

## Multiparameter segmentation and quantization of brain tumor from MRI images

Rajeev Ratan<sup>1</sup>, Sanjay Sharma<sup>2</sup> and S. K. Sharma<sup>3</sup>

<sup>1</sup>Department of E & IE, Apeejay College of Engineering, Sohna, Gurgaon, Haryana, India.

<sup>2</sup>Department of ECE, Thapar University, Patiala, Punjab. India.

<sup>3</sup>Department of ECE, Apeejay College of Engineering, Sohna, Gurgaon, Haryana  
sanjay.sharma@thapar.edu

**Abstract:** In this paper, a method for segmentation of brain tumor has been developed on 2D-MRI data which allows the identification (10-15 minutes operator time) of tumor tissue with accuracy and reproducibility comparable to manual segmentation (2-6 hours operator time) making the automatic segmentation practical reality for malignant tumors. In this scheme, after a manual segmentation procedure the tumor identification has been made for the potential use of MRI data for improving the approximate brain tumor shape and 2D visualization for surgical planning.

**Keywords:** Brain tumor, MRI, MATLAB.

### Introduction

Three dimensional segmentation is a reliable approach to achieve a proper estimation of tumor volume. The segmentation can be grouped under: Snakes (Gradient Vector Flow), Level Set Segmentation and Watershed Segmentation (Abbasi & Mokhtarian, 2001). Among all possible methods for this purpose, watershed can be used as a powerful tool which implicitly extracts the tumor surface. Watershed segmentation uses the intensity as a parameter to segment the whole image data set. Moreover, the additional complexity of estimation imposed to such algorithms causes a tendency towards density dependent approaches (Abdel-Halim Elamy & Maidong Hu, 2007).

The aim of this work is to design an automated tool for brain tumor quantification using MRI image data sets. This work is a small and modest part of a quite complex system. The whole system will when completed visualize the inside of the human body, and make surgeons able to perform operations inside a patient without open surgery. More specifically the aim for this work is to segment a tumor in a brain. This will make the surgeon able to see the tumor and then ease the treatment. The instruments needed for this could be ultrasound, Computer Tomography (CT Scan) and Magnetic Resonance Imaging (MRI). The technique employed for this study is Magnetic Resonance Imaging (MRI). Watershed segmentation based algorithm has been used for detection of tumor in 2D and in 3D. MATLAB software was employed to construct 2D structure of tumor. The rest of the paper is organized as follows. Section-2 presents the methodology of the problem, section 3 and 4 gives materials and implementation of the problem. The section 5 gives the results and section 6 leads to conclusion.

### The proposed framework

A conceptually simple supervised block-based and image-based (shape, texture, and content) technique has been used to analyze MRI brain images with relatively lower computational requirements. The process flow of our proposed methodology may be shown as Fig.1:

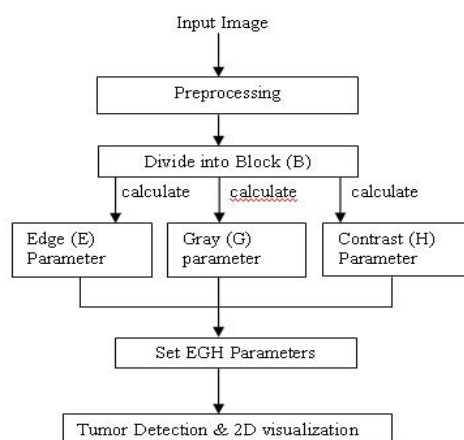


Fig. 1. Proposed Framework

The first section discusses how images are divided into regions using a block-based method. The second section shows how each classified block is studied individually by calculating its multiple parameter values. In this instance, the multiparameter features refer to the following three specific features: the edges (E), gray values (G), and local contrast (H) of the pixels in the block being analyzed (Epifano & Ayala, 2002).

### Input Image

The images we got from MRI are of three types: axial Images, saggital Images, coronal Images. The number of images depend on the resolution of the movement of the MRI magnets.

### Preprocessing

In preprocessing the first step is to load the MRI image data set on to the MATLAB workspace and after loading they will be processed in such a way that instead of processing 128 images in one direction a whole clip of 128 images is processed by one command, otherwise it would have been very hectic situation for processing each and every image independently. Thus after this processing there are only three clips instead of 384 separate images, i.e. one clip for axial images, one clip for saggital images and one clip for coronal images. After that all the clips

are combined to get the single clip for further processing (Bailet *et al.*, 1992, 1997).

#### Multiparameter Calculations

Recent advances in medical image analysis often include processes for an image to be segmented in terms of a few parameters and into smaller sizes or regions, to address the different aspects of analyzing images into anatomically and pathologically meaningful regions. Classifying regions using their multiparameter values makes the study of the regions of physiological and pathological interest easier and more definable. Here, multiparameter features refer to the following three specific values for the edges (E), gray values (G), and local contrast (H) of the pixels (Nakajima *et al.*, 1997; Bountris *et al.*, 2005; Nacim Betrouni *et al.*, 2007).

**Edge (E) Parameter.** Edge information is often used to determine the boundaries of an object. This is mainly used for analysis to derive similarity criterion for a pre-determined object. The incidences of cerebral compression reduce the edge. Given this understanding, we use the Sobel edge detection method to detect image edges ( $I_E$ ) is obtained by filtering an input image with two convolution kernels concomitantly, one to detect changes in vertical contrast ( $H_x$ ) and the other to detect horizontal contrast ( $H_y$ ), shown in equation (1). Image output ( $I_E$ ) is obtained by calculating the gradient magnitude of each pixel, as shown in equation (2). Subsequently, the edge parameter (E) is calculated, whereby  $E(r,c)$  is increased by one each time when  $I_E(x,y) = 1$  in a supervised block, as shown in equation (3)

$$H_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, H_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (1)$$

$$I_E(x,y) = \sqrt{I_x^2(x,y) + I_y^2(x,y)} \quad (2)$$

$$E(r,c) = \sum_{(x,y) \in B} (I_E = 1) \quad (3)$$

**Gray (G) Parameter.** The gray parameter (G) for each block of the brain is accumulated, and controlled by a binary image ( $I_T$ ) using the  $G_D$  value as a threshold, as shown in equation (6).  $G_D$  value is calculated using the average pixel value ( $I_{av_s}$ ) of each image slice (S) for total image slices (T) of an image dataset, shown in equation (4) and (5).

$$I_{av_s} = \frac{1}{65536} \sum I_p(x,y) \quad (4)$$

$$G_D = \frac{\sum_{S=0}^T I_{av_s}}{T} \quad (5)$$

$$G_{(r,c)} = \sum_{(x,y) \in B} I_p(x,y), \forall I_T(x,y) = 1 \quad (6)$$

The pixels intensity for each slice was calculated to establish the threshold values and thus provide the basis for analysis of clinical MR images from patients with brain tumors (Gupta & Undril, 1995; Gering *et al.*, 2002).

**Contrast (H) Parameter.** Contrast (H) is often used to characterize the extent of variation in pixel intensity. In the present technique, the computational program analyses the differences, especially in instances of strong dissimilarity, between entities or objects in an image  $I(x,y)$ .

We adopt the minimum/maximum stretch algorithm for the 8-neighborhood connectivity, where  $\min H$  and  $\max H$  represent the minimum and maximum intensity values of the neighborhood pixel  $C_8(I_H)$ , as shown in equation (7). In the previous studies, tumor cells are often associated with higher value of contrast (H) parameter (Senaratne *et al.*, 2006).  $H_d$  is obtained by totaling the contrast of a supervised block, as shown in equation (8).

$$I_H(x,y) = \left( \frac{I(x,y) - \min H}{\max H - \min H} \right) \times \max H \mid H \in C_8(I_H) \quad (7)$$

$$H_d(r,c) = \sum_{(x,y) \in B} I_H(x,y) \quad (8)$$

#### Materials

The computational analysis is implemented on a IBM Think Centre Pentium IV 2.80GHz computer with 512 MB RAM. The support analysis software used is MATLAB and 3D Slicer. In order to evaluate the performance of our algorithms and methodology, the experiments were conducted on MRI data set.

#### Implementation

##### Preprocessing

Axial, sagittal & coronal images were loaded and viewed in the MATLAB. After this, axial, sagittal & coronal movie clips were prepared and are shown in Fig. 2.

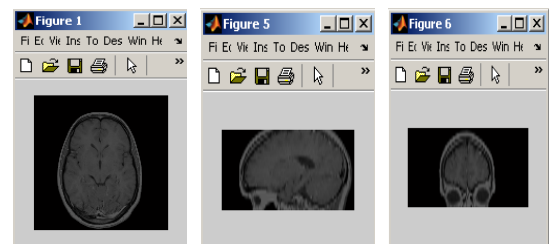


Fig. 2. Axial, sagittal & coronal movie clips

Now all the clips were combined together to produce a single clip.

##### Multiparameter calculations

Recent advances in medical image analysis often include processes for an image to be segmented in terms of a few parameters and into smaller sizes or regions, to address the different aspects of analyzing images into anatomically and pathologically meaningful regions. Classifying regions using their multiparameter values makes the study of the regions

Fig.3. Edge image of MRI data set

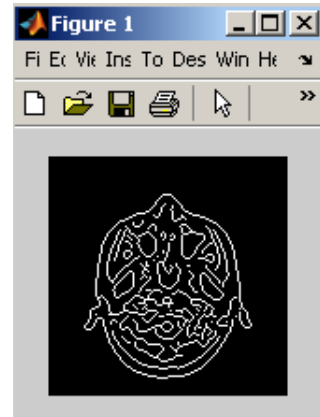


Fig. 5. Intensity image of MRI data set using Watershed Segmentation

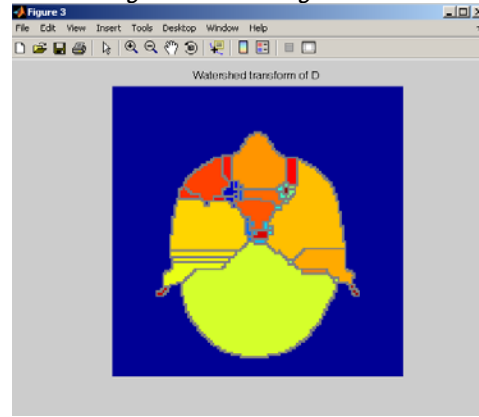


Fig. 4. Binary image of MRI data set

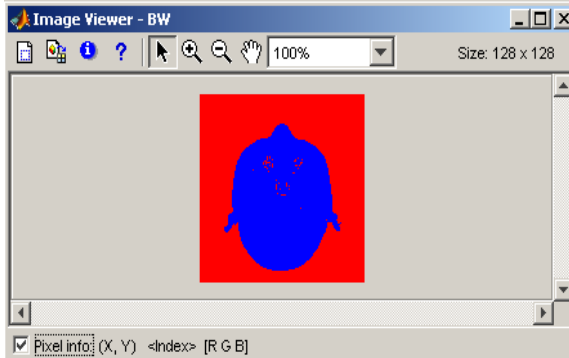


Fig.6. Constructed image after application of ROI command on MRI intensity image

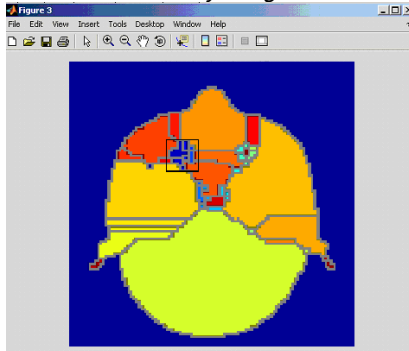


Fig. 7 Enhanced image of the area after application of the ROI command

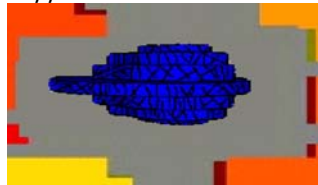
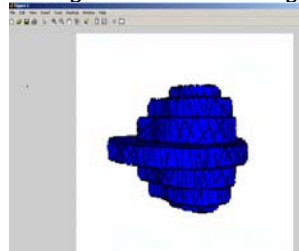


Fig. 8. Segmented Tumor Image-2D



of physiological and pathological interest easier and more definable. Here, multiparameter features refer to the following three specific values for the edges (E), gray values (G), and local contrast (H) of the pixels.

**Edge parameter calculation (E):** Edge information is often used to determine the boundaries of an object. This is mainly used for analysis to derive similarity criterion for a pre-determined object. The reduction of edge count for tumor images is due to the fact that the substance has been pushed aside and compressed by the growth of the tumor within a confined space, the

intracranial cavity. This can be achieved by executing the algorithms and the result obtained may be shown as in Fig. 3.

**Gray parameter(G) calculation:** The gray parameter (G) for each block of the brain is accumulated, and controlled by a binary image using the value as a threshold. Pixels intensity for each slice was calculated to establish the threshold values and thus provide the basis for analysis of clinical MR images from patients with brain tumors. This can be achieved by executing the algorithm and the result obtained may be shown as in Fig. 4.

**Contrast parameter (H) calculation:** Contrast (H) is often used to characterize the extent of variation in pixel intensity. A computational program analyses the differences, especially in instances of strong dissimilarity, between entities or objects in an image using Watershed Segmentation. As we know that malignant tumor cells contain highly proteinaceous fluid, which is represented as high signal intensity on MRI images of the brain (Haney *et al.*, 2001; Hinz *et al.*, 2002). Watershed segmentation can be used for segregating the different intensity portions and this can be achieved by executing the algorithm in MATLAB and the result obtained may be shown as in Fig.5.

**Tumor Block Detection & Visualization(2D):**

**Segmentation of brain tumor using Region of Interest (ROI) Command:**

As it has been seen from the above result that high density images have been separated from the MRI images using Watershed Segmentation. Here main aim is to segment the tumor from the MRI images. This can

be done by using the ROI command in MATLAB. After the application of the ROI command, the tumor may be segmented. This can be achieved by executing the algorithm in MATLAB and the result obtained may be shown as in Fig. 6. The image after the application of the ROI command may be shown as in Fig.7.

**Visualization of Brain Tumor in 2D:** Now the watershed segmentation in 2D is applied to the above figure and the tumor may be segmented. This can be achieved by

executing the algorithm and the result obtained may be shown as in Fig. 8.

### Results

The result of 2D in the form of pixels in X, Y directions are shown in Fig. 5. As the display settings are 1028 X 768 pixels on the monitor of the computer and the dimensions of the monitor are 280mm X 210mm, so the dimensions of the one pixel comes out to be 0.2734mm X 0.2734mm.

Viewing the tumor from different angles the dimensions of tumor appear to be made up of seven different layers. As viewed from upside down the tumor's layer may be given the names as 1<sup>st</sup> upper layer, 2<sup>nd</sup> upper layer, 3<sup>rd</sup> upper layer, middle layer, the layer below middle layer, the second last layer, the last layer. The dimensions of the different layers may be tabulated as:

Name of Layer	Dimensions (Max) (pixels)	Dimensions (Max) (mm-mm)	App. Area (mm <sup>2</sup> )
1 <sup>st</sup> Upper Layer	33*7	9.02*1.91	17.23
2 <sup>nd</sup> Upper Layer	54*11	14.76*3.01	44.43
3 <sup>rd</sup> Upper Layer	63*14	17.22*3.83	65.95
Middle Layer	87*12	23.79*3.28	78.03
Layer Below the Middle	62*13	16.95*3.55	60.17
The Second Last Layer	52*10	14.22*2.73	38.82
The Last Layer	31*19*6	8.48*1.64	13.91
		<b>Total</b>	<b>318.54</b>

Thus we see that the total approximate area of tumor comes out to be 318.14 mm<sup>2</sup> (3.1814 cm<sup>2</sup>)

### Conclusion

The results show that Watershed Segmentation can successfully segment a tumor provided the parameters are set properly. The watershed method did not require an initialization while the others require an initialization inside the tumor. The visualization and quantitative evaluations of the segmentation results demonstrate the effectiveness of this approach. Watershed Segmentation algorithm performance is better for the cases where the intensity level difference between the tumor and non tumor regions is higher. It can also segment non homogenous tumors providing the non homogeneity is within the tumor region. This paper proves that methods aimed at general purpose segmentation tools in medical imaging can be used for automatic segmentation of brain tumors. The quality of the segmentation was similar to manual segmentation and will speed up segmentation in operative imaging.

Among the segmentation methods investigated, the watershed segmentation is marked out best out of all others. The user interface in the main application must

be extended to allow activation of the segmentation and to collect initialization points from a pointing device and transfer them to the segmentation module. Finally the main program must receive the segmented image and present the image as an opaque volume.

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