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A Survey: Image Segmentation Techniques of Brain Tumor Detection through MRI Images

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Abstract- The most common imaging technique for brain is MR imaging which is a non-invasive method. Brain tumor detection from MRI images is one of the most challenging tasks in today's modern Medical imaging research. Magnetic Resonance Images are used to capture images of soft tissues in human body. This technique is used to analyze the human organs without the need for surgery. In order to detect brain tumor the fundamental process need to be implement called as image segmentation which is one of the most important and challenging aspect of computer aided clinical diagnostic tools. It is process of partitioning an image into distinct regions to segment out region of interest (ROI). Noises present in the Brain MRI images are multiplicative noises and reductions of these noises are difficult task. The noise removal process should not destroy minute anatomical details. This makes accurate segmentation of brain MRI images a challenge. A large variety of algorithms for segmentation of MRI images has been developed. The purpose of this paper is to succinctly review recent progress and current state of art knowledge related to various methods and techniques used to detect brain tumor through MRI image segmentation.

Keywords- Brain, MRI, ROI, segmentation

I. INTRODUCTION

Brain tumor is one of the most common major causes for the increase in Mortality among children and adults in the world. Brain tumor is a group of abnormal cells that grows inside of the brain or around the brain [1]. Many different types of brain tumors exist. Some brain tumors are noncancerous (benign), and some brain tumors are cancerous (malignant). The National Brain Tumor Foundation (NBTF) for research in United States estimates that, in children, brain tumors are the cause of one quarter of all cancer deaths. Also, NBTF reported most research in developed countries show that the number of people who develop brain tumors and die from them has increased perhaps as much as 300% over past three decades [2]. Early detection of the brain tumor is very important and the motivation for further studies. In the brain magnetic resonance imaging (MRI), the tumor may appear clearly but for further treatment, the physician also needs the quantification of the tumor area. The computer and image processing techniques can provide great help in analyzing the tumor area [3]. On the other side, computer-aided detection (CAD) has been developing fast in the last two decades. The main idea of CAD is to assist radiologists in interpreting medical images by using dedicated computer systems to provide 'second opinions'. Studies on CAD systems and technology show that CAD can help to improve diagnostic accuracy of radiologists, lighten the burden of increasing workload, reduce cancer missed due to fatigue, overlooked or data overloaded and improve inter- and intra-reader variability[3] [4]. The final medical decision is made by the radiologists. Consequently, radiologists expect that CAD systems [5] can improve their diagnostic abilities based on synergistic effects between the radiologist and the computer with medical image analysis and machine learning techniques [7]. Therefore, the CAD systems should have abilities similar to the radiologists in terms of learning and recognition of brain diseases. For this reason, pattern recognition techniques including machine learning play important roles in the development of CAD systems [7]. Pattern recognition is the act of extracting features from objects (e.g. lesions) in raw data and making a decision based on a classifier output, such as classifying each object into one of the possible categories of various patterns. In general, there are two types of CAD systems for brain evaluation i.e. systems that detect lesions (normal or pathological brain) and those that differentiate diseases (benign or malignant lesions).

II. BRAIN IMAGING TECHNIQUES

Brain imaging techniques allow doctors and researchers to view activity or problems within the human brain, without invasive neurosurgery. There are a number of accepted, safe imaging techniques in use today in research facilities and hospitals through out the world. The cells which supplies the brain in the arteries are tightly bound together thereby routine laboratory test are inadequate to analyze the chemistry of brain. There are many imaging modalities that allow the doctors and researchers to study the brain by looking at the brain non-invasively. Computed tomography (CT), positron emission tomography (PET) and MRI can provide information about brain tissues, from a variety of excitation sequences. Compared to all other imaging modalities, MRI provides superior contrast for different brain tissues. MRI is efficient in the application of brain tumor detection and identification, due to the high contrast of soft tissues, high spatial resolution and since it does not produce any harmful radiation, and is a non-invasive technique (Georgiadis et al., 2008).

Additionally, MR images encapsulate valuable information regarding numerous tissue parameters (proton density (PD), spin–lattice (T1) and spin–spin (T2) relaxation times, flow velocity and chemical shift), which lead to more accurate brain tissue characterization. These unique advantages have characterized MRI as the method of choice in brain tumor studies. MRI is often the medical imaging method of choice when soft tissue delineation is necessary. This is especially true for any attempt to classify brain tissues. Radiologist used it for the visualization of the internal structure of the body. MRI provides rich information about human soft tissues anatomy. MRI helps for diagnosis of the brain tumor. Images obtained by the MRI are used for analyzing and studying the behavior of the brain. The strength of the MRI signal depends primarily on three molecules. Other two parameters are T1 and T2 relaxation, which reflect different features of the local environment of individual protons (Latif et al., 2010). The 'pathological' T2 scan is useful for locating the lesioned region in the brain. The 'anatomical' T1 scans usually have the best scan resolution, and are useful for localizing anatomical structures. The PD scan shows overall hydrogen density per cubic mm.Fig. 1 shows the sample brain MRI. An attractive feature of MRI is that different contrasts between tissue types (multispectral image data of the same subject) can be easily obtained. For that in the recent years, MRI has evolved into a popular technique to study the human brain. This non-invasive technique can provide high resolution spatial images and its rich information content can be suitably utilized to develop automated diagnostic tools, which can aid the medical fraternity to draw quicker and easier inferences about the condition of the brain under study.

III. GENERIC METHODOLOGY OF MRI (CAD) SCHEME

The development of automated tools can be of immense importance to help in diagnosis, prognosis and pre-surgical and post-surgical procedures, depending on whether the subject is a healthy one or is a pathological subject, suffering from some brain disorder, e.g. Alzheimer's disease, Parkinson's disease, etc. The extraordinary level of detail that can be obtained with brain MR images can be efficiently utilized by performing some powerful signal or image processing techniques, especially suitable

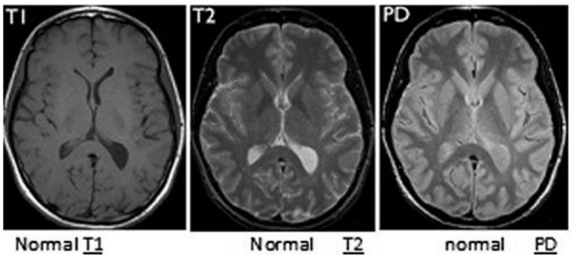


Fig. 1.Sample of MRI images for a normal brain: (a) T1-weighted, (b) T2-weighted, and (c) PD- proton density (Parizel et al., 2010)

for automated analysis. This is because, with the huge information repository associated with MRIs, it becomes almost impossible to manually interpret each image, necessitating the development of automated tools [8]. Fig. 2shows the details of the system. First MR image for diagnosis is provided to the system as an input. Second step of the proposed system is to extract features from this input image. After feature extraction, these features independently are used for classification as malignant and benign MR image. It classifies the brain image on the bases of multiple classifiers. No more processing is required once the MR image is determined as benign. But when the MR image is determined as malignant by the classifier it is further processed for extracting tumor portion from it [1]. In the following two subsections various segmentation, feature extraction, and classification methods and their performances of CAD brain tumor through MRI have been reviewed and compared for the last 10 years and most of them are in the last 3 years. We identified the strengths and the weaknesses of the reviewed algorithms from the literature.

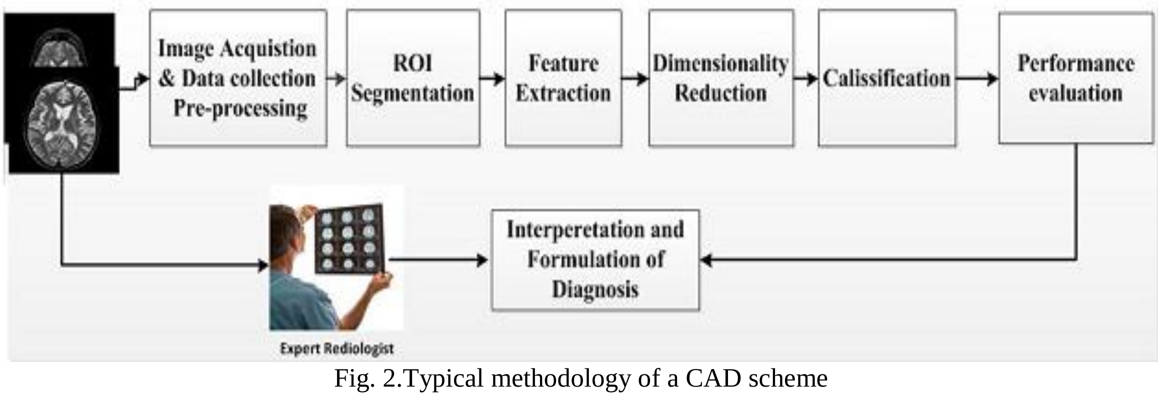


Fig. 2.Typical methodology of a CAD scheme

3.1. Image acquisition and preprocessing

To obtain a real brain images (e.g. MRI) and to make up a research is a very complex because of a privacy issue. Most of the data are obtained from the web ((https://ida.loni, 2014; Brainweb, 2014; Department of Radiology, 2014; Harvard Medical School, 2014; http://buscahospital, 2014; Indian Devaki Cancer Institute, 2014). The state-of-the-art of now-a-days technologies of digital medical image acquisition are improving tremendously, which gives images of high quality and resolution but the noise on the images is still an issue. Image preprocessing and enhancement stage is the simplest stage of medical image analysis. This stage is used to reduce the noise and improve resolution contrast the image. Several de-noising approaches can be used (Gonzalez & Woods, 2008). The median filter is most de-noising method used to reduce noise and improve the quality in an image. The median filter preserves the edges of the images

SEGMENTATION

In Image segmentation process an image is partitioned into multiple segments i.e. sets of pixels also known as super pixels. Segmentation carried out subdivides an image into its constituent regions or objects. The level to which the subdivision takes place depends on the problem being solved i.e. segmentation should not stop until the objects of interest in an image have been isolated. T he aim of segmentation is to simplify or change the representation of an image so that it can become more meaningful and easier to analyze. In other words, segmentation can be described as a process of separation of suspicious region from background image. Image segmentation algorithms are generally based on one of two basic properties of intensity values:

1) Discontinuity
2) Similarity

The aim of a large number of image processing applications is to extract important features from the image data, which can provide a description, interpretation or understanding of the scene for the machine.

SEGMENTATION METHODS

Many types of methods are available for segmentation of MRI images:

1. Fuzzy c-means (FCM) clustering: Fuzzy cmeans (FCM) is a clustering method in which one piece of data belongs to two or more clusters. Firstly, the algorithm selects the initial cluster centers from SOM clustering algorithm. Then, after many iterations of the algorithm, the final result converges to actual cluster centre; thereby a good set of initial cluster is generated. FCM algorithm fails to deal with images that contain noise. In order to deal with noise sensitivity BCFCM has been proposed i.e. Bias Corrected FCM.

2. K-Means Clustering: The simplest and most commonly used algorithm, employing a squared error criterion is the K-means algorithm. K-mean is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The K-mean clustering is a popular approach to partition d- dimensional data into K clusters such that an objective function providing the desired properties of the distribution of feature vectors of clusters in terms of similarity and distance measures is optimized. A generalized K-mean clustering algorithm initially places K clusters at arbitrarily selected cluster centroids = 1, 2…k and modifies centroids for the formation of new cluster shapes optimizing the objective function. The K-means clustering method optimizes the sum-of squared-errorbased objective function.

3. The region growing: The region growing starts with a seed, selected in the centre of the tumor region. During the region growing phase, pixels in the neighbor of seed are added to region based on homogeneity criteria which thereby resulting in a connected region.

4. The active contour model: The active contour model is a framework for delineating an object outline from a noisy image and is based on a curve, X(s) = [x(s), y(s)], defined in the image domain where s in range of [0,1] is an arc length. It deforms in a way that minimizes an energy function. The internal energy and is used to control the tension and rigidity of the deforming curve. The external energy is used to guide the deforming curve toward the target. [9] used Gaussian Gradient Force to compute external force. Advantages of this method are insensitiveness to contour initialization, boundary concavities, saving computation time, and high accuracy.

5. A Markov random field models: A Markovrandom field, Markov network or undirected graphical model is a set of random variables having a Markov property described by an undirected graph. It is a statistical model used to model spatial relations that exist in the neighbor of pixels [11]. Image segmentation methods use MRF to take advantage of neighborhood information in the segmentation process, like, in medical images most neighborhood pixels have the same class and thus by using neighborhood information, influence of noise in segmentation is decreased.

6. LVQ: Learning vector quantization [10] is a supervised competitive learning technique that obtains decision boundaries in input space based on training data. It defines class boundaries prototypes, a nearest-neighbor rule and a winnertakes-it-all paradigm. LVQ is composed of three layers: input layer, competitive layer and output layer. The input data is classified in the competitive layer and those classes or patterns are mapped to target class in the output layer. In the learning phase weights of neurons are adjusted based on training data. The winner neuron is calculated based on the Euclidean distance, then the weight of the winner neuron is adjusted [12]. There are several algorithms to learn LVQ networks.

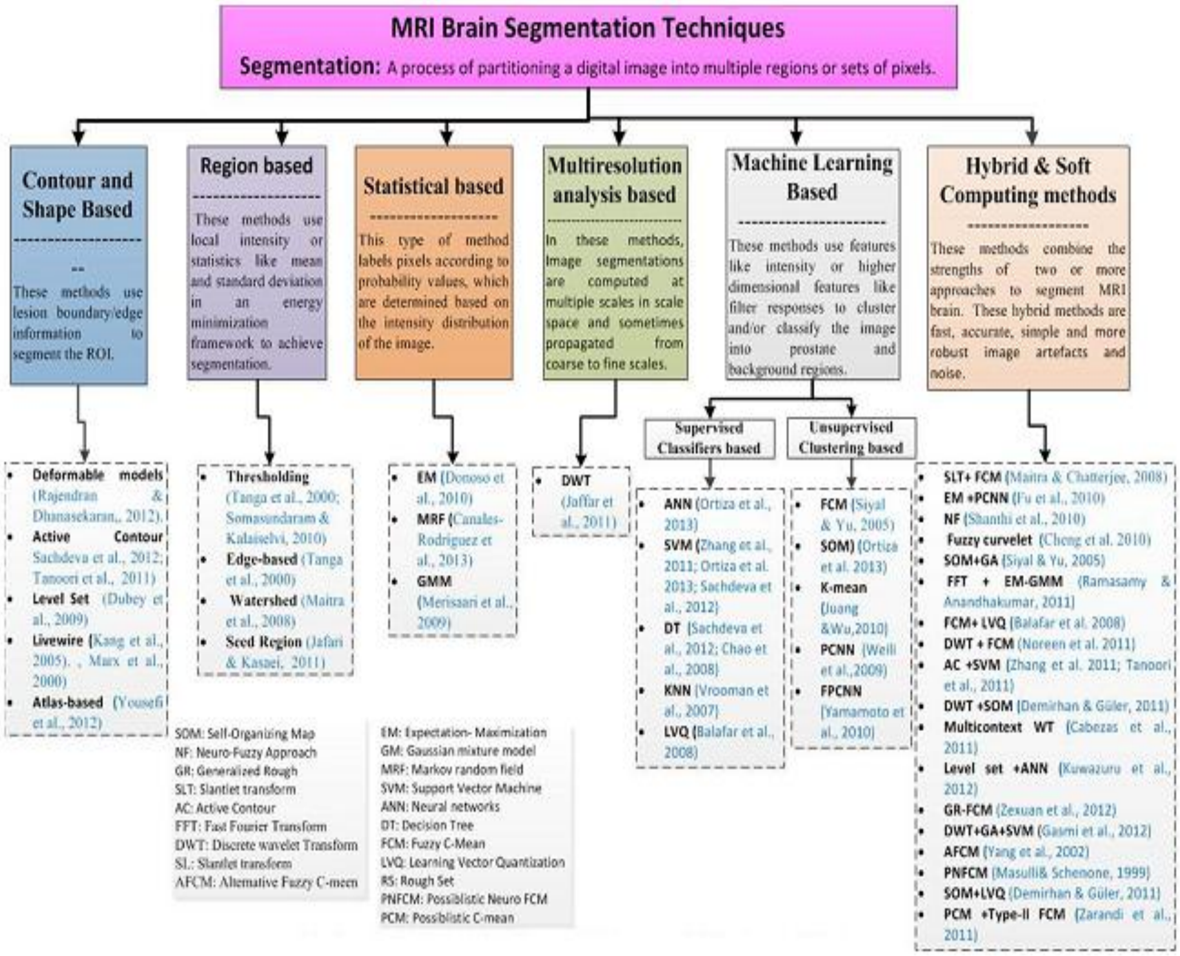
7. Watershed: Watershed is a gradient-based segmentation technique where different gradient values are considered as different heights. A hole is made in each local minimum and immersed in water, the water will rise until local maximums.When two body of water meet, a dam is built between them. The water rises gradually until all points in the map are immersed. The image gets segmented by the dams. The dams are called watersheds and the segmented regions are called catchments basins [13] [14]. Its fast implementation method is proposed by [15] and [16]. The over segmentation problem still exists in this method.

8. Graph cut based: In this method the problem of image segmentation is considered as a graph partitioning problem and global criterion that measures both total dissimilarity among the different groups and the total similarity inside those groups is used. An efficient method used to optimize the criterion to segment image is based on generalized eigen value treatment [17].

Table 1: Overview of the segmentation techniques For MRI images :

Author	Segmentation Technique	Purpose	Features
Ortiz, Gorriz, Ramırez, and Salas-Gonzalez(2013)	Two unsupervised approaches for brain image segmentation. The first one is based on the use of relevant information extracted from the whole volume histogram which is processed by using SOM. The second method proposed consists of four stages including MRI brain image acquisition.	Brain image segmentation	The proposed algorithms have been successfully evaluated providing a good Segmentation results.
Ortiza et al. (2013)	Segmentation method based on the growing hierarchical self-organizing map (GHSOM) and multi-objective-based feature selection to optimize the performance of the segmentation process	Brain image segmentation	Provide new and additional ways to d some brain disorders such as schizoph the Alzheimer disease
Mohsen et al(2012)	Feedback pulse-coupled neural network (FPCNN)	Segmentation of tumor in brain MRI	Use the feedback feature where the input experience feedback shunting that is not uniform for the entire input.
ajendran and Dhanasekaran (2012)	Fuzzy clustering and deformable model.	Tumor Segmentation on MRI Brain image	The method is more accurate and robust for brain tumor segmentation.
Sachdeva et al. (2012)	Intensity-based active contour models such as gradient vector flow (GVF), magneto static active contour (MAC) and fluid vector flow (FVF) have been proposed to segment homogeneous objects/tumors in medical images	The proposed method content-based active contour (CBAC) uses both intensity and texture information present within the active contour to overcome above-stated problems capturing large range in an image.	Tumor volume is efficiently extracted from 2-dimensional slices and is named as 2.5-dimensional segmentation
Jafari and Kasaei(2011)	eeded region growing segmentation (SRGS) + connected component labeling (CCL	tarts by brain detection from skin–neck–bone and ventricles and then distinguish brain regions from scalp and pathological tumor tissues from normal tissues in Brain MR	A hybrid technique been used to select and improve of a rugged segmentation results
Tanoori et al. (2011)	Active contour models and SVM.	The method is based on the idea of active contour models and SVM classifiers. The main contributions of the presented method are effective modifications on brain images for active contour model and extracting simple and beneficial features for the SVM classifier.	A novel automatic approach to identify brain structures in magnetic resonance imaging (MRI) is presented for volumetric measurements. This method validation is done using the gold standard brain MRI data set.

Fig. 3.Overview of the most commonly used segmentation techniques in CAD systems for MRI brain



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IV. CONCLUSION

With the advance of computational intelligence and machine learning techniques, computer-aided detection attracts more attention for brain tumor detection. It has become one of the major research subjects in medical imaging and diagnostic radiology. In this study, we reviewed current studies of the different segmentation, feature extraction and classification algorithms. As this paper focuses on various methods available for segmentation and all the methods more or less are used to segment tumor from the brain MRI.

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