F010
Quantifying Structural Uncertainty in Anisotropic Model Building and Depth Imaging: Hild Case Study

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SUMMARY
The paper describes a collaborative project between Total and WesternGeco on quantifying structural uncertainty in application to the development of the Hild field. The key motivation for the project was to improve the seismic uncertainty inputs into the workflows for assessing uncertainty for the gas reserves and risks associated with the development well placement. The main focus of this work was related to the anisotropy ambiguity analysis for more accurate quantifying the structural uncertainty of the BCU top. The workflow used a novel technology of uncertainty analysis in anisotropic model building based on eigen decomposition of the tomography operator and a null-space projection. The main lesson learned was that prior information about anisotropy should be defined thoroughly from the geologic and rock physics perspective and also to be calibrated with the available well data. Overall, the project turned out to be successful and the results enabled more confident decision making in the Hild field development.
Introduction

Due to the inherent non-uniqueness of the seismic experiment, many different Earth velocity models can exist that match the observed seismic data, which results in uncertainty in the true position of events. These structural uncertainties can lead to volumetric uncertainties and impact field development planning (Chavanne et al., 2008). While the underlying ambiguity can never be fully eradicated, a quantified measure of these uncertainties provides deeper understanding of the risks and related mitigation plans. This paper describes a collaborative project between Total and WesternGeco that was carried out between June 2009 and 2010 to implement the uncertainty analysis workflow as per Osypov et al. (2008a, 2008b, 2010). The objective was to understand and quantify these uncertainties so they could be used later by Total as input to the in-house uncertainty workflow for development risk assessment.

Methodology

The uncertainty analysis method of Osypov et al. (2008a, 2008b, 2010) is applied after the last non-linear iteration of tomography when the solution has converged and driven the flatness of the gathers to acceptable levels. The quantitative analysis basic workflow can be summarized in six steps:

1. Iterative eigen decomposition of the anisotropic tomographic operator.
2. Random model generation for a given prior covariance.
3. Modify the models to fit data using the decomposition results. The resultant posterior models are all valid solutions to the original tomography problem: they both keep the misfit at the noise level and satisfy the original prior information and geological constraints.
4. Validate the models by checking the predicted residual moveout.
5. Perform map migrations of horizons of interest for the set of obtained perturbations in velocity and the anisotropic parameters ε and δ.
6. The resulting sets of target horizons are statistically analyzed and structural uncertainty estimates are derived.

More specifically, eigen decomposition at step 1 is performed on a Fisher information operator in the preconditioned space $F = (LP)^T D^{-1} (LP)$ by use of Lanczos iterations. Thus, the resulting decomposition is $F = UΛU^T$, where $U$ is a matrix of eigenvectors and $Λ$ is the corresponding diagonal matrix of eigenvalues. Note that, at step 2, the prior covariance matrix is parameterized as $C_0 = PP^T$, where $P$ is the preconditioner.

One of the key elements of the posterior-distribution sampling process at step 3 is the interplay between the geomodel space (defined by a velocity, $ε$, and $δ$ vector) and the so-called preconditioned space (defined such that application of the preconditioner to a vector from this space produces the vector from the geomodeled space). The posterior covariance matrix, by definition, is the inverse of the sum of the Fisher operator and the inverse of the prior covariance matrix. Because the prior covariance matrix in the preconditioned space is the identity matrix, it has full rank, and thus, the posterior matrix also has full rank. Because the model vector typically has more than one million elements, rather than explicitly storing the posterior covariance matrix whose size is the square of the model vector, it is more practical to store random samples of it. For this objective, we first consider two components of the $C_p$, posterior covariance matrix in the preconditioned domain. The first component is $U(Λ + I)^{-1}U^T$ and it corresponds to the eigen decomposition of $F$. The second component is $I - UU^T$ and it corresponds to the null-space projection operator. Combining these two components we get:

$$C_p = I - UU^T + U(Λ + I)^{-1}U^T = I - U\frac{Λ}{Λ + I}U^T.$$
Each random sample vector, $\Delta \hat{X}'$, drawn from the posterior distribution is computed as:

$$\Delta \hat{X}' = C_p^{1/2} r = \left[ I - U(I - (A + I)^{1/2})U^T \right] r.$$  

Here, $r$ is a random vector sampled from a unit multinormal distribution. Application of the preconditioner to the resultant vectors maps the sample models pulled from the posterior distribution into the geomodel space. The resultant models are all valid solutions to the original tomography problem; they both keep the misfit at the noise level and satisfy the original prior information and geological constraints.

Having performed the iterative eigendecomposition once, multiple posterior models are derived, from which a subset of models can be selected by performing recursive sifting based on fits with well data.

**Case Study**

The Hild field is located approximately at 60° 30' N and 2° E, 180 km west of Bergen. The reservoir, broken by numerous faults, lies in the Middle Jurassic Brent formation at depth greater than 3600 m. The area studied was 22.5 km x 20.1 km ($450 \text{ km}^2$).

The input data for the project was taken from the output of a final migration with a multilayered hybrid tomographic model. This consisted of common-image-point (CIP) gathers from three azimuths of streamer data and CIP gathers from the all-azimuth output of the ocean-bottom cable (OBC) data (Douillard et al., 2009). Sonic velocities and markers for six wells were used for interactive vertical transversely isotropic (VTI) ray tracing and anisotropy analysis to build the model. The tomographic model contained a total of nine layers. Anisotropy parameters $\varepsilon$ and $\delta$ within the layers were constant values (Figure 1). The objective was to analyze the uncertainty related to the tomography process and quantify the vertical uncertainty at the base Cretaceous unconformity (BCU) horizon above target Brent reservoirs.

![Figure 1 Reference anisotropic model.](image)

Defining range and scale of priors for each layer in the model was one of the most challenging and important aspects of this project. The use of existing wells to address the sensitivity of gathers flatness to velocity and anisotropy changes turned out to be far too conservative to describe the variability of priors. Alternatively, a thorough lithologic and rock physics analysis for all layers of the model allowed us to derive reasonable ranges of a priori anisotropic parameters. In particular, an important decision was made to include the short scale length variability anticipated in the turbiditic sediments in Layer 4. By means of the above priors, we parameterized the covariance matrix and generated 618 models sampled from this prior distribution.
Next, we applied the algorithm above such that these samples become samples out of the posterior distribution. The next step is the anisotropic map migration of the target BCU horizon with the 618 posterior models to derive a set of posterior depth maps in line with the model uncertainty. Well misties at eight locations were then used as cross-validation to sift the models to a given threshold (based on an estimate of the average gather flatness sensitivity from 1D modelling). As a result of the sifting, the total number of eligible models was reduced from 618 to 108.

Standard deviation maps (STDs) of the map-migrated BCU surfaces were produced for both the unsifted 618 models and the sifted 108 models (Figure 3).

The standard deviation map at BCU was then used as one of the key uncertainty maps (together with, e.g., Brent interpretation uncertainty maps) as input to the Total uncertainty workflow (Chavanne et al., 2008). The resulting output was the range of gas-bearing gross rock volume and the spatial distribution of structural uncertainties over the target field, Hild-East (Figure 4). The former is a primary input to the evaluation of possible ranges of gas in place and reserves, while the latter can be used to define risks attached to each fault panel for development well placement.
Figure 4 Combined structural uncertainty map (1σ in meters) at top Brent reservoir with fault panels – Gas-bearing gross rock volume histogram within field perimeter.

Conclusions

Decisions for field development well placement should take into account the structural exploration risks associated with the uncertainty of our knowledge of the velocity model used in seismic imaging. The Hild case study demonstrates the workflow for the statistical analysis of structural uncertainties associated with the ambiguity of tomographic velocity model building. This approach leads towards risk analysis in appraisal by incorporating the structural ensembles from the seismic imaging uncertainty analysis into the multiple realizations of geological and reservoir models.

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References


