A Study of MRI Segmentation Methods in Automatic Brain Tumor Detection

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***Abstract*—Brain tumor occurs due the uncontrolled growth of brain tissues. The detection of size, shape, type, location and orientation of the brain abnormality is highly essential for planning effective treatment. Magnetic resonance imaging (MRI) is a traditional and most commonly used technique for detecting brain tumors, cancer, multiple sclerosis and other abnormalities. Nowadays Computer Aided Diagnosis (CAD) systems are commonly used for systematic and explicit detection of brain abnormalities. Image segmentation is an effortful and tedious step in CAD. Image segmentation is used to subdivide an image, and is an important step in a CAD system. The representation of the image is changed and a meaningful image is obtained, which can be used for better analysis. The effectiveness of abnormality detection depends on the accuracy and robustness of segmentation algorithm. Segmentation techniques with different level of sensitivity, efficiency, and accuracy have been developed. In this paper we summarize, and discuss the advantages, capabilities and drawbacks of the most commonly used MRI segmentation methods.**

Keywords- Brain tumor, Magnetic resonance imaging (MRI), Computer aided diagnosis (CAD), Hybrid Segmentation.

I. INTRODUCTION

Brain tumors are classified into different types based on their characteristics. Different treatment methods are followed on the basis of these characteristics [24]. World health organization (WHO) classifies brain tumors into 4 grades. Grade I and Grade II are benign brain tumor (Low grade). Grade III and Grade IV are malignant tumor (High grade) [25]. Magnetic Resonance Imaging (MRI) is an efficient imaging technique to detect brain tumors without using harmful radiations [26]. It is possible to find the shape, size and position of tumors using MRI. It is a tedious job for the technicians to categorize and analyze these images manually. Hence the use of automatic segmentation methods became popular. Abnormal tissues can be easily identified using segmentation methods. It is possible to obtain three different images from the body of same person based on echo time (T_E) and repetition time (T_R). The T1 weighted MR images from sagittal plane, axial plane and coronal plane are shown in Fig.1 (*Image Courtesy: Department of Radiology, University of Wisconsin, School of Medicine and Public Health*) [42].

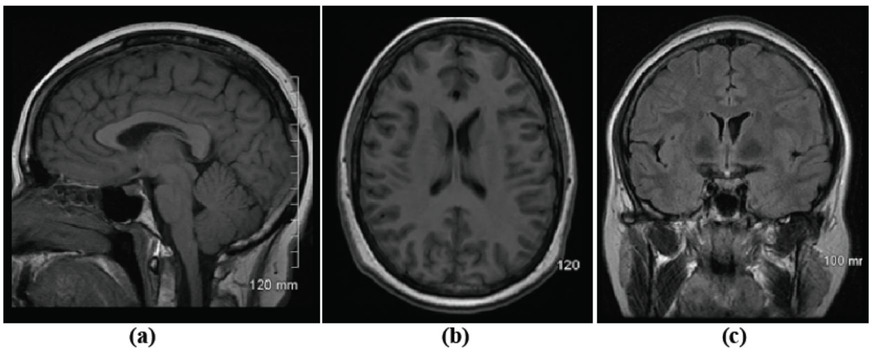

Fig.1. Brain MRI obtained from (a) Sagittal Plane, (b) Axial plane and (c) Coronal plane.

Magnetic field inhomogeneities restrict the reliability and speed of automatic MRI segmentation techniques. Noise is one of the major inhomogeneities associated with MR images. The random noises associated with MR images have Rician distribution [7]. Intensity inhomogeneity occurs due to the non-uniformity in the Radio Frequency (RF) field during the data acquisition, which will result in shading artifact [6]. Another inhomogeneity normally occurs is the partial volume effect, in which more than one type of tissues or class occupies same pixel or voxel. These pixels or voxels are generally called muxels [1].

The rest of this paper is arranged as follows: In section II MRI segmentation techniques and different algorithms are reviewed. In section III we evaluate and analyze the validity of currently used hybrid brain MRI segmentation methods. And finally in section IV conclusion and future scope is provided.

II. BRAIN MRI SEGMENTATION METHODS

Brain MRI segmentation methods can be classified into 6 major categories. They are (A) Threshold Based Segmentation, (B) Region Based Segmentation, (C) Edge Detection, (D) Clustering, (E) Statistical Models and (F) Artificial Neural Networks.

A. Threshold Based Segmentation

Thresholding is one of the oldest methods for brain MRI segmentation. This method is very much effective in image binarizartion, which is an important step in segmentation. Brain MRI can be defined as regions with pixels having discrete gray level ranges. A particular intensity value known as threshold is defined, which separates the desired regions [28]. Otsu method and Th-mean method are some of the well known and well established thresholding techniques. Otsu method is a global thresholding method [27] in which the pixels in an image are partitioned into two classes (objects and background) at a particular gray level. Total variance, variance within a class and variance between classes, are calculated. Due to large intensity variation between foreground and background regions, this algorithm will not work perfectly on all Brain MR Images. Th-mean algorithm [29] deals with thresholding of a small region in an image. Selection of threshold value is done by calculating the threshold of all these small regions. The intensity variation affects the quality of segmentation.

B. Region Based Segmentation

Region growing in an image starts with a small element called seed pixel. The adjacent regions having similar properties are combined to form a bigger region. The combination process stops when there are no further regions to merge [30]. The main criterion for segmentation is the homogeneity of the regions. Gray level, colour, texture, shape etc are the major criteria for homogeneity. Region splitting and merging is another type of region based segmentation technique. Here the image is sub divided into a set of arbitrary regions these regions are merged or split according to the segmentation algorithm. The set of disjoint regions are coherent to themselves [32]. This method is implemented based on quad tree data [31]. Advantages of region based segmentation methods are accuracy, simplicity and choice of multiple criteria. The major disadvantages are extended computational cost and noise sensitivity.

C. Edge Detection

Local change in image intensity is defined as edge. Edges normally occur in the boundary between two regions [33]. Edge detection technique makes use of the discontinuities in image values to separate regions. The segmentation algorithm can accurately identify the boundary between these regions. An edge is a region which consists of connected regions of edge pixels. The complexity of edge detection algorithm depends on the ability to localize the edges, noise handling capability and elimination of false responses. Objects in an image are localized using the edges and the discontinuities will represent the object boundaries. In a sharp image edges are stronger, whereas blurred image consist of weaker edges. The discontinuities in intensity can be calculated using the derivative operator (First order derivative or second order derivative). Merits of this method are simplicity and efficiency in object detection. Demerits of this method are sensitivity to noise, inaccuracy, time consumption etc.

D. Clustering

Clustering is a segmentation technique in which a set of objects in an image are grouped into continuous regions of a multi dimensional space containing relatively high density of points and low density of points. These regions are separated from each other to form uniform density regions called clusters. Clustering can also be done based on the intensity of the pixels. Hard clustering [34] is a type of clustering in which data elements belong to only one cluster and the membership value of a region to a particular cluster is exactly 1. In soft clustering, data elements belong to more than one cluster and the membership value of a region to a particular cluster ranges from 0 to 1. Fuzzy C- Means (FCM) is a simple and efficient image clustering algorithm. Here the whole data set is arranged into n distinct groups (clusters). Each data point in the data set is associated with each cluster to a predefined degree. For a particular data point which is closer to the center of a cluster will have high degree of association with that cluster. If the distance between a data point and the cluster center is large, then that data point has less association with the cluster. Initial centers are assumed to mark the location for mean of each cluster. FCM assign a membership function for each data points in a cluster. Then the cluster centers are randomly moved towards the right. Thus the membership function gets minimized and represents the distance between any data point to the center of a cluster weighted by the membership function of that point [35]. The fuzziness of an image and its information content are illustrated by the membership function. FCM provides good segmentation efficiency for overlapped data and data points can belong to more than one cluster. Number of clusters should be assigned manually and lower number of clusters provides better performance.

K-means is an unsupervised clustering algorithm. Initially K number of clusters is selected from the whole image as per a predefined rule. The center of the clusters is chosen randomly during the first iteration. Then the distance (Euclidean) between pixels and center of clusters are calculated. If the distance is near to the center of a particular cluster, then the pixel is moved to that cluster. Otherwise the pixel is moved to the next cluster and so on. The next step is to re-estimate the cluster center [35]. Again each pixel is compared with all centroids and the iteration continues until the center converges. The advantages of this method are faster computation, reduced complexity, robustness, efficiency and better result for distinct data sets. The disadvantages are the requirement of prior knowledge (number of clusters) and the inability to handle noisy data.

E. Statistical Model

Segmentation problem can be solved using statistical classification methods. This can be done in two different ways [8]. First method is to assign class label for particular pixels based on the algorithm. In second method, the relative amounts of various tissue types within a pixel are estimated. Expectation Maximization (EM) algorithm [20] is a method to find the maximum a posteriori estimator of a hidden parameter θ with a particular probability distribution. There are two steps in EM method, such as expectation step and maximization step. In the expectation (E) step, each and every pixel in an image is classified into one cluster with respect to the current estimates of the posterior distribution over hidden variables. The maximum value of likelihood function (f) is estimated. According to current classification of pixels, the values of hidden parameters are re-evaluated. These two steps are repeated until convergence is assured [10]. The EM algorithm can be modified according to the specification of the user [9]. The demerits of this method are the requirement of pre-knowledge of known number of classes and computational complexity. Another statistical model used in brain MRI segmentation is Markov random field model [19]. In this method the information about spacial interactions between neighbouring pixels are used to deal with segmentation problem. While considering brain MRI, most of the nearby pixels come under same class [11]. By using spatial correlation data, fine details in the image can be preserved. Iteration of conditional modes and simulated annealing with maximized a posterior estimate is used to update the pixel value. The advantages of MRF algorithm are reduced effective noise, smooth segmentation and stable outputs. The demerits of this method are computational complexity and reduced spacial interaction.

F. Artificial Neural Network

Artificial neural networks (ANN) consist of multiple level of processing elements called nodes which can act like biological neural networks. Elementary computation is performed by each node in an artificial neural network. Highly complex architecture enables the system to produce real time outputs. The system is robust and can perform parallel processing [5]. The variables and functions in an artificial neural network are described in Fig.2.

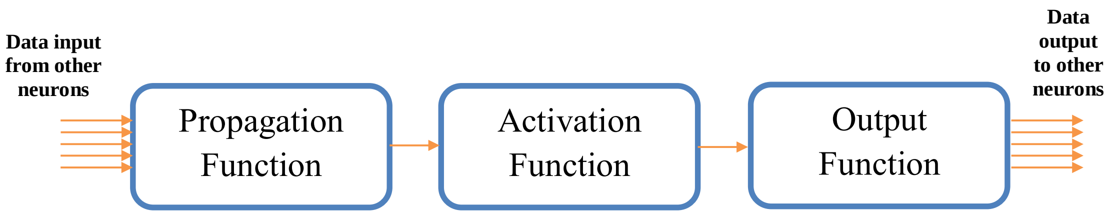

Fig.2. Variables and functions in an artificial neural network

Propagation function is often a weighted sum, transform or outputs of other neurons in the network. Activation function transforms the network input and sometimes converts old activation function to new activation function. Output function is often an identity function, which transforms activation to output for other neurons. In segmentation scenario ANN can be used as a clustering method. The major advantages of ANN based segmentation are accuracy, efficiency, robustness etc. Requirement of training data and high processing time are the major disadvantages of ANN.

III. EVALUATION OF HYBRID SEGMENTATION METHODS

Due to the rise of different specifications and new applications in MRI segmentation problem, new algorithms and methods are continuously evolved and introduced [2]. It is a difficult task to select the most appropriate technique for a particular application [3]. In such cases a combination of different techniques may be obligatory to obtain the desired segmentation goal [4]. Therefore, in current scenario hybrid or combination of segmentation methods are used substantially in various brain MRI segmentation applications [12]. By combining different complementary methods into a hybrid method it is possible to avoid most of the disadvantages of each method alone, which will improve the segmentation accuracy. Here we discuss some relatively good hybrid segmentation algorithms.

Bandhyopadhyay et.al [13] proposed a brain tumor segmentation method based on K-means algorithm and local standard deviation. The entire regions of the brain are divided into two segments. Normal brain regions such as white matter, grey matter and cerebral-spinal fluid are arranged in one segment and the next segment comprises of tumor cells in brain. The main constrain of this segmentation technique is the necessity of adjacent imaging layer. Another disadvantage is the loss of intensity. This method ignores the finer anatomic details of the brain. The advantages of this method are high efficiency, robustness and reduced complexity.

Tatiraju et.al [14] proposed a hybrid brain MRI segmentation method using the combination of Expectation Maximization (EM), Normalized Cuts (NC) and K-means clustering. A partitioning algorithm is applied to gray-scaled images by varying value of k (number of clusters). For smaller values of k, the K-means and EM algorithms are fast and have good efficiency. For larger values of k, many clusters appear in the images are undistinguishable. The combination of K-means and NC algorithm gave good results for larger value of k, but due to computational complexity, it requires more time to obtain the segmentation output.

Christe et al. [15] combined K-means and Fuzzy C-means algorithm for brain MRI segmentation. They chose various parameters such as number of clusters (k), distance, fuzziness and stopping criterion. The membership values are initialized randomly. Iterations for recalculating centers and membership values are done until the objective function converges. The major advantage of this method is that overlapping gray scale intensities can be taken into account. It minimizes the mean square errors within the output images. The borders between tissues are not clearly defined successfully. The performance of the proposed algorithm degrades when applied to noise corrupted images. This problem can be solved by applying pre-processing before integration.

M.P. Gupta et.al [16] proposed a hybrid method for brain MRI segmentation using K-means and Fuzzy C-means algorithm. Noise present in the MR image is removed before K-means process. Tumor region is extracted from the noise removed MRI using k-means algorithm. Fuzzy C-means algorithm extracts the accurate shape of malignant tumor present in brain. This method gives more accuracy and better signal to noise ratio. The disadvantages of this method are computational complexity and extended computational time.

N. Zhang et.al [17] combined Support Vector Machine (SVM) classification and kernel feature selection for efficient brain MRI segmentation. Kernel class separability is an important criterion which affects the feature selection. Initially the algorithm learns the properties of brain tumor and the features are selected from the previous MRI of patients. After that, the algorithm can segment the tumor in new MRI inputs by using SVM. Tumor contours in the MRI are extracted using region growing technique. The advantages of this method are robustness and separability. The computational time increases due to computational complexity of algorithm.

D. Zikic et al [18] proposed a method for tissue-specific automatic brain MRI segmentation of high grade gliomas. This approach is based on decision forests and Gaussian mixture model. This method requires little pre-processing time and no explicit regularization. Model complexity is reduced due to these features of the algorithm. The main advantages are computational efficiency, robustness and segmentation accuracy. It can segment individual tissues simultaneously. These results are well suited for volume measurements of tumors and can be used as high-quality initial estimates for interactive treatment.

A. Ortiz et.al [4] proposed a mixture of Self-Organizing Maps (SOM) and Genetic Algorithms (GA) for unsupervised MRI segmentation. Feature selection was efficiently done using evolutionary computation method. SOM and sharp map clustering were used for voxel classification. A relation between output space and input space was considered to delineate cluster borders. This method did not use prior knowledge of voxel classes, but dissimilar tissue classes were identified directly.

G.C. Lin et.al [22] used fuzzy knowledge to obtain relationship between pixels in multispectral MR images. Region growing process is implemented by applying these relations and modified seed pixels. A Target Generation process is proposed to find out the number of final regions and applied to support conventional regions merging. Thus Fuzzy Knowledge Seeded Region Growing (FKSRG) method will be able to segment images clearly. Experimental results show that the FKSRG method is more effective than K-means and Support Vector Machine methods.

Islam and Ahmed [23] proposed image segmentation method based on K-means, K-mediods, and Hierarchical clustering techniques. These clustering techniques are applied on natural images to find the merits and demerits of each algorithm. After implementing these algorithms and testing on a large set of MR images, they concluded that K-means clustering provides better performance, reduced complexity and simplicity in implementation. The number of clusters can be suitably selected to get desired segmentation output.

IV. CONCLUSION

During the past decades various image segmentation methods have been proposed with different level of accuracy, computational time, complexity, efficiency etc. The accuracy of brain MRI segmentation should be increased to reduce false diagnosis. Brain MRI segmentation and classification is one of the most active research area in image processing. Large amount of MRI data is generated daily and requires computer aided processing for decision making. In this work the advantages and disadvantages of various segmentation algorithms are discussed in detail. This survey shows that K-means has better performance and less computational complexity. By applying K-means in conjunction with other method, it is possible to increase the segmentation performance to a higher level. Robustness of the algorithm is an important criterion for the laboratories to adapt a new MRI segmentation technique. Our future work is to develop a better hybrid segmentation technique using K-means algorithm and FCM.

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