Simultaneous lithofacies inversion from prestack amplitudes

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SUMMARY

Lithofacies prediction from well and seismic data is the challenge for the oil and gas industry to accurately describe the subsurface geology.
This paper describes how lithofacies represented by probability vectors can be inverted using simultaneously all the amplitudes corresponding to various distances between source and receiver (offset) reflecting on the same interface.
The inverse problem is solved using a maximum likelihood approach similar to the one described by Tarantola (1987).
Prior information deduced from well is introduced to add high frequency and better conditioning.

INTRODUCTION

Lithofacies are an interpretive view of a group of rocks that have been formed under similar conditions and have similar reservoir properties. This concept is an interesting way of characterizing the subsurface geology.
Well data provides local direct information related to a small volume around the borehole. Seismic data provides large scale indirect information. Both data are usually used to predict lithofacies through seismic impedance inversion and cross plot based transformation.
The approach proposes to invert lithofacies from seismic response. This necessitates a pre-stack seismic modeling technique that can reconstruct amplitudes from series of lithofacies. This forward modeling interpolates amplitude from a known contingency set provided by Democratic Neural Network Association (DNNA) (Hami-Eddine and al., 2009).
Commonly, lithofacies are a qualitative description and are not easily usable within mathematical formulation.
The combination of probabilistic description with forward modeling techniques will open the possibility to perform a lithofacies simultaneous pre-stack inversion.

METHODOLOGY

The current inverse problem is highly ill posed therefore prior information must be introduced for a better conditioning. This prior information is built by predicting well data at any location using structural seismic marker. The prior model introduces high frequency and constrains the inversion. Several techniques can be used to build the a priori model cubes. DNNA (Hami-Eddine et al., 2011) offers an attractive alternative. It allows dealing with multi wells and multi depositional environments, and is structurally consistent. This technique gives for each spatial location of a study area a probability vector, describing the likelihood of a given lithofacies type. The probability vectors collected for the area of interest are used for this lithofacies joint seismic inversion.

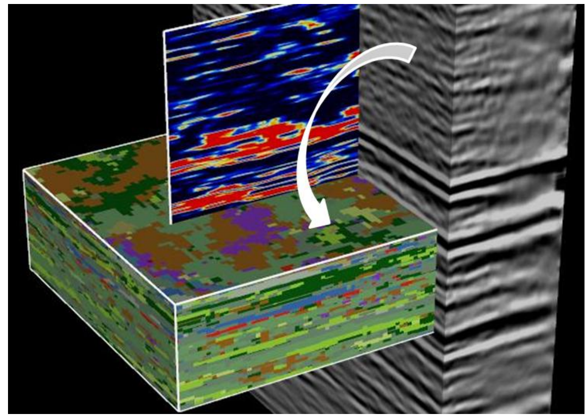

Figure 1: From prestack time migrated gather to most probable lithofacies.

Lithofacies inversion from pre-stack seismic (Figure 1) is a non-trivial innovative approach.
Indeed, common facies description are made using a categorical variable and therefore do not have numerical meaning, or natural sense of ordering. Consequently they are not easily usable in an inversion process. We propose to substitute this common lithofacies categorization by a probabilistic description. Unfortunately, Euclidean geometry is not suitable to work in a probabilistic space. For example, the Euclidean distance between two probability vectors is meaningless. Forward modeling techniques described in (Tarantola, 1987) are meant for data coded in a Euclidean space. The probabilistic space must then be transformed to fit Euclidean space criterion to be usable in an inversion workflow. In order to map probabilities into an Euclidean space, the vectors can be considered as compositional data. Aitchison transform gives the tool needed to bring that probability space to a multi-dimensional Euclidean space.
We propose to directly model the time migrated pre-stack seismic amplitude from lithofacies using multidimensional amplitude interpolation. This approach does not relate to any physical equation but provides interesting results.
After designing the prior model, the maximum likelihood point wise joint inversion can be performed.
To prevent abnormal lithofacies discontinuities, a structural oriented smoothing is applied a posteriori.
The final delivery is a collection of probability cubes related to each lithofacies from which the most likely facies as well as its uncertainties can be deduced.

Stochastic description of the subsurface

At each spatial location, a vector of probability describes the confidence to find a given lithofacies. The set and the confidence of lithofacies are proposed after analyzing the well data. For example, for three lithofacies (1:sand, 2:shale, 3:carbonate) described, a probability vector $\boldsymbol{p} = (p_1, p_2, p_3)$ will be assigned at each spatial location p_i is the probability of occurrence of each of these lithofacies.
The most likely lithofacies is classically taken as the one with the highest probability.

From probability space to Euclidian space

Probability vector can be seen as a particular case of compositional data like volume percent, ppm or molar properties. Instead of considering a probability vector component as a probability value, we consider it as a proportion.

Egozcue (2003) shows that it is mathematically possible to represent compositional data in a Euclidean space.

Using this compositional data Aitchison transformation is a direct way to integrate probability cubes to inversion models.

Pre-stack forward modeling using lithofacies

Pre-stack amplitudes forward modeling consists in rebuilding collection of amplitudes from lithofacies series.

The forward modeling of pre-stack seismic amplitudes uses interpolation of seismic amplitude.

A collection of known pre-stack seismic amplitudes corresponding to a probability vector is provided by the Democratic Neural Network Association (DNNA). The probability vectors maps the different transition from one lithofacies to another.

Pre-stack seismic amplitude is estimated with multivariate inverse distance weighting interpolation method (Shepard).

To prevent possible artifacts, a band-pass filter is applied a posteriori to fit seismic frequency content (Figure 2).

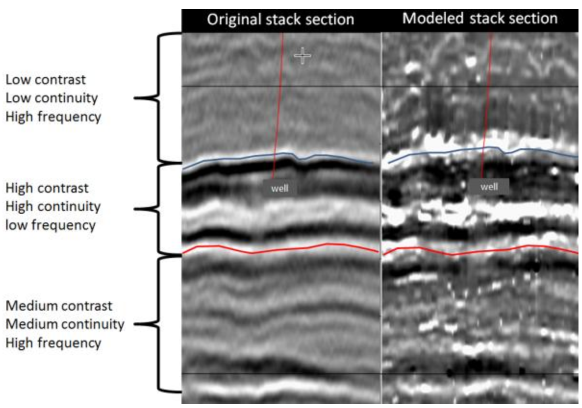

Figure 2: Cross section: Original stack section (left) compared with modeled (from prior model) stack section (right). From top to bottom three different areas can be analyzed: contrast, continuity and frequency are rather well modeled.

Inverse problem: maximum likelihood

The inverse problem aims at reconstructing the model from a set of measurements. Unfortunately, in our case, the seismic response forward modeling is not linear and several models can fit the data. To solve this ill posed inverse problem, a comparison between the estimated model and the true model must be implemented. The appraisal relationship quantifies how much properties have been recovered by the estimated model (Figure 3).

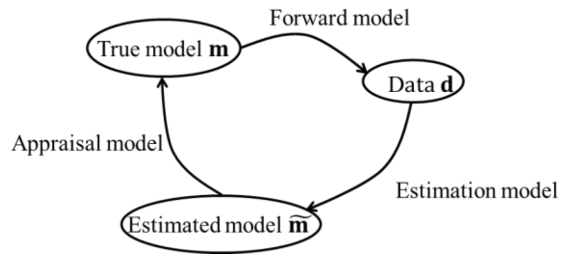

Figure 3: Inverse problem schemes.

We adopt a Bayesian inverse calculation to estimate lithofacies. This mathematical approach is similar to the one developed by Tarantola (1987).

We made the hypothesis that a priori information on data and the model follow Gaussian distributions. Therefore the posterior density can be written as follows:

$$F_M(\boldsymbol{m}) = K e^{-S(\boldsymbol{m})}$$

The maximum likelihood model can be found by minimizing the objective function S(**m**).

This model based approach jointly inverts pre-stack gather on three main steps.

The first step consists in defining the prior model. The confidence associated with the model and the observed seismic amplitude can also be defined.

The second step inverses the data by minimizing the objective function. The objective function is the weighted sum of two terms. The first term measures the mean square error between predicted pre-stack amplitude and the observed pre-stack amplitude.

$$O_d = \|g(\boldsymbol{m}) - \boldsymbol{d}_{obs}\|_{C_D^{-1}}$$

The second term quantifies how much properties have been recovered by the estimated model from the true model. It measures the mean square error between prior model and estimated model.

$$O_m = \left\|\boldsymbol{m} - \boldsymbol{m}_{prior}\right\|_{C_M^{-1}}$$

The steepest decent algorithm such as Newton can help solving the solution of minimizing the objective function S(m).

$$\boldsymbol{m}_{n+1} = \boldsymbol{m}_n - \mathbf{H}_n^{-1}\boldsymbol{\gamma}_n$$

Where $\mathbf{H}_n$ and $\boldsymbol{\gamma}_n$ are respectively the Hessian matrix and the gradient of S at iteration n.

To speedup computation, we use the Quasi-Newton variant that avoids calculating explicitly the Hessian matrix.

Structural oriented smoothing

The smoothing of the facies cube is done by smoothing the probability vector distribution.

Given the orientation (dip and azimuth) and the orientation confidence volumes, the structural smoothing is performed using the weighted median filter. The weighted median filter is a data-driven tool that reduces random noise and enhances laterally continuous events. The filter collects all

amplitudes inside a user-specified rectangle and replaces the center value by the weighted median of values. Weights are taken as confidence values. The effect is an edge preserving smoothing of the seismic data.
This structural oriented smoothing (Figure 4) is applied on the prior model as well as on final delivery of the inversion.

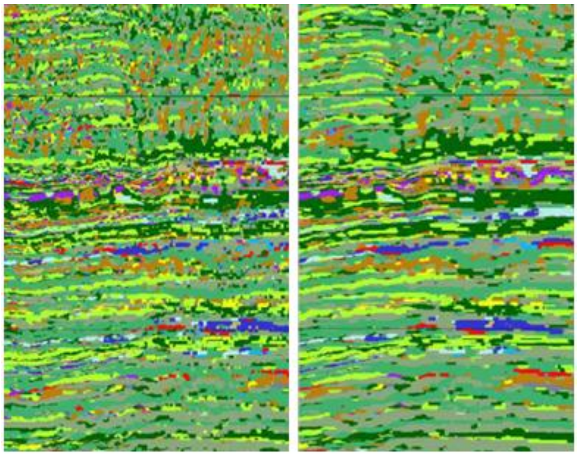

Figure 4 Section of the most probable facies cube before (left) and after (right) structural oriented smoothing. Better continuity, less noise keeping information in place.

MAIN RESULTS ON REEF CARBONATES

The technique has been applied on an existing oil field.
The prior model has been computed using a lithofacies prediction algorithm. At each location, a vector of probability is predicted from wells and guided by seismic data. The prior model has been structurally smoothed to take into account the well data and the structural information.
Confidence on prior model has been chosen as simple as possible, using a diagonal covariance matrix with marginal variance equal to one.

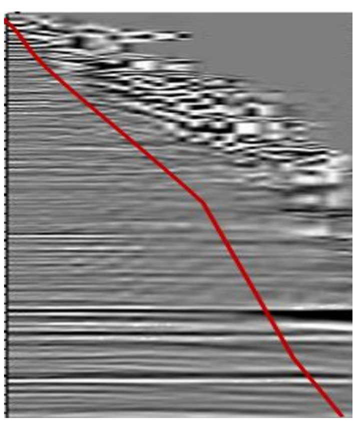

Figure 5: original pre-statck time migrated gather with mute curve (red curve)

Seismic data shows a poor quality at far offsets and a low correlation between offsets. Due to the bad seismic quality, far offsets have been muted (Figure 5). As for the prior model, diagonal covariance matrix with marginal variance has been used. Weights attached to fidelity to model criteria and fidelity to observed data are identical.
The convergence is observed before 30 iterations.

The result is a new collection of probabilities related to each lithofacies (Figure 6).

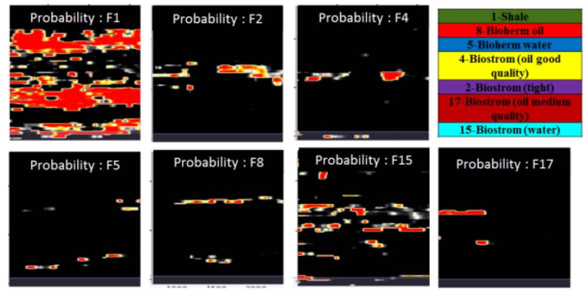

Figure 6: Probabilities section from facies group 1, shale (top left) to facies group 17 Biostrom water (bottom right). High confidence areas are shown in red. Facies lateral continuity can be analyzed on probability sections. Good reservoir facies (4 and 8) probabilities.

From this collection the most likely lithofacies cube corresponding to the highest probability can be computed.
The optimized results are similar to the prior model even if some important changes are noticed (Figure 7).
The shaly lithofacies is more represented than in the prior model. The volume and the continuity of the good quality reservoir are slightly increased. It is noticeable that the result is still consistent with the well data.

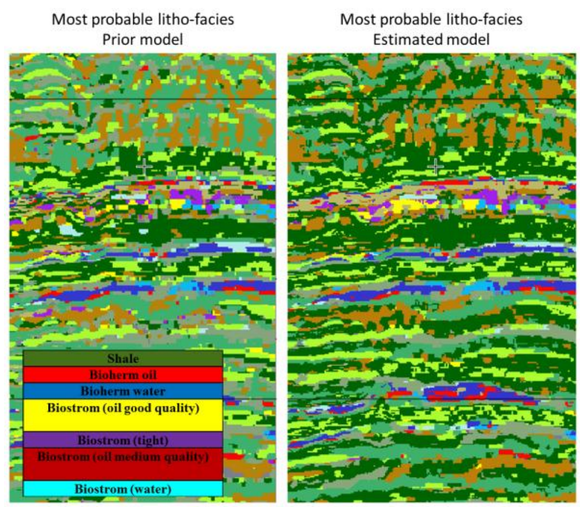

Figure 7: Cross section of the most probable facies: on the left most probable facies corresponding to the prior model. On the right most probable facies after joint inversion. The volume and the continuity of the good reservoir are increased.

CONCLUSIONS

The lithofacies joint inversion can be performed directly using pre-stack seismic data and lithofacies description.

This technique brings added value by optimizing the Democratic Neural Network Association (DNNA) and preserving associated uncertainties.
The probabilistic description associated to Aitchison transformation enlarges the way to use categorical variable. For example, Kriging techniques could be considered to build the prior model.
Simple multivariate interpolation may be used to model pre-stack seismic amplitude. We should be able to enhance the current implementation to have better continuity.

ACKNOWLEDGMENTS
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