## **Bayesian lithological inference for a sandstone reservoir**

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## Abstract

This work illustrates a methodology to infer porosity and clay volume in a clastic reservoir. This methodology follows the principles of probability theory with the goal of extracting lithological information from a variety of sources of information including petrophysical and seismic data while accounting for the uncertainties associated with the data. The main source of information is the prestack seismic data, previously processed in an amplitude preserved fashion and the petrophysical information provided from well log data and rock physical relationships.

The methodology outputs a collection of volumes composed of reservoir cell blocks that represent probability parameters related to porosity and clay volume. These probability parameters are extracted from a set of probability density functions for porosity and clay volume named local joint probability density functions (local PDF's). Each local PDF represents the lithological information associated with one individual reservoir cell. The computation of these local PDF's from the seismic data and petrophysical information follows the Bayesian methodology of inference which is an application of probability and inverse theory.

The main effort in this process is to construct local PDF's from the data. This process follows four steps: i- an AVO inversion to estimate elastic impedances (P- and S- impedances); ii- a petrophysical analysis to build empirical rock physics models that relate these elastic parameters to porosity and clay volume; iii- applying Bayes Theorem to obtain the posterior probability density functions for the parameters under investigation (porosity and clay volume), given all pieces of information. The posterior PDF's represents our local PDF's and iv- once we have the posterior PDF's for porosity and clay volume, the work is to extract the probability parameters are the framework for our inference work that is the uncertainty analysis about porosity and clay volume.

## Introduction

The evaluation of the exploration risk in the oil industry is a fundamental component of the decision process related to permit acquisition, potential production, and exploratory drilling and production development. Seismic data together with well log data are the main source of information to determine reservoir properties. The most frequently employed methodologies are based on multivariate regression, which treat the data as spatially independent or geostatistical methods. The latter is highly dependent on a model describing the spatial variability constructed from the data. These methodologies do not lend themselves to quantifying the uncertainty in the estimate. This paper develops a methodology to provide an estimate of the reservoir's lithology and porosity and the related uncertainty from geophysical and petrophysical data. This work is based on and is an extension of previous work presented by Loures and Moraes (2001), Loures and Moraes (2002) and Loures and Moraes (2003).

In the work presented by Loures and Moraes (2003) the final solution is a set of PDFs for median block cell porosity in a reservoir and an associated measure of the uncertainty calculated from the seismic attributes and the porosity well log data (neutron log). The theory is developed based on inverse theory, following Bayesian inference. Rather than using analytic relations linking the elastic parameters to rock properties from mathematical physics empirical formulas from rock physics are employed.

Here, we have implemented a methodology incorporating AVO inversion and modified the rock physical model so as to infer a joint porosity and clay volume inference along with its' uncertainty for each particular reservoir cell. The joint probability, which may be used to define a sandstone reservoir, may be estimated with greater reliability than the individual inferences.

## Methodology

The methodology follows four basic steps:

i- AVO inversion to estimate P- and S- impedances from prestack seismic data. Today, we have several different linear Zoeppritz approximations available that allow us to perform a linearized AVO inversion. For a good understanding of the AVO inversion and a large bibliographic review we suggest Castagna (1993);

ii- Analysis using well log data and if available core sample laboratory analysis. This petrophysical analysis is the framework to construct the empirical rock physics models used in the Bayes theorem application. This step is based on the work presented by Loures (2003) and provides the rock physics models and an analysis for the correlation between the lithological parameters and the elastic impedances;

iii- Probabilistic approach, following the work presented by Loures and Moraes (2003), Bayes' theorem is applied to construct a posterior distribution for the parameters under investigation associated to each reservoir cell. This work extends the inference from just estimating porosity to porosity and lithology. The result is a collection of local joint PDFs for porosity and clay volume given the seismic data and the petrophysical information. Each reservoir cell has one local PDF which is result from the posterior PDF from the application of Bayes' Theorem.

iv- Once we have computed the posterior PDFs, we extract a series of probability parameters that enable us to infer the reservoir lithological properties. These probability parameters are listed below:

the mode of the local PDFs- this is a vector of two elements that represents the values for porosity and clay volume with highest probability given the knowledge of the information provided by the seismic and petrophysical data. For each local PDF, associated with one reservoir block cell, its' mode can be considered an estimated value for the median porosity and clay volume for the associated reservoir block cell.

0.95 probability confidence interval- the methodology provides a quality measure associated to the mode of each local PDF. This quality measure represents the accuracy of the porosity and clay volume estimate represented by the mode of the local PDFs. The length of 0.95 probability interval of the local PDFs centered on the mode represents this measure of guality. If the associated local PDF has a large dispersion, it will result in a large confidence interval. Conversely in the other extreme, if the local PDF has the shape of a spike, it has a small 0.95 confidence interval and we consider the estimate very accurate. For each local PDF a pair of confidence intervals are computed, one associated with the porosity and the other the clay volume. Different tests have shown that porosity has a small confidence interval, but clay volume a relatively large confidence interval.

range limits of 0.95 confidence intervals- sometimes we wish to be more conservative than just to assume the modes of the local PDFs are the estimates. For a conservative choice, the methodology provides the minimum and maximum values for each 0.95 confidence interval for each cell block for both porosity and for clay volume. We can say with high confidence that for each cell block that the actual porosity (or clay volume) will fall between these extremes, i.e. the minimum and maximum value of the range of the 0.95 confident interval.

probability of clay volume bellow a specific threshold value- tests have demonstrated that the estimate of porosity and clay volume from seismic and petrophysical data is a unstable. Usually, the length of the 0.95 confidence interval for clay volume is large implying large uncertainty related to the lithology estimate. To treat this ill posed problem we choose to decrease the information demand from the data. We would be satisfied if we have an indicator that provides with good confidence that a particular cell block is a "good sandstone" (in the oil exploration point of view) or not. So, consider a target clay volume value that represents a maximum clay volume for a good productive sandstone reservoir. If the clay volume is above this target value, the associated cell block is out of consideration as part of the reservoir. The methodology computes from the local PDFs the probability that the clay volume is bellow this target interval. This probability should be a good indictor for a "good sandstone" or not a "good sandstone". A specified probability value can be used as minimum acceptable value to allow a cell block to be considered a "good sandstone". For example, if the geologist had decided that a good sandstone must have clay volume less than 0.20, then we consider cells that have probability greater than or equal to 0.95 that the clay volume less than 0.20 a "good sandstone" or vice versa. If we wish to be more conservative, we can use a higher value for this probability limit or the opposite if we wish to be less conservative.

probability of clay volume bellow a specific threshold value and porosity above an specific value- in addition to what has been previously discussed that a good reservoir sandstone must have the clay volume bellow an specific value we add the additional condition that the porosity must be above a certain threshold porosity value. The methodology computes from each local PDF the probability of this happening. We consider that cell blocks that have a probability higher than 0.95 that they are good reservoirs and conversely not part of the reservoir. We use a probability limit value of 0.95 but if one wants to be more conservative (or less conservative) this value can be increased (or decreased).

This methodology have been recently tested on synthetic and real data. Next, we present the results of the application of this methodology to an interval with a sandstone gas reservoir.

### A real example

We have selected an CDP location to illustrate the result of the application of this methodology. Figure 1 shows a set of plots that represents the resulting 1D analysis at the selected CDP location . The plot (a) represents P- and S- impedances estimated from the AVO inversion. The plot (b) represents the porosity modes of the local PDFs (red line) and the minimum and maximum values of the range of 0.95 confident interval, plot (c) shows the length of the 0.95 confident interval for porosity, plot (d) shows the clay volume modes of the local PDFs (red line) and the minimum and maximum values of the range of 0.95 confident interval, plot (e) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability that the clay volume is bellow 0.20 and plot (g) represents the probability t

We can see that for porosity, the confidence interval is very small, that means the porosity estimated by the mode is very accurate. The narrow range of the 0.95 confidence intervals shows that the porosity values along the profile are very confident. The clay volume inference has a larger 0.95 confidence interval. This means that the clay volume estimated by the modes are less reliable. Further, we can see that the minimum and the maximum values of the 0.95 confident interval do not provide good quality information about the lithology. When we analyze the plot of the probability for a "good sandstone" we can identify some layers as sandstone between shale. We can easily use this plot to identify the "good sandstone". Finally we can identify the layers for a "good reservoir" were the probability for a good sandstone with porosity higher than 0.08 is higher than 0.95. For this example, we have prior knowledge that the reservoir are sandstones layers that vary between the interval at approximately 3200 and 3600 ft.

Figure 2 represents the elastic impedances and probability parameters from a section selected to illustrate the methodology. The images (a) and (b) represent respectively the P- and S- impedance estimated from an AVO inversion. Images (c), (d), (e) and (f) represent respectively the porosity mode values, the minimum porosity value of the range of 0.95 confident interval, the maximum porosity value of the range of 0.95 confidence interval and the length of the 0.95 confident interval. Images (g), (h), (i) and (j) represent respectively the clay volume mode values, the minimum clay volume value of the range of 0.95 confidence interval and the length of the 0.95 confidence interval. Images (g), (h), (i) and (j) represent volume value of the range of 0.95 confident interval and the length of the 0.95 confidence interval. Images (k) and (l) represent the probability that the clay volume is be below 0.20 and porosity higher than 0.08.

These images shows structures that represents "good reservoir" between 3200 and 3600 feet. We can analyze all images together and use different criterion to determine the potential reservoir cells.



FIGURA 1: Plots that represents the probability parameters resulting from the application of this inference methodology at the selected CDP location.



FIGURA 2: Images that represents the probability parameters in a section resulting from the application of this inference methodology.

#### Conclusion

The methodology presented demonstrates an efficient way to combine information from the seismic data and petrophysical data, accounting for the uncertainty associated with this information and the level of resolution of each these parameters under investigation. The local PDF's provide a set of probability parameters that help the explorationist understand the reliability of the prediction. Using these tools the explorationist can identify the probability that a particular cell contains reservoir sand.

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