct from conventional well logs. Then, we present an automatic method to identify lithologies in a borehole from well log data, starting from an artificial neural network, which emulates the interpretation of the classical M-N plot with the addition of one new axis, in the third dimension, represented by gamma ray log. We show the behavior of this method with well log data from one borehole in Namorado oil field in the Campos basin, Brazil.

Introduction

The complex constitution of reservoir rocks and the need of lithology knowledge from conventional well log data induced the combination of three porosity tools in attemption to remove the porosity effect in their measurements to deduce the rock matrix. The first one was the so-called M-N cross-plot (Burke, 1969). The combination of density and sonic measurements is used to define the parameter M and the parameter N uses the density and neutron measurements combination. The graphical presentation of these two parameters produces the cross-plot – The M-N plot, where are marked the characteristic values for matrix of principal reservoir rocks.

We show here, a modification of classical M-N cross-plot adding the gamma ray log as the third axis, called GR-M-N cross-plot and a method to identify the lithology by a new approach using competitive neural network architecture, which emulates the interpreter behavior.

The performance of our approach is shown over actual data from Namorado field in the Campos basin, Brazil.

Method

We do in the next sections some comments about competitive neural network and the M-N plot in way to show a new method to lithology identification.

Neural networks with competitive layer

The neural networks based on a competitive learning are characterized by competitive neurons that are forced to compete between them; in such way that only one neuron stays active or produce a non-null output signal to each time. A way to induce competition among neurons is the introduction of inhibitory lateral connections (synapses) among them. From biological motivation, the lateral connections are mathematically described by a function like Mexican hat (Haykin, 2001). In this function we can distinguish the central area, of excitatory character and the lateral areas nearby, of inhibitory character.

This neural network presents two important characteristics:

The net tends to concentrate its activity inside clusters, in the stimulus space, referred as activity bubbles.

The activities bubbles location is determined, fundamentally by the stimulus nature.

Take $x_1,\ldots,x_P$ as the stimulus applied to neural network, with p sensorial elements in its input layer. Be $w_{j1},\ldots,w_{j1}$ the corresponding neuron j synaptic weights in the competitive layer and $c_{jk},c_{jo},\ldots,c_{jk}$, the lateral connections weights that are Mexican hat function values, in the discretized form, with k samples. Be $y_1,\ldots,y_n$ the competitive neural network output signals. The neuron j output signal is expressed by

$$y_j\,(n+1)=\varphi\left(P_j+\beta\sum_{k=-k}^{k}c_{jk}\,y_{j+k}\,(n)\right),\quad j=1,2,\ldots,N. \qquad (1)$$

In equation (1), φ is an activation function like the sigmoid function, responsible for output signal quantization of the output signal in [0,1]. The P_j term is neuron j weight input potential; n denotes discrete time. Thus, $y_J\,(n+1)$ is the output of neuron j at time n+1, and $y_{j+K}(n)$ is the output of neuron j+k at the previous time n. The parameter β in the argument on the right-hand side of last equation controls the rate of convergence of the process (Haykin, 2001).

The M-N plot

The M-N plot (Burke et al, 1969) is a graphical method for lithologies identification from well log data that works with three porosity logs defining two parameters, expressed in metric units:

1. The M parameter is defined by

$$M = \frac{\Delta t_w - \Delta t_{ma}}{\rho b_{ma} - \rho b_w} 0.003 \,. \qquad (2)$$

2. The N parameter is defined by

$$N = \frac{\phi n_w - \phi n_{ma}}{\rho b_{ma} - \rho b_w} \,. \qquad (3)$$

In equations (2) and (3), Δt_w represents the water transit time; Δt_{ma}, the matrix transit time; pb_{ma}, the matrix density; pb_w, the water density; ϕn_w, the water neutron porosity and ϕn_{ma}, the matrix neutron porosity.

The parameters M and N are quite independent of rock porosity, unless the neutron measurements influence. The use of convenient values for rock matrix (sandstone, limestone, etc) defines the fixed points or matrix points, which can be obtained and plotted in a graphical form. This points act like a fixed patterns to lithologies identification with the M-N plot.

The GR-M-N cross-plot

We introduce a modification on the classical M-N plot adding a third axis with the GR measurements, in a way to focus the principal problem in deduce lithologies from well log data using the M-N plot, which is to identify the shales, once its complex constitution do not permit the existence of unique values for M or N to be represented in the M-N plot. The principal effect of this 3-D plot is to enable the separation of the shale effect in the porosity logs measurements, which permits to identify distinct lithologies with the same M-N values and different shale content. We show in Figure 1 the so-called GR-M-N plot and some input data, represented by red crosses.

To perform the automatic lithology identification using the GR-M-N plot, we construct a competitive neural network with the values of M, N and GR as input of each one of three neurons in its input layer. The competitive layer is composed by 20 neurons. Here our intention is to provide a sufficient number of neurons in a way to address all clusters in the input space. We use the instar learning rule (Kohonen, 1989) to find the center of all clusters of input data. Some of competitive neurons could address the same cluster. Blue circles in Figure 1 show the final position of weight connections of each competitive neuron after the end of training phase.

Now, we decide about the competitive neuron that represents the shales. We start the following rule: The shale is represented by the competitive neuron with lower values of M and N and higher value of GR. Taking the values of weight connections associated to input neurons that receive the values of N and M, we have the orthogonal projection of competitive neurons in the M-N plane, or in other words we have the projection of spatial clusters of input data in the M-N plane, as is shown in Figure 2, where the points in the original M-N plot are represented by black circles and projection of competitive neurons by blue circles. In fact this method produces a considerable data reduction for the M-N plot interpretation. We find the shale point and insert it in the M-N plot, as can be seen in Figure 2 by the green circle.

We are ready to associate lithology to centers of input clusters or identify the lithologies crossed by a borehole. We construct a competitive neural network with two neurons in the input layer that receive the clusters center values of M and N. This input layer is full connected with the competitive layer, which is composed by 10 neurons. We associate each one neuron to each one of the fixed points in the M-N plot, including the shale point; taking as weight connection, exactly theirs coordinates in the M-N plane (Andrade & Fischetti, 1999).

We induce the competition for each cluster center; the winner neuron indicates the lithology addressed to all depth points associated to this particular cluster center. We take the values of GR log for those depth points and created a log for each lithology, with those GR values in the correspondent depth positions and zeros for all other positions.

Results

We show in the figure 1 the GR-M-N plot and some depth points of a cored well in the Namorado oil field, represented by red crosses. Also are represented the weight connections of the 20 neurons used in the first competitive neural network, showed by blue circles after the training phase.

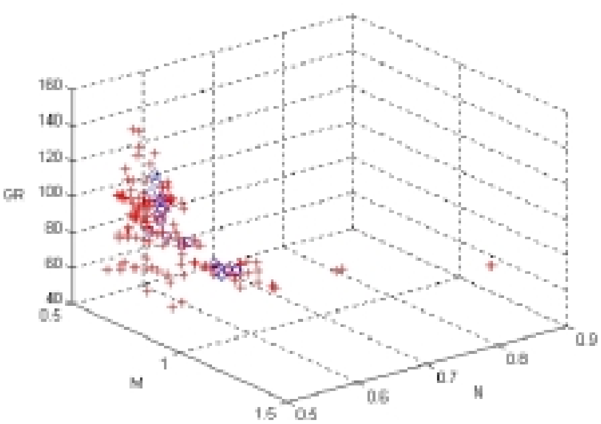

Figure 1. The GR-M-N plot, with the input data (red crosses) and final stage of competitive neural network to shale point identification (blue circles).

In the Figure 2 we show the conventional M-N plot with lithology or fixed points represented by black circles and clusters center originated in the final stage of competitive neural network training to shale point identification (blue circles). We note that borehole crosses three distinct lithologies: sandstones, dolomites and shales. A green circle indicates the shale point.

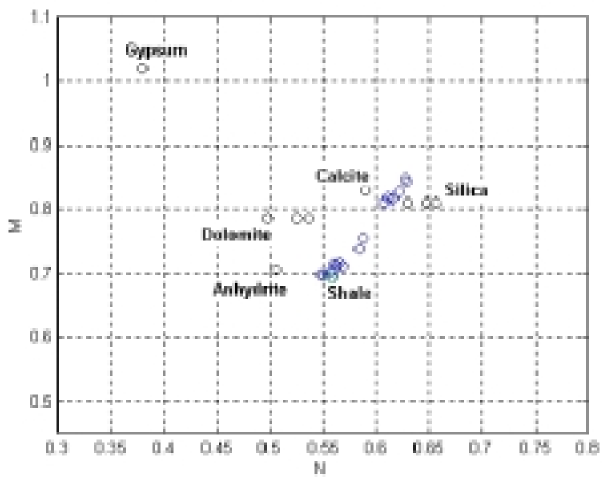

Figure 2. M-N plot, with clusters center represented by blue circles, lithologies points by black circles and shale point by green circle.

After the computing of the second competitve neural network we have all the points classified in agreement with theirs lithologies. We show in Figure 3 a small interval of our test well showing the lithology identification performed by our method compared with lithological description from cores as validation of the method.

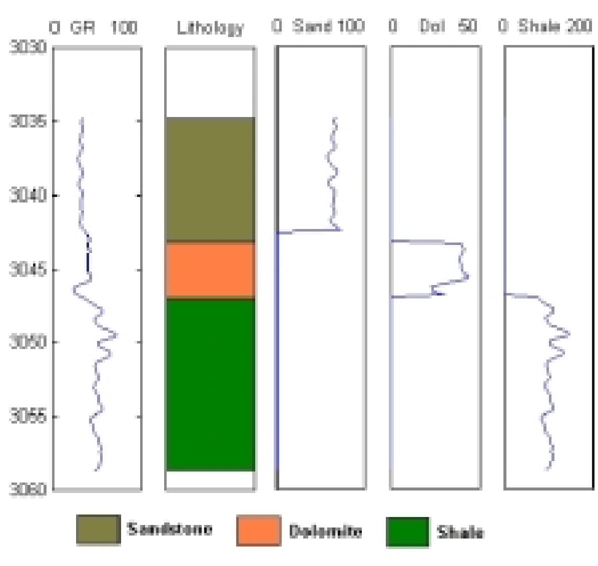

Figure 3. Comparison betwen lithology identification from cores and from GR-M-N crossplot.

In Figure 4 we show the lithology identification for all logged interval. In track 1 we show the gamma ray log; in track 2 the same gamma ray log just in the depth intervals identified as sandstones. The tracks 3 and 4 are the same for dolomites and shales.

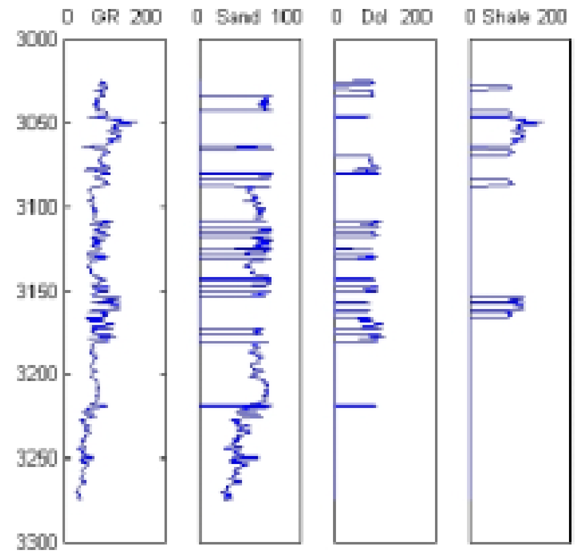

Figure 4. Lithology identification of all logged intervals.

Conclusions

We present a method that promotes the lithologic identification from well log data, even in complex depositional setting, without the interpret intervation based on the automation of the conventional M-N plot by a convenient couple of competitive neural networks. Our tests have been show a good agreement between our results and core description.

Acknowledgments

The authors would like to extending their acknowledgments to CAPES and ANP/FINEP/UFPa for support this work.

References

Andrade, A., Fischetti, A., 1999, Automatic Lithologies Identification from Well Log. CD-Rom of the 6th International Congress Brazilian of the Geophisics

Burke, J., Campbell, R. & Schimidt, A., 1969, The Lithoporosity Crossplot. SPWLA 10th Logging Symposium.

Haykin, S. 2001, Redes Neurais: Princípios e Práticas. Bookman, SP, Brasil.

Kohonen, T., 1989. Self-organization and associative memory. Springer-Verlag, Berlin. 312 pp.