Optimization Techniques and the Detection of Layer Boundaries in Polar Radar Imagery

The dynamic responses of the polar ice sheets can have substantial impacts on sea level rise. Accurate predictions of future sea level rise are limited by an incomplete understanding of an ice sheet's internal and subglacial layers, which preserve variations in accumulation, ice thickness, and ice flow. Identifying layers is performed with time-consuming, dense hand-selection and interpolation between sections for each echogram. There is a need for innovative algorithms to support automatic analysis of bedrock and internal layers.

In order to satisfy qualifying exam requirements adhered to by the School of Informatics and Computing, I will provide an overview of past work and explain a few optimization techniques, which can be used to improve automatic interpretation of layer boundaries.

Introduction

The polar ice sheets interact with climatic forces, and the impact of their retreat on global sea level would be profound. Forecasting the evolution of ice sheets in Greenland and Antarctica will depend on the development of accurate numerical models. Currently, ice sheet models suggest a response to climate change on a millennia timescale, an idea, which advocates considerable time to develop planning strategies for responding to global climate effects. However, existing models cannot explain the recent satellite observations showing rapid thinning of ice sheet margins, the speedup of several outlet glaciers in Greenland, and the disintegration of ice shelves in West Antarctica. In order to better understand the mechanisms controlling either the net loss or gain of ice, there is a need to use radio echo sounding techniques to collect ice thickness over ice sheet margins and mapped internal layers in polar firn.

A number of remote sensing technologies, such as radar, have surveyed remote locations about the Earth in order to infer its properties. For example, airborne radio echo sounding (RES) has been used for many years to determine variations in ice thickness, subglacial topography, and the mass balance. Radars use antennas to transmit and receive energy of a particular target, and the travel time of a signal provides information on the reflection intensity and depth. Based on the intensity and travel time, different properties of a target can be characterized. A specific imaging instrument, such as the ground-penetrating radar (GPR) offers the ability to observe properties of the subsurface, and when acquiring data about the ice sheets in Greenland and Antarctica, the targets are typically internal layering within the ice and the bedrock. The first (surface) and last (bedrock) reflections determine ice thickness while a number of internal reflections are used for calculating the accumulation rate. These reflections occur when the complex dielectric constant of electromagnetic waves change [1]. A number of researchers have investigated the sudden changes in the complex permittivity of ice and identified three major causes: changes in density, acidity, and crystal-orientation fabrics [2], [3], [4], [5], [6].

Radar sounding, however, is challenging due to the rigid surface interface, various stages of melting, and subtle variations of ice thickness and bedrock topography. The Center for Remote Sensing of Ice Sheets (CReSIS), a Science and Technology Center established by the National Science Foundation to increase measurement capabilities, has developed and deployed nonintrusive instruments capable of imaging the ice-bed interface through a 3 km thick of ice, which is critical to understanding rapid glacial changes. Analyzing large amounts of echograms is important to validate models, but identifying ice features, particularly internal layers, are challenging since multiple, non-existence layers cause domain experts to skip and misclassify them. The polar science community has developed brute force techniques for manually selecting key layer boundaries but, the custom software provides a tedious and time - consuming task to be performed efficiently and consistently. There is a need for techniques to support the automatic analysis of internal layers.This qualifying exam will focus on the internal layer problem and discuss a few global optimization techniques, specifically simulated annealing, dynamic programming, and genetic algorithms, for minimizing energy to improve boundary detection.

Related Literature

There has been considerable work dedicated to estimating internal and subsurface layers from echograms. Most related work has focused on identifying either basal boundaries or other coarse properties of echograms. For example, Freeman et al. [7] used a unique coordinate transformation approach and Ferro and Bruzzone [8] proposed a novel, four step technique for investigating how shallow ice features can be automatically detected in icy regions from echograms of Mars. Ferro and Bruzzone techniques include denoising and enhancement of an echogram, removal of the first return, and extraction measurements of interest. In other work, Ferro and Bruzzone [9] detected the bedrock by studying how statistical distributions can accurately model the amplitude fluctuations of different subsurface targets. Approaches to identifying surface and bedrock layers in polar radar imagery have been addressed in Reid et al. [10], Ilisei et al. [11], and Crandall et al. [12]. Reid et al. used an active contours ("snake") model, Illisei et al. generated a statistical map of the subsurface by exploiting properties of the radar signal and applying a segmentation algorithm tuned to an investigated area, and Crandall et al. used a markov random field model, which allowed evidence from local features and global features to be combined into a single probabilistic framework.

For work addressing the internal layer identification problem in polar radar imagery, Fahnestock et al. [13] 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 [14] present a ramp function based approach for predicting internal layers. Sime et al. [15] 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.

Deformable Models

Segmentation has been widely studied, but remains a difficult technique because of the large variations in object shapes and image quality. In particular, radar echograms are corrupted by either image noise or other image artifacts, which can cause hindrance when applying traditional segmentation methods, such as edge detection, region growing, and thresholding. To address these difficulties, deformable models or snakes, have been used as a promising alternative. Deformable models are curves defined in an image, which gravitate using external and internal force. The internal forces allow for continuity and smoothness while the external forces move the model towards an object boundary or desired features. Using constraints of smoothness and incorporating prior information for extracted boundaries allow deformable models to provide robustness and accuracy from image noise and boundary gaps.

Although contour models have been deployed for extracting regions of interest, there exist some limitations. For example, snakes, in a non-interactive application, are initialized near the interest boundary in order to guarantee good performance. The internal energy constraints of snakes limit their geometric flexibility by preventing them to target shapes with significant topology. Also, since deformable models are parametric, knowledge of an object's shape has to be known in advanced.

There has been much effort to develop various methods for improving the automation of deformable contour models. Cohen and Cohen [16] used an internal "inflation" force to expand a snake model's past spurious edges towards the read edges of a structure, making the snake less sensitive to initial conditions. Amini et. al [17] used dynamic programming to carryout a more extensive search for a global minima. Poon et al [18] and Grzeszczuk and Levin [19] minimized the energy of active contours models using simulated annealing, which is known to give global solutions and allows the information of non-differentiable constraints. Other researchers [20], [21], [22], [23], [24] have integrated region-based information into deformable contour models or used other techniques in an attempt to decrease sensitivity to insignificant edges and initial model placement.

Near Surface Internal Layers

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 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.

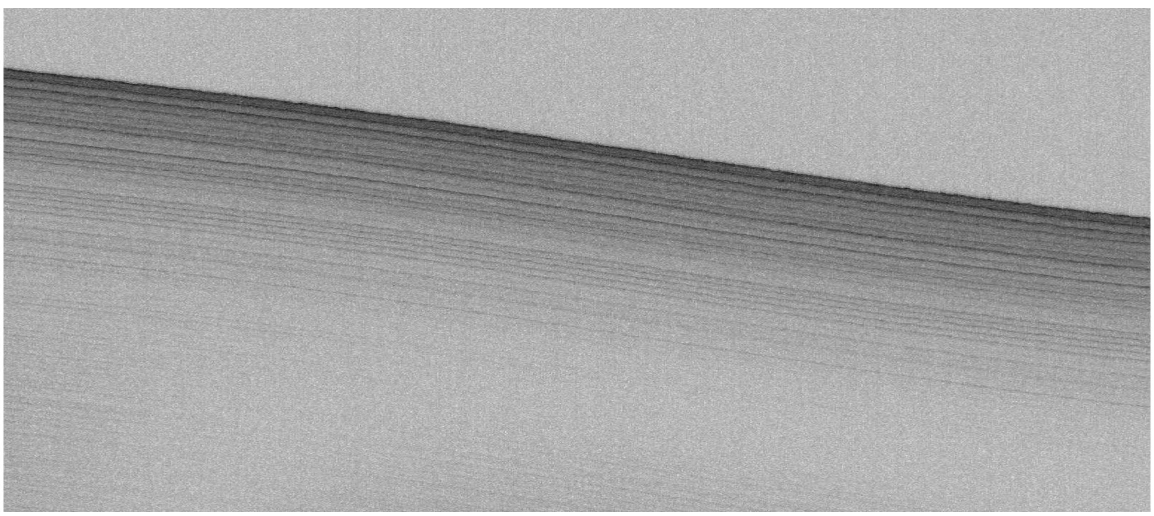

Figure 1 Original Echogram

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 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:

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 [25] because of its performance in detecting strong intensity contrasts for our near surface layer dataset (shown in Figure 1). 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.

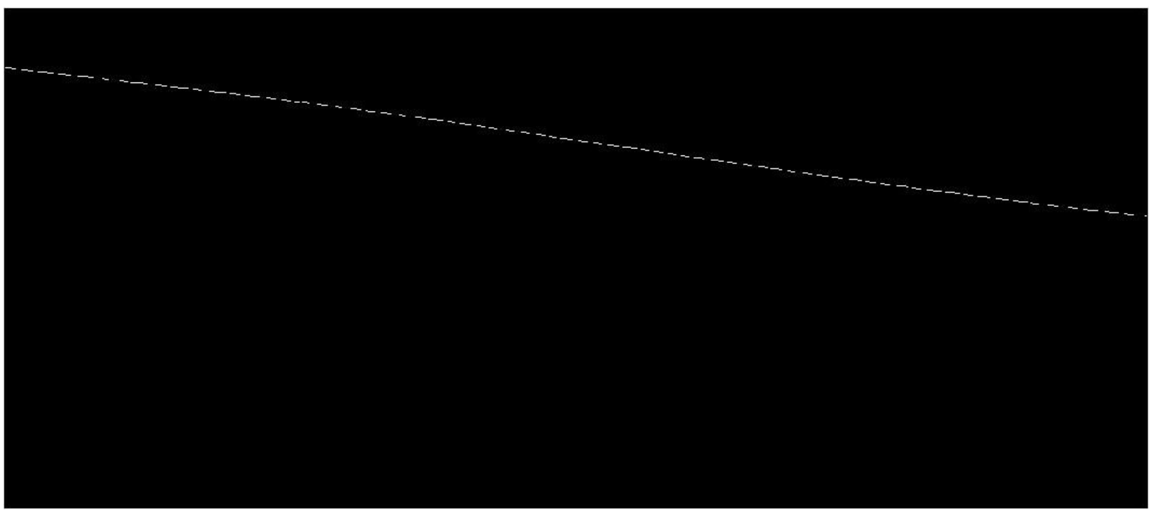

Figure 2: Edge Detection of the Ice Surface

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 [26] to identify points in an echogram (shown in Figure 2), 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 3 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.

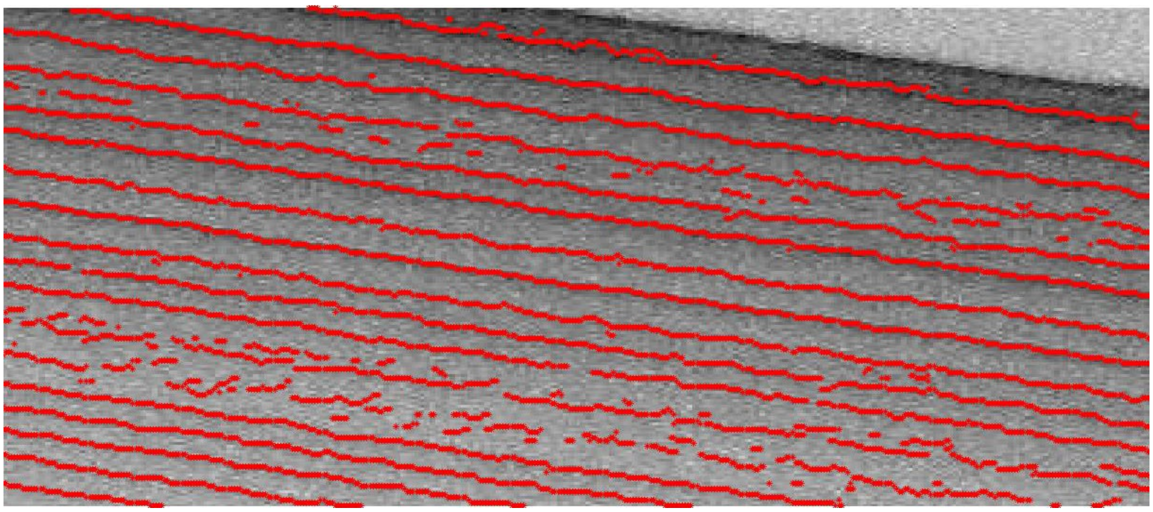

Figure 2: Curve Point Classification

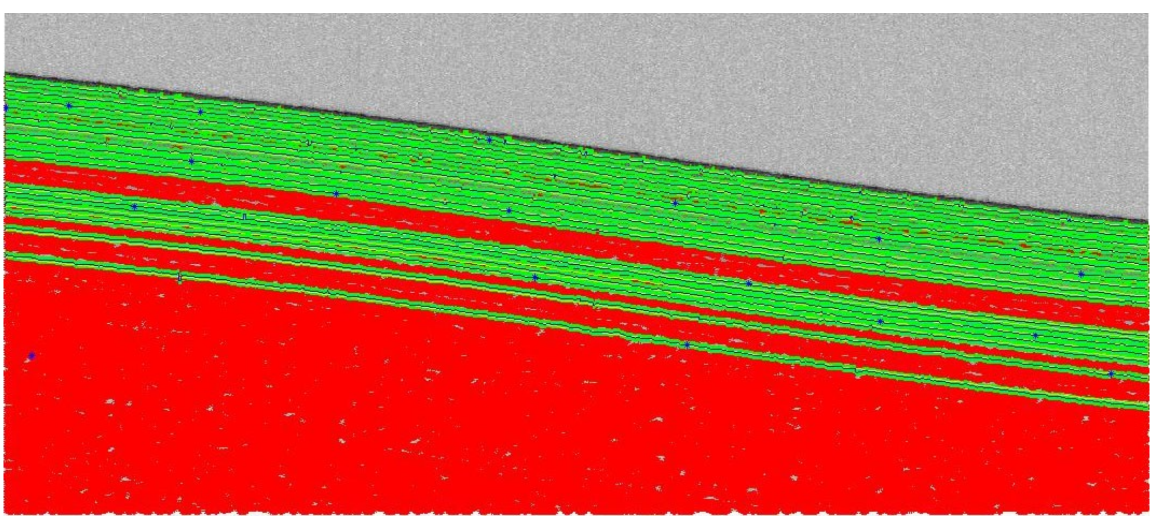

Figure 3 Detected Layers (Green) and Maximum Curve Points (Blue Asterisks)

Active Contours

To refine the curve shape and position estimates from the previous section, we used an active contours (snakes) model [27], 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.

Results

Figure 1 shows the result of our approach for Figure 4. 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 shows results for 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, which the estimates skip from one layer boundary to another)

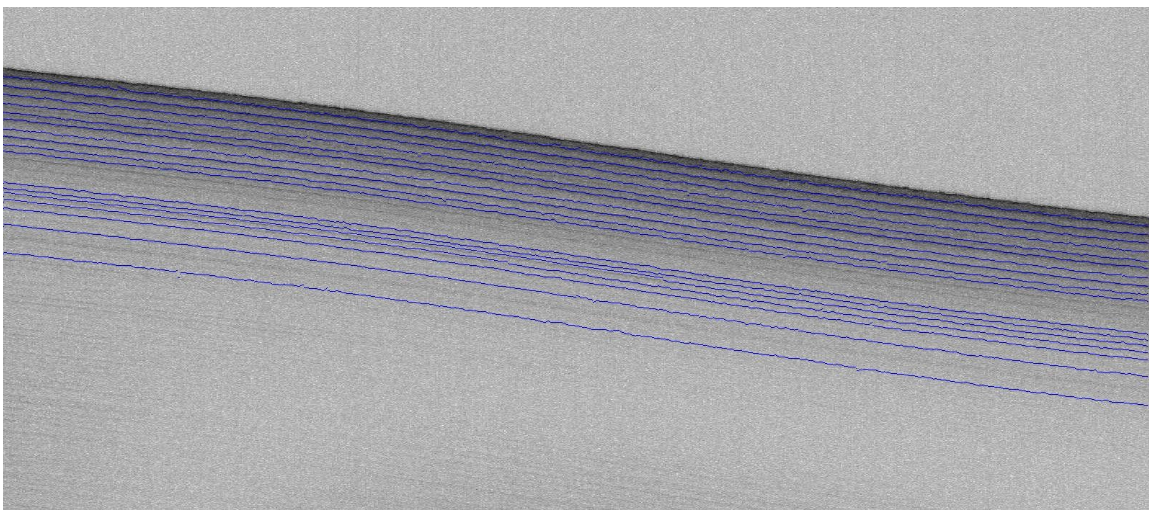

Figure 4

Optimizations

Optimization provides a framework for discriminating among solutions. The framework consists of an objective and energy minimizing functions. An objective function is formulated from the set of all possible solutions and measures the quality for a particular solution. In order to design an objective function for a problem, it is necessary to formulate a set of constraints for an acceptable solution, which satisfy a condition. For example, two constraints used in computer vision are: data and prior knowledge. The data constraint restricts a desired solution to be in approximation of the observed data while the prior constraint confines the desired solution to the prior knowledge. Smaller values evaluated from an objective function typically suggest a better solution, and a global minimum provides an optimal solution to the problem.

The second step of the approach is to minimize the energy function. Although the design of a good energy function is not trivial, its optimization is even harder

Simulated Annealing

Simulated annealing [28] was inspired by the natural process of annealing solids. The physical process of annealing involves slowing cooling metal, so it adopts a low energy, crystalline state. When the temperature of the metal is high, the particles within the metal are active, changing the metal structure. As the temperature is lowered, the particles are limited in movement since a high energy cost are very limited to configurations with a lower energy. Simulated annealing uses the idea of a physical process, in a computational model. The basic algorithm maintains both a state and a temperature, which is initially high and is reduced to near-zero according to a cooling schedule. The configuration is typically a solution to the optimization, and at each iteration of the algorithm, this solution is changed to produce a new solution. The quality of the solution is evaluated using the objective function, and a new state is selected from the two solutions. When a new solution is better than the previous, the new solution is chosen, but when the new solution has a lower quality than the existing solution, it may be accepted with a probability depended on the current temperature and the difference in quality. With certain cooling schedules, annealing can be guaranteed to find a global minimum.

Genetic Algorithms

A genetic algorithm [29] is search technique based upon principles of genetics and natural selection. Genetic algorithms allow a population composed of many chromosomes, which is a unique solution to the problem, to evolve until the population includes better solutions and converges, into a single solution. Of the three operators for generating new solutions crossover and mutation, are the most popular. In the crossover method, two chromosomes, called parents, are combined to form new chromosomes, called offspring. The parents are selected among existing chromosomes in the population with preference towards fitness, so offspring is expected to inherit good genes, which make the parents fitter. By iteratively applying the crossover operator, genes of good chromosome are expected to appear more frequently in the population, eventually leading to convergence to an overall good solution. The mutation operator introduces random changes into characteristics of chromosomes. Mutation reintroduces genetic diversity back into the population and assists the search escape from local optima. Reproduction involves selection of chromosomes for the next generation. In most cases, the fitness of an individual determines the probability of its survival for the next generation.

Dynamic Programming

Dynamic programming [30] decomposes a problem into a set of subproblems, which the solution of a subproblem is used multiple times, for solving several the problem. Dynamic programming algorithms different from traditional recursive methods because of this concept.

Conclusion

Optimization techniques, such as dynamic programming, simulated annealing, and genetic algorithms, provide a measure of quality for a particular solution. Also, 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 Stegers curve classification. Our technique is a step towards the ultimate goal of unburdening domain experts from the task of dense hand selection and an insight into global optimization techniques would better provide autonomy to layer detection.

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