# A simple method for automatic brain extraction from T1-W Magnetic Resonance Images (MRI) of human head scans

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*Abstract*— A simple method to extract brain portion from T1-Weighted Magnetic Resonance Image (MRI) of human head scans is proposed in this article. The proposed method employs mean filter and morphological operations. This method is experimented on five volumes of normal T1-W MRI of human head scans taken from the Internet Brain Segmentation Repository (IBSR). The chosen method gives comparable results with the existing popular methods such as Brain Extraction Tool (BET) and Brain Surface Extractor (BSE). The performance of the proposed method is evaluated using Jaccard (J) similarity index and Dice coefficient (D) and a corresponding mean value of 0.936 and 0.965 is obtained.

Keywords— Magnetic Resonance Image (MRI), Brain Extraction, Mean filter, Morphological Operations and Connected Component analysis.

# I. INTRODUCTION

Magnetic Resonance Imaging (MRI) technique is a nonionizing, non-destructive and non-invasive method. It is one of the efficient techniques to diagnose abnormalities in the human brain. The structure of soft tissues can be effectively identified using this technique. Molecules that constitute the soft tissues decide the characteristics of MRI scan. MRI can be taken in the following three different orientations: axial, coronal and sagittal. Variable image contrast of MRI scans can be achieved for different relaxation times such as longitudinal relaxation time (T1), transverse relaxation time (T2) and Proton Density (PD) [1]. MRI of head scan is usually subjected to several pre-processing operations. Some of them are image registration [2], brain tissue classification [3], intensity inhomogeneity correction [4], identifying brain parts [5] etc. Brain extraction is one of the primary stages of these pre-processing operations. Brain extraction can also be performed by a human but it is a time-consuming process. Hence, automated methods for brain extraction are needed.

In this article, we propose a brain extraction algorithm with mean filter and morphological operations. Here, we use mean filter and morphological erosion to extract brain from the coronal image. Remaining part of the article is organized as follows: In section II, related works are given. Methods and materials are given in section III. In section IV, results and discussion are presented. Finally, conclusions are given in section V.

# **II. RELATED WORK**

Plenty of brain extraction algorithms were reported in the literature. Few methods are semi-automatic and the Further, they are also remaining are fully automatic. classified based on the techniques used, into region based method, edge based method or hybrid method [6], intensity based, morphological operations based and deformable methods [7]. Intensity based methods are more sensitive to intensity bias while morphological operation based methods require more parameters to execute. Deformable model needs brain template to execute. However, intensity and morphological operation based methods have less time complexity than the deformable model. Atkins and Mackiewich [8] proposed an efficient brain extraction method. Smith [9] reported a brain extraction algorithm named as Brain extraction tool (BET). BET is a parameterized method that needs two parameters, one to start the process and the other to extract exact brain portion. BET creates a center of gravity (COG) and the sphere is expanded to generate the rough brain mask. Shattuck et al [10] reported a brain extraction method named as Brain surface extractor (BSE). BSE needs three parameters, diffusion constant, diffusion iteration and edge constant. BSE employs anisotropic diffusion process, Marr- Hildreth [11] edge detector and a series of morphological operations. BET and BSE are widely quoted methods. Hybrid Watershed Algorithm (HWA) [12] is a combination of two concepts: watershed and deformable surface models, to extract the brain portion. 3d-Intracranial [13] method makes use of

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histogram, probability density function and threshold value to classify the input image into brain and non-brain voxels. A comparative study of BET, BSE, HWA and 3d-Intracranial is reported in [14] and it was found that all the methods failed to extract the brain portion from abnormal MRI of human head scans. Their performance is also affected due to the presence of noise in the images and HWA is more sensitive than others. A deformable model is proposed for brain extraction named as Model-based Level Sets (MLS) [15]. Mikheev et al [16] proposed a method based on Bridge Burner algorithm to extract brain from T1-W images. This method uses thresholding, connectivity, surface detection and operator constrained growth to reach brain boundary. Simplex Mesh and Histogram Analysis based Skull Stripping (SMHASS) method can be found in [17]. Somasundaram et al proposed two brain extraction algorithms named as Brain Extraction Method (BEM-T1W)[18] for T1-W images and Brain Extraction Method (BEM-T2W)[19] for T2-W images. Recently few brain extraction algorithms such as Multispectral Adaptive Region Growing Algorithm (MARGA) [20], Multi-Atlas skull stripping (MASS) method [21] and a simple skull stripping algorithm [22] are reported. Different types of MRI head scans, different orientations and different scanners are the major factors that keep brain extraction from MRI head scans as a challenging task [23].

## III. METHOD AND MATERIALS

#### Materials

We used 5 normal volumes of MRI of head scans acquired from Internet Brain Segmentation Repository [24]. The details of dataset are given in Table 1.

Table 1. Details of the 5 Normal Volumes of T1 weighted Coronal MRI of head scans

Volume Index	Volume Label	Gender	Age at the time of the scan		
1.	100_23	М	23		
2.	111_2	М	27		
3.	191_3	М	32		
4.	202_3	F	28		
5.	205_3	F	24		

Methods

The flowchart of the proposed method is given in Figure 1.



Figure 1. Flowchart of Proposed Method

#### A. Background Removal

Normally in MRI, the number of background (non-object) pixels is quite prominent. The processing time of brain extraction can be much reduced by distinguishing object pixels from the non-object pixels (background pixels). Since the intensity values of non-object pixels are low, background pixels are separated using a threshold value T. For computing optimal threshold value, Ridler- Calvard [25] method is used. The resultant image  $I_{BR}$  after removing background pixels from the input image I(x,y), is obtained using T as:

$$I_{BR} = \begin{cases} I(x,y) & \text{if}(I(x,y) \succ T) \\ 0 & \text{otherwise} \end{cases}$$
(1)

# B. Mean Filter

 $I_{BR}$  consists of scalp, neck, few skull regions, CSF, brain and other non-brain tissues. Few skull regions and CSF are connected through scalp and brain tissues. In some images, the brain tissues of lower intensity might be removed during brain extraction. These two problems can be eliminated by smoothing. Mean filter is employed for smoothing. In the mean filter, a sliding window is moved from left top of the image to right bottom. The size of the window is chosen to

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be odd numbers. The mean filter is applied only for object pixels. The mean filtered image  $I_M$  obtained as:

$$I_{M}(x, y) = \begin{cases} x+m & y+m \\ \sum & \sum I(r,c) \\ \frac{r=x-mc=y-m}{n^{2}} & \text{if}(I(x,y)\neq 0) \\ 0 & \text{otherwise} \end{cases}$$
(2)

where, n is the size of the window(3,5,7,9,11...),  $m = \left\lfloor \frac{n}{2} \right\rfloor$ 

x=m to h-m, y=m to w-m, h and w height and width of the image respectively.

We found that window size of 7x7 pixels is optimal after testing various sizes from 3x3 to 13x13. When the size of the window is small, weekly connected regions are diluted. Larger window size reduces lower intensity problem

#### C. Image Binarization

Binarization of the filtered image can be done using the threshold value T. The binary image  $I_B$  is obtained as:

$$I_{\rm B} = \begin{cases} 1 & \text{if}(I_{\rm M}(x,y) > T) \\ 0 & \text{otherwise} \end{cases}$$
(3)

#### D. Erosion

In image  $I_B$ , the brain region and non-brain regions are weakly connected. Isolating the brain region make brain segmentation task easier. For that, erosion operation has been performed. Various sizes of structuring elements E such as 3x3, 5x5, 7x7, 9x9 and 11x11 has been tested. After several trials, it was found that the size of structuring element  $E_9$ (9x9) gives a better result.

$$I_{E} = I_{B} \Theta E_{9}$$
 (4)

The image  $I_E$ , has several isolated regions. Connected component analysis is then performed on  $I_E$ .

## E. Connected Component Analysis

It is well known that brain is the largest connected component in the middle slice of MRI head scans. Based on this knowledge, connected component analysis [26] has been carried out on image  $I_E$ . Run length method [26] and region colouring technique have been employed to find the connected component. The image  $I_E$  consist of N number of isolated regions R(i), with the number of pixels  $R_{np}(i)$  where i=1,2,... N. From  $R_{np}(i)$ , the largest connected component L has selected as:

$$L = R(\arg\max(R_{nn}(i)))$$
(5)

The brain region is obtained from L as:

$$I_{L}(x, y) = \begin{cases} l & \text{if } I_{E}(x, y) \in L \\ 0 & \text{otherwise} \end{cases}$$
(6)

The binary image  $I_L$  contains only one largest object, the brain portion.

#### F. Dilation

The boundary of brain portion is shrunk due to image binarization and erosion operations. The shrunken brain portions can be recovered by dilation operation. For that, structuring element D of sizes 3x3, 5x5, 7x7, 9x9, 11x11 and 13x13 were tested. After several trials, it was found that structuring element D<sub>11</sub> (11x11) gives good results. Dilation operation on largest connected component I<sub>L</sub> is performed to obtain brain mask I<sub>BM</sub> as:

$$\mathbf{I}_{\rm BM} = \mathbf{I}_{\rm L} \oplus \mathbf{D}_{11} \tag{7}$$

Brain portion is extracted using brain mask  $I_{BM}$  from input image I to get  $I_{BP}$  as:

$$I_{BP}(x, y) = \begin{cases} I(x, y) & \text{if } I_{BM}(x, y) \in I \\ 0 & \text{otherwise} \end{cases}$$
(8)

#### IV. RESULTS AND DISCUSSION

Experiments were carried out by applying proposed scheme on five volumes of MRI of human head scans taken from IBSR. For illustration, input images of volume index 4 is shown in Figure (2) and Gold standard hand segmented image of Figure 2 are given in Figure 3. The results of the proposed method are shown in Figure 4.



Figure 2. Input images from volume index 4

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Figure 3. Hand segmented brain regions of Figure 2.



Figure 4. Brain extracted from Figure 2 using the proposed method

Quantitative performance analysis was done for the proposed method by computing the similarity measures, Jaccard index (J) [27] and Dice (D) [28] coefficient. IBSR provides hand segmented "gold standard" images and they are used for computing J and D.

The Jaccard index is given by:

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$$\mathbf{J} = \frac{|\mathbf{P} \cap \mathbf{Q}|}{|\mathbf{P} \cup \mathbf{Q}|} \tag{9}$$

The Dice D is given by

$$\mathbf{D} = \frac{2|\mathbf{P} \cap \mathbf{Q}|}{|\mathbf{P}| + |\mathbf{Q}|} \tag{10}$$

where P is set of pixels in standard image and Q is set of pixels in the segmented image. J and D are related [10] by:

$$\mathbf{D} = \frac{2\mathbf{J}}{\mathbf{J} + 1} \tag{11}$$

False Positive Rates (FPR) and False Negative Rates (FNP) [29] are estimated by using:

$$FPR = \frac{FP}{TP + FN}$$
(12)

$$FNR = \frac{FN}{TP + FN}$$
(13)

where FP is False Positive, TP is True Positive and FN is False Negative.

The computed values of J, D, FPR and FNR are given in Table 2.

 

 Table 2. Computed values of J, D, FPR and FNR using our method on 5 data sets

. No	1	2	3	4	5	Avg.	Stdev.
J	0.916	0.938	0.985	0.911	0.929	0.936	0.029
D	0.962	0.958	0.992	0.949	0.962	0.965	0.016
FPR	0.044	0.251	0.122	0.042	0.057	0.103	0.088
FNR	0.052	0.03	0.007	0.044	0.035	0.033	0.017
J	0.918	0.915	0.927	0.919	0.926	0.921	0.005
D	0.957	0.956	0.962	0.958	0.961	0.958	0.002
FPR	0.066	0.071	0.055	0.071	0.062	0.065	0.006
FNR	0.017	0.014	0.017	0.01	0.012	0.014	0.003
J	0.827	0.855	0.846	0.858	0.711	0.819	0.061
D	0.905	0.922	0.916	0.924	0.831	0.899	0.039
FPR	0.167	0.143	0.154	0.14	0.089	0.138	0.029
FNR	0.006	0.002	0.0003	0.001	0.2	0.041	0.088
	No J D FPR J D FPR FNR J FNR J D FPR FPR FPR	No         1           J         0.916           D         0.962           FPR         0.044           FNR         0.052           J         0.918           D         0.957           FPR         0.066           FNR         0.017           J         0.827           D         0.905           FPR         0.167           FPR         0.107	No         1         2           J         0.916         0.938           D         0.962         0.958           FPR         0.044         0.251           FNR         0.052         0.03           J         0.918         0.915           D         0.957         0.956           FPR         0.066         0.071           FNR         0.017         0.014           J         0.827         0.855           D         0.905         0.922           FPR         0.167         0.143           FNR         0.167         0.143	No         1         2         3           J         0.916         0.938         0.985           D         0.962         0.958         0.992           FPR         0.044         0.251         0.122           FNR         0.052         0.03         0.007           J         0.918         0.915         0.927           D         0.957         0.956         0.962           FPR         0.066         0.071         0.055           FNR         0.017         0.014         0.017           J         0.827         0.855         0.846           D         0.905         0.922         0.916           FPR         0.167         0.143         0.154           FPR         0.167         0.143         0.154           FPR         0.167         0.143         0.154	No         1         2         3         4           J         0.916         0.938         0.985         0.911           D         0.962         0.958         0.992         0.949           FPR         0.044         0.251         0.122         0.042           FNR         0.052         0.03         0.007         0.044           J         0.918         0.915         0.927         0.919           D         0.957         0.956         0.962         0.958           FPR         0.066         0.071         0.055         0.071           D         0.957         0.956         0.962         0.958           FPR         0.066         0.071         0.055         0.071           J         0.827         0.855         0.846         0.858           D         0.905         0.922         0.916         0.924           FPR         0.167         0.143         0.154         0.14           FNR         0.167         0.143         0.154         0.14	No         1         2         3         4         5           J         0.916         0.938         0.985         0.911         0.929           D         0.962         0.958         0.992         0.949         0.962           FPR         0.044         0.251         0.122         0.042         0.057           FNR         0.052         0.03         0.007         0.044         0.035           J         0.918         0.915         0.927         0.919         0.926           D         0.957         0.956         0.962         0.958         0.961           FPR         0.066         0.071         0.055         0.071         0.062           FNR         0.017         0.014         0.017         0.01         0.012           J         0.827         0.855         0.846         0.858         0.711           D         0.905         0.922         0.916         0.924         0.831           FPR         0.167         0.143         0.154         0.14         0.089           FPR         0.167         0.143         0.154         0.14         0.089	No         1         2         3         4         5         Avg.           J         0.916         0.938         0.985         0.911         0.929         0.936           D         0.962         0.958         0.992         0.949         0.962         0.965           FPR         0.044         0.251         0.122         0.042         0.057         0.103           FNR         0.052         0.03         0.007         0.044         0.035         0.033           J         0.918         0.915         0.927         0.919         0.926         0.921           D         0.957         0.956         0.927         0.919         0.926         0.921           D         0.957         0.956         0.922         0.958         0.961         0.958           FPR         0.066         0.071         0.055         0.071         0.062         0.065           FNR         0.017         0.014         0.017         0.01         0.012         0.014           J         0.827         0.855         0.846         0.858         0.711         0.819           D         0.905         0.922         0.916         0.924

\*PM- Proposed Method; Avg-Average; Stdev-Standard deviation.

From Table 2, it is inferred that the proposed method gives an average value of 0.936 for Jaccard similarity indices and 0.965 for Dice coefficients and the results are better when compared to BSE and BET. No major difference is found in the result of proposed method experimented with and without the mean filter.

The proposed method was implemented in 32bit Windows 7 ultimate operating system, Pentium R Dual-core 3.00 GHz

processor, 2GB Ram in Java-JDK1.8. The computation of proposed method took an average execution time between 190 to 210 milliseconds/ slice with mean filters and it took 145 to 171 milliseconds/slice without the mean filter. But BET took time between 0.6 sec to 0.8 sec/slice and BSE took time between 0.5 sec. to 0.7 sec/slice. This exhibits that the proposed method produced better results with minimum time complexity.

# V. CONCLUSION

In this article, a simple method for brain extraction has been proposed. The proposed method employed mean filter and morphological operations. The method was experimented with and without the mean filter on five volumes of MRI of human head scans which were obtained from public repository IBSR. The results of both the cases are similar and no significant difference is found. Therefore, it is inferred that the mean filter does not have major impact on the segmentation of T1-W MRI images. The values of J and D are 0.936 and 0.965 respectively which is comparable with the existing popular methods BET and BSE.

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