A Semi-Automatic Approach for Estimating Bedrock and Surface Layers from Multichannel Coherent Radar Depth Sounder Imagery

Jerome E. Mitchell,[1] David J. Crandall,[1] Geoffrey C. Fox,[1] Maryam Rahnemoonfar,[2] and John D. Paden[3]

[1] School of Informatics and Computing, Indiana University, Bloomington, IN 47403 USA
[2] School of Engineering and Computing Sciences, Texas A & M Corpus Christi, Corpus Christi, TX 78412 USA
[3] Center for Remote Sensing of Ice Sheets, University of Kansas, Lawrence, KS 66045 USA

ABSTRACT

The dynamic responses of the polar ice sheets in Greenland and Antarctica can have substantial impacts on sea level rise. Understanding the mass balance requires accurate assessments of the bedrock and surface layers, but identifying each layer is performed subjectively by time-consuming, dense hand selection. We have developed an approach for semi-automatically estimating bedrock and surface layers from radar depth sounder imagery acquired from Antarctica. Our solution utilizes an active contours method ("level sets") to propagate an initial estimation of a layer's position based upon curvature and image intensity gradients. This allows the initial curve to gravitate with topological changes while providing smooth boundaries for discriminating between bedrock and surface layers. We evaluated the proposed semi-automatic method on 20 images with respect to hand labeled ground-truth. Compared to an automatic technique, our approach reduced labeling error by factors of 5 and 3.5 for tracing bedrock and surface layers, respectively.

Keywords: Radar Image Processing, Bedrock and Surface Layers

1. INTRODUCTION

In the central portion of Greenland and Antarctica, ice is slow-moving and can be observed using radar sounding techniques. However, the large attenuation and off-vertical, rough-surface scattering around the margins present challenges to radar sounding in these areas.[1] The influence of the margins (especially the outlet glaciers) on an ice sheet's stability requires accurate measurements of the bed topography. This is important to developing and refining ice sheet models for quantifying the contribution to sea level rise.

The Center for Remote Sensing of Ice Sheets (CReSIS) has developed a multichannel coherent radar depth sounder[2] in order to map the thickness and underlying bed topography beneath the ice sheets. In depth-sounding, the strongest, first reflection is considered as an interface between the air and ice sheet surface. As energy propagates through ice, near surface internal layers provide reasonably strong reflections, which are dependent on their density, composition, and thickness. The deepest reflector is caused by an interface between the bottom of the ice sheet and the underlying bedrock. For estimating ice thickness, we are interested in the first (surface) and last peaks (bedrock), but identifying these features in radar imagery typically requires time-consuming, dense hand selection. Additionally, it is a common for domain experts to skip many measurements and interpolate between layers for each echogram to save time. There is a need for the development of automatic techniques to support objective identification of layers and allow for large volumes of data to be analyzed with either little or no human intervention. However, automatically tracing layers in images is challenging due to the limited resolution, large degree of noise, faint layer boundaries, and rigid structures.

In this paper, we present an approach to semi-automatically estimate surface and bedrock layers from polar radar imagery. After requiring a user to initialize an ellipse as an estimate for each boundary, our approach detects layers by evolving an initial contour in order to reshape the curve until a cost function is minimized.

2. RELATED WORK

There has been relatively little work on estimating bedrock and surface layers from echograms acquired in either Greenland or Antarctica. Other studies focused on tracing near surface internal layers in radar imagery. For example, Fahnestock et al.[3] developed an algorithm which uses cross-correlation and a peak-following routine, Karlsson and Dahl-Jensen[4] present a ramp function-based approach, and Sime et al.[5] developed a technique to obtain layer dip information from two datasets in the Antarctic. For techniques in detecting bedrock and surface layers, Ilisei et al.[6] generated a statistical map of the subsurface by exploiting the properties of the radar signal and used a segmentation algorithm for estimating investigated areas, but identifying curves can also be accomplished using image processing and computer vision techniques. Approaches have focused on incorporating edge fragment routines to connect disjointed curves to one or more image features, such as Czerwinski et al.[7] Other techniques have used adaptive contour fitting, which allows a cost function to be represented as energy.[8,9] The contour's shape evolves towards the targeted boundary as energy is minimized. Examples include work in Kratky and Kybic[10] for medical imagery, tracking curves in clutter demonstrated in Isard and Blake,[11] boundary detection, and a image segmentation technique used in Ma and Manjunath.[12] Also, pyramid-based edge detection is a popular and robust technique for identifying objects and lines.[13] In more relevant studies, Gifford et al.[14] used an active contours method ("snakes"), but in their work, snakes require an accurate location for an initial contour to sufficiently select layer boundaries, and snakes cannot detect more than one boundary simultaneously. Crandall et al.,[15] with whom we compare our work, used a probabilistic framework based on graphical model inference to automatically trace layer boundaries. We present an alternative technique, similar to work proposed for using level sets to segment synthetic aperture radar imagery,[16,17] which requires greater manual interaction, but performs significantly better in some images.

3. METHODOLOGY

Our images were acquired from a ground-penetrating radar mounted on an aircraft, which the horizontal axis corresponds with distance along the flight path and the vertical axis corresponds with echo depth. These images provide a noisy "cross section" of the ice structure. An example is shown in Figure 1. The key features of these images suggest the position and contour of the boundary between the bedrock and the ice, and the boundary between the ice and the air. The bedrock boundary is generally continuous but does suffer from occasional discontinuities caused by either sudden changes in topography, changes in signal attenuation through the ice column (usually due to the presence of liquid water), or unresolved clutter masks the bed signal. The surface is generally more easily identifiable since it has the strongest return in the image. Some of the noise in the images is structured; for instance, surface reflections often repeat once or twice because the radar signal resonates between the surface and the radar platform.

We applied an active contours method ("level sets") to estimate bedrock and surface layers by starting two contours provided by a users and refine them on the basis of gradient information. This technique "snaps" to prominent, near-continuous boundaries close to the initialized region.

3.1 Active Contours (Level Sets)

The level set method is used as a segmentation approach for propagating a contour to object boundaries using properties of an image. Earlier applications have employed level sets to identify edges, but more recently, it has focused on detecting textures, shapes, and colors in an image.

We have used the method proposed in Mehrotra et al.[18] to detect bedrock and surface layers from polar radar imagery. A level set, briefly described in image processing, is a 1D curve embedded in a 2D space. This space defines the level set function, $\phi(x, y)$, where every point is closest in distance to the boundary. Specifically, the sign of each point determines whether it is either inside or outside the boundary. The boundary is defined as the zero level set of the function. For each layer, an ellipse was manually initialized, so its zero level set contained the boundary of interest (as shown on the left in Figure 1). In order to evolve the contour, a partial differential equation (Hamilton Jacobi) used the curvature and magnitude of the $\phi(x, y)$ gradient, introduced by Osher and Sethian,[19] for deforming the boundary over time. We also used a cost function, which served for stopping the contour's movement when the gradient was maximum at layer boundaries. As the level set function evolved

Table 1. Evaluation of Level Set Method and Hidden Markov Model, in terms of mean and mean squared errors (in pixels).

Approach	Bedrock		Surface	
	Mean Err	Mean Squared Err	Mean Err	Mean Squared Err
Level Set	7.1	342.0	4.1	31.8
Hidden Markov Model	37.5	11700.0	14.6	490.3

with time, the shape changed from an ellipse to the exact bedrock and surface topologies (as shown on the right in Figure 1). The level set function can develop numerical instabilities, such as sharp or at shapes may occur, which may lead to computational inaccuracies and an improper result. In order to avoid this problem, we used reinitialization to reshape the embedding function periodically after a number of iterations.

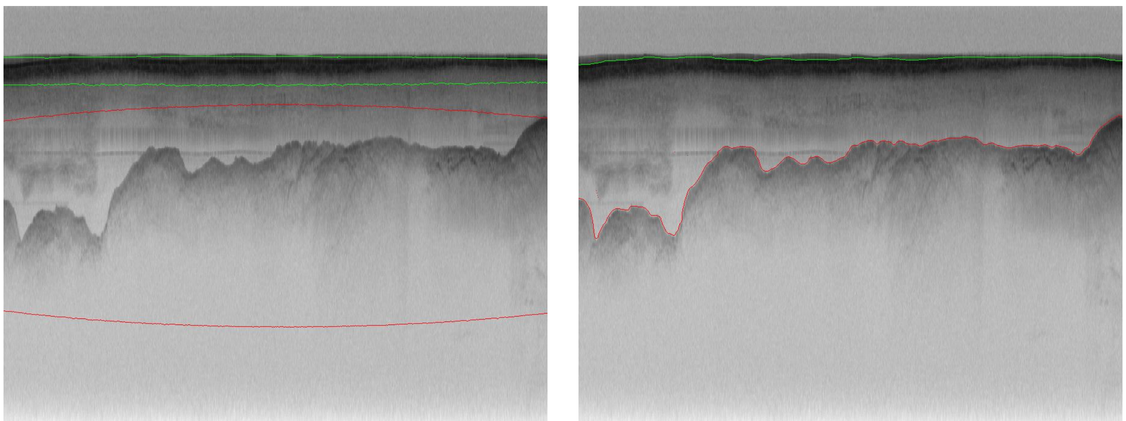
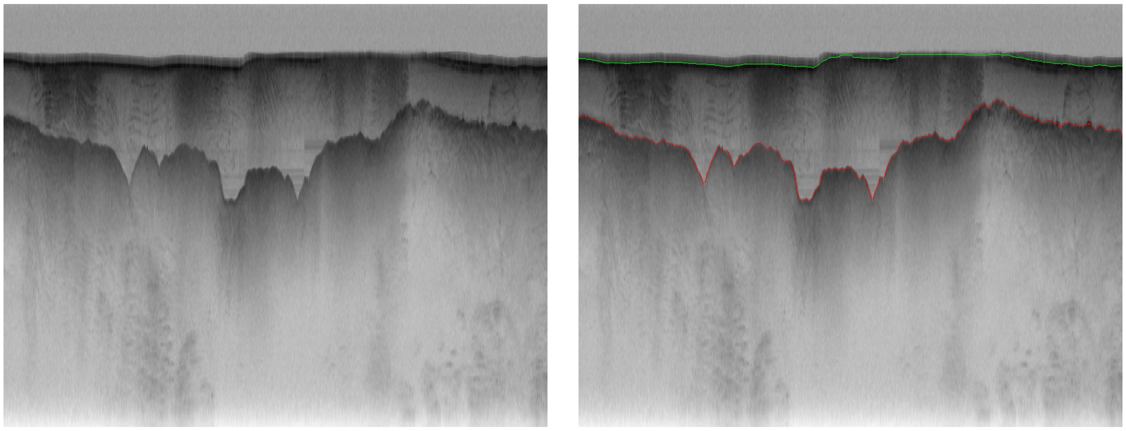


Figure 1. (left) Initialization of ellipse and Detected bedrock/surface layers

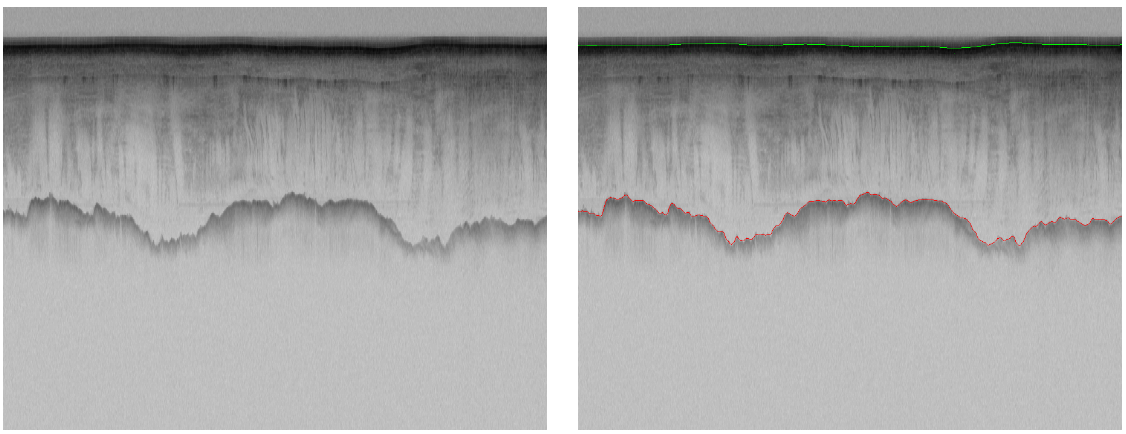
4. RESULTS

The level set method was applied to 20 random, representative sample images collected by CReSIS,[20] and Figure 2 shows a set of sample results. Our results are encouraging, as in most cases, the bedrock and surface layers were detected correctly and were obtained automatically, except for the manual initialization for each layer boundary and hand tuning the step size in addition to the number of iterations between reinitializations. Since we relied on image intensities to terminate the curve evolution, the cost function may not be zero for weak edges and may cause the curve to pass through the boundary, as can be shown in Figure 2(d).

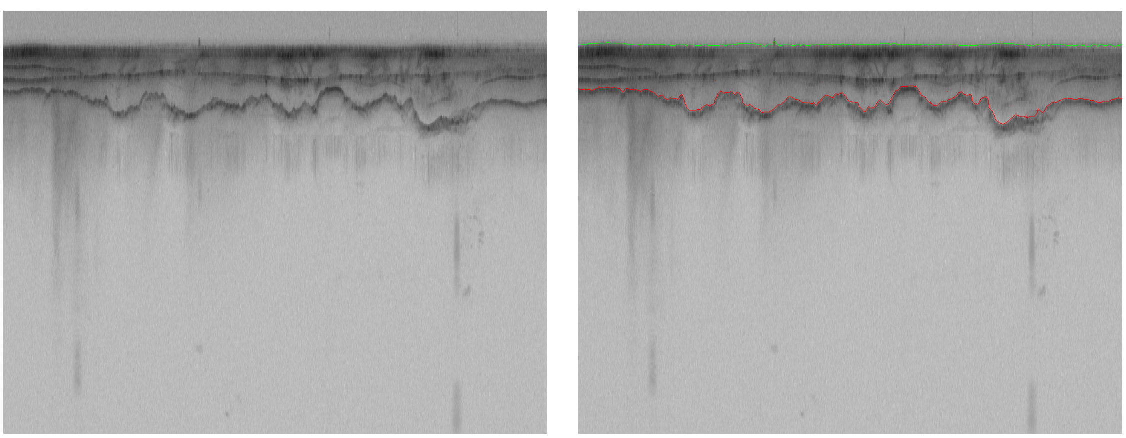
In order to quantify the effectiveness, we compared our technique to the Hidden Markov Model (HMM) approach developed by Crandall et al.[15] We used the same performance metric introduced in the author's paper, by viewing each boundary as a 1D function and computing the mean and mean squared errors with respect to hand labeled ground truth. As shown in Table 1, there is a 7 and 4 pixel difference between our approach and the ground-truth for bedrock and surface layers, respectively. We performed, on average, 5 times better for bedrock layers and 3.5 times for surface layers compared to the HMM approach. However, our approach requires some (minimal) user intervention, whereas their technique is completely automatic.



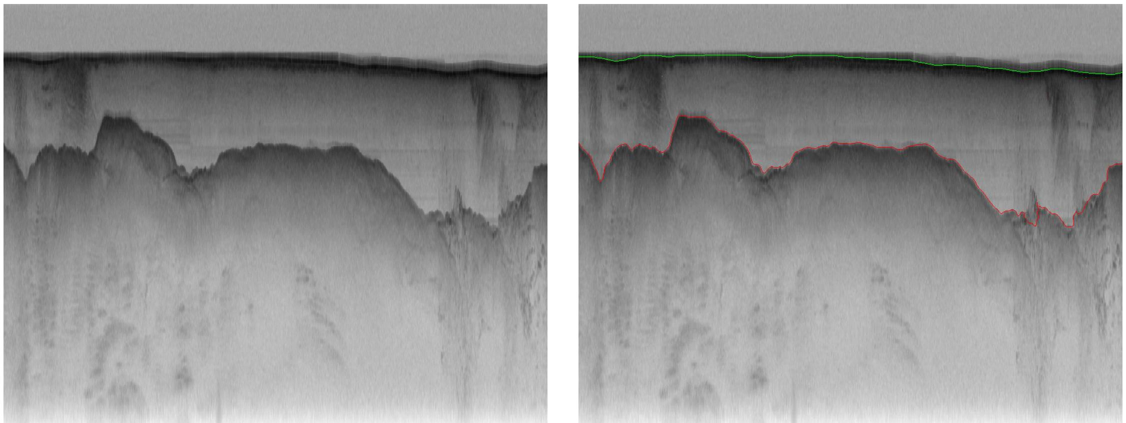
(a)



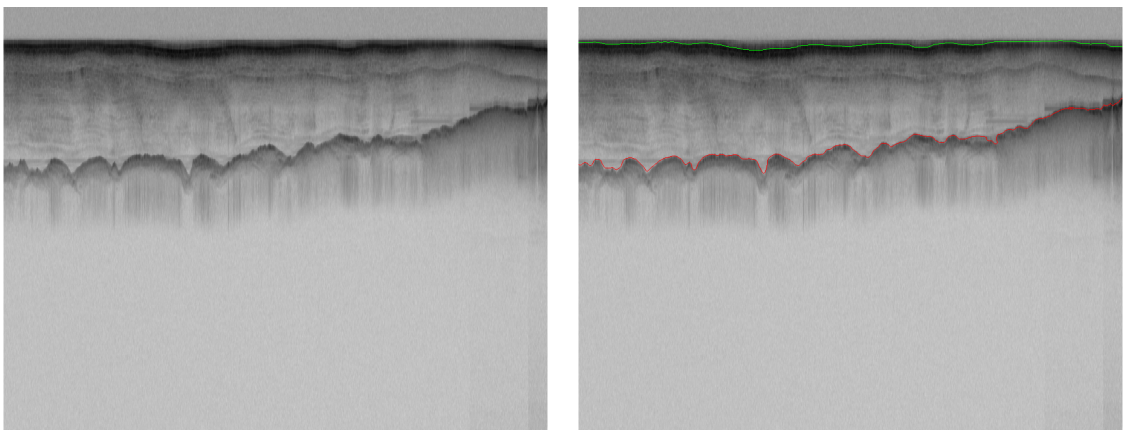
(b)



(c)



(d)



(e)

Figure 2. Sample results of our approach on five radar depth sounder echograms

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5. CONCLUSIONS AND FUTURE WORK

We have developed a semi-automated approach to estimate bedrock and surface layers from multichannel coherent depth sounder imagery. Our solution utilizes an active contour model and is a step towards the ultimate goal of unburdening domain experts from the task of dense hand selection. By providing tools to the polar science community, high resolution ice thickness maps can be readily processed to determine the contribution of global climate change to sea level rise. In the future, we intend to explore automated algorithms using learning techniques for identifying bedrock (with discontinuities) and surface layers.

6. ACKNOWLEDGMENTS

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