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Analytical Review on Segmentation based Detection of Brain Tumor

Madhvi Arya[1], Reecha Sharma[2]
[1,2]*M. Tech Scholar, Department of Electronics Communication & Engineering, University College of Engineering, Punjabi University, India*

Abstract: *The goal of this research paper is to study various previous techniques of segmentation used for brain tumor detection. The paper incorporates discussion for image post processing techniques. Finally the region of interest specified by tumor area is defined as confirmation step. Brain tumor is one of the most common kinds of cancer, as well as the leading cause of mortality among human. Rates of brain tumor around the World vary a great deal. Early detection of brain tumor is really important in order to improve recovery rates to a great extent. MRI is currently the most effective imaging modality for the detection of brain tumor and the diagnosis of the anomalies which can identify cancerous cells. Retrospective studies show that, in current brain tumor screenings approximately 15 to 30 percent of brain tumor cases are missed by radiologists. With the advances in digital image processing techniques, it is envisaged that radiologists will have opportunities to decrease this margin of error and hence, improve their diagnosis. Various image processing techniques are available to enhance the images for the computerized detection of brain tumor. Digital images have become the most effective techniques for the detection of brain tumor.*

Keywords: *MRI of Brain, Tumor Segmentation, Tumor Detection, Pre-processing, Filtering.*

I. Introduction

Brain Tumors can Indirectly cause inflammation, compress various parts of the brain or can exert internal pressure as they grow due to which cells of brain get destroy or can even get damaged[7]. For early detection Brain tumor segmentation is a process of extracting information from complex MRI of brain images. It helps in finding the location and size of tumor.

For segmentation of tumor cells several methods have been proposed which differentiate the tumor region from normal region on the basis of intensity because brain tumor cells have very high density and hence very high intensity due to high protein containing fluid[5].

Some of quite effective techniques used for segmenting tumor cells are Threshold Based Segmentation, Support Vector Machine (SVM), Fuzzy c-means algorithms; Morphology-based, Artificial neural networks (ANNs), Watershed Methods, Edge-based segmentation methods, Region Based Processing. These techniques are discussed in the next section.

The image is passed through number of processes described below:

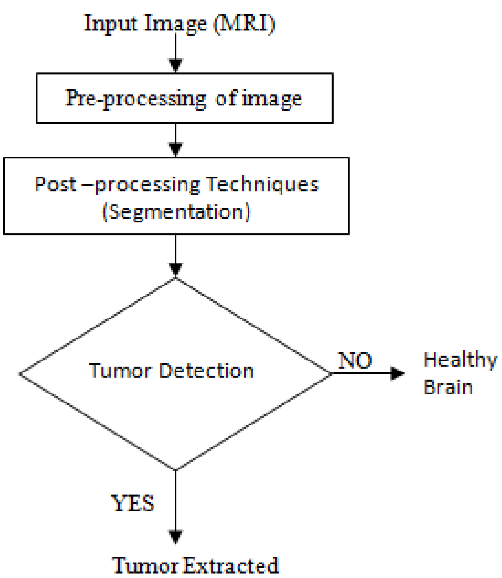

Fig.1: - Steps for brain tumor extraction

II. Literature Review

Kusum Rani et al. (2013) [15] introduces an efficient technique for detection of brain tumor from MRI images. DMWT algorithm fuses two medical images having different modality and accordingly different qualitative metrics like standard deviation, entropy are calculated. Finally multi-wavelet transformation will fuse the images to produce the output image. This method provides good results about the edges of fused image. Sudipta Roy et al. [13] discussed different techniques for brain tumor segmentation and detection, describing advantages and disadvantages of each technique. B.Sathees et al. (2015) [4] compared three different intensity based feature extraction method and concluded that GLCM (Gray Level Co-Occurance) method provides better results when compared with Intensity Histogram Features method, Feature Extraction Methods, Intensity based features method. But still the problem is about inbound masses which are still unable to expose which results in poor decision making. Ehab F. Badran et al. (2010) [5] introduced neural network algorithm for extracting tumor region in human brain. It consists of these steps: pre-processing, image segmentation, feature extraction, neural network algorithm, region of interest and final decision. K. S. Angel Viji et al. (2013) [2] proposed texture based region growing segmentation. The advantage of texture based approach over region or intensity based approach is the specificity and sensitivity for tumor detection and discrimination, classification of different intensity pattern. Swe Zin Oo et al. (2014) [1] proposed a paper which includes morphological operation, image filtering, segmentation, skull stripping, calculation of the tumor area and determination of the tumor location. The proposed method remove the skull tissues accurately. To extract the exact result volume of the tumor is calculated by the use of Frustum model. Mohammed sabbih hamoud al-tamimi et al. (2014) [8] reviewed the different techniques Threshold and outlier detection and Gaussian models, OTSUs Threshold, Seed-Based Region Growing Adaptive Network- Based Fuzzy , Fractal wavelet texture features Inference System, ANN using canny edge detection adaptive Thresholding, Fuzzy models Image Fusion, Cluster index K-means used for tumor detection and extraction of required region.

III. Techniques

3.1 Threshold Based Segmentation

Threshold techniques differentiate the foreground pixels from the background pixels on the basis of proper selection of threshold value. There exist a number of threshold techniques for segmentation and some of them are Otsu Binarization, P-tile method, Mean Technique, Histogram Dependent Technique, EMT Technique, Visual Technique.

Fig.2: a) original image, **b)** threshold value=0.35, **c)** threshold value=0.75

3.2 Support Vector Machine (SVM)

The SVM approach provides very good performance, especially when the dimensional space is very high.it is mainly preferred for dataset having exactly two classes and identically distributed. The best hyperplane which is find by SVM will separates all data points of one class from that of the other class. SVM is used for object detection & recognition, speech recognition, biometrics, content-based image retrieval, text recognition, etc.

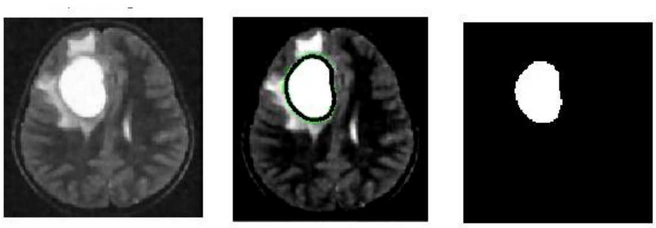

Fig.3: a) original image**, b)** SVM classifier **c)** segmented image

Kernal functions operate with SVM classifier to improve the accuracy of results. Some of them are [18]:

1. Linear kernel:

It is one of the simplest kernel.

$$K(x_{i,} x_j) = x_i^T x_j \qquad (1)$$

2. Fisher kernel: It is defined as

$$K(x_i, x_j) = U_{xi}^T I^{-1} U_{xj} \qquad (2)$$

3. ANOVA kernel: It is defined as

$$K(x_i, x_j) = \sum_k \exp(-\sigma(x_i^k - x_j^k)^2)^d \qquad (3)$$

Where $1<k<n$

4. Polynomial kernel: It is defined as

$$K(x_i, x_j) = (\alpha x_i^T x_j + c)^d \qquad (4)$$

5. Multilayer Perceptron kernel:

This is also called Sigmoid kernel. It is defined as

$$K(x_i, x_j) = \tanh(\gamma x_i^T x_j + \gamma) \qquad (5)$$

SVM classifiers also make use of morphological functions in order to reduce error percentage while classification of brain as tumor and non-tumor. Though it provides good accuracy, but for large data sets required training time is very high. It does not work well, if data of targeted class is overlapping.

3.3 Fuzzy c-means Algorithm

FCM analysed given set of data and partition it into several groups. The partition should be such that there is a good degree of association of data between the same group and no degree of association between the data which belongs to different groups. The data can belong to more than one group, and to define degree to which data belong to particular group is introduced by membership function. The dataset which is located near to the origin of a cluster, for them degree of association or membership will be high and dataset which is located too away from the origin of a cluster, for them degree of association or membership will be low. The FCM algorithm minimizes the following equation.

$$J_m = \sum_{j=1}^{c} \sum_{i=1}^{n} \mu_{ij}^m d_{ij} \qquad (6)$$

where

$$d_{ij} = \left\| x_i - y_j \right\|$$

The traditional FCM clustering algorithm is very fast and simple, but its accuracy is very less. This method produces very unsatisfactory results for the images with noise. Another drawback of the FCM algorithm is the difficulty in selecting proper parameters.

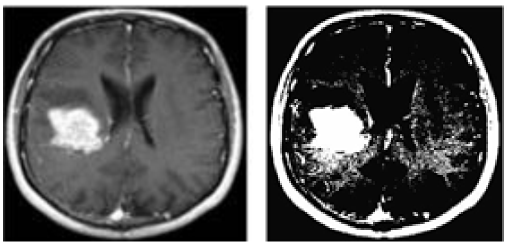

Fig. 4: a) Original image b) segmented image having noise

3.4 Morphological Processing

One of the important applications of morphology is to describe image components that are useful in the representation of shape, mainly while dealing with binary images.

Morphological algorithms are also useful for extraction of connected components, the convex hull, extraction of boundaries, and the skeleton of a region. Methods like region filling, pruning, filling, thinning, and thickening are used as pre or post-processing steps. The combination of erosion and dilation provide very good results. In a morphological opening, erosion removes small objects and the dilation restores the shape of objects that remain.

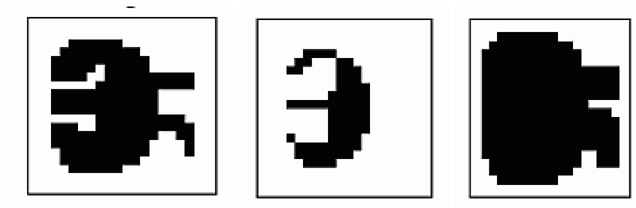

Fig.5: a) original image b) Erosion c) Dilation

Structuring element is denoted by s which is positioned at origin (x, y) and image by f. The new pixel value [16] is given by:

g (x, y)= 1 if s fits f (7)
0 otherwise

For dilation new pixel value [16] is given by:

g (x, y)= 1 if s hits f (8)
0 otherwise

3.5 Artificial Neural Network

Artificial Neural Networks are based on the neural structure of the brain that have the ability to learn from a set of data and then weight matrices are constructed to represent the learning patterns. Neural Networks have remarkable ability to detect patterns and extract trends from complex data [7]. ANN have tendency of adaptive learning, self-organisation, real time operation. It consists of two or more than two layers; in which each layer consist of number of neurons. The nodes receive inputs, and process them to obtain an output. In ANNs the weights of the connections are modified according to some 'learning rules' and the input that it is presented to them. The outputs of layers are passed through activation functions according to which these outputs are scaled into proper ranges. Three activation functions are

a) The Sigmoid Function

$$f(x) = \frac{1}{1+e^{-x}} \quad (9)$$

b) Hyperbolic Tangent Activation Function

$$f(x) = \frac{e^{2x}-1}{e^{2x}+1} \quad (10)$$

c) A Linear Function

$$f(x) = x \quad (11)$$

One of the disadvantages of using neural networks for tumor segmentation is patient-specific learning which a very time consuming process. Another disadvantage of neural network is that they do not give representation in the form of rules. The model is hidden in the network structure between the nodes with optimized weights.

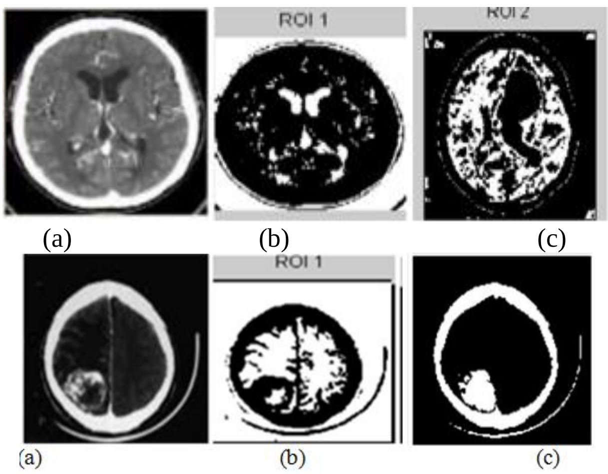

Fig.6: Output presented by A. Padma for different ROI, ANI

3.6 Region Based Segmentation

In region based processing firstly seed points are being selected by user manually. In next step, on the basis of homogeneity criteria, neighbouring pixels are added to the region. The process keeps on repeating itself until all pixels belong to some region [2]. This process groups the pixels having same values and put dissimilar pixels in different group.

3.7 Edge Based Segmentation

In edge-based segmentation, pixels are defined as edge or non-edge depending on the output of filter to which image is applied, and pixels which are not differentiated by an edge are allocated to other category. The edge pixels which appear as connected chains results into division of image into regions. All non-edge pixels which are not differentiated by an edge are allocated to a single category. An image f having one edge can be represented by equation:

$$f(x) = \frac{I_r - I_l}{2}\left(\mathrm{erf}\left(\frac{x}{\sqrt{2}\sigma}\right)+1\right)+I_l. \qquad (12)$$

I_l =Intensity level on the left side of edge.
I_r = Intensity level on the right side of edge.
σ = blur scale of edge

Prewitt edge-finding filter:-

The Prewitt edge detector estimates the orientation and magnitude of an edge in a very appropriate way.

Sobel edge operator:-

In input grayscale image, absolute gradient magnitude at each point is found by this operator. This operator focused on regions of high spatial frequency that correspond to edges and performs a 2-D spatial gradient measurement on an image [17]. The components of gradient vector measures the change in pixels value with distance in the x and y direction. The components are:

$$\frac{\partial f(x,y)}{\partial x} = \Delta x = \frac{f(x \quad - f(x,y)}{dx} \qquad (13)$$

$$\frac{\partial f(x,y)}{\partial x} = \Delta y = \frac{f(x \quad) - f(x,y)}{dx} \qquad (14)$$

dx = distance measured along x direction
dy = distance measured along y direction

Kirsch edge operator:-

In kirsch edge detector, eight filters are applied to the image which detects edges with the maximum being retained for the final image. The eight filters are basically a rotation of compass convolution filter. On comparison of Kirsch edge operator with Sobel and Prewitt operator, in sobel and prewitt only two directions convolution kernels (3x3) are considered i.e. horizontal and vertical.

Canny edge detector:-

The canny edge detector firstly eliminates the noise from image and then highlights regions with high spatial derivatives after finding the image gradient.

$$g(m,n)=G_\sigma(m,n) * f(m,n) \qquad (15)$$

$$G_\sigma = \frac{1}{\sqrt{2\Pi\sigma^2}} exp\left(\frac{-m^2-n^2}{2\sigma^2}\right) \qquad (16)$$

The algorithm keeps track of these regions and suppresses any pixel that is at the Non-maximum suppression. In order to reduce gradient array further hysteresis is used. Hysteresis keeps the track of the remaining pixels that have not been suppressed. In Hysteresis two thresholds are used and if the magnitude is less than the first threshold, it is set to zero and is defined as no edge. If the magnitude is more than high threshold, it is defined as edge. If the pixel value is between two thresholds, then zero is assigned to it but before this it is checked if there is a path exist from pixel to a pixel with a gradient above T2.

$$M(m,n) = \sqrt{(g_m^2(m,n) + g_n^2(m,n))} \qquad (17)$$

$$\theta(m,n)=\tan^{-1}[g_n(m,n)/g_m(m,n)] \quad (18)$$

$$M_T(m,n)= \begin{cases} M(m,n) & \text{if } M(m,n) > T \\ 0 & \text{otherwise} \end{cases} \quad (19)$$

3.8 Watershed Based Segmentation

Watershed segmentation is a mathematical tool based on morphology. It used to separate touching objects on the basis of pixels grouping in an image. This transformation treats an image as surface and finds watershed ridge lines and catchment basins in image where light pixels are considered as high and dark pixels are considered as low [1]. The meaning of watershed is the ridge that divides areas drained by different river systems. If image is viewed as geological landscape, the watershed lines determine boundaries which separate image regions. The watershed transform computes catchment basins and ridgelines (also known as watershed lines), where catchment basins corresponding to image regions and ridgelines relating to region boundaries Steps for watershed segmentation are:-

Compute a segmentation function, foreground markers, background markers, and transformation for modified function. This method provides very good accuracy as compared to other methods for the detection of brain tumor.

The main disadvantage of watershed segmentation is it is very much sensitive to intensity variations, due to which over segmentation which is spatially homogeneous occurs, this happens mainly when the image is segmented into large number of regions which is not required.

Table 3.1 Comparison of Image Segmentation Methods

Parameter	**Speed**	**Noise Resistance**	**Accuracy**	**Computation Complexity**
Threshold Based Segmentation	Fast	Less	Moderate	Less
Support Vector Machine	Slow	Moderate	Good	More
Fuzzy c-means Algorithm	Moderate	Moderate	Moderate	Moderate
Morphological Processing [16]	Moderate	Moderate	Fine	Less
Artificial Neural Network [7]	Moderate	Less	Good	Moderate
Region Based Segmentation [2]	Slow	Less	Fine	Rapid
Edge Based Segmentation	Moderate	Less	Good	More
Watershed Based Segmentation[1]	Fast	Moderate	Fine	Less

IV. Summary and Conclusions

The existing techniques for MRI of brain image brain tumor segmentation and detection have been discussed. The advantage of thresholding method is that, it firstly obtains a binary image which reduces the complexity of the data and the process of recognition and classification become easy. The main disadvantage is that, thresholding technique is implemented on image having only two values either black or white. it cannot be applied to multichannel images. Fuzzy C –means method is sensitive to noise, computationally expensive and determination of fuzzy membership is not very easy. The watershed method has the drawback that it is very much sensitive to local minima, because at each minima, a watershed is created. If there is an image with noise, this will affect the segmentation. The main disadvantage of region growing method is that for each region user have to select seed point which is very time consuming process. The advantage of edge based method is that it firstly reduces the amount of data which is to be processed, then analysed the images drastically, and object boundaries are also preserved using structural information. But high quality cannot be achieved for MRI images with only edge detector algorithms which have inherent speckle noise and texture characteristics. Due to this edge based method is not used alone.

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