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A SURVEY ON DETECTION AND SEGMENTATION OF BRAIN TUMORS IN MR IMAGES

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ABSTRACT

Brain tumor segmentation is one of the crucial procedures in surgical and treatment planning. However, at present brain tumor segmentation in brain tumor images is mostly performed manually in clinical practices. Apart from being time consuming, manual brain tumor delineation is difficult and depends on the individual operator. Currently, multimodal MRI images are used simultaneously by radiologists in segmenting brain tumor images because they can provide various data on tumors. Although multimodal MRI images can provide complementary information in the tumor area, brain tumor segmentation is still a challenging and difficult task. Varying intensity of tumors in MRI makes the automatic segmentation of such tumors extremely challenging. In this paper, a survey on different methods for the automatic detection and segmentation of brain tumors in MRI images is presented. Finally a stochastic model for characterizing tumor texture using a multi-resolution fractal model known as multifractional Brownian motion (mBm) is proposed. A novel tumor segmentation scheme is proposed by modified AdaBoost algorithm. The fusion of multi-FD with fractal and intensity features significantly improves brain tumor segmentation and classification.

Key words - AdaBoost Classifier, Brain tumor, Magnetic Resonance Imaging, Multi-fractal, Radiosurgery, Segmentation

INTRODUCTION

Tumor is generally defined as the abnormal growth of the tissues. A brain tumor is a mass of unnecessary cells growing in the brain or central spine canal. Brain cancer can be counted among the most deadly and intractable diseases. Brain tumors can be primary or metastatic, and primary tumors are again classified as either malignant or benign tumors. A tumor that starts int brain is a priary brain tumor. A metastatic brain tumor is a cancer that has spread from elsewhere in the body of the brain. It is a kind of brain disorder in which clusters of nerve cells, or neurons, in the brain sometimes signal abnormally.

The National Cancer Institute (NCI) estimated that 22,070 new cases of brain and other central nervous system (CNS) cancers would be diagnosed in the United States in 2009. The American Brain Tumor Association (ABTA) clarifies this statics further by estimating that 62,930 new cases of primary brain tumors would be diagnosed in 2010 [1]. According to the Central Brain Tumor Registry of the United States (CRTRUS), there were 64,530 new cases of primary brain and central nervous system tumors diagnosed by the end of 2011 and they are increasing every day [2]. This necessitates greater effort in the field of brain tumor diagnosis. Today, tools and methods to analyse tumors and their behaviour are becoming more prevalent. Clearly, efforts over the past century have yielded real advances. However, we have also come to realize that gains in survival must be enhanced by better diagnosis tools. Although we have yet to cure brain tumours, clear steps forward have been taken toward reaching this ultimate goal, more and more researchers have incorporated measures into clinical trials each advance injects hope to the team of caregivers and more importantly, to those who live with this diagnosis [1-2].

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 [3].MRI is an effective tool that provides detailed information about the targeted brain tumor anatomy which in turn enables effective diagnosis, treatment and monitoring of the disease. Its techniques have been optimized to provide measures of change within and around primary and metastatic brain tumors, including edema, deformation of volume and anatomic features within tumors, etc [4].MRI provides a digital representation of tissue characteristics 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 makes the MRI-scan images an ideal source for detecting, identifying and classifying the right infected regions of the brain.

Most of the current conventional diagnosis techniques are based on human experience in interpreting the MRI-scan for judgment; certainly this increases the possibility to false detection and identification of the brain tumor. On the other hand, applying digital image processing ensures the quick and precise detection of the tumor [5]. One of the most effective techniques to extract information from complex medical images that has wide application in medical field is the segmentation process. 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 homogenous with respect to a predefined criterion. Widely used homogeneity criteria include values of intensity, texture, colour, range, surface normal and surface curvatures.

KNOWLEDGE-BASED TECHNIQUES

Knowledge is any chunk of information that effectively discriminates one class type from another [6]. Tumor will have certain characteristics that other brain tissues will not have and vice-versa. This is a system that automatically segments and label tumors in magnetic resonance images (MRI's) of the human brain. Intial segmentation is performed by an unsupervised clustering. The segmented image, along with cluster centers for each class is provided to a rule-based expert system which extracts the intracranial region. Multispectral histogram analysis separates suspected tumor from the rest of the intracranial region, with region analysis used in performing the final tumor labelling. The system provides a completely automatic segmentation and labelling of tumor after a rule set was built from a set of training images. The strength of knowledge based systems is their coarse-to-fine operation. Instead of attempting to achieve the task in one step, incremental refinement is applied with easily identifiable tissues located and labelled first. Removing labeled pixels from further consideration allows the focus to be placed on the remaining fewer pixels, where more subtle trends may become clearer. The guidance of the knowledge base gives this system additional power and flexibility by allowing unsupervised segmentation and classification decisions to be made through iterative/successive refinement. The disadvantages are a knowledge base is required, more time consuming and less accurate.

FLUID VECTOR FLOW MODEL

Active contour models are considered as effective tools for segmentation and object tracking [7]. A parametric active contour model called Fluid Vector Flow (FVF) is proposed to address problems of insufficient capture range and poor convergence for concavities. Given an intial contour, the evolution of a parametric active contour model is driven by external forces while the shape of the contour is maintained by the internal forces. FVF simulates fluid flowing along object boundary and generates external force fields dynamically to drive the contour evolution. FVF has the largest capture range. FVF is also able to extract acute concave shapes due to its nonstatic external force fields. In this model, the external force field changes dynamically with the contour evolution. Thus, the FVF contour does not get stuck and acute concavities can be extracted. In the first stage, we apply a Gaussian smoothing filter to the input image and apply a gradient operator to find edges in the image. A threshold is then used to generate the binary boundary map. At the second stage, the contour can be initialized to initialize the external force field. The programme automatically detects the initialization and generates the external force field accordingly. The computation of the internal energy follows. The intial forces will push the active contour to the neighbourhood of the target object. At the last stage, a control point is automatically selected from the object boundary and generates new external force field to evolve the active contour. This point can flow freely along the object boundary like a drop of fluid, dynamically update the external force field to and thus further evolve the active contour until convergence is achieved. The main disadvantage of this method are it suffers from boundary leakages, makes assumption that there is a single continuous region associated with tumor and it does not easily determine the initializations.

TUMOR-CUT: SEGMENTATION METHOD

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 developed [8]. Particularly, cellular automata (CA) based seeded tumor segmentation method on contrast enhanced T1 weighed magnetic resonance images, which standardizes the volume of interest (VOI) and seed selection, is proposed. The CA algorithm is re-examined to establish the connection of the CA-based segmentation to the graph-theoretic methods to show that the iterative CA framework solves the shortest path problem with a proper choice of the transition rule. Sufficient information to initialize the algorithm is gathered from the user simply by a line drawn on the maximum diameter of the tumor, in line with the clinical practice. Furthermore, an algorithm based on CA is presented to differentiate necrotic and enhancing tumor tissue content, which gains importance for a detailed assessment of radiation therapy response. First the user draws a line over the largest visible diameter of the tumor and using this line, a VOI is selected with foreground and background seeds. Then tumor CA algorithm is run on the VOI for each two sets of seeds to obtain strength maps for foreground and background at each voxel. The two strength maps are combined to obtain the tumor probability map and a level set surface is initialized and the map is used to evolve the surface which converges to the final segmentation map. Finally the necrotic region of the tumor is segmented using a CA based method with the chosen enhanced and necrotic seeds. The main disadvantage of this method is under-segmentation of tumor and also this can be applied only on contrast enhanced T1 images.

USING WAVELET TRANSFORM AND K-MEANS ALGORITHM

This is an efficient method for the detection of brain tumor from cerebral MRI images [9]. The methodology consists of three steps: enhancement, segmentation and classification. Segmentation is preceded by a pre-treatment step called enhancement. The segmentation phase is also followed by a post treatment step known as classification which ensures the tumor extraction. To improve the quality of images and limit the risk of distinct regions fusion in the segmentation phase an enhancement process is applied. We adopt mathematical morphology to increase the contrast in MRI images. Then apply Wavelet Transform in the segmentation process to decompose MRI images. At last, the k-means algorithm is implemented to extract the suspicious regions or tumors. This method reduces the extraction steps. But the method is less accurate and is more affected by noise.

CANNY EDGE DETECTION ALGORITHM

A modified image segmentation techniques were applied on MRI scan images inorder to detect brain tumors [10]. The method uses modified Canny Edge Detection algorithm for tumor detection which consists of the stages smoothing, filtering, non-maximum suppression, double thresholding and edge tracking by hysteresis. Here the region of interest (ROI) is proposed to identify different tumor types and different infected areas. It is also introduced to enhance the processing time by executing the features processing algorithm in the identified areas instead of the whole image frame. The Canny algorithm can be used as an optical edge detector based on a set of criteria which include finding the most edges by minimizing the error rate, marking edges as closely as possible to the actual edges to maximize localization, and marking edges only once when a single edge exists for minimal response. The optimal filter that meets all three criteria above can be efficiently approximated using the first derivative of a Gaussian function. These derivatives are used to calculate gradient magnitude and gradient direction of most rapid change in intensity. The proposed approach is based on the information of anatomical structure of the healthy parts and compares it with the infected parts. It starts by allocating the anatomical structure of the healthy parts in a reference image of a normal candidate brain scan. Then it allocates the abnormal parts in the unhealthy patient brain scan image by comparing it with the reference image information. This method is able to accurately detect and identify the contour of the tumor and is also less affected by noise. The main disadvantage of this method is its computational complexity.

ADAPTIVE, TEMPLATE MODERATED, SPATIALLY VARYING STATISTICAL CLASSIFICATION

A novel image segmentation algorithm was developed to allow the automatic segmentation of both normal and abnormal anatomy from medical images [11. The algorithm is a form of spartially varying statistical classification, in which an explicit anatomical template is used to moderate the segmentation obtained by statistical classification. The algorithm consists of an iterated sequence of spatially varying classification and nonlinear registration, which forms an adaptive, template moderated (ATM), spatially varying statistical classification (SVC). Classification methods and nonlinear registration methods are often complementary, both in the tasks where they succeed and in the tasks where they fail. By integrating these approaches the new algorithm avoids many of the disadvantages of each approach alone while exploiting the combination. This method is unable to segment structures which have similar characteristics in all feature channels and is also not spatially distinct.

PROPOSED METHOD

A formal stochastic model to estimate multi-fractal dimension (multi-FD) for brain tumor texture extraction in brain MRI is proposed. Due to complex appearance in MRI, brain tumor texture is formulated using a multiresolution-fractal model known as multifractional Brownian motion (mBm). Fractal geometry describes objects in non-integer dimension. While a straight line has a dimension of exactly one, a fractal curve may have a dimension between one and two. The main attraction of fractal geometry stems from the ability to describe the irregular or fragmented shape of natural features as well as other complex objects that traditional Euclidean geometry fails to analyse. This phenomenon is often expressed by spatial or time domain statistical scaling laws and is mainly characterized by the power-law behaviour of real world physical systems. A multi-fractal feature based brain tumor segmentation method is developed next. The fusion of multi-FD with fractal and intensity features significantly improves brain tumor segmentation and classification. Boosting is a general method for improving the accuracy of any given learning algorithm. Due to ineffectiveness in classifying complex tumor texture, an ensemble boosting method is considered. Such boosting methods yield a highly accurate component classifier. Here AdaBoost classifier is used. Adaboost is an algorithm for constructing a strong classifier as linear combination of simple weak classifiers. Final classification is based on the weighted vote of weak classifiers. This algorithm is fast, simple and easy to program, no parameters are required for tuning and no prior knowledge is needed about weak learner.

CONCLUSION

In this paper, different methods for the detection and segmentation of brain tumors in MRI images are discussed. The varying sizes and shapes and also the artifacts and noise in brain tumor images increase the difficulty when segmenting tumors. Thus, designing of a semi-automatic or automatic brain tumor segmentation approach is necessary. The different automatic segmentation methods overcome the difficulty of manual detection of brain tumor. But the varying intensity of tumors in brain magnetic resonance iages makes the automatic segmentation of tumors extremely challenging. A novel multifractal feature extraction and supervised classification technique for improved brain tumor detection and segmentation is also proposed in this paper. The multi-FD feature characterizes intricate tumor tissue texture in brain MRI as spatially varying multifractal process in brain MRI. The AdaBoost algorithm considers wide variability in texture features in MRI slices for improved tumor and non-tumor classification. This feature based segmentation does not require deformable image registration with any predefined atlas. The computation complexity of multi-FD feature is linear and increases with slice resolution, block size etc.

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