ROUGH SET THEORY BASED SEGMENTATION OF TUMOR FOR MR IMAGES WITH CA APPROACH

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Abstract—

Population atlases provide an important prior to improve brain tumour segmentation by measuring the deviation from the normal brain. The application is in the clinical radio surgery planning, where manual segmentation of tumours are carried out on contrast enhanced T1-MR images by a radio-oncology expert, modify the cellular automata (CA) segmentation towards the nature of the tumour properties undergoing radiation therapy by adapting relevant transition rules. The proposed system is a novel semi supervised scheme with roughest theory for abnormality detection and segmentation in medical images. Semi supervised learning does not require pathology modelling and, thus, allows high degree of automation. Here formulates and maximize a strictly concave likelihood function estimating abnormality for each partition and fuse the local estimates into a globally optimal estimate that satisfies the consistency constraints, based on a distributed estimation algorithm.

Index terms-- Brain tumor segmentation, cellular automata, contrast enhanced magnetic resonance imaging (MRI), necrotic tissue segmentation, radio surgery, radiotherapy, seeded segmentation,

Shortest paths.

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INTRODUCTION

The body is made up of many types of cells. Each type of cell has special functions. Most cells in the body grow and then divide in an orderly way to form new cells as they are needed to keep the body healthy and working properly. When cells lose the ability to control their growth, they divide too often and without any order. The extra cells form a mass of tissue called a tumor. Tumors are benign or malignant. The aim of this work is to design an automated tool for brain tumor quantification using MRI image data sets. Magnetic Resonance Imaging (MRI) is the state of the art medical imaging technology, which allows cross sectional view of the body with unprecedented tissue contrast. MRI plays an important role in assessing pathological conditions of the ankle, foot and brain. It has rapidly evolved into an accepted modality for medical imaging of disease processes in the musculoskeletal system, especially the foot and brain due to the use of non-ionizing radiation.

Magnetic resonance imaging (MRI) is often the medical imaging method of choice when soft tissue delineation is necessary. This is especially true for any attempt to segment brain tissues, normal or abnormal. MRI provides a digital representation of tissue characteristic that can be obtained in any tissue plane. The images produced by an MRI scanner are best described as slices through the brain. MRI has the added advantage of being able to produce images which slice through the brain in both horizontal and vertical planes. This work is a small and modest part of a quite complex system. The whole system when completed visualizing the inside of the human body, it makes surgeons able to perform operations inside a patient without open surgery. More specifically the aim for this work is to segment a tumor in a brain. This will make the surgeon able to see the tumor and then ease the treatment.

Perfusion Imaging, Diffusion Imaging, or Spectroscopic Imaging provide lower resolution images compared to T1 or T2 weighted sequences, and the former are not preferable for geometric measurements. Multimodality images are used such as T2 weighted MRI is to segment edema/infiltration region which is generally not observable in T1 images. It is not possible to distinguish edema and infiltration, so usually this region is not included in primary target planning of radio surgery.

For image segmentation Region-based active contour models are widely used [10]. These region-based models have many advantages over gradient-based techniques for segmentation that includes greater robustness to noise. Many small structures, mainly blood vessels, are classified as tumor as they also enhance with contrast because the tumor class does not have a strong spatial priority. Minimization problem can be solved by using Graph based seeded segmentation framework has been generalized such that graph-cuts (GC) [12], random walker (RW) [13], shortest paths, and power watersheds [14] have been interpreted as special cases of a general seeded segmentation algorithm.

CA (Cellular automata) algorithm uses on generic medical image problems. The iterative CA framework solves the shortest path problem with a proper choice of the transition rule. It can be applied in the clinical radio surgery planning, where manual segmentation of tumors are carried out on contrast enhanced T1-MR images by a radio-oncology expert. The CA algorithm is modified for segmentation towards the nature of the tumor properties undergoing radiation therapy by adapting relevant transition rules. A smoothness constraint using level set active surfaces is imposed over a probability map constructed from resulting CA states.

By using Rough set theory imperfect pixel or distorted regions of tumor can be detected. Rough set theory can be regarded as a new mathematical tool for imperfect data analysis. The theory has found applications in many domains, such as decision support, engineering, environment, banking, medicine and others. Rough set philosophy is founded on the assumption that with every object of the universe of discourse some information (data, knowledge) is associated. Objects characterized by the same information are indiscernible (similar) in view of the available information about them. The indiscernibility relation generated in this way is the mathematical basis of rough set theory.

I. METHODOLOGY

The methodology section includes the complete segmentation framework of brain tumors and the necrotic regions enclosed in the brain are presented in detail. An overview of the algorithm with the pseudo-code of the implementation is described here.

A. *Tumor-Cut Algorithm*

Steps of the cellular automata based tumor segmentation algorithm is shown in Fig. 1. First, the user draws a line over the largest visible diameter of the tumor; second, using this line, a VOI is selected with foreground(red)-background(blue) seeds; third, tumor CA algorithm is run on the VOI for each two sets of seeds (for the foreground and background) to obtain strength maps for foreground and background at each voxel; then, two strength maps are combined to obtain the tumor probability map ; a level set surface is initialized at and the map is used to evolve the surface which converges to the final segmentation map . Finally, the necrotic regions.

By introducing a local update rule in each individual cell at specific state and changes synchronously depending on the states of some neighbours as determined. Since the state of any cell depends only on the states of the local neighbours, they are parallel, local and homogeneous, at the previous time step and the update rules are same for every cell. The cellular automata are initialized by providing corresponding labels at seeds with a strength value between 0 and 1 where a higher value reflects a higher confidence in choosing the seed. Strengths for unlabeled cells are set to 0.

Cellular automaton (CA) is a triple A=(S, N, δ), S is a nonempty set, known as the state set, N is the neighbourhood, and $\partial: S^N \rightarrow S$ is the local transition function (rule); S^N is the argument of δ, indicates the states of the neighbourhood cells at a given time, while, S is its value, is the state of the central cell at the next time step [20].

B. *Seed Selection Based on Tumor Response Measurement Criteria*

Segmentation using "Response Evaluation Criteria In Solid Tumors" (RECIST), is a generally used procedure to evaluate the treatment response of the solid tumors, tumor progress is classified by measuring the longest in plane tumor diameter in one dimension (axial, coronal, sagittal) [32]. Seed selection algorithm implements the same idea to which the clinicians are used.

The volume of interest (VOI), the tumor seeds and the background seeds are determined by using the line already drawn by the user to measure the longest diameter of the solid tumor. The seed selection procedure starts with a single line drawn by the user along the longest visible diameter of the tumor, focusing on tumor segmentation problem.

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.

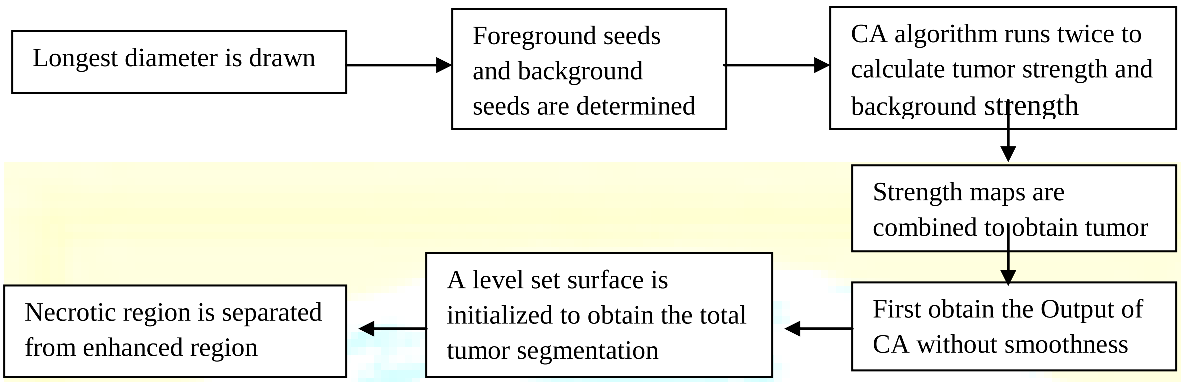

Fig.1 Block Diagram of Tumor cut Segmentation

Each path connecting inside and outside the VOI is blocked by a seed, since the VOI is completely bounded by the background seeds, then; labelling using data inside the region is equivalent to labelling the whole volume whereas the computation time is significantly reduced. One main drawback is that the user draws the line on only a single slice of the tumor volume, so there is no guarantee that the depth of the tumor will also coincide with the VOI. The enlargement ratio for the bounding box size, the percentage of the volume enclosed in the sphere to the total tumor volume and is shown in Fig. 2. The average Dice Overlap between the sphere drawn around the longest diameter line and the tumor is found to be 56 %, which is very efficient. The maximum diameter line will not be enclosed by the tumor completely in some special cases of slightly concave-shaped tumors, an input 1-D line is correctly drawn to fall inside the tumor region, the algorithm can perform the segmentation successfully. The line enlargement parameter selected for VOI formation is determined by taking such cases into account, hence, the VOI contains the whole tumor.

C. Abnormal tissues extraction

It is a comparison between two image segmentation's methods; the first method is based on normal brain's tissue recognition then tumor extraction using thresholding method. The second method is classification based on EM segmentation which is used for both brain recognition and tumor extraction. The goal of these methods is to detect, segment, extract, classify and measure properties of the brain normal and abnormal (tumor) tissues.

Brain recognition methods to separate the abnormal tissues. In this approach a method is applied method based on thresholding used for tumor extraction. We have found that the local thresholding gives a good results comparing with the others. We conclude that when we combine median filter, local thresholding and post processing in such way that the resultant and post processing in such way that the resultant algorithm is more robust. As a general method, we have implemented classification based on EM segmentation

D. Rough set Theory Implementation

An approach first forwarded by mathematician Zdzislaw Pawlak at the beginning of the eighties; it is used as a mathematical tool to treat the vague and the imprecise data. Rough Set Theory is similar to Fuzzy Set Theory, however the uncertain and imprecision in this approach is expressed by a boundary region of a set, and it is not by a partial membership as in Fuzzy Set Theory. Rough Set concept can be defined quite generally by means of interior and closure topological operations know approximations. Indiscernibility relation is a central concept in Rough Set Theory, and is considered as a relation between two objects or more, where all the values are identical in relation to a subset of considered attributes. Rough sets theory provides a novel approach to knowledge description and to approximation of sets. Rough theory is based on an approximation space-based approach to classifying sets of objects. In rough sets theory, feature values of sample objects are collected in what are known as information tables. Rows of a such a table correspond to objects and columns correspond to object features. Various rough image processing methodologies have been applied to handle the different challenges posed by medical imaging. Rough sets can bound such sets and provide a mechanism for modelling the spatial uncertainty in the image of the object.

Rough set theory can be used as a feature subset selection algorithm. A particular Rough set Model-RSM determines and removes the dispensable attributes representing the redundant information within the data while it aims to keep the core attributes representing the minimum essential information. By relaxing the core algorithm, more attributes can be selected which are called Reduct. In this paper, Reduct attributes are considered as the minimum selected features. The selected Reduct should have the same discernibility and representation power as the original data. Cardinality is used to replace traditional rough set theory operations. Therefore, algorithm efficiency will be improved with reduced complexity. The cardinality of a set is defined as the number of elements in the set.

The MR image *X* can be expressed as a linear mixture of a set of features or basis functions U_i is given as

$$Xi=\sum_i UiSi \qquad (1)$$

Where Si are stochastic coefficients that are data dependent. The equation (1) can be expressed in terms of Matrix notations as shown in (2):

$$\mathbf{X} = \mathbf{US} \qquad (2)$$

Where *S* is a matrix contains the source components and *U is* the mixing matrix. This means that a MR image consists of a mixture of source components S. Their combination can be described using the coefficients of the mixing matrix U which can be used as extracted features that describe efficiently any normal and suspicious region. Rough set model is used in this proposed work to reduce number of inconsistent objects.

i) Rough representation of a region of interest

A region of interest (ROI), is a selected subset of samples within an image identified for a particular purpose. The ROI is commonly used in medical imaging. In the proposed work, the boundaries of a tumor may be defined on an image or in a volume, for the purpose of measuring its size. The main advantage of this method is its ability to represent inconsistency between the knowledge-driven shape and image-driven shape of a ROI using rough approximations. The method consists of three steps. First, the discretized feature values that describe the characteristics of a ROI. Secondly, using all feature extracted values, they build up the basic regions in the image so that each region contains voxels that are indiscernible on all features. Finally, according to the given knowledge about the ROI, they construct an ideal shape of the ROI and approximate it by the basic categories.

II. EXPERIMENTS

i) Description of input data:

MR scans of the head are given as input to the algorithm. Currently working with gradient echo images acquired using a General Electric Sigma 1.5 Tesla clinical MR imager. Tissue classes visible in such MRI scans include white and grey matter, cerebrospinal fluid (csf), meninges (the protective membranes surrounding the brain), skull, muscle, fat, skin or air . Pathology introduces the additional classes of edema, tumor, haemorrhage or other abnormality.

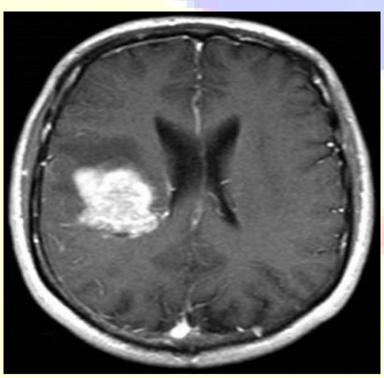

Fig.2 Input MR Image of brain with abnormalities

ii) Analysis:

By using Tumor cut segmentation algorithm the 90% of tumor is detected and using rough set theory, abnormal boundary detection and closed contour method the tumor located is precise and very accurate. The CA algorithm is applied twice and imperfect pixel regions are obtained by rough set.

The Rough set theory is introduced for obtaining the exact statistical values of the blurred pixel values and is taken as feature extraction. According to the extracted features analysis is carried out. By applying threshold value energy map of tumor and background region is separated. From the input image user can select the affected region with the help of rough set theory. Energy map and the output after CA approach are given below.

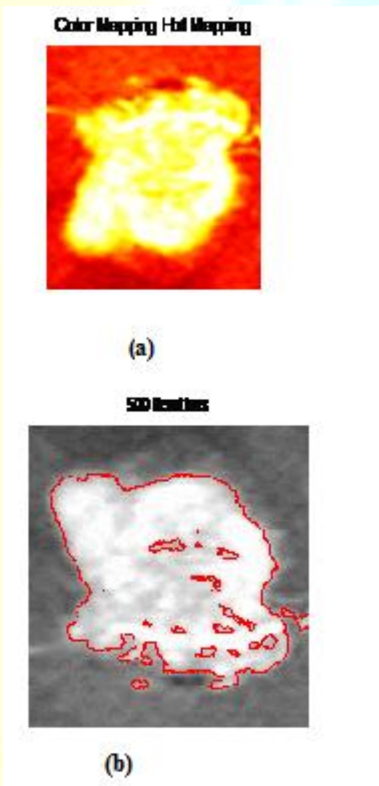

Fig.3 (a) Energy map of tumor (b) After applying CA algorithm

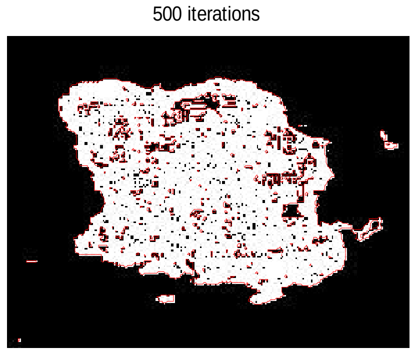

Fig.4 After applying Rough set

iii) Results

The tumor segmentation is carried out in effective manner. than manual segmentation provide better results. Rough set theory is also introduced for feature extraction.

After 500 iterations the exact tumor region is obtained as the segmented region. The output image is shown below.

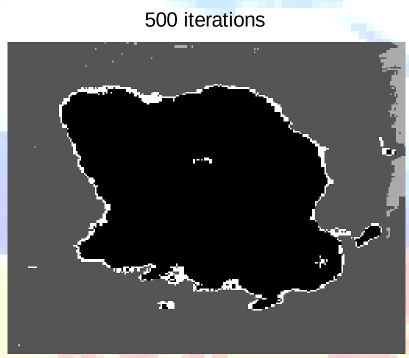

Fig.5 The output obtained after Tumor-cut segmentation (The black region inside the tumor is the enhanced cell)

III. CONCLUSION

In this project three approaches for segmentation of brain tissue in MR images is presented. The results show that this method can successively segment a tumor provided the parameters are chosen properly. The visualization and detective valuations of the results of the segmentation show the success of the approaches. In this study, the tumor identification and the investigation are carried out with the help of roughest theory for the potential use of MRI data for improving the tumor shape and 2D visualization of the surgical planning. Using rough set theory feature extraction is performed efficiently and this made segmentation easier. A segmentation algorithm for the problem of tumor delineation which exhibit varying tissue characteristics. A single modality is used for radio surgery that has an advantage of computational efficiency and ease of use. Future research works can be performed in this project.

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