Introduction

An inversion for geological parameters such as spatial distribution of facies is one of the fundamental goals of seismic inversion/interpretation, since facies mapping is an important step for well planning and field development. In this seismic reservoir characterization exercise, we continuously strive to improve the accuracy and resolution of our results. In addition, any reservoir related decision-making process should require an assessment of the uncertainties associated with interpretations and statements based on the seismic data.

A wide variety of information/knowledge, which could reduce the inherent ambiguity present in the seismic inverse problem, is typically not used to improve/condition the seismic inversion results. Variations in rock properties are only partly resolved by the seismic data, which is inherently noisy and has limited frequency content. In addition, many spatial facies configurations are able to fit the data equally well, even those that do not make sense from an a priori knowledge standpoint (e.g. gravitational fluid ordering). Other examples of information that are typically not used to constrain the inversion could be geological ordering of facies with depth, statements such as “coal does not exist in a marine sequence”, and in particular, the fact that the spatial structure of specific facies is known to be thin. The amount of knowledge over the lifetime of a field is constantly increasing and it is difficult to integrate this knowledge into traditional seismic inversion workflows to deliver more certain results.

The Bayesian method is an analytical method for merging multiple diverse sources of information to arrive at a unified interpretation with uncertainty using Bayes’ theorem. Bayesian methods allow for stronger conclusions from the observed data by integrating information about what is already known a priori (Bosch 2010). Bayesian inversion directly from AVO seismic gathers to facies ensures that the spatial structure from the facies, to elastic to seismic domain is correctly propagated. This has the potential to quantify the uncertainty of a particular facies given the seismic data. This also has the potential to improve resolution below seismic scale and distinguish facies that are elastically overlapping (depending on noise levels and the level of a priori information).

An additional component of the seismic inverse problem that requires consideration is handling of the residual noise. It is well known that the residual noise in seismic data after processing consists primarily of correlated noise. White/uncorrelated noise is handled with signal processing techniques and stacking. Correlated noise on the other hand, is a more complex phenomenon, generated by approximate seismic forward models that do not adequately describe the process and limited frequency content. Correlated noise will typically tend to have the same frequency spectrum as the signal and be hard to distinguish from the true signal (Madsen *et. al* 2017).

If no information exists on a given noisy signal, the safest approach is to assume that the noise is uncorrelated white noise. This assumption has the largest information entropy and assumes the same noise level on all frequencies. Uncorrelated noise has an autocorrelation function, which is zero everywhere except at zero lag. The Wiener–Khinchin theorem states that the autocorrelation function of stationary noise has the spectral decomposition given by the power spectrum of that process and vice versa. Therefore white noise has the same energy at all frequencies, which is fundamentally different from correlated noise with a colored spectrum. Knowledge of the fact that the seismic noise is primarily made up of correlated noise is information that should be used. At the same time, we should be cautious not to assume there is something wrong about the statistical properties of the noise since it is hard to come by for real seismic data. In the following, various noise models including correlated and uncorrelated will be investigated to determine their effect in a facies inversion.

Method

A synthetic study was conducted to demonstrate the potential of including a conservative colored noise model in a direct probabilistic inversion from AVO seismic data to facies. In the following we will use the general approximate Bayesian framework outlined in Jullum and Kolbjørnsen (2016) and adapted to invert for categorical variables such as facies.

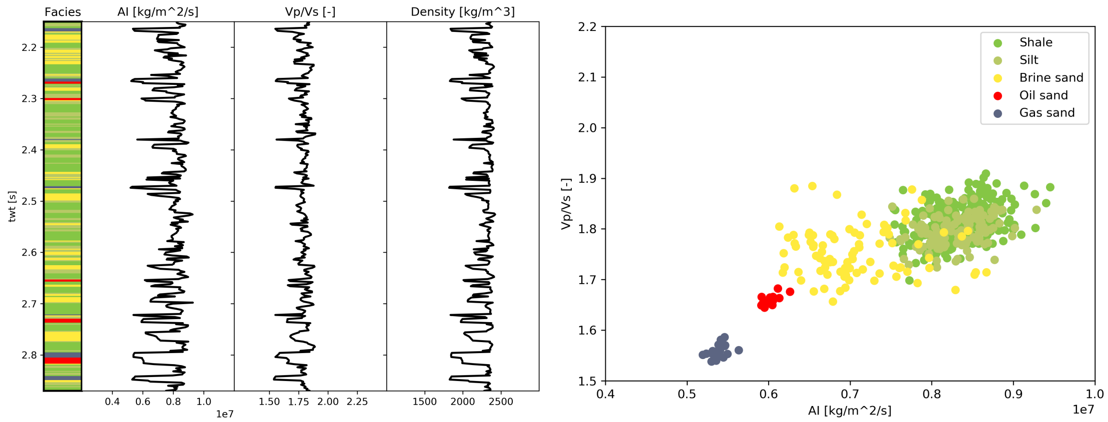

***Figure 1** Synthetic data, which in the following will be the ground truth.*

An exact solution of the complete posterior is not computationally feasible. However, by localization of the problem by defining spatial neighbourhoods in the facies-, elastic- and seismic-domain that influence a certain point in space the most and an approximation of the rock physics likelihood function, it is possible to arrive at a computationally feasible method.

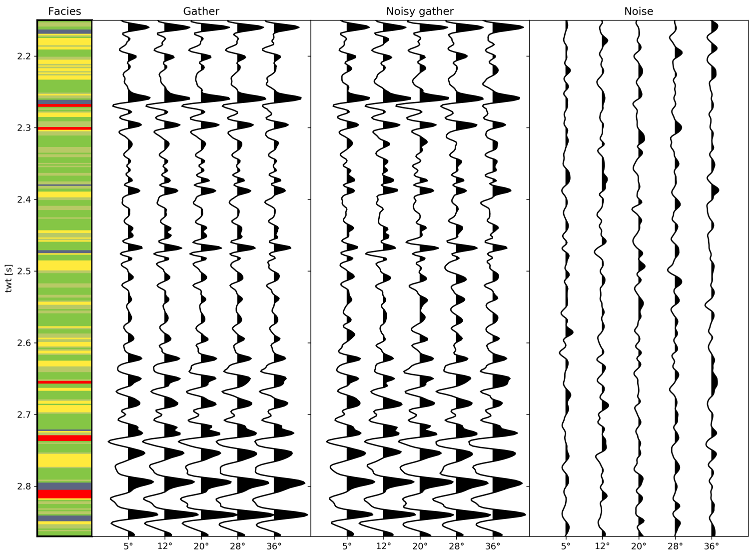

***Figure 2** Synthetic seismic AVO gather used as input for direct probabilistic inversion.*

Example

In the following we will study a challenging synthetic data set with relatively thin facies, some acoustically overlapping facies and strong tuning effects. We define 5 facies: shale, silt, brine sand, oil sand and gas sand. A priori assumptions include gravitational fluid ordering and relative thicknesses from the distributions of the various facies. Using a first order Markov process, a facies sequence is generated (see top figure in **Figure 1**), which in the following will be the ground truth to be inferred. The sample rate is 2 ms. From simple stochastic rock physics models defined for each facies, a realization of acoustic impedance (AI), Vp/Vs and density is computed for each sample (see **Figure 1**). In the cross-plot we can see that the brine sand show large acoustic variability and overlaps with the shale and silt facies, and partly with the oil sand. The gas sand shows strong separation in the elastic domain. Notice that the silt and shale facies are almost indistinguishable. The reflectivity sequence generated from the elastic logs using an Aki-Richards reflectivity model is convolved with realistic angle dependent wavelets with center frequency 25 Hz (bandwidth around 5 to 50 Hz and close to zero-phase) to generate 5 synthetic angle stacks (see **Figure 2**). Correlated noise with same frequency spectrum as the wavelets is then added to generate a more realistic seismic angle stack gather. For simplicity the noise is not correlated between stacks. This data will be the input from which we will try to infer the facies log. Notice how the AVO response is disturbed by the noise.

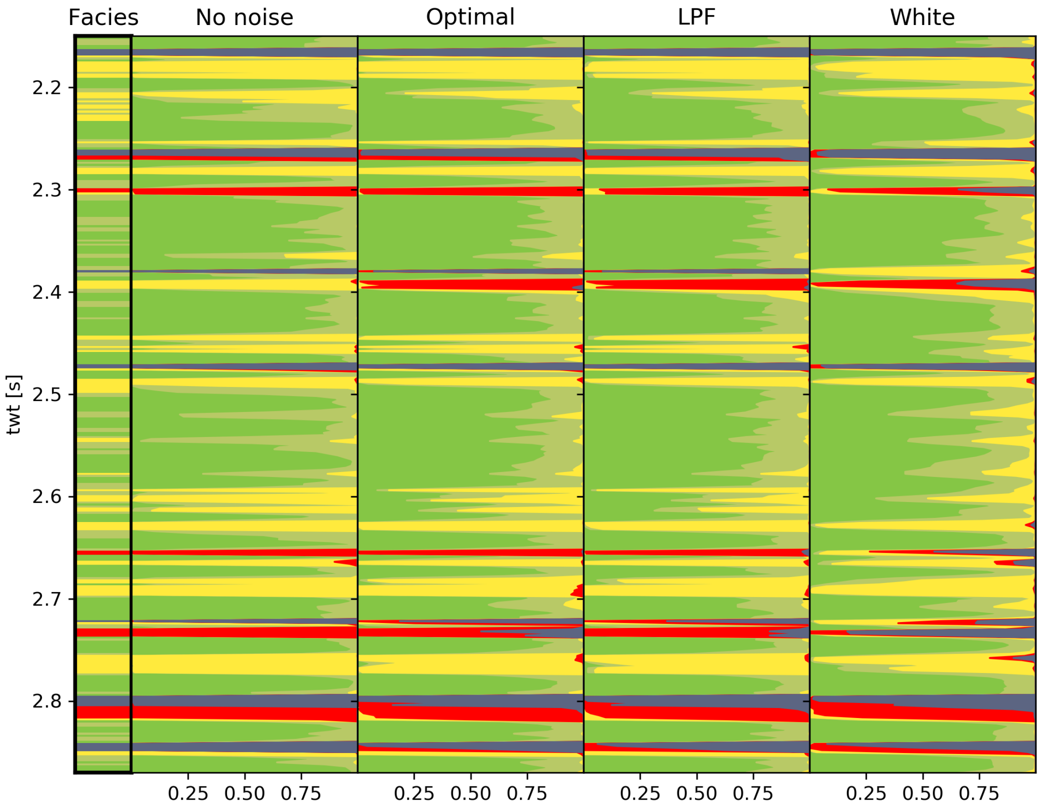

Figure 3 *Probability of finding a given facies from direct probabilistic inversion. Tracks from left to right: ground truth, no seismic noise, optimal noise model (same as generated noise), LPF noise model and white noise model.*

The results of running the direct probabilistic inversion with different noise models can be seen in **Figure 3** and **Figure 4**. The upper limit for what we can infer is when the input is noise free (labelled "No noise" in **Figure 3**). Not surprising, the strong overlap and weak a priori information of spatial differences between shale and silt make it difficult to separate the two facies. However very thin features down to one sample are resolved by the inversion. A few brine sands are not resolved which is due to the large variability of the brine sand facies. The remaining tracks show three different noise models used for inverting the noisy seismic data.

The optimal noise model is one with the same statistical properties as the generated noise. The optimal noise model performs almost as well as the noise free model, however with a few more misclassifications (as defined by the most probable facies). Notice that when the result struggles to identify the correct facies, it is primarily due to the large variability of the brine sand properties (see **Figure 1**) or the noise realisation (see **Figure 2**). The particular noise realisation at around 2.4 s alters the noise free result AVO response from correctly identifying brine sand to identifying it as an oil sand.

The result of using a white noise model clearly shows stronger smoothing of the results including a higher ratio of misclassification as compared to correlated noise models. In particular the very thin facies, even of the acoustically very distinct gas sands are not resolved.

A simple conservative correlated noise model can be constructed that has an autocorrelation function equal to the corresponding frequency spectrum of a low-pass filter (LPF) using a Hann window with a cut-off chosen to be 90 Hz and a gentle slope response not to interfere with the bandwidth of the wavelets. As compared to a white noise model, the LPF model simply states that the seismic noise above 90 Hz is attenuated. The LPF model is not as good as the optimal model, but very close and significantly better than the white noise model in term of resolution and accuracy (see **Figure 3**). **Figure 4** displays the statistical mean of the elastic transfer variables and 95% confidence intervals. The uncertainty is decreased with the LPF model as compared to the white noise model.

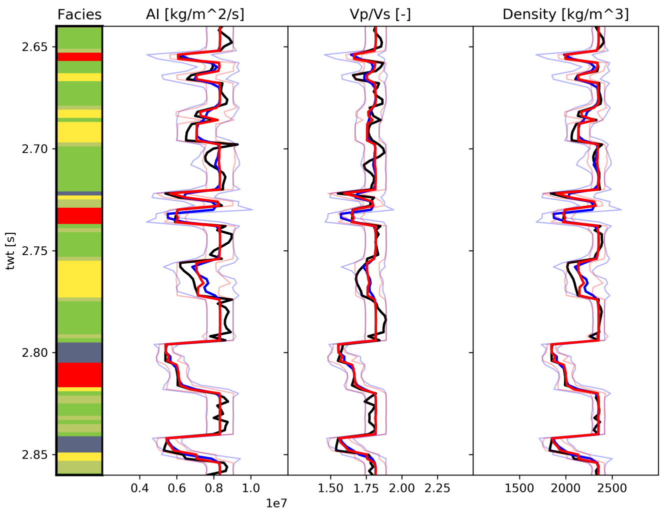

Figure 4 *Statistics of the transfer variables: AI, Vp/Vs and density. Black is the observed synthetic data from Figure 1, blue is the average using the white noise model, and red is using the LPF noise model. The thin lines are 95% confidence intervals.*

Conclusions

It has been shown that using a correlated noise model in a direct probabilistic inversion for facies significantly improved the resolution and detail as compared to an uncorrelated white noise model. The conservative LPF noise model shows potential to increase resolution for the inversion of real seismic data. However, real seismic noise is much more complex than a correlated Gaussian noise model and can be augmented by adding a weak white noise term (assuming that the correlated and the uncorrelated noise is independent).

Acknowledgements

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References

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