Facies probabilities from multidimensional crossplots of seismic attributes

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Summary

We propose a simple method to estimate facies probabilities based on statistical analysis of multidimensional crossplots of seismic attributes. After careful petrophysics and rock physics diagnostics, log scale facies flags related to thick sand bodies are created. These flags are then used to color crossplots of seismic scale attributes derived from AVO inversion of PP data (Vp, Vs, and density) and inversion of post stack fast and slow PS components of a 3C-3D survey. We show that by jointly using these five seismic attributes and facies flags (like a colored five dimensional crossplot), we can estimate the probability of thick sand bodies much better than when we crossplot two attributes at a time. Unlike commonly used approaches to map facies or lithologies from seismic data based on selecting regions in seismic attribute crossplots, our approach accounts properly for overlap among different facies and quantifies the probability of their occurrence.

Introduction

Crossplots are commonly used in the geosciences to gain qualitative insight about relations between different variables, typically three (for two dimensional colored crossplots). In rare occasions, the relations among four variables are explored by using three dimensional colored crossplots. The variable used to color the crossplot is usually related to the property of interest, sand or pay for instance. In these cases, crossplots can be used in a quantitative sense by selecting (drawing) a region in the crossplot where most of the property of interest "lives". This approach is the extension to 2D of cutoff based approaches commonly applied to separate scenarios in 1D time series. One drawback of this approach is that it works best only when there is no overlap between the region occupied by the property of interest and the region occupied by the background. Another drawback is that it is difficult to extend to three dimensional crossplots and impossible to apply for dimensions higher than three.

In this paper, we propose a simple method to overcome these difficulties for extracting quantitative information from crossplots and estimate facies probabilities based on joint statistical analysis of multiple seismic attributes and log scale facies flags. Other methods to estimate facies probabilities have been proposed before. Gallop (2006) and Ng et al. (2008) describe different continuous approaches using well data to estimate conditional probability density functions and then apply Bayes' formula to refine prior facies probability volumes. Both approaches are more computationally intensive than ours and require various normality assumptions (in particular, Gaussian distribution of data noise). Stright et al. (2009) gives a thorough discussion of support issues and uses a crossplotting approach similar to the one presented here but with a different way of handling scaling.

Since crossplots of seismic derived attributes are the heart of our method to estimate probabilities, we will start by revisiting the use of crossplots for facies/lithology qualitative classification. Then, we summarize the method to extract facies probabilities from multidimensional crossplots of seismic attributes colored by facies flags. Finally, we apply this method to help the characterization of a typical tight gas reservoir, the Mesaverde Group at Mamm Creek field, located in the Piceance Basin, State of Colorado, in the United States.

Crossplotting revisited

Typical colored crossplots range from perfect-separation to complete–overlap of the target scenario with respect to the background. Intermediate cases include scenarios that range from clustered-response with some-overlap to clustered-response with complete-overlap. Figure 1 shows an example of the later scenario which occurs very often in practical situations. For this reason, we will examine it in more detail. Let's assume that the target (red dots) in Figure 1 corresponds to gas saturated sandstones embedded in a wet background (blue dots). Even in this case where there is a complete overlap of red and blue dots, the likelihood of finding red dots is larger for the attribute values where the target cluster "lives" (right side of the crossplot).

The method we use in this paper tries to account for clustering of the response of the desired property in multidimensional crossplots of seismic attributes, going beyond drawing polygons or using cut-offs to separate regions of interest. It quantifies the statistical differences in the responses of the different scenarios. Next section shows how to do this in detail starting from basic probability definitions.

Probabilities from crossplots

We use conditional probabilities and the correspondence of the different log scale scenarios with seismic scale attributes sampled at well locations to estimate the likelihood of the target scenario away from wells. Similar results can be obtained using Bayes' formula to estimate the probability if a prior estimate of probability is known.

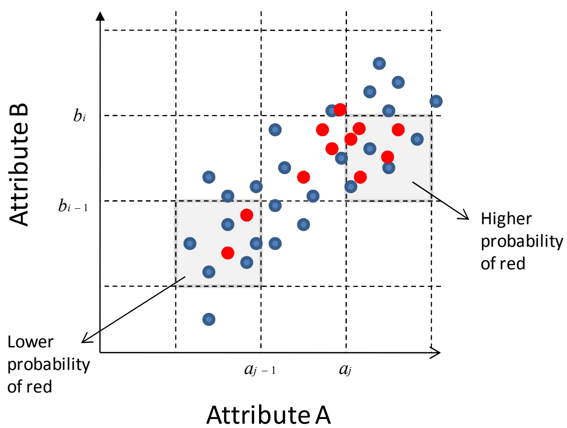

Figure 1. Probability estimations from crossplots. A rectangular grid is superimposed on the crossplot and individual probabilities of the different scenarios (red and blue dots) are calculated for each rectangle. These probabilities are then assigned throughout the whole seismic volume.

A conditional probability estimates the likelihood of an event of interest given that a conditioning event is known to occur:

$$P(S) \approx P(S \mid A) = \frac{P(S \cap A)}{P(A)}.$$

Here, ***P(S)*** is the probability of observing the target scenario *S* (e.g. facies flag related to thick sand bodies), and *A* is a conditioning event providing extra information (in our case, inverted seismic attributes).

Conditional probabilities are well suited to this application because they do not require that any particular form of relationship, or even any relationship at all, exists between scenarios (facies) and conditioning events (seismic attributes). Additionally, no assumptions are made about probability distributions or independence.

We define conditioning events by superimposing an $M \times N$ grid on the 2D attribute crossplot; each rectangle in the grid defines a conditioning event $A_{ij}, 1 \le i \le M, 1 \le j \le N$ (see Figure 1). These events should tend to capture any relation between facies and seismic attributes. Moreover, the conditional probabilities using these conditioning events can be estimated simply by counting the number of samples in the rectangle that belong to the target scenario and dividing by the total number of samples in that rectangle:

$$\frac{P(S \cap A_{ij})}{P(A_{ij})} \approx \frac{N_L(S \cap A_{ij})/N_L}{N_L(A_{ij})/N_L} = \frac{N_L(S \cap A_{ij})}{N_L(A_{ij})}.$$

Here $\boldsymbol{N_L}$ is the count over samples. This approach easily generalizes to cases where more than two attributes are believed to be related to the target scenario. Examples using two, three, and five attributes at a time are shown in this paper.

Selection of *M* and *N* for defining conditioning events involves a tradeoff and should be done on a case-by-case basis: Large *M* and *N* (small rectangles) will tend to group very closely related samples and give stronger separation, but too-small $\boldsymbol{N_L}$ values could mean sensitivity to noise and other errors. On the other hand, small *M* and *N* (large rectangles) will group more loosely related samples and give weaker separation, but larger $\boldsymbol{N_L}$ values mean more stable estimates.

Next section shows an example of the application of this method.

Field data example: Mamm Creek field

Mamm Creek field is located in the Piceance Basin, northwestern Colorado, in the United States. Most of the gas production in Mamm Creek comes from fluvial tight sands (~5000 ft deep) in the Williams Fork formation, but marine sands in the Corcoran, Cozzette and Rollins members (~7000 ft deep) of the Iles Formation and the middle and upper sands of the Williams Fork Formation also contribute (Scheevel and Cumella, 2009). Mapping the distribution of sands is critical for early effective development of the field but, unfortunately, seismic data have not been used extensively for this purpose because elastic properties of sands and shales show large overlap in rock physics diagnostics. The method presented in this paper was applied to both fluvial and marine intervals but results presented here focus on the marine section only.

The data set used for this study consisted of log data from 102 wells, 3D pre-stack compressional seismic data and two PS (fast and slow) stacked volumes from a 3D converted-wave multicomponent data set. The size of the study area was 2.5 square miles. Gamma Ray, Neutron and density logs are available in most wells. Sonic data was available at three wells only; one well had a dipole sonic and another well had an oriented cross-dipole sonic.

A summary of our workflow follows:

1) Petrophysical analysis and generation of facies flags based on lithology and thickness. Only sand intervals with more than 6% effective porosity and thickness greater than 10-15 feet were kept for seismic calibration. This approach acknowledges the difficulty of seismic data to detect thin sand bodies of less than 10 ft. and therefore, no attempt is made to map them.
2) Log scale analysis of relations between petrophysical properties of target facies and seismic attributes derived from AVO inversion and inversion of PS stacked data. Vp, Vs, density, and shear impedances derived from PS data were the key attributes in this analysis.

3) Three-term AVO inversion of PP pre-stack gathers and post stack inversion of 3D PS stacked data. The results of this step are volumes of Vp, Vs, density, pseudo S-impedance fast (pSIf) and pseudo S-impedance slow (pSIs). Pseudo S-impedances from PS data were estimated using the algorithm described in Guliyev and Michelena (2009).
4) Velocity model building and time to depth conversion of seismic derived information honoring depths of five formation tops picked along 102 wells.
5) Crossplots of seismic derived attributes colored by log scale facies within intervals of similar geologic characteristics. Figure 2 shows examples of these crossplots for the marine section of Mamm Creek field. Inverted seismic attributes along 30 well trajectories were extracted from 3D attribute volumes in depth. Red sand flags in Figure 2 fall in the same crossplots areas predicted by log scale analysis. Different criteria were used to create thickness related sandy facies flags. We selected the one that produced more clustered seismic response in 2D crossplots.

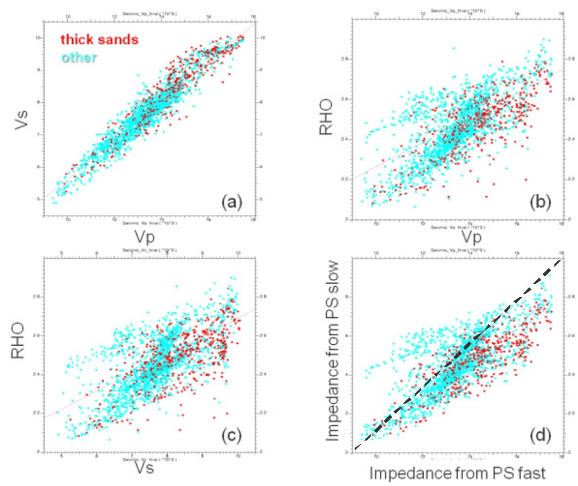

Figure 2. Crossplots of seismic scale inverted attributes at 30 well locations and colorcoded by facies flags at log scale. The overall position in the crossplot of thick sands (red) with respect to the background (cyan) is as expected from rock physics diagnostics at well scale. Departures from the 45 degree line in crossplot (d) of impedances from PS fast vs PS slow data indicate anisotropy. As expected in this field, thick sand facies tend to be more anisotropic.

6) Estimation of probabilities of thick sand bodies using different combinations of inverted seismic attributes. Among the attribute combinations (crossplots) tested, the most relevant were Vp-Vs, Vp-RHO, Vs-RHO, Vp-Vs-RHO, and Vp-Vs-RHO-pSIf-pSIs. Figure 3 shows the results of probabilities estimated from different attribute combinations at a selected well location. The poorest predictions are obtained by using Vp-Vs alone (Figure 3d). Predictions are considerably improved by including density in the analyses (Figures 3e and 3f). The best predictions when using P-wave data attributes only are obtained by combining Vp, Vs, and RHO (Figure 3g). Finally, when P-wave and multicomponent derived attributes are used simultaneously (Figure 3h), we obtain the best predictions: estimated probabilities resemble very closely average facies flags from well data (Figure 3c). As shown in Figure 2d, PS attributes are sensitive to sand anisotropy and for this reason including these attributes in the analysis helps to improve the detection of thick sand facies.

Notice that even though none of the crossplots in Figure 2 shows separation between thick sands and background facies, the joint probabilistic analysis of all attribute responses still yields good estimates of probabilities of thick sand facies.

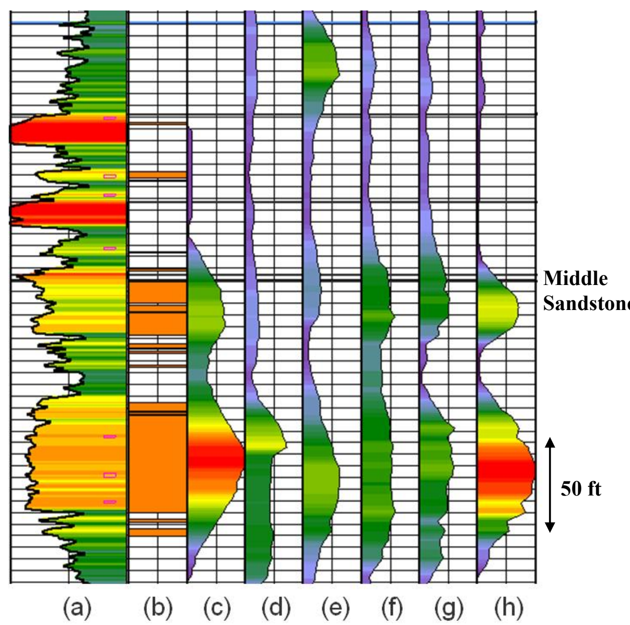

Figure 3. Log data vs. probability estimates from seismic data using different combinations of attributes at well 21B-28. (a) Gamma Ray; (b) Sand flag; (c) Moving average of sand flag; (d) to (h) Probabilities from seismic attributes. (d) Vp-Vs; (e) Vp-RHO; (f) Vs-RHO; (g) Vp-Vs-RHO; (h) Vp-V,-RHO-pSIf-pSIs.

Results shown in Figures 2 and 3 were obtained after training (or coloring the crossplots) the seismic data with log scale flags at 30 well locations that sample the study area evenly. Probabilities were also computed by training the seismic data extracted along all 102 wells with facies flags generated at the same wells. The purpose of this test was to understand how much predictions could be improved by introducing all well data available. Figure 4 shows a cross section of the 5-seismic-attributes derived probabilities along the 102 wells. A cross section of facies flags used to color the five dimensional crossplot is shown in Figure 5 over posted on the seismic derived probabilities. Notice how facies distribution expected from log data agrees well with estimated probabilities.

Conclusions

Facies probabilities can be easily estimated from multidimensional crossplots of seismic attributes using basic probability definitions. The method yields useful results even when there is complete overlap of seismic attributes of target and background facies.

Application of this method at Mamm Creek field shows that even when no single attribute or pairs of attributes yields good separation of sandy and background facies, probability estimates obtained by combining more than two attributes compare favorably with facies information at well locations. When using PP data only, good results are obtained by using simultaneously Vp, Vs and density derived from 3-term AVO inversion. However, the best results are obtained when using jointly these three attributes from PP data with pseudo S-impedances fast and slow derived from inversion of PS data. Sensitivity of PS amplitudes to azimuthal anisotropy helps to improve sand identification where sands are more anisotropic than the background.

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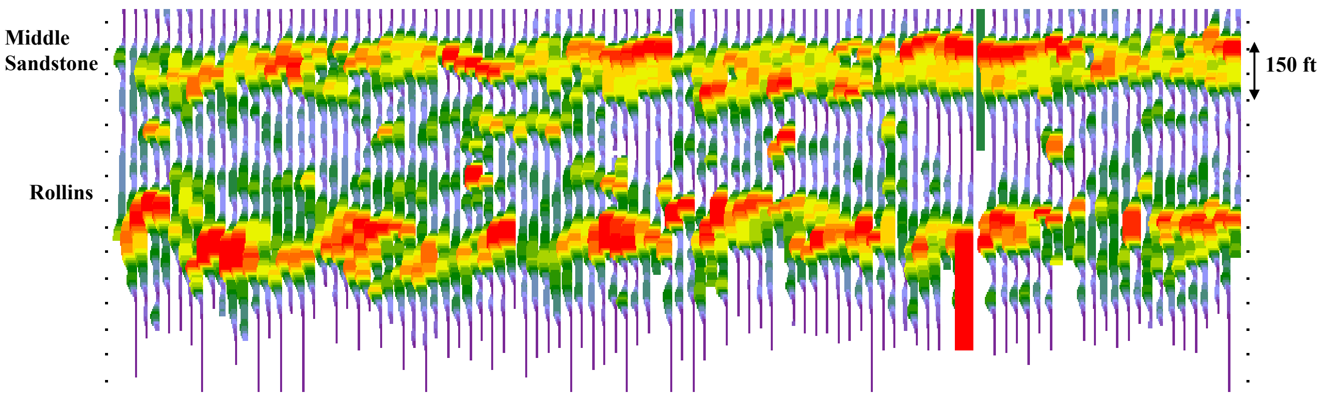

Figure 4. Thick sand probability from seismic data extracted along a cross section of 102 wells from a 3D probability cube for the marine interval of Mamm Creek field. These probabilities were estimated by using five inverted seismic attributes and thick sand flags shown in Figure 5. (Red: high probability; green: lower probability).

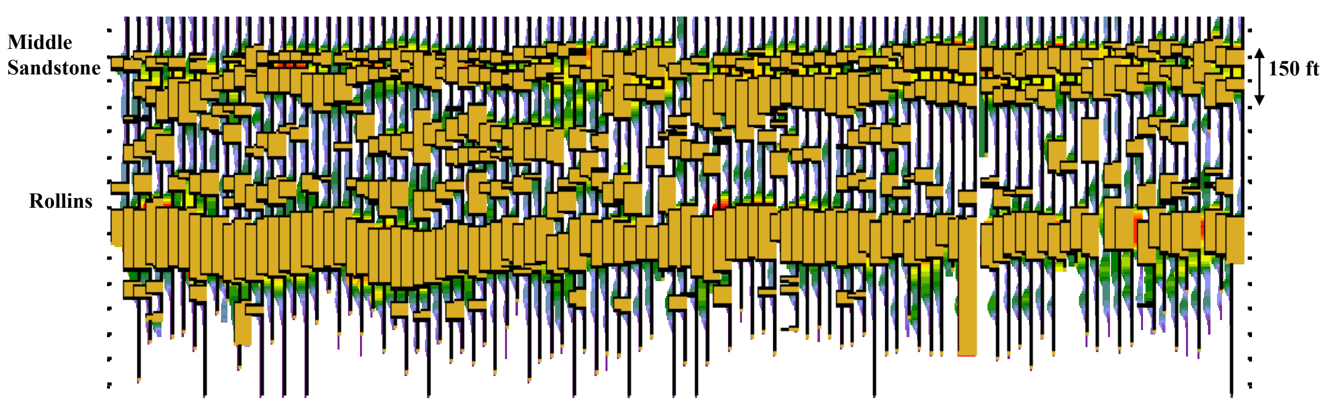

Figure 5. Log scale thick sand facies flags along a cross section of 102 wells overposted on seismic probabilities shown in Figure 4.

EDITED REFERENCES

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