Brain Tumor Segmentation based on Rough Set Theory for MR Images with CA Approach

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Abstract—Brain Tumor detection and diagnosis is very important nowadays because the treatment is based on radio surgery. The exact boundary should be detected for the proper treatment by segmenting necrotic and enhanced cells, 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. Here, modification of the cellular automata (CA) segmentation towards the nature of the tumour properties undergoing radiation therapy by adapting relevant transition rules with the help of Rough set theory. 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 with less computation speed.

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

I. INTRODUCTION

The brain is made up of many different types of cells. Brain cancers occur when one type of cell transforms from its normal characteristics and grows and multiplies in an abnormal way.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. Usually they are named after the part of the brain or the type of brain cell from which they arise. Many of them are benign and can be successfully removed. Malignant primary brain tumors cause problems by spreading into the normal brain tissue thereby increasing the pressure and causing damage to the surrounding areas of the brain.

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These tumors rarely spread outside the brain to other parts of the body. The most common primary brain tumors are gliomas. They begin in glial cells. Magnetic Resonance Imaging (MRI) is the state of the art medical imaging technology, which allows cross sectional view of the body with 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. Brain tumors are the most common solid tumors that occur in children. Children of any age may be affected. Boys are affected more often than girls. Two types of brain cancers that are more common in children than in adults are medulloblastoma and ependymoma. Treatment and chance of recovery depend on the type of tumor, its location within the brain, the extent to which it has spread, and the child's age and general health.

Magnetic resonance imaging (MRI) provides detailed images of living tissues, and is used for both brain and body human studies. Data obtained from MR images is used for detecting tissue deformities such as cancers and injuries; MR is also used extensively in studies of brain pathology, where regions of interest (ROI's) are often examined in detail, for example in multiple sclerosis (MS) studies. In order to perform good quantitative studies, ROI's within the brain must be well defined. In traditional methods, a skilled operator manually outlines the ROI's using a mouse or cursor. More recently, computer-assisted methods have been used for specific tasks such as extraction of MS lesions from MRI brain scans , or extraction of the cerebral ventricles in schizophrenia studies . Many of these computer-assisted tasks require segmentation of the whole brain from the head. MRI provides a digital representation of tissue characteristic that can be obtained in any tissue plane.

Many issues inherent to medical imagery make segmentation a difficult task. The objects to be segmented from medical imagery are true (rather than approximate) anatomical structures, which are often non-rigid and complex in shape, and exhibit considerable variability from person to person. Moreover, there are no explicit shape models yet available that fully captures the deformations in anatomy. Magnetic resonance images are further complicated due to the limitations in the imaging equipment that lead to a non-linear gain artifact in the images. In addition, the signal is degraded by motion artefacts due to voluntary or involuntary movement of the patient during the scanning process.

Magnetic resonance imaging (MRI) provides rich three-dimensional (3D) information about the human soft tissue anatomy. It reveals fine details of anatomy, and yet is non-invasive and does not require ionizing radiation such as r -rays. It is a highly flexible technique where contrast between one tissue and another in an image can be varied simply by varying the way the image is made. There are different types of MR images, from that T1-weighted and T2-weighted images are used to detect tumor. T1 is the longitudinal relaxation time. It indicates the time required for a substance to become magnetized after first being placed in a magnetic field or, alternatively, the time required to regain longitudinal magnetization following an RF pulse T2 is the "transverse" relaxation time. It is a measure of how long transverse magnetization would last in a perfectly uniform external magnetic field. Alternatively, it is a measure of how long the resonating protons remain coherent or process (rotate) "in phase" following a 90° RF pulse. T2 decay is due to magnetic interactions that occur between spinning protons.

The shape of an object can be described in terms of its boundary or the region it occupies. Image region belonging to an object generally have homogeneous characteristics, e.g. similar in intensity or texture. Region-based segmentation techniques attempt to segment an image by identifying the various homogeneous regions that correspond to different objects in an image. Unlike clustering methods, region-based methods explicitly consider spatial interactions between neighbouring voxels. In its simplest form, region growing methods usually start by locating some seeds representing distinct regions in the image. The seeds are then grown until they eventually cover the entire image. The region growing process is therefore governed by a rule that describe the growth mechanism and a rule that check the homogeneity of the regions at each growth step. Region growing technique has been applied to MRI segmentation. A semi-automatic, interactive MRI segmentation algorithm was developed that employ simple region growing technique for lesion segmentation. In, an automatic statistical region growing algorithm based on a robust estimation of local region mean and variance for every voxel on the image was proposed for MRI segmentation. The best region growing parameters are automatically found via the minimization of a cost functional. Furthermore, relaxation labelling, region splitting, and constrained region merging were used to improve the quality of the MRI segmentation. The determination of an appropriate region homogeneity criterion is an important factor in region growing segmentation methods. However, such homogeneity criterion may be difficult to obtain a priori. An adaptive region growing method is proposed where the homogeneity criterion is learned automatically from characteristics of the region to be segmented while searching for the region.

The CA algorithm is modified for segmentation towards the nature of the tumor properties undergoing radiation therapy by adapting relevant transition rules.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. A smoothness constraint using level set active surfaces is imposed over a probability map constructed from resulting CA states.

Nowadays, it is widely recognized that rough sets applications have a great importance in several fields, such as granular computing, data mining and approximate reasoning. Rough set philosophy is founded on the assumption that with every object of the universe of discourse some information (data, knowledge) is associated. This is witnessed by the increasing number of papers and conferences about rough sets and by the implementation of real-life applications based on rough sets. This fact leads to a continuous and useful development of applicative aspects of rough sets methodologies. Even though this attention to application is of great importance, it is not excluded that theoretical aspects concerning with foundations of rough sets, both logical and mathematical, must be taken into account. 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.

II. METHODOLOGY

This section includes the complete segmentation framework of brain tumors and the enhanced regions enclosed in the brain are presented in detail. An overview of the tumor segmentation with rough set theory and Cellular Automata is used.

A. *Tumor-Cut Segmentation Algorithm*

Steps of the cellular automata based tumor segmentation algorithm is shown in the following Figure. 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. They are parallel, local and homogeneous, since the state of any cell depends only on the states of the local neighbours 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.

B. *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). Seed selection algorithm implements the same idea to which the clinicians are used. Region growing approaches is the opposite of the split and merge approach: An initial set of small areas are iteratively merged according to similarity constraints.

- Start by choosing an arbitrary *seed pixel* and compare it with neighbouring pixels.
- Region is *grown* from the seed pixel by adding in neighbouring pixels that are similar, increasing the size of the region.
- When the growth of one region stops we simply choose another seed pixel which does not yet belong to any region and start again.
- This whole process is continued until all pixels belong to some region. A *bottom up* method

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.

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, and the algorithm can perform the segmentation successfully.

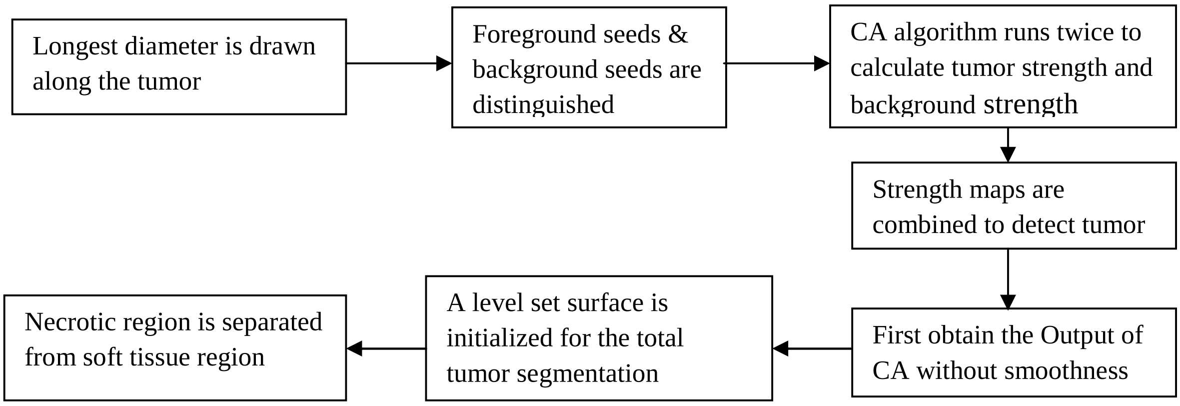

Fig.1 Block Diagram of Tumor cut Segmentation

C. Abnormal tissue extraction

The second method is the classification based on Expectation Maxima 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) tissue. Here tissue extraction is the comparison between two image segmentation's methods; the first method is based on normal brain's tissue recognition then tumor extraction using thresholding method.. 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. Here 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

Rough set theory was first forwarded by mathematician Zdzislaw Pawlak at the beginning of the eighties; used as a mathematical tool to treat the vague and the imprecise data. Various rough image processing methodologies have been applied to handle the different challenges posed by medical imaging. We can define rough image processing as the collection of all approaches and techniques that understand, color images, followed by the various rough based approaches developed for handling the different functional aspects to solve medical imaging problems. 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 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 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 featuresTherefore, 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

The ROI is commonly used in medical imaging. A region of interest (ROI) is a selected subset of samples the image that can be identified for a particular purpose. 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 set approximations. The method consists of three steps. First, the discredited 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.

III. EXPERIMENTS

A) 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 T1 weighted and T2 weighted, white and grey matter, cerebrospinal fluid (csf), meanings (the protective membranes surrounding the brain), skull, muscle, fat, skin or air . Pathology introduces the additional classes of edema, tumor, haemorrhage or other abnormality.

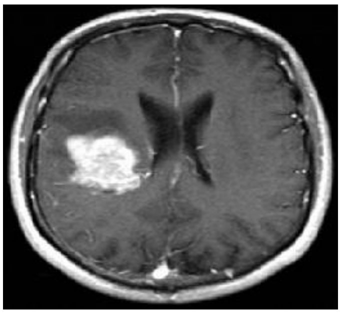

Fig.2 Input MR Image of brain

B) ANALYSIS:

By using Tumor cut segmentation algorithm the exact necrotic region,i.e, tumor is detected and using rough set theory, abnormal boundary detection and closed contour method the tumor located is precise and very accurate. Stronger region is the deeply affected region, blue indicates the affected region and yellow starting stage. 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. The intensity along with the changes in the tumor cell is also represented. Strength of tumor is indicated by different colours. Also the histogram values are plotted.

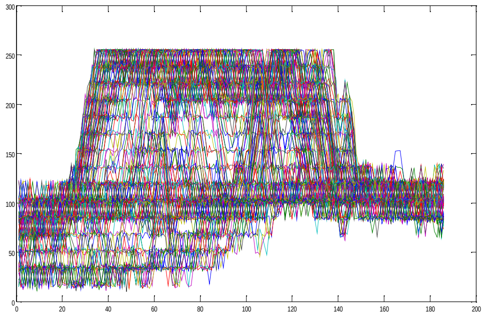

Fig.3 Intensity variations of necrotic pixel (red-strong region, blue-tumor affected region, yellow-initial stage)

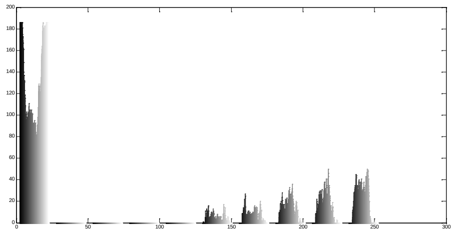

Fig.4 Histogram representation applying Rough set

C) RESULTS

The tumor segmentation is carried out in effective manner than manual segmentation provides better results. Rough set theory is also introduced for feature extraction of texture, colour, pixel intensity etc.. Histogram value where introduced for abnormality detection

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

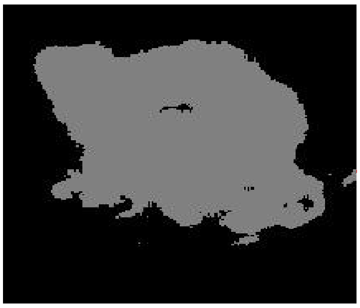

Fig. 6 The output obtained after Tumor-cut segmentation (The white region inside the tumor is the enhanced cell)

IV. 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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