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Tumor Extraction and Volume Estimation for T1-Weighted Magnetic Resonance Brain Images

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Strictly as per the compliance and regulations of:

Tumor Extraction and Volume Estimation for T1-Weighted Magnetic Resonance Brain Images

S.Satheesh α, Dr.K.V.S.V.R Prasad σ & Dr.K.Jitender Reddy ρ

Abstract - Magnetic Resonance Imaging (MRI) is a significant imaging technology for brain tumor diagnosis because physicians can identify precise pathologies by studying the variations of tissue characteristics that occurs in various kinds of MR brain images. Segmentation of MRI is a pre-process in determining the volume of different brain tissues, but here tumor detection is of primary concern. We proposed a method to extract tumors as seen through MR brain images using co-clustering and morphological operations and its volume estimation was done by Cavalier's estimator of morphometric volume method. Quantitative analysis showed that the proposed method yielded better results in comparison with Fuzzy C-Means algorithm (FCM).

Keywords : tumor extraction, co -clustering, morphological operations, skull removal, magnetic resonance imaging, volume estimation.

I. Introduction

Tumor is one of the most common brain diseases; hence, its diagnosis and treatment are compulsory. In recent years, developments in medical imaging techniques have aided experts in numerous domains of medicine, such as computer-aided diagnosis, follow-up of pathologies, surgical planning and surgical guidance. Among the available medical imaging techniques, MRI is a popular neuroimaging technique for the evaluation and treatment of brain tumors. MRI devices generate images in sagittal, axial, and coronal planes that give a better localization of a lesion in a 3D space of the brain.

The segmentation of MR brain images is a complex task, as it involves a large amount of data. Few artifacts might arise due to a patient's motion or limited acquisition time; also, soft-tissue boundaries of tumor are vaguely defined. There exist a numerous classes of tumors with different shapes and sizes that appear at any location with dissimilar image intensities. A few of them might also deform the nearby structures or be associated to necrosis or edema that affects the image intensities in and around the tumor.

The conventional analysis of MR brain images with tumor by an expert is a complex and timely process. Thus, an automatic tumor segmentation method is desirable to give an adequate performance. As a result, tumor volume can be evaluated for follow-up of the disease effectively.

A number of popular brain tumor segmentation methods are briefly mentioned here. Clark et al. [1] proposed a tumor segmentation method by a set of rules with fuzzy classification and a knowledge base. Dou et al. [3] proposed a fuzzy information fusion frame work for tumor segmentation. Gordillo et al.[4] developed a fully automatic and unsupervised brain tumor segmentation method. Hassan Khotanlou et al. [5,6] introduced a tumor segmentation using symmetry analysis, fuzzy classification, and spatially constrained deformable models. Jingxin Nie et al.[9] proposed expectation maximization and a spatial accuracy-weighted hidden markov random field for tumor segmentation. Vida Harati et al.[15] proposed an automatic tumor segmentation technique based on improved fuzzy connectedness algorithm.

Despite various efforts and promising results in the medical imaging area, exact segmentation and characterization of tumors are still difficult and challenging.

This paper proposes a method that combines coclustering and morphological operations such as erosion, dilation and hole filling [12]. Firstly, morphological operations [13, 14] are performed on contrast-enhanced axial T1-weighted MR Head scans to remove non-brain data (skull, fat, skin, and muscle) to enhance tumor segmentation efficiency. These external tissues often interfere with a brain tissue during segmentation which accounts for poor segmentation efficiency. Secondly, coclustering algorithm [2, 10] is applied to segment brain tumor, and the volume of the tumor was evaluated by taking patient 1 of Table I. Performance of the proposed method was judged by comparing it with the most popular FCM algorithm [8].

II. Methodology

Our proposed method was divided into two parts. The output obtained from one part was taken as an input to the next part. The process flow chart is given in Figure1.The skull region was removed in stage I by morphological operations, and the tumor was extracted in stage II using co-clustering algorithm.

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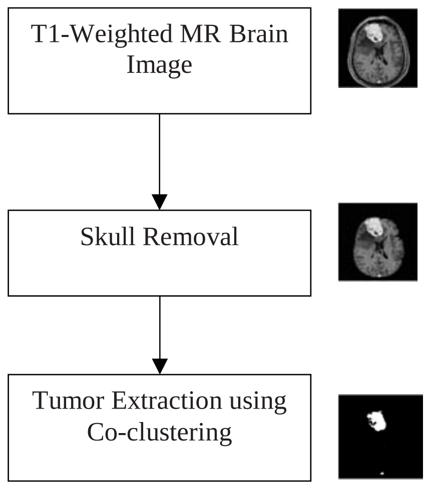

Figure 1 : Proposed methodology for tumor extraction

a) Skull removal

The objective of the process was to generate the brain region of the axial T1-weighted MR head scans by morphological operations namely, erosion and dilation [13, 14].

Erosion

Erosion operation was performed on the selected image (I) and used to split the image's weakly attached regions. The image was eroded by an octagonal structuring element. The eroded image I_1, would have several disconnected regions and was obtained using (1).

$$I_1 = I \ominus B \qquad (1)$$

Where B is the octagonal structuring element with a size of 15 × 15.

Binarization

The preceding process decomposed the given image into several isolated regions. Then, the eroded image was converted to a binary image, I_2, using (2).

$$I_2(x,y) = \begin{cases} 1 & \text{if } I_1(x,y) \neq 0 \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

Dilation

We performed a dilation operation on I_2 to recapture the brain tissues that were lost in the process of erosion. It was done with the same structuring element that was used for erosion. The dilated image, I_3, was obtained using (3).

$$I_3 = I_2 \oplus B \qquad (3)$$

Thereafter, the binary mask was obtained by filling the holes in the dilated image. The binary mask was, thus, convolved with the original image to get the final brain portion. The results of the skull removal process are shown in Figure 2.

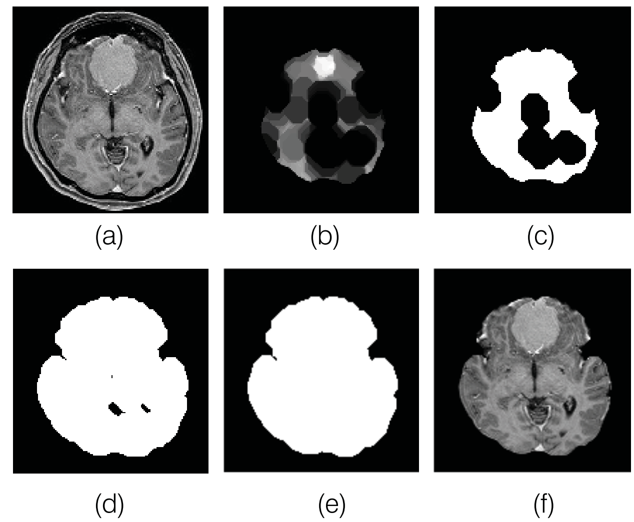

Figure 2 : Skull removal process results (a) Original MR brain image I; (b) Eroded image I_1; (c) Binarized image I_2; (d) Dilated image I_3; (e) Brain mask ;(f) Segmented brain image

b) Co-clustering algorithm

Clustering is a collection of similar image gray levels divided into segments. Co-clustering [2, 10] is the simultaneous partitioning of the rows and columns of an image matrix. This algorithm could be used to find *k*-clusters of MR brain images. The co-clustering algorithm can be summarized as follows:

Input: MR brain image of size $i \times j$ ($I_{i,j}$) and number of clusters (k)

Output: Segmented MR brain image with k clusters

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1. Form $I_n = D_1^{\frac{-1}{2}} \times I \times D_2^{\frac{-1}{2}}$ where $D_1(i,i) = \sum_j I_{i,j}$ and $D_2(j,j) = \sum_i I_{i,j}$
2. Compute [$L = \log_2 k$] singular vectors of I_n
3. Apply singular value decomposition (SVD) technique on I_n to obtain

$$[U\ S\ V] = SVD(I_n) \qquad (4)$$

Where U and V represent the left and right eigenvector of 2[nd] to (L+1)[th] eigenvalues.

$$U = [u_2, u_3, \ldots, u_{L+1}] \text{ and } V = [v_2, v_3, \ldots, v_{L+1}]$$

4. Form the matrix

$$Z = \begin{bmatrix} D_1^{\frac{-1}{2}} \times U \\ D_2^{\frac{-1}{2}} \times V \end{bmatrix}$$

5. The *k*-means algorithm is applied on the *L*-dimensional data *Z* to get the *k* number of clusters.
6. Find out the mean of the centers and their indices from the obtained clusters.

7. Extract the segmented portion by indexing the obtained L-dimensional data with respect to the original image.
8. Apply the morphological region filling operator to refine the tumor region.

III. Evaluation Metrics

a) Performance estimation

The evaluation of tumor extraction results by the proposed method and the FCM algorithm was compared with the manually segmented tumors to measure its effectiveness. The manual segmentations were provided by medical experts, which might include abnormal tissues, like edema, along the tumor region. Let M be the manually segmented tumor and A be the segmented tumor by the proposed method or the FCM algorithm asshown in Figure 3. Here, the Similarity Index (SI), Correct Detection Ratio (CDR), Under Segmentation Error (USE), Over Segmentation Error (OSE), Hausdorff Distance (HD) and Average Surface Distance (ASD) were used for efficiency evaluation.

SI is a measurement that gives the true segmented region, which is relative to the total segmented region in both the segmentations.CDR value indicates the degree of trueness of the actual tumor. USE is the ratio of the number of voxels falsely identified as tumor portion by the proposed method to the manually segmented tumor. OSE is the ratio of number of voxels falsely identified non tumor region by the proposed method to the manual segmented tumor. Total Segmentation Error (TSE) is the sum of USE and OSE. HD is the largest difference between two surfaces and ASD illustrates how much the two surfaces differ on average. All these performance metrics also apply to FCM algorithm. The evaluation metrics SI, CDR, USE, OSE, HD, and ASD were obtained by using equations (5), (6), (7), (8), (9) and (10) respectively [5,6,7,15].

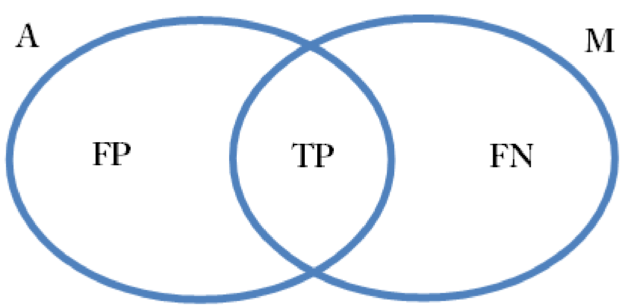

Figure 3 : Venn diagram representation of M, A, TP, FP and FN

$$\mathrm{SI} = \frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FP}+\mathrm{FN}} \times 100\% \quad (5)$$

$$\mathrm{CDR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \times 100\% \quad (6)$$

$$\mathrm{USE} = \frac{\mathrm{FP}}{\mathrm{TP}+\mathrm{FN}} \times 100\% \quad (7)$$

$$\mathrm{OSE} = \frac{\mathrm{FN}}{\mathrm{TP}+\mathrm{FN}} \times 100\% \quad (8)$$

Where True Positive (TP) is the number of pixels detected correctly, False Positive (FP) is the number of pixels detected falsely as tumor and False Negative (FN) is the number of pixels detected falsely as non tumor.

$$\mathrm{HD}\ (\mathrm{M,A}) = \max\ (\mathrm{h(M,A)},\ \mathrm{h\ (A,M)}) \quad (9)$$

Where $h(M,A) = max_{m \in M} min_{a \in A} d(m,a)$, and $d(m,a)$denotes the Euclidean distance between m and a (m and a are points of M and A respectively)

$$\mathrm{ASD(M,a)} = \frac{1}{2}[\mathrm{d_{mean}(M,A)} + \mathrm{d_{mean}(A,M)}] \quad (10)$$

$$\text{where } \mathrm{d_{mean}(M,A)} = \frac{1}{\mathrm{N_M}} \sum_{\mathrm{m \in M}} \mathrm{D(m,A)}$$

$$\mathrm{D(m,A)} = [\mathrm{min}_{\mathrm{a \in A}} \mathrm{d(m,a)}]$$

b) Volume estimation

The volume of tumor V_t was estimated by Cavalier's estimator of morphometric volume method [11].The Cavalier's method was formulated on equally spaced slices of images using equation (11).

$$\mathrm{V_t} = \mathrm{d}(\textstyle\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{y_i}) - \mathrm{t y_{max}} \quad (11)$$

Where'd' is the distance between each slice, 'y_i' is the area of slice 'i', 'n' is the total number of slices, 't' is the slice thickness, and 'y_{max}' is the maximum value of 'y'.

IV. Results and Discussions

The proposed method was verified on MRI brain image data sets of five patients named as patient 1 to patient 5, and one slice was selected from each patient's data set in random to evaluate the performance of the proposed method. Volume estimation has been done by taking all necessary slices of patient 1. These data sets have been acquired on a Philips Achieva 1.5T apparatus by an axial T1-weighted sequence. The slice thickness for patient 1 was 1.5mm, and the spacing between the adjacent slices was 0.9mm. The details of the data sets used are given in Table I. Data sets were collected from the Department of Radiology and Imaging Science, Apollo Health City, Hyderabad, India.

The evaluated segmentation results at pixel level are shown in Table II, and the extracted result of a meningeal tumor is shown in Figure.4 for the slice 105 of patient 3. It can be observed that the results exhibit close proximity to the manually segmented images by the experts and are superior to FCM. Quantitative results obtained by the proposed method in comparison with FCM are given in Table III.

From the Table III, the SI of the proposed method varies from 87.73% to 94.08% but for FCM it is

72.16% to 87.76% .The CDR of the proposed method ranges from 85.52% to 95.86%, and for FCM it is 85.69% to 91.61%. The TSE of the proposed method changes from 12.07% to 26.24%, and for FCM it is 24.75% to 70.69%.HD ranges from 5.4772 to 6.8557 for the proposed method and 5.6569 to 6.8557 for FCM, which proves a good position of the periphery of the tumors of the proposed method. ASD changes from 0.6375 to 1.3081 for the proposed method and 0.8761 to 1.5530 for FCM. The volume of tumor for patient 1 is 41,486mm^3 for the proposed method when compared with the value of 43,547mm^3 for manual segmentation shows close proximity as shown in Table IV.

Table I : Details of Data Sets Used

Patient	Gender	Age	Tumor Type
1	Male	54	Meningioma
2	Male	42	Cystic glioma
3	Female	48	Meningioma
4	Male	31	Dural tumor
5	Male	46	Metastatis

Table II : Evaluation of Segmentation Results at Pixel Level

Patient	Slice Number	FCM			Proposed Method		
		TP	FP	FN	TP	FP	FN
1	83	420	243	64	454	97	30
2	95	988	133	165	986	92	167
3	105	1255	191	159	1239	12	175
4	112	1201	258	150	1260	78	91
5	120	797	542	73	834	69	36

Table III : Evaluation of Segmentation Results of Tumors by the Proposed Method and Fcm

Patient	Slice No.	FCM							Proposed Method						
		SI	CDR	USE	OSE	TSE	HD	ASD	SI	CDR	USE	OSE	***TSE***	***HD***	***ASD***
1	83	72.23	86.78	50.21	13.22	63.43	5.6569	0.8761	87.73	93.80	20.04	6.20	26.24	5.4772	0.6375
2	95	86.90	85.69	11.54	14.31	25.85	6.3246	1.1738	88.39	85.52	7.98	14.48	22.46	6.4807	1.1296
3	105	87.76	88.76	13.51	11.24	24.75	6.7823	1.4961	92.98	87.62	0.85	12.38	13.23	6.5574	1.3025
4	112	85.48	88.90	19.10	11.10	30.20	6.8557	1.5530	93.72	93.26	5.77	6.74	12.51	6.8557	1.3081
5	120	72.16	91.61	62.30	8.39	70.69	6.2450	1.4178	94.08	95.86	7.93	4.14	12.07	6.4031	0.9403

Table IV : Estimation of Tumor Volume for Patient-1

Volume of tumor using manual segmentation (mm^3)	Volume of tumor using the proposed method (mm^3)
43,547	41,486

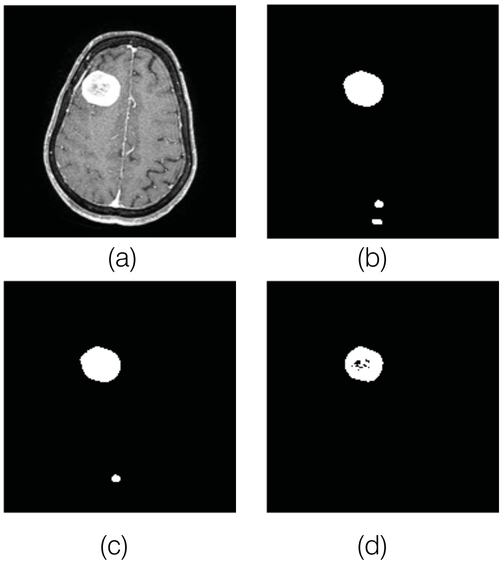

Figure 4 : Tumor extraction result of a meningeal tumor: (a) One axial slice of the selected tumor class; (b) Extracted tumor by the FCM; (c) Extracted tumor by the proposed method; (d) Manually segmented tumor

V. Conclusion

The presented tumor segmentation method was tested on five abnormal MRI brain slices of different patients, and the volume was evaluated for one of the patients. It was observed that integrating co-clustering with morphological operators minimizes segmentation error when compared with FCM. The qualitative evaluation of the obtained results for the proposed tumor extraction method achieved a good performance. A future scope in this area intends in finding the type of tumor based on ontology of tumors and segmentation of edema.

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