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Automatic Lithologies Identification from Well Log.

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Abstract

The complex mineralogical constitution of reservoir rocks and the need of correct lithology identification in a borehole from well log data, makes lithologic identification of a rock possible, not by means of a complete mineralogical description, but through the identification of its main mineral constituents or essential mineral.
For identification of essential mineral, through the well log data, several numeric methods were developed, like the compositional analysis and graphical methods, such as the M-N plot (BURKE et al,1969).
We show here, the mineral essential determination method from well log data, by means of a simulation of interpretation performed by log analyst utilization of the M-N plot, through an artificial neural network architecture with competitive layer, intending to simulate the decision problem of log analyst, when the M-N plot is used.

In the enviroment of artificial neural network computations, the log analyst decision problem simulation, when M-N plot is used, can be understood as a decision problem with an alternative finite number or as non-linear classification of stimulus group in the patterns set .
The perfomance of this approach is shown over real data from PETROBRAS obtained at Amazon Basin**.**

INTRODUCTION

When a sedimentary rock does not have any porosity and it is constituted of only one homogeneous material, this lithological identification through the well log data is immediate, as the evaporites case, the halite for example (NaCl). In this case, the log is plenty and enough to diagnose this mineral presence, starting from its characteristic density value obtained by the desity log. Unfortunately, the evaporites are not reservoir rocks and do not have any interest for reservoir geology. The important reservoir rocks have much more complex mineralogical constitution, as is the sandstone case, that is a reservoir rock quite common. This rock, in the great majority of the occurrences, is not composed exclusively by quartz, but for a complex combinations of quartz , clay-minerals, limestone ciment etc.

The complex constitution of interest rocks and the need for correct lithology identification in a borehole, carry to lithologic characterization of a certain rock type in a simplified form, not by means of a complete mineralogical description, but through the identification of its main mineral constituent or essential mineral.

For the litological characterization or identification of the essential mineral of a rock ,through the well log data, several numeric methods were developed, like the compositional analysis and graphs, like M-N plot (BURKE et al,1969).

We show here, the mineral essential determination method, starting from well log data, by means of a simulation of interpretation accomplished by a log analyst with the M-N plot, through an artificial neural network architecture with competitive layer, meaning to simulate the decision problem of the log analyst, when the M-N plot is used.

In the ambit of artificial neural network computations, when M-N plot is used, the simulation of the log analyst behavior, can be understood as a decision problem with an finite number of alternatives or as non-linear classification of stimulus group in the patterns set .

The perfomance of our approach is shown over real data from PETROBRAS obtained at Amazonian Basin.

NEURAL NETWORKS WITH COMPETITIVE LAYER

The neural networks based on a competitive learning, are constituted by sensorial elements layer (input layer) and only one element layer processor, called competitive layer.

These neurals networks are characterized by a competitive layer neurons that ara forced to compete between them, in such way that only one neuron stays active, or produce a non null output signal to each time instant. A way to induce competition among neurons is the introduction of inhibitory lateral connections (synapses) among them .

To explore a little more on inhibitory synapses, let us consider the neural network showed in Figure 1 which in competitive layer is showing the primary connections with neural network input layer and the inhibitory connections, that are considered a second source of stimulus. Each connection type serves to a defined purpose. The pondered sum of input signals (stimulus) in each competitive neuron, supplies to patterns detection in the stimulus space. Thus, each neuron will produce a selective answer for each particular stimulus group. The lateral (side) connections, then, produce excitatory and inhibitory effects, depending on the relative distance of the neurons connected.

For biological motivation force, the lateral connections are mathematically described by a function like mexican hat (HAYKIN, 1994). In this function we can distinguish two interest areas in lateral interaction among neurons. The central area, of excitatory character and the lateral areas near by, of inhibitory character.

This neural network type 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 stimulus nature.

Be $x_1,...,x_p$ the stimulus applied to neural network, with p sensorial elements in its input layer. Be $w_{j1},....,w_{jp}$ the corresponding neuron j synaptic weights of competitive layer and $c_{j,-k},c_{j,0},...,c_{j,k}$ the lateral connections weights, that are mexican hat function values, in the discretized form, with k samples. Be $y_1,...,y_N$ the neural network output signals of the N neurons output signal of competitive layer. The neuron j output signal is expressed by

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

In this equation, φ is an activation function like the sigmoid function, responsible for output signal quantization of the output signal in the [0,1] interval. The P_j term is neuron j input potential, in the form

$$P_j = \sum_{l=1}^{p} w_{lj}\, x_l \qquad (2)$$

The solution to the non-linear equation (1) is found iteratively, using a *relaxation* technique. Specifically, we reformulate it as a difference equation as follows:

$$y_j(n+1) = \varphi\left(P_j + \beta \sum_{k=-k}^{k} c_{jk}\, y_{j+k}(n)\right), \qquad j = 1,2,...,N \qquad (3)$$

where 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 equation (3) controls the rate of convergence of the relaxation process (HAYKIN, 1994).

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

$$M = \frac{\Delta t_w - \Delta t_{ma}}{\rho b_{ma} - \rho b_w}\; 0.003$$

2. The N parameter is defined by

$$N = \frac{\phi n_w - \phi n_{ma}}{\rho b_{ma} - \rho b_w}$$

In the expressions above, Δt_w represents the water transit time; Δt_{ma}, the matrix transit time; ρb_{ma}, the matrix density; ρb_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, unless the neutron log influences, of rock porosity and use of convenient values for rock matrix (sandstone, limestone, etc), the fixed points can be obteined and ploted in a graphical form, like one shown in Figure 2 by circles. This points act like a fixed patterns to lithologies identification with the M-N plot.

AUTOMATIC LHITOLOGIES IDENTIFICATION

For obtaining the neural network architecture here presented, the problem of lithologies identification is formulated in a certain well log interval in a simplified form. The artificial neural network architecture is able to identify only the essential mineral of rocky matrix that appears in a certain depth interval in a borehole. This way, we can interpret the behavior of neural network as being the accomplishment a classification of points (M_i, N_i), representative of geological layers defined on well logs, in function of fixed points in M-N plane (Table 1).

The artificial neural network architecture, shows at Figure 2, drawn to perform the (M_i, N_i) points classification is formed by two layers:

1- The input layer is composed by two sensorial elements, representing the points (M_i, N_i) obtained from the well logs, shown in Figure 2, like crosses. Those points act like inputs (stimulus) to neural network.

2- The competitive layer will represent the eight fixed points (Table 1) marked in M-N plot with cicles. We defined that each fixed point will be represented by one processor element in the neural network competitive layer, composed then, for eight competitive neurons.

For the final construction of neural network competitive layer, we associated to synaptic weight (w_{ij}), each one of its neurons are fixed points value representative of a particular mineral, as seem in Table 1.

Starting out from our experiments, the β parameter in equation 3, was taken equal to the unit. The lateral connections representative function was approached by the Euclidian distance multiplicative inverse function, between a fixed point (synaptic weight) and any point (M_i, N_i), in M-N plane. The neural network, like this drawing, is prepared for the classification of stimulus space in eight different patterns (minerals).

RESULTS

An application of this neural network was accomplished over three porosity logs from a borehole at Amazon Basis. The depth interval used here, can be seen by the gamma ray log (the right side of Figure 3) and have a complete lithological description, shown in the midle of Figure 3, for comparison.

The values of M and N parameters were obtained to representatives points in every layer defined in lithological description, after depth correction to agree with the porosity logs.

To show the results of application of neural network we created a graphical lithology representation, in Figure 3 left side. It is easy to see the good job produced by neural network.

CONCLUSION

The lithologies identification from well log data using the M-N plot is a routine task accomplished by log analysts. The complexity of this work arises when the numbers of points at M-N plot increases. Then, an automatic lithologies indetification, performed by neural network can be a usefull help to log analyst work.

REFERENCES

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Number	M	N
1	0,771	0,553
2	0,628	0,838
3	0,650	0,838
4	0,585	0,830
5	0,537	0,785
6	0,520	0,785
7	0,505	0,705
8	0,380	1,020

Table 1- Fixed points, in M-N plot, representative of each neuron in a competitive layer.

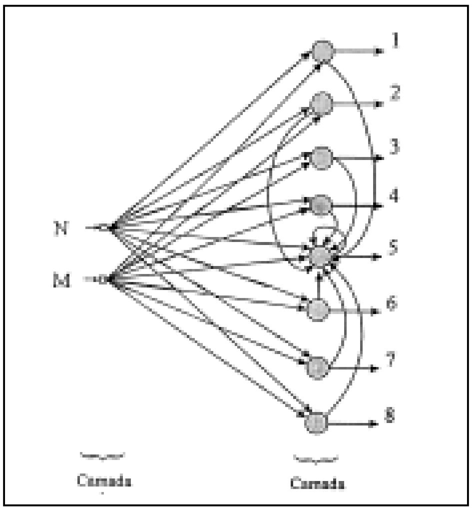

Figure 1: Neural Network Architecture.

Figure 2: M-N plot showing the fixed points (circles) and borehole points (crosses).