Edge-preserving smoothing: Applications to seismic image segmentation

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ABSTRACT
Automated image segmentation can be an important tool for interpreting seismic images, but segmenting raw images can lead to inaccurate results. Pre-processing images by smoothing is a common solution; however, traditional smoothing blurs boundaries and can be counterproductive, especially for seismic images. Here, an edge-preserving smoothing technique based on directional maximum homogeneity is introduced for 3D seismic images, and tested on both synthetic and field data with encouraging results. In addition, a “hybrid” smoothing technique blending traditional and edge-preserving smoothing is proposed in order to combine the advantages of each.

INTRODUCTION
Automatic image segmentation is a tool employed in a variety of disciplines – for example, medical imaging, photo editing/image processing, and seismic imaging and interpretation. Because image segmentation can reduce the time and effort required for human-intensive tasks involving image interpretation, a great deal of research has been aimed at developing different algorithms and improving existing ones. A particular area of interest involves the pre-processing of images prior to automatic segmentation. Here, I investigate the usefulness of an edge-preserving smoothing (EPS) technique for segmentation of seismic images.

A primary use for automatic seismic image segmentation is for identification and location of complex subsurface salt bodies, a task that is extremely time-consuming when undertaken manually. A variety of techniques from the image processing community, originally developed for use with photographs or medical images, have been adapted to account for the unique characteristics of seismic images. Recently, two different graph-based segmentation techniques (based on relationships between pixels in an image) have been found to be particularly suitable for seismic images. The Normalized Cuts segmentation algorithm (Shi and Malik, 2000), adapted for seismic data by Lomask et al. (2007), calculates an eigenvector of the image in order to partition it into regions. A significant drawback of this approach, however, is its computational expense, especially in three dimensions. In contrast, the pairwise region comparison (PRC) algorithm (Felzenszwalb and Huttenlocher, 2004) is designed to operate extremely efficiently, even when extended to three dimensions and adapted...
for seismic data (Halpert et al., 2010). However, like any segmentation algorithm, its accuracy can suffer, especially where boundaries are discontinuous or chaotic (for example, see Figure 8(a)). In such cases, smoothing the image before the segmentation procedure can reduce unwanted noise and improve performance of many image processing algorithms (Zahedi and Thomas, 1993).

For seismic images, naive box or Gaussian smoothing has clear disadvantages. When segmenting seismic images, clear and sharp boundaries are preferable for an accurate result; simple smoothing tends to blur these boundaries, or even render them uninterpretable if two reflectors are very close together (see Figure 3(a)). A variety of “smarter” smoothing or noise-reduction approaches for seismic data have been proposed, including inversion-based techniques like PEFs (Claerbout, 2005; Guittton, 2005), structure or dip-oriented filtering (Fehmers and Hocker, 2003), or bilateral filtering (Hale, 2011). Unfortunately, these algorithms require computationally-intensive inversions and/or solutions to differential equations like the diffusion equation, or prior information in the form of dip or structure interpretations. Therefore, a cheap, efficient smoothing algorithm that preserves sharp boundaries would represent a useful pre-processing step for seismic image segmentation.

### EPS Technique

Edge-preserving smoothing is a common goal in many image processing disciplines. An early form of EPS was median smoothing (Tukey, 1971), in which a central pixel is assigned the median pixel value from a neighborhood around it. Later, a method aiming for increased directional accuracy in EPS was proposed by Tomita and Tsuji (1977). In this approach, a gradient operator was calculated for several different rectangular neighborhoods, each oriented in a different direction around the (no longer central) pixel. The average value of the most homogeneous neighborhood was then assigned to the pixel in question. More recently, Zahedi and Thomas (1993) introduced the concept of “bar masks,” one-dimensional vectors of pixels that extend in different directions from the central pixel (Figure 1). This approach further increases directional discrimination in “maximum homogeneity” filtering approaches. Furthermore, Zahedi and Thomas (1993) assigned the median of the most homogeneous bar mask to the central pixel, rather than the average value; this improved the preservation of sharp edges in an image, and makes it attractive for use in seismic images.

A very similar approach has already been proposed for use on three-dimensional seismic images. AlBinHassan et al. (2006) constructed many 3D neighborhoods around a central pixel, and used the average value of the most homogeneous block. For this method and that of Zahedi and Thomas (1993), maximum homogeneity is determined by calculating the variance of the individual bar masks or 3D blocks:

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\sigma = \left[ \frac{1}{n} \sum_{i=1}^{n} (d_i - \bar{d})^2 \right]^{1/2},
\]
where \( n \) is the number of pixels in the bar mask or block \( d \), and \( \bar{d} \) is the average value of those pixels. The mask or block with the smallest variance has the greatest homogeneity.

The method presented here improves on this approach by incorporating two ideas from Zahedi and Thomas (1993). First, 1D bar masks, extending from a central pixel in all three dimensions, are used instead of the 3D blocks. Instead of constructing four individual bar masks for a given pixel as shown in Figure 1, nine masks are constructed extending in all three dimensions (plus a single 3D block to handle the case of isotropic noise). This greatly simplifies the computational complexity of the algorithm, while at the same time preserving sharp boundaries with arbitrary orientations. Second, I use the median value of the bar mask with maximum homogeneity, rather than the average value. Again, this enhances the edge-preserving characteristics of the filter.

**EXAMPLES**

The effectiveness of this method is best demonstrated through examples, and comparison to the traditional smoothing approach. Figure 2(a) is a 2.5D synthetic featuring a dipping reflector pinching out onto a flat reflector. Figure 9(a) is the same image with a significant amount of random, uniform noise added. Because of the noise, it is difficult to differentiate the two reflectors near their intersection.

Ideally, smoothing the noisy image would clean up the image, and allow an interpreter to clearly see where the reflectors intersect. However, a traditional 5x5x5 box filter fails to produce this result (Figure 3(a)). While much of the noise is indeed removed, the filter has blurred the reflectors, making it impossible to distinguish
Figure 2: A simple 2.5-D synthetic consisting of two planar reflectors (a), and the same image contaminated with random noise (b). The high level of noise makes it difficult to distinguish the two reflectors at the indicated location.
between them. Furthermore, taking the difference between the noisy image and the filtered image gives an unwanted result (Figure 4(a)); it is obvious that a significant amount of coherent signal has been removed. In contrast, the maximum homogeneity (MH) filter with a mask length of 5 pixels performs better (Figure 3(b)). Not only are the two reflectors able to be distinguished much more easily in the filtered result (Figure 3(b)), but the difference calculation (Figure 4(b)) shows much less coherent signal being removed. Despite these advantages, though, more noise does remain in the MH-filtered image; this is a problem we will return to later.

Figure 5 shows a 3D field data image from the Gulf of Mexico, and its corresponding amplitude of the envelope volume, shown for this example to ease the comparison between the methods. Figure 6 shows the result of smoothing the image with traditional filtering (a), and the MH method (b). While it is clear from this figure that the MH result does a much better job of preserving the sharpness of the reflectors, the difference results (7) show the advantage even more clearly. Figure 7(a) looks exactly like the image itself, which is extremely undesirable. The MH-filtered information (7(b)) is much less coherent, and more desirable.

Finally, we should examine the effect of MH filtering on automatic segmentation results – the ultimate goal of this project. Figure 8(a) is the result of segmenting the original, unfiltered image in Figure 5(a). Clearly, the chaotic salt boundary has caused problems for the algorithm, including “leakages” from the salt body into the surrounding sediments. When the MH-filtered image is segmented, however, these problems are greatly ameliorated (Figure 8(b)). Here, MH filtering has successfully removed unwanted noise and cleaned up the image, allowing for a more accurate segmentation result. Furthermore, the computational efficiency (and simple parallelization) of the algorithm make it especially attractive; smoothing the image in this example required only a few seconds, a fraction of the time required for the already-efficient PRC segmentation algorithm.

A HYBRID APPROACH

Finally, we examine the problem of a higher level of noise remaining in an MH-filtered image compared to a traditionally-smoothed image, even though the edge-preserving advantages of the MH approach are clear. From the examples in Figure 3, it appears that traditional smoothing does perform very well in areas devoid of sharp boundaries or edges. Therefore, we can develop an approach that combines the characteristics of box smoothing in areas without edges, and takes advantage of the edge-preserving features of MH filtering when edges are present. For the MH algorithm, for every pixel we already calculate variances for each of the bar masks passing through the pixel. We can therefore compare the largest and smallest of these calculated variances to learn about the likelihood that an edge is present. If the ratio between the smallest and largest variances is large (close to 1), we are in a relatively “isotropic” area, and an edge is unlikely to be present. Conversely, a smaller ratio implies that an edge is present in at least one of the bar mask orientations. If we set $\sigma$ to be a user-
Figure 3: Results of smoothing the image in Figure 9(a) with (a) traditional box smoothing, and (b) maximum homogeneity (MH) filtering of the same operator length.
Figure 4: Results of differencing the images in Figures 2 and 3. The filtered information when using the MH filter (b) contains much less coherent signal than when using traditional smoothing (a).
Figure 5: A 3D image from the Gulf of Mexico (a), and its corresponding envelope amplitude (b).
Figure 6: The image in Figure 5(b), smoothed with (a) a traditional box filter, and (b) an MH filter of the same length.
Figure 7: Results of differencing the original image in Figure 5(a) with (a) the image smoothed with a traditional box filter, and (b) the image smoothed with the MH filter. Again, the result in (b) shows that much less coherent signal has been removed from the image.
Figure 8: Automatic image segmentation results when using (a) the original envelope image in Figure 5(b), and the MH-smoothed envelope in Figure 6(b). The MH smoothing has helped correct some obvious leakages in the original segmentation result.
determined threshold value, then if $\frac{\text{min}(\sigma)}{\text{max}(\sigma)} > \alpha$, traditional smoothing can safely be used in lieu of MH filtering.

Figure 9 demonstrates this strategy on the synthetic example shown earlier. As the threshold value $\alpha$ decreases, the algorithm is more biased toward traditional smoothing; consequently, the amount of “speckle” noise decreases. However, near the two reflectors, MH filtering still holds sway. The final result is an image with the speckle noise removed as well as in the traditional smoothing result in Figure 3(a), but with the reflector edges preserved as well as the standard MH result in Figure 3(b).

![Figure 9: The original noisy synthetic image (a), and the results of applying the hybrid-MH filter with $\alpha$ set at (b) 0.5, (c) 0.25, and (d) 0.1. As $\alpha$ decreases, more speckle-noise is removed from the image, while the sharpness of the reflectors is preserved.](image)

Similarly, Figure 10 shows results of this hybrid approach for the field data example. As $\alpha$ decreases, the image becomes noticeably smoother, even though the reflector boundaries remain clear. In this example, though, it is evident that the reflectors’ amplitudes are being modified, which is an important consideration.

**CONCLUSIONS**

Automated seismic image segmentation schemes can benefit from preprocessing such as smoothing prior to segmentation. An edge-preserving smoothing method based on
Figure 10: Results of applying the hybrid-MH filter on the image in Figure 5(a), with $\alpha$ set at (a) 0.5, (b) 0.2, and (c) 0.1 and (d) 0.01. While the reflector amplitudes are affected, a great deal of speckle noise is removed at low $\alpha$ values.
direction maximum homogeneity can de-noise and clean up an image, while preserving important edges such as salt boundaries. Applying the MH filtering algorithm to 3D field seismic data improves segmentation results by reducing “leakages” through boundaries. In addition, a hybrid approach combining the best aspects of traditional smoothing and MH filtering can improve noise removal while still preserving edges well.

REFERENCES

Tukey, J. W., 1971, Exploratory data analysis: Addison-Wesley.