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# REVIEW OF VARIOUS TECHNIQUES IN BRAIN TUMOUR SEGMENTATION USING MRI

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***Abstract:*** **-**A tumour is an abnormal growth of cells within the brain, which is one of the major causes of death among people. Chances of survival is high if the tumour are detected in the early stages so, there is a need for a fast and accurate method for detection of brain tumour. As medical imaging techniques have been developed, efficient manipulation and visualization of the obtained images are important topics to improve diagnostic accuracy and to expand their applications. Brain tumour segmentation aims to separate the different tumour tissues such as active cells, necrotic core, and edema from normal brain tissues of White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF). It is highly necessary that segmentation of the MRI images must be done accurately before asking the computer to do the exact diagnosis. With the development of almost two decades, the innovative approaches applying computer-aided techniques for segmenting brain tumour are becoming more and more mature and coming closer to routine clinical applications. MRI-based brain tumour segmentation studies are attracting more and more attention in recent years due to non-invasive imaging and good soft tissue contrast of Magnetic Resonance Imaging (MRI) images. However, this paper presents a comprehensive review of the methods and techniques used to detect brain tumour through MRI image segmentation.

***Keywords:*** Cells, Tumours, Preprocessing, Segmentation Techniques, Brain Tumour, MRI (Magnetic Resonance Image)

## I. Introduction

A tumor is an abnormal growth of cells within the brain, which is one of the major causes of death among people. A very exigent task for radiologists is early brain tumor [1] detection. Brain tumor raises very fast, its average size doubles in just twenty-five days. If not treated properly, the survival rate of the patient is normally not more than half a year. It can rapidly lead to death. For this reason, an automatic system is required for brain tumor detection at an early stage. As medical imaging techniques have been developed, efficient manipulation and visualization of the obtained images are important topics to improve diagnostic accuracy and to expand their applications. Brain tumour segmentation aims to separate the different tumour tissues such as active cells, necrotic core, and edema from normal brain tissues of White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF) [2]. These days, cancer is one of the diseases that scares people the mos. Brain cancer may be considered among the most difficult cancers to treat, as it involves the organ which is not only in control of the body, but is also responsible for the self-definition of the person. During surgery or any kind of treatment, eloquent areas must not be affected in order to minimize iatrogenic risks. Therefore, good diagnosis and planning of treatment choices is essential. This is why images are now of paramount importance in the evaluation of brain tumors, provided by computational techniques to take advantage of the information retrieved from them. Everybody agrees that images are now an invaluable service in the practice of medicine. In addition, numerous image modalities are used frequently at different time points; therefore, there is also a need for integration of the features reflected by these different sources of images. In order to provide support for this integration, automatic processing methods have been developed.

MRI images must be done accurately before asking the computer to do the exact diagnosis. With the development of almost two decades, the innovative approaches applying computer-aided techniques for segmenting brain tumour are becoming more and more mature and coming closer to routine clinical applications. MRI-based brain tumour segmentation [3] studies are attracting more and more attention in recent years due to non-invasive imaging and good soft tissue contrast of Magnetic Resonance Imaging (MRI) images.

The paper discusses the recent trends and related work on brain tumor detection in the recent years. The focus of the paper is to list different algorithms developed in the recent days.

## II. Methods for Brain Tumor Image Segmentation

The brain tumor segmentation is very hard and time-consuming work. The MRI scan segments into different regions. The tumor part marked slice by slice as it creates the rough image. The automated segment is very helpful for image segmentation process as itself segment the image which takes the information within the entire 3D muti-parameter images into account. Brain tumors may be benign or malignant. There are some general

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characteristics of brain tumors such as large size and position, may have overlapping power with normal tissues, great image intensities, may be space occupying, may enhance partially, fully or not at all with a contrast agent and may be followed by surrounding edema(swelling). Depending on the feature extraction brain tumor segmentation methods [4][5] are classified as different kinds. The below picture (Fig. 1) describe various image segmentation techniquesused for brain tumor segmentation.

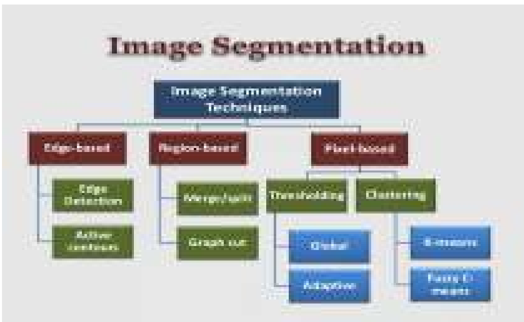
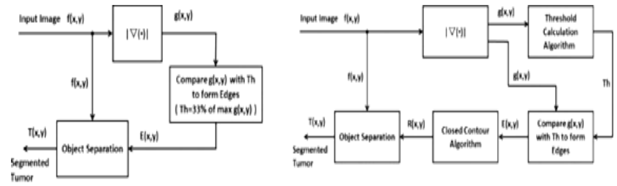



Fig. 1 Image segmentation Techniques

**1. Edge-basedalgorithms:** - Edge-based detection [6][7] is the approach most widely used for detecting edges and is based on detecting abrupt local changes in the intensity of image. Edge pixels are those pixels at which the intensity of an image function changes abruptly. The earliest operator in the field of edge detection is Roberts cross-gradient operator [8]. The extensions of 2D masks to 3D masks gives a new operator known as Prewitt's Operator [8]. The Canny edge detection algorithm [9] is another approach used for edge detection. It has three salient characteristics: low error rate, edge points should be well localized, and single edge point response. The Canny edge detector first smooths the image to eliminate noise, and then it finds the image gradient. Also, it requires threshold for detecting edges and thinning thereafter. It is more complex and has a relatively higher execution time and sometime gives false edges. Improved Edge Detection Algorithm for Brain Tumor Segmentation [10] proposed by AsraAslamaet all has following steps:

1. Finding gradient image using Sobel Operator
2. Calculate image dependent threshold iteratively
3. Apply Closed-Contour Algorithm
4. Object segmentation based on pixel intensity within closed contour

The block diagram of the above approach withconvention algorithms are shown in Fig. 2.




**(**a) Conventional Algorithm(b) Improvised Sobeledgedetection Algorithm

Fig. 2: Block Diagram of Conventional and ImprovedSobeledgedetection Algorithm

The Fig 3.gives the comparison of performance of conventional v/s Improved Sobel algorithm.

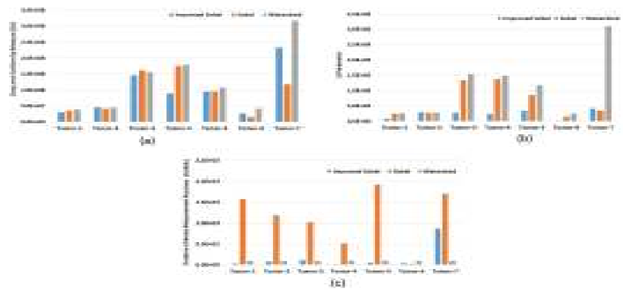


Fig. 3.Performance comparison in terms of (a) Gray level Uniformity measure (GU); (b) Q-parameter; (c) Relative Ultimate Measurement Accuracy (RUMA).

**2. Region Based Algorithms: -**These can be classified into two main classes:

Merging algorithms [11]: in which neighboring regions are compared and merged if they are close enough in some property.

Splitting Algorithms [12]: in which large non-uniform regions are broken up into smaller areas which may be uniform. There are algorithms which are a combination of splitting and merging. In all cases some uniformity criterion must be applied to decide if a region should be split, or two regions merged.

Cellular Automata (CA) are promising model being success. More specifically, CA-based segmentation algorithms [13] were introduced to address the global optimization for different datasets which are robust to noise (Huang, Yang,rithms establish the connecting of graph-based seed segmentation to CA model. Grow-Cut is a beginning CA-based segmentation pro-posed by Vezhnevets et al. (2005) [14]. It is an efficient algorithm, but has some drawbacks when cope with specific structures which anatomical structure exhibits relative smooth boundaries. Subsequently, Tumor-Cut (Hamamcietal., 2012) [15], which is a CA-based direct-purposed tumor segmentation algorithm, was proposed. It modified the local transition function of Grow-Cut to eliminate the drawbacks. In addition, it figured out the shortest path problem encountered in the graph-based seed segmentation. Tumor-Cut provides an outstanding result superior to other graph-based seed segmentation techniques; Grow-Cut, Graph-Cut and random walker.

Unlike other semi-automatic segmentation algorithms, Tumor-Cut requires a minimal degree of user interaction to draw a line over diameter tumor (Huang et al.,2014) [16]. Although Tumor-Cut provides an outstanding result for tumor segmentation, it has still faced the problem of robustness in seed growing. CA's state energy defined by the similarity function in Tumor-Cut will decrease significantly when moving from seed pixels. This leads to under segmentation. The Fig 4. Describes the overview of the brain segmentation using tumor cut algorithms

Fig. 4.Overview of brain tumor segmentation system**.**

The TABLE 1. Lists various region based algorithms developed in recent years.

Table 1. Different region based algorithms.

| **Method** | **Segmentation technique** | **Multimodal MRI** |
|---|---|---|
| Njeh et al. (2015) | Graph cut distribution matching. | T1C, FLAIR |
| Hamamci et al. (2012) | Tumor-cut algorithm based on CA model. | T1C, FLAIR |
| Zikic et al. (2012) | A classification forest with spatially non-local features. | T1, T1C, T2 FLAIR |
| Guo et al. (2013) | Edge-based active contour model and level set technique | T1, T1C, T2, FLAIR |
| Cordier et al. (2013) | The similarities between multi-channel patches. | T1, T1C, T2, FLAIR |
| Zhao et al. (2013) | Markov Random Field (MRF) on super-voxels clusters. | T1, T1C, T2, FLAIR |
| Huang et al. (2014) | Local independent projection-based classification based on sparse representation. | T1, T1C, T2, FLAIR |
| Subbanna (Menze et al., 2014) | Hierarchical MRF approach with Gabor features. | T1, T1C, T2, FLAIR |

**3. Pixel based thresholding brain tumorprocessing: -** Thresholding is one of the simplest approaches for image segmentation based on intensity levels. Threshold based technique [17] works on the assumption that the pixels falling in certa in range of intensity values represents one class and remaining pixels in the e image represents the other class. Thresholding can be implemented either locally or globally. For global thresholding brightness threshold value is to be selected to segment the image into object and background. It generates binary image from given input image. The pixels satisfying threshold test are considered as object pixels with binary value '1' and other pixels are treated as background pixels with binary value '0'.

Selection of threshold is very crucial in image segmentation process. Threshold value can be determined either by an interactive way or can be the outcome of automatic threshold selection method. Threshold based approaches are computationally inexpensive fast and can be used for real time applications. A single global threshold partitions image into objects and background, but objects may have different characteristic grey value. In such situations multiple threshold values are needed, for applying over different areas of the image. Threshold value for eachregion is local threshold and the process is multilevel thresholding [18] which helps to detect different objects in an image separately.

The following thresholding algorithms are used in brain tumorsegmentation: -

- Threshold Selection based on Histogram based
- Threshold Selection based on Iterative
- Threshold Selection based on Otsu's method
- Thresholding based on Maximum correlation
- Multithresholding Methods

**4. Clustering based image segmentation algorithms: -**

Fuzzy c-means (FCM) [19]is a data clustering technique in which a dataset is grouped into n clusters with every data point in the dataset belonging to every cluster to a certain degree of the MRI signal.

Fuzzy c-means (FCM) clustering [20] is an unsupervised technique that has been successfully applied to feature analysis, clustering, and classifier designs in fields such as astronomy, geology, medical imaging, target recognition, and image segmentation. Fuzzy C-means its improvement methods algorithm and strategies for remote sensing image segmentation can offer less iterations times to converge to global optimal solution. Its good effect of segmentation can improve accuracy and efficiency of remote sensing image threshold segmentation [21] problem is based on a simple iterative scheme for finding a locally minimal solution. This algorithm is often called the k-means algorithm.

Clustering based on k-means [22] is closely related to a number of other clustering and location problems. These include the Euclidean k-medians (or the multisource

Weber problem) in which the objective is to minimize the sum of distances to the nearest center and the geometric k-center problem [ in which the objective is to minimize the maximum distance from every point to its closest center. There are no efficient solutions known to any of these problems and some formulations are NP-hard. This method works well if the spreads of the distributions are approximately equal, but it does not handle well the case where the distributions have differing variances.

K-Means clustering: - K-means clustering is an efficient method of threshold selection. Using this algorithm, the image is divided into k segments using (k-1) thresholds and minimizing the total variance within each segment. One of the most popular heuristics for solving the k-means

**5. Hybrid/ Fully Automatic image segmentation algorithms**: -Hybridtechniques [23] use combination of different conventional techniques listed above. Hence compared to traditional techniques which only focuses on one feature of image the hybrid techniques [24] more often use more than one feature and hence the performance and efficiency of hybrid techniques are more.

The TABLE 2.lists some of the hybrid techniques used in brain tumor segmentation

Table 2. Different Cnn Based Brain Tumor Segmentation Techniques.

| The TABLE 2. lists some of the hybrid techniques used in brain tumorsegmentation.Table 2. Different CNN Based Brain Tumor Segmentation Techniques.Author | Method | Level of user interaction | Performance (Dice Scores) | | |
|---|---|---|---|---|---|
| | | | Whole Tumor | Core Tumor | Active Tumor |
| Rater5 Pereira et al. | CNN with small (3x3) filters for deeper architecture | Fully automatic | 0.88 | 0.83 | 0.77 |
| Kwon et al | Generative model that performs joint segmentation and registration | Semi-automatic | 0.88 | 0.83 | 0.72 |
| Havaei et al | Cascaded Two-pathway CNNs for simultaneous local and global processing | Fully automatic | 0.88 | 0.79 | 0.7 |
| Tustison et al. | Concatenated RFs, trained using asymmetry and first order statistical features | Fully automatic | 0.87 | 0.78 | 0.74 |
| Urban et al. | 3D CNN architecture using 3D convolutional filters | Fully automatic | 0.87 | 0.77 | 0.73 |
| Havaei et al. | Uses SVM; training and segmentation implementedwithin the same brain | Semi-automatic | 0.86 | 0.77 | 0.73 |
| Dvorak and Menze | Local structured prediction with CNN and k-means | Fully automatic | 0.83 | 0.75 | 0.77 |
| Davy et al | Two-pathway CNN for simultaneous local and global processing | Fully automatic | 0.85 | 0.74 | 0.68 |
| Zikic et al. | 3D input patches are interpreted into 2D input patches to train a CNN | Fully automatic | 0.837 | 0.736 | 0.69 |
| Hamamci et al. | Generative model, uses cellular automata to obtain tumor probability | Semi-automatic | 0.72 | 0.57 | 0.59 |

| | | | | | |
|---|---|---|---|---|---|
| | map | | | | |
| Rao et al. | Four CNNs, one for each modality, with their outputs concatenated as an input into a RF | Fully automatic | Not reported | Not reported | Not reported |

## III. Conclusion

In this paper we have accomplished a partial survey of various classification techniques for MRI brain image. A comparative study is made on various techniques. After evaluation of well-known technique, it is clearly shown the various methods which can detect the tumor efficiently and provide accurate result. Since this is a review the TABLE 3. Lists advantages and disadvantages of the common methods used for brain tumor segmentation without pointing to any one method.

Table 3. Lists Advantages And Disadvantages Of The Common Methods.

| **Method** | **Advantages** | **Disadvantages** |
|---|---|---|
| Threshold based Method [25] | Does not require prior information of the image.<br>Computationally inexpensive.<br>Fast and simple for implementation.<br>Can be used in real time applications. | For an image with broad and flat valleys or without any peak, it doesn’t work well.<br>Neglects spatial information of an image, cannot guarantee that the segmented regions are contiguous.<br>Highly noise sensitive.<br>Selection of threshold is crucial, wrong choice may result into over or under segmentation. |
| Region based Method [26] | Gives better result in comparison with other segmentation methods.<br>Provides flexibility to choose between interactive and automatic technique for image segmentation.<br>Flow from inner point to outer region generates clear object boundaries.<br>Proper selection of seed gives accurate result than any other method. | Sequential by nature and quite expensive in both computation time and memory.<br>To decide stopping criteria for segmentation is difficult task.<br>Scan order dependencies may be yielded in SRG and can have considerable impact on minute regions.<br>Selection of noisy seed by user leads to flawed segmentation. |
| Cluster based Method [27] | For small values of k, k-means is computationally faster.<br>Eliminates noisy spots.<br>Reduces false blobs.<br>More homogeneous regions are obtained | Difficult to predict k with fixed number of clusters.<br>Sensitive to initialization condition of cluster number and centre.<br>Computationally expensive.<br>Doesn’t works well with non-globular clusters |
| Fuzzy C – means Method [20] | FCM is better than K- means.<br>FCM Unsupervised and converge very well. | Sensitive to noise.<br>Computationally expensive.<br>Determination of fuzzy membership is not very easy. |

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