Brain Tumor Extraction from T1- Weighted MRI using Co-clustering and Level Set Methods

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Abstract

The aim of the paper is to propose effective technique for tumor extraction from T1-weighted magnetic resonance brain images with combination of co-clustering and level set methods. The co-clustering is the effective region based segmentation technique for the brain tumor extraction but have a drawback at the boundary of tumors. While, the level set without re-initialization which is good edge based segmentation technique but have some drawbacks in providing initial contour. Therefore, in this paper the region based co-clustering and edge-based level set method are combined through initially extracting tumor using co-clustering and then providing the initial contour to level set method, which help in cancelling the drawbacks of co-clustering and level set method. The data set of five patients, where one slice is selected from each data set is used to analyze the performance of the proposed method. The quality metrics analysis of the proposed method is proved much better as compared to level set without re-initialization method.

Keywords: Magnetic Resonance Imaging, Tumor Extraction, Co-clustering Method, Level Set Method.

1. INTRODUCTION

Brain tumor is considered to be one of the significant diseases which require a controlled and timely diagnosis and treatment. It alarms an emergence of improved medical imaging techniques to be developed for treating the disease [1]. These technological innovations lead to early pathological diagnosis, their follow-ups, planning and guidance for surgeries along with quantitative analysis of the images. Among all imaging techniques, Magnetic Resonance Imaging (MRI) plays a vital role due to its ability in generating multi planar, good contrast, spatial resolution with anatomical details and capability to create 3D images for analyzing anatomy of brain in more in depth way in order to identify pathologies.

In brain tumor analysis, segmentation of abnormal tissues, anatomical structures and pathologies from MRI in particular, plays a predominant role. The results from this segmentation are the foundation for further analysis. It is necessary to change the segmentation methods depending on the hard and soft tissues and image modalities. In addition to, segmentation of MR brain images is a daunting task because they generally involve a large amount of data. While undergoing MRI some artifacts will occur due to the patient's movements. Leading to the soft tissue boundaries which also can not be well defined.

When we deal with brain tumors, various other problems also arise making their segmentation more difficult. There are large number of types of tumors having a variety of shapes and sizes. These may be located at any place in the brain with various intensities. Sometimes, some of them will deform the surrounding structures that alter the intensities around the tumor. With the existence of different MR acquisition protocols different information is provided on the brain highlighting the region of the tumor.

Several segmentation methods such as thresholding, watershed, level set, zero crossing and region-based segmentation are used for tumor segmentation. In these methods, some methods are region based and they have a main disadvantage at the boundary of tumors. They suffer from misclassification of pixels and hence, it is hard to have a crisp region of tumor. Some of the methods are edge based and are suffer from initialization problems. But the medical images have both of two properties that are required to be overcome to get effective brain tumor extraction. Looking at the advantages of boundary based and region based methods, the third class of tumor segmentation methods was designed , which is the combination of region and boundary based techniques.

The first approach of this type was presented by Zhu and Yang [2].In their study they used thresholding and morphological operations. Law et al.,[3] proposed another method by integrating FCM clustering with the conventional snake. Chen et al.,[4] presented a new hybrid framework by integrating Gibbs model, marching cubes and parametric deformable models. Ho et al.,[5] presented a method to segment brain tumors by combining level set and fuzzy clustering. Taheri et al.,[6] combined threshold based method and level set to segment the brain tumor.

It is observed that co-clustering [7, 8], which is the region based segmentation method, is the effective clustering technique for the brain tumor extraction [9]. The level set without re-initialization [10], which is edge-based technique, is also efficient for the tumor extraction from MR brain images. Hence, in this paper both co-clustering region based technique is integrated with level set [10] edge based technique for taking advantages of both techniques while reducing their drawbacks to acquire effective tumor extraction of MR brain image. For this hybrid approach firstly tumor is extracted using co-clustering and then given this as the initial contour to level set. The experimental analysis of the proposed method is proved much better when compared with level set without re-initialization.

The overall structure of the research paper is demonstrated as follows; the second section provides the overview of co-clustering method. Third section illustrates level set without re-initialization overview. Fourth section describes the proposed technique steps, which is combining the co-clustering and level set methods. Fifth section illustrates regarding collected results with the evaluation of performance based on chosen evaluation metrics. Sixth section summarizes the proposed methodology of the research problem and gives future recommendations.

2. CO-CLUSTERING

The clustering is a collection of similar gray levels in the image, where gray levels are divided into diverse segments. On the other hand, co-clustering is partitioning of rows and columns simultaneously for an image [7, 8]. This kind of algorithm is significant in finding k-cluster of MR brain images. The T1-weighted MR brain images are skull stripped using [9] before applying to co-clustering algorithm.

The algorithm of co-clustering is summarized as follows:

Input: Skull stripped T1-weighted MR brain image of size $i \times j$ ($I_{i,j}$) and Number of clusters (k)
Output: Segmented MR brain image with k clusters

1. Form $\mathrm{I_n} = \mathrm{D}_1^{\frac{-1}{2}} \times \mathrm{I} \times \mathrm{D}_2^{\frac{-1}{2}}$ where $\mathrm{D_1(i,i)} = \sum_j \mathrm{I_{i,j}}$ and $\mathrm{D_2(j,j)} = \sum_i \mathrm{I_{i,j}}$

2. Compute $\mathrm{L} = \lceil \log_2 \mathrm{k} \rceil$ singular vectors of $\mathrm{I_n}$

3. Apply singular value decomposition (SVD) technique on $\mathrm{I_n}$ to obtain

   $[\mathrm{U\ S\ V}] = SVD(\mathrm{I_n})$

   where U and V represent the left and right eigenvector of 2nd to (L+1)th eigen values.
   $\mathrm{U} = [\mathrm{u_2, u_3, \ldots.., u_{L+1}}$ and $\mathrm{V} = [\mathrm{v_2, v_3, \ldots.., v_{L+1}}]$

4. Form the matrix $\mathrm{Z} = \begin{bmatrix} \mathrm{D}_1^{\frac{-1}{2}} \times \mathrm{U} \\ \mathrm{D}_2^{\frac{-1}{2}} \times \mathrm{V} \end{bmatrix}$

5. The k-means algorithm is applied on the L -dimensional data Z to obtain 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 respective to original image.

8. Apply morphological region filling operator to refine the tumor region.

Co-clustering is found taking advantage from the duality between the columns and rows, in order to deal with the high dimensional data influentially. There is a limitation of over segmentation, associated with co-clustering based image segmentation. Thus, in order to overcome the issue of over segmentation, integration of edge based segmentation will give better results.

3. LEVEL SET WITHOUT RE-INITIALIZATION

Osher and Sethian [11] initially introduced level set methods for capturing moving fronts. The level set method is the effective way to demonstrate active contour, which helps in MR brain tumor segmentation. Recently, several research works have been done on the geometric active contours [12-16], where active contours applied through level set method to address the broad range of image segmentation problems in image processing and computer vision.

Active contours employed through level set methods can be formulated as zero level set of a time dependent function ϕ *that varies according to the equation (1).*

$$\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0 \qquad (1)$$

Equation (1) is known as level set equation. Here, F is called speed function depending on image data and level set function ϕ. While implementing the level set method, it is compulsory to keep the evolving level set function close to a signed distance function in order to sustain stable curve evolution. Yet, the process of re-initialization makes the total computation expensive. It also causes numerical error in the location of the zero level set.

In this paper, we have used a level set evolution method which is based on energy penalty term without re-initialization introduced by Li Chunming et al., [10].

Let I be an image, and g be the edge indicator function defined by equation (2).

$$g = \frac{1}{1+|\nabla G_\sigma * I|^2} \qquad (2)$$

where G_σ is the Gaussian kernel with standard deviation σ.

The external energy for a function $\phi(x, y)$ is defined as

$$\mathcal{E}_{g,\lambda,v}(\phi) = \lambda\mathcal{L}_g(\phi) + v\mathcal{A}_g(\phi) \tag{3}$$

where $\lambda > 0$ and v are constants.

The terms $\mathcal{L}_g(\phi)$ and $\mathcal{A}_g(\phi)$ can be defined as

$$\mathcal{L}_g(\phi) = \int_\Omega g\delta(\phi)|\nabla\phi|dx\, dy \tag{4}$$

$$\mathcal{A}_g(\phi) = \int_\Omega gH(-\phi)dx\, dy \tag{5}$$

where δ is the univariate Dirac function, and H is the Heaviside function.

The total energy function is defined as

$$\mathcal{E}(\phi) = \mu\mathcal{P}(\phi) + \mathcal{E}_{g,\lambda,v}(\phi) \tag{6}$$

Here, the total energy function contains both an internal energy term and an external energy term. The internal energy term $\mathcal{P}(\phi)$ penalizes the deviation of the level set function from a signed distance function and the external energy term $\mathcal{E}_{g,\lambda,v}(\phi)$ drives to motion of the zero level set to the required image features like object boundaries.

The evolution equation of the level set function is defined as

$$\frac{\partial\phi}{\partial t} = \mu\left[\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] + \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + vg\delta(\phi) \tag{7}$$

4. PROPOSED METHODOLOGY

The hybrid approach is being proposed to acquire the best possible methodology for effective tumor extraction results. The proposed algorithm can be summarized as follows:

Step 1: The first step of the combined methodology is to read the T1-weighted MR brain image.

Step 2: Apply morphological operations [9] on T1-weighted MR brain image to remove non brain data (skull, fat, skin, muscle).

Step 3: After removing the non brain region from the T1-weighted MR brain image, use co-clustering algorithm, in order to extract the tumor region [9].

Step 4: The tumor region obtained in the step 3, is to be defined as initial contour for level set method.

Step 5: Use the initial contour, which is defined in the step 4 of the methodology in order to obtain final tumor contour, by level set without re-initialization [10], which is defined in equation (7).

In order to understand the proposed methodology more clearly diagrammatic illustration is provided in Figure 1. It can be observed that after doing initial segmentation of tumor through co-clustering, there is a need to refine the segmentation by the level set without re-initialization. Thus, after applying both the methods in this proposed methodology, evaluation of the segmentation is done systematically.

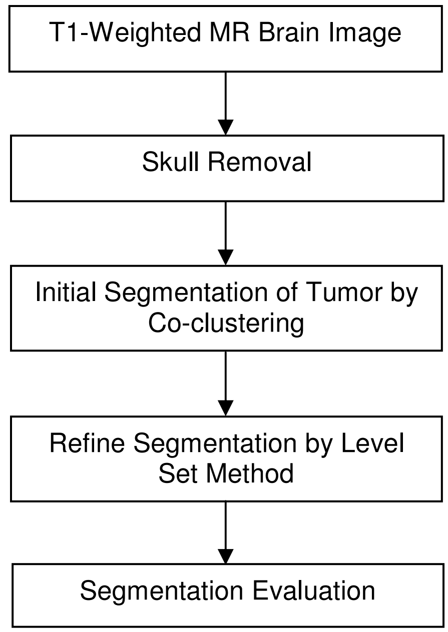

FIGURE 1: Diagrammatic Illustration of the Proposed Methodology.

5. RESULTS AND DISCUSSION

5.1 Data Sets

Data sets were collected from the Department of Radiology and Imaging Science, Apollo Health City, Hyderabad, India and Lucid Diagnostics, Hyderabad, India. These data sets have been acquired on 1.5T Philips achieva apparatus and 1.5T G.E apparatus using an axial T1-weighted sequence with contrast agent. The proposed method was verified on MR brain image data sets of five patients named as Patient 1 to patient 5 where one slice was selected from the data set of each patient to analyze the performance of the proposed method.

5.2 Evaluation Metrics

The evaluation metrics for analyzing the proposed methodology includes:

Similarity Index (SI): SI is the measurement, which provides true-segmented region relative to the total segmented region.

$$SI = \frac{2TP}{2TP+FP+FN} \times 100\% \quad (8)$$

where TP is the number of pixels detected correctly, FP is the number of pixels detected falsely as tumor and FN is the number of pixels detected falsely as non-tumor.

Correct Detection Ratio (CDR): The CDR value indicates the degree of trueness of the actual tumor.

$$CDR = \frac{TP}{TP+FN} \times 100\% \quad (9)$$

Total Segmentation Error (TSE): It is the sum of Under Segmentation Error (USE) and Over Segmentation Error (OSE).

$$TSE = USE + OSE \quad (10)$$

where $USE = \frac{FP}{TP+FN} \times 100\%$ and $OSE = \frac{FN}{TP+FN} \times 100\%$

5.3 Discussion

In this paper, we have evaluated the tumor extraction results based on the suitable evaluation metrics like SI, CDR and TSE, and analyzed the outcomes of the proposed methodology quality metrics values with the level set method [10]. The extracted results of proposed methodology of the tumor are demonstrated in Figure 2 for the slice 95 of patient 2. It is observed that close proximity to the manually segmented images by the experts and are better than level set method. The quantitative results attained by the proposed method in comparison with level set method are provided in Table 1.

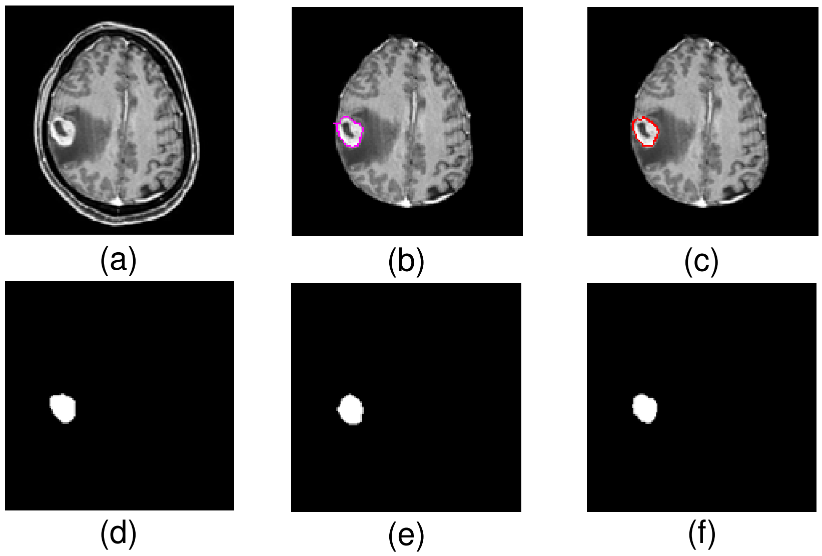

Figure 2: Tumor extraction result of patient 2 of slice 95 (a) One axial slice of the selected tumor class (b) Initial contour for proposed method (c) Final contour of proposed method (d) Final extracted tumor by the proposed method (e) Extracted tumor by the level set without re-initialization (f) Manually segmented tumor.

Patient	Slice No.	Method	SI (%)	CDR (%)	TSE (%)
1	101	Level Set	85.246	100	34.615
		Proposed Method	88.954	96.795	24.038
2	95	Level Set	91.12	100	19.491
		Proposed Method	96.305	98.488	07.5577
3	167	Level Set	80	100	50
		Proposed Method	87.826	91.818	25.455
4	120	Level Set	83.119	100	40.618
		Proposed Method	93.268	98.284	14.188
5	83	Level Set	81.569	100	45.192
		Proposed Method	90.942	97.5	19.423

Table 1: Comparison of evaluation metrics obtained using the proposed method and level set method.

It is observed from the Table 1 that the SI of the proposed methodology varies from 87.826% to 96.305% but for level set method it is 80% to 91.12%. The CDR ranges from 91.818% to

98.488% for the proposed method. But for the level set method for all the five images CDR is 100% which is due to under segmentation. The TSE ranges from 07.5577% to 25.455% for the proposed method and for level set method it is 19.491% to 50%, which confirms good results of the proposed methodology as compared to level set without re-initialization.

6. CONCLUSION

The proposed tumor extraction method was tested on five abnormal brain slices of different patients ranges from patient 1 to patient 5 and the performance was evaluated based on the SI , CDR and TSE evaluation metrics. It is observed that combining level set without re-initialization with the co-clustering technique in the proposed methodology reduces the segmentation error and provided much better quality metrics values as compared to the level set without re-initialization. In the future research, the effect of the prior information on the object boundary extraction with the level set method such as shape and size can be further analyze. Moreover, the performance of the image segmentation method can be evaluated with other quality metrics along with SI, CDR and TSE to analyze the results more efficiently.

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