ADAPTIVE GRAPH CUTS WITH TISSUE PRIORS FOR BRAIN MRI SEGMENTATION

MIP Project Report

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Abstract:

This is a detailed report about the course project, which was to implement “ADAPTIVE GRAPH CUTS WITH TISSUE PRIORS FOR BRAIN MRI SEGMENTATION [6]” and understand the usefulness of Graph cuts and energy minimization in brain MRI segmentation. The concept of graph-cuts was introduced by a famous paper “Fast Approximate Energy Minimization via Graph Cuts” [3] and it has been wildly used and applied in all kinds of Image segmentation. The rest of the report is organized as follows. Section I is basic problem formulation and introduction to segmentation followed by methods that was used prior to this work. Section II describes the algorithm proposed by this paper, section III gives the details about implementation and include a short description of tools used. Section IV report the obtained results and final conclusion are analysed in section V.

I. Introduction:

Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. [1]

In brain MRI images each voxel is labelled as one of three main tissue types, i.e. white matter (WM), gray matter (GM), or cerebrospinal fluid (CSF). WM, GM and CSF are three main parts of the brain and typically our task is to segment each of these parts. There are needs to develop specific algorithm for brain MRI and normal image segmentation doesn’t give good results because brain MRI has some unique challenges such as, partial volume effects, intrinsic tissue variation due to neurodevelopment and neuropathologies, and the highly convoluted geometry of the cortex. Initially some classical stochastic methods such as Gibbs Sampler was used for this purpose, but these functions are very slow and hardly useful for any real time processing. Iterated conditional modes (ICM), has been previously applied to brain tissue segmentation [2]. Graph cuts are a relatively recent development in minimizing context-dependent MRF problems.

II. Proposed Algorithm:

The basic framework of this method is derived from the framework described by "Fast Approximate Energy Minimization via Graph Cuts". Given an image represented by a weighted undirected graph, G = V, E, in which each image voxel p is represented by a node in the graph and each edge links the voxel p to its neighbouring voxel q, a binary graph cut associates each node in the graph with either of two special terminal nodes (labels) called the 'source' node S or the 'sink' node T. Now the segmentation problem has been transformed to binary graph cut problem. This approach can be extended to multiple labels by using α expansion algorithm [3].

This graph cut problem (min cut/max flow problem) can also be formulated in such a way so that it minimizes certain energy functions. These energy functions are given by MRF, this particular function has the form

$$E_I(f) = \lambda \sum_{p \in \mathcal{P}} D_p(f_p) + \sum_{\substack{\{p,q\} \in \mathcal{N} \\ \{f_p \neq f_q\}}} V_{p,q}. \quad \text{.........(1)}$$

Above equation gives the energy term associated with assigning each voxel, p ∈ P, one of the labels in the label set L = {S,T }.

Here $D_p(f_p)$ denotes the data term that measures how well label f_p can be assigned to voxel p. $V_{p,q}$ represents the neighbourhood term that penalizes discontinuities between each voxel pair {p, q}, this term is dependent on voxel neighbourhood N. Coefficient λ weights the relative contribution between the data term and the neighbourhood term, this value is set manually depending on the input data property. The success of graph cut segmentation relies heavily on the metric of the edge weights for the terminal links and neighbourhood links in the graph. If this metric is more efficient than the method will perform better.

In the energy formula (eq. 1) there are two terms, data term and neighbouring term. These terms are explained below:

II. I. **Terminal Links**

The edge weight of the terminal links (T-links) in the graph is calculated from

$$T_p(L_i) = \lambda D_p(L_i),$$

$$D_p(L_i) = -\ln P_I(I_p | L_i),$$

λ gives the relative contribution between the terminal links and the neighbourhood links. $D_p(Li)$ is defined as the negative log-likelihood of the image intensity distribution,

II. II. **Neighbourhood Links**

In graph cuts smoothness is enforced by N-link weights. Intensity and other features can be combined into the calculation of the neighbourhood links (N-links) weights. In this paper they have used only intensity term for calculation of N-link term. In this paper they have used Lorentzian error norm [4] to measure the intensity difference between two voxel nodes p and q within a neighbourhood.

$$\rho(p,q) = \ln\left[1 + \frac{1}{2}\left(\frac{|I_p - I_q|}{\sigma}\right)^2\right]$$

where robust scale σ can be estimated from the input image [4]. The N-links weights are than given by:

$$N_{p,q} = V_{p,q} = 1/(1+\rho).$$

II. III. **Graph cuts with atlas prior**

Including atlas in brain MRI segmentation refer to incorporating prior knowledge of brain anatomy and tissue properties into the segmentation framework. The MRF energy function given in equation (1), is reformed to include this atlas-based prior knowledge. The MRF energy equation now becomes

$$E(f) = \gamma E_I(f) + (1-\gamma)E_A(f),$$

$E_A(f)$ is the atlas-based energy term which is derived below. The user-selected parameter, $\gamma \in [0, 1]$, moderates the trade-off between the two terms and is derived empirically.

These probabilistic priors are generated by registering a sufficient number of pre-segmented MRIs to a canonical atlas space. The choice of registration method is important for effective atlas construction. A diffeomorphic flow-based registration method guaranteed to maintain topology [5] was used in their works.

The prior probability that a voxel is assigned a label is estimated by averaging the manual labelling of that pixel over the set of registered subjects within the canonical atlas space. They denote this average as PA. They define the energy contribution from each voxel labelling as

$$E_A(f_p) = -\ln P_A(f_p),$$

where fp ∈ {S,T }. Combining all the energies, the total energy function needs to be minimized is given by

$$E(f) = \sum_{p\in\mathcal{P}} \{\lambda\gamma D_p(f_p) + (1-\gamma)E_A(f_p)\} + \gamma \sum_{\substack{\{p,q\}\in\mathcal{N} \\ \{f_p\neq f_q\}}} V_{p,q}.$$

III. Implement details:

The implementation was done in two phases, first I tried to do the segmentation using only data term and neighbouring term (N-link). The atlas term was than considered to make the segmentation more efficient. For segmentation without atlas prior, I tried to use the source code of paper [3], problem faced in using original Graph Cut paper implementation (written in C) is that it needs to be initialize in order to perform segmentation. This is not the case with our problem so we can't just use their method here. The possible solution was to initialize the labels using another (previous) segmentation technique, but our work doesn't use the original paper exactly and introduce some variation in neighbouring term. This variation in neighbouring term is followed from [4].

The paper uses dataset generated by BrainWeb MR Simulator, with 9% noise and 40% intensity inhomogeneity level. BrainWeb simulator uses .mnc file format for data and it's not supported by either Matlab or ITK. Only some inefficient external toolkits are available. I was not able to process the BrainWeb database, so I used ibsr dataset provided by Harvard university, it has data in the form of .img and .hdr(much easier to handle using mri toolkit). The dataset I used had 20MRI images of Normal Brain along with ground truth. All these images were of size 256*256*60 with voxel size of (1x1x3)mm. Brief description of used dataset is given below:

III. I. **Brief description of dataset:**

For first 10 images the size of each image is 256*256*60 with the voxel size of (1x1x3)mm. Other details and the parameters used in the data acquisition are:
First 10 are FLASH scans on four males and six females on a 1.5 tesla Siemens Magnetom MR System with:
TR = 40msec, TE = 8msec, flip angle = 50 degrees, field of view = 30 cm,
slice thickness = contiguous 3.1 mm, matrix = 256x256, averages = 1

Next 10 are 3D-CAPRY scans on six males and four females on a 1.5 tesla General Electric Signa MR System with:
TR = 50 msec, TE = 9 msec, flip angle = 50 degrees, field of view = 24 cm, slice thickness = contiguous 3.0mm, matrix = 256x256, and averages = 1.

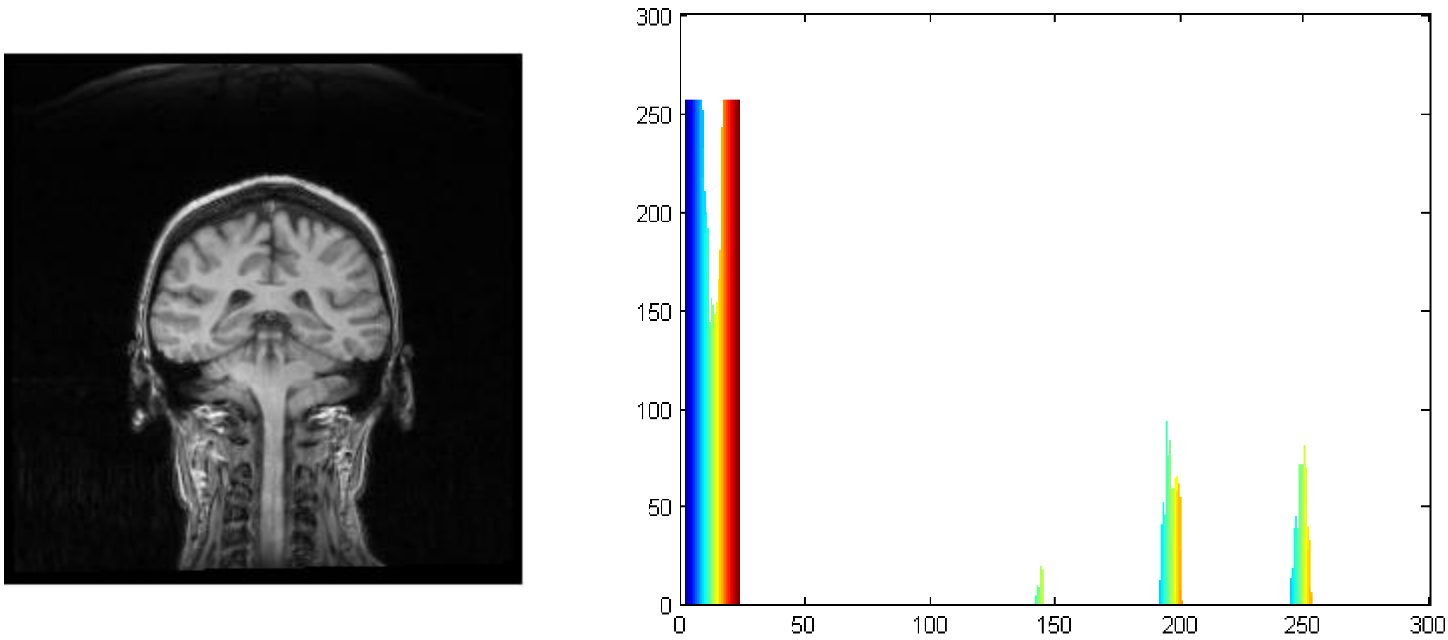
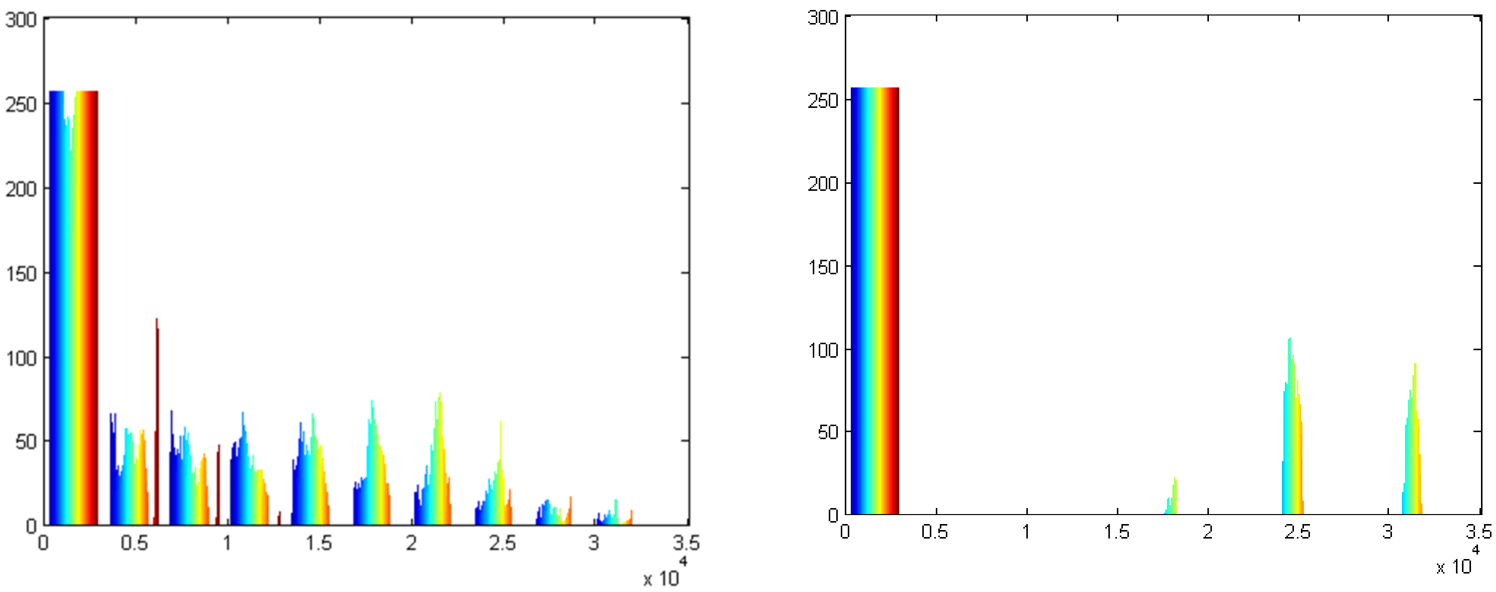


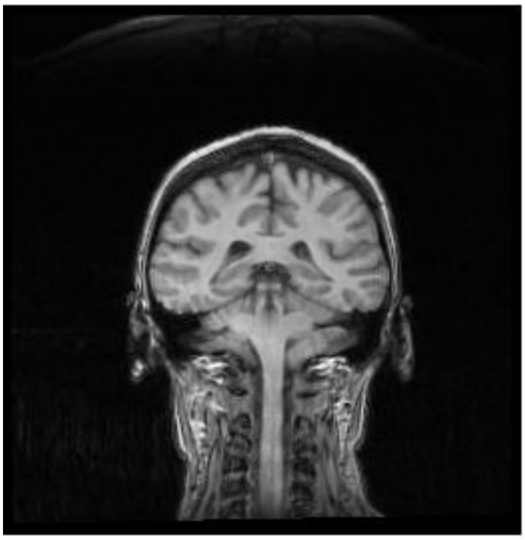
Fig.1 Slice of input image and its histogram

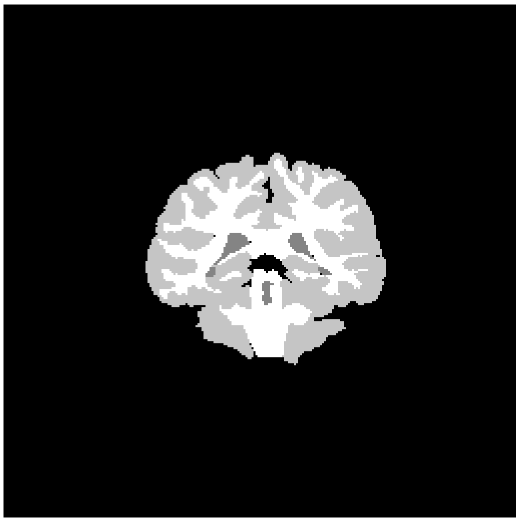
Above is the sample input slice and corresponding histogram. We can see that the histogram peaks in three locations, these are the intensity values corresponding to the intensity of Gray matter, White matter and CSF. The highest peak of histogram is at zero values. This peak represents the background pixels, which does not belongs to any of the category. This histogram corresponds to a sample slice, if we look at the histogram of whole image than it turns out to



(a). The histogram Is shown for 16-bit image. X-axis is Values and Y axis corresponding freq.
(b). Histogram for label image (ground truth)

As you can see from the above histogram the maximum intensity value present in the given image is around 3.3k, which is much more than 255 (highest value supported by 8-bit monitor/projecter). There is a need of converting these 16bits to 8bits. These techniques are called windowing. Windowing is the process of choosing 8-bits out of 16-bits effectively. Here we have chosen 8 MSB's of the 16-bit data as our 80bit data.



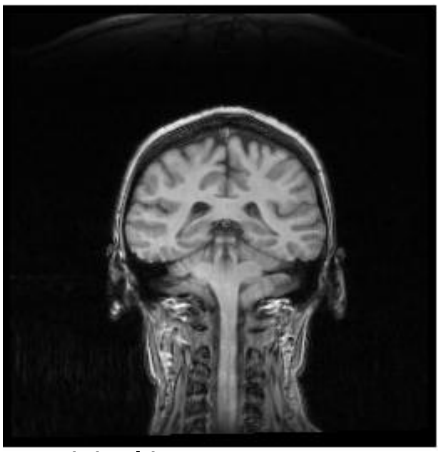


Sample slice along with GT

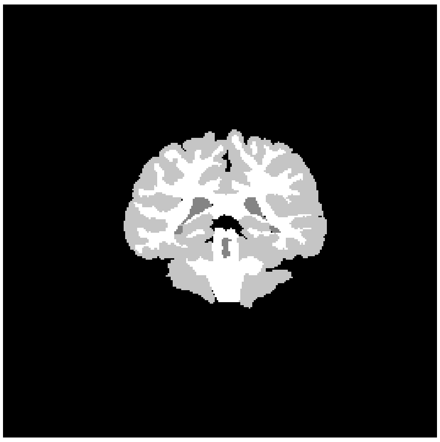
IV Results

The results of implemented algorithms are presented in this section. These results are shown in three parts. First the segmentation results are shown using only data term. Then the results are presented using both data and neighboring terms. Finally the results are presented after considering atlas term also.

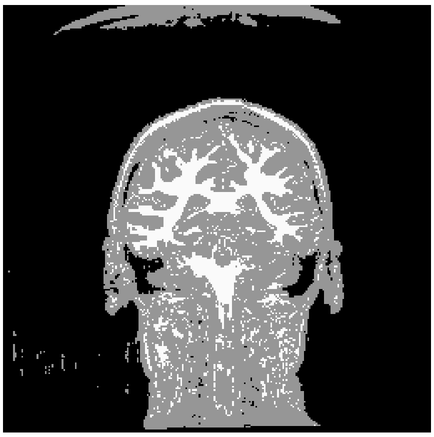
IV.I. **Data term:**



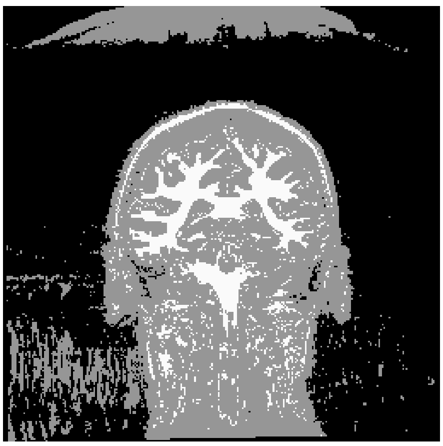
Original image



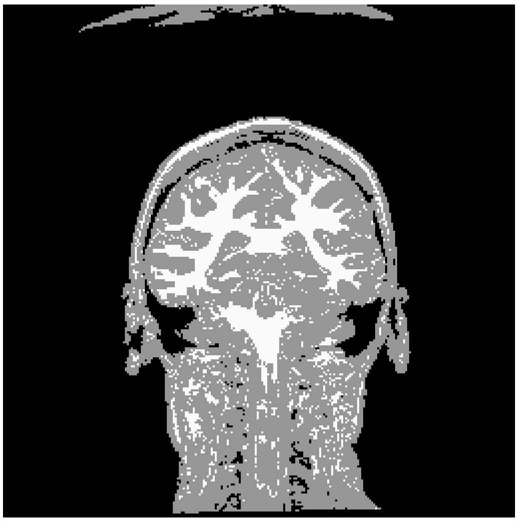
Ground truth



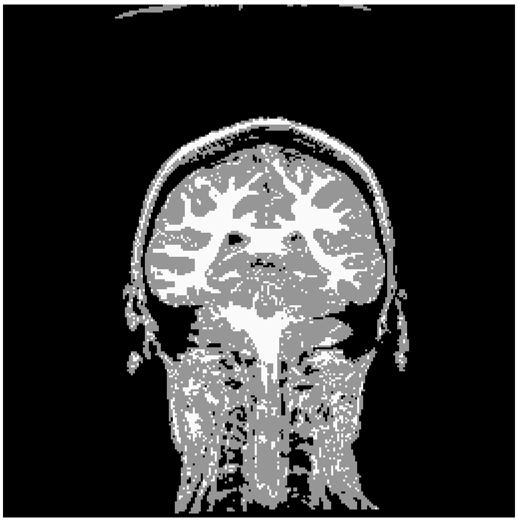
10



20



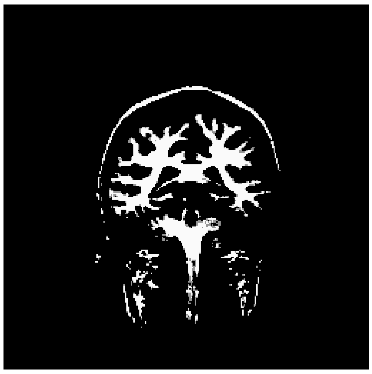
30



50

100

125



150

The algorithm is confusing the gray matter and background because their intensity value is Overlapping and we are only considering intensity values here.

NOTE: in the last presentation ma'am told me to first segment and then applies this segmentation technique. I will try that and update the results in updated report(depends on the deactivation time of the portal).

IV. II. Data term and neighbourhood term:

(a). Segmented image with thres. 125 (b). After applying data term and (c). After Opeing with strel('disk',3) object.

V. Final words and conclusion:

The problem of image segmentation is an essential problem in IP, and there is need of robust system for this problem. Current technologies don't solve the problem very efficiently and introduction of graph cuts have helped in the improvement of the overall segmentation accuracy. This topic was chosen as a MIP project because it seemed interesting approach and it was among the very popular technique for segmentation.

VI. References:

1. http://en.wikipedia.org/wiki/Image_segmentation
2. M. Yan and J Karp, "An adaptive bayesian approach to three dimensional mr brain segmentation," in *Proc. XIVth Int. Conf. Information Processing Medical Imaging*, 1995, pp. 201–213
3. Boykov, Yuri, Olga Veksler, and Ramin Zabih. "Fast approximate energy minimization via graph cuts." Pattern Analysis and Machine Intelligence, IEEE Transactions on 23.11 (2001): 1222-1239.
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6. Song, Zhuang, et al. "Adaptive graph cuts with tissue priors for brain MRI segmentation." Biomedical Imaging: Nano to Macro, 2006. 3rd IEEE International Symposium on. IEEE, 2006.