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Direct probabilistic inversion: Improving interpretation of the Mannville sequence by injecting geology back into geophysics

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Summary

Seismic reservoir characterization seeks to improve the understanding of rock properties and reservoir conditions through seismic amplitude analysis. This information is used in all stages of production from exploration to development and monitoring. Accurate reservoir characterization leads to improved well placement and design, helps identify geohazards and is used to help monitor production effects. AVO inversion is now a commonly applied reservoir characterization technique that seeks to calculate the elastic properties of the subsurface from angle dependent seismic observations. This technique is applied across the industry to various reservoir settings around the world. Unfortunately, the connection between the elastic properties from AVO inversion and the underlying rock properties or facies is ambiguous as various lithology, porosity and fluid configurations result in similar elastic responses. Adding to this fundamental rock physics issue is the fact that seismic data is band limited and as such the effective elastic response extracted from seismic data is equally represented as either thinly interbedded facies or a single package of their average properties. Direct probabilistic inversion (DPI) formulates the inversion problem in a Bayesian framework and allows us to use valuable geologic information, previously ignored in standard deterministic AVO inversions, to help mitigate these fundamental ambiguities. In this study, DPI is applied to a 3D dataset in Southern Alberta to improve reservoir characterization of the Mannville sequence, an interval known to have interpretation challenges due to thin reservoirs, extreme elastic responses in thin organic rich shales and complex structural control in the underlying Paleo unconformity.

Direct probabilistic inversion overview

The following section provides a brief, high-level description of DPI. DPI is a single-step inversion process which inverts pre-stack seismic data directly for geologic facies. This one step process potentially allows us to overcome the ambiguities associated with interpreting standard inversion attributes. It is based on the Bayesian probabilistic framework developed by Jullum and Kolbjørnsen (2016). This flexible framework allows us to model key geologic information as first order Markov processes. We use this approximation to encode geologic rules and statistics directly into our prior model. Combining this framework with AVO modelling of our defined facies yields a likelihood model. This allows us to include information such as geologic ordering, facies thicknesses, mean and standard deviations of elastic properties for each facies, intra property correlations and any meaningful data that can be described as a probability. Not only does adding this extra information potentially resolve ambiguities in the inversion, but also provides opportunity for resolution beyond the seismic bandwidth. The outputs of DPI include interpreted surfaces and probabilistic rock properties which accurately propagate uncertainty into the solution and can be used directly in P10, P50, P90 type risk analysis.

Workflow

DPI begins by following the workflow of standard AVO inversion as the input seismic data and wavelets are the same. This allows us to leverage the relative speed and functionality of our standard AVO inversion to optimize the seismic and wavelet inputs prior to DPI testing, which is more computationally expensive and thus not well suited to extensive seismic conditioning and wavelet testing. In this process, we also get a feel for the quality of the seismic data and what limitations might exist in conventional AVO inversion workflows. The process of seismic pre-conditioning and the choice of appropriate angle-dependent wavelets are fundamental to any pre-stack inversion workflows, including DPI.

Once seismic and wavelets are chosen, we move on to the new prior framework for DPI. This framework replaces the conventional low-frequency models used in standard inversions. As the inversion problem is now posed as a Bayesian inference problem, we instead seek to characterize the likelihood function in Bayes' theorem. In the DPI workflow, the likelihood function is directly calculated by AVO modelling of very densely sampled facies solutions from the geologic framework. For this study, the geologic framework consists of stratigraphic ordering rules, thickness analysis and a statistical rock physics model.

The first step in this process is to define all the facies which exist within the target interval. In this case, the facies are separated both by petrophysical cut-offs to denote lithology and/or fluid fill, and formation. Here, we have defined five target formations, two non-target formations (overburden, Glauc, Bantry, Ellerslie, Detrital, Pekisko and underburden), and six possible lithology and fluid combinations (clean sand brine, shaley sand brine, clean sand hydrocarbon, shaley sand hydrocarbon, carbonate and shale). Most formations have only a subset of these lithologies. Parameterizing the problem in this way allows us to potentially capture depth trends and invoke simple geologic ordering rules restricting the solution space to only allow transitions from younger rocks to older rocks and not vice-versa. With these possible combinations we defined eighteen facies classes for this study. The colour coding for each of these facies is shown in Figure 1.

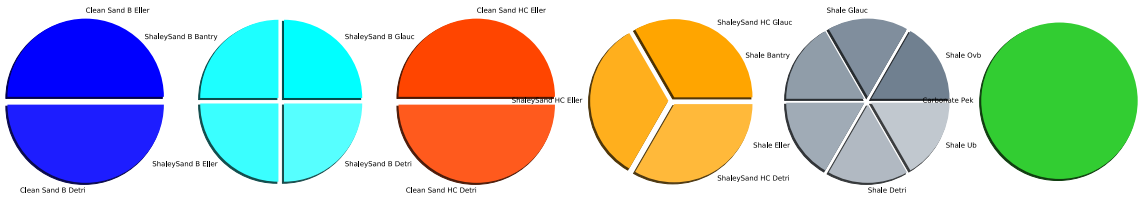

Figure 1: Facies colour legend. Brine sands in blue, hydrocarbon sands in orange, shales in grey and carbonate in green.

After facies are defined, we can begin to extract statistics and other relevant information that help differentiate the facies. In this study, thickness probabilities were calculated for the facies defined in each formation. The global facies thicknesses are plotted in Figure 2. The logarithm of the probability is plotted against the facies thickness in samples. Note that each facies can be

approximated with a straight line indicating that thicknesses are exponentially distributed in line with a first order Markov spatial model. This plot also highlights a very common pattern in clastic settings that the shales occur as thicker packages than the sands.

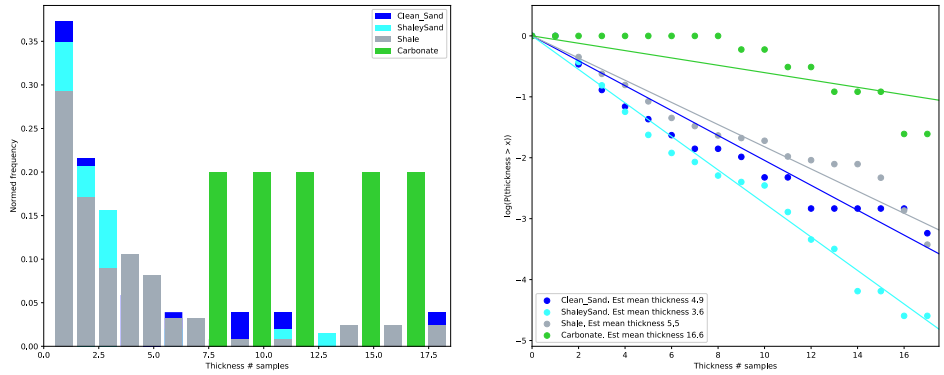

Figure 2: Nominal frequency vs. thickness (left) and logarithm of probability vs. thickness (right) for all data. Thickness is measured in number of samples.

Next, a transition matrix is created to describe the probability of transitioning from one of these eighteen facies to another. The transition matrix developed for this study is shown in Figure 3. This matrix is calculated from well log data but can be adjusted to reflect patterns or rules not observed in data such as general fining sequences, higher or lower probability for hydrocarbon fill and other known geologic trends. Note that the strongest probabilities are in the diagonal, indicating the most likely transition is to a neighbouring facies. The off-diagonal terms include many zero probabilities as the solution space is restricted to dis-allow skipping formations in our framework. The only formation where this is not true is in the Ellerslie and Detrital formations. As the Detrital does not exist everywhere, transitions from the Ellerslie directly to the Pekisko formation are permitted. In this way, facies and formations that may not be regionally extensive or may have been eroded away are allowed. Similarly, only transitions from young formations to old formations are allowed. In over-thrust settings these transitions may in fact be geologically plausible and these off-diagonal terms may not be zero. Finally, gravitational fluid ordering is directly imparted into the solution such that only transitions from lighter to heavier fluids are allowed (i.e. hydrocarbon overlies brine).

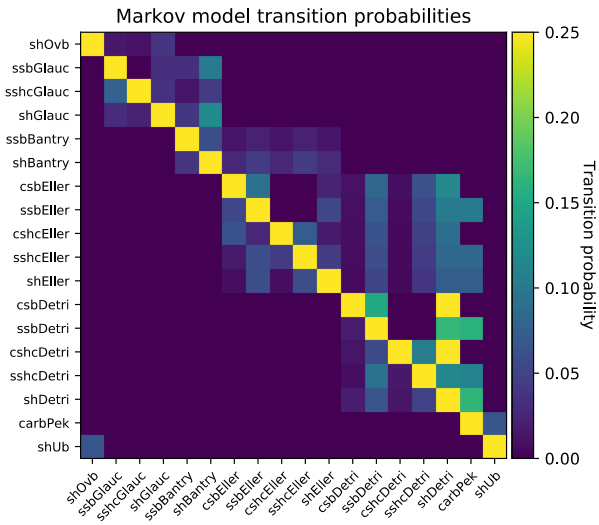

Figure 3: Facies transition matrix. Facies names are abbreviated such that sh=shale, ss=shaley sand, cs=clean sand and carb=carbonate. For fluids, b=brine and hc=hydrocarbon. Notice that most off-diagonal terms are zero as we are enforcing geologic ordering. Non-zero off-diagonal terms are used as soft constraints in our framework and are either calculated from well logs or general geologic knowledge expressed as probabilities.

As a final component of the geologic framework, a statistical rock physics model is created for each facies. These data are calculated from well log data with the low-frequency component removed such that the frequencies match the seismic data. An analysis on the log data is performed to calculate mean, standard deviations and correlations between each inversion parameter, in this case acoustic impedance (AI), Vp/Vs ratio and Density. The final statistical rock physics model is shown in Figure 4. Well data is plotted as points and the ellipse defined by the mean, standard deviation and correlations are overlain. Colour coding follows Figure 1. The general observed rock physics trends match theoretical expectations. Hydrocarbon filled sands occupy a space in low AI, low Vp/Vs, low density; cleaner, more porous sands have a stronger signature than shaley sands; shales are generally higher Vp/Vs; and carbonates are high AI. There is however a significant amount of overlap between many of these defined facies.

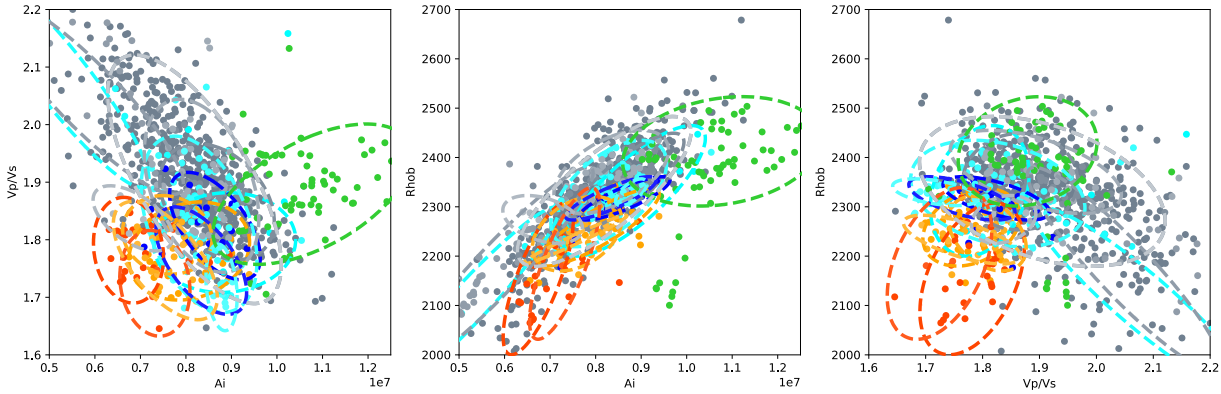

Figure 4: Statistical rock physics model. Observed well log data is plotted and is overlain by the ellipse described by the calculated mean, standard deviation and correlations of each elastic property from analysis. Colour coding is according to Figure 1. Note that the data generally follows rock physics trends, but can contain a high degree of overlap.

Results

The seismic data for this study is from a large merge of 3D land seismic surveys over Southern Alberta. The key target reservoir is that of the regionally extensive Ellerslie, with intermittent overlying channel targets in the Glauc sequence. Conventional AVO inversion and rock physics methods on this same dataset are successful at improving reservoir understanding and well placement, but resolution issues from thin overlying soft shales of the Bantry, thin reservoir in the Ellerslie, and structural uncertainty of the underlying Pekisko carbonate persist.

Several realizations from the prior framework are shown in Figure 5. Once again, the colour coding is consistent with Figure 1. On the left of the figure are the eight observed wells and their facies that were used in the prior building. In the realizations shown in this figure, the rules from the prior framework are preserved. In the upper Glauc package, the shaley sands tend to be thicker, but not as prevalent as shown in the observed facies tracks. In the reservoir zone above the Pekisko formation, all facies are generally thinner, more interbedded and more rapidly changing. Additionally, there are no direct transitions from brine sand facies to hydrocarbon facies unless separated by a shaley facies.

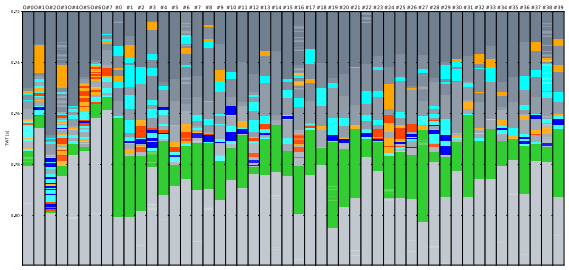

Figure 5: Facies realizations from the prior framework. Facies logs for eight observations wells are on the left along with forty realizations. The facies configurations in the realizations mimic the observed wells.

Subsequently, the statistical rock physics model is applied to these facies realizations to model the elastic response. Figure 6 shows the results of this modelled data in AI, Vp/Vs space. This forward modelled data of these randomized samples is consistent with the scatter and overall trends and character of the observed data shown in Figure 4.

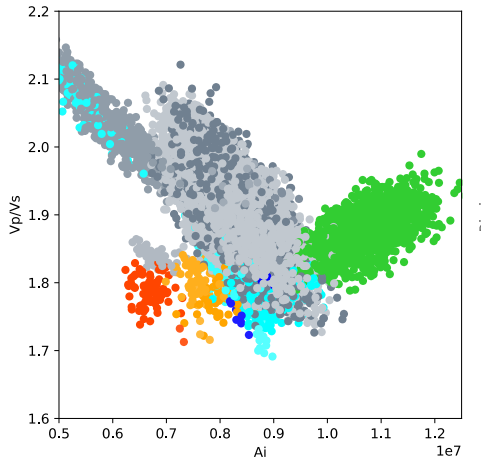

Figure 6: Forward modelling of the facies realizations from Figure 5 in AI, Vp/Vs space. The trends and shape are consistent with observed data in Figure 4.

This framework is applied to a DPI inversion using eight partial-stacks from zero to forty-five degrees. The results of this inversion at a well are shown in Figure 7. This figure compares panels including the input seismic, the prior model, the DPI posterior output, the DPI most probable facies and the actual facies log. The results from the DPI output are considerably sharper and higher resolution compared to the input seismic data. The raw seismic has a two millisecond sample rate, but results are shown to one millisecond. At this finer scale, the resulting most probable facies accurately match the observed facies log. Particularly impressive is the resolution of the thin, upper sequence where the we have correctly predicted the very thin hydrocarbon saturated shaley sand to shale to brine saturated shaley sand. Compared to the frequency content of the input seismic, this is a significant uplift in resolution. Additionally, the carbonate unconformity, which is a key structural control and is difficult to pick exactly, is very well defined. However, the very thin hydrocarbon sands just above the unconformity are still not able to be distinguished from the general interbedded package. It is likely that the very strong response of the carbonate makes detecting these thin facies very difficult.

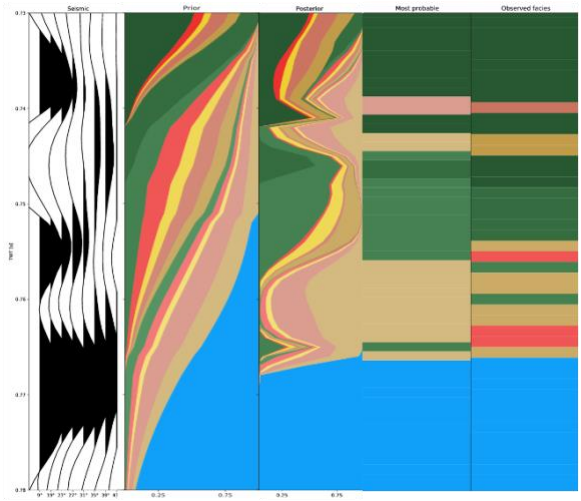

Figure 7: DPI result at well location. Input seismic is shown in the left panel followed by the prior model. The central panel is the posterior output from the inversion, the fourth panel is the most probable facies and the final panel is the true well facies. Hydrocarbon facies are in orange, brine saturated facies are in beige and carbonate is in blue.

Conclusions

DPI is a Bayesian inversion framework that formulates the seismic inversion problem in such a way that previously ignored geologic information is used directly to produce more accurate and reliable inversion results. By creating a prior framework that includes stratigraphic ordering rules, thickness information and statistical rock physics we are able to approximate the seismic likelihood. Applied to a Bayesian inversion in DPI, we use this framework to calculate the marginal posterior. The results accurately propagate uncertainty while achieving resolution beyond the seismic bandwidth. The resulting interpreted surfaces and probabilistic rock properties provide a robust reservoir characterization and can be used directly in P10, P50, P90 type risk analysis. In the oral presentation for this study, the DPI results will be compared directly to rock physics inversion results obtain through a standard two-step deterministic inversion.

Acknowledgements

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