Automatic polar ice thickness estimation from SAR imagery

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ABSTRACT

Global warming has caused serious damage to our environment in recent years. Accelerated loss of ice from Greenland and Antarctica has been observed in recent decades. The melting of polar ice sheets and mountain glaciers has a considerable influence on sea level rise and altering ocean currents, potentially leading to the flooding of the coastal regions and putting millions of people around the world at risk. Synthetic aperture radar (SAR) systems are able to provide relevant information about subsurface structure of polar ice sheets. Manual layer identification is prohibitively tedious and expensive and is not practical for regular, long-term ice-sheet monitoring. Automatic layer finding in noisy radar images is quite challenging due to huge amount of noise, limited resolution and variations in ice layers and bedrock. Here we propose an approach which automatically detects ice surface and bedrock boundaries using distance regularized level set evolution. In this approach the complex topology of ice and bedrock boundary layers can be detected simultaneously by evolving an initial curve in radar imagery. Using a distance regularized term, the regularity of the level set function is intrinsically maintained that solves the reinitialization issues arising from conventional level set approaches. The results are evaluated on a large dataset of airborne radar imagery collected during IceBridge mission over Antarctica and Greenland and show promising results in respect to hand-labeled ground truth.

Keywords: ice thickness, radar, level set, automatic, global warming

1. INTRODUCTION

Precise calculation of ice thickness is an important factor in predicting ice flow and their contribution to sea level rise in response to a changing climate. The hidden terrain beneath the thick ice can take any shape from smooth to mountainous. Radar sensors are the only instruments that can penetrate through ice and give information about the hidden bedrock over large areas. Ice thickness can be determined by distinguishing layers of different dielectric constants such as air, ice, and rock in radar echograms. Figure 1 shows a sample echogram image produced by the radar. The horizontal axis is along flight path and the vertical axis represents depth. The dark line on the top of the image is the boundary between air and ice while the more irregular lower boundary represents the bedrock which is the boundary between the ice and the terrain.

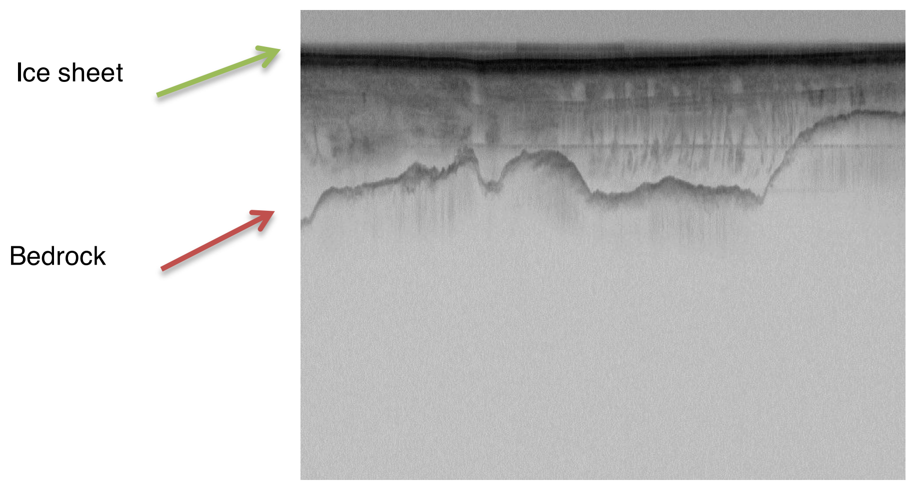

Figure 1: Ice sheet and bedrock depicted in radar echograms.

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The identification and interpretation of bedrocks are a difficult procedure due to complex patterns of bedrocks. Moreover, the images contain speckle noise due to the coherent nature of SAR. Usually human experts mark ice sheet layer and bedrock by hand for further processing. Manual layer identification is very time consuming and is not practical for long-term ice-sheet monitoring. Therefore, it is essential to develop intelligent methods to automate the process and reducing the delivery time.

Several semi-automated and automated methods have been introduced in the literature for layer finding and ice thickness in radar images [1-12]. Methods based on statistical properties of subsurface targets [2] provide only approximate locations and fail to find exact layers. Probabilistic graphical models [4] [5] are able to detect the exact location of ice layer boundary in echogram images. However, these models need a lot of training samples and therefore they are not practical for large dataset. The main disadvantage of the active contour model [6] is the incapability of maintaining the topology of the evolving curve. This difficulty does not arise in the level set model as it embeds the evolving curve into a higher dimensional surface. A level set technique for estimating bedrock and surface layers was applied in [11]. However the re-initialization was applied manually for each single image which considerably reduced the functionality.

This paper proposes a novel level set approach to automatically identify the ice and bedrock layers in a large dataset of radar imagery. Here we used a variational level set function in which the regularity of the level set function is maintained intrinsically using a distance regularization term. Therefore, it does not need any manual re-initialization and was automatically applied on a large dataset.

2. METHODOLOGY

The complex patterns of bedrock cannot be detected effectively using ordinary image segmentation algorithms such as edge detection or statistical approaches. Here we propose to use the level set technique to extract the exact layer boundaries in radar echogram images.
The level set method (LSM) is essentially a successor to the active counter method. Active contour method (ACM), also known as Snake Model, was first introduced in the context of image processing [14]. Starting with certain parametric curves, the ACM moves the curves in order to capture the desired boundaries and interfaces; however, it does not have any control over the topology of the curves. This can accumulate irregularities that eventually mislead the moving curves. The LSM method overcomes this issue by taking the problem to a higher dimension. It defines the boundaries of desired objects as the zero-level set of a higher dimensional surface, called the Level Set Function (LSF).

In image segmentation applications, the conventional LSM is expressed as

$$\frac{\partial \varphi}{\partial t} = F\,|\nabla\varphi| + A \,.\, \nabla\varphi \qquad (1)$$

In this formulation, the first term presents the edge functional, with *F* being a scalar function; the second term is the area term with *A* being a vector valued function. To avoid irregularities that can lead to re-initialization procedure, a new technique was suggested in [15]. In this work we will consider the model proposed in [16], where a diffusion type functional is introduced to stabilize the process without need of re-initialization. The new formulation reads

$$\frac{\partial \varphi}{\partial t} = F\,|\nabla\varphi| + A \,.\, \nabla\varphi + \mathrm{div}(D\nabla\varphi) \qquad (2)$$

where the last term represents *the distance regularization* contribution, with a diffusion coefficient $D = D(\varphi)$. The diffusion coefficient is constructed from a double-well potential function p as follows

$$D(\varphi) = \frac{p'(|\nabla\varphi|)}{|\nabla\varphi|}, \qquad (3)$$

where

$$p(s)=\begin{cases}(1-\cos(2\pi s))/4\pi^2 & s\le 1\\ (s-1)^2/2 & s\ge 1\end{cases} \tag{4}$$

Obviously p is twice differentiable, and enjoys the following properties

$$|\frac{p'(s)}{s}|<1 \text{ for } s>0 \text{, and } \lim_{s\to 0}\frac{p'(s)}{s}=\lim_{s\to\infty}\frac{p'(s)}{s}=1. \tag{5}$$

Given the above property, one can easily see that

$$|\mu\frac{p'(|\nabla\varphi|)}{|\nabla\varphi|}|\le\mu. \tag{6}$$

This will guarantee the boundedness of the diffusion rate in (2).

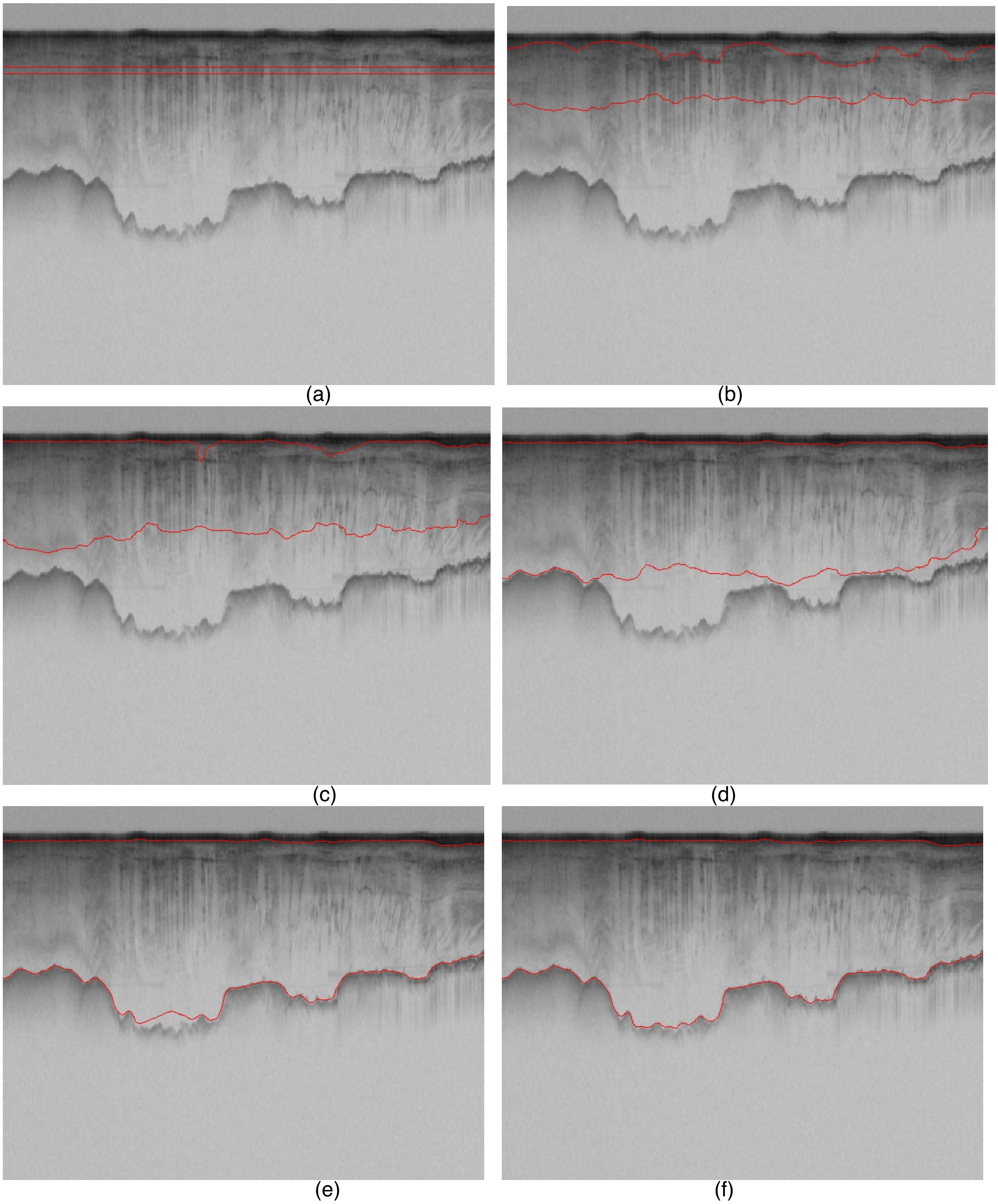
3. EXPERIMENTAL RESULTS

The Level set ice layer identification approach was applied on publicly available radar images from NASA Operation Ice Bridge program. The images were collected with the airborne Multichannel Coherent Radar Depth Sounder system described in [17]. We applied the method on 150 images and compared the results with the ground truth. The ground-truth images have been produced by human annotators. Figure 2a through 2f show the results of our approach with respect to the ground-truth. Figure 2a shows the initial curve. This initial curve was drawn automatically and there is no need for user input in any step of the procedure. Figure 2 b-f shows the results after iteration 150, 300, 450, 600 and 650 respectively. Figure 2g shows the ground-truth which is the result of labeling the layers by a human operator. Comparing Figure 2f, the result of the proposed approach, with Figure 2g, the ground-truth, we notice that our result is very close to the ground-truth.

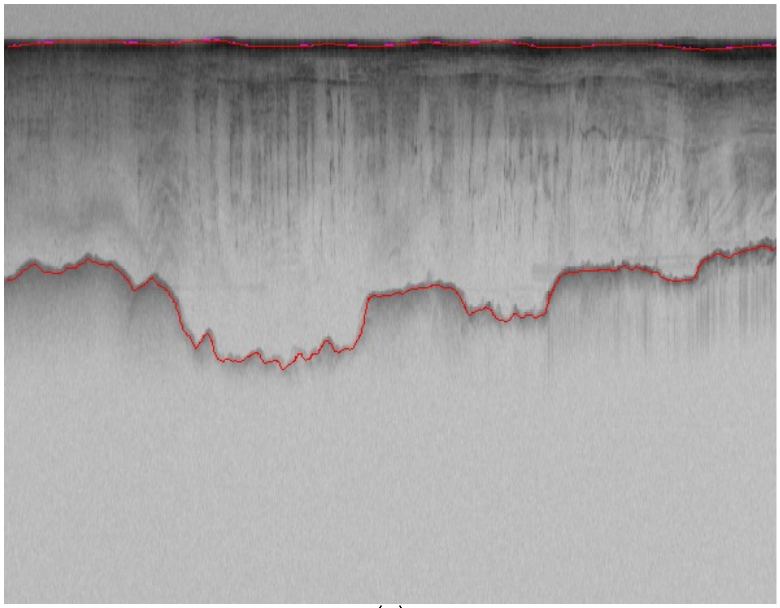
We measure the accuracy by calculating the mean absolute difference between ground-truth and our results for both surface and bedrock layers (in pixels). Table 1 shows the average result for 150 images. The mean error is 3.1 pixel for surface layer and 11.8 pixel for bedrock boundary. Our approach is very fast; it takes an average of 30 second to process each image on a 2.7 GHz machine.

Table 1- Evaluation of our approach in comparing to ground truth (in pixels)

	Absolute Mean error ice layer	Absolute Mean error Bedrock
Our approach	3.1 pixels	11.8 pixels



(a) (b) (c) (d) (e) (f)



(g)

Figure 2 : Contour evolution throughout processing. a) Initial curve, (b)-(f) contour adaptation to bedrock and ice layer after 150, 300, 450,600, and 650 iterations correspondingly, (g) ground-truth image.

4. CONCLUSION

We presented an automatic approach to estimate bedrock and ice layers in radar echo sounding imagery. In this approach the complex topology of ice and bedrock boundary layers were detected by using level set algorithm. The results were evaluated on a large dataset of airborne radar imagery collected during the IceBridge mission over Antarctica and Greenland and show promising results in respect to hand-labeled ground truth.

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