[PS]The Prediction Error Filters Applied to the Seismic Interpretation Process of a Mississippian Tripolitic Chert Reservoir*

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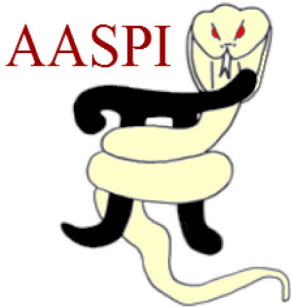
Abstract

One of the main problems faced in reservoir characterization is the need to infer subsurface properties from seismic data. Due to scarcity of well-log information, seismic attributes can be applied as delimiters of zones with similar seismic response that may be due to a set of reservoir properties. These techniques are called "classification techniques" and are based on the fact that seismic waves collect information from the physical properties of the subsurface.

Currently, Self-Organizing Maps (SOM) and Applied Neural Networks (ANN) are the two most popular methods in classifying seismic stratigraphic patterns. We compare the relative power of these two methods against the relatively underutilized Prediction Error Filter (or PEF, also known as an Autoregressive Filter) to identify user-defined patterns across multiple attribute volumes. The "vector of reference" can either be a suite of seismic amplitudes (giving rise to horizon-controlled waveform classification), a vector of attributes such as impedance, coherence, curvature, texture, and amplitude curvature at each sample (giving rise to volumetric classification), or a combination of the two Whatever their design, these filters are also used to compare and classify the seismic response with respect to a vector of reference. Unlike most implementations of SOM and ANN, the main advantage of using the PEF is that it provides a measure of confidence in the classification, thereby providing a measure of uncertainty to the interpretation. In this study, we compare these three methods to a gas shale and Mississippi-lime targets from the Midcontinent of the United States.

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Introduction

The Mid-Continent Mississippian Lime Play:

A warm, shallow sea with plentiful marine life covered most of Oklahoma during the Mississippian, approximately from 359 Ma to 318 Ma (Elebiju et al., 2011; Rogers, 2001). An extensive shelf margin existed, trending east-west along the Oklahoma-Kansas border showed on Figure 1 (Watney et al., 2001).

Our dataset is located at Osage County, Oklahoma, which sits on top of the Cherokee Platform and is bounded to the west by the Nemaha Uplift and to the east by the Ozark Uplift (Johnson, 2008). Figure 2 shows the location of the study area (Elebiju et al., 2011; Walton, 2011). This area has an extensive history of hydrocarbon exploration and production and nowadays interest has been renewed in the Mississippian Lime play with the advent of horizontal drilling and hydraulic fracturing.
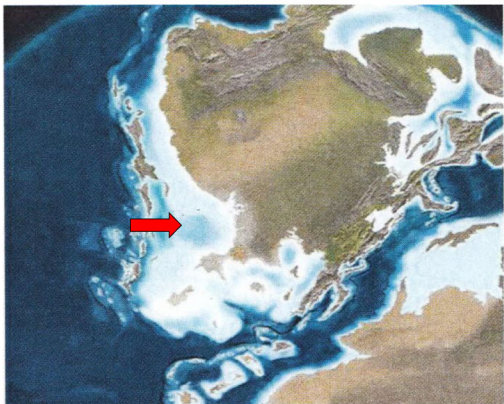

Figure 1. Paleogeographic map of the North American continent as it looked in the Mississippian Period. The red arrow points to the area where Oklahoma would be in present day (Modified after Blakely, 2009).
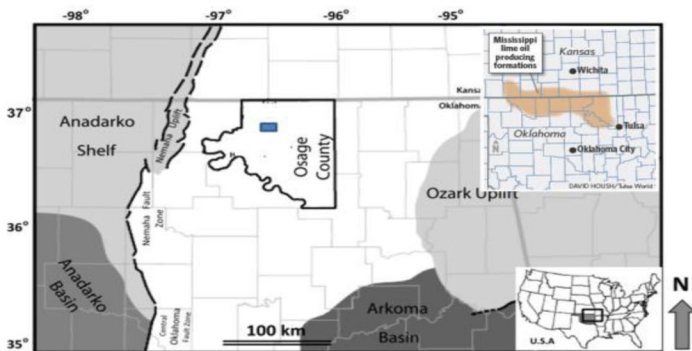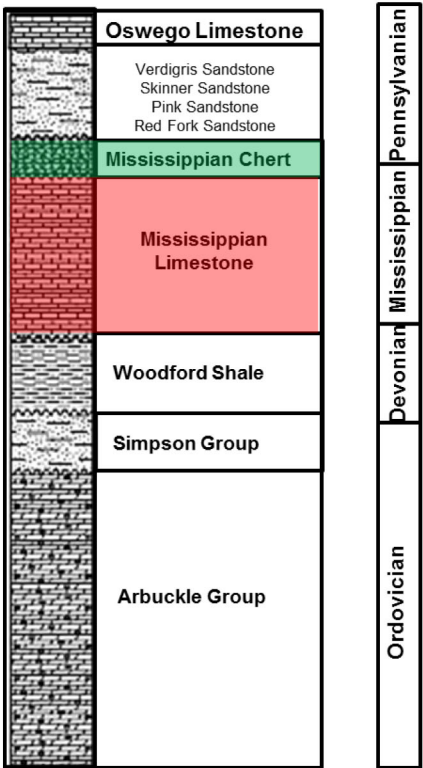

Figure 2. Map showing location of Osage County and the major geologic provinces in Oklahoma. Top right inset shows location of oil producing formations within the Mississippian lime. Blue box location of study area (Modified from Elebiju et al., 2011; Walton, 2011).
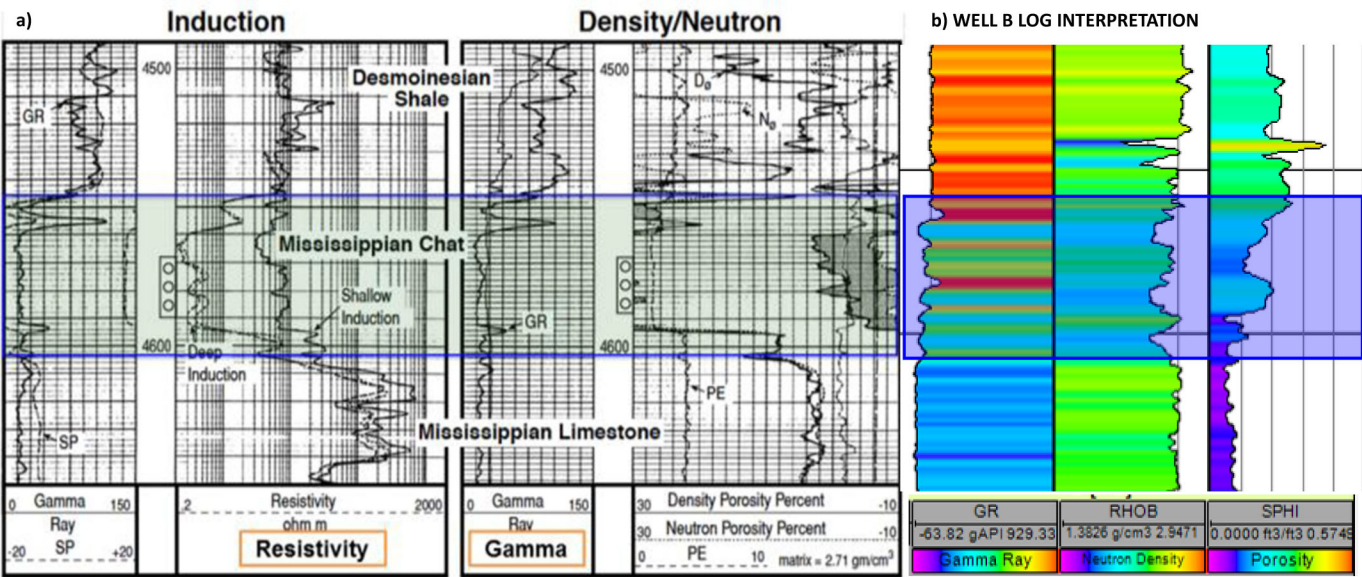

Figure 3. Generalized stratigraphic column for Osage County, Oklahoma (from Elebiju et al., 2011). The zone of interest is the Mississippian chert (Green), which represents an unconformable surface over the Mississippian Limestone (Red).

Rogers (2001) describes a model for Mississippian tripolitic chert development primarily from weathered or eroded Mississippian Lime, which was deposited as debris flows downslope into the mud matrix. First, silica replacement of carbonates occurred at the molecular level. Then, with continuing basement uplift, leaching occurred and meteoric waters dissolved the remaining calcite present in the rocks resulting in abundant secondary moldic and vuggy porosity. The tripolitic chert reservoirs are heterogeneous and have high porosity and low permeability forming sweet spots in the reservoir . The lower Mississippian section contains highly fractured limestone and nonporous chert (Figure 3). The log responses of Tripolitic chert zones show low-resistivity, low density and high porosity of 25-30% (Figure 4).

Figure 4. a) A representative log highlighting the response of the Mississippian tripolitic chert. Tripolitic chert log response is characterized by high porosity, low permeability, low resistivity and low density (Rogers, 2001). b) Interpretation over the well "B" used in this study.
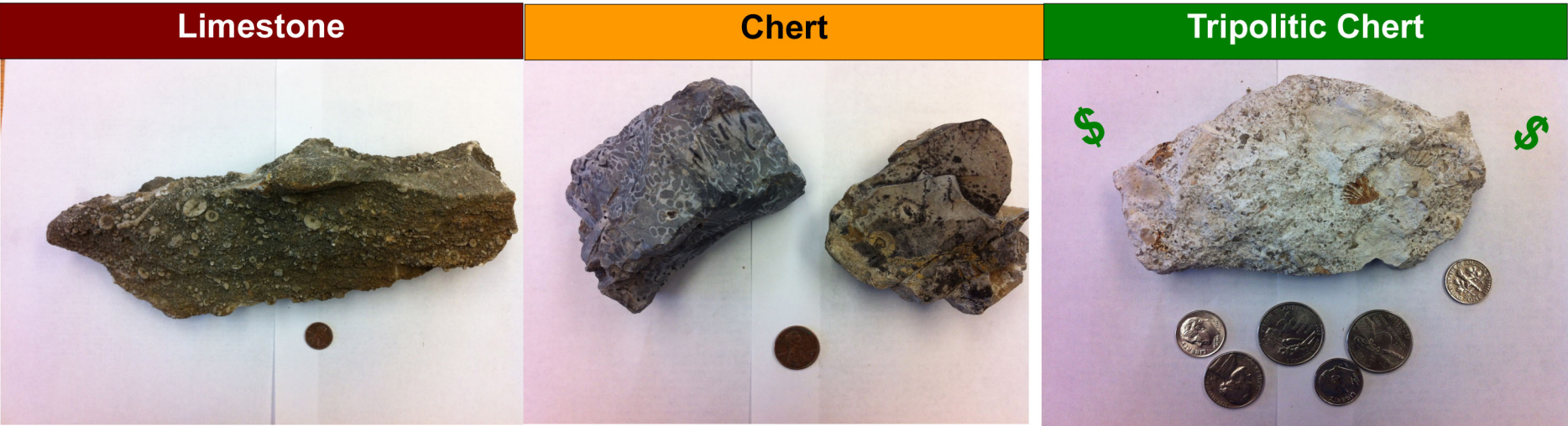

Figure 5. Photos of a) Limestone, b) Chert, and c) Tripolitic Chert rock samples. These samples are not from the study area, but they give an idea of the difference between the high density, low porosity Limestone and Chert and the lower density, higher porosity Tripolitic Chert (More coins indicate this is the target zone!)

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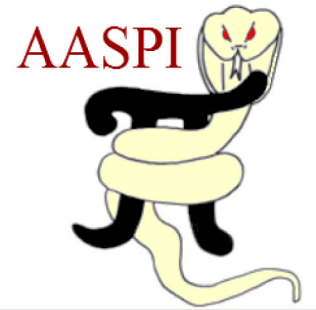
Methods

Kohonen Self Organized Maps (SOM):

SOM is one of the most commonly used unsupervised pattern recognition techniques that uses a known input dataset to classify, which in this case is used to classify different rock facies. In this 3D SOM algorithm, the input consists of several mathematically independent volumetric attributes where the number of input attributes determines the mathematical dimensionality of the data. To illustrate this complex algorithm let us imagine a fanciful example. Figure 6a show some different fruits. Considering their aspect ratio (shape) and peak frequency (color) and group the fruits according to these properties. After training the fruits get arranged mainly in three groups as shown in Figure 6b.
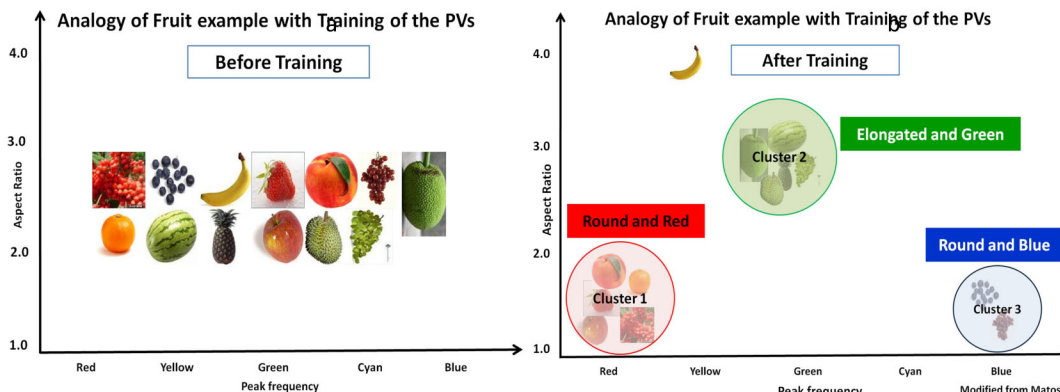

Figure 6: Example of a Fruits to show an analogy of clustering analysis. (a) The unorganized fruits. Clustering of the fruits after training considering their attributes (color and aspect ratio). (Modified after Roy et al., 2011)

In this case, the hypothesis assumes that magnitude of reflector convergence, coherency, coherent energy and dip magnitude would be good to differentiate chert response. The coherency and the dip will better highlight the discontinuities within the reservoir thus adding a structural feature combined with the irregular amplitude variation (from coherent energy) of the chert zone. These volumetric attributes when clustered help to identify the different discontinuities of the lithological settings of the seismic facies within the survey based on the seismic response and wavelet form.

Prediction Error Filter (PEF):

Given a user-defined target zone over a trace corresponding to the well location or any zone of interest (waveform pattern), the Prediction Error Filters will identify other zones with similar seismic response. To calculate the PEFs, we apply the concept of "Auto-regression" to the seismic signal. Specifically, given two vectors y_t and y_{t-1}, we wish to predict a third vector y_{t+1} using the least-squares method to find the best scale factor or prediction filter. Waveforms that can be predicted with less error will be similar to the user-defined waveforms and are highlighted to form a prediction volume. Figure 7 explains more graphically the process of the PEF generation and application. The windows were taken over the interpreted Mississippian Tripolitic chert zone over the well in the amplitude and acoustic impedance inversion cubes.
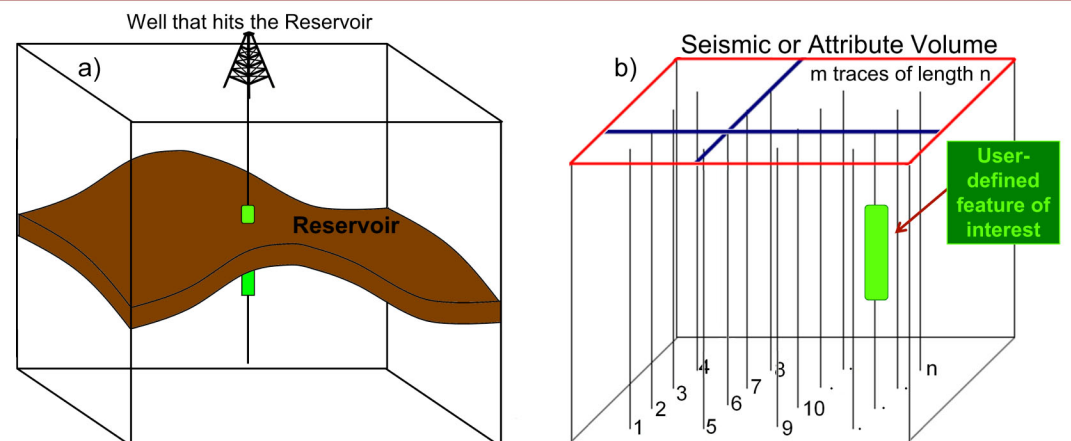

Figure 7. a) Earth model showing the reference over a well that reaches the reservoir. b) Schematic showing the reference trace with respect to the user-defined target.
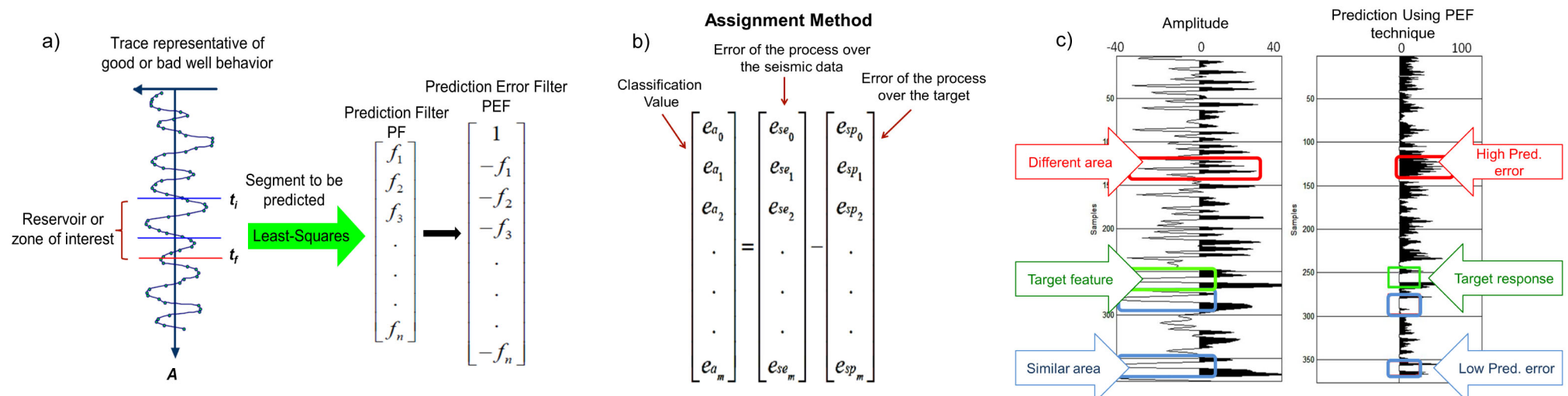

Figure 8. Schematic sequence of a) How the Prediction Error Filter vector is obtained, b) Assignment of the prediction values, and c) comparison of a trace and the classification of the PEF when using a user-defined window over a zone of interest.

Supervised Neural Networks:

Similar to biological neurons in the brain, Artificial Neural Networks are systems for parallel and adaptive processing of information. They are able to create functional and related relationships between the input data (Nikravesh and Wong, 2001). Figure 9 shows that the computational neural networks are constituted by simple units as neurons or cells that are related by weights. These weights modify the inputs so if they reach a certain threshold or critical value, the neuron will be excited and will produce an output. In this case, the input will be the amplitude and acoustic impedance cubes, and also the waveform classification obtained using the PEF over the amplitude and acoustic impedance inversion cubes. This process is also supervised because it takes into account picks made by the user over zones interpreted as target (Mississippian tripolitic chert) and zones that can be classified as non-economical (Mississippian limestone and chert).
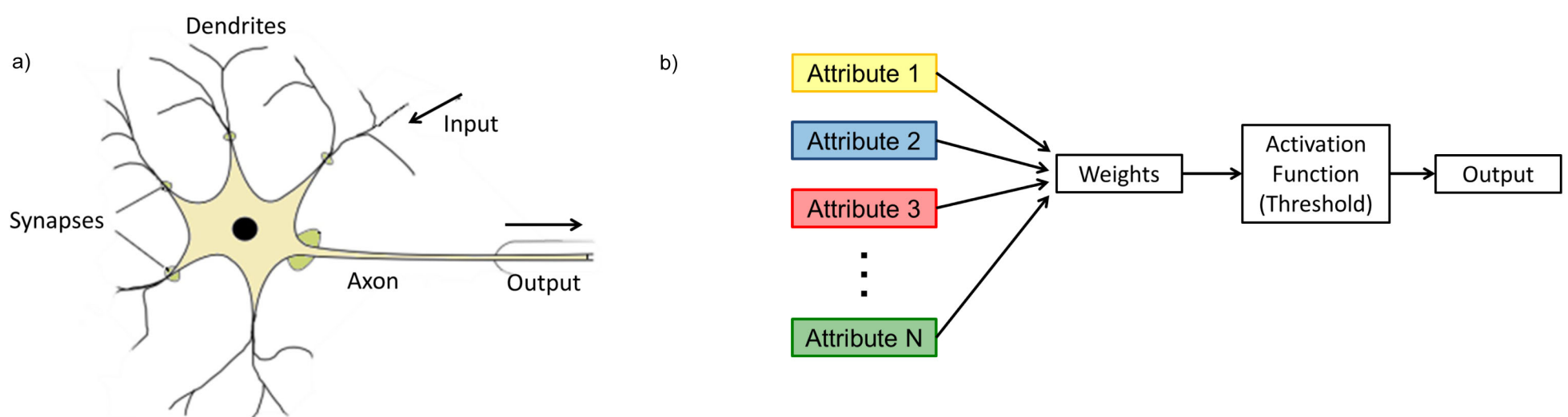

Figure 9. Neural Network scheme where a) represents a biological neuron with dendrites where several inputs enters the neuron through the synapses. It the inputs excite the neuron above a given threshold, it will transfer the output to the next neuron or the muscles by the axons (Modified from Golda, 2005). The similar process is shown on b), where the inputs are the seismic attributes, they will be weighted and if they are summed and if the threshold is crossed, the output will be the classification. In this case this classification is guided by the interpreter picks over the data.

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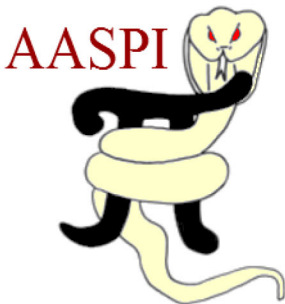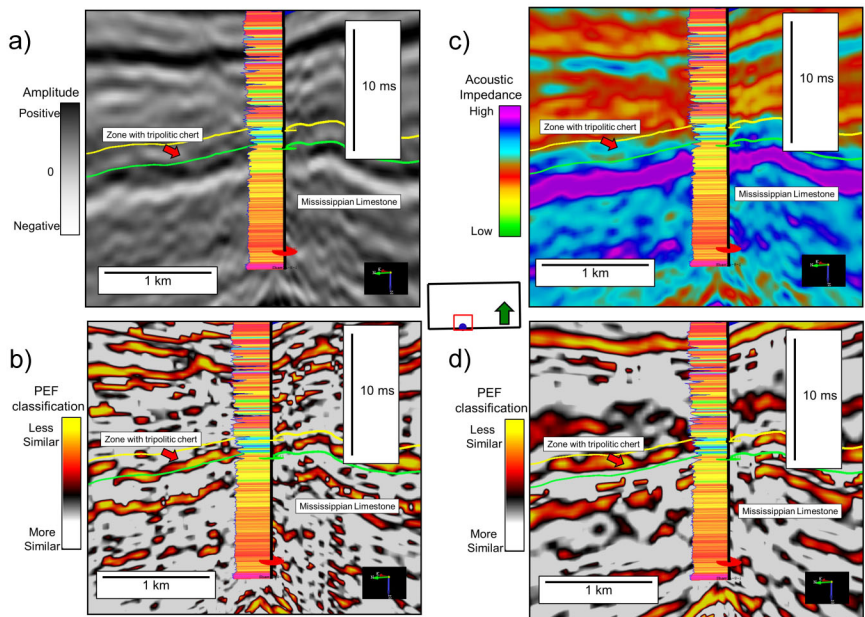
Results

Figure 10. Interpretation of the low density tripolitic chert above the Mississippian Limestone near Well B over: a) Amplitude Inline and crossline, b) the response of the PEF over the amplitude using a window between both horizons, c) Acoustic impedance, showing the relative low impedance of the low density tripolitic chert and the high density Mississippian Limestone below; and d) the PEF classification using the same user-define window over the acoustic impedance inversion cube.
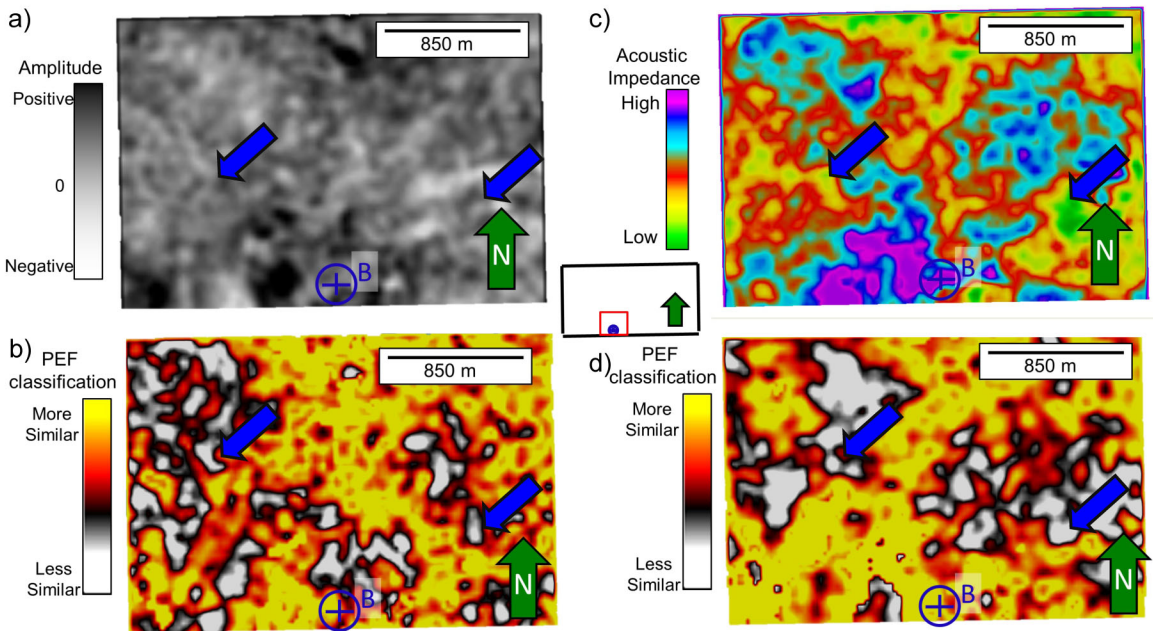

Figure 11. Time slice at 586ms, between the Mississippian tripolitic chert and the Mississippian Limestone near Well B. The blue arrows indicate zones of low impedance that could be related with low density tripolitic cherts: a) Amplitude b) the response of the PEF over the amplitude using a window between both horizons showing zones with similar seismic response, c) Acoustic impedance, showing the relative low impedance of the low density tripolitic chert and the high density Mississippian Limestone below; and d) the PEF classification using the same user-define window over the acoustic impedance inversion cube.
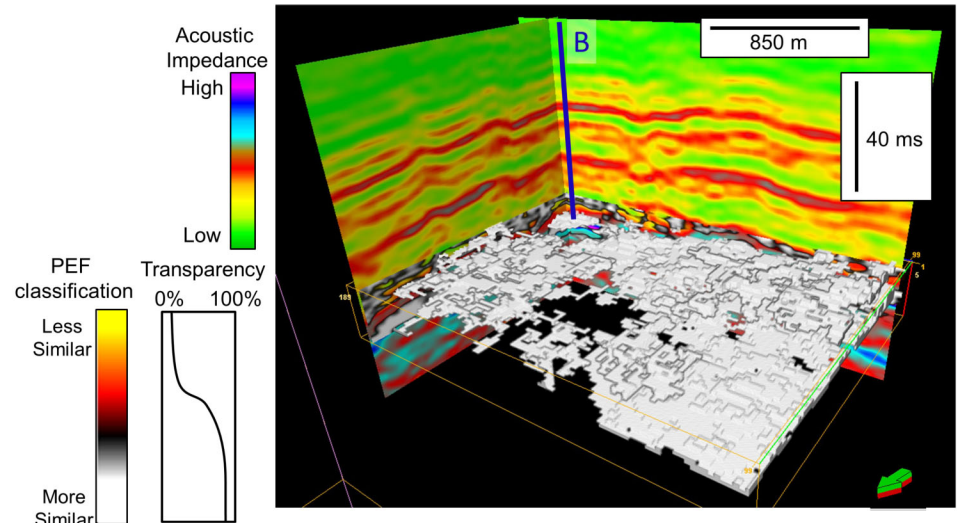

Figure 12. 3D volume extraction using the PEF classification with the user-defined window over the tripolitic chert with low acoustic impedance. The white body indicates zones with low acoustic impedance and very similar waveform of the acoustic impedance over the well. For a more accurate and direct relation between the waveform and the rock properties, it is necessary to crossplot the classification and the well log to better distinguish target zones.
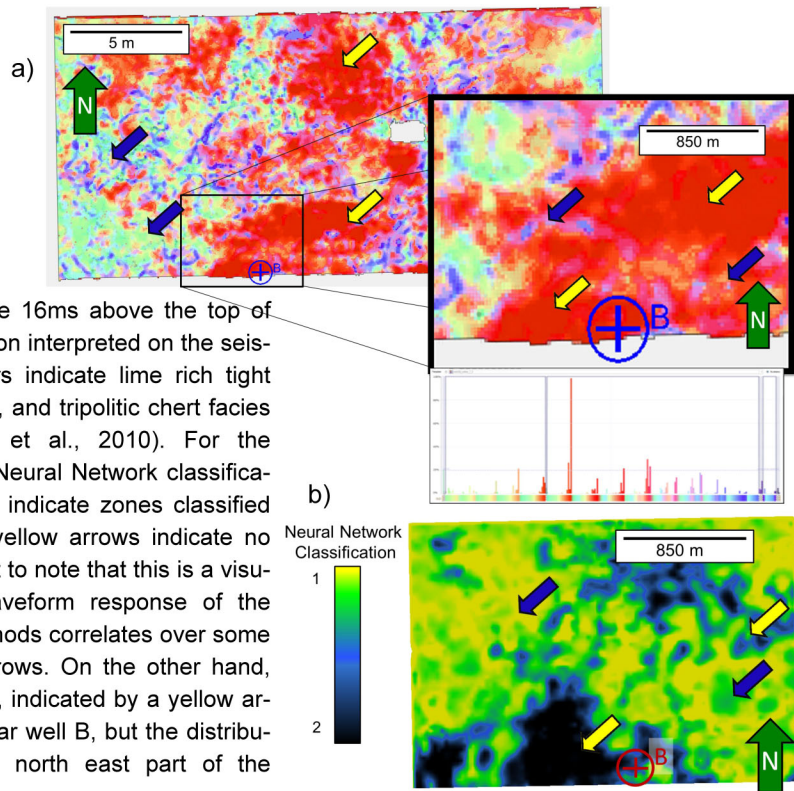

Figure 13. In a) stratal slice 16ms above the top of the Mississippian lime horizon interpreted on the seismic where the bright colors indicate lime rich tight chert facies (yellow arrows), and tripolitic chert facies (blue arrows) (After Roy et al., 2010). For the timeslice at 586ms, b) the Neural Network classification where the blue arrows indicate zones classified as tripolitic chert and the yellow arrows indicate no tripolitic chert. It is important to note that this is a visual classification of the waveform response of the tripolitic chert and both methods correlates over some areas pointed with blue arrows. On the other hand, the Mississippian limestone, indicated by a yellow arrow, correlates very well near well B, but the distribution looks different in the north east part of the timeslice.

Conclusions

. Based on these observations, we expect to find zones of high porosity/low density (low-impedance) predicted from impedance inversion related with the Mississippian tripolitic chert on the upper part of the Mississippian Limestone interval.

. The prediction Error Filters can accurately predict any feature of interest. This method could be used in combination with other attributes to better discriminate ones with similar response. The method "mimics" the interpreter, but of course there are both good and bad interpreters!

. Both the Self Organized Maps and the Prediction Error Filters methods can classify the waveform response and locate zones with similar behavior using attributes.

. The supervised neural networks are a powerful tool during the interpretation process. The dataset used to train the neural networks are vital in this process

. It is important to use the correct combination of attributes in order to better delineate or interpret targeting zones.

Recommendations and Future Works

Well Data:
. Further well control will improve interpretation
. If available. Horizontal drilling logs.

Prediction Error Filters
. Better classification using more than one trace.
. Other attributes.

Acoustic Impedance:
. More wells and horizons.
. Check the Caliper correction for the density log.

Supervised Neural Networks
. More attributes that differentiate lithology.

Waveform Classification
≠
Facies interpretation
Crossploting of the Impedance and PEF results with well log data is important in order to find a relationship between the inversion and classifications and the rock properties.
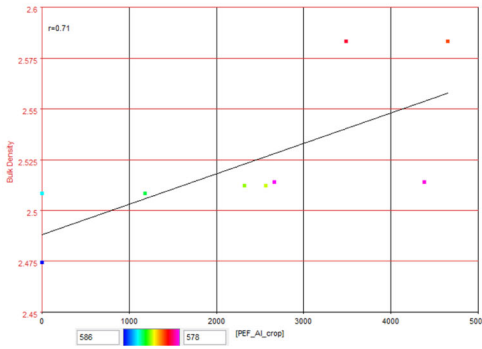

Figure 14. Crossplot over the Mississippian tripolitic chert bed of the PEF Classification using the Acoustic Impedance inversion over the trace corresponding to the well location and the Bulk Density, and the colors represent depth in time. Note that points with low bulk density correspond with low error (meaning more similar to the samples on the window) and deeper intervals.

Acknowledgements

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