Image Understanding Paper Presentation

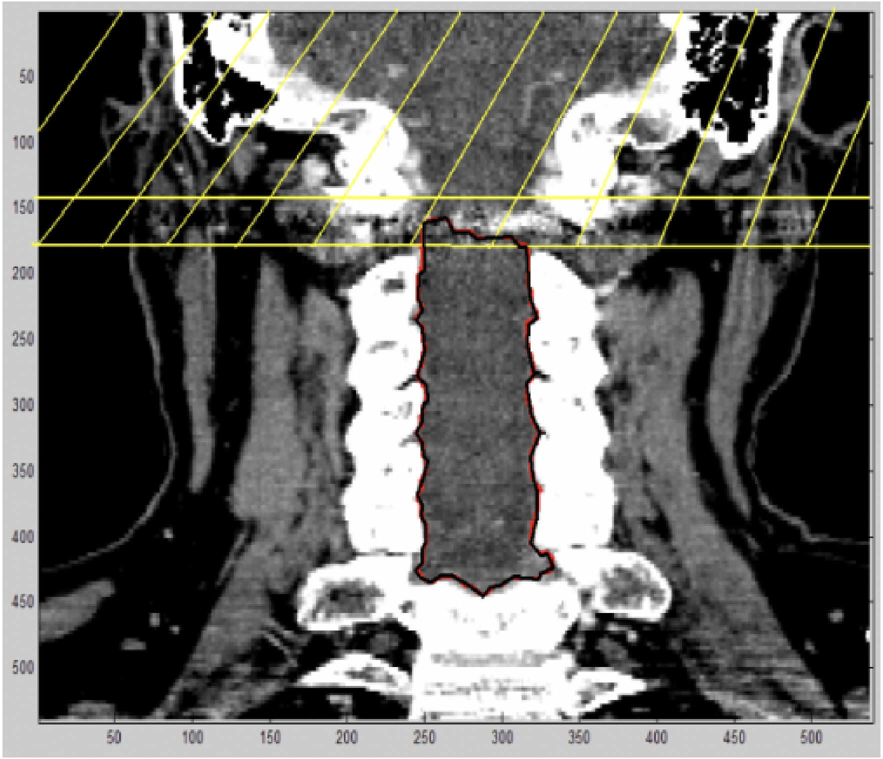
Segmentation Using a Region Growing Thresholding

Olaoluwa Ogunleye, Serin Yoon

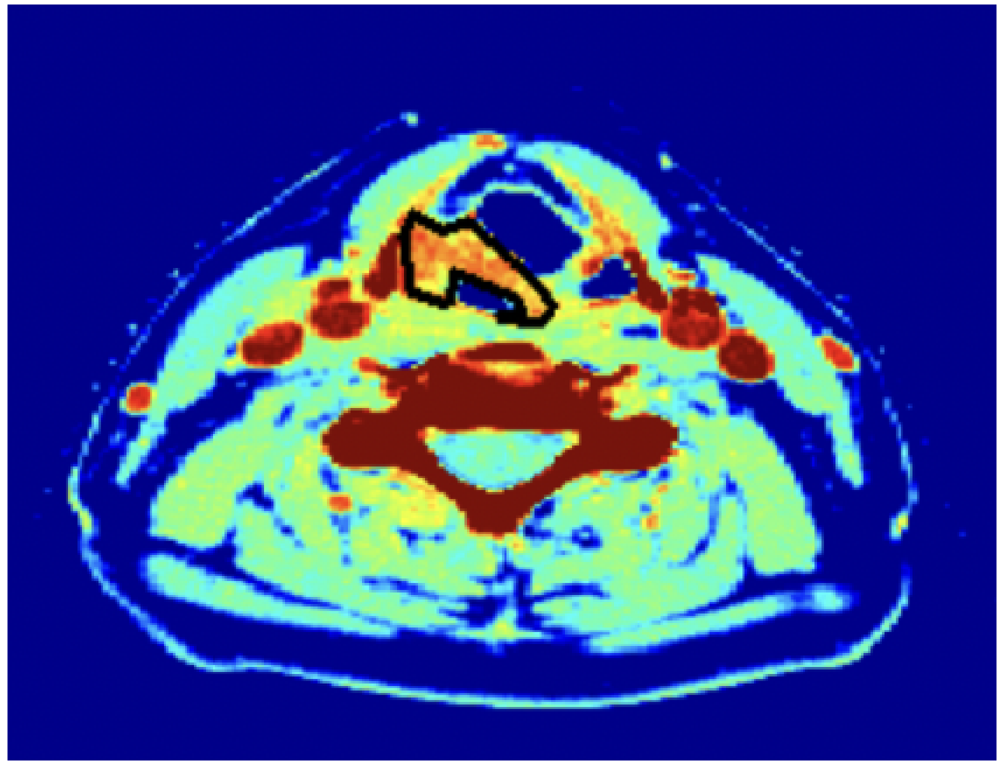
1. Problem Overview

Image Segmentation

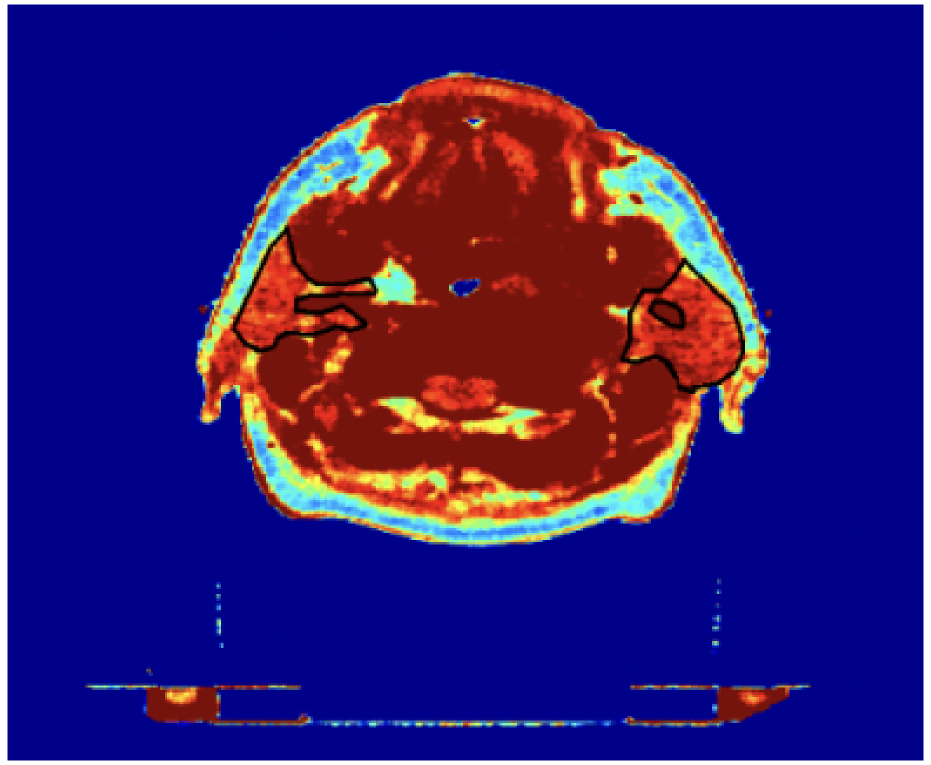
medical imaging by facilitating the delineation of regions of interest (ROI)



Spinal Cord



Tumor



Parotid Glands

precise position or volume of tumors and risk areas → radiotherapy planning

(doses of radiation depend on tumor's volume, rays avoid the risk areas)

1. Problem Overview

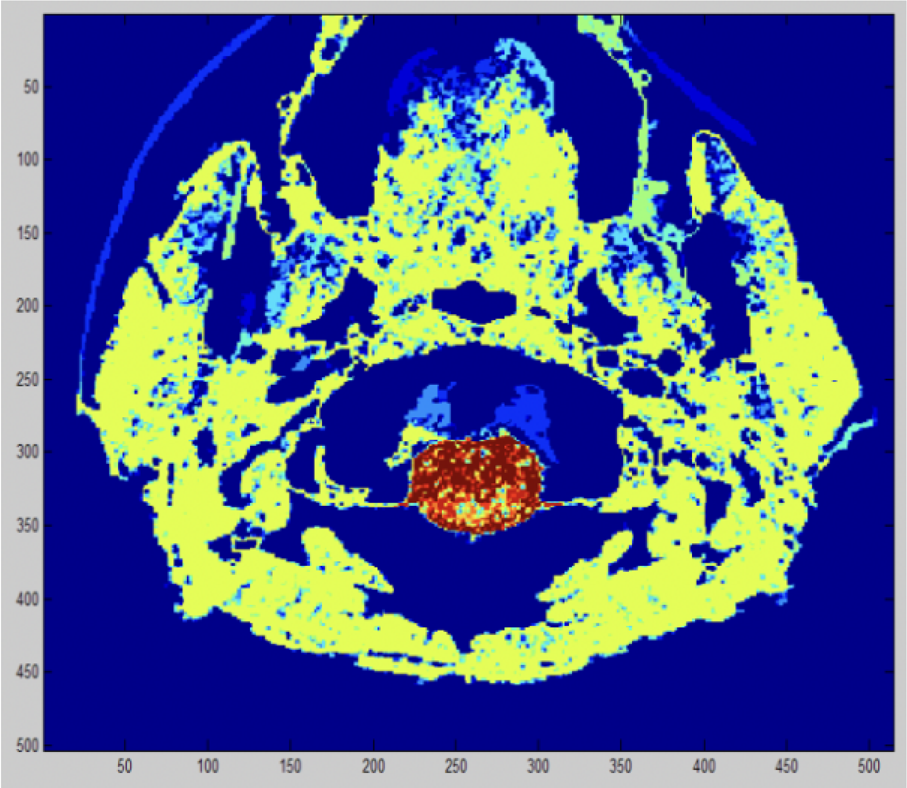
1. Atlas-guided technique

- works well for the spinal cord segmentation
- doesn't work well for the parotid glands and the tumors (very complex structures)

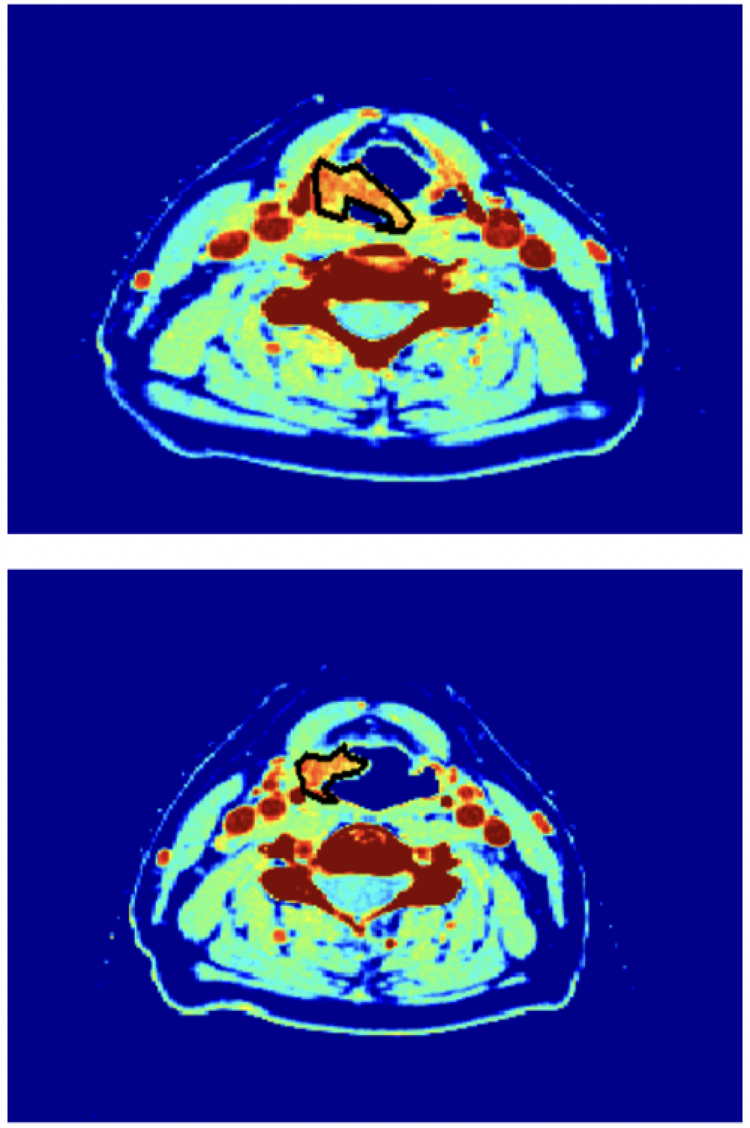
2. Region growing segmentation method ✓

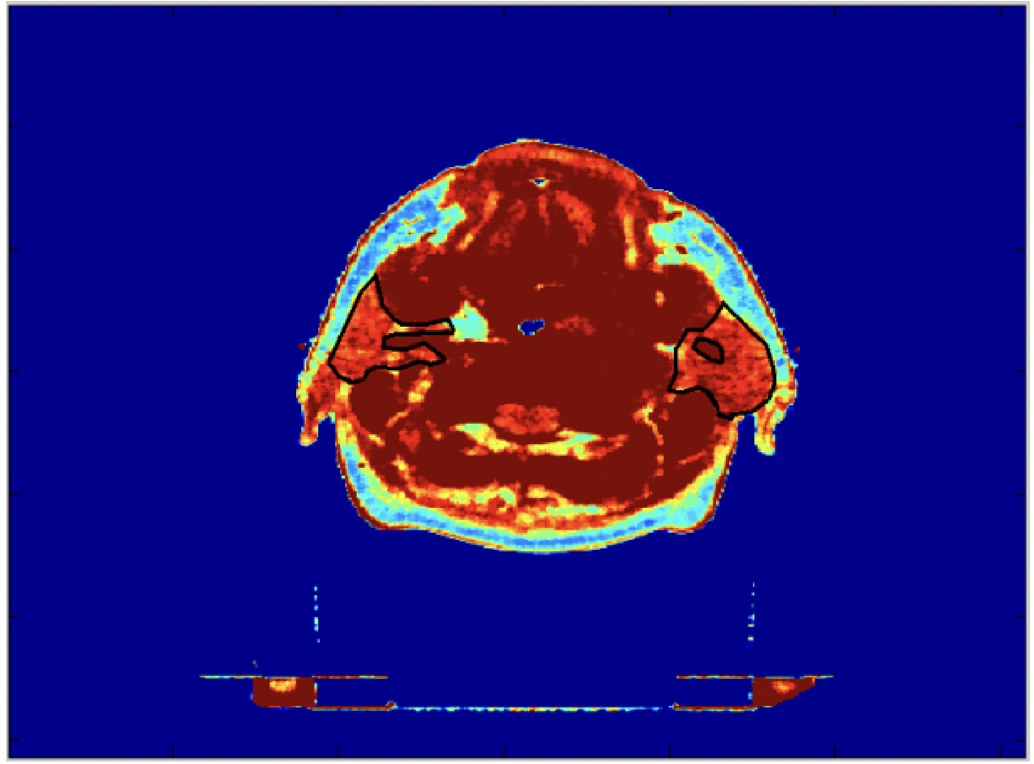
2. Dataset Description

The dataset for this project are simply sets of medical images.
Specifically these includes the following :

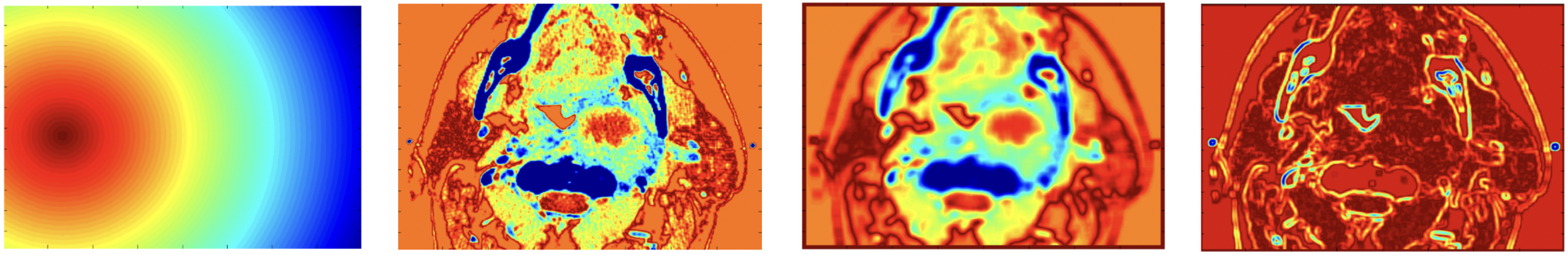


Spinal Cord Image


Tumor Image


Parotid Gland Image

3. Method (1) ROI visualization using distances and probability maps

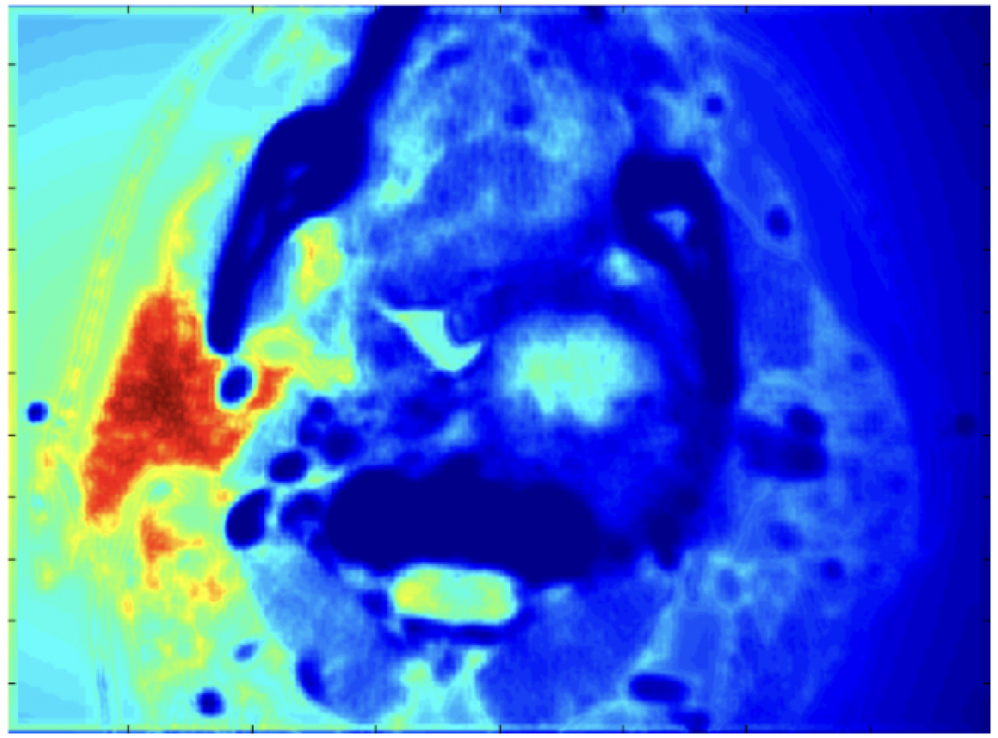


1: Probability map based on spatial Euclidean distance (from the initial seed point to all other pixels)
2: Probability map based on gray level value Euclidean distance (from the initial seed point to all other pixels)
3: Probability map based on gray level mean (from the window centered in the initial seed to all other windows)
4: Probability map based on gray level standard deviation (from the window centered the initial seed to all other windows)

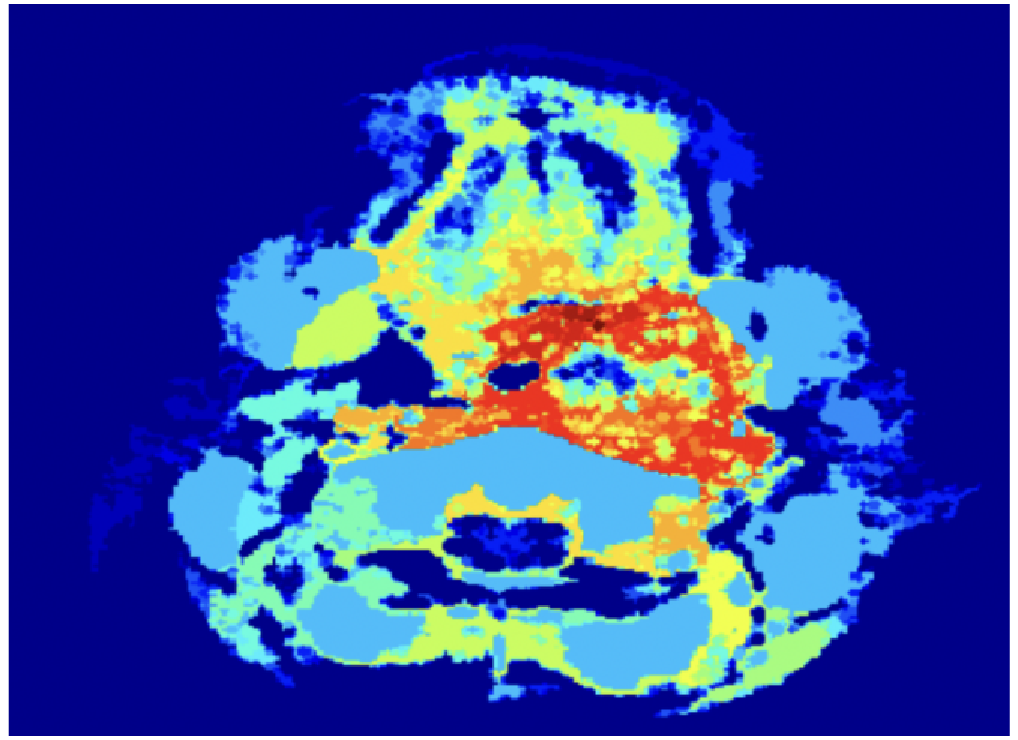
- Computed from the distance maps
- k-means
    - Similarity: Uses a distance from a seed point to all other pixels
    - Difference:
        only 1 cluster centroid
        only classified with a probability of belonging to the same class with the initial seed
- Probabilities are independent → combine them using a multiplication

3. Method (2) The need of a new Gray-Space (GS) map

Spatial Euclidean distance does not depend on images dimensions or structures dimensions
→ Gray-Space map



Result of combining the probability maps



Result of calculating GS map

3. Method (2) The need of a new Gray-Space (GS) map

Algorithm

Compute the seed gray level
$V = I(\text{seed})$

→

Find structures that have the same gray level as the seed and that overlap the seed position

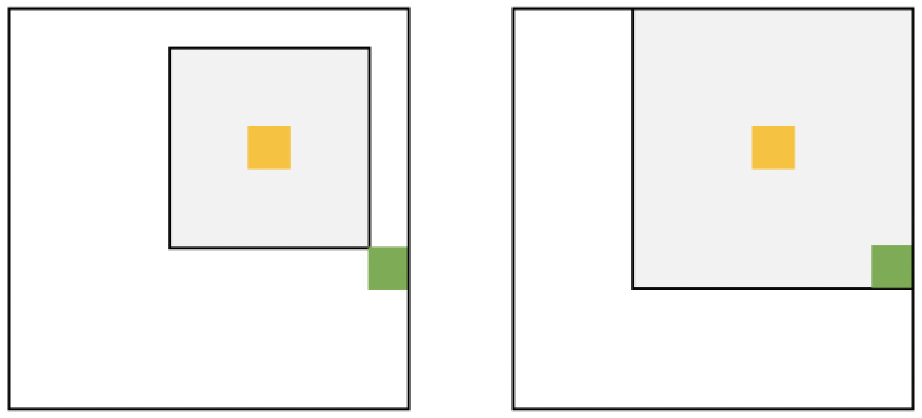
→

Find structures that have the small gray level difference from the seed and that overlap the seed position : $\text{Tmp} = \text{AND}(I > (V + D), I < (V - D))$

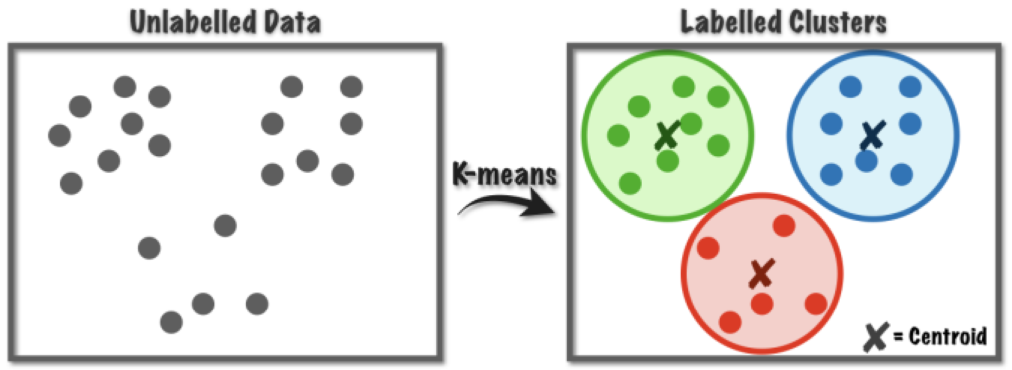
at each iteration, increase the difference (D) by 1
(highlight structures that are close from a spatial & intensity point of view to the seed with higher values)

Refinement

Find structures that have a small gray level difference from the seed and that overlaps after dilatation of the seed position



3. Method (3) From visualization to segmentation



k-means

Region Growing
- good visualization but bad segmentation
- ∵ we have just 1 seed and no concurrent cluster

Approach
- verify if the homogenity of the area is constant
- statistics change too much = introducing heterogeneous areas in the region → stop growing
- include large areas in ROI → big area variation & big statistic variation

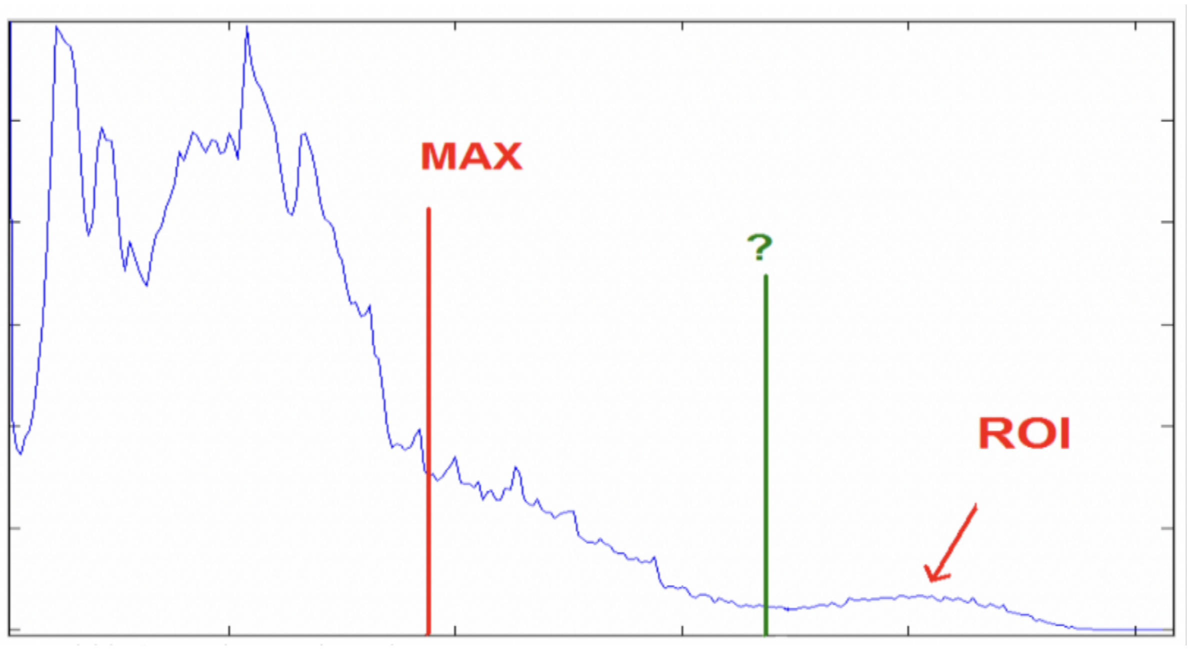
use area variation function of the GS map value

3. Method (3) From visualization to segmentation

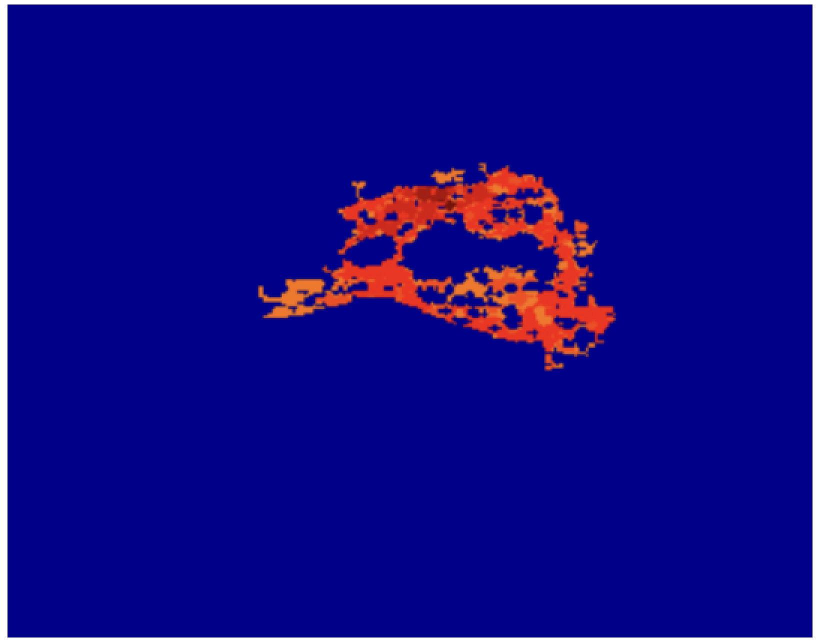
Find the maximum area variation (which means that from this intensity to 0, it's not the ROI)

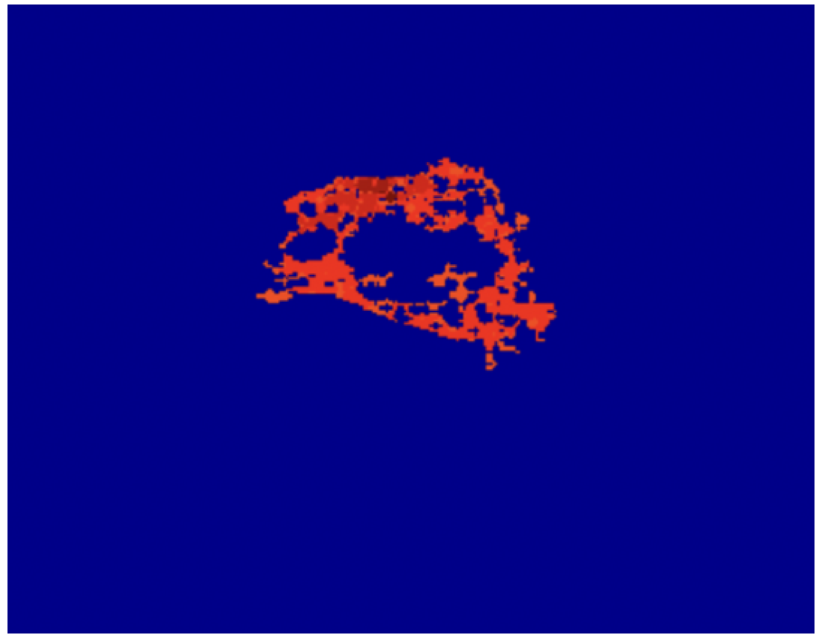
Cut the histogram from MAX to 0 → Find the threshold from MAX to the highest intesity (which separates the uncertainty area from the ROI)

Otsu thresholding method
(more accurate in cutting into 2 classes than k-means)

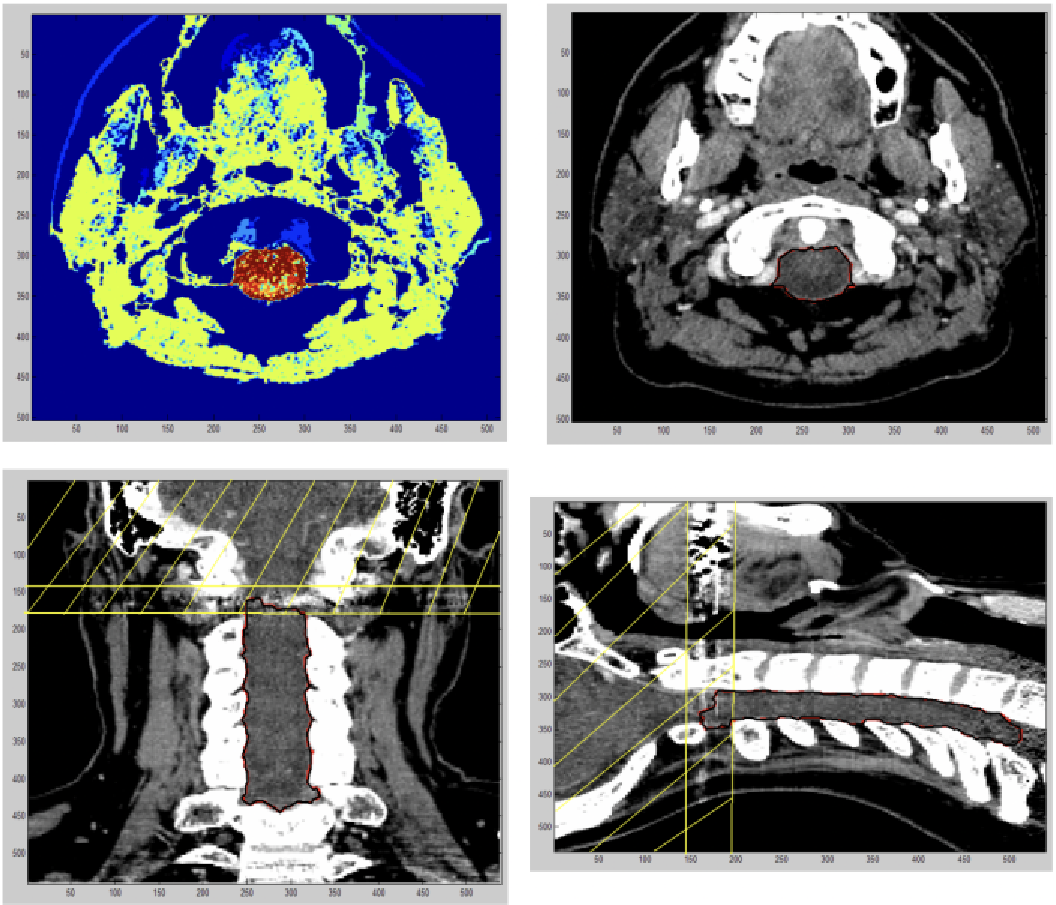


x: GS map value / y: area (numer of points)
Area variation function of the GS map values
(visualization techinque is applied)

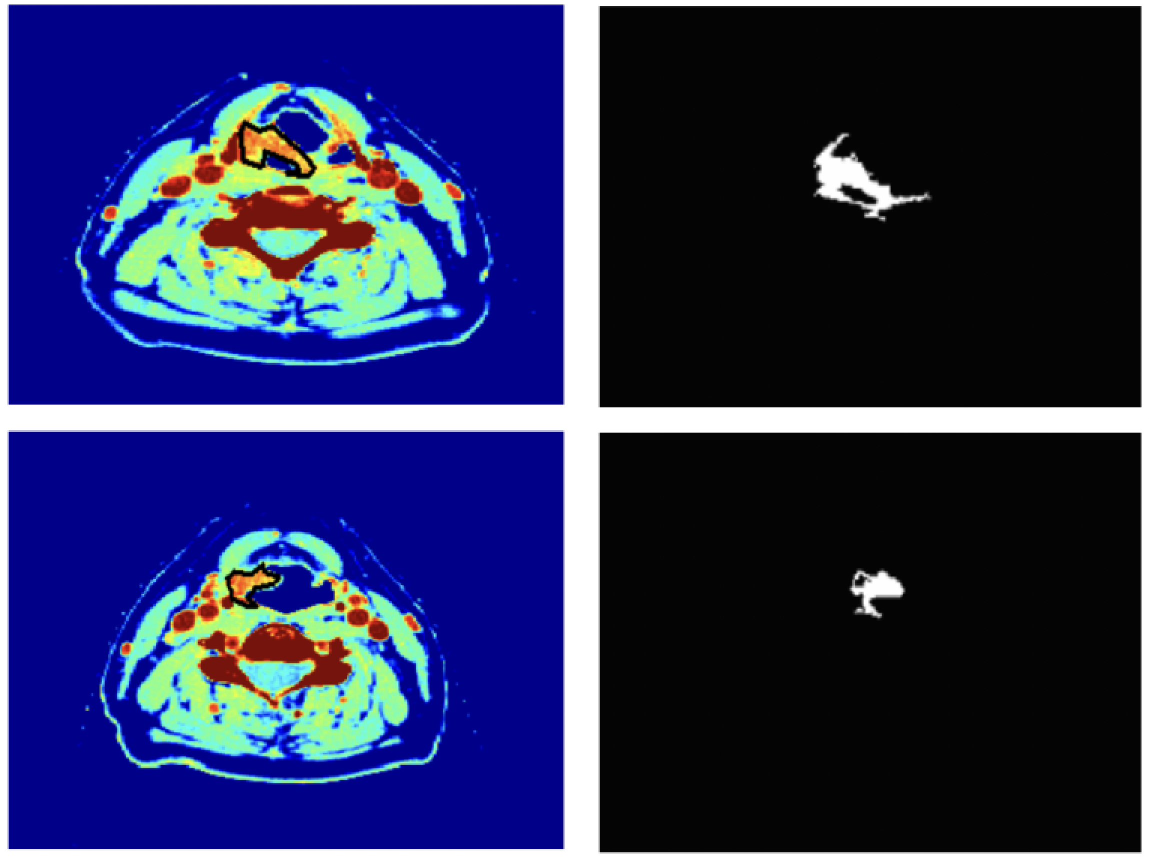

Result after Step 2


Result after Step 3

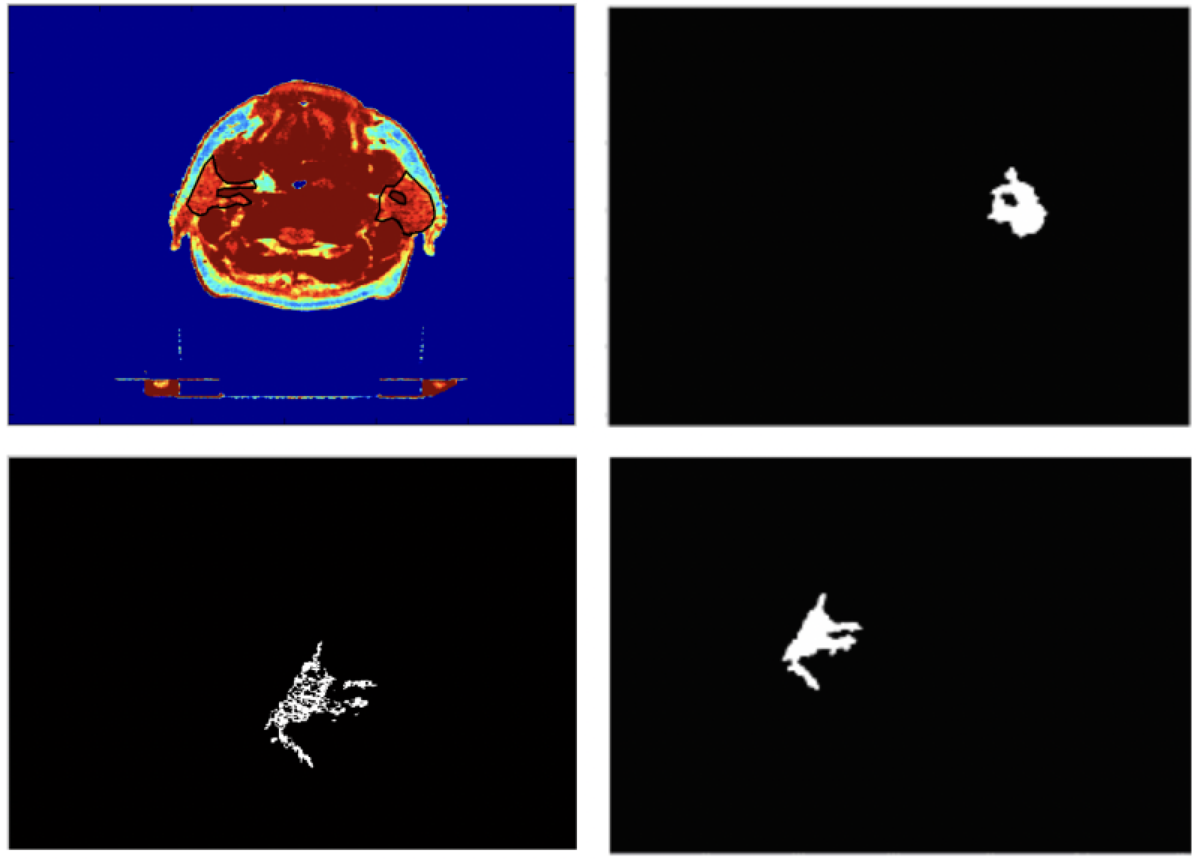
4. Result



Spinal Cord Segmentation Result



Tumor Segmentation Result



Parotid Gland Segmentation Result

5. Training, Validation, and Test accuracy

This method has :

- a problem of reproducibility which is common to most semi-automatic methods
- high dependent on initial seed position

Computational complexity

- Computing probability maps on a volume of 612 x 612 x 5 voxels takes approximately 30 secs
- Computational complexity for implementing GS map is very efficient since it is implemented locally and in 2D

Summary

- Main theme of the paper is a presentation of a new growing thresholding method based on probabilistic maps
- and a new Gray-Space map which takes into account the image topology and intensity

6. Conclusion

Strength

- compares the result before and after applying a specific method through showing the images
- developed an applicable methods not only for spinal cords but also for tumor and parotid glands (that have complex structures)

Weakness

- does not explain what the x-axis and y-axis of the graph means
- when describing the method, it does not exactly specify what the input image is
- does not explain which method they used to find the maximum area variation