Brain Tumor Image Segmentation in MRI Image

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Abstract

Brain tumor segmentation plays an important role in medical image processing. Treatment of patients with brain tumors is highly dependent on early detection of these tumors. Early detection of brain tumors will improve the patient's life chances. Diagnosis of brain tumors by experts usually use a manual segmentation that is difficult and time consuming because of the necessary automatic segmentation. Nowadays automatic segmentation is very popular and can be a solution to the problem of tumor brain segmentation with better performance. The purpose of this paper is to provide a review of MRI-based brain tumor segmentation methods. There are number of existing review papers, focusing on traditional methods for MRI-based brain tumor image segmentation. This paper, we focus on the recent trend of automatic segmentation in this field. First, an introduction to brain tumors and methods for brain tumor segmentation is given. Then, the state-of-the-art algorithms with a focus on recent trend of full automatic segmentation are discussed. Finally, an assessment of the current state is presented and future developments to standardize MRI-based brain tumor segmentation methods into daily clinical routine are addressed.

1. Introduction

Brain tumor is one a player in the tumor in the sensory system, notwithstanding spinal tumors and fringe nerve tumors. This brain tumor can be an essential tumor or a metastasis from a tumor in another organ. Clinical issues in brain tumors are fairly not quite the same as different tumors on account of their impact, and restricted remedial confinements. Harm to the brain tissue straightforwardly will cause useful disability of the focal sensory system, as engine unsettling influences, tangible, faculties, and even psychological capacity. Furthermore, the impact of mass caused by brain tumor will likewise give a difficult issue considering the tumor is in the cranial hole which in grown-ups is a shut space with settled size.

According to The Central Brain Tumor Registry of the United States (CBTRUS), primary brain tumors are among the top 10 causes of cancer-related deaths. It is estimated that about 13,000 people in the United States die from this tumor every year. Data from Mayo Clinic, based on analysis from 1950 to 1989, it was said that the incidence of primary brain tumors was 19.1 per 100,000 people per year (11.8 per 100,000 for symptomatic tumors and 7.3 per 100,000 for asymptomatic tumors). This data is similar to the data from CBTRUS which gives the figure of 11.47 per 100,000 per year. In Europe the average survival rate of adult malignant brain tumor patients was 18.7%. The prognosis of primary brain tumors varies, in malignant primary malignant brain tumors whose survival is ± 12 months. In another study that measured the survival rate of patients with brain tumor, the survival rate was found in 5 years. The worst brain tumor patients were glioblastoma 3% while the highest was ependimoma, 74%.[1]
Alongside the progress of therapeutic imaging, imaging modalities assume a critical part in the assessment of patients with cerebrum tumors and significantly affect quiet care. Late years, the rising new imaging modalities, for example, XRay, Ultrasonography, Computed Tomography (CT), Magneto Encephalo Graphy (MEG), Electro Encephalo Graphy (EEG), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT), and Magnetic Resonance Imaging (MRI), not just demonstrate the point by point and finish parts of mind tumors, yet additionally enhance clinical specialists to contemplate the component of cerebrum tumors at the point of better treatment. Clinical specialists assume an imperative part in cerebrum tumor evaluation and treatment. Once a mind tumor is clinically suspected, radiologic assessment is required to decide the area, the degree of the tumor, and its relationship to the encompassing structures. This data is imperative and basic in settling on the diverse types of treatment, for example, surgery, radiation, and chemotherapy. Accordingly, the assessment of cerebrum tumors with imaging modalities is presently one of the key issues of radiology offices.

Magnetic Resonance (MR) imaging produces images of the human tissues in a noninvasive manner, revealing the structure, metabolism, and function of tissues and organs. The impact of this image technique in diagnostic radiology is impressive, due to its versatility and flexibility in joining high-quality anatomical images with functional information [2]. MRI is attracting more and more attentions for the brain tumor diagnosis in the clinical.

Four standard MRI modalities used for glioma diagnosis include T1-weighted MRI (T1), T2-weighted MRI (T2), T1-weighted MRI with gadolinium contrast enhancement (T1-Gd) and Fluid Attenuated Inversion Recovery (FLAIR)[3]. Generally, T1 images are used for distinguishing healthy tissues, whereas T2 images are used to delineate the edema region which produces bright signal on the image. In T1-Gd images, the tumor border can easily be distinguished by the bright signal of the accumulated contrast agent (gadolinium ions) in the active cell region of the tumor tissue. Since necrotic cells do not interact with the contrast agent, they can be observed by hypo intense part of the tumor core making it possible to easily segment them from the active cell region on the same sequence. In FLAIR images, signal of water molecules are suppressed which helps in distinguishing edema region from the Cerebrospinal Fluid (CSF).

Lately, restorative imaging and delicate figuring have made huge progressions in the field of brain tumor division. As a rule, the vast majority of strange brain tumor tissues might be effortlessly identified by brain tumor division strategies. In any case, exact and reproducible division results and portrayal of variations from the norm have not been tackled the distance. Since mind tumor division has incredible effect on analysis, checking, treatment making arrangements for patients, and clinical trials, this paper centers around MRI-based cerebrum tumor division and presents a generally nitty gritty review for the current existing techniques for MRI-based cerebrum tumor division.

The rest of this paper is organized as follows: In Section 2, we briefly introduce the segmentation methods of MRI images., in Section 3, an objective assessment is presented and future developments and trends are addressed for MRI based brain tumor segmentation methods.

2. Brain Tumor Segmentation Methods

Nowadays, brain tumor segmentation methods can be organized into different categories based on different principles. In the clinic, brain tumor segmentation methods are usually classified into three main categories including manual, semi-automatic, and fully automatic segmentations based on the degree of required human interaction.

For semi-automatic brain tumor segmentation, it mainly consists of the user, interaction, and software computing. In the semi-automatic brain tumor methods, the user needs to input some parameters and is responsible for analyzing the visual information and providing feedback response for the software computing. The software computing is targeted at the realization of brain tumor segmentation algorithms. The interaction is in charge of adjusting segmentation information between the user and the software computing. The semi-automatic brain tumor segmentation methods were divided into three main processes: initialization, feedback response, and evaluation. Although brain
tumor semi-automatic segmentation methods can obtain better results than manual segmentation, it also comes into being different results from different experts or the same user at different times. Hence, fully automatic brain tumor segmentation methods were proposed.

For fully automatic brain tumor segmentation, the computer determines the segmentation of brain tumor without any human interaction. In general, a fully automatic segmentation algorithm combines artificial intelligence and prior knowledge. With the development of machine learning algorithms that can simulate the intelligence of humans to learn effectively, the study of fully automatic brain tumor segmentation has become a popular research issue. The semi-automatic and fully automatic segmentation of tumor brain images are faced with great challenges due to usually exhibiting unclear and irregular boundaries with discontinuities and partial-volume effects for brain tumor images. The segmentation method for various segmentation listed in Table 1.

| Author | Image Segmentation Method | Performance |
|--------|---------------------------|-------------|
| Xiaoxiao Liu et.al [4] | low rank atlas | accuracy, Geodesic distance, entropy |
| Mohammad Majid al-[5] et.al | PSO-LVQ | Efficiency |
| V. Anitha et.al [6] | adaptive pillar K-means clustering algorithm | sensitivity, accuracy, positive predictive value, negative predictive value, false discovery rate, Mathews correlation coefficient |
| Atiq Islam et.al[7] | Fractal and Fractional Brownian Motion | Similarity coefficients: Jaccard, Dice, |
| Matthew C. Clark et.al [8] | Adaptive Histogram | TP, FP, FN, Tumor Ratio, Corr Ratio |
| Meiyan Huang et.al [9] | local independent projection-based classification | computation time, dice similarity, jaccard similarity |
| Bjoern H. Menze et.al [10] | expectation-maximization | Dice score, sensitivities and specificities |
| Elisee Ilunga-Mbuyamba et.al[11] | Localized Active Contour Model with Background Intensity Compensation (LACM-BIC) | Dice Coefficient, housedroff distance |
| Charutha S. [12] | Modified Texture Based Region Growing, Cellular Automata Based Edge Detection, Modified Texture Based Region Growing + Cellular Automata Edge Detection | Coefficient of similarity, Spatial overlap |

3. Conclusion
Automatic segmentation of the brain tumors for cancer diagnosis is a challenging task. Recently, availability of public datasets provided a common medium for the researchers to develop and objectively evaluate their methods with the existing techniques. In this paper, we provided a review segmentation method based automatic segmentation, and a brief overview of traditional techniques in
traditional automatic brain tumor segmentation methods, translating prior knowledge into probabilistic maps or selecting highly representative features for classifiers is challenging task. Future improvements and modifications in modified segmentation method architectures and addition of complementary information from other imaging modalities such as Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS) and Diffusion Tensor Imaging (DTI) may improve the current methods, eventually leading to the development of clinically acceptable automatic brain tumor segmentation methods for better diagnosis.

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