Automatic Segmentation Framework for Primary Tumors From Brain MRIs Using Morphological Filtering Techniques

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Abstract— **This paper describes a novel framework for automatic segmentation of primary tumors and its boundary from brain MRIs using morphological filtering techniques. This method uses T2 weighted and T1 FLAIR images. This approach is very simple, more accurate and less time consuming than existing methods. This method is tested by fifty patients of different tumor types, shapes, image intensities, sizes and produced better results. The results were validated with ground truth images by the radiologist. Segmentation of the tumor and boundary detection is important because it can be used for surgical planning, treatment planning, textural analysis, 3-Dimensional modeling and volumetric analysis.**

Key words- *Segmentation; Morphological filtering; Dilation; Erosion; Primary tumor; Tumor boundary; Brain MRI.*

I. INTRODUCTION

A primary brain tumor is one that originates in the brain itself. The gray level segmentation of brain tumors is most important because it can be used for guiding therapy, surgical planning and overall prognosis in patients with brain tumors. The segmentation task becomes more challenging when one wants to derive common decision boundaries on different object types in a set of images. There are many issues and challenges associated with brain tumor segmentation. Due to the complex structure of different tissues such as white matter (WM), grey matter (GM) and cerebrospinal fluid (CSF) in the brain images, extraction of useful feature is a fundamental task. Brain tumors may be of any size, may have a variety of shapes, may appear at any location, and may appear in different image intensities. Some tumors also deform other structures and appear together with edema that changes intensity properties of the nearby region. Manual segmentation is a difficult and time consuming task, which makes an automated brain tumor segmentation method preferable [1].

The most common MRI modalities used to assess tumors are Fluid Attenuated Inversion Recovery (FLAIR), T1 and T2-weighted modalities. T1-weighted modalities highlight fat tissue in the brain whereas T2-weighted modalities highlight tissue with higher concentration of water. FLAIR images are T2 or T1-weighted with the cerebro spinal fluid (CSF) signal suppressed. In general, edema, border definition and tumor heterogeneity are best observed on FLAIR and T2-weighted images [2]. Intensity is an important feature in discriminating different tissue types in brain MR images. However, using intensity feature alone to segment complex brain tissue and tumor in a single modality MR image has been proved to be insufficient [3]. Therefore, there is a strong need to have an efficient automated system that accurately defines the boundaries of brain tumor tissues along with minimizing the chances of user interaction with the system.

Various segmentation techniques have been cited in the literature for improving the segmentation processes and for introducing maximum possible reliability. Currently available segmentation can be categorized into unsupervised and supervised methods [4]. Unsupervised fuzzy clustering techniques [5], Tumor Extraction by Combining k-means Clustering and Perona-Malik Anisotropic Diffusion Model [6], Brain Tumor segmentation from MRI Based on Energy Functional [7], unsupervised automatic segmentation algorithm using expectation maximization [8] technique, binary mathematical morphology [9, 10], Automatic seeded region growing method [11] and Segmentation with Radix4 FFT [12] are some of the examples based on unsupervised method. Segmentation using knowledge based techniques [13], fuzzy based segmentation [14, 15], segmentation using texture analysis [16], Adaptive template moderated [17] and Atlas based segmentation [18] are some of the supervised segmentation techniques. Supervised algorithms are usually very slow to train and require a lot of manually segmented data. These algorithms are often inadequate for the segmentation of glioma, because the heterogeneity within and between different MR images of the same type makes it difficult to distinguish between different tissue types based on pixel intensity values alone. Unsupervised techniques do not employ a priori information, the final segmentations are sensitive to noise and usually do not result in continuous regions. Unsupervised segmentation methods divide an image into homogenous regions based on an objective measure of homogeneity. Problems in brain volume extraction arise [16] because there is a great deal of overlap in intensity values between the non-brain and brain tissues and because the two can often appear connected. One method to deal with these difficulties is to allow for some loss of brain tissue in a preliminary segmentation step and then to recover the tissue using morphological filters [15, 18].

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This work highlights a novel method for automatic extraction of primary tumor mainly glioma and its boundary using morphological methods. In this method, T2 weighted and T1 FLAIR images were used for extracting these features. Section II provides a brief overview of image enhancement, and segmentation techniques. Section III details results obtained and discussion and finally, a conclusion about the results is presented.

I .METHODS AND MATERIALS

Fig.1 shows the flow chart for the entire procedure. The steps involved are image pre-processing, segmentation of ROIs, Feature extraction process and validation.

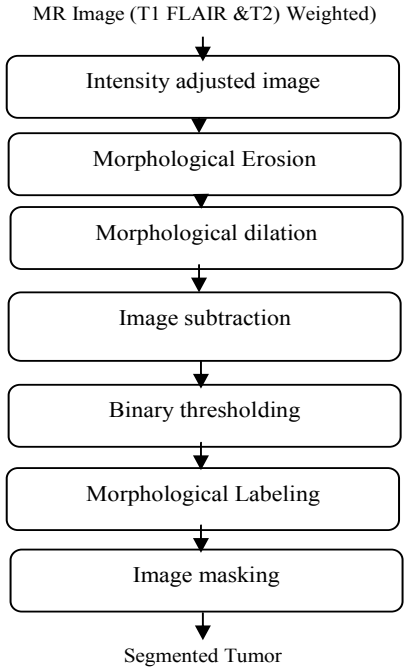

Figure 1 The flow chart for Segmentation of tumor and its boundary

A. Image Acquisition

In this work, MRI images were collected from the Department of Radiology, Sree Chitra Institute of Medical Sciences and Technology (SCIMST) and Regional Cancer Centre, Thiruvananthapuram, Kerala, India. The images were gray scale images. Axial slices of T2 weighted and T1 FLAIR brain MRI data were considered. In this method, segmentation of Regions of Interest (ROI) was calculated on fifty MR image data sets with each set contains 20 slices. Image database development and validation of the algorithms were based on this MRI database which was already manually identified and segmented by the Radiologist. The selected images were histo-pathologically tested by the radiologists and have confirmed the presence of the disease.

B. Image preprocessing and segmentation of tumor and its boundary

The goal of this segmentation process in this work is to extract the tumor and its boundary from the surrounding tissues for each slice which includes the presence of tumor. T1 FLAIR and T2 weighted images of the same slice are used for tumor extraction and boundary detection as shown in Fig.2a and b.

As a part of pre processing skull stripping was performed. Skull stripping is a method of removing the skull and non brain intracranial tissues like fat, muscle, skin etc., which surrounds the surface of brain cortex and cerebellum in the brain. Brain Extraction was necessary to avoid the misclassifications of surrounding tissues, skin and scalp as WM or GM. By removing this object, non-brain tissues will be removed and only soft tissues will remain in the image. Skull stripping was based the on morphological operation known as erosion, using a disc shaped structuring element, which resulted in the removal of thin connections between brain the and non brain portions. Thus a skull stripped brain mask (Fig.2c) was obtained and this method was automated for every image slice

Mathematical expression for erosion of A by B is given by: $I_1 = A \ominus B = \{w: B_w \subseteq A\}$ where 'A' is the image being processed, and 'B' is a small set of pixels called the structuring element (SE). It is a thinning operation. The level of thinning depends upon the structure and shape of the SE chosen. The image obtained after erosion is the skull stripped image 'I_1'.

Next the brain component 'I_1' was dilated by a SE 'B1', slightly smaller in size than the one used in the morphological erosion, this corresponds approximately to restoring the boundaries of the brain component that were distorted in the erosion step.

Dilation of 'I_1' by 'B_1' is given by: $I_2 = I_1 \oplus B_1 = \bigcup_{x \in B_1} I_{1x}$. It is a thickening operation. For the entire morphological operations in this work, disc shaped structuring elements were selected with varying diameter depending upon the nature of the structure to be segmented.

Intensity adjustment (Fig.2d) and thresholding was done to obtain binary thresholded image (Fig.2e). Binary image thus obtained was morphologically labeled for obtaining the largest connected component. This leads to obtain a binary mask (Fig.2f) of the brain tumor. A gray level volume was obtained by masking the initial MR image by this mask. In this way, all pixels outside the tumor were set to 0, while the others keep their initial value that was used for further analysis as shown in Fig. 2g.

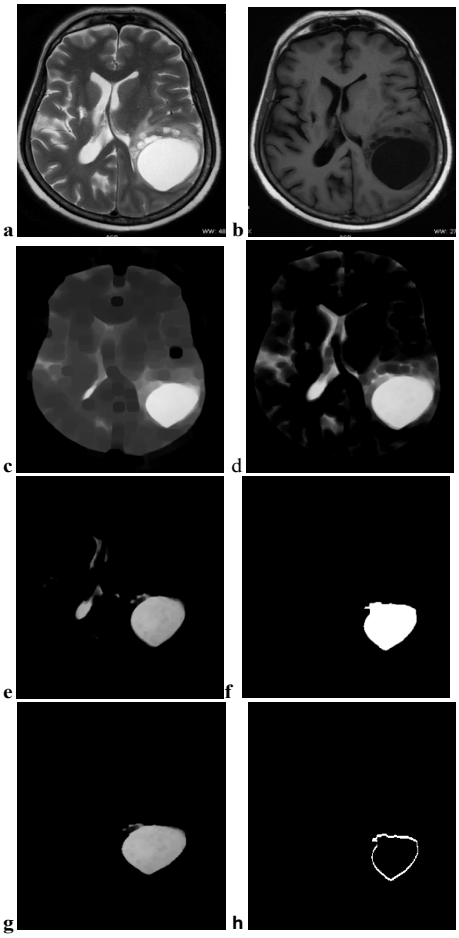

Figure2 Shows the segmentation procedures for tumor and its boundary. a.T2-weighted image b. T1-FLAIR image c. Skull stripped image after erosion d. Subtracted image from dilated image and complemented image e. Thresholded image f. Binary tumor mask g. segmented grey level tumor **h.** Tumor boundary

The heterogeneous tumor border as shown in Fig. 2h was defined and the maximum perimeter of the tumor was determined from the benchmark images. Bench mark images are the slices which provide maximum information about tumor shape and size.

C. Validation

An experienced radiologist manually segmented 20 tumors contained in our dataset (Ground Truth, GT) and Tanimoto index were calculated [19]

$$Tanimoto\ index: TI[\%] = \frac{TP}{TP + FP + FN} . 100$$

Where TP=true positives, i.e pixels labeled as tumor in the GT and by the algorithm, FP= false positives, i.e. pixels labeled as tumor by the algorithm, but not in GT and FN-false negative, pixels labeled as tumor in the GT, not in the algorithm. Tanimoto index represents percentage ratio between the number of pixels classified as tumor by GT and the algorithm and/or by the GT. The value 100% signifies there are FP and FN

III. RESULTS AND DISCUSSION

This section presents the results obtained from automatic segmentation using morphological methods on T1 FLAIR and T2 weighted axial MR images of the same slice. Segmentation

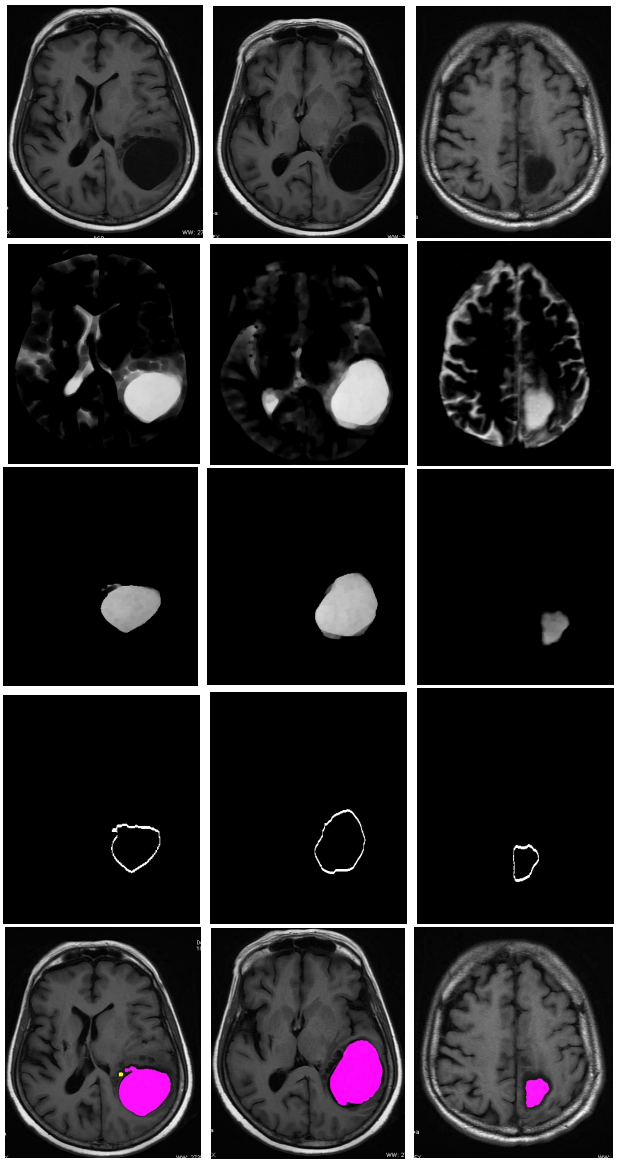

Figure 3 Segmentation results. Each column corresponds to one patient. The rows from left to right illustrates abnormal FLAIR image, Intensity adjusted image, segmented tumor, tumor boundary and segmentation result in FLAIR image after validation

is only implemented for tumor-contained slice. A novel algorithm for the extraction of primary tumors (glioma), preserving its shape and gray level information is developed. Segmented glioma tumors are obtained and are shown in Fig. 3. Presence of partial volume effect on tumors was eliminated using this method by defining the tumor boundary using this robust technique for every segmented tumor. Bench mark images, two or three slices from each patient, were selected for obtaining exact area and perimeter of the tumor and its boundary. The major advantage of this segmentation procedure is that, segmented structures are preserving the gray level values of the original image for processing. For further texture based analysis and classification gray level intensity images are very essential.

The goal of this automated segmentation tool was to make segmentation of MR images more practical by replacing manual outlining of the tumor by Radiologist without any loss in accuracy. Fig.3 shows the results of segmentation algorithm and validated on the different patients' MRI slices. This algorithm showed better performance. The number FP and are very less and TP was very high. Tanimanto index confirms the best performance (98.9 % to 99.8%) with the GT.

IV. CONCLUSION

A novel framework for unsupervised segmentation primary (glioma) tumors and its boundary, using morphological operations is presented in this paper. This method is suitable for segmentation of tumor and its boundary from the heterogeneous features of brain MRI. It is observed that using morphological filtering techniques produced reliable results. Due to un-supervised nature of the approach, the method is very efficient, less error sensitive and less time consuming. Radiologist validated the presence of segmented tumor with ground truth estimates already derived by them. Performance of segmentation was validated by calculating Tanimoto index, which showed better performance with GT. This segmentation procedures are suitable for image registration for surgical planning, detection of tumor growth and thus by determining prognosis of patients in the case of high grade tumors. Partial volume effects were very much reduced in low grade tumors by defining the boundary of the tumor. It may be noted that, the use of this method is fairly simple when compared with other frequently used methods. The segmented ROIs were retaining the gray level values of each pixel. Hence texture quantification using statistical, structural and spectral approach will be more accurate. This leads to the development of new methods for classification and performance of different grades of primary tumors.

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