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

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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. Layers, however, are manually traced in large data volumes requiring time-consuming, dense hand-selection and interpolation between sections.

We have developed an approach for semi-automatically estimating near surface internal layers in snow radar echograms acquired from Antarctica. Our solution utilizes an active contour model (called snakes) 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 report considerable associated with projected in sea level rise over the coming decade and century [1]. Understanding the ice flow dynamics in Greenland and Antarctica poses a significant climate problem but 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 NASAs Operation Ice Bridge Ice program in order to image near-surface internal layers for producing high-resolution accumulation maps. Identifying near surface internal layers in radar imagery is important for studying climate variability, but it requires subjective human intervention to complete an echogram with an invariable amount of measurements. 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.

In this paper, we semi-automatically estimate near surface internal layers in snow radar data by allowing the user to visually determine a number of layers as a detection parameter for our algorithm.

2. RELATED LITERATURE

Developing techniques for estimating near surface layers acquired in either Greenland or Antarctica has been insufficiently addressed. Most related works focused on echograms collected by orbital sounders on Mars. For example, [2] and [3] investigated how shallow ice features can be automatically detected in icy regions. [4] used echograms of the Martian subsurface to detect basal returns. Approaches to polar radar imagery have been addressed in [5], [6], and [7]. The authors in their respective works identified surface and bedrock layers.

For more relevant methods, [8] developed an algorithm, which uses cross-correlation and a peak-following routine to trace near surface layers in northern Greenland. In [9], the authors present a ramp function approach for predicting internal layers. Also, a collection of techniques was explored in [10]. We propose a novel approach by utilizing off-the shelf computer vision techniques for estimating high intensity near surface internal layers from snow radar echograms.

3. METHODOLOGY

As shown in Figure 1 and 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 parallel, but may have modest changes in slope, to one another and to the ice surface. Using observations about how domain experts detect layer boundaries can aid in the development of a semi-automated algorithm to mimic these behaviors.

Our semi-automatic algorithm uses an active contours method, called snakes, in addition to edge detection and curve point classification for estimating near surface internal layers; each can be explained in detailed in subsections 3.1, 3.2, and 3.3, respectively. Figure 1 will be used for demonstrating the proposed approach.

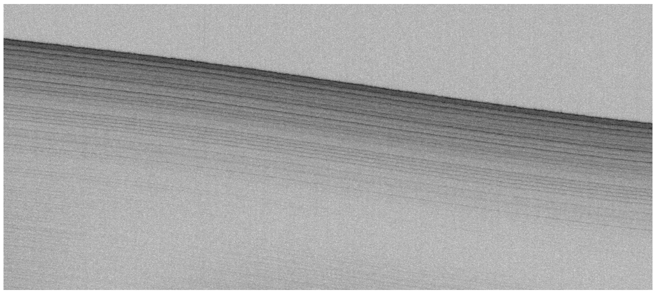

Fig. 1. Original Snow Radar Image

3.1. Edge Detection

We used a canny edge detector [11] (shown in Fig 2) because of its performance in detecting strong intensity contrasts for our near surface dataset. Since the ice surface is symmetrical to subsequent layers, it provides a good starting template. In detecting the initial ice curve, three specified were 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.

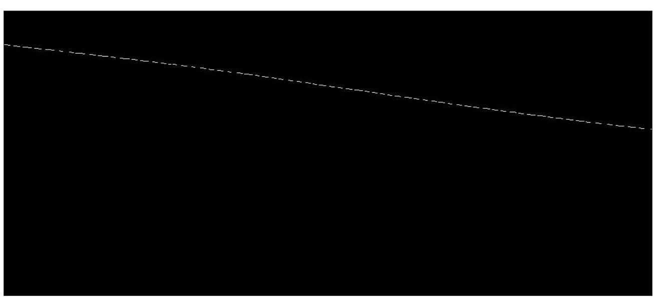

Fig. 2. Canny Edge Detected Ice Surface

3.2. Curve Point Classification

Curve points from layer boundaries were classified using Steger's approach [12] to suggest an initial curve position for estimating near surface internal layers (shown from the blue asterisks in Fig. 4). The gaps (shown in Fig. 3) were produced from weak curve points since layer intensity decreases as depth increases. For each layer, the initial layer is shifted in the y direction from the previous maximum curve point of the detected layer to the next maximum curve point; this process is repeated until x number of specified layers are detected (shown from the green layers in Fig 4).

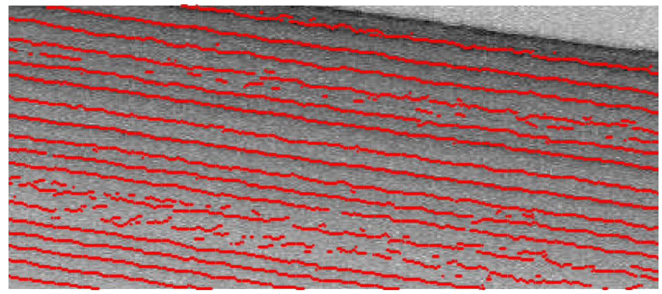

Fig. 3. Curve Point Classification

3.3. Active Contours (Snakes)

We used an active contour's technique (called snakes) [13], which is an energy minimization function for allowing an initial contour to gravitate towards an object boundary. It is defined as:

$$\int_0^1 \alpha E_{elastic} + \beta E_{bending} + \gamma E_{image},$$

where $E_{elastic}$, $E_{bending}$, and E_{image} represent the rigidity, tension, and attraction to layer boundary, respectively.

In our methodology, an active contour warped our initial template to the original layer. The initial contour must be close to the original layer in order for the snake to move through either noises or other undesired edges in the image. Selecting α, β, and γ values were chosen arbitrarily and were optimized through trial and error depending on the best fit for a particular layer. A layer is fit when the maximum number of iterations has reached its threshold.

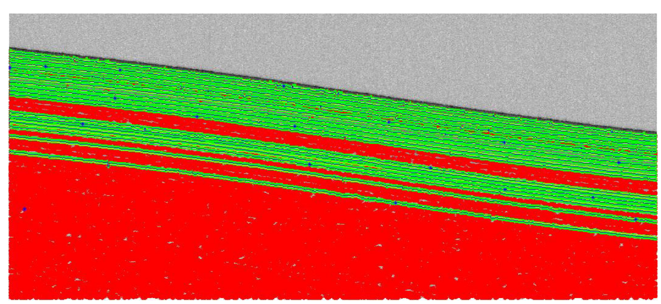

Fig. 4.

Although a maximum curve point was detected towards the bottom of the echogram (shown from the blue asterisk outlier in Fig. 4), our effort to detect continuous layers in the lower portion were suboptimal because of the noisy, weak layers. (shown in Fig. 8)

4. CONCLUSIONS

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 Stegers curve classification ultimately unburden domain experts from selecting incorrect ice interfaces and 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. Figures 5-8 show our approach evaluated on snow radar images.

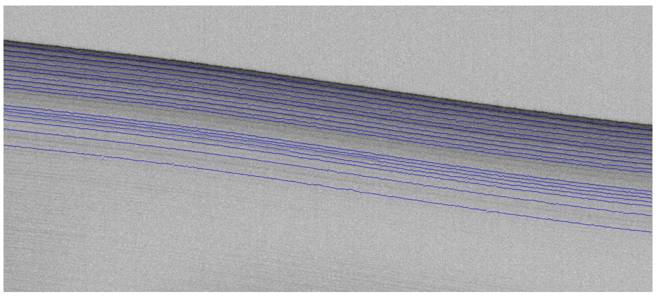

Fig. 5.

5. ACKNOWLEDGEMENTS

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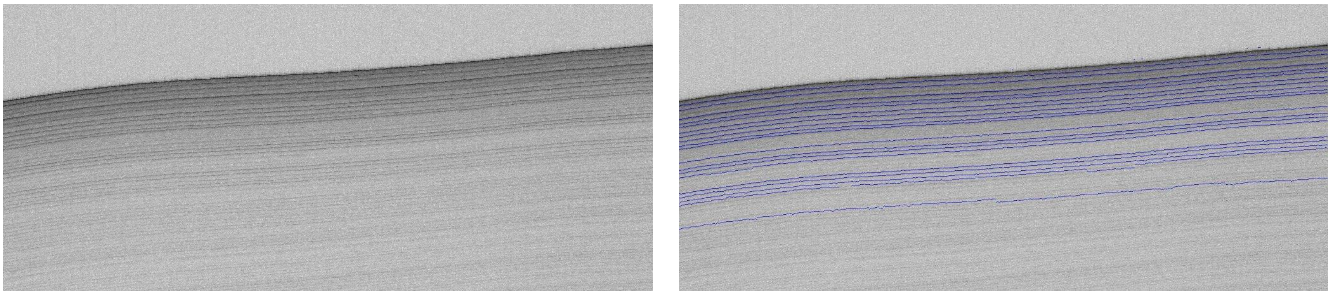

Fig. 6.

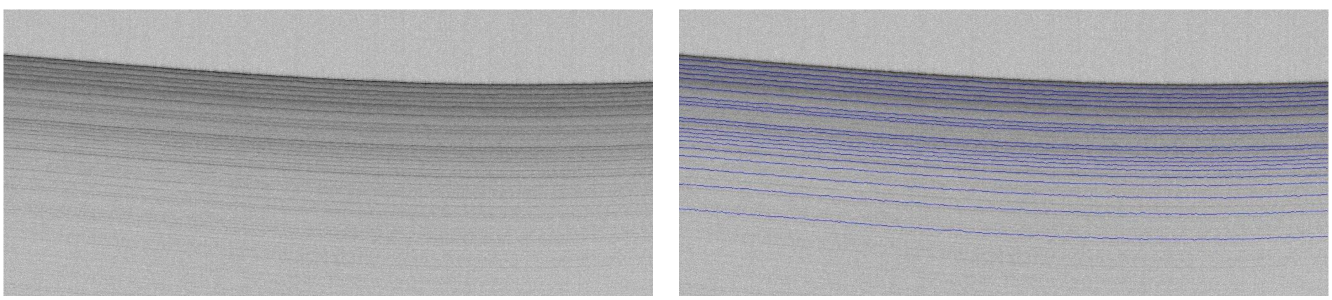

Fig. 7.

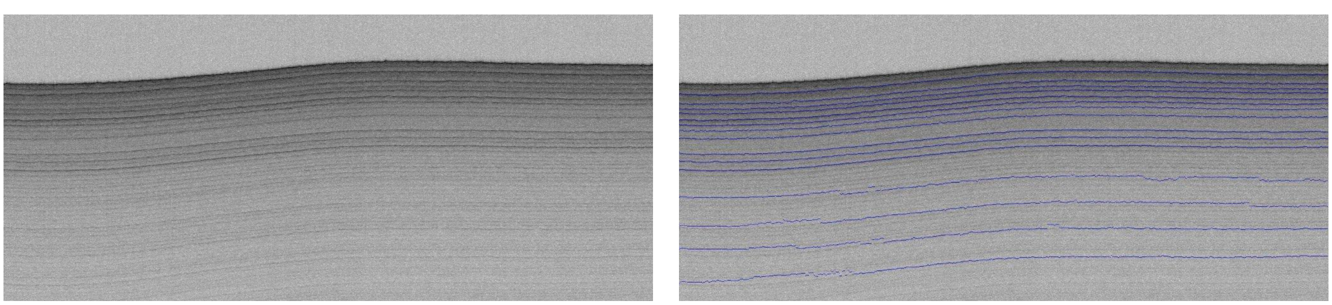

Fig. 8.