Automatic Brain Extraction from MRI of Human Head Scans using Fuzzy Logic and Bridge Building Algorithm

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***Abstract*- Brain extraction or skull stripping is a primary process in the brain image analysis. In this paper, we have proposed an automatic brain extraction method for Magnetic Resonance Images (MRI) using fuzzy logic, bridge building algorithm and morphological operations. We applied our proposed method on 5 volumes of MRI head scans taken from Internet Brain Segmentation Repository (IBSR) and extracted the brain portion. The performance of the proposed method is evaluated by computing similarity indices Jaccard (J) and Dice (D).**

Keywords- Brain Extraction, Magnetic Resonance Image (MRI), Fuzzy logic, Bridge building algorithm.

I. INTRODUCTION

Brain is one of the vital organs in our body. It controls all the organs of the body through central nerves system. It has three major parts, Cerebrum, Brain stem (medulla) and Cerebellum. It is covered by skull and cerebral spinal fluid (CSF) which protects the brain from physical shocks [1]. The brain is afflicted by several diseases which are classified as hormonal disorders, tumors, degenerative diseases, bleeding and infections. These abnormities are identified by taking brain images using X- rays, CT- scans, Positron emission tomography (PET), Magnetic Resonance Image (MRI) and so on. MRI is a powerful imaging modality to inspect the internal structure of soft tissues in our human body. MRI is a non-invasive, non-ionizing and non-destructive method. MRI is taken in three different types, T1 weighted, T2 weighted and Proton Density (PD), each of them differ in their relaxation time. MRI is taken in three orientations axial (top to bottom), sagittal (left to right) and coronal (front to back). MRI of human head scans gives structure of human brain in three dimensional view of brain from a sequence of two dimensional images.

A Collection of two dimensional images is called volume and each volume contains about 20 to 120 slices. The physicians need to see all the 120 images to detect the abnormality. Physician need to get clear perception of the brain from these images. For that, extraction of brain portion from MRI is essential for further analysis. Segmenting brain manually will consume more time and also biased by the person performing the segmentation. Hence automated methods are needed. Moreover, brain extraction is a primary process to detect abnormality, image registration, tissue classification and to understand the brain parts. So skull stripping is an important process. There are plenty of methods on skull stripping. Brain Extraction Tool (BET) [2] and Brain Surface Extractor (BSE) [3] are the two famous methods among the brain extraction methods. BET initially computes two threshold values based on histogram and generates a binary image using the threshold values. An expandable sphere is created on the binary image by using Center of Gravity (COG). The sphere is expanded with the help of a smoothing and local threshold value and finally the brain is extracted. BSE method makes use of edge detection and morphological operations. This method starts with a preprocessing using anisotropic diffusion. The Marr-Hildreth [4] technique is used for edge detection followed by morphological operations to extract the brain surface. BSE need several parameters to start the algorithm. They are diffusion constant, diffusion iteration and edge constant. This method is based on edge detection. Edge detection fails on low contrast images. So BSE did not work well with low contrast images [5]. Few methods are Model Based Level set (MLS)[6], Region growing based method[7], Histogram and simplex mesh based method[8], Brain Extraction Algorithm [9], Brain Extraction Method[10] and a brain extraction method based on K-means cluster [11]. Recent methods are Multispectral Adaptive Region Growing Algorithm (MARGA) [12], a brain extraction method [13] reported based on intensity transformation and a brain extraction method [14] reported by using templates, registration and labeling. Each of above methods has some merits and demerits. In this paper we propose a novel Bridge Building Algorithm (BBA) for brain extraction process. The remaining part of the paper is organized as follows. The proposed method and materials used are given in Section II, experimental results and discussions are given in Section III and finally the conclusions are given in Section IV.

II. MATERIALS AND METHODS

A. Materials Used

We used a material pool with 5 volumes of MRI head scans taken from Internet Brain Segmentation Repository (IBSR) [15] for our experiments. Each volume contained 50 to 60 slices of images. Each volume also has hand segmented gold standard results. Table I shows the details of data sets used in our experiment.

TABLE I. DETAILS OF VOLUMES OF DATA SET USED IN OUR EXPERIMENT

Index	Volume Name	Gender	Age
1.	111_2	Male	27
2.	112_2	Male	32
3.	191_3	Male	32
4.	202_3	Female	28
5.	205_3	Female	24

B. Proposed Method

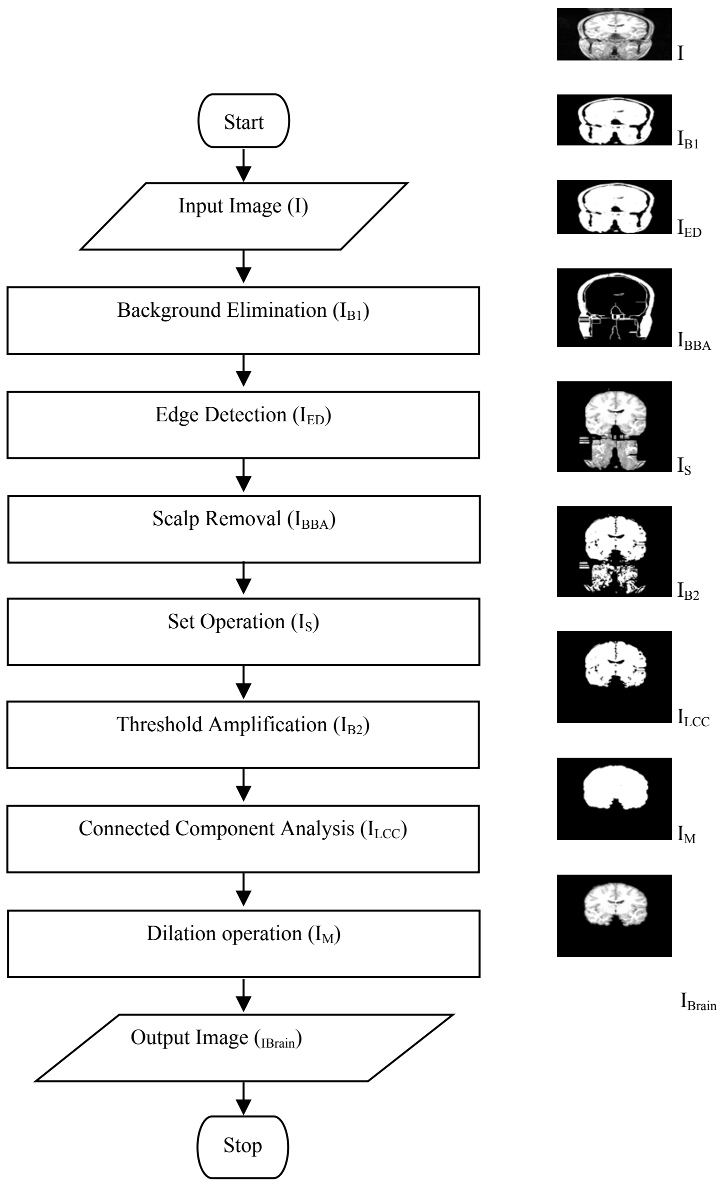


Figure 1. Flow chart of the proposed method

The proposed method consists of several image processing steps to segment the brain portion. The flow chart of the proposed method is shown in Figure 1.

C. Background Elimination

The input image has brain, non-brain and background pixels. The background pixels are other than the object taken for scans. These pixels are removed in the first step. We used an intensity threshold value T to remove background from the input image. For computing threshold value (T), we make use of Riddler's method [16]. Riddler's method gives an optimal threshold value. We can compute threshold value T in four or five iterations. We eliminate the background pixels by using the threshold T as:

$$I_{B1}(x,y) = \begin{cases} 1 & \text{if } f(x,y) > T \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The resulting image I_{B1} is a binary image.

D. Edge Detection Using Fuzzy Engine

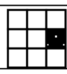
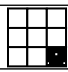
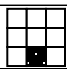
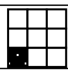
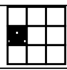
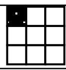
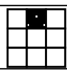
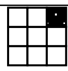
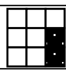
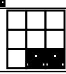
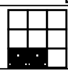
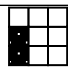
We then process the binary image I_{B1} with Fuzzy engine to detect edges. In a 3x3 sliding window we take the central pixel of the window as the current pixel and its eight neighbors are used for this edge detection process. Current pixel X and its eight neighbors N_1, N_2, N_3, N_4, N_5, N_6,N_7 and N_8 are shown in Figure 2.

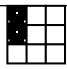
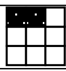
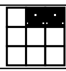
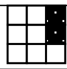
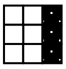
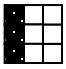
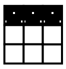
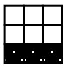
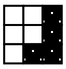
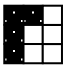
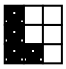
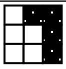
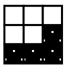
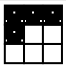
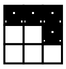
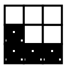
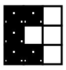
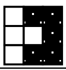
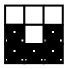
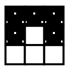
N_6	N_7	N_8
N_5	X	N_1
N_4	N_3	N_2

Figure 2. 3x3 window

We have framed 32 fuzzy rules and categorized into five groups to detect edges on a binary image [17]. The fuzzy based edge detector [17] detects boundary points of MRI head scans better than Canny [16] and Sobel [16] methods. The fuzzy rules are shown in Table II.

TABLE II. 32 FUZZY RULES TO EDGE DETECTION

Index	Rules	Diagram
1	$N_1=1$ N_2 &N_3&N_4&N_5&N_6&N_7&$N_8=0$	
	$N_2=1$ N_1&N_3&N_4&N_5&N_6&N_7&$N_8=0$	
	$N_3=1$ N_1&N_2&N_4&N_5&N_6&N_7&$N_8=0$	
	$N_4=1$ N_1&N_2&N_3&N_5&N_6&N_7&$N_8=0$	
	$N_5=1$ N_1&N_2&N_3&N_4&N_6&N_7&$N_8=0$	
	$N_6=1$ N_1&N_2&N_3&N_4&N_5&N_7&$N_8=0$	
	$N_8=1$ N_1&N_2&N_3&N_4&N_5&N_6&$N_7=0$	
	$N_8=1$ N_1&N_2&N_3&N_4&N_5&N_6&$N_7=0$	
	N_1&$N_2=1$ N_3&N_4 &N_5&N_6&N_7&$N_8=0$	
	N_2&$N_3=1$ N_1&N_4 &N_5&N_6&N_7&$N_8=0$	
	N_3&$N_4=1$ N_1&N_2 &N_5&N_6&N_7&$N_8=0$	
	N_4&$N_5=1$ N_1&N_2 &N_3&N_6&N_7&$N_8=0$	

	$N_5 \& N_6$ $=1$ $N_1 \& N_2 \& N_3 \& N_4 \& N_7 \& N_8 = 0$	
	$N_6 \& N_7 = 1$ $N_1 \& N_2 \& N_3 \& N_4 \& N_5 \& N_8 = 0$	
	$N_7 \& N_8 = 1$ $N_1 \& N_2 \& N_3 \& N_4 \& N_5 \& N_6 = 0$	
	$N_1 \& N_8 = 1$ $N_2 \& N_3 \& N_4 \& N_5 \& N_6 \& N_7 = 0$	
3	$N_8 \& N_1 \& N_2 = 1$ $N_3 \& N_4 \& N_5 \& N_6 \& N_7 = 0$	
	$N_4 \& N_5 \& N_6 = 1$ $N_7 \& N_8 \& N_1 \& N_2 \& N_3 = 0$	
	$N_6 \& N_7 \& N_8 = 1$ $N_1 \& N_2 \& N_3 \& N_4 \& N_5 = 0$	
	$N_2 \& N_3 \& N_4 = 1$ $N_5 \& N_6 \& N_7 \& N_8 \& N_1 = 0$	
4	$N_8 \& N_1 \& N_2 \& N_3 = 1$ $N_4 \& N_5 \& N_6 \& N_7 = 0$	
	$N_4 \& N_5 \& N_6 \& N_7 = 1$ $N_8 \& N_1 \& N_2 \& N_3 = 0$	
	$N_3 \& N_4 \& N_5 \& N_6 = 1$ $N_7 \& N_8 \& N_1 \& N_2 = 0$	
	$N_7 \& N_8 \& N_1 \& N_2 = 1$ $N_3 \& N_4 \& N_5 \& N_6 = 0$	
	$N_1 \& N_2 \& N_3 \& N_4 = 1$ $N_5 \& N_6 \& N_7 \& N_8 = 0$	
	$N_5 \& N_6 \& N_7 \& N_8 = 1$ $N_1 \& N_2 \& N_3 \& N_4 = 0$	
	$N_6 \& N_7 \& N_8 \& N_1 = 1$ $N_2 \& N_3 \& N_4 \& N_5 = 0$	
	$N_2 \& N_3 \& N_4 \& N_5 = 1$ $N_6 \& N_7 \& N_8 \& N_1 = 0$	
5	$N_3 \& N_4 \& N_5 \& N_6 \& N_7 = 1$ $N_8 \& N_1 \& N_2 = 0$	
	$N_7 \& N_8 \& N_1 \& N_2 \& N_3 = 1$ $N_4 \& N_5 \& N_6 = 0$	
	$N_1 \& N_2 \& N_3 \& N_4 \& N_5 = 1$ $N_6 \& N_7 \& N_8 = 0$	
	$N_5 \& N_6 \& N_7 \& N_8 \& N_9 = 1$ $N_2 \& N_3 \& N_4 = 0$	

The image I_{B1} is subdivided in to overlapping windows of size 3x3 and sent to the fuzzy engine. The fuzzy engine counts non-zero elements. The engine takes the count and check if there is any rule match. If the engine found any rule match then the pixel is considered as an edge pixel. We retain the same pixel element in the binary image I_{B1} when the fuzzy engine return false. If an edge is found in the pixel then that pixel is marked with label 2. Sliding window operations are performed on I_{B1}. By this process a new image I_{ED} is created with three labels 0,1and 2. In the image I_{ED}, pixels with label 0 are background pixels, label 1 are brain pixels and label 2 are the edges of the brain. Using the 32 fuzzy rules, we construct a Fuzzy Engine as shown in Figure 3.

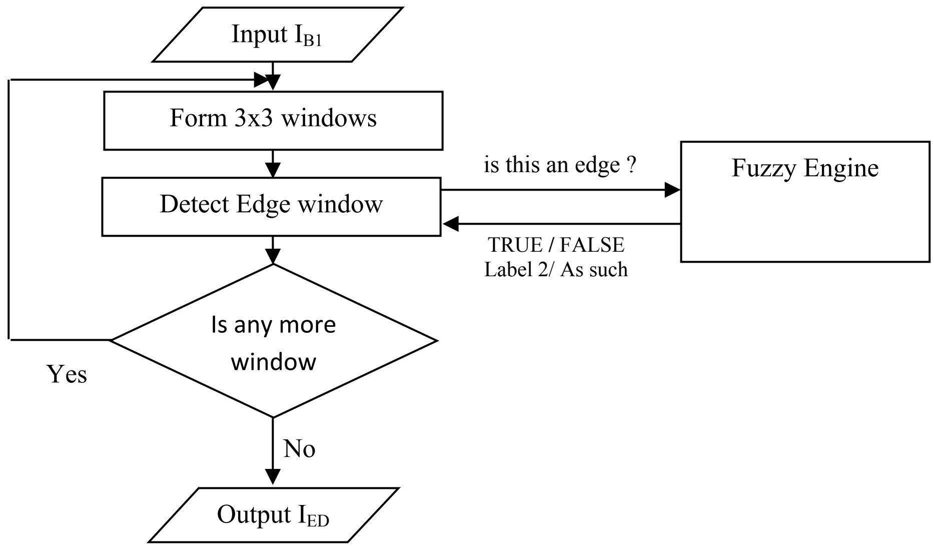


Figure 3. Edge detection using Fuzzy Engine

$$I_{ED}(x,y) = \begin{cases} 2 & \text{if } FZ(I_{B1}(x,y)) = TRUE \\ I_{B1}(x,y) & \text{otherwise} \end{cases} \tag{2}$$

where, FZ() is the fuzzy engine.

E. Bridge Building Algorithm

In some places on image I_{ED}, the brain portion is connected with non-brain portions with narrow links. The link may occur vertically or horizontally. These links may be surrounded by brain tissues, non-brain tissues and backgrounds. We device Bridge building algorithm, to connect the two pixels belonging to label 2 if they are on a straight line.

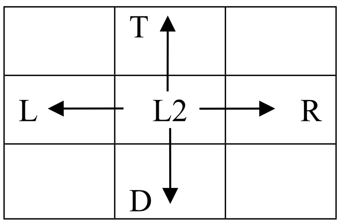


Figure 4. L2 searching directions

Figure 4 shows search directions of searching in four directions (R, D, L and T). We have a pointer to check each pixel for label 2, if found then the pointer is moved in four directions, one by one, and look for label 1 or label 2 pixels. If no such pixel is found then it moves to next pixel for finding pixel with label 2. If label 1 pixel is found, it moves further until a label 2 pixel is found. Once label 2 pixel is found for the second time, after crossing label 1 pixel, first label 2 pixel and second label 2 pixel are joined in a straight line to form a new image I_{BBA}. This process is repeated for the entire label 2 pixel in the image I_{ED}. After performing this operation we get a new image I_{BBA}.

F. Set operation on Image

The image I_{BBA} consists of still few non-brain portions which are not removed by background elimination. In the set operation we are going to extract the brain portions from I_{B1} with help of image I_{BBA}. The brain portion is extracted by using set operations as:

$$I_{S1}(x,y) = I^{C}_{BBA}(x,y) \cap I_{B1}(x,y) \tag{3}$$

where, I^{C}_{BBA} is complement of I_{BBA}. I_{S1} is a binary image. From the image I_{S1} we obtain another image I_S as:

$$I_S(x,y) = \begin{cases} I(x,y) & \text{if } I_{S1}(x,y)==1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

G. Threshold Amplification

After the set operations, most of the non-brain tissues are removed, but still few non-brain tissues are attached to I_S. For removing the remaining non-brain tissues we compute a new mean value m1 for the image I_S and estimate another threshold value. The amplified threshold value, based on [8], is given by:

$$T1 = T + 0.7 * (T - m1) \tag{5}$$

Using the new threshold T1, we get a binary image I_{B2} as:

$$I_{B2}(x,y) = \begin{cases} 1 & \text{if } I_S(x,y) > T1 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

This binary image contains several connected regions.

H. Connected Component Analysis

It is a fact that the brain is the largest portion in the middle slice of the MRI scan. So we apply connected component analysis [16] on the image I_{B2}. We make use of run-length scheme and region labeling for this connected component analysis. The image I_{B2} consists of n number of independent regions R (i), with area $R_A(i)$ where i=1…n. From the $R_A(i)$, the largest connected component (LCC) as:

$$LCC = R(\arg\max(R_A(i))) \qquad 1 \le i \le n \tag{7}$$

The brain portion is extracted from LCC as:

$$I_{LCC}(x,y) = \begin{cases} 1 & \text{if } I_{B2}(x,y) \in LCC \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

The image I_{LCC} consist only one largest component the brain.

I. Dilation Operation

The image I_{LCC} lost few brain regions due to the earlier operations. The eroded regions are recovered by dilation operation. Brain surface is curved and so we used a disk shaped structuring element S9 of size 9x9 as shown in Figure 5.

0	0	1	1	1	1	1	0	0
0	1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
0	1	1	1	1	1	1	1	0
0	0	1	1	1	1	1	0	0

Figure 5. Disk shaped structuring element

By dilating the I_{LCC}, we get the brain mask as:

$$I_M = I_{LCC} \oplus S9 \tag{9}$$

The brain mask I_M is used to extract the brain portion I_{Brain} from I(x,y).

III. RESULTS AND DISCUSSION

We carried out experiments by applying our method on the material pool given in Table I and we extracted brain portion. For visual inspection the original images in one volume are shown in Figure 6 and brain portion extracted from the images shown in Figure 6 are shown in Figure 7. For quantitative evaluation of the performance of the proposed method, we compute similarity indices Jaccard (J) and Dice (D). For this computation, we made use of the “gold standard” hand segmented results available in IBSR for this volume.

The Jaccard co-efficient is computed as [18]:

$$J = \frac{|A \cap B|}{|A \cup B|} \tag{10}$$

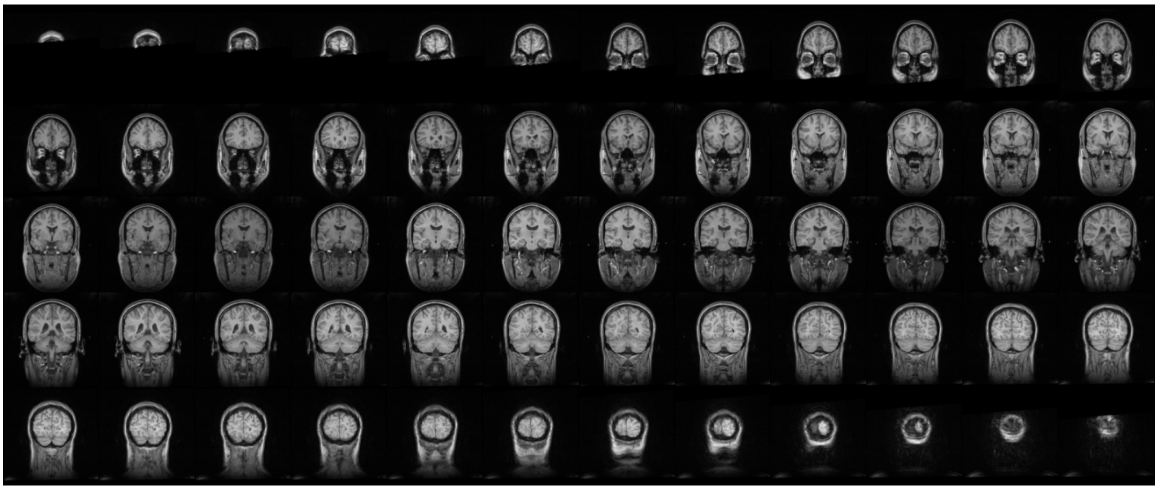


Figure 6. Original images in one volume

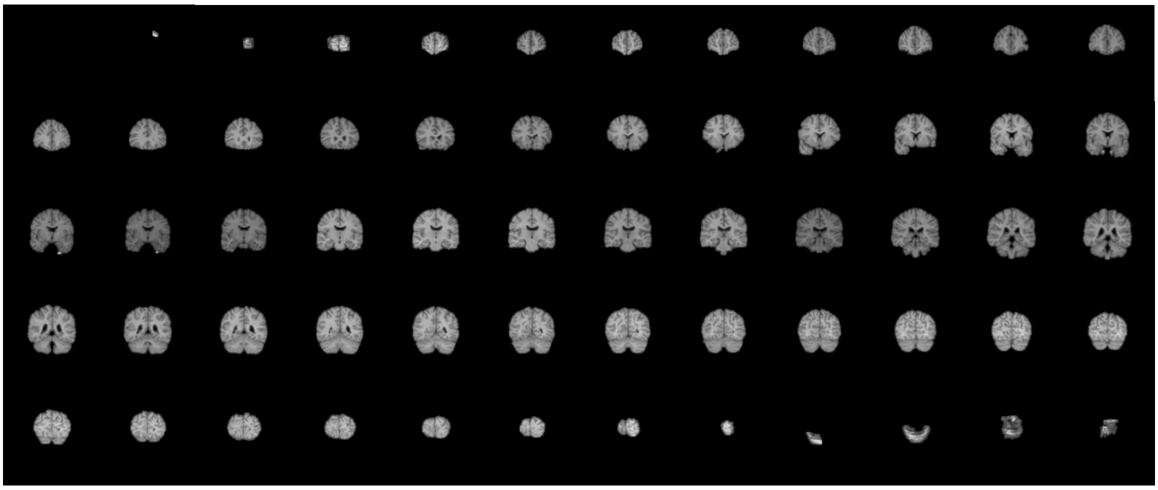


Figure 7. Brain extracted from slices shown in Figure 6

and Dice similarity co-efficient [19] as:

$$D = \frac{2|A \cap B|}{|A| + |B|} \tag{11}$$

where, A is the pixel in the gold standard image and B is the pixels in the segmented image by our method. Values closer to 1 for J and D show a good agreement between A and B, and closer to 0 mean total disagreement. We also compute the parameters False Positive Rate (FPR) and False Negative Rate (FNP) using:

$$FPR = \frac{|A \cap B^C|}{|A \cup B|} \tag{12}$$

and

$$FNR = \frac{|A^C \cap B|}{|A \cup B|} \tag{13}$$

where, X^C is the complement of X.

Table III shows the computed values of J, D, FPR and FNR for the 5 volumes of T1 weighted coronal MR Head Scans along with the values obtained by BET and BSE. The values of BET and BSE are taken from [5]. From Table III, we observe that the proposed method gives an average value of 0.951 for J and 0.975 for D, which are better than the values obtained by the popular methods BET and BSE.

TABLE III. MEAN VALUES OF JACCARD , DICE , FALSE POSITIVE RATE AND FALSE NEGATIVE RATE

Index	Proposed Method				BET				BSE			
	J	D	FPR	FNR	J	D	FPR	FNR	J	D	FPR	FNR
1	0.953	0.976	0.020	0.003	0.855	0.922	0.143	0.002	0.915	0.956	0.071	0.014
2	0.950	0.974	0.019	0.006	0.779	0.876	0.221	0.0001	0.906	0.950	0.084	0.010
3	0.942	0.969	0.012	0.017	0.846	0.916	0.154	0.0003	0.927	0.962	0.055	0.017
4	0.962	0.981	0.016	0.002	0.858	0.924	0.140	0.001	0.919	0.958	0.071	0.010
5	0.948	0.973	0.014	0.012	0.711	0.831	0.089	0.200	0.926	0.961	0.062	0.012
AVG	**0.951**	**0.975**	**0.016**	**0.008**	0.810	0.894	0.149	0.041	0.919	0.957	0.069	0.013
SD	0.007	0.004	0.003	0.006	0.064	0.040	0.047	0.089	0.009	0.005	0.011	0.003

Avg. - Average, SD – Standard Deviation.

IV. CONCLUSION

We have developed a novel brain extraction method using fuzzy logic and bridge building algorithm. The proposed method gives better results than the existing popular methods BET and BSE. The proposed method is simple and efficient than the BET and BSE. The proposed method gives an average value of 0.951 for J and 0.975 for D.

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