© 2016 IJSRSET | Volume 2 | Issue 2 | Print ISSN : 2395-1990 | Online ISSN : 2394-4099
Themed Section: Engineering and Technology

BTS Identification Technique

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ABSTRACT

Brain tumor segmentation consists of separating the different tumor tissues (solid or active tumor, edema, and necrosis) from normal brain tissues: gray matter (GM), white matter (WM), and cerebrospinal fluid(CSF). In brain tumor studies, the existence of abnormal tissues may be easily detectable most of the time. In the past, many researchers in the field of medical imaging and soft computing have made significant survey in the field of brain tumor segmentation. Both semiautomatic and fully automatic methods have been proposed. Interactive or semiautomatic methods are likely to remain dominant in practice for some time, especially in these applications where erroneous interpretations are unacceptable. This article presents an overview of the most relevant brain tumor segmentation methods, conducted after the acquisition of the image. Given the advantages of magnetic resonance imaging over other diagnostic imaging, this survey is focused on MRI brain tumor segmentation. Semiautomatic and fully automatic techniques are emphasized.

Keywords: Brain Tumor, Tumor Tissues, White Matter, Gray Matter, Cerebrospinal fluid, MRI

I. INTRODUCTION

The ultimate goal of brain tumor imaging analysis is to extract the patient-specific important clinical information, and their diagnostic features. This information embedded within the multidimensional image data, can guide and monitor interventions after the disease has been detected and localized, ultimately leading to knowledge for clinical diagnosis, staging, and treatment of disease [1].

In the specific case of brain tumors, segmentation consists of separating the different tumor tissues such as solid or active tumor, edema, and necrosis (Fig. 1), from normal brain tissues, such as gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF). In brain tumor studies, the existence of abnormal tissues may be easily detectable most of the time. Nevertheless, accurate and reproducible segmentation and characterization of abnormalities are not straightforward. In the last years many researchers in the field of medical imaging and soft computing have made significant advances in the field of brain tumor segmentation. Both semiautomatic and fully automatic methods have been proposed. Clinical acceptance of segmentation techniques has depended on the simplicity of computation and the degree of user supervision [1]. Until better solutions are proposed, semiautomatic or interactive methods will likely be dominant in practice for a long time to come, because erroneous interpretations are not acceptable under any circumstances. This paper presents an overview of the most relevant existing brain tumor segmentation methods applied after the acquisition of the image. Given the advantages of magnetic resonance imaging (MRI) over other diagnostic imaging techniques, this survey is focused on MRI brain tumor segmentation. Semiautomatic and fully automatic techniques are emphasized.

II. METHODS AND MATERIAL

Manual and Automated Brain Tumor Segmentation

Brain tumor segmentation methods can be classified into three categories according to the degree of required human interaction as described by Foo et al. [2], Olabarriga et al. [3], and Yao [1]: manual segmentation, semiautomatic segmentation, and fully automatic segmentation.

1. Manual Segmentation

Manual segmentation of brain tumors involves manually drawing the boundaries of the tumor and structures of interest [1]. In manual segmentation, human experts make use of the information presented in the image as well as make use of additional knowledge such as anatomy. Manual delineation is a tedious and time-consuming task.

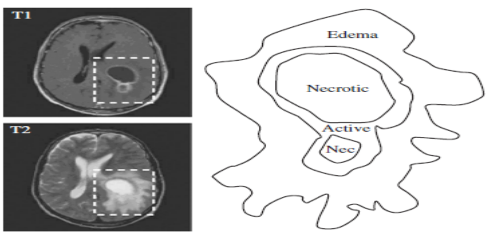

Figure 1. Labeled example of a brain tumor in the T1 with contrast and T2 modalities.

The task of marking the tumor regions manually slice by slice sometimes limits the human rater's view and generates jaggy images and the segmented images are less than optimal showing a "stripping" effect [4]. Manual ROI delineation is also operator dependent and the selected regions are subject to large intra and inter rater variability [5]. For example, the study in [5] quantified an average of 28% ± 12% variation in quantified volume between individuals performing the same brain tumor segmentation task (the variation ranged from 11% to 69%), and quantified a 20% ±15% variation within individuals repeating the task three times at 1 month intervals. Fig. 2 gives an example presented in [8] of inter rater variability, where four different experts performed a manual segmentation of a glioma on the same slice and patient. The resulting segmentation of each expert presents notable differences. Methodologies providing semi auto-mated or, ideally, fully automated segmentation will present clear advantages over the manual delineation. However, manual segmentation is still widely used in clinical trials, especially where a lot of human knowledge and expertise are required to distinguish tissues.

2. Semiautomatic and Fullyautomatic Segmentation

In semiautomatic brain tumor segmentation, the intervention of a human operator is often needed to initialize the method, to check the accuracy of the result, or even to manually correct the segmentation result. Most of the current research is targeted at semiautomatic segmentation of brain tumors with the intention of having the least human interaction possible. According to Olabarriaga et al. [3], the main components of an interactive brain tumor segmentation method are the computational part, the interactive part, and the user interface.

The semiautomatic methods use different strategies to combine computers and humans' expertise, the outcome of these methods depends on the strategy as much as on computation. These strategies could include involving the user in the initialization of segmentation process, keeping the user in the control during the whole process, or adding intelligent behavior to elevate the abstraction of interaction.

In fully automatic methods, the computer determines the segmentation of tumor without any human interaction. Fully automatic methods generally incorporate human intelligence and prior knowledge in the algorithms, and are usually developed making use of soft computing and model-based techniques such as deformable models.

However, developing highly accurate automatic methods remains a challenging problem. The ability of humans to use three-dimensional information in segmentation is also reduced in this task since there is no three-dimensional modeling of structures based on a large range of views of the object. Currently, fully automatic segmentation methods are desirable in processing large batch of images and are mainly restricted to the research environment.

Unsupervised and Supervised segmentation

The brain tumor segmentation requires an objective measure that can be used to define the homogeneity of each tissue. There exist two ways of obtaining the objective measure, namely the unsupervised and supervised segmentation methods [9]. The next sections give a description of unsupervised and supervised segmentation methods.

A. Unsupervised Segmentation

In unsupervised segmentation the clusters are found algorithmically. Unsupervised segmentation can be performed using an anatomic objective measure or an image-based objective measure to assess segmentation quality. Brain tumor unsupervised segmentation approaches that use an anatomic objective measure aim to segment the image into at least two anatomically meaningful regions, one of which is tumor or edema. These approaches have been of limited applicability. The unsupervised segmentation methods that use image-based features, rather than dividing the image along anatomically meaningful distinctions, divide the images into homogeneous regions using image-based features such as intensities and or textures.

B. Supervised Segmentation

Supervised classification involves both a training phase that uses labeled data to learn a model that maps from features to labels, and a testing phase that is used to assign labels to unlabeled data based on the measured features. A major advantage of using a supervised formulation is that supervised methods can perform different tasks simply by changing the training set. Supervised methods have the potential of reducing the manual engineering task by providing labeled data, appropriate features, and appropriate parameters for the learning algorithm.

Segmentation Methods

Detection, localization, diagnosis, staging, and monitoring treatment responses are crucial procedures in clinical medicine and oncology. Early detection and localization of the diseases, and accurate disease staging could lead to changes in patient management that will impact on health outcomes. Four major classes of segmentation are:

- Threshold-based techniques
- Region-based techniques
- Pixel classification techniques
- Model-based techniques

- **Threshold-Based Methods**

Thresholding is a simple and effective region segmentation method, in which the objects of the image are classified by comparing their intensities with one or more intensity thresholds. These thresholds can be either global or local. The image may be segmented by applying several individual thresholds or by using a multithresholding technique.

1. Global Thresholding
2. Local Thresholding

- **Region-based methods**

Region-based segmentation approaches examine pixels in an image and form disjoint regions by merging neighborhood pixels with homogeneity properties based on a predefined similarity criterion [2]. The region growing and the watershed segmentation methods are part of the region-based methods [1], and are the most commonly used for brain tumor segmentation.

1. Region Growing
2. Watershed

- **Pixel Classification Methods**

Pixels in an image can be represented in feature space using pixel attributes that may consist of gray level, local texture, and color components for each pixel in the image. In brain tumor segmentation the methods based on pixel classification are constrained to the use of supervised or unsupervised classifiers to cluster pixels in the feature space. Clustering is the process of grouping similar objects into a single cluster, while objects with dissimilar features are grouped into different clusters based on some similarity criteria.

1. Fuzzy C-Means
2. Markov Random Fields
3. Artificial Neural Networks

- **Model-Based Segmentation Techniques**

In previous sections the most successful solutions for the extraction of brain tumor boundary were analyzed, mainly for 2D MRI data. The segmentation of volumetric (3D) image data is a challenging problem that has been mainly approached by model based segmentation techniques as parametric deformable models and geometric deformable models or level sets. In model-based segmentation, a connected and continuous model is built for a specific anatomic structure by incorporating a priori knowledge of the object such as shape, location, and orientation. Existing deformable models can be broadly divided into two categories:

1. Parametric Deformable Models
2. Geometric Deformable Models

III. RESULTS AND DISCUSSION

Summary of Brain Tumor Segmentation:

Threshold-based techniques are generally used as a first step in the segmentation process. Region-based techniques for brain tumor segmentation are mainly used as refinement step for defining a connected boundary of the tumor [7]. Pixel classification techniques for brain tumor segmentation are limited to clustering nevertheless they are the most frequently used for brain tumor segmentation. The unsupervised technique of FCM, which is the most popular for medical image segmentation [10,11]. permits the use of vague concepts in the definition of clusters, and gives highly accurate results in cases of non-homogeneous tumors. Model-based techniques have been widely used for its sensitivity in searching the boundary of brain tumors [8]. It is important to address the segmentation towards fully automated method. This can be done incorporating within the algorithms human intelligence and prior knowledge about intensity and other tissue information, shape, size, symmetry, and normal anatomic variability to improve segmentation results.

IV. CONCLUSION

Detecting the existence of brain tumors from MRI in a fast, accurate, and reproducible way is a challenging problem. Medical image processing is a very active and fast-growing field that has evolved into an established discipline. Brain tumor segmentation techniques have already shown great potential in detecting and analyzing tumors in clinical images and this trend will undoubtedly continue into the future. Medical image analysis needs to address real-world issues that have been outside the realm of computer vision. These issues come largely from the fact that the end systems are mostly used by the physician. The human factor is essential, since any successful solution will have to be accepted by a physician and integrated into the medical procedural work flow. Although the reported accuracy on brain tumor segmentation of the proposed automated methods is quite promising, these approaches still have not gained wide acceptance among the pathologists for every day clinical practice. One of the principal reasons might be the lack of standardized procedures. Another two reasons could be the substantial differences with the traditional specialists' way of work, and the deficiency of the existing methods in assisting medical decision with a transparent and interpretable way.

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