



Towards an Improved Unsupervised Graph-Based MRI Brain Segmentation Method

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Abstract. Brain disorders are becoming more prevalent, and accurate brain segmentation is a vital component of identifying the appropriate treatment. This study introduces an enhanced graph-based image segmentation technique. The node selection process involves creating an ellipsoid centered at the image's center of mass. The proposed approach is evaluated using the NFBS dataset and demonstrates superior visual and numerical outcomes compared to some of existing approaches.

Keywords: Brain segmentation · Unsupervised segmentation · Graph-based segmentation

1 Introduction

Brain segmentation is a commonly used technique in the analysis of various neurological diseases and represents the preliminary step in neurosurgical operations and in finding an appropriate treatment.

Recently, there has been a significant surge in the number of individuals experiencing various brain disorders. Developmental delay, cerebral palsy, epilepsy, cortical dysplasia, brain malformation (hemimegalencephaly) are just a few of the problems where an accurate segmentation is crucial. According to the World Health Organisation (WHO) over 50 million people across the world develop epilepsy.

Fortunately, early examination could lead to a treatment. MRI, being a quick, painless, and precise diagnostic tool that generates 3D volumetric data, is extensively utilized for screening purposes. However, as various brain disorders necessitate periodic screening and the process of manual analysis is time-intensive, the creation of precise computer-aided tools is inevitable.

Brain segmentation, also referred to as skull stripping, is the process of separating the brain from the skull. There are numerous studies in the literature that employ both supervised and unsupervised techniques to achieve this segmentation. Recent literature has shifted towards unsupervised methods to extract the brain, as supervised approaches are time-consuming and require more effort and input from doctors.

Brain extraction tool (BET) [7] is a widely used unsupervised brain segmentation method due to its speed and robustness. This technique uses surface tessellation to extract the brain in 1000 iterations. However this approach fails to segment the top and the bottom of the brain, by including non-brain tissue in the segmentation. Improved BET (BET*) [9] tries to overcome those problems, by using an ellipsoid to approximate the brain. Although the number of iterations is reduced to 50 and BET* achieves more accurate segmentation of the top and middle portions of the brain, it still fails to include non-brain tissue in the bottom region of the brain.

Graph-Based Unsupervised Brain Segmentation (GUBS) [2] is another segmentation method that relies on graph-based techniques to extract the brain. This approach utilizes a minimal spanning tree (MST) to accomplish the segmentation. However, one limitation of GUBS is its reliance on the user to define specific parameters for each dataset. Sphere-GUBS [3] improves upon GUBS by eliminating the need for user interaction and reducing the time complexity. This is achieved by introducing a sphere-based approach for selecting brain nodes during the segmentation process. While Sphere-GUBS achieves a higher level of accuracy in brain segmentation, it still encounters difficulties in accurately segmenting the top and bottom regions of the brain.

This paper presents an enhanced unsupervised graph-based method for brain extraction, which addresses the limitations of Sphere-GUBS while maintaining a user intervention-free approach and achieving improved segmentation accuracy. The proposed method is evaluated on the NFBS dataset [4] and the results are compared with those obtained using Sphere-GUBS and the original GUBS.

The rest of the paper is structured as follows: Sect. 2 presents the related work; in Sect. 3 the novel approach is detailed; in Sect. 4 the obtained results are described and Sect. 5 refers to the conclusion and future work.

2 Related Work

Among all the available approaches, BET is commonly utilized for brain segmentation. BET* differs from the initial BET by using an ellipsoid to approximate the brain surface. It improves BET by reducing the iterations to 50 and removing the false positives by using fuzzy C-Means and morphological operations.

Graph-CUTS [5] is another popular method for skull stripping, as it involves segmenting the brain using morphological operations and then representing the MRI as a graph, followed by the use of graph-cuts to eliminate narrow connections. One drawback of this method is that it relies on the region growth of the white matter, which can be time-consuming.

GUBS is an unsupervised brain segmentation method that utilizes a minimal spanning tree (MST) approach. The process of constructing the weighted graph involves edge detection within the MRI data, as well as calculating the weights between the nodes. In this method, node selection is influenced by dataset-specific parameters and requires human intervention to determine the selection threshold for nodes. These nodes are chosen from three distinct categories: voxels within the brain tissue, nodes from the skull, and nodes outside the skull.

The weights assigned to edges are determined based on the intensity difference between adjacent voxels. However, GUBS necessitates the initialization of parameters for each dataset and fails to accurately segment the brain without incorporating non-brain tissue into the segmentation.

In a previous study [3], a method called Sphere-GUBS was introduced. Even though it uses a minimal spanning tree to segment the brain, as presented in [2], it eliminates the need for parameter setting and human intervention by selecting nodes within a sphere with the center in the center of mass for the MRI and the radius equal to $\frac{r}{3}$, where r is computed by taking into consideration the volume of all voxels greater than the multi-otsu threshold. While this method improves segmentation compared to GUBS, it is not without flaws. To enhance the Sphere-GUBS method, the proposed method considers more slices in the node selection process. The use of a sphere results in the removal of some slices from the MRI, which means missegmentation of the brain.

The paper [6] presents a graph-based neural network (GNN) approach for the segmentation of brain tumors. This technique involves representing the 3D MRI data as a graph, with supervoxels serving as the nodes. These supervoxels are generated using the Simple Linear Iterative Clustering (SLIC) algorithm [1], with the cluster number set to 15,000. While this deep learning approach delivers promising results, it needs a considerable training duration, often spanning several hours, and relies on robust hardware resources.

3 Proposed Approach

The proposed approach is based on the main idea of Sphere-GUBS. In this method, an MRI is represented using a weighted graph, and a minimum spanning tree (MST) is applied to segment the brain. The construction of the MST follows the same process as Sphere-GUBS, where voxels are selected only from two regions: inside and outside the brain, in contrast to GUBS, which selects nodes from three categories. Unlike the method mentioned in [3] but similar to [2], the novel approach eliminates the need for parameters and human intervention in node selection. The main point of distinction from Sphere-GUBS lies in the way voxels are selected. The method can be divided in three steps: Preprocessing, Nodes selection, MST construction & Brain segmentation.

3.1 Preprocessing

The preprocessing part consists of resizing the images to $128 \times 128 \times 128$ and scaling the intensities to the range 0–1.

3.2 Nodes Selection

Nodes are sampled from two regions, brain and background. Unlike the Sphere-GUBS method where the brain nodes are selected within a sphere, the proposed approach selects the nodes within an ellipsoid.

The idea of using an ellipsoid was inspired by [9], which utilized an ellipsoid to approximate the brain surface instead of a sphere in the tessellation model.

Although the Sphere-GUBS method, which uses a sphere, enhances results compared to GUBS, it includes non-brain tissue into the segmentation for certain planes or missegments the brain. This is because a sphere includes the same number of slices in all three planes, whereas an ellipsoid varies in three dimensions.

$$9 \cdot \frac{x^2}{r^2} + 9 \cdot \frac{y^2}{r^2} + \frac{9}{16} \cdot \frac{z^2}{r^2} \leq 1 \quad (1)$$

The brain's nodes are chosen from the ellipsoid, as outlined in Eq. 1, where x , y , z represent the voxel coordinates and r is determined by considering the volume of voxels that surpass the multi-otsu threshold. Increasing the dimensions of the ellipsoid axes results in a growth in the number of the selected nodes, which denotes a more complex graph. On the other hand, reducing the size for the dimensions results in a too small graph.

The center of the ellipsoid is calculated in the same manner as for the Sphere-GUBS, by calculating the center of mass for the image.

The selection of nodes from the background follows the same approach as presented in [2] and Sphere-GUBS, randomly choosing 20000 nodes from the all six faces.

3.3 MST Construction and Brain Segmentation

Because of the complexity of the graph, similar to [2] and [3] the nodes are collapsed in such a way that a minimal spanning tree is built. When encountering node collapse, the method follows specific constraints. Firstly, any edge that connects two nodes located in the same region is discarded. Then, for any remaining edges, the node found in the selected seeds is replaced by the first seed in that region. Finally, all remaining selected nodes, except the first, are discarded. The segmentation process involves a final step, which entails dividing the image into two regions - brain and background - by eliminating the edge with the highest weight from the MST path [3].

We call the proposed method Ellipsoid-GUBS.

4 Results

To conduct the testing, the Neurofeedback Skull-stripped repository (NFBS) [4] was utilized. This repository comprises T1W MRI images from 125 subjects between the ages of 21 to 45, with varying clinical and subclinical psychiatric symptoms. The images are manually skull-stripped, and have a resolution of $256 \times 256 \times 192$ with isotropic voxels of 1.00 mm. For testing purposes the images were resized to $128 \times 128 \times 128$ and the intensities were scaled in the range 0 to 1.

To effectively evaluate and highlight the advancements of the novel approach, Ellipsoid GUBS is compared against other MST-based methods, namely the

original GUBS and Sphere-GUBS. This comparative analysis aims to showcase the improvements achieved by Ellipsoid-GUBS in brain segmentation.

4.1 Evaluation Metrics

To assess the performance of the proposed approach, six metrics were used: accuracy, precision, sensitivity, specificity, Jaccard Index, and Dice Coefficient. These similarity measures were calculated between the predicted and ground truth MRI images. TP represents the voxels that have been correctly identified as brain tissue, TN represents the voxels inaccurately identified as non-brain tissues, FP represents the voxels that are inaccurately identified as brain tissues, FN refers to the voxels within the brain region that are inaccurately identified as non-brain tissues.

Voxel accuracy [10] is defined as $\frac{TP+TN}{TP+TN+FP+FN}$ and denotes the proportion of accurately classified voxels.

Precision [8] is computed with the formula $\frac{TP}{TP+FP}$ and denotes the percentage of the accurately classified voxels in the brain tissue.

Sensitivity [8], calculated as $\frac{TP}{TP+FN}$ measures the percentage of brain tissue voxels in the ground truth that are accurately detected as brain tissue in the prediction.

Specificity [8], determined with $\frac{TN}{TN+FN}$ represents the ratio of non-brain tissue voxel in the ground truth that are correctly identified as non-brain in the prediction.

Jaccard Index [8], defined as $\frac{TP}{TP+FP+FN}$ presents the overlap between the ground truth and segmentation results, divided by the union between the ground truth and segmentation results.

Dice Coefficient [8], having the formula $\frac{2TP}{2TP+FP+FN}$ quantifies the resemblance between the two sets of labels.

4.2 Visual and Numerical Results

Ellipsoid-GUBS demonstrates considerable improvements compared to Sphere-GUBS and significant enhancements compared to GUBS. Figure 1 illustrates the visual comparison. In Slice 80 of the coronal plane, the segmentation results for Ellipsoid-GUBS, Sphere-GUBS, the original GUBS, and the Ground Truth are presented. GUBS failed to segment the brain, while Sphere-GUBS closely approximated the ground truth. However, Sphere-GUBS included non-brain tissue at the bottom of the segmentation and mis-segmented the top.

Ellipsoid-GUBS achieved enhanced segmentation results. It no longer includes non-brain tissue from the bottom, as seen in Sphere-GUBS. Additionally, Ellipsoid-GUBS slightly improved the segmentation at the top of the image, particularly in the left-top region.

It can be seen that even though there is still room for improvements, Sphere-GUBS fails by including non-brain tissue into segmentation, while Ellipsoid-GUBS not. In addition to this, at the top of the brain, the proposed method better segments the brain compared to Sphere-GUBS, where the tissues is missed.

The numerical comparison is presented in Table 1. The novel method presents improved results for all six metrics. There is an increased with 3% in the precision for Ellipsoid-GUBS compared to Sphere-GUBS, while a 28% compared to initial GUBS, meaning that the method identifies better the voxels inside the brain. This can be also observed at the top of Fig. 1, as indicated in the visual comparison. The Jaccard Index and Dice coefficient, which represent the percentage of the overlapping between the prediction and ground truth are increased with 2% compared to Sphere-GUBS. The improvements to the other metrics underline an overall better segmentation.

Visual comparison for MRI A00056097, slice 80 - Coronal plane

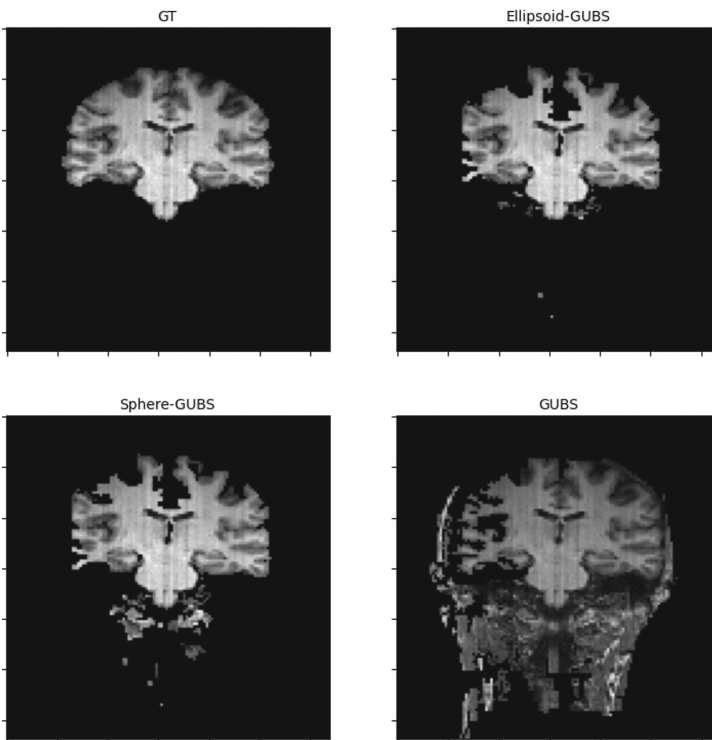


Fig. 1. Visual Comparison for slice 80, coronal plane for GUBS, Sphere-GUBS, Ellipsoid-GUBS and ground truth (GT)

Table 1. Numerical results on all six metrics for GUBS, Sphere-GUBS and Ellipsoid-GUBS

	GUBS	Sphere-GUBS	Ellipsoid-GUBS
Accuracy	0.9041 \pm 0.0138	0.9401 \pm 0.0198	0.9432 \pm 0.0206
Precision	0.5200 \pm 0.0498	0.7732 \pm 0.1223	0.8077 \pm 0.1242
Jaccard Index	0.4568 \pm 0.0594	0.5024 \pm 0.1520	0.5214 \pm 0.1613
Dice coefficient	0.6245 \pm 0.0670	0.6523 \pm 0.1577	0.6681 \pm 0.1649
Specificity	0.9163 \pm 0.0157	0.9781 \pm 0.0189	0.9797 \pm 0.0222
Sensitivity	0.7975 \pm 0.0903	0.6015 \pm 0.1997	0.6167 \pm 0.2088

5 Conclusion and Future Work

The paper presents Ellipsoid-GUBS, a pioneering unsupervised graph-based brain segmentation method that demonstrates enhanced performance in brain extraction. This approach involves constructing a graph by selecting nodes within the brain and the background. To identify brain tissue nodes, an ellipsoid is employed. The method underwent rigorous testing using the complete NFBS dataset, which comprises 125 MRI images.

Ellipsoid-GUBS presents visual as well as numerical improvements in brain segmentation, compared to Sphere-GUBS. In the previous study the nodes selection method used a sphere, while in the presented approach an ellipsoid was used. Ellipsoid-GUBS presents an increased with 3% in precision and 2% in the dice coefficient which means an overall better segmentation. In term of visual analysis, Ellipsoid-GUBS segments better the brain in comparison to Sphere-GUBS which includes non-brain tissue into segmentation.

Future work involves testing the method on more datasets and comparing it with other approaches, including supervised methods. Exploring alternative methods for defining the ellipsoid's center is another objective. Collaboration with hospitals to gather doctor feedback and creating a dataset with diverse patient disorders are also planned. This initiative aims to enhance the algorithm's accuracy through rigorous evaluation.

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