Stratigraphic differentiation from geophysical well logs using a combination of wavelet transform and neural network

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Abstract

On well logging there is a great interest in improving the vertical resolution of the different layers along the borehole. In this sense, this study aims to identify the geological formation interfaces from logs using a combination of wavelet transform and neural network. The first was applied to smooth the logs, while the second was utilized to fit them to a lithological log. The input variables were gamma-ray, resistivity and sonic logs from Shui-Lin area, Taiwan. The results from this approach were better than those from conventional log analysis or fuzzy logic results of the original publication.

Introduction

Formation interface identification is essential and routine work in interpreting geological or geophysical data in petroleum exploration (Serra & Abbot, 1989). Geophysical well logs are one of the best sources for obtaining formation properties and identifying interfaces. Log recordings vary as formation lithology or properties change. Generally, logs as spontaneous potential (SP), resistivity (RT) and gamma ray (GR) logs respond to formation lithology (Crain, 1986). Log interpretations include manually or visually discerned formation boundaries to separate adjacent lithologic units. Different interpreters may use subjective criteria for choosing boundaries that may lead to different results (Dewan, 1983). If 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 log data (Pana et al., 2008).
In this work, logs from Shui-Lin area, southwest Taiwan, were used to identify lithologies of a groundwater aquifer system. This area makes part of the south branch of the Chou-Shui river alluvial fan system, whose deposits consist of unconsolidated sand, silt, and clay from the Chou-Shui river and its tributaries. The upper section of the alluvial fan consists primarily of gravel deposits, whereas the lower section (Shui-Lin area) consists mainly of sand or clay. The interbedded shale aquitard and the sand aquifer were deposited because alternating transgression and regression processes. In Shui-Lin area, the shale materials (silt and clay) are aquitards, and the sands are aquifers. The geophysical logs used in this study include GR, RT and Borehole Compensated Sonic (BHC) logs, this last also called transient time (DT). Lithologic types from core analyses from a monitoring well in the area include clay, silt, fine sand, medium sand and coarse sand. Both the geophysical logs and the core analysis lithology represent continuous data over the depth range from 100 to 198 m (Hsieh et al., 2005).
Thus, the purpose of the present study was to combine wavelet transform and neural network technique to analyze GR, RT and DT logs from Shui-Lin area, in order to obtain low-noise signals to identify in an easier way the formation interfaces.

Methodology

To accomplish this work, firstly, well logs data (GR, RT and DT) from Shui-Lin area were used. These logs were processed through the Wavelet Transform (WLT), and then it was applied an inverse approach, which uses neural networks to make this process, to fit each log to a lithologic log. All the codes were developed in MATLAB (2010) platform. On the other hand, the lithologic log was created by doing a conversion of geological information to mathematical values. A code number from 1 to 5, ranging from coarse sand to clay, respectively, was assigned for each lithology, in accord with the work of Hsieh et al. (2005).
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).
Traditionally, the term neural network had been used to refer to a network or circuit of biological neurons. The modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes. Artificial neural networks are made up of interconnecting artificial neurons, which may either be used for solving artificial intelligence problems without necessarily creating a model of a real biological system. The real, biological nervous system is highly complex and includes some features that may seem superfluous based on an understanding of artificial networks (Hopfield, 1982).

Results

Figure 1 shows real logs (GR, RT and DT, tracks 1 to 3) and litologic logs (track 4) of a well in Shue-Lin area. Lithologic types from core analysis reveals a presence of clay, silt, fine sand, medium sand and coarse sand, which have a respective identification with the numbers 5,4,3,2, and 1 in the lithologic log of Figure 1 (last track).

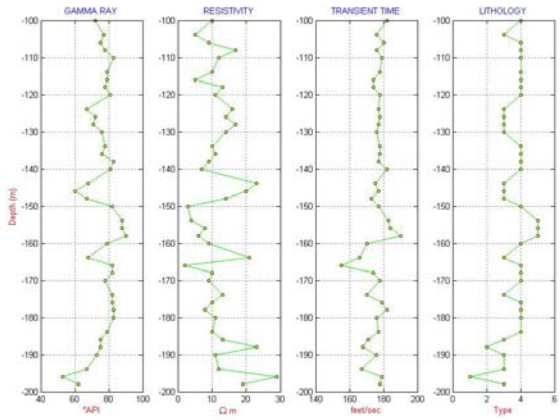

Figure 1 – Well logs and lithologic log from Shui-Lin area.

GR and RT logs are admittedly lithological logs, because they can be used to highlight the lithology. DT log, however, lacks these characteristics. This becomes clear when the correlation between these logs is calculated (Figure 2), where it is observed high correlation for GR-RT (76%) and low correlations for GR-DT (21%) and RT-DT (12%).

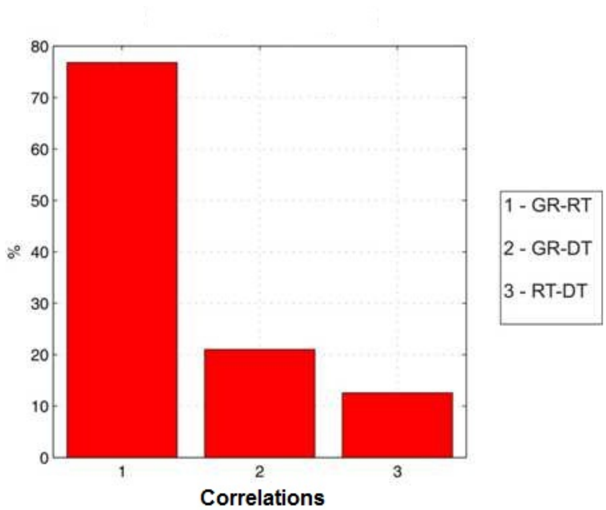

Figure 2. Correlations between logs.

On the other hand, Figures 3, 4 and 5 show the WLT transform of these logs (second track) using Haar approach, besides the derived coefficients s1, d1 and d2 (third to fifth track). Visually, it can be seen that WLT filters the noise and smooths the original logs of track 1, being also sensitive to lithology differences, such as discontinuities and gradual changes in sedimentation rate. The coefficients derived from the transform could be considered as noise or signal, but more studies are necessary to assign a feature or another.

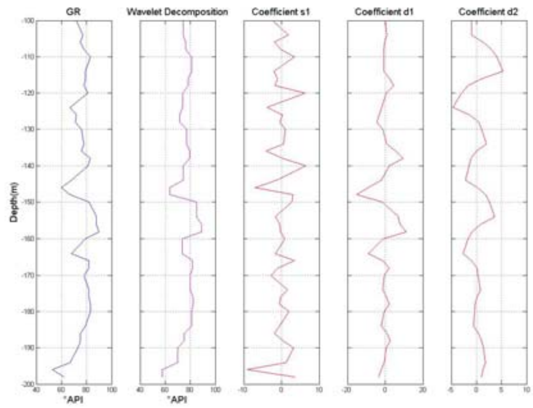

Figure 3. GR log and its respective wavelet transform with coefficients.

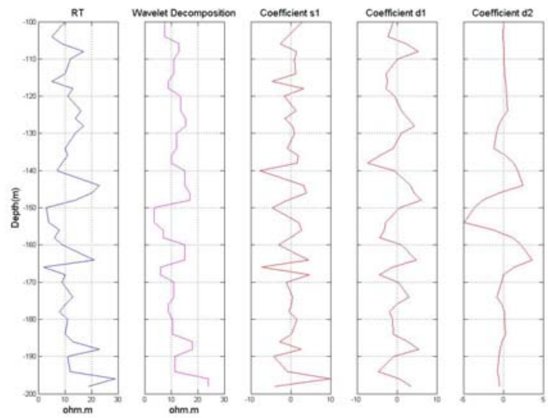

Figure 4. RT log and its respective wavelet transform with coefficients.

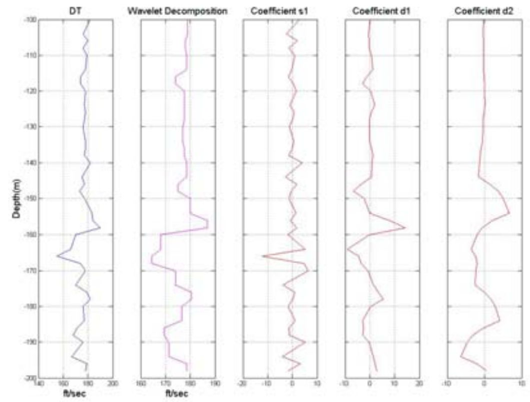

Figure 5. DT log and its respective wavelet transform with coefficients.

Following this work, Figure 6 shows a lithology log (target) derived from the core analysis (Hsieh et al., 2005), besides the real logs GR, RT and DT (input) and the difference between them. The vertical axis shows the depth ranging between 100 - 198 m, and the horizontal axis shows the lithology log and the real logs, all normalized to values ranging between 1 and 5. In this figure, it is also observed that the greatest differences appear in the case RT log, because it has the opposite correlation regarding lithologic log. The minor differences appear in the case of the GR log, while for DT log, the differences are greater than in the RT log, but lesser than GR log.

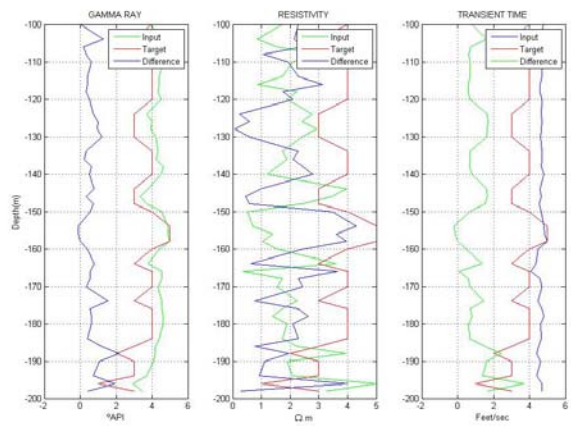

Figure 6. Well logs, true lithology and its respective wavelet transforms.

Figure 7 shows the normalized real logs (output) adjusted to the lithologic log (target) through an inversion process that used 20 interactions employing neural networks technique. As can be seen, there was a good approximation between them, however GR and RT logs show a closer fit with the lithologic log, providing an error less than 10%. In the case of DT log, the fitted error is bigger, around 30%. Comparing the fits of GR and RT logs, it is possible to see a better fit in the case of GR log.

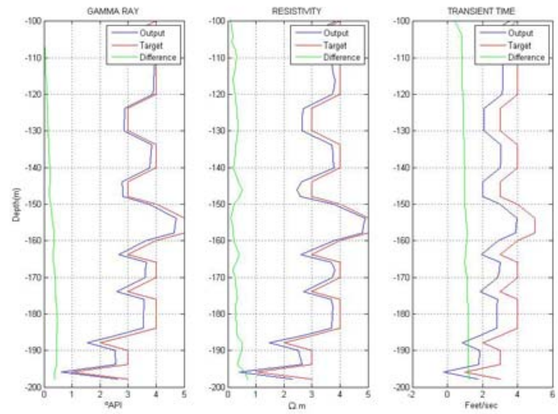

Figure 7. True lithology fitted with the transform of each log using 20 interactions with neural network approach.

The correlation between the real logs and lithological log after the adjustment is shown in Figure 8. It is observed, from this figure, that the highest correlation is for GR log (79%), followed by RT log (76%) and finally, by DT log, with a low correlation of 37%.

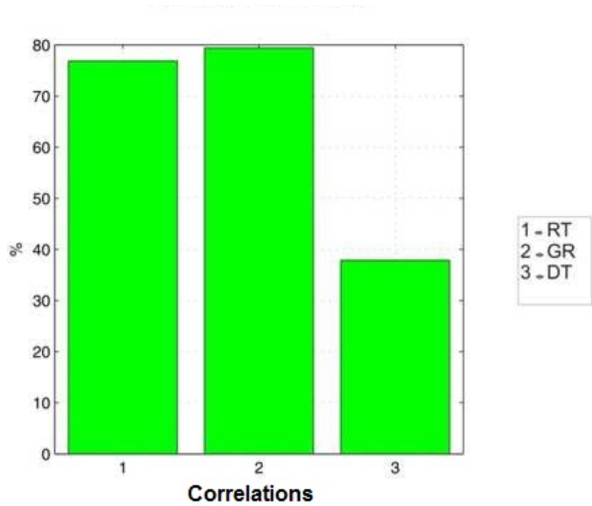

Figure 8. Correlation between logs.

In Figure 9, the real logs (target) were compared with the logs (output) fitted to lithologic log, but now in a normal range. The difference between these two kind of logs also appears in this figure. The smallest differences are in the case of RT log (less than 30%), as well as the GR log, where the differences may reach 50%. In the case of the DT profile, these differences are much larger, reaching up to 100%. These results show that both GR log as the RT log are lithological logs, and in this specific case the RT log worked better than the GR one in the identification of the lithology. However, the DT profile, as already knew, was inadequate to identify the lithology.

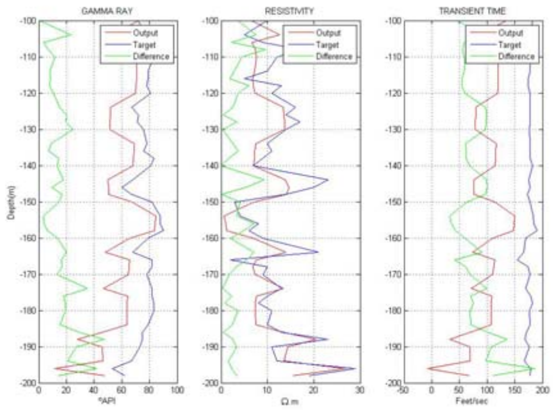

Figure 9. True lithology, fitted log and adjust difference.

Conclusions

This work shows that coupling WLT with neural networks technique 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 GR and RT logs evidence more the lithology when they are compared with DT log, and in the case of data of Shui-Lin area, RT log is closer to the lithological log than GR one , as shown in the fitting process by neural networks. Moreover, it was evident that in this particular case, the used methodology was more skillful than the fuzzy logic approach to differentiate lithology used by Hsieh et al. (2005).

Acknowledgements

We thank Darcy Ribeiro North Fluminense State University (UENF) by the computational support.

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