Scientific Journal Impact Factor (SJIF): 1.711

e-ISSN: 2349-9745
p-ISSN: 2393-8161

International Journal of Modern Trends in Engineering and Research
www.ijmter.com

Survey on Brain MRI Segmentation Techniques

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Abstract: Image segmentation is aimed at cutting out, a ROI (Region of Interest) from an image. For medical images, segmentation is done for: studying the anatomical structure, identifying ROI ie tumor or any other abnormalities, identifying the increase in tissue volume in a region, treatment planning. Currently there are many different algorithms available for image segmentation. This paper lists and compares some of them. Each has their own advantages and limitations.

Keywords: Segmentation, thresholding, region based, pixel classification, model based

I. INTRODUCTION

Currently, the Medical Imaging Technology provides the clinician with a number of complementary diagnostic tools such as Computed Tomography (CT), Ultrasound, X-ray, Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET). From the different existing imaging modalities, magnetic (MRI) is the one which is most widely used, (especially for the brain). This is because, MRI images have a high spatial resolution, high signal to noise ratio and can do an excellent discrimination of soft tissues of the body and can thus provide detailed information about human anatomical structure.
Radiologists perform visual and qualitative analysis of these medical images. However, for detailed diagnosis and treatment, an elaborate quantitative analysis is required and to facilitate this assessment, Computer aided diagnosis is inevitable. CAD systems are effective due to the below factors.

- Less impact on diagnosis results from manual mistakes / missing steps
- Availability of fast and accurate results.
- Faster communication even to distant areas is possible.

Image segmentation is the major step for image analysis and computer vision. Image Segmentation is the process of partitioning an image into non - overlapping, constituent regions which are identical with respect to some characteristics such as intensity, color and texture [2]. During these years many significant advances have been made by researchers in the field of brain segmentation. Both semi-automated and automated methods have been proposed.
Brain segmentation methods are categorized according to the required extend of human interaction as: a) manual segmentation b) semi-automated segmentation c) fully automated segmentation [5].
Section 2 explains the most relevant existing brain MRI segmentation methods. The paper is concluded in Section 3. Finally, in Section 4, a comparison is done between the different segmentation techniques.

II. DIFFERENT SEGMENTATION TECHNIQUES

Major existing segmentation methods are discussed in the below sections.
According to [1], the fundamental roles of segmentation are to: (1) permit quantification, (2) reduce the dataset by focusing the quantitative analysis on the extracted regions that are of interest, and (3) establish structural correspondences for the physiological data sampled within the regions.
In general, 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 used for two-dimensional image segmentation [6]. Model based techniques such as parametric and geometric deformable models (level sets), are mostly employed in volumetric (3D) image segmentation [7].

A. Threshold based segmentation

Thresholding is a simple and effective region segmentation method, in which the objects of the image are classified by comparing their intensities with one or more intensity thresholds.
These thresholds 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, corresponding to different objects, the segmentation must be carried out using local thresholding. Such images are segmented by applying several individual thresholds or by using a multithresholding technique. A local threshold is determined adaptively in a local region around a pixel. According to Yao [4] the values of thresholds are generally estimated based on prior knowledge. Local threshold values are usually estimated using the local statistical properties [6] or by calculating partial volumes of each region [8] or by the Gaussian distribution of data values as threshold in normal brain T2-weighted MRI [9].

B. Region based segmentation

Region-based segmentation approaches examine pixels in an image and form disjoint regions by merging neighborhood pixels with homogeneity properties based on a predefined similarity criterion [1]. These methods can be sketched in general as follows: Let X be an image that is segmented into N regions, each of which is denoted as Ri where i = 1, 2… N. The original image can be exactly assembled by putting all regions together and there should be no overlapping between any two regions Ri and Rj for i ≠ j. The logical predicate L (·) contains a set of rules (usually a set of homogeneity criteria) that must be satisfied by all pixels within a given region, and it fails in the union of two regions since merging two distinct regions will result in an inhomogeneous region. The regions must satisfy the following properties:

$R_1 \cup R_2 \cup R_3 \cup \ldots \cup R_i = I$
where R_1, R_2, R_3, …R_i are the region in the image I,
and further, $R_1 \cap R_2 \cap R_3 \cap \ldots \cap R_i = 0$
This is as per the set theory of homogeneity.

Region growing and watershed methods are common region based segmentation techniques. The simplest region-based segmentation technique is the region growing, which is used to extract a connected region of similar pixels from an image [10]. In watershed method, to avoid over-segmentation some pre or post processing methods are used in order to produce a more reasonable segmentation that reflects the layout of objects [11,12]

C. Pixel classification based segmentation

Another type of 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. Segmentation methods based on pixel classification are constrained to the use of supervised or unsupervised classifiers to cluster pixels in the feature space.

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. Common distance measures used are: Euclidean distance or cosine measure. Many clustering techniques like Fuzzy CMeans (FCM), Markov Random Fields (MRF) (unsupervised), Artificial Neural Networks (ANN) (supervised) are available. In FCM method, for brain segmentation, the tissue classes are first identified and then pixels are assigned membership values (0-1) to the tissue classes according to its attributes (intensity, texture etc.). MRF provides a way to integrate spatial information into the clustering process. Markov Random Fields are widely used not only for modeling classes of segmentation, but also to model texture properties and in homogeneities of the intensities. In ANN, the classifier feeds the features through a series of nodes, where mathematical operations are applied to the input nodes and a classification is made at the final output nodes. Although ANN training is complex, it has the ability to model non-trivial distributions.

D. Model based segmentation

The segmentation of volumetric (3D) image data is a challenging problem that has been mainly approached by model based segmentation techniques such as parametric deformable models and geometric deformable models or level sets. In model-based segmentation, a connected and continuous model is built for a specific anatomic structure by incorporating a priori knowledge of the object such as shape, location, and orientation. Some models incorporate prior statistical information drawn from a population of training datasets [4]. The statistical parameterization provides global constraints and allows the model to deform only in ways implied by the training sets. Segmenting structures from medical images and reconstructing a compact geometric representation of these structures are difficult due to the sheer size of the datasets and the complexity and variability of the anatomic shapes of interest [13].Existing deformable models can be broadly divided into two categories: parametric and geometric. The parametric deformable models (also known as active contour models or snakes) have 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. But they are incapable of naturally handling topological changes in the image, while geometric deformable models or level sets have that capability.

III. CONCLUSION

This paper has surveyed the principle methods for brain MRI image segmentation. A brief description of these methods along with their key advantages and limitations has been narrated above.
Even though there is an availability of latest segmentation techniques, medical image segmentation still remains as the most challenging area for research in the field of image processing, because medical images are basically very complicated (example the structure of brain) and a precise segmentation is quintessential for effective medical diagnosis and treatment. The majority of research in medical image segmentation pertains to the use for MR images, especially in brain imaging, because of its ability to derive contrast from a number of tissue parameters. Moreover different pulse sequences exist for acquiring MR images. Hence to determine the optimal pulse sequence for obtaining accurate segmentations is another important task which requires knowledge about the underlying tissue properties of the anatomy to be segmented. Thus image segmentation is still the most challenging research area in the field of image processing.

IV. COMPARISONS

Table 1. Comparison of Segmentation Methods based on level of human interaction

Comparison Factor	**Manual Segmentation**	**Semi Automated**	**Fully Automated**
Level of Human Interaction involved	- involves manually drawing the boundaries of the structures of interest, or painting the region of anatomic structures with different labels	- includes the intervention of a human operator. Role of the human operator is to: initialize the method, check the accuracy of the result,manually correct the segmentation result.	- does not involve human interaction, the computer system or program determines the segmentation
Application	- is still widely used in areas where a lot of human knowledge and expertise is required. - is used as a golden standard against which semi and fully automated methods are validated	- uses different strategies to combine computers and humans' expertise to obtain an efficient brain segmentation	- can provide an efficient segmentation for a large batch of images
Limitation	- if the person drawing ROI is not a radiologist/anatomist/trained technologist who is well versed with brain anatomy, segmentation results will be poor. - may have inter or intra rater variability	-May be subject to variations both between expert users and within the same user.	- not widely accepted -lacks interpretability and transparency in the segmentation process. - developing the fully automated system is extremely difficult(as high-level visual processing, and specialized domain knowledge is required)[7]

Table 2. Comparison of major segmentation methods

	Sample technique or Algorithm	Major Advantage	Major Constraint	Impact of Noise	Computational time& memory requirement
Threshold based	Global thresholding,	- simple and fast segmentation is done when good	-Threshold selection becomes difficult	Less immune to noise than other techniques	Simple and computationally fast

	Local Thresholding	threshold values are defined. -Global thresholding performs well if the image contains objects with homogeneous intensity or the contrast between the objects and the background is high.	with increasing number of regions or noise levels, or low contrast in image. - Unable to exploit all the information provided by MRI, so mostly used as a first step in the segmentation process.		
Region Based	Region growing, Watershed	Work best when the region homogeneity criterion is easy to define.	- Region growing has inherent dependence on the selection of seed region and the order in which pixels and regions are examined; - generally these approaches are constrained to be semi-automatic	- Noise or variation of intensity may result in holes or over-segmentation.	Are by nature sequential and quite expensive both in computational time and memory;
Pixel Based	Fuzzy C Means, ANN, MRF	-Unsupervised technique - FCM, permits the use of vague concepts in the definition of clusters -Unsupervised method - MRF can represent complex	FCM-The determination of fuzzy membership is a difficultl job MRF- Difficult to select parameters that control	FCM is generally sensitive to noise	For ANN -Training time is long; All the methods are computationally intensive

		dependencies among data -Supervised clustering method of ANN has the ability to model non-trivial distributions	the strength of spatial interactions. ANN- gathering of training samples is not easy. It can affect the result		
Deformable Model Based	Parametric deformable models, Level Sets	-can accommodate the variability of biological structures over time and across different individuals [13] -Can be implemented as a fully automated technique	The model may converge to wrong boundaries in case of in homogeneities [3].	Less immune to noise	computationally intensive

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