Brain Extraction Algorithm for T1-W and T2-W MRI of Human Head Scans

K Somasundaram
Department of Computer Science and applications, Gandhigram Rural Institute-Deemed University, Gandhigram-624302, Tamilnadu ,India.
ka.somasundaram@gmail.com

P A Kalaividya
Department of Computer Science and applications, Gandhigram Rural Institute-Deemed University, Gandhigram-624302, Tamilnadu, India.
vidya.kalai08@gmail.com

T Kalaiselvi
Department of Computer Science and applications, Gandhigram Rural Institute-Deemed University, Gandhigram-624302 ,Tamilnadu ,India.
kalaivpd@gmail.com

***Abstract*- In this paper, we extend a brain segmentation algorithm developed for T1-W and T2-W Magnetic Resonance Images (MRI). The proposed scheme consists of image denoising, intensity thresholding and largest connected component analysis. Usually an image diffusion is done to blur the image without losing edge properties and an intensity threshold is found for the diffused image. Using the diffused image and threshold T, a binary image is obtained for extraction of brain. In the proposed method, after computing the threshold T using diffused image, we use the undiffused image. We used T1-W and T2-W images collected from Internet Brain Service Repository (IBSR) and The whole Brain Atlas (WBA). Experimental results show that the proposed scheme works well on T2-W images and gave satisfactory results on T1-W images. The performance of the method is evaluated using the Jaccard and Dice similarity coefficients.**

Keywords- T1-W MRI, T2-W MRI, diffusion process, thresholding, largest connected component, morphological operations, Otsu method

I. INTRODUCTION

Medical imaging is used to study the structure and pathological condition of human organ. Such studies are required to diagnose diseases/ deformities in the human organs. Few of the medical imaging modalities are X-ray, Computed Tomography(CT) and Positron Emission Tomography(PET) to quote. Magnetic Resonance Imaging (MRI) technique is employed to visualize detailed internal structure of soft tissues in our body. There are three different types of images T1-weighted (T1-W), T2-weighted (T2-W) and Proton Density (PD). MRI is taken in three different orientations, axial (bottom to top), coronal (back to front) and sagittal (side to side). This method is non-ionizing and produces no side effects. MRI technique is widely used to study the brain structure and the brain related diseases.

Segmentation of brain MRI is an important process in brain related study. Segmentation is necessary for image registration, image compression for transmission and storage, image fusion etc. In certain cases a neurologist also require the volume of brain to identify brain related diseases like Alzheimer Diseases[1],dementia[2] etc. Brain portion can be segmented manually by an expert. But segmenting brain portion form MRI slices manually take more time. Further, segmentation results may differ from one expert to another. Hence semi-automatic brain segmentation methods, were developed. To avoid human intervention fully automatic methods were developed. Few such methods to quote are the work by statistical parameter mapping (SPM) [3], brain extraction tool (BET) [4],brain surface extractor (BSE) [5], 3D Intracranial [6].

Fully automatic Segmentation methods are based on intensity [8], level set[7], graph cut[9], watershed[9], morphology based[8] , region growing[10] etc. In a recent work by Somasundaram and Kalaiselvi [11] a method has been proposed for extracting brain from T2-W MRI scans using region labeling and morphological operations. In this paper we propose a new scheme to extract brain portion by modifying the method in [11]. Experiments were conducted on T1-W and T2-W images collected from Internet Brain Service Repository (IBSR) and The whole Brain Atlas (WBA).

The remaining part of the paper is organized as follows. In section II we explain the proposed scheme, in section III the results and discussion are given and in section IV the conclusion is given.

II. PROPOSED METHOD

The goal of a segmentation method is to identify the boundary separating the brain and non-brain tissues in the MRI slices. In this scheme, we make use of intensity threshold value to identify the boundary. Noises present in the MRI scans will affect the boundary detection. We therefore, apply a low pass filter in the frequency domain. The filtered image is then subjected to diffusion. The diffusion process blurs the image, while keeping the major boundaries highlighted. We make use of the diffused image to find a threshold value, T. Using this threshold value, the filtered image is binarized, from which the brain is segmented. The flowchart of the proposed method is shown in Figure1.

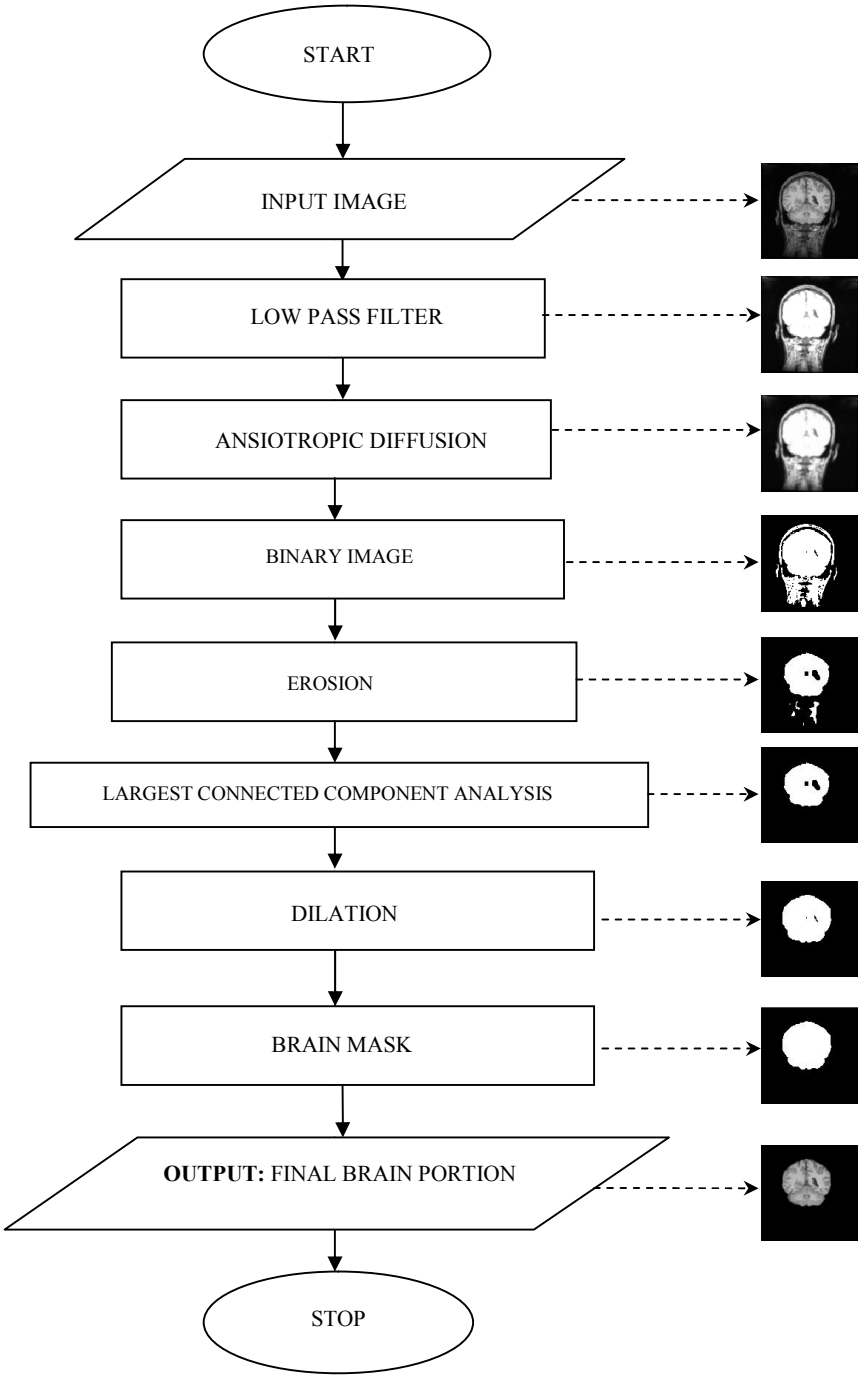

Figure 1. Flowchart of the proposed method

A. Low Pass Filtering (LPF)

The input image I is filtered using a low pass filter in the frequency domain. The input image I(x,y) is transformed to frequency domain by applying Fourier Transform (FT) to get the frequency domain image F(u,v) as:

$$F(u,v) = FT(I(x,y)) \quad (1)$$

F(u, v) is the Fourier Transform of input image I, u and v are frequency variables. We construct a low pass filter H(u,v) and make the convolution to get the Fourier Transform of output image $G(u,v)$, as :

$$G(u,v) = F(u,v) \cdot \big(H(u,v)\big) \quad (2)$$

LPF produces a blurred or smoothed image. As the size of LPF increases it will smooth out the entire image including the sharp edges. Hence we consider a small filter of size 3×3 pixel (Figure2) that is used to remove the noise in the MR image.

$$¼ \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}$$

Figure 2. 3×3 Kernel used for LPF

The filtered image (I_L) in the spatial domain is obtained by applying Inverse Fourier Transform (IFT) as:

$$I_L(x,y) = IFT(G(u,v)) \quad (3)$$

B. Anisotropic Diffusion

We then apply a diffusion process on the filtered image I_L. For diffusion we use the anisotropic diffusion equation given by Perona and Malik [12].

$$\frac{\partial I}{\partial T} = div(C(\nabla I)\nabla I) \quad (4)$$

where (∇I) is a local image gradient and $C(\nabla I)$ is the diffusion function, which is a monotonically decreasing function of the image gradient magnitude. We have chosen the diffusion function as given by Perona and Malik [12] as

$$C(\nabla I) = exp(-(|\nabla I|/k)2) \quad (5)$$

where k is a diffusion constant. Eq.(3) can be discretized using the four nearest neighbors as

$$I_{i,J}^{n+1} = I_{i,J}^{n} + \Delta t(C_N \nabla_N I + C_S \nabla_S I + C_E \nabla_E I + C_w \nabla_w I)_{i,j}^{n} \quad (6)$$

where , N, S, E and W represent north, south, east and west direction, respectively. ∇I is the local gradient and ∇t is an iteration constant. The local gradient ∇I is calculated using nearest neighbor differences. The 2-D anisotropic diffusion process is controlled by the number of iterations (n) and diffusion constant (k). The diffusion constant k controls the relation between the diffusion strength and the local edge strength and is to be tuned for a particular application. In our method, we have set k to 60 to produce a diffused image $I_d(x,y)$. Small number of iterations (n=2) is considered. The main goal of diffusion in this work is to obtain a threshold T value, to binarize the undiffused image I_L ,unlike the earlier work[11], where diffused image $I_d(x,y)$ is used for binarization.

C. Thresholding

The Diffused image $I_d(x,y)$ is further processed to generate a threshold value (T_{opt}) using Otsu's method given by [13]. T_{opt} is used to separate objects from the surrounding uniform background. Using the filtered image $I_L(x, y)$ and the threshold value T_{opt} a binary image $I_B(x, y)$ is obtained as:

$$I_B(x,y) = \begin{cases} 1 & if\ I_L(x,y) \geq T_{opt} \\ 0 & otherwise \end{cases} \quad (7)$$

D. Erosion

Erosion helps to disconnect weakly disconnected object in a cluster of objects. The boundary of the brain is a curved one and therefore we use a disk shaped structuring element S of radius 3 as shown in the Figure.3.

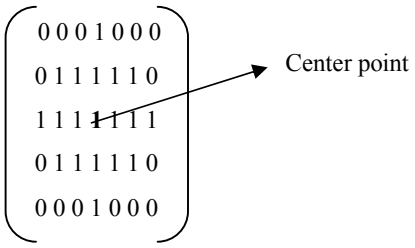

Figure 3. Structuring Element Used For Morphological Operations

The eroded image I_E is obtained as:

$$I_E = I_B \ominus S \quad (8)$$

where, $\ominus$ represents erosion operation. Erosion detaches the weakly connected regions from the brain portion.

E. Largest Connected Component Analysis

The eroded image has n number of isolated connected regions. It is known that the brain portion is the largest connected component (LCC) among the substructures in the MRI. Therefore, we perform LCC analysis on the eroded image I_E.If $R_A(i)$ is the area of the i^{th} region in I_E, where, i=1,2,….n, then,

$$LCC = R(\arg\max(R_A(i))) \quad 1 \leq i \leq n \quad (9)$$

Using LCC, we obtain the rough brain mask using the filtered image I_L as:

$$I_{RB} = \begin{cases} 1 & \text{if } I_L(x,y)\ \varepsilon\ LCC \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

F. Dilation

During the binarization and erosion, few brain pixels are lost. We recover the lost tissues by morphological dilation by using same structuring element S.

The dilated image is obtained as:

$$I_D = I_{RB} \oplus S \quad (11)$$

The I_D is the mask for the brain. I_D contains several holes inside it. The holes are filled using hole filling algorithm and we get the final brain mask as M. Using the mask M, the brain is extracted from original MRI scan I(x,y) as:

$$I_{brain\,(x,y)} = \begin{cases} \mathrm{I(x,y)} & \text{if } \mathrm{M(x,y)} = 1 \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

III. RESULTS AND DISCUSSIONS

We carried out experiments by using the proposed method on one volume of T1-W and one volume of T2-W MRI collected from IBSR and WBA. We used MATLAB 7.1 for implementing the method. For qualitative analysis, the original T1-W images collected are shown in Figure 4 and the brain portion extracted is shown in Figure 5. The original T2-W images are shown in Figure 6 and the brain portion extracted are shown in Figure 7. From Figure 5 and Figure 7, we observe that the proposed method gives satisfactory results. However in T1-W images, brain portion in the upper slices and bottom slices are not properly extracted. The same problem has been reported in BET [4] and BSE [5] also. For Quantitative evaluation of the performance of the proposed method, we also computed the similarity indices Jaccard [14] given by

$$J(A,B) = \frac{A \cap B}{A \cup B} \quad (13)$$

and the Dice coefficient(D)[15] given by

$$\mathrm{D}(A,B) = \frac{2|A \cap B|}{|A| + |B|} \quad (14)$$

where, A is the result obtained by the proposed method and B is the gold standard hand segmented result. The value D varies from 0 for complete disagreement to 1 for complete agreement, between A and B. The IBSR contains hand segmented gold standard only for T1-W image. Hence we computed J and D for T1-W images and are given in Table1. For comparison, the value obtained by BET and BSE is also given.

TABLE 1 : COMPARATIVE VALUES FOR T1-W MRI

Method	**Similarity Measures**		
	Data Set	***Jaccard***	***Dice***
BET	205_3	0.7107	0.8309
BSE	205_3	0.9256	0.9613
Proposed	205_3	0.9200	0.9528

Further, we also carried out experiments by varying the iteration value from 2 to15 to diffuse the image. The degree of diffusion changes the threshold value T_{opt} .Therefore, to get the best segmentation, we found that n=2 is enough. We also found by experiment that one can avoid filtering and diffusion process and still get 70-80% result for T1-W and T2-W images.

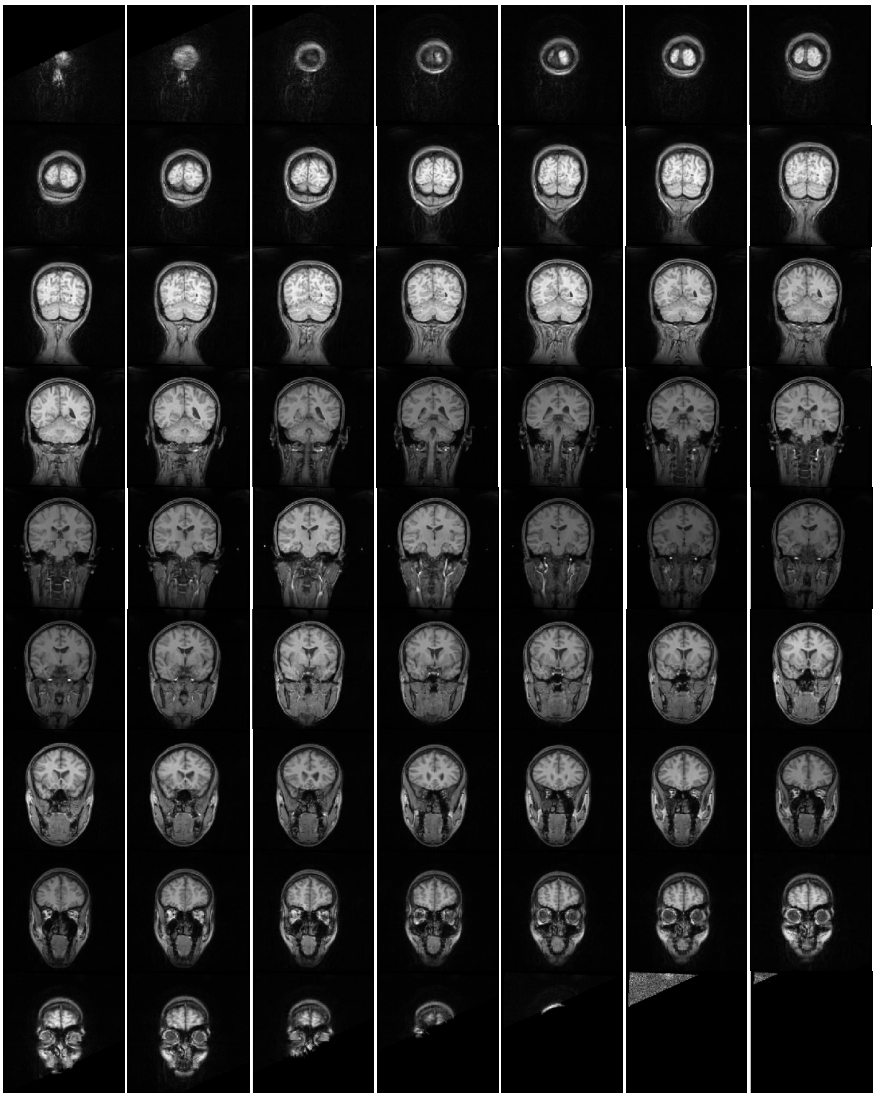

Figure 4 . T1-W Coronal brain volume (205_3)

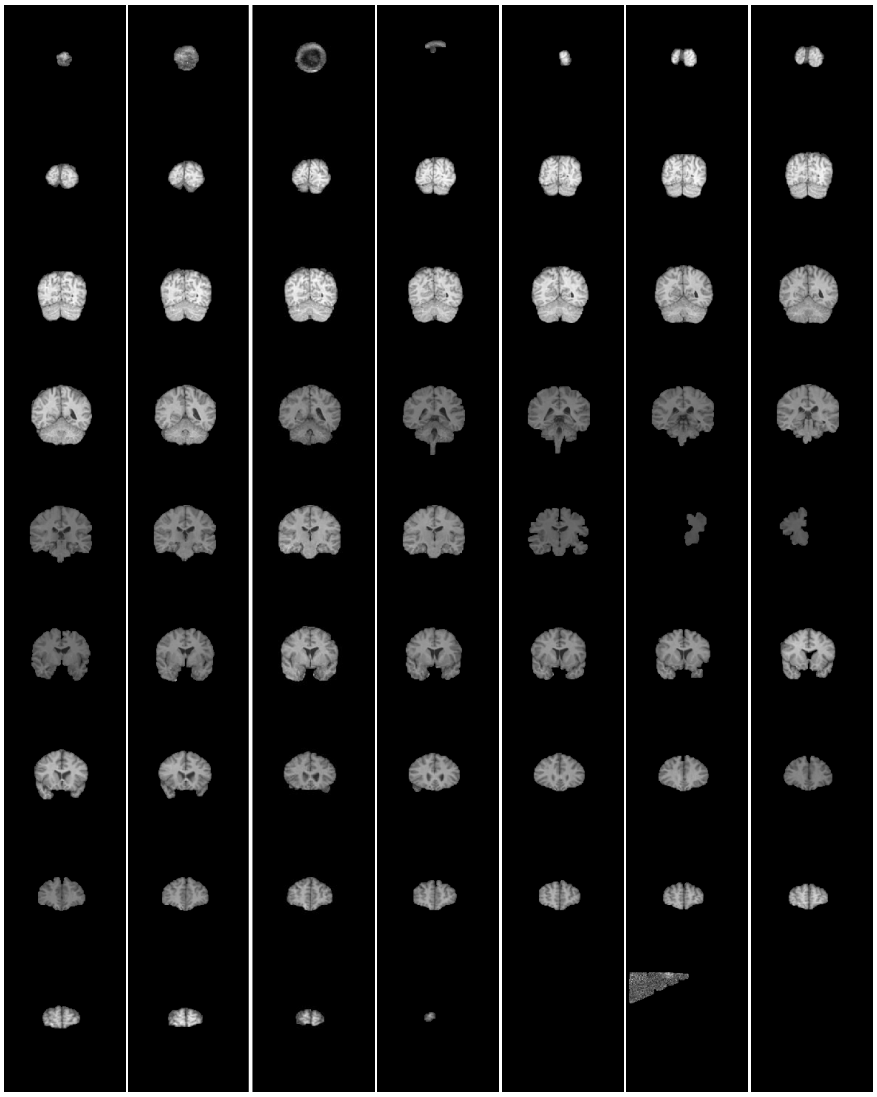

Figure 5. Brain Portion Extracted from T1-W Coronal images shown in Figure.4.

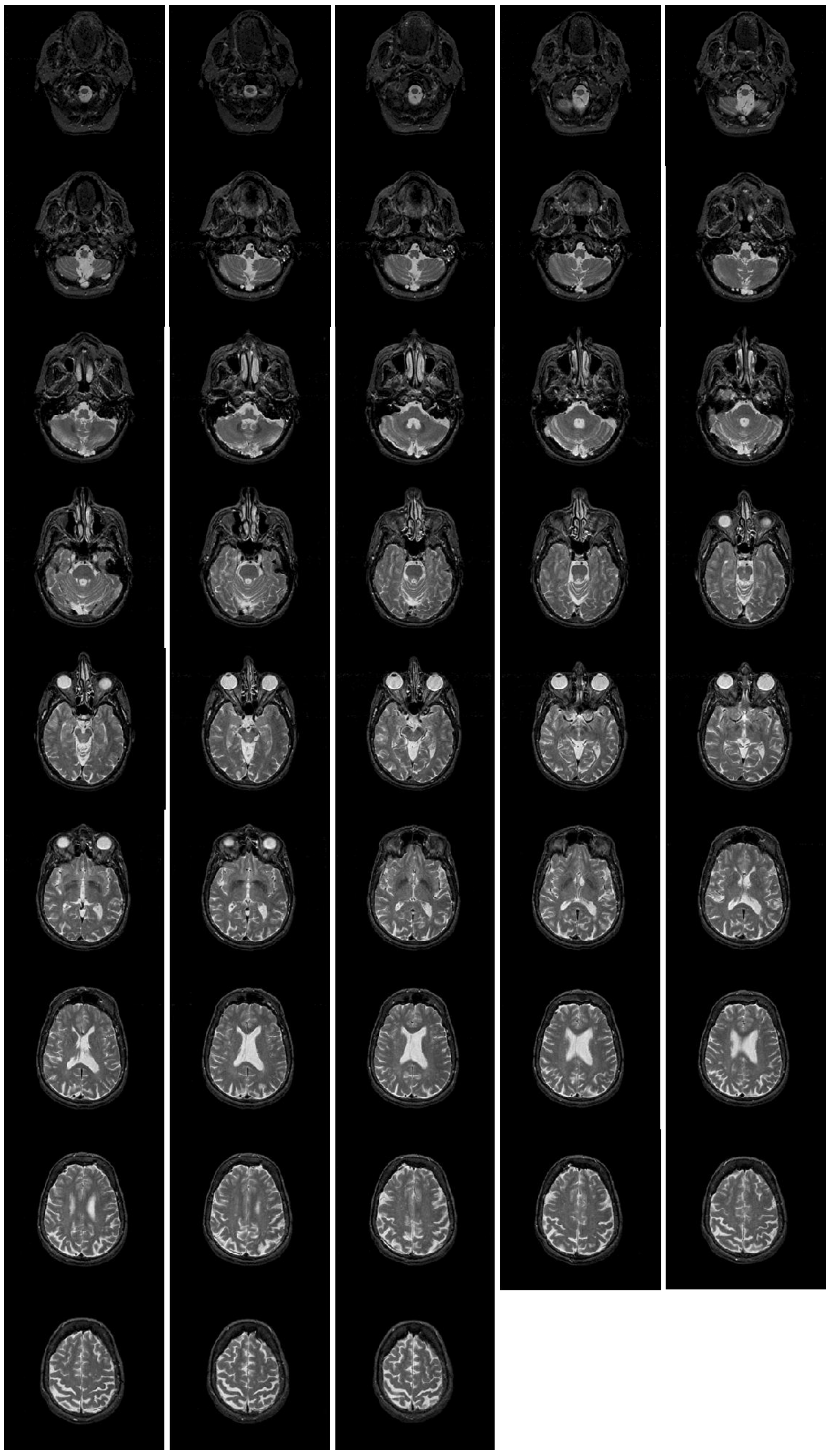

Figure 6 . T2-W axial brain volume (205_3)

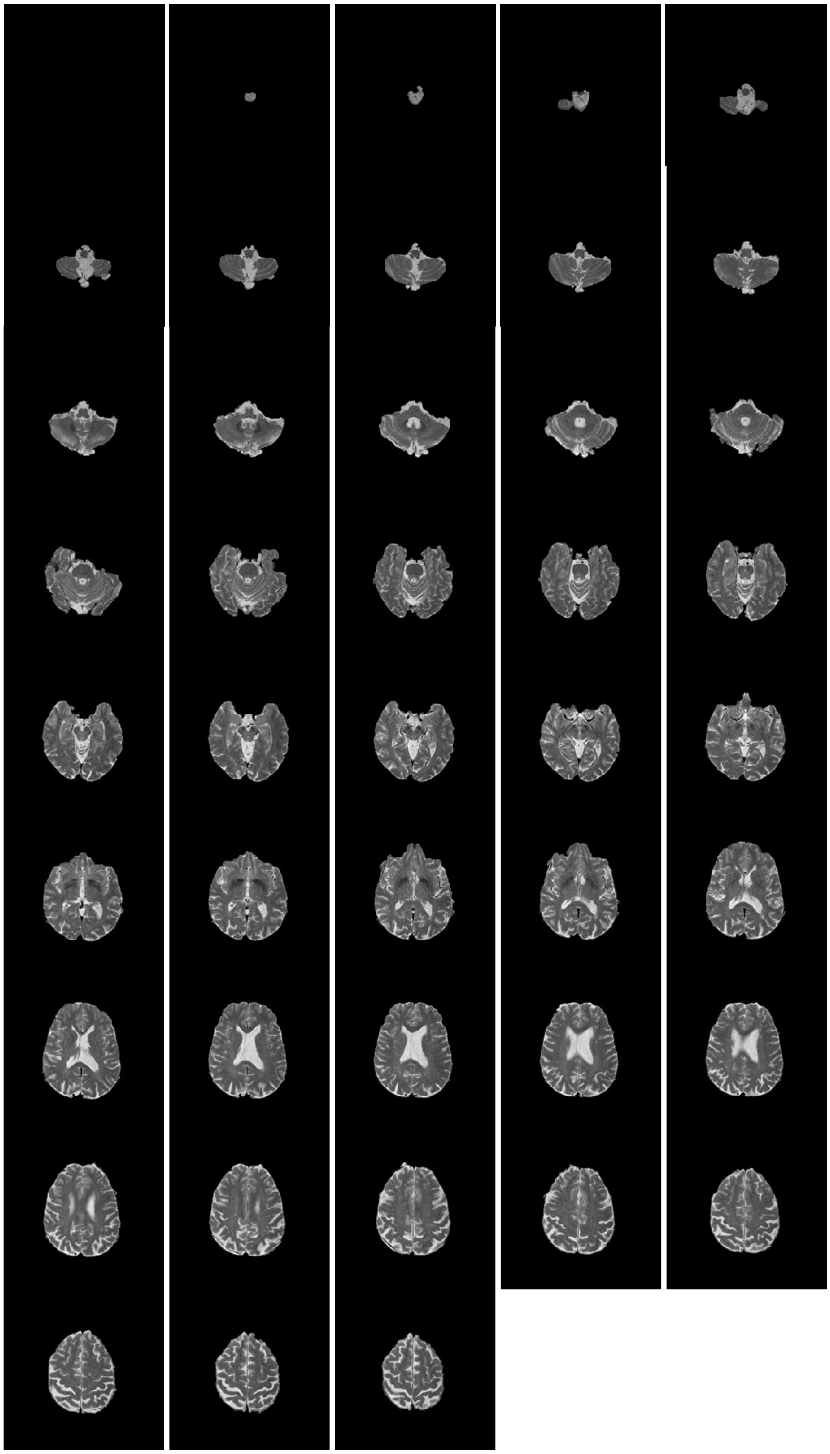

Figure 7. Brain portion extracted from T2-W axial images shown in Figure.6.

IV. CONCLUSIONS

In this paper, we have presented an automatic brain extraction scheme to extract brain from T1-W and T2-W MRI head scans. Experimental results show that our method worked well on normal brain datasets. It is found that diffused image can be used as means to automatically obtain the threshold T_{opt} by varying the iteration n. Further, it is observed that for all T2-W images and most T1-W images, good results can be obtained by omitting filtering and diffusion. The proposed scheme gives competitive results to that of BET and BSE.

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