Qualifying Exam

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Abstract

In order to satisfy qualifying exam requirements adhered to by the School of Informatics and Computing, I will provide an overview of related and work in layer identification and explain

Introduction

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 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.

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. [1] and Ferro and Bruzzone [2] investigated how shallow ice features can be automatically detected in icy regions from echograms of Mars. In other work, Ferro and Bruzzone [3] 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. [4], Ilisei et al. [5], and Crandall et al. [6].

For more relevant solutions to the internal layer identification problem, Fahnestock et al. [7] 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 [8] present a ramp function-based approach for predicting internal layers. Sime et al. [9] 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 combining 'off-the shelf' computer vision techniques for estimating high intensity near surface internal layers from snow radar echograms.

Near Surface Internal Layers

We used observations about how domain experts detect layer boundaries in order to develop a semi-automated algorithm to mimic these behaviors. As shown in Figure 1a 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 proposed a technique, which attempts to find the prominent surface reflection and searches for similar (but invariably weaker) layer structures below the surface. We used 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 the following sections:



Figure 1: Original Snow Radar Echogram

Edge Detection

To find the location of the surface boundary, which is typically the most prominent edge in the echogram, we used a Canny edge detector [10] because of its performance in detecting strong intensity contrasts for our near surface layer dataset (shown in Figure 2). In detecting this initial ice surface, the following fixed Canny parameters were used: 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.



Figure 2: Canny Edge Detector of Ice Surface

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 used Steger's approach [11] to identify points in an echogram (shown in Figure 3a), 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 identified peaks for scores computed by Steger (shown as blue asterisks in Figure 3b) and used these to suggest initial curve positions for estimating near surface internal layers. For the first layer, we used the ice surface estimated previously and shifted it down, (in the y direction) so it intersected the first maximum point. This process was repeated until the number of near surface internal layers specified by the user has been found and gave initial estimates of layer positions and shapes, which we refined in the next step.



Figure 3a: Curve Point Classification



Figure 3b: Detected Layers (green) and Maximum Curve Points (blue asterisks)

Active Contours

To refine the curve shape and position estimates from the previous section, we used an active contours (snakes) model [12], 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 tradeoff 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.

Results

Figure 4 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 4: Estimated Near Surface Internal Layers from Echogram in Figure 1

Conclusions

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.

References

[1] G. Freeman, A. Bovik, and J. Holt, "Automated detection of near surface Martian ice layers in orbital radar.

[2] Ferro and L. Bruzzone, "Automatic extraction and analysis of ice layering in radar sounder data," IEEE Transactions on Geoscience and Remote Sensing, 2013.

[3] 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.

[4] MyAsia Reid, Christopher M Gifford, Michael Jefferson, Eric L Akers, Gladys Finyom, and Arvin Agah, "Automated polar ice thickness estimation from radar imagery," in Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International. IEEE, 2010, pp. 2406–2409.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] J. Canny, "A computational approach to edge detection," IEEE Transactions on Pattern Analysis and Machine Intelligence, no. 6, pp. 679–698, 1986.

[11] C. Steger, "An unbiased detector of curvilinear structures," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20, no. 2, pp. 113–125, 1998.

[12] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," International Journal of Computer Vision, vol. 1, no. 4, pp. 321–331, 1988.