A REVIEW OF COMPLETE BRAIN EXTRACTION METHODS OF MRI IMAGES

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Abstract

Analyzing the tissues of human brain is now an important area in medical technology field. The segmentation helps physicians diagnose brain disorders like dementia, brain tumor etc. Magnetic Resonance Imaging (MRI) is an imaging modality used for taking brain images. In the past years, the segmentation methods were focused on conventional techniques. These techniques are classified as supervised, unsupervised, parametric models etc. The objective of these methods involves dividing brain regions into tissue types, localized structures etc. Nowadays, research has moved to neural networks and deep learning techniques that achieve robustness and accuracy. This article gives a complete literature study of various methods of segmenting brain regions. Every method includes the calculation of qualitative analysis such as Jaccard, Dice etc. These analyses are performed to compare the effectiveness of various segmentation methods.

Keywords: *Diagnosis, MRI, Human brain, Diagnosis, Segmentation.*

Introduction

In earlier days, the medical imaging was used for basic purposes such as inspection and visualization of anatomical structures. Now it has become an important tool both for diagnosis and plan of treatment of various diseases. On the clinical side, MRI and Computerized Tomography (CT) are commonly - used imaging techniques, where CT gives bone details and MRI provides more details about soft tissues [1].

Skull stripping is the necessary work even for fetal brain segmentation [2], adult brain segmentation, and, further, the segmented brain image is used for tissue classification, sub- structure segmentation, volume rendering etc.[3-6]. Several research works have been done for skull-stripping [7-9] using region-based, edge-based and hybrid of both methods. All such existing works have their own merits and demerits.

Automatic and semi-automatic methods

Deep learning method is used in medical image analysis [10] to make the computers to learn the features of human brain automatically. Instead of extracting brain portions, the feature- learning approach was used. In the medical field, the deep learning method is improved by Convolution Neural Networks (CNN). The application of CNN determines the protocol in the field of radiology. The quality of the image can also be improved by CNN. CNN is also used in image registration which enables a quantitative analysis of various types of images.

Most of the methods produce good results for T1W images, but fail in other type of modalities. To achieve this, a 3D convolutional architecture is proposed [11]. The binary mask is generated by changing the threshold increases the value of sensitivity. The dataset of patients who are affected with brain tumor is experimented. The dataset consists of various types of images such as T2 weighted and FLAIR. The data are collected from various repositories like OASIS and IBSR. The Dice value is obtained as 0.9502 for OASIS dataset and 0.9632 for IBSR dataset. This method is proved to be useful for larger datasets.

Active contour method [12] has been developed to

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classify the tissues of human brain. A 3D level set architecture is applied to classify the data based on intensity homogeneity. Prior information about data is avoided by initializing random seed. Three volumes of MRI data are used for experimentation. This method classifies the human regions into gray matter and white matter successfully. Quantitative analysis is performed to prove the efficiency and robustness of the method.

A hybrid technique [13] is proposed by combining watershed and deformable models. The white matter in T1W image is localized and then watershed approach is applied. This approach works well even though non-uniform voxels are present. The upper bound region of cerebrospinal fluid (CSF) is taken as a threshold and the brain and non-brain regions are labeled. This method does not need any user intervention. The method is validated with manual segmentation results and leads to misclassification of some regions.

The Skull-stripping problem is addressed using histogram analysis by partitioning gray levels [14]. The background region of an image is removed using the threshold. After the background of an image is removed, the pixels nearer to head region are considered to generate histogram. Two levels of histogram are generated for white matter and gray matter. Totally 80 volumes of datasets of different modalities are used and experimented. The result of this method is compared with popular existing methods like BET and BSE.

The region based methods are intended to get the regions by using the spatial details of an image. Balan et al. [17] proposed a region based method an in this method they have used histogram analysis and mathematical morphology methods to extract the brain region from non brain region. Another region based method proposed by Atkin & Mackiewich [18] make use of histogram analysis and non-linear anisotropic filter. In the successive step active contour is applied to find the brain boundary. A 3D skull-stripping automated method proposed by Lemiux et al. [19]. Park & Lee [20] proposed a region growing method which initially selects a seed point and then grows by adding similar neighbor pixels and this process continues till the brain boundary.

S.A. Sadananathan et al. [21] intensity based thresholding technique followed by graph cuts. The method supports to eliminate thin connectivity between brain regiona and its surrounding non brain regions. Shattuck et al.[22] proposed brain surface extraction (BSE) method by applying anisotropic diffusion filter. The characteristic of this filter smoothen unnecessary gradient of MR signals in the input image. They have also applied an edge detection technique along with morphological operations to detect the brain boundary.

Smith proposed a brain extraction technique (BET), which uses intensity based histogram for obtaining rough brain mask. Inside the brain region, a triangular tessellation of sphere's surface is initialized and it is gradually increased towards edge of the brain. Zhuang et al. [23] proposed model based level set (MLS) method to eliminate skull region from input MR images. Segonne et al. [24] combined watershed and deformable surface method to provide accurate skull stripping method. Rehm et al. [25] proposed a skull stripping method which makes use of atlas based technique. The atlas is obtained using histogram of the input image and it is associated with BSE. A comparative analysis is done by Fennema-Notestine [26] on BET, BSE, HWA and 3D Intracranial. They concluded that BSE and HWA were found to be more efficient in brain segmentation.

Conclusion

The segmentation of brain tissues is very important for the physician to diagnose and plan his treatment. Many computer assisted-algorithms have been developed for the purpose. This article discussed the recent techniques used for segmenting brain tissues from skull portions. Every method has some limitations in terms of shape, structure and number of datasets used. The drawbacks and the comparison metrics used to know the performance were also discussed.

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