

# Parallel implementation of image segmentation for tracking 3D salt boundaries

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## SUMMARY

We distribute the modified normalized cuts image segmentation with random boundaries algorithm on a parallel network to track 3D salt boundaries. We identify two key steps of this algorithm for parallelization. Firstly, we parallelize the calculation of the weight matrix. Secondly, we parallelize the matrix-vector product of the eigenvector calculation. This method is demonstrated to be effective on a 3D seismic cube.

## INTRODUCTION

Salt boundary picking is a difficult and time consuming component of constructing a velocity model. Although the amplitude of salt reflections is often bright, traditional autotrackers regularly fall prey to local discontinuities and misspick the boundary. Consequently, many hours of manual editing are often required. This is compounded by the iterative process of updating the velocity model and re-migrating the data. A modified version of normalized cuts image segmentation provides an alternative global optimization picking method that looks for the best overall picking result and is thus less sensitive to local discontinuities. We have already applied this method to 2D seismic salt boundaries (Lomask and Biondi, 2003; Lomask et al., 2004). However, to reduce the significant computational time of this method for application to 3D seismic salt boundaries, it is necessary to distribute it on a parallel network.

Normalized cuts image segmentation (Shi and Malik, 2000) is a pattern analysis technique developed to extract global impressions from images. Hale and Emanuel (2003, 2002) adapted this technique to painting 3D atomic meshes. In addition to sparse matrix storage and random sampling (Shi and Malik, 2000), other memory saving measures such as random bounds (Lomask and Biondi, 2005) have been implemented in order to reduce the size of problem thus reducing the exorbitant cost of applying this technique. However, to tackle realistic 3D data sets, the computational time of this algorithm still needs to be reduced significantly.

There are two significant computational time bottlenecks in the normalized cuts image segmentation with random bounds algorithm. This image segmentation technique creates a matrix containing weights relating each pixel to every other pixel in a local neighborhood. The weights are dependent on the negative absolute value of the complex trace (instantaneous amplitude) of the seismic. The matrix is then used to cut the image where the normalized sum of weights cut is minimized. This normalized cut is minimized by solving an eigenvector problem. The first bottleneck is the creation of the weight matrix as it can become quite large requiring a lot of computation time to build. The second bottleneck is the estimation of the eigenvector which requires numerous matrix-vector products involving the large sparse weight matrix.

In this paper, we present a parallel implementation of the normalized cuts image segmentation with random bounds technique for tracking 3D salt boundaries. We first review the algorithm. We then describe how we have distributed the calculation of the weight matrix on a parallel network. We then describe how we have parallelized the matrix-vector products of the eigenvector calculation. Lastly, we test this technique on a 3D field seismic cube.

## METHODOLOGY

Normalized cuts image segmentation partitions images into two groups. To do this, it first creates weights relating each sample to randomly selected samples along paths within local neighbor-

hoods. These weights are stored in a sparse matrix  $\mathbf{W}$ . It then finds the cut that partitions the image into two groups,  $A$  and  $B$ , by minimizing the normalized cut:

$$N_{cut} = \frac{cut}{total_A} + \frac{cut}{total_B} \quad (1)$$

where  $cut$  is the sum of the weights cut by the partition.  $total_A$  is the sum of all weights in Group  $A$ , and  $total_B$  is the sum of all weights in Group  $B$ . Normalizing the cut by the sum of all the weights in each group prevents the partition from selecting overly-small groups of nodes.

The minimum of  $N_{cut}$  can be found by solving the generalized eigensystem:

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

created from the weight matrix ( $\mathbf{W}$ ) and a diagonal matrix ( $\mathbf{D}$ ), with each value on the diagonal being the sum of each column of  $\mathbf{W}$ . The eigenvector ( $\mathbf{y}$ ) with the second smallest eigenvalue ( $\lambda$ ) is used to partition the image by taking all values greater than zero to be in one group, and its complement to be in the other. For a more detailed description, see Shi and Malik (2000).

## Application to seismic

To apply this segmentation method to seismic data, the weight calculation needs to be modified. Rather than looking for clusters of pixels with similar intensity, we are now looking for groups of pixels on each side of the bright amplitude salt boundary. Therefore, we want the weights connecting pixels on either side of the salt boundary to be low and the weights connecting pixels on the same side of the salt boundary to be relatively high. Taking the negative of the maximum amplitude along the shortest path between two nodes as the weight would insure that the weights connecting pixels on either side of the salt boundary will be low. However weights on the same side would be alternating from low to high as they go from peak to trough on the seismic data. This could make the grouping more uncertain. To correct this problem, we take the negative of the maximum of the absolute value of the complex trace (instantaneous amplitude) along the shortest path between two nodes.

## 3D implementation

The most significant difference between 3D image segmentation and 2D image segmentation is during the generation of the weight matrix, the rest of the algorithm is almost identical. When creating the weight matrix, instead of randomly sampling from a circular neighborhood, we sample from a sphere. Of course this means that more points are sampled per node. This, in turn, means that the sparse matrix is considerably less sparse and the entire algorithm more expensive. Therefore, even with sparse matrices and tight boundaries, we still need to look for ways of reducing the computational-time cost of this algorithm for 3D problems.

## PARALLEL IMPLEMENTATION

### Parallel calculation of the weight matrix

We have distributed the calculation of the weight matrix on a beowulf cluster using the parallel infrastructure described in Clapp (2005). The complete image and masks are distributed to each node. This is necessary because the random bounds requires random jumps around the image. Different jobs are assigned different rows of the weight matrix, no communication between nodes is necessary while calculating the weight matrix. Upon completion, the weights are collected into a single sparse matrix on the master node

## Segmentation

### Parallel calculation of the eigenvector

To calculate the eigenvector with the second smallest eigenvalue, we use ARPACK Fortran77 software (Lehoucq and Scott, 1996) as recommended by Shi and Malik (2000). This is a package of routines designed specifically for computing a few eigenvectors and eigenvalues for large sparse matrices.

The ARPACK interface requires the user to supply the subroutine that does the matrix-vector multiplication. The matrix-vector multiplication is the most expensive portion of calculating the eigenvector, and therefore the obvious target for parallelization. We implement the eigenvector calculation in a modified master-slave scheme.

The slave nodes are initialized with a portion of the off-diagonal elements of the matrix. The master node is given a vector by the ARPACK library. It sends that vector to the first slave node and then begins to create the output vector by multiplying the diagonal terms of the matrix. Upon receiving the input vector the first slave node, it passes the vector to the second slave node, and then begins multiplying the input vector by its portion of the off-diagonal terms creating its own output vector. This process is repeated by all of the slave nodes. The master node upon finishing multiplying the diagonal terms passes the output vector to the first slave node. It adds it to its output vector, and passes it to the second slave node. The process is repeated until the last slave node, which passes the completed matrix multiplication to the master node.

By implementing the matrix multiplication in this form, a good level of load balancing, and minimal communication wait time is achieved. We ran the approach on a Infiniband network and were able to do 200 iteration of 2 billion non-zero matrix elements in 55 minutes.

### Parallel Issues

Our current bottleneck is a software design issue. Much of SEPlib, assumes axes no larger than  $2^{31}$  by using integers. If we exceed this number we get semi-random errors. Another potential problem is the way we implemented the eigenvector calculation. If we scale to many nodes, the communication time will dominate, and we will significantly degraded performance. We have so far avoided this problem by running on a low-latency, high-bandwidth network.

### FIELD TEST CASES

We tested this method on a Gulf of Mexico 3D data set provided by Unocal.

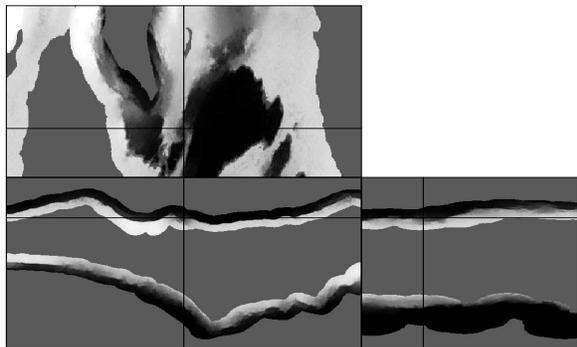


Figure 1: The second smallest eigenvector that is used to partition the image.

The second smallest eigenvector from the method is displayed in Figure 1. The resulting picked boundary is shown in Figure 2.

### CONCLUSIONS AND FUTURE WORK

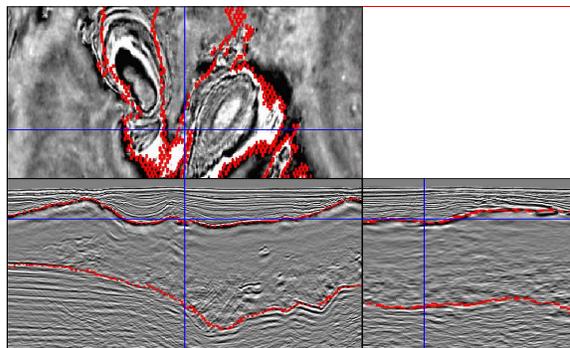


Figure 2: The boundary is overlain on the data itself. Notice it accurately tracks the boundary.

We have successfully parallelized two key steps of this segmentation method: the calculation of the weight matrix and the estimation of the eigenvectors. Now, with a large enough cluster, almost any sized post-stack 3D data set can be globally segmented. This is an exciting development in that this algorithm is becoming significantly more practical.

In many places on salt boundaries the amplitude can become weak and the boundary can more easily be tracked using another attribute such as instantaneous frequency. On first glance it seems straight forward to estimate the weights of the normalized cuts image segmentation method using multiple attributes but to balance the weights in an optimal way may be somewhat challenging. We hope to address this problem in the near future.

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