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2-D and 3-D BRAIN MRI SEGMENTATION

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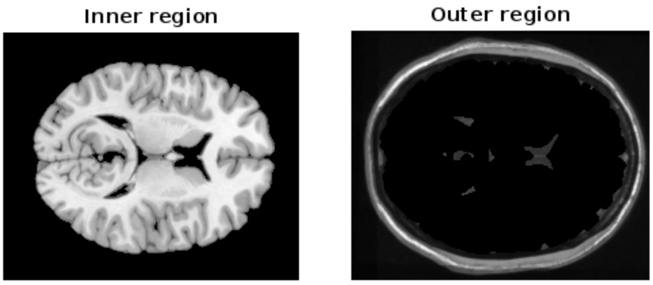
AIM: Various 2D segmentation algorithms are to be applied to each slice of the MRI data. The segmented results are to be compared with the true labels using suitable evaluation metrics. A 3D segmentation algorithm should be used to segment the entire MRI data simultaneously and evaluated using the metric used for comparing 2D segmentation.

2D TISSUE SEGMENTATION

METHOD: The input image slices are sharpened using the Laplacian filter [0 1 0; 1 -4 1; 0 1 0]. The Laplacian filter is first applied to each image slice. Then, the result of this operation is added to the initial image to enhance the edges detected by the filter. The features in the slices are grown and the gaps are filled using the dilation operation. It basically connects the values of 1 of an image. This is done using the morphological structural element ‘strel’ with a disk of radius 2. A structural element is a mask of any size that is used to perform morphological operations. They are of various shapes such as cube, hexagon, disk and ball.

Otsu‘s thresholding technique is used to binarize each slice into an inner part image and an outer part image. The CSF, Gray Matter and White Matter are separated from the air, skin and skull regions using ‘bwareafilt’. This method is used to extract the largest connected component from the thresholded binary image. The reason for this extraction is to ensure better segmentation of each slice, as the segmentation algorithm is applied separately to each extracted part.



(a) (b)

Figure 1: (a) Inner region. (b) Outer region.

The image slices are then morphologically opened using a disk structural element of radius 2. This method first uses an erosion operation which is used to shrink the connected structures of the images. It removes components such as branches and protrusions. Then, it applies the dilation operation on the eroded image to fill any holes. This is followed by an erosion operation again to shrink features further. Each segmentation algorithm is applied separately to the inner and outer parts of the image, which were separated previously.

2-D SEGMENTATION TECHNIQUES

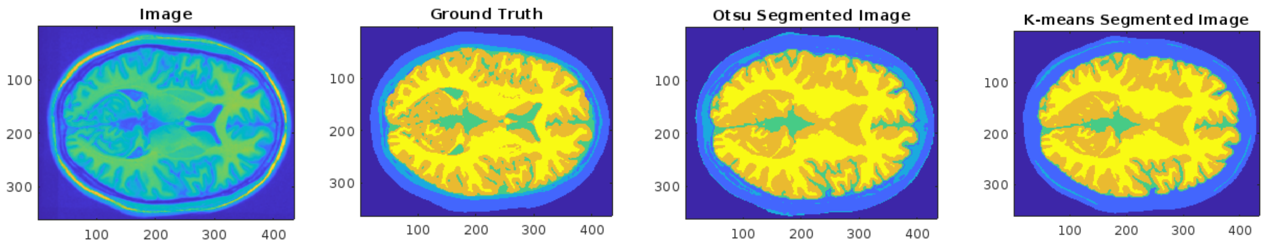
K-Means algorithm

The K-means algorithm allocates arbitrary centres to the number of clusters specified. The inner part was segmented into four clusters using the K-means algorithm. Similarly, the outer part was also segmented into four clusters where two clusters were assigned the same value. This achieved a significant boost in performance. The values for each cluster centre are updated until the mean value converges so that there are no further changes. It is key to observe that the K-means algorithm assigns the labels to each cluster region randomly. Thus, after convergence, the cluster labels are allocated to the regions corresponding to its label according to the final cluster centres obtained. After both the inner and outer regions have been segmented separately, the resultant values are combined to obtain the final segmented image slices.

Otsu's algorithm

Otsu's algorithm is applied to both inner and outer regions separately and then the results are combined to obtain the final segmented image. The thresholds used for both the regions are 3.

RESULT EVALUATION



(a) (b) (c) (d)

Figure 2: (a) Original image (b) Ground truth labels (c) Otsu segmented image (d) K-means segmented image

	Sensitivity	Specificity	Jaccard	Dice
K-Means	0.9894	0.9965	0.6351	0.7196
Otsu	0.9940	0.9975	0.6594	0.7526
Tree Bagger	0.5115	0.8145	0.1447	0.2386

Table 1: Evaluation metrics averaged across all labels of all image slices

As this segmentation is an imbalance class problem, using the accuracy metric would not reveal the true performance of the algorithm. This is because predicting the majority of classes correctly would make it look like the algorithm is performing well. However, it does not represent the algorithm's performance on minority classes accurately. Jaccard's index, also known as the Intersection over Union (IoU) metric, calculates the intersection area with respect to the union area.

Dice index, derived from the Sørensen-Dice similarity coefficient, calculates the similarity between the ground truth labels and the segmented result. It is defined as Dice = 2TP / (2TP + FP + FN). This metric is quite similar to the IoU metric. However, it counts the intersection between the masks twice.

Dice coefficient is chosen as the evaluation metric as it penalises the false positive labels in the segmented results. Thus it is more reliable than the accuracy metric. But it differs from precision as it double-counts the true positives. Generally, the Dice coefficient is preferred over Jaccard IoU because the former is differentiable while the latter is not. Papers which use deep learning methods widely use the Dice coefficient for this reason. While DL segmentation methods are not used in this experiment, it would be useful to compare the results obtained in this report with those of Deep learning methods.

Based on the Dice coefficient, **Otsu's method is the segmentation algorithm** which performs the best on given data. On a closer look at individual label dice scores, Otsu segments the region of skin and skull better than K-means.

3D TISSUE SEGMENTATION

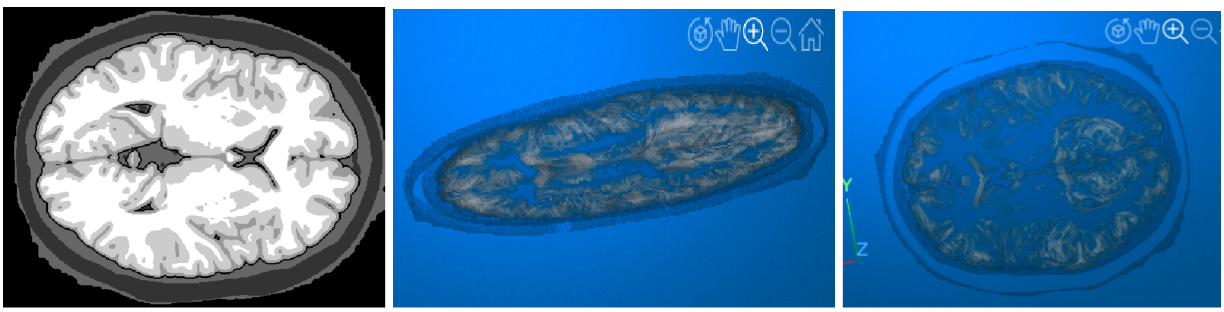
GMM-HMRF based segmentation algorithm

The paper "GMM-Based Hidden Markov Random Field for Color Image and 3D Volume Segmentation" introduces a volume segmentation technique based on Gaussian Mixture Models (GMM) and Hidden Markov Random Fields (HMRF). This technique is used to represent the volume as a graph where the nodes indicate their dependencies. GMM models the distribution of each pixel in the 3D volume. It assumes that each pixel in the volume is sampled from a Gaussian distribution.

The HMRF captures the spatial dependencies between the pixels of the volume. It is represented as an undirected graph where the pixels near each other depend on one another. It allocates a probability to each categorical label. The Expectation-Maximization (EM) algorithm, which consists of two steps, is used for estimating the model's parameters. The E-step is used to calculate the probabilities of every pixel belonging to a component of the mixture model. The M-step is used to maximize the conditional expectations and recalculate the parameters. These steps alternate until convergence. The main difference in this method is that it uses weighted probability as an additional parameter to the Gaussian Mixture Model.

	GMM-HMRF	**Otsu**
Label 0: Air	0.9175	0.8978
Label 1: Skin/ Scalp	0.9093	0.8753
Label 2: Skull	0.6058	0.2841
Label 3: CSF	0.5322	0.5755
Label 4: Gray Matter	0.8964	0.9236
Label 5: White Matter	0.9903	0.9902
Average score of all labels	**0.8085**	**0.7577**

Table 2: **Dice coefficient** scores of 3-D segmented volume using GMM-HMRF and Otsu algorithms



(a) (b) (c)

Figure 3: (a) XY slice of the 3D segmented volume. (b) and (c) indicate the 3D volume segmented using GMM-HMRF segmentation algorithm.

The preprocessing steps used to segment the 2-D images are also followed in the case of 3-D segmentation. The volume is split into two parts, namely, inner and outer regions. The GMM-HMRF algorithm is used separately on these regions and the results are combined. Four clusters/ regions are allocated in each case with a single GMM component. Five iterations of the E-M algorithm and MAP estimation are carried out. These values are selected through trial and error and by observing which ones perform the best on this data.

It can be observed that the GMM-HMRF segmented volumes achieve higher scores than 3-D Otsu thresholding segmentation. This is due to HMRF applying spatial constraints to the regions being segmented. As thresholding (Otsu) and clustering (K-means) algorithms use only pixel intensities to segment 2D and 3D images, they fall short of the previous approach in terms of extracting the maximum amount of information available.

CONCLUSION

The best performing algorithms for 2D and 3D segmentation are Otsu's method and GMM-HMRF based algorithms respectively. GMM-HMRF achieves better dice scores in 3D than that of 2D Otsu because it makes use of the spatial information available in the 3D space. Future work could include providing more features to the TreeBagger algorithm as well as more data to observe its performance. Techniques like data augmentation could be used to extend the dataset in a supervised learning setting. Watershed, active contour and region growing algorithms are some examples of other techniques that could be used to perform segmentation and their performance could then be compared.