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

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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"), which identifies surface and bedrock boundaries by evolving two geometric functions as initial estimates of a layer's position and depth until a gradient-based cost function was minimized. We evaluated the semi-automatic proposed method on 20 images with respect to hand labeled ground-truth. Compared to an existing 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 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, and 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 practice among domain experts to skip many measurements and interpolate between layers for each echogram. 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. Here, we present an alternative technique, which requires greater manual interaction, but performs significantly better in some images.

3. METHODOLOGY

Our images come from ground-penetrating radar systems 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 thus give a noisy "cross section" of the ice structure. An example is shown in Figure 1. Key features of these images, which are of interest to scientists include 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 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 apply an active contours method ("level sets") to estimate bedrock and surface layers by starting with two initial contours provided by a human, and then refining them on the basis of gradient information. This technique thus "snaps" to prominent, near-continuous boundaries close to the initialized region.

3.1 Active Contours (Level Sets)

We use the level set method of Osher et al.[16] to perform the boundary detection. Briefly described, this is a deformable model implicitly representing a curve which has geometric characteristics and motion determined by the zeroth level set of a scalar function. In the image space, the level set function is defined as the signed distance function from the zeroth level set. Specifically, for a given closed curve, this function is zero for a pixel lying on the curve and otherwise is the signed distance from the point to the curve, with a negative sign for pixels outside the curve and positive sign for pixels inside the curve. This level set function can be used for image segmentation by minimizing a cost function, defined to encourage partitioning along strong image boundaries, using gradient descent.

Since gradient descent is a hill-climbing algorithm, it is prone to falling into local minima and thus requires a good initialization. We use human interaction to provide this initialization, asking a human user to mark the approximate layer boundaries with coarse ellipses whose zero level sets contain the contours of interest (as shown on the left pane of Figure 1). Then gradient descent is used to identify the layer boundaries, as shown on the right pane in Figure 1. Even with a good initialization, the level set function can develop numerical instabilities,

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

such as sharp or flat shapes, which may lead to an improper result. In order to avoid this problem, we used reinitialization to reshape the embedding function periodically after a number of iterations.

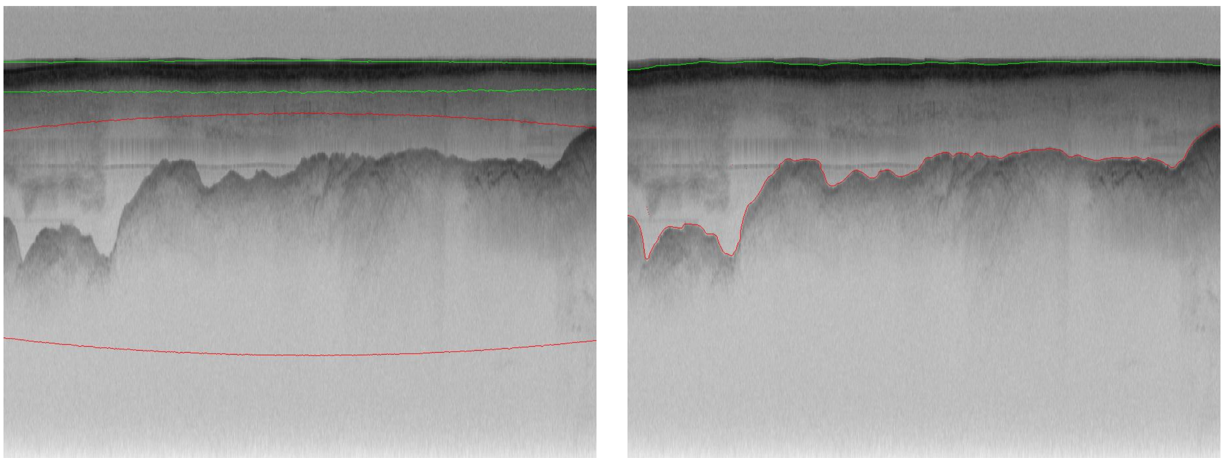
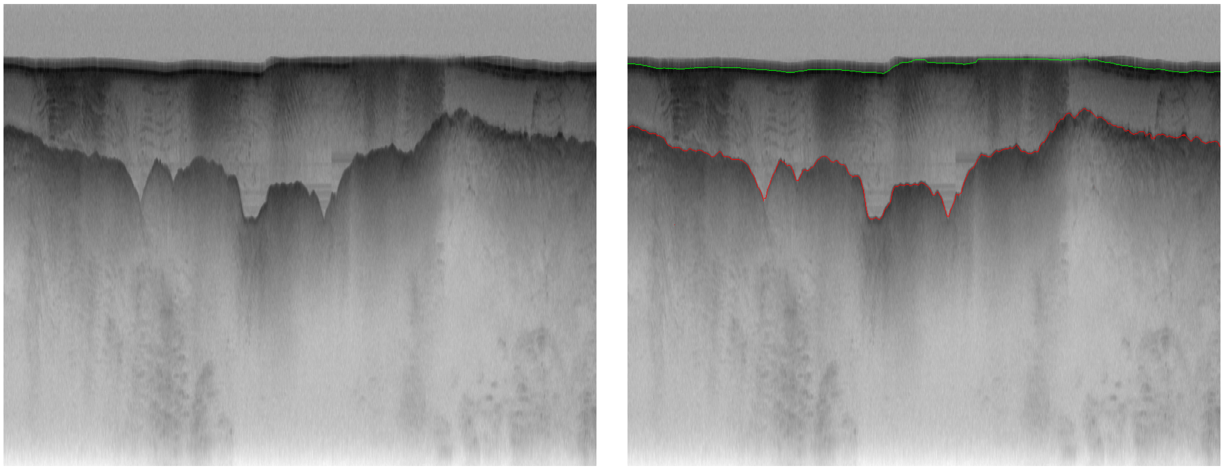


Figure 1. (left) Initialization of Ellipse and Detected Bedrock/Surface Layers

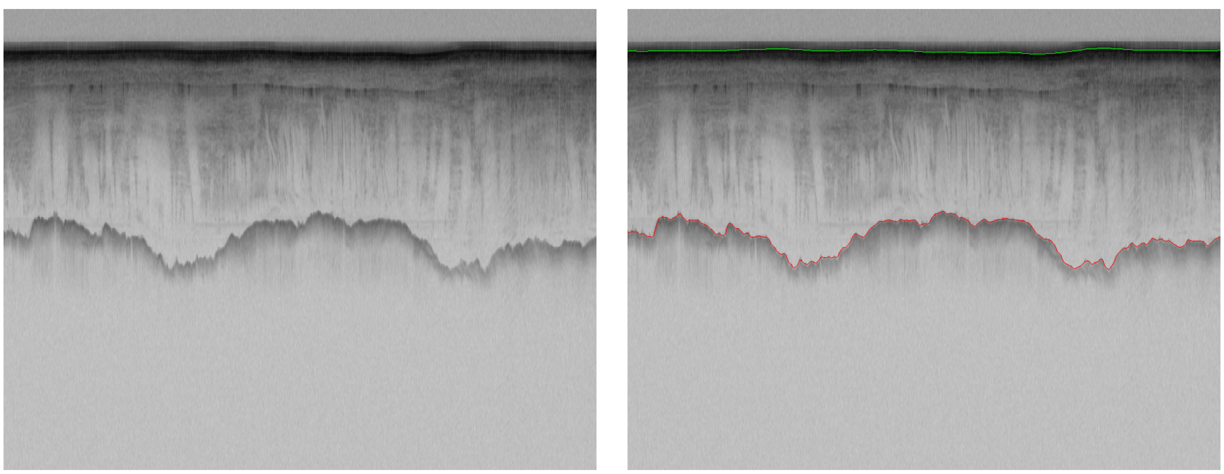
4. RESULTS

The level set method was applied to 20 images produced by CReSIS,[17] and Figure 2 shows a representative set of sample result images. These preliminary results are encouraging, as in most cases the bedrock and surface layers were correctly found. The results were obtained automatically from our approach, except humans provided the initialization (by drawing a coarse ellipse around the layer boundaries), and the step size and number of iterations between reinitializations were tuned by hand. 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).

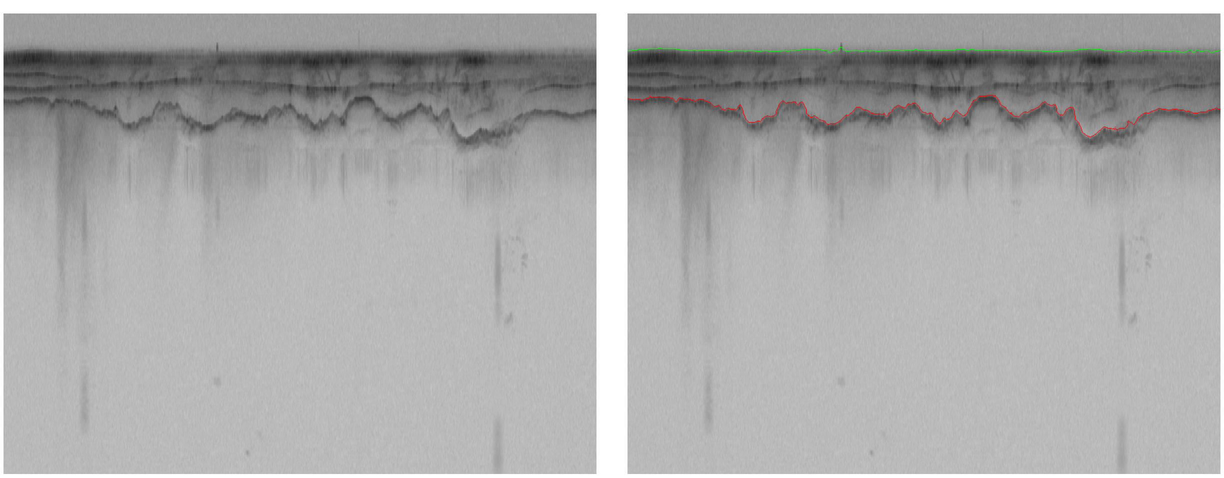
In order to quantify the effectiveness, we compared our technique to the Hidden Markov Model approach of Crandall et al.[15] We used the same performance metric they introduced, by viewing each boundary as a 1-d function and then computing the mean and mean squared errors with respect to hand labeled 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 perform, 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) human intervention, whereas their technique is fully automatic.



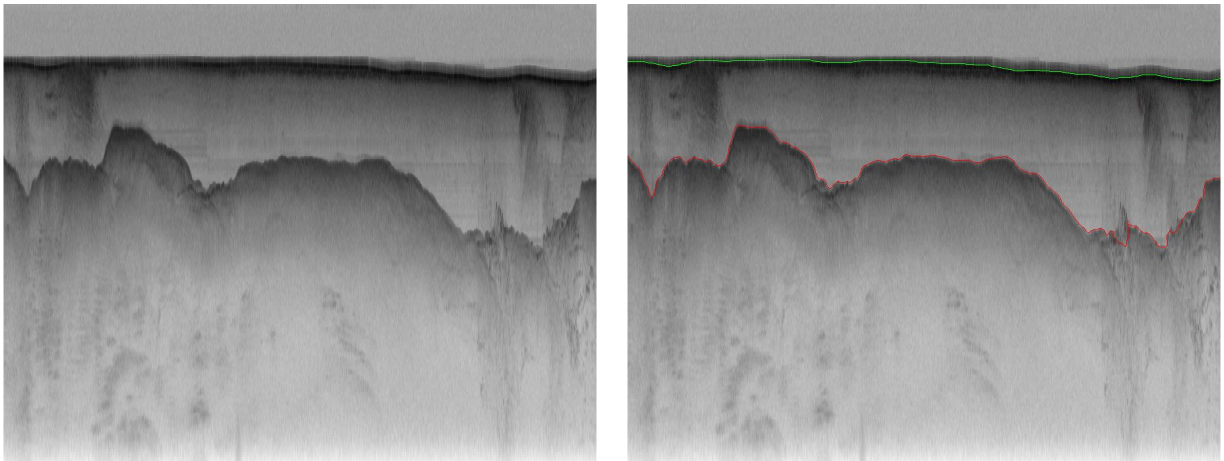
(a)



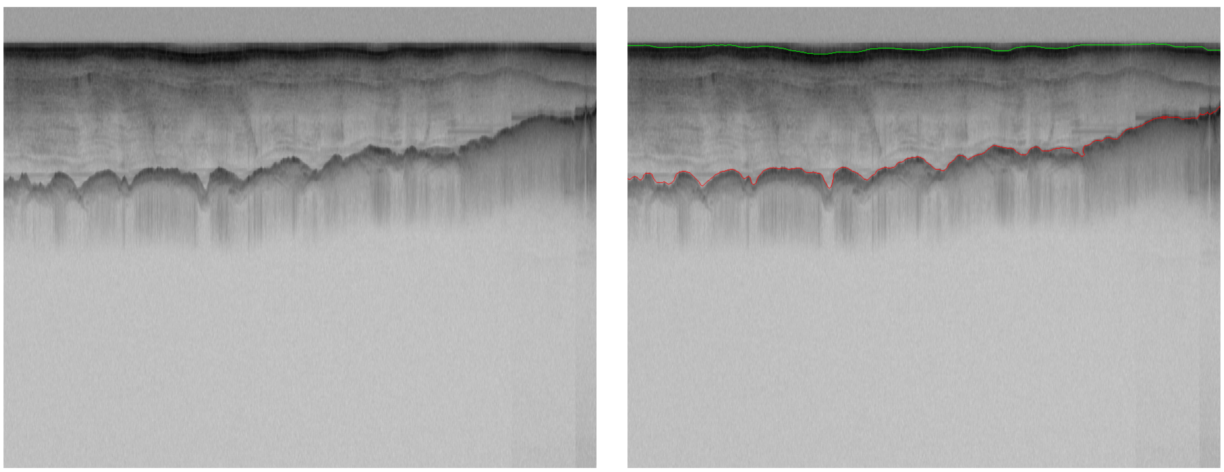
(b)



(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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