High-resolution reservoir characterization by 2-D model-driven seismic Bayesian inversion: an example from a Tertiary deltaic clinoform system in the North Sea

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Summary

In order to retrieve a high-resolution reservoir model from seismic and well data, an approach was developed based on an *a priori* layered model from well data, specifically the acoustic impedances derived from the sonic and density logs. The procedure consists of using a forward model of the well data as *a priori* information that is then iteratively matched with the seismic data using a Bayesian inversion process. The inversion is then extended to 2D, whereby the extrapolation is guided by a simple geometric envelope described with a small number of parameters. It is tested on a seismic data set containing a deltaic clinoform in the North Sea, whereby the clinoform geometry is parameterized by a sigmoid and used as prior information. In the subsequent optimization the clinoform geometry is further refined with a limited number of local knots to improve the match with the seismic data. This low-parameterization inversion approach thus uses geological shapes and well constraints to obtain a subsurface model than can have a substantially higher resolution than the seismic wavelength.

Introduction

Most problems in geophysical inverse theory are ill-posed in the sense of Hadamard. For inverse problems with real-world data, *e.g.* a signal contaminated by noise, very different models may fit the data equally well. One of the possible methods to overcome such problems of ill-conditioning and noise inherent to solving inverse problems is a technique known as Bayesian approach. This technique incorporates data-independent *a priori* information in order to favor realistic models over unrealistic models.

Several recent studies have emphasized the importance of high-resolution inversion techniques in order to resolve thin-bedded reservoirs, having thicknesses at the sub-wavelength scale. The primary focus of this paper is the development of a 2D method (in *x-t* cross-sections of the data set) that estimates the acoustic parameters and thicknesses of a clinoform sequence composed of layers at the sub-seismic scale.

Clinoforms are typical progradational patterns that occur over a wide range of scales and in a broad spectrum of depositional environments, all of which may be conducive to form potential reservoirs. The method was tested on an example of the Upper Cenozoic fluvio-deltaic system in a 3D seismic dataset of block F3 in the North Sea.

Field description

Geological setting

F3 is a block in the Dutch sector of the Southern North Sea. During the Cenozoic era, much of the North Sea region was characterized by a thermally subsiding epicontinental basin most of which was confined by landmasses (Sørensen *et al.*, 1997). During the Neogene, sedimentation rates exceeded the subsidence rate and consequently shallowing of the basin occurred. A large fluvio-deltaic system dominated the basin, draining the Fennoscandian High and the Baltic Shield. The Cenozoic succession can be subdivided into two main packages, separated by the Mid-Miocene Unconformity MMU (Figure 1). The lower package consists mainly of relatively fine-grained aggradational Paleogene sediments (Steeghs *et al.*, 2000), while the package above the MMU consists of coarser-grained Neogene sediments with much more complex geometries. Most of it is a progradational deltaic sequence that can be subdivided into three units, corresponding to three sequences of delta evolution, depicted in Figure 1 as Unit 1, 2, and 3. The dominant direction of progradation is towards West-Southwest and is expressed as sigmoidal lineaments in the dip section (Tigrek, 1998). A seismic cross-section through this delta sequence is displayed in Figure 2. Unit 2, containing a conspicuous clinoform package, was chosen as target zone for this study.
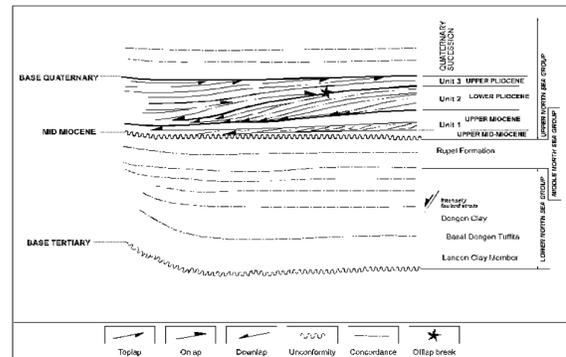

Figure 1: Schematic seismic interpretation of the Tertiary sequence in the area of interest (after Tigrek 1998)

Data

A 3D seismic survey in block F3 covering an area of approximately 16×23 km^2 has become publicly available

and is provided by a monograph of Aminzadeh & de Groot (2006). The data volume consists of 646 in-lines and 947 cross-lines. The line spacing is 25 m for both in-lines and cross-lines, and the sample rate is 1 ms. A standard seismic data processing sequence was applied to the data. Data from four wells in the area are available, in particular well logs in true vertical depths, including sonic and gamma ray logs. Density logs were reconstructed from the sonic logs using neural network techniques. The sonic logs were also used to calculate porosity logs for all wells. Unit 2 has a time thickness of about 90 ms and is fully penetrated by well F03-04, whose location is shown in Figure 2. Its check-shot and well logs have been used for time–depth conversion and to validate the general seismic interpretation.
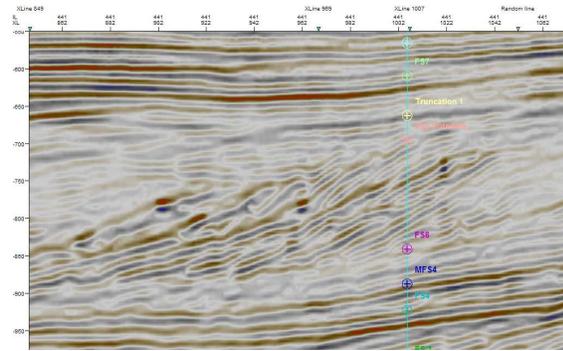

Figure 2: Seismic line with the clinoform in Unit 2 and the location of well F03-04

Method

In order to achieve the main goal of this paper - a 2D sub-seismic characterization of the deltaic sequence - two major steps are performed. First the acoustic parameters of the clinoform package are estimated close to the well location. Then the clinoform elements are geometrically modeled using a Bayesian optimization procedure. These then will guide the prediction of the initial acoustic properties and layer thicknesses for the next trace as priors.

Step 1: 1D Sub-seismic characterization of the deltaic sequence

Construction of the a priori information
Over the last 30 years the Bayesian-based seismic inversion technique has been extensively enhanced in its accuracy and efficiency (Tarantola, 1984, Duijndam, 1988). Tikhonov & Arsenin (1977) developed a regularization method that restricts the family of models that fit the data. The two main issues in the Bayesian approach that received most attention are how to obtain _a priori_ information and how to evaluate parameter uncertainty. Gouveia & Scales

(1998) described an approach where _in situ_ (borehole) measurements are used to derive an empirical prior for seismic data. The _a priori_ knowledge of parameters usually consists of the expected values expressed as the mean and the standard deviation (to indicate the uncertainties of these values). A frequently used probability density function to describe this type of information is the Gaussian distribution. Here the log data of well F03-04 were used to estimate the _a priori_ parameters.

Lithofacies Analysis
The vertical resolution of seismic data is in the order of tens of meters, whereas the resolution of well data is in the order of tens of centimeters. Therefore a "Thick-layer Model" with typical thicknesses of 2-30 m was created based on sonic, density and gamma ray logs. These layers are below the seismic resolution, with thicknesses of up to 1/15th of the wavelength, but considerably thicker than the resolution of the well logs. Thus they are expected to have some indirect effect on the seismic signal. The logs were first smoothed with a 2 m long arithmetic, box-shaped filter along the entire length to reduce noise and remove smaller details. From the gamma-ray and the sonic log 24 sand- and shale-rich layers were determined over the main clinoform, resulting in the "Thick-layer Model" depicted in Figure 3 (left). The acoustic properties (P-velocity and density) were then averaged within each layer and an acoustic impedance trace for the normal-incidence-angle case was generated, together with a reflectivity trace to serve as _a priori_ means. The standard deviation of these parameters was calculated based on the parameter distribution along the target zone.
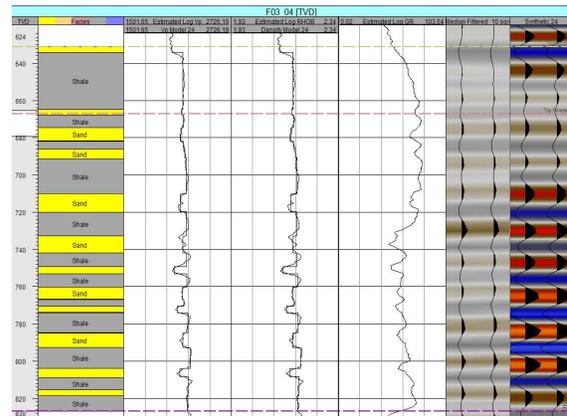

Figure 3: Well data with: The "Thick-layer Model", sonic, density and gamma ray logs, the seismic trace at the well location, and the synthetic seismic trace.

The Forward Model
The forward model consists of a 1D convolution method using primaries. The source wavelet is convolved with the

normal-incidence reflectivity time-series to simulate a 1D seismic trace. The time sampling step was set to $dt = 1$ms, which is identical to the time sampling step of the actual seismic data set.

Wavelet Extraction
The statistical extraction method used in estimating the wavelet assumes that the autocorrelation of the wavelet is the same as the truncated autocorrelation of the seismic trace. The average autocorrelation from several seismic traces is used to provide a more representative estimate. The wavelet depends on the depth and rock properties of the target zone. Therefore, the seismic data cube was cropped to a sub-volume of 100 in-lines by 100 cross-lines around the well in the lateral directions and from 661 to 840 ms (the target zone) in the vertical direction. The resulting extracted wavelet is a zero-phase wavelet with a central frequency of 55 Hz and is shown in Figure 4 together with its spectrum.
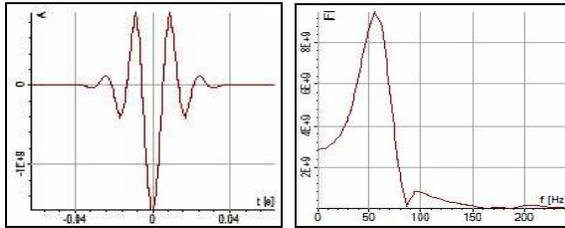

Figure 4: The extracted wavelet and its spectrum

A well-based synthetic seismogram was then created by convolving the reflectivity trace (computed from the "Thick-layer Model") with the extracted wavelet. The resulting synthetic seismogram, depicted in Figure 3 (right), does not show a good match with the real data. A better match can be obtained by refining the thicknesses and the acoustic layer properties, and hence the reflectivity trace, through Bayesian inversion by employing a nonlinear least-squares estimator that maximizes the *a posteriori* probability. Here the quasi-Newton method with the Broyden-Fletcher-Goldfarb-Shanno update formula for the Hessian matrix is used as an optimization tool. The P-velocities, densities and thicknesses of the "Thick-layer Model" in the clinoform are then obtained through optimization of the match between the updated synthetic and the real seismic.

Step 2: 2D Sub-seismic characterization of the deltaic sequence

Once the acoustic parameters of the seismic data are estimated at the well location, the next step is to extrapolate this knowledge in a lateral direction along the clinoform

dip. For this, we first have to determine the exact clinoform shapes.

The Forward Model
From a geometrical point of view a clinoform sequence can be approximated by a set of translated sigmoidal curves. The sigmoid function $f_i(x)$ may be described by four parameters using

$$f_i(x) = c_i + \frac{b_i}{1 + e^{-(x-d_i)/a_i}} \, ,$$

where a_i is a lateral scaling, b_i is a depth scaling, c_i is a depth offset and d_i is a lateral translation.

Although the sigmoid may qualitatively describe the global trend, such a simple analytical function cannot be expected to exactly match an actual geological body. Since our aim is to arrive at a sub-wavelength resolution in the description of the clinoform, it needs to be modeled with a higher accuracy. We use a nonlinear geometric disturbance by locally stretching or compressing the sigmoid in the lateral direction. This is done between a set of equi-lateral spaced control points (knots) along the sigmoid. Only in areas where the discrepancy between the clinoform and the sigmoid curve exceeds a certain threshold, the knots are displaced to improve the fit. The number of knots depends on the ratio of the lateral size of the clinoform and the amount of seismic traces available in that area. The more knots are used, the more unknown variables are needed in the minimization procedure, but, on the other hand, more knots allow a better approximation of the actual clinoform. Therefore, an optimum model complexity needs to be strived for.

For the current clinoform model, a set of tests was done in order to find an optimum number of knots (25 per curve) needed for the best approximation. This geometrical disturbance was applied separately to each curve, after which the clinoform boundaries remain monotonic functions resembling a sigmoid, but are mathematically no longer exact sigmoidal curves. The advantage of using this method above a standard approach, where every point of the clinoform is perturbed, is the considerably smaller amount of parameters that needs to be estimated.

Construction of the a priori information
An initial guess of the four parameters describing the sigmoid function $f_i(x)$ for the first (oldest) clinoform curve is made from the seismic section by visual inspection. The parameters accounting for local stretching/compressing are initially zero and have a prior with zero mean. The Bayesian inversion method is used to optimize all sigmoid parameters.
We assume that geological objects are not random structures, but that they follow certain typical patterns

caused by the depositional processes that formed them. Therefore, three sigmoid parameters are expected not to vary significantly for subsequent clinoforms within a clinoform package. Only the lateral translation parameter d_i requires to be adjusted by introducing a shift (equal to a small fraction of the length of the clinoform) for every curve. Since local stretching or compressing parameters are individual for every clinoform their initial value and prior mean remain zero. The procedure uses the output of the optimization routine of the preceding clinoform as the initial value and prior, and this is repeated for every following clinoform within the deltaic sequence.

Results
The acoustic parameters (P-velocity and density) and thicknesses for each layer of the "Thick-layer Model" were estimated with an error of less than 10%. Based on these data, an updated reflectivity trace was computed for a normal-incidence case. Then new synthetic seismograms were calculated by convolution of the updated reflectivity time-series with the extracted wavelet. The comparison of the real data, well-based synthetic seismogram and optimized synthetics are represented in Figure 5.

Figure 5: Comparison of traces of the well-based synthetic seismic (1), the estimated model (2) and the actual seismic data (3)

Four selected clinoforms from the deltaic package were subsequently estimated in 2D using the results of the preceding clinoform as *a priori* means. The resulting optimized clinoforms are depicted in Figure 6 in red, together with a semi-automated pick from the seismic section in blue and the a priori model in green. Although the *a priori* lines differ greatly from the optimized results, the latter are seen to match the blue ("ground truth") lines very well. Figure 7 shows an enlargement of the same area with the optimized clinoforms plotted over the seismic section. As can be seen here as well, the match with the real data is very good.

Figure 6: Comparison of the clinoforms of the a priori (green), the estimated model (red) and the seismic interpretation (blue)

Figure 7: Enlargement of the seismic line showing the estimated clinoforms (dotted line) and the seismic interpretation (solid lines)

Conclusions

The Bayesian seismic inversion method presented here uses *a priori* information obtained from well data and shows encouraging results when applied to a clinoform field example from the North Sea.
Acoustic parameters (P-velocity and density) of the sub-seismic layers with thicknesses as thin as 1/15th of the seismic wavelength were estimated with a high accuracy (errors of less than 10%).
The proposed automated procedure results in a two-dimensional geological model of the subsurface and to incorporate these models in the high-resolution Bayesian inversion process. The results demonstrate a good match with the measured seismic and the *a priori* information. The clinoform model can be used to steer the trace inversion. From the estimated acoustic parameters and layer thicknesses a depositional model with sub-seismic resolution can be constructed.

Acknowledgements