Auto-Segmentation of Spine CTs using Graph Cut Optimization

Computer Integrated Surgery II
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Introduction

We developed a Graph-Cut Based Segmentation method for Spine CTs. We validated our approach on a manually segmented N20 dataset containing patients from TCIA archives. To define graph weights, we used intensity profiles and centroid-based distance weighting. We implemented a cylinder-based convolutional mask to identify inter-disc space.

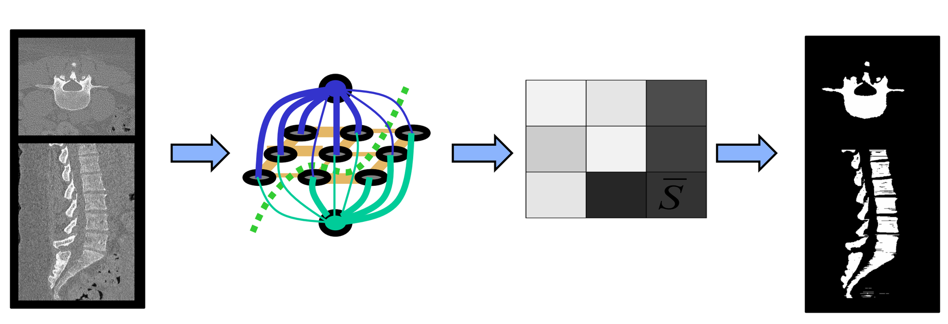
We are motivated to pursue this project as an extension of "Spine Cloud", a big data approach to improve spine surgery outcome. Our project provides an exploration into developing an automatic method for spine CT segmentation.

Problem

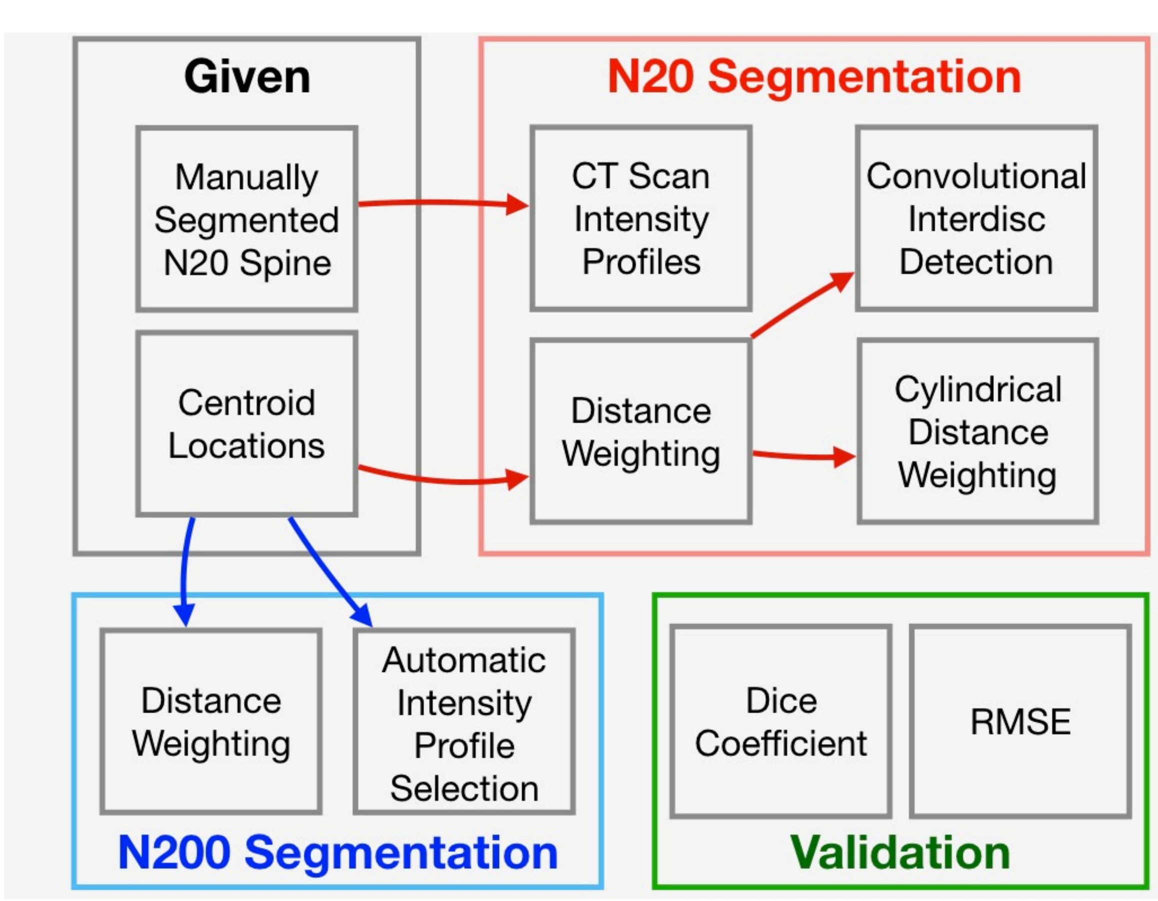
- Currently spine surgery outcomes have high variability
- "Spine Cloud" seeks to remedy this through a big data approach to improve spine surgery outcome
- "Spine Cloud" requires a large database of segmented spine CT images

Solution / Methods

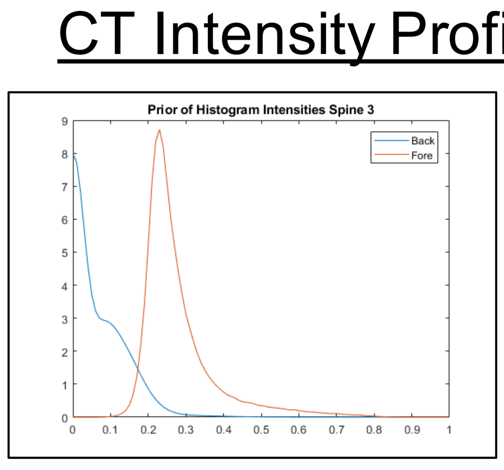
- Our approach to automatic spine segmentation uses 3D Graph Cut Optimization Methods



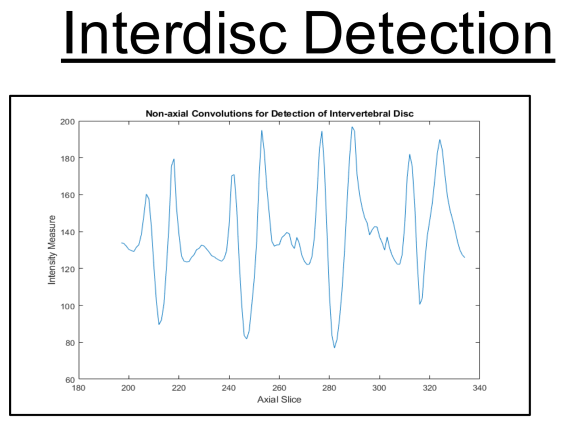
- There were 3 Major Aspects of our Project Timeline
  1. N20 Segmentation and Parameter Analysis
  2. Development of Quantitative Validation Metrics
  3. Foray into N200 Segmentation

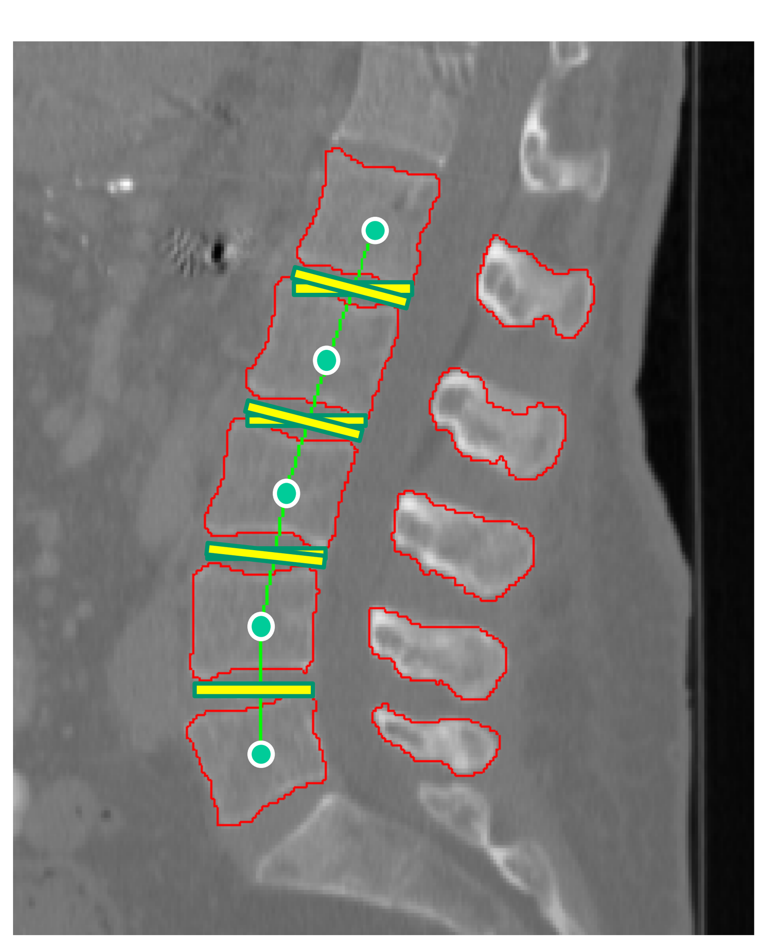


CT Intensity Profile



Interdisc Detection

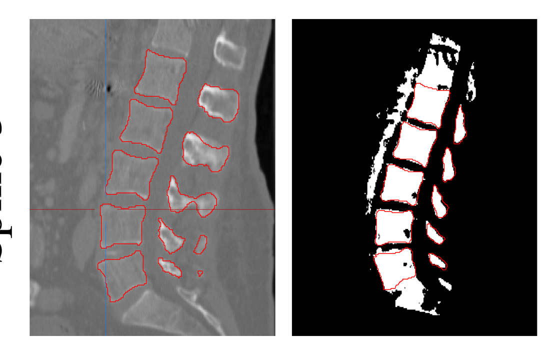




Outcomes and Results

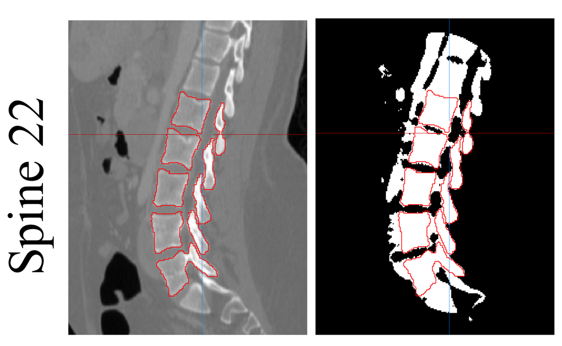
In order to quantify the accuracy of our algorithm, we segmented the entire N20 dataset. We achieved an average Dice Coefficient of >0.7. Below are two different patients segmented within the N20 dataset.

Spine 3



DICE : 0.8318
RMSE : 5.6321 voxels

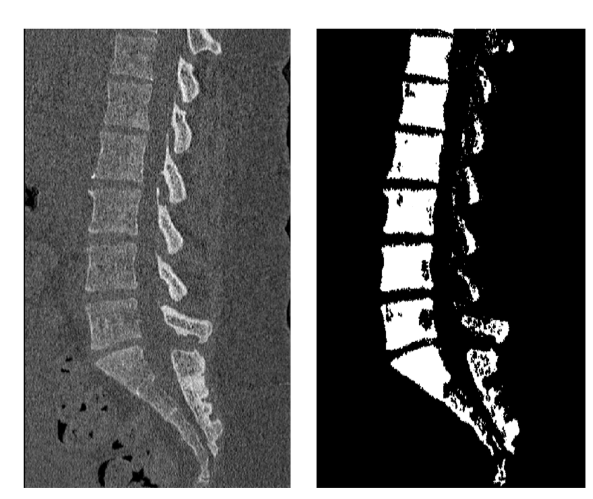
Spine 22



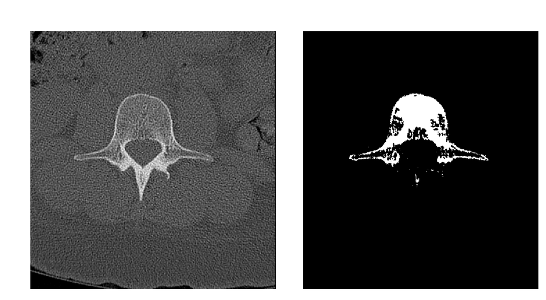
DICE: 0.6568
RMSE: 22.0022 voxels

We then moved on to the N200 dataset and used automatic histogram profiling and distance weighting in order to segment. Within the N200 dataset there is high variability of spine morphology. We validated quantitatively on Spine 0018 for which we had a manual segmentation. This was a case of abnormal morphology, and our segmentation achieved a dice coefficient of 0.6545 and RMSE of 4.85 voxels. Additionally, we qualitatively validated our model on Spine 0001, a patient with normal morphology

Spine 0018



Segmentation of Spine 0001 for N200



Future Work

- Accommodate Irregularities in N200
- Patient Specific Parameter Selection
- Manually Segment more of N200 for quantitative validation

Lessons Learned

- Validation of algorithms must be quantitative
- Learning how to work with multiple supervisors & work as a single part of a greater project
- Every dataset has its own set of problems

Credits

- The 3D Graph-Cut Implementation was provided by our mentor Tharindu de Silva. Ben and Niko contributed equally in all parts of the project. Ben was in charge of the gitlab, while Niko focused more on the reports.

Publications

Yuan, Jing, et al. "A Study on Continuous Max-Flow and Min-Cut Approaches." *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2010

Boykov, Y.y., and M.-P. Jolly. "Interactive Graph Cuts for Optimal Boundary & Region Segmentation of Objects in N-D Images." *Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001*

Boykov, Yuri, and Vladimir Kolmogorov. "An Experimental Comparison of Min-Cut/Max-Flow Algorithms for Energy Minimization in Vision." *Lecture Notes in Computer Science Energy Minimization Methods in Computer Vision and Pattern Recognition*, 2001, pp. 359–374.

Acknowledgements

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