Matrix Porosity Paramet stimation by Intelligent Algorithm

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Abstract

Matrix is the solid part of oir rock. Thus, matrix porosity parameters are th ty log readings (density, sonic and neutron poros a zero porosity rock. In formation evaluation is imp obtain a more realistic value for porosity to get a priated porosity cut-off and better oil reserve ate. In many instances, core information is not and may be a hard problem to estimate the mat ity parameters, which have a critical influence on values, which are calculated using porosity e present an intelligent algorithm, based on petitive neural network architecture and an efficie tionary process This method is presented on synthetic data and ed with actual well log data from one borehole rado's oil field, Campos Basin, Brazil.

Introduction

In formation evaluation, matr framework of a sedimentary rock, fundamentally d by minerals, which surrounds the pore. Conv reservoir rock model assumes porosity log r influenced by properties of matrix and pore, prop to their relative volumes. This explains the impo of the physical properties of matrix for por lculation and consequently, for oil reserves estir

Methods using porosity logs sity, sonic and neutron porosity involving only on an association of two or more of them require tl information to porosity calculation. This informa be translated as matrix porosity parameters, c lues would be recorded by a porosity tool in front porosity rock. Thus, matrix porosity parameters esented by the and neutron porosity, respectively.

Conventional core analysi furnish some measurements of matrix porosity ers. A common measurement is the grain density ly assumed as matrix density (. Minerals pres stant values for transit time and neutron porosity. Matrix transit time ( ) and matrix neutron porosity ( ) can be estimated from proportional mineral volumes in the composition of rock samples. The problem arises when cores are unavailable.

The well-established crossplot, the M-N plot may help in the matrix identification for shale free reservoir rocks. M-N plot involves in the N parameter the neutron porosity and density log readings and the M parameter is obtained with sonic and density log readings. M-N plot assumes the matrix formed by only one mineral and takes as matrix porosity parameters, the correspondent mineral physical properties. In a simple geological simplification, the matrix of a reservoir rock is composed by only one mineral. The interpretation of M-N plot consider the properties of principal mineral as the matrix properties, for example, porosity parameters for a sandstone matrix is associated with the physical properties of quartz. This procedure simplifies the mineral composition of sandstone to only quartz, ignoring the possibility of any other minerals occurrence.

For porosity calculation, other important requisite is to consider the shale occurrence in a reservoir rock, which has profound impact on porosity values. In this case, the shale correction requires the information about matrix porosity parameters. In common circumstances, fluid parameters can be easily obtained.

Our goal here is to reduce the possibility of visual misinterpretation of M-N plot for matrix identification. We present an intelligent algorithm that integrates new competitive neural network architecture with an efficient evolutionary process in the sense of genetic algorithm with the aim to produce a more realistic estimate of matrix porosity parameters

Intelligent algorithms are a large class of computing techniques, as artificial neural network, evolutionary computing, and fuzzy inference, 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 (Aminian & Ameri, 2005; Jeirani & Mohebbi, 2006) and genetic algorithms (Velez-Langs, 2005). These techniques aim at the incorporation of all available logging data to produce improved oil reserves estimation.

We present an intelligent algorithm that determinates the matrix porosity parameters in two parts. In the first one, the identification of reservoir layers present in a well interval is performed by a competitive neural network with a new learning technique, which is able to perform an interpretation of the M-N plot. The net

result is the location of particulars points in the M-N plot those representing the reservoir rocks present in the well interval. In the second part, the matrix porosity parameters are estimated, for each reservoir rock previously identified by an evolutionary algorithm, inspired in bacterial reproduction, which takes the triple of matrix parameters as chromosome and a fitness function based in the M-N plot interpretation criterion to approximate the point obtained in the first part. We show the behavior and evaluate this method with actual well log data from one borehole in Namorado's oil field, Campos's basin, Brazil

Methodology

Conventional reservoir rock model assumes porosity log readings influenced by properties of matrix and fluid, proportional to their relative volumes in the rock constitution. A common assumption is the use of physical properties of principal mineral in the rock composition, as matrix porosity parameters. This assumption considers the matrix composed by only one mineral, ignoring the occurrence of any other minerals, for example, the matrix porosity parameters for sandstone is assumed equal the physical properties of quartz.

For common rock forming minerals is well know their physical properties related with porosity logs, as listed in Table 1.

Table 1 – Physical properties of common minerals.

Mineral	ρ_m	Δt	ϕ_{Nm}
Quartz	2.65	55.5	-0.05
Calcite	2.71	47.5	0.00
Dolomite	2.87	43.5	0.04
Anhydrite	2.96	51.8	0.02
Gypsum	2.32	55.7	0.60

For shale free reservoir rocks, this simplification in the matrix constitution may works well and a well-established method as M-N plot can be used to determine the principal mineral and consequently, assume its physical properties as matrix porosity parameters.

The M-N plot

The M-N plot (Burke et al., 1969) uses a combination of sonic, density and neutron porosity logs and attempts to remove the effect of porosity on these measurements. A combination of the sonic and density measurements is used to define the M parameter, which is the slope of the curve for each particular lithology in the sonic-density crossplot that varies slightly among the three common lithologies of reservoir rocks due the matrix endpoints. The slope of neutron-density crossplot is designated as N. Thus, each one rock forming mineral produces a slightly different value of N and M. Porosity variations affect both the numerators as well as the denominators of M and N, making them almost independent of porosity (Luthi, 2001).

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

$$M = \frac{\Delta t_w - \Delta t_m}{\rho_m - \rho_w} 0.003 \quad (1)$$

$$N = \frac{\phi_{\mathrm{Nw}} - \phi_{Nm}}{\rho_m - \rho_w} \quad (2)$$

In equations (1) and (2), Δt_w represents the transit time for fresh water; Δt_m, 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 M and N values can be obtained with log readings by replacing the matrix values in the respective equations by the appropriate log readings.

Some common minerals have well-defined values of M and N, some of which are listed in Table 2. Those points are plotted in the M-N plot as fixed points or matrix reference points, as shown in Figure 1. If a pair of M and N calculated with log readings in a particular depth of a borehole are plotted on the overlay of the M-N plot, the intersection of those M and N defines a depth point in the M-N plot. The location of depth point with relation to fixed points may permit simplified lithology identification.

Table 2 – M and N values for common minerals.

Mineral	*Composition*	*M*	*N*
Quartz	SiO_2	0.81	0.64
Calcite	$CaCO_3$	0.83	0.59
Dolomite	$CaMg(CO_3)_2$	0.78	0.49
Anhydrite	$CaSO_4$	0.70	0.50
Gypsum	$CaSO_4.2H_2O$	1.01	0.30
Clay Minerals			
Illite		0.6	0.49
Kaolinite		0.6	0.45
Smectite		0.6	0.50

If the characteristics of actual fluid approximate the fluid properties used in the M-N plot construction and there is no evidence of secondary porosity in the reservoir rock, the location of any depth point in the M-N plot depends primarily on the matrix characteristics.

The conventional interpretation of M-N plot considers only minerals as matrix, because they present constants physical properties and fixed points can be plotted. For a shale free rock composed by more than one mineral, there is not fixed point that may help in the lithology identification and consequently, in the determinations of matrix porosity parameters. In this case,

the minerals present in the rock composition define an approximated location for the matrix point in the M-N plot. For example, a distribution of points inside the quartz-calcite-dolomite triangle indicates the presence of these components in the rock composition. In this case, the proportional volume of each mineral, determined by advance core analysis, is used to calculate the matrix porosity parameters.

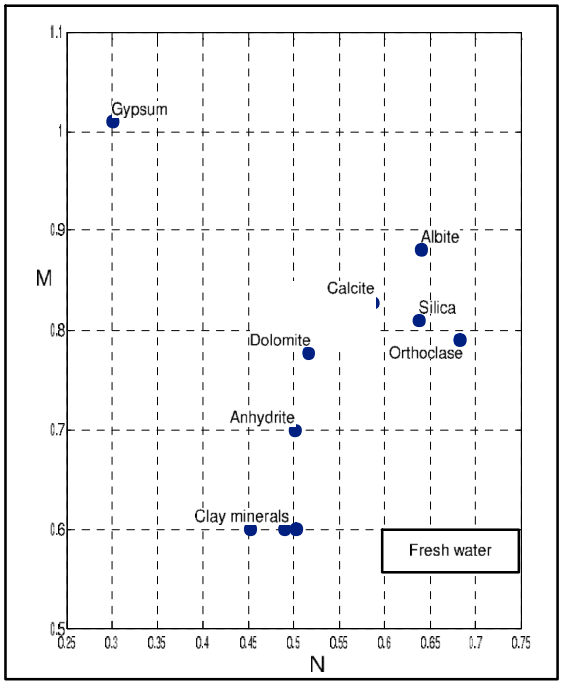

Figure 1 – The M-N plot.

In general, it is necessary to consider the presence of shale in the rock composition, which may profoundly N plot works only with clean rocks and conventional shale correction requires the matrix porosity parameters, this may seem incoherent, reducing the utility of M-N plot for mineral identification.

We modify the shaly rock model, including the shale in the matrix constitution. The conventional porosity log equation is

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

In equation 3, p is neutron porosity, density, or sonic 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

$$p = \phi p_w + (1 - \phi) p'_m \qquad (4)$$

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

$$p'_m = \frac{V_{sh}}{(1-\phi)} p_{sh} + \sum_{i=1}^{N} V_i p_i \qquad (5)$$

In equation 5, V_i is the relative volume and p_i is the porosity parameter for one of N minerals in the matrix constitution.

This rock model considers the shale properties in the reservoir as equal the properties of neighborhoods shale layers. In this approach, the visual interpretation of porosity logs, as shale cut-off and porosity cut-off are eliminated, with M and N values calculated with raw logging readings.

This rock model permits the conventional interpretation of M-N plot if a fixed point for shale is located. In other words, if a fixed point for shale can be located in the M-N plot, the shale has the same hole as common mineral in the matrix constitution. It is done by a computer aid interpretation as an intelligent algorithm using competitive neural network.

Bi-Competitive Neural Network

A common architecture of a competitive neural network is composed by two layers, the first layer is called input layer and contains only sensorial units that receive and pass the input data to the second layer, which is the processing layer or 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 competitive learning is unsupervised, i.e. during the training, only input patterns are presented to the neural network, which adapts the synaptic weights in order to group the input patterns into clusters with similar statistical features. A learning rule defines the competition strategy and the adaptation of synaptic weights (Haykin, 2001). The competitive learning uses the Kohonen rules (Kohonen, 1989), where the competitive neuron that most resembles the input vector wins the competition and has its synaptic weights moved close to the input vector.

The solution of a cluster analysis problem claims for two answers: the number and real meaning of actual classes present in the data. Common characteristics of traditional competitive neural network trained with Kohonen rules are the possibility of more than one competitive neuron to be addressed to the same cluster and the occurrence of a concentration of neurons close to the center of all clusters. The occurrence of those effects separately, or in association is dependent of the spread of input data or the form of clusters distribution in the n-dimensional Euclidian space of input data. In may situations a conventional competitive neural network is not able to solve a cluster analysis problem.

We introduce the bi-competitive neural network (Figure 2) and a new training algorithm that make it able to solve a cluster analysis problem. The bi-competitive network has two competitive layers that are trained separately. The first layer (I) receives the input data and is trained using the Kohonen rules. The second

competitive layer (II) receives as input the synaptic weights of layer I. The same weight matrix is taken as synaptic weights linking the competitive layers II and I. The neurons in the layer II compete for the survival. The t
the end of the training phase, remaining in the layer II, only the neurons most activated. The number of remaining neurons represents, in many cases, the number of actual clusters in the input data.

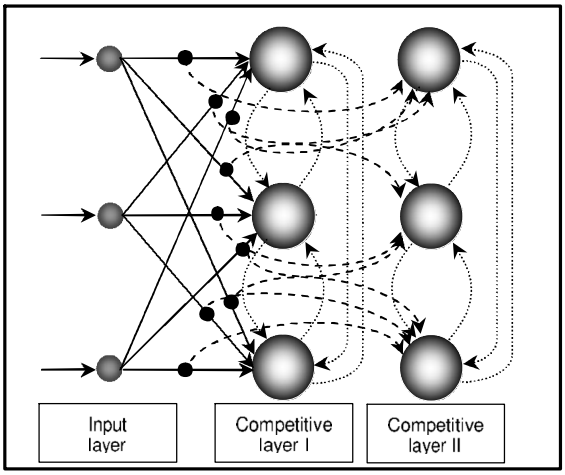

Figure 2 – Architecture of bi-competitive neural network.

Genetic Algorithm

Reproduction is the biological process by which new individual organisms are produced. The known methods of reproduction are broadly grouped into two main types: sexual and asexual.

Our interesting here is in asexual reproduction. In this case, an individual organism creates a genetically similar copy of itself without a contribution of genetic material from another individual. Bacteria divide asexually via binary fission. Organisms that reproduce through asexual reproduction tend to grow in number exponentially. However, they rely on mutation for variations in their DNA, all members of the species have similar vulnerabilities. Indeed, in an aggressive ambient, just one adapted individual originates itself a new adapted population.

Genetic algorithms are powerful and broadly applicable stochastic search and optimization techniques based on principles from reproduction and evolution theory (Holland, 1975; Romero & Carter, 2001; Tettamanzi & Tomassini, 2001; Tzeng, 2004). The genetic algorithm was inspired in biology, particularly in those biological processes that describe the growth of populations and the adaptation to their environment: genetic inheritance and survival of the fittest. The genetic algorithm acts similarly to the evolutionary cycle, where a group of individuals or chromosomes is put to develop through the crossover and mutation operators. Crossover is the main genetic operator, which does a mixture of parent chromosomes to generate an offspring. Mutation is a genetic operator, which produces random changes in the offspring chromosomes.

The parent population is real-valued and the chromosomes represent possible solutions to the problem. A new generation is formed by action of genetic operators and according to the fitness function, only the better chromosome in each offspring is permitted to reproduce. After several generations, the algorithm converges to the best chromosome, which represents an optimal solution for a particular problem.

We take the triple $(\varphi_m, \Delta t_m, \phi_{Nm})$ of matrix porosity parameters for density, sonic and neutron porosity, respectively, representing the fundamental chromosome of evolutionary process and a fitness function based in the M-N plot interpretation to approximate the matrix point obtained by competitive neural network.

Matrix Porosity Parameters

To consider clean and shaly rocks, we proceed to shale point identification (Andrade, 2007). After that, we can eliminate the shale of posterior computation. In the next steps, we work only with reservoir rocks. The determination of matrix porosity parameters proceeds with the identification of matrix points. We assume matrix 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, matrix points can be interpreted as near the centroid of each cluster formed by points of same zone.

We define the number and the location of matrix points in the M-N plot using the bi-competitive neural network, which assumes the final weights associated with the winner neuron as the center of a cluster representing the M and N values associated with a particular matrix point in the M-N plot. The number and the weights of remaining neurons in the final stage of bi-competitive neural network, in many cases, represent the number and location of matrix points in the M-N plot.

To estimate the matrix porosity parameters, we introduce the genetic algorithm based on bacteria's)
as chromosome unit and use only mutation, as genetic operator to create the next generation or the offspring chromosomes. The environment defines the survival conditions of fittest individual. Here, the fitness function is N
plot, generated by one offspring chromosome, to the matrix point. The fittest chromosome is the triple representing the matrix porosity parameters for each rock type in the well interval.

In the asexual reproduction, lake bacteria reproduction, must exist one chromosome nominated as progenitor or the ancient chromosome, which is more adapt to ambient than any other. This chromosome is responsible for all the next generation. We take as progenitor the triple $(\varphi\ , \Delta t\ , \phi_N)$ corresponding to the closest point, in the input data, with each matrix point in the M-N plot. In a new iteration, an offspring is generated

by a random alteration of progenitor. The application of fitness function to this new generation selects a new progenitor. The generation and evaluation of offspring continue until a tolerance value for the fitness function is reached. The last progenitor is taken as matrix porosity parameters.

Results

Synthetic points in the M-N plot are obtained from equations (1) e (2), considering the rock model expressed in equation (4). We present three tests, which results are shown in Table 3. In Figure 3, we show the M-N plot, with synthetic M and N pairs marked by red crosses for the first case of a rock matrix with 80% of quartz. A visual interpretation of this M-N plot does not indicate a clear mineral dominating the matrix composition. A black asterisk indicates the matrix location and a black circle indicates the M and N pair obtained with the matrix porosity parameters defined by this method and presented in Table 3. Notice that shale point is not show in the next figures.

Table 3 – Estimation of matrix porosity parameters

Matrix		ρ_m	Δt	ϕ_{Nm}
80% qtz+20%sh	Calc.	2.60	65.1	0.03
	Est.	2.60	65.1	0.03
40%qtz+40%cal	Calc.	2.63	61.9	0.05
+20%sh	Est.	2.63	61.9	0.05
30%qtz+30%cal+	Calc.	2.71	54.4	0.03
30%dol+10%sh	Est.	2.71	54.4	0.03

In Figure 4, we show the M-N plot, with synthetic M and N pairs marked by red crosses for the second case of a rock matrix with 40% of quartz and 40% of calcite. As the first example, the visual interpretation of this M-N plot does not indicate a clear mineral dominating the matrix composition. A black asterisk indicates the matrix location and a black circle indicates the M and N pair obtained with the matrix porosity parameters defined by this method and presented in Table 3.

In Figure 5, we show the M-N plot, with synthetic M and N pairs marked by red crosses for the second case of a rock matrix with 20% of quartz, 20% of calcite, and 20% of dolomite. As the other examples, the visual interpretation of this M-N plot does not indicate a clear mineral dominating the matrix composition. A black asterisk indicates the matrix location and a black circle indicates the M and N pair obtained with the matrix porosity parameters defined by this method and presented in Table 3. Notice that shale point is not show in Figure 5.

In Figure 6, we show the M-N plot with actual M and N pairs marked by red crosses of a well interval in a borehole drilled in Namorado's oil field. This particular data was extract close to the middle of a tick sandstone layer and the distribution of correspondent points in the M-N plot occurs around the quartz point. We notice that matrix porosity parameters estimate by the method here presented are equal to the quartz.

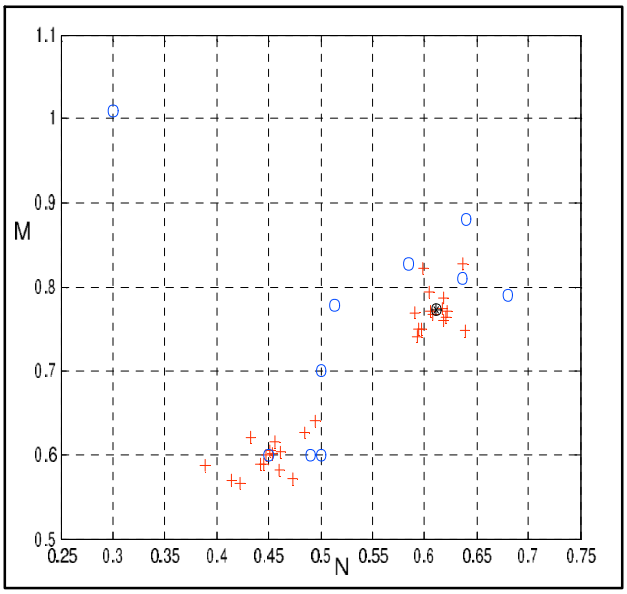

Figure 3 – The M-N plot. Red crosses mark a reservoir rock (80% quartz and 20% shale) and shale. Matrix point is marked by the black circle.

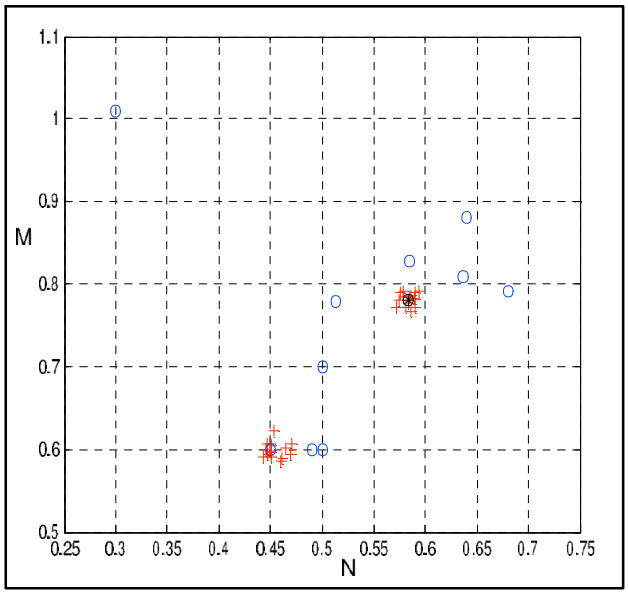

Figure 4 – The M-N plot. Red crosses mark a reservoir rock (40% quartz, 40% clacite and 20% shale) and shale. Matrix point is marked by the black circle.

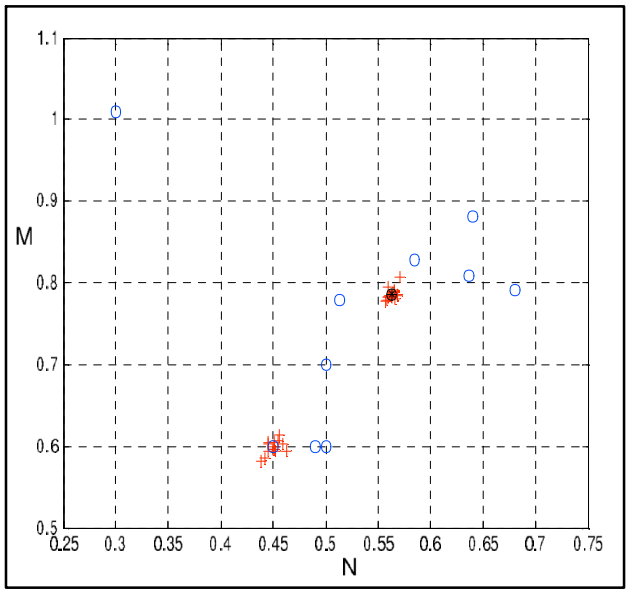

Figure 5 – The M-N plot. Red crosses mark a reservoir rock (20% quartz, 20% calcite, 20% dolomite, and 10% shale) and shale. Matrix point is marked by the black circle.

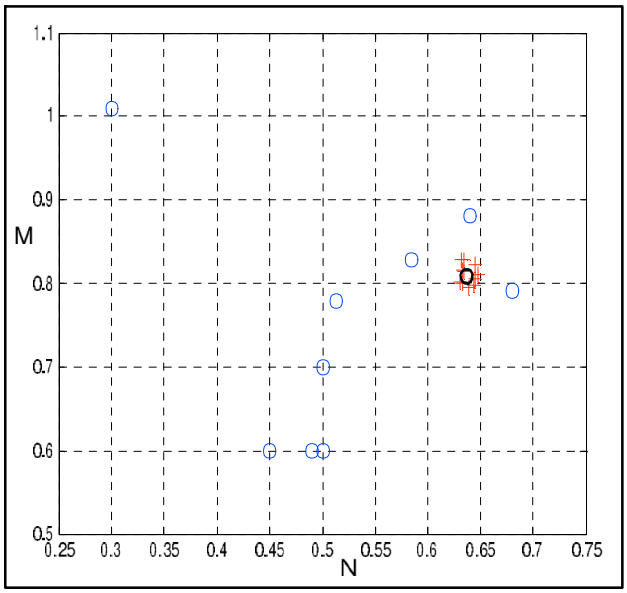

Figure 6 – The M-N plot. Red crosses mark actual values.

Conclusion

A log analysis problem has an iterative nature in its solution process can be described as extracting information from logs, calculate and evaluate a rock property, in some cases, go back to logs or check core analysis results. Many times, extract information from logs is not a so trivial problem. Here was presented an intelligent algorithm that produces the matrix characterization or estimates the matrix porosity parameters necessary for porosity calculations. We show an example of this method in a simple case, where a visual interpretation validate the results. A better application will be in cases of more difficult visual extraction of information from well logs.

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