Improving the Random Walker algorithm for interactive 3D medical image segmentation using AI predictions

Modify the weight function to rely on an ensemble of segmentation predictions

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1.Introduction

The segmentation of anatomical structures in 3D medical images is often performed using Active Learning (AL), due to the limited accuracy of automated algorithms. As proposed by [1], segmenting a 3D image using AL is an interactive process where a user iteratively improves the algorithm by annotating initial labels aswell as additional labels.

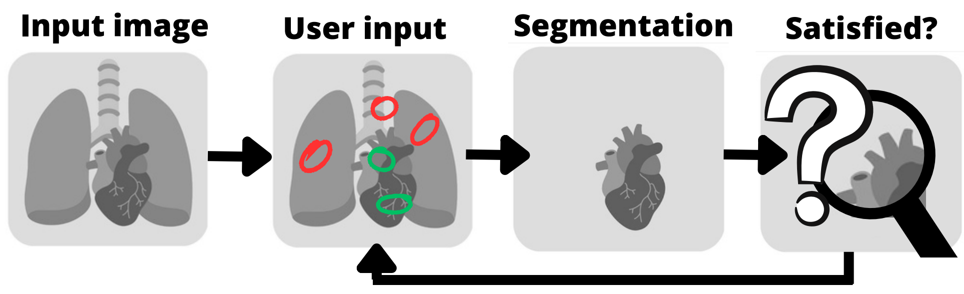


Figure 1: Simplified illustration of interactive image segmentation

2. Research Question

A Random Walker (RW) [2] is used by [1] as the segmentation algorithm. In this research, we will replicate [1] and combine the input data with an ensemble of segmentation predictions obtained by a trained Bayesian Deep Neural Network [3]. This research aims to answer the following question:

How can the performance of the Random Walker for interactive 3D image segmentation be improved by integrating an ensemble of AI-based segmentation predictions?

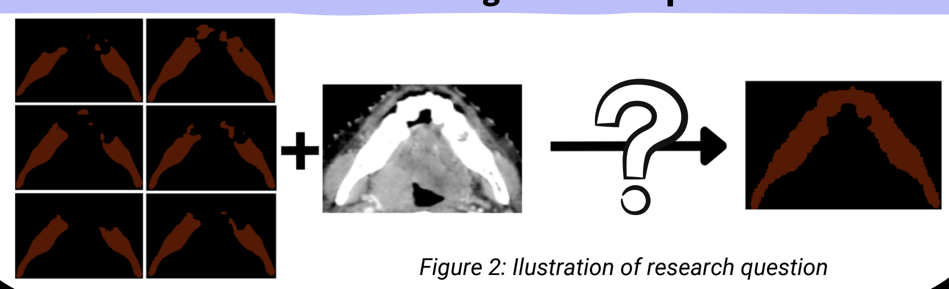


Figure 2: Ilustration of research question

5. Discussion

- All methods performed the **worst** on **optical organs**. This is likely because these are the smallest organs and thus there is limited information and more sensibility for artifacts.
- α = 0 **outperforms** all other values for α. This is likely because seedpoints are far away from most voxels, as 2 iterations only provide little user input and the original weight function **decreases faster** than prediction based, as image intensities have more variance overall.
- Unanimous Vote performs **better** than the Mean Prediction. This is likely because by minimizing the influence of non-unanimous votes it **reduces sensitivity** to prediction variances.
- Adaptive Alpha **outperforms** all methods. This makes sense as by summing the data beforehand, it gives a representation of edges/boundaries in the image depending on both the predictions and intensities.

3.Methodology

Random Walker

The Random Walker works by assigning labels to voxels based on their likelyhood to arrive at a labeled seed point. This likelyhood is defined by a weight function $w_{i,j}$ that indicates weights between neighbouring voxels i and j , based on their similarity. For the original RW this is based on **intensity.**

Integrate AI predictions

We have an ensemble P consisting of N predictions, each labeling a voxel in the image, either 1 or 0. To modify the weight function to integrate P, we compare **4 methods:**

1. Original RW:
- Based on similarity in **intensities:** $(I_i - I_j)^2$

2. Mean Prediction:
- Based on similarity in **average prediction:** $(P_{mean,i} - P_{mean,j})^2$

3. Unanimous Vote:
- Based on similarity in **unanimous prediction:** $0.5 \;\; if \;\; 0 > P_{mean,i} < 1 \vee 0 > P_{mean,j} <$ $|P_{mean,i} - P_{mean,j}| \;\; else$

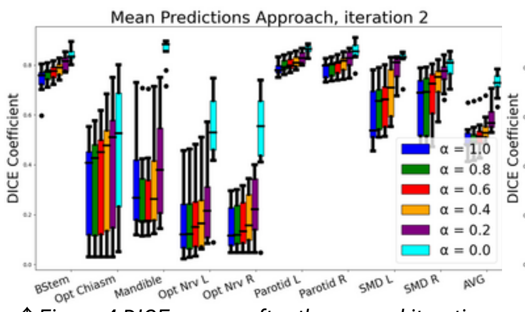
4. Adaptive Alpha:
- Based on similarity in **average prediction + intensities:** $(S_i - S_j)^2$ $S = \frac{P_{mean}}{\sigma_{P_{mean}}} + \frac{I}{\sigma_I}$

Figure 3: The 4 methods presented in this research. I_i corresponds to the intensity of voxel i and P_mean,i the mean prediction for voxel i. σ represents the standard deviation.

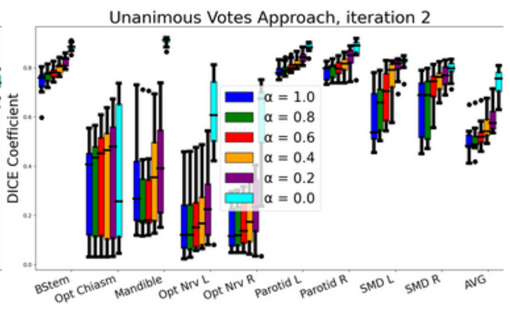
Lastly, methods **2** and **3** will be evaluated as a **weighted sum** with method **1** for some α: $w = \alpha \cdot w_{original} + (1 - \alpha) \cdot w_{new}$

4. Results

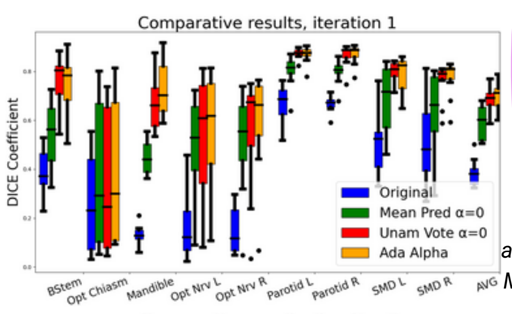
The following results are obtained by testing on a MICCAI dataset [4]. Each figure shows boxplots indicating the average DICE Coefficients of 10 patients, for 9 different organs. The last position on the x-axis shows the average of all organs.



↑ *Figure 4:DICE scores after the second iteration using Mean Prediction method for different α.*



↑ *Figure 5: DICE scores after the second iteration using Unanimous Vote method for different α.*



Both fig 4 and 5 show:
- α = 0.0 performs the best
- Correlation between α and score seems exponential
- Optics produce worst results

←*Figure 6: DICE scores after first iteration (top) and second (bottom). This figure shows results of Mean Prediction, Unanimous Vote (both using α = 0), the Original RW and Adaptive Alpha.*

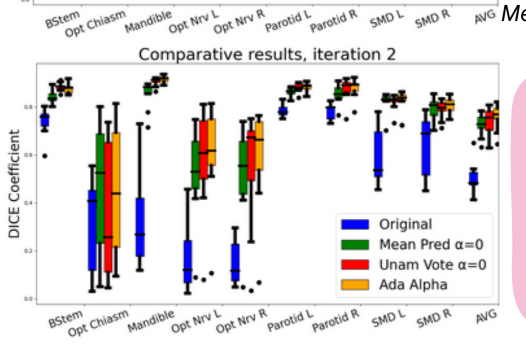


Fig 6 shows:
- Adaptive Alpha performs the best
- Unanimous Vote outperforms Mean Prediction
- All better than Original RW
- All perform worst for optics

6. Conclusion & Future Work

The **main findings** are:

- By minimizing the dependence on non-unanimous predictions it performs **better** than considering only the average predictions
- When combining normalized average prediction with the image intensities beforehand, it **outperforms** all other methods including the original RW.
- Summing the different weight functions afterwards with the original weights does **not** increase performance.

For **future work**:

- It would be beneficial to test on **less accurate** predictions.
- Additionally, it would be beneficial to define an **indication of certainties** for each voxel, both for the predictions and the image intensities. This could be based on for example the standard deviation.
- Lastly, to make the certainty values less sensitive for outliers, it is a desired future work to only take into account values in a **local neighbourhood** around each voxel.

References

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[2] L. Grady. Random walks for image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 28(11):1768–1783, 2006.

[3] Mody, P.P., de Plaza, N.C., Hildebrandt, K., van Egmond, R., de Ridder, H., Staring, M.: Comparing Bayesian models for organ contouring in head and neck radiotherapy. In: Colliot, O., I˘sgum, I. (eds.) Medical Imaging 2022: Image Processing. vol. 12032, p. 120320F. International Society for Optics and Photonics, SPIE (2022). https://doi.org/10.1117/12.2611083

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