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A Survey on Automated Brain Tumor Detection and Segmentation from MRI

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Abstract - *In medical image processing the Brain tumor segmentation is an important task; for improving treatment possibilities and to increases the survival rate of the patients the early diagnosis of brain tumors plays an important role. Segmentation of the brain tumors for cancer diagnosis can be done manually from large amount of data of Magnetic resonance imaging (MRI), but it is a difficult and time consuming task. Therefore there is a need for automatic and reliable brain tumor image segmentation method. However the detection of tumor still is a challenging task for researchers because tumor possesses complex characteristics in appearance and boundaries. The purpose of this paper is to understand brain tumor, its types and different methods for detection and segmentation of brain tumor. The objective of this survey paper is to presents a various automatic Brain tumor segmentation methods from MRI of brain.*

Key Words: **-Brain Tumor, Brain Tumor Segmentation, FCM, Magnetic Resonance Imaging (MRI).**

1. INTRODUCTION

Brain is the center of human central nervous system. The brain is a complex organ as it contains 50-100 billion neurons forming a gigantic network. Brain tumor is an abnormal growth of group of cells that grows inside of the brain or around the brain. The types of Brain tumors are benign tumor and malignant tumor. Benign tumors are non-malignant/non-cancerous tumor. A benign tumor is usually localized and does not spread to other parts of the body. Most benign tumors respond well to treatment. Benign tumor is less harmful than malignant tumor.Malignant tumors are cancerous growths. They are often resistant to treatment, may spread to other parts of the body. Malignant tumors are classified into primary and secondary tumors. The malignant tumor spreads rapidly invading other tissues of brain, progressively worsening the condition causing death. Brain tumor detection is very challenging problem due to complex structure of brain [1]-[4].

In medical imaging technique, magnetic resonance imaging (MRI) images are used to provide detailed information about the internal tissue of respective image. In the diagnosis of brain tumor, determination of the exact location is an important task, using which helps to find out the shape & size of tumor. In brain tumor detection techniques, image segmentation plays a vital role there are many image segmentation methods are used to extract tumor from magnetic resonance imaging images of brain. Whereas segmentation provides the detailed information about the soft brain tissues such as gray matter (GM), white matter(WM), cerebral spinal fluid (CSF)etc. There are two types of segmentation involves a manual segmentation and automatic segmentation. Manual segmentation technique depends on experience or expert knowledge of human and time consuming technique but reduces the computational efficiency. Whereas automatic segmentation deals with histogram. Which is only based on the intensity of pixels. In this survey, various existing image segmentation techniques are introduced for detection and segmentation of brain tumor from MRI images i.e. thresholding-based, edge-based, region-based and clustering-based segmentation have been explained. [5]-[9]

The survey on automated brain tumor detection and segmentation from MRI has following objectives

- To use fully automated tumor segmentation approach for patches extraction.
- To provide software (computer code) to detect the size and location of tumor in brain with quality approach.
- It suggests good classification of brain tumor.
- It provides early and precise detection of brain tumor.

The paper is organized as follows. The section II introduces the brain tumor segmentation technique. The section III gives clustering algorithm. The section IV describes briefly proposed method. The section V describes the conclusion. And the section VI gives future scope.

2. TUMOR SEGMENTATION ECHNIQUES

MRI is mainly used for brain tumor diagnosis and treatment in the clinic. MRI offers various beneficial features like multiplanar capabilities, potential of tissue characterization and no bone and teeth artefacts.

The different techniques of brain tumor segmentation using MRI images are given in Fig.1.

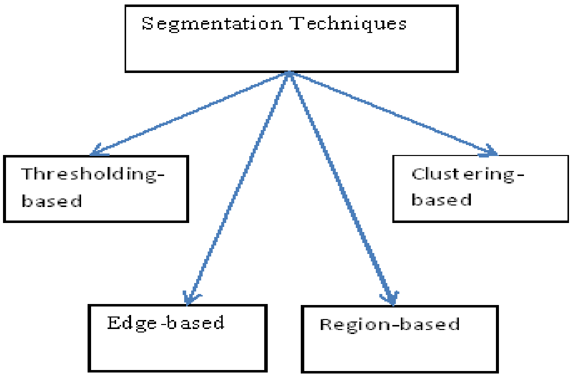


Fig. 1. Classification of segmentation techniques on the basis of pixel intensity.

2.1 Thresholding

Thresholding is one of the frequently used methods for image segmentation [10]. This method is suitable for images with different intensities of pixels. Using this method, the image is partitioned directly into different regions based on these intensity values of the pixels. There are three types of thresholding algorithms. • Global thresholding • Local thresholding • Adaptive thresholding In adaptive thresholding, different threshold values for different local areas are used.

A. Global thresholding

Global thresholding method chooses only one threshold value T for the entire image. The following condition is imposed.

$$g(x,y) = \begin{cases} 1 \; if \; f(x,y) \geq T \\ 0 \;\; otherwise \end{cases}$$

(1)

Where T is the threshold parameter,

g(x,y) is the global threshold in 2D image,

f(x,y) is the original input image.

Global thresholding is used for bimodal images. It is simpler and faster in computational time only if the image has uniform intensity distribution and high contrast between foreground and background.

Traditional Thresholding method depends on a discriminant analysis which divides the image into two classes based on the intensity of gray levels in image [11]. The main advantage of Traditional/Otsu's method is simple and effective to implement but it can segment only larger objects from background and fails, if the image has variable contrast distribution.

B. Local thresholding

Threshold values are chosen locally by dividing an image into sub-images and threshold value for each part is calculated. A local thresholding technique takes more computational time than the global thresholding. Its result is satisfactory in an image with background variations. It can extract only smaller regions.

Histogram thresholding : This segmentation is based upon the thresholding of histogram features and gray-level thresholding in an image. It gives better results but the computational time is more for histogram thresholding.

The limitations of thresholding as follows.

- The main limitation of thresholding techniques is that in its simplest form, only two classes are generated and it cannot be applied to multi- channel images.

- A Thresholding technique does not take into account the spatial characteristics of an image. Therefore a Thresholding technique is sensitive to noise and intensity inhomogeneities.

C. Adaptive Thresholding

In many cases background gray level is not constant, and object contrast varies within an image. In such cases a threshold that works well in one area might not work well in other areas of the image in these cases, it is convenient to use a threshold gray level that is a slowly varying function of position in the image. In adaptive thresholding, different threshold values for different local areas are used.

2.2 Edge Based Segmentation

Edge based segmentation methods divide an image based on abrupt changes in the intensity of pixels near the edges [12]. The result is a binary image with edges of the objects being detected. Based on the theory, there are two basic edge based segmentation methods viz. gray histogram and gradient based methods.

A. Gray Histogram Technique

The result of the technique of gray histogram mainly depends upon selection of threshold (T). The image is converted into gray scale image and after that gray-level thresholding is applied on the histogram of that image.

B. Gradient Based Method

In the gradient based method, the difference between intensity values of neighbouring pixels is taken into account [13]. So, when there is an abrupt change in the intensity in a region of an image and there is very less image noise then gradient based methods works well. These methods involve applying gradient operators on the image. The basic edge detection operators used in this method are Roberts operator, Prewitt operator, Sobel operator, Canny operator, Laplace operator, Laplacian of Gaussian (LOG) operator, Frei-chen edge detector Difference of Gaussians filter etc. out of which Sobel and Canny operators produce better results Edge detection methods exhibit a balance between accuracy and noise immunity. If the level of detecting accurate edges is too high, then noise may produce fake edges and if the degree of noise immunity is too high, then some parts of the image containing important information might go undetected. These operators work well for images with sharps edges and low amounts of noise. The detected boundaries using these operators may not necessarily form asset of closed connected curves, so some edge linking may be required.

2.3 Region Based Segmentation

Region based methods divide an image into regions that are similar on the basis of a set of a particular criterion [14]. The existing region segmentation techniques mainly consist of the following methods:

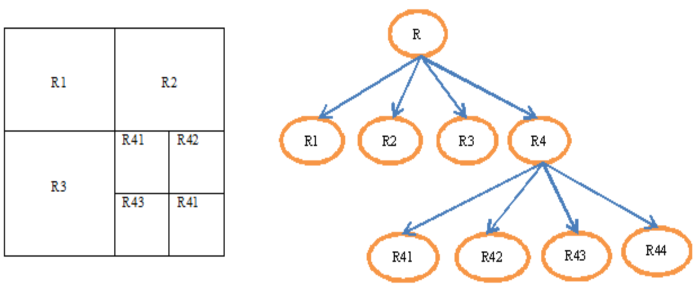
A. Region growing

Region growing method is one of the most frequently used segmentation methods. This method requires initiates with a seed pixel and grows the region by incorporating the neighbouring pixels based on some threshold if no edges are detected. Region growing process is iterated for each boundary pixel in the region. If adjacent regions are found, a region-merging algorithm is used in which weak edges are dissolved and strong edges are left intact. Region growing algorithms vary depending on the criteria used to decide whether a pixel should be included in the region or not, connectivity type used to determined neighbours, and the strategy used to visit neighbouring pixels.

B. Region splitting and merging

The region splitting is a top-down approach. The image is split into a number of different regions depending on some criterion and after the splitting, it is merged. The whole image is initially considered as a single region and then the internal similarity of the image is calculated using standard deviation. If the variation is very large, then the image is split into regions using some threshold value. This process is repeated until no more further splitting of the region is possible. A merging phase after the splitting phase is always desirable ,which is done by split-and-merge algorithm. Quad tree is a common data structure used for splitting.as shown in Fig.2.

Where R represent the entire image.



(a) (b)

Fig.2. (a) Splitting of an image (b) Representation by a quad tree.

C. Watershed segmentation

Watershed segmentation algorithm can be used if the image has uniform contrast distribution and the intensity of the foreground and background is distinguishable. Watershed algorithm is also used to find the weak edges in the images.

3. CLUSTERING

Clustering is the technique which is most frequently used in the MRI Segmentation, where it divides pixels into classes, without having prior information or training [15]. It classifies the pixels having largest probability into the same class. In the clustering technique, the training is done by utilizing the pixel characteristics with properties of each class of classified pixels. Clustering methods can be divided in to two categories are Hierarchical and Partitional.

A. K-means

Clustering is a method to divide a set of data into a specific number of groups. It's one of the popular method is k-means clustering. In k-means clustering, it partitions a collection of data into a k number group of data [16]. It classifies a given set of data into k number of disjoint cluster. K-means algorithm consists of two separate phases. In the first phase it calculates the k centroid and in the second phase it takes each point to the cluster which has nearest centroid from the respective data point. There are different methods to define the distance of the nearest centroid and one of the most used methods is Euclidean distance. Once the grouping is done it recalculate the new centroid of each cluster and based on that centroid, a new Euclidean distance is calculated between each center and each data point and assigns the points in the cluster which have minimum Euclidean distance. Each cluster in the partition is defined by its member objects and by its centroid. The centroid for each cluster is the point to which the sum of distances from all the objects in that cluster is minimized. K-means is an iterative algorithm in which it minimizes the sum of distances from each object to its cluster centroid, overall clusters.

Let us consider an image with resolution of x × y and the image has to be cluster into k number of cluster. Let p(x, y) be an input pixels to be cluster and ck be the cluster centers. The algorithm for k-means [17] clustering is as follow:

1. Initialize number of cluster k and Centre.

2. For each pixel of an image,

calculate the Euclidean distance d, between the center and each pixel of an image using the relation given below

$$d = ||\ p(x,y) - ck\ || \tag{3}$$

3. Assign all the pixels to the nearest center based on distance

4. After all pixels have been assigned, recalculate new position of the Centre using the relation given below.

$$ck = \frac{1}{k} \sum_{y \in ck} \sum_{y \in ck} p(x, y) \qquad (4)$$

5. Repeat the process until it satisfies the tolerance or error value.

6. Reshape the cluster pixels into image.

Although *k*-means has the great advantage of being easy to implement, it has some drawbacks. The quality of the final clustering results is depends on the arbitrary selection of initial centroid. So if the initial centroid is randomly Chosen, it will get different result for different initial centers. So the initial center will be carefully chosen so that we get our desire segmentation. And also computational complexity is another term which we need to consider while designing the *K*-means clustering. It relies on the number of data elements, number of clusters and number of iteration. [18].

K-means clustering algorithm is the simplest of the existing clustering algorithms that can do clustering of pixels into numerous regions based on pixel properties. This method is called hard clustering as the clusters must be distant enough from each other and every pixel is assigned the membership function in such a way that it belongs to one particular region only. 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.

Fuzzy C-means (FCM)

Fuzzy clustering is a powerful unsupervised method for the analysis of data and construction of models. In many situations, fuzzy clustering is more natural than hard clustering. Objects on the boundaries between several classes are not forced to fully belong to one of the classes, but rather are assigned membership degrees between 0 and 1 indicating their partial membership. Fuzzy c-means algorithm is most widely used. Fuzzy c-means clustering was first reported in the literature for a special case (*m*=2) by Joe Dunn in 1974. The general case (for any *m* greater than 1) was developed by Jim Bezdek in his PhD thesis at Cornell University in 1973. It can be improved by Bezdek in 1981. The FCM employs fuzzy partitioning such that a data point can belong to all groups with different membership grades between 0 and 1.

The algorithm is describe as under:

1. Initialize U= [u_{ij}] matrix, $U^{(0)}$
(5)

2. at k-step: calculate the centers vectors $C^{(k)}$= [C_j] with

$$U^{(k)} \quad Ci = \frac{\sum_{j=1}^{n} U_{ij}^{m} xj}{\sum_{j=1}^{n} U_{ij}^{m}} \qquad (6)$$

3. Update $U^{(k)}, U^{(k=1)}$

4. $d_{ij} = \sqrt{\sum_{i=1}^{n} (x_i - c_i)}$

(7)

$$U_{ij} = \frac{1}{\sum_{i=1}^{n} (\frac{d_{ij}}{d_{kj}})^{2/(m-1)}} \qquad (8)$$

5. $if \|U(k+1) - U(k)\| < \in \; then$ STOP; otherwise

Return to step 2.

Where- m is any real number greater than 1,

U_{ij} Is the degree of membership of x_i in the cluster j,

x_i Is the ith of d-dimensional measured data,

c_j Is the d-dimension center of the cluster,

The algorithm works by assigning membership to each data point corresponding to each cluster center on the basis of distance between the cluster center and the data point. More the data is near to the cluster center more is its membership towards the particular cluster center. Clearly, summation of membership of each data point should be equal to one. After each iteration membership and cluster centers are updated according to the equation (5)-(8).

The suggested algorithms has advantages

1. Unsupervised

2. Converges

But it has few limitations on:

- Long computational time.
- Sensitivity to the initial guess (speed, local minima).
- Sensitivity to noise and One expects low (or even no) membership degree for outliers (noisy points). [19].

FCM clustering is an unsupervised method for the analysis of given input image [20]. The fcm clustering algorithm assigns membership functions to every pixel in an image corresponding to each cluster center based on the distance of the cluster center from that particular pixel. The pixels near to the cluster center have higher membership function towards the particular cluster center.

Hierarchical clustering

Hierarchical clustering method works by grouping data objects in an image into a tree of clusters. Hierarchical clustering does not need to specify the number of clusters in advance. The two main categories of algorithms used in this clustering are agglomerative and divisive. Agglomerative algorithms seek to merge clusters to be larger and larger by starting with N single point clusters. Divisive clustering begins with the entire dataset in the same cluster, followed by iterative splitting of the dataset until the single-point clusters are attained on leaf nodes. It follows a reverse clustering strategy against agglomerative clustering. Some of the hierarchical algorithms are COBWEB, CURE, and CHAMELEON.

Hierarchical clustering algorithms describes as under-

Algorithmic steps for Agglomerative Hierarchical clustering

Let $X = \{x_1, x_2, x_3, ..., x_n\}$ be the set of data points.

1. Begin with the disjoint clustering having level L(0) = 0 and sequence number m = 0.

2. Find the least distance pair of clusters in the current clustering, say pair (r), (s), according to d[(r),(s)] = min d[(i),(j)] where the minimum is over all pairs of clusters in the current clustering.

3. Increment the sequence number: m = m +1.Merge clusters (r) and (s) into a single cluster to form the next clustering m. Set the level of this clustering to L(m) = d[(r),(s)].

4. Update the distance matrix, D, by deleting the rows and columns corresponding to clusters (r) and (s) and adding a row and column corresponding to the newly formed cluster. The distance between the new cluster, denoted (r,s) and old cluster(k) is defined in this way: d[(k), (r,s)] = min (d[(k),(r)], d[(k),(s)]).

5. If all the data points are in one cluster then stop, else repeat from step 2.

6. Divisive Hierarchical clustering - It is just the reverse of Agglomerative Hierarchical approach.

4. PROPOSED METHOD

The propose method for segmentation of brain tumors in MRI images based on convolutional neural networks. This method consists of mainly, pre- processing stage, classification stage by using CNN and post processing stage. Bias field correction, patch and intensity normalization are done in the pre-processing stage. In our proposed method the distortion caused by multi-site multi-scanner acquisition of MRI images is removed by intensity normalization method proposed by Nyul et al. intensity normalization is help to improve the effectiveness of the classification. For classification CNN found to be effective due to the use of deal with variability in brain tumor.

The advantages of this method are as follows

- It takes only less computational time.
- This method has higher potential in tumor detection and classification.
- It improves the achieved segmentation results.
- It not only shows the detailed and complete aspects of brain tumors, but also improves clinical doctors to study the mechanism of brain tumors at the aim of better treatment.

The Block diagram of propose automatic image segmentation method as shown in Fig.3

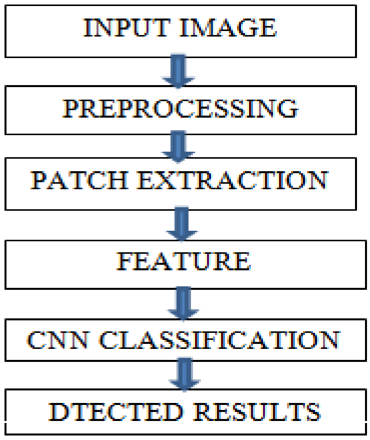


Fig 3. Block diagram of brain tumor detection and classification system

5. CONCLUSION

In this paper, some existing brain tumor detection and segmentation techniques for brain MRI images have been explained. The survey suggests intensity-based thresholding methods provide good results but fail for the images with large intensity differences. The region-based segmentation is good for high contrast images but for low contrast images, it does not provide efficient results. Edge-based segmentation provides better results but fail for noisy images as it produces false edges for them. Clustering-based segmentation is very simple, fast and provides good results but for noisy images, it produces inaccurate results. The present survey and review of the current technologies suggests Brain tumor segmentation by using CNN are provide less computational time, higher potential in tumor detection and classification. It improves the achieved segmentation results.

6. FUTURESCOPE

From the literature survey, it has been found that there is no universal system that can detect the tumor accurately regardless of its location, shape and intensity. Therefore, this topic further can further be explored, so that a better tumor detection system can be built which can help the doctors in evaluating MRI scans as the automated system will take lesser time than manual analysis and will provide more accurate results which will eventually be helpful in the treatment of patients suffering from brain tumor.

All above explain methods shows good results on the basis of performance parameters. However, it does not classify the brain tumor on the basis of its type. In future, dataset of brain MRI images with different stages of tumor can be collected and based on which a good classification system can be designed. So, in future, data collection and classification are the significant steps which need to be carried out so that a fully automated brain tumor diagnosis system can be designed.

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