Introduction

Inversion of seismic data is a widely used tool in the oil and gas industry for refining the reservoir geometry and characterization. The low vertical resolution of seismic amplitude data is the main motivation for implementing a stochastic Bayesian inversion, where information from all available sources is integrated into a consistent reservoir model. The improved vertical resolution is mainly due to the well-log data whereas the lateral structures are inherited from the seismic data (Van Riel and Mesdag, 1988; Van Riel and Pendrel, 2000).

The objective of this study is to develop a quantitative, 2D inversion method which allows characterization of fluvio-deltaic sequences at a subseismic scale. Specifically, the study focuses on fluvio-deltaic clinoform systems which are known to have complex internal lithofacies distributions that are difficult to image by conventional seismic methods. However, these sedimentary systems often contain prolific oil and gas reservoirs, and their accurate characterization is therefore desired in exploration and production. An earlier attempt to clinoform characterization at subseismic scale was done on a method that integrates a stratigraphic model constructed with quantitative knowledge of the reservoir architecture (Tetyukhina et al., 2008). The innovation of the proposed method lies in its goal to adopt a 'super-resolution' technique that favors sparse solutions (Van Eekeren et al., 2008) for the characterization at a subseismic scale. This inversion method was applied to a 3D seismic data set of an Upper Cenozoic fluvio-deltaic system in block F3 in the North Sea.

Field description

F3 is a block in the northeastern part of the Dutch sector of the North Sea. During the Cenozoic era, much of this region was occupied 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 (Figure 1(a)). The upper package consists of coarser-grained Neogene sediments with very complex geometries (Steeghs et al., 2000). Most of it is a progradational deltaic sequence that can be subdivided into three units corresponding to three phases of delta evolution (Figure 1(a)). Unit 2, containing a conspicuous clinoform package, was chosen as target zone for this study and forms the delta foreset with a coarsening upward sequence. Its age is estimated as Early Pliocene.

A 3D seismic survey in block F3 was acquired to explore for oil and gas in Upper Jurassic - Lower Cretaceous strata. It has become publicly available and is accompanied by a monograph of Aminzadeh and de Groot (2006). The seismic data are poststack, time-migrated data. A standard seismic data processing sequence was applied to the raw data. The seismic cross section displayed in Figure 1(b) was selected to be characterized. Unit 2 has a time thickness of about 230 ms and is fully penetrated by well F03–04, whose location is shown in Figure 1(b). Only sonic and gamma-ray logs are available in the well. A density log was reconstructed from the sonic logs using neural network techniques (Aminzadeh and de Groot, 2006).

Method

The forward model is a well known one-dimensional convolution model, in which transmission effects and multiples are neglected. Under the assumption of normal incidence of the downgoing waves on the reflectors, reflection coefficients are determined by the acoustic impedances.

The exact source wavelet was not available and therefore a statistical extraction method was used to estimate the wavelet from the seismic data. The extracted wavelet is a zero-phase, symmetrical wavelet with a central frequency of 55 Hz (the wavelength is approximately 40 m). We used the sonic and density logs of the well F03–04 as a priori information. In order to use as much a priori information as possible, an impedance log – computed from the velocity and density logs – served as the a priori mean vector. One way to estimate uncertainties in the parameters when only a single well is available is by using the histogram of all well measurements obtained from the target zone. We used the standard deviation of the best-fit Gaussian distribution to the histogram of the acoustic impedance as the basis for the a priori covariance matrix.

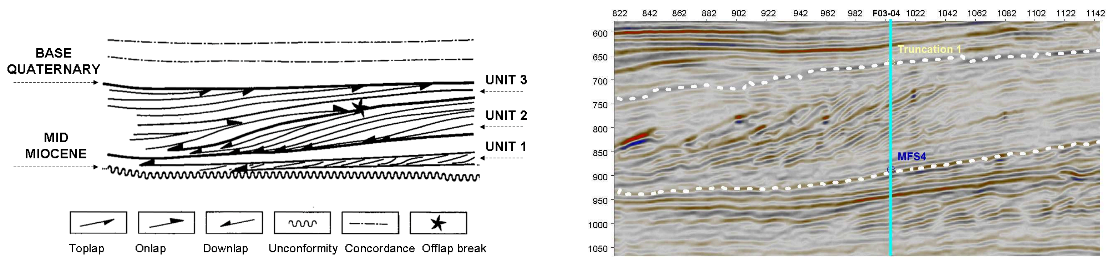
To enforce a sparse solution we adopted a method by Van Eekeren et al. (2008) that was successfully applied to obtain super-resolution reconstruction of small moving objects. This method employs a similar data misfit term as in the Bayesian cost function (Duijndam, 1988), but employs regularization terms that favor sparse solutions, i.e., solutions for which $\|\nabla \boldsymbol{x}\| \approx 0$ for the majority of the samples. The regularization within one trace is performed by a so-called 'vertical operator'. This vertical operator favors a sparse inversion solution in vertical direction, i.e. promotes a blocky, layer like solution. Additionally, a 'horizontal operator' enforces lateral continuity of the 2D inversion results and thereby supports propagation of the well data along the clinoform sequence.

1D Inversion In order to create the initial model, the well impedance data are resampled with a constant time step. The sampling time step determines the desired vertical resolution of the inversion results. An initial model for the current trace is the resulting estimate of the previously inverted trace. The first additional term, the so-called vertical operator, is the sum of absolute differences between adjacent samples in the solution vector of the trace. This term favors solutions in which the sum of gradient magnitudes is small and is responsible for a sparse layering by penalizing absolute differences between adjacent samples.

The minimization is done in an iterative way using the Levenberg-Marquardt method, which assumes that the cost function has first and second derivatives that exist everywhere. However, the L_1-norm does not satisfy this assumption. Therefore, we use a hyperbolic norm as introduced by Van Eekeren et al. (2008), for which these derivatives exist while behaving as an L_1-norm. The model parameters are found by minimizing

$$F(\boldsymbol{x}) = (\boldsymbol{y} - \boldsymbol{g}(\boldsymbol{x}))^T \boldsymbol{C}_n^{-1} (\boldsymbol{y} - \boldsymbol{g}(\boldsymbol{x})) + \lambda(\boldsymbol{x} - \hat{\boldsymbol{x}})^T \boldsymbol{C}_x^{-1} (\boldsymbol{x} - \hat{\boldsymbol{x}}) + \\ + \mu \sum_j \left(\sqrt{(x_j - x_{j-1})^2 + 1} - 1\right), \tag{1}$$

where $\boldsymbol{x}$ is the vector of unknown acoustic impedances, $\boldsymbol{y}$ is the vector of poststack seismic reflection data at the location of the well, $\boldsymbol{g}(\boldsymbol{x})$ is the forward model based on a 1D convolution with the estimated wavelet, $\boldsymbol{C}_n$ is the covariance matrix of the poststack seismic data, $\hat{\boldsymbol{x}}$ is the mean prior, $\boldsymbol{C}_x$ is the covariance matrix, j the sample number, and λ is the regularization parameter.



(a) (b)

Figure 1 *(a) Sketch of the Neogene fluvio-deltaic system in the Southern North Sea (from Steeghs et al., 2000). (b) The seismic section (inline 441) used in our analysis and containing well F03–04.*

2D Inversion of the Clinoforms The second additional term, named horizontal operator, is a sum of absolute differences between lateral samples in two neighbouring seismic traces. This term accomplishes two tasks at once. First, it promotes continuity of the inversion results along the clinoform sequence. Second, it propagates the a priori knowledge from the well to the current trace. Based on the above mentioned consideration, a hyperbolic instead of the L_1-norm is used.

The original second term in the cost function, which is the weighted L_2-norm of the deviations of the parameters from their a priori mean values, is omitted starting with the second seismic trace. Here, the horizontal operator propagates the well data to the current trace and, at the same time, takes lateral variations of the impedances along the sequence into account. The functional to be minimized for traces $m > 1$ is

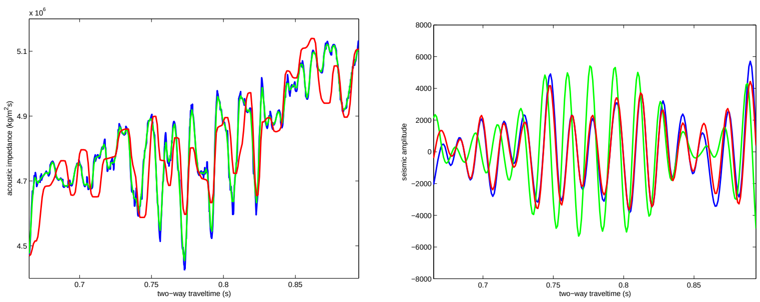
$$F(\boldsymbol{x}^m) = (\boldsymbol{y}^m - \boldsymbol{g}(\boldsymbol{x}^m))^T \boldsymbol{C}_n^{-1}(\boldsymbol{y}^m - \boldsymbol{g}(\boldsymbol{x}^m)) + \mu \sum_j (\sqrt{(x_j^m - x_{j-1}^m)^2 + 1} - 1) + \\ + \gamma \sum_j (\sqrt{(x_j^m - x_j^{m-1})^2 + 1} - 1). \tag{2}$$

Regularization Minimization (of our modified version) of the Bayesian cost function is an ill-posed problem and therefore regularization needs to be applied. The parameter λ sets the balance between the data misfit and the deviation with the a priori information. Although this term is used in inversion of the first trace only, it still plays an important role in transferring the well data into the entire sequence. The regularization parameter μ, in front of the vertical operator term, restricts the amount of layers in the inverted trace. The regularization parameter γ, in front of the horizontal operator term, causes continuity inside a layer, but it permits a discontinuity if a layer appears or disappears. We have chosen a follow set of the regularization parameters λ=1, μ=4, γ=1.

Results

Figure 2(a) illustrates the difference between the initial model (green) and the estimated model (red) of the first trace, that are superimposed on the actual impedance log (blue). The estimated impedance depicts a good correlation with the well data. The vertical resolution of the method is high and lies beyond the seismic resolution; layers with thicknesses of up to 1/10$^{\text{th}}$ of the wavelength are well resolved. Figure 2(b) shows the synthetic seismic trace based on the initial model (green), the synthetic seismic based on the estimated model (red), on top of the actual seismic data (blue). The method yields a good match between the estimated model and the actual seismic.

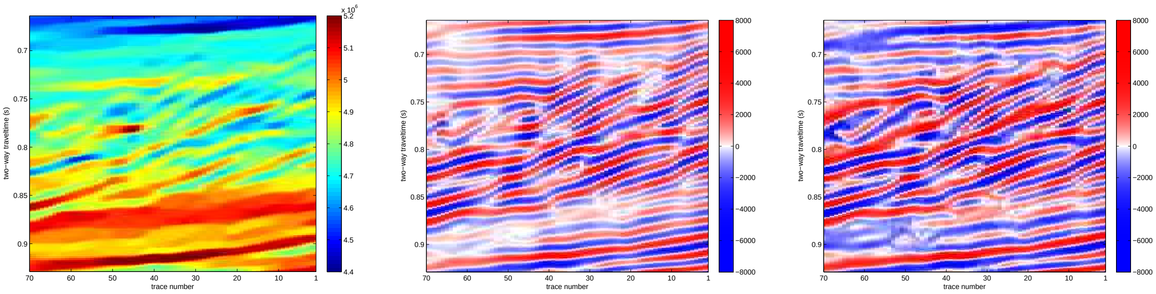
The estimated impedance model of the selected 2D seismic section is shown in Figure 3(a). The result reveals a high degree of lateral continuity of the impedance properties along the sequence. The simulated



(a) (b)

Figure 2 *Results of the 1D Inversion for the method: initial model (green) and the estimated model (red) superimposed on the actual impedance log (blue) (a); traces of the synthetic seismic based on the initial model (green), the seismic based on the estimated model (red), and the actual seismic data (blue) (b).*

seismic sections based upon the estimated impedance model are displayed in Figure 3(b). The figure illustrates that the method provides a good match with the seismic data. The actual seismic section is displayed in Figure 3(c).



(a) (b) (c)

***Figure 3** Resulting 2D impedance model of the Clinoforms (a); the simulated seismic sections based upon the estimated impedance model of the clinoforms (b) and the actual seismic (c).*

Conclusions

The present study proposes a 2D inversion method that allows characterizing a fluvio-deltaic clinoform sequence at a subseismic scale. The method is quantitative and especially useful when important architectural elements of a reservoir lie below the resolution of the seismic data. The inversion method presented here shows encouraging results when applied to a clinoform sequence from the North Sea. The results demonstrate a good match with the measured seismic data and well information.

The innovation of the method presented here is that the Bayesian objective function is successfully modified by adding vertical and horizontal operators, which favor a sparse inversion solution and promote continuity of the inversion results along the sequence. The latter is responsible for the propagation of well data from trace to trace. The vertical resolution of the seismic data was largely increased by incorporating the well data. The method has the capability to increase the vertical resolution of the resulting 2D geological model to a level defined by the user.

Acknowledgments

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