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Computerised Segmentation of Brain Tumor

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ABSTRACT

A new method for segmentation of brain tumor has been developed on 2D-MRI data. The method allows the identification (10-15 minutes operator time) of tumour tissue with accuracy and reproducibility comparable to manual segmentation (2-6 hours operator time) making the automatic segmentation practical reality for malignant tumours. In this scheme, after a manual segmentation procedure the tumour identification has been made for the potential use of MRI data for improving the approximate brain tumour shape and 2D visualization for surgical planning. The results show that proposed scheme can successfully segment a tumor provided the parameters are set properly.

Keywords: Brain tumor, Magnetic resonance imaging (MRI), image segmentation, Watershed segmentation.

INTRODUCTION

An uncontrolled growth of cells in the brain is called a brain tumor. Brain tumours may be malignant or benign. Suspicious of a brain tumour may first arise from abnormal behaviour or other symptoms. Symptoms are investigated with a series of tests aimed at making a diagnosis. There are many types of brain tumours that differ based on which types of cells make up the tumour. Also, determining the extent of the cancer helps the doctors to understand the likelihood of the tumor spreading into other brain tissues, a characteristic which may also be referred to as the aggressiveness of the tumor.

Computer assisted surgical planning and advanced image guided technology have become increasingly utilized in neurosurgery [1-5]. The availability of accurate anatomical two dimensional (2D) models significantly improves the spatial information concerning the relationships of critical structures and pathology [3-6]. In daily clinical practice, however, commercially available intra operative navigational systems only provide the surgeon with 2D cross-sections of the intensity value images and a 2D model of the skin. The main limiting factor in the routine use of 2D models to identify (segment) important structures is the amount of time and effort that a trained operator has to spend on the preparation of the data. The development of automated segmentation methods has the potential to significantly reduce the time for this process and make such methods practical 3-6].

Although 2D images accurately describe the size and location of anatomical objects, the process of generating 2D views to visualize structural information and spatial anatomic relationships is a difficult task and usually carried out in the clinician's mind. Image processing tools provide the surgeon with interactively displayed 2D visual information which is somewhat similar to the view of the surgeon during surgery, thus facilitating the comprehension of the entire anatomy.

Image based modeling requires computerized image processing methods which include preprocessing, segmentation and display. Segmentation using statistical classification techniques [7,8] has been successfully applied to gross tissue type identification. Because the acquisition of tissue parameters is insufficient for successful segmentation due to the lack of contrast between the normal and the pathologic tissues, statistical classification may not differentiate between the non-enhancing tumour and the normal tissue. Explicit anatomical information derived from a digital atlas has been used to identify normal anatomical structures [11-16].

The authors have developed a segmentation tool which can identify the skin surface, the ventricles, the brain and tumour in patients with brain neoplasm's [17-20, 25]. The purpose of the current study is to compare the accuracy and reproducibility of this tool with those of manual segmentation carried out by the trained personnel.

THE PROPOSED FRAMEWORK

An image-based (shape and texture) technique has been used to analyze MRI brain images. The first block in Figure 1 discusses how images are divided into regions using a block-based method. The second block shows how to classify

each block by calculating the multiple parameter values. In this study, the multi-parameter features refer to: the edges (E), gray values (G), and local contrast (H) of the pixels in the block being analyzed. The proposed methodology is shown in Figure 1[20-25].

Firstly, MRI data is processed in such a way to obtain one movie clip each for axial, saggital and coronal slices. Finally all the clips are combined together to form a single clip. When a single clip of all the images is available, then the edge detection algorithm is applied to the obtained clip, which separates out the edges of different tissues and masses in the image. Then an algorithm is applied to the edge image which separates out the high and low density areas of the brain as shown in MRI image and then watershed algorithm is applied to the binary image which results in the segmentation of the tumour as high density area and the tumour is segmented out using ROI (Region of Interest) command in MATLAB.

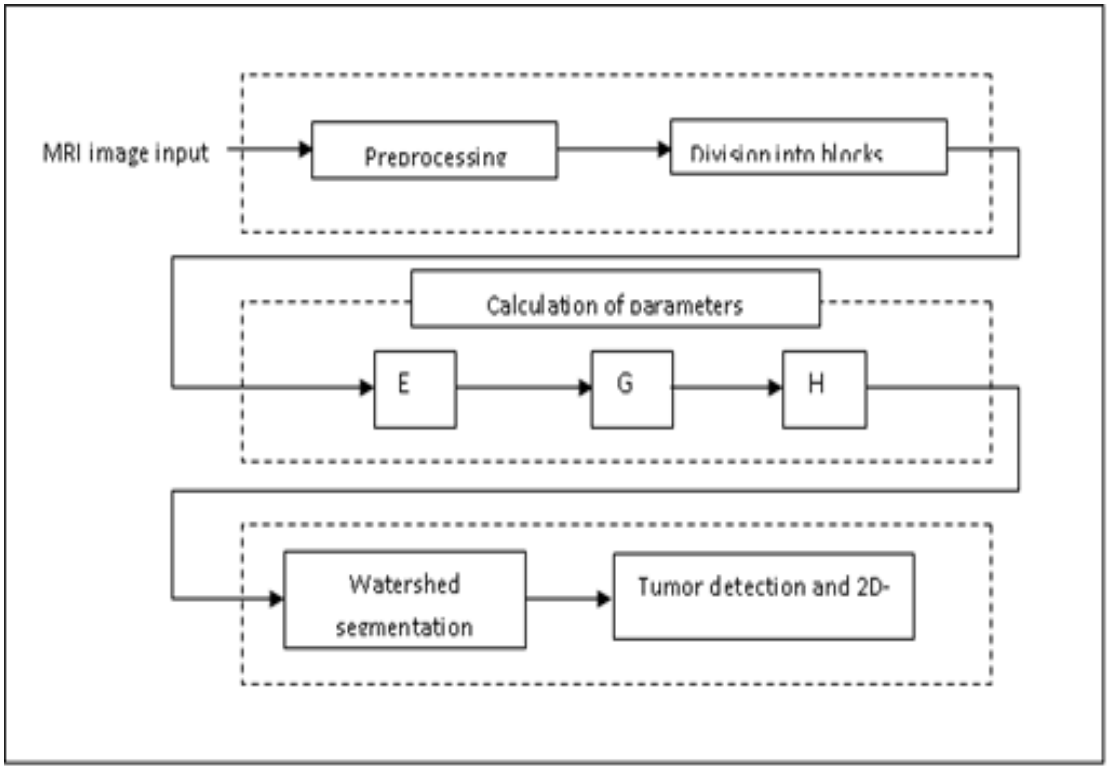

Fig.1: Proposed Framework

IMPLEMENTATION

The computational analysis is performed using MATLAB on a Pentium IV 2.80GHz computer with 512 MB RAM. In order to evaluate the performance of our algorithms and methodology, the experiments are conducted on MRI data set.

Processing

Axial, saggital and coronal images were loaded and viewed in the MATLAB. After this, axial, saggital and coronal movie clips were prepared and are shown in Figure 2.Now all the clips were combined together to produce a single clip.

Edge, Gray and Contrast Parameter Calculations

Edge information is often used to determine the boundaries of an object. 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 tumours. Contrast (H) is often used to characterize the extent of variation in pixel intensity. The result is shown in Figure 3

Fig 2: Axial, Saggital and coronal movie clips

A computational program analyses the differences, especially in instances of strong dissimilarity, between entities or objects in an image using watershed segmentation. Malignant tumour cells contain highly proteinaceous fluid, which is represented as high signal intensity on MRI images of the brain.

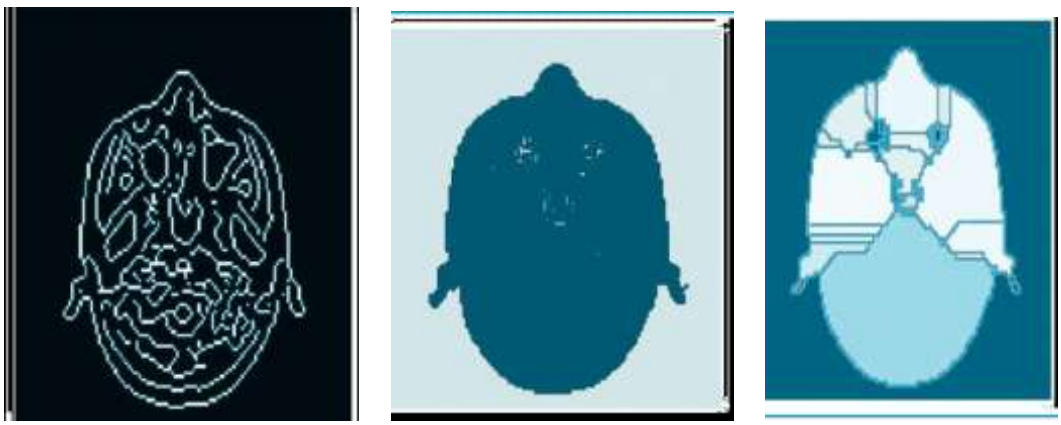

Fig. 3: Edge, gray and intensity image of MRI data set

Tumor Block Detection and Visualization (2D)

The high density images have been separated from the MRI images using the watershed segmentation. The main aim here is to segment the tumour from the MRI image. This can be done by using the ROI command and its application is shown in Figure 4. After initiating the ROI command, the tumour may be segmented and the enhanced image is obtained. With the use of the watershed segmentation in 2D the tumour is segmented and the results are obtained as in Figure 5.

Fig. 4: Image after application of region of interest (ROI) command

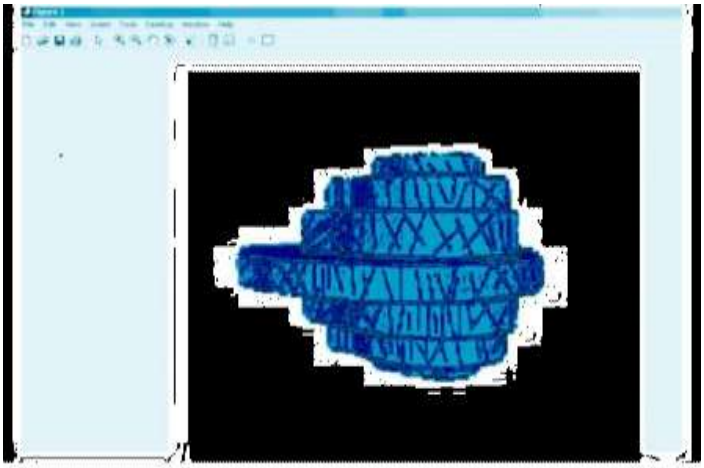

Fig. 5: Segmented tumor image (3D)

RESULT

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

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 1st upper layer, 2nd upper layer, 3rd 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 in Table 1. It is seen from Table 1 that the total approximate area of tumour comes out to be 318.54 mm^2 (3.1854 cm^2).

Table 1: Area of tumor

Name of layer	Maximum dimensions, pixels	Maximum dimensions, mm×mm	Approximate area, mm^2
1st upper layer	33 × 7	9.02 × 1.91	17.23
2nd upper layer	54 × 11	14.76 × 3.01	44.43
3rd upper layer	63 × 14	17.22 × 3.83	65.95
Middle layer	87 × 12	23.79 × 3.28	78.03
The layer below middle layer	62 × 13	16.95 × 3.55	60.17
The second last layer	52 × 10	14.22 × 2.73	38.82
The last layer	31 × 6	8.48 × 1.64	13.91
		Total	**318.54**

CONCLUSIONS

The results show that proposed scheme can successfully segment a tumour provided the parameters are set properly. The visualization and detective evaluations of the results of the segmentation show the success of this approach. In this study, the tumor identification and the investigation are carried out for the potential use of MRI data for improving the tumour shape and 2D visualization of the surgical planning.

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