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High-resolution Tomography Using Offset-dependent Picking and Inversion Conditioned by Image-guided Interpolation

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SUMMARY

An approach to generating high-resolution velocity models through tomography is described which limits the impact of simplifications introduced by traditional tomography, in order to provide timely, accurate, and geologically reasonable models. First, offset-dependent picking tracks events in gathers better than curvature-based picking, particularly in areas of complex geology and anisotropy. This implementation can allow quicker and simpler gather flattening and reveal fine detail in models. Similarly, unguided tomographic inversion may yield velocity updates which appear geologically implausible by violating faults or layering, or updates which are very low resolution due to necessary post-processing. Applying image-guided interpolation as a preconditioning step within the inversion process leads to updates which automatically respect geological structures observed in stacked images. When implemented within a current tomography flow, these refinements make generation of high-resolution velocity models reasonable without trade-offs in computation time or accuracy.

Introduction

Traditional methods of updating velocity models via tomography rely on several assumptions and simplifications, which may extend the amount of time required to flatten gathers, as well as lead to unlikely velocity models. Our high-resolution tomography method uses an offset-dependent residual moveout (RMO) picking technique, as well as image-guided interpolation (IGI) preconditioning in the inversion process, to flatten gathers more simply and quickly than traditional methods, with more geologically plausible velocity models.

Mainstream RMO picking methods fall into two categories (Woodward et al., 2008). In polynomial-based techniques, moveout is approximated by a parabola, hyperbola, or higher order polynomial curve. Alternatively, offset-dependent methods pick moveout independently for numerous offsets. When implemented, offset-dependent picking may flatten gathers more accurately, and in fewer tomography iterations, than polynomial-based methods.

Traditional tomographic inversion can yield reasonable velocity updates, but results may not follow any geologically-consistent pattern. This is a problem when velocity trends cross layers or faults in an implausible manner. Likewise, for the highest resolution inversion results, the best option previously was to use as fine an update grid as possible. This was computationally impractical and yielded updates which needed smoothing to remove variations and outlying values. Hale (2009a) proposes using IGI to describe an image with a sparse set of values which are interpolated along structures, and suggests possibilities for restricting seismic imaging processes. Applying IGI automatically enforces velocity updates which honor layering and faults, leading to more believable subsurface models.

The combination of these two methods creates higher resolution velocity models. The ability to attain greater gather flatness from offset-dependent picking leads directly to more complex and variable velocity updates, and can even speed up tomography iterations. When the inversion process is restricted by IGI to follow image-related structures, results can be attained more rapidly, and do not need the same post-processing which may create low resolution updates from even the densest inversions.

Offset-dependent Picking

Polynomial-based RMO picking methods are effective for events with smooth curvature coinciding with low order polynomial terms, and significant improvements have been made by industrial institutes to improve this technique in real data processing (He and Cai, 2011; Bartana et al., 2011; Siliqi et al., 2007; Koren et al., 2008). However, problems arise when the real curvature is complex, and the polynomial assumption may be inaccurate (Liu et al., 2010). Events with multiple turning points may arise in a variety of situations, particularly near faults and in areas with high anisotropy. For these events, flattening the near offset may lead to worse fits at far offset, or vice versa. As an alternative to polynomial-based methods, and due to the increasing demand for high-resolution imaging, offset-dependent techniques, such as the plane-wave destruction method described by Fomel (2002; Liu et al., 2010), have gained attention in the past decade. By picking the RMO at all available offsets, we may ensure that complex moveout is being appropriately considered in tomography updates.

In our novel offset-dependent RMO picking method, each common-image-point gather is considered as a two-dimensional plot. RMO curves are viewed as paths composed of connected nodes with similar patterns. RMO picking is thus turned into a path-finding problem, which can be solved via a dynamic programming algorithm. Various geophysical factors, including event amplitude, displacement field, dip continuity, and flatness constraint, are utilized by an object function. This can be easily extended to include more factors to guide the event-finding process. Offset-dependent picking can pick RMO curves with multiple turning points, which is often problematic for polynomial-based methods. It has been tested with synthetic and real data, and has shown stable and accurate results.

Image-guided Interpolation Inversion Conditioning

Our structure-oriented IGI inversion method begins by selecting a grid of sparse control points, used to define an array of zones to cover the update region. In order to ensure that these zones follow the underlying image, we define their boundaries based on propagation time within the image. A set of tensors is calculated from image gradients to describe the directionality and continuity of reflectors. The structure-related propagation time is determined by solving the Eikonal equation from each control point, based on the structure tensors. Propagation time is lower along coherent structures, such as clearly-defined layers, and propagation time is higher across coherent structures or at disruptions in the image, such as faults. Each control point is then assigned to the zone of grid locations nearest it in propagation time. These zones will be anisotropic and extended along coherent structures, and will tend to be more isotropic in incoherent areas, or when interrupted by faults.

During tomographic inversion, a matrix of equations is inverted to find a velocity update which converges to a solution to minimize RMO. The basic relations governing this are

$$Am = d \text{ and } Lm = 0, \quad (1)$$

where A is the relation between the actual and current models, m is the actual model, d is the current model, and L is the Laplacian operator used to stabilize the update. The objective is to solve for an update to our model, given the RMO, which represents the inaccuracy in the current model.

IGI-conditioned inversion revises the first of the two relations in equation (1) to

$$Apx = d, \quad (2)$$

by replacing m with px. Here p is the preconditioning IGI matrix. This is applied in the inversion by averaging all values within each zone, and then performing structure-oriented smoothing (Hale, 2009b), using the previously-calculated structure tensors. This enforces the update's resemblance to the base image.

To ensure our approach is consistent, we have adopted the priority-based selection process described by Cullision (2011) to choose optimal control point placement automatically, rather than based on constant or smoothly-varying spacing. Coherent structures need fewer, more sparsely spaced control points, as their properties will be more consistent along their length, while in incoherent areas control points should be more closely spaced. Our adaptive method ranks locations based on importance, by building a priority map of the image based on its amplitude envelope, semblance value, and local planarity, which is represented by the level of anisotropy in the structure tensors. Control points are then picked in order of priority, while ensuring each is spaced appropriately from others.

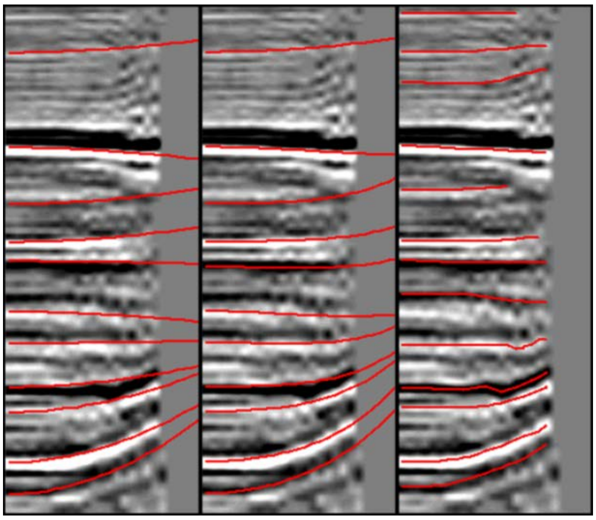

Figure 1 *Comparison of RMO picking methods: (left panel) one-parameter polynomial, (center panel) two-parameter polynomial, and (right panel) offset-dependent Dynamic Picking.*

Examples

A demonstration of the capabilities of different RMO picking methods is shown in Figure 1. One-parameter polynomial fitting can describe only the events with the simplest curvature. Two-parameter fitting is more effective on complex curvature, particularly for events with multiple turning points. However, offset-dependent picking is the only way to accurately fit each complex event, particularly for locations where events do not span the entire offset range.

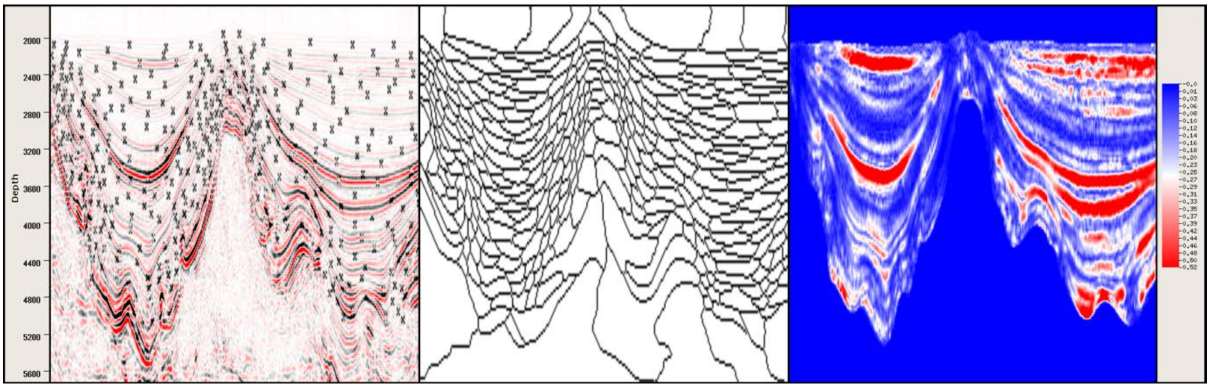

Figure 2 *(Left panel) Adaptively-selected control points overlaid on the image used to guide interpolation in the update. (Center panel) The boundaries of the selected update zones. (Right panel) The priority map used to pick control points.*

Adaptive control point selection results are displayed in Figure 2. Each ‘x’ in the left panel is a control point selected by picking locations of high value in the priority map, displayed in the right panel. Points of high priority usually lie on strong, flat reflectors, and will tend to be spaced far apart along layers, but close together in the direction normal to the layering. This creates zones, depicted in the center panel, which are very anisotropic in strongly layered locations, lying along the reflectors. Points in less coherent areas tend to have zones which are smaller and nearly isotropic, so they are more clustered and less patterned.

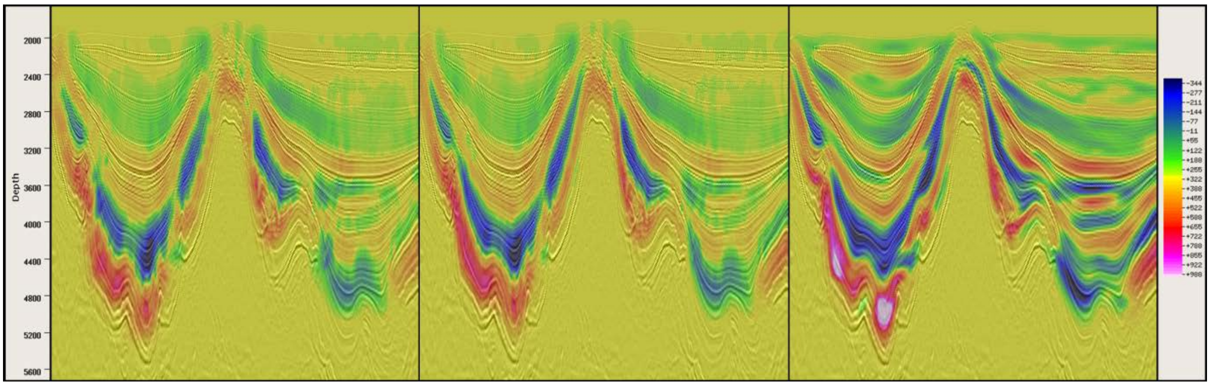

Figure 3 *Velocity update following inversion, overlaid on a migrated image, for: (left panel) traditional tomography methods with normal Laplacian regularization, (center panel) with dip-oriented Laplacian regularization, and (right panel) using IGI to precondition the inversion matrix.*

A comparison between traditional inversion methods and the presented IGI method is demonstrated in Figure 3. The left panel shows a stacked image overlaid with a velocity update from an inversion process with traditional Laplacian regularization, without dip-guiding or other structure-constraint methods. The center panel is similar, but with dip-guided Laplacian regularization. This update more closely follows structure seen in highly-dipping locations, but with little improvement in resolution. The right panel shows the velocity update for the same input data, with the inversion conditioned by the IGI constraint. The update with IGI tends to be much more strongly constrained to the layers observed in the stacked image, and it demonstrates a noticeably higher resolution, with layers being distinctly separated from their neighbors, particularly in the shallow regions which have a very low resolution update with more traditional approaches.

Conclusions

Offset-dependent RMO picking can accurately describe complex events to yield more accurate velocity updates without relying on ineffective polynomial-based curvature fitting. Gathers which display multiple turning points, or events which do not span the entire offset range, which would previously be incorrectly picked, are well-fit and appropriately flattened.

With traditional inversion algorithms, tomographic velocity updates may not follow geologic trends or resolve thin layers. Inversion using IGI as a preconditioner encourages updates to follow structure, which leads to geologically plausible and higher resolution velocity models which honor layering and faults automatically.

Our high-resolution tomography approach combines these methods into a new tomography flow, melding easily with earlier techniques. New results are a vast improvement over those obtained with conventional methods, yielding more accurate velocity models, and frequently saving time and effort.

Acknowledgments

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