Hyperparameter Optimization on Viterbi Algorithm Using Random Search for Ice Bottom Detection

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Abstract

The Center for Remote Sensing of Ice Sheets (CReSIS) collects radar imagery of ice sheet bottom topography in regions such as Antarctica and Greenland, to help scientists and engineers understand the role of polar ice sheets in sea level change. An essential task in our long term study of this imagery is to locate the position of the bedrock beneath the ice sheet. However, since we add a large volume of imagery data each year, to manually label the position of the ice bottom is very time consuming. Thus, advanced computer algorithms, such as the Viterbi algorithm*, have been employed to automatically track the bed-rock locations [1]. The objective in our project is to tune the Viterbi algorithm parameters to improve the accuracy of detecting the ice bottom location, as compared to manually tracked data.

Problem Formulation

Why do we collect the ice topography imagery, and how do we collect it?

It is useful to have precise ice-bed topographic imagery to study glaciers and ice streams. For example, ice velocity is roughly proportional to the fourth power of ice thickness [2], and bed and surface geometry can be used to determine the hydraulic potential and consequently, subglacial hydraulic pathways [3]. As the Intergovernmental Panel on Climate Change (IPCC) reports that models used to generate sea-level rise estimates do not include the dynamic processes being observed in Greenland and Antarctica as of 2014, our data helps improve modelling of these dynamic processes in order to improve predictions of the contribution of polar ice sheets to sea level.

Multiple airborne ice thickness surveys have been undertaken since 1970. For example, more than 344,000 line kilometers of airborne data were collected in Greenland between 1970 and 2012, with a majority of them having been collected since the year 2000 [6]. Aircraft equipped with ground-penetrating radar devices such as the Multichannel Coherent Radar Depth Sounder (MCoRDS) [5] , map the underground structural information of the ice (Fig. 1). By applying a series of signal processing techniques to the collected data, we can generate images (Fig.2 and Fig.3) such that we can distinguish the interface between air and ice (ice-surface), and the interface between ice and bed-rock (ice-bottom) along the flight profile.

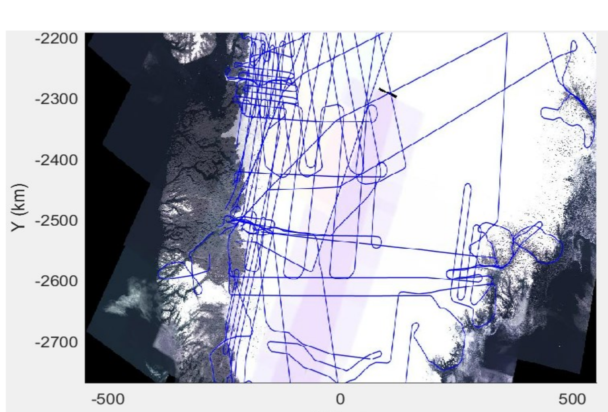

Fig.1 Satellite image with the flight paths used for data collection

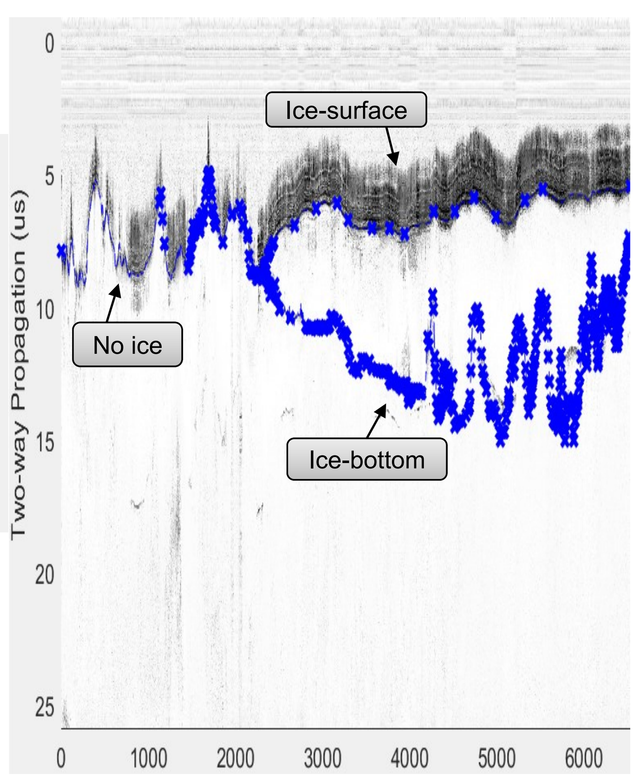

Fig.2 2D echogram of the ice sheet

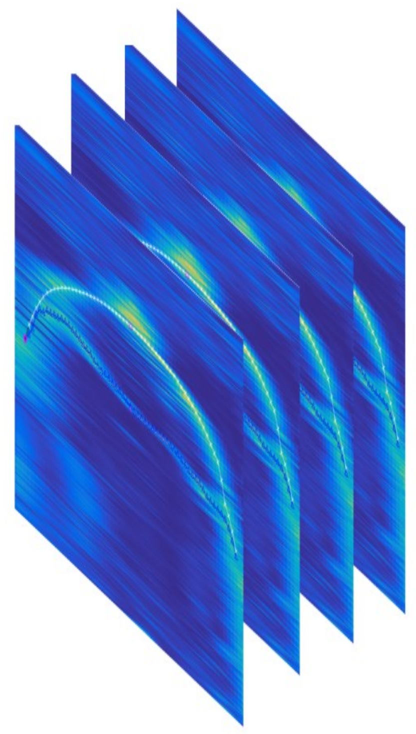

Fig.3 3D echogram of the ice sheet

Hyperparameter optimization

Although computer algorithms do a good job at depicting where the interfaces are, several parameters of the algorithm can be "tuned" so that the algorithm may be able to return an even more accurate result. Specifically, in this work we explore the parameter space to find better combinations of parameters that can further reduce the difference between the automated result and the ground truth (manually labeled data).

Optimization using Random Search

The hyperparameter optimization method we employed to explore the parameter space is Random Search. The reason we use Random Search is because error functions oftentimes are more sensitive to the change in some of the parameters than others, and this is apparent with our high dimensional parameter space (dimension > 2).

Compared to the method such as Grid Search (Fig. 4), we can see that the sampled points in Random Search are more evenly distributed in each subspace. This helps us to find the optimal value of the parameter more effectively. To achieve the same sampling for each parameter would require a much higher number of test points if using grid search.

Further, just like Grid Search, by using Random Search, each combination of parameter can be tested independently. This allows us to implement the tests that runs in parallel, so now we can use the cluster at CReSIS that is capable of running multiple processes at the same time.

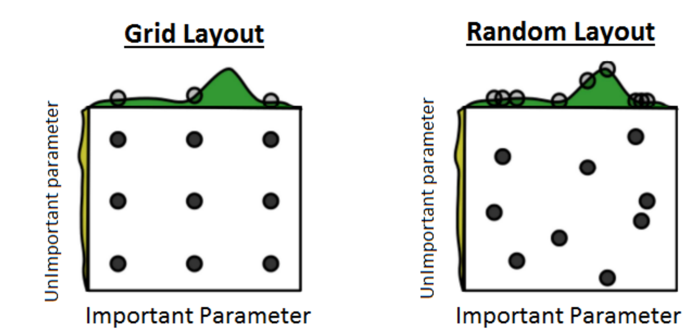

Fig. 4 Comparison of the subspace distribution between Grid and Random Search; from *Random Search for Hyperparameter Optimization*, Bengio et al [5].

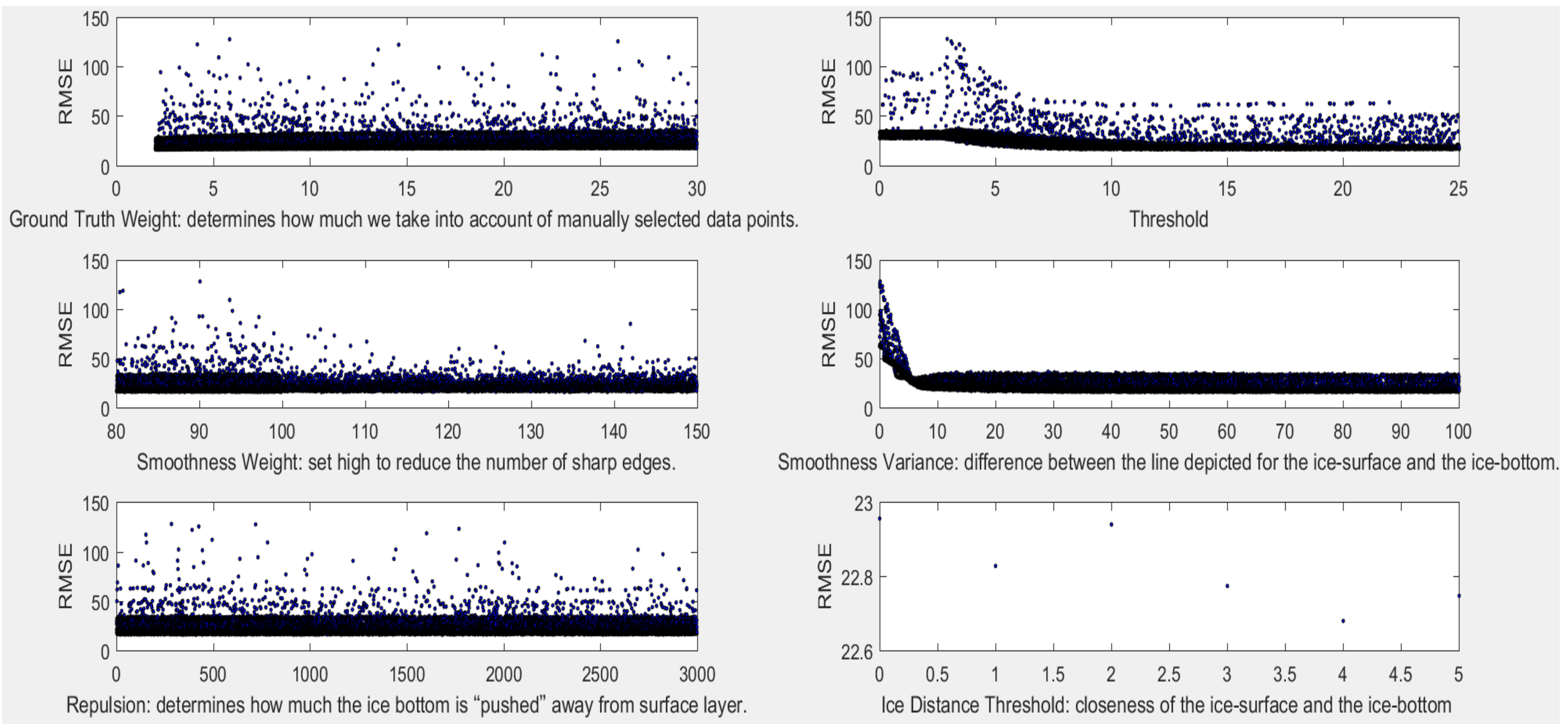

Fig. 5 A sample of 18599 randomly selected parameters and the error (results by Viterbi versus the hand picked data).

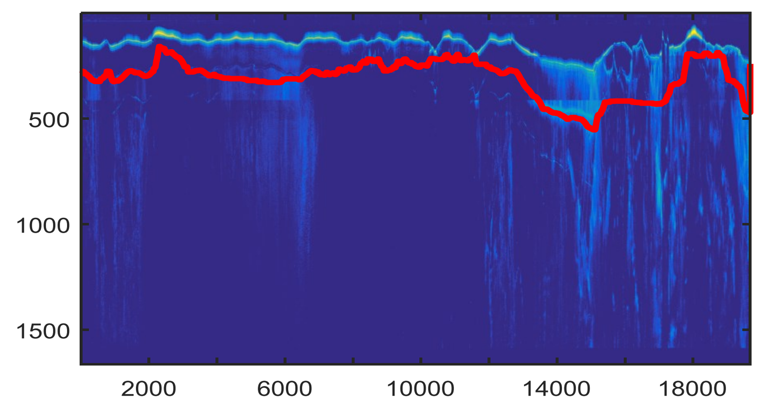

Fig.6 Applying the Viterbi algorithm with our optimized parameters to detect the bedrock location in the cross-section of a 2D image (red line).

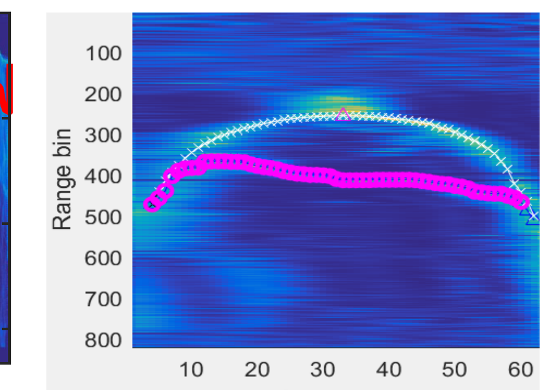

Fig.7 Applying the Viterbi algorithm with our optimized parameters to detect the bedrock location in the cross-section of a 3D image (pink dotted line).

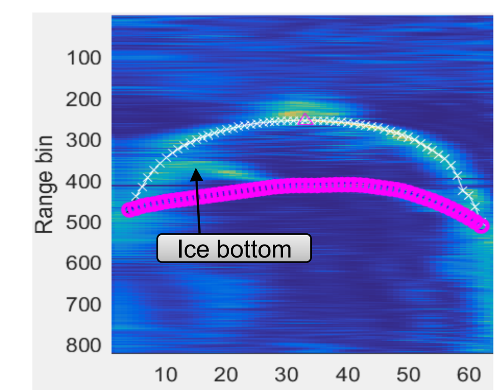

Fig.8 Applying the Viterbi algorithm with bad parameters to detect the bedrock location in the cross-section of a 3D image (pink dotted line).

Results

The result shows that, relative to the original hand tuned parameters, we have improved the median error of the Viterbi algorithm on ice bottom detection on 3D and 2D imagery from 3.687 to 3.186 (13.6% improvement) and 59.244 to 58.756 (0.8% improvement), respectively. This result is obtained from the 2014 Greenland P3 field campaign to detect the interface of the ice-bottom.

Below is a parallel plot (Fig. 9) that shows the result from the random search on 3D imagery. Three different groups of parameters (10 each) are chosen to see the range of what best, middle, and bottom set of parameter combinations tends to.

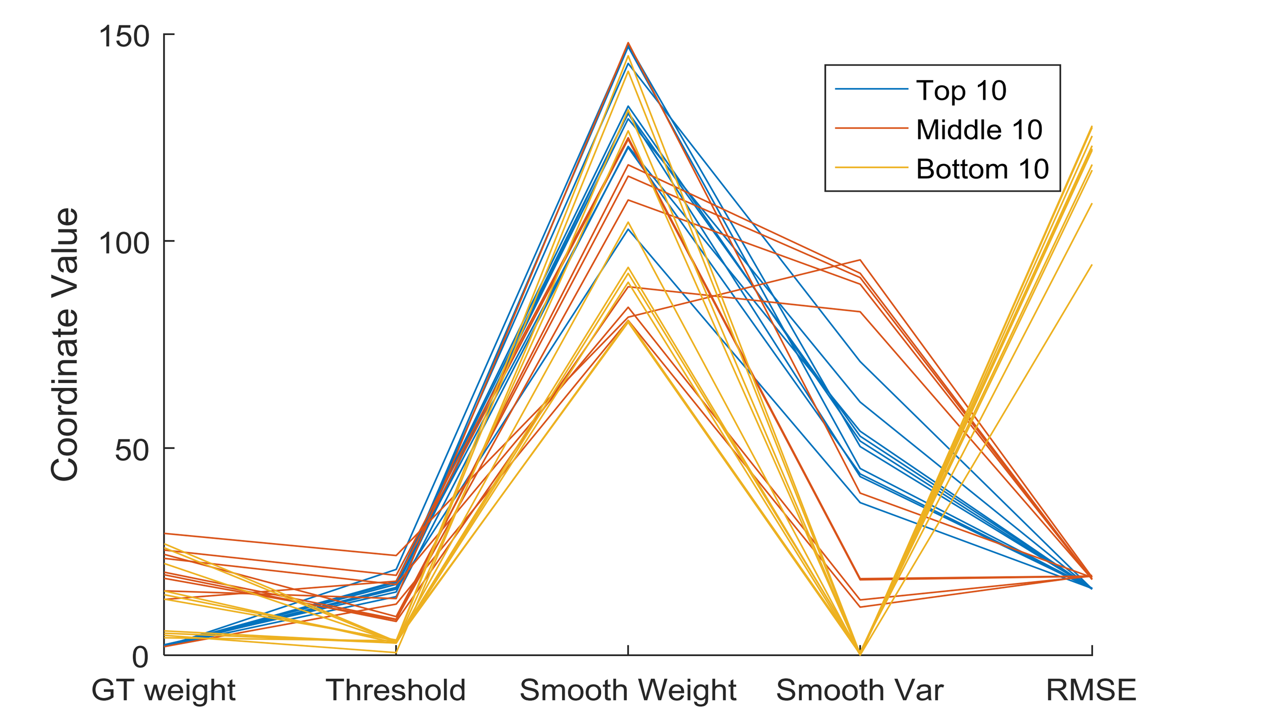

Fig.9 A parallel plot showing how each parameter interact with each other

We hope that by observing these test results, we can extend our testing to a variety of other computer vision algorithms to see if we can further improve their accuracy.

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Acknowledgements

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