Post-Stack Seismic Inversion and Facies Prediction using Bayesian Inference, Boonsville Field, Fort Worth Basin, USA: A Case Study

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Abstract

The present work shows a methodology to derive facies and sand probability volumes from post-stack 3D seismic data. The seismic data was inverted to a p-impedance volume using a constrained sparse spike algorithm. Then probability density functions, derived from well logs, together with Bayesian inference were used to derive sand probabilities and facies volumes at each voxel in the impedance volume. A real data example from Boonsville field, Texas (USA) was used to verify the proposed workflow.

Introduction

Seismic attributes have been routinely used, for decades, to distinguish different facies within several types of reservoir. However, the tuning effect associated with thin reservoirs may result in misleading interpretations from seismic attributes. In contrast, the seismic inversion process attenuates the wavelet effect, reduces the side-lobes and as a consequence results in less tuning effect.

In the present study, we show the benefits of implementing a deterministic seismic inversion workflow followed by facies prediction with Bayesian inference to estimate the facies distribution and its associated uncertainty (Pendrel et al., 2006).

Generally speaking, the use of elastic attributes derived from seismic inversion, when calibrated with well-log data, may improve the geologic interpretation (Pendrel, 2006). Major benefits of the direct comparison between well logs and seismic data are calibrating the inverted p-impedance volume, the possibility of producing facies volumes, and accounting for uncertainty in the interpretation.

Facies logs of a certain cutoff are used to build probability density functions (PDF) of acoustic impedance values. The retrieved PDF's are then applied to the acoustic impedance volume recovered from inversion. The outputs are the probability cubes of each facies and the most- probable facies volume.

We have applied the proposed workflow to study the Boonsville reservoir at the Boonsville Field, Fort Worth Basin, Texas, USA (Figure 1). Our goal is to predict the sand distribution and the main reservoir facies in the field. We have used a public domain dataset composed of a 3D PSTM seismic volume; the energy source used during acquisition was explosives and the processing bin size was 33m x 33m with maximum offset of 2000m (Hardage et al 1996). Density, sonic, gamma ray and resistivity logs of four wells were also provided.

Boonsville Reservoir

The lower Atoka Group reservoirs comprise fluvial and deltaic sandstones in a stratigraphic trap (Hentz et al., 2012).

The Boonsville gas field is by far the largest of the lower Atoka fields and is bounded by the Marble Falls limestone at its base and by the Caddo Limestone or Pregnant Shale at its top. These represent a transgressive sequence with dark shale and thin sections of conglomerates that have a variety of fine to coarse sandstones from well-cemented to porous (Huber & Lahti, 1982).

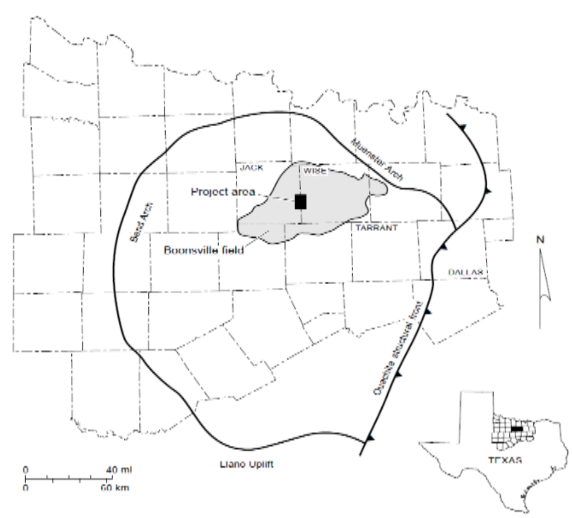

Figure 1: Boonsville field and project area map (source Hardage et al. 1996)

Method

We inverted the PSTM 3D seismic data to retrieve an acoustic impedance volume using the constrained sparse spike algorithm. Next, we applied a PDF designed from the well logs and Bayesian inference to generate facies probability volumes.

The constrained sparse spike method assumes the seismic to be the convolution of a reflectivity time series with a wavelet with additive, non-correlated noise. The inversion solves for the reflectivity series given a wavelet and seismic traces.

Debeye and Van Riel (1990) showed that the inversion problem could be addressed by minimizing a sum of Lp norms, one for the reflectivity and another for the noise, or the difference between seismic and synthetics generated by the convolution of the reflectivity and the wavelet.

In the present work, the algorithm used minimized the sum of four Lp norms, one for the reflectivity or simplicity of the model, one for the noise, one for the spatial variability and one for the match with a prior low-frequency model.

The employed wavelet was extracted using the reflectivity from well logs and the requirement to minimize the difference between the synthetics generated from well logs and the seismic traces near the wells.

Due to the band-limited characteristic of the seismic data, the algorithm uses a low frequency model to constrain the frequencies not explained by the seismic. This model can be created in different ways and plays an import role in the results (Pendrel, 2015). In this work, we used a solid model created with the horizon interpretation and inverse distance interpolation of the acoustic impedance from the four wells.

Once the inversion is finished and the proper quality controls are assessed, the next step is to perform Bayesian inference. To accomplish this, we need the acoustic impedance volume from seismic inversion, the PDF created using facies and acoustic impedance from well logs. To calculate the posterior distribution, we first estimated the priors based on the proportion of each facies from well logs and edit them to obtain geologically plausible most-probable facies volumes. In this meter, additional external information from conceptual models or potential methods can also be used (e.g. gravimetry).

Results

Acoustic seismic inversion deliverables are a p-impedance volume along with residuals or seismic synthetic difference generated with reflectivity from inversion convolved with the previous estimated wavelet.

P-impedance inversion results are shown in an arbitrary section (figure 2). It is common to use the relative impedance results to quality control the match to wells; in this result no constraint to wells or prior models are applied. The result used in interpretation is the full-band p-impedance shown in figure 3 with wells in overlay.

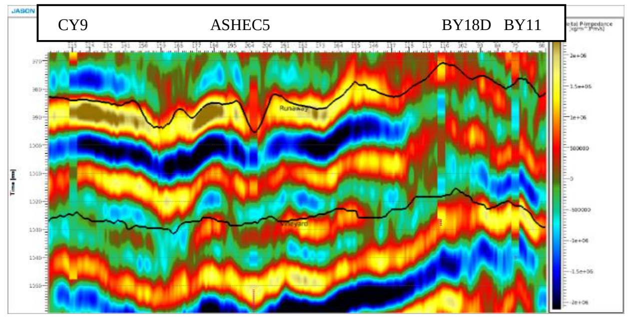

Figure 2: Arbitrary sections passing through the four wells displaying relative p-impedance wells in overlay. Hot colors represent high impedances and cold colors low impedance.

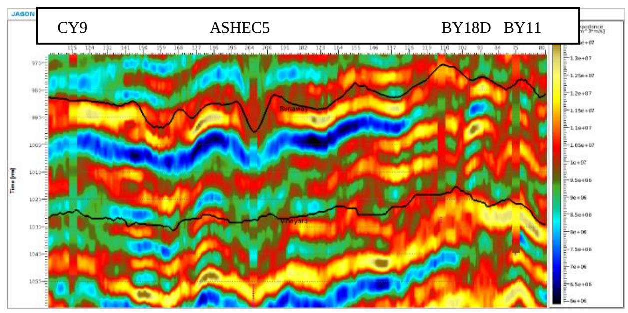

Figure 3: Arbitrary sections passing through the four wells displaying absolute p-impedance wells in overlay. Hot colors represent high impedances and cold colors low impedance.

Signal-to-noise ratio and residuals maps can benefit the user during the interpretation where the areas with low signal to noise ratio and high residuals are of higher uncertainty compared to those of higher seismic quality and lower residuals. The inverted signal to noise ratio map (Figure 4) shows the lateral variation in seismic quality.

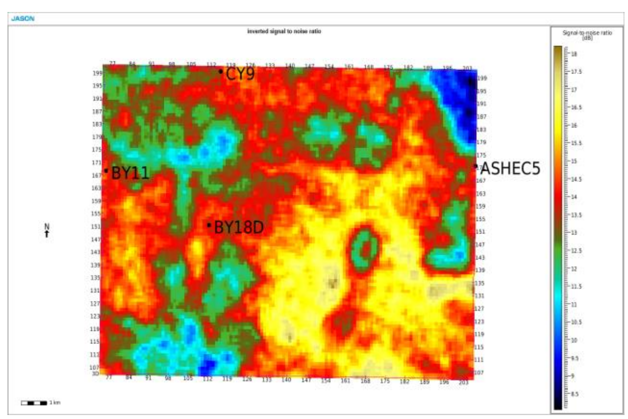

Figure 4: Signal to noise ratio map: cold colors represent areas where the ratios of residual energy over seismic energy are high.

Lithology logs were created based on v clay logs derived from gamma ray logs. The sand facies were set to include all the clay volume values less than 0.4 while the shale facies were set for the values higher than 0.4 (figure 5)

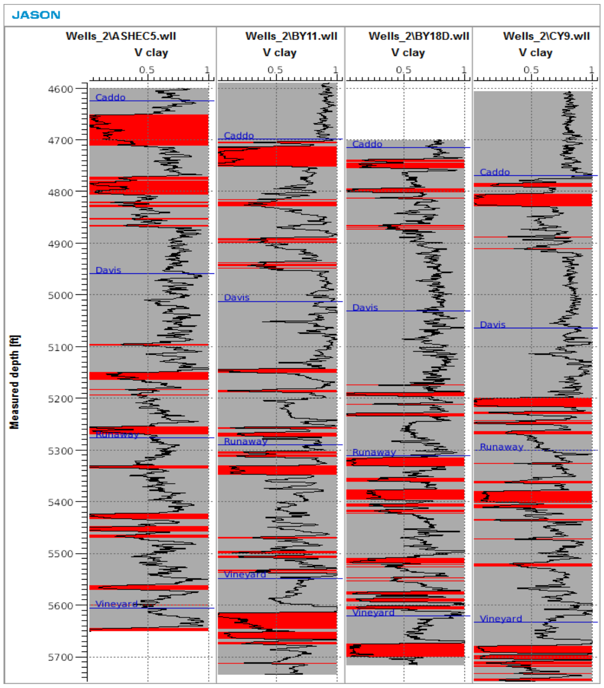

Figure 5: Clay volume well log in black and lithology log created, red is sand gray is shale

The PDF used to create the sand occurrence volume were normal Gaussians fitted to histograms generated from well samples (Figure 6).

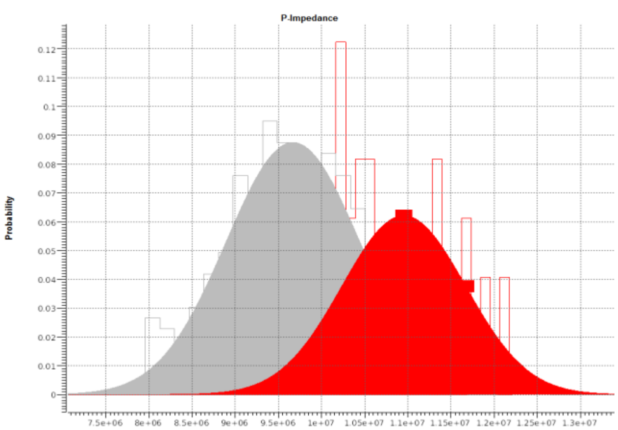

Figure 6: PDF and Histograms from well log data, shale PDF in gray and sand PDF in red. There is a substantial overlap between both PDFs, this will result in higher uncertainty in the interpretation

These PDFs applied to the p-impedance volume resulted in the probability of sand occurrence shown in figure 7, and most-probable facies volume (figure 8).

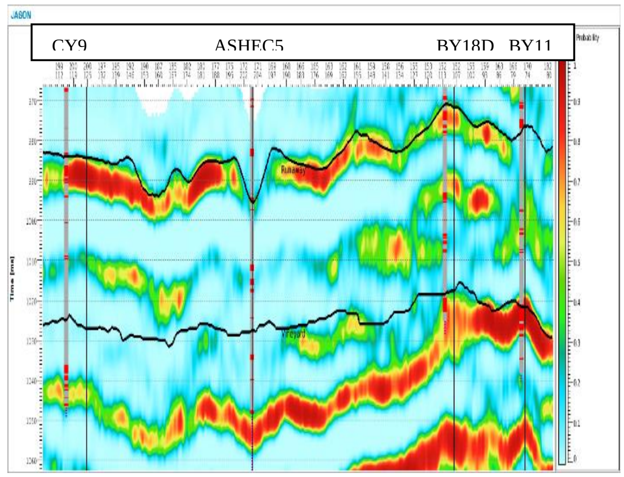

Figure 7: Arbitrary section passing through the wells, hot colors represent high probability of sand occurrence, well logs are overlain, gray is shale and red is sand

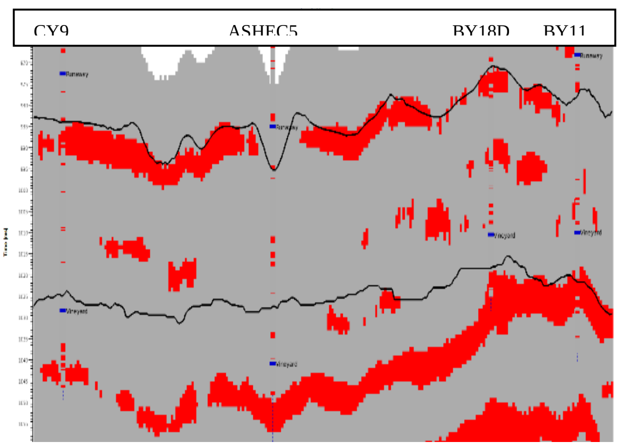

Figure 8: Arbitrary section passing through the wells, most-probable facies volume, well logs are overlain, gray is shale and red is sand

Both results show a fair match to sand occurrence in the wells. Places where the seismic to well synthetics match were not good will result in misclassification; this is due to mismatch in p-impedance values from inversion and p-impedance from well logs. These intervals should be further investigated; the source of the mismatch can be due to problems in the seismic as well as problems with the well logs. In addition, we should expect that the inversion results would not be able to map the thin sand that is way below tuning thickness due to the limitation in seismic resolution.

Conclusions

We have shown a method to integrate post stack seismic, well logs and structural interpretation in order to generate facies volumes and account for uncertainty in the process. The results obtained showed a reasonable match to the measured logs (within the seismic resolution). They represent benefits to the geologic interpretation since the results are themselves, a geologic model of the subsurface. The results can also be assessed to evaluate risk and uncertainty involved in the process by looking to the probability sand volumes and driving different scenarios from different PDF models. It is also good to mention that other inversion methods (i.e. AVO simultaneous Inversion) improve the results and add s-impedance information with the requirements of angle or offset stack/gathers as input.

Acknowledgments

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