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Brain Nuclei Segmentation from Transverse MRI Brain Images

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Abstract

Brain nuclei segmentation is the process of stripping skull from Magnetic Resonance (MR) brain images. It is one of the important preprocessing steps in analyzing intracranial volumes. In this paper, a fully automatic method to strip the skull and extract the brain nuclei from the given T1, T2 and PD weighted MR images is proposed. In the proposed method, the brain nuclei of the middle slice is first extracted and then the brain nuclei of the remaining slices are extracted. The steps involved in the proposed methodology for skull stripping are: selection of middle slice, binarization via thresholding, morphological operations, region based binary mask extraction and brain nuclei extraction. The proposed method extracts the normal, abnormal and one full patient dataset accurately in T1, T2 and PD weighted MR images. The simulation result shows that the proposed method extracts the brain nuclei more accurately than Brain Extraction Tool (BET) and Brain Surface Extractor (BSE) methods.

Keywords: Brain nuclei, Morphological operator, MRI segmentation, Region growing, Skull stripping

1. Introduction

Brain nuclei segmentation is the first processing step in the segmentation of brain tissue. Brain nuclei segmentation is widely used in multi-modality image fusion and inter-subject image comparisons [8], examination of the progression of brain disorders such as Alzheimer's disease [9,10], multiple sclerosis [11-14] and schizophrenia [15,16]. Several skull stripping methods have been proposed by different researchers [3-7] based on anisotropic diffusion filter and morphological processing, thresholding techniques and deformable models. Most of these methods are applicable to T1-weighted MR brain images and does not extract the brain completely in all the slices. Moreover none of these existing methods give satisfactory performance when evaluated for large dataset.

Skull stripping algorithms can generally be categorized into four types: morphological based, deformable surface based, atlas based and hybrid based. However, the performance of these methods are influenced by numerous factors like MR signal heterogeneities, type of MR image data set, gradient performance, stability of system. As indicated in [1, 2] skull stripping that uses intensity thresholding followed by morphological operations to remove narrow connections is the most common. But, this method first uses operator input to determine certain threshold value, the region of interest (ROI) or a seed for a region growing phase which is a error prone as operator might not provide appropriate input and also it is time consuming.

In this paper, a fully automatic method for brain nuclei segmentation from MR brain head scans based on thresholding is proposed. In this work, the threshold value is selected automatically using otsu's algorithm [25]. Then mathematical morphology operations are applied on a binarized image to obtain the brain nuclei. The remaining part of this paper is organized as follows. Section 2 represents the proposed brain nuclei segmentation method. Performance Validation Metrics are discussed in section 3 and Simulation results are discussed in section 4. Finally the paper is concluded with the conclusion in section 5.

2. Proposed Method

In the proposed method for brain nuclei segmentation, the brain surface is seen as a smooth manifold with relatively low curvature that separates brain from non-brain regions. Also, the brain cortex can be seen as a distinct dark ring surrounding the brain tissues of MR images.

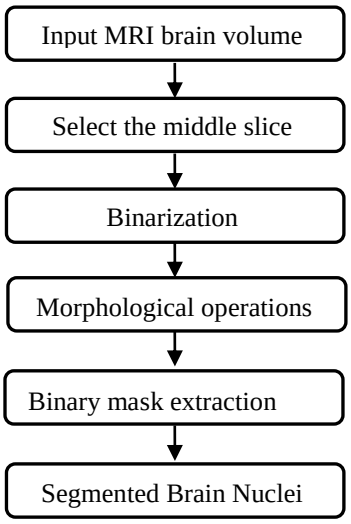


Fig. 1: Proposed brain nuclei segmentation framework

The steps involved in the proposed methodology for brain nuclei segmentation is shown in Figure 1. Initially, the middle brain slice is selected and a binary image is constructed using threshold value obtained from Otsu's threshold selection algorithm. Then, morphological operators like opening and closing are used to eliminate obstacles and noise. Next, the largest connected component from binarized image is selected by considering the brain as the largest connected structure in the input image. Finally, the brain nuclei is obtained by

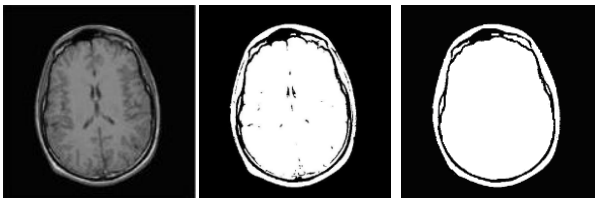
multiplying brain mask with input image. The above steps are described in detail in the following sections.

2.1 Binarization

Binarization is the process of converting a grey level image (Figure 2(a)) into a binary image I (Figure 2(b)). The binarization process involves examining the grey-level value of each pixel in the enhanced image with the global threshold 'Thres' (Equation 1),

- If the pixel value (i, j)of the original image is lower than threshold, pixel (i, j) of binary image is black (value 0);
- If the pixel value (i, j) of the original image is higher than threshold, pixel (i, j) of binary image is white (value 1).

$$I = \begin{cases} \text{imbinary } (i,\ j) = 0;\ \text{if } I(i,j) < \text{Thres} \\ \text{imbinary } (i,\ j) = 1; \text{otherwise} \end{cases} \quad (1)$$



(a) (b) (c)

Fig. 2: (a) Middle slice (b) Binarized image (c) Image after applying morphology operator

2.2 Morphological Operations

The morphological operators are then applied on the binarized image (Figure 2(b)). Elimination of any obstacles and noise from the image is the primary function of the morphological operators. The morphological operators, namely opening and closing are used in the proposed method. White pixels are considered as foreground region and black pixels are considered as background pixels (Figure 2(c)).

Closing operation**:** $I \bullet S = (I \oplus S) \Theta S$ (2)

The syntax used in MATLAB for closing operation is I' = imclose (I,S). Implementation of closing operator needs 2 processing steps: Binary erosion and dilation. It is represented as Equation (2).

Opening operation: $I \circ S = (I \Theta S) \oplus S$ (3)

The syntax used in MATLAB for opening operation is I' = imopen (I, S). Implementation of closing operator needs 2 processing steps: Binary dilation and erosion. It is represented as Equation (3).

The syntax in MATLAB for erosion operation is I' = imerode (I, S) and the syntax in MATLAB for dilation operation is I' = imdilate (I, S). Dilation and Erosion operation is given in equation (4) and (5).

$$I \Theta S = \{(i,j): S_{ij} \subseteq I\} \quad (4)$$

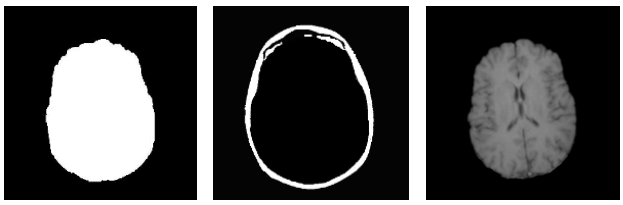
$$I \oplus S = \{j : S_{ij} \cap I \neq \phi\} \quad (5)$$

2.3 Largest Connected Component Selection

Binarization on brain MR images classifies the image into background and foreground leaving the foreground into a number of connected components. Connected component labelling is used to detect connected regions in the binary images. It scans an image pixel-by-pixel (from top to bottom and left to right) and groups its pixels into components based on pixel connectivity, that is, all pixels in a connected component share similar pixel intensity values and are in some way connected with each other. Once all groups have been determined, each pixel is labelled with a grey level or a colour (colour labelling) according to the component it was assigned to.

Connected component labeling works on binary or grey level images and different measures of connectivity are possible. However, for the proposed framework binary input images and 8-connectivity are considered. The connected components labeling operator scans the image by moving along a row until it comes to a point p (where p denotes the pixel to be labeled at any stage in the scanning process) for which value V={1}. When this is true, it examines the four neighbours of p which have already been encountered in the scan (i.e. the neighbours (i) to the left of p, (ii) above it, and (iii) the two upper diagonal terms). Based on this information, the labeling of p occurs as follows:

- If all four neighbours are 0, assign a new label to p, else
- If only one neighbour has V={1}, assign its label to p, else
- If more than one of the neighbours have V= {1}, assign one of the labels to p and make a note of the equivalences.



(a) (b) (c)

Fig. 3: (a) Brain mask and (b) Stripped skull (c) Brain nuclei

After completing the scan, the equivalent label pairs are sorted into equivalence classes and a unique label is assigned to each class. As a final step, a second scan is made through the image, during which each label is replaced by the label assigned to its equivalence classes. The brain mask and stripped skull is shown in Figure 3(a) and 3(b).

2.4 Brain Extraction

The brain is extracted by performing bitwise multiplication operation between the original head MRI scans, Fig. 2(a), with the binary mask, Fig. 3(a). This process also removes background noise and other non brain artefacts. Thus brain cortex stripped image is obtained as shown in Fig. 3(c).

3. Performance Validation Metrics

The performance of the proposed brain nuclei segmentation method is validated using the most commonly used validation metrics in the literature [17 – 20] which includes: Jaccard Similarity Index (JSI) [21], Dice Similarity Score (DSS) [22],

specificity and sensitivity [23, 24]. Validation is performed by comparing the proposed method's output with that obtained from manually segmented image. Let O_{S1} be the output obtained from manually segmented image and O_{S2} be the output result of the proposed method. For brain nuclei extraction technique O_{S1} and O_{S2} are compared based on pixels labeled as brain.

JSI for the two sets is defined as the size of intersection of the two sets divided by the size of their union as given in Equation (6). A JSI value of 1 indicates a perfect agreement between the two sets.

$$JSI = \frac{|O_{S1} \cap O_{S2}|}{|O_{S1} \cup O_{S2}|} \quad (6)$$

DSS is defined as the size of intersection of the two sets divided by their average size as shown in Equation (7).

$$DSS = \frac{|O_{S1} \cap O_{S2}|}{\frac{1}{2}(|O_{S1} + O_{S2}|)} \quad (7)$$

The evaluation of brain abnormality detection in different images is carried out using the following metrics namely Sensitivity (SE), Specificity (SP), as given in Equations (8) and (9). In order to find these metrics, some of the terms like True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP) are calculated based on the definitions given in Table 1.

$$SE = \frac{TP}{TP + FN} \quad (8)$$

$$SP = \frac{TN}{TN + FP} \quad (9)$$

SE is the proportion of TPs that are correctly identified by a diagnostic test. It shows how good the test is at detecting a disease. SP is the proportion of the TNs correctly identified by a diagnostic test. It suggests how good the test is at identifying normal (negative) condition. Accuracy is the proportion of true results, either TP or TN, in a population. PPV and NPV describe the performance of a diagnostic test.

Table 1: Table Defining the Terms TP, FP, FN, TN

Experimental Outcome	Condition as determined by the Standard of Truth		Row Total
	Positive	Negative	
Positive	TP	FP	TP+FP
Negative	FN	TN	FN + TN
Column Total	TP+FN	FP+TN	TP+TN+FP+FN

4. Simulation Results

In this section, the simulation results are presented. A sample normal and abnormal brain MR images (Figures 4(a), 5(a) and 6(a)). The skull stripped images are given in Figures 4(c), 5(c) and 6(c). After obtaining input MR brain images, the first step is to select the middle slice and segment the brain nuclei from it. The procedure is repeated for all the slices above and below the middle slices.

The efficiency and precision of skull stripping stage is highly important since subsequent stages in the pipeline of the tumour segmentation, use the output of this stage. The skull stripping method is tested on IBSR and diagnostic centre datasets. Fig. 4(c) and Fig. 5(c) show the skull stripped images of different patients with and without tumour.

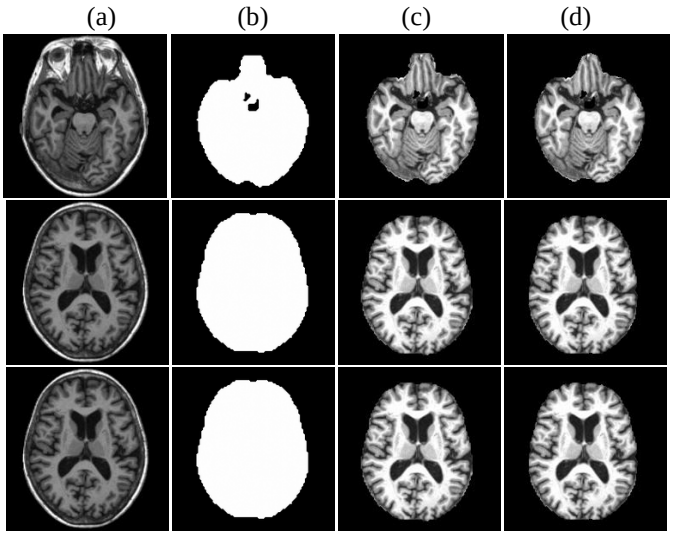


Fig. 4: Skull stripped normal brain MR images: a) Input brain MRI, b) Brain mask, c) Skull stripped MR image by proposed method and d) Skull stripped by BET

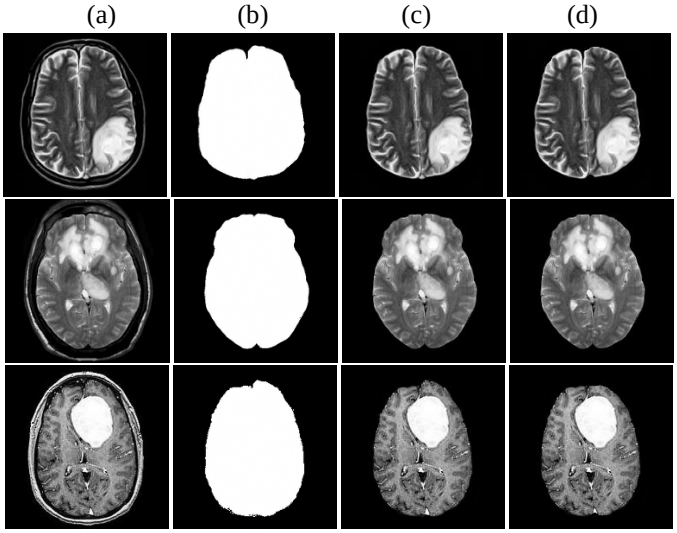


Fig. 5: Skull stripped abnormal brain MR images: a) Input brain MRI, b) Brain mask, c) Skull stripped MR image by proposed method and d) Skull stripped by BSE

JSI and DSS are used to measure the matching percentage of the proposed skull stripping method with manual segmentation by overlapping these two methods. If both the methods are perfectly overlapping then the score will be '1'

and the score will be '0' if there is no overlap between these two methods.

Sensitivity measures how well the performance of skull stripping method is in avoiding removal of brain tissues together with non-brain tissues. On the other hand, specificity measures how well the performance of the method on not wrongly classifying non-brain tissues as brain tissues.

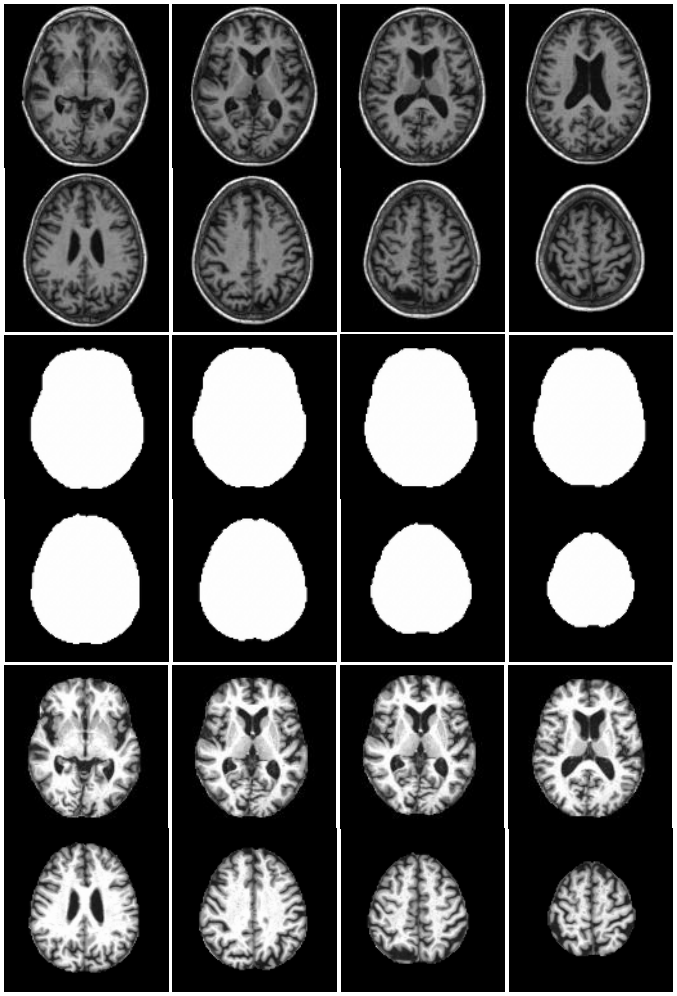


Fig. 6: Skull stripped brain MR images of a patient for one full data sequence in transverse plane

Table 2: Brain extraction algorithm performance

Performance Measure/ BSA		JSI	DSS	SE	SP	Time (sec)
BET	Dataset 1	0.84	0.89	0.90	0.94	22
	Dataset 2	0.87	0.92	0.93	0.88	34
BSE	Dataset 1	0.92	0.94	0.97	0.97	112
	Dataset 2	0.96	0.92	0.99	0.97	143
PROPOSED	Dataset 1	0.977	0.979	0.978	0.978	164
	Dataset 2	0.966	0.959	0.980	0.979	151

Table 3: Mean and SD value of JSI, DSS, SE and SP of proposed method

Image		JSI	DSS	SE	SP
Mean	Dataset 1	0.977	0.979	0.978	0.978
	Dataset 2	0.966	0.959	0.980	0.979
	Dataset 3	0.978	0.956	0.966	0.968
SD	Dataset 1	0.022	0.027	0.019	0.027
	Dataset 2	0.037	0.035	0.031	0.043
	Dataset 3	0.022	0.025	0.02	0.028

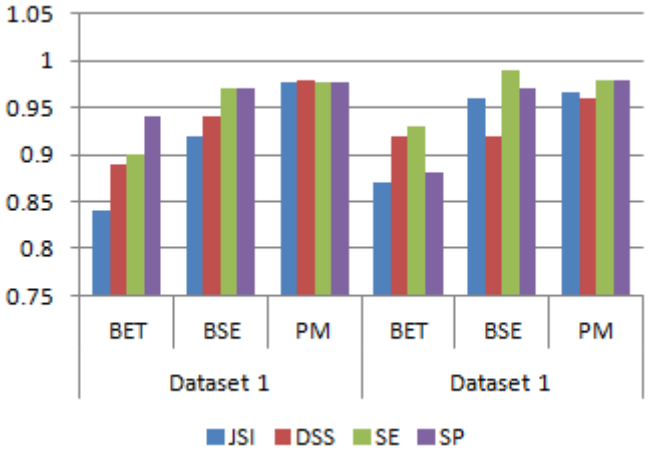


Fig. 7**:** Brain extraction algorithm performance

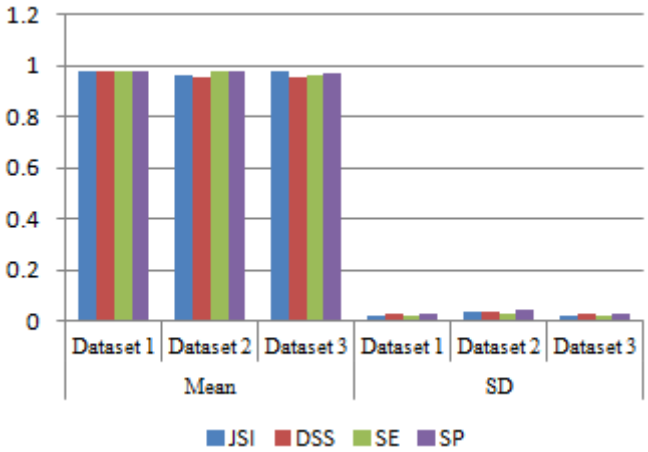


Fig. 8**:** Mean and SD value of JSI, DSS, SE and SP of proposed method

5. Conclusion

In this paper, a full automatic method for brain nuclei segmentation has been proposed and it is validated with two standard methods. From Tables 2 and 3, it can be observed that the obtained results are at an acceptable level, even to datasets where there is weak connection between brain tissues and darker intensities at the brain boundary. It can also be observed that the SE of the proposed method is on average,

well above 98%. Having higher SE is more important to avoid removal of brain tissues, which is critical for accuracy of subsequent stages.

Qualitatively Figures 4 to 6 show the result of skull stripping by the proposed method on IBSR and diagnostic centre datasets (patient1 and patient2) respectively. Mean and SD value of JSI, DSS, SE and SP of proposed method is shown in Fig. 8 and the comparison of JSI, DSS, SE and SP value of BET, BSE and proposed method is shown in Fig. 7. In this paper, skull stripping results obtained by implementing the proposed technique are at an acceptable level.

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