Quantitative Interpretation of Neural Network Seismic Facies -Oriente Basin Ecuador

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ABSTRACT

Summary

Interpretation of several 3D volumes from the Oriente basin suggests that faults may define the extent of a given field. However the subtle stratigraphic boundaries characterized by the clay-filled zones of low porosity compartmentalize oil pools. Therefore to be successful, identification of these zones is as important as the identification of the high porosity thick sands. In our experience, neural network based waveform classification has proven to be a very successful tool to identify these zones. Qualitative analysis of seismic facies derived from the classification is a common practice, however this paper focuses on the quantitative interpretation of these seismic facies. Extensive 1D-modelling was carried out to comprehend the trace shape variations due to changing isopach of the sand/shale sequences. This was fundamental to assign a realistic geological model to each facies. The paper discusses the workflows and also describes a methodology developed to derive "Net thickness" of reservoir sands from the seismic facies. Rigorous study of this technique on several 3D data sets from Ecuador's Oriente Basin has produced results that have been the foundation for understanding the depositional environments and reservoir models, validated by subsequent drilling.

Fig. 1 Location of study area

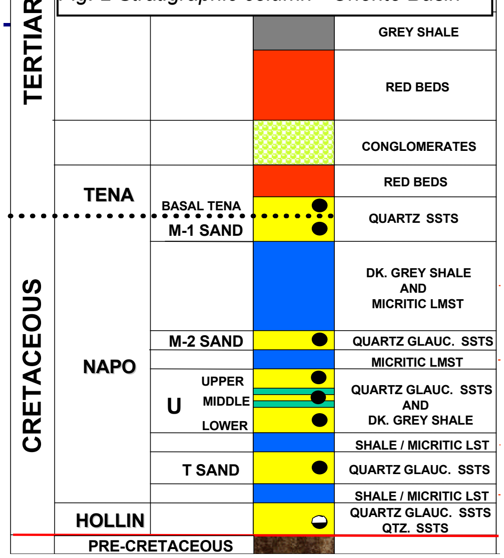


Fig. 2 Stratigraphic column - Oriente Basin

Introduction

Ecuador has three distinct geographical provinces, from west to east: the coast, the mountains and the headwaters of the Amazon jungle. The Oriente basin underlies the jungle region and is bounded on the west by the Andes Mountains and on the east by gradual rise onto the Guyana shield (Fig.1, study area shown in red). In this study we focus only on the Napo formation of the Cretaceous sedimentary cycle of the Oriente basin (Fig.2). Several of the Napo sandstones, the T, Lower_U, Upper_U, M2 and M1 are significant oil reservoirs. The Napo ‘U’ sandstone member, whose wavelet signatures are modelled and studied in this paper, comprises a sequence of stacked sandstones (up to 150ft thick with a porosity range of 10-25% porosity) with interbedded siltstone and carbonaceous claystones.

Neural network based waveform classification method

Seismic waveform classification is a useful tool for reservoir characterization and facies identification. Seismic traces extracted over a time interval tracking a target horizon are input to the classification process. The neural network trains on the variety of waveforms and generates a series of synthetic traces called *neurons* that best represent the diversity of shapes. The neurons are organized in pre-defined and numbered classes. Every trace of 3D volume within the interval is then compared to the neurons and assigned the class number of the neuron to which it has the highest correlation.

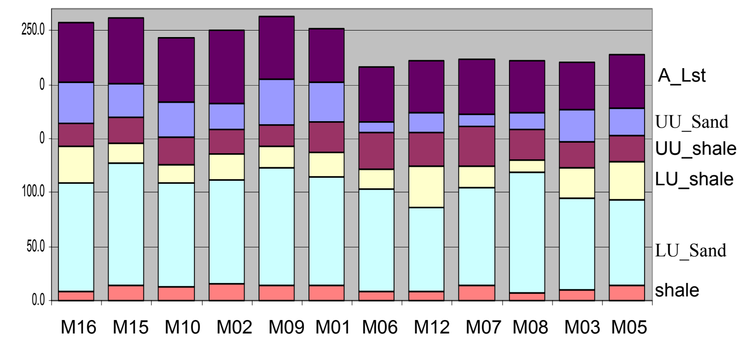


Fig.4 Thickness of different stratigraphic units based on well data.

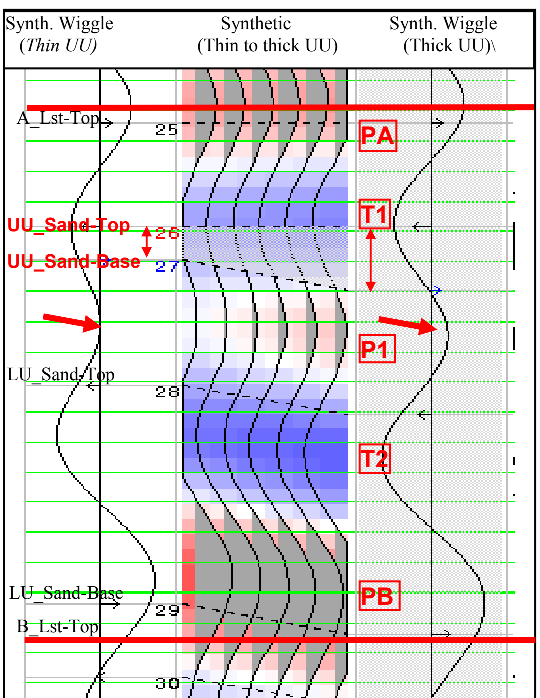


Fig.4 Modelling: Synthetic trace shape due to thickening of UU_sand. The peak P1 exhibits much higher amplitude as the UU_sand thickens.

Depending upon the thickness of the target zone and its surrounding stratigraphic column a time window needs to be determined to identify the representative seismic character for the classification. Extensive 1D-modelling carried out to estimate the optimum time-window is discussed in the first part of this paper. Fig.3 shows different units within the target stratigraphic column, whose signature is under study for the waveform classification. The objective is to study how the thickness variation, mainly of LU_sand, shale and UU_sand affect the seismic waveform so that suitable time-intervals can be estimated for the waveform classification of the UU and LU_sand.

Modelling

The well impedance logs were blocked so that all the main interfaces are represented by a change in impedance. Synthetics were generated using zero-phase wavelets and compared to the seismic data. Impedance was not varied in these experiments as it exhibited little variation in the available well data. Well thickness were cross-plotted to study the inter-relation within the thickness variations of these units. Based on these results several geologically realistic models developed and 1D modelling was carried out using several combinations of thickness of the LU_sand, shale and UU_sand. Two such modelling experiments are discussed below:

Thickening of UU-sand: Fig.4 shows a model where thickness of only UU_sand was increased from 24ft to 48ft, keeping thickness of other stratigraphic units constant. It can be seen that the tops of A_Lst and B_Lst are well-defined peaks (PA & PB respectively), however at the seismic frequencies (6-12-65-75Hz) it is not possible to resolve the top and base of the UU_sand, Shale and LU_sand. Instead we see thin layer interference at these boundaries resulting in trough T1, peak P1 and trough T2. From the comparison of the traces on the left and the right, it is clear that thickening of UU_sand causes higher amplitude of P1.

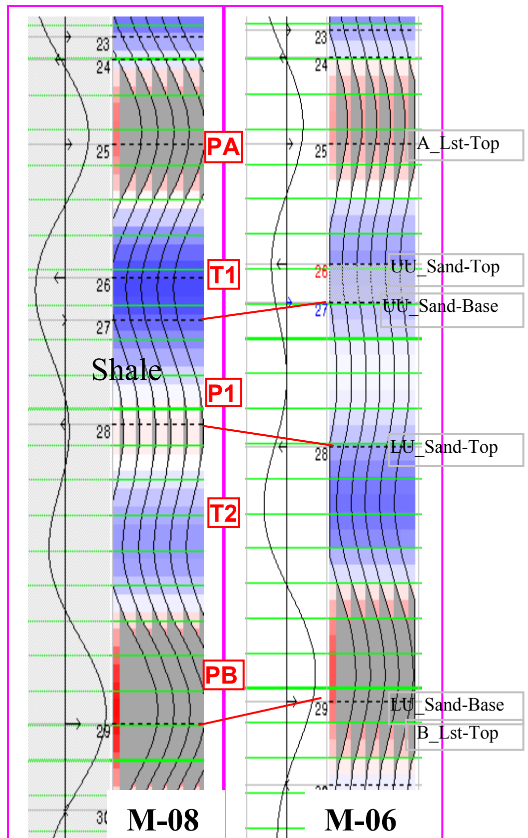


Fig. 5 Modelling: Synthetic trace shape due to thickening of shale and thinning of LU_sand (well M-08 vs. M-06).

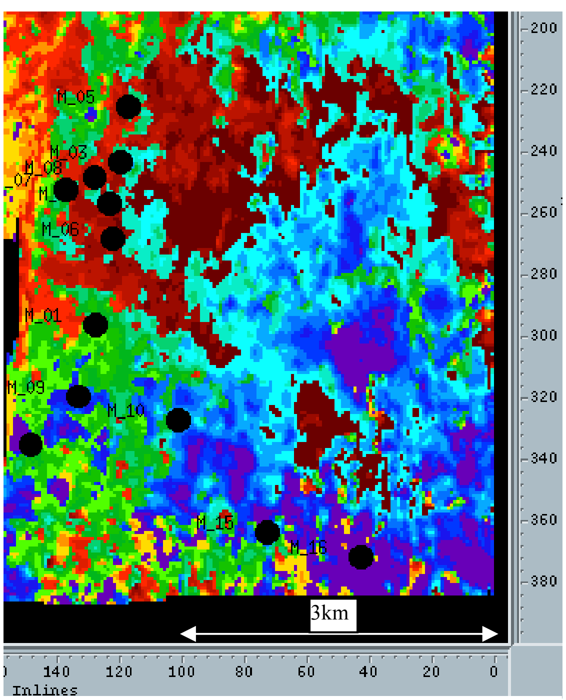


Fig.6 Waveform classification for the time interval A_Lst-to-16ms-down showing trends of UU_sand thickness.

Thickening of LU-sand and thinning of shale: Another realistic scenario to model is the reciprocal relation observed between the shale and the LU_sand. Well M-08 and M-06 provide such an opportunity to study the effect on the trace shape due to thickening of shale and thinning of LU_sand at the same time. From the simple modeling (Fig.5) it is clear that thinner shale and thicker LU_sand (M-08) give stronger T1 and weaker T2. It provides a useful signature for the waveform classification process to track and to identify thicker reservoir LU_sand.

Waveform Classification Process

Modelling results provided a thorough understanding of how the seismic trace shape over the target interval is affected by the thickness of the different stratigraphic units. Hence it was easy to determine a representative time window over which a particular geological model can be associated. Based on these modeling results a few unsupervised waveform classification runs were carried out to map particularly the UU_sand and LU_sand. One such map of UU_sand is shown in Fig.6, where a time window of A_Lst_pick-to-16ms_down was used. This time interval was selected so that the peak P1 related to the UU_sand thickness (as modelled in Fig.4) can be mapped over the field. The facies corresponding to a weaker peak P1 (red) indicating thinner UU_sand exhibit a remarkable geological trend, which matches to the well thickness shown in Fig.3. For example, wells M-06, M-07, M-08 and M-12 show relatively thin UU_sand (10-18ft) in comparison to M-01, M-09, M-10 and M-15 (~31-42ft). Seismic facies maps at the different sands LU_sand, M1_sand etc. were also prepared and successful locations have been drilled.

Seismic Facies Analysis – Top of Porosity Prediction

The detailed analysis and modelling of the seismic signatures to assign a geological meaning to each neuron resulted in an important methodology, which can be used to predict the top of porosity. This analysis was carried out at the M1_sands - the top of the Napo formation (Fig.2), which are also excellent producers in the Oriente basin.

Fig.7 shows well logs where M1_zone_Top and M1_zone_Base are marked, which are well-defined seismic picks. The base of porous M1_sands corresponds to the base of M1_zone, however the top of porosity of the M1_sand does not provide a pickable seismic event. In an effort to predict the top of the porosity neurons from the waveform classification run were studied and cross-plotted with the Net/Gross data available from about 80 wells on this field. An excellent correlation was obtained between the Net/Gross and the neuron class "C", which can be expressed as :

Net/Gross = 0.0188*C + 0.6836, *where C is neuron class number*

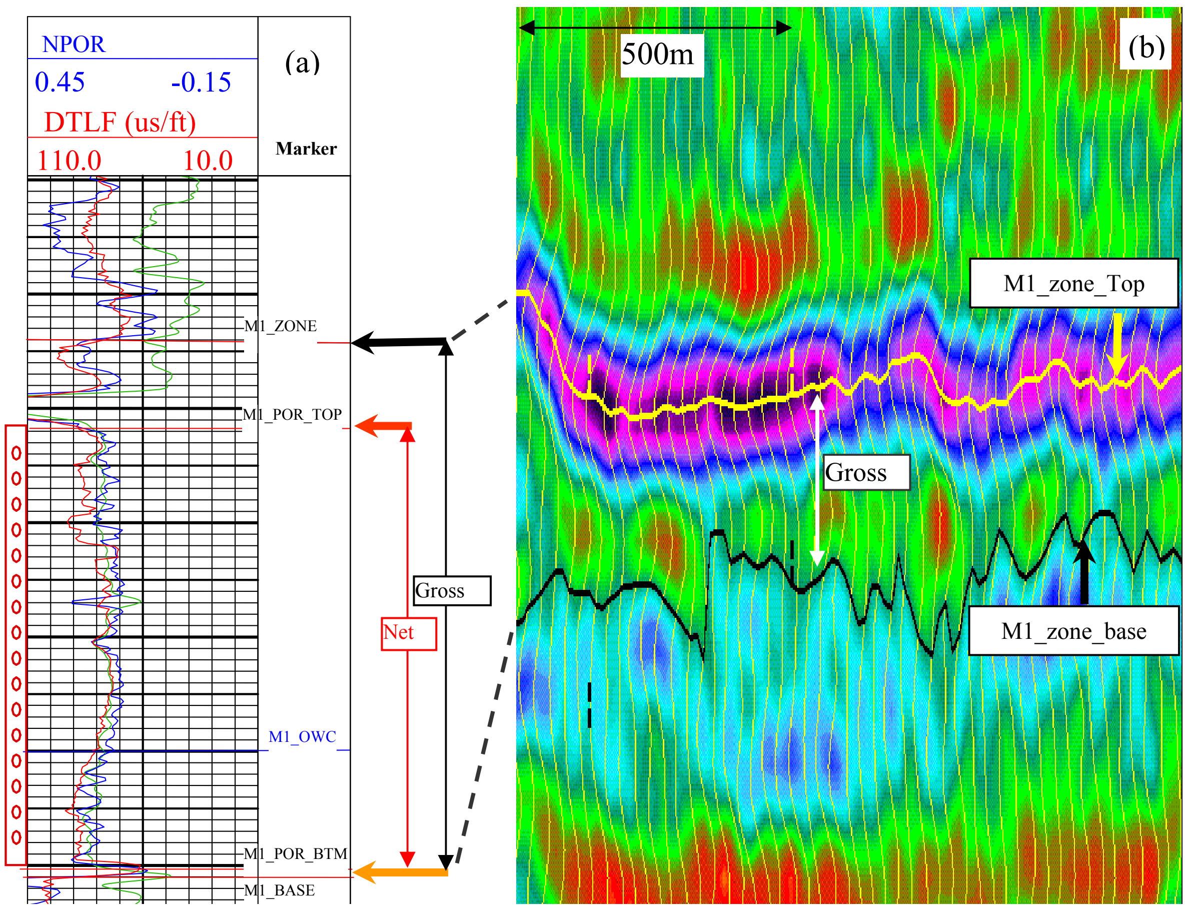


Fig.7 (a) Log data showing the Net and Gross thickness of the M1_zone. (b) Seismic data showing top and base of M1_zone are well-defined seismic events. Base of porosity is very close to the Base of M1_zone so can be considered same.

Fig.8 shows neuron classes from 1 to 12 so that "No reservoir" corresponds to Neuron-1 and "High Net/Gross" corresponds to Neuron-12. The gross thickness is readily computed from isopach maps derived from depth-converted surfaces from the top and base of the M1_zone. Therefore, multiplying seismic gross thickness to the Net/Gross from the above equation gives the total thickness of the porous zone. As shown in fig.7b the depth of the base of porosity is known from the seismic pick. Hence adding the total thickness to the depth of the base of the porosity gives us the top of porosity surface in depth. The scheme

No reservoir **High Net/Gross**

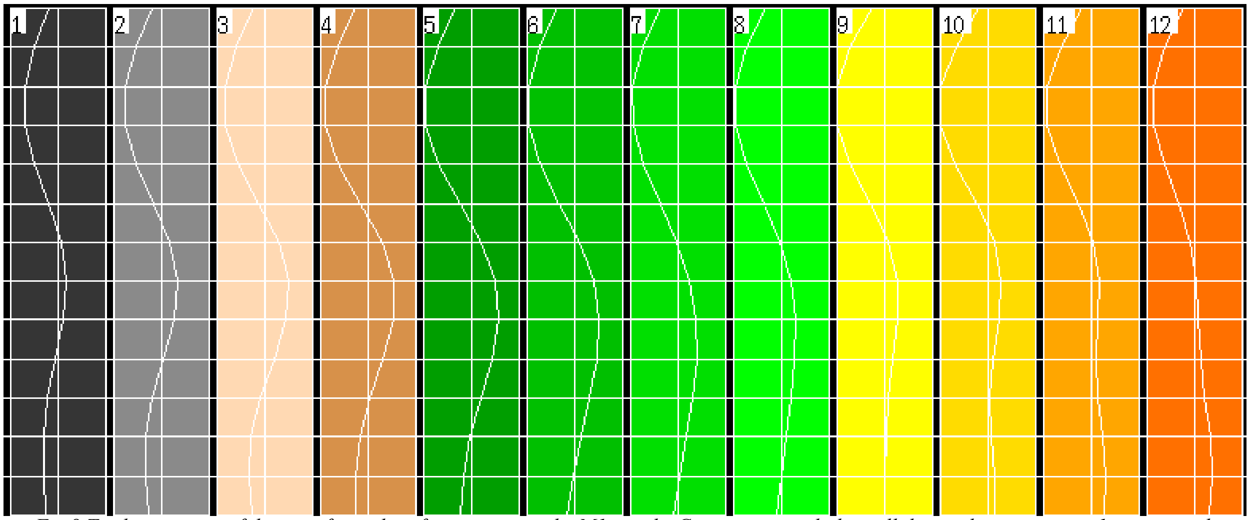
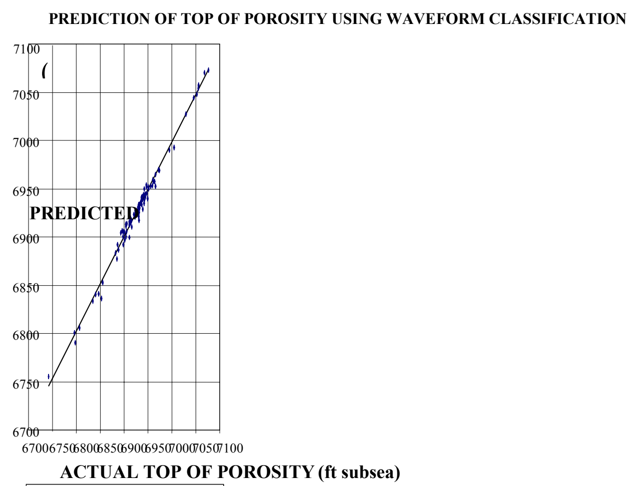


Fig.8 Twelve neurons of the waveform classification run at the M1_sands. Comparison with the well data indicates neuron-1 corresponds to "No reservoir' and neuron-12 corresponds to "High Net/Gross".

discussed above was applied and the predicted top of porosity was compared with the actual top of porosity of about 80 wells (Fig.9).

Conclusions

We successfully demonstrated that the quantitative interpretation of the seismic facies map derived from waveform classification is possible provided a geological understanding of the seismic signatures is accomplished. Extensive modelling and interpretive processing greatly helped in assigning a geological model to each neuron obtained from the waveform classification process. Further analysis of these seismic signatures resulted in an important technique, which can be used to predict the top of porosity of M1_sands. Comparison of predicted depth of top of porosity with the well data confirmed the accuracy of the methodology.



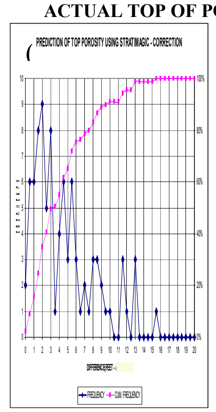


Fig.9 (a) Actual top of porosity vs. predicted top of porosity from waveform

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