Ensuring Geologic Ordering in Bayesian Facies Estimations

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Summary

There are no geologic ordering constraints in Bayesian facies estimation apart from the provision of 3D priors. The resulting facies are determined independently at each time (or depth) sample from one or more outcomes of inversions or their derivatives. Errors in geologic ordering can easily occur, especially when the seismic is significantly band-limited. We use an iterative learning scheme to determine the most-reliable facies and add them to the knowledge reservoir. At each iteration, we update the Bayesian priors for other facies in the set using a conditional probability based on certain pre-determined geologic layering rules. Then the Bayesian probabilities are re-computed and the most-probable facies updated. The process iterates with ever-decreasing demands on what constitutes learned information. In this way the most-reliable facies estimates impose geologic constraints on those less-reliable estimates. We demonstrate the method on both a synthetic data set and field data from Blackfoot.

Introduction

The application of Bayes' rule maps prior probabilities to posterior probabilities, given some new information. In the context of reservoir characterization, the new information comes from the results of a seismic inversion or its derivatives. Per-facies elastic probability density functions (PDFs) are constructed from elastic log and rock physics model cross-plots, over which the inversion results are superimposed. The PDFs are the basis for the Bayesian analysis. The results are volumes of the probabilities of occurrences of each of the facies at all points in 3D space (Pendrel et al., 2006). The procedure can be augmented by the measurement and inclusion of inversion uncertainties and bias corrections along with the additional constraints of 3D priors, themselves with associated uncertainties. (Pendrel and Schouten, 2020).

One missing element is the influence of geologic layering rules. They can be included in the 3D prior information but only in a probabilistic sense on a layer-by-layer basis. There is no ready way to enforce geologic rules on particular adjacent layers. This can be a problem, for example, when limitations on the upper bound of the seismic band create transition zones in elastic properties between geologic layers marked by otherwise sharp boundaries. The consequence is that the Bayesian process will dutifully report a transition facies. Of course, the transition facies might be real. All too often it is not, creating the familiar water-over-oil scenarios which are obviously not real. It is this problem which we seek to address here.

Method

We use the strategy described by Pendrel (1981) to automatically interpret events in seismic gathers for use in tomography experiments. The method was simply to draw initial conclusions from attributes of the strongest most-obvious events, add them to the reservoir of knowledge and then use them to make further assertions about less well-defined reflections. Nowadays, in the machine learning lexicon, we would say that the system learns and self-trains itself on the clearest information and uses it to expand its learning on the remaining data. This procedure was again used successfully to determine first breaks in Vibroseis data (Pendrel and Hislop, 1989).

In our present context, we judge the reliability of Bayesian facies from their probabilities of occurrence. Those facies associated with probabilities above a certain high threshold are assumed to be valid. Then geologic rules are defined in terms of conditional probabilities. For a particular key facies, the probabilities of other facies lying above or below it are set, depending upon our understanding of the prevailing geology. These probabilities should be uncorrelated with the 3D prior probabilities used in the first pass of Bayesian inversion. Therefore, they are invoked by multiplying them against the existing priors. Once all the high-probability facies instances have been addressed in this way, the Bayesian inference is updated. We refer to this method as one of *Dynamic Priors*. It is an iterative technique as we follow successive iterations with ever-decreasing thresholds.

Example

We first test the above ideas with a synthetic data set. We assume an inversion result for P Impedance and Vp/Vs but generate those results randomly across a project volume with a sample interval of 2 ms. To give the data a seismic look and feel, we laterally smoothed these data and then high-cut-filtered them at 80 Hz. A facies set with Shale, Limestone, Sand, Gas and Oil members was defined according to the template in Figure 1. Then Bayesian inference was used to generate a facies volume (Figure 2). The geologic rule was simply that Oil should overlay Sand and Gas should overlay Oil. Figure 2 shows many violations of that rule as would be expected from randomly generated data. We can measure the number of those occurrences and they are shown as a map which sums them along each trace (Figure 3a).

We begin to apply the Dynamic Prior method with an initial probability threshold of 0.9. In this experiment the conditional probability on sand and oil above gas was the three-term sequence, 0.0, 0.25, 0.50. It is applied to the prior probabilities in the three samples above known (greater than threshold) gas. There are of course, other possibilities, including deriving geologic rules from observations over larger volumes of real data. The effects of this iteration are shown in Figure 3b where the number of violations has been significantly reduced. Further iterations with thresholds of 0.8 and 0.7 are shown in Figure 3c and 3d, respectively. One final pass to remove isolated interior facies members reduced the total number of violations to zero (not shown). The final facies analysis is shown in Figure 4 where there are no violations of the geologic rules.

Figure 5 shows the results of applying the procedure on facies derived from an inversion of the Blackfoot data. In the left panel there is sand over gas due to missing high frequencies and the subsequent creation of a transition zone between gas and shale. The imposition of geologic rules has fixed this issue in the right panel.

Conclusions

We have introduced the Dynamic Prior method of applying geologic rules to Bayesian facies estimation procedures. The strategy involves a self-learning procedure where high probability facies occurrences are identified and geologic rules are applied to adjacent facies by the modification of their 3D priors. The procedure is iterative, working first on highly-probable and subsequently on less-probable data with the system learning as it progresses. The method was successful in resolving violations of the geologic rules in randomly-generated elastic data. We also successfully applied the method to facies from a field inversion of the Blackfoot data.

Acknowledgments

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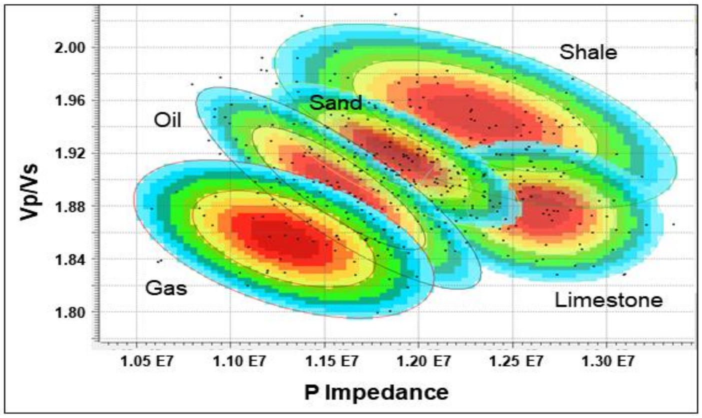

Figure 1: Facies template for Bayesian inference. The members of the facies set were Shale, Limestone, Sand, Oil and Gas. The data points were generated from pseudo wells derived from the randomly-generated elastic properties, P Impedance and Vp/Vs.

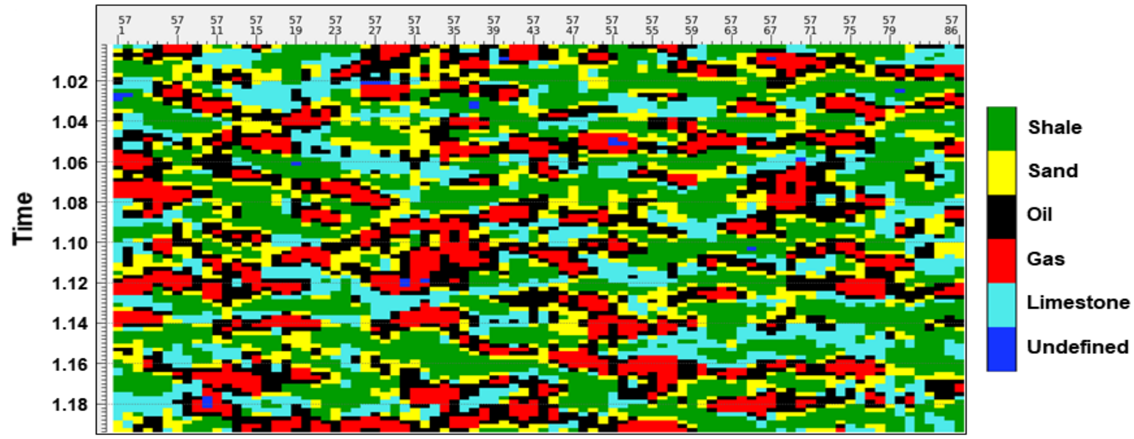

Figure 2: Line from the synthetic volume showing the results of the initial facies analysis of the random data. There are many violations of the geologic rules where facies appear with Gas overlying Oil or Oil overlying Sand.

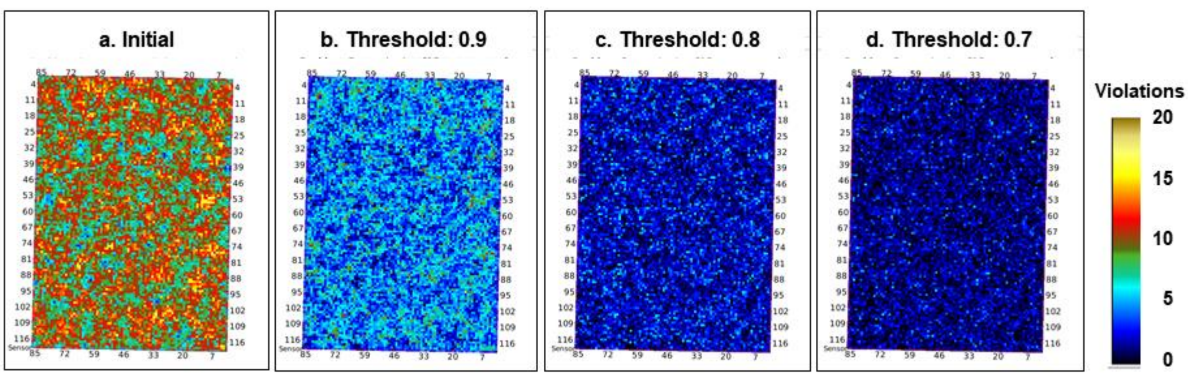

Figure 3: Maps of the cumulative number of per-trace geologic rule violations are shown for successive iterations. Figure 3a shows the initial state before application of the Dynamic Prior method. Figures 3b, 3c, and 3d are for successive iterations with probability thresholds of 0.9, 0.8 and 0.7, respectively. The number of violations is reduced in successive iterations. A final iteration to remove single isolated violators reduced that number to zero.

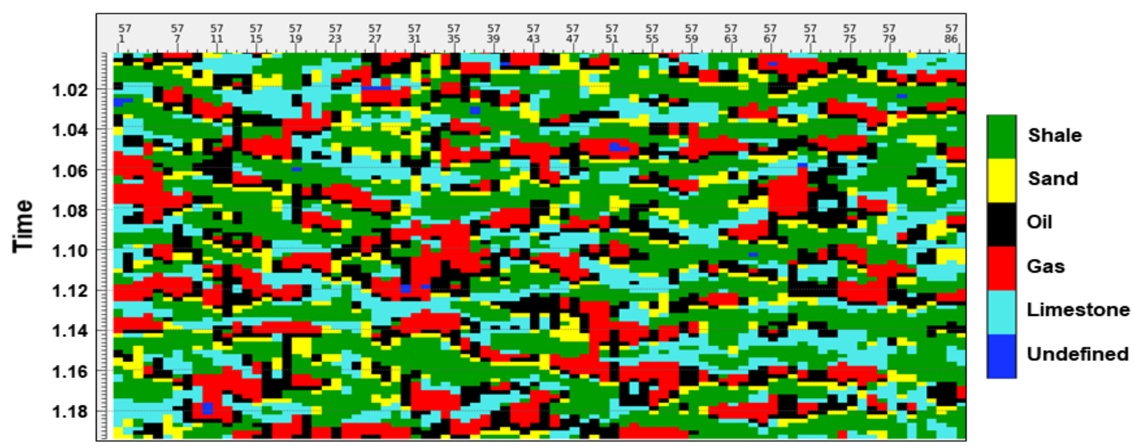

Figure 4: Final facies analysis with no rule violations.

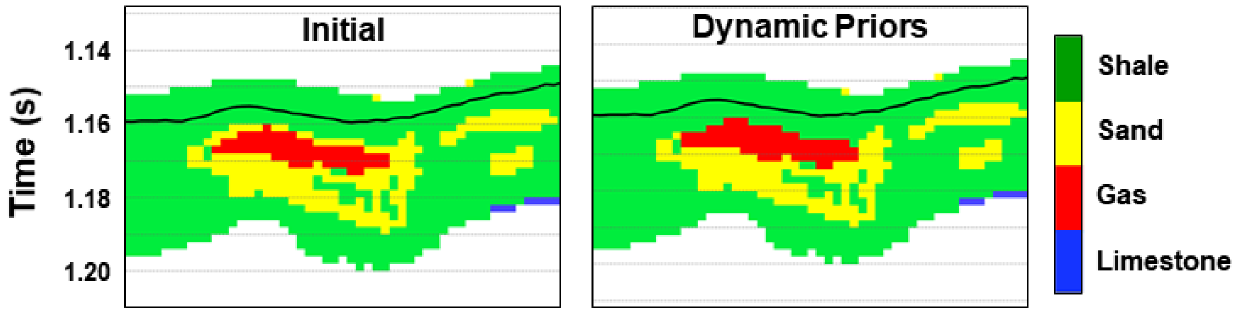

Figure 5: On the left, facies derived from a Blackfoot inversion show sand over gas in the Glauconitic due to missing high frequencies resulting in a transition phase between gas and shale. In the left figure, the application of Dynamic Priors has fixed the problem.