Ray-Based Stochastic Inversion: improving reservoir characterisation in a Gulf of Mexico field

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SUMMARY

The potential has been tested, for the first time on field data, of a newly developed method for reservoir parameter estimation: Ray-Based Stochastic Inversion [RBSI, Verdel et al. (2004)]. A special case of RBSI offering practical advantages, 1D convolutional RBSI, was applied to invert seismic field data from the Gulf of Mexico.
A comparison was made of the new method's estimates for reservoir-layer thickness and P-velocity, with the estimates found by conventional stochastic trace inversion (SI), and with the actual values at a well drilled after the inversion was done. Despite the fact that this special case of RBSI uses only 2% of the pre-stack data, the result indicates it has improved accuracy on the dipping part of the reservoir, where SI suffers from wavelet stretch due to migration.

INTRODUCTION

Seismic trace inversion techniques are aimed at determining subsurface rock and pore-fluid parameters from seismic reflections. Commonly, SI is applied to invert traces from the migration image in the reservoir zone, to obtain reservoir-layer parameter estimates including uncertainties. SI inverts migrated data using a 1D convolutional forward modelling kernel; it thereby relies on the preceding migration procedure to take into account the wave propagation path effects through the subsurface given a coarse subsurface migration velocity macro-model.

In practice however, even true-amplitude pre-stack depth migration (TA PreSDM) does not yield the perfect band-limited image of the Earth's reflectivity as assumed by SI: the migration image has finite lateral resolution, and limited illumination of reflectors, see e.g. Chen and Schuster (1999) and Toxopeus et al. (2003). Moreover, reflection angle information — crucial for resolving the reservoir parameters — is often blurred (Levin, 1998) by processing steps such as angle-range substacks for enhancing signal-to-noise ratios. Furthermore, on the migration image wavelet distortion inevitably occurs (Tygel et al., 1994), while most trace inversion algorithms make use of a stationary wavelet. Finally, the migration image is the fixed result of an extensive, separate processing scheme. Any possible flaws in the migration preceding the inversion have to be accepted and cannot be accommodated for by the inversion. The above-mentioned complications are suspected to degrade inversion results, especially in a structurally complex subsurface with substantial lateral velocity variations.

To extend the validity range of trace inversion methods to such complex media, a ray-based approach to stochastic inversion was proposed in Verdel et al. (2004), that employs the original wave-path and reflection angle information inside the inversion kernel. In RBSI, a close link is provided between Kirchhoff-type pre-stack depth migration and stochastic inversion for reservoir properties, via the 3D elastodynamic ray-tracer that is used in the forward modelling step of the inversion loop.

An RBSI-variant which utilises a 1D convolutional forward modelling kernel as found in common inversion software, offering great practical benefits, was presented in van der Burg et al. (2005). This scheme applies 1D convolution along normal-incidence (NI) ray-paths, whereas SI follows the vertical direction of the traces from the migration image (see also Fig. 8). In the current paper, 1D convolutional RBSI is applied to a field dataset from the Gulf of Mexico, containing the reflection response of a reservoir having a strong structural dip: it is our suspicion that SI overestimates reservoir-layer thickness with increasing dip, due to dip-dependent migration-induced wavelet stretch

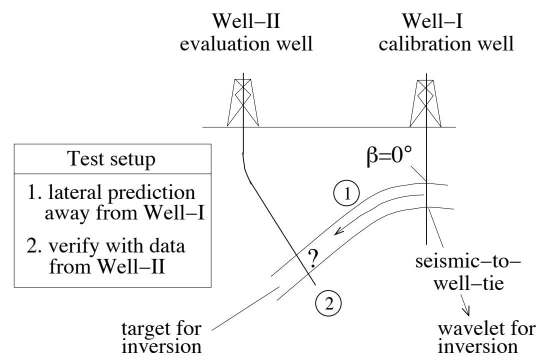

Figure 1: *The capabilities in lateral prediction of target reservoir parameters away from Well-I to the dipping part of the target at Well-II are tested for SI versus 1D convolutional RBSI.*

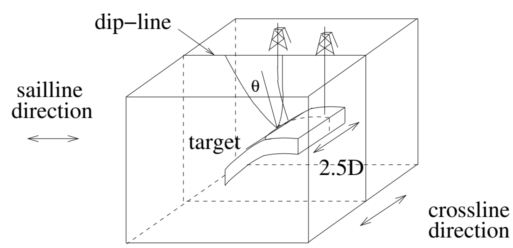

Figure 2: *Dip-line in 3D seismic data-cube: around this selected sailline, the subsurface is laterally invariant in the crossline direction. A ray-pair reflects on the top interface of the target with angle θ.*

(van der Burg et al., 2005). The comparative test of 1D convolutional RBSI versus SI is set up as shown in Fig. 1. The evaluation well mentioned in the figure is assumed to have been drilled after the inversion was done.

PREPARATIONS BEFORE INVERSION

The considered field in the Gulf of Mexico is a hydrocarbon reservoir consisting of layers of sheet sands and shales. The reservoir consists of a horizontal part and a slope with dips to a maximum of 31°. A high-resolution seismic survey was conducted over the area, where the marine acquisition vessel sailed approximately in 'dip-lines' over the target (of which the geometry was already known from a previous seismic survey), see Fig. 2. The acquired data were subsequently migrated using Kirchhoff-type TA PreSDM to obtain an image suitable for inversion with SI. Fig. 3 gives an impression of the data quality before and after migration.

From the 3D data cube, a dip-line was selected on a part where the subsurface is approximately 2.5D, such that it is located close to the vertical exploration well, Well-I, where the seismic-to-well tie is done, and to Well-II where the validation of the inversion results is done. The data at target level from this dip-line, to be inverted by SI and 1D convolutional RBSI, are shown in Figs. 4 and 5, respectively. The inversion interval extends ~ 100 m above the reference reflector, indicated by a red line. Fig. 4 shows the migrated near-offset substack of 16 offsets ranging from 450-2325 m. Fig. 5 displays the common offset gather (offset 575 m) selected for inversion with 1D convolutional

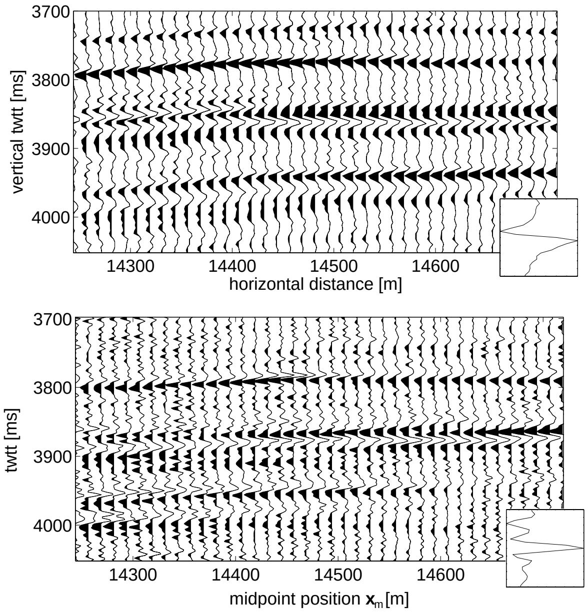

Figure 3: *Good data quality on target level around Well-I, on the migrated substack (above) and on the 575 m offset-gather, containing more high-frequency information. Insets show derived wavelets.*

RBSI; the traces from this pre-stack unmigrated dataset containing the reflection information from the inversion interval were selected on the basis of ray-tracing (Fig. 6). The angles of incidence visible in the last-mentioned figure amount to $\theta = 6^\circ$, close to $\theta = 0^\circ$ (NI) assumed by 1D convolutional RBSI in the target.

Notice from Fig. 6 that a range of shot/receiver pairs exists, for which more than one reflection point per reflector is found: this limits the reservoir-range that can be inverted well by the new method to the part on the right-hand side of the steepest dip, because in the inversion window a trace is assumed to contain only a single response from the same reflector.

INVERSION FOR P-VELOCITIES AND THICKNESSES

Standard SI

A seismic-to-well tie was done at Well-I on the horizontal part of the reservoir, to obtain the wavelet with which to invert the nearstack migrated data (Fig. 3). A prior model for layer P-velocities (v_p) was used which has little variation in the lateral direction, whereas more variations are in layer-thicknesses (h) which come from geological modelling and seismic interpretation (Figs. 10-11).

Posterior mean v_p and h obtained from SI, inverting the migrated near offset substack, are depicted in Fig. 12-13. The trend of increasing thickness of the total package with increasing dip present in the prior model, seems to have been strengthened by SI.
Before plotting, a five-point moving average was applied, so that with a trace spacing of 12.5 m on the migration image, lateral variations smaller than 62.5 m are smoothed away; a distance not chosen too large, since the lateral resolution on the migration image, at target level is $\Delta r \approx \lambda_d z/L \approx 210$ m (Chen and Schuster, 1999), with dominant wavelength $\lambda_d = v_p/f_d = 2500$ m/s $/35$ Hz ≈ 70 m, depth of observation $z = 3500$ m and half-aperture $L = 2325/2$ m.

1D convolutional RBSI

The seismic-to-well tie was done anew for the pre-stack unmigrated data: it was expected that the derived wavelet would be much different because of a wavelet shaping applied to the migrated data. In the wavelet derivation, the spherical spreading and transmission losses in the reservoir zone were neglected, as well as the small extra traveltime in the target due to having small offset data while assuming zero offset.

Apart from associating the reflection points $\mathbf{x}_R$ on the reference horizon with the surface source/receiver midpoint positions $\mathbf{x}_m$, the elastodynamic ray-tracing through the migration velocity model to the reference horizon also yields the laterally varying overburden losses needed for pre-processing the pre-stack unmigrated data in 1D convolutional RBSI (Fig. 7). Note that for these purposes, the original migration velocity model needed to be somewhat smoothed, in a trade-off between kinematic accuracy and dynamic stability of the ray-tracing.

In Fig. 8, the layering obtained from 1D convolutional RBSI, inverting the near offset-gather, is shown; notice the different evaluation direction along the normals to the reference reflector, which should improve capability of resolving reservoir-layers: as shown before in synthetic data tests, SI is hampered by dip-dependent migration-induced wavelet stretch. After resampling, using linear interpolation, to the grid used by SI (upper part of Fig. 8) and after applying a five-point moving average filter, the h and v_p-estimates are shown in Figs. 14-15. The estimated thickness of the total package seems more laterally constant with increasing dip than was the case for SI.

COMPARISON AT WELL-II

The inversion results obtained with the old and new method are compared with the values found at Well-II in Fig. 9. Standard deviations are higher for the new method, due to the higher amount of noise on the offset gather as compared to the nearstack migrated section.
In general, SI overestimates the layer-thicknesses, while 1D convolutional RBSI estimates are slightly better, with the values from Well-II within one standard deviation from the estimated means; however for the two thin sand-layers SI thickness-estimates are better. The total package thickness of 86.5 m at Well-II is overestimated by SI, as suggested by theory, to 99$\pm$3.5 m - the new method somewhat underestimates the package-thickness, but remains within one standard deviation from the true value: 81$\pm$6.5 m. A synthetic test is planned to quantify the effect of the migration wavelet stretch (amounting $1/\cos\beta$ with β the local reflector dip) on SI estimates at Well-II. The v_p-estimates are closer to the actual values using the new method.
Finally, note that Well-II is at a crossline distance of 200 m from the section; changes in reservoir properties may have occurred in that interval, although an inspection of the seismics does not suggest this.

CONCLUSION AND OUTLOOK

Inversion results from a Gulf of Mexico field dataset indicate that the new method, 1D convolutional RBSI, has improved accuracy on the dipping part of the reservoir, where SI suffers from wavelet stretch due to migration.
A further investigation of the performance of RBSI on these data is opportune: only 2% of the available pre-stack data has been used with 1D convolutional RBSI, whereas with ‘full’ RBSI each of the remaining common offset gathers could be used as an independent means of verification of the result obtained with 1D convolutional RBSI. Also, contrary to the 1D convolutional variant, the general method is capable of dealing with caustics.

ACKNOWLEDGMENTS

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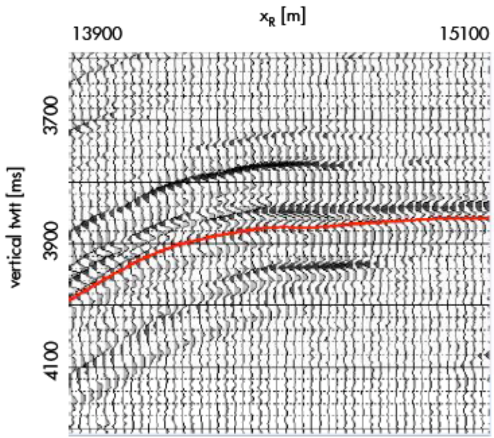

Figure 4: *Migrated near-offset substack. The solid line indicates the reference reflector, above which the inversion interval extends* ~ 100 *ms.*

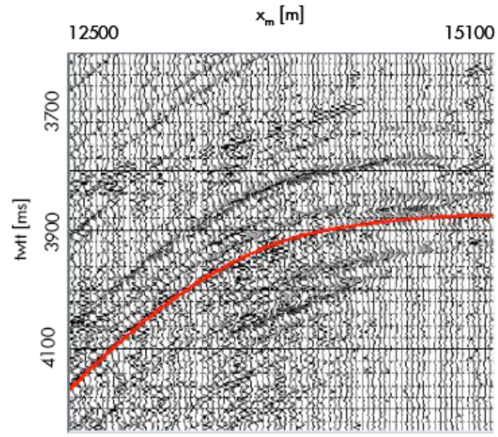

Figure 5: *Common offset gather with small offset of 575 m. The position of the reference reflector (solid line) was calculated via ray-tracing (Fig. 6).*

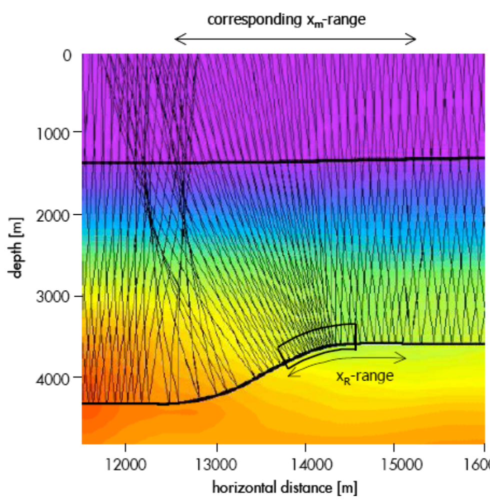

Figure 6: *Elastodynamic ray-tracing in the migration P-velocity model to the reference reflector. P-velocity ranges from 1480 to 3200 m/s. Water-bottom is at 1300 m.*

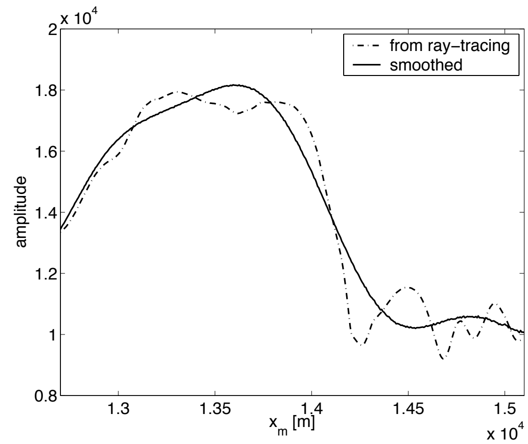

Figure 7: *Overburden amplitude correction. After smoothing, the corrections are applied to the traces from the offset gather.*

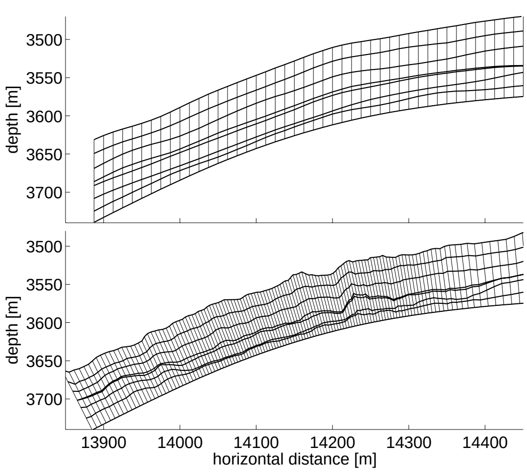

Figure 8: *Difference in evaluation directions for SI (top) and 1D convolutional RBSI; plotted with the posterior layer positions.*

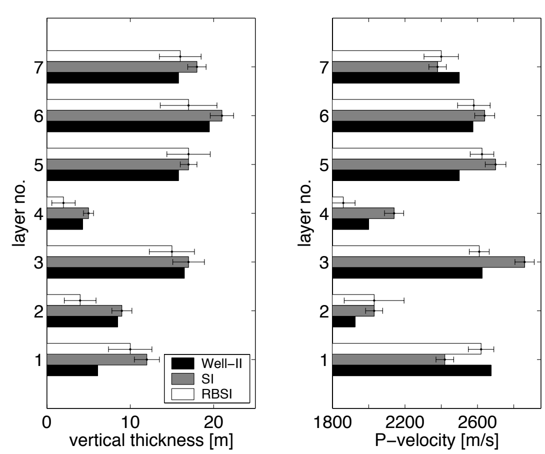

Figure 9: *Thickness* h *and P-velocity* v_p *at Well-II versus estimations for SI and 1D convolutional RBSI. Error bars denote standard deviations. Layer-numbering upward from reference reflector.*

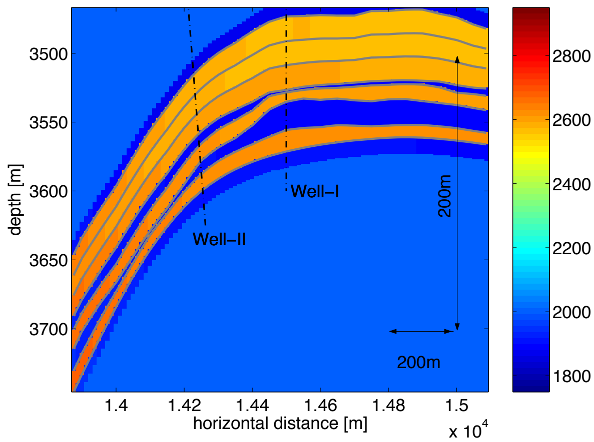

Figure 10: *Prior mean layer-thicknesses and P-velocities.*

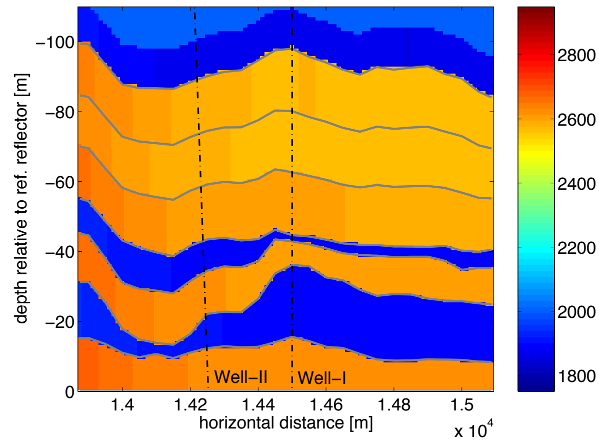

Figure 11: *As Fig. 10, but flattened along the reference reflector.*

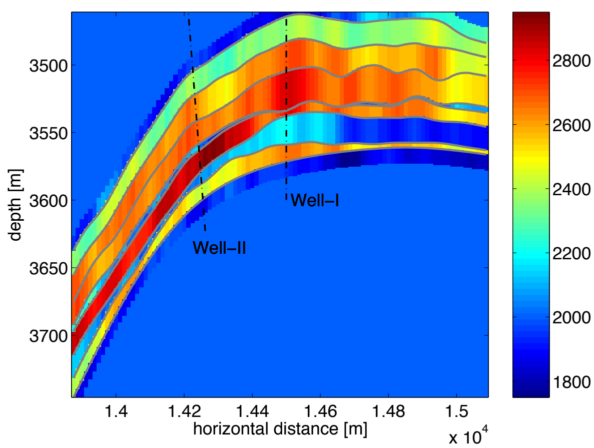

Figure 12: *SI: estimated mean layer-thicknesses and P-velocities.*

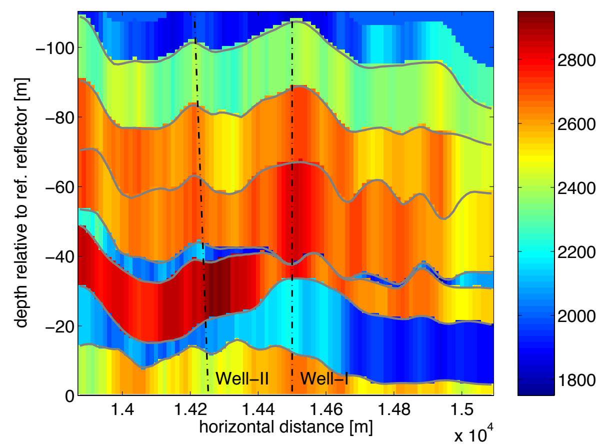

Figure 13: *As Fig. 12, but flattened along the reference reflector.*

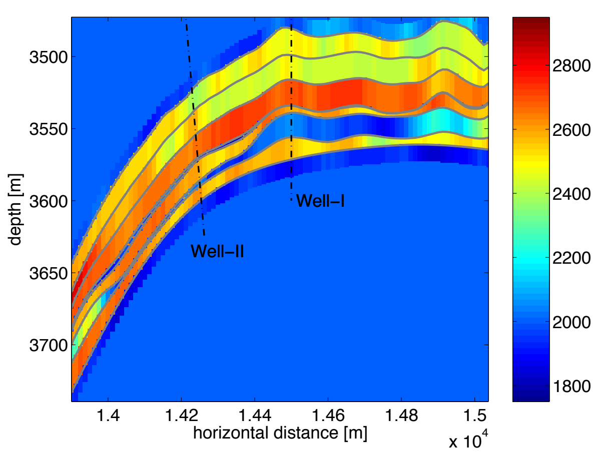

Figure 14: *1D convolutional RBSI: estimated mean layer-thicknesses and P-velocities.*

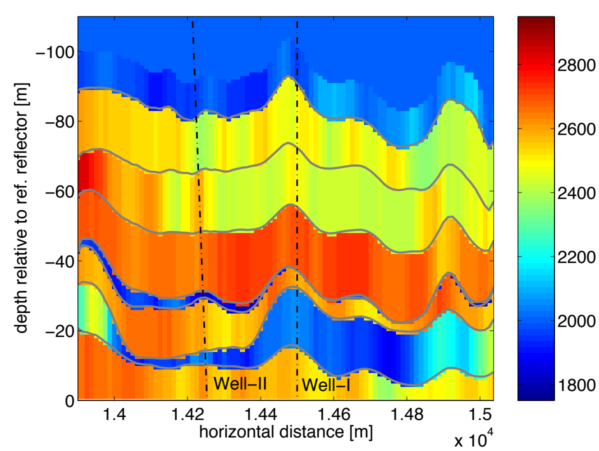

Figure 15: *As Fig. 14, but flattened along the reference reflector.*

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