Lithology Identificatio elligent Algorithm

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Abstract

Lithology focus on m hand-sample description of rocks, thus) identification is one of the main performed by a geologist. Unfortunately, this n easy work, depending of the occurrence ops or cored the sea, there are not outcrops or in horizont here cores are not produced, direct lithology id is not feasible. In any case, in an oil field, a b always logged and the well-established M-N be used for lithology estimation. As a graph the M-N plot is subject to human visual misinte Here, we try to mitigate the imprecision in the interpretation, assuming the data spread pattern and introduce an intelligent algorith on competitive neural networks. The principal ned as angular competitive neural network tl o produce an estimate of lithology based on a ern recognition. This method is evaluated with and actual well log data from Namorado´s o mpos's basin, Brazil.

Introduction

The depth variation of litho is fundamental to construct the stratigraphic a sedimentary basin. In formation evaluation, r ic and numeric methods were developed to id ogy (rock type) Ve focus on a particular graphic method – Th t (Burke et al., 1969) that combines three po (sonic, density and neutron porosity) to deduc identifying the ndependent of porosity effect in those log rea combination of density and sonic measure efines the M parameter and the parameter N om the density and neutron porosity logs. Th presentation of these two parameters produces r plane, the M-N plane, where can be marke alled matrix or fixed points using N and M a tes, which are calculated taken the physical p more common minerals in sedimentary rocks. The lithology of any depth in a borehole can be estimated by the smallest distance from the point defined by M and N coordinates calculated with correspondents log readings to each matrix point. In a simple geological simplification, the matrix or the solid framework of a sedimentary rock is composed by only one mineral. This procedure simplifies the mineral composition of a sedimentary rock, thus rock type is identified, not by means of a complete geological description, but through the identification of the mineral with highest relative volume in the rock composition. Of course, this simplification does not permit the separation between two different sandstones, but is strong enough to separate sandstones from limestones, which may helps in the construction of stratigraphic column.

The principal limitation of M-N plot is the presence of clays, which can strongly shift the points in the M-N plane, leading to erroneous lithology and limits its application to clean reservoir rocks (Luthi, 2001). The conventional use of M-N plot for a logged interval of a borehole supposes a previous log interpretation and the application of a convenient shale correction. This procedure may introduce errors in the M and N values, once the methods for shale correction need the information about lithology of reservoir rock (matrix) and about neighborhood shales. Normally, the porosity parameters of matrix and shale are unknown at this moment and guessed values can be assumed resulting in erroneous lithology and non-realistic porosity values.

We present an intelligent algorithm to approximate the lithology identification using raw well log data, without core calibration and free of porosity and shale effects on log readings. We explore the interesting geometric characteristics exhibited by the N plot using competitive neural networks.

Intelligent algorithm is a generic name for a set of numeric methods such as artificial neural network, fuzzy inference, and genetic or evolutionary computing, mostly used for data analysis and interpretation. Intelligent algorithms are an increasingly powerful tool for making breakthroughs in the science and engineering fields by transforming data into information and information into knowledge (Nikravesh, 2004). In recent years, some papers have been published involving the solution of a series of well logging problems with artificial neural networks (Aminian & Ameri, 2005) and genetic algorithms (Velez-Langs, 2005). These techniques aim at the incorporation of all logging data available to produce improved oil reserves estimation.

We consider the occurrence of angular patterns in the spatial data spread in the M-N plot and introduce a new competitive neural network specialized to find statically relevant angular patterns in the input data. This characteristic of angular competitive neural network permits the realization of angular pattern recognition producing the mapping and the classification of input data (M, N) in lithology information based on the criterions of M-N plot interpretation. Additionally, this method can handle with raw well log data; so, we present a convenient treatment to treat shaly-reservoir rocks without shale corrections. Our goal is to overcome the lack of accuracy and improve the lithology identification from conventional well logging data without the use of guessing parameters or core calibrations.

We show the behavior and evaluate this method with synthetic data and actual well log data from boreholes in Namorado's oil field, Campos's basin, Brazil.

Methodology

Namorado`s oil field in Campos's basin is located offshore Rio de Janeiro in southeastern Brazil and covers an area of about 100,000 Km^2 from the coastline to the 3400-m isobaths. The Campos basin presents an evolutionary sequence of a rift to drift basin and it is part of the Atlantic Ocean passive margin and presently, is the mostly productive and prolific offshore Brazilian is characterized by a sequence of clastics rocks (conglomerates, sandstones and shales) and carbonate rocks (marls and diamictites), both of transgressive characteristics.

The M-N plot

The M-N plot (Burke et al., 1969) was one of several methods that were devised to extract lithology information from porosity logs that were published and put to commercial use. It uses a particular combination of sonic, density and neutron porosity logs and attempts to remove A combination of the sonic and density measurements is used to define the M parameter, which is the slope of the straight line in the sonic-density crossplot that varies slightly between the three major lithologies due the matrix endpoints. The neutron-density crossplot yields a similar slope, designated as N. Once again, the three matrix N plot shows the two slopes plotted one against the other.

The M and N parameters can be expressed in metric units as

$$M = \frac{\Delta t_w - \Delta t_m}{\rho_m - \rho_w} 0.003 \tag{1}$$

$$N = \frac{\phi_{Nw} - \phi_{Nm}}{\rho_m - \rho_w} \tag{2}$$

In equations (1) and (2), Δt_w represents the transit time for fresh water. Δt_m is the matrix transit time; ρ_m, the matrix density; ρ_w, the fresh water density; ϕ_{Nw}, the water neutron porosity and ϕ_{Nm}, the matrix neutron porosity. The use of convenient values for the matrix of reservoir rocks (quartz, calcite, etc) defines the matrix or N plot, as shown in Figure 1. These points act like a fixed patterns to lithologies identification.

The M and N values can be obtained with log readings by replacing the matrix values in the respective equations by the appropriate log readings. If those M and N values are plotted on the overlay of the M-N plot, it is possible to approximate the lithology.

The presence of shale can strongly shift the points in the M-N plane, leading to erroneous mineral assemblages. Part of this is due the nonlinearity of the neutron response, whereas the apparent values of M are determined by passing a straight line in the appropriate space to the fluid-filled case (Luthi, 2001).

To consider clean and shaly rocks, we modify the shaly rock model, including the shale in the matrix constitution.

The conventional porosity log equation is

$$p = \phi p_w + V_{sh} p_{sh} + (1 - \phi - V_{sh}) p_m \tag{3}$$

In equation 3, p represents one porosity log or a neutron porosity, sonic or density log reading. V_{sh} is the shale volume and ϕ is the porosity. p_{sh} and p_m are porosity parameters for shale and matrix, respectively. With the rock model adopted, the porosity log equation can be expressed as

$$p = \phi p_w + (1 - \phi) p'_m \tag{4}$$

In equation 4, the term p'_m is the modified matrix porosity parameter, in the form

$$p'_m = \frac{V_{sh}}{(1 - \phi)} p_{sh} + (1 - V_{sh}) p_m \tag{5}$$

This rock model considers the shale properties in the reservoir rock as equal the properties of neighborhoods shale layers. In this approach, the visual interpretation of porosity logs, as shale cut-off is eliminated. The M and N can be normally calculated with equations 1 and 2 using raw logging readings. This approach treats the shale as part of rock framework and conventional interpretation of M-N plot can be realized.

The M-N plot does not supply the shale identification directly, once the variability in shale composition produces a large variation in its physical properties, impeding the calculus of characteristic values for M and N, as were done for common minerals in the sedimentary rocks.

We use an intelligent algorithm with competitive neural networks (Andrade, 2007) to locate the shale point in the M-N plot.

Angular Competitive Neural Network

The most common architecture of a competitive neural network has two layers in its design. The first one, called as input layer, receives the external input data. This layer contains only sensorial units that receive and pass the input data to second layer, which is the processing layer, also called as competitive layer, composed by competitive neurons. These two layers are full connected by synaptic weights. The competitive neurons are forced to compete among them; in such way, that only one neuron (winner neuron) stays active or produces a non-null output signal in each time step. The useful output of a competitive neural network can be the location of winner neuron in the competitive layer, as much as its synaptic weights values.

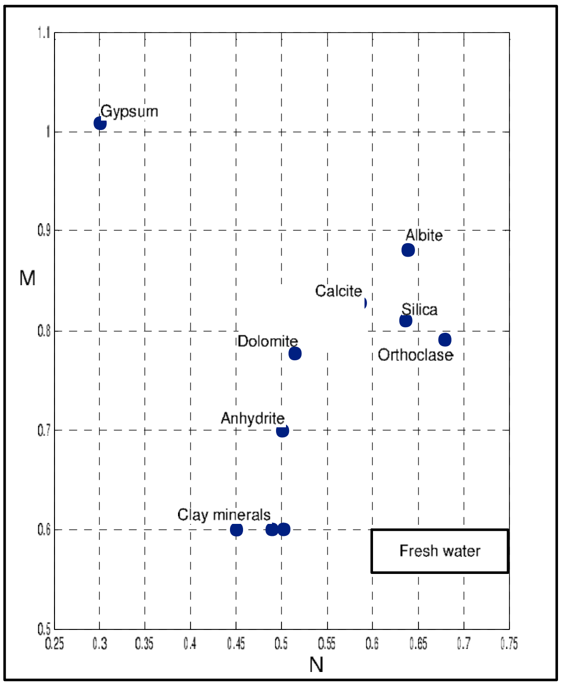

Figure 1 – The M-N plot.

The architecture of angular competitive network is composed by three layers: the input layer, the competitive layer and one intermediate layer, the selective layer, as shown in Figure 2.

The selective layer operates to promote the selection of input data. A special activation function defines the selection criterion that acts in the sense of allowing or not the production of an effective output. Each selective neuron represents a point of training set or one column of weight matrix.

The competitive layer acts exactly as a classical competitive layer, promoting a competition among their neurons and allowing that only one of them wins the competition and produce the layer output.

Training set is the subset of input data used for determination of the weight matrix. The training set acts as angular patterns to be discovered in the input data. Each training set defines dynamically the number of neurons in the selective layer and in the competitive layer.

The learning process of angular competitive neural network associates each point in the training set to a position vector and calculates unitary vectors resulting of the subtraction of one position vector by all the others in the training set.

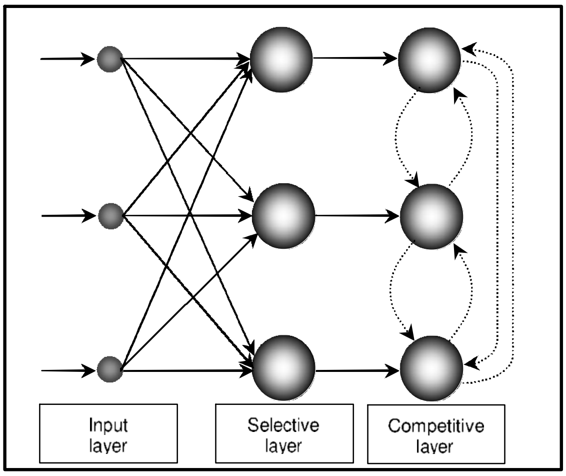

Figure 2 – Architecture of angular competitive neural network.

The weight matrix between the input and selective layers is defined in a convenient form to storage the coordinate pair of each unitary difference vector as complex number, with the abscissa as real part and the ordinate as imaginary part. This square complex matrix has order equal to the number of position vectors in the training set and null diagonal.

The input data in the angular competitive network will be formed by the difference vectors resulting from the subtraction of each position vector in the input data for each position vector in the training set. We take the unitary vector of each difference vector. The form of storage of those unitary difference vectors is equal to the form used for the weight matrix as column of a complex matrix. This global difference matrix has a number of rows equal to the number of neurons in the input layer and a number of columns equal to the number of input data.

For each time step, a column of the global difference matrix is presented to the input layer. The input potential (u) of each selective neuron is the real part of the complex product of each element in the input vector (column of the global difference matrix) and the complex conjugated of each element of the weight vector (column of the weight matrix). This operation computes the cosine of the angle between those unitary difference vectors. The condition for two vectors have the same direction says that cosine of the angle between then is equal to 1 or -1. The activation function for each selective neuron is a piecewise linear function that verifies the absolute value of input potential $(|u|)$ to produce the output (y), as shown in Figure 3.

After the presentation of one column of global difference matrix, the selective layer produces outputs that are sent as input to the competitive layer. The neurons in the output layer compete among them and the winner neuron is the one with highest input.

The output of competitive layer is a binary vector with the value one in the position of winner neuron and zeros for all the others. The useful information is the position of non-null value, which indicates the vector in the training set approximately aligned with the input vector or with the same angular pattern.

The behavior of angular competitive neural network can be appreciated in the lithology identification.

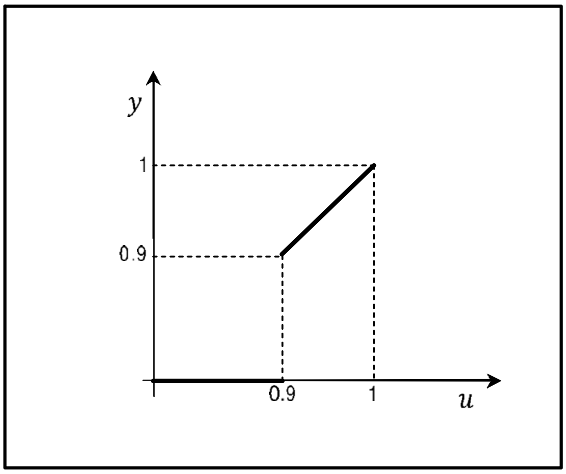

Figure 3 – Activation function.

Lithology Identification

Different branches of geosciences may use the same term with different meaning. Lithology is a good example of this fact; while the geologist is free to use linguistic terms to describe a hand-sample, the log analyst cannot do the same. The lithology identification is made by the principal mineral determination, i.e. the principal N plane.

The solution of a pattern recognition problem claims for the number and the meaning of actual classes in the input data. In these terms, we present the method for lithology identification in three steps. In the first one, we locate the shale point in the M-N plot. In the second step, we produce the identification of representative points in the M-N plot for each rock type in the logged interval and finally, we realize the lithology identification.

To produce the location of shale point, we use a competitive neural network, which is able to interpret a z-plot composed by the M-N plot and the natural gamma ray log in the sense of a pattern recognition technique. The competition rule states that winner neuron has synaptic weights with largest GR and smallest M and N values (Andrade, 2007). The shale point is the orthogonal projection in the M-N plane of identified shale point in this z-plot.

We assume lithologic points as particular points in the M-N plot that represent different rock types. Similar values of M and N calculated with log readings are grouped in the M-N plot for each lithology in the logged interval. Thus, lithologic points can be interpreted as near the centroid of each cluster formed by points of same zone. A characteristic of competitive neural network is the possibility of more than one competitive neuron to be addressed to the same cluster in the training phase. This makes its interpretation susceptible to naive errors. We try to mitigate this kind of misinterpretation, introducing a competitive network with two competitive layers. The first competitive layer is training with Kohonen`s rules (Kohonen, 1989). We introduce a new training algorithm to define the weights associated with the second competitive layer, which receives as input the weight matrix of the first trained competitive layer. The neurons in the last layer compete for the survival. The training algorithm eliminates neurons in such way that, at the end of the training phase, remaining in the second competitive layer only the neurons most activated. The number of remaining neurons represents, in many cases, the number of actual clusters in the input data and the remaining weights are the coordinates of lithologic points that are located closed to the centroid of actual clusters.

The number of lithologic points in the M-N plot in many cases, cannot be interpreted in lithologic terms. Particularly for shaly rocks, the smallest Euclidian distance to a fixed point does not indicate lithology. However, lithologic points exhibit an angular pattern that is explored. The lithology identification is performed by the angular competitive neural network, which receives as input the unity vectors formed by the subtraction of each lithologic position vector and the shale position vector. The training set is formed by unity vectors calculated from the subtraction of each fixed position vector and the shale position vector.

Results

Synthetic Data

We construct a synthetic data set with three porosity logs, sonic, neutron porosity and density, as described by equation 4, which relates log readings with rock physical properties. We consider only fresh water as interstitial fluid and shale is taken as pure smectite. We construct two random vectors, with Guassian distribution (zero mean and unity variance) to represent the shale volume (V_{sh}) in the interval $[0,0.2]$ and porosity in the interval $[0,0.25]$. These two random vectors are used in equation 5 to calculate matrix porosity parameters for each reservoir rock. Figure 4 shows an example of M-N plot generated with this synthetic porosity log readings considering two zones with calcite and quartz, as matrix of two reservoir rocks. The large spread of those points in the M-N plot may confuse the lithology identification. The rock points are marked by red crosses plotted on the overlay of the M-N plot in Figure 4.

Our intention is to show the effect of shale occurrence in the matrix of reservoir rocks producing a displacement of correspondent points in the M-N plot. The rock model showed by equation 4 assumes this displacement, which may be responsible for incorrect lithology identification, as similar to one produced by reservoir rocks with more than one mineral in matrix constitution.

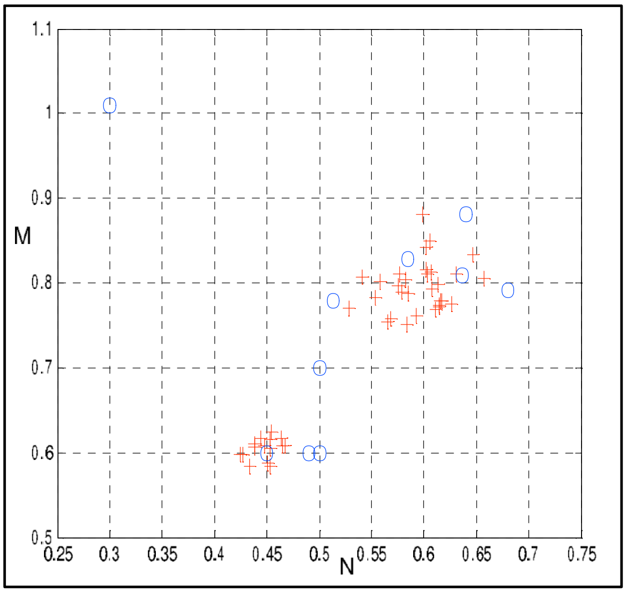

Figure 4 – The M-N plot. Red crosses mark two reservoir rocks (limestone and sandstone) and one shale layer.

Figure 5 resumes the three steps performed by this method for lithology identification. The shale point locate by the competitive network that interprets the z-plot composed for by M-N and GR is marked by the black square and is positioned very close to the smectite point. The log zonation or in simplified form, the location of the lithologic points in the M-N plot was performed by the specialized competitive network, with two competitive layers and we can note the efficiency of proposed training algorithm to identify the correct number of clusters or rock types in the M-N plot. The lithologic points are marked by black stars in Figure 5.

The visual interpretation of those lithologic points does not help in the lithology identification. It is evident that the rule of minimum distance is failed and the shale occurrence is the only responsible by the displacement from the fixed points in the M-N plot. Here, we can note the existence of an angular relation or angular pattern among lithologic and fixed points. This is explored by angular competitive neural network to perform the correct lithologic identification, as shown by black circles in Figure 5.

Real data

We show the behavior of the present method for lithology identification using actual wireline logging data from one borehole drilled in Namorado`s oil field. We choose one borehole that crosses a shale layer followed by a dirty sandstone layer. The core analysis indicates 60% quartz, but the presence of fine-grained minerals and shale confuse the porosity logs. Figure 6 shows those data on the overlay of the M-N plot. We can note that visual interpretation does not permit the identification of these two layers.

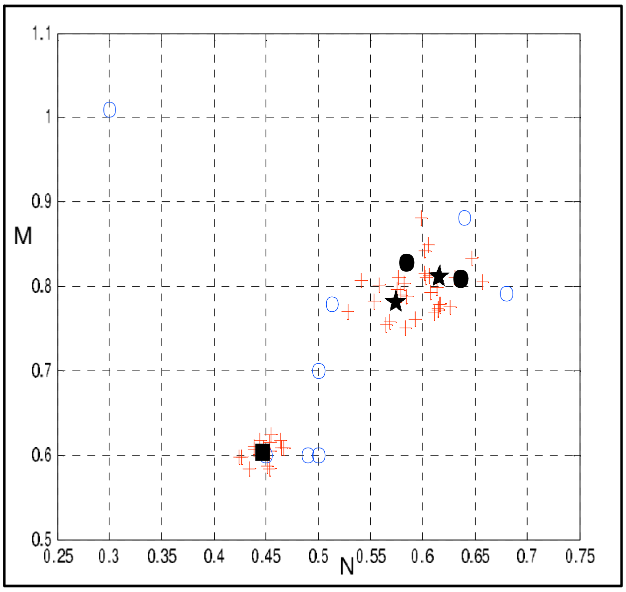

Figure 5 – The interpreted M-N plot. The shale point is marked by a black square. The lithologic points are black stars and lithologies are identified by black circles.

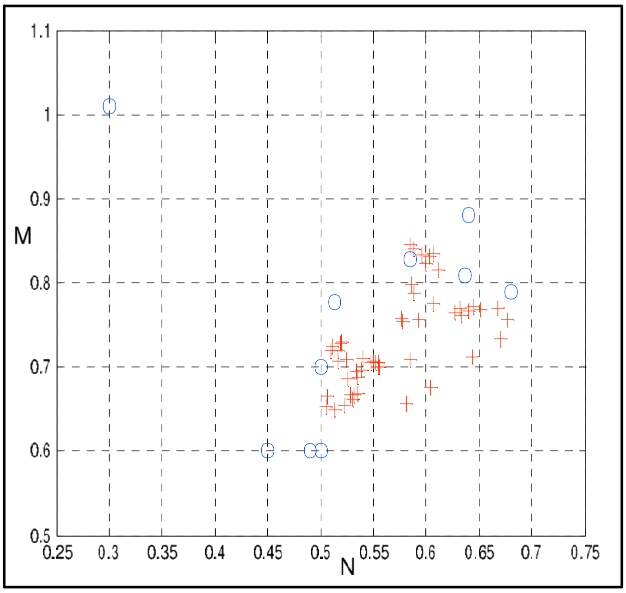

Figure 6 – The M-N plot. Red crosses mark two layers shale and dirty sandstone.

The disambiguation can be visualized in the interpreted z-plot showed in Figure 7, where the black square marks the shale and the black star marks the clean sandstone.

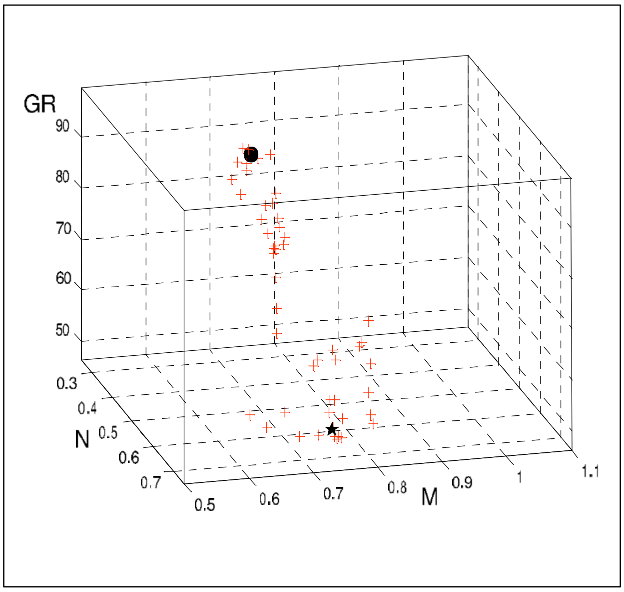

Figure 7 – The z-plot. Red crosses mark actual data. The black square marks the shale and the black star marks the lithologic point (clean sandstone).

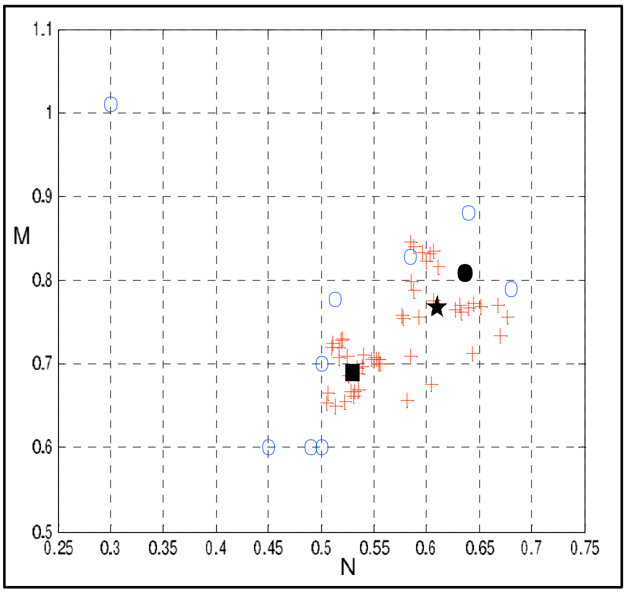

Figure 8 – The interpreted M-N plot. The shale point is marked by a black square. The lithologic point is the black star and lithology is identified by the black circle.

The lithologic identification performed by the angular competitive neural network here presented can be interpreted as the identification of principal mineral in the reservoir rock constitution. This work is translated in the location of correspondent fixed point in the M-N plot, as shown in Figure 8 by black circle on the quartz point.

Conclusions

We presented a new method for lithology identification using conventional well log data, which may be quite different of the conventional methods, permitting the simultaneous treatment of clean and shaly reservoir rocks. This method can be used with raw data and real time data, as LWD. Although this method is based on M-N plot, it is not a graphic method. This kind of presentation is only a topological data arrangement that permits us to overcome the principal problem with the clustering or pattern recognizing methods, the correct representation and classification of clusters in an n-dimensional space. This method presents an intelligent algorithm as powerful technique to cluster identification and classification, besides it is presented a new competitive algorithm and the new angular competitive neural network, which working together makes possible the automatic geological interpretation of well log data.

The application of this intelligent algorithm or the introduced competitive neural networks isolate is not restrict to formation evaluation or geology and may be used to solve other problems in geophysics and petroleum engineering.

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