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, which requires time-consuming, dense hand-selection and interpolation between sections, for each echogram. We have developed an approach for semi-automatically estimating near surface internal layers and have applied it to snow radar 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 ambiguity 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) has developed a snow radar for operation in NASA's 2011 Operation Ice Bridge program in order to image near surface internal layers (as shown in Figure 1(a)) and to produce high-resolution accumulation maps. Identifying snow layers in radar imagery is important for studying climate variability, but tracing layers in 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, automatically tracing layers in echograms are challenging due to the limited resolution, large degree of noise, faint layer boundaries, and complex structures In this paper, we present an approach to semi-automate the most labor-intensive portion of near surface internal layer identification. After requiring a user to estimate a global parameter for determining the number of visible layers, our approach attempts to trace those layers using image processing techniques by applying high-level constraints, such as how the ice-air boundary should be most prominent and how snow layers should be modestly parallel.

2. RELATED LITERATURE

There has been relatively little work on estimating near surface internal layers from echograms acquired in either Greenland or Antarctica. Most related work has focused on identifying either 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 have been addressed in Reid et al. [5], Ilisei et al. [6], and Crandall et al. [7].

For more relevant solutions to the internal layer identification problem, Fahnestock et al. [8] developed an algorithm, which uses cross-correlation and a peak-following routine 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. The authors obtained good results in estimating and characterizing dips but do not attempt to trace complete layers, which are useful in other applications. We propose a novel approach to trace complete layers by combin-

Copyright 2013 IEEE. Published in the IEEE 2013 International Geoscience & Remote Sensing Symposium (IGARSS 2013), scheduled for July 21-26, 2013 in Melbourne, Australia. Personal use of this material is permitted. However, permission to reprint/republish this material for advertising or promotional purposes of for creating new collective works for result or redistribution to servers or lists, or to reuse any copyrighted component of this work in other works, must be obtained from the IEEE. Contact: Manager. Copyrights and Permissions / IEEE Service Center / 445 Hoes Lane / P.O. Box 1331 / Piscatuway, NI 08855-1331, USA. Telephone: + Intl. 108-562-3966.





Fig. 1. Illustration of our Semi-Automatic Near Surface Internal Layers Detection Algorithm: (a) Original Snow Radar Echogram, (b) Result of Canny Edge Detection to Find Ice Surface, (c) Result of Curve Point Classification, (d) Detected Layers (green) and Maximum Curve Points (blue asterisks)

ing 'off-the shelf' computer vision techniques for estimating high intensity near surface internal layers from snow radar echograms.

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 propose a technique, which attempts to find the prominent surface reflection and searches for similar (but invariably weaker) layer structures below the surface. We use each layer as an estimate of the appearance for the layer below it and an active contours ("snakes") model to snap the correct layer structure given this estimate. We describe the process of detecting the surface, estimating layer location using curve point classification and refining the use of snakes in subsections 3.1, 3.2, and 3.3, respectively, and use Figure 1 as a demonstration of our proposed approach.

3.1. Edge Detection

We 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 layer dataset (see Figure 1(b)). In detecting this initial ice surface, 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 ice surface can be readily detected by edge detection, using it for near surface internal layers is not possible because of the very weak layer boundaries and the noise inherent in echograms. As a consequence, we use Steger's [12] approach to identify points in an echogram, which were likely to be part of curvilinear structures. In short, this approach computes statistics on gradient structures within local image patches and investigates 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 near surface internal layers. For the first layer, we use the ice surface estimated previously and shift it down, (in the y direction) so it intersects the first maximum point. This process is repeated until the number of near surface internal layers specified by the user has been found and gives initial estimates of layer positions and shapes, which we refine in the next step.











(b)

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 previous section, we used an 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, which 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 either discontinuities or sharps 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, which 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 either noise or other edges in the image. A layer is fit when the energy function converges to a either 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, which work well on most images and allow the user to further tune them on a per-image basis, if needed.

4. RESULTS

Figure 3 shows the result of our approach for Figure 1. We observe it has successfully found over a dozen layers correctly, although it misses some of the very faint layers towards the bottom of the echogram. Figure 2 shows results for three ad-



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

ditional 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 estimate near surface internal 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 to sea level rise. In the future, we intend to explore automated algorithms for determining internal layers in other data products and to develop metrics for allowing us to quantify the quality of our layer identification approaches and to evaluate them against other methods (including hand-traced echograms).

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

- 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.