Combining Wavelet Transform and Neural Network to differentiate the stratigraphy from logs of Namorado Oilfield in Campos Basin

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Abstract

On well logging, there is a great interest to improve the vertical resolution of the logs, aiming the identification of different layers or geological formations along the borehole and the construction of a reservoir model. Generally, the identification of hydrocarbon formation lithology from geophysical logs employs several approaches as lithology crossplots (such as ''M–N lithology plot'' which requires a sonic log, density log, and neutron log) or the combination gamma-ray neutron-density log method. Also, numerous mathematical approaches have been proposed to perform this task computationally, between them, artificial intelligence techniques. In this sense, the purpose of this study was to identify the formation interfaces from geophysical well logs using a combination of wavelet transform and neural network methods. The first technique was applied to smooth the logs, while the second was utilized to fit them to a selected lithological model. The input variables were gamma-ray, resistivity, density, neutron porosity and sonic logs from Namorado Oilfield in Campos Basin. This method is easy to implement in a computer with MATLAB platform and it showed a good performance in the discrimination of main layers.

Introduction

Formation interface identification is essential and routine work in interpreting geological or geophysical data in petroleum exploration (Serra & Abbot, 1989). In this sense, well logs are considered one of the best sources for obtaining formation properties and identifying interfaces. Well log recordings can vary in according to changes in formation lithology or physical properties. Generally, the permeable zone logs, such as the spontaneous potential and gamma ray logs, are able to detect the lithology of the formations (Dewan, 1983). Thus, well log interpretations include manually or visually discerned formation boundaries to separate adjacent lithologic units (Crain, 1986). Different interpreters may use subjective criteria for choosing boundaries that may lead to different results (Pan et al., 2008). On the other hand, if well log recordings are treated as the signals responding to the specific input energy source from a formation, a signal-process technique, such as signal transforming and filtering, could be used to detect the formation interfaces from the well log data. And the results from the signal process technique may be somewhat objective (Hsieh et al., 2005).

In this work, logs from Namorado Oilfield in Campos Basin were used to identify lithologies of its main reservoir, the Namorado Sandstone. This oilfield has a tectonic - sedimentary evolution very similar to other marginal sedimentary basins of east coast of Brazil (Figure 1). These basins are defined by three distinct stratigraphic sequences: continental, transitional and marine, which represents the main former and modifier geological events of these basins. In this basin there are dozens of oil producer fields, among them the Namorado Oilfield. This field was the first giant of Brazilian continental shelf to be discovered in 1975. It is within the intermediary zone of the basin, which is in north-central portion of lineament accumulations of oil, at 80 km from the coast, in bathymetric quotas ranging between 110 and 250 m. This field presents as its main reservoir the Namorado sandstone, which has turbidite origin and lower Cenomiana age. This unit consists of sediments to the upper portion of Macae Formation and, in the area of the field, it occurs at varying depths between 2.900 and 3.400 m (Meneses & Adams, 1990).

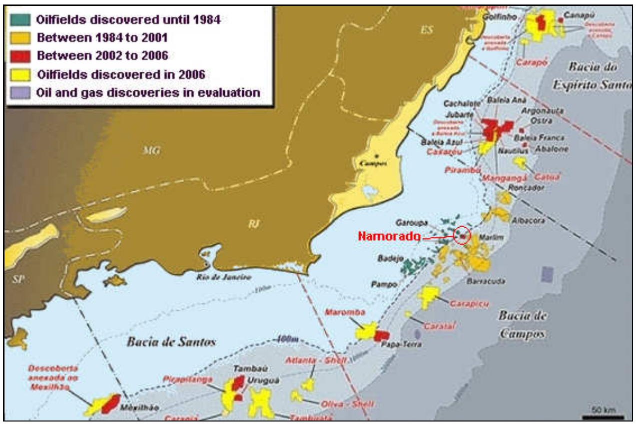

Figure 1. Main oilfields in Campos Basin between them Namorado Oilfield (source www.anp.gov.br).

Thus, the purpose of the present study was to combine WaveLet Transform (WLT) and Neural Network (NN) techniques to analyze gamma ray (GR), resistivity (RT), density (RHOB), neutron porosity (NPHI) and sonic (DT) geophysical logs from the borehole NA12 of Namorado Oilfield, in order to obtain low-noise signals to identify in an easier way the formation interfaces. In Figure 2, lof of well NA12 are shown along all the interval of the borehole, while Figure 3 show the studied interval (2.850 – 3.120 m) and the lithology, in the first track of this figure, is as follows (Meneses & Adams, 1990): marl and shale with calcilutite intercalations (1), conglomerate and carbonate breccias (2), amalgamated coarse sand (6), massive medium sand (8), sand with intercalated shale (10) and rhythmites (18).

The WLT provides varying time and frequency resolutions by using windows of different lengths. The kernel of the WLT includes two variables, phase (or location) and scale, instead of only one, as in the Fourier Transform, which is called the wavelet function. The result derived from the WLT is called the wavelet coefficient and the type of WLT depends on the wavelet functions used. The Haar function is the first, simplest, discontinuous and resembles a step function. Other kernels commonly used in the WT are the Coiflet, the Daubechies, and the Morlet. In this study, we used Haar wavelet functions to analyze the logs (Mallat, 1998).

Artificial NN have been used in a large variety of nonlinear modeling and classification problems in engineering, medical, and biological sciences for complex problems which cannot be solved using first principles (Luthi & Bryant, 1997). NN can be defined as a parallel, distributed information processing structure consisting of processing elements, which can possess a local memory and can carry out localized information processing operations, interconnected via unidirectional signal channels called connections. The processing element possess a memory which assumes a state depending only on the input signals; the information processing within the processing element is arbitrary but may feature a nonlinear transfer function prior to feeding the information to the output connections (Hopfield, 1982).

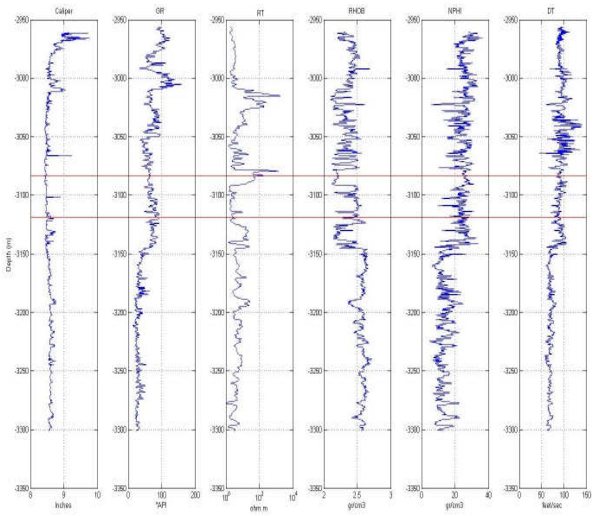

Figure 2. Logs of well NA12 with studied interval in red (3.085 – 3.120 m).

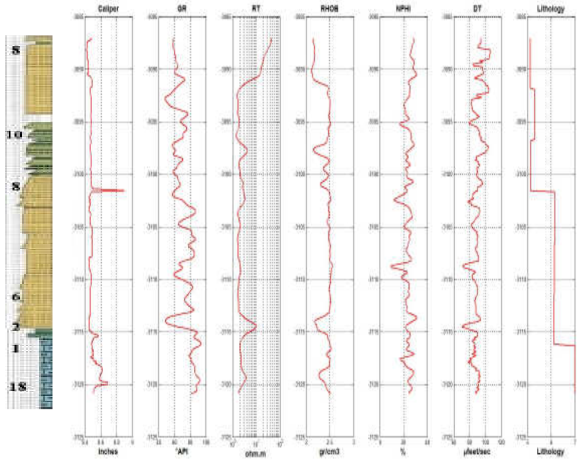

Figure **3**. Lithological column on track 1 (calcilutite intercalations (1), conglomerate and carbonate breccias (2), amalgamated coarse sand (6), massive medium sand (8), sand with intercalated shale (10) and rhythmites (18), logs of studied interval (tracks 2 to 7) and lithological model in the last track.

Methodology

To accomplish this work, firstly, a set of well log data of well NA12 from Namorado Oilfield was used (GR, RT, RHOB, NPHI and DT). These logs were processed through WLT in order to filter the noise presents in the logs. Immediately, it was applied an inverse process, which uses NN approach, to fit each log to a lithological model. Thus, the lithological model was created considering each WLT log as an indicator of lithology and considering as target in the inverse process. The lithological model and the input logs were all normalized based on the number of layers of the lithological column (first track of Figure 3), and then, the process of inversion was started. Finally, the conclusions were prepared analyzing the fit errors and correlations between logs. On the other hand, all the codes were developed in MATLAB (2010) platform, following the work developed by Carrasquilla & Delesposte (2010).

Results

Figure 4 shows the WLT of the logs using Haar approach, which filters the noise and softens the original logs, being also sensitive to lithology differences, such as discontinuities and gradual changes in sedimentation rate. In this particular case, we forced WLT to have 7 layers, following the numbers of layers of the lithological column of the first track of this figure.

GR, RT and DT logs are admittedly lithological logs, because they can be used to highlight the interfaces between layers. Thus, Figure 5 shows the correlations between the real logs of well NA12, where it is observed high correlations for RT-RHOB (-70%) and NPHI-DT (+62%); medium correlations for RHOB-NPHI (-57%) and RHOB-DT (-53%); and, low correlations for GR-RT (-30%), GR-RHOB (-38%), GR-NPHI (-5%), GR-DT (-19%), RT-NPHI (+35%), RT-DT (+30%). Generally, GR and RT show high negative correlation, for this reason, a low correlation of -30% means that something different is happened in this well. May be the present of an arcosian sand in Namorado reservoir can explain this (Delesposte, 2010).

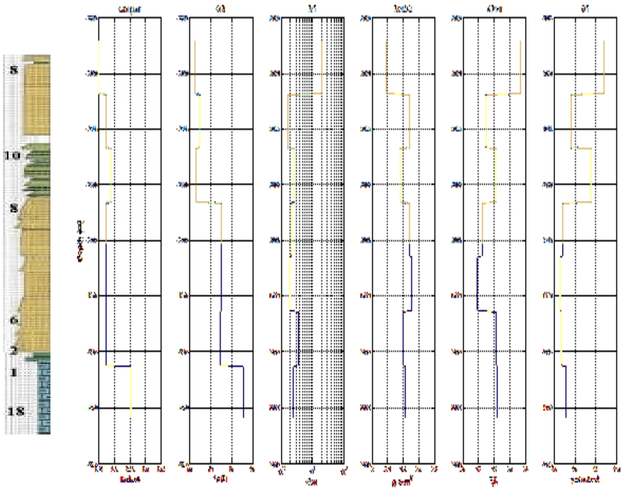

Figure 4. Lithological column on track 1, WLT logs of studied interval (tracks 2 to 6).

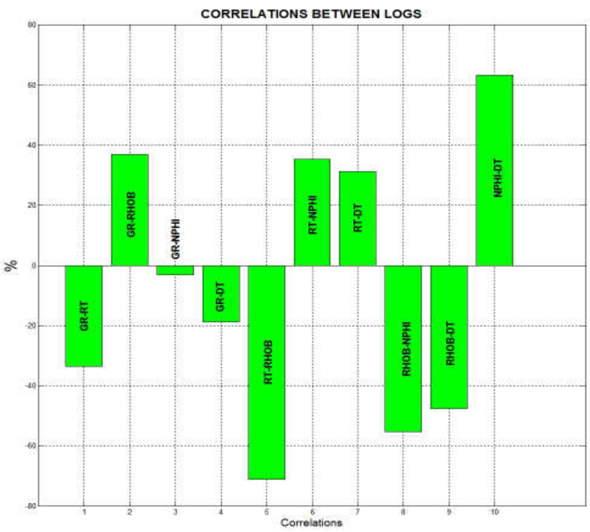

Figura 5. Correlations between real logs of well NA12.

Following this work, Figure 6 shows a lithological model (considered as target) derived from WLT, besides the real logs GR, RT, RHOB, NPHI and DT (considered as input) and the difference between them. Note that in this particular case, GR WLT log was selected as target, but along the work the process was repeated for each log. In this figure, the vertical axis shows the depth ranging between 2.850 – 3.120 m, and the horizontal axis shows the lithology log and the real logs, all normalized to values ranging between 1 and 7, following the number of layers used in the target lithological model. It is also observed that the greatest differences appear in the case RT log, because it has the opposite correlation regarding lithological model. The minor differences appear, logically, in the case of the GR log, while for DT log, the differences are lesser than in the RT log, but greater than GR log.

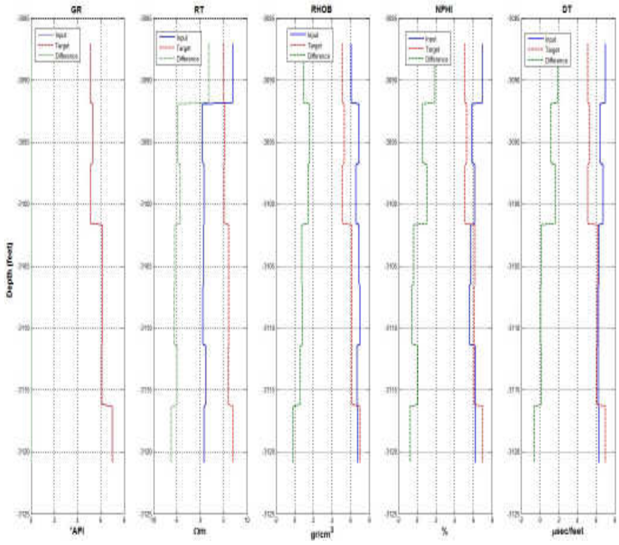

Figura 6. Logs of well NA12 (targets), lithological model (input) and difference between them.

Figure 7 shows the normalized WLT logs (outputs) adjusted to the lithological log (target) through of NN inversion process that used 20 interactions, as well as the adjust errors at the bottom of the each track. As can be seen, there was a good adjustment between them, however GR, RHOB, NPHI and DT logs show a closer fit with the lithological model, providing an error less than 10%. In the case of RT log, the fitted error is bigger, around 15%.

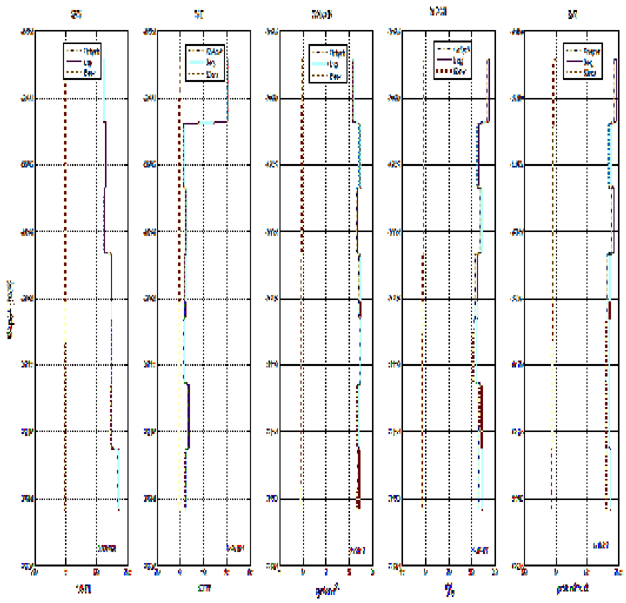

Figure 7. Normalized real logs (output) adjusted to the lithologic log (target) through an inversion process that used 20 interactions.

When other WLT logs (RT, RHOB, NPHI and DT) are used as lithological input models, the results (fit errors) can be seen in the Table 1. Note that the data of this table indicate the order of the logs when its WLT log is used as input model. In this sense, this order is RT, GR, NPHI, DT and RHOB, as show in this first column.

Table I. Adjust error between input – target logs.

INITIAL MODEL	LOGS				
	GR	RT	RHOB	NPHI	DT
GR (2°)	0.82	15.81	2.58	4.60	5.95
RT (1°)	0.09	0.97	0.43	0.61	0.82
RHOB (5°)	1.04	22.13	3.32	6.01	7.75
NPHI (3°)	0.86	17.03	2.81	4.96	6.42
DT (4°)	0.95	19.80	3.11	5.55	7.17

In the same way, it is interesting to observe that the correlations between input and target for all the cases show the same values, as shown in Figure 8, with high values for RT and RHOB (80%) and GR (68%), and medium values for DT (58%) and NPHI (48%).

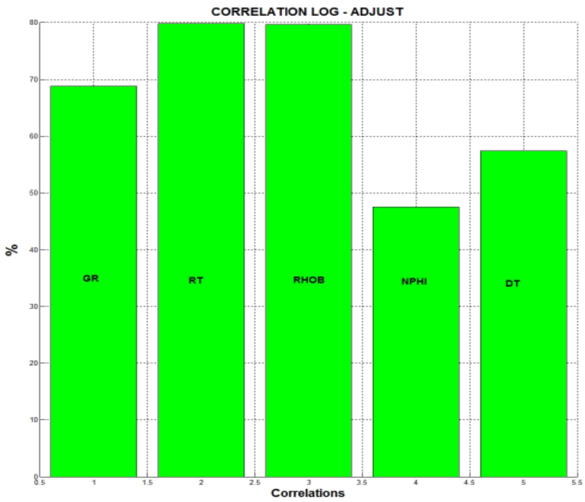

Figura 8. Correlations between logs (targets) and adjusted inputs.

Conclusions

This work shows that coupling WLT with NN can significantly improve the logs reliability in identifying the lithology, especially to eliminate noise and to smooth the logs, but retaining the sharp differences between lithologies, which can certainly facilitate interpreter work. The used methodology also clearly shows that RT, GR, NPHI, DT and RHOB logs (in this order) evidence more the lithology in the case of logs data of well NA12 in Namorado Oilfield, Campos Basin. This was shown through the approach proposed in this work, which used WLT followed by a NN fit process, considering as evaluation parameters the adjusment errors and the correlations between logs.

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