Multi-Task Spatiotemporal Neural Networks for Structured Surface Reconstruction

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1. Introduction

- Problem: A ground-penetrating radar system flies over a polar ice sheet, yielding a sequence of 2D tomographic slices. Each slice captures a vertical cross-section of the ice, where two material boundaries (the ice-air and ice-bed layer) are visible as bright curves in the radar echogram. Given such a sequence of tomographic slices, our goal is to reconstruct the 3D surfaces for each material boundary.

- Data: Radar imagery of the Canadian Arctic Archipelago (CAA) ice sheets, collected by the Multichannel Coherent Radar Depth Sounder (MCoRDS) instrument. It contains a total of 8 tomographic sequences, each with over 3,300 radar images corresponding to about 50km of flight data per sequence.

2. Multi-Task Spatiotemporal Neural Networks

Approach: We propose a multi-task spatiotemporal neural network that combines 3D ConvNets (C3D) and Recurrent Neural Networks (RNNs) to reconstruct structured 3D surfaces from sequential tomographic slices. In particular, we use the C3D network as a robust feature extractor to capture local-scale within-slice and between-slice features in 3D space, and use the RNN to capture longer-range structure both within single slices and across the entire image sequence.

3. Sample Results

The left shows the sample results of both ice-air (red) and ice-bed (green) layers in each tomographic slice; the middle shows sample results of ice-bed surfaces; the right shows sample results of ice-air surfaces.

4. Experimental Results

|                 | Averaged Mean Error (pixels) | Time (sec) |
|-----------------|-----------------------------|------------|
| Xu et al. [35]  | 11.9                        | 306.0      |
| Ours (C3D + RNN)| 10.6                        | 51.6       |

Table 1. The accuracy of our approach is computed on the average of the ice-air and ice-bed surfaces and the accuracy of Xu et al. [35] is computed only on the ice-bed surfaces. The running time is measured by processing a sequence of 330 tomographic images.

|                  | Ice-air surface | Ice-bed surface |
|------------------|----------------|-----------------|
| Crandall [8]     | —              | 101.6           |
| Lee [23]         | —              | 35.6            |
| Xu et al. (w/o ice mask) [35] | —       | 30.7            |
| Xu et al. [35]   | —              | 11.9            |
| Ours (RNN)       | 10.1           | 21.4            |
| Ours (C3D)       | 8.8            | 15.2            |
| Ours (C3D)       | 9.4            | 13.9            |
| Ours (C3D + RNN) | 8.4            | 14.3            |
| Ours (C3D + RNN) | 8.1            | 13.1            |

Table 2. Error in terms of the mean absolute column-wise difference compared to ground truth, in pixels.

5. Conclusion

We have presented an effective and efficient framework for reconstructing structured surfaces with significant improvements: (1) extracts and reconstructs different material boundaries simultaneously; (2) avoids the need for extra evidence from other instruments or human experts; and (3) improves the feasibility of analyzing large-scale datasets by significantly decreasing the running time.

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*References and acknowledgments are not included in this snippet.*