

TUMOR VOLUME CALCULATION OF BRAIN FROM MRI SLICES

Shally HR

Dept. of Computer Science & Engineering
SCT College of Engineering
Trivandrum, India
shalu.it88@gmail.com

Chitharanjan K

Assistant Professor
Dept. of Computer Science & Engineering
SCT College of Engineering
Trivandrum, India

Abstract— The main objective of this paper is to calculate volumes of brain tumors from sagittal, axial and coronal orientations. Brain tumor detection is a most important area in medical image processing. Brain cancer is a disease in which cells grow uncontrollably in the brain. It may affect any person at any stage. Brain tumor effects may not be the same for each person. Brain tumors can have a variety of shapes and sizes, it can appear at any location and in any different image intensities. Accurate measurements in brain diagnosis are quite difficult because of diverse shapes, sizes and appearances of tumors. The appearance of tumors on MR images varies greatly, due to tissue variation inside the tumor area and the diffuse growth of the tumor. Hence a variety of segmentation methods should be reviewed and a suitable method should be chosen to distinguish the tumor tissue from the surrounding brain to gain exact volume values. This includes implementation of a spectral clustering segmentation method and 2-dimensional (2D) visualization can be done to each MRI slices. For calculating the tumor volume its important to get the tumor area. Normally its very difficult to calculate the tumor area from a irregular tumor shape. To overcome this problem detect the convex hull region from segmentation result and calculate the convex area from convex hull image. At last frustum model method is used for calculating the tumor volume.

Index Terms—Magnetic Resonance Image , Connected Component Labeling

I. INTRODUCTION

A brain cancer is a disease in which cells grow uncontrollably in the brain. Brain tumors are of two main types : 1) Benign tumors 2) Malignant tumors Benign tumors are incapable of spreading beyond the brain itself. Benign tumors in the brain usually do not need to be treated and their growth is self limited. Sometimes they cause problems because of their location. Surgery or radiation can be helpful. Malignant tumors are typically called brain cancer. These tumors can spread outside of the brain. Malignant tumors of the brain will always develop into a problem is left untreated and an aggressive approach is almost always warranted. Brain malignancies can be divided into two categories Primary brain cancer originated in the brain. Secondary or metastatic brain cancer spreads to the brain from another site in the body.

Imaging plays a major role in the diagnosis and treatment planning. Imaging of tumors can be done by CT scan, Ultrasound and MRI etc. With respect to other biomedical imaging modalities, the MRI technique is far superior at imaging soft tissue. This is because MR image contrast is formed directly from the magnetic properties of water molecules in their local chemical environment and the density of water in soft tissue is high compared to other tissues such as bone. MR imaging method is the best due to its higher resolution. Magnetic Resonance Imaging (MRI) are used to locate brain tumor. The image captured from a tumors brain shows the place of the infected portion of the brain. Thus it does not give the numerical information about numerical parameters such as area and volume of the tumor.

II. RELATED WORKS

2.1 MRI SLICE ORIENTATIONS

A. Sagittal Plane

Sagittal plane is also called lateral plane. This is a vertical plane running from front to back that divides the body or any of its parts into sinister(left) and dexter (right) sides. The two basic movements in the sagittal plane are flexion and extension.

B. Coronal plane

Coronal plane is also called frontal plane. This is a vertical plane running from side to side that divides the body or any of its parts into anterior and posterior (or dorsal and ventral) parts. The primary movements in the frontal plane are abduction (movement of any part of the body in line with the frontal plane) and adduction.

C. Transverse plane or axial Plane

It is also called horizontal plane that divides the body or any of its parts into upper and lower parts, or superior and inferior. Most movement that occurs along this plane involve rotation. Movement that takes part of the body outward is called lateral or external rotation, and movement that takes part of the body inward is called medial or internal rotation.

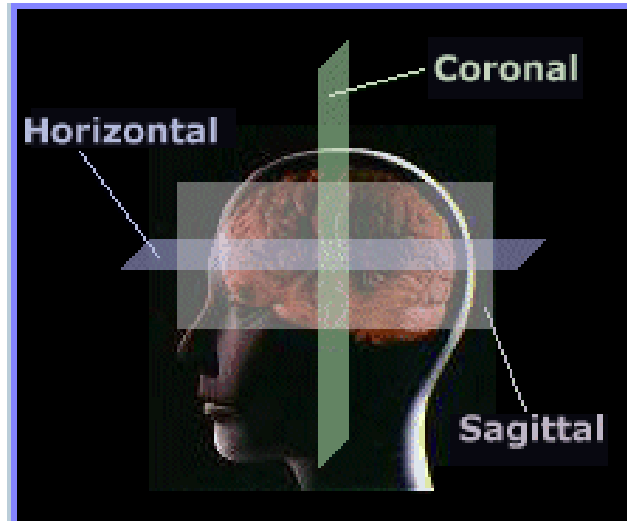


Fig1:Sagittal,Axial,Coronal orientations

2.2 TYPES OF SEGMENTATION

Segmentation is an important process to extract information from complex medical images. Segmentation has wide application in medical field. The main objective of the image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneous with respect to a predefined criterion. Widely used homogeneity criteria include values of intensity, texture, color, range, surface normal and surface curvatures.

Image thresholding is the most popular segmentation method due to its intuitive properties and simple implementation. Threshold selection plays a very crucial role for efficient segmentation results. Intuitively, the thresholds for multimodal histograms should be the minima between the two maxima. Some techniques sharpen the histogram peaks in image enhancement stage so as to facilitate the threshold detection. The main disadvantage of this method is the difficulty to separate object from background if the object and background are of the same intensity distribution or texture as in MRI-scans.

Edge-based segmentation is described in terms of discontinuities in image attributes as Gray level, texture, color etc. These discontinuities are known as edges and are detected using edge detection operators. Some of the commonly used operators are Sobel, Prewitt, Laplace, etc. Segmentation resulting from edge-based method cannot be used as partial segmented output due to the presence of broken, stray, or noise edges.

Region-based segmentation is then used which is based on finding similarity measures to merge and split regions in an image so as to form semantic or useful division in the processed image.

The objective of this paper is to calculate volumes of brain tumors from sagittal, axial and coronal orientations. The appearance of tumors on MR images varies greatly, due to tissue variation inside the tumor area and the diffuse growth of the tumor. Hence a variety of segmentation methods should be reviewed and a suitable method should be chosen to distinguish the tumor tissue from the surrounding brain to gain exact volume values. This includes implementation of a spectral clustering segmentation method and 2-dimensional (2D) visualization can be done to each MRI slices. For calculating the tumor volume its important to get the tumor area. Normally its very difficult to calculate the tumor area from a irregular tumor shape. To overcome this convex hull algorithm is applied to the segmented region. Simpler methods such as geometric models provide only a rough estimate of the tumor volume and may not be indicated the accurate determination.

MATLAB is used as programming platform to implement a graphical user interface, which should allow segmentation, morphological operation, segmented boundary, convex hull, convex area visualization and

volume calculation. Frustum model is used for volume calculation. To evaluate the segmentation method and to calculate tumor volumes, two MR image data sets are used.

III. PROPOSED METHOD

MRI Slices of Axial, Coronal and Sagittal Planes of the same person is used as input dataset. Segmentation done in these slices to get the exact tumor portion. Convex hull and convex area was done with MATLAB 7.10. Method used to segment out Tumor is Connected component labeling.

IV METHODOLOGY

4.1 Spectral clustering

Here we use a new central technique called Spectral clustering. It is a more powerful and specialized algorithm (compared to K-means), derives its name from spectral analysis of a graph, which is how the data are represented. It is a way of grouping N data points into a predefined number of clusters, K . For creating . For spectral clustering first we have to create a similarity graph. Given a set of data points x_1, \dots, x_n and some notion of similarity $s_{ij} \geq 0$ between all pairs of data points x_i and x_j . Divide the data points into several groups such that points in the same group are similar and points in different groups are dissimilar to each other. Representing the data is in form of the similarity graph $G = (V, E)$. Each vertex v_i in this graph represents a data point x_i . Two vertices are connected if the similarity s_{ij} between the corresponding data points x_i and x_j is positive or larger than a certain threshold, and the edge is weighted by s_{ij} . The main tools for spectral clustering are graph Laplacian matrices. Assume that G is an undirected, weighted graph with weight matrix W , where $w_{ij} = w_{ji} \geq 0$. When using eigenvectors of a matrix, not necessarily assume that they are normalized. There are two matrices in normalized laplacians.

$$L_{sym} := D^{-1/2} L D^{-1/2} = I - D^{-1/2} W D^{-1/2},$$

$$L_{rw} := D^{-1} L = I - D^{-1} W.$$

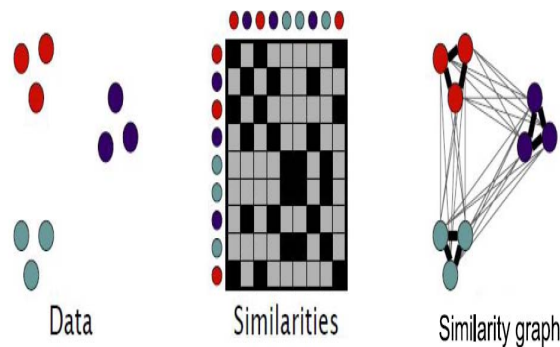


Fig 2. Similarity graph

There are 2 types of similarity graphs are used they are normal graph and mutual graph. Normal graph is also called k -nearest neighbor graph. In k -nearest neighbor graph connect v_i and v_j with an undirected edge if v_i is among the k -nearest neighbors of v_j or if v_j is among the k -nearest neighbors of v_i . In fully connected graph Simply connect all points with positive similarity with each other, and weight all edges by s_{ij} . The main tools for spectral clustering are graph Laplacian matrices. Assume that G is an undirected, weighted graph with weight matrix W , where $w_{ij} = w_{ji} \geq 0$. When using eigenvectors of a matrix, not necessarily assume that they are normalized. There are two matrices in normalized laplacians calculated by following equations.

$$L_{sym} := D^{-1/2} L D^{-1/2} = I - D^{-1/2} W D^{-1/2},$$

$$L_{rw} := D^{-1} L = I - D^{-1} W.$$

- L_{sym} is a symmetric matrix.
- L_{rw} is closely related to a random walk.

Three types of spectral clustering algorithms are present. They are

1. Unnormalized spectral clustering
2. Normalized spectral clustering according to Shi and Malik.
3. Normalized spectral clustering according to Jordan and Weiss.

1. Normalized spectral clustering according to Shi and Malik

- Input: Similarity Matrix $SCR^{n \times n}$, number k of clusters to construct
 - Construct a similarity graph ,let W be its weighted adjacency matrix.
 - Compute the normalized Laplacian Lrw .
 - Compute the first K eigenvectors v_1, \dots, v_k of the generalized eigenproblem $Lv = \lambda Dv$.
 - Let $V \in R^{n \times k}$ be the matrix containing the vectors v_1, \dots, v_k as columns.
 - For $i = 1, \dots, n$, let $y_i \in R^k$ be the vector corresponding to the i -th row of V .
 - Cluster the points $(y_i)_{i=1 \dots n}$ in R^k with the k -means algorithm into clusters $C_1 \dots C_k$.
- Output: Clusters $A_1 \dots A_k$ with $i = \{j | y_j \in C_i\}$

This algorithm works with eigenvectors of the normalized Laplacian Lrw . Hence it is called normalized spectral clustering.

2. Normalized spectral clustering according to Jordan and Weiss

- Input :Similarity Matrix $SCR^{n \times n}$, number k of clusters to construct
 - Construct a similarity graph ,let W be its weighted adjacency matrix.
 - Compute the normalized Laplacian $Lsym$.
 - Compute the first K eigenvectors v_1, \dots, v_k of $Lsym$.
 - Let $V \in R^{n \times k}$ from V by normalizing the row sum to have norm 1, that is $U_{ij} = v_{ij} / (\sum_k V_{ij}^2)^{1/2}$.
 - For $i = 1, \dots, n$, let $y_i \in R^k$ be the vector corresponding to the i -th row of U .
 - Cluster the points $(y_i)_{i=1 \dots n}$ in R^k with the k -means algorithm into clusters $C_1 \dots C_k$.
- Output: Clusters $A_1 \dots A_k$ with $A_i = \{j | y_j \in C_i\}$

Here we have done a comparison with Shi & Malik and Jordan & Weiss algorithms. Compare to Jordan & Weiss Shi & Malik takes less computing time.

3.3 Morphological Opening

Morphological operations are used to remove small or unwanted pixels. Two morphological operations are dilation and Erosion. The basic effect of an opening is somewhat like erosion in that it tends to remove some of the foreground (bright) pixels from the edges of regions of foreground pixels. The effect of the operator is to preserve foreground regions that have a similar shape to structuring element, or that can completely contain the structuring element, while eliminating all other regions of foreground pixels. Very simply, an opening is defined as an erosion followed by a dilation using the same structuring element for both operations. While erosion can be used to eliminate small clumps of undesirable foreground pixels, e.g. 'salt noise', quite effectively, it has the big disadvantage that it will affect all regions of foreground pixels indiscriminately. Opening gets around this by performing both an erosion and a dilation on the image. The effect of opening can be quite easily visualized.

3.4 Segmentation

Segmentation done by Connected component labeling algorithm. (CCL) is a commonly used operation in image processing applications. In machine vision most objects have surfaces and the points in a connected components form a candidate region for object representation. The image object, which is the component separated from background image on binary image. Each component is labeled and displayed as output images. Points belonging to a surface are projected to spatially closed points. The CCL algorithm works by scanning the image from top to bottom and left to right. It assigns labels to each pixel until the labels for the pixels no longer change.

It Convert labeled image to binary image. Then find the connected components. Create a label matrix. Display labels with different colors. Find the region properties of label matrix. Find the area of each segments and sort in descending order. Create a new image of largest area segment. Find the boundary of largest area segment. Mark that boundary in the input image.

3.5 Convex hull

The Convex hull problem is to find the convex polygon of smallest perimeter which contains a given set of points. The most common form of this algorithm involves determining the smallest convex set (called the "convex hull") containing a discrete set of points.

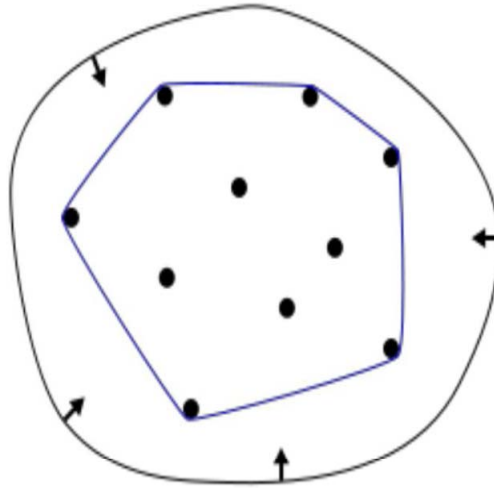


Fig 3. Convex hull

Let S be a set of points in the plane. The convex hull of S is the smallest convex polygon that contains all the points of S . 'Convex Image' — Binary image (logical) that specifies the convex hull, with all pixels within the hull filled in.

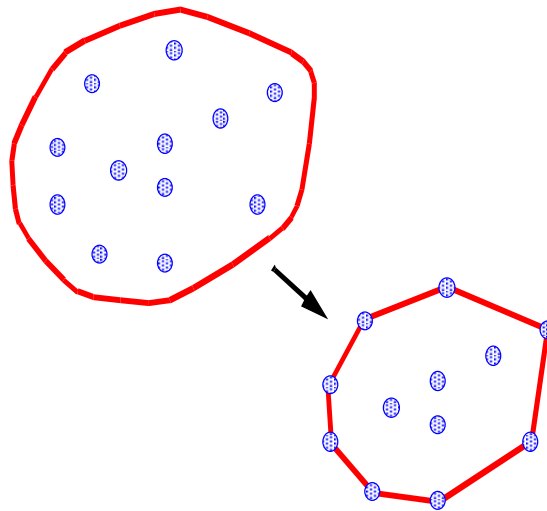


Fig 4. Smallest convex polygon from a set of points

3.6 Convex Area

Convex hull and convex area calculated from matlab region properties. It helps to calculate the exact hull area. Scalar that specifies the actual number of pixels in the Convex Image.

3.7 Area in Pixel to Actual area Conversion

Number of pixels in convex area is converted into actual area size by using the relation $1 \text{ pixel} * 1 \text{ pixel} = (512/22)^2 \text{ mm}^2$ in the image slice i . 512 is the matrix size of MRI and 22 is the field of view of MRI.

3.8 Volume calculation

Tumor volume can be calculated using frustum model. Calculate the object area of each slice. A frustum model is used for calculating the tumor volume between two consecutive slices with Area A_i . The given formula is used to calculate the tumor volume.

$$V = \sum (h/3 * (A1 + A2 + (A1 * A2)^{1/2})).$$

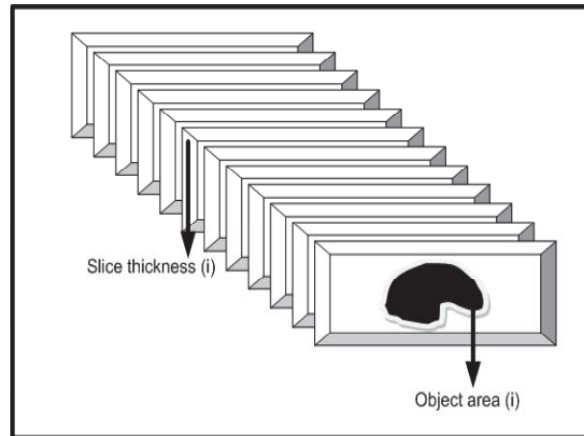


Fig 5.MRI Slices

Height h = slice thickness + slice separation. Volume V of the tumor is given by the summation of volumes of two consecutive slices. Where A_1 and A_2 denote the areas of the two consecutive slices having tumor. Calculate each slice using frustum model.

Flow Chart of our Proposed Method

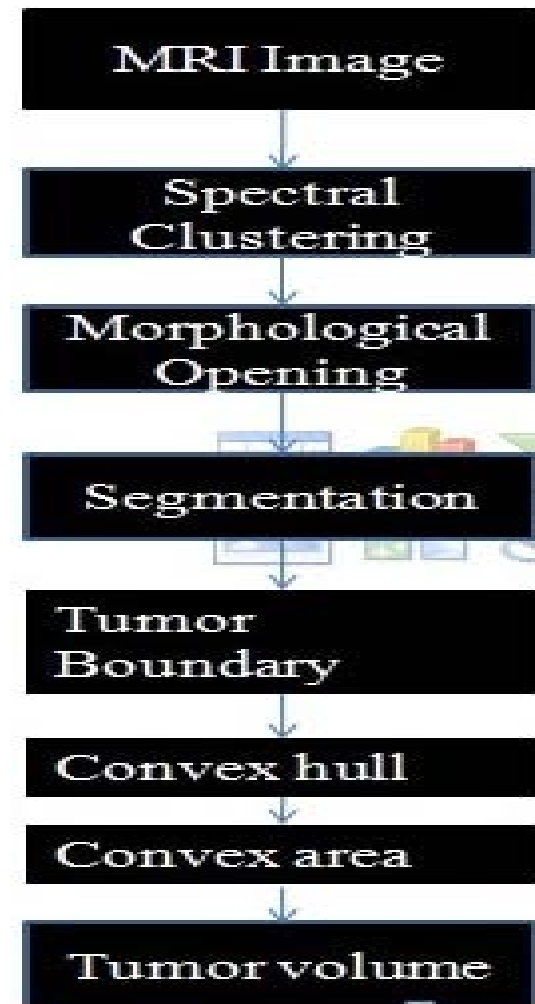


Fig 6. Flow Chart

V. EXPERIMENTAL RESULT

A relevant set of MRI Slices with Tumor where acquired from the Dept. of Radiology, Medical College Thiruvananthapuram. There were 60-70 MRI Slices for each of the three Coronal, Axial and Sagittal planes. Among these 60-70 MRI Slices few slices shows the presence of Tumor. Those Slices with the Tumor were selected manually and given as the input sequence for the Extraction of Tumor, calculation of area and the Evaluation of Volume measurement.

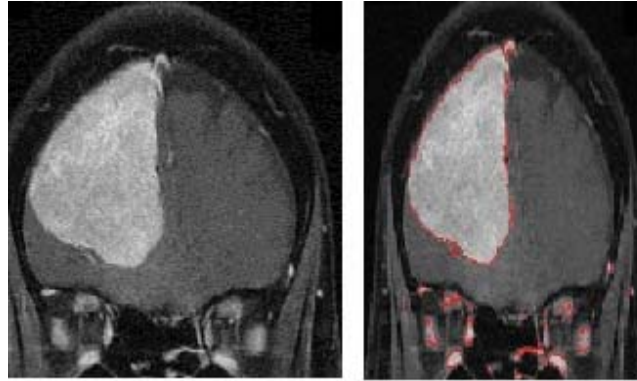


Fig 7. Input image and spectral clustering result

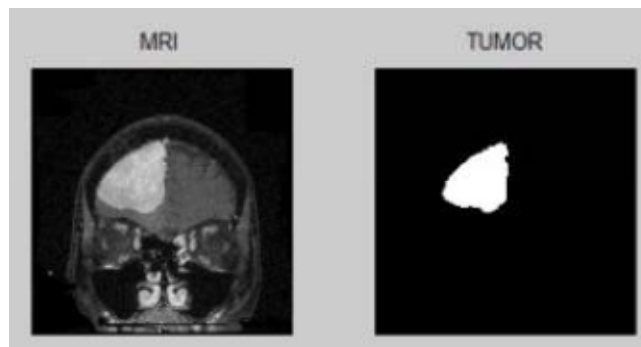


Fig 8. Segmentation result

VI. CONCLUSION

The use of computer technology in medical decision support is now widespread and pervasive across a wide range of medical area. MRI plays an important role in progressive research's. Spectral clustering methods are attractive. Easy to implement and reasonably fast. Especially for sparse data sets up to several thousands Help to cluster the MRI image into Black and white pixels. So it is easy to segment the actual tumor region. Clean Up the image using morphological operation. Segmentation done by using connected component labeling. Calculated the exact tumor boundary of tumor. Applied convex hull algorithm to segmented image. Then calculate the area of convex image. Frustum model is used to get the tumor volume.

REFERENCES

- [1] J. A. Hartigan and M. A. Wong. A k-means clustering algorithm. *Applied Statistics*, 28(1):100–108, 1979.
- [2] L. Huang, D. Yan, M. I. Jordan, and N. Taft. Spectral clustering with perturbed data. In *Advances in Neural Information Processing Systems (NIPS)*, December 2008.
- [3] J. Shi and J. Malik. Normalized cuts and image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(8):888–905, 2000.
- [4] X.Li,S.Lebonvallet, T.Qiu and S.Raun .An Improved Level Set Method for Automatically Volume Measure, August 23-26 2007.
- [5] A. Ng, M. Jordan, and Y. Weiss. On spectral clustering: Analysis and an algorithm. In *Neural Information Processing Systems 14*, 2001.
- [6] D. Yan, L. Huang, and M. I. Jordan. Fast approximate spectral clustering. Technical report, Department of Statistics, UC Berkeley, 2009.
- [7] S. Yu and J. B. Shi. Multiclass spectral clustering. *In Proceedings of ICCV, 2003*
- [8] Soniya goyal, Sudhanshu shekar. Automatic detection of brain abnormalities and tumor segmentation in MRI sequence.
- [9] Hossam M.Moftah , Mahmoud A.Ismail.Volume Identification and Estimation of MRI Brain tumor,2012 12th International conference on HIS.
- [10] Marc pouget ,Inria Nancy ,Convex Hull and Point Location,vegas research team 2013.
- [11] Samir Kumar Bandyopadhyay,Debasree Saha ,Brain Region Extraction and Volume Calculation,UNIASCIT Vol - 1 ,2011.