Automatic Anisotropy Inversion with Well Control

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SUMMARY

Tomography is commonly used to build the anisotropic model for depth imaging, which requires human intervention for residual picking and quality control. In addition, tomography is typically implemented with a gradient descent optimization that can lead to a local extremum. We present an automatic inversion approach to estimating Thomsen parameters ε and δ when vertical velocity is known from well data with the assumption of 1-D vertical transverse isotropy (VTI). It employs the very fast simulated annealing as the global optimization algorithm and a fast model based moveout technique for re-migration/de-migration engine. We demonstrate the automatic inversion with both synthetic and field data.

Introduction

Advanced imaging algorithms implement some level of anisotropy in imaging, which requires a means to estimate the model parameters. Estimating the model parameters is inherently an iterative process that requires imaging, some measure of residual depth error and an inversion process that maps the residuals onto model updates. For example, reflection tomography (Zhou *et al*. 2011) describes a joint inversion process to build transverse isotropy (TI) models where the goal is to jointly solve for Thomsen parameters velocity, ε and δ by attempting to reduce the residual depth errors on the seismic common image gathers (CIG). Typically multiple iterations of migration and tomography are applied in order to reduce the offset depth errors. The iterative process employed in the regular tomography typically consists of the following steps: depth migration, residual picking and model updating. Obtaining accurate residuals requires complex picking algorithms and can incur significant quality control overhead.

To avoid picking residuals for tomography, alternate measures of model feasibility and updating must be employed. Typically this involves minimizing measures such as differential semblance (Symes and Carazzone 1991) or by obtaining a measure of stacking power, from which model updates are sought by seeking to maximize this stacking power. These types of measures are often used in migration velocity analysis, where some form of gradient descent methods attempt to update the model by reducing the error in the objective functions. One issue with these methods is that they may end up finding local minima (or maxima), in which case they do not sample the feasible model space. To avoid these local minima (or maxima) a global searching method is required.

It is critical to note that a global searching method requires significantly larger number of iterations when compared to standard reflection tomography. So, more efficient and localized imaging methods are required for more model iterations. A specular de-migration-remigration method, which we refer to as model based moveout (MMO) (Liu *et al*. 2014), can be employed for such purpose.

Finally, whether using tomography or global searching strategies, anisotropic inversion is a non-unique process because ambiguities exist among anisotropy parameters. When the vertical velocity (or velocities along the symmetry axis) can be accurately measured, for example, from the sonic log or checkshot data, it can be added as a constraint to the tomography process to improve the resolution of the model parameters. (Zhou *et al*. 2011).

In this paper, we present an automatic inversion approach to estimating Thomsen parameters ε and δ when vertical velocity is known from well data with the assumption of 1-D vertical transverse isotropy (VTI). It uses the very fast simulated annealing (VFSA) (Ingber 1989) for global searching and MMO for localized de-migration/re-migration engine near well control.

Method

As mentioned in the introduction, gradient descent methods may lead to local minima or maxima. To help mitigate falling into a local extremum some form of non-gradient global optimization method can be employed. One of such global methods is VFSA. It is a powerful stochastic search algorithm that samples the model space randomly and then accepts the model that has a better objective value at each iteration. To avoid local minima (maxima) some models that have worse objective function values are accepted according to a probability criterion. In the examples to follow, a staged implementation of VFSA is used to estimate parameters in the vicinity of well control. It should be noted, that global optimization methods can be used by themselves or to augment gradient based optimization. However, in the examples below, only the VFSA method is used.

A key component of an optimization problem is the objective function. We choose a filtered semblance function that is similar to the partial stack-power-maximization objective function (Zhang and Shan 2013):

$$\phi = -\frac{\sum_{j=0}^{M-1}\left(\sum_{k=0}^{N-1}\left(f(k) * I[j,k]\right)\right)^2}{N\sum_{j=0}^{M-1}\sum_{k=0}^{N-1} I[j,k]^2}, \tag{1}$$

where $I[j, k]$ and $f(k)$ are the CIG and the filter and "*" denotes convolution. The negative sign makes the inversion a minimization problem. N is the number of offsets and M is the number of samples of the CIG.

In order to measure the objective function during each iteration, a pre-stack migration is needed to generate CIGs. Instead of a costly full migration, the fast local MMO algorithm is employed as the re-migration/de-migration engine. We define the MMO process by mapping the image from each specular point from a model to a new specular point in a new model defined by

$$MMO : \beta(\mathbf{y}_{\mathbf{m}}, \mathbf{m}) \rightarrow \beta(\mathbf{y}_{\mathbf{m}+1}, \mathbf{m}+1)$$

1) Kinematic "de-migration" (remapping): for model $\mathbf{m}$ and image point $\mathbf{y}_m$, compute travel times and emergent ray parameters $\{t_{\mathbf{m}}(\mathbf{x}_s,\mathbf{y}), \mathbf{p}(\mathbf{x}_s,\mathbf{y})\}$ and $\{t_{\mathbf{m}}(\mathbf{x}_g,\mathbf{y}), \mathbf{p}(\mathbf{x}_g,\mathbf{y})\}$ and extract data $\beta(\mathbf{y}_{\mathbf{m}}, \mathbf{m})$,
2) Kinematic "re-migration" (remapping): for model $\mathbf{m}+1$ from surface points $\mathbf{x}_s$ and $\mathbf{x}_g$ compute new specular point at $\mathbf{y}_{m+1}$ remap the data $\beta(\mathbf{y}_{\mathbf{m}}, \mathbf{m})$ to $\beta(\mathbf{y}_{\mathbf{m}+1}, \mathbf{m}+1)$

The workflow of the automatic inversion is:

1) Given a starting model do a full migration of the data
2) Apply the MMO "de-migration" to obtain the needed depth to time mapping of the specular image
3) For each model iteration, apply MMO to re-migrate the specular reflection to new image depth positions
4) Compute the objective function
5) Accept or reject the model according to the defined criteria
6) Repeat steps 3-5 until a satisfactory model has been generated
7) Apply a full prestack migration for verification and repeat 2-6 if necessary.

A synthetic example

The BP 2D TTI model (http://www.freeusp.org/2007_BP_Ani_Vel_Benchmark/) is chosen to verify the proposed approach. A pseudo-well is chosen between the two salt bodies where the structural dip is mild. A velocity trace is extracted from the true velocity model as the vertical velocity for this pseudo-well location. The de-migrated gather at the pseudo-well location (Fig. 1a) is obtained by a Kirchhoff isotropic migration followed by a de-migration. Within VFSA, the initial guess consists of 36 control depth points (72 variables) with constant values of $\varepsilon = 0.01$ and $\delta = 0.005$ for the model below the water bottom and $\varepsilon = \delta = 0$ for the water layer. The strong curvatures observed on the CIG (Fig. 1b) based on the initial model indicate the need of significant anisotropy correction in the model. The search range is set to [0.0, 0.2] for both ε and δ. A mild mute is applied on the CIG to cut out the refractions after the critical angle before the objective function is calculated. After 9000 iterations, the CIG (Fig. 1c) becomes flat and the inverted ε and δ follow the true profiles (Fig. 1d and Fig. 1e).

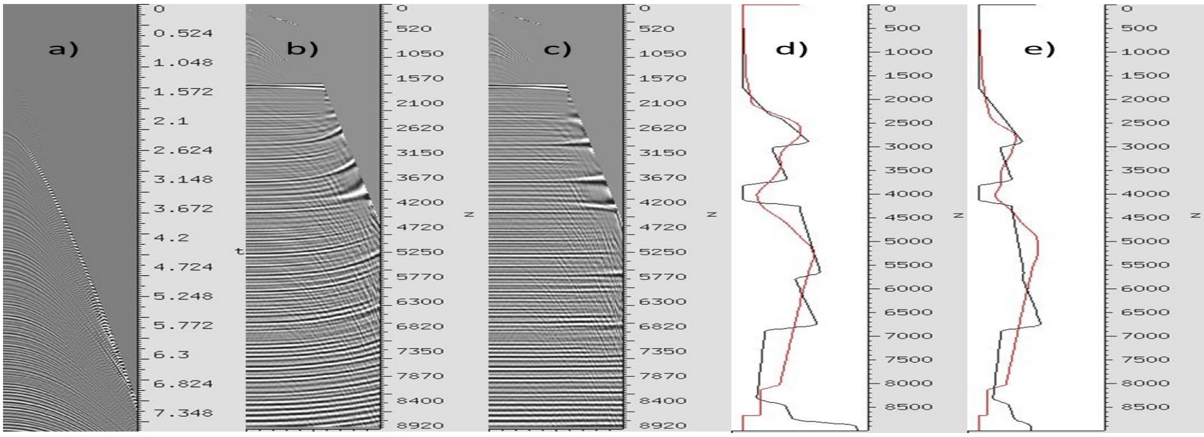

Figure 1: *Anisotropy inversion on the BP synthetic data: a) The de-migrated gather; b). CIG based on the initial model; c). CIG after 9000 iteration of inversion; d). True and inverted ε; e). True and inverted δ. The offset range is 0 to 10 km and the anisotropy scales range from 0 to 0.2*

A field example

The field example is at a well location in the Gulf of Mexico where a 2D dual sensor seismic dataset was acquired with a maximum offset of 12 km. The pre-processing includes de-ghosting and wave field separation. The sonic log data are available between depths 3270 m and 7272 m and are converted to seismic vertical velocity and resampled to 6.25m. Above this level, the water velocity is obtained by velocity scanning and the velocity from the water bottom to the top of the log is a vertical gradient chosen to ensure a depth tie at of the unconformity within the sonic data. Then all three pieces of velocity are assembled (Fig. 2) and extrapolated laterally by hanging the portion of the assembled velocity profile below the water layer along the water bottom. Using this velocity model a full isotropic Kirchhoff migration and an MMO de-migration are performed. The large far offset residuals in the isotropic CIGs (Fig. 2a) indicate significant anisotropy in this area.

The automatic VFSA inversion starts with $\varepsilon = \delta = 0.005$ with search range [0.0, 0.2] and [0.0, 0.1] respectively for the earth below the water bottom. It converges after 10000 iterations and produces reasonable ε and δ profiles (Fig. 2). The inverted ε and δ profiles are then extrapolated laterally by the same way as the velocity and another full Kirchhoff VTI migration is conducted for verification. For comparison, a full MMO is also conducted. The CIGs from the final full migration (Fig. 2c) match the final MMO CIGs (Fig. 2b) in the region close to the well location. Due to the lateral geological variation, CIG residuals appear to be flat at the well location but gradually show an increase in residual moveout with distance from the well (Fig. 2b and Fig. 2c). The final VTI migration stack (Fig. 2f) and the final MMO stack (Fig. 2b) reveal more details and are better focused compared to the initial isotropic migration stack (Fig. 2d). We note that some of the remaining residual moveout at the unconformity is due to wide angle refractions. While not shown here, improvements in the imaging can obtained by extrapolating the velocity and anisotropy parameters laterally along structure and then reapplying this inversion method or a tomographic inversion to estimate an improved model away from the well.

Conclusions

We demonstrate an automatic approach to estimate the anisotropy parameters at the well location. No residual picking or any other human intervention is needed. We also demonstrate the inversion with a synthetic example and apply it to a field example near an actual well location. While in the case shown here, only a VFSA algorithm is employed and thus requires a very large number of iterations, which are only made possible by employing a fast model based moveout (MMO) technique for the de-migration/re-migration step. While not shown here, we also note that global inversion techniques could be combined with gradient decent methods to reduce the number of required model iterations.

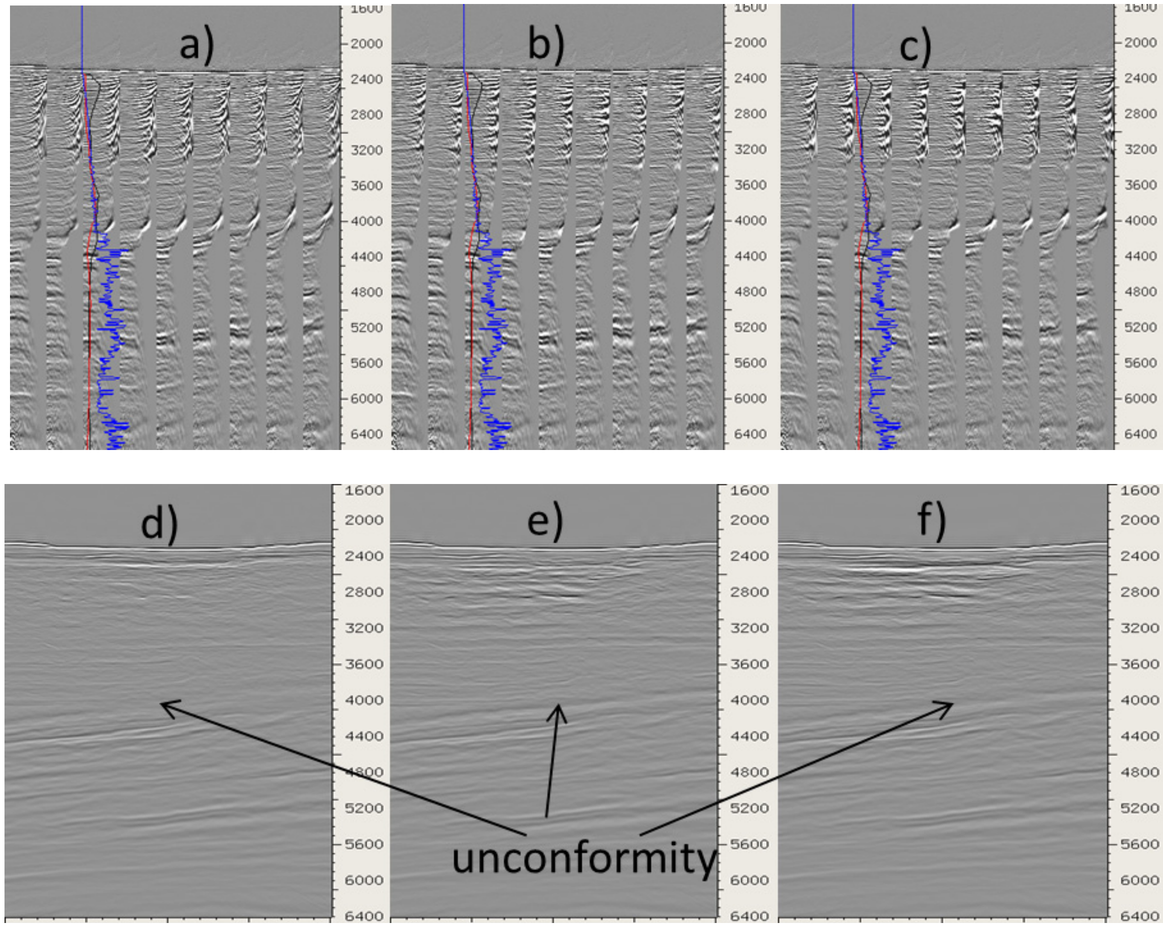

Figure 2: *Gulf of Mexico anisotropy inversion: a) the initial isotropic migration CIGs overlaid by the velocity (blue), inverted* ε (black) and inverted δ (red) profiles at the well *; b) the MMO CIGs from the inverted model overlaid by the velocity (blue), inverted* ε (black) and inverted δ (red) profiles at the well*; c) the full migration CIG from the inverted model overlaid by the velocity (blue), inverted* ε (purple) and inverted δ (red) profiles at the well *; d) The initial isotropic migration stack; e) the MMO stack from the inverted model; f) the full migration stack from the inverted model.*

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References

Ingber L. [1989] Very fast simulated re-annealing. *Mathematical Computer Modeling* **12**(8), 967-973.
Liu Z., Whitmore D. and Zhou C. [2014] Anisotropy Estimation and image remapping using model based moveout. *76th Conference and Exhibition*, EAGE, Extended Abstracts.
Symes W.W. and Carazzone J. [1991] Velocity inversion by differential semblance optimization. *Geophysics* **56**, 2061–2073.
Zhang Y. and Shan G. [2013] Wave-equation migration velocity analysis using partial-stack power maximization. *83rd Annual SEG Meeting*, Expanded Abstract, 4847-4952.
Zhou C., Jiao J., Lin S., Sherwood J. and Brandsberg-Dahl S. [2011] Multi-parameter joint tomography for TTI model building. *Geophysics* **76**(5), WB183-WB190.