AUTOMATIC IDENTIFICATION OF ICE LAYERS IN RADAR ECHOGRAMS

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1. INTRODUCTION

Recent work has developed reliable ground-penetrating radar systems to study the subsurface structure of the polar ice sheets [1]. These systems and associated processing algorithms produce radar echograms that give (noisy) cross-sectional view of ice sheets, as illustrated in Figure 1. Work in other domains has also used radar systems to study subterranean structures, such as the makeup of other planetary bodies [2, 3] and to search for landmines and other buried objects on Earth [4, 5]. These systems can produce vast amounts of data, to the extent that manually reviewing and labeling them can be prohibitively tedious and expensive.

In this paper we describe our recent work on automating one such labeling task: automatically finding ice layer boundaries in noisy echogram images [6]. Once these boundaries are found, subsequence processing can produce derivative data useful for scientists, like ice sheet thickness. As an example, consider the echograms of Figure 1. In these images, the horizontal axis is distance along the flight path (of the airplane on which the radar system was mounted), the vertical axis represents depth, and pixel intensity represents degree of radar signal return. The dark line near the top of the echogram is the boundary between the air and the ice sheet, while the irregular lower line is the boundary between the bottom of the ice and the terrain underneath. The echograms are noisy and interpreting them can be difficult, due to unpredictable signal scatter and reflection, and variation in the basal terrain (which may be smooth or mountainous, wet or dry, and made of till, sand, soil and/or rock). Automatic layer finding in these images is thus quite challenging.

Our approach applies modern techniques in the fields of computer vision and machine learning to this problem. In particular, we pose layer-finding as an inference problem on a statistical graphical model. A major advantage of graphical models is that they can naturally incorporate various noisy sources of information and a priori constraints. In our work, these constraints include that layer boundaries should lie along areas of high image contrast and that they should be continuous and not intersect. We also optionally allow input from human operators to be incorporated into the labeling process; this input may be based on human domain expertise or on actual ground truth from ice borings. To learn the parameters of these models, we take a machine learning approach, using a set of training data labeled by humans to infer parameter values automatically. We have tested the approach on a set of about 800 echograms and measured error quantitively using a variety of metrics, and shown that our approach performs more accurately than several baselines. Figure 2 presents sample results on three radar echograms, including one in which human-in-the-loop feedback was used to improve the layer-finding results.

2. REFERENCES

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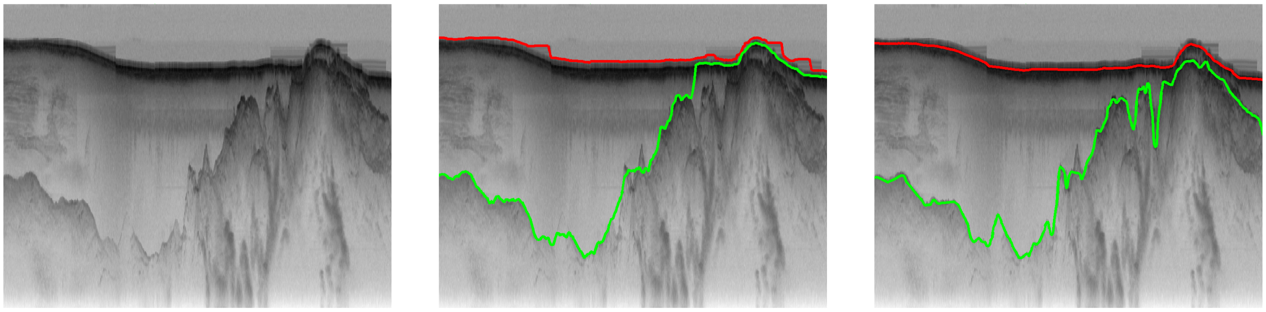

Fig. 1. Sample radar echogram of part of the Antarctic ice sheet, produced by the Multichannel Radar Depth Sounder instrument onboard an aircraft [1]. (Left) raw echogram, (center) layer boundaries found with our approach, and (right) ground truth. The upper (red) boundary is between air and ice layers, and the lower (green) boundary is between ice and terrain. *Best viewed in color.*

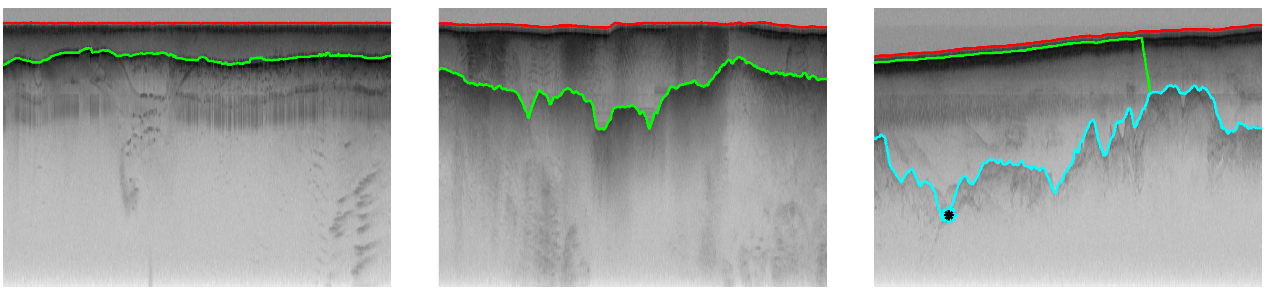

Fig. 2. The automatic algorithm found correct layers in the left and center images, but in the right image found an incorrect terrain-ice boundary (green). A user provided a single constraint point (black/cyan asterisk) and layer-finding was re-run, giving a correct result (cyan line). *Best viewed in color.*

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