Low frequency models for seismic inversions: strategies for success

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Summary

A critical issue in all seismic inversion procedures is the accounting for missing information below the seismic band. We need that if we are to determine absolute reservoir properties. Typically, inversionists create some sort of structural model from workstation interpretations and then use well logs to populate it with the native outcomes of elastic inversion – P Impedance, Vp/Vs and Density. However, the problem is how to go about interpolating the logs between the wells. We are usually uncertain about how to do this and often uncomfortable with the result.

We will demonstrate by example, a joint deterministic inversion – facies estimation procedure which makes minimal prior assumptions and obviates the need for the building of a low frequency model (LFM) which interpolates log curves between wells. We then apply the same procedure to geostatistical inversion and show that facies can successfully convey low frequency trend information between the two domains.

Introduction

All seismic inversion strategies require knowledge of the low frequency trends corresponding to the required reservoir properties – usually P Impedance, Vp/Vs and Density. Typically, this low frequency band ranges from 0 Hz to 8-10 Hz. Interval velocities derived from stacking velocities can often be used to complete the lowest 2 or 3 Hz when they can successfully be related to the native products of inversion. When broadband acquisition and processing technology is not available, the remainder of the low frequency band information typically comes from a low frequency model (LFM) derived from workstation horizon interpretations and logs. (Pendrel and van Riel, 2000). This method promotes good agreement between inversion and well logs at the well locations for obvious reasons. The problem is how to interpolate log curves between wells. There are many analytic relationships which can be used. Kriging is also a possibility. Whatever the strategy, the simple truth is that, in the absence of further information, we do not know the true 3D heterogeneity of the reservoir in the low frequency sense. We strive to design seismic acquisition programs so that all required information about the play in question is contained within the seismic band. When we succeed, a simple background model will suffice to place the seismic in the correct geologic setting. All too often, the reverse is true and we find ourselves in a real dilemma regarding the determination of absolute reservoir properties.

In this paper, we follow an approach beginning with the identification of simple property trends, usually from logs. Of course these trends would be expected to be facies-dependent. This is true but, initially, we do not know the facies distribution. We test the notion that the combination of initial trends and a first pass of inversion will be sufficient to determine it. With facies identified, initial trends can be upgraded to become facies-dependent, ready for a second pass of inversion. In this approach we follow the ideas of Jarvis, (2006) and Mesdag et al. (2010). Finally, we investigate methods to transfer the essential low frequency information to geostatistical inversions.

Method

The first step is to define the reservoir facies. This begins in the petrophysical domain where we consider properties such as water saturation, shale volume, porosity and fluid type. These can be used to define the relevant facies. We seek to demonstrate that the native outcomes of inversions can act as proxies for the petrophysical properties toward the identification and mapping of these facies. In this context, density is usually quite useful although commonly, not available from inversions. Density reflectivities are typically an order of magnitude smaller than those from shear measures such as Vp/Vs for most acquisition scenarios. They then become lost in the noise and require strong stabilizing constraints (e.g. Gardner) in an inversion workflow. Therefore, the typical elastic proxies for petrophysical facies are in P Impedance – Vp/Vs space.

Facies can be identified from field data in this space by a Bayesian approach (Pendrel et al., 2006). Facies probability density functions (PDFs) describe the distribution of the facies in this space and using a first pass of inversion, facilitate the estimation of the probabilities of

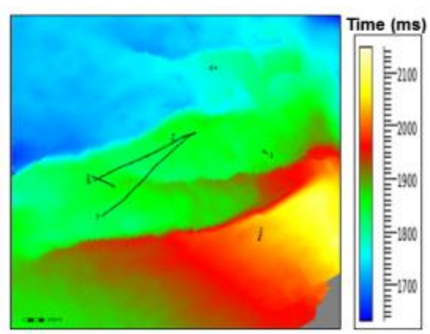

Figure 1: Project map with the wells and Green horizon

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occurrence of each of the facies across the project. PDFs can be defined parametrically or by following a free-form binning approach. The method works in time or depth and facilitates the determination of the most-likely facies and estimations of probablistic net pay. Various nesting-type rules can be applied in the course of the analysis.

We begin the inversion workflow by testing simple trends defined at a few workstation horizons. If reservoir heterogeneity does not manifest in the low frequency band, then these simple trends might suffice. Running the inversion, performing the Bayesian facies analysis and overlaying petrophysical facies on the facies from inversion will quickly answer the question. When the reservoir facies do imprint on the low frequency band, then some estimate of this effect needs to be made. We simply draft in a finer set of horizons, following the existing ones and define the trends more richly. Although we allow ourselves to hang these trends on structure, there is no other lateral variability – the trends are constant cross the project. Using these in inversion usually provides enough extra information for successful facies identification to occur. Facies mapping can be improved by introducing limited variability in the lowest frequencies via interval velocities from stacking velocity analyses. The results of this first pass of facies analysis are vetted by the petrophysical facies.

With a preliminary facies analysis in hand, we can now upgrade the trend models by substituting values from the individual facies trends at locations indicated by facies analysis. Facies trends usually come from logs but could also contain information from rock physics and pressure modelling. A shale background model might be little-changed by this procedure but sandstones and hydrocarbon-bearing facies could show significant effects. A second round of inversion and another of facies analysis is typically sufficient to achieve a final result. We prefer such a two-stage workflow (inversion and Bayesian facies analysis) because it facilitates QC of a wide range of potential problems. These include

- Dealing with hybrid facies (e.g. sandy-shales)
- Conditioning density from inversions where necessary
- Identification of previously-unknown facies
- Inversion QC and correction for bias, etc.
- Facies PDF options: i.e. normal, log normal, binned
- Facies transitions: sharp vs gradational
- Regions where facies become almost equi-probable

To this point, spatial variability has been introduced only by very low frequency stacking velocities and heterogeneous distribution of facies. Any other technique will involve some sort of assumptions. Sophisticated methods are available but beyond the scope of this paper.

Example

We test the above ideas with a Gulf of Mexico data set (Figure 1). The key horizon is the top of the Green sand which is shown in the figure. Sharp discontinuities are the results of faulting. Geologically, we have a set of two vertically-stacked deltaic systems of middle Pliocene age. They average about 400 ft. thick and are separated by about 500 ft. Within the play area are delta slope deformation, slump-induced turbidites, thin mouth-bed deposits and the absence of any delta plain facies.

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.

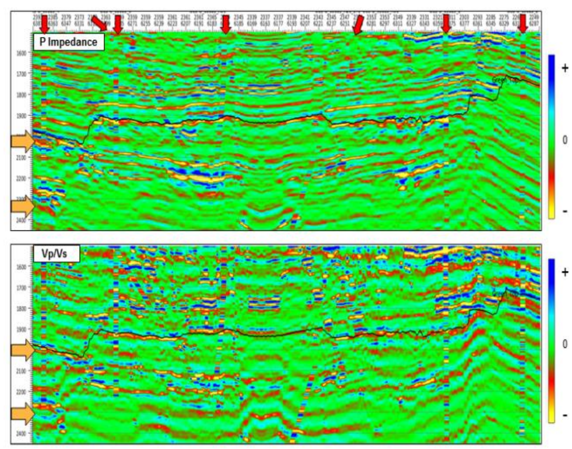

Figure 2: P Impedance and Vp/Vs from a relative (no low frequencies) inversion. Band-pass-filtered logs have been overlain at the well location (red arrows). The inversion algorithm was blind to the wells in the seismic band.

The log sets each 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 can be supplied to this inversion in the form of 3D models or by constant trends interactively defined at horizons and hung on structure.

Subsequently, facies were identified by a Bayesian

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approach (Pendrel et al., 2006), employing facies-based probability density functions and P Impedance and Vp/Vs from inversion. The technique produces, as output, the most-probable facies at each point in 3D space and also, as QC, the probabilities of occurrence of each of the facies.

The petrophysical facies were defined from the Sw and Vshale logs. Facies with a maximum of 40% shale were classified as Sandstones. Pay Sand was required to exhibit water saturations of less than 40%. Facies were not strictly defined by these rules but rather through PDFs and the Bayesian approach described above. Although Pay could be sub-divided into gas sand and oil sand through use of neutron and density porosity logs, it was found that the required elastic proxies implied knowledge of density. P Impedance and Vp/Vs would not suffice. So, for our purposes here, we talk about Pay Sand, Sand and Shale. We also have defined a hybrid Tight Sand which we might choose to populate post-analysis, based on QC results.

The results of the *relative* 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. This relative inversion contains no low frequencies and so is not absolute. The region of interest is the G sand (between the orange arrows) where there is the possibility of hydrocarbon deposits. The P Impedance agreement to wells is good and the Vp/Vs fair. In the following, we show not the result of the inversions themselves but of the resulting Bayesian classifications with the petrophysical facies from the wells overlain.

We first experimented with using a simple trend from logs, defined only at four major geologic horizons (not shown). No Pay facies were identified in the reservoir interval. This was because the imprint of the reservoir sands in the LFM

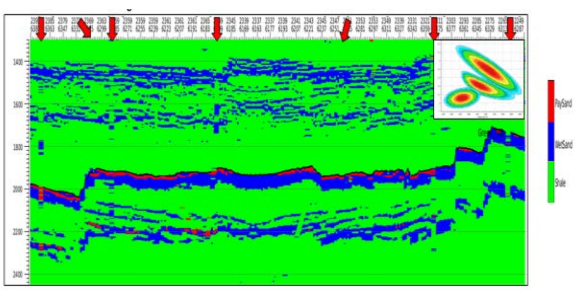

Figure 3: Information about the sandstones in the low frequency band has been added to the low frequency model for inversion. These are best-fit to the logs, laterally-invariant and hung on structure. Sand (red) and Pay (blue) have been identified which correlate to well log facies.

was completely missing. When we improved the LFM trend with a little more detail so that it included the low frequency imprint of the sandstones, the result was much better. This is shown in Figure 3 where no lateral-variation has been assumed except that the facies-independent trends used have been hung on structure. The facies identification template is also shown inset. The pay sand in the figure is clearly visible. Agreement with the logs is reasonable.

We can improve the low frequency model from two more sources of known information. First, we replace the 0-2 Hz band with information from interval velocities from NMO, against which relationships to the native outcomes of inversion have been established. Second, we replace property information at the identified facies by facies-dependent trend information from the logs. The result of the Bayesian classification from this new inversion is shown in Figure 4. Agreement with the logs is better and the result appears more geologic. In addition, a pay-water contact seems to have developed. There are also indications of bypassed pay.

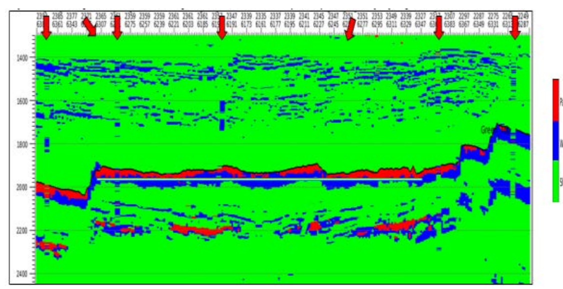

Figure 4: Information from processing interval velocities and facies trends have been added as described in the text. Agreement with the wells has improved and there is an indication of a pay-water contact.

Finally, we investigate the applicability of our approach to geostatistical inversion. We use the Bayesian joint facies-property inversion described by (Zawila et al., 2010). In geostatistical inversion, lateral low frequency variations are communicated by log properties and facies at well locations and by prior 3D constraints and variograms between wells. When prior 3D trends are not available, variograms might be insufficient. In our Gulf of Mexico data set, we expect this to be the case. Variogram ranges might have to be made artificially large to convey the message of omnipresent sand. We test the idea that the Bayesian facies estimation from our deterministic inversion procedure might be a better messenger.

Figure 5 shows the results of 40 realizations of geostatistical facies estimation wherein all wells were used as constraints and a laterally-invariant facies proportion prior was used that was constant across all layers and times.

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The figure shows not only the most-probable facies at each point in time and space but also a confidence measure. Any locations where the winning facies was less than 70% probable are flagged yellow. Agreement at the wells is guaranteed. Between wells, the G sand is poorly imaged and many points are flagged yellow.

Figure 6 follows the same procedure but with a spatially constant facies prior (following structure) but vertically variable from an average of all the well logs. The sands and pay are now defined with greater confidence. Figure 7 shows the results of using a full 3D facies prior from the deterministic inversion. Confidence is improved again with an attendant improvement in the imaging of the reservoir.

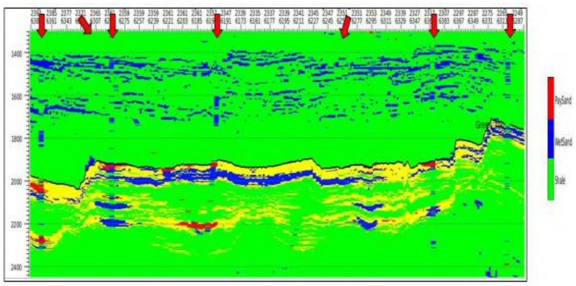

Figure 5: Most probable facies after 40 realizations of joint facies-property geostatistical inversion. The constraint prior was a fixed constant proportion. The yellows flag regions wherein the most-probable facies occurred in fewer than 70% of realizations. Geostatistical inversion was done in the G sand interval only and the results superimposed on the deterministic result over the larger time window.

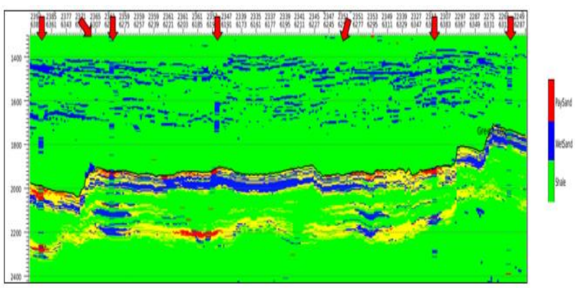

Figure 6: The same procedure in Figure 5 was used here except that the facies prior, while laterally-invariant, was allowed to vary vertically in a manner suggested by the petrophysical facies in the wells. The sands and pay are defined with greater confidence.

The results in Figure 8 use the same 3D facies prior as in Figure 7 but with all the wells set to be blind. Lateral low frequency variability comes only from the 3D facies prior and the variograms. There has been no degradation in confidence. While some of the matches to the petrophysical facies in the well logs are imperfect, many are outstanding. The key Pay facies is largely unchanged.

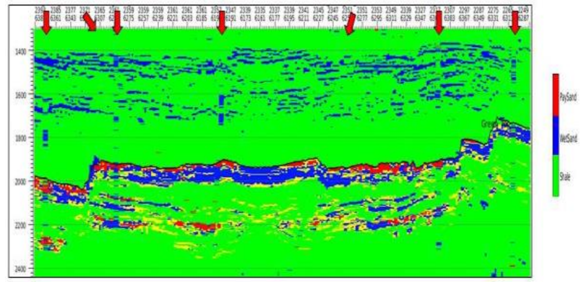

Figure 7: A full 3D prior from the deterministic inversion was used. The facies confidence is improved again.

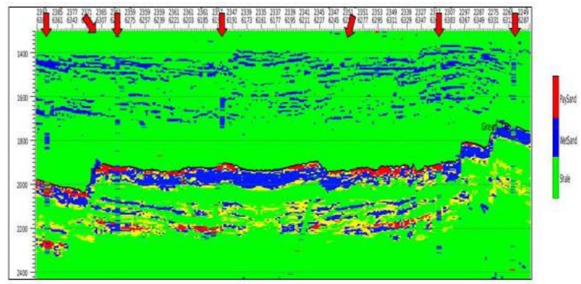

Figure 8: The inputs to geostatistical inversion are identical to Figure 7 except that all the wells were blind. The only prior information was derived from the facies distribution derived from the deterministic inversion.

Conclusions

We have demonstrated a joint deterministic inversion – Bayesian facies estimation procedure which makes use of property trends and facies property templates to construct missing low frequency information for inversions. The result is structurally compliant in a 3D sense but avoids complicated low frequency modeling. We have successfully applied the technique to geostatistical inversion, showing that the Bayesian facies estimation can successfully act as the conveyor of low frequency information between the two domains. The latter was successful enough to give a very meaningful result even when no constraining wells were used.

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EDITED REFERENCES

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