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Image Segmentation Techniques for Brain MRI Images: A Survey

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Abstract – Brain tumor analysis from Magnetic Resonance Images (MRI) is one of the mainly challenging tasks. Brain MRI provides details of soft tissues. The image segmentation is done to simplify and to change the representation of an image into meaningful image for better analysis. The image segmentation is a very difficult job in the image processing and challenging task for clinical diagnostic tools. Accuracy in segmentation of the MRI images is extremely important and essential for the exact diagnosis by computer aided clinical tools. There are various types of segmentation algorithms for MRI brain images. This paper is to study existing approaches of current segmentation techniques in brain MRI images. This review discusses the general principle upon which Brain MR image analysis is based.

Keywords – Central Nervous system, MRI, Image Segmentation, Thresholding, FCM.

I. INTRODUCTION

A brain tumor means growth of abnormal cells in the tissues of the brain. Brain tumors can be of two basic types benign, with no cancer cells, or malignant, with cancer cells that grow quickly. Some are primary brain tumors, which start in the brain. Others are metastatic, and they start somewhere else in the body and move to the brain. Figure 1 show the sample MRI of brain. Doctors diagnose brain tumors by doing a neurologic exam and tests including an MRI, CT scan, and biopsy. When tumors arise in the central nervous system(CNS), they are especially problematic because a persons thought processes and movements can be affected. These tumors can also be difficult to treat because the tissues surrounding a tumor that may be affected by surgery or radiation may play a vital role in functioning [1].

Figure1. Brain MR Image showing Tumor

Computer Aided Diagnosis (CAD) is a rapidly growing dynamic field. It helps radiologist who uses the output from a computerized analysis of medical images as a second opinion in detecting lesions, assessing extent of disease, and improving the accuracy and consistency of radiological diagnosis to reduce the rate of false negative cases. The typical architecture of a CAD system includes selection of training samples, image pre-processing, definition of region(s) of interest, features extraction and selection, classification and segmentation. Figure 2 showes the General processing environment needed for brain tumor detection

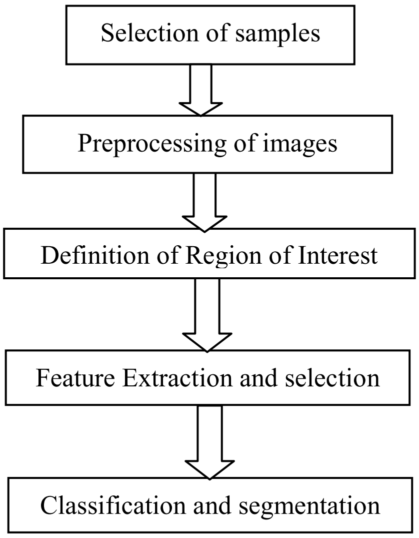

Figure 2. General Processing steps of Brain MRI

The general approach for CAD is to find the location of a lesion and also to determine an estimate of the probability of a disease. The most important process involved in automatic CAD schemes are: (1) Image classification– a stage where features are extracted and categorization of objects into classes are done. i.e. normal or abnormal. (2) Image segmentation – a stage where the pixels are grouped into regions based on image features. The result of the segmentation is a set of objects that can be analyzed and quantified individually, representing determined ROC (Receiver Operating Characteristics) characteristic of the original image. The efficiency of the system is based on the following parameters: Sensitivity - Sensitivity (also called recall rate in some fields) measures the proportion of actual positives which are correctly identified as such (e.g. the percentage of sick people who are correctly identified as having the condition). Specificity - Specificity measures the proportion of negatives which are correctly identified (e.g. the percentage of healthy people who are correctly identified as not having the condition). Efficacy –the results of different treatments can be more properly evaluated and validated [3].

This paper reviews various methods for segmentation in detection of Tumor. Segmentation from magnetic resonance imaging (MRI) data is an important but time-consuming manual task performed by medical experts. Automating this process is a challenging task because of the high diversity in the appearance of tumor tissues among different patients and in many cases similarity with the normal tissues. MRI is an advanced medical imaging technique. It provides rich information about the human soft-tissue anatomy. It is advantageous over other imaging techniques, enabling it to provide three-dimensional data with high contrast between soft tissues. The amount of data present in MRI is far for manual analysis, which has been one of the biggest obstacles in the effective use of MRI [2].

There are many image segmentation techniques available for MRI brain images. In this paper, we have reviewed of the recent image segmentation techniques for MRI brain images. The rest of this paper is organized as follows. In Section 2, various available databases are presented. In Section 3, current segmentation techniques used to detect tumors are presented along with their advantages and disadvantages. A proposed block diagram is presented in Section 4. Section 5 presents the conclusions.

II. DATABASES

BRAIN WEB: The Simulated Brain Database contains a set of realistic MRI data volumes produced by an MRI simulator. These data can be used by the neuroimaging community to evaluate the performance of various image analysis methods in a setting where the truth is known. Currently, the SBD contains simulated brain MRI data based on two anatomical models: normal and multiple sclerosis (MS). For both of these, full 3-dimensional data volumes have been simulated using three sequences (T1-, T2-, and proton-density- (PD-) weighted) and a variety of slice thicknesses, noise levels, and levels of intensity non-uniformity. These data are available for viewing in three orthogonal views (transversal, sagittal, and coronal), and for downloading

BITE: The goal of this database is to share in vivo medical images of patients wtith brain tumors to facilitate the development and validation of new image processing algorithms. Pre- and post-operative MR, and intra-operative ultrasound images have been acquired from 14 brain tumor patients at the Montreal Neurological Institute in 2010. Each patient had a pre-operative and a post-operative T1-weighted MR with gadolinium and multiple B-mode images pre- and post-resection. Corresponding features were manually selected in some image pairs for validation. All images are in MINC format.

Table1.

Database	**Image Size**	**Number of Images**
BRAIN WEB The Mc Conneell Brain Imaging Centre	512 X 512	20 normal anatomical models available Full-3D data volumes are simulated. [T1,T2,PD]
BITE The Mc Conneell Brain Imaging Centre	256 X 256	14 with tumor patient dataset
Open-I beta	352 X 512 110 X 137	50 images in .png format with the detailed description

III. LITERATURE SURVEY ON IMAGE SEGMENTATION TECHNIQUES

The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. Fig 3 show different methods of segmentation available in the literature. Image segmentation may be region based, thresholding, edge detection, feature based model based or any combination of these techniques [4]. The output of the segmentation step is usually a set of classified elements. Most segmentation techniques are either region-based or edge based.

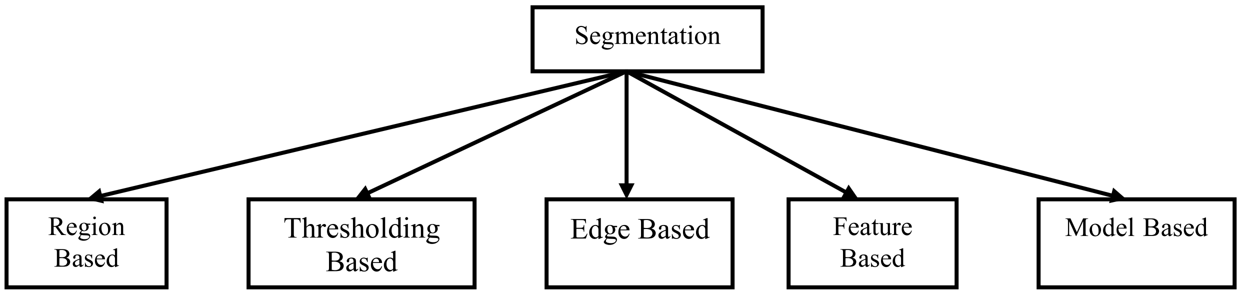

Figure3. Different methods of segmentation

a) Region Based Segmentation: These techniques rely on common patterns in intensity values within a cluster of neighboring pixels. The cluster is referred to as the region, and the goal of the segmentation algorithm is to group regions according to their anatomical or functional roles. In 2013, A.K. Chaudhari and J. V. Kulkarni proposed the segmentation of MR images using textural features based on gray level co-occurrence matrix. Texture is one of the most important characteristics used in identifying objects or region of interest in an image. The texture properties carry useful information for discrimination which is important to develop features for texture. The texture information in the image is adequately specified by a set of gray tone spatial dependence matrices, computed from various angular relationships and distance between neighboring resolution cell pairs on the image. All the Haralick texture features are derived from these angular nearest- neighbor gray tone spatial dependence matrices. The co-occurrence matrix is divided into four quadrants and from these quadrants threshold value between the background and foreground is calculated. The scalar plot is obtained to decide the threshold. The method is tested on 10 MRI images of different type like T1 weighted, T2 weighted and Flair sequences [12].

b) Thresholding based: Thresholding is the simplest way to perform segmentation, and it is used extensively in many image processing applications. Thresholding is based on the notion that regions corresponding to different regions can be classified by using a range function applied to the intensity values of image pixels. In 2012, Natarajan P, Krishnan.N, Natasha Sandeep Kenkre, Shraiya Nancy, Bhuvanesh Pratap Singh proposed methodology consisting of preprocessing done with some gray level conversions by applying median filter and enhancement of image is performed by histogram equalization. Line structures and edges are obtained by applying a difference operator on the image. Segmentation of the image is performed by simple thresholding. In the end morphological operations are performed to extract the exact shape of the image [11] the simple segmentation technique may not be useful for tumors of small size.

c) Edge-based Segmentation: These techniques rely on discontinuities in image values between distinct regions, and the goal of the segmentation algorithm is to accurately demarcate the boundary separating these regions. In the work first they detect all the edge of brain including weak edge by the canny algorithm. It helps to make get all the edges. Then by 8-connected labeling we give all the connected edge the same number, and no connected having the different number, At last by interactive histogram exact edge is obtained[13]. In 2012, Ahmed Faisal, Sharmin Parveen, Shahriar Badsha, Hasan Sarwar, applied fourth order partial differential equation based technique for removing MRI noises and thereby applied segmentation using automatic seeded region growing algorithm for detecting brain tumor automatically. The use of compass operator to preserve the anatomically significant information at the edges and a new morphological technique for skull removal from the brain MRI image which leads to the process of detecting tumor accurately[15].

d) Feature Based Segmentation: Muhammad Faisal Zafar, Fahad Ahmed, Javaid Khurshid (2014) applied some textural features along with fractal analysis have been employed for brain tumor detection and segmentation in MR images. the different features taken into consideration are fractal dimension, Lacunarity, Entropy, Standard Deviation Filter, Eccentricity. Fractal dimension (FD) which shows the texture complexity tends towards higher values for tumor region in comparison to non-tumor region, same is the case for entropy (shows randomness) and standard deviation filter (which measure the deviation of data from mean value), Lacunarity exhibits exactly the opposite relation from former features. Also eccentricity has the smaller value for tumor region in contrast to non-tumor region. Among all these five features, FD and Lacunarity are the vital features, however, remaining three features significantly facilitate the classification. Fuzzy IF-THEN rule base is formed using these tendencies which are used for discriminating between tumor and non-tumor region. Mamdani inference model is opted for its less complications and better performance. [7]. Kharrat, A. ; Comput. & Embedded Syst. Lab. (CES), Nat. Eng. Sch. of Sfax, Sfax, Tunisia ; Benamrane, N. ; Ben Messaoud, M. ; Abid, M. (2009) proposed a Wavelet Transform in the segmentation process which decomposes MRI images and then k-means algorithm is applied to extract the suspicious regions or tumors [9].

e) Model based Segmentation/knowledge-based segmentation: These techniques involve active shape and appearance models, active contours and deformable templates.

Koen Van Leemput, Frederik Maes, Dirk Vandermeulen, and Paul Suetens (2003) used a parametric statistical image model in which each voxel belongs to one single tissue type, and introduce an additional down-sampling step that causes partial voluming along the borders between tissues. An expectation-maximization approach is used to simultaneously estimate the parameters of the resulting model and perform a PV classification. The results are tested on both simulated 200 samples and 500 real time samples [5].

In 1998, Matthew C. Clark, Lawrence O. Hall, Dmitry B. Goldgof, Robert Velthuizen, F. Reed Murtagh, and Martin S. Silbiger developed a system which has five primary steps. In the first step i.e. preprocessing stage is used to detect deviations from expected properties within the slice. Slices that are free of abnormalities are not processed further. The slices with abnormalities are used to extracts the intracranial region from the rest of the MR image based on information provided by preprocessing.

In stage two, initial segmentation is done by an unsupervised clustering algorithm. The segmented images, along with cluster centers for each class are provided to a rule-based expert system which extracts the intracranial region. Multispectral histogram analysis separates suspected tumor from the rest of the intracranial region, with region analysis used in performing the final tumor labeling. This system has been trained on three volume data sets and tested on thirteen unseen volume data sets acquired from a single MRI system. The results of segmentation are compared with supervised, radiologist-labeled "ground truth" tumor volumes and supervised k-nearest neighbors tumor segmentations. The system can process any trans-axial slice (intersecting the long axis of the human body) starting from an initial slice 7 to 8 cm from the top of the brain and upward. A total of 120 slices containing radiologist diagnosed glioblastoma-multiforme tumor were available for processing [6].

Modern methods for Image segmentation involve Multi-resolution and multi-channel feature, Feature fusion techniques, Multi-classifier decision combination, HMM, GMM, CRF- and GMRF-based techniques, Artificial Neural Networks – SVM and FFNN, Active contours, watershed transform, Decision Trees and hierarchical analysis, Probabilistic, Neuro-fuzzy and soft-computing (SA) techniques. In 2010, Logeswari, T. ; Dept of Comput. Sci., Mother Theresa Women's Univ. Kodaikkanal, Kodaikkanal, India ; Karnan, M. adapted ACO hybrid with Fuzzy and Hybrid Self

Organizing Hybrid with Fuzzy. Segmentation consists of two steps. In the first step, the MRI brain image is segmented using HSOM Hybrid with Fuzzy and the second step ACO Hybrid with Fuzzy method to extract the suspicious region [8]. Walaa Hussein Ibrahim, Ahmed AbdelRhman Ahmed Osman, Yusra Ibrahim Mohamed (2013), proposed Neural Network technique consisting of three stages, preprocessing, dimensionality reduction, and classification. In the first stage, we The MR image will obtain and convert it to data form (encoded information that can be stored, manipulated and transmitted by digital devices), in the second stage have obtained the dimensionally reduction using principles component analysis (PCA), then In the classification stage the Back-Propagation Neural Network has been used as a classifier to classify subjects as normal or abnormal MRI brain images [10]. In 2009, D.Jude hemanth, D.Selvathi and J.Anitha, the applied of modified FCM algorithm for MR brain tumor detection. Abnormal brain images from four tumor classes namely metastase, meningioma, glioma and astrocytoma are used in this work. A comprehensive feature vector space is used for the segmentation technique. Comparative analysis in terms of segmentation efficiency and convergence rate is performed between the conventional FCM and the modified FCM [14].

IV. PROPOSED BLOCK DIAGRAM

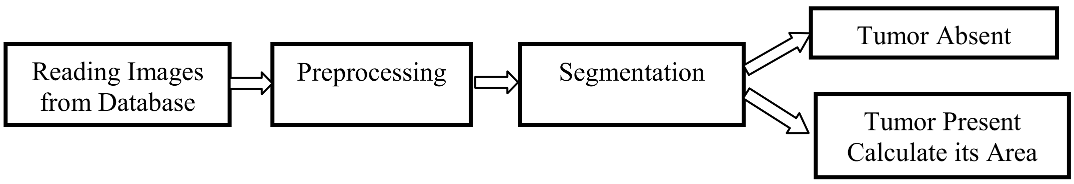

Figure4. Proposed Block Diagram

The fig. 2 show the proposed block diagram. It includes three basic steps preprocessing, segmentation and tumor area calculation if tumor is present. In the preprocessing step, we enhance some features of images to increase the clarity of the images. In segmentation step we find the Region of Interest from the preprocessed image. At the end, we decide whether tumor is present or not and if tumor is present its area is calculated.

V. CONCLUSION

In this paper, we have performed a partial survey of various techniques for MRI brain image segmentation. All the techniques may obtain satisfaction results but not able to produce 100 % of accuracy. Future research in the segmentation will strive toward improving the accuracy, precision, and computational speeds of segmentation methods, as well as reducing the amount of manual interaction. Accuracy and precision can be improved by incorporating prior information from atlases and combining discrete and continuous spatial domain segmentation methods. For achieving the computational efficiency particularly important in real-time processing applications, multistage processing and parallelizable methods such as neural networks are promising. The image segmentation remains a challenging problem in medical MRI brain image processing. In further works, we planned to develop a novel efficient technique to produce more accuracy than existing methods for the detection of brain cancer or tumor

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