Hyperparameter Optimization of the Level Set 2D Layer Tracker

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Abstract:

The Center for Remote Sensing of Ice Sheets (CReSIS) studies how the melting of ice sheets in Greenland and Antarctica might affect sea-level change. A key geophysical parameter for this research is the ice thickness, which can be estimated by calculating the exact location of the ice surface and subglacial topography beneath the ice in radar sounder imagery. The dark line on the top of the image, represents the ice surface, which is the boundary between air and ice. The irregular line below, represents the ice bottom, which is the boundary between the ice and the subglacial topography (see Figure 9(b)). In the past, identification of the surface and bottom of each of the layers was performed manually and is usually very time-consuming. In addition, as the volume of radar data increases, it is important to improve the automation of the boundary identification. To this end, we evaluate and tune a level set algorithm for the automatic tracking of the ice surface and bottom.

Level Set Method:

The level set method takes an initial contour or curve for the layer and builds it into a surface. It evolves the surface that intersects the 2D radar image instead of just evolving the contour – the contour is defined as the intersection of the surface with the 2D image. It starts with a best initial guess contour and iterates for a prescribed number of iterations until they accurately align with the surface and bottom. The level set algorithm tracks the zero-level set of the surface through a number of iterations using a mathematical function (Rahnemoonfar 2017). The main objective of this current work is to tune the hyperparameters for this level set algorithm by minimizing the absolute error compared to the training data. In this work, we parallelize the code, try different initial contours and numbers of iterations to improve the accuracy of detecting the ice bottom and surface as compared to the manually picked images, and then assess the accuracy and precision with our test dataset. These results will then be compared with other automated tracking algorithms.

Hyperparameter Optimization:

A hyperparameter is a parameter whose value is set before the learning process. They are important because they control the behavior of an algorithm. The performance of an algorithm can be highly dependent on the choice of these hyperparameters. The process of finding the optimal hyperparameters in machine learning is called hyperparameter optimization. For the level set algorithm we are tuning 3 hyperparameters:

1. The initial location of the ice surface layer (parameter y). This y value was initially set to 160 and was iterated over 9 total values ranging from 160, 180, 200,…, 300 along with the mean value of the surface calculated from the manually picked interfaces. As our algorithm iterates over these values, the location of the ice surface determined by our approach changes, to detect the shape of the ice surface.
2. Vertical distance between the initial ice surface and ice bottom layers (parameter Δ_y). The initial bottom layer is then initialized to be $y + \Delta_y$. This Δ_y value was initially set to 5 and iterated over values of 10, 20, 40. As our algorithm iterates over these values and calculates the corresponding $y + \Delta_y$ value, the location of the initial ice bottom contour changes.
3. Optimal number of iterations to detect the ice surface and bottom. Checked for up to 400 outer iterations, saving results at 25, 50, 75, …, and 400 outer iterations.

The hyperparameter optimization method we employed to explore the parameter space is grid search. Grid search trains the algorithm for all possible combinations of the parameters. The performance of this search was verified by cross validation. The goal of cross validation is to test the level set algorithm and optimized parameters on data that was not used during training. The algorithm was tested on a total of 36 combinations of y and Δ_y values for each of the 16 different outer iteration counts for a total of 36x16=576 unique settings of the hyperparameters.

Result:

We calculated the accuracy of the level set algorithm by computing the mean absolute deviation between the manually picked and the estimated layer boundaries by our algorithm. After tuning the hyperparameters, we found the results for the best combination of level set iterations, y, and Δ_y values. Figures 1-3 and Figures 4-6 show the mean absolute error of the ice surface and ice bottom respectively. To find the optimal combination of the 3 parameters, we performed a 3D search. However, since it is only possible to show results in 2D, we have shown results in 2D slices through the 3D grid search results in these figures. These slices are each aligned at the optimal value of the 3 parameters respectively. The white cross indicated on the figures gives us information about which level set iteration, y, and Δ_y value gave us the best result (Figures 1-6). In addition, we found the optimal combination for just the ice surface and just the bottom layer alone and one combination for the detection of both layers simultaneously. The optimal combinations for the layers can be seen in Table I.

Figure 7(a)–(d) and 8(a)–(d) show the results after 25, 100, 200 and 325 iterations respectively for two example radar images. As can be seen in Figure 7(c) and 8(c), after 200 iterations, the ice surface and ice bottom are partly detected. After 325 iterations, both the ice surface and bottom layers are detected well by our approach. For many images that the ice bottom was only faintly visible in the imagery, our approach was not able to detect the weak radar scattering sections accurately. Figure 9 shows the manually picked interfaces and the ice surface and bottom estimated by the level set method. For these images, the optimal number of iterations seemed to be lower than other images with a clear ice bottom, but we have not tested this hypothesis yet.

Layer	Level Set Iterations	y	Δ_y
Ice Surface	325	160	10
Ice Bottom	325	220	20
Both	400	160	40

Table I
Table 1: Optimal Combinations of Level Set Iterations, y and Δ_y values for Ice Surface and Bottom

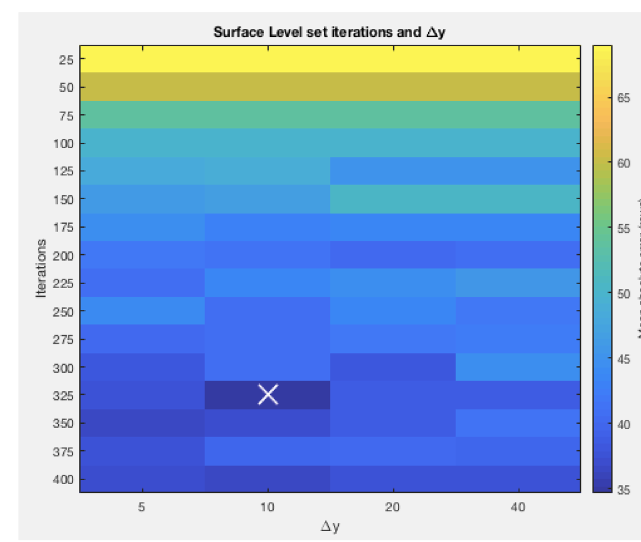

Figure 1: Mean absolute error as a function of surface level set iterations and Δ_y with y = 160.

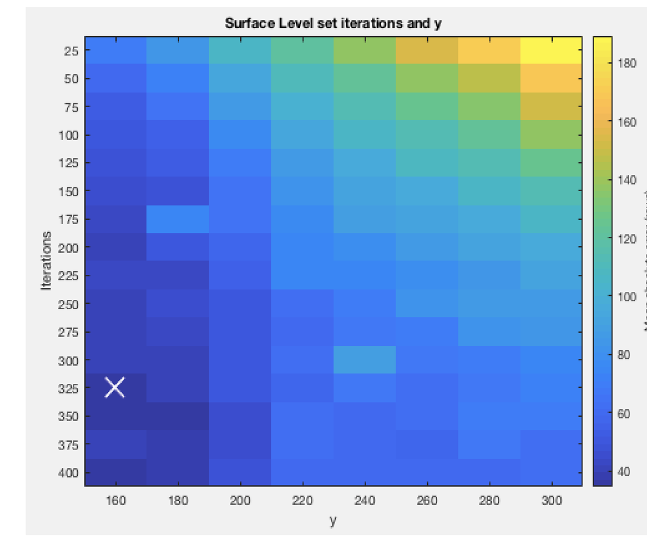

Figure 2: Mean absolute error as a function of surface level set iterations and y with Δ_y = 10.

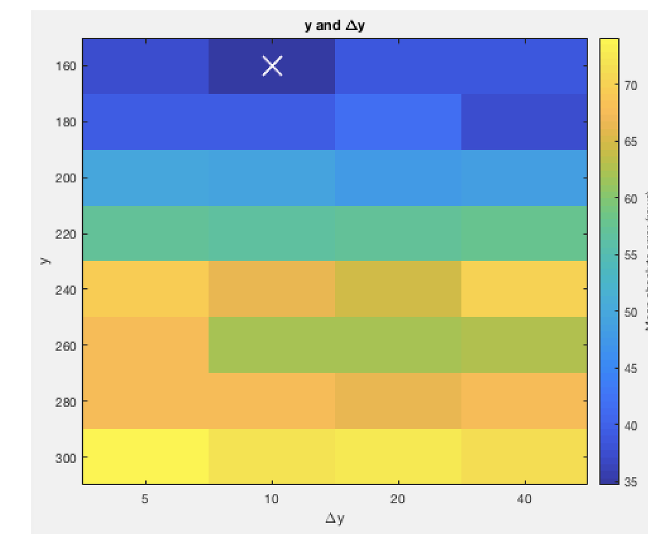

Figure 3: Mean absolute error as a function of y and Δ_y with surface level set iterations = 325.

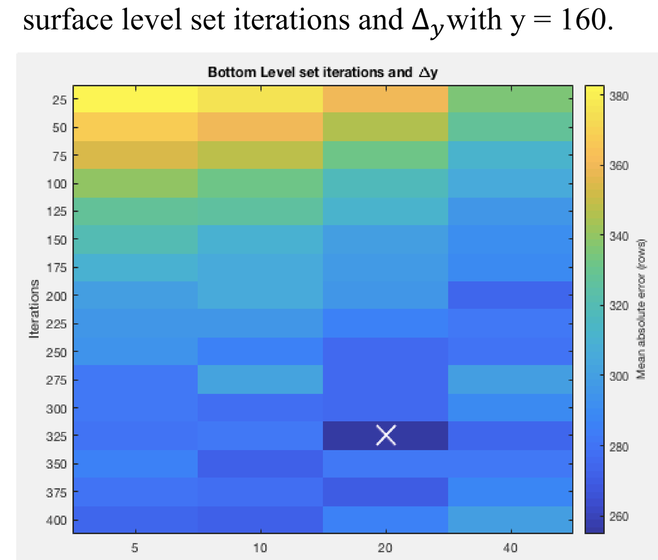

Figure 4: Mean absolute error as a function of bottom level set iterations vs Δ_y with y = 220.

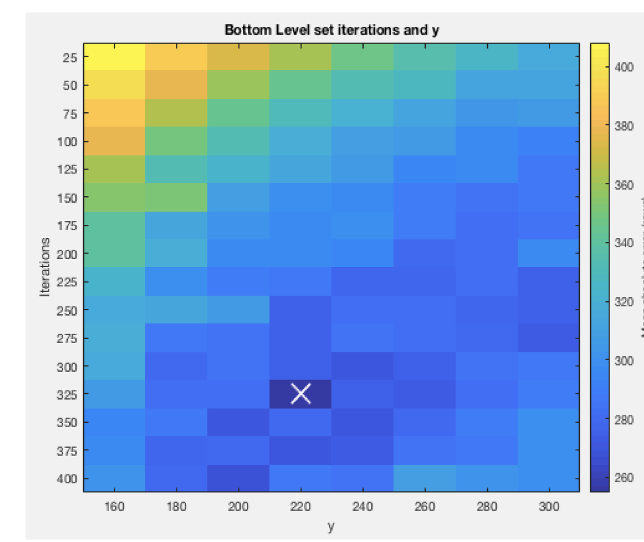

Figure 5: Mean absolute error as a function of bottom level set iterations and y with Δ_y = 20.

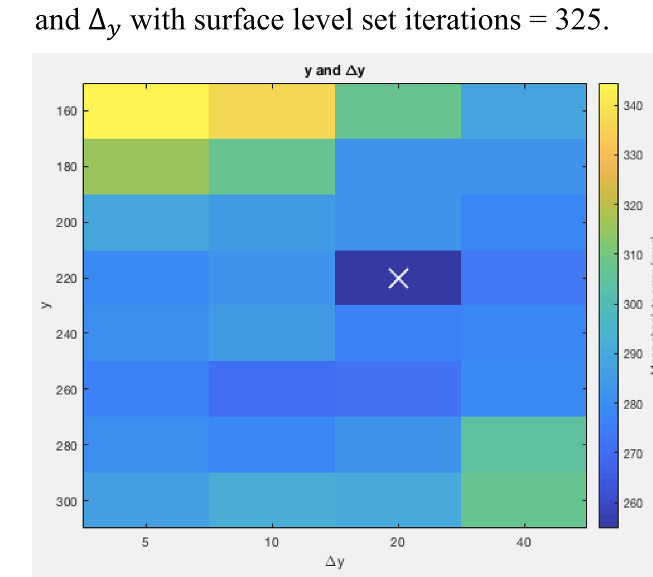

Figure 6: Mean absolute error as a function of y and Δ_y with bottom level set iterations = 325.

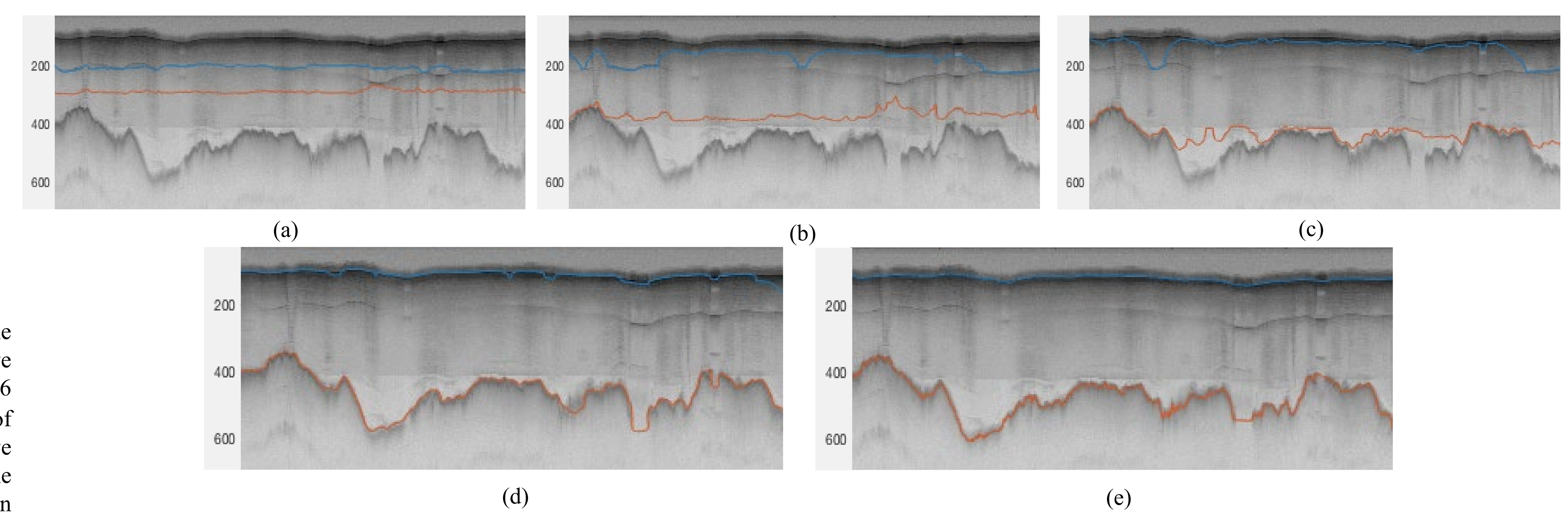

Figure 7: Contour evolution throughout processing. (a)–(d) Contour adaptation to ice surface and bottom after 25, 100, 200, and 325 iterations correspondingly with y = 220, and Δ_y = 20. (e) Manually picked interfaces.

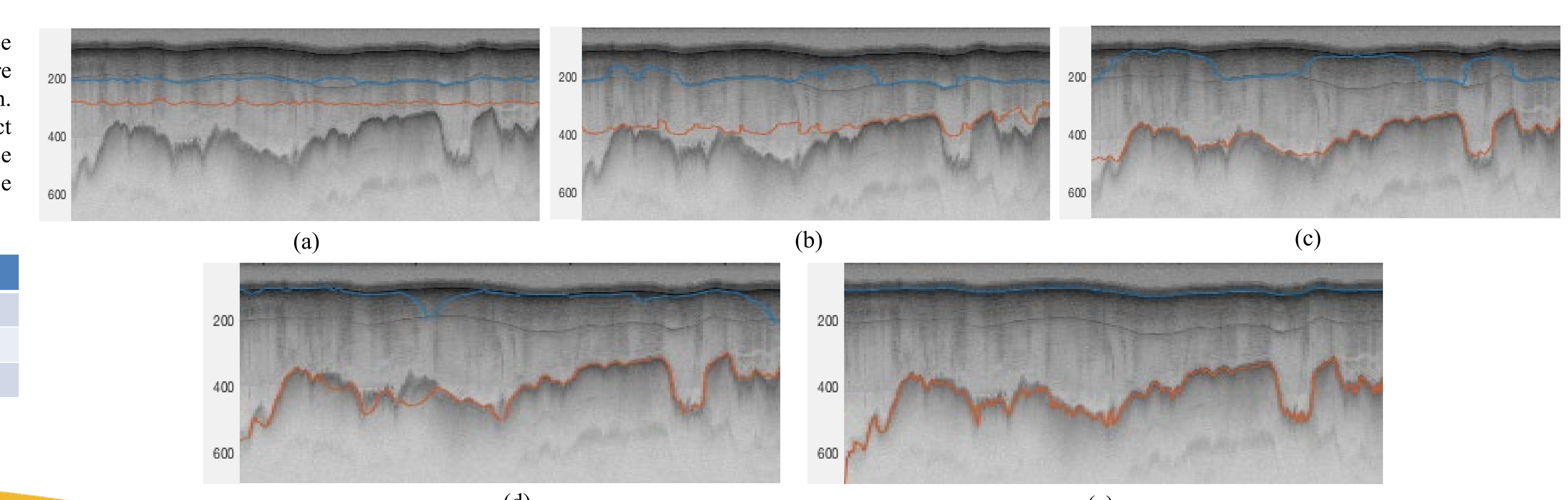

Figure 8: Contour evolution throughout processing. (a)–(d) Contour adaptation to ice surface and bottom after 25, 100, 200, and 325 iterations correspondingly with y = 220, and Δ_y = 20. (e) Manually picked interfaces.

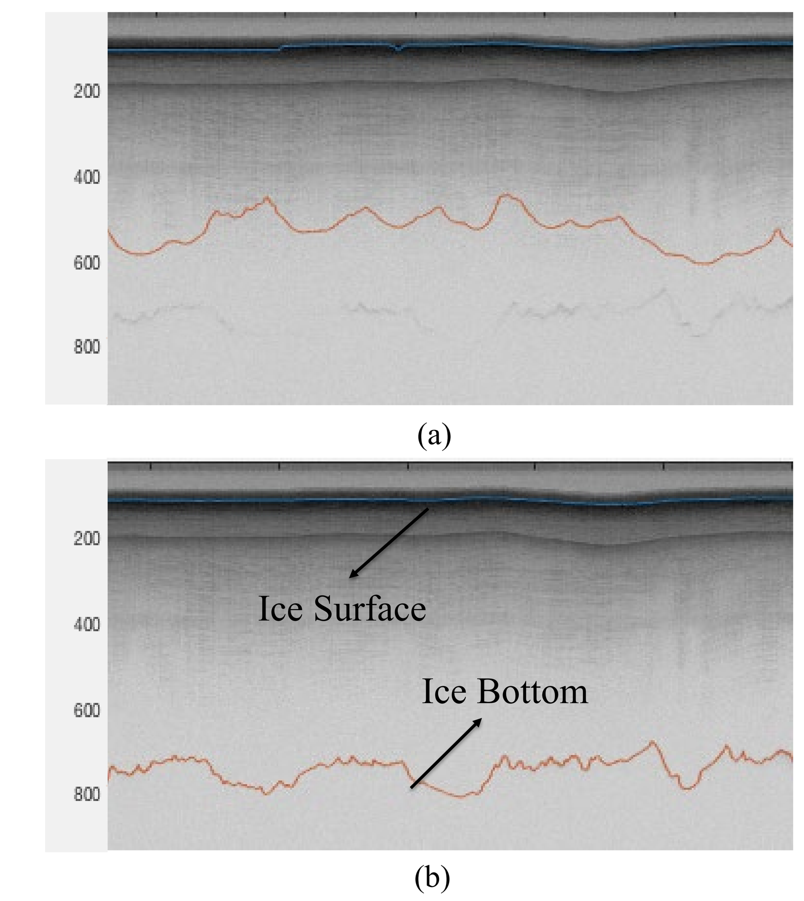

Figure 9: Our approach was not able to detect the faint ice bottom accurately in this example image. (a): ice surface and bottom detected by our approach with y = 160, and Δ_y = 40. (b): manually picked interfaces.

Conclusion and Future Work:

The main objective of this project was to optimize the hyperparameters to improve the performance of the level set algorithm. Our project was able to evaluate and tune this algorithm to automatically track the complex topology of the ice surface and bottom by evolving an initial curve using the level set method. The results were evaluated on a large data set of radar imagery collected over Greenland. We also took into consideration images with noise, diverse ice bottom topology, surface multiples, and faint ice bottom echoes when finding the optimized parameters for the level set algorithm. For the images with a faint ice bottom signal, our algorithm was generally not able to accurately detect the shape of the ice bottom perfectly. For such images, we suspect that it is better to first separate them from the images that have a clearly visible ice bottom layer and then apply the level set algorithm with different numbers of iterations, y and Δ_y values. The combination of parameters for detecting the ice bottom only, was able to detect the shape of the bottom better as compared to the combination of parameters used for the detection of both the ice surface and ice bottom. A disadvantage to this, however, is that to use the parameters for the layers separately, we would have to essentially run the level set layer tracker twice – once to get the optimal ice surface result and once to get the optimal ice bottom result.

Next, based on the trendlines of the plots in Figures 1 - 6, in the future, we plan to center further searches on the following regions in the surface and bottom optimization to get a smaller error and be more confident in our results:

- *Surface*
  - Initial surface contour, y, for values less than 160.
  - Number of level set iterations for values greater than 400.
- *Bottom*
  - Initial bottom contour delta to initial surface contour, Δ_y for values greater than 40.
  - Number of level set iterations for values greater than 400.

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References:

[1] Maryam Rahnemoonfar, Geoffrey Fox, Masoud Yari, John Paden, "Automatic Bedrock and Ice Layer Boundaries Estimation in Radar Imagery Based on Level Set Approach," IEEE Transactions on Geoscience and Remote Sensing, 2017, vol. 55, no. 9, 2017, pp. 5115 – 5122.
In,200,400,GT,153

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