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Medical Image Segmentation using Weighted Identification Level Set Evolution based on Local Edge Features

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Abstract- *Image Segmentation is the process of identifying features in images and marking them as distinct from one another. These features can be things like grey and white matter in an MRI of the brain or individual organs in an MR or CT image. Magnetic resonance imaging (MRI) provides detailed images of living tissues, and is used for both brain and body human studies.*

In this project, we propose a color based segmentation method that uses the K means clustering technique to track tumor objects in magnetic resonance (MR) brain images. The key concept in this color based segmentation algorithm with k means to convert a given gray level MR image in to a color space image and then separate the position of tumor objects from other items of an MR image by using K means clustering And histogram clustering .Experiments demonstrates that the method can successfully achieve segmentation for MR brain images to help pathologists distinguish exactly lesion size and region.

Keyword: Image Segmentation, EMR, Dataset.MRI.

1. INTRODUCTION

Image segmentation is the partition of an image into a set of non-overlapping regions whose union is the entire image. In the simplest case, one would only have an object region and a background region. A egion cannot be declared a segment unless it is completely surrounded by edge pixels. It is not an easy task to make it known to a computer what characteristics constitutes a" meaningful" segmentation. Magnetic resonance imaging (MRI) is often the medical imaging method of choice when soft tissue delineation is necessary. This is especially true for any attempt to segment brain tissues, normal or abnormal. Image segmentation is a tool that has been applied to medical imaging modalities to differentiate tissue types for purposes of volume measurement and visualization [1].

Healthy brain tissue can generally be classified into three broad tissue types on the basis of an MR image. Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and other imaging modalities provide an effective means for noninvasive mapping the anatomy of a subject. These technologies have greatly increased knowledge of normal and diseased anatomy for medical research and are a critical component in diagnosis and treatment planning. With the increasing size and number of medical images, the use of computers in facilitating their processing and analysis has become necessary. In particular, computer algorithms for the delineation of anatomical structures and other regions of interest are a key component in assisting and automating specific radiological tasks [2]. These algorithms, called image segmentation algorithms, play a vital role in numerous biomedical imaging applications such as the quantification of tissue volumes , diagnosis , localization of pathology , study of anatomical structure , treatment planning , partial volume correction of functional imaging data , and computer integrated surgery [3].

Image Segmentation is the process of identifying features in images and marking them as distinct from one another. These features can be things like grey and white matter in an MRI of the brain or individual organs in an MR or CT image [4]. Magnetic resonance imaging (MRI) provides detailed images of living tissues, and is used for both brain and body human studies. Data obtained from MR images is used for detecting tissue deformities such as cancers and injuries; MR is also used extensively in studies of brain pathology, where regions of interest (ROI's) are often examined in detail, for example in multiple sclerosis (MS) studies. In order to perform good quantitative studies, ROI's within the brain must be well defined. In traditional methods, a skilled operator manually outlines the ROI's using a mouse or cursor. More recently, computer-assisted methods have been used for specific tasks such as extraction of MS lesions from MRI brain scans, or extraction of the cerebral ventricles in schizophrenia studies [5]. Many of these computer-assisted tasks require segmentation of the whole brain from the head.

2. EXISTING METHOD

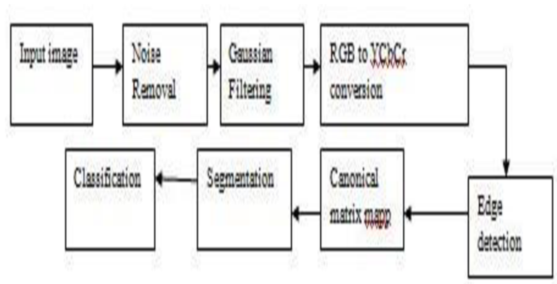
Image segmentation is defined as the partitioning of an image into no overlapping, constituent regions that are homogeneous with respect to some characteristic such as intensity or texture. If the domain of the image is given by, then the segmentation problem is to determine the sets $S_k \subset \Omega,$ whose union is the entire domain. Thus, the sets that make up segmentation must satisfy

$$\Omega = \bigcup_{k=1}^{K} S_k \quad \text{where,}$$

$S_k \cap S_j = \phi \text{ for } k \neq j,$ and each Sk is connected. Ideally, a segmentation method finds those sets that correspond to distinct anatomical structures or regions of interest in the image. When the constraint that regions be connected is removed, then determining the sets Sk is called pixel classification, and the sets themselves are called classes. Pixel classification, rather than classical segmentation, is often a desirable goal in medical images, particularly when disconnected regions belonging to the same tissue class require identification. Determination of the total number of classes K in pixel classification can be a difficult problem [6]. Often, the value of K is assumed to be known based on prior knowledge of the anatomy being considered.

For example, in the segmentation of magnetic-resonance (MR) brain images, it is common to assume that the K = 3, corresponding to gray-matter, white-matter, and cerebrospinal-fluid tissue classe. In many image processing tasks, segmentation is an important step toward the analysis phase. It allows quantification and visualization of the objects of interest. They concluded that segmentation of medical images is still a difficult task and fully automatic segmentation procedures are far from satisfying in many realistic situations. Merely when the intensity or structure of the object differs significantly from the surroundings, segmentation is obvious [7]. In all other situations manual tracing of the object boundaries by an expert seems to be the only ”valid truth” but it’s undoubtedly a very time-consuming task. On MR data, fully automatic image segmentation techniques have been developed which can be subdivided in two major classes:

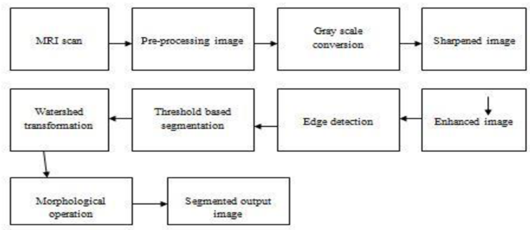
1. Gray scale single image segmentation
2. Multispectral segmentation



The part of the image that has the tumor has more intensity in that portion and we can make our assumptions about the radius of the tumor in the image, these are the basic things considered in the C-Means algorithm [8]. First of all some image enhancement and noise reduction techniques are used to enhance the image quality, after that some morphological operations are applied to detect the tumor in the image. The morphological operations are basically applied on some assumptions about the size and shape of the tumor and in the end the tumor is mapped onto the original gray scale image with 255 intensity to make visible the tumor in the image [9]. The algorithm has been tried on a number of different images from different angles and has always given the correct desired result.

3. PROPOSED METHOD:

Here, we will implement Interactive Segmentation using graph cut based on the paper Yuri Boykov Marie –Pierre Jolly “Interactive Graph Cuts for Optimal Boundary & Region Segmentation of Objects in N-D Images”. Here Interactive segmentation involves imposing both Hard Constraints (Indicate the pixels of the object region and the background region by the user) and soft constraints (Boundary and region properties of the segments). Implemented algorithm will be tested on both the Synthetic medical images (Brain MRI) and Non-medical images. The effect of adding noise to the original image on the actual segmentation is studied. This approach is compared with the Existing [10].



System Requirements:
Operating system: Windows 7/8
System Type: 32-bit/64-bit
Software Tool: Matlab 2014a

Gray scale single image segmentation

The most intuitive approach is the threshold-based segmentation method where the threshold is chosen globally or locally. The method is restricted to relative simple structures and is hindered by variability of anatomical structures as well as image artefacts. Other approaches make use of edge detection for image segmentation [11]. These however suffer from over or under segmentation, induced by improper threshold selection. In addition, the edges found are usually not closed such that edge linking techniques are further required.

Multispectral segmentation

Segmentation techniques using clustering techniques like k-means clustering , adaptive hierarchical clustering , fuzzy k-means , etc. are applied [. Like all unsupervised segmentation techniques, multispectral data analysis is fully automatic and superior in reproducibility, but it can only be exploited when the MR characteristics of the object of interest differ significantly from those of the surrounding structures [12]. On the other hand, results of supervised segmentation are less reproducible but the segmentation process can be controlled by the operator. We choose for a semiautomatic single image segmentation procedure for 3D MR images in which user interaction is allowed to control the segmentation process and in which data is pre-processed as far as possible such that the posterior user-interaction time is strongly reduced

Problems Associated with MR medical image segmentation:

Methods for performing segmentations vary widely depending on the specific application, imaging modality, and other factors. For example, the segmentation of brain tissue has different requirements from the segmentation of the liver. General imaging artefacts such as noise, partial volume effects, and motion can also have significant consequences on the performance of segmentation algorithms. Furthermore, each imaging modality has its own idiosyncrasies with which to contend. There is currently no single segmentation method that yields acceptable results for every medical image that are more general and can be applied to a variety of data. However, methods that are specialized to particular applications can often achieve better performance by taking into account prior knowledge. Selection of an appropriate approach to a segmentation problem can therefore be a difficult dilemma [14].

Many issues inherent to medical imagery make segmentation a difficult task. The objects to be segmented from medical imagery are true (rather than approximate) anatomical structures, which are often non-rigid and complex in shape, and exhibit considerable variability from person to person. Moreover, there are no explicit shape models yet available that fully captures the deformations in anatomy. Magnetic resonance images are further complicated due to the limitations in the imaging equipment that lead to a non-linear gain artifact in the images. In addition, the signal is degraded by motion artifacts due to voluntary or involuntary movement of the patient during the scanning process.

Importance of Image segmentation

- Fully automatic brain tissue classification from magnetic resonance images (MRI) is of great importance for research and clinical studies of the normal and diseased human brain
- Segmentation of medical imagery is a challenging problem due to the complexity of the images
- Accurate and robust tissue classification is the basis for many applications such as the quantitative analysis of tissue volume in healthy and diseased populations

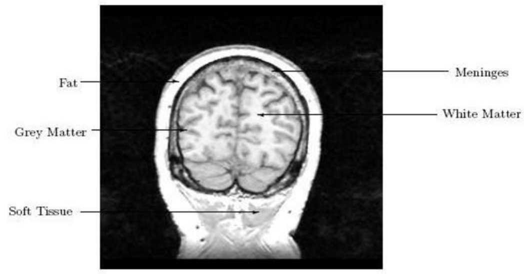


Figure 1: An Annotated Gradient Echo MR Slice (Air, CSF and Cranium are Dark in These Images)

Echo MR slice

Categories of image segmentation: Accurate segmentation of magnetic resonance (MR) images of the brain is of interest in the study of many brain disorders. A review of some of the current approaches in the tissue segmentation of MR brain images [15]. We broadly divided current MR brain image segmentation algorithms into three categories:

1. Classification based
2. Region based
3. Contour based

Region based method:

- **Growth of regions**

The first region growing method was the seeded region growing method. This method takes a set of seeds as

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input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean, δ, is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region [18]. This process continues until all pixels are allocated to a region. The growth of the regions is carried out from the seeds that were determined as input, where each one of them contains the following information:

- **Position**. These are x, y and z coordinates within the image. It is known that this point belongs to the region of interest.
- **Intensity**. The voxel intensity is important to determine the rank of intensities that will be included in the region (if the inclusion criterion makes use of this value).

Another input data of the algorithm is the three-dimensional image with a cubical matrix shape. The algorithm output will be a matrix with the same dimensions as the input image. This output matrix is initially filled out with zeroes in all the positions, and the seeds will be marked to let the region grow.

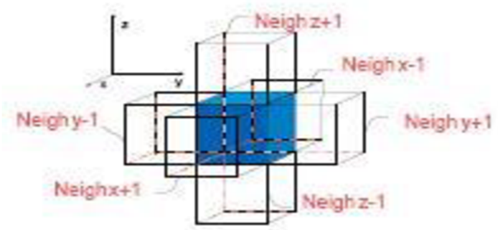

Fig.3: connected region growing

Growth Algorithm

An auxiliary FIFO (First In First Out) structure is used where the seeds are initially located, and where the Neighbors that belong to the region to be visited are queued up. In algorithm 1 it is possible to see the pseudo code of Voxel Grow algorithm in detail. The algorithm successively takes elements from the queue. Each one of these elements is one of the volume's Voxel that have already been accepted. For each one of them we must visit its neighbors, and decide if that neighbor belongs or not to the region according to the selection criterion. In order to compare neighbors, 6-connectedness is used. One of the most remarkable aspects of this technique is that it always grows by neighbors, so it maintains connectivity between the elements that are included within the segmented region [16].

- **Growth Types:** Three growth variations are provided to consider if a voxel belongs or not to the region of interest. The first one considers the variation of voxel intensity in relation to the seed intensity. The second one considers the local intensity variation in relation to the neighbor being visited. The last one considers the three-dimensional gradient of the image.
- **Seed Growth:** In this case the seed intensity is taken always as reference. Each new Voxel that is added to the region is included if the intensity difference that exists between it and the intensity of the seed maintains within a threshold determined previously. This threshold is compared directly with the intensity difference. This technique gives as result regions that contain voxels whose intensities are within acertain rank.
- **Neighbor Growth:** Unlike the previous case, this variation considers that the voxel belongs to the region if the intensity difference with its neighbor remains underneath the threshold. In this technique, voxels that have great variations of intensity with their neighbors are excluded.

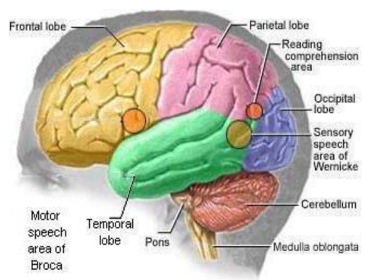

Fig.4: Sagittal orientation of Brain

Disadvantages of Region growing:

The primary disadvantage of region growing is that it requires manual interaction to obtain the seed point. Thus, for each region that needs to be extracted, a seed must be planted. Split-and-merge is an algorithm related to region growing, but it does not require a seed point. Region growing can also be sensitive to noise, causing extracted regions to have holes or even become disconnected. Conversely, partial-volume effects can cause separate regions to become connected. To help alleviate these problems, a homo topic region-growing algorithm has been proposed that preserves the topology between an initial region and an extracted region. Fuzzy analogies to region growing have also been developed [17].

Thresholding

Suppose that an image, f(x,y), is composed of light objects on a dark backround, and the following figure is the histogram of the image.

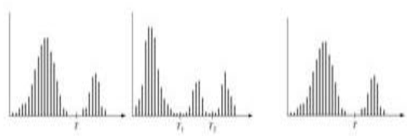

Fig.5: Thresholding

Then, the objects can be extracted by comparing pixel values with a threshold T. Then, the objects can be extracted by comparing pixel values with a threshold T. Non-uniform illumination may change the histogram in a way that it becomes impossible to segment the image using a single global threshold. Choosing local threshold values may help.

4. CONCLUSION

.Generally, an MR brain image consists of regions that represent the bone, soft tissue, fat and background. In the gray and color test images suggest three primary clusters in the test image shown . When k=3 the image labelled by cluster index from the K -means process for different kinds of feature vectors. Using index labels, we can separate objects in the brain image by three colors: *white, gray and black*.

The final segmentation results generated by histogram clustering are shown in k mean cluster image by combining the histogram cluster image we can see that not only a tumor is identified but also the white matter, cerebrospinal fluid, and the ventricles are. In other words, the segmentation result cannot exactly identify the position of the tumor shown in compared image.

However, the segmentation result generated by the proposed method can ignore most of the white matter locating the position of the tumor. Therefore the segmentation performance of the proposed features derived from the CIE Lab color model and the propped method is confirmed.

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