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A Study of Brain MR Image Segmentation Techniques

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Abstract - In the field of image processing, segmentation is a crucial issue. The extent of the complexity is extrapolated when we consider brain image segmentation which is a focused problem in neuroscience. Several methods are created to perform segmentation of brain images efficiently. Another major concern with regards to brain segmentation are the types of images used. Common examples are Magnetic Resonance Imaging, Computer Tomography, and X-ray. In this study, we will consider Magnetic Resonance Images of the brain. The aim of this paper is to provide an exhaustive study of most of the brain MR image segmentation techniques that are currently prevalent.

Key Words: Magnetic Resonance Imaging(MRI), Supervised segmentation, Unsupervised segmentation, Morphological segmentation, Fuzzy clustering, Finite Mixture Models, Neural networks

1.INTRODUCTION

By current standards, one of the most powerful tool for representing the soft tissue or organs in the human body is MR imaging. The visible advantages of MR imaging is that it is relatively safe as compared to other imaging techniques. MR imaging also provides different modalities to capture the images. The modalities are T1-weighted, T2-weighted and proton density(PD) weighted. This capability helps in the diagnosis of various invasive diseases[1]. Functional activity of the brain can be recorded using MR imaging.

Image segmentation refers to the partitioning of an image into a defined set of regions that are covered by it. [2] The regions must represent meaningful areas of the image or the regions might be sets of border pixels. Regions may also represent groups of pixels having both a border and a particular shape such as a circle or ellipse or polygon. The major goal of brain tissue classification or segmentation is detection and diagnosis of normal and pathological tissues. In addition, some of the psychiatric disorders such as Alzheimer's, Parkinson's and Huntington's disease, autism, depression etc may also be diagnosed using MRI segmentation. Furthermore, image segmentation of the brain MRI is the key procedure in clinical diagnostic tools. Also, the procedure is important in visualization for measuring the volume of different tissues in the brain such as gray matter, white matter, cerebrospinal fluid etc.[3] Brain images basically contain a lot of outliers such as Partial Volume Effect(PVE), Intensity Non-Uniformity(INU) and other noises and deviations.[4] Partial volume effect occurs when multiple tissues are placed in the same pixel. Intensity Non-Uniformity is percieved due to Radio Frequency(RF) coil in the magnetic resonance imaging machine and other hardware limitations. These drawbacks in imaging techniques causes a raised level of difficulty in acquiring accuracy in segmentation techniques. On the other hand, accuracy is the prime requirement for proper diagnosis. However, the golden standards in the present day is manual segmentation which is time consuming, labor intensive and prone to human error. Hence there is a widespread demand for efficient automatic image segmentation technique.

Internet Brain Segmentation Repository(IBSR) provided by the Center of Morphometric Analysis (CMA) at Massachusetts General Hospital and BrainWeb which has been collected at McConnell brain imaging center of Montreal Neurological Institute, McGill University are two well known datasets for research in this area.[5]

This study provides a compact review of the different segmentation techniques, which are proposed in the recent years for MRI brain segmentation.

2. Methods of Image Segmentation

In this paper, we concentrate on brain image segmentation techniques. We try to categorize these methods into two main important classes namely, supervised(and semi-supervised) and unsupervised methods. Further, in unsupervised we have thresholding, edge based, region based and clustering methods. In supervised methods we see atlas based and machine learning based methods.

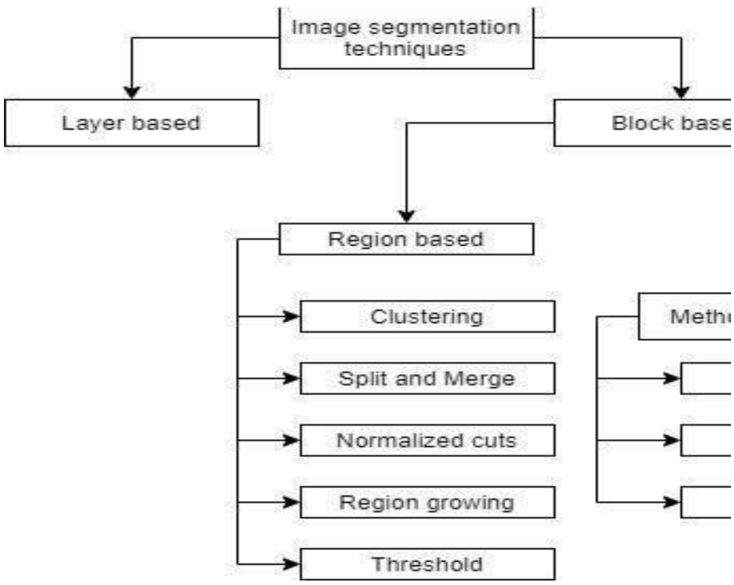

Figure1: Categorization of image segmentation techniques

2.1 Unsupervised Methods

The basic concept of unsupervised methods is the absence of pre determined class labels for segmentation. We can broadly categorize the unsupervised methods into two major categories which are the Finite Mixture Model (FMM) and Fuzzy C-means (FCM) based methods. Other methods that may be included in the unsupervised category are Neural Network methods and morphological methods.

2.2 Supervised Methods

The underlying concept for supervised methods is the presence of class labels for the process of segmentation. Two major classes in this supervised category are machine learning based methods and atlas based methods.

3. Unsupervised Methods

The major groups of unsupervised methods are Finite Mixture Models, Fuzzy C-Means, Neural Network, and morphological methods.

3.1 Morphological Methods

The three major categories under morphological methods are thresholding segmentation, edge-based segmentation, and region-based segmentation. Each of the above mentioned methods have their own advantages and disadvantages. We cannot choose a single method that can be used with all the different types of images. This is because different images have different features and properties. Therefore, for different images, different technique must be used.

a. Thresholding

Thresholding segmentation is a pixel-based method for image segmentation. It is the simplest method. It based on the variation of intensity between the object pixels and background pixels. [8] Therefore, it is often used to separate regions of an image representing the objects. The procedure to differentiate the pixels located in the region of interest from the background is to compare each pixel intensity value with respect to a threshold. Generally, pixels are divided into two classes. Pixels with values less than threshold are placed in one class, and the rest are placed in the other class. Therefore, this method is often used to convert a grayscale image into a binary image.

b. Edge based segmentation method

An edge is the boundary between two regions; it depicts the transition from one object to another. There is often a sharp change in intensity at the region boundaries. This method is often used to divide images into areas corresponding to different objects. The basic idea of edge-detection techniques is the calculation of a local derivative of an image.[9] The first-order derivative of choice in image processing is the gradient; presence of an edge can be easily determined. Second-order derivatives in image processing generally are computed using the Laplacian. The decision of whether a pixel on the edge is on the dark or the light side is derived from the sign obtained after applying the second derivative. The first order derivative type operators that are used to detect edges are Sobel edge detector, Robert detection, Prewitt operator, Kirsch edge detector, and Frei-Chen edge operator. The second order derivative type operators are mainly Laplacian and Laplacian of Gausssian(LoG) filter. However Laplacian operator is used only for edge detection as it is highly susceptible to noise. Another major example in this category is Canny edge detector which detects a number of edges in the image. The Canny edge detector is applies Gaussian smoothing on the image and this is followed by application of first order derivative.

c. Region-based segmentation

Segmentation algorithms that are region-based are iterative processes that work by grouping together neighboring pixels that have similar properties and bifurcate groups of pixels that are dissimilar. [10] Region based segmentation may be divided into two types:

Region growing method

Among image segmentation methods, the region growing method appears to be the simplest. The concept of selection of initial seed points in this method may lead to it being classified as a pixel-based segmentation method. In this approach to segment an image, there exists a predefined criteria based on which pixels or subregions are grouped into larger regions. The first step involves deciding upon some criterion preferable to the user inorder to select a set of seed points. Second, the regions are grown from these seed pixels to neighboring pixels, which are examined to ascertain if they should be added to the region, according to a region membership criterion (e.g., pixel intensity, grayscale texture, or color). This second step is iterated, as in general data clustering algorithms. Presence of noise in images renders edge based detection useless as it is very difficult to identify edges. However, region based methods work well with noisy images but on the other hand they are computationally expensive.[11]

Split-and-merge method

This method consists of two steps: region splitting and region merging. Region splitting begins with the entire image as a single region and while a condition of homogeneity is not satisfied, the image is subdivided recursively into subsidiary regions. Region merging is an antonym process for region splitting and is applied to curtail over-segmentation. It starts with the smallest segments and merges the segments that have similar characteristics (such as gray level, variance).

3.2 Fuzzy C-Means based segmentation

FCM algorithm is an important clustering algorithm, which was proposed in 1981. This method assigns with each pixel a degree of the membership to each cluster. Therefore, FCM algorithm has a good robustness against Partial Volume Effect, a serious problem with MRI. A number of versions of the FCM algorithm have been proposed with increasing invariance of the method towards INU and noise in MRI brain images.

Based on the criteria used to evaluate the correctness of the partition, the conventional clustering algorithms are inclinded to identify a "hard partition" of a given dataset. “Hard partition” may be defined as each datum being a part of exactly one cluster of the partition. On the other hand, soft clustering algorithms find “soft partition” of a given dataset. In “soft partition” each datum may belong to different clusters with different degree of membership. An additional constraint in a special category of soft clustering ensures that the degree of membership of each datum adds up to one. The objective function of fuzzy clustering varies from the basic hard clustering in two ways (1)fuzzy membership degree and (2) weight.

FCM for Brain MR image segmentation

Here we state some existing algorithms for MRI brain image segmentation using different types of FCM algorithms:

a. Silhouette method

This method combines FCM, Silhouette Method and Programming language R.

The steps are given below,

1. Coverts from image to data matrix, which is to be classified.

2. Separate matrices in terms of Images, if more than one image to be classified.

3. Construct a new data matrix with three columns to be structured, the columns are correspond to data of T1, T2, PD.

4. Initialize the cluster centers at first time [n classes].

5. Use FCM to make partition(clusters) into data matrix.

6. If clusters Average width is > = 0.6 silhouette (stop algorithm) or otherwise, repeat from step 4 until the clusters average width reach 0.6. (clusters average width may be changed according to the problem).

7. Separate the elements of Matrix according to clusters.

8. Get segmented MR image using data matrices of Step7.[12]

b. Spatial FCM

Correlation between pixels is an important characteristic of an image. In other words, we could say, the neighboring pixels possess similar feature values Hence, a higher probability of the fact that neighboring pixels shall belong to the same cluster. Spatial relationship is paramount and impactful in clustering, but basic FCM algorithm does not seem to use it. Following equation defines the spatial function.

Incorporation of the spatial function into the membership value of the objective function of FCM is done as follows:

Applying spatial function in a homogenous region will consolidate the results that would be obtained by the use of the original membership. On the other hand, presence of a noisy pixel results in reduced weight of the noisy cluster by the labels of its neighboring pixels.

Therefore the outcome of the use of spatial function is that the previously misclassified pixels that were either noise or spurious blobs can be correctly classified.[13-15]

c. HMRF-FCM

The hidden Markov random field model (HMRF) models class labels on the basis of fuzzy clustering principle. It also considers the mutual influences of the neighboring sites in order to formulate the class labels. The method, being a combination of HMRF model and fuzzy clustering, requires incorporation of explicit assumptions of HMRF model. The final yield is an efficient fuzzy clustering model as the resulting model is an amalgam of the spatial coherency modelling capabilities of the HMRF model, and the amplified flexibility obtained by the fuzzy clustering algorithm. The HMRF-FCM segmentation framework is corroborated with both images with noise as well as brain MR images. This merger technique allows us to give FCM type treatment to the coveted HMRF model.[16-17]

3.3 Finite Mixture Models

The appropriate distribution of various tissues in the brain can be procured by the use of Finite Mixture Model(FMM) method, like the Gaussian Mixture Model(GMM). Finite mixture model calls for the use of statistical mathematics, where each brain tissue should be approximated by a distribution. The next step is to address the segmentation problem that can now be done by estimating the parameters of the previous distributions. Parameter estimation step is commonly solved using Expectation-Maximization(EM). Recent years have drawn attention towards research outcomes using an amalgam of EM algorithm with an appropriate variant of MRF algorithm for brain MRI segmentation.

Unsupervised methods are the most widely used for MRI segmentation. However, these methods consider only the intensity level values in an image for the segmentation process. Therefore a need arises for the use of additional approaches like the Markov Random Field(MRF) or Level Sets(LS) that incorporate contextual, textural, spatial, and spectral information.[19-24]

3.4 Neural network methods

Fuzzy clustering methodology and Expectation-Maximization(EM) algorithms are most widely used. As mentioned earlier, fuzzy clustering methods consider only intensity levels in an image. This leads to use of fuzzy clustering methods in association with additional methods to incorporate other information. EM algorithms have a major drawback that is the it does not consider noisy images or exceptions and models intensity distribution of all the brain images as a normal distribution.

These disadvantages and complications deviate attention towards the use of neural networks for digital image segmentation. The ability to self learn, tolerance to fault or noise and optimum search are the characteristics of the neural networks that allure attention towards its use in image segmentation.[25-26] Self learning ability is the most coveted feature of neural networks that allows its use in multiple fields. The most interesting methods are Self Organizing Maps(SOM) [27]and Adaptive Resonance Theory(ART).

3.5 Hybrid methods

The research in the field of image processing, in general and image segmentation in particular lean towards the use of clustering methods for MRI segmentation. Even though we know that there is a growing consensus towards the use of unsupervised methods for image segmentation, these methods are not void of any drawbacks. After going through the previous section, the sole use of intensity values and neglecting other factors like spatial relationship appears to be recurring and prominent drawback in supervised methods. This leads to a requirement for the hybrid section in this paper. Most of these unsupervised methods require the use of additional methodologies that are partially supervised. Research shows that use of methods like Markov Random Field (MRF)] and Level Sets (LS) approaches demonstrate efficient results when used in combination with previously discussed unsupervised methods.[28-32]

4. Supervised Method

There are two major categories in this class of image segmentation methods namely, machine learning based methods and atlas based methods.

4.1 Machine Learning based:

The Machine learning based methods consider the use of a database. The database is usually divided into two different parts such as training and test set. The learning curve of the algorithm is performed on the training set and the evaluation or validation is done on the test set. Support Vector Machine (SVM) [33-34] and Neural Network (NN) methods like Multi-Layer Perceptron (MLP) are the two most important machine learning approaches which are mostly used in this area.

4.2 Atlas based:

Now let us consider atlas based bethods. Here, we gather data from a subjects belonging to different demographic depending on the problem at hand. The next step is to compile all the data and construct an atlas. Therefore, we can draw a conclusion that an atlas contains the prior information about different tissues in the brain. The atlas-based methods use these pre-labeled images and prior anatomical information for the segmentation process. These methods usually are consisted of three main steps such as registration, label propagation and final segmentation. A huge amount of work has been done in this area, because of the ability of these methods for MRI image segmentation.[35-40]

Now that we have gone through most of the segmentation methods prevailing in the field of image processing, let us try to consolidate the data. For the summary about the discussed information, refer to table 1.

3. CONCLUSIONS

The study provides a comprehensive view of the different segmentation techniques available for different image segmentation problems. There are no conclusive statements that can be drawn regarding the choice of segmentation techniques because the choice depends on the problem under consideration. If we go through the comparison table, the subtle trend that is observed is that the complexity of the techniques is increasing. Also, another observation is that increase in complexity of the segmentation problem leads to use of more complex segmentation technique. Though this is not a rule, it is the general trend. Segmentation problems that only use the intensity distribution in the image(histogram) can be solved using thresholding. It is important to note that the segmentation is performed on global data. These methods are easy to use and used widely for segmentation of the image into two parts like detection of tumor from all the other parts in the brain. However the accuracy is comparatively low in this case. Further detection of sharp edges call for edge based segmentation methods but these methods are not resistant to noise. Presence of noise in the image shall lead to extreme errors. Detection of tumor border or skull lining or sulcus in the brain are examples of applications of edge based methods. In this case it has been observed that further changes are needed for tackling error detection as accuracy is of utmost importance for medical analysis. Next improvement to segmentation techniques is the error resistant region based methods which uses intensity information of neighboring pixels. Region based methods may result in more number of regions than required as global information is not considered. Segmentation of brain tissues and detection of brain tumor is an important example in this case. Segmentation problems that use image as a whole and also include spatial information need to use clustering techniques. However, the biggest drawback in this case is the process used to make an initial choice regarding the number of clusters. All brain segmentation problems with known number of classes can be easily implemented using clustering methods. The accuracy obtained is also good. All the above problems have led us to the state of art neural network techniques that allow self learning and error detection through large training set and back-propogation. Most of the segmentation problems involved in brain MRI analysis can be solved with high percentage accuracy using neural networks. But it is difficult to gather the large amount of data needed for training. In addition training is a time consuming process. Therefore, choice of segmentation technique depends on the problem under consideration, information about image(s) available, amount of data available and accuracy requirements.

TABLE I
BASIC COMPARISON OF SEGMENTAT

Sr. No.	Segmentation method	Process details	
		Unsupervised	
1.	**Thresholding based**	Based on intensity values	a l i
2.	**Edge based**	Pixel discontinuity (Difference in pixel intensity)	
3	**Region based**	Grouping neighboring pixels having similar properties or splitting regions having dissimilar properties	a v l w
4.	**Clustering based**	Grouping pixels in an image into 'k' clusters according to intensity values	in
		Supervised	
5.	**Neural network based**	Use of neural networks.	a.S s b. U er

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