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Brain Extraction from MRI Human Head Scans using Outlier Detection based Morphological Operations

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Abstract — In medical imaging, segmentation of skull from MRI Brain images is an important task in detecting and diagnosis of brain related diseases. Due to homogeneous nature of intensities, segmenting brain and non brain tissues became an challenging task. In this paper, we proposed a method using Outlier Detection based Morphological Operations (ODMO) to segment brain from MRI head scans. First, we used outlier detection to find the threshold value followed by the morphological operations and Largest Connected Component (LCC) to extract the brain. We tested our method from the images obtained from Internet Brain Segmentation Repository (IBSR) and real time images from SBC Scan, Dindigul. In order to estimate the results of our proposed method, similarity measures and overlapping measures like Jaccard (J), Dice (D), Sensitivity (S) and Specificity (SP) are used and it is compared with manual segmented images. Our proposed technique yields exceeding results when compared with existing standard techniques such as Brain Extraction Tool (BET) and Brain Surface Extractor (BSE).

Keywords — Brain Extraction, Outlier Detection, Morphological Operations, MRI Brain Image.

I. INTRODUCTION

Brain is an small organ which plays an vital role in human body. It controls all the functional activities of the body. It collects information from the farther side and brings together the messages which are meaning for us and accumulate them into the memory. Brain is made of three major parts namely cerebrum, cerebellum and brain stem. Cerebrum occupies more place in the brain and it divides into left and right hemisphere. The main function of cerebrum is for interpret touch, perception and hearing. Moreover, it also maintains language, reasoning, despair, knowledge and action control. Cerebellum which is placed beneath under the cerebrum are used to correlate the movement of muscles, preserve attitude and tension. Brain stem acts as a connecting bridge between cerebrum and cerebellum to the spinal cord. Some automatic function such as breathing, vomiting, body temperature, sleep cycle, coughing and swallowing are controlled by brain stem.

The cerebral cortex is covered by soft tissues called Gray Matter (GM) and White Matter (WM). GM is made of number of nerve cells which are in the form of grey - brown in color. WM is associated with prolonged connecting fibers of neurons. Another one is the Cerebral Spinal Fluid (CSF) is the colorless liquid and it flows between the brain and spinal cord in order to safeguard from injury. Based on this soft tissues, there are many degenerative diseases such as Alzheimer's disease, Parkinson's disease, Schizophrenia, Multiple Sclerosis are caused. Mostly the brain is moulded with skull part to avoid any damage to brain. This process can be analyzed by using medically visualized procedures like X-ray, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). Among them, we have used MRI which is a non invasive technique and clearly visualize the soft tissues of brain.

In order to diagnosis the diseases, some preprocessing process such as skull removal has to be done. There are several existing methods for extraction of brain are available in the literature [1] - [5]. Brain Extraction Tool (BET) [6] and Brain Surface Extractor (BSE) [7] are the two prominent methods used by researchers for segmentation of brain. BET uses intensity histogram, center of gravity of head image and enlarge the sphere surface to segment the brain portion. BSE segment the brain portion using spatial intensity values, anisotropic diffusion filter and edge detection technique.

Gao and Xie [8] proposed a method by three process, first of all to smooth and remove noise from the image, anisotropic diffusion filter is used. Secondly it uses edge detector to spot out the position of skeletal boundaries and finally they apply morphological operation to detect the brain portion. They implement their method on real time slices and it gives better segmentation result. A method in [9] uses histogram information to eliminate the background pixels and they used morphological operation to produce the mask of brain and non brain region automatically by two seeded regions points and the results of proposed method works better than existing techniques of BET and BSE and it is robust to noise and intensity homogeneity. In order to bring accurate segmentation result, we must perform skull stripping process, Sadananthan et. al., [10] presented a technique in three ways, intensity thresholding to obtain brain mask by cutting narrow links, false connections of brain and non brain regions are removed by using Graph Cut (GCUT) with precious locations of changing width, and finally post processing process is done to regain CSF and partial volume voxels. This technique is combined with earlier method Hybrid Watershed Algorithm (HWA) by intersecting brain mask. The combined approach gives superior segmentation result when it is done by HWA alone.

To control the transformation of zero level curve in level set function, a new algorithm called Model based Level Set (MLS) is refined in [11] by two forces such as mean curvature of the curve and intensity component of cortex in MRI images to takeout the curve to the brain surface. It works robust than BET and BSE and acts as promising tool in large institutions and for neuroimaging studies. The combination of discriminative model and point distribution model called Robust learning based Brain Extraction (ROBEX) in [12] are applied for variety of datasets and it improves the performance of segmentation result compared to BET, BSE, Free Surfer, AFNI, Bridge Burner, and GCUT.

Bauer et. al., [13] implement ITK with affine transformation and level set function for skull stripping process which are applied on T1WI, T1C, T2WI, T2F and CT images which gives sufficient segmentation result for neuro analysis task. An automated skull stripping method was implemented in [14] uses deformable model and tissue classification for T1 - Weighted images and the results are compared with BET with average value of 0.948 and finally it is successfully applied for T2 - Weighted images. Mostly, brain tumor is found at the regions of boundary so when detecting edges, there will be some unwanted edges are found, so a method described in [15] subsists of three stages, first they apply anisotropic diffusion filter for smoothening the region of edges and in the second stage, skeletonization algorithm for removing unwanted edges and in the third stage, morphological operation and LCC are employed on the images to give segmentation result.

Prastawa et. al.,[16] refined a method for segmentation of brain tumor by detecting abnormal regions using outliers, then it composed the location of both tumor and edema. Once the intensity parameter of tumor and edema are calculated then finally they applied spatial and geometric properties to determine appropriate location and this method gives relevant features of tumor and edema region for better diagnosising process. Kalavathi and Surya Prasath [17] have surveyed different automatic methods for skull stripping process and they revealed that getting feasible solution for skull stripping is still becoming a challenging task in area of research.

In this paper, we have used Outlier Detection based Morphological Operation (ODMO) to extract the brain. In order to experiment and analyze our proposed method, we retrieved images from the IBSR database and the results are compared with manual segmented images and these method is evaluated with similarity and overlapping measures such as Jaccard (J), Dice (D), Sensitivity (S), and Specificity (SP).

The rest of the paper is constructed as follows: Basic methods and materials used for our proposed technique are described in Section II. In Section III, implementation of proposed work is done. Our proposed method is evaluated in Section IV, Experimental results and discussion is given in Section V and at last conclusion in Section VI.

II. METHODS AND MATERIALS

A. Outlier Detection based Morphological Operation (ODMO)

Outlier detection [18] comes from the theory of statistics and it is defined as a data point which is isolated from other data observations. Outlier is a technique to bargain the values of patterns in a data which are not accommodate to the normal behavior. It is also used in many applications such as military observation for foe movements, interruption identification in digital security, misrepresentation identification for credit cards, protection or human services, blame identification in safety critical frameworks and abnormality detection in mammographic MRI images. Outlier can be detected by using three methods Z - Score method, Modified Z - Score method and Inter Quartile Range (IQR) method. In that we have used IQR method for identifying outliers. IQR is also called as an H - Spread technique which subtracts lower quartile from the upper quartile. It is an variability measure which divides the dataset into three quartiles Q1, Q2 and Q3 and this can be viewed by using box plot diagram and it is shown in Figure 1.

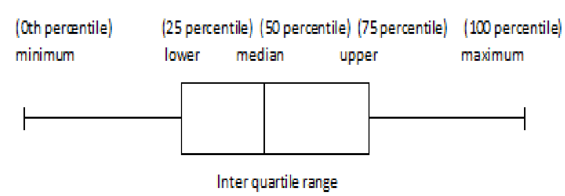

Figure 1. Box plot diagram of IQR

In order to find the IQR value, first of all, we have to find the quartiles range. Quartiles which segregate the data range into lower as Q1, upper as Q3 and median point as Q2 and this can be calculated by using the formula as given below.

$$Q1 = (n+1|4) \tag{1}$$
$$Q2 = (n+1|2) \tag{2}$$
$$Q3 = (3(n+1)|4) \tag{3}$$

where 'n' is the number of terms.

Then IQR is calculated by applying this quartile value as follows

$$IQR = Q3 - Q1 \tag{4}$$

Using this IQR values, lower and upper extreme value of outlier can be detected using the following equation.

$$Lower = Q1 - 1.5 * IQR \tag{5}$$
$$Upper = Q3 + 1.5 * IQR \tag{6}$$

where 1.5 is a constant value for IQR computation.

B. Morphological Erosion and Dilation Operation

Mathematical morphology [19][20] uses the technique such as set theory, lattice theory, topology and random function for analyzing and processing the geometric structures of images. In mathematical morphology, a small probe called structuring element which is used to fits or misses the shape of the image.

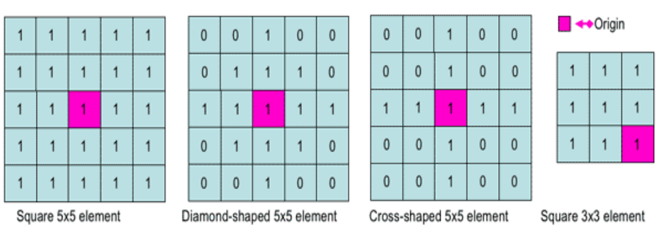

Figure 2. Examples of structuring element.

Figure 2 shows the different shapes of structuring element. The basic functions of morphological operations are erosion, dilation, opening and closing operations.

C. Erosion

Erosion operation is used to remove the unwanted regions of an image with the help of structuring element. Let us consider an image f and structuring element as S with an subset of Z and it is denoted by the formula as follows

$$f \ominus S = \{z|(S)_z \subseteq f\} \tag{7}$$

D. Dilation

Dilation operation is opposite to erosion operation, it adds some extra pixels values to an image to show the growing or thickening values of an image.

Let us consider an image f and structuring element as S with an subset of Z and it is denoted by the formula as follows

$$f \oplus S = \{z|(\hat{S})_z \cap f \neq \emptyset\} \tag{8}$$

E. Opening

Opening is an operation used in morphology technique to eliminate precarious collar and thin protrusions. Sometimes it smoothes the contour of an object.

The opening function for an image f with structuring element S and it is denoted as

$$f \circ S = (f \ominus S) \oplus S \tag{9}$$

F. Closing

Closing is a reversed process of opening it merges the breaks and thin gulfs. It avoids small holes and fills gaps in the contour.

The closing function for an image f with structuring element S and it is denoted as

$$f \cdot S = (f \oplus S) \ominus S \tag{10}$$

G. Largest Connected Component (LCC)

From the observation, we can know that middle slice of brain is the largest portion in the head region, so we employ LCC technique to extract the brain portion and it is denoted by

$$f_{LCC} = f(\arg\max_{1 \le i \le n} f_A(i)) \tag{11}$$

where $f_A(i)$ is the area of the i^{th} region in f(i)

H. Materials

Dataset 1:

The twenty volumes of T1 weighted MR brain images obtained from IBSR [21] of the Center for Morphometric Analysis (CMA) at the Massachusetts General Hospital are taken to be tested for proposed system. It contains MR brain volumes obtained from young-middle aged normal individuals. Each volume consists of T1-weighted 2D sequential coronal slices with dimensions of 256x256 pixels. The number of slices ranges from 60 to 65 and the slice thickness is 3.1 mm. Several volumes of the dataset had severe intensity inhomogeneities caused by the non-uniformity of magnetic fields, radio frequency coils, and noise factors, therefore for the efficient performance comparison these volumes have been used in the existing methods.

Dataset 2:

We collected six volumes of T1 weighted, T2 weighted and proton density of coronal slices [22] from SBC Scan, Dindigul. The slices are taken from 1.5T siemens machines with a dimension of 305 x 448 pixels, slice thickness =

4.5mm with 1.4 mm interslice gap. The field of view read =230m, The field of view phase = 90.6%, The field of view fixed = 230x208.4mm, and dataset size is nearly 25 slices per volume for all the sequences. No gold standard is provided for this dataset.

III. IMPLEMENTATION

We implement the outlier detection function to find the threshold value by using the formula as follows

$$T = (Lower + Upper)/2 \tag{12}$$

By using this threshold value, we binarize the image f(x,y) and then apply morphological erosion operation with diamond shaped structuring element of 5x5 to erode the non brain regions. LCC algorithm is applied to extract the brain mask and at last dilation operation performed on the brain mask with the same structuring element of 5x5 in order to recover the pixels which are eroded during the process of thresholding and these brain mask is assigned on input image to get the brain portion. The flowchart of our proposed method is shown in Figure 3.

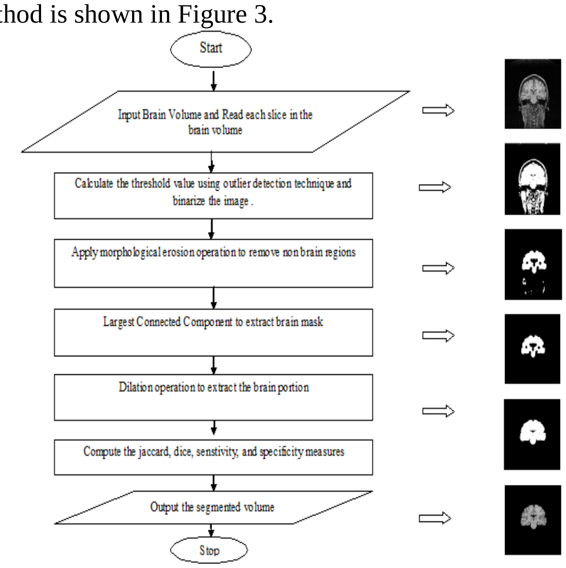

Figure 3. Flowchart of our proposed method.

IV. PERFORMANCE ANALYSIS METRICS

To measure the performance of our proposed strategies with the existing techniques by using the similarity measures of Jaccard (J) and Dice (D). These evaluation technique will take two images as input and produce the value between 0 and 1.

The Jaccard J [23] value is calculated by:

$$J(S_1,S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \tag{13}$$

The Dice (D) [23] value is measured by

$$D(S_1,S_2) = \frac{2|S_1 \cap S_2|}{|S_1| + |S_2|} \tag{14}$$

where, S_1 represents the aggregate pixels of the image obtained by the proposed segmentation method and S_2 represents the aggregate pixels in the image obtained from ground truth image. Overlap measure is defined for a given voxel class assignment as the sum of the number of voxels that both have the class assignment in each segmentation divided by the sum of voxels where either segmentation has the class assignment.

We deliberated our proposed method using overlapping measures such as sensitivity and specificity. Sensitivity and specificity are statistical measures of the performance of a binary classification test, also known in statistics as classification function.

Sensitivity (S) [24] is the measure of positive proportions that are correctly identified as

$$S = TP / (TP+FN) \tag{15}$$

where TP denotes True Positive and FN denotes False Negative respectively.

Specificity (SP) [24] is the measure of negative proportions that are correctly identified as

$$SP = TN / (TN+FP) \tag{16}$$

where TN represents True Negative and FP represents False Positive respectively.

V. RESULTS AND DISCUSSION

The proposed method was analyzed on dataset 1 and dataset 2 to extract the brain portion and examined with manual segmented images. The results of our proposed method was evaluated with similarity and overlapping measures such as J, D, S, and SP and it is compared with existing techniques such as BET and BSE. The segmented result for our proposed method is shown in Figure 4.

In Figure 4, First column denotes original brain image, Second column represents manually segmented images. Third and Fourth column denotes the skull stripped result of existing techniques BET and BSE. The last column in Figure 4 shows the result of our proposed method. The calculated values of similarity measures and quantitative measures for dataset 1 are retrieved by our proposed method and the results are compared with existing techniques like BET and BSE are shown in Table 1.

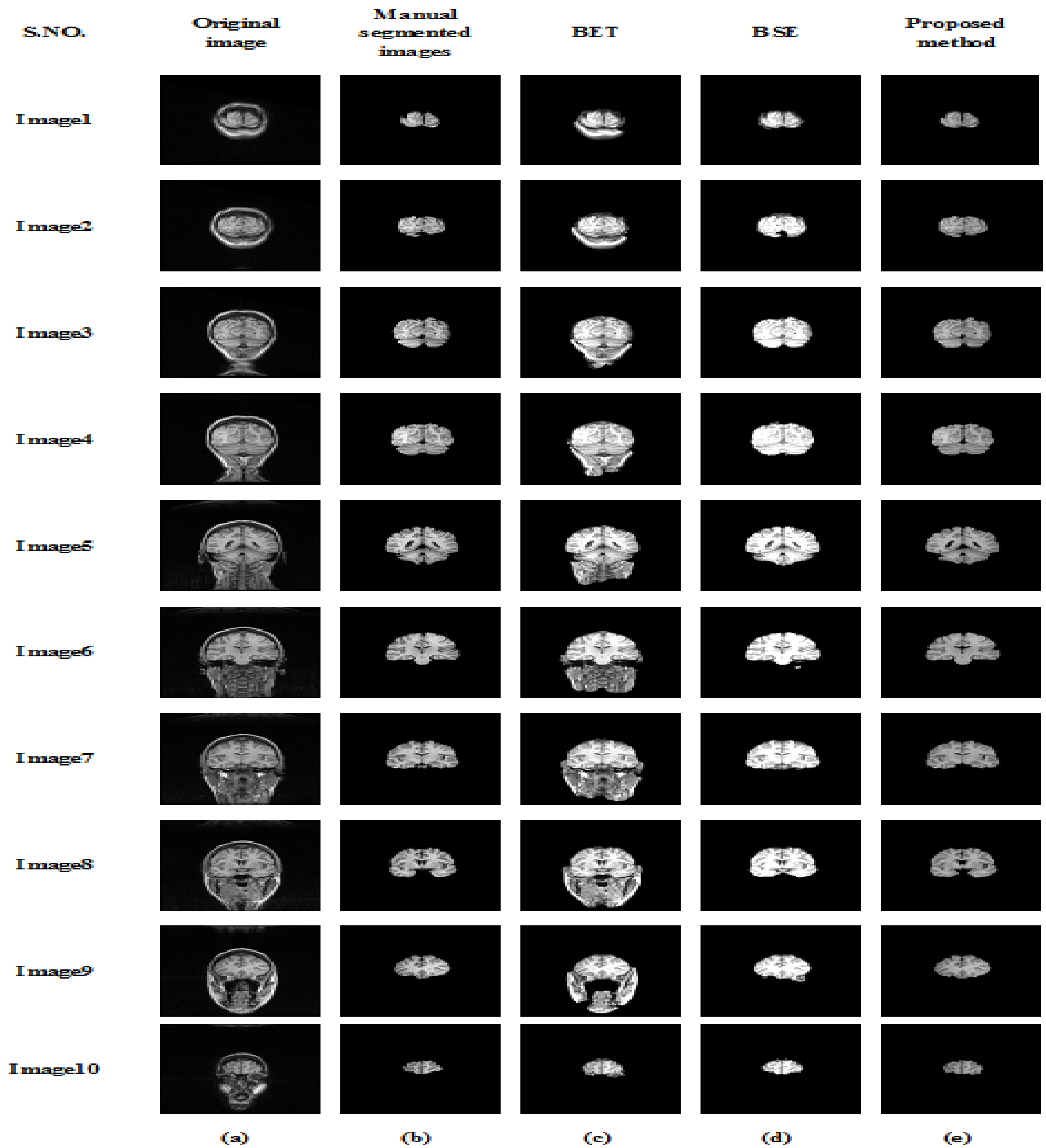

Figure 4. Extraction of brain by our proposed method a) Original image b) Hand Stripped Segmented images c) - d) Segmented result of existing techniques (BET and BSE) e) Segmented result of our proposed method.

Table 1. Calculated Jaccard (J), Dice (D), Sensitivity (S) and Specificity (SP) of skull stripped images for dataset 1 by our proposed method.

V	Proposed Method				BET				BSE			
	J	**D**	**S**	**SP**	**J**	**D**	**S**	**SP**	**J**	**D**	**S**	**SP**
1_24	0.9056	0.9406	0.9274	0.9275	0.5555	0.6933	0.8438	0.9184	0.8208	0.8711	0.9199	0.9269
2_4_	0.8855	0.9336	0.9298	0.9300	0.7150	0.8132	0.8966	0.9237	0.7961	0.8597	0.9161	0.9260
4_8	0.8529	0.9222	0.9127	0.9257	0.7306	0.8338	0.8992	0.9233	0.8344	0.8888	0.9094	0.9244
5_8_	0.8682	0.8993	0.9199	0.9186	0.4042	0.5581	0.7961	0.9044	0.6183	0.7390	0.8724	0.9137
6_10_	0.8645	0.9012	0.9131	0.9143	0.3964	0.5202	0.7782	0.8966	0.7915	0.8520	0.9037	0.9125
7_8_	0.9082	0.9293	0.9152	0.9174	0.4346	0.5901	0.7960	0.9033	0.8210	0.8687	0.9134	0.9164
8_4	0.8842	0.9200	0.9170	0.9204	0.3358	0.4678	0.7580	0.8993	0.8581	0.9089	0.9121	0.9180
11_3	0.9337	0.9660	0.8637	0.8713	0.6237	0.7463	0.7947	0.8483	0.7940	0.8569	0.8406	0.8569
12_3	0.8541	0.9019	0.8651	0.8805	0.6242	0.7505	0.8084	0.8660	0.7679	0.8388	0.8544	0.8738
13_3	0.9042	0.9413	0.8627	0.8791	0.6820	0.7905	0.8309	0.8705	0.7483	0.8154	0.8560	0.8745
15_3	0.8787	0.9290	0.9208	0.9163	0.3890	0.5337	0.7546	0.8918	0.8220	0.8679	0.9052	0.9120
16_3	0.9048	0.9409	0.9278	0.9296	0.3853	0.5180	0.7862	0.9091	0.8343	0.8780	0.9193	0.9245
17_3	0.9082	0.9428	0.9247	0.9254	0.3466	0.4888	0.7987	0.9110	0.8234	0.8890	0.9126	0.9226
100_23	0.9092	0.9310	0.8863	0.8931	0.7207	0.8202	0.8496	0.8862	0.8171	0.8682	0.8788	0.8907
110_3	0.8687	0.9024	0.8847	0.8932	0.6328	0.7506	0.8366	0.8858	0.8002	0.8631	0.8619	0.8921
111_2	0.8979	0.9398	0.8871	0.8940	0.6184	0.7404	0.8323	0.8830	0.8455	0.9063	0.8768	0.8896
112_2	0.8802	0.9185	0.9011	0.9079	0.6490	0.7628	0.8583	0.9010	0.7856	0.8503	0.8915	0.9056
191_3	0.9063	0.9354	0.9078	0.9089	0.6780	0.7821	0.8752	0.9047	0.8589	0.9139	0.8978	0.9073
202_3	0.9015	0.9331	0.8910	0.8967	0.6727	0.7769	0.8568	0.8909	0.8272	0.8908	0.8802	0.8936
205_3	0.9233	0.9548	0.8930	0.8968	0.6829	0.7891	0.8575	0.8918	0.8491	0.9066	0.8844	0.8954
M	**0.8920**	**0.9292**	**0.9025**	**0.9073**	0.5639	0.6863	0.8254	0.8955	0.8057	0.8667	0.8903	0.9038

*V - Volume, *M - Mean

From the Table 1, the values of Jaccard, Dice, Sensitivity and Specificity of proposed method give better results than the existing techniques such as BET and BSE.

We have also implemented our proposed method on real time Alzheimer's disease and Dementia images which are obtained from SBC Scan and the sample of images are shown in Figure 5.

From the Figure 5, Figure 5(a) shows the original real image, Figure 5(b) &(c) denotes the segmented result of existing techniques BET and BSE and the Figure 5(d) shows the segmented result of our proposed method.

VI. CONCLUSION

Outlier Detection based Morphological Operation (ODMO) method is implemented to segment the brain on twenty volumes of T1-weighted MRI images which are obtained from IBSR website and real time images of Alzheimer's and Dementia from SBC Scan. The performance of proposed method was evaluated by means of similarity and overlapping measures such as Jacquard, Dice, Sensitivity and Specificity gives better results compared to existing techniques. In future, this method will be modified to segment the brain efficiently in the slices with little brain tissues.

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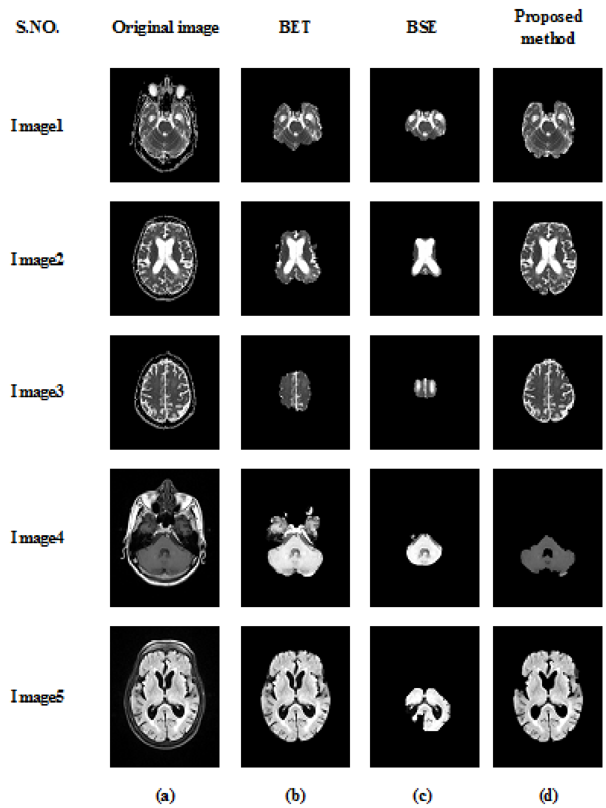

Figure 5. Extraction of real brain images (dataset 2) by our proposed method a) Original images b) - c) Segmented result of existing techniques (BET and BSE) d) Segmented result of our proposed method.

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