Detection of Glioma (Tumor) Growth by Advanced Diameter Technique Using MRI Data

S.Karpagam   and   S. Gowri

Abstract - **The tumor volume is a significant prognostic factor in the treatment of malignant tumors. Manual segmentation of brain tumors from MR images is a challenging and time consuming task. In this study a new approach has been discussed to detect the volume of brain tumor using diameter and graph based method to find the volume. Here MRI data set from 200 patients were collected. The graph based on pixel value is drawn taking the various points from the tumor cells lies in the original position from the affected region. Here the affected region is considered as ellipse shape and the volumes have been calculated from it. In this system the mean has been found from the volumes grown in the affected region. The experimental results show that 96% brain tumor growth and volume can be measured by graph and diameter method.**

Index Terms - **Brain tumor, MRI, Imaging, Segmentation, Advanced graph based technique, Diameter method.**

I.   INTRODUCTION

Brain tissue and tumor segmentation in MR images have been an active area of research today [1-3]. In general the problem of image segmentation involves clustering of similar feature vectors. Extraction of good features is thus fundamental to successful image segmentation. The Segmentation task becomes more challenging when one wants to derive common decision boundaries on different object types in a set of images. Due to the   complex structure of different tissues such as white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) in the brain images, extraction of useful feature is a fundamental task. 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.

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The MR imaging method is the best due to its higher resolution than the other methods. Its resolution is approximately 100 microns [9-10]. MR imaging is currently the method of choice for early detection of brain tumor in human brain. However, the interpretation of MRI is largely based on radiologist's opinion. Generalization of brain screening programs requires efficient double reading of MR image, which allows reduction of false negative interpretations, but it may be difficult to achieve. Computer aided detection systems are dramatically improving and can now assist in the detection of suspicious brain lesions, suspicious masses. The task of manually segmenting brain tumors from MR imaging is generally time consuming and difficult. An automated segmentation method is desirable because it reduces the load on the operator and generates satisfactory results [11]. The region growing segmentation is used to segment the brain tumors due to its wide range of applications and automatic features. After taking the image of the tumorous brain there is a need to process it. The image clearly shows the place of the tumorous portion of the brain. The image does not give the information about the numerical parameters such as area and volume of the tumorous portion of the brain. After segmentation the desired tumor area is selected from the segmented image. This selected region is used to calculate the area and volume of the tumor present in the MR image.

II. MATERIALSAND METHODS

From Eight hundred twenty-five MRI studies in 219 patients formed the database for study. These MRI studies were part of a multicenter, randomized, controlled, phase III clinical trial of a novel biologic therapy in glioblastoma multiform. Of these, 207 were preoperative studies and 618 were postoperative. The diagnosis was confirmed pathologically in each patient. All participants in this study remained Blinded as to the arms to which any patients had been assigned. Each MRI study was performed according to a standardized protocol that included pre- and post contrast T1-weighted imaging in multiple planes, as well as a high-resolution (3- or 1.5-mm slice thickness) gradient echo acquisition. Clinical data, such as Patient survivals, treatment parameters, and so on, are not described in this report because they are not relevant to the main focus of this work, the reproducibility of the measurement techniques.

III. PROCESSES

Implementation of this novel approach contains various processing steps, like raw image collection, image preprocessing, thresholding image segmentation and volume calculation. The sequences of the processing steps are arranged in a meaningful manner as shown in Fig.1
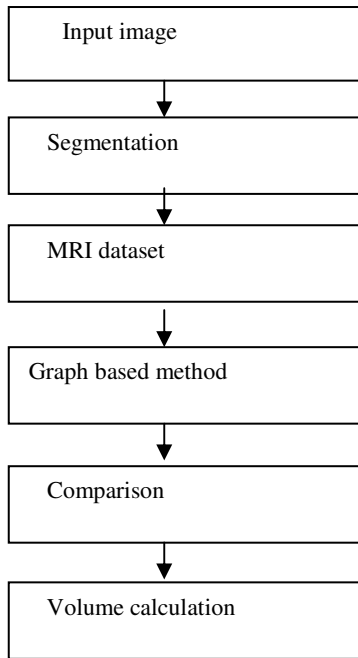
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┌─────────────────────────┐
│      Input image        │
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│      Segmentation       │
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│      MRI dataset        │
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│    Graph based method   │
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│   Volume calculation    │
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Fig.1: The Proposed methodology

A. MRI data

The MR images are acquired on a 1.5T using T2-weighted axial contrast images.

B. Preprocessing

Image preprocessing is the very first step in the image processing. In this process the image is converted into the accessible form. Also image „intensity adjustment" and „noise reduction" processes are carried out. After this the Gaussian image filtering is performed. Filtering is necessary because it reduces the noise present in the image.

C. Form region

Region growing group's pixels or sub regions into larger regions based on predefined criteria. The basic idea is to start with a pixel or a group of pixels and examine the neighboring pixels. If a neighboring pixel meets a certain criteria, it is added to the group and if it does not meet the criteria, it is not added. This process is continued until no more neighboring

pixels can be added to the group. Thus, a region is defined. In this method, the point is to group pixels of the same or similar brightness or color into region according to the given membership criteria. The membership criteria are based on some threshold value. The membership in a region can be based on multiple criteria.

The confidence connected region-growing algorithm based on extraction of connected set of pixels whose pixel intensities are consistent with the pixel of a seed point. First, the mean and variance across an 8-connected neighborhood are calculated for a seed point. The pixels connected to this seed point whose values are within the confidence interval for the seed point are grouped. The width of this confidence interval is controlled by the user Defied factor f according to equation (1).

$$I(x) \in \left[m - f\sigma, m + f\sigma \right] \quad (1)$$

Where m and σ are₃ the mean and standard deviation of the region intensities, f is a factor defined by the user. Small values of the factor f will restrict the inclusion of pixels to those having very similar intensities to those in the current region. Larger values of this multiplier factor will relax the accepting condition and will result in more generous growth of the region -I is the image and x is the position of the particular neighbor pixel being considered for inclusion in the region.

IV. RESULT AND DISCUSSION

In this study the tumor growth has been measured by graph based technique. Here input is the MRI image which is divided into four sections by one horizontal and vertical line shown in fig .2
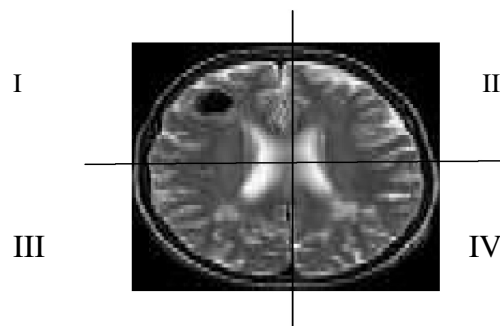

Fig.2: MRI Sections-I affected area

The divided four sections of the MRI have been denoted as I, II, III and IV   The MRI image divided into 4 sections that is I, II, III, and IV. If the affected region lies in section the graph has been drawn from it. This type of approach is better than other approaches because this system has been taken by only

the affected region. The graph has been drawn based on the daily report from the MRI dataset as shown in fig 3(b). The graph has been drawn based on pixel values from the tumor cells that lie in the affected region from day by day report from MRI data. Here the Experimental result (graph) shows the growth of brain tumor cells.
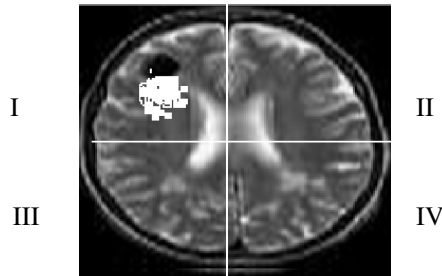

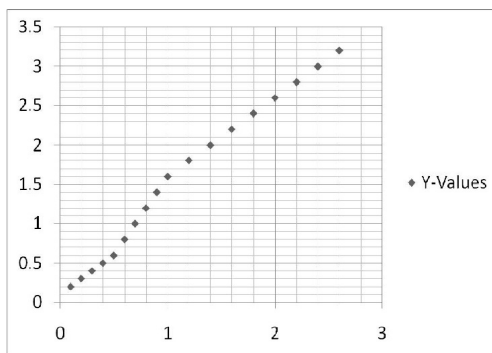Fig.3 (a): MRI Sections-I affected area

Fig.3 (b) MRI Section-I Glioma Growth

Here the First step is to mark the affected region in section-I (fig 4.) Now take the affected region from the MRI data and match it with the graph as shown in fig(5).After matching them ,from the affected regions the points have been selected and using them the graph has been drawn as shown in fig.5.
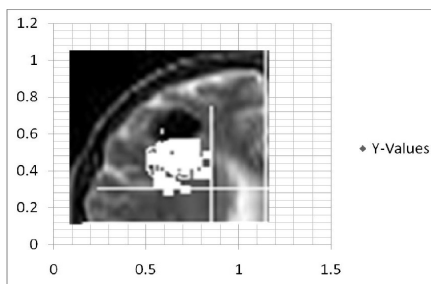

Fig.4: MRI Sections-I affected area lies in graph

Here 1 cm in x axis and 0.5 cm in y axis have been taken .So plot the graph based on the daily report. The graph has been drawn based on the daily report It given a detail picture of the growth rate of the brain cells. picture of the growth rate of the brain cells. Fig 5(a) shows the original input of MRI of data set and Fig.5 Gaussian filtered image of dataset 1.

In fig.6 (a) graph has shown the glioma growth in section –I from select the appropriate points from the affected regions by day by day report of patients MRI data and in fig.6 (b) has been shown the glioma growth in section –II from the affected MRI data set-2. Likewise, in section III and section IV the graphs have been drawn in the same method.

Fig. 5 (a): Original input MR image of dataset - 1.
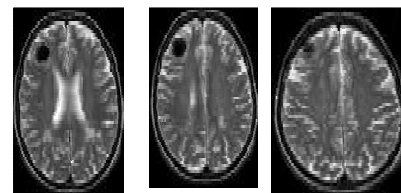

Fig.5 (b): Gaussian filtered image of dataset - 1.

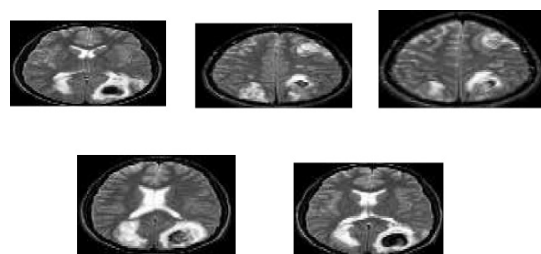Fig.5(c): Intensity adjusted image of dataset 1.

Fig. 5(d): The results after segmentation for data set 1.
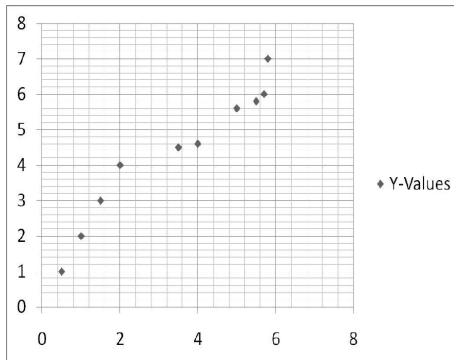
V. GRAPH RESULT FOR GLIOMA GROWTH

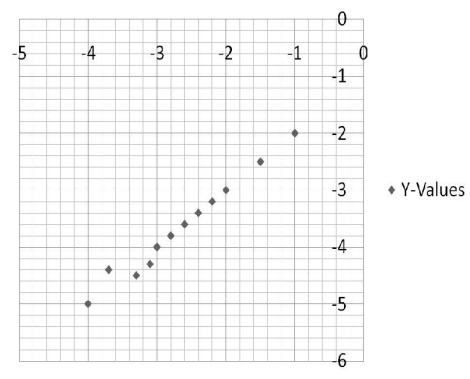Fig.6(a): Graph result for section-1 affected region

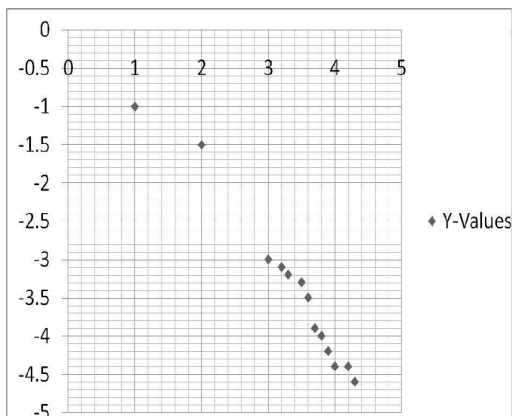Fig..6(b): Graph result for section-II affected region

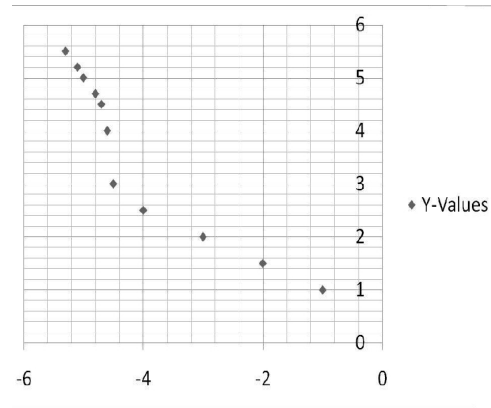Fig.6(c): Graph result for section-III affected region

Fig.6(d): Graph result for section-IV affected region

VI. DIAMETER METHOD

Readers were instructed to identify the three largest orthogonal diameters of the lesion. Diameters were manually measured on MRI films with calipers (dividers) (Fig 7(a)). In each case where a second lesion was present, or the shape of the lesion was best characterized by two ellipsoids, a second set of three diameters was also recorded, and the volumes were summed. If one or more necrotic or cystic areas were thought to be present, additional diameters for the cystic component were recorded, and the computed cystic volume was Subtracted from the overall volume Readers were not aware that an end point of this study was the determination of how many sets of diameters (one *v* two *v* three diameter measurements) were thought to be required to accurately characterize the lesion volume. The formula used to compute volumes was the standard volume of an ellipsoid, as follows:

$$V = 4/3 \ pi \ (a *b*c*) \qquad (2)$$

Where a, b, and c are the three radii (half the diameters). In addition to the total volume, the individual diameters were also recorded to allow analysis on a single- or dual-diameter basis, ie, diameter or area rather than a volume estimate.
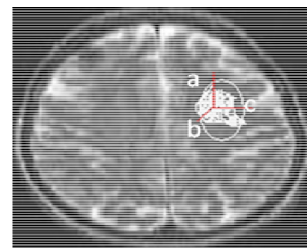

Fig.7(a): Diameter method

In this diameter method the volume has been calculated using formula-2. Table-I shows the volumes it has been calculated from dataset-1 and dataset-2.

Table.1 graph result for section-I affected region

MRI data	a (cm)	b(cm)	c(cm)	Volume(cm^3)
Data set-1	0.5	0.61	0.72	0.49455
Data set-2	0.6	0.857	0.92	1.0898469

Volume calculation has been done in a step by step process from our input MRI image; the affected region has been changed as ellipse or circle shape. In formula -2 the volume has been found from MRI data set using different parameters (a, b, c). to find out the volume from MRI data set-1. This result will produce out the volume of brain tumor. Again this same diameter method has been used and has found out the volume -2 upto N times. N is a number of steps to determine the volume by different parameters as shown in fig. 8 (a), 8(b), 8(c). The mean has been measured from these volumes using formula-3 which is equal to average of volumes calculated using different parameters. From this mean the volume of glioma has been determined from day by day MRI report. The graph shows the brain tumor growth affected in brain cells.

$$\text{Mean} = V_1 + V_2 \ldots + V_n \qquad (3)$$

Where v1,v2 are the volumes it has been calculated from dataset-1 and dataset-2.

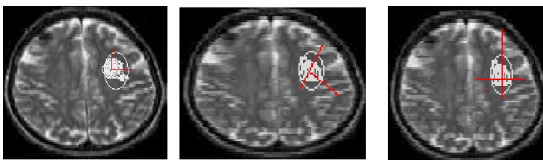
Fig.8(a)& (b) & (c): volume detection

VII. CONCLUSIONS

Imaging plays a central role in the diagnosis and treatment planning of brain tumor. Tumor volume is an important diagnostic indicator in treatment planning and results assessment for brain tumor. The measurement of brain tumor volume can assist tumor staging for brain tumor volume measurements is developed which overcome the problem of inter-operator variance, besides partial volume effects and shows satisfactory performance for segmentation. This method is applied to 8-tumor contained MRI slices from 2 brain tumor

patients" data sets of different tumor type and shape, and better segmentation results are achieved In this study a new approach has been discussed to detect the volume of brain tumor using diameter and graph based method to find the volume. Here MRI data set from 200 patients were collected. The graph based on pixel value is drawn taking the various points from the tumor cells lies in the original position from the affected region. Here the affected region is considered as ellipse shape and the volumes have been calculated from it. In this system the mean has been found from the volumes grown in the affected region. The experimental results show that 96% brain tumor growth and volume can be measured by graph and diameter method

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