Facies Identification – Using all the Information

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Summary

Facies determination from the outcomes of seismic inversions has become an integral part of reservoir characterization workflows. Modern applications use a Bayesian approach which maps prior facies information to final distributions, given the evidence provided by the inversions. This is implemented by designing probability density functions defined in elastic property space (ePDFs) for each facies. These are then applied to the input inversions. We will review our approach and show how we incorporate several key features, including

- 3D Priors
- Rock Physics templates
- Estimating inversion uncertainty and incorporating in facies analysis
- Inversion bias detection and correction
- Estimating petrophysical facies and relating to elastic properties

Introduction

The application of Bayes' rule maps prior probabilities to posterior probabilities, given some new evidence. In modern reservoir characterization it has been successfully applied to determining the probability distributions of geologic or geophysical facies (Pendrel et al., 2006). The evidence used to update the prior probabilities is usually the results of seismic inversions or their derivatives (Pendrel et al., 2014). Log or rock physics data are cross-plotted in the inversion elastic space and elastic probability density functions (ePDFs) are designed to represent the facies under consideration. Then, for each inversion data sample, the ePDFs for each facies are sampled. The results are volumes of the probabilities of occurrences of each of the facies at all points in 3D space. There several important details in the implementation of this procedure which we discuss below.

Method

In order to achieve optimum results, there are a few points which require consideration. First, since the ePDFs are density functions, their sampling should involve integration along the elastic axes to extract an area or volume when more than one elastic property is being considered. Although the results of deterministic inversions produce single values, there is an associated uncertainty whether we care to acknowledge it or not. We estimate the uncertainty by cross-plotting inversion outcomes at well locations vs high-cut-filtered logs (Pendrel et al., 2016). The residuals referenced to best-fit regressions are plotted as a histogram and modelled with uncertainty probability density functions (uPDFs). The uPDFs are quite often Gaussian or log Gaussian but need not be. The use of uPDFs has another benefit. Certain bias conditions existing in the inversions will result in the means of the uPDFs becoming non-zero.

However, once that information is encoded in the uPDFs, that bias is automatically corrected during the Bayesian procedure.

Next, the choice of prior probabilities can be critical. It is important to fairly represent the state of our present knowledge before the addition of further evidence from the inversions. It has become usual to use the Uniform (all facies equal) or some different percentages based on the relative occurrences of the facies in well logs. However this approach ignores any relative facies ordering which is a part of our prior information (Pendrel et al., 2017). We make use of 3D prior volumes which are laterally constant although structurally compliant. The vertical variations are determined in an interesting way. We first apply the Bayesian procedure to petrophysical logs in order to define the log facies. This involves the design of petrophysical probability density functions (pPDFs) corresponding to the petrophysical logs being used (e.g. Vshale, Sw, etc.). This is done before any elastic analysis involving inversions and provides us with native logs facies or updates of existing facies. The by-products of this analysis are facies probabilities at each well location. We simply average these in a structurally-compliant way in order to get the vertical variation in the 3D priors for our elastic analysis.

The Bayesian estimation of the petrophysical facies has another benefit. We can quickly observe how our petrophysical definitions manifest in elastic space. At the end of the day, the elastic properties are intended to be proxies for the petrophysical properties and allow us to estimate petrophysical facies from elastic data. We need to ensure, as a QC step, that this assumption is correct within the seismic band. This could require redefinition of the petrophysical facies or the selection of alternate elastic properties.

When the process is complete and we have determined facies from the inversion elastic data everywhere in space and time (or depth in the case of depth inversions) the output facies probabilities can be used for one further purpose beyond ascertaining the most-probable facies. Coupled with per-facies elastic trends measured from logs or computed from rock physics, they can be used to create a new low frequency model with 3D variability (Pendrel et al., 2016). At each 3D data point, the trend value corresponding to the most-probable facies is chosen. This new low frequency model can then be used in a second pass of inversion and subsequent facies analysis.

The facies probability volumes will serve one final purpose. That is to compute reservoir attributes such as Net Pay. They can be used to implement a cut-off probability, below which, data samples will not count toward Net Pay calculations, allowing the User to bring the required level of confidence to this measure.

Example

We test the above ideas with a Gulf of Mexico data set. The key horizon is the top of the Green sand which is shown in Figure 1. Below the Green horizon, we recognize both upper and lower Green sandstones. Sharp discontinuities are the results of faulting. Geologically, there is a set of two vertically-stacked deltaic systems of middle Pliocene age. They average about 400 ft. in thickness and are separated by about 500 ft. Within the play area are delta slope deformation, slump-induced turbidites, thin mouth-bed deposits but without the presence of any delta plain facies. The principle facies are Shale, Gassy Silt, Wet Sand and oily Pay sand. The challenge is to differentiate between these types.

The available seismic consisted of five partial-angle stacks with the maximum angle in the farthest stack being 50 degrees This was not judged to be sufficient to resolve density with any degree of certainty. A single set of wavelets, one for each partial stack, was obtained by matching elastic synthetics to the seismic at each of the seven available wells. The log sets included full-wave sonic logs over the reservoir interval, facilitating the creation of the AVO wavelets. A simultaneous AVO inversion algorithm (Pendrel et al., 2000) was used to complete the inversions. Low frequency information was supplied in the form of structurally-compliant, facies-based constant trends interactively defined at horizons.

The results of the relative (no low frequencies) simultaneous inversion are shown in Figure 2 along an arbitrary line passing through all the wells. Band-pass-filtered logs are overlaid. The matches are not perfect since the inversion has no prior knowledge of the high frequency component of the logs. The region of interest is the Green sand (between the orange arrows) where there is the possibility of hydrocarbon deposits. The P Impedance agreement with the wells is good and the Vp/Vs fair.

The three log curves were used to define the facies described above were water saturation (Sw), shale volume (Vsh) and density porosity minus neutron porosity (ΦND). These petrophysical facies were created using the procedure described above. Figure 3 shows these same facies in P Impedance – Vp/Vs elastic space. In this figure, elastic PDFs have been defined. A rock physics template has been overlain and the ePDFs further adjusted to honour it.

Using the Bayesian procedure, facies were determined away from the wells and throughout the seismic volume. The inputs were P Impedance and Vp/Vs from the simultaneous AVO inversion. The petrophysical facies have been overlaid for comparison at the well locations. The agreement is generally quite good, especially for the prospective facies. Where the agreement is poor, further QC and analysis should be undertaken. We are aware, for example, that pressure differences across fault blocks account for some of these effects in our data.

Probablistic Net Pay maps were created for the upper sand. The cut-off used was 0.90 and the data samples were further weighted by probability. The result for the simple approach using a laterally-constant, structurally-compliant low frequency model for the inversion and uniform Bayesian priors is shown in Figure 4 (left). On the right, a low frequency model created from per-facies trends and most-probable facies from the simple case along with facies-driven volume priors were used. The sand is much better defined on the right.

Conclusions

We have demonstrated that a Bayesian procedure can be used to both determine petrophysical facies in wire line log data and then image reservoir facies from elastic inversion outcomes. Optimum results can be achieved when 3D Bayesian priors are incorporated and uncertainty and bias measurements are made and used. The results can be used not only for facies identification but also to risk Net Pay estimations and compute 3D elastic models without the need for any well log interpolation.

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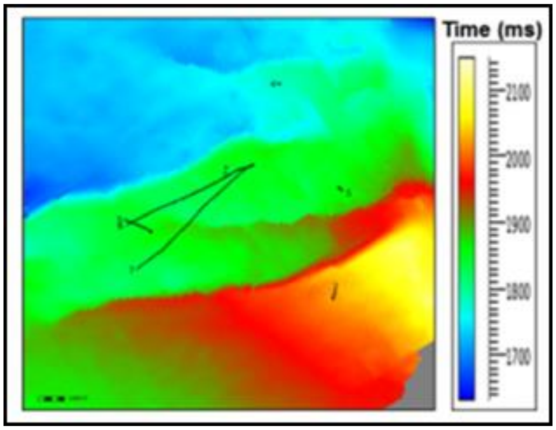


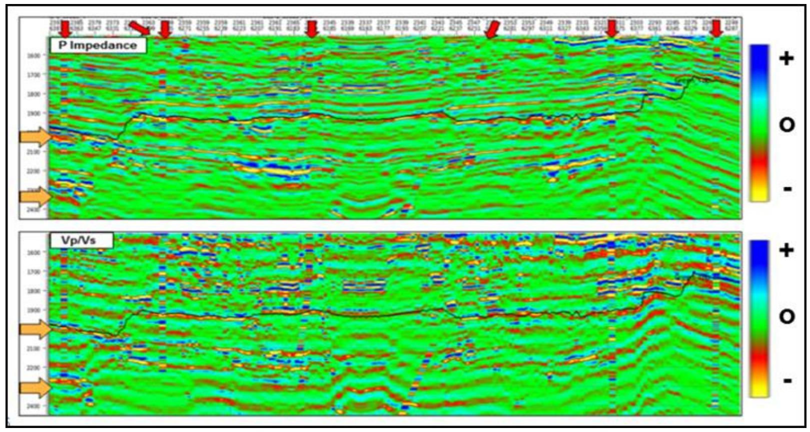
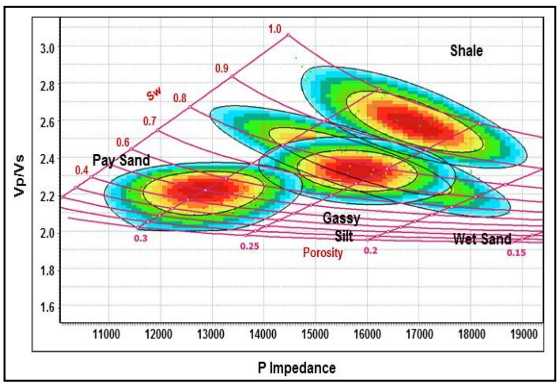


Figure 1: Project map showing the green horizon and the well locations

Figure 2: P Impedance and Vp/Vs from a relative inversion (no low freq.) Band-pass-filtered logs are overlain at the well locations (red arrows). The inversion algorithm was blind to the wells in the seismic band.



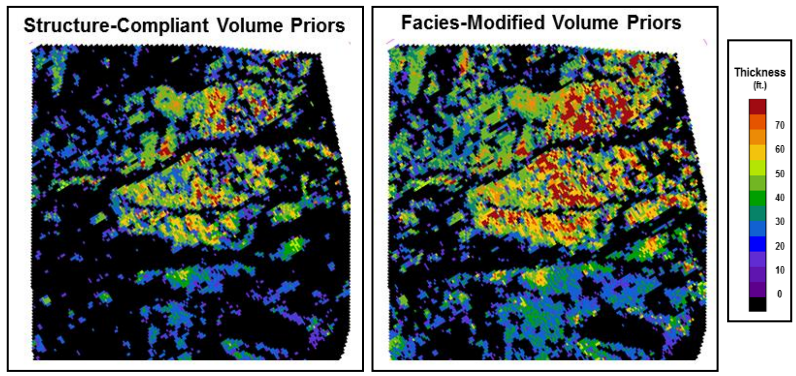


Figure 3: Facies log data points have been plotted in elastic property space and elastic PDFs designed. The rock physics template is used as a design guide.

Figure 4: The figures show probablistic Net Pay (cut-off 0.90, weighted by probability) for the upper Green sand. The left figure used laterally constant, structurally-compliant Bayesian priors and elastic models while the left followed the updated elastic model from per-facies trends and volume priors workflow.

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