Review of Brain Tumor Detection Concept using MRI Images

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Abstract **– Today image processing techniques plays a significant role in medical imaging. It is a very growing and challenging field. Medical imaging is advantageous in identification of the disease. Numerous people suffer from brain tumor; it is a serious and dangerous disease. Medical imaging provides appropriate diagnosis of brain tumor. There are many techniques to detect brain tumor from Magnetic Resonance Images (MRI) images. These techniques face many challenges like finding the location and size of the tumor, image segmentation is useful to detect the tumor from the brain image. Already, number of algorithms are developed and tested successfully for image segmentation. In this study paper we cover the basic concept and practices of brain tumor detection from MRI images; review of different brain tumor segmentation method is presented in this paper.**

Keywords– Brain Tumor, Magnetic Resonance Image, Medical Imaging, Image Segmentation, Clustering.

I. INTRODUCTION

Brain tumor detection is very tedious job for any medical practitioner. They use the very effective tool for this purpose is Magnetic Resonance Imaging (MRI). This technique makes the use of pulses of radio wave energy and magnet to reconstruct the images containing the structure inside the body and the organs. A particular area of the body is placed inside the scanning machine that contains strong magnetic field at the time of MRI test. In MRI test images are obtained are digital images which is stored in the computer system for detail study. Tumors are developed because of abnormal and uncontrolled proliferation of cells in the brain. There are two types of brain tumors i.e. some are originated in the brain itself are termed as primary and the one which are spread from other parts of the body to the brain through metastasis are termed as secondary. Both types of tumors are capable of potentially disabling the body parts may results in threatening of life [1]. When the tumor grows, there is an increase in intracranial pressure in the skull, and cause Edam, which results in reduction in the blood flow and displacement as well as degeneration of healthy tissue. MRI images are used in brain tumor detection as the MRI provides detailed information about the anatomy, structure of brain cell and vascular supply. So it is an important and competent tool for the effectively diagnosing the disease as well as the dealing and monitoring of the disease [2].

However, in brain MRI, large number of MRI scans taken for every patient, manually detecting and segmenting brain tumors is monotonous and tedious job. Therefore, there is a need for computer aided brain tumor detection and segmentation from brain MR images to overcome the problems [3].

II. BRAIN AND TUMOR OVERVIEW

The major function of the brain is to control the overall parts of the human body. It is a one kind of important organ that allows human to adapt and learn in varying environmental condition. The brain enables human to think, execute action, share thoughts and feeling [4]. In this section we describe the structure of the brain for the basic understanding; the schematic is shown in figure 1.

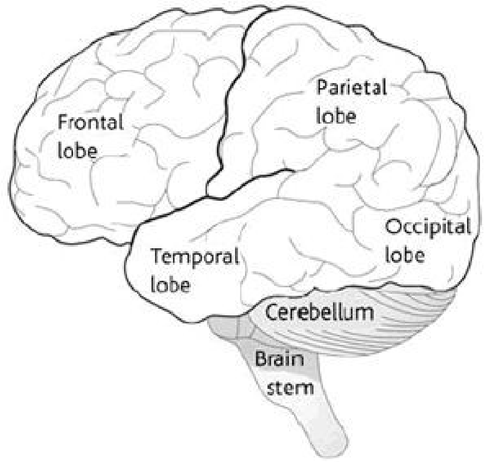

Fig. 1. The major part of human brain [4]

Primary brain tumor originates in the brain itself, in first type i.e. benign it can be non-cancerous and second is malignant (cancerous). Benign tumors grow slowly, and its one type is gliomas. It originates from astrocytes non-neuronal brain cells. Some primary tumor are less aggressive but these can exercise much pressure on the brain and make it dysfunctional, and more aggressive tumor grow more quickly and spread to other tissues. The secondary brain tumor originates through other part of the body. These tumors have cancer cells somewhere else in the body that have metastasis or spread to the brain. Secondary brain tumors are always malignant. These type of tumor caused majorly because of lungs cancer, kidney cancer, bladder cancer etc. [6].

III. MAGNETIC RESONANCE IMAGING

The first Magnetic image is invented by Raymond V. Damadian in 1969 later on in 1977 the MRI images were invented for human body. This MRI technique is most reliable in radio because with the help of MRI images it is possible to visualize the details of internal structures of brain. MRI images observe different soft tissues of the human body and is capable to contrast between these tissues. MRI images

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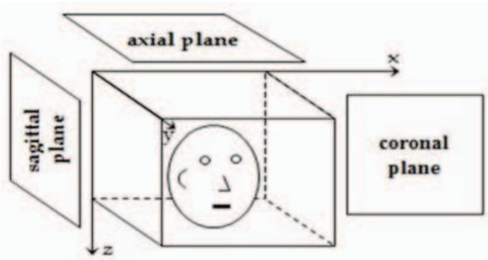
have better quality as compared other medical imaging techniques such as Computer tomography or X-rays [7].

MRI gives three types of brain MRI images viz a) T1-weighted b) T2-weighted and c) Proton density images. MRI images are captured into three Planes or coordinates axial plane, coronal plane and sagittal plane as shown in fig. 2 [7].

T1 and T2 weighted images are based on image's signal intensity and third PD-weighted based on proton density in the MRI images. In T1 images high fat content tissues are present as bright areas and high water content tissues are present as dark areas. Signal intensity is high for fat and low for water. In T2 images high fat content tissues present are as dark areas and high water tissues as present bright areas and signal intensity low for fat and high for water. In PD images low proton density tissues are present as dark areas and signal intensity is low, high proton density tissues are present as bright areas with high signal intensity as shown in fig. 3 [7].



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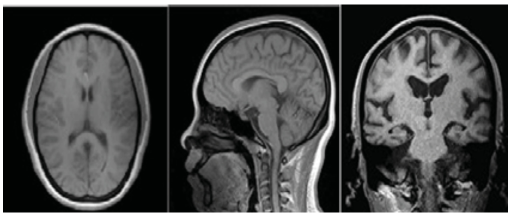


ii. iii. iv.

Fig.2. (i) Schematic of MRI, Brain MR Images From (ii) Axial Plane (iii) Sagittal Plane And (iv) Coronal Plane

IV. LITERATURE REVIEW

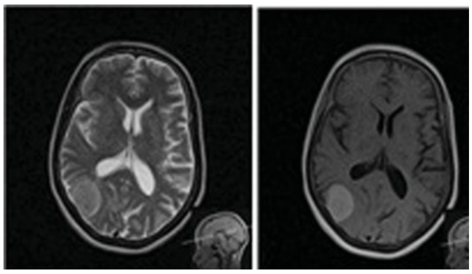
A. *Image Segmentation*

Image segmentation divides an image into meaningful regions based on the similarity of the regions. Image segmentation is used in various applications like image analysis, object detection and its representation, visualization of region of interest [8]. It makes easier to analyze an image for some purpose. In medical field image segmentation plays an important role in clinical diagnosis, most of the medical images have poor contrasts, it may effected by noise, or diffusive boundaries [9]. Preprocessing steps involve noise removal from these images [10]. Image segmentation algorithms are work on two fundamental properties of image intensity values: 1.Image discontinuity and 2.Image similarity [11]. So the segmentation is operated in two ways, first changes the intensity of a pixel in an image, such as edges and corners. The second one is based on partitioning an image into region .On the basis of these, there are many segmentation techniques which are broadly used in many applications.

Ivana Despotovi, presented a new FCM-based method for spatially coherent and noise-robust image segmentation. It presents two major contributions first the spatial information of local image features is integrated into both the similarity measure and the membership function to compensate for the effect of noise and in the second I uses an anisotropic neighborhood, based on phase congruency features, is introduced to allow more accurate segmentation without image smoothing. The segmentation results, for both synthetic and real images, demonstrate that this method efficiently preserves the homogeneity of the regions.

Maoguo Gong, presented an improved fuzzy C-means (FCM) algorithm for image segmentation by introducing a tradeoff weighted fuzzy factor and a kernel metric. The tradeoff weighted fuzzy factor depends on the space distance of all neighboring pixels and their gray-level difference simultaneously. The new algorithm adaptively determined the kernel parameter by using a fast bandwidth selection rule based on the distance variance of all data points in the collection. Furthermore, the tradeoff weighted fuzzy factor and the kernel distance measure are both parameter free. Experimental results on synthetic and real images show that the new algorithm is effective and efficient, and is relatively independent of this type of noise.

Maksoud et al. used hybrid segmentation techniques, and proposed well-formed image segmentation approach. K-Means clustering algorithms is integrated with fuzzy C-Means [12] algorithm. This techniques provide an accurate brain tumor detection. It takes the benefit of the K-Mean clustering algorithm for image segmentation in the aspects of minimal computation time and the advantages of Fuzzy C-



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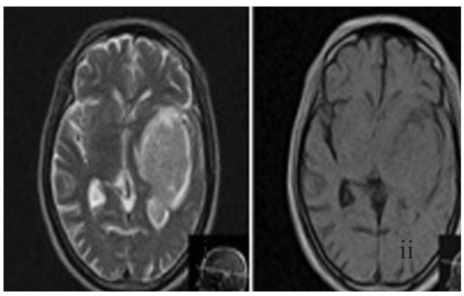

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Fig.3. Tumor Region Intensity Characteristics, T2-w images (i) And (ii), T1-w Images (iii) and (iv) Tumour Region in Low Intensity

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Means aspects of accuracy. With the help of K-Means clustering algorithm brain tumor is detected faster than fuzzy C-Means but fuzzy C-Means give information of cells accurately. Those images that are affected by noise, outliers, and other imaging artifacts are not segmented correctly by FCM. In future work of proposed method, the 3D evaluation of the brain tumor detection using 3D slice will be carried out [13].

Melegy et al. worked on a fuzzy approach for the segmentation of normal and pathological brain from MRI images. This method is based on fuzzy c-means algorithms and was used for automatic segmentation of the normal and pathological brain. PIGFCM segmentation algorithm segmented the brain tissues as gray matter, white matter, cerebrospinal fluid. Prior information based on the expertise was used for tissues segmentation. Pathological brain had some additional classes like abnormal tissues such as necrosis and edema. Authors have worked on both simulated and real images [14].

Huang et al. proposed a method to segment the tumor as a classification problem. Numerous brain tumor segmentation is still a challenging task, such as high diversity in tumor appearance, ambiguity in tumor boundaries. To solve this problem author proposed a novel automatic tumor segmentation method for MRI image. LIPC classification based method was used to classify each voxel into different classes. LIPC divides the data into different class model. LIPC used local independent projection for classification model. Author evaluated the proposed method using both synthetic and publically available MRI image data [15].

Makropoulos et al. worked on neonatal brain. Author used Expectation maximization algorithm for the automatic segmentation of neonatal brain. This method is robust and is used on neonatal brain images aging 24 weeks .Future work that can be done in this paper is to apply this method on neonatal brain aging more than 24 weeks [16].

Hamamci et al. demonstrated cellular automata based seeded method. In this paper author used the T1 weighted magnetic images. The cellular automata method is used to find the shortest path in graph theory. Firstly author established it for the segmentation .Then to use the sensitive parameter it is established for heterogeneous brain tumor segmentation. Author developed a type of tool where user interaction is minimum and it is robust. Author performed validation studies on synthetic, clinical and real datasets. Tumor-Cut segmentation technique is used here for partitioning the tumor tissues into various part and enhancing them. When user interaction is less, efficiency is greater in terms of computation time [17].

V. SEGMENTATION METHOD REVIEW

Image segmentation is the primary step and the most critical tasks of image analysis. Its purpose is that of extracting from an image by means of image segmentation. The mechanization of medical image segmentation has established wide application in diverse areas such as verdict for patients, treatment management planning, and computer-integrated surgery.

There are three broad approaches to segmentation, termed, Boundary approach, Edge- based approach, Region-based approach [17].

A. Boundary Approach (Thresholding)

In thresholding, pixels are allocated to categories according to the range of values in which a pixel lies. Thresholding is the simplest and most commonly used method of segmentation. Given a single threshold, t, the pixel located at lattice position (i, j), with greyscale value fij , is allocated to category 1 if

$$f_{ij} \leqslant t$$

else, the pixel is allocated to category 2.

B. Edge-Based Approach

In edge-based segmentation, an edge filter is applied to the image, pixels are categorized as edge or non-edge depending on the filter output, and pixels which are not divided by an edge are owed to the same category. Edge-based segmentation is based on the fact that the position of an edge is given by an extreme of the first-order derivative or a zero crossing in the second-order derivative. There a pixel is classified as an object pixel judging solely on its gray value independently of the context. To improve the results, feature computation and segmentation can be repeated until the procedure converges into a stable result.

C. Region-Based Approach

Region-based segmentation algorithms operate iteratively by grouping together pixels which are neighbors and have similar values and splitting groups of pixels which are dissimilar in value. Segmentation may be regarded as spatial clustering. Clustering in the sense that pixels with similar values are grouped together whereas spatial in that pixels in the same category also form a single connected component. Clustering algorithms may be agglomerative, conflict-ridden or iterative.

Clustering is the group of a collected works of patterns into clusters based on similarity[16]. Patterns within a valid cluster are more analogous to each one other than they are to a pattern belonging to a dissimilar cluster. Clustering is useful in pattern-analysis, grouping, decision-making, and machine-learning situations, data mining, document recovery, image segmentation, and pattern organization. On the other hand, many such problems, there is little prior information existing about the statistics, and the decision - maker must make as few suppositions about the data as probable [4][6]

VI. CONCLUSION

There are many method proposed for image segmentation, to accurately diagnose the brain tumor, a proper segmentation method is needed to separate out the brain tumor from MRI images. The detailed data needs to be interpreted which is provided by many images from various slices is required for accurate diagnosis, planning and treatment purpose. The main focus is on improvement of information obtained from the images through the slice orientation and perfecting the process of segmentation to get an accurate region of the brain tumor i.e. region of interest.

In this paper, some of the recent methods of segmentation used for brain tumor detection are reviewed. Different techniques used by various researchers to detect the brain tumor from the MRI images are described. This paper also describes the overview of the brain and brain tumor as well

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as it describes the MRI images in detail. This review work concludes that the automatic tumor detection and proper segmentation from the MRI images is one of the key area for research.

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