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Brain Tumor Segmentation: The Survey on Brain Tumor Segmentation Techniques

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Abstract: The brain tumor detection using segmentation method is the differentiation of different kinds of tumor areas using various types of techniques. There are numerous techniques which have been proposed for the segmentation of brain tumor. But it's difficult to detect the brain tumor using Magnetic Resonance (MR) images. In segmentation process the extraction of different tumor tissues such as active, tumor, necrosis and edema from the normal brain tissues such as white matter (WM), Grey Matter (GM) and cerebrospinal fluid (CSF). The segmentation of brain tumor comprises of many stages. In this paper, our main goal is to present the review of different brain tumor segmentation methods using various techniques and propose the comparison between each of them along with their respective pros and cons.

Index terms- Brain Tumor, Classification, Disease Identification, Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Segmentation, Tumor Detection.

I. INTRODUCTION

In medical practices, the early detection of brain tumors accurately plays a very vital role. A brain tumor or intracranial neoplasm occurs when abnormal cells form within the brain. There are mainly two types of tumors: malignant or cancerous tumors and benign tumors. In literature, many techniques has been proposed by different researchers for the purpose of segmentation of the brain tumors accurately. Some discoveries are X-rays, ultrasound, radioactivity, magnetic resonance imaging (MRI) or computed tomography. The development of various tools that can generate medical images have facilitated the development of some of the most efficient exploration tools in medicine. Such tools are capable of exploring the structure, function and the diseases which is affecting the human brain, it also deals with the cancer-affected region in the brain. The main goal for the medical researchers since from last few decades is to cure brain tumors, however the building of new methods for treatments consumes more time as well as money.

Medical science still needs to find all the major causes for the emergence of the various types of cancers and then develop the methods to cure them before brain tumor development starts.

Magnetic resonance imaging (MRI) is high-quality medical imaging technique, particularly for brain imaging. For the early detection of brain tumors there are many imaging methods for diagnostics purpose. These imaging techniques are Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI) and Computed Tomography (CT). Among the various imaging techniques, MRI is most efficient for the brain tumor detection. This is because of its pros such as high contrast of soft tissues, high spatial resolution, it does not produce any harmful radiation, Reliable and fast detection and classify the brain cancer. Although MRI provides information about the size of the tumor, its con is that it is unable to classify the tumor types. The invasive techniques such as biopsy and spinal applications, which are painful and also are time consuming methods.

In this paper, we are aiming to take review of different methods of brain tumor image segmentation and present the different MRI image segmentation methods.

II. RELATED WORK

In recent years, various methods have been proposed for image segmentation, classification and detection techniques for brain tumors. The performance [1] of HMRF-EM segmentation with reference to a number of examples. First, we show a comparison between the standard FM-EM method and our HMRF-EM method for segmenting and parameter estimating piecewise-constant images with small numbers of classes. We define the signal-to-noise ratio (SNR) as the following:

$$\mathrm{SNR} = \frac{\text{mean interclass contrast}}{\text{standard deviation of the noise}}$$

To measure the segmentation accuracy, we also define the misclassification ratio (MCR), which is

$$\text{MCR} = \frac{\text{number of mis-classified pixels}}{\text{total number of pixels}}$$

SA was measured as follows:

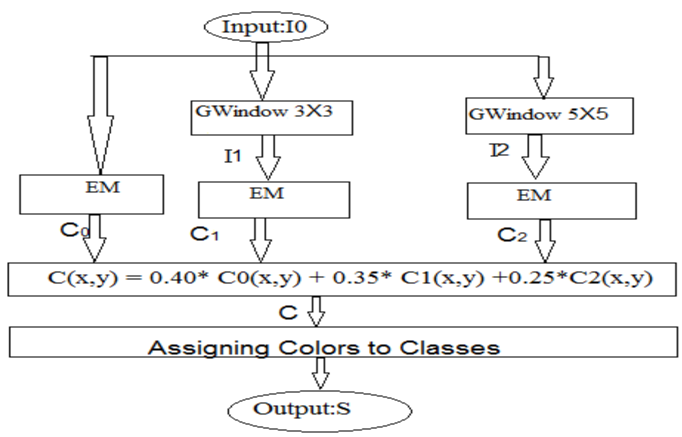
$$\text{SA} = \frac{\text{Number of corretly classified pixels}}{\text{Total number of pixels}} \times 100\%$$

The standard [2] FCM objective function for partitioning into clusters is given by,

$$\text{U}\{u_{ik} \in [0,1] \mid \textstyle\sum_{i=1}^{c} u_{ik} = 1 \; \forall\, k \; and \; 0 < \sum_{k=1}^{N} u_{ik} < N \; \forall\, i\}$$

The parameter is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. The FCM objective function is minimized when high membership values are assigned to voxels whose intensities are close to the centroid of its particular class, and low membership values are assigned when the voxel data is far from the centroid.
The GMEM algorithm [3] can be summarized in the following steps and as depicted in the flowchart shown in Figure 2.

A. Start with an image Io as input and generates its parent I1 and grandparent I2 using the Gaussian moving windows of sizes 3x3 and 5x5, respectively.
B. Apply the conventional EM algorithm for image segmentation on the images Io, the parent I1, and the grandparent I2. The outputs of this step are the classification matrices C0, C1, and C2, respectively.
C. Reclassify the original image I. using the weights specified previously to generate the final classification matrix C. That represents the classification of the image I0 after taking into account the spatial correlation between pixels.
D. Assign colors or labels to each class and generates the segmented image S.



\Figure 1: The GMEM flowchart, the input is the image to be segmented, I0 and the output is the segmented image S.

To make [4] the RBF-NN fuzzy adaptive, ϕj(xi) has been diluted (increased) or concentrated (decreased) by a fuzzy membership function, which is defined as follows:
If (ϕj(xi)) < 0.5 then,

$$y_j(x_i) = (\phi_j(x_i))^r$$

else

$$y_j(x_i) = (\phi_j(x_i))^{1/r}$$

where r (r>0) defines the degree of fuzziness imposed on the output of hidden layer neurons and its value has been selected experimentally for which minimum mean square error (MSE) is achieved in the output layer during the training period. Therefore, the output of the k^{th} output layer neuron has been defined as follows:

$$z_{ik} = \sum_{j=1}^{n} [\ y_j\ (x_i\ ) w_{kj}\ +\ b_k\ w_k\ ],$$

Where, k =1,2,...,c & i = 1, 2,…,N.

Where w_{kj} is the weight between the j[th] neuron of the hidden layer and the k[th] neuron of the output layer, b_k and w_k are unit positive bias and weight to the k[th] output neuron from the bias neuron, respectively.

2-D histogram [5] combined with multi-dimensional fuzzy partition entropy. Two groups, each including three member functions, namely Z-function, ∏-function and S-function, are used for fuzzy division of 2-D histogram to get nine fuzzy subsets. Experiments show that our method can obtain better segmentation results than Tao's method. The Multi-dimensional Fuzzy Partition Entropy, which includes Fuzzy Partition Entropy. Let (Ω,E,p) be a probability space in which Ω is the sample space. E ⊂ P(Ω) is the σ –field of Borel sets in Ω and p: E→[0,1] is a probability measure over Ω . Let $\tilde{A}$ ∈ F(Ω) be a fuzzy set in (Ω, E, p) whose membership function is μ_A , (μ_A: E →[0,1]). The probability of a fuzzy event $\tilde{A}$ is defined by $p(\tilde{A})=\int_{\Omega} \tilde{A}(\omega)dp$. Let $\tilde{A}, \tilde{B}$ be fuzzy sets in probability space (Ω ,E ,p), the conditional probability of $\tilde{A}$ given $\tilde{B}$ is:

$$p\ (\tilde{A}|\tilde{B})=p(\tilde{A}\tilde{B})/p(\tilde{B})$$

The method [6] proposed has divided into four subparts. The output obtained from one part is taken as input to the next part. This can be represented by following work flow graph:

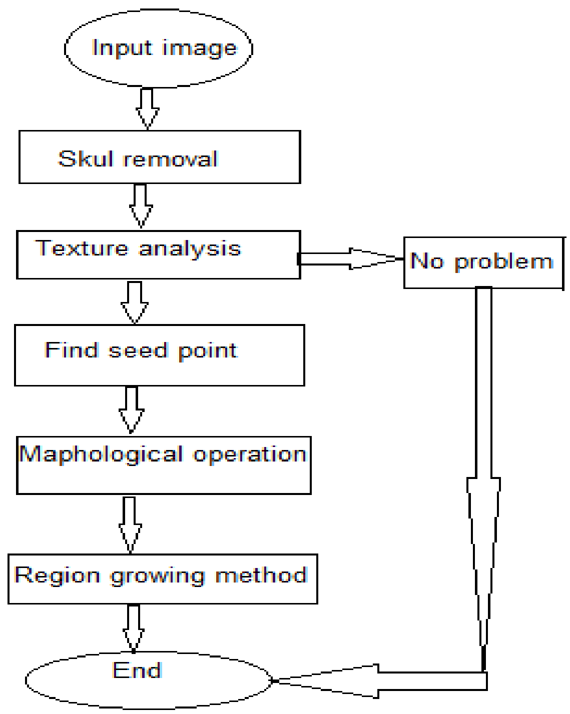


Figure 2: Work flow graph

Given a [7] set of observations (x_1, x_2, …, x_n), where each observation is a *d*-dimensional real vector, *k*-means clustering aims to partition the *n* observations into *k* (≤ *n*) sets **S** = {S_1, S_2, …, S_k} so as to minimize the within-cluster sum of squares (WCSS) (i.e. variance). Formally, the objective is to find:

$$\arg_S \min \sum_{i=1}^{k} \sum_{x \in S_i} \left|\left|x - \mu_i\right|\right|^2 = \arg_S \sum_{i=1}^{k} |S_i| \operatorname{Var} S_i$$

Where μ_i is the mean of points in S_i. This is equivalent to minimizing the pairwise squared deviations of points in the same cluster:

$$\sum_{Cluster\ c_i} \sum_{Dimension\ d} \sum_{x,y \in C_i} (x_{d-y_d})^2$$

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Because the total variance is constant, this is also equivalent to maximizing the squared deviations between points in different clusters (Between-Cluster Sum of Squares, BCSS).

They have proposed an interactive segmentation method [8] that enables users to quickly and efficiently segment tumors in MRI of brain. We proposed a new method that in addition to area of the region and edge information uses a type of prior information also its symmetry analysis which is more consistent in pathological cases. Since tumor is a rather general concept in medicine, limitations of the proposed approach might become apparent as soon as unforeseen pathologic tissue types that could not adequately be captured by the discriminative model appear in previously unseen patients. Especially secondary tumors might be composed of an enormous variety of tissue types depending on the primary tumor site. Its application to several datasets with different tumors sizes, intensities and locations shows that it can automatically detect and segment very different types of brain tumors with a good quality.

The concept [9] of quantization originates in the field of electrical engineering. The basic idea behind quantization is to describe a continuous function, or one with a large number of samples, by a few representative values. Let x denote the input signal and $\hat{x}$=Q(x) denote quantized values, where Q (.) is the quantizer mapping function. There will certainly be a distortion if we use $\hat{x}$ to represent x. In the least-square sense, the distortion can be measured by,

$$D=\int_{-\infty}^{\infty}(x-Q(x))^2 f(x)\, dx,$$

Where $f(x)$ is the probability density function of the input signal. Consider the situation with L quantizers $\hat{x} = (\hat{x}1, \hat{x}2, \dots, \hat{x}\, L)$. Let the corresponding quantization intervals be,

$$T_i = (a_{i-1}, a_i) \quad i=1,2,\ldots,L. \text{ Where } a_0=-\infty \text{ and } a_L=\infty.$$

The critical review of the discussed Brain tumor segmentation techniques in different papers are shown in table 1:

Table 1: Brain tumor segmentation techniques in different papers form [1] to [9].

Title	Author & Year	Proposed Technique	Algorithm Used	Pros	Cons
Segmentation of Brain MRI through a Hidden Markov Random Field Model and the Expectation Maximization Algorithm[1]	Yongyue Zhang (2001)	Segmentation	Expectation Maximization	This technique possesses ability to encode both spatial and statistical properties of the image	The method requires estimating threshold and does not produce accurate results most of the time.
A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data[2]	Mohamed N. Ahmed (2002)	Bias field Estimation	Modified fuzzy C-means	Faster to generate results	Technique is limited to a single Feature input.
MR-Brain Image Segmentation Using Gaussian Multi resolution Analysis and the EM Algorithm[3]	Mohamed Tolba (2003)	Gaussian Multi resolution Analysis	Expectation Maximization	Less sensitive to noise	Much of the error occurred because we used the classification of parent and grandparent images to reclassify the pixels near the edges.

Segmentation of MR Images of the Human brain using Fuzzy Adaptive Radial Basis function Neural Network[4]	J. K. Sing (2005)	Neural Network	Fuzzy adaptive radial basis function	It preserves sharpness of Image	Able to do only one task related to Fusion.
Three-level Image Segmentation Based on Maximum Fuzzy Partition Entropy of 2-D Histogram and Quantum Genetic Algorithm[5]	Hai-Yan Yu (2008)	Fuzzy partition entropy of 2D histogram and genetic algorithm	Quantum genetic algorithm (QGA)	QGA is selected for optimal combination of parameters	Practically Impossible
A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method[6]	Mukesh Kumar (2011)	Texture based Tumor detection and automatic segmentation	Seeded Region Growing	It is possible to determine wether abnormality is present in the image or not	Time consuming
Brain Tumor Identification in MRI with BPN Classifier and Orthonormal Operators[7]	Meenakshi (2012)	Brain Tumor Identification in MRI with BPN Classifier and Orthonormal Operators	k-means clustering, BPN classifier.	It combines clustering and Classification algorithm	Accuracy can be improved in less Time.
Detection and Quantification of Brain Tumor from MRI of Brain and it is Symmetric Analysis[8]	Sudipta Roy (2012)	Modular Approach To Solve MRI Segmentation	Symmetry analysis.	The proposed approach can be able to find the status of increase in the disease using quantitative analysis	Time consuming.
Brain Tumor Identification using MRI Images[9]	Vishal Shinde (2014)	Segmentation	K-means Clustering	Simplest & faster	Difficult to predict k-value.

III. ANALYSIS OF BRAIN TUMOR SEGMENTATION

The analysis states that, the above proposed technique which are forwarded are having their respective algorithms which are unique to their data, which are computed to give the results as outputs. The processing capability differ from one technique to the other. Also there are numerous advantages and disadvantages for the proposed techniques and algorithms used. Each and every technique is best to their own approach towards segmenting the images, which is depending on the data to be taken as an input. When keenly observed to the techniques based on the minor to major points, we can find in the analysis that they vary in minor from each other. Keeping this as the major point in our paper, we compared these proposed techniques along with algorithm used and came to a conclusion with a graph. Which shows not only the performance but also the advantages as well as the disadvantages with respect to all these proposed techniques with their algorithm used.

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We have made a survey from reference papers [1] to [9], hence the graph below shows the same. From the graph, we can see that it's showing the linear increase in performance for each of the brain tumor segmentation techniques from the published papers (i.e. from [1] to [9]). Hence we can conclude that the published papers are showing better performances from reference paper [1] to [9], Since the research on the "Brain tumor segmentation technique" topic from year to year is improving with respect to performance.

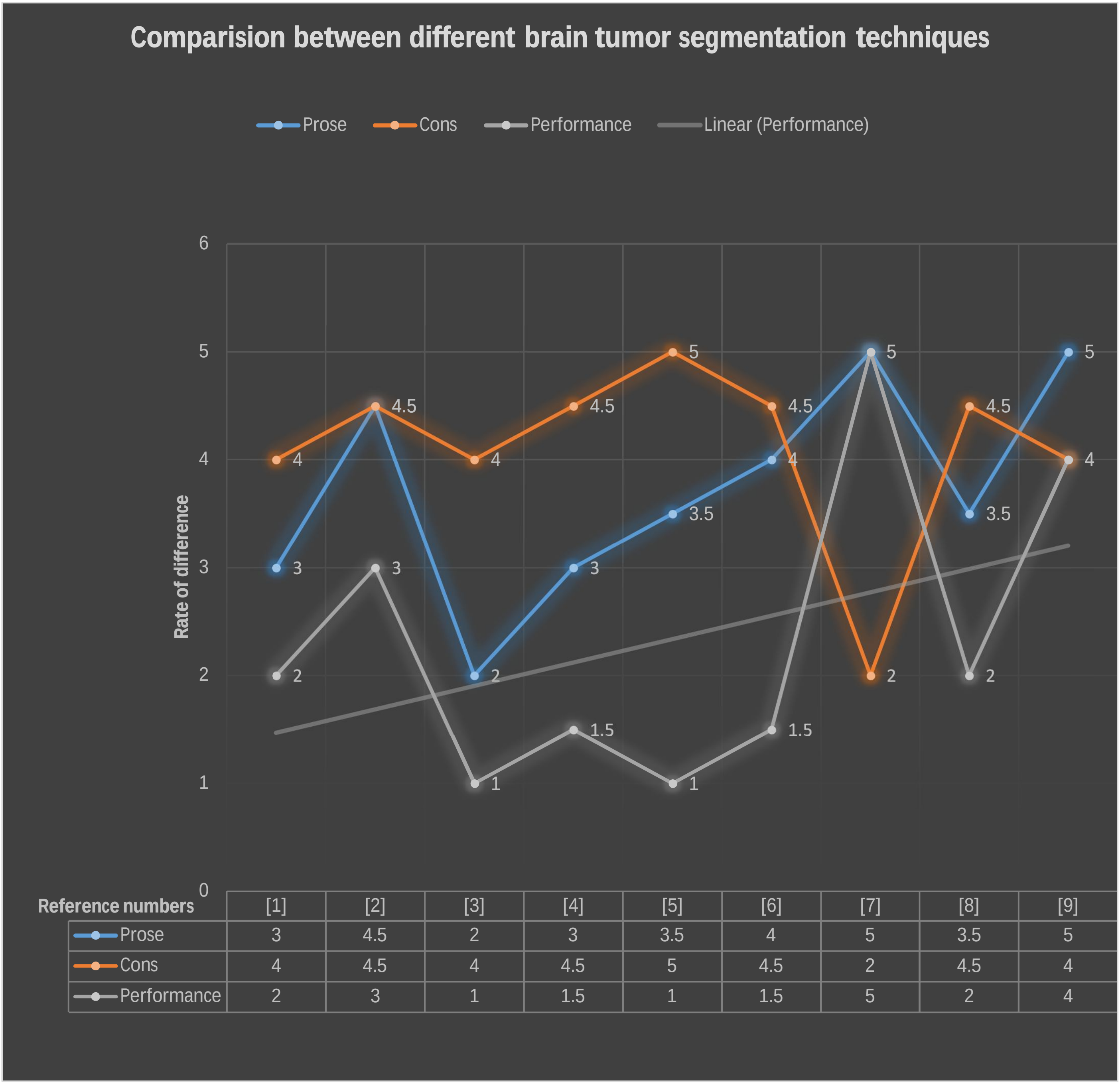

Figure 3: Comparision between different brain tumor segmentation techniques.

IV. CONCLUSION

We have presented the review of different brain image segmentation methods presented so far. The advantages and disadvantages are discussed as comparative analysis. In addition to this we have given the information about different kinds of proposed techniques and the algorithm used which are frequently used for research studies as well as performance evaluation metrics.

In spite of huge research, there is no universally accepted method for image segmentation, as of the result of image segmentation is affected by lots of factors. Thus there is no single method which can be considered efficient. All methods are equally good for that particular type of image. Due to this, image segmentation remains a challenging problem in image processing.

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