Lithology identification and porosity estimate from 3-D cross-plot.

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

Abstract

Lithology identification and porosity estimate are important tasks realized by well log interpreters in oil reservoir characterization. Here, we present a method to emulate the interpreter behavior to solve these well log interpretation problems. We take the concept of interpretative algorithm to obtain the lithology and apparent porosity estimate, from well log data and classical well log cross-plot interpretation procedures with artificial neural networks, introducing the concept of 3-D well log cross-plot, starting from a space with the so-called porosity logs (neutron porosity, density porosity and acoustic transit time) as principal axis. We discuss and present an application of this method to actual well log data from the Namorado oil field in the Campos basin, Brazil.

Introduction

Traditionally, lithologies are identified from cores. Core data provide direct observations of lithologies; however, cores are costly to collect and core recovery is often less 100% (Ellis, 1987). Moreover, core description can be time consuming and dependent on geologists' experience. In other hand we consider the horizontal wells, which are increasingly becoming a fundamental component of the successful development of oil reservoirs. The prediction of lithologies penetrated by such wells can be difficult, principally, because these kinds of wells are for the most part never cored (Sagaff and Nebrija, 2000). Identifying lithologies from well log data may be difficult due heterogeneous nature of rocks. Then lithologies are defined by variations in its physical properties that affect well log responses (Serra, 1984).

Unlike lithology identification, the apparent rock porosity may be easily obtained from well log data if the solid part of rock (lithology) is well known. Conventional computing algorithms or statistical methods have shown efficiency to solve this problem, but they need direct interpreter interference in a way to supply information and calibrate them to field data.

Many studies have shown the applicability and efficiency of artificial neural networks to solve a great number of geophysical problems (Fischetti and Andrade, 2002; Chang et al., 2001; Ali and Chawathe, 2000; Banchs and Michelena, 2000; Jamialahmadi and Javadpour, 2000; Crocker et al., 1999).

Here, we take the concept of interpretative algorithm (Fischetti and Andrade, 2002), which should integrate all available information from geology, geophysics and well logging to produce an autonomous and geologically plausible interpretation of those data on a field wide basis. Then, we introduce the concept of 3-D cross-plot with the so-called porosity logs (neutron porosity, density porosity and acoustic transit time) as principal axis and apply it to obtain the lithology identification and apparent porosity estimate from well log data and classical well log cross-plot interpretation procedures associated with competitive neural networks.

Conventionally, geological well log interpretation tasks require a large degree of interpreter expertise (Luthi, 2001). However, we show that interpretative algorithm can simulate the decision process involved in this kind of well logging interpretation problems for some complex depositional setting. In the next sections, we discuss and present an application of this method to actual well log data from the Namorado oil field in the Campos basin, Brazil.

Method

We are interested to produce the porosity zonation log (Fischetti and Andrade, 2002), which is a graphical representation of lithology expressed in porosity units. Now, we introduce the 3-D cross-plot concept starting from a space with the so-called porosity logs (neutron porosity, density porosity and acoustic transit time) as principal axis. Then, we have in this particular space a hypercube whose faces are formed by the conventional well logs cross-plots: neutron-density, neutron-transit time and density-transit time. Inserted in this hypercube, we construct three planes representing the three major reservoir rocks. These planes are constructed in such way that the projection of their principal diagonal (the straight line linking the matrix point to fluid point) in each one of its faces is the same line showed in the original cross-plot for each lithology, based on solution of time average equation.

We start with few comments about competitive neural network and finish discussing all the steps needed to obtain the lithology and apparent porosity from the 3-D cross-plot.

Competitive neural networks

We start with some comments about the foundations of competitive neural network. We do not intend to provide a complete discussion about the theory of artificial neural network, but rather to focus on its theoretical basis on way it is indispensable to understand the interpretative algorithm, here presented.

The simplest architecture of an artificial neural network with competitive layer corresponds to one input layer composed only by sensorial units full connected with one processing layer composed by competitive neurons. Each competitive neuron is connected with all sensorial units by synaptic weights (weight connections), which will be changed in the network training process.

In competitive learning, the competitive neurons compete with each other for each input data to produce a winner, which then carries the output signal, and at a given time, only one competitive neuron is active (Haykin, 2001). The output signal corresponding to the winner neuron is assumed to be 1 (one) and the output signal of all other competitive neurons is null. If a neuron does not answer to a particular input vector, then no learning will happen in that neuron or its synaptic weights are unchanged.

The most common competitive learning uses the Kohonen training rule (Kohonen, 1989), where the competitive neuron that most resembles the input vector wins the competition and has its synaptic weights moved closed to the input vector. Thus, each competitive neuron has its synaptic weights progressively migrated close to a group, or cluster of input vectors and after some iterations, the network stabilizes, having the weight connections of each competitive neuron close at the center of each cluster in the input space. Those connections produce a direct association between the competitive neuron and the cluster that it represents.

The data analysis realized by this type of artificial neural network is commonly called feature-discover scheme, which performs clustering or quantization of the input space and can be used to detect statiscally significant patterns in the input space and to classify them (Haykin, 2001). If the input is not randomly permuted before presentation to the network, then the method always converge to the same network after training. In other words, given exactly the same training set to the method, the network obtained is always the same (Kohonen, 1989). Also, once the network is obtained, its output is always reproducible, no matter how many times this is repeated, because the process is deterministic, particularly in its learning rules.

Lithology identification

The objective of this work is to produce the log zonation or to segregate the well into distinct lithologies classes based on the log behavior. This mode emulates what an interpreter would do by performing a careful examination of the log characteristics at various depth intervals.

To obtain the lithology identification we starting from the classical concepts of well log cross-plots, which are the graphical representation of time average equation for binary minerals mixtures (Ellis, 1987). It was inserted in well log interpretation about 40 years and remains in use. In the recent years, other methods had been presented and an interpreter intervention is even required in different degrees. Our goal here is to produce a method where the interpreter intervention is not required.

We take the concept of 3-D well log cross-plot, starting from a particular space, with the so-called porosity logs (neutron porosity (PhiN), density porosity (PhiB) and acoustic transit time (DelT)) as principal axis. Then, we have in this space a hypercube whose faces are formed by the conventional well logs cross-plots: neutron-density, neutron-transit time and density-transit time.

Inserted in this hypercube, we construct three particular planes, representing the three major reservoir rocks (sandstones, limestones and dolomites). Those planes are constructed in such way that a particular lithologic plane in the 3-D cross-plot crosses the face represented by neutron-density cross-plot and the face represented by neutron-transit time cross-plot with the same inclination of the correspondent lithology straight line in the 2-D cross-plots. As shown in Figure 1, for the limestone case. Observe we solve the time average equation in the space and the lithologic plane touch the density-transit time, in the base of hypercube exactly in the matrix point.

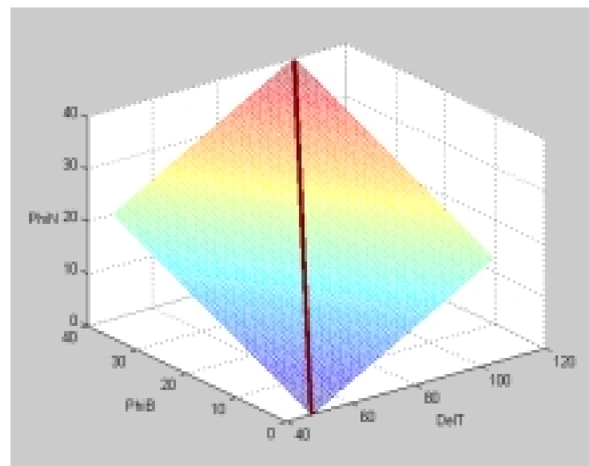

Figure 1.The 3-D cross-plot and limestone plane with its principal diagonal showed by the red line.

Our interest here is to construct a competitive neural network to produce the log zonation or the separation of depth points with matrix dominated by quartz from those dominated by calcite or dolomite, for example. In other words, we want to identify and classify the characteristics clusters formed by the input logs measurements in the 3-D cross-plot.

We construct a competitive neural network composed by three input neurons; each one receives, as input, the density porosity log (PhiB), the neutron porosity log (PhiN) and the acoustic transit time (DelT) for each depth point of logged borehole interval. The competitive layer is composed by three competitive neurons; each one represents one lithologic plane. Each neuron represents a plane and has as weight connections the values associated to constants in the plane equation corresponding to each coordinate and a bias representing the independent term of this plane equation. Thus we associate each lithologic plane to one neuron, which competes with others for each depth point, guided by a modification of the classical Kohonen competitive rule (Fischetti and Andrade, 2002).

In Figure 3, we show the three lithologic planes and examples of depth points, object of competition, represented by red crosses. The top plane represents the dolomite, the intermediary, the limestone and the bottom one represents the sandstone.

Porosity determination

Now we have the zonation of the whole log interval. To determine the porosity of each depth point, we use a particular porosity scale defined for each lithologic plane. From the rule of lithologic plane construction, its principal diagonal links the matrix point (null porosity) to theoretical fluid point (100% porosity). In this case, the orthogonal projection of this diagonal in each hypercube face (2-D cross-plot) is the straight line representative of particular lithology represented by the plane. We construct over each diagonal a convenient porosity scale to agree with each lithology from the porosity scale defined by neutron-density and neutron-transit time cross-plots. In Figure 1 we show an example of principal diagonal for the limestone case, represented by the red line.

Now we are ready to construct a competitive neural network to apparent porosity determination. This competitive neural network is composed by three input neurons; each one receives, as input, the density porosity log (PhiB), the neutron porosity log (PhiN) and the acoustic transit time (DelT) for each depth point previously selected for a particular lithology. The competitive layer is formed by a number of competitive neurons choose in reason of adopted porosity scale for each lithology. Each neuron has as weight connections its coordinates in the 3-D cross-plot. Thus each porosity value is associated to one neuron in the competitive layer. Each competitive neuron competes with others for each depth point. The winner neuron position, in the competitive layer, represents the apparent porosity value for this depth point.

Results

We show an application of this method taking the porosity logs from one cored well drilled in Namorado oil field, Campos basin, Brazil. Figure 2 shows all the logs involved in this method. The GR (gamma ray) log is added to provide further comparisons in the other figures.

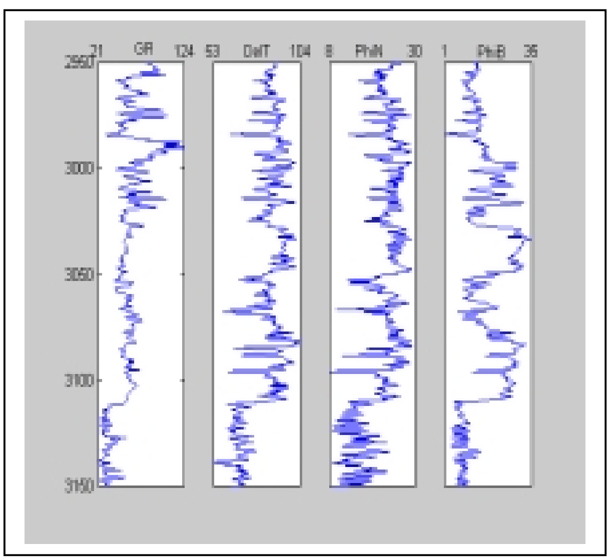

Figure 2. Well log data from one well in Namorado oil field.

In Figure 3, we show the distribution of depth points in the 3-D cross-plot and we can see its spread in the space region occupied by the lithologic planes, also showed in this figure.

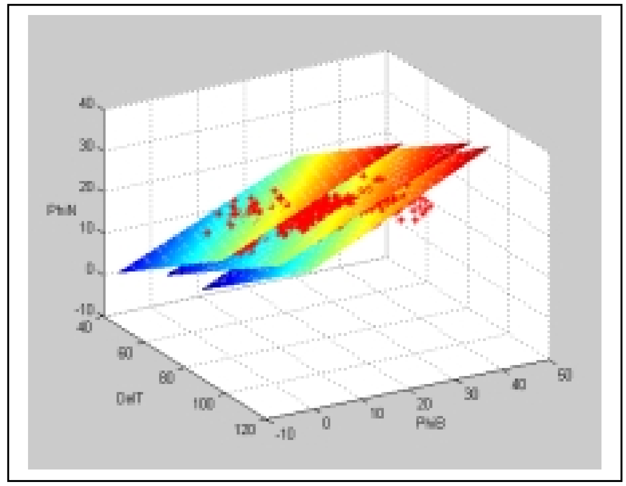

Figure 3. The lithologic planes and depth points distribution in the 3-D cross-plot.

We produce the log zonation, as explained above and show in Figure 4, inserted in 3-D cross-plot, the limestone plane and the depth points identified as limestone, represented by red crosses.

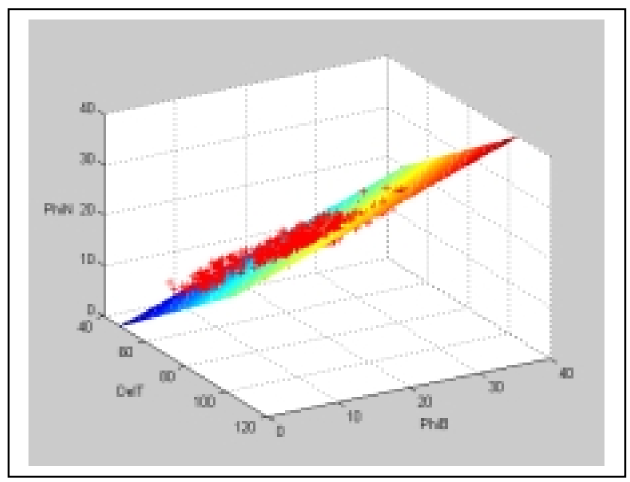

Figure 4. The limestone plane and the depth points identified as limestone.

The next step is to estimate its apparent porosity as described above. Performing this procedure for all lithologies, we finally produce the porosity zonation log. In Figure 5, we show a part of whole logged interval with the presence of the three reservoir rocks. We add a track showing the lithologic description from cores in the porosity zonation log in a way to validate our results. In Figure 5, the first track shows the gamma ray log; the second shows the lithology obtained from cores; the third shows the depth porosity variation for sandstones and the fourth shows the same for limestones and the last one, for dolomites.

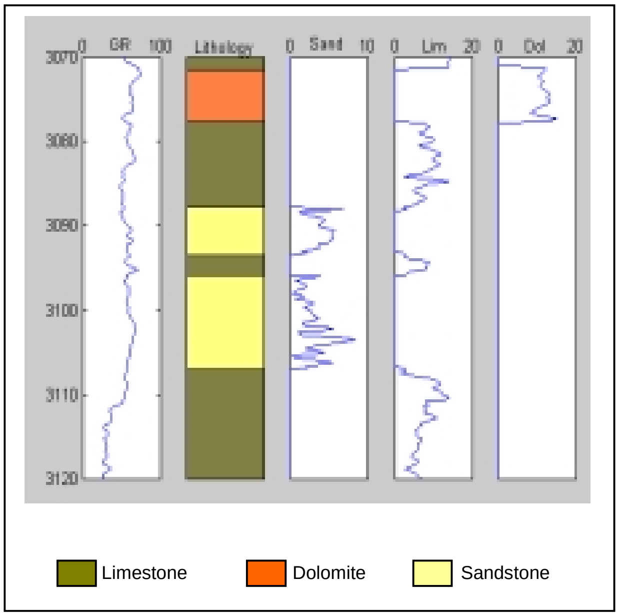

Figure 5. Detail of porosity zonation log showing the lithology column from core.

In Figure 6, we show the porosity zonation log for whole logged interval. The first track shows the gamma ray log; the second shows the depth porosity variation for sandstones, the third shows the same for limestones and the last one, for dolomites.

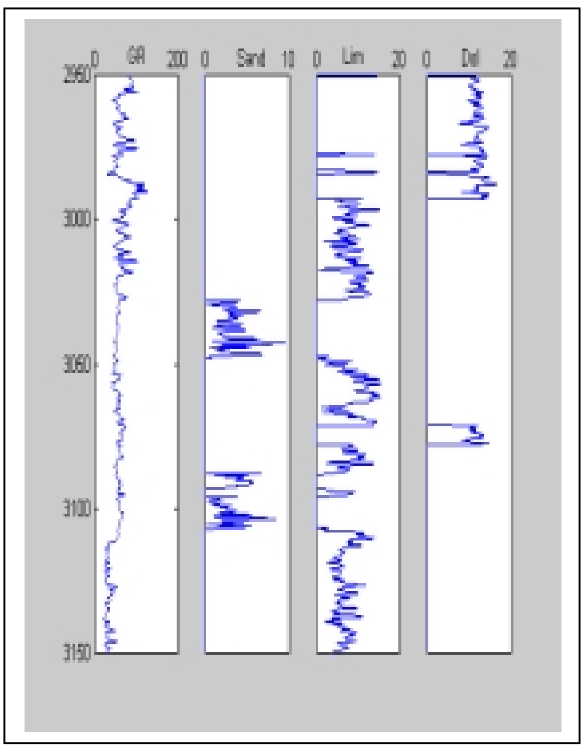

Figure 6.Test well porosity zonation log.

Conclusions

We introduced the concept of 3-D cross-plot based on classical well log cross-plot. This makes possible the construction of convenient competitive neural networks embedded in the interpretative algorithm to produce the porosity zonation log involving all the information furnished by the three porosity logs in a way to avoid some misclassification commons in the use of classical well logs cross-plots.

Acknowledgments

The authors would like to acknowledge the support extended by CNPq and ANP/FINEP-UFPa for this work.

References

Ali, M., Chawathe, A., 2000. Using artificial intelligence to predict permeability from petrographic data. Computers and Geosciences 26, 915-925.

Banchs, R., Michelena, R., 2000. Well log estimates and confidence intervals by using artificial neural networks. CD-ROM of the Society of Exploration Geophysicists Annual Meeting.

Chang, H.C., Kopaska-Merkel, D.C. and Chen, H.C., 2001. Identification of lithofacies using Kohonen self-organizing maps. Computers and Geosciences 28 (223-229).

Crocker, H., Fung, C.C., Wong, K.W., 1999. The stag oil field formation evaluation – a neural network approach. Australian Petroleum Production and Exploration Association Journal 38 (451-459).

Ellis, D.V., 1987. Well Logging for Earth Scientists. Elsevier, USA.

Fischetti, A. I. and Andrade, A., 2002. Porosity images from well logs. Journal of Petroleum Science and Engineering 36 (149-158). Elsevier.

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

Jamialahmadi, M., Javadpour, F.G., 2000. Relationship of permeability, porosity and depth using an artificial neural network. Journal of Petroleum Science and Engineering 26 (235-239).

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

Luthi, S., 2001. Geological Well Logs – Their Use in Reservoir Modeling. Springer - Verlag, Berlin.

Saggaf, M.M., Nebrija, E.M., 2000. Estimation of lithologies and depositional facies from wireline logs. AAPG Bulletin 84.

Serra, O., 1984. Fundamentals of Well Log Interpretation – The Acquisition of Logging Data. Amsterdam, Elsevier.