Accounting for bias and uncertainty in facies estimations from deterministic inversions

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Summary

Bayesian inference procedures can be used as interpretation tools for seismic inversions. The results are facies and their probabilities of occurrence derived from the native outcomes of inversions or their derivatives. Although deterministic inversions produce a single outcome, they have uncertainties associated with them. Further, due to inappropriate low frequency models or thin bedding, biases in the inversion properties can arise. We use a phenomenological approach to model these effects and separately correct for them in the subsequent Bayesian inference. The results are facies interpretations and pay maps which account for bias and uncertainties and will provide greater confidence in reservoir volume estimates.

Introduction

Bayesian inference can be used to infer the probabilities of occurrence of geologic facies from seismic reflection data and in particular, from full-stack and AVO inversions (Pendrel et al., 2006). It is observed that facies, when displayed in a cross-plot space defined by inversion outcomes, commonly exhibit a clustering behaviour. This clustering can be described by assigning a joint probability density function (fPDF) to each facies. Applying Bayes' rule with optional priors provides the probability of occurrence of each of the facies at every location in 3D space. Volumes of the most-probable facies are then easily computed. The design of the fPDFs comes initially from well log data but can be augmented by rock physics modeling or any other available information. The cross-plot space need not be restricted to the native outcomes of inversions but can be other useful derivatives. For example, in unconventional shale plays, Vqtz and Brittleness have been used (Pendrel et al., 2014).

It has been recognized that deterministic seismic inversions, while producing one single set of most-likely reservoir properties, contain inherent uncertainties and possibly, biases. We broadly categorize these effects into two classes – seismic band-based and low frequency band-based. Seismic band uncertainties can arise, for example, from random, and coherent noise in the seismic data and gather misalignment. Biases can be variable from one geologic layer to the next and result from attempts to image thin layers and uncertainties in the estimated angles of incidence and the inversion wavelets. In the low frequency band, bias can be caused by attempts to account for lateral variabilities in facies property trends by the interpretation of well logs. Extension of the low frequency model (LFM) with ultra-low frequency stacking velocity information and trend replacement from facies identification can cause both bias and uncertainty.

A rigorous approach might be to estimate the uncertainties in each of the inversion inputs and from these, the net uncertainty in the inversion outcomes. Here we take a more phenomenological approach. We use the differences between inversion outcomes at well locations and high-cut-filtered well logs as inputs to the bias-uncertainty analysis procedure. This method is described in greater detail below. However, it is important to ask what types of errors the difference data represent. Certainly they contain information from the seismic band. Should the LFM used for inversion be computed by well log interpolation, then there will always be low frequency agreement. But if the LFM is derived from other information or perhaps an average over the available logs hung on structure, then the difference measure will be a mixture of the two types. Previous works (Pendrel et al., 2016) have used the method to identify bias and uncertainty effects while not attempting to separate the two. Here, we address that and extend the analysis to the probabilistic estimation of pay thicknesses.

Method

The inversion algorithm which we employ makes no use and has no knowledge of any well log information within the seismic band so that we can say that the inversion algorithm is blind to the logs within that band. It then follows that an effective QC is the comparison of the inversions to high-cut-filtered logs at the well locations. A cross-plot of high-cut filtered logs vs inversion outputs should result in a set of data points clustering along a line with a slope of unity. Any deviation from this slope is an indication of bias. The observation that the data points in the QC cross-plot cluster along the best-fit line rather than lie on it is an indication of uncertainty. We measure the distance of each data point from the best-fit line and use these to construct a residual histogram. To this we fit an uncertainty PDF (uPDF).

The contribution of the LFM band to the uncertainty and bias in this QC depends upon how the LFM was constructed. There will be no contribution when it is built by a process involving the interpolation of the logs. When it is constructed from any other method, then the QC described could contain an LFM component.

After uPDFs are computed for each layer and each of the inversion outputs, they are incorporated into the Bayesian facies analysis. The outcomes of inversion are no longer represented by single points in the inversion cross-plot space on which the facies PDFs are defined but by ellipses. Should a bias correction be necessary, then the ellipses are shifted. The effects of bias alone can be investigated by simply setting the standard deviation of the uncertainty PDF to be small or zero. We recognize the possibility that the uncertainties from associated inversion outputs could be correlated. This would mean that the multi-dimensional uPDFs would be rotated. We have not seen this effect in real data and so do not pursue that notion further here. We also note that the PDFs could be defined through a non-parametric approach which we have also not considered in this writing. The effect of the uPDFs is to add uncertainty to the individual facies probabilities. As the standard deviations of the uPDFs become larger, the probabilities of occurrence of the facies become more similar and the ability to discriminate between them is reduced.

Example

We test the above ideas with a Gulf of Mexico data set. Geologically, there is a set of two vertically-stacked deltaic systems of middle Pliocene age. They average 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 key horizon is the top of the Green sand which is shown in Figure 1. The sharp discontinuities are the results of faulting. Below the Green horizon, we recognize both upper and lower sandstones.

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 to the inversion in the form of facies-based constant trends interactively defined at horizons and hung on structure. The lowest frequencies were further modified using stacking velocity information (Pendrel, 2015).

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 overlain. The matches are not perfect since the inversion has no prior knowledge of the high frequency component of the logs. The regions of interest are the

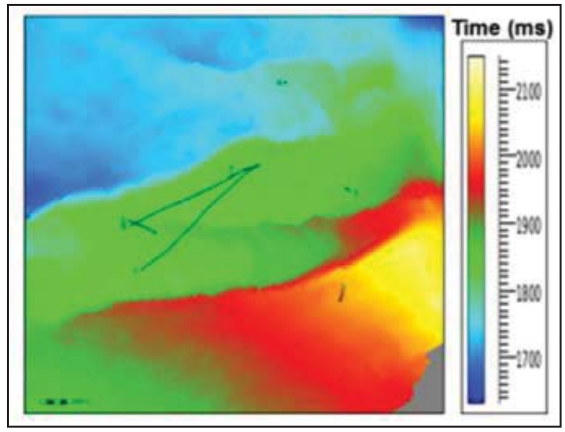

Figure 1: Project map shows the green horizon and the well locations

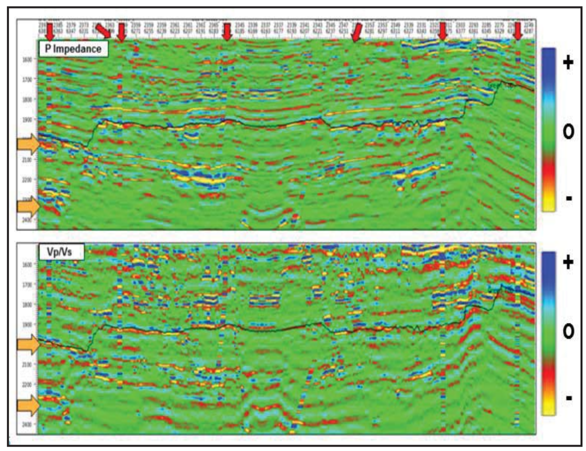

Figure 2: P Impedance and Vp/Vs from a relative inversion (no low frequencies). Band-pass-filtered logs have been overlain at the well locations (red arrows). The inversion algorithm was blind to the wells in the seismic band.

sands (between the orange arrows) where there is the possibility of hydrocarbon-bearing sands. The P Impedance agreement to wells is good and the Vp/Vs fair.

Bias QCs for P Impedance and Vp/Vs are shown in Figure 3 for the upper sandstone. There is considerable scatter (uncertainty) as well as significant bias. These can be seen clearly in the difference histogram plots in Figure 3. Biases of 2.4% and 0.6% exist for P Impedance and Vp/Vs, respectively. Since the modelled uPDFs in Figure 3 are used in the Bayesian analysis, a bias correction is effectively made.

Figures 4a and 4b show the Facies PDF templates used in

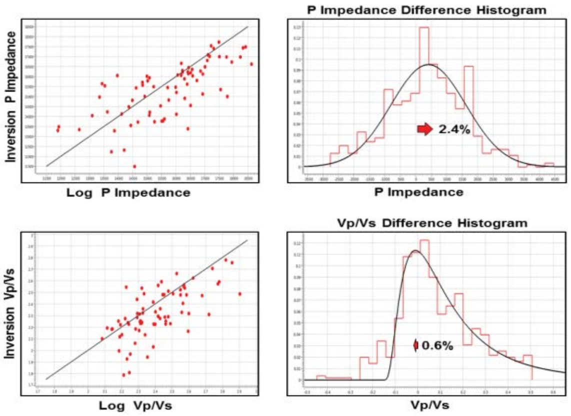

Figure 3: Cross-plots of P Impedance and Vp/Vs from inversion with their high-cut-filtered log counterparts (upper left, lower left) for the upper Sandstone indicate deviations from a one-to-one line and therefore, bias. There is also significant scatter representing uncertainty in the inversion results. On the right are the modelled uPDFs for P Impedance and Vp/Vs

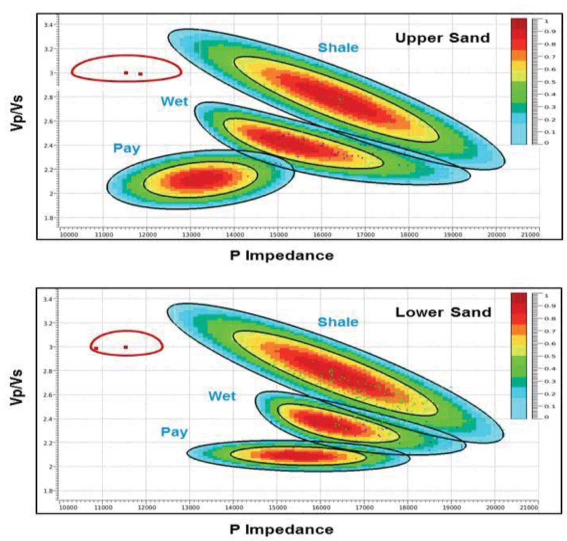

Figure 4: Bayesian facies analysis templates for the upper and lower sandstones. Also shown are the uPDFs (red ellipses). The distance between the centric and non-centric red dots inside the ellipses represent the bias.

the Bayesian inference for the upper and lower sandstones. Note how the characteristics of the sandstones change in this short time interval.

Figure 5 compares the results of the Bayesian facies classifications when bias is ignored (upper) and when it is incorporated (middle). There is more Pay in the upper sandstone in the bias-corrected version. The opposite is

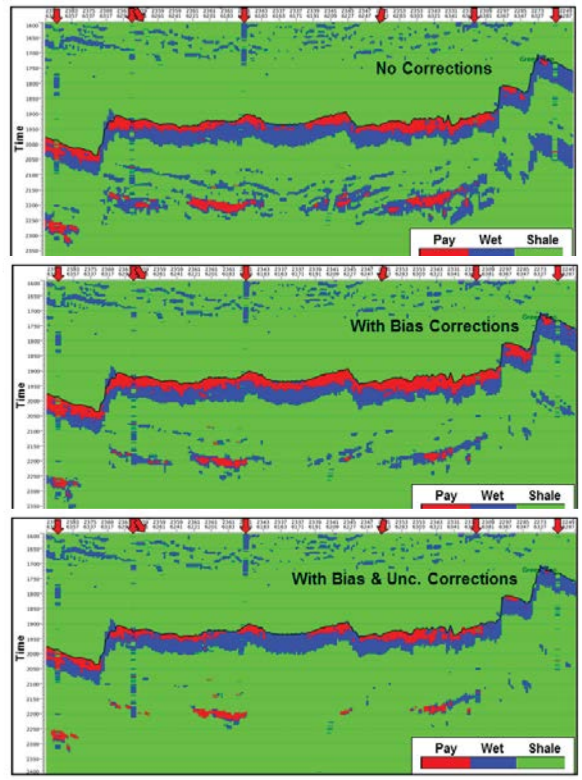

Figure 5: Three versions of the most-probable facies are shown, corresponding to no corrections (upper), bias corrections (middle) and both bias and uncertainty corrections (lower). Bias corrections have increased the Pay in the upper sand and reduced it in the lower. Uncertainties reduce probability contrasts generally but have also reduced Pay due to the asymmetry in the Vp/Vs component of the uPDFs.

true in the lower sandstone. Apparently, the biased inversions had resulted in wrong classifications of some facies. As expected, the Pay probabilities in Figure 5 (lower panel) are reduced when both uncertainty and bias are taken into account. There is increased confidence in the surviving high probability areas however, since imperfections in the inversion have been addressed.

The surprisingly large uncertainty indicated by the QC process, especially for P Impedance (Figure 3) has had a rather dramatic effect on the probability of Pay facies and deserves further investigation. Figure 6 shows the histogram of P Impedance residuals for the upper sand, but now colored by wells. The contributions of each of the wells are not the same. While some are approximately centered about zero (black, cyan, magenta) other are not (red, green orange). The implication is that the LFM for inversion obtained from an average over all wells was not appropriate for some. In this example, it is known that

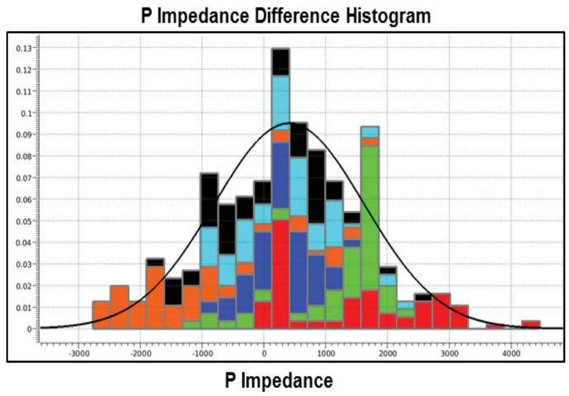

Figure 6: P Impedance residual histogram for the upper sand, colored by wells. The contributions of some wells (red, green, orange) are not centered about zero, indicating that the LFM obtained from the average of all wells will exhibit bias at these locations.

pressure differences can exist across faults and that fault block-specific LFMs might be more appropriate. We judge that if these were to be undertaken, the P Impedance uncertainty might be reduced by a factor of two.

Finally, we investigate the effects of the above processes on the estimation of net pay thickness for the upper sand. We first mask the Pay by probability of occurrence, accepting only those Pay facies with probabilities which exceed a particular threshold. Here, the threshold was chosen to be 0.6. The results are shown in Figure 7 for the same scenarios as in Figure 5. We include the additional possibility of an uncertainty reduction by a factor of two according to the alternate LFM approach suggested above. The results are consistent with the most-probable facies sections in Figure 5. Bias, in this case, increases the projected net Pay while increases in uncertainty reduce Pay probability.

Conclusions

We have demonstrated that small biases and uncertainties in seismic inversions of only a few percent can significantly affect critical facies identifications. These can be estimated and input to a Bayesian inference procedure on a layer-by-layer basis to both correct the inversions for bias and produce meaningful facies interpretations which take uncertainty into account.

It has been shown that LFM-building strategies that do not rely on well log interpolation can contribute to inversion bias. Laterally-varying LFMs, if they are reasonable, can assist in reducing bias and overall uncertainty. Fault blocked-based LFMs were suggested in the example presented. In our future research we will investigate "smart" well log interpolators which will base their interpolation weighting on relevant attributes and further, suggest LFM uncertainties away from well control.

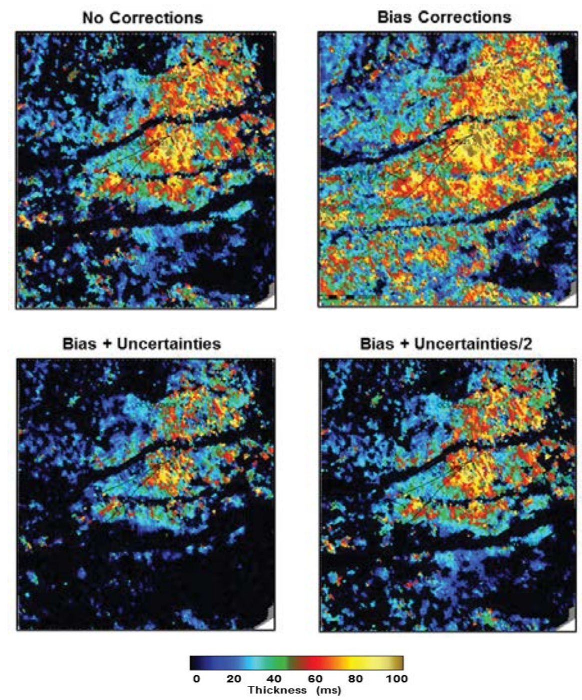

Figure 7: Net pay thickness maps for the upper sandstone wherein it was required that the pay probability meets or exceeds 0.6. The figures show the results for no bias or uncertainty corrections (upper left), bias corrections only (upper right), both bias and uncertainty corrections, (lower left) and bias corrections with a 2X-reduced uncertainty (lower right).The potential benefits of a more appropriate LFM are demonstrated in the lower right figure.

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EDITED REFERENCES

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