Image segmentation for velocity model construction and updating

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SUMMARY

Image segmentation offers a means of automatically delineating salt bodies in seismic images, an otherwise human-intensive and time-consuming task. Current segmentation algorithms successfully pick salt boundaries; a logical extension of such work is to apply these methods to the task of building and updating seismic velocity models. The method presented here successfully applies image segmentation tools in conjunction with sediment- and salt-flood migration techniques to identify the top and base of a salt body. Furthermore, previously existing velocity models may be updated based on the results of segmentation and automated boundary picking. In the latter case, the prior model acts as a priori information for the picking algorithm in areas of relative uncertainty, producing an "optimized" boundary path across an image. For both synthetic and real seismic data, migrations with velocity models derived from this method produce greatly improved images.

INTRODUCTION

The purpose of image segmentation is to automatically divide an image into sections based on specific attributes. Because of its global optimizaton properties, one algorithm with a variety of potential applications to seismic interpretation is Normalized Cuts Image Segmentation (NCIS) (Shi and Malik,2000). The NCIS method was first applied to seismic data by Hale and Emanuel (2002;2003), who used it to paint 3D atomic meshes of seismic images. Recent work by Lomask and others (Lomask,2007; Lomask et al.,2007) presents an image segmentation algorithm for automatic picking of salt boundaries. Such a scheme offers many potential benefits for the seismic velocity model building process, which we explore in this paper.

Segmentation

Lomask's algorithm divides a seismic image into two segments; the boundary separating them is the salt interface. The segmentation is based on a specific seismic attribute, in most cases instantaneous amplitude, that can clearly differentiate between a salt body and the surrounding sediments. The most basic step is to create a weight matrix **W** that relates each pixel in a migrated seismic image to a random collection of neighboring pixels. Low weights are assigned to pixel pairs most likely to be separated by a salt boundary. A path across the image which minimizes the sum of the weights through which it passes is the salt boundary.

Following the NCIS algorithm of Shi and Malik (2000), Lomask showed that the determination of a boundary path across a seismic image may be set up as an eigenvector problem via the Rayleigh quotient

$$\min_{\mathbf{y}} \frac{\mathbf{y}^{\mathbf{T}}(\mathbf{D}-\mathbf{W})\mathbf{y}}{\mathbf{y}^{\mathbf{T}}\mathbf{D}\mathbf{y}} , \qquad (1)$$

where **y** is the eigenvector and **D** is a diagonal matrix whose elements are the sum of each column of **W**. Because of constraints introduced on the Rayleigh quotient, it will be minimized by the eigenvector corresponding to the second smallest eigenvalue of the eigensystem

$$(\mathbf{D}-\mathbf{W})\mathbf{y} = \lambda\mathbf{D}\mathbf{y} , \qquad (2)$$

where λ is the eigenvalue. The eigenvector **y** will have values ranging from -1 to 1 across the boundary; in most cases, following the "zero contour" across the image yields the most appropriate salt interface pick. When the zero contour is not clearly defined (see Figure 1), it may be necessary to use another value of the eigenvector to pick the boundary; the determination of this value in different parts of the image can be posed as an optimization problem, and is discussed later.

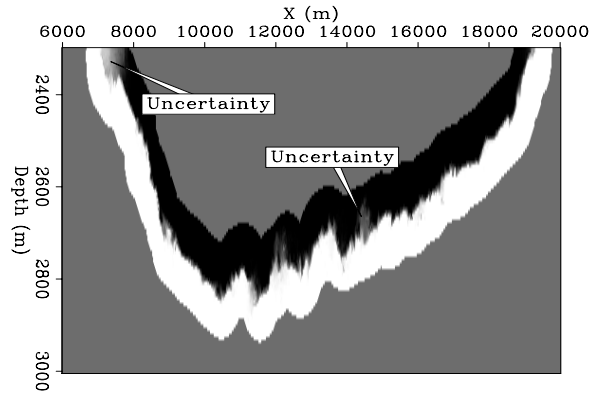

Figure 1: Eigenvector produced during the image segmentation process, and used for automatic picking of the salt boundary. Uncertainty arises when the there is no clear transition from positive to negavtive values.

Extension to velocity estimation

In this paper, we adapt the methods outlined above for use in iterative velocity model construction and updating. A reasonably accurate velocity model is an essential component of the seismic imaging process. Much of today's seismic data is acquired in regions characterized by complex salt bodies; in such cases, clearly delineating salt interfaces is often one of the most human-intensive, time consuming and inexact aspects of velocity estimation. Correct salt interface interpretation becomes especially important when the imaging target is located sub-salt, as is often the case for modern surveys. The method we propose here is designed to function as a tool for either velocity model construction, or updating. We show our method to be highly effective when combined with widely used sediment- and salt-flooding migration techniques to make original salt interface interpretations. We also propose a means of producing an optimum boundary path by solving a global, non-linear optimization problem. Since this optimization is taking place in order to update a velocity model, the scheme incorporates the original model as prior information about the boundary in areas of uncertainty. We will show both real and synthetic data examples of this method producing an improved velocity model.

VELOCITY MODEL CONSTRUCTION

A typical procedure for locating salt boundaries in seismic data is to perform migrations using "flood" velocity models. The top of a salt body is found by migrating strictly with sediment velocities throughout the entire section; theoretically, the top salt interface will be well resolved. A second migration with salt velocities filled in below the top boundary pick is then performed in order to resolve the base of the salt. In both cases, manually picking the salt boundaries can be time-consuming and inexact, especially for salt bodies with complex geometries. Here, we show that image segmentation can greatly expedite this process.

For this example we use a portion of the Sigsbee 2a synthetic dataset featuring a salt canyon. Figure 2 shows the result of migration with a sediment flood velocity model, created by infilling the salt por-

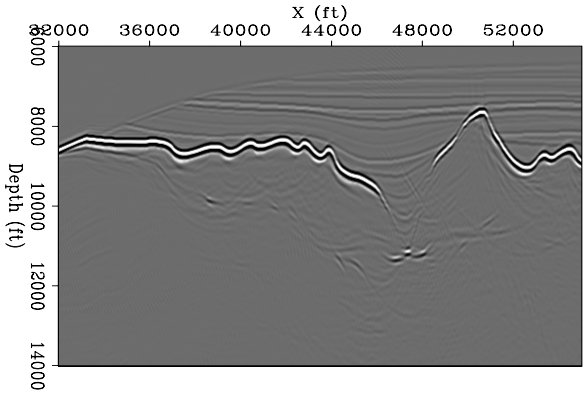

Figure 2: A sediment flood migration of the Sigsbee data. Much of the top salt boundary is well resolved, but the details of the salt canyon are highly ambiguous.

tions of the Sigsbee model with sediment velocities. Much of the top salt interface is extremely well resolved and relatively easy to pick; however, the boundary "disappears" inside the salt canyon, and would be difficult to pick manually. The top row of Figure 3 illustrates the image segmentation process: image (a) is the eigenvector calculated for the image, and image (b) is the boundary pick corresponding to the zero countour of the eigenvector. The method accurately picks the complex geometry along the top of the salt, and correctly interprets the presence of the canyon.

One way to measure the quality of the method's top boundary pick is to observe the quality of a salt flood migration using a velocity model derived from the top boundary pick. Figure 3c shows the result of migrating with salt velocities flooded below the top boundary pick. The base salt reflection is strong and clear throughout the image, an indication that that the top salt interface was reasonably interpreted. Picking the boundary is a mostly trivial task, and image (d) of the figure confirms that the segmentation algorithm tracks the boundary well.

VELOCITY MODEL UPDATES

Image segmentation may also be used as part of an iterative boundary-picking process to update a previously existing velocity model or salt body interpretation. For this task, such a preexisting model offers a potential advantage over "starting from scratch," as was the case for the sediment- and salt-flood models. Namely, the prior model can act as prior information - either as a guide or a penalty for the boundary-picking algorithm - in areas where the appropriate boundary choice is not obvious.

Uncertainty in the method's salt interface pick arises when the eigenvector transitions smoothly from negative to positive values. These "areas of uncertainty" appear grey on depictions of the eigenvector such as Figure 1, rather than sharp transitions from black to white indicative of a relatively certain boundary pick. In a given area of uncertainty, the boundary pick may be improved by manually selecting a non-zero eigenvector contour value to follow throughout the image. However, Lomask (2007) notes that any such improvement in one part of the image may be "matched by a reduction of picking quality in other uncertain areas." Thus, a natural extension of Lomask's work is to pose the boundary picking task as a global optimization problem, in which the boundary is allowed to follow different contour values throughout the image.

We set up a non-linear inverse problem that attempts to find the optimal depth for the salt-sediment interface at each x position.

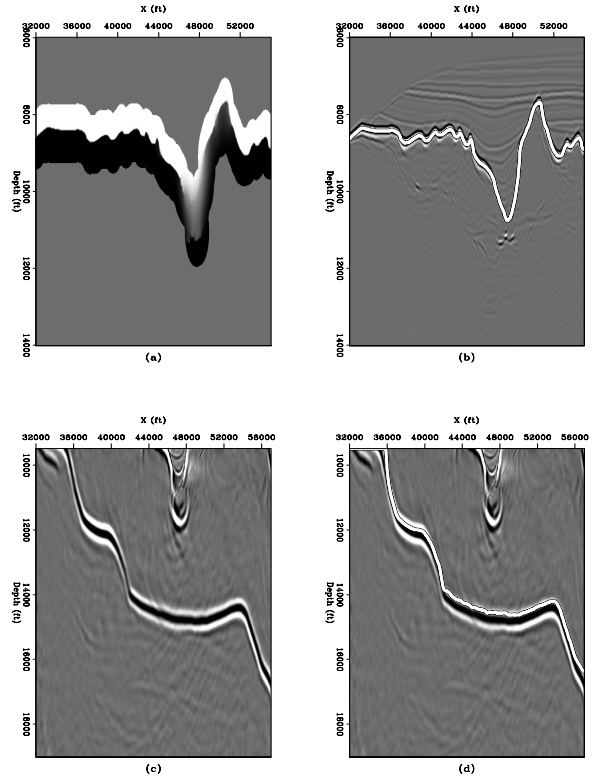

Figure 3: Top: Eigenvector (a) and picked boundary (b) from a sediment-flood migration of the Sigsbee data. Bottom: Image (c) and boundary pick (d) for the base of the Sigsbee salt body after a salt-flood migration.

1. In most cases, the eigenvector's zero contour is the most appropriate path. Therefore, a first order fitting goal should seek to follow the zero contour whenever possible. This goal results in a non-linear system; we cannot create a linear system that maps between reflector depth and the eigenvector. As a result, we linearize around the zero-contour boundary $\mathbf{m}_0$ and use the depth gradient of the egienvector at $\mathbf{m}_0$ as our linear operator, $\mathbf{G}$.

2. The zero contour may be inappropriate in areas of great uncertainty. Here, it is beneficial to rely more upon the a priori information - a previous boundary manually suggested by an experienced interpreter, or the results of the flood migration procedure detailed above. In the former case, the prior boundary can act as a guide; the optimized boundary will tend to follow the previous one in uncertain areas. In the latter case, however, it may be obvious that the prior boundary is placed either too deep or too shallow in the model. In this circumstance, the previous boundary may be "penalized" so that the optimized boundary will move *away* from the previous one rather than toward it. To implement this goal, a weighting vector $\mathbf{W}$ is constructed such that areas of uncertainty are given greater weights. The weights in this vector may have positive or negative values, depending on the need to either penalize or "reward" the prior boundary.

3. Finally, to avoid unwanted fluctuations in the boundary pick, a smoothing constraint is imposed on the boundary in the form of a 1D gradient roughening operator ($\mathbf{A}$).

Since the problem posed is non-linear, we use an iterative Newton method to solve for a new boundary model $\mathbf{m}_i$. Defining the previous boundary model as $\mathbf{m}_{i-1}$, and our current model as a function of non-linear iteration j as $\mathbf{m}_{i,j}$, and two relative weighting parameters ϵ_1 and ϵ_2 we iterate to convergence using the following scheme:

Iterate over j
{
Construct $\mathbf{L} = [\mathbf{G}\mathbf{m}_{i,j} \quad \epsilon_1 \mathbf{W} \quad \epsilon_2 \mathbf{A}]^{\mathrm{T}}$
Calculate current residual $\mathbf{r} = [0 \quad -\mathbf{W}\mathbf{m}_{i-1} \quad 0]^{\mathrm{T}} - \mathbf{L}$
Solve the linear system
$\mathbf{r} = \mathbf{L}\Delta\mathbf{m}_{i,j}$
$\mathbf{m}_{i,j} = \mathbf{m}_{i,j-1} + \Delta\mathbf{m}_{i,j}$
}

For 2-D cases on the scale of the examples shown here, computational expense for this scheme is virtually negligible. A possible future enhancement to the algorithm presented here is to incorporate residual map migration to remap the original boundary, $\mathbf{m}_0$. This would help eliminate bias introduced by movements of the migrated reflectors with respect to the image obtained with the original velocity model.

Velocity model update: Examples

Here, updated velocity models are produced both for the section of the Sigsbee synthetic data used previously, and for a section of the 2D Gulf of Mexico dataset Lomask (2007) used to demonstrate the segmentation algorithm. Once an optimized boundary has been calculated using the procedure detailed above, an updated velocity model is generated based on a comparison with the original velocity model. Any sediment velocities below the picked boundary are filled with salt velocities, and salt velocities above the boundary pick are replaced with nearby sediment velocities. After remigrating with the updated velocity models, improved images are obtained.

Figure 4 displays a typical sequence for producing an improved image by updating a preexisting velocity model. In this case, the "prior model" is the boundary picked after the sediment-flood migration, shown in Figure 3. It is clear that this boundary places the bottom of the canyon too shallow, as the image of the canyon bottom is pushed down by the presence of excess salt velocities. Image (b) in the figure confirms that the zero contour boundary would still be picked too shallow at the bottom of the canyon. Therefore, the prior boundary is penalized in the optimization scheme; the optimized boundary will move away from the previous one in uncertain areas (in this case, only the canyon bottom). Image (c) of Figure 4 shows the result of the boundary optimization process - as expected, the bottom of the canyon is now placed deeper in the section. After remigration with a velocity model derived from the new boundary, the resulting image (d) is vastly improved.

In his thesis work, Lomask used a real Gulf of Mexico dataset provided by WesternGeco to demonstrate his segmentation algorithm. Here, the optimized boundary/updated velocity model method is used to produce an improved image. Figure 5 compares the original and updated velocity models used for migration, and Figure 6 shows the results of boundary optimization and remigration. The boundary on the original image is highly discontinuous, and would be difficult to pick either manually or with most horizon tracking algorithms. In this case, it is much more difficult to tell whether the originally interpreted boundary is picked too deep or too shallow; therefore, it is advantageous to use the prior boundary as a guide rather than a negative example. The optimized boundary (Figure 6b) and resulting updated velocity model (Figure 5b) are smoother and feature fewer dramatic changes in the salt interface geometry. After migrating with the updated velocity model, the imaged boundary (Figure 6c) is smoother and more continuous than in the original image.

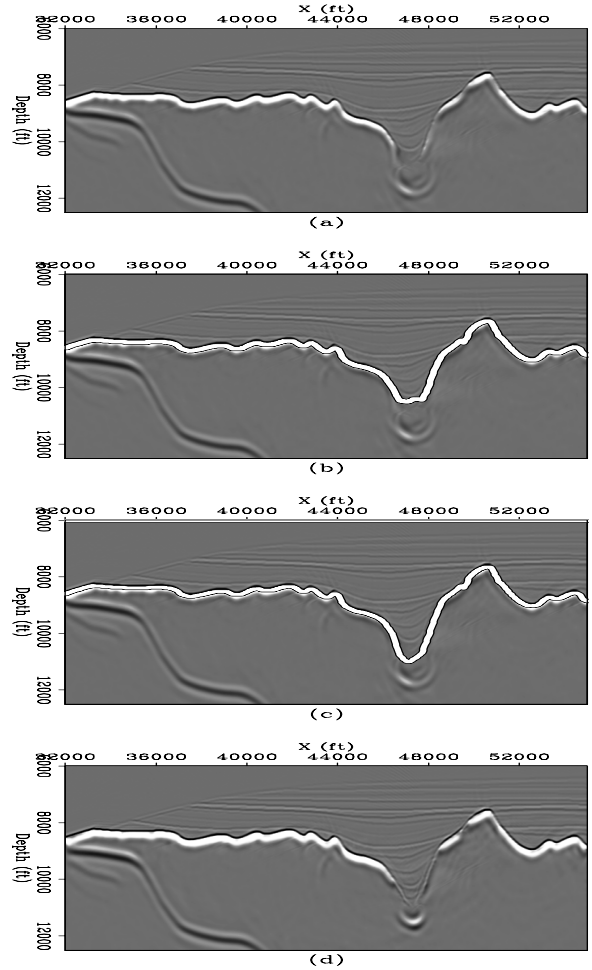

Figure 4: Sequence for using an updated velocity model to produce an improved image. (a) Salt canyon image after migration with the salt-flood velocity model. The original velocity model places the canyon bottom too shallow, pushing the image down. (b) The zero-contour boundary is still clearly too shallow, so the original boundary will be "penalized." (c) Optimized, deeper boundary pick used to create an updated velocity model. (d) A much improved image of the canyon after remigration with the updated velocity.

CONCLUSIONS

Lomask's 2007 work on salt body delineation via image segmentation is extended to the problem of velocity estimation. When applied to sediment- and salt-flood migrations of the Sigsbee synthetic dataset, this method provides relatively accurate picks of the top and bottom salt boundaries, which are used to construct a seismic velocity model. The method is also used to update preexisting velocity models, both for the Sigsbee data and a real 2D Gulf of Mexico dataset. To do so, the segmentation algorithm is extended to allow for an optimized boundary pick, rather than picking a constant eigenvector contour value. The boundary choice is posed as a non-linear optimization problem, allowing for different contour values to be used throughout the same image. Velocity models derived from the optimized boundary pick produce improved migrated images, both for synthetic and real data.

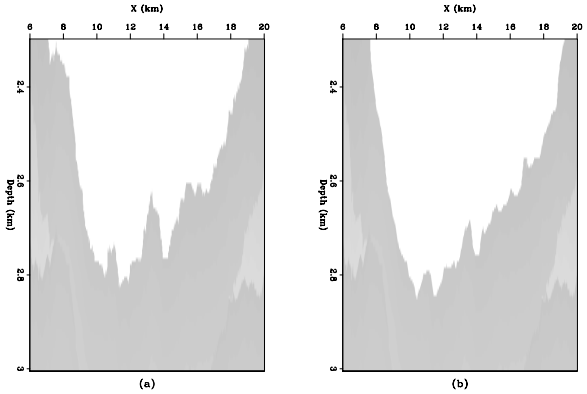

Figure 5: Original (a) and updated (b) velocity models for the section shown in Figure 6.

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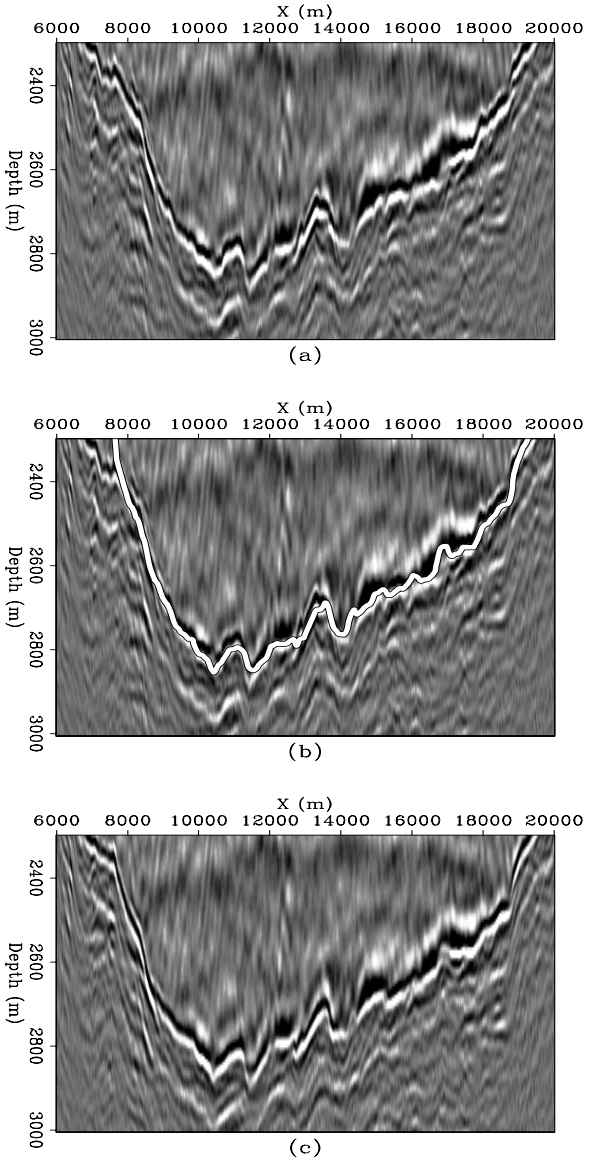

Figure 6: Original image (a), optimized boundary path (b), and updated image (c) for a portion of a Gulf of Mexico dataset. The updated image features a more continuous salt interface than in the original.

EDITED REFERENCES

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REFERENCES

Hale, D., and J. U. Emanuel, 2002, Atomic meshing of seismic images: 72nd Annual International Meeting, SEG, Expanded Abstracts, 2126–2129.

———2003, Seismic interpretation using global image segmentation: 73rd Annual International Meeting, SEG, Expanded Abstracts, 2410–2413.

Lomask, J., 2007, Seismic volumetric flattening and segmentation: Ph.D. thesis, Stanford University.

Lomask, J., R. G. Clapp, and B. Biondi, 2007, Application of image segmentation to tracking 3D salt boundaries: Geophysics, **72**, P47–P56.

Shi, J., and J. Malik, 2000, Normalized cuts and image segmentation: Institute of Electrical and Electronics Engineers Transactions on Pattern Analysis and Machine Intelligence, **22**, 838–905.