Advances in Computer Science and Information Technology (ACSIT)
Print ISSN: 2393-9907; Online ISSN: 2393-9915; Volume 2, Number 4; April-June, 2015 pp. 387-392

http://www.krishisanskriti.org/acsit.html

A Survey on MRI Brain Tumor Image Segmentation

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Abstract—*This paper presents effectiveness of biomedical imaging & medical image processing. Brain tumor segmentation consists of separating the different tumor tissues from normal brain tissues. In the brain tumor studies, the existence of abnormal tissues may be easily detectable most of the time. In the past, many researchers in the field of medical imaging and soft computing have made significant survey in the field of brain tumor segmentation MRI is a non-invasive imaging technology that produces three dimensional detailed anatomical images without the use of damaging radiation. Brain tumor or intracranial neoplasm occurs when abnormal cells form within the brain. This article presents an overview of the most relevant brain tumor segmentation methods, conducted after the acquisition of the image. Given the advantages of magnetic resonance imaging over other diagnostic imaging, this survey is focused on MRI brain tumor segmentation.*

Keywords: *Brain tumor, Image Segmentation, Magnetic Resonance Imaging, Tumor Detection*

1. INTRODUCTION

Image Segmentation is an essential step in image analysis, object representation, visualization, and other image processing task. Brain Tumor segmentation requires the more efficient knowledge of diagnosis and understanding the intensity and shape of MRI image. The major goal of medical imaging analysis is to extract the patient specific important clinical information and their diagnostic features. The effective extraction of useful information features and attributes present in different types of multidimensional images plays a vital role in image segmentation [12]. Automatic brain tumor segmentation and detection of MRI images face many Challenges. The major limitation of most of the segmentation, specifically when defining and depicting abnormal tissues types, because brain tumors to be segmented are relating to anatomical structures which are usually non-rigid and complex in shape, differ greatly in size and position, and exhibit significant variability from patient to patient [9,11].

Magnetic Image Resonance (MRI) of the brain is often used to monitor tumor response to treatment process [13]. Magnetic Resonance Imaging (MRI) is a non invasive medical test that helps physicians to diagnose disease. MRI can give result more clearly and without any harm [16].

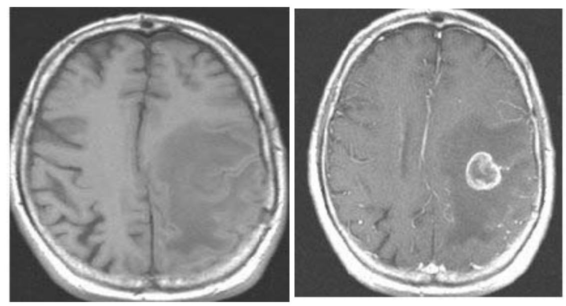

Fig. 1: T1 brain tumor image with no contrast and with contrast.

This paper presents an overview of the most relevant existing brain tumor segmentation techniques applied after the acquisition of the image.

2. SEGMENTATION METHODS

Segmentation means to partition an image into its constituent parts or objects from the background and it is a crucial analysis function for which several algorithms have been developed in the field of medical image processing [1, 5]. In automatic segmentation method, the computer determines the segmentation of tumor without any human interaction. For clinical examination the detection, localization, diagnosis, staging, and monitoring treatment responses are essential task [15].

The segmentation techniques have been divided into four major classes:

- Threshold-based techniques
- Region-based techniques
- Pixel classification techniques
- Model-based techniques

Threshold-based, region-based and pixel classification techniques are generally applied in two-dimensional image segmentation [7]. Model based techniques such as parametric and level sets deformable models, are mostly applied in volumetric (3D) image segmentation [13].

2.1 Threshold Method

Thresholding based segmentation method is a simple and powerful approach to segment brain tumor, in which the objects of the image are grouped by comparing their intensities with one or more intensity threshold values [24]. The thresholds value can be either global or local. If the histogram of an image expresses a bimodal pattern, the object can be separated from the background in the image by a single threshold called global thresholding. However, if the image contains more than two types of regions, analogical to different objects, the segmentation must be carried out using local thresholding. The image may be segmented by applying various individual thresholds or by using a multi-thresholding technique.[5].

The crucial problem with thresholding is that only the intensity is considered, not any relationships between the pixels. There is no surety that the pixels identified by the thresholding process are contiguous. Irrelevant pixels that are not part of the required region can easily be included, and sometimes isolated pixels within the near boundaries of the region are ignored. These effects get worse as the noise gets worse, simply because it is more likely that pixel intensity does not represent the normal intensity in the region. When thresholding method is used, sometimes losing too much of the region and sometimes getting too many irrelevant background pixels. Shadows of objects in the image are also a problem, not just where they fall across another object but where they mistakenly get included as part of a dark object on a light background. Another problem with global thresholding is that changes due to intensity inhomogeneity across the scene may cause some parts to be brighter (in the light) and some parts darker (in shadow) in ways that have nothing to do with the objects in the image [1].

2.1.1 Global thresholding [14] implement well if the image contains objects with homogeneous intensity or the contrast between the background and the objects is high. Thresholding creates binary images from gray-level ones by turning all pixels below some threshold to zero and all pixels about that threshold to one.

If g (x, y) is a thresholded version of f (x, y) at some global threshold T,

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

in which pixels with value of 1 correspond to the region of interest (ROI), while the pixels with value 0 correspond to the background.

It may not proceed itself to fully automatic segmentation, and may fail when two or more tissue structures have overlapping intensity levels. The accuracy of the region of interest (ROI) is also not certain because it is separated from the background based on a single threshold value which may lead to very large statistical fluctuations. When the number of regions or noise levels increasing, or when the contrast of the image is low, threshold selection will become more difficult [12].

2.1.2 Local Thresholding techniques may be usable when a thresholding value cannot be determined from a histogram for the entire image or a single threshold cannot give accurate segmentation results [13]. Local thresholding can be effectively used when the gradient effect is small with respect to the chosen sub image size. If the gradient is too large the segments found within sub images will no longer match up adequately [12].

2.2 Region Based Method

The main objective of region-based segmentation method is to partition an image into regions, analyze pixels in an image and form disjoint regions by merging neighborhood pixels with homogeneity properties based on a pre determined similarity criterion [1]. These methods can be outline in a general way as follows: Let X be an image that is segmented into N regions, each of which is denoted as R_i where i = 1, 2,…, N. The original image can be completely assembled by putting all regions together and there should be no overlapping between any two regions R_i and R_j for $i \neq j$. The logical predicate L (·) contains a set of rules that must be satisfied by all pixels within a given region, and it fails in the union of two regions since merging two different regions will result in an inhomogeneous region. The regions must satisfy the following properties:

$$X = \bigcup_{i=1}^{N} Ri$$

$$Ri \cap Rj = 0 \; \forall i,j = 1,2,\dots,N \tag{2}$$

$$L(Ri) = \; TRUE \; for \; i = 1,2,\dots,N$$

$$L(Ri \cup Rj) = FALSE \; for \; \forall i,j = 1,2,\dots,N; i \neq j$$

The region growing and the watershed segmentation methods are part of the region-based methods [4], and are the most commonly used for brain tumor segmentation. The description of these methods is given in the next sections, and some applications in the paper for brain tumor segmentation [13].

2.2.1 Region Growing procedure that groups pixels or subregions into a larger region based on predefined criteria. It is simplest region-based segmentation technique, which is used to extract a connected region of similar pixels from an image. This approach is starts with at least one seed that belongs to the region of interest. Neighbors of the seed are checked and those satisfying the similarity criteria are appended to the region. The similarity criteria are determined by a range of pixel intensity values or other features in the image. Seeds can be selected manually or provided by an automatic seed-finding procedure. The procedure performed until no more pixels can be added to the region. The advantage of region growing is that it is capable of correctly segmenting regions that have similar properties and generating connected region [2].

The technique associated with the iteration of statistical classification to divide an image into different tissue classes on the basis of the signal intensity value. The objects of interest were identified on the classified images with local segmentation operations (mathematic morphology and region growing). Region growing is an effective approach and requires less computation time than other non region-based methods for brain tumor segmentation, especially for the homogeneous tissues and regions. The major disadvantage of region growing method is the partial volume effect which limits the accuracy of MR brain image segmentation [1, 26].

2.2.2 Watershed segmentation method watershed is formed by 'flooding' an image from its local minima, and forming 'dam' where waterfronts meet. When the image is fully flooded, all dams together form the watershed of an image [14]. The watershed of an edgeness image or the watershed of the original image can be used for segmentation. When visualizing the edgeness image as a three dimensional landscape, the catchment basins of the watershed correspond to objects, means the watershed of edgeness image will show the object boundaries. The landscape in the image shows, the object boundaries mark the catchment basins, but there are small defects because of image artifacts. Watershed forms 'Dams' where waterfronts meet these small defects do not disturb the watershed segmentation. When the water level has reached the highest peak in the landscape, the process is stopped. As a result, the landscape is partitioned into regions separated by dams, called watershed lines. It produces a complete contour of the images and avoids the need for any kind of contour joining [12]. Watershed method performed segmentation of brain tumors using multi-scale watershed transformation in brain tumor segmentation. Dam presented an interactive method for T1 MRI brain tumor segmentation, the method builds blocks at different scales that the user can select and deselect in order to sculpt the desired anatomical object. Supervised learning is used to predict which building blocks are to be included in the segmentation [10].. Failures in the watershed technique will occur, where edges were poorly defined in the data, and noted a trend in the manual segmentation results toward systematically larger segmentations. [13]

The watershed transform usually suffers from over segmentation. As any local maximum in the image will generate a shape boundary it is obvious that watershed segmentation has a strong potential for over segmentation, if not for other reasons then because of noise.

Swe Zin Oo [15] implemented a marker-based watershed segmentation method, sobel operator was used as the marker to calculate gradient magnitude, and utilizing the prior knowledge of the test images for the segmentation of brain tumor.

Hemang J. Shah [6] implemented watershed method using canny edge detector as a marker to enhance performance. To avoid over-segmentation some pre or post processing methods have been proposed in order to produce a more reasonable segmentation that reflects the layout of objects applied on brain tumor MRI a merging process for the over segmented regions using Fuzzy C-Means clustering algorithm [3].

2.4 Pixel Classification Method

This segmentation method is based on pixel classification. Pixels in an image can be represented in feature space using pixel attributes that may consist of gray level, local texture, and color components for each pixel in the image. In the case of single-channel (or single-frame) image, pixel classification is typically based on gray level and image segmentation can be performed in a one-dimensional feature space. For multichannel images or multispectral (multimodality) images the segmentation can be performed in multidimensional feature space. The pixel classification is constrained to the use of supervised or unsupervised classifiers to cluster pixels in the feature space for brain tumor image segmentation [8]. Clustering is the process of grouping similar objects into a single cluster, while objects with dissimilar features are grouped into different clusters based on some similarity criteria. The similarity is quantified in terms of an appropriate distance measure. A prominent similarity measure is given by the distance between two vectors in the feature space which can be expressed as:

$$d(xi, xj) = (\sum_{k=1}^{n} \|xi - xj\|^{p})^{\frac{1}{p}} \quad (3)$$

Where $x_i = (x_i^1, \ldots, x_i^n)$ R^n are the two vectors in the feature space. It can be seen that the above measure corresponds to Euclidean distance when p=2 and Mahalanobis distance when p=1.

The unsupervised clustering methods are: Fuzzy C-Means (FCM), K-means, and statistical methods as Markov random Fields among others. The supervised methods are Artificial Neural Networks (ANN) and Bayes. The FCM technique is analyzed in this section.

2.4.1 Fuzzy C–Mean clustering purpose is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. It is not easy to determine a pixel should belong to a region or not in many situations. It is because the features to determine homogeneity may not have sharp transitions at region boundaries [1]. FCM clustering is a very popular technique in the area of unsupervised image segmentation by pixel classification, particularly in the case of brain tumor segmentation.

When the FCM method is applied for brain tumor segmentation, the first step is to determine a set of tissue classes. Then each pixel is assigned membership values to the tissue classes according to its attributes (intensity, texture, shape etc.). The fuzzy membership functions, constrained to be between 0 and 1, to reflect the similarity degrees between the data value at a specific location and the prototypical data value, or centroid, of its class. Thus, a membership value near one means that the data value at that location is close to the centroid of the class. The algorithm can be faster and clustering results can be improved, if the initialization can be carried out by accurate estimation of cluster centers. The splitting technique of discrete curve evolution (DCE) in order to find the most accurate estimation of cluster centers for T1, T2 and PD MR brain image segmentation. The proposed technique reduced the convergence time resulting in lower computational time [12].

Moumen T EI [19] proposed PIGFCM algorithm segments the brain MRI volume into main tissues. Tissues related to gray matter (GM), white matter (WM), cerebrospinal fluid (CSF), in addition to the background. Sneha khare [18] make use of genetic algorithm with curve fitting, and support vector machine. The segments obtained using genetic algorithm might be losing information for this curve fitting is used to improve segment process. Hassan Khotanlou [25] proposed a histogram based FPCM method, using 3D T1-weighted image with hyper intensity tumor. The author detects tumor using symmetry analysis to overcome the lack of generality.

2.5 Model Based Segmentation Methods

The segmentation of volumetric (3D) image data is a challenging procedure that has been mainly approached by model based segmentation techniques as parametric deformable models and geometric deformable models or level sets. In model-based segmentation, a connected and continuous model is built for especial anatomic structure by include a priori knowledge [12] of the object such as shape, location, and orientation. Some models include prior statistical information drawn from a population of training datasets [4].

Segmenting structures from medical images and reconstructing a condense geometric representation of these structures are difficult due to the skew size of the datasets and the complexity and variability of the anatomic shapes of interest [17]. The challenge is to extract boundary elements belonging to the same structure and merge these elements into a coherent and consistent model of the structure. Deformable models involve the formulation of a propagating interface (a closed curve in 2D and a closed surface in 3D) that moves under a speed function determined by local, global and independent properties. The deformable models can be broadly divided into two categories: parametric and geometric methods.

2.5.1 Parametric Deformable Models represent curves and surfaces explicitly in their parametric form. The strength of parametric deformable models also known as active contour models or snakes stems. The ability to segment, match, and track images of anatomic structures by exploiting constraints derived from the image data together with a priori knowledge about the location, size, and shape of these structures [12]. Parametric deformable models are capable of accommodating the often significant variability of biological structures over time and across different individuals. Moreover, these models support highly inherent interaction mechanisms that allow medical scientists and practitioners to bring their expertise to carry on the model based image evaluation task when necessary [20]. Deformable models are parametrically defined curves or surfaces that move under the influence of weighted forces that have two components named internal and external forces. The internal forces are used to satisfy the smoothness of the model during deformation process, while external forces are defined to push/pull the model toward the boundaries of the structure [25]. The active contour model, or snake, is defined as an ordered collection of n points in the image plane V = {v1,..., vn}, vi = (xi, yi), i = {1,..., n}.

The points in the contour iteratively approach the boundary of an object through the solution of an energy minimization problem. For each point in the neighborhood of v_i, an energy term is computed:

$$E_{snake}\ (V) = E_{int}\ (V) +\ \beta E_{ext}\ (V) \tag{4}$$

where E_{int} (V) is an energy function dependent on the shape of the contour and E_{ext} (V) is an energy function dependent on the image properties, such as the gradient, near point v_i. α and β are constants providing the relative weighting of the energy terms.

E_{snake}, E_{int}, and E_{ext} are matrices. The value at the center of each matrix corresponds to the contour energy at point v_i. Other values in the matrices correspond (spatially) to the energy at each point in the neighborhood of v_i. Each point, v_i, is moved to the point, v_i', corresponding to the location of the minimum value in E_{snake} (V). If the energy functions are chosen correctly, the contour, V, should access, and stop at, the object boundary.

Contour deformable models have been widely used for its sensitivity in searching the boundary of brain tumors. In fact, the sensitivity of the boundary found by the snake is better than the conventional edge detection methods, such as the Sobel and Laplacian. [17].

2.5.2 Geometric Deformable Models or Level Sets using parametric deformable models for the segmentation of volumetric (3D) image, it is difficult to naturally handling topological changes for the splitting and merging of contours [12]. This problem was solved by introducing the use of geometric deformable models, or level sets. In the level set method, the object is segmented from the image using curve evolution. The object is to be segmented is initialized with a closed curve. The main component of the level set method is the implicit representation of the interface. If the interface is given by Γ, Γ is represented as the zero level set {ϕ = 0} of a level set function ϕ. The function is a surface defined over the image area with the following property:

$$\emptyset(x, y, t = 0) = \pm d(x, y) \quad (5)$$

Where d is the distance function from (x, y) to Γ (t = 0), and the plus (minus) sign is chosen if the point (x, y) is outside (inside) the initial interface. Thus, the surface ϕ evolves along its normal direction with speed F as:

$$\frac{\partial_\emptyset}{\partial t} + F|\nabla\emptyset| = 0 \ given \ \emptyset(x, y, t = 0) \quad (6)$$

and at any time the propagating front is given by the zero level set:

$$\Gamma(\mathrm{t}) = \{(\mathrm{x}, \mathrm{y}) | \emptyset(\mathrm{x}, \mathrm{y}, \mathrm{t}) = 0\} \quad (7)$$

A geometric deformable contour with an image gradient method have been improved the initialization of parametric active contours, the initial contour was placed symmetrically with respect to the boundaries of region of interest, in practice this is not easy to achieve since many medical image segmentation problems are not dealing with regularly shaped objects [25]. Paresh Chandra [21] implemented variational level set method with image processing, morphological operation namely thresholding and erosion.

3. SUMMARY OF BRAIN TUMOR SEGMENTATION METHODS

Threshold-based techniques are the existence of conducting a simple and fast segmentation when good threshold values are defined. Although with many restrictions, these techniques are generally used as a first step in the segmentation process (Table 1).

Region-based techniques for brain tumor segmentation are mainly used as refinement step for defining a connected boundary of the tumor [9]. Some region-based approaches such as watershed transform, have reported very accurate results in segmenting tumors, but generally these approaches are constrained to be semi-automatic [16].

Pixel classification techniques for brain tumor segmentation are limited to clustering instead of this they are the most frequently used for brain tumor segmentation. The unsupervised technique of FCM, which is the most popular for medical image segmentation [15] gives highly accurate results in cases of non homogeneous tumors. The unsupervised method of MRF provides a way to integrate spatial information into the clustering process, reducing the overlapping of clusters and the effect of noise on the result [17].

Model-based techniques have been widely used for its sensitivity in searching the boundary of brain tumors. Segmenting tumors using methods of geometric deformable models or level sets best permits the development of fully automatic and highly accurate segmentation approach. In spite this methods are still computationally expensive [16].

Table 1: Summary table of segmentation methods.

Segmentation Method	Advantages	Disadvantages
Threshold Based Global and Local Thresholding	Simple and computationally fast	To enhancing tumor areas Limited applicability are provided.
Region Based Region growing	Simple and capable of correctly segmenting regions that have similar properties and generating connected regions.	Partial volume effect. Noise or variation of intensity may result in holes or over segmentation.
Watershed	Segments multiple regions at the same time. It produces a complete contour of the images and avoids the need for any kind of contour joining	Over Segmentation.
Pixel Based Fuzzy C Means	Unsupervised. Always converges the boundary of tumor	Long computational time
Model Based Parametric Deformable Models	Capable of accommodating to the variability of biological structures over time and across different individuals.	The model may converge to wrong boundaries in case of in homogeneities.
Level Sets	Topological changes are naturally possible	Computationally Expensive

4. CONCLUSIONS

Image segmentation is active research field for the last several decades. Moreover, it is a most challenging and active research field in the medical image processing. Image segmentation is the preliminary stage of almost all image analyzing tools. There exist variety of image segmentation methods and good prior knowledge for brain MRI segmentation. But still, brain MRI segmentation is a challenging task and there is a need for future research to improve the accuracy, precision and speed of segmentation methods. Using improved atlas based methods parallelization and combining different methods can be the way for making improvement in brain segmentation methods.

5. ACKNOWLEDGEMENTS

The authors like to thank Dr. Raghvendra Pratap Singh of Calcutta National Medical College, for their help and effort to assess MRI Brain Tumor.

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