Facies Mapping by Intelligent Algorithms

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Abstract

Facies mapping is a cross-section representation of the lateral variation of a petrophysical property based on stratigraphic correlation criterions and involving all logged boreholes in an oil field. The procedure to produce the facies mapping can be divided in three steps. In the first one, in a cored borehole is performed the calibration among facies and log readings that establish a log zonation for non-cored boreholes. Second step calculates the petrophysical property to be mapped in all boreholes. The last step performs the well correlation based on the log zonation and stratigraphic sequence. The influence of clay occurrence in the L-K plot interpretation may be attenuated adding a third axis scaled in clay volume, as the GR-L-K plot. Admitting the existence of angular patterns in the points distributed in the GR-L-K plot, we introduce a new competitive neural network, nominated as generalized angular competitive neural network, specialized in the search of angular patterns present in n-dimensional data. This characteristic allows the classification of the points in the GR-L-K plot in terms of sedimentary facies previously identified. Well correlation determines the correlation lines by a fuzzy inference system able to identify the stratigraphic sequence in a cored borehole and promote the sequence match in others boreholes in oil field. Thus, facies mapping is constructed interpolating the petrophysical property guided by the correlation lines. This method is presented with synthetic and evaluated with porosity logs and core analysis from two boreholes in the Namorado oil field, Campos' Basin, Brazil.

Introduction

In sedimentary geology, facies refer a set of all characteristics of a rock layer formed in a particular sedimentary environment, which permits the distinction among adjacent layers. Generally, facies description occurs during conventional core analysis and may be used for interpretation of depositional sequences, definition of stratigraphic surfaces in well to well correlation and in the identification of stratigraphic traps, with the purpose of evaluating the stratigraphic context of a potential petroleum system.

Stratigraphic correlation is the study of relationships among rock units or facies from different stratigraphic sections by the identification of a sequence of marker beds that can be clearly identified in both sections. Correlation is a hypothesis that facies in different stratigraphic sequences are equivalent and marker beds are time parallel surfaces considered isochronous or laid down at the same time representing any widespread activity that took place in a geological instant.

The applicability of facies description, locally in one borehole and the lateral continuity established by stratigraphic correlation is limited by the small number of cored wells in an oil field. Depositional environment impacts directly on the rock physical properties registered in wireline logs (Luthi, 2001), but their visual association with facies is doubtful. Well correlation is a way to extend laterally the local information produced by wireline logs and permits the definition of lateral continuity and geometric disposition of rock layers that are crossed by different boreholes (cored or non-cored).

The spatial and temporal geological information contained in the definition of a facies sequence is fundamental geological activities to improve the geological model of an oil reservoir. This kind of work is deeply affected by geologist experience and dependent of his interpretative criterions to read and choose the log readings and appropriated log patterns to be used.

Facies mapping is a cross-section representation of the lateral variation of a petrophysical property based on stratigraphic correlation criterions and involving all logged boreholes in an oil field. The procedure to produce the facies mapping can be divided in three steps. In the first one, in a cored borehole is performed the calibration among facies and log readings that establish a log zonation for non-cored boreholes. Second step calculates the petrophysical property to be mapped in all boreholes. The last step performs the well correlation based on the log zonation and stratigraphic sequence.

Log zonation treats with the identification or calibration among the variations of the physical properties registered in the logs with the sedimentary environment, in which a rock layer was built. In the formation evaluation, were developed many methods for lithology identification using porosity logs (density, sonic and neutron porosity), as the M-N plot (Burke et al., 1969; Luthi, 2001) that emphasizes the quality of density log. However, in several practical situations as a borehole with large diameter, collapsed or drilled with high density mud, the density log may need great corrections (Crain, 1986). These facts do not affect the sonic log and L-K plot (Pantoja et al., 2010) may more suitable to use. The main limitation in the L-K plot interpretation is clay occurrence affecting the sensibility of porosity logs for mineral identification (Luthi, 2001).

Well correlation using the interpretation of patterns present in wireline logs tries to establish the lateral continuity of log readings from one borehole to another. This manual task is important for geologic modeling of oil reservoir and in the development of production strategies that aim to improve oil recovery. The difficulties in the conversion from well correlation to stratigraphic correlation reside in facies recognition and in the establishment of a stratigraphic sequence in the well logs.

Here we present a methodology to produce facies mapping in an oil field by an intelligent algorithm working with porosity logs that produces a convenient log zonation and well correlation, with the transport of facies information acquired in cored boreholes to non-cores ones. This method may aid to produce an oil system characterization more realistic using all available information.

The concept of intelligent algorithm involves many numeric methods, as the artificial neural networks, the fuzzy inference and the evolutionary computation. The intelligent algorithms are a tool quite promising to solve computational real problems, for bringing innovations in the science and in engineering, transforming data in information and information in knowledge (Nikravesh, 2004).

The influence of clay occurrence in the L-K plot interpretation may be attenuated adding a third axis scaled in clay volume, the so-called GR-L-K plot. Admitting that points from the same facies form a cluster following an angular pattern in the GR-L-K plot, we introduce a new competitive neural network, nominated as generalized angular competitive neural network, specialized in the search of angular patterns present in a n-dimensional data set. This characteristic of generalized angular competitive neural network allows the association of facies description with porosity log readings, coded as points in the GR-L-K plot, in terms of the information about sedimentary facies previously identified in a cored borehole. Well correlation determines the correlation lines by a fuzzy inference system able to identify the stratigraphic sequence in one cored borehole and promotes the sequence match in others core or non-cored boreholes in the oil field. (Barros e Andrade, 2009). Thus, well correlation can be performed with non-cored boreholes having all geological applications of stratigraphic correlation. Facies mapping is constructed interpolating the petrophysical property guided by the correlation lines.

This method is presented with synthetic and porosity logs and core analysis from two boreholes in the Namorado oil field, Campos' Basin, Brazil.

Method

Here, we focus our attention on the interpretation of GR-L-K plot performed by generalized angular competitive neural network producing the log zonation.

GR-L-K plot

Several methods that emphasize the matrix effect on the measures accomplished by porosity tools (density, sonic and neutron porosity) are in use in formation evaluation and try to produce lithology information in way relatively independent of the porosity effect on these measurements.

The GR-L-K plot adopts a combination of logging readings from sonic and density log to define the parameter L (equation 1) and a combination of sonic and neutron porosity in the definition of parameter K, as presented in the Equation 2. The third axis shows the GR log (natural gamma ray log) scaled in shale volume, as presented in the Equation 3.

$$L = \frac{\rho_m - \rho_w}{(\Delta t_w - \Delta t_m)} 100 \qquad (1)$$

$$K = \frac{\phi_{Nw} - \phi_{Nm}}{(\Delta t_w - \Delta t_m)} 100 \qquad (2)$$

$$V_{sh} = \frac{GR - GR_{min}}{GR_{max} - GR} \qquad (3)$$

In equation 1, ρ_m is the matrix density and ρ_w is the interstitial fluid density. In equation 2, ϕ_{Nm} the matrix neutron porosity and ϕ_{Nw} is the fluid neutron porosity. In both equations, Δt_m is the matriz transit time and Δt_w is the fluid transit time. Equation 3 is the classic equation for shale volume using natural gamma ray log. The multiplicative constant (100) in equations 1 and 2 is just a scale factor.

The substitution of matrix parameters by correspondents log readings in equations 1 and 2 and considering the interstitial fluid as fresh water result in a point in the GR-L-K plot. Figure 1 shows GR-L-K plot, the GR axis is not show to emphasize the points of reference.

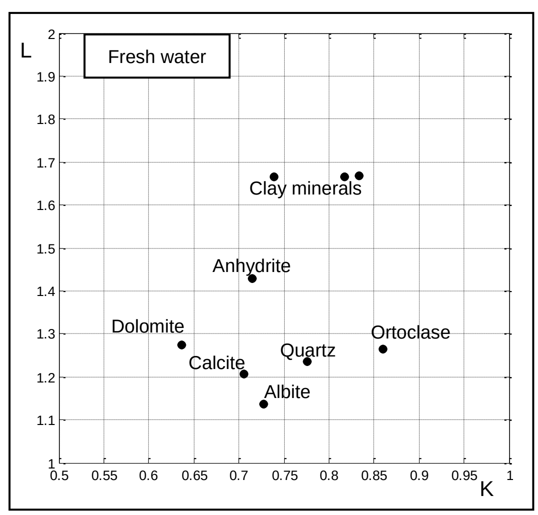

Figure 1 – GR-L-K plot. GR is not show to emphasize the reference points

Points of reference promote the classification of facies that are not occurring in the cored borehole in the interpretation of GR-L-K plot. In Table 1 is shown L and K values for some common minerals in sedimentary rocks. The variability in shale volume prevents the existence of a non null value in third axis.

Table 1 – L and K values for some common minerals.

Mineral	Composition	K	L
Quartz	SiO_2	0.78	1.23
Calcite	$CaCO_3$	0.70	1.20
Dolomite	$CaMg(CO_3)_2$	0.65	1.28
Ortoclase	$KAlSi_3O_8$	0.86	1.26
Albite	$NaAlSi_3O_8$	0.72	0.72
Anhydrite	$CaSO_4$	0.71	1.42
Kaolinite		0.75	1.66
Illite		0.81	1.66
Smectite		0.83	1.66

Generalized Angular Competitive Neural Network

Competitive neural networks are characterized by a single competitive layer, where their neurons compete among them, such that, only one neuron is active at a time. This characteristic turns the competitive neural networks appropriated to extract statistic characteristics, in terms of the geometric distribution of input data. Different of any other artificial neural network, the output of a competitive network has no interest. The useful result can be the position in the competitive layer or the weights of winner neuron.

Generalized angular competitive neural network is a new model of competitive neural network, designed to find statistically relevant angular patterns in the n-dimensional data. Angular pattern can be understood as an angle or direction that relates several vectors and may be used to classify them. This particular angle can be measured in relation to an orthogonal axis or any vector of reference in the training set.

The vector dimension in input data determines the number of sensorial neurons in input layer. The training set can be arbitrarily chosen in input data or determined by the problem to be solved. The number of neurons in competitive layer is the number of elements in training set. The coordinates of vectors in the training set form the weight matrix linking input layer and competitive layer.

Generalized angular competitive neural network treats only with unitary vectors. An input vector (x) in input layer is sent to the competitive layer. Equation 4 shows the input for each competitive neuron. The output of any competitive neuron results of the activation function evaluation, as in Equation 5.

$$u_i = \cos(\theta) = xw_i^t \quad (4)$$

$$Y_i = f(u_i) \quad (5)$$

In Equation 4, w_i^t is transpose of coordinate vector of neuron i in the competitive layer.

A typical architecture of generalized angular competitive neural network is shown in Figure 2. The activation function of all competitive neurons is shown in Figure 3. The winner neuron has the largest output.

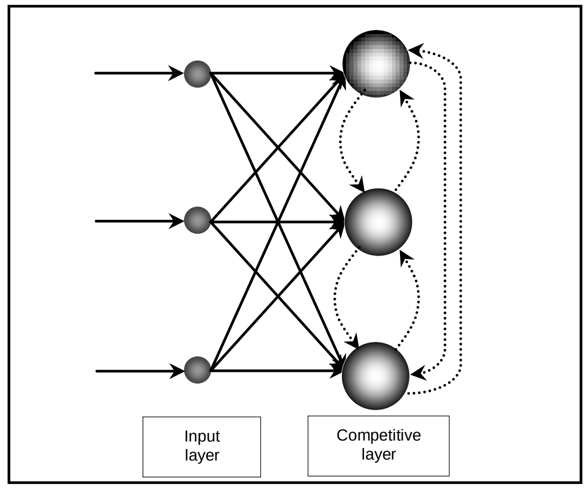

Figure 2 – Typical architecture of generalized angular competitive neural network.

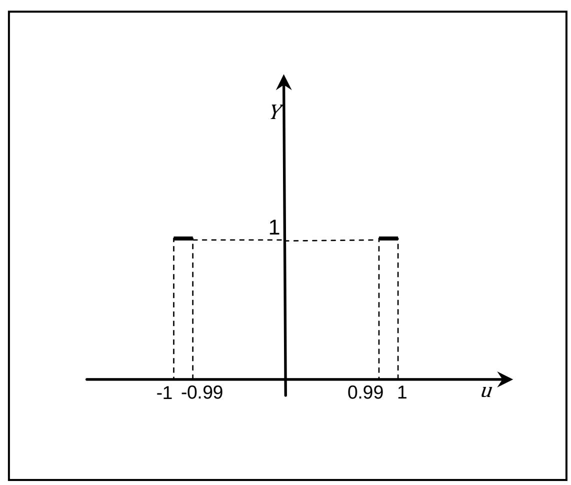

Figure 3 – Activation function. u is the input potential and Y is the output of a competitive neuron.

Example

We take two cored boreholes crossing the same sandstone sequence chosen as facies of reference to produce the facies mapping. The facies description is shown in Table 2.

Table 2 – Facies description.

Facies	Description
A	Laminated sand-shale
B	Sandstone well graduated
C	Silt-sandstone
D	Shale

Synthetic gamma ray (GR) and porosity logs (density, sonic and neutron porosity) are constructed for both boreholes. Porosity logs are used to calculate the L and K parameters, following Equations 1 and 2. Gamma ray log is used to calculate shale volume (Vsh). Figure 4 shows the GR-L-K plot for cored borehole (well A). Facies of reference are represented by blue squares. These points and points of reference in L-K plot represent the competitive neurons and their coordinates form the weight matrix linking input and competitive layer.

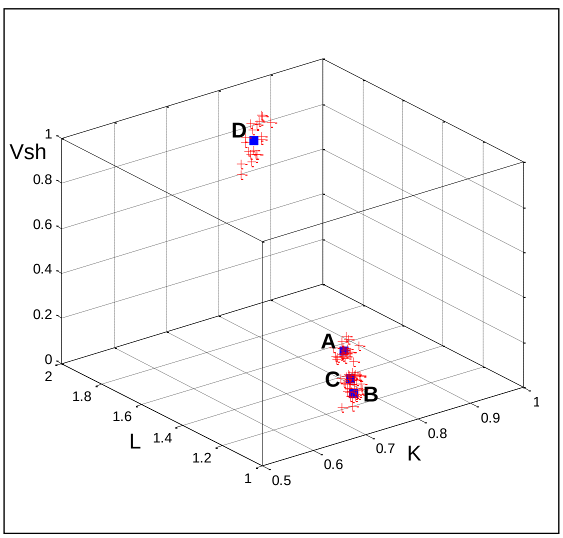

Figure 4 – Synthetic data. GR-L-K plot for borehole A. Blue squares represent facies of reference.

Figure 5 shows the GR-L-K plot for the considered non-cored borehole (B).

Facies mapping construction starts with the application of generalized angular competitive neural network that produces the facies zonation working under premise that similar facies will be represented by similar points in the GR-L-K plot.

Figure 6 shows the interpretation of GR-L-K plot of borehole B. The GR axis is not show.

Figure 7 shows the facies zonation of borehole B performed by generalized angular competitive neural network. Figure 7-A shows the natural gamma ray log. Figure 7-B shows the facies zonation and Figure 7-C presents the facies description obtained in core analysis of borehole B. The same color code is used in Figures 6 and 7 to represent facies.

One can observe that calcite facies (pink) and dolomite facies (yellow) are not present in the set of reference facies described in borehole A. They are classified following the points of reference in the L-K plot.

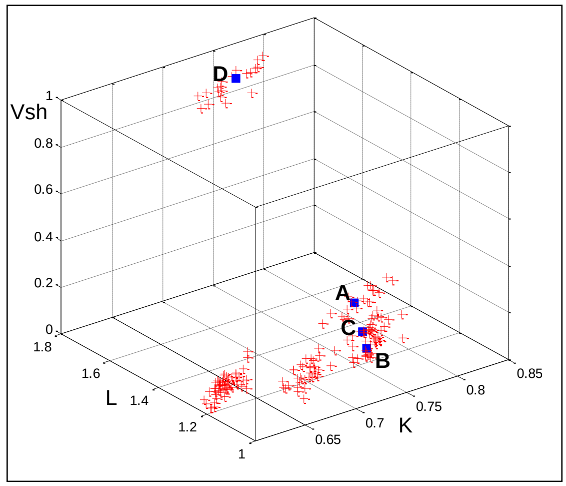

Figure 5 – Synthetic data. GR-L-K plot for borehole B. Blue squares represent facies of reference established in borehole A.

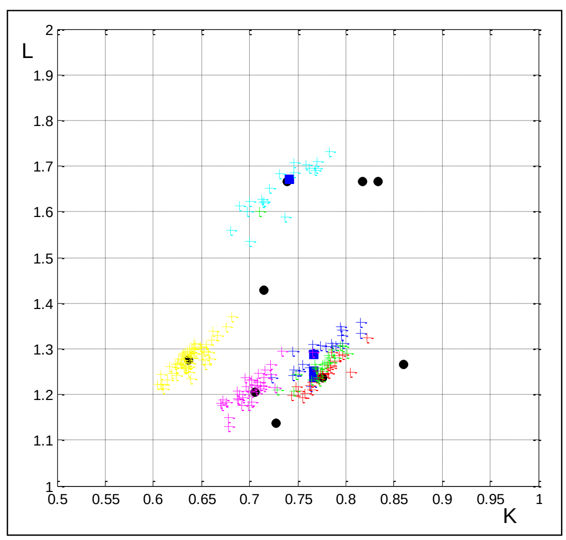

Figure 6 – Synthetic data. GR-L-K plot of borehole B interpreted.

Well correlation determines the correlation lines by a fuzzy inference system able to identify the stratigraphic sequence in one cored borehole and promotes the sequence match in others core or non-cored boreholes in the oil field. (Barros e Andrade, 2009). Figure 8 shows the well correlation of boreholes A and B. Figure 8-A shows the gamma ray log of borehole A. Figure 8-B shows the gamma ray log of borehole B.

Facies mapping is constructed interpolating the petrophysical property calculated in each borehole guided by the correlation lines. We take the shale volume as petrophysical property to be mapped. Any other petrophysical property can be mapped by intelligent algorithm.

We use the radial basis function neural network (Haykin, 2001) to perform the facies mapping. This mapping is guided by the direction dictated by the correlation lines that link all boreholes involved in the process. It works as if we put a number of hypothetical wells between each two actual wells, so we can estimate the shale volume distribution and present the result as a cross-section, showing the geometric behavior of layers and the lateral variation shale volume in each rock layer.

Figure 9 shows the facies mapping for boreholes A and B constructed using shale volume as petrophysical property. One may observe the lateral continuity of shale layer and the variations in the shale volume in sand A and sand B**.**

Results

The evaluation of intelligent algorithms developed to produces the facies mapping to investigate the lateral variations of the shale volume is performed using two cored boreholes in Namorado oil field.

We choose a reference facies sequence composed by one tick shale (fine mixture including marl and silt) in the depth interval from 2975 to 2987 meters and a sandstone layer (well cemented and selected) in the depth interval from 2990 to 3001 meters in borehole A.

This reference facies sequence determines the facies identification, the zoning of borehole B and the determination of the correlation lines liking the boreholes A and B.

We notice the agreement between the zoning performed by generalized angular competitive neural network and the facies description of cores from well B

Figure 10 shows de natural gamma ray logs of boreholes A and B. For clarity in the figure, we only represent the correlations lines link the reference facies.

Figure 11 shows the facies mapping for boreholes A and B from the Namorado oil field and constructed using shale volume as petrophysical property. One may observe the complexity of lateral distribution of shale volume and that in the right bottom side there is an appreciable reduction in shale volume indicating a cleaner reservoir rock.

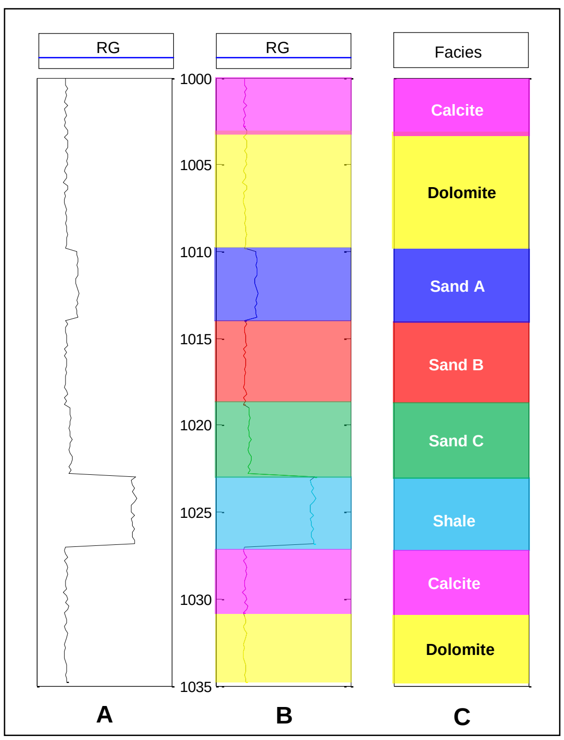

Figure 7 – Synthetic data. Facies zonation of borehole B. 7-A shows the natural gamma ray log. Figure 7-B shows the facies zonation and Figure 7-C presents the facies description obtained in core analysis.

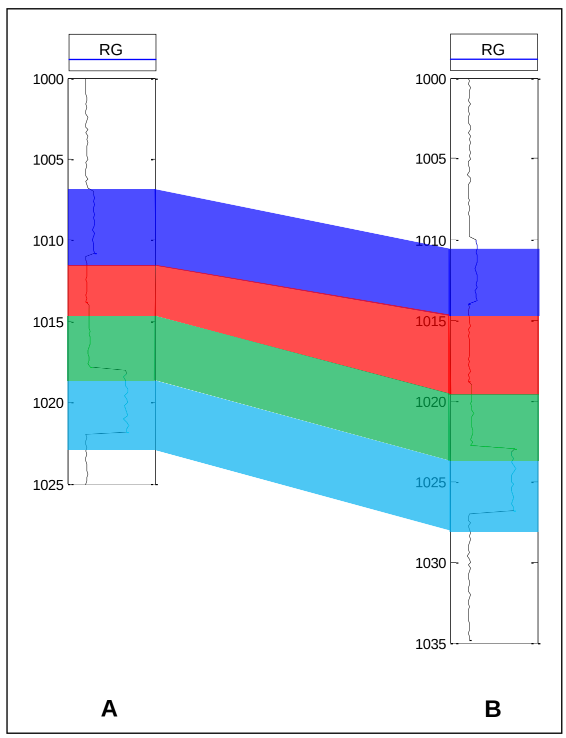

Figure 8 – Synthetic data. Well correlation of boreholes A and B. 8-A gamma ray log of borehole A. 8-B gamma ray log of borehole B.

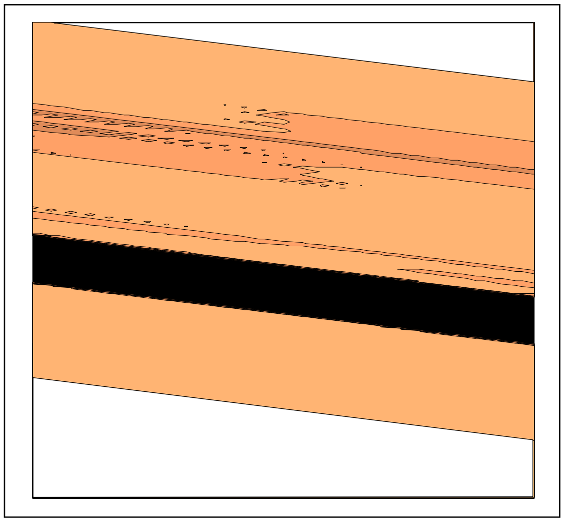

Figure 9 – Synthetic data. Facies mapping of boreholes A and B constructed using shale volume as petrophysical property.

Conclusion

The solutions of actual problems in oil reservoir characterization or geological modeling appear in the sense of a larger integration among information produced by the several different areas of petroleum industry.

In this work, we present an intelligent algorithm that integrates facies information from core analysis and well log readings; making possible the transport of relevant geological information from one core borehole to other non-cored wells, generating valuable subsidies for the definition of lateral continuity of oil reservoirs.

Facies mapping may help in the production of a more accurate model of the oil reservoir and improve oil field development making possible more realistic decisions about the placement of new boreholes and in the predictions about production volumes.

Acknowledgments

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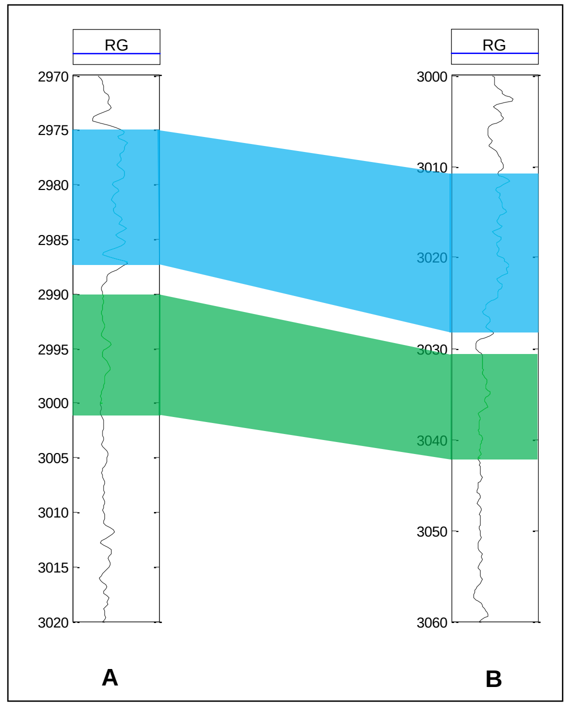

Figure 10 – Real data. Well correlation of boreholes A and B. 8-A gamma ray log of borehole A. 8-B gamma ray log of borehole B.

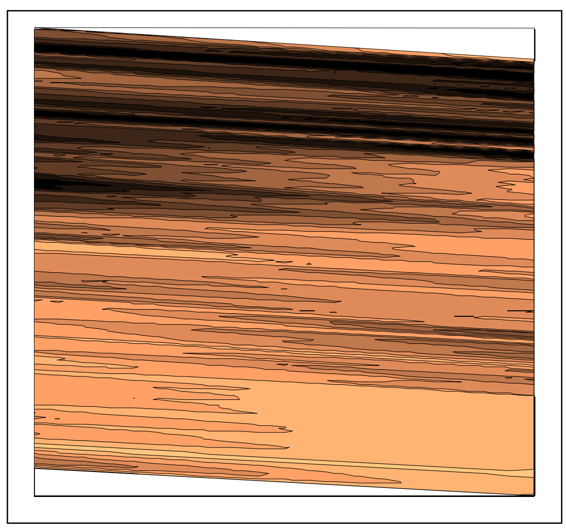

Figure 11 – Real data. Facies mapping of boreholes A and B constructed using shale volume as petrophysical property.