

A SEMI-AUTOMATIC APPROACH FOR ESTIMATING NEAR SURFACE INTERNAL LAYERS FROM SNOW RADAR IMAGERY

Jerome E. Mitchell¹, David J. Crandall¹, Geoffrey C. Fox¹, and John D Paden²

¹School of Informatics and Computing, Indiana University, Bloomington, IN 47403 USA

²Center for Remote Sensing of Ice Sheets, University of Kansas, Lawrence, KS 66045 USA

ABSTRACT

The near surface layer signatures in polar firn are preserved from the glaciological behaviors of past climate and are important to understanding the rapidly changing polar ice sheets. Identifying and tracing near surface internal layers in snow radar echograms can be used to produce high-resolution accumulation maps. This process is typically performed manually, however, requiring time-consuming, dense hand-selection in each echogram and interpolation between echogram sections. We have developed an approach for semi-automatically estimating near surface internal layers in snow radar echograms, and we have applied it to echograms acquired from Antarctica. Our solution utilizes an active contour (“snakes”) model to find high-intensity edges likely to correspond to layer boundaries, while simultaneously imposing constraints on smoothness of layer depth and parallelism among layers.

Index Terms— Radar Image Processing, Near Surface Internal Layers

1. INTRODUCTION

The IPCC Fourth Assessment reports considerable uncertainty associated with projected sea level rise over the coming decade and century [1]. Understanding the ice flow dynamics in Greenland and Antarctica poses a significant challenge, but the uncertainty can be substantially reduced by more and better observations of the polar ice sheets’ internal structure.

The Center for Remote Sensing of Ice Sheets (CReSIS) developed a snow radar system for operation in NASA’s 2011 Operation Ice Bridge Ice program in order to image near-surface internal layers and produce high-resolution accumulation maps (such as in Figure 1(a)). Identifying near surface internal layers in radar imagery is important for studying climate variability, but finding layers in these echograms by hand is labor-intensive and subjective. The data growth from past and projected field campaigns will require automated techniques in order to provide results to the polar science community in a timely manner. However, automatic layer-finding is challenging due to the limited resolution, large degree of noise, faint layer boundaries, and confusing structures that exist in these echograms.

In this paper, we present an approach that automates the most labor-intensive part of layer finding. Our semi-automatic approach requires a human to estimate some global parameters of an echogram, such as the number of layers that are visible. Our approach then attempts to trace layers using automated image processing techniques that also apply high-level constraints, such as that the ice-air boundary should be most prominent and that snow layers should be roughly parallel. We evaluate the technique on several echograms from Antarctica.

2. RELATED LITERATURE

There has been relatively little work on estimating near surface snow layers from echograms acquired in either Greenland or Antarctica; most related work has focused on finding basal boundaries or other coarse properties of echograms. For example, Freeman et al. [2] and Ferro and Bruzzone [3] investigated how shallow ice features can be automatically detected in icy regions from echograms of Mars. In other work, Ferro and Bruzzone [4] used echograms of the Martian subsurface to detect basal returns. Approaches to identifying surface and bedrock layers in polar radar imagery include Reid et al. [5], Ilisei et al. [6], and Crandall et al. [7].

More relevant to the internal layer finding problem we study here, Fahnestock et al. [8] developed an algorithm which uses cross-correlation and a peak-following routines to trace near surface internal layers in northern Greenland. Karlsson and Dahl-Jensen [9] present a ramp function-based approach for predicting internal layers. Sime et al. [10] developed a technique to obtain layer dip information from two Antarctic datasets: the ground-based Fletcher Promontory and the airborne-based Wilkes Subglacial Basin. They applied a horizontal averaging technique to reduce layer noise, identified layers, isolated individual ‘layer objects,’ measured the orientation and other object properties, and collected valid dip information. They obtain good results in finding and characterizing dipo, but do not attempt to trace the complete layers that are useful in other applications. We propose a novel approach to trace complete layers, by combining ‘off-the shelf’ computer vision techniques for estimating high intensity near surface internal layers from snow radar echograms.

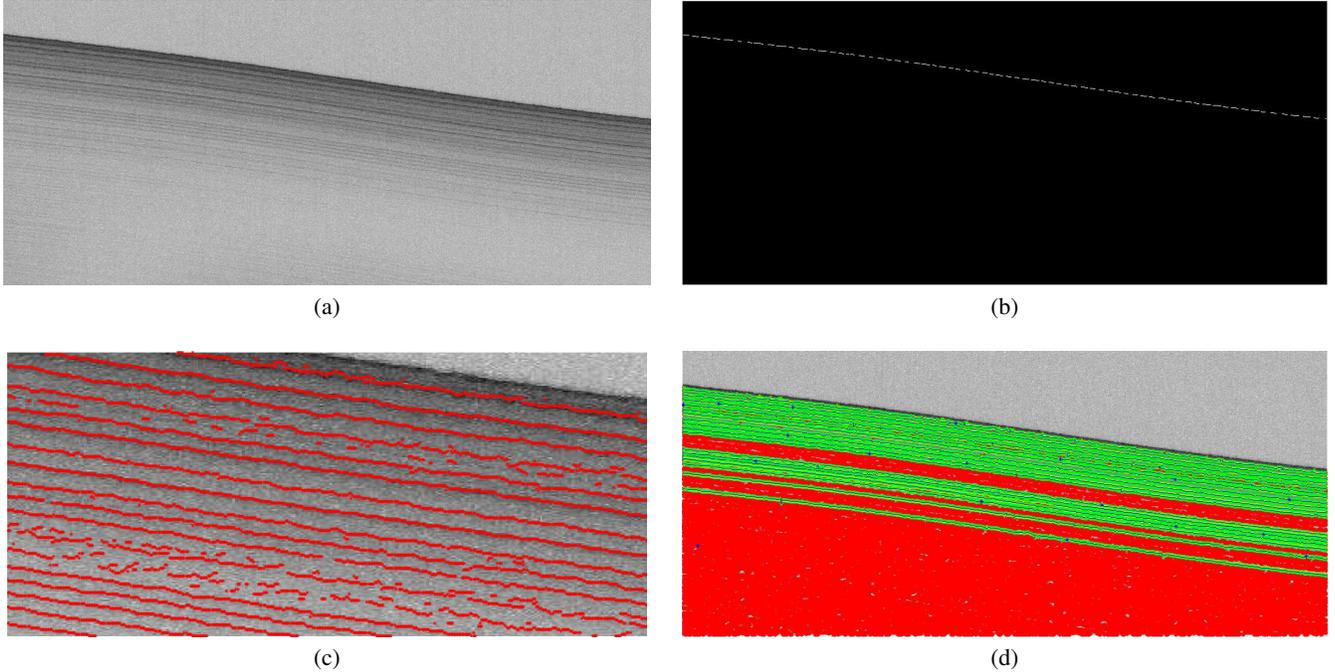


Fig. 1. Illustration of the steps of layer-finding: (a) Original snow radar image, (b) Result of Canny edge detection to find ice surface, (c) Result of curve point classification (close-up of a portion of the echogram for ease of visualization), (d) Detected layers (green) and maximum curve points (blue asterisks). Figure best viewed in color.

3. METHODOLOGY

We use observations about how domain experts detect layer boundaries in order to develop a semi-automated algorithm to mimic these behaviors. As shown in Figure 1(a) and as is typical for our experimental images, the surface reflection is very strong and near surface layer intensity generally decreases as depth increases. Also, near surface layers are approximately parallel, but may have modest changes in slope both to one another and to the ice surface. We thus propose a technique that first attempts to find the prominent surface reflection, and then searches for similar (but invariably weaker) layer structures below the surface. We use each layer as an estimate of the appearance of the layer below it, and then use an active contours (“snakes”) to snap to the correct layer structure given this estimate. We describe the process of detecting the surface, estimating layer location using curve point detection and then refining the estimate using snakes in subsections 3.1, 3.2, and 3.3, respectively, and use Figure 1 as a running demonstration of the proposed approach.

3.1. Edge Detection

We first find the location of the surface boundary, which is typically the most prominent edge in the echogram. We use a Canny edge detector [11] because of its performance in detecting strong intensity contrasts for our near surface dataset (see Figure 1(b)). In detecting this initial ice curve, we used

the following fixed Canny parameters: a sigma of 2 for the standard deviation of the Gaussian filter and a low and high thresholds of 0.7 and 1.8, respectively. Since the ice surface is symmetrical to subsequent layers, it provides a good starting template.

3.2. Curve Point Classification

While the surface layer can be readily detected by edge detection, using edge detection to detect internal layers is not possible because of the very weak layer boundaries and the noise inherent in echograms. We thus instead use the approach of Steger [12] to identify points in an echogram that are likely to be part of curvilinear structures. In short, this approach computes statistics on gradient structure within local image patches, in particular looking for areas with prominent gradients in a coherent direction. We identify peaks in the scores computed by Steger (shown as blue asterisks in Figure 1(d)) and use these to suggest initial curve positions for estimating the near surface internal layers. To handle the first layer, we take the surface layer estimated above and shift it down (in the y direction) so that it intersects the first maximum point. This process is repeated until the number of layers specified by the human operator has been found. This process gives initial estimates of the layer positions and shapes, which we refine in the next step.

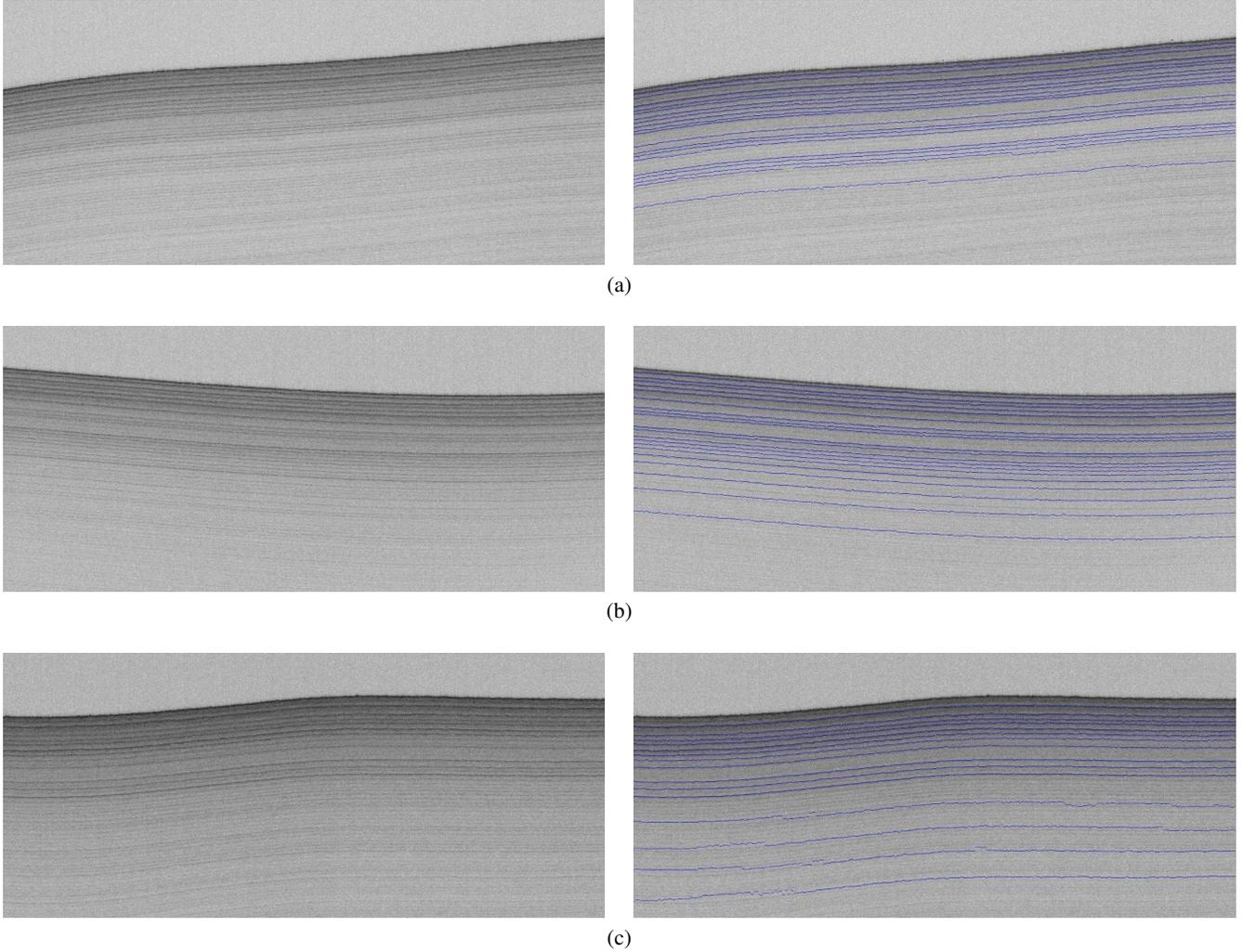


Fig. 2. Sample results of our approach on three snow radar echograms.

3.3. Active Contours (Snakes)

To refine the curve shape and position estimates from the last section, we used the active contours (snakes) model [13], a procedure for allowing an initial contour to gravitate towards an object boundary. Briefly summarized, the snakes model defines an energy function that computes the “cost” of a particular curve (sequence of points). The function is defined to encourage the curve to align with high-gradient edge pixels, but to discourage the curve from having discontinuities or sharp bends. These two goals are often in tension, and the energy minimization function is used to find the curve with the best trade-off between them. An iterative gradient descent (hill-climbing) algorithm is used to find the curve with the best (local) minimum, given an estimate of the correct answer as initialization.

In our methodology, active contours are used to warp the initial templates from the last section into a refined estimate

that better matches the local image data. For this to succeed, the initial contour must be close to the actual layer in order for the snake to find the correct boundary, and not be confused by noise or other edges in the image. A layer is fit when the energy function converges to a minimum or when a maximum number of iterations has reached its threshold. Using active contours requires setting several parameters (α , β , and γ values – these are weights on the terms in the energy minimization function and control the trade-off between the forces mentioned above). We tuned these parameters empirically to find values that work well on most images, and then also allow the human operator to further tune them on a per-image basis if needed.

4. RESULTS

Figure 3 shows the result of layer-finding on the echogram of Figure 1. We observe that it has successfully found over

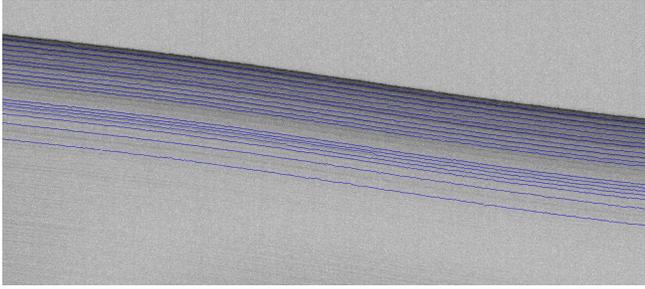


Fig. 3. Estimated near surface internal layers from the echogram in Figure 1.

a dozen layers correctly, although it misses some of the very faint layers towards the bottom of the echogram. Figure 2 shows results on three additional echograms. While the algorithm works quite well for layers near the surface, it does miss or incorrectly identify some of the deeper layers (such as the discontinuities in Figure 1(c)) in which the estimates skip from one layer boundary to another).

5. CONCLUSION AND FUTURE WORK

We have developed a semi-automated approach to estimating near surface layers in snow radar imagery. Our solution utilizes an active contour model in addition to edge detection and Steger’s curve classification. Our technique 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 accumulation maps can be readily processed to determine the contribution of global climate change on sea level rise. In the future, we intend to explore automated algorithms for determining internal layers in other data products, and to develop metrics to allow us to quantify the quality of our layer-finding approaches and evaluate them against other methods (including hand-tracing by domain experts).

6. ACKNOWLEDGEMENTS

This research was supported by the National Science Foundation under grants CNS-0723054 and OCI-0636361. Any opinions, findings, and conclusions or recommendations expressed in this work are those of the authors and do not necessarily reflect the views of the National Science Foundation.

7. REFERENCES

[1] M. Parry, *Climate Change 2007: Impacts, Adaptation and Vulnerability: Working Group I Contribution to the Fourth Assessment Report of the IPCC*, vol. 4, Cambridge University Press, 2007.

- [2] G. Freeman, A. Bovik, and J. Holt, “Automated detection of near surface Martian ice layers in orbital radar data,” in *IEEE Southwest Symposium on Image Analysis & Interpretation*, 2010, pp. 117–120.
- [3] A. Ferro and L. Bruzzone, “Automatic extraction and analysis of ice layering in radar sounder data,” *IEEE Transactions on Geoscience and Remote Sensing*, 2013.
- [4] A. Ferro and L. Bruzzone, “Analysis of radar sounder signals for the automatic detection and characterization of subsurface features,” *IEEE Transactions on Geoscience and Remote Sensing*, 2012.
- [5] M. Reid, C. Gifford, M. Jefferson, E. Akers, G. Finyom, and A. Agah, “Automated polar ice thickness estimation from radar imagery,” in *IEEE International Geoscience and Remote Sensing Symposium*, 2010, pp. 2406–2409.
- [6] A.-M. Ilisei, A. Ferro, and L. Bruzzone, “A technique for the automatic estimation of ice thickness and bedrock properties from radar sounder data acquired at Antarctica,” in *IEEE International Geoscience and Remote Sensing Symposium*, 2012, pp. 4457–4460.
- [7] D. Crandall, G. Fox, and J. Paden, “Layer-finding in radar echograms using probabilistic graphical models,” in *International Conference on Pattern Recognition*, 2012, pp. 1530–1533.
- [8] M. Fahnestock, W. Abdalati, S. Luo, and S. Gogineni, “Internal layer tracing and age-depth-accumulation relationships for the northern greenland ice sheet,” *Journal of Geophysical Research*, vol. 106, no. D24, pp. 33789–33, 2001.
- [9] N. Karlsson and D. Dahl-Jensen, “Tracing the depth of the holocene ice in north greenland from radio-echo sounding data,” *Annals of Glaciology*, 2012.
- [10] L. Sime, R. Hindmarsh, and H. Corr, “Instruments and methods automated processing to derive dip angles of englacial radar reflectors in ice sheets,” *Journal of Glaciology*, vol. 57, no. 202, pp. 260–266, 2011.
- [11] J. Canny, “A computational approach to edge detection,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, , no. 6, pp. 679–698, 1986.
- [12] C. Steger, “An unbiased detector of curvilinear structures,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 2, pp. 113–125, 1998.
- [13] M. Kass, A. Witkin, and D. Terzopoulos, “Snakes: Active contour models,” *International Journal of Computer Vision*, vol. 1, no. 4, pp. 321–331, 1988.