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Automatic Brain Tumor Segmentation on Preoperative and Postoperative MRI Using Region Growing Algorithm

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ABSTRACT

Detection and segmentation of mixed necrotic and tumor tissue along with the neighboring vessels is a challenging scenario in radiation oncology application. The MRI image is an image that produces a high contrast images indicating regular and irregular tissues that help to distinguish the overlapping in margin of each tissue. All automatic seed finding methodologies may suffer with the problem if there is no growth of tumor and if any small white part or grey part is present there. Segmentation of images with complex structures such as magnetic resonance brain images is difficult using general purpose methods. Region based active contour models are widely used in brain tumor segmentation. But when the edges of tumor is not sharpen, then the segmentation results are not accurate i.e. segmentation may be over or under that may happened due to initial stage of the tumors. Here a method of tumor detection based on texture of the MRI and if it is detected then to segment it automatically using automatic seeded region growing method is proposed in to separate the irregular from the regular surrounding tissue to get a real identification of involved and non-involved area that help the surgeon to distinguish the affected area precisely. The methods used in this paper are texture analysis and automatic seeded region growing method and is implemented on MRI of brain to detect the tumor boundaries in 2D MRI for different cases.

Keywords— Brain tumor segmentation, MR Image, region growing, necrotic tissue segmentation, enhancing cell, radio surgery, radiotherapy.

I. INTRODUCTION

Segmentation of brain tissues in gray matter[2], white matter[3], and tumor[4] on medical images is very difficult in the radiation oncology application. The brain tumor contour is a major step in planning spatially localized radiotherapy (e.g., Cyberknife) [6], [7] which is usually done manually on contrast enhanced T1-weighted magnetic resonance images (MRI) in current clinical practice. This type of T1 MR Images are acquired after the administration of a contrast agent (gadolinium), blood vessels and parts of the tumor, where the contrast can pass the blood–brain barrier are observed as hyper intense areas.

There are various attempts for brain tumor segmentation which use a single modality, combine multi modalities and use priors obtained from population atlases. Modalities which give relevant information on tumor and edema such as Perfusion Imaging, Diffusion Imaging provide lower resolution images compared to T1 or T2 weighted sequences. The main reason to use multimodality images such as T2 weighted MRI is to segment edema/infiltration region which is generally not observable in T1 images. This method combines region growing and edge detection for magnetic resonance (MR) brain image segmentation. Initializing with a simple region growing algorithm which produces an over segmented image, we apply a sophisticated region growing and merging methodology which handles complex image structures. Boundary information is then integrated to verify and to correct region boundaries. Texture based automated seed segmentation is applied here. The result shows that this method is accurate and efficient for MR brain image segmentation.[5] Automatic segmentation of medical images serves as the key step in applications such as computer aided diagnosis and quantification studies by registration for different imaging modalities. Segmentation of images with composite structures such as magnetic resonance image of brain is difficult using general principle methods. Region-based techniques often fail to yield the expected formation due to the complexity of choosing a reasonable starting "seed".

Region based active contour models are widely used in brain tumor segmentation [30]. These region based techniques have several advantages over gradient based techniques for segmentation, including greater robustness to noise and efficiency.[11], [12] Classical active contours had the problem of being only as good as their initialization even when using level-set surfaces in 3D, because the tumor class does not have a strong spatial preceding, many small structures, mainly blood vessels, are classified as tumor as they also enhance with contrast. More interactive algorithms have become popular for image segmentation problem in recent years [1], [5]. Many graph based seeded segmentation framework has been generalized such that graph-cuts (GC) , random walker (RW) , shortest paths, and power watersheds [5], [6], [23] which solves a minimization problem involving a graph's edge weights constrained by adjacent vertex variables or probabilities. Image segmentation is one of the fundamental techniques in medical application. Tumor segmentation from brain Magnetic Resonance Images (MRI) is a difficult task. The Region Growing algorithm is a classical region-based approach for medical image segmentation.

II. BACKGROUND

A. Seeded Image Segmentation

An un-directed graph is given with vertices $v \in V$ and edges $e \in E$, a weighted graph assigns a value w_{ij} to each edge e_{ij} between the vertices v_i and v_j.[1] In image segmentation problems, vertices are corresponding to the image pixels and the edge weights are similarity measures between neighboring pixels based on image features (e.g., intensities). Each vertex v_i has an attribute x_i ,which is an indicator of the probability of a label such as a foreground and a background label. With the foreground F and background B seeds are supplied by the user. In the final solution, the vertices which have the value x_i <0.5 as background and $x_i \geq 0.5$ are labeled as foreground. The first region growing method was the seeded region growing method which takes a set of seeds as input along with the image. The seed marks each of the matter to be segmented and the region are iteratively grown by comparing all unallocated bordering pixels to the regions. The dissimilarity between a pixel's strength value and the region's mean δ , is used as a measure of likeness. The pixel with the minimum difference calculated this way is allocated to the respective region. This process is continued until all pixels are allocated to a region [23].

B. Region Growing in Image Segmentation

Seeded region growing requires seeds as supplementary input. [30]The segmentation result depends on the option of seeds. Noise in the image may cause the seeds to be badly placed. Un-seeded region growing is a personalized algorithm that does not require explicit seeds. In region growing, it is the case for briefing the homogeneity criterion, as its requirement depends also on image arrangement properties that are not known to the user. We have developed a region growing algorithm that learns its homogeneity criterion automatically from distinctiveness of the region to be segmented. The method is based on a replica that describes homogeneity and simple outline properties of the region. Parameters of the homogeneity principle are estimated from sample locations in the region. These locations are selected one after another in a random walk starting at the seed position, and the homogeneity criterion is updated constantly. This approach was extended to a fully automatic and absolute segmentation method by using the pixels with the negligible gradient length in the not yet segmented image region as a seed position. The methods were experienced for segmentation on experiment images and of structures in CT and MR images. We found the methods to work consistent if the model hypothesis on homogeneity and region characteristics are true. In addition, the model is simple but strong, thus allowing for a definite degree of divergence from model constraints and still delivering the predictable segmentation result.

Frequently the analysis of medical images for the reason of computer-aided analysis and treatment planning contains segmentation as a beginning stage for the visualization or quantification [14], [15]. For medicinal CT and MR images, many methodologies were recently employed for segmentation, for instant communicative thresholding aided by morphological information, region growing and region splitting and merging, active contours, the use of cluster analysis methods, or watershed transformation. In the individual segmentation methods different complex models of the a-priori information about the expected contents of the image are used.

The applied a-priori knowledge consists of a grouping of anatomical/physiological information and of information about the image configuration process. The more the contributed model information is demonstrable, the more likely is the opportunity of automation of the segmentation process. The result of the algorithm can be predicted easily, particularly in medical segmentation tasks the replica information is often too composite or not accurate to specify so that entirely automatic withdrawal is not possible. The aim of the growth of a segmentation technique should be to lessen the part of the interactively introduced replica information and to maximize the element of the repeatedly analyzed model information. Model information should be given interactively only in those cases where it represents information that is readily available to the client and where it can be entered in a strong fashion. Contravening this rule may source reactions of the procedure to user communication which are perceived as being conflicting with the user's expectations.

It starts off with a single region A_1, the pixel chosen here does not considerably influence final segmentation. Each iteration considers the adjacent pixels in the same way as seeded region growing. It is different from seeded region growing in that if the least amount δ is less than a pre-defined threshold T then it is added to the respective region A_j. If not, then the pixel is measured considerably different from all current regions A_i and a new region A_{n+1} is created with this pixel. One variant of this technique is based on pixel intensities. The mean and scatter of the area and the strength of the candidate pixel is used to compute a test statistic. If the test statistic is adequately small, the pixel is added to the region, and the region's mean and scatter are computed again. Or else, the pixel is discarded, and is used to form a new region. The Region Growing algorithm is a standard region-based approach for medicinal image segmentation. The basic approach is to start with a set n, of seed points v_i, i = 1..n, of voxels interactively selected. From these seed points regions grow by adding to each seed those neighboring voxels that have similar properties based on pre-defined criteria[19], [20]. In this successive growing process n regions R_i, i = 1..n, will be formed. The similarity criteria to consider a voxel as member of the region R_i is established according to the image properties, etc. In our implementation, let x be a neighbor voxel to some voxel belonging to the region R_i. If the Euclidean distance involving the voxel x and the seed point$v_i$is less than a threshold θ then the voxel x is included to the region R_i. Finally, the region of interest is obtained by merging each grown region i=1..n of R_i.

III. METHOD

In this section, the complete segmentation framework to segment the enhancing cells and the necrotic regions in brain tumors is presented in detail. Segmentation is a process of identifying an object or pattern in the given work space. In this project magnetic resonance image is considered as work space. Here the abnormalities in tissues are detected. Actually the MRI produces a high contrast image representing each part very clearly, but sometimes due to be determined correctly so a problem of segmenting it is always there. In these cases the physiologist always need to have keen observation of the anatomical structure. But this process is too much time consuming and if the initial segmentation result is not correct then other consequent results like volume calculation also produces incorrect measurement results.

Also in this method the users no need to select the seed point manually, therefore there is no need of human interaction. In this work our assumption is that the brain tumor had grown in considerable size and their structure may be of any considerable shape.

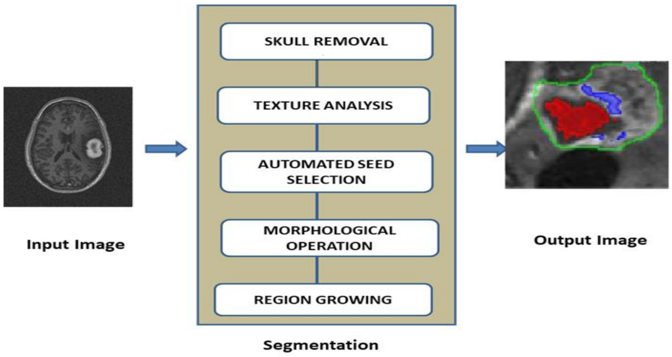


Fig. 1. Block diagram of brain tumor segmentation on MRI using Region Growing method

A. Input Image

The input image here is the magnetic resonance image of brain. One of the main reasons to use MR images such as T2 weighted MRI is to segment edema/infiltration region which is generally not observable in T1 images.[This study is focused on an efficient and robust segmentation of brain tumors on contrast enhanced T1 weighted MR images with minimal user interaction. T1 weighted image is used to detect fat or tumors.

B. Skull Part Removal

This is pre processing step which is required to produce better results while processing. Skull is outer part of the brain neighboring it i.e. the exclusion of its non-cerebral tissues[30]. The main difficulty in skull-stripping is the segmentation of the non-cerebral and the intracranial tissues due to their homogeneity intensities. So it may affect the product of seed point selection. Some interpretations are required to find the range of gray value of skull portion. Following are involved in skull removal process.

1) Initially find the size of the image and store the number of rows and columns in separate variables.
2) Carry out iteration for half of the columns and all rows.
3) Progress half of image to convert white pixels into the black pixels by setting their gray value to zero.

4) The above steps are repeated for the remaining column and row.

C. Texture Analysis

MR images contain a lot of microscopic information which may not be assessed visually and texture analysis technique provides the means for obtaining the information. Texture can be of many forms such as soft or rough, regular or irregular, rude or fine. Some patterns are very complex but they can be clearly represented by texture and can be easily visualized. Texture analysis on the images we have performed using the stastical methods of the second order that utilizes gray level run length measures and gray level co-occurrence matrix. We have taken Run length parameters in four directions 0, 90, 45 and 135. During the gray level normalization image intensities are distributed from [μ-3α, μ+3α]. Finally, according to the distribution we detect the abnormality in the image.

D. Automated Seed Selection

The image obtained after skull removal is taken as input in this part of the project. For the seed position selection our assumption is that tumor's region has grown in significant size. The following steps are performed to find the seed point:

1. Convert the given colored image into the gray image.
2. First of all count no pixels whose intensities are greater than hundred and less than hundred and store them in separate variables.
3. Find difference between both variables if difference is small then go to step 4, else convert the image intonegative and again set the intensity of external part ofthe brain to zero and go to step 4.
4. Convert the obtained gray image into the binary image.
5. Find maximum length and breadth of the brain then from the center convert the pixels in the area of rectangle shape of size twenty rows and ten columns to black color.
6. Find the sum of all rows individually and store it in the array.
7. Find the sum of all the columns and store the results in another array.
8. Find the intersection of row and column having maximum sum .This is taken as seed point.

E. Morphological Operation

Morphology mainly deals with the contour and structure of the object. And so this is used to perform object extraction, noise removal procedure etc. For the same purpose we are applying these operations to enhance the object boundary and to remove the noise from the image.

The most basic morphological operations are dilation and erosion. Dilation adds pixels to the borders of objects in an image, while erosion eliminates pixels on object boundaries. The quantity of pixels added or removed from the objects in an image depends on the size and shape of the structuring component used to process the image. In the dilation and erosion operations, the condition of any given pixel in the output image is determined by applying a rule to the equivalent pixel and its neighbors in the input image. The rule used to process the pixels defines the procedure as dilation or erosion. Another important part in morphological operation is to decide the structuring component. A structuring component is a matrix consisting of only 0's and 1's that can include any random shape and size. The pixels with values of 1 describe the neighborhood. Two dimensional or smooth, structuring elements are characteristically much lesser than the image being processed. The centre pixel of the structuring element, called the origin, determines the pixel of interest and then pixel being processed. The pixels in the structuring element containing 1's define the neighborhood of the structuring element.

In this project work we are taking DISK shape as structuring element. In the operation of image dilation and erosion we are considering disk structuring element of varying radii so that the obtained image is free from small unwanted parts.

The morphological functions position the origin of structuring element, its center element over the pixel of interest in the input image. For pixels at the border of the image, parts of the neighbourhood defined by the structuring element can extend past the border of the image. The value of these padding pixels varies for dilation as well as erosion operations.

F. Seeded Region Growing

The result obtained after morphological operation is taken as input in this stage. The automatic seeded region growing method along with edge detection method is applied here for identifying mixed necrotic and enhancing tissues in the given MRI. This approach to segmentation examines neighboring pixels of initial "seed points" and determines whether the pixel neighbors should be added to the region.

The process is iterated on, in the same manner as general data clustering algorithms. The major objective of segmentation is to partition an image into regions. Some segmentation methods such as "Thresholding" attain this target by looking for the borders between regions based on discontinuities in gray levels or color properties. Region-based segmentation is a method for determining the region directly. In our project work ten samples of brain MRI is used for experimenting with it. This uses connected neighbor region growing method has been used and the results are observed. The fundamental formulation for Region-Based Segmentation is:

(a) $U^{n}_{i=1} R_i = R_0$

This means that the segmentation must be complete and every pixel must be in the region. Here R_i is a connected region.

(b) $R_i \cap R_j = \phi$

Equation (b) means that the regions must be dis-joint. So that a clear separation from each other can be identified.

(c) $P(R_i)$ = TRUE For $i=1, 2,\ldots,n$

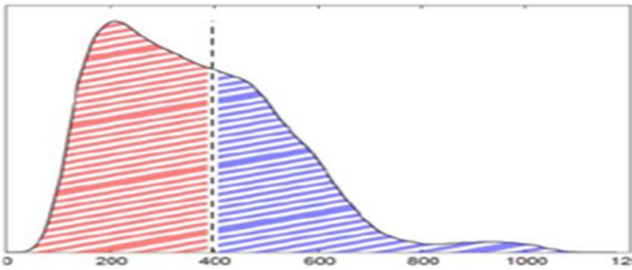
Means a pixel may belong to the region when it satisfies the condition that gray level of pixel is in the range of Region.

(d) $P(R_i U R_j)$ = FALSE

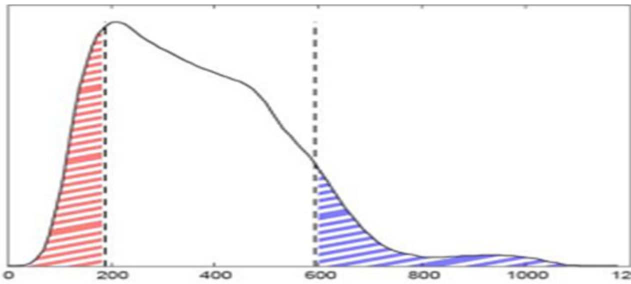
Means regions R_i and R_j are different in the sense of predicate P.

G. Necrotic Segmentation

Quantification of the necrotic regions within tumor is an important problem in processing of the tumor progress. Delayed radiation necrosis, which typically occurs three months or more after treatment, is the primary risk associated with stereotactic radio surgery. Necrosis of the tumor can occur as a result of the radio surgery as well as by the tumor progress itself like in gliomas.



(a)



(b)

Fig.2.(a) Segmentation with a single threshold. (b) Necrotic and enhanced thresholds to determine initial seeds

Necrotic class naturally arises in segmentation using multi-modality intensity classifiers due to its different intensity characteristics. However, our aim in this study is to quantify the necrotic and enhanced parts of the tumor using solely contrast enhanced T1weighted MRI of brain.

In T1 MR images, necrotic parts of the tumor are observed as hypo-intense for there is no blood flow into theseregions where enhanced parts are hyper-intense. In enhancing tissues there will be blood flow and so there will be growth in tumor tissues. Without any prior information, segmentation using an intensity threshold can be applied by assigning necrotic label to the voxels lower than the chosen threshold and enhanced label to those that are higher.

TABLE II: COMPARISON OF MANUAL AND AUTOMATIC BRAIN TUMOR SEGMENTATION

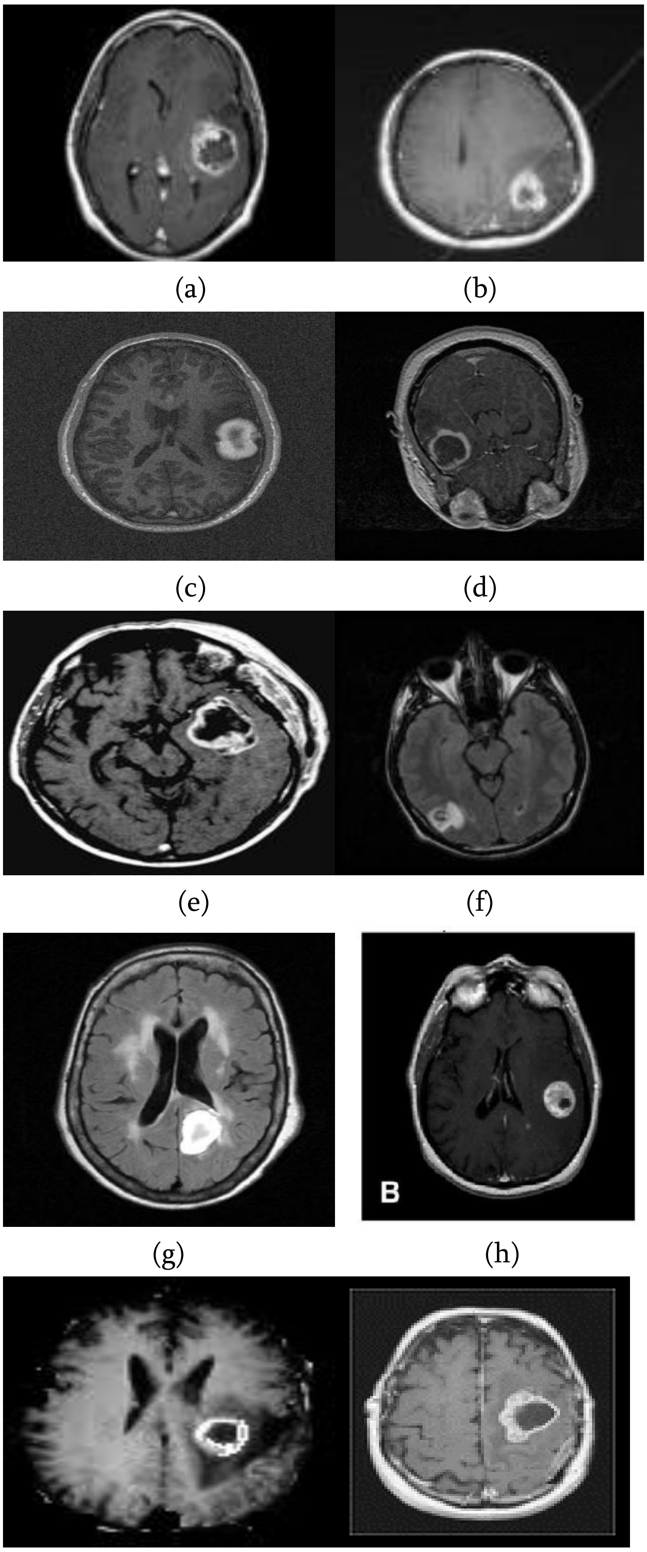
Sl. no	**Analysis**	**Manual Segmentation**	**Automatic Segmentation**
1.	User Interaction	More	Very less
2.	Iteration	More	Less
3.	Accuracy	High	Low
4.	Time Consuming	Yes	No
5.	Shortest Path Problem	Exists	Reduced

IV. RESULTS

We have implemented our work and used a set of ten images to perform the operations. We have found the presence of necrotic tissues in the tumor and the observed results for those images are included in the following observation table:

TABLE I : RESULTS OF BRAIN TUMOR SEGMENTATION

Sl. No.	**Image No.**	**Abnormality**	**Necrotic tissues**
1	A	Present	Absent
2	B	Present	Absent
3	C	Present	Absent
4	D	Present	Absent
5	E	Present	Absent
6	F	Present	Absent
7	G	Present	Absent
8	H	Present	Present
9	I	Present	Present
10	J	Present	Present



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Fig.3.(a),(b),(c),(d),(e),(f) and (g) MRI of brain with tumor. (h), (i) and (j) MRI of brain with necrotic inside the tumor

V. CONCLUSION

This is region growing segmentation method fornecrotic and enhancing cell segmentation of brain tumor on MRI; in which it is possible to determine abnormality is present in the image or not. We proposed a new, robust, fast andfully automatic algorithm for necrotic segmentation. The algorithm needs no prior information or training process. By taking into description both the uniform texture features and spatial features of the MRI, we successfully find the seed points and the segmentation results obtained are very much accurate. So we can say that this method gives better results compared to other methods. The future work is to reduce the total execution time and to work with segmentation of necrotic tissues to find the accurate size of necrotic and tumor cells.

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