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SEGMENTATION OF BRAIN TUMOR ON MR IMAGES

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Abstract: Detection and segmentation of Brain tumor accurately is a challenging task in MRI. In this paper, two seeded algorithms are used for segmentation which are the interactive grow-cut algorithm based on cellular automata & region growing algorithm. In proposed work Region Growing method is used for segmentation of ROI selected. The unsupervised grow-cut algorithm (UGC) starts with a random number of seed points and automatically converges to a natural segmentation. The number of classes derived by the UGC is independent of the number of initial seed points. The unsupervised grow-cut algorithm is compared against region growing algorithm based on evaluations measures such as Dice overlap ,Jaccard index & volume error such as true positive fraction, false positive fraction, true negative fraction ,false negative fraction used to evaluate the performance of these algorithms on Magnetic Resonance (MR) brain images. Comparative values shows grow cut algorithm gives better segmentation results than region growing.

Keywords: Brain Tumor, Seeded segmentation, grow cut algorithm, region growing algorithm, Magnetic Resonance Imaging (MRI)

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INTRODUCTION

Brain image segmentation from MRI images is complicated and challenging but its precise and exact segmentation is necessary for tumors detection and their classification, edema, hemorrhage detection and necrotic tissues. In recent years a great effort of the research in field of medical imaging was focused on brain tumors segmentation. Brain tumors may be of any size, variety of shapes, may appear at any location, and may appear in different image intensities.

The segmentation is crucial for monitoring tumor growth or shrinkage in patients during therapy, for tumor volume measurements and it also plays an important role in surgical planning or radiotherapy planning, where not only the tumor has to be outlined, but also surrounding healthy structures are of interest. In current clinical practice, the segmentation is usually still done manually, which is time consuming and tedious for the radiologists and is also of limited use for an objective quantitative analysis. Semiautomatic method alleviates the burden from the clinician to spend a large amount of time for the segmentation.[40] Outlining the brain tumor contour is a major step in planning spatially localized radiotherapy which is usually done manually on contrast enhanced T1- weighted magnetic resonance images (MRI) in current clinical practice [4].In this paper, a fast and robust practical tool for segmentation of solid tumors with minimal user interaction to assist clinicians and researchers in radio surgery planning and assessment of the response to the therapy is presented.

Image segmentation has often been defined as the problemof localizing regions of an image relative to content However, recent image segmentation approaches have provided interactive methods that implicitly define the segmentation problem relative to a particular task of content localization.[4]. There are various attempts for brain tumor segmentation which use a single modality, combine multi modalities. Region-based active contour models are widely used in image segmentation. Interactive algorithms have become popular for image segmentation problem in recent years. Graph based seeded segmentation framework has been generalized such that graph-cuts (GC) [6], random walker (RW) [5], shortest paths, and power watersheds [7] have been interpreted as special cases of a general seeded segmentation algorithm, which solves a minimization problem involving a graph's edge weights constrained by adjacent vertex variables or probabilities. Cellular automata algorithm shows potential on generic medical image problems.

II. SEEDED IMAGE SEGMENTATION FRAMEWORK

Given an graph consists of a pair $G = (V, E)$ with vertices $v \in V$ and edges $e \in E \subseteq V \times V$ with cardinalities $n = |V|$ and $m = |E|$. An edge, e, spanning two vertices, vi and vj is denoted by eij. A weighted graph assigns a value (typically real and nonnegative) to each edge between vertices. In image segmentation problems, vertices are corresponding to image pixels, while 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 (e.g., a foreground and a background label). With the foreground F and background B seeds supplied by the user, the labeling problem is solved by

$$x^{\mathrm{opt}} = \arg\min_{x} \left[\sum_{e_{ij} \in E} (w_{ij}|x_i - x_j|)^q \right]^{\frac{1}{q}}$$
$$\text{s.t. } x(F) = 1, \quad x(B) = 0$$

In the final solution, the vertices $x_i \geq 0.5$ which have the value are labeled as foreground and $x_i < 0.5$ are labeled as background. that graph cuts gives the solution to this model when $q = 1$, random walker gives the solution to this model when $q = 2$ and shortest paths (geodesics) give the solution to this model as $q \to \infty$.[5]

III. CELLULAR AUTOMATA

*C*ellular automata(CA) algorithm motivated biologically from bacteria growth and competition, is based on a discrete dynamic system defined on a lattice, and iteratively propagates the system states via local transition rules. A cellular automata is basically a computer algorithm that   discrete in space and time and operates on a lattice of cells [11]. Since it was first proposed by Von Neumann and Ulam [12],Cellular Automata has attracted researchers from various fields in both physical and social sciences because of its implicity and potential in modeling complex systems.

Each individual cell is in a specific state and changes synchronously depending on the states of some neighbors as determined by a local update rule [13]. They are parallel, local and homogeneous, since the state of any cell depends only on the states of the local neighbors at the   previous time step and the update rules are same for every cell.

Formally, a cellular automaton (CA) is a triple $A=(S,N,\delta)$ where S is a nonempty set, called the state set, N is the neighborhood, and $\delta: S^N \to S$ is the local transition function (rule); S^N which is

the argument of δ, indicates the states of the neighborhood cells at a given time, while S which is its value is the state of the central cell at the next time step [11].

There are various attempts of using CA in image processing problems including image enhancement, sharpening and smoothing, image filtering, edge detection and image segmentation (Grow-cut). Grow-cut method uses a continuous state cellular automata to interactively label images using user supplied seeds. The cells are corresponding to image pixels, and the feature vector is RGB or gray scale intensities[14]. Cellular automata were introduced they have been progressively used to model a great variety of dynamical systems application domains.

IV. TUMOR SEGMENTATION METHODS

The aim is to provide a stable and accurate solution for the segmentation of brain tumor. The main steps are performed by the methods to extract tumor surface from MR images.

A. Grow cut algorithm

The unsupervised grow-cut algorithm incorporates a CA based framework using low-level image features such as color/gray-level pixel intensity values to derive state transition rules. The initial labels and the number of seed points are derived randomly from the space of positive integer values. The state of each cell is given by a 3-tuple (l, ϑ, I), where l is the label, $\theta \in [0,1]$ is the strength of the cell and I is the pixel intensity. The strength of a cell is a function of image features and is used to define the state transition function for updating the labels of cells at each time step. Pixels with initial random labels are assigned the cell strength 1. The state transition rule between two pixels p and q is defined using a monotonically decreasing function g

$$g\left(\left\| I_p - I_q \right\|\right) \cdot \theta_q > t \; ,$$

$$\text{where, } g(x) = 1 - \left(\frac{x}{\max|I|}\right).$$

The algorithm to update cell labels l and strengths ϑ is described below:

```
// For each cell...
    for ∀p ∈ X
// Copy previous state
        l^{t+1} = l^t ;
        θ^{t+1} = θ^t ;
// neighbors try to attack current cell
        for ∀q ∈ N(p)
            if g(|I_p − I_q|)·θ_q > t  AND l_p ≠ l_q
                l_p^{t+1} = l_q^t ;
                θ_p^{t+1} = g(|I_p − I_q|)·θ_q^t ;
                // create equivalence class
                if l_p^t ≠ 0
                    [l_p^{t+1}] = {p ∈ X | p ∼ l_p^t}
                end if
            end if
        end for
    end for
end for
```

The algorithm is iterated until the local label update stops occurring.[14]

B. Region Growing algorithm

1) *VOI Selection:* The seed selection procedure starts with a single line drawn by the user along the longest visible diameter of the tumor. Afterwards, the VOI and the seeds are computed as follows: 1) The line is cropped by 15% from each end and thickened to three pixels wide to obtain tumor seeds; 2) VOI is selected as the bounding box of the sphere having a diameter 35% longer than the line; 3) One-voxel-wide border of this VOI is used as background seeds. Since the VOI is completely bounded by the background seeds, each path connecting inside and outside the VOI is blocked by a seed. Then, the result of labeling using only the data inside the region is equivalent to using the whole volume whereas the computation time is significantly reduced. Edge detection uses the difference in color between the background color and foreground.

2) *Seed Point Selection :*For the seed point selection our assumption is that tumour's region has grown in considerable size .The following steps are performed to find the seed point:

(a) Convert the given coloured image into the gray image.

(b) First of all count no pixels whose intensities are greater than hundred and less than hundred and store them in separate variables.

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(c) Find difference between both variables if difference is small then go to step 'd' else

convert the image into negative and again set the intensity of external part of the brain to zero and go to step 'd'

(d) Convert the obtained gray image into the binary image.

(e) 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 colour.

(f) Find the sum of all rows individually and store it in the array.

(g) Find the sum of all the columns and store the results in another array.

(h) Find the intersection of row and column having maximum sum .This is taken as seed point.

3) *Tumor segmentation*

The first region-growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighbouring pixels to the regions. The difference between a pixel's intensity value and the region's mean,δ , is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. Region growing algorithm partition image directly into regions, without first looking for boundaries or thresholds Algorithm uses bottom up approach.

The steps of the algorithm is as follows

a) Start from seed point

b) Look at its neighborhood

c) For each point p in nhood:

d) If P(p) == TRUE then include pin region L

e) Else p is a border

f) In each iteration, look at neighbors of each point in L, to save computation, "order" the points in L and don"t check the points that have high score (e.g. the ones that are in the middle of the region).

V. RESULTS

A. Input

In the experimental setup 256x256 input images extracted. During testing Brain Image including healthy and diseased cells are taken for analysis. The images are taken are that of MRI scan. The test image can be of any size. The input image is shown in Fig.1. The input images are contrast enhanced during training phase. Input image is labeled as foreground (Green) and background (Blue).
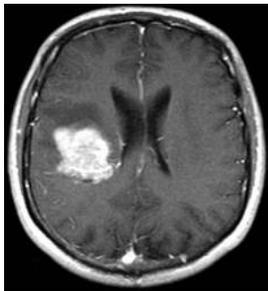

Fig. 1 Input Brain MR Image

B. Output

Both the algorithms are implemented on given input image & final segmented tumor area for each algorithm is as shown below.
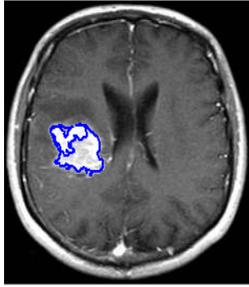

Fig.2 Selected ROI image

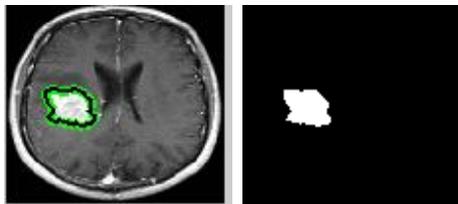Fig.3 Segmented tumor area using region growing algorithm

Fig.4 Segmented tumor area using grow cut algorithm

VI. FUTURE SCOPE

In future this work will pave the way to reach automatic assessment of the tumor response to therapy, due to reasonable and acceptable success rate of algorithm. CA is used in various image processing task such as image filtering,text extraction,image enhancement. In future, tumor growth is simulated with a cellular automaton modeling. Tumor cell proliferation, which was coupled to a Eulerian FEM method to handle the tumor mass effect.

VII. CONCLUSION

In this paper segmentation algorithms are presented for the problem of brain tumor which exhibit varying tissue characteristics. Grow cut combines the advantages, distributed between the mentioned methods such as multi-label segmentation, N-dimensional images processing, speed high enough for interactive segmentation and offers more - algorithm extensibility by varying the automaton evolution rule, more interactivity and user control of the segmentation process. Region growing method finds the seed points and the segmentation results obtained are very much accurate. There are only a small amount of pixels which are misclassified.

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