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Facies-Based Modelling of Reservoir Properties from Seismic Partial-Angle Stacks

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Summary

We show how reservoir property estimates can be made from partial-angle stacks using Bayesian inference and the concept of *facies mapping*. Facies are defined to cover the input data property space and are parameterized by probability density functions (PDFs). Since this construction includes the well locations, a mapping of the seismic to the well logs will be in place. This then facilitates the modelling of a wide variety of properties as long as their corresponding well curves exist. Uncertainty measures are included. Starting directly from the seismic, the new method facilitates the quick estimation of reservoir properties and at the same time, can create prior inputs to more rigorous seismic inversions.

Introduction

Bayesian inference combines prior information and newly available evidence to make probabilistic assessments of hypotheses. Prior information can be in the form of well curves, geologic models or previous geophysical measurements. Traditionally, the goal is facies estimation and the new evidence is from the outcomes of seismic inversions (Pendrel et al., 2006). Facies estimation is implemented by the construction of per-facies, per-layer probability density functions (PDFs) in multi-dimensional cross-plot space. Integrating over the probability density functions centered at the inversion values with a range governed by the inversion uncertainties results in estimates of the probabilities of occurrence of each of the possible facies at each sample in the 3D project (Pendrel et al., 2016).

Previously, we demonstrated how this method could be used to create superior 3D low frequency models for inversions (Pendrel et al., 2022, Pendrel and Schouten, 2020). Here, we show how a similar approach can be applied when seismic partial-angle or offset stacks are the inputs. The facies that are designed, model the input seismic and serve the purpose of making a connection between the input seismic and the well logs at the well locations. With this mapping in hand, the estimation of a wide variety of reservoir properties across the project becomes possible.

Method

We complete the estimation of reservoir properties in two stages – Facies Mapping and Property Modelling. Both stages incorporate the ideas of Bayesian inference.

Facies Mapping: So-called *mapping facies* are designed from the input seismic which connect to the well property curves. Seismic traces are considered across the project to ensure complete coverage of the input data space. Optional conditioning of the seismic can be done such as alignment, zero-phasing, quadrature rotation, signal-to-noise enhancement and wavelet removal. Although the method is somewhat robust with respect to phase, zero phasing followed by a 90 deg. rotation to align peaks and troughs with their corresponding geologic layers is recommended. The mapping facies are not specifically geophysical but are each mathematical representations of specific areas in the input parameter space. We design PDFs for these facies on a per-geologic layer basis (Pendrel et al., 2017). It is important that a sufficient number of mapping facies be defined to adequately cover the input data range. Most-probable facies and probabilities for all the facies are computed across the project using Bayesian inference. The most-probable facies at the well locations are also recorded as facies log curves.

Property Modelling: The mapping facies and their associated probabilities across the project can now be used to estimate various reservoir properties corresponding to curves in the well logs. With the mapping facies part of the well logs sets, their relationship to properties represented by various log curves can be explored. Facies PDFs designed specifically for these reservoir properties need to be created at modelling time. The design is automatic but can be edited to taste. Then, the property to be modelled becomes the weighted average of the facies PDF means, the weights being the probabilities. A more rigorous strategy is to use per-facies trends instead of PDF means, allowing more intra-layer variability. The trends (or PDF means) can be adjusted on a per-layer and per-facies basis to create different scenarios and test the robustness of the models. Finally, calibration of the models against the logs can be done by making small *ad hoc* corrections to the trends, again, per-facies, per-layer and per-property.

The PDF standard deviations provide inputs to an estimate of the net uncertainty in the models. A set of simulated results is obtained by sequentially adding and subtracting standard deviations to each of the N facies trend values. This generates a total of 3^N different models. Then, the standard deviation in this set of models is determined at each 3D project sample. Typically, the uncertainties, are not constant but variable spatially and vertically.

Results

We demonstrate the above ideas using a Gulf of Mexico data set. Geologically, this 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 and thin mouth-bed deposits. Below the key Green horizon, we recognize both upper and lower gas-charged sandstones. Over-pressuring is observed in certain areas.

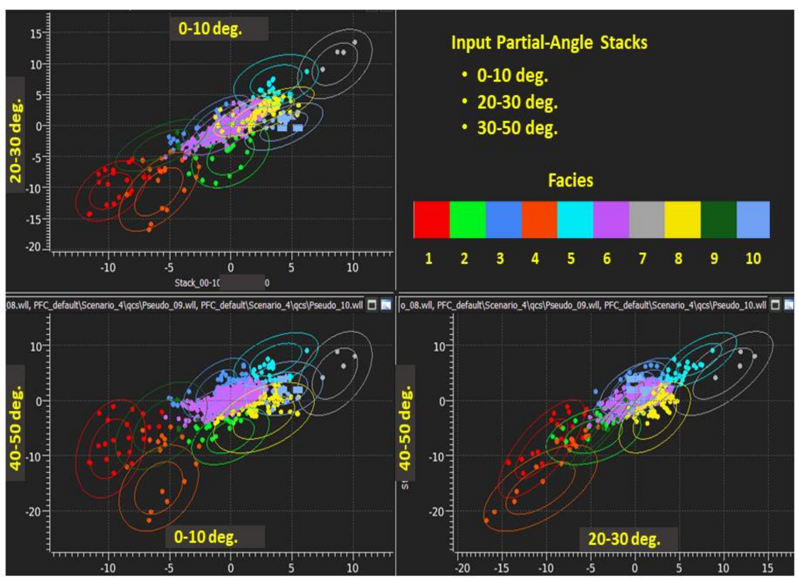

Figure 1: The figure shows the mapping facies design for the upper Green layer from the three partial-angle stacks. PDFs have been constructed corresponding to the 10 facies. The first two standard deviations are shown.

The input data consisted of three partial-angle stacks: 0-10 deg., 20-30 deg. and 40-50 deg. Partial-stack alignment was done. The data were confirmed to be near zero phase before alignment and a subsequent 90 deg. phase rotation was applied.

Facies Mapping: Figure 1 shows the PDFs in the Green layer for 10 facies designed from the seismic partial-stacks. Data away from the well locations were incorporated to verify the PDF design. The facies are simply named 1-10, their positions in the input space being not relevant. It is important, however, that they thoroughly cover the input data range.

In Figure 2 are the most-probable facies from Bayesian inference using the three partial-angle stacks and the mapping facies PDFs. Probability volumes for each facies were also computed for use in the next stage.

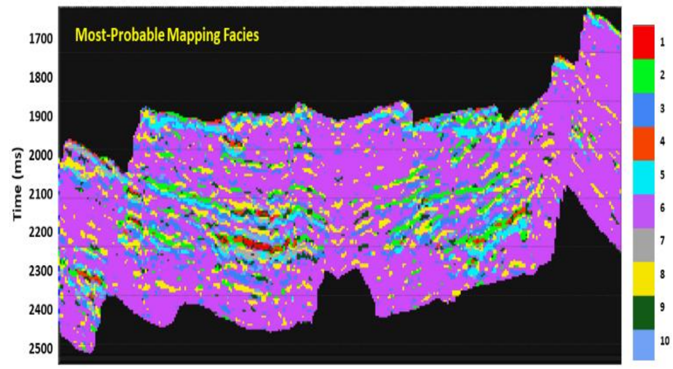

Figure 2: Most-probable facies from the Bayesian inference process described in Facies Mapping. The inputs were the three partial-angle stacks. The probabilities of all the facies were used in the property modelling.

Property Modelling: Here, we computed the final models from the facies probabilities and PDF means . In this manner, we have computed models for density, P Impedance, Vp/Vs, Vclay, water saturation, effective porosity and net-to-gross (Vernik et al., 2002). The PDF design for Vclay in the upper Green layer is shown in Figure 3. The facies are distributed along the Vclay axis, indicating that Vclay can be considered a good candidate for modelling. The mean result for Vclay with four Vclay logs overlaid is shown in Figure 4 (upper) along with the Vclay standard deviations determined by the method described above (Figure 4, lower). Agreement with the logs is qualitatively good. Correlations with the well curves in the seismic band for these wells averaged 0.79. Across all the properties modelled it was 0.77. We have not followed up on disagreements to determine if the quality of the Vclay logs might be suspect in some areas. We also expect that further conditioning of the input data, especially wavelet removal might improve the result.

There were three other wells (not shown) where the matches to the modelled Vclay were poor. Known over-pressure conditions existed at these locations and a different model was clearly required. Disagreements such as these are red flags and a re-analysis specific to these locations which represent different conditions is advisable.

Discussion

Note that other inputs to this process are possible and are being studied. These could include a wide range of attributes based on or derived from the partial stacks used here. Depth inputs and outputs are also possible. Wavelet removal could have improved the results both in terms of accuracy and resolution. The inputs do need to carry information about the properties being modelled. Should they not, then we expect that the uncertainty estimates will rise correspondingly. To this end, we are considering additional uncertainty metrics relating to sensitivity and resolution. Mapping facies which lack specificity with respect to the modelled properties typically have large standard deviations and should be omitted from the modeling.

The process is essentially self-trending, gathering trend information from the wells collectively. Otherwise, the process is effectively blind to the wells, making them available for quality control. Should no wells be available, then rock physics models could be used instead. Again, this is a matter of ongoing research.

Since the facies-modelling described here is a forward process involving mostly simple multiplications in the final property modelling stage, it is fast in execution. This makes it useful for quick reservoir properties assessments consistent with the input data.

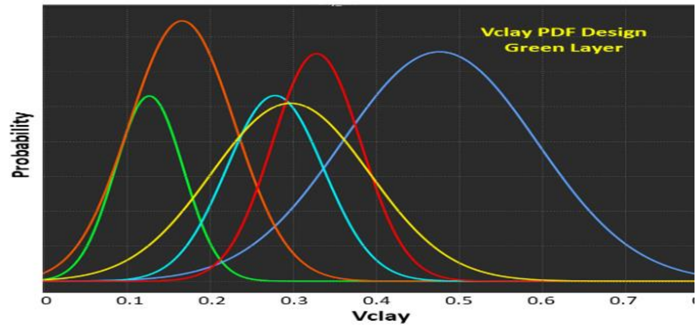

Figure 3: PDF design for Vclay estimation in the Green layer is shown. The background histograms for the log data have been omitted for clarity.

Conclusions

We have demonstrated how the notion of facies mapping can be used to create rapid estimates of disparate reservoir properties from input seismic partial-angle stacks. In our implementation, no inversions or pre-existing trend information are required. The method includes an estimation of uncertainties from property standard deviations which are observed to be facies-dependent and variable both laterally and vertically.

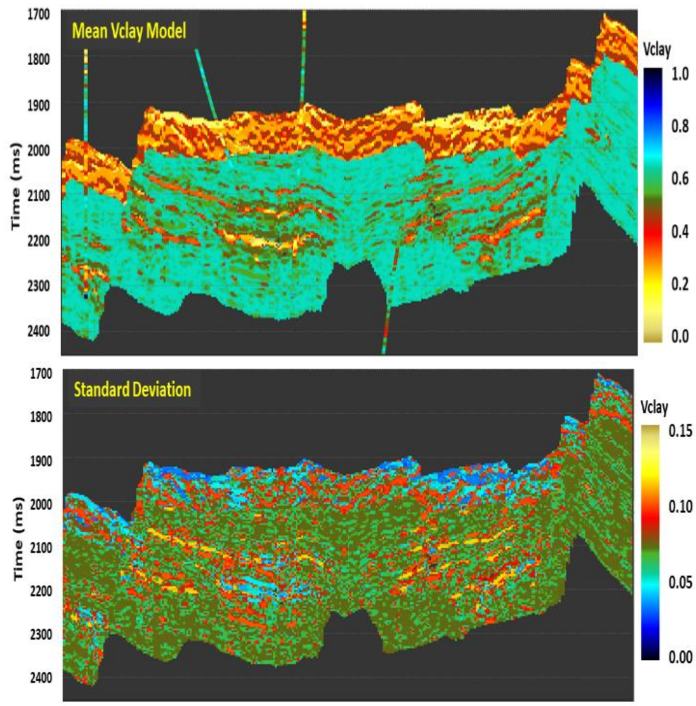

Figure 4: The upper panel shows the modelled Vclay with filtered Vclay logs overlaid. The lower panel is the standard deviation in Vclay. Note the variability in standard deviation across the figure.

Acknowledgments

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