Interactive semantic segmentation of 3D medical images

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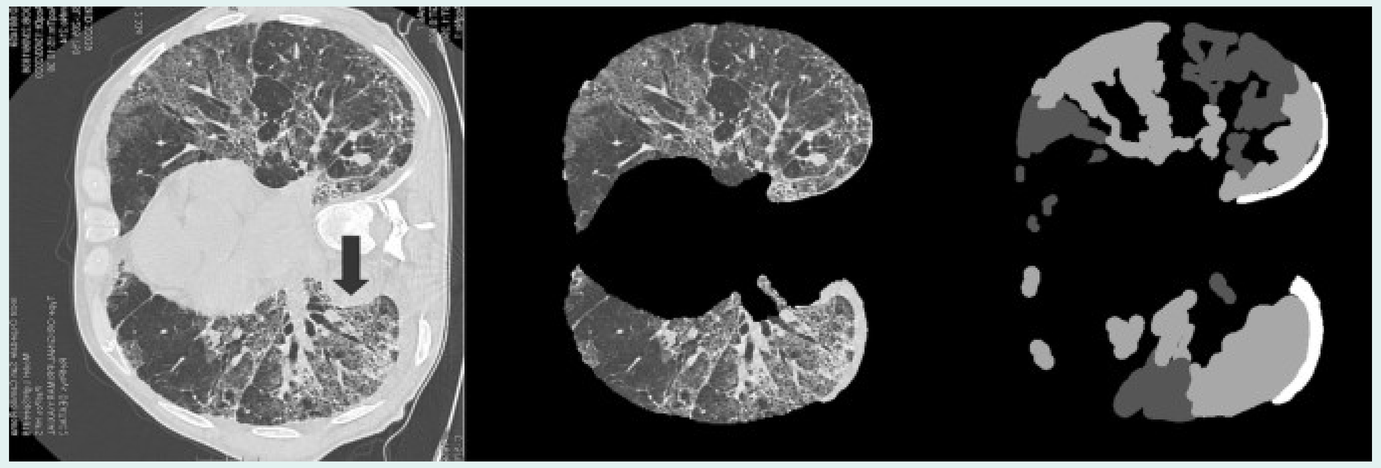
1) What is the problem?



Medical images are massive sets of images (500+) that take images of parts of the body, however, these images do not delineate between organs. To do so these images must be segmented in order to highlight regions of interest. This segmentation can be done as follows:

- Manual: A professional will trough each image and label the regions. However, this is very slow and expensive.
- Automatic: A trained algorithm will go through the images and label them. However, this has the disadvantage of the result not being up to clinical standards.
- Hybrid methods: Methods that try to incorporate algorithms with human assistance. Tries to achieve the best of both worlds

2) The solution

We deal with this problem with a hybrid method, known as active learning (image 1), whose goal is to use a trained random walker algorithm to do the segmentation, where the user can then in the case that the segmentation is not good provide some help to the algorithm. The pipeline works as follows:

1. Segmentation
2. Run an algorithm to find the best region for a user to provide input on.
3. The user provides input and segmentation is done again.
4. The user then evaluates new segmentation. If good enough, end the pipeline, else go back to step 2.

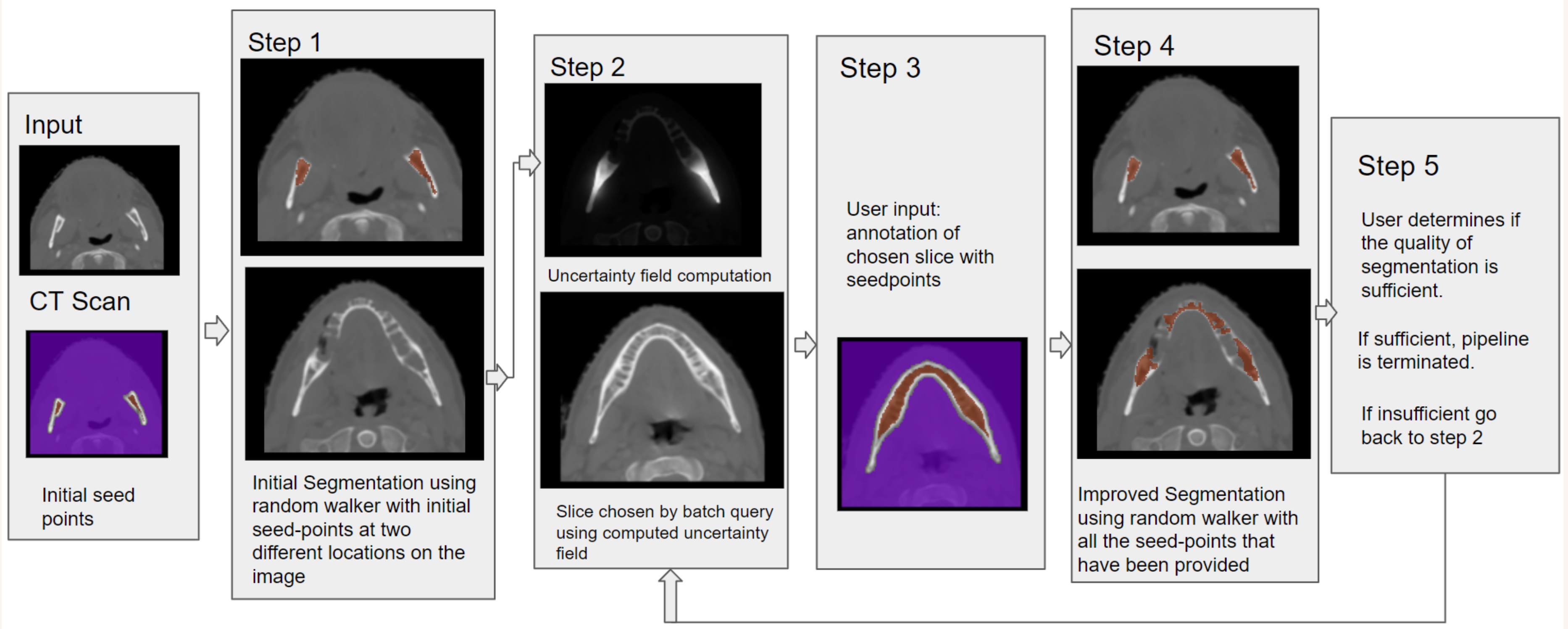


Image 1

[1] Andrew Top, Ghassan Hamarneh, and Rafeef Abugharbieh. Active learning for in interactive 3d image segmentation. In Medical Image Computing and Computer-AssistedIntervention–MICCAI 2011: 14th International Conference, Toronto, Canada, September 18–22, 2011, Proceedings, Part III 14, pages 603–610. Springer, 2011

3) My reserach

The Question:
How does a discrete method for finding the plane (region) of maximal uncertainty fare against the proposed gradient descent-based approach in [1]? Comparison will be done in terms of how well each method segments the image, how many times a user needs to provide input on each method, and how user-friendly each method is.

The proposed algorithm:
The implementation given in the paper [1] does step 2 of the solution using a gradient descent algorithm which is a continuous method. To compare a discrete algorithm the following discrete method is proposed:

1. Discretization Based on Axes of Symmetry: In this research, the process involves discretizing the volume and finding the plane with the highest uncertainty. To achieve this, the constraints for discretization are based on the axes of the plane symmetries of a cube seen in image 2.
2. Iteration through Discretized Planes: By defining the axes of iteration, the uncertainty field, represented by a 3D array, can be traversed. The iteration takes place through the planes in the uncertainty field, starting from the baseline formed by the (y, z), (x, z), and (x, y) axes. Iteration with Diagonal Axes: Additionally, the other six axes corresponding to the cube diagonals are considered. The uncertainty field is rotated to align the diagonal axes parallel to the x-axis. This rotation allows for iteration through the planes formed by the (y, z) axes.
3. Finding the Optimal Plane: To determine the most uncertain plane, all nine iterations through the uncertainty field (axes and diagonals) are executed. During each iteration, the sum of uncertainties for each plane is calculated. By considering all iterations, the plane with the largest sum of uncertainty is determined.

The Testing:
First, both methods are implemented, the proposed one and the gradient descent one from the instructions in the paper. And two tests are done:
1) Synthetic data (Image 3) To find how each method works in a vacuum.
2) Real data: To see how each method performs on real images and evaluate the programs in a real use case. Image 4 Is a slice of a real uncertainty filed.

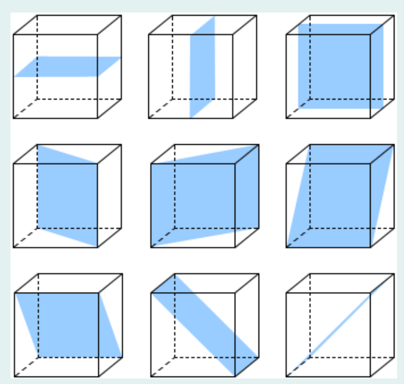


Image 2

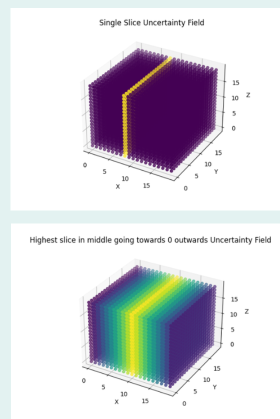


Image 3

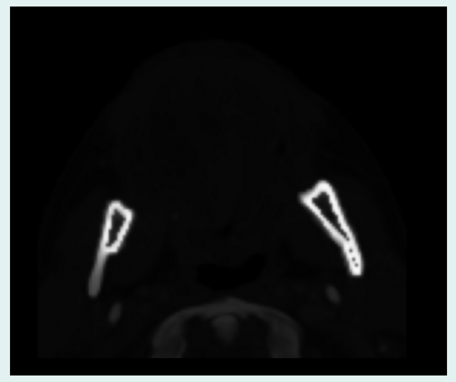


Image 4

4) Results

Synthetic data:

Table 1: Single slice test

Orientation of most uncertain slice	x	y	z	d1	d2	d3	d4	d5	d6
Testing with slice on same axis as discrete	T	T	T	T	T	T	T	T	T
Gradient descent	F	F	F	F	F	F	F	F	F

Table 2: Slice with middle highest and going to 0

Orientation of most uncertain slice	x	y	z	d1	d2	d3	d4	d5	d6
Testing with slice on same axis as discrete	T	T	T	T	T	T	T	T	T
Gradient descent	T	T	T	T	T	T	T	T	T

Table 3: Type of Uncertainty Field

Type of Uncertainty Field	Slice with middle highest and going to 0	Single slice of 1's
Orientation of most uncertain slice	Unaligned	Unaligned
Testing with a slice on the same axis as discrete	F	F
Gradient descent	T	F

Real data:

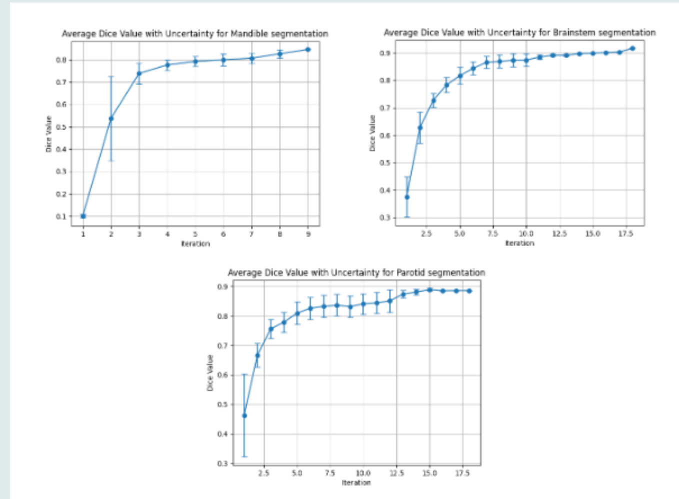


Figure 1

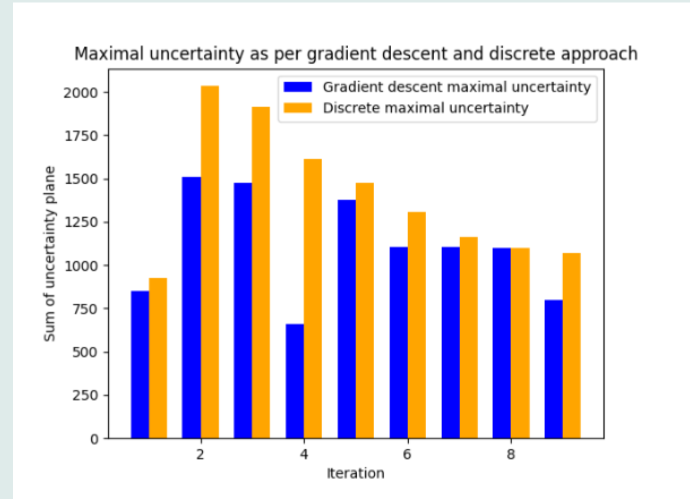


Figure 2

Table 4: Frequency of chosen axis for each feature

Axis	Mandible	Brainstem	Parotid
$[1, 0, 0]$	41	61	63
$[0, 0.707, -0.707]$	0	6	4

5) Conclusion

Experimental results highlight the functionality and significance of the discretization approach in the context of active learning.

For synthetic data:

- The discrete method successfully identifies optimal slices aligned with planes of symmetry but struggles with unaligned slices, requiring multiple iterations.
- The baseline method consistently fails to identify optimal slices on a single slice field but works perfectly on more complex fields but chooses non-intuitive slices. These chosen slices have both advantages and disadvantages, eliminating user control but potentially finding the maximum uncertainty slice.

Synthetic data analysis provides insights but real data examination is necessary to strengthen the arguments.

- The discrete approach achieves dice coefficients around 0.8 (Figure 1) but not reaching higher standards like 0.95 which means it may not be up to clinical standards.
- The discrete method consistently selects slices mostly sharing the same orientation (Table 4), offering predictability and benefits compared to the gradient descent-based approach.
- The discrete method is significantly faster, deterministic, and user-friendly compared to the baseline method.
- The discrete method consistently performs on par with or better than the baseline method in terms of the sum of uncertainty (SOU) of chosen planes. (Figure 2)
- The baseline method shows potential for higher dice coefficients by identifying unique planes but with different orientations.
- The discrete approach may not be suitable for higher segmentation quality standards, requiring approximately a dice coefficient of 0.85.

Conclusion: Discretizing the query retrieval strategy improves system performance but exhibits lower precision compared to the gradient descent approach. This leads to possible future research:

- Further research is needed to address limitations and refine the discretization process.
- Investigating alternative approaches, hybrid methods, and adaptive strategies are recommended for future investigation.