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MRI Brain image segmentation using graph cuts

Master of Science Thesis in Communication Engineering

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Göteborg, Sweden, 2010   Report No. EX072/2010

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Abstract

Over the last few years the graph cuts method became very popular in image processing and analysis area due to smoothness and energy minimization. Brain Magnetic Resonance Image (MRI) segmentation is a complex problem in the field of medical imaging despite various presented methods. MR image of human brain can be divided into several sub-regions especially soft tissues such as gray matter, white matter and cerebrospinal fluid. The graph cuts are used in medical image segmentation following few dynamic algorithms. The combinatorial optimized algorithm with the minimum cut and maximum flow techniques provides solution to overcome the associated challenges of segmented brain MRI. The min-cut/max-flow algorithm comprises three predominant stages- growth, augmentation and adoption with two non-overlapping search trees S and T and roots at the source s and the sink t respectively. This thesis paper investigates two algorithms to segment brain tissues and to implement the competent one through simulations by MATLAB software. Image pre-processing, edges and boundaries detection, histogram thresholding and segmentation with graph cuts will be performed in applying the selected method. Segmentation results comparison by the existing software tool of the normalized cut algorithm and applied simulations of the min-cut/max flow algorithm provide quantitative brain image analysis. Evaluation of segmented tissues by these methods is based on ground truth labeling and time consumption and will represent the standard benchmarks for segmentation. Further research will lead this pixel based automatic segmentation in distinguishing more brain tissues and performance improvement.

Key words: Magnetic Resonance Imaging (MRI), segmentation, graph cuts, min-cut/max flow, normalized cut.

Contents

Acknowledgements

This thesis work wouldn't have been successfully completed without the constant support of a number of people and I would like to express my sincere gratitude to them for their spontaneous help and encouragement.

First of all, I would like to thank my supervisor and examiner Prof. Irene Yu-Hua Gu for providing me the opportunity to work on the brain MR image segmentation. Throughout the entire project period her depth of knowledge on the topic, suggestions for continuous improvement, encouragement and supervision helped me to conduct this research work productively. Besides, she has been very concerned on the project progress, which has made this project as a successful one.

I would also like to thank Mr. Fhang and Dr. Imad for assisting me out during the entire project period with various resources, constructive suggestions and ideas which helped me in a number of ways.

I am deeply thankful and want to express my honest appreciations to my dear friends Kallol, Tilak, Johan, Shuvo, Asif, Rupok who helped me time to time with problem solving, idea generation, and providing required project related information. I appreciate their precious time, assistance and moral support.

Finally, my heartfelt thanks go to my wife, Rifat Sharmelly, my parents and all my family members for believing in me and inspiring me during the project duration.

1. Introduction

Segmentation subdivides an image into its regions of components or objects and an important tool in medical image processing [1]. As an initial step segmentation can be used for visualization and compression. Through identifying all pixels (for two dimensional image) or voxels (for three dimensional image) belonging to an object, segmentation of that particular object is achieved [2]. In medical imaging, segmentation is vital for feature extraction, image measurements and image display [2, 3]. Segmentation of the brain structure from magnetic resonance imaging (MRI) has received paramount importance as MRI distinguishes itself from other modalities and MRI can be applied in the volumetric analysis of brain tissues such as multiple sclerosis, schizophrenia, epilepsy, Parkinson's disease, Alzheimer's disease, cerebral atrophy, etc [4]. Graph cuts is one the image segmentation techniques which is initiated by interactive or automated identification of one or more points representing the 'object'. In this technique one or more points representing the 'background' are called seeds and serve as segmentation hard constraints where as the soft constraints reflect boundary and/or region information. An important feature of this technique is its ability to interactively improve a previously obtained segmentation in an efficient way.

1.1 Background

In image segmentation the level to which the subdivision of an image into its constituent regions or objects is carried depends on the problem being solved. In other words, when the object of focus is separated, image segmentation should stop [1]. The main goal of segmentation is to divide an image into parts having strong correlation with areas of interest in the image. Segmentation can be primarily classified as complete and partial. Complete segmentation results in a set of disjoint regions corresponding solely with input image objects. While in partial segmentation resultant regions do not correspond directly with input image [5]. Image segmentation is often treated as a pattern recognition problem since segmentation requires classification of pixels [2].

In medical imaging for analyzing anatomical structures such as bones, muscles blood vessels, tissue types, pathological regions such as cancer, multiple sclerosis lesions and for dividing an entire image into sub regions such as the white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) spaces of the brain automated delineation of different image components are used [2, 3]. In the field of medical image processing segmentation of MR brain image is significant as MRI is particularly suitable for brain studies because of its excellent contrast of soft issues, non invasive characteristic and a high spatial resolution.

Graph-cuts are one of the emerging image segmentation techniques for brain tissue identification. It has been introduced for image analysis since 2001 through global energy minimization [6]. It is used with various algorithms for quantitative analysis, content based image search. The efficient graph cuts algorithm performs optimal and accurate segmentation with minimum cut and maximum flow.

Image segmentation is an essential tool in medical image processing and is used in various applications. For example, in medical imaging filed is used to detect multiple sclerosis lesion

quantification, surgical planning, conduct surgery simulations, locate tumors and other pathologies, measure tissue volumes, brain MRI segmentation, study of anatomical structure etc [3]. Other practical applications of image segmentation are machine vision, traffic control system, face and finger print recognition and locate objects in satellite images. Image segmentation with graph cuts technique has potential usefulness for everyday applications like image cropping and colorization along with the multi-view image stitching, video texture synthesis, image reconstruction, n-dimensional image segmentation etc [5].

1.2 Problems and challenges of brain image segmentation

There are a number of techniques to segment an image into regions that are homogeneous. Not all the techniques are suitable for medical image analysis because of complexity and inaccuracy. There is no standard image segmentation technique that can produce satisfactory results for all imaging applications like brain MRI, brain cancer diagnosis etc. Optimal selection of features, tissues, brain and non–brain elements are considered as main obstacles for brain image segmentation. Accurate segmentation over full field of view is another hindrance. Operator supervision and manual thresholding are other barriers to segment brain image. During the segmentation procedure verification of results is another source of difficulty.

1.3 Scopes and objectives of the thesis

Various medical imaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT) provide different perspectives on the human brain. Many segmentation techniques such as mean shift, region growing, water shed, graph cuts, fuzzy connectivity etc. are available for medical imaging especially for brain MRI. Graph-cuts are one of the leading segmentation techniques to efficiently solve a wide variety of brain tissue identification. Energy minimization along with image smoothing is performed with the graph cuts method. Different types of algorithms such as new minimum-cut/maximum flow (min-cut/max-flow), push-relabel, augmenting paths etc. are used in graph cuts method as well as the normalized cut.

The aim of this thesis is to perform brain MR image segmentation applying the min-cut/max-flow algorithm of graph cuts technique. In this regard, MATLAB simulations with the mentioned algorithm will be conducted to implement in graph cuts technique. Results comparison of the min-cut/max-flow algorithm with the normalized cut will be accomplished to evaluate segmentation quality.

1.4 Outline

The thesis is organized as follows. Chapter 1 provides the introductory part and background information of the thesis topic as well as research scopes and goals identification. Literature review of various segmentation techniques and different kinds of algorithms are discussed in Chapter 2. Theoretical analysis of graph-cuts technique, problem formulation and methodological approach of the new minimum cut/maximum flow algorithm is depicted in Chapter 3 which is the foundation of this thesis work. Simulation results with MATLAB software applying the algorithm are presented in Chapter 4. Detailed discussions and quantitative evaluation of the results are explored and analyzed in Chapter 5. Finally conclusions have been made in Chapter 6 along with recommendations for future research work.

2. Brief review of segmentation methods

This chapter provides a brief literature study of the segmentation techniques used in medical image analysis. Segmentation of an object in an image is performed either by locating all pixels or voxels that form its boundary or by identifying them that belong to the object. In medical imaging, segmentation is an important analysis function for which lots of algorithms and methods have been built up. Variability of data is quite high in medical image processing especially for analyzing anatomical structure and tissue types [2]; hence segmentation techniques that provide flexibility, accuracy and convenient automation are of paramount importance.

2.1 Mean shift

Mean shift method is a non-parametric technique to examine a complex multi-modal feature space and to classify feature clusters. Size and shape of the region of interest are the only free parameters in this method. In mean shift segmentation in order to estimate the density gradient, the density estimation is changed. A two step sequence of discontinuity preserving filtering and mean shift clustering is utilized in this segmentation technique [5]. In mean shift process for each point in data space first, the region of interest is obtained like a spherical window [hs hr]. Next, the mean shift is calculated as below.

$$m_{h,G}(x) = \frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x - x_i}{h}\right\|\right)^2}{\sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|\right)^2} - x$$

Here, x_i is the initial estimate of this iterative method, $g\left(\left\|\frac{x-x_i}{h}\right\|\right)$ can be considered as the kernel function which determines the weight of nearby points for re-estimation of the mean. Lastly, the center is shifted to the new one unless the mode is found. This algorithm places $x \leftarrow m_{h,G}(x)$ and repeating is occurred until $m_{h,G}(x)$ is converged to x.

2.2 Histogram thresholding

The most uncomplicated image segmentation process is histogram thresholding since thresholding is fast and economical in computation. For segmenting background and objects, a threshold which is defined as brightness constant is used. Band thresholding, local thresholding, multi thresholding and semi- thresholding are some of the modifications of this technique. Single thresholds that can differ in image elements are known as local threshold whereas Single thresholds that can be applied to the complete image are known as global threshold. In order to determine the threshold automatically, threshold recognition approaches are exploited. Threshold recognition approaches can employ optimal thresholding, p-tile thresholding and histogram shape analysis. Optimal thresholding results in minimum error segmentation as the threshold as the closest gray-level corresponding to the minimum probability between the maxima of two or more normal distributions is established through this approach. For color or multi band images multi-spectral thresholding is suitable. As a minimum between the two highest local maxima, in bi-modal histograms the threshold is verified [5].

In the approach where based on the image histogram only one threshold is chosen for the complete image, then it is called global thresholding. It is assumed that the object in interest can be extracted from the background comparing image values having threshold value T (32,132) and the image has a bimodal histogram. In Figure 1, the bimodal histogram of an image $f(x, y)$ with selected threshold T has been illustrated.
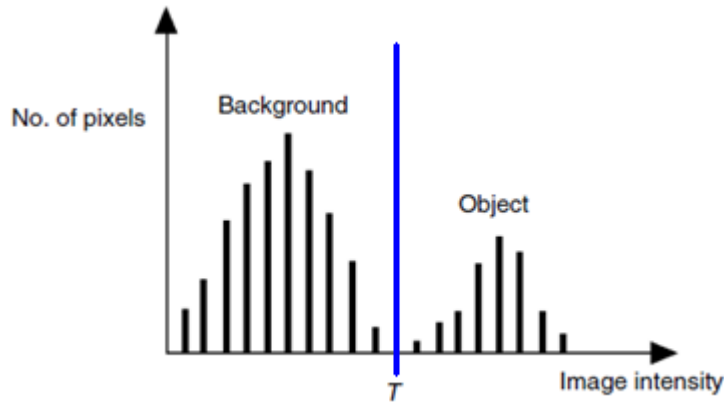

Figure 1. Bimodal histogram of an image f(x, y) with selected threshold T [2].

The threshold image $g(x,y)$ can be represented as below:

$$g(x,y) = \begin{cases} 1 & if\ (x,y) > T \\ 0 & if\ (x,y) \leq T \end{cases}$$

The resultant image is a binary image from global thresholding where pixels that correspond to objects and background have value 1 and 0 respectively. Simple and rapid calculation is the main advantages of global thresholding [2]. When thresholding relies on local properties of some image regions, then it is called local thresholding. It can be established in either of the two ways. In the first way through dividing an image into sub images and calculating threshold for each sub image thresholding can be obtained. In the other way image intensities in the region of each pixel is studied and thresholding is obtained.

Image histogram can be made better through applying image preprocessing techniques. Image smoothing is one this preprocessing technique. Gaussian filter is one of the smoothing filters where based on a Gaussian function convolution mask coefficients are $g\ [i, j]$ for each pixel $[i, j]$.

$$g[i,j] = exp\frac{-(i^2 + j^2)}{2\sigma^2}$$

Here σ refers to the spread parameter. Better image smoothing is implied through larger σ.

2.3 Region growing

In region growing / region merging segmentation technique pixels with similar intensities are grouped. With a pixel or group of pixels known as seeds belonging to the structure in focus, the first step of this technique is started. Pixels in small neighborhood region are examined in the next step and added to the growing region on the basis of homogeneity criterion. Until no more pixels can be adjoined to the growing regions, this step continues. Finally, the object illustration is done by all added pixels to the growing regions.

In the medical image segmentation field region growing technique can be applied in kidney segmentation, cardiac images, extraction of brain surface etc. The capability of generating joined regions and appropriately segmenting regions having matching property are the benefits of this segmentation method. One of the drawbacks of this method is that dissimilar starting points may not result growing into identical regions. In addition to this, since outcome of region growing is dependent on homogeneity criterion, failure in correctly choosing criterion may result in adjacent areas or regions not belonging to the object of interest [2].

'Hill climbing' which is a modification of region growing segmentation method was applied for identifying micro calcifications in mammograms. In hill climbing a slope value s(x, y) for each pixel is symbolized as

$$s(x,y) = \frac{f(x_0, y_0) - f(x, y)}{d(x_0, y_0, x, y)}$$

Here *f(x,y)* refers to the given image, pixel *(x_0,y_0)* refers to the edge of a micro calcifications to be segmented and $d(x_0, y_0, x, y)$ defines the Euclidean distance which exist between pixel *(x,y)* and the local maximum pixel [2].

2.4 Edge based segmentation

In edge based segmentation technique boundary on an image or an edge is defined by the local pixel intensity gradient. An estimation of the first order derivative of the image function is called a gradient. The magnitude of the gradient for a given image *f(x,y)* can be calculated as

$$|G| = \sqrt{[G_x^2 + G_y^2]}$$

The direction of gradient is represented as

$$D = \tan^{-1}(\frac{G_y}{G_x})$$

Here, gradients in directions x and y are expressed as G_x and G_y.

Edge-based techniques are fast in computation and usually in this approach a priori information about image content is not required. The most general problem of this approach is that often the edges do not enclose the object completely. In this segmentation technique the direction and magnitude can be presented as images. A post processing step of linking or grouping edges is required to structure closed boundaries neighboring regions. Weighed summation of the pixel

intensities in a small neighborhood can be represented as a numerical array in this method which is called as kernel/ window/mask. In a two 3X3 mask the following matrices are used.

$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

To compute G_x and G_y, first and second mask are used respectively. Finally, joining G_x and G_y using the mentioned equation, gradient magnitude image is obtained [2].

2.5 Graph cuts segmentation

Solving the pixel labeling problem is one of the most frequent applications of energy minimization in Computer Vision. Through pixel labeling problems image restoration, segmentation, problems as stereo and motion are generalized. In general energy functions like E are non convex functions in large dimension spaces and hence very difficult to minimize. However, when these energy functions have special characteristics, it is possible to find their exact minimum using dynamic programming. Nonetheless, it is usually necessary to rely on general minimization techniques, in the general case, like Simulated Annealing [7], which can be very slow in practice. A property of a graph cut C is that it can be related to a labeling f, mapping the set of vertices V−{s, t} of a graph G to the set {0, 1}, where f(v) = 0, if v ∈S, and f(v) = 1, if v ∈ T. A binary partitioning of the vertices of the graph is defined through this labeling.

Graph cut optimization has become well accepted in the area of early vision since it was proposed as an efficient way to minimize a larger class of energy functions. Various problems as image segmentation [8], [9], image restoration [10], [11], [12], image synthesis [13], stereo and motion [10], [11], [14], [15], [16] can be solved by graph cuts. The optimality of graph cut minimization methods depends on the number of labels and the exact form of the smoothness term V. In [12] is proved that when the problem is a binary labeling problem, the method yields global minimum solutions, while in [14] proved that, it is possible to compute global minimal, if the smoothness term is restricted to a convex function. Creation of a specific graph for every specific problem was required in the early proposals utilizing graph cut optimization as a technique for energy minimization. A common scheme for graph cut minimization of energy functions has been introduced in [17].

Numerous graph techniques are existed which are exploited in image segmentation such as minimum spanning trees, shortest path, graph-cuts etc. Among all these typical graph partitioning methods graph-cuts are comparatively new and the most powerful one for image segmentation [5]. Flexible and accurate global optimization and computation efficiency are achieved with graph cuts segmentation. Graph-cut segmentation was first initiated as binary image reconstruction approach in Greig et al. 1969. The graph optimization algorithm such as the combination of min-cut and max-flow was presented in Boykov and Jolly, 2001 as a powerful method of optimal boundary and region segmentation in n-D image data. The method was initiated by them for automated identification of 'object' and 'background' with the terms seeds, segmentation hard constraints and soft constraints for region information.

Image segmentation relates basically background and object which can be employed as binary labeling problem. Boykov and Jolly [9] mentioned the segmentation of a monochrome image that solves a two labels problem in the graph cut method. Considering a set of labels L and a set of sites S, the labeling problem can be assigned as a label $f_p \epsilon L$ and each of the site $p \epsilon S$. The label set $L = \{0,1\}$ where 0 indicates background and 1 indicates object. For a labeling problem if $f = \{f_p | f_p \epsilon L\}$ for all pixels, the energy minimization Markov Random Field (MRF) equation [5] can be written as:

$$E(f) = \sum_{p \epsilon S} D_p(f_p) + \lambda \sum_{\{p,q\} \epsilon \mathcal{N}} \omega_{pq}.T(f_p \neq f_q)$$

In the energy minimization equation, the first term called as data term consists of constraints from the observed data and measures how the labels are assigned. Label f_p fits with site p and is measured by D_p. The second term which is the smoothness term measures to what extent f is not piecewise smooth. N represents the neighborhood system like 4 or 8-connected system. If $f_p = f_q, T(f_p \neq f_q)$ becomes 0 and 1 otherwise. In image segmentation it is expected the boundary to be positioned on the edges. Hence the typical selection of ω_{pq} is:

$$\omega_{pq} = e^{-\frac{(I_p - I_q)^2}{2\delta^2}} . \frac{1}{dist(p,q)}$$

Color values of Sites p and q are represented by I_p and I_q along with distance between p and q is presented by $dist\ (p,q)$. Level of variation between neighboring sites is expressed by the parameter δ. The relative importance of the data term versus smoothness term is revealed by the parameter λ.

Most of the existing graph-cuts algorithm can be categorized in two predominant groups viz. augmenting path method of Ford and Fulkerson , 1969 and push-relabel method of Goldberg and Tarjan , 1988 [5]. The augmenting path algorithm shows that the flow is pushed through the graph from source, s to sink, t until the maximum flow is reached. If no flow is present between s and t, the process is initialized with zero flow status. In the push-relabel algorithm, the excess flow is pushed towards the nodes with shorter estimated distances to the sink. A labeling of nodes is maintained with lower bound estimate of its distance is maintained to the sink node. Beside these two categories, min-cut/fax flow algorithm is initiated by Boykov and Jolly with minimization of the energy function. Normalized cuts algorithm by Jianbo and Jitendra [18] is another new dimension for graph-cuts segmentation in the field of image analysis.

2.6 Fuzzy connectivity
In this method the hanging-togetherness is utilized for recognizing image essentials that from the same object. The hanging-togetherness is explained applying the fuzzy logic. The local fuzzy relationships are explicated using fuzzy affinity. In this segmentation technique one global fuzzy relationship is fuzzy connectedness where every pair of image components are assigned with a value base on the affinity values along all possible paths between these two image elements [5].

2.7 Optimal single and multiple surface segmentation

In this medical image segmentation technique in a transformed graph through optimal graph searching single and multiple interactive surfaces are categorized. In this technique transforming the problems into calculating combinatorial explosion in calculation is evaded. Minimum s-t cuts, this technique is dissimilar to the direct graph cut method. Through integrating mutual surface-to-surface interrelationships as inter-surfaces arcs in $n + I$-dimensional graphs, multiple interrelating surfaces can be recognized in this method [5].

3. Graph Cuts: Theory

Since this work will be focused on graph cut based segmentation, the basic theory of graph cuts is reviewed in more details in this chapter. Further two algorithms that implement graph cuts are described, one is normalized cut from [18] and the other is min-cut/max-flow algorithm from [6]. Segmentation of brain image comprises mainly two types of classification viz. tissue segment and brain, non-brain element segment. Tissue segmentation like WM, GM and CSF divides brain matter into three labeled classes. This type of segmentation is done with various algorithm and techniques for direct analysis e.g. to measure brain atrophy and for correlation with functional metrics from other modalities e.g. positron emission tomography (PET) [19]. Graph cuts are quite a new technique to segment the brain tissues accordingly.

3.1 Graph partitioning for image segmentation

Image segmentation relates graph theory very closely especially in medical image analysis. Graph partitioning in imaging basically follows general version of the Gibbs model [5] with cost or capacity function C and image segmentation f as the solution is globally optimal for an objective function. The equation of the Gibbs model is narrated as follows.

$$C(f) = C_{data}(f) + C_{smooth}(f)$$

The first term of the above equation is the data term $C_{data}(f)$ and the second one is called smoothness term $C_{smooth}(f)$. A special class of arc-weighted graphs, $G_{st} = (V \cup \{s,t\}, E)$ is used to minimize $C(f)$. The set of nodes (vertices) V correspond to the pixels or voxels of the image. The terminal nodes such as source, s and sink, t represent segmentation labels object (O), background (B) as well as are hard linked with the seed points of segmentation. The arcs or edges E are categorized in two parts viz. n-links and t-links. The n-links connect neighboring pixels deriving from $C_{smooth}(f)$ and the t-links join pixels and terminals deriving from $C_{data}(f)$. Based on order of V and direction of E, the graph construction $G_{st} = (V, E)$ can be classified as undirected and directed graph.

Assuming all nodes are linked to source $s \in S$, all nodes are linked to sink $t \in T$ and no directed path is established from s to t, an s-t cut can be defined as a set of edges $C \subset E$ such that it is partitioning the terminal nodes into two disjoint subsets S and T on the induced graph, $G'_{st} = (V, E \backslash C)$. The minimum s-t cut represents a cut whose cost is in the minimal state over all cuts of G_{st}. According to graph theorem [20], the maximum source to sink flow is possible if it equals to the capacity of the minimum cut in graph G. The graph cuts are determined in way that the object seed terminal is connected with all object pixels and background seed terminal is joined with all background pixels along with general considerations: $O \subset V, B \subset V$ and $O \cap B = \emptyset$. An example is illustrated in Figure 2 to demonstrate the use of graph cuts segmentation.

(a) Image with seeds. (d) Segmentation results.
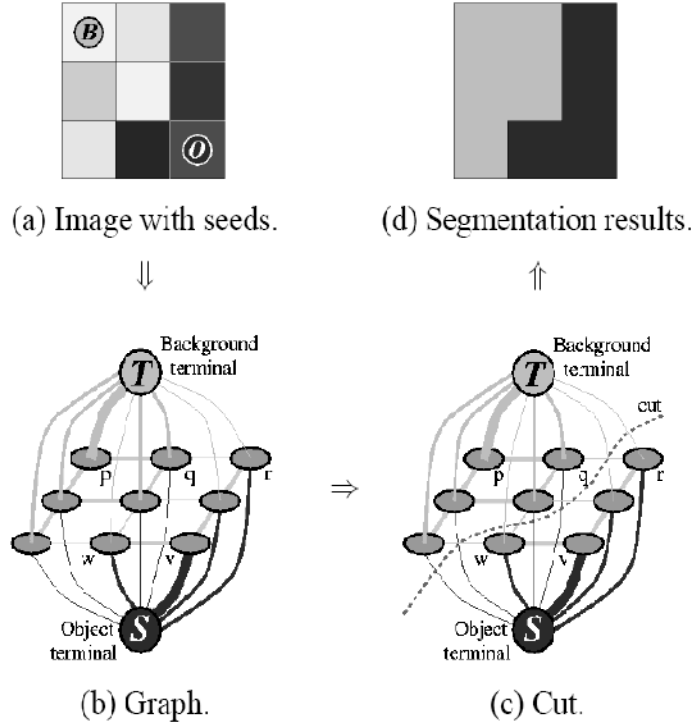
(b) Graph. (c) Cut.

Figure 2. Example of graph construction from a 3x3 image and 2D segmentation (a) Image with seeds such as background, B and object, O (b) Graph construction for two kinds of vertices, edges and pixels $(\mathbf{p}, \mathbf{q}), \mathbf{p}, \mathbf{q}, \mathbf{w}, \mathbf{v}, \mathbf{r} \in \mathbf{I}$ (c) Graph cuts segmentation (d) Segmentation results. (figure is copied from [9]).

Let a binary label $L_k \in \{o, b\}$ for each image pixel i_k of image I where o is for object label and b is for background label. The resulting binary segmentation is represented by labeling vector $\mathbf{L} = (L_1, L_2, \ldots \ldots, L_{|I|})$. A λ-weighted regional property term $R(\mathbf{L})$ and boundary property term $B(\mathbf{L})$ are used to minimize the cost function C to achieve optimal labeling. The Gibbs model can be formulated in the following way.

$$C(\mathbf{L}) \quad = \lambda\, R(\mathbf{L}) + B(\mathbf{L})$$

where,

$$R(\mathbf{L}) \quad = \sum_{p \epsilon I} R_p.\, L_p$$

$$B(\mathbf{L}) \quad = \sum_{(p,q) \epsilon N} B_{p,q}.\, \delta(L_p, L_q)$$

$$\delta(L_p, L_q) = \begin{cases} 1 \ if \ L_p \neq L_q \\ 0 \ otherwise \end{cases}$$

In the above equations, $R_p(o) \ and \ R_p(b)$ are utilized for costs of labeling the pixel p as object and background respectively. $R_p(o)$ will be large in dark pixels and small in bright pixels. For

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neighboring pixels p,q the term $B_{(p,q)}$ acts as cost associated local labeling function. $B_{(p,q)}$ will be large if both p and q are included either in object or background i.e. similar ; it will be small across the object or background boundary and will be close to 0 if p and q are fully different. The entire graph construction comprises both the n-links such as $\{p,q\}$ and t-links viz. $\{p,s\}$, $\{p,t\}$. Weights of each graph edges are employed to the graph according to Table 1. After finding a maximum flow from s to t the minimum s-t cut problem can be solved.

Table 1. Cost terms for graph cuts segmentation [5]

Graph edge	Cost	Condition
n-link $\{p, q\}$	$B_{\{p, q\}}$	$\{p, q\} \in N$
t-link $\{s, p\}$	$\lambda \cdot R_p(b)$	$p \in I, p \notin (O \cup B)$
	K	$p \in O$
	0	$p \in B$
t-link $\{p, t\}$	$\lambda \cdot R_p(o)$	$p \in I, p \notin (O \cup B)$
	0	$p \in O$
	K	$p \in B$

If an edge has non-negative capacity, a flow network can be identified. The maximum required flow capacity of the edge from source s to $p \in O$ or from $p \in B$ to sink t is represented by the below mentioned equation [5],

$$K = 1 + max_{p \in I} \sum_{q:(p,q) \in N} B_{(p,q)}$$

The graph cuts method is aimed to minimize the objective function i.e. energy of the image corresponding all required labeling for the object and background seeds. The summarization of steps used in graph cuts method can be depicted as below.

    i.   An edge directed graph representing size and dimension of the target segmenting image has to be created.

    ii.   Object and background seeds have to be distinguished properly with formation of two graph nodes-source s and sink t. Based on the object or the background labels, all seeds have to be connected with either source or sinks node.

    iii.   According to table 1 each link of the formed graph is to be associated with suitable edge cost.

    iv.   Any minimum s-t cut method is to be used which indicates the graph nodes representing image boundaries for object and background.

    v.   A suitable maximum flow solution for graph optimization is to be determined for graph cuts segmentation.

Graph-based segmentation is one of the commonly used techniques in imaging analysis. Often image segmentation is compared to graph partition procedures with the terminologies- source node i, sink node j, capacity based weight matrix W_{ij}.
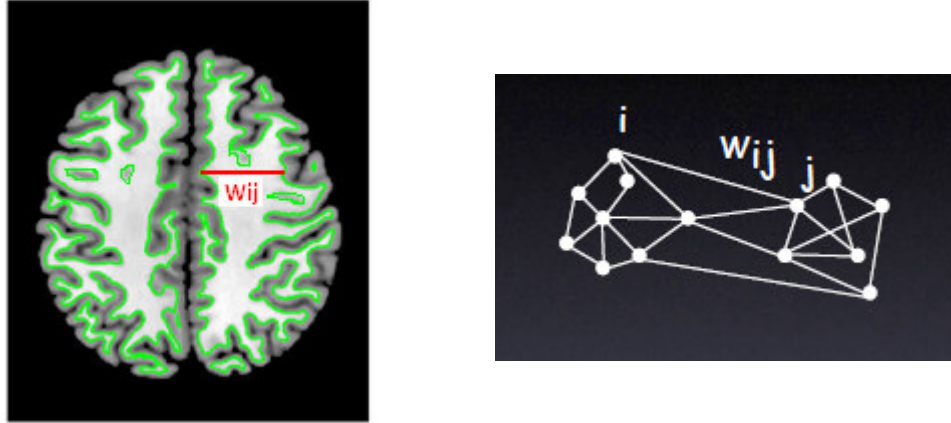
Figure 3. Graph formation from an image, I = {pixels} having source, sink and edge connection nodes (the right figure is copied from the tutorial used in [25]).

A brain MR image (Figure 3) can be represented by the set of pixels which are used as vertices V with source and sink nodes in graph formation. Similar pixels i.e. red, green, blue etc. of the image are equivalent to edge connecting nodes E in the graph theory. Prior knowledge of brain tissue characteristics is essential to deal with segmentation of brain MRI for complication and unpredictability.

The image considered in 3D format can be presented with a cost weighted graph $G = \{V, E\}$ for a set of voxel or source nodes P. The set of nodes V includes all voxels and terminals; $V = P \cup T$ where T is used for set of terminal nodes. The set of edges E comprises all n-links and t-links; $E = E_N \cup E_T$ where t-links nodes E_T is the set of voxel to terminal edges as well as n-links nodes E_N is the set of voxel to voxel edges in a certain neighborhood system. In formation of the graph from the brain image, three brain tissues- WM, GM and CSF are considered as terminal nodes [24] which are shown in Figure 4. E_T plays major role in segmentation representing the data term while E_N employs efficiency in a certain neighborhood corresponding the smoothness term. Costs are associated with E_T and E_N based on energy distribution of every tissue kind and measured similarity of nodes.

If a graph cut is done on the G i.e. $cut\ C \in E$, it implies that a set of edges are obtained maintaining the n-links and t-links nodes in two disjoint sets- $voxels\ P$ and $terminals\ T$. In this situation, each voxel node is connected with only one terminal node that indicates to its label and energy. The cost or capacity of this graph cut is equivalent to the sum of its edge weights indicated in the edge set C [10]. The graph cuts produce the segmented result $G = (V, E \backslash C)$.
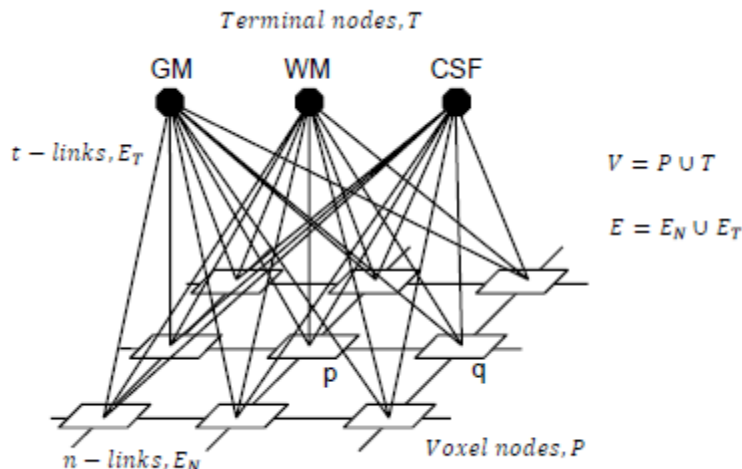
Figure 4. Graph formation, $G = \{V, E\}$ with three tissues-GM, WM and CSF for brain MRI segmentation (the figure is copied from [24]).

3.2 Min-cut/max-flow algorithm for graph cuts

The energy minimization procedures for machine vision and automated image segmentation are explored by Boykov and Kolmogorov in [6]. Based on augmenting paths, the min-cut/max flow algorithm is presented with two reusable and non-overlapping search trees- S: from source s and T: from sink t. Tree S has the direction of non-saturation from parent node to children and tree T has non-saturation from children to parent node. There can be active or passive node in S or T based on outer border and internal border respectively. Free nodes are those who are not in S or T considering the conditions: $S \subset V, s \in S, T \subset V, t \in T$ and $S \cap T = \phi$. The graphical illustration of this new algorithm is shown in figure 4.
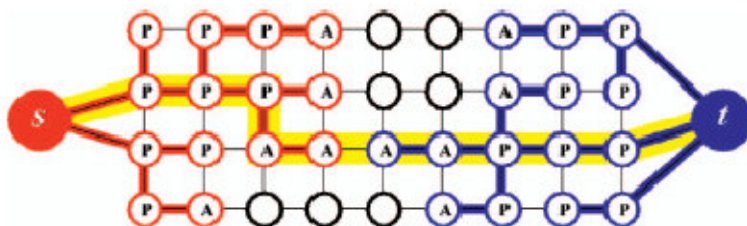
Figure 5. Example of the min-cut/max-flow algorithm in graph cuts segmentation (the figure is copied from [6]).

Red nodes indicate search tree S, blue nodes represent search tree T and yellow line is for the path from the source s to sink t. Free nodes are represented as black circle while active node is by A and passive node is by P in Figure 5. The combination of minimum s-t cut and maximum flow optimizations is accomplished with three steps-growth, augmentation and adoption in the segmentation procedure.

3.3 Normalized graph cut

The normalized cut is a global criterion for segmenting graph used in image data rather than focusing on local features and consistencies [18]. This algorithm is used as a criterion to measure total dissimilarity between various groups and total similarity within the groups. This technique can be applied on static general and medical imaging. The normalized cut, $Ncut(p, q)$ described as balanced cut is presented with the equation mentioned below.

$$Ncut(p, q) = cut(p, q).\left(\frac{1}{vol\ (p)} + \frac{1}{vol\ (q)}\right)$$

where

$$cut(p, q) = \sum_{i \in p, j \in q} S_{i,j}$$

volume of set: $\quad vol(p) = \sum_{i \in p} d_i, \quad p \subseteq V$

volume of set: $\quad vol(q) = \sum_{j \in q} d_j, \quad q \subseteq V$

Degree of node: $\quad d_i \quad = \sum_{i} S_{ij}$

Similarity matrix: $\quad S = [S_{ij}]$

In some cases, the minimum cut of the graph cuts can produce bad partition and the normalized cut can provide better cut [18] as the min-cut algorithm supports connected and isolated nodes which is shown in Figure 6.
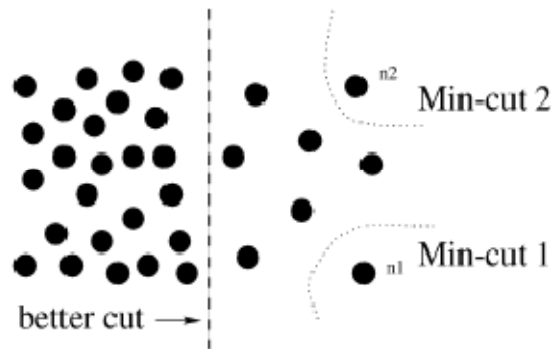
Figure 6. An example of minimum cut that provides bad partition (the figure is copied from [18]).

However, the combination of min-cut and max-flow algorithm optimize the isolation of nodes based on energy minimization [6] that provides outstanding performance for brain tissues segmentation.

3.4 Brain image segmentation using a combination of softwares

3.4.1 The MRIcroN software [21]

MRIcroN is widely used public software to view image of the neuroimaging informatics technology initiative (NIfTI) format. To convert the digital imaging and communications in medicine (DICOM) standard images into NIfTI and non-parametric statistical mapping (NPM) formats, MRIcroN software is applied with *dcm2nii* parameter. Multiple layers of images can be loaded easily in this software along with drawing volumes of interests and generating volume renderings. Several color schemes can be chosen for every layer. A series of slices of the currently open image in the 3D format can be seen with multi-slice windows option. This software can be downloaded from the link provided in [21] and installation instruction is provided.

3.4.2 FMRIB Software Library (FSL) [22]

Different kinds of analysis tools for brain imaging data such as MRI, functional MRI (fMRI), diffusion tensor imaging (DTI) etc. can be investigated by publicly available FMRIB software library (FSL). In structural MRI, FSL is used with several tools viz. brain extraction tool (BET), FMRIB's automated segmentation tool (FAST), FMRIB's linear image registration tool (FLIRT), FMRIB's nonlinear image registration tool (FNIRT) etc. BET and FAST are the predominant ones to analyze brain image segmentation especially brain and non-brain components are segmented by BET. The FSL software can be downloaded from the link provided in [22] and is easy to install in the personal computer.

4. Test systems for brain image segmentation

This chapter describes the test system used in this thesis for segmentation of brain images. The systems combine several software packages as building blocks to reach the goal of graph cuts-based image segmentation. The systems have been investigated to apply the min-cut/max-flow algorithm [6] in segmenting MRI brain image. The steps which are followed for the tests are: pre-processing, edge detection and boundaries selection, histogram thresholding and segmentation. A block diagram is shown representing the steps in Figure 7.
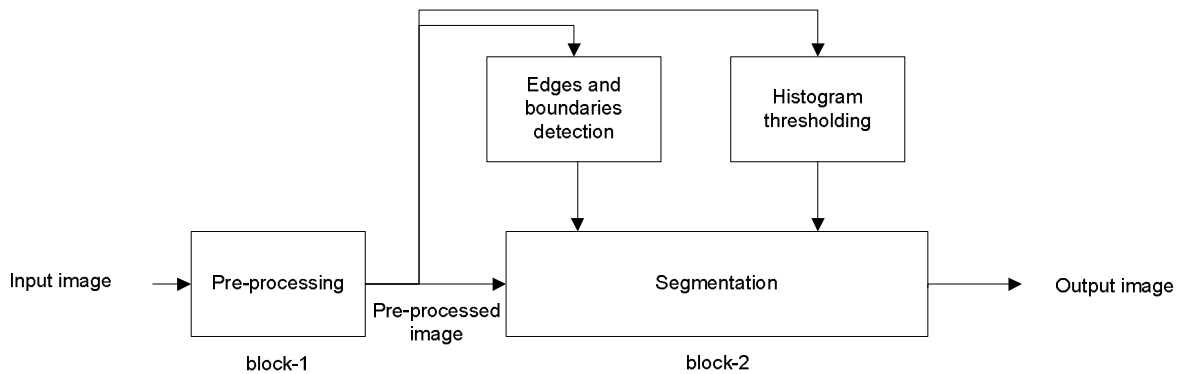
Figure 7. Block diagram of MRI brain image segmentation based on min-cut/max-flow algorithm in [6].

4.1 Pre-processing (block-1)

The input of this block is one slice of MRI brain image. A three dimensional (3D) slice of brain image is first pre-processed by MRIcroN software [21] followed by FMRIB Software Library (FSL) [22, 23]. This pre-processing step is attempted with two possible approaches: A or B. Approach A generates a pre-processed image through MRIcroN software, while approach B provides a pre-processed image by using FSL software followed by MRIcroN software. The 3D images are converted into two dimensional (2D) formats by taking the slices of brain MRIs. The output of this block is pre-processed image which is the input for segmentation block.

In Figure 8, block diagram of two different pre-processing methods is shown. The main difference between these two methods is that resulting images are with bones in approach A and approach B results images without bones.
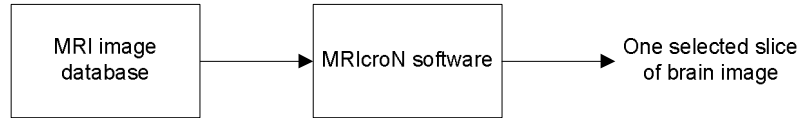
(a) approach A
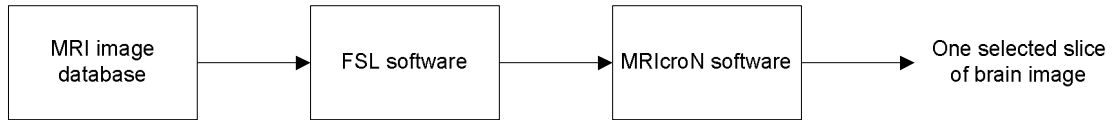
(b) approach B

Figure 8. Block diagram of two different pre-processing approaches for MRI brain image analysis (a) pre-processing approach A: extracted using MRIcroN software (source: NITRC- The source for neuroimaging tools and resources) (b) pre-processing approach B: extracted using FSL software (source: FMRIB software library) followed by MRIcroN software.

Pre-processing approach A:

An MRI brain image is chosen from the database of brain images to be pre-processed. Soft brain tissues such as WM, GM and CSF are surrounded by outward bone structure. A slice is selected on the brain image with bones using MRIcroN software. The segmentation accuracy depends on the slice selection; manual process is followed to select a slice of the displayed brain image (Figure 9). Finally, the selected slice is converted into two dimensional image format using MATLAB code.
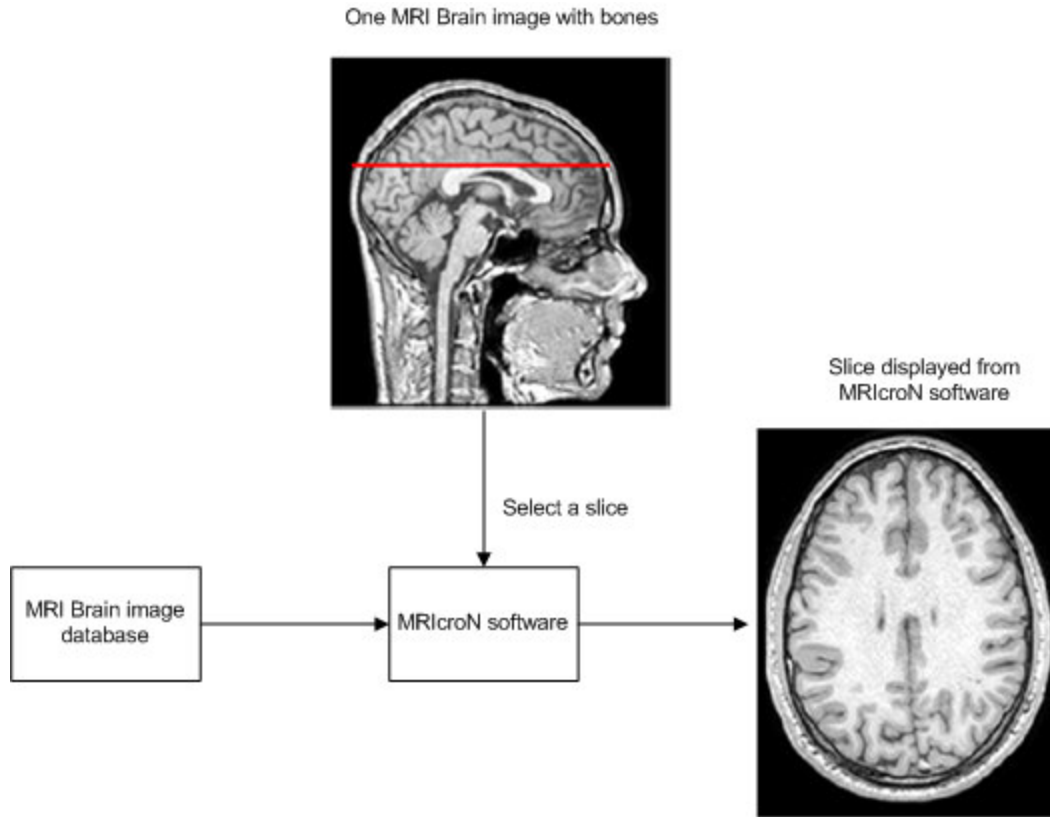
Figure 9. Pre-processing approach A using MRIcroN software for displaying the selected slice of brain image.

Pre-processing approach B:

It is important to extract the internal part of the tissues from the brain MRI for experiment results. Hence the FSL software [22, 23] is used to eliminate outward bone rings and the WM, GM and CSF are remained intact in the obtained brain MR image. An MRI brain image is chosen from the database of brain images to be pre-processed. A slice is selected on the FSL extracted brain image (without bones) using MRIcroN software. The segmentation accuracy depends on the slice selection; manual process is followed to select a slice of the displayed brain image (Figure 10). Finally, the selected slice is converted into two dimensional image format using MATLAB code.

One MRI Brain image with bones

One MRI Brain image without bones

Select a slice

Slice displayed from MRIcroN software

MRI Brain image database → FSL software → MRIcroN software →
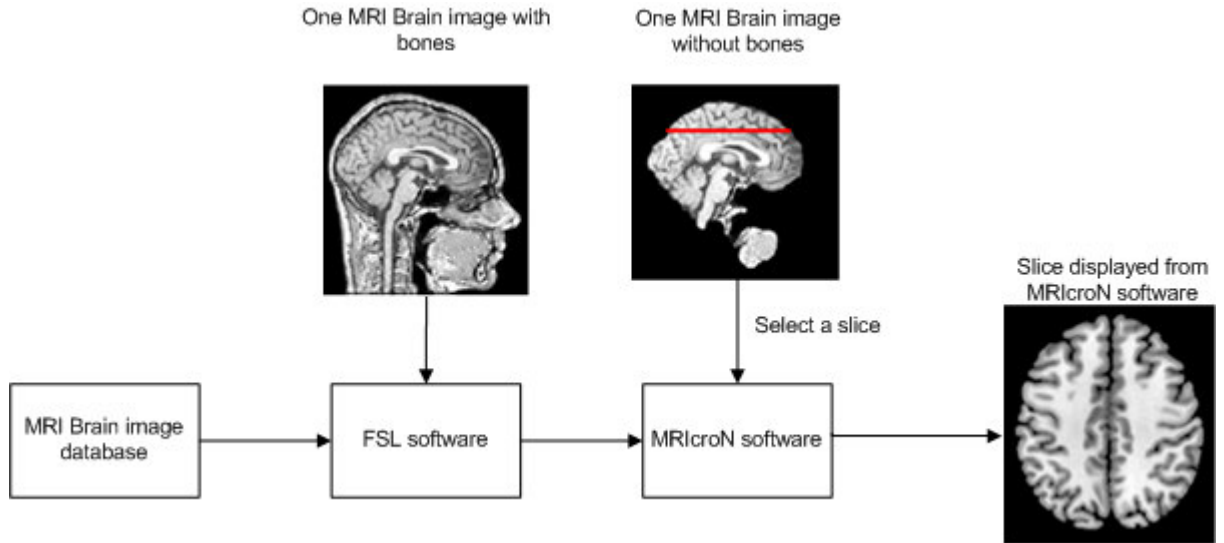
Figure 10. Pre-processing approach B using FSL software followed by MRIcroN software for displaying the selected slice of brain image.

4.2 Segmentation (block-2)

The input of this block is pre-processed image from block-1 which can be obtained by approach A or B. Edges and boundaries detection along with histogram thresholding are associated with segmentation process of block-2. We considered the pre-processed with approach B image of Figure 11 for test system purpose. The WM, GM and CSF of brain are represented by white, gray and black colors respectively except the background black color.
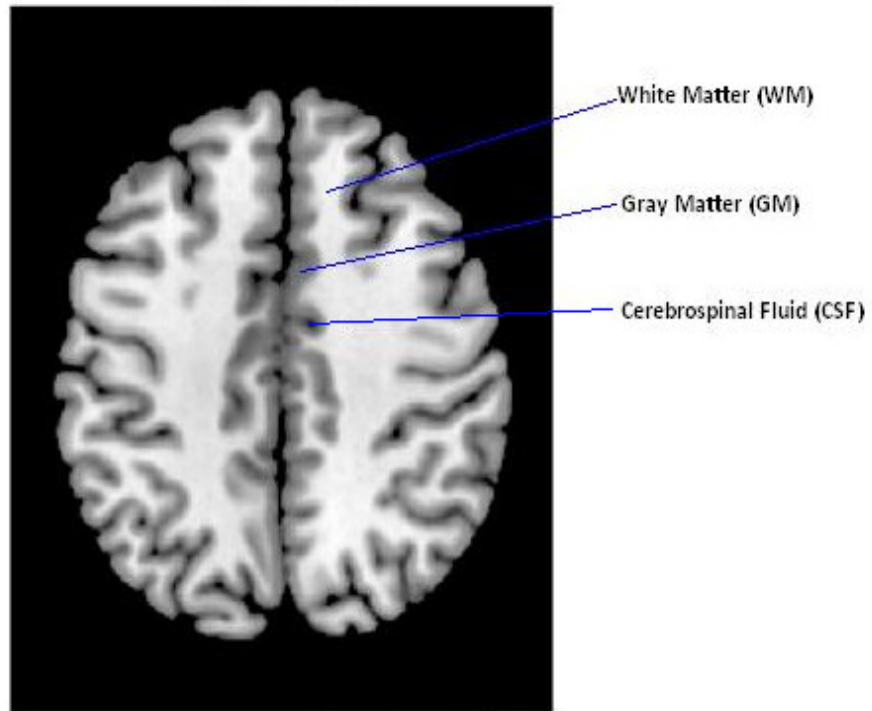
Figure 11. Pre-processed (using approach B) MRI image: Gray matter (GM), white matter (WM) and Cerebrospinal Fluid (CSF).

In the edge detection step, a two-dimensional (3x3) median filter is chosen to minimize the cost function of the image data and to reduce noise and preserve edges simultaneously. Every output pixel includes the median value in the 3 by 3 neighborhood around the corresponding pixel in the input brain image. To find the accurate edges, 'canny' detection method is used to construct the graph G_{st} on the filtered image as it finds edges by looking for local maxima of the gradient calculating the derivative (Figure 12). This method uses two main thresholds: detecting strong and weak edges along with the output of weak edges if they are connected to strong edges. The edge detected image has to be much smooth and intensity oriented for both connected and non-connected components. Hence, we used full two dimensional convolution of the edge detected image to make it smooth for both connected and non-connected components of different intensity and energy levels. Convolution is done for finding the connected (active or passive nodes) components and non-connected (free nodes) components in the search trees S and T, and costs are assigned on the edges of G_{st}. The boundaries of the brain tissues are detected also based on the different pixel intensity levels to apply in further segmentation process. Both the connected and non-connected components of the image like WM, GM or CSF are important to analyze for segmentation. The image is converted into red-green-blue (RGB) matrix format for viewing distinctly all connected and non- connected nodes.

Edges from the Canny edge detection algorithm | Outer and inner boundaries detection for the both connected and non-connected regions
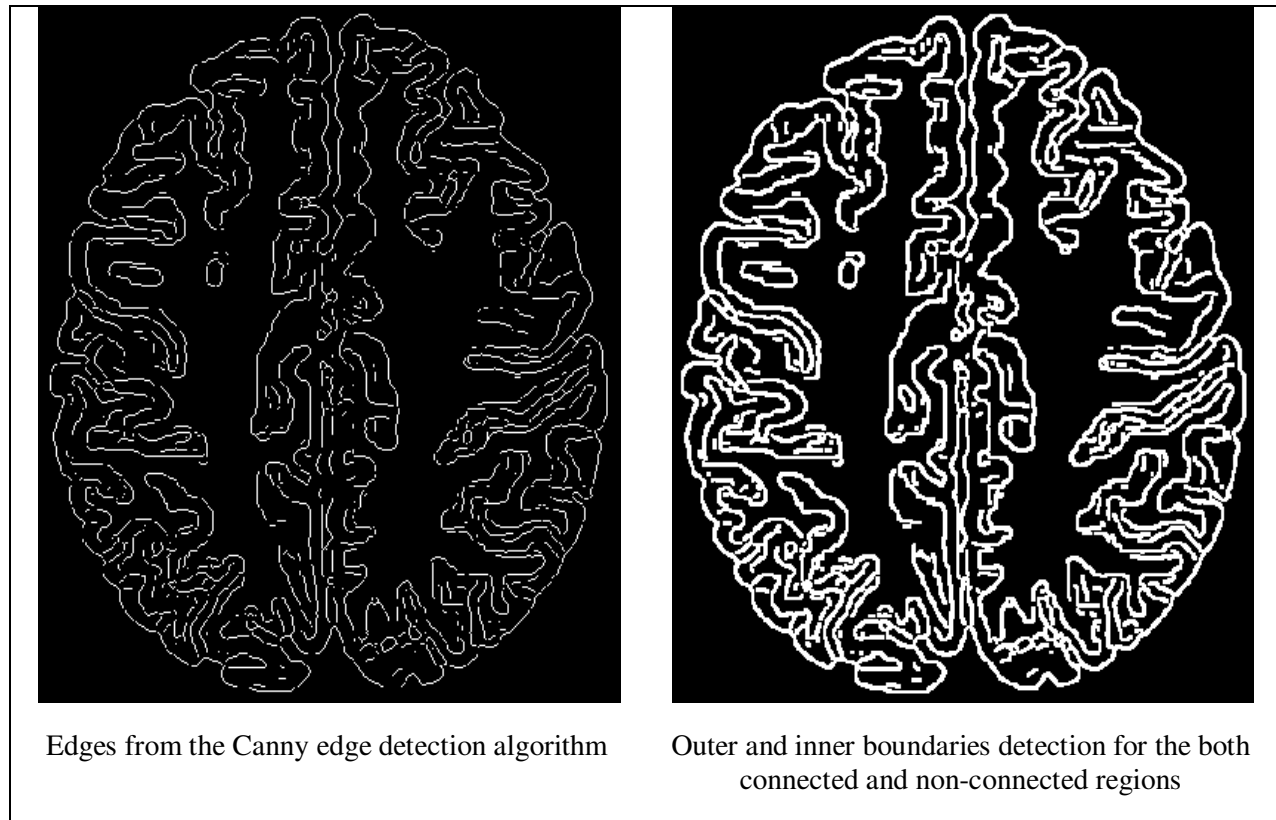
Figure 12. Left: Edges detection, right: boundaries detection of the pre-processed (using approach B) MRI image.

Histogram Thresholding step is essential in applying the graph cuts for the formation of two graph nodes – source s and sink t. Thresholding is selected manually based on each image. Histogram computation in accordance with pixel density and gray levels plays a vital role to identify objects and background of the image. Local thresholding technique is used in our approach after binary conversion of the brain image. The experimental brain image data are analyzed with its histogram for 256 gray levels and pixel counts as input. It is apparent to look the proportion of pixel numbers in each gray level of the image where 0 gray level represents the black image data and 255 white image data. From Figure 13, it can be described that in the range of 100 to 240 gray levels the pixel density contains image data information with black-white pixel combinations. The histogram analysis of the experimental image provides scientific explanation of the manual threshold value to be converted the image into binary format. In the histogram analysis the optimum threshold can be determined from 1 to 254 gray levels to get binary converted image. If the threshold level is changed, the binary image changes accordingly. Manual threshold values for pixel density have been fixed at threshold $T1 = 166$ gray levels for WM-GM and threshold $T2 = 115$ gray levels for GM-CSF to obtain output for the further image analysis.
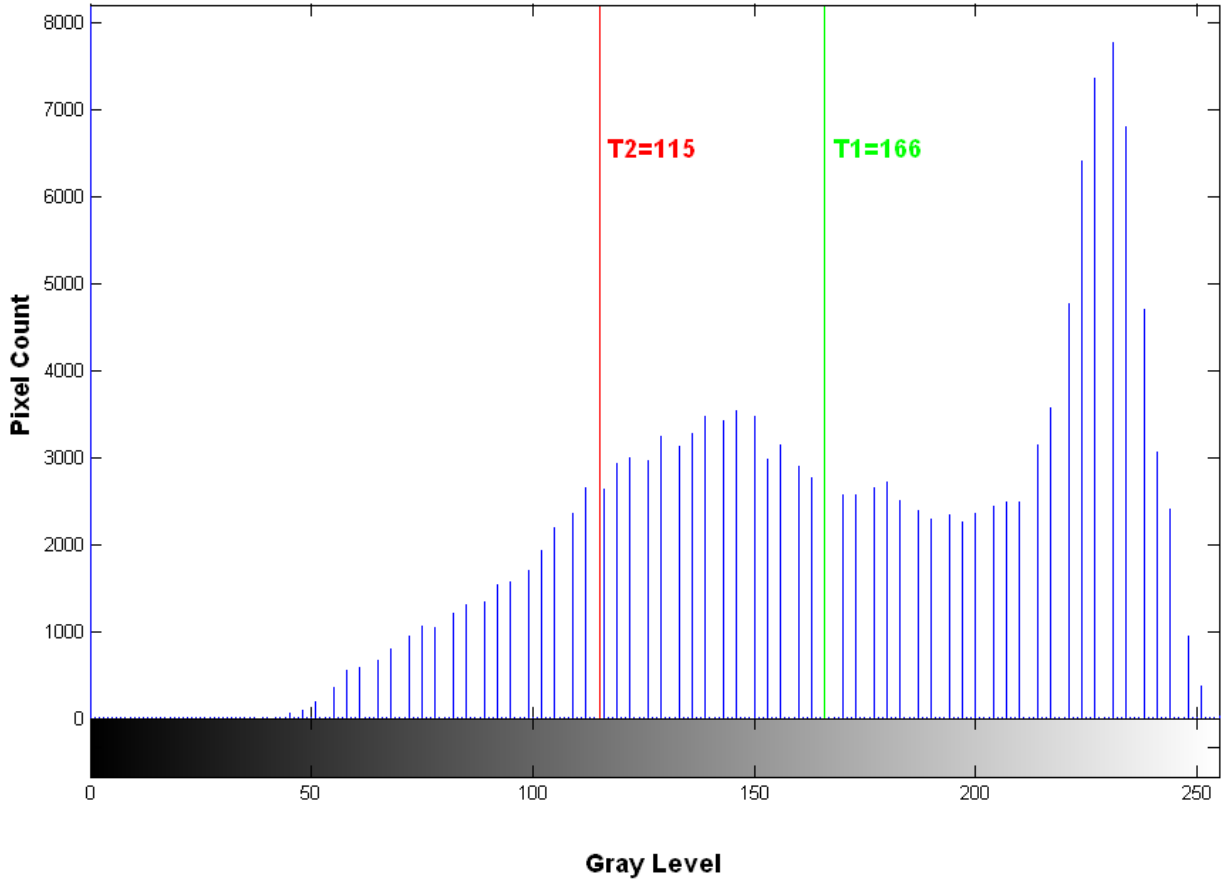
Figure 13. Histogram computation of an MRI image using two thresholds T1 and T2 where T1 is the threshold for white matter-gray matter; T2 is the threshold for gray matter-CSF.

The segmentation step is the crucial part which uses the min-cut/max flow algorithm of [6]. Energy minimization for the maximum connected components (active or passive nodes) ensuring max-flow optimization. Finally three main stages- growth, augmentation and adoption are employed to achieve brain tissues segmentation applying the minimum s-t cut. Let, $Tr(p)$ is the flag affiliated with each node p in search trees S and T,

$$Tr(p) = \begin{cases} S, & p \in S \\ T, & p \in T \\ \emptyset, & p \ is \ free \end{cases}$$

Parent, $Pt(p)$ stores information about p if it belongs to S or T. $Pt(p) = \emptyset$ if the source s, the sink t, orphans and all free nodes have no parents. Residual capacity or cost $RC(p \to q)$ is considered either for edge (p,q) if $Tr(p) = S$ or edge (q,p) if $Tr(p) = T$. The edges are regarded as non-saturated for node p to be valid parent of its child q based on S or T. In the growth stage new children are acquired by active nodes from a set of free nodes while S and T grow till their touch in a path, P from s to t. The found path is enhanced in the augmentation stage and search trees are broken into forests. In the initial state the orphan set is empty; there is possibility of having orphans in the end of this stage as path P becomes saturated with at least

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one edge. In the adoption stage, S and T are restored by processing all orphan nodes, O. In the same search tree, each node p tries to identify new and valid parent; p becomes children of a new parent or becomes free node.

| Pre-processed (approach B) image | Segmented image: Thresholds (T1,T2) (white-gray, gray-CSF) = (166,115); connected regions (CR) (white-gray, gray-CSF)=(6,2) |
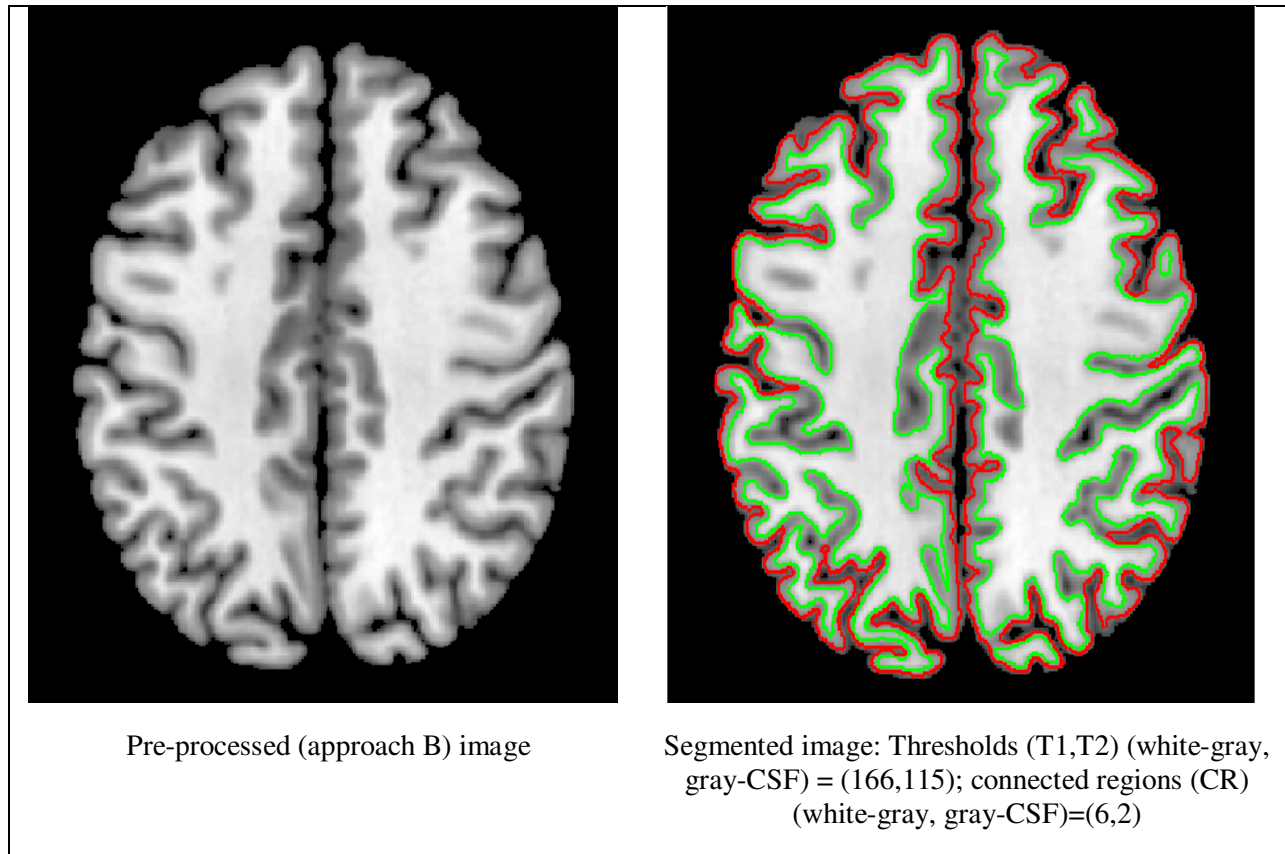
Figure 14. The graph-cuts segmented image of different tissues (white matter, gray matter and cerebrospinal fluid) using minimum-cut/maximum flow algorithm [6].

In Figure 14, the tissue-WM is segmented with green lines while tissue-GM is segmented with red lines. The set of edges is indicated by $E = E_N \cup E_T$ where E_N denotes the set of pixel-to-pixel edges in the defined neighborhood system (n-links) and E_T denotes the set of pixel-to-terminal edges (t-links). The segmentation is performed by applying the min-cut/max flow algorithm described in [6] taking into account directed and connected graph, $G = (V, E)$ where V represents for vertices and E for edges. If the list of all active nodes, A and all orphans, O are considered, the general structure of the algorithm can be described as:

Initialize:
Source,S = {s}, Sink, T = {t}, Active node, A = {s,t}, Orphan, Or = null
While
*   Grow   S or T to find an augmenting path, P from s to t*
*   if P = null, end.*
*   Augment   on P*
*   Adopt   orphans*
end

Active node helps the tree to grow by searching adjacent non-saturated nodes and acquiring new children from a set of free nodes while the passive node cannot grow as blocked by other nodes of the same tree. In this growth stage, newly acquired node becomes active member of the corresponding search tree. The certain active node becomes passive after finishing exploration of all the neighbors. The growth stage will be ceased if an active node finds a neighbor comprised of opposite search tree.

The path found in the growth stage is followed by the active nodes and is augmented through the excavated route which represents the augmentation stage. The input of this stage is a path P from s to t. The augmentation phase can split the search trees into forest. In the forest, s and t are the roots of the mentioned search trees while other orphans constitute roots of all other trees.

Adoption stage is used in our graph-cuts algorithm to restore the single tree structure of sets S and T with specific roots in source s and sink t. Each orphan is helped to find valid parent who will be in the same set S or T and connected through non-saturated edges. The orphan will be free node if there is no valid & qualifying parent found. In this way, if no orphans are left to be explored, the adoption stage is terminated and search tree S and T are formed.

In the brain tissues segmentation by the graph cuts method, three of the mentioned stages are iteratively performed and image data can be segmented based on minimum cut and maximum flow process. Let, $P(I|O)$ is the probability of a particular gray level corresponding to the image object and $P(I|B)$ is the probability of a particular gray level corresponding to the image background. The regional cost, R_p and the boundary cost B(p,q) are determined with the following equations [5].

$$R_p(object, o) = -\ln P\big(I_p|O\big)$$

$$R_p(background, b) = -\ln P\big(I_p|B\big)$$

$$B(p, q) = \exp\left(-\frac{(I_p - I_q)^2}{2\sigma^2}\right) \cdot \frac{1}{\|p,q\|}$$

Here, the distance between pixels p,q is denoted by $\|p, q\|$. σ is represented as expected intensity variation for the object and background of the brain image. If the image values within small differences ($|I_p - I_q| < \sigma$) for object or background, the boundary cost is high. In boundary locations positioned at $|I_p - I_q| > \sigma$, cost B(p,q) is low.

Discussion: variable thresholding in histogram based on local statistics:

Image thresholding enjoys a central position in application of image segmentation for its intuitive properties and simplicity of implementation. Global thresholding, optimum global thresholding with Otsu's method, image smoothing, image edges, variable thresholding based on local statistics and thresholding with moving averages are commonly used for image thresholding process [1].

In applying the min-cut/max-flow algorithm of graph cuts image segmentation, variable thresholding based on local statistics is used. If the background illumination of the image is non-uniformed, global thresholding methods typically fail. In that case variable thresholding is used to compensate for irregularities in illumination or in cases where there is more than one dominant object intensity. A threshold value at every point (x, y) in the image is computed for local statistics technique based on one or more specified properties of the pixels in a neighborhood of (x, y). We determined the basic approach to local thresholding using the standard deviation and mean of the pixels in a neighborhood of every point in the brain MR image because they are descriptors of local contrast and average intensity. The images below (Figure 15) illustrate some Matlab simulation results for different thresholdings in applying the graph cuts segmentation.

| Pre-processed (approach B) image | Segmented image: Thresholds (T1,T2) (white-gray, gray-CSF) = (115, 64); connected regions (CR) (white-gray, gray-CSF)=(2,1) |

(T1,T2)=(166,115), CR=(6,2)

(T1,T2)=(191,140); CR=(10,6)

(T1,T2)=(217,166); CR=(22,6)

(T1,T2)=(230,179); CR=(58,11)
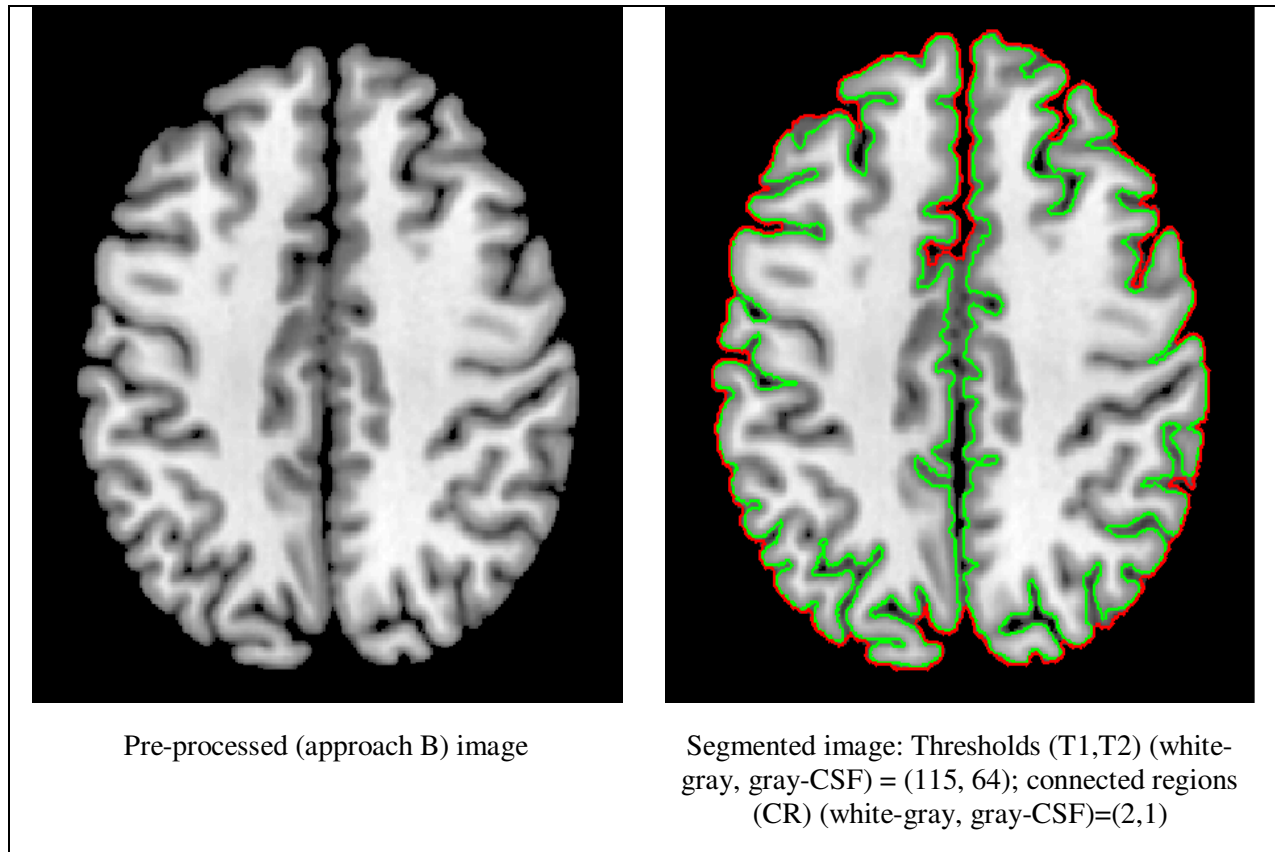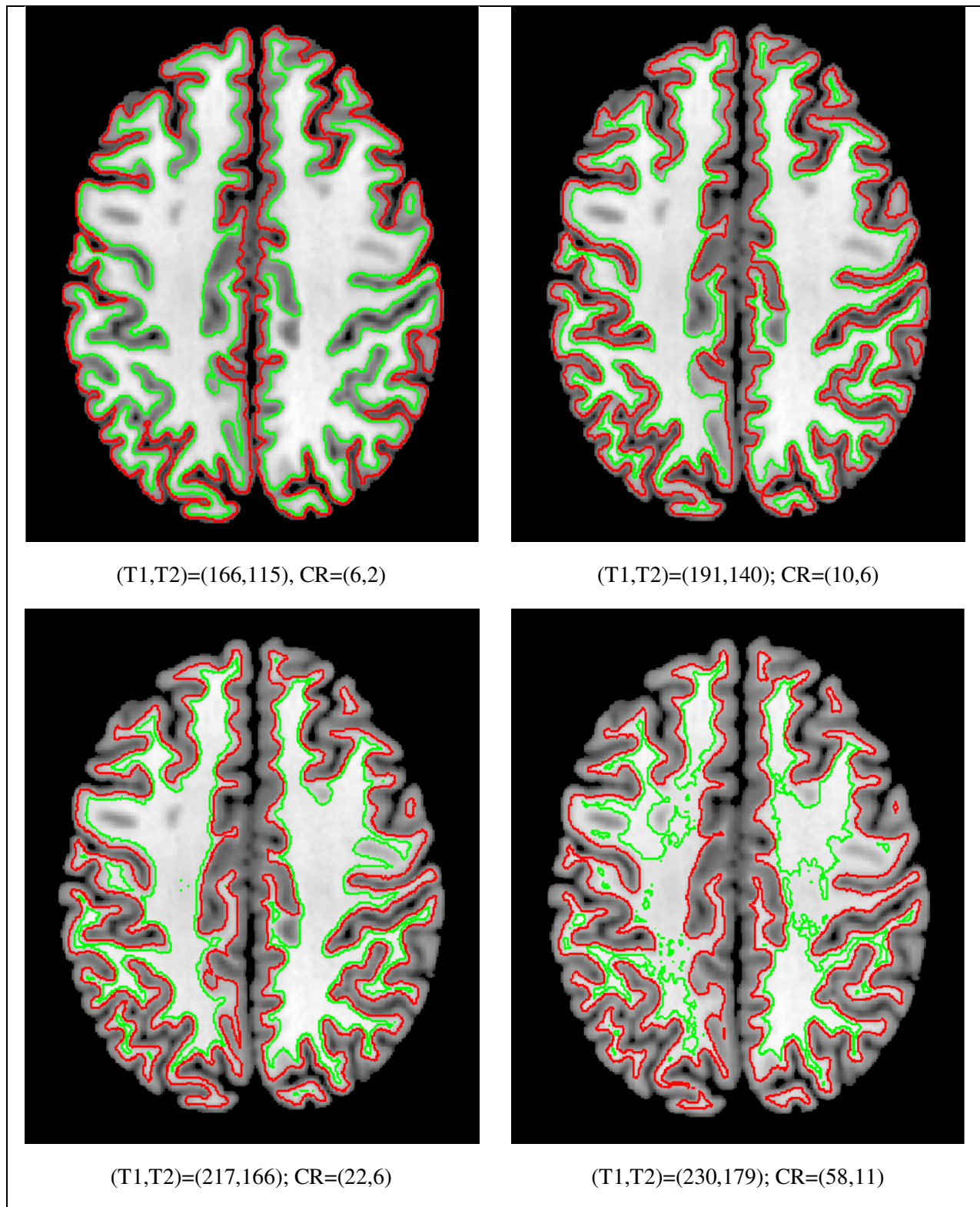
Figure 15. Segmented results from a pre-processed image (approach B) using different thresholds.

In 50 and 100 gray levels of variable thresholding, local statistics provide WM, GM segmentation to a little extent because of poor contrast and intensity. If the local threshold value exceeds 240 gray levels, the brain tissue segmentation level is decreased. Hence, the threshold values can be chosen in the range of 150-200 gray levels to obtain acceptable segmentation results with the min-cut/max-flow algorithm of graph cuts. Binary threshold varies the maximum connected energy levels which also reflect on augmentation and adoption stages of graph cuts. Threshold values are selected manually for the image slice especially for WM, GM and CSF tissues segmentation. Threshold T1 provides the number of connected regions between WM and GM in certain gray level and threshold T2 remarks the number of connected regions between GM and CSF in a gray level.

Discussion: pre-processing A (MRIcroN software) approach in segmentation

The pre-processing stage of brain MR image is important to perform analysis and segmentation appropriately. The brain MR images can be captured with human head's bone structure with MRIcroN software. Randomly five slices of one brain MR image have been chosen through the MRIcroN software to conduct test of our Matlab simulated program for the graph cuts. Brain tissues are segmented along with the bone structure which is not expected in the further analysis. Effects of pre-processed (approach A) brain MR images are illustrated in Figure 16 using five different image slices (slices 1-5).
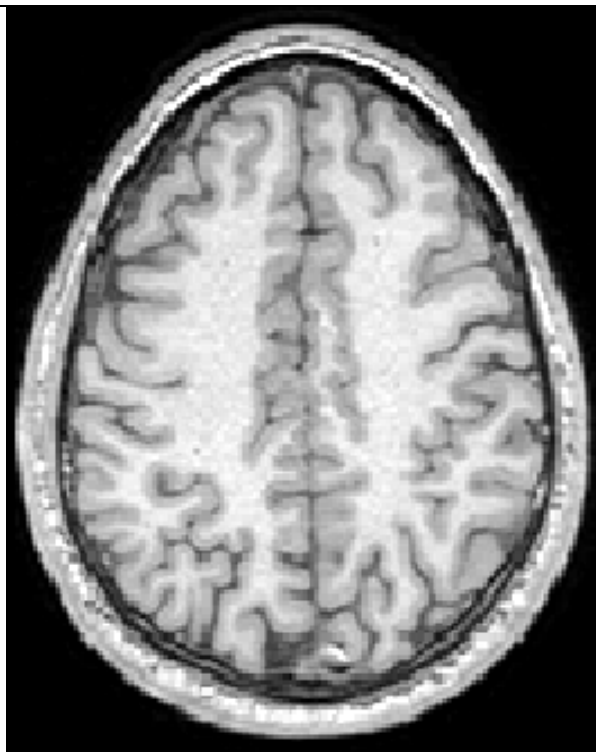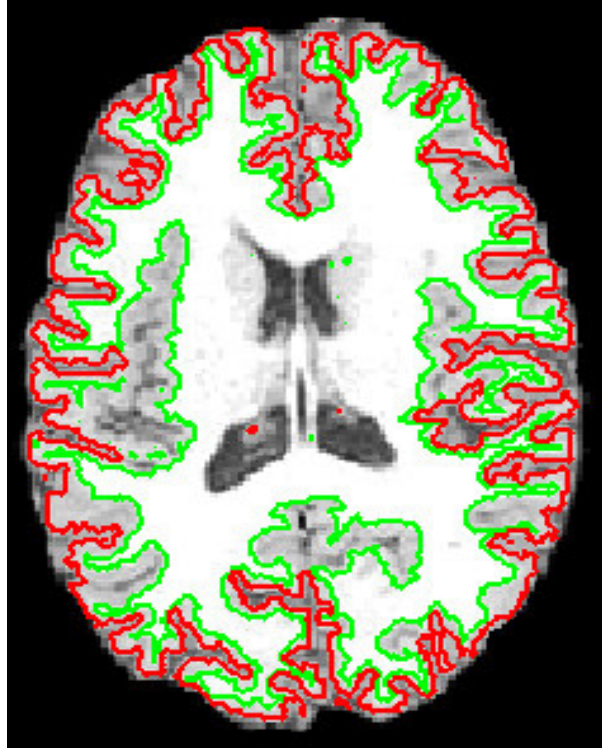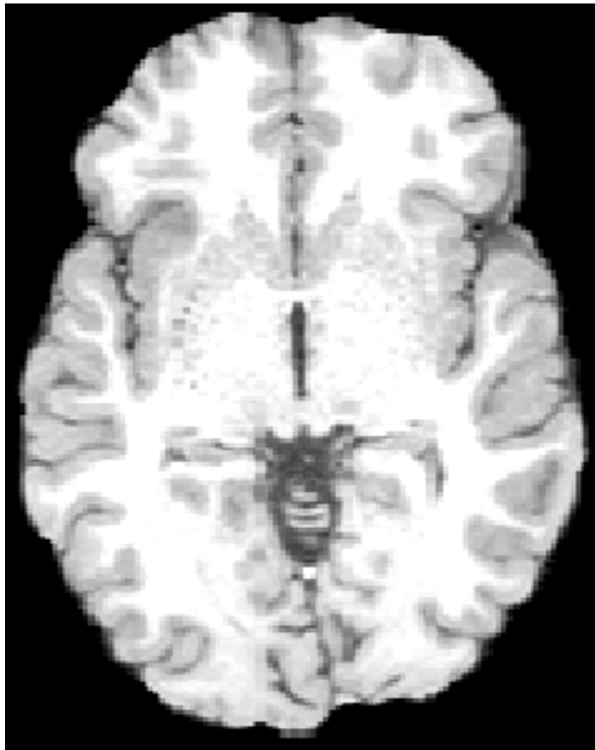

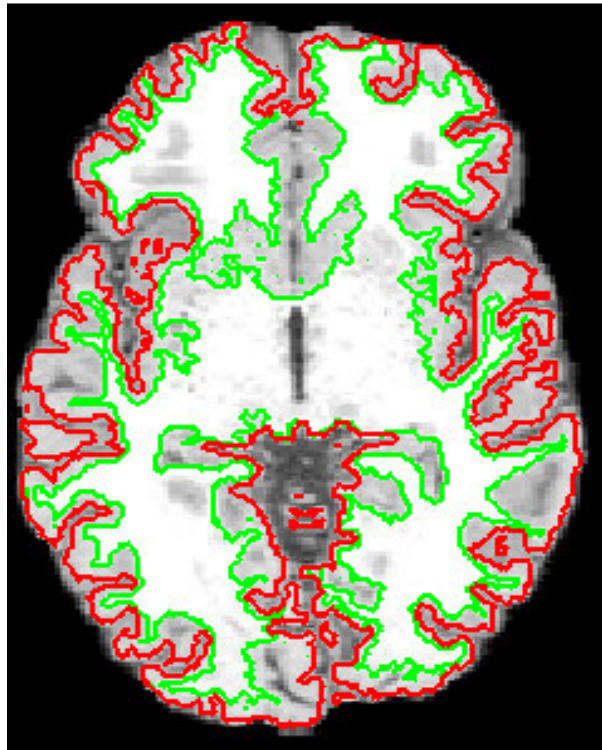| Pre-processed (approach A) image: slice-1 | Segmented from slice-1: connected regions (CR) (white-gray, gray-CSF)=(86,25) |
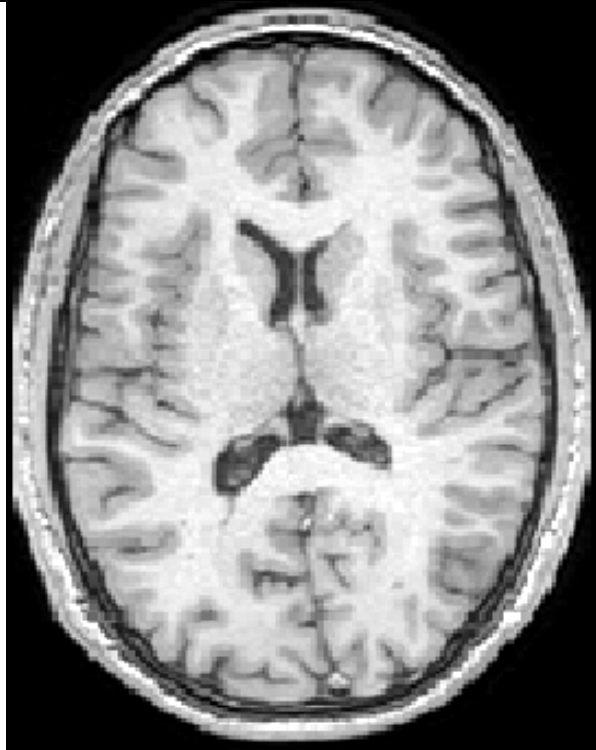
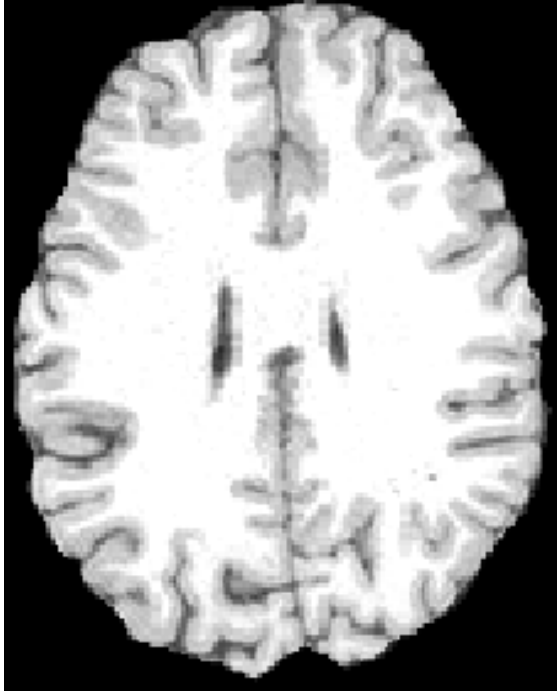Pre-processed (approach A) image: slice-2
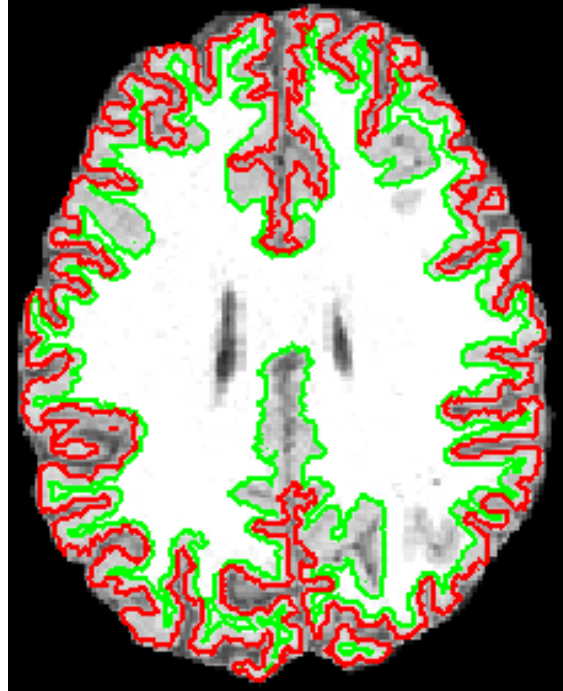
Segmented from slice-2: CR=(79,26)
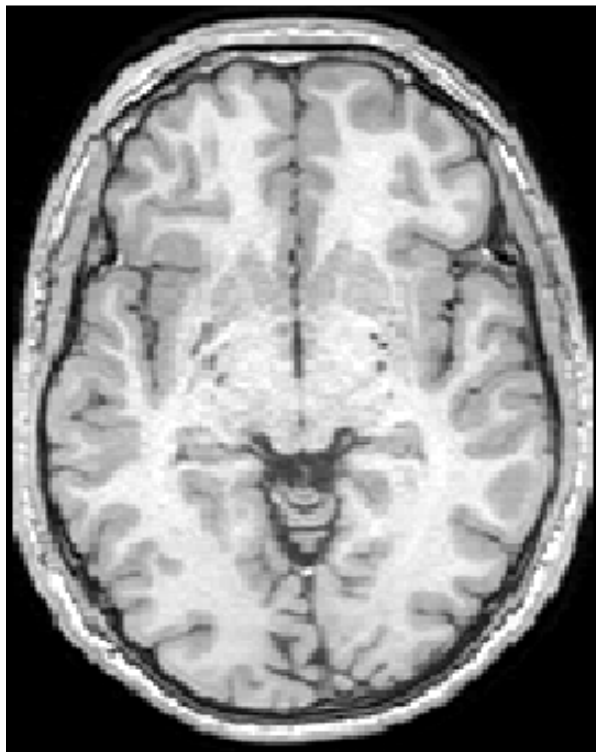
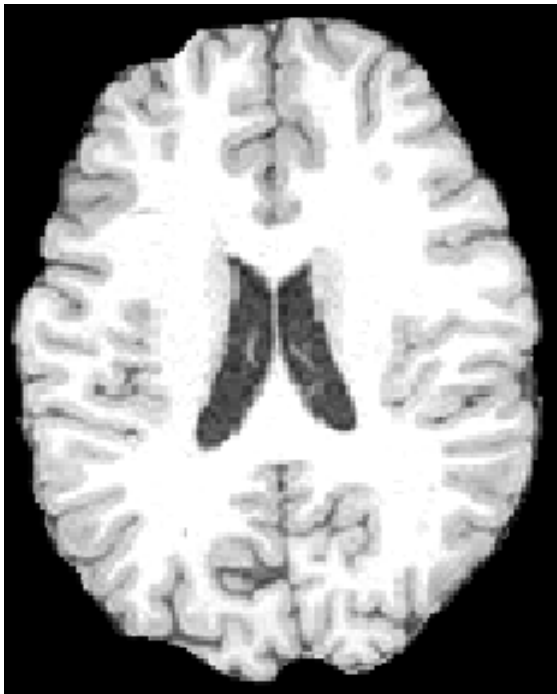Pre-processed (approach A) image: slice-3
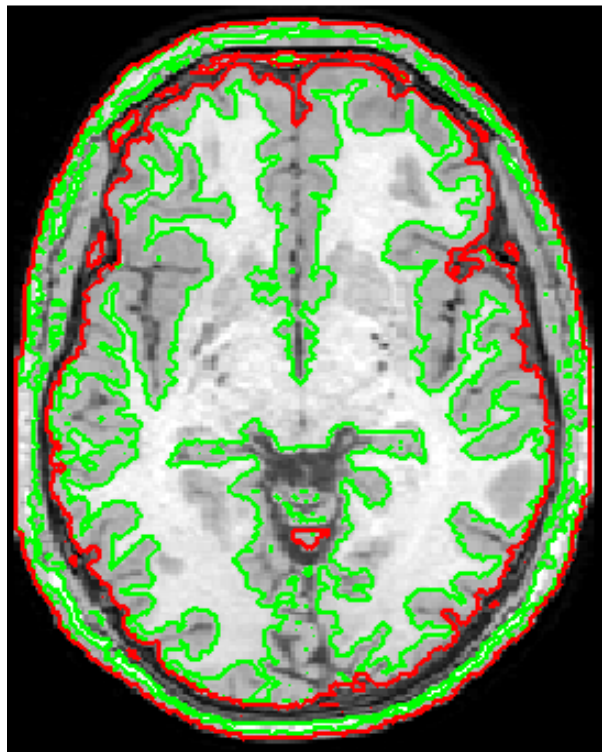
Segmented from slice-3: CR=(107,22)
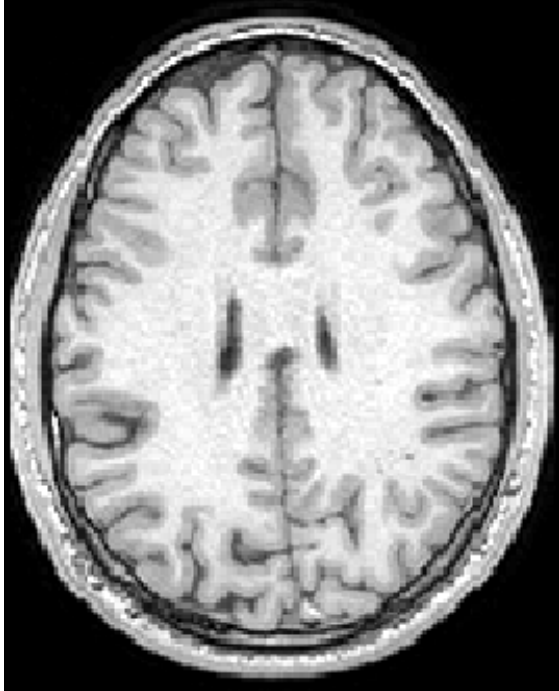
Pre-processed (approach A) image: slice-4   Segmented from slice-4: CR=(123,22)
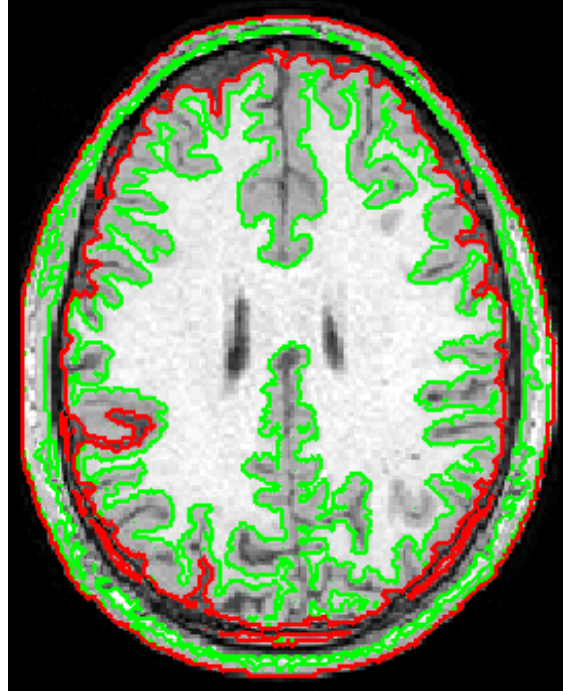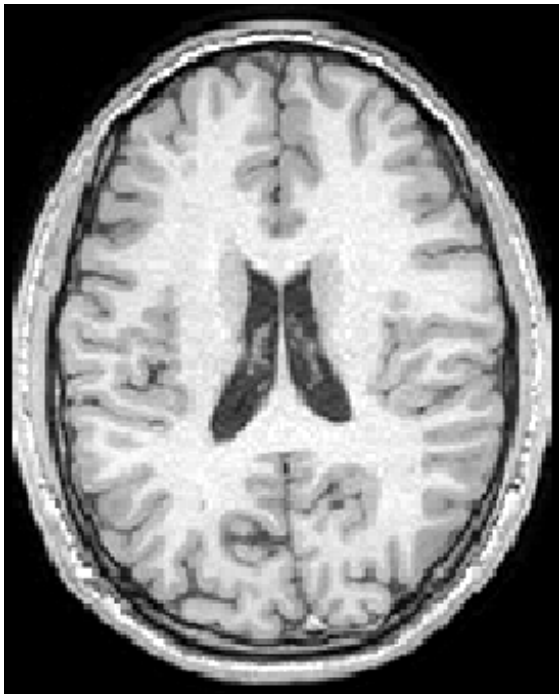
Pre-processed (approach A) image: slice-5   Segmented from slice-5: CR=(89,27)

Figure 14. Segmentation results using pre-processed (approach A) MRI image with MRIcroN software. Same thresholds are used for these 5 images: $(T1,T2)=(191,115)$,where T1 is the threshold for white matter-gray matter; T2 is the threshold for gray matter-CSF.

Discussions: pre-processing B (FSL and MRIcroN softwares) approach in segmentation

In the pre-processing B approach the human head image is captured without the bone structures and external fluids with FSL software; after that the MRIcroN software is used for supplementary segmentation procedures. The final segmentation of the brain tissues is obvious and extracted with this approach. Arbitrarily five slices of one brain MR image have been chosen through the FSL & MRIcroN software to conduct test of our MATLAB simulated program for the graph cuts. Effects of pre-processed (approach B) brain MR images are illustrated in Figure 17 using five different image slices (slices 1-5).
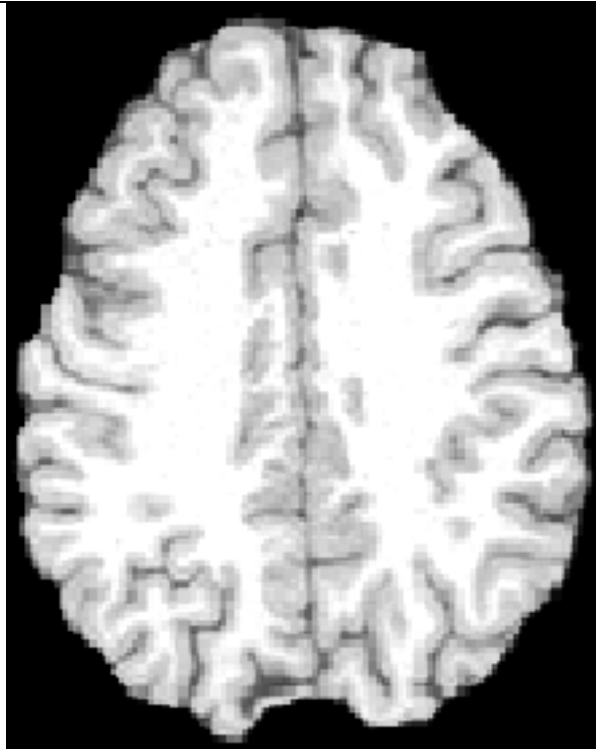
| Pre-processed (approach B) image: slice-1 | Segmented from slice-1: connected regions (CR) (white-gray, gray-CSF)=(13,6) |
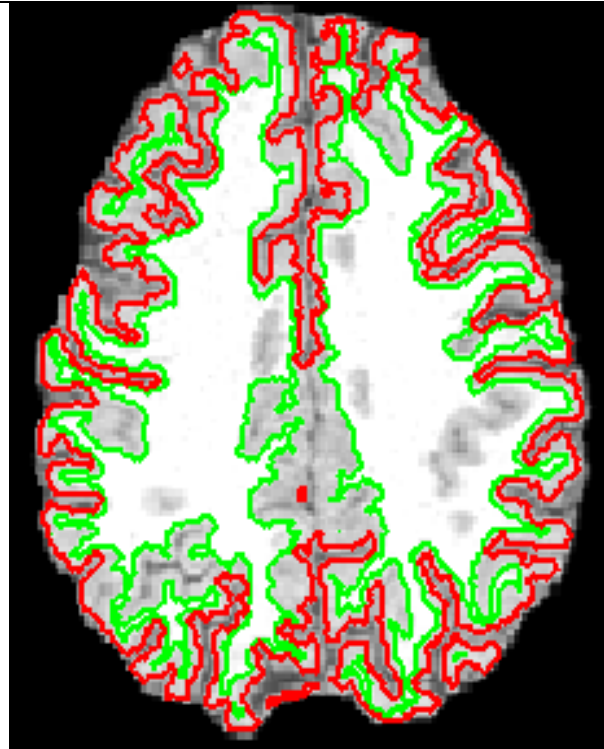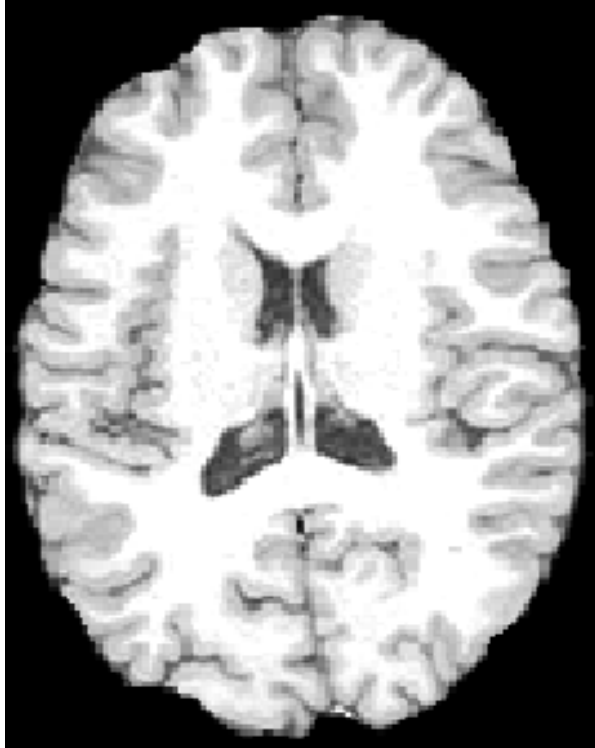
Pre-processed (approach B) image: slice-2

Segmented from slice-2: CR=(30,13)

Pre-processed (approach B) image: slice-3

Segmented from slice-3: CR=(30,17)

Pre-processed (approach B) image: slice-4   Segmented from slice-4: CR=(20,9)

Pre-processed (approach B) image: slice-5   Segmented from slice-5: CR=(25,12)

Figure 15. Segmentation results using pre-processed (approach B) MRI image with FSL software followed by MRIcroN software. Same thresholds are used for these 5 images: (T1,T2)=(230,191) ,where T1 is the threshold for white matter-gray matter; T2 is the threshold for gray matter-CSF.

5. Experimental Results

Medical image segmentation for brain MRI is an emerging field with upcoming new techniques and algorithms. We performed experiments with some existing algorithms used in the graph cuts method on the synthetic brain MR images. MATLAB simulation results with the min-cut/max-flow algorithm provide better segmentation outputs comparing with the normalized cut methods. This chapter is organized for the simulated results with existing MATLAB tools by the normalized cut and then our approach to implement the min-cut/max-flow algorithm and comparison of our implementation with the normalized cut with two techniques. We initially segmented the brain MR image applying the normalized cut algorithm with available simulation tools; finally the segmentation is done applying the min-cut/max-flow algorithm with our own MATLAB programming codes.

The synthetic images used in our experiments were collected from the MRI scans of adult brains with general intrinsic tissue variation. T2-weighted MRI has better contrast than T1-weighted one [24] because of long echo time (T_E) and long repetition time (T_R); but T1-weighted BRI brain image is prudent to analyze in fundamental research. Hence, axial T1-weighted images scanned with spin-echo pulse sequence were used in the simulation having long partial volume effect and low contrast to noise ratio. The voxel of the image was selected in $0.30 \, x \, 0.30 \, x \, 2.5 \, mm$ for MRIcroN software which was sliced and converted into 2D form by MATLAB. Segmentation of GM and WM were considered; the skull and other brain tissues were not included in applying the min-cut/max flow algorithm for simplicity. 10 different slices of human brain images have been tested where 5 slices were pre-processed using approach A and another 5 slices by approach B. Thresholding change impacts the segmentation result which is described in earlier section.

Parameters required in the tests:

In our experiments various test parameters were required to segment WM, GM and CSF tissues. Two different medical image analysis softwares, FSL and MRIcroN, are used to pre-process the MRI images from database. Brain image slice selection using MRIcroN software was essential for both pre-processing A and B approaches. Image slices without bones were used for few test cases in our experiments which were obtained by FSL software. While applying two algorithms in MATLAB, some functions and factors were involved. The canny edge detection method (Matlab function: edge(I,'canny')) was used for image edges detection in both the normalized cuts and min-cut/max-flow algorithms. Images were required to smooth by 2D nonlinear median filter (size 3x3, using Matlab function: MEDFILT2(I)) to reduce "salt and pepper" noise and convolute the image to obtain boundaries for connected and non-connected nodes. The numbers of connected nodes were identified for three types of brain tissues. After computing the histogram (Matlab function: hist(I), for 10 bins), obtaining binary image requires two thresholds (T1, T2) which are necessary to segment between white matter-gray matter and between gray matter-CSF regions.

In the min-max graph cuts, each region of the image was labeled according to pixel intensity (using Matlab function: bwlabel). Providing the cost for energy of each pixel value was required
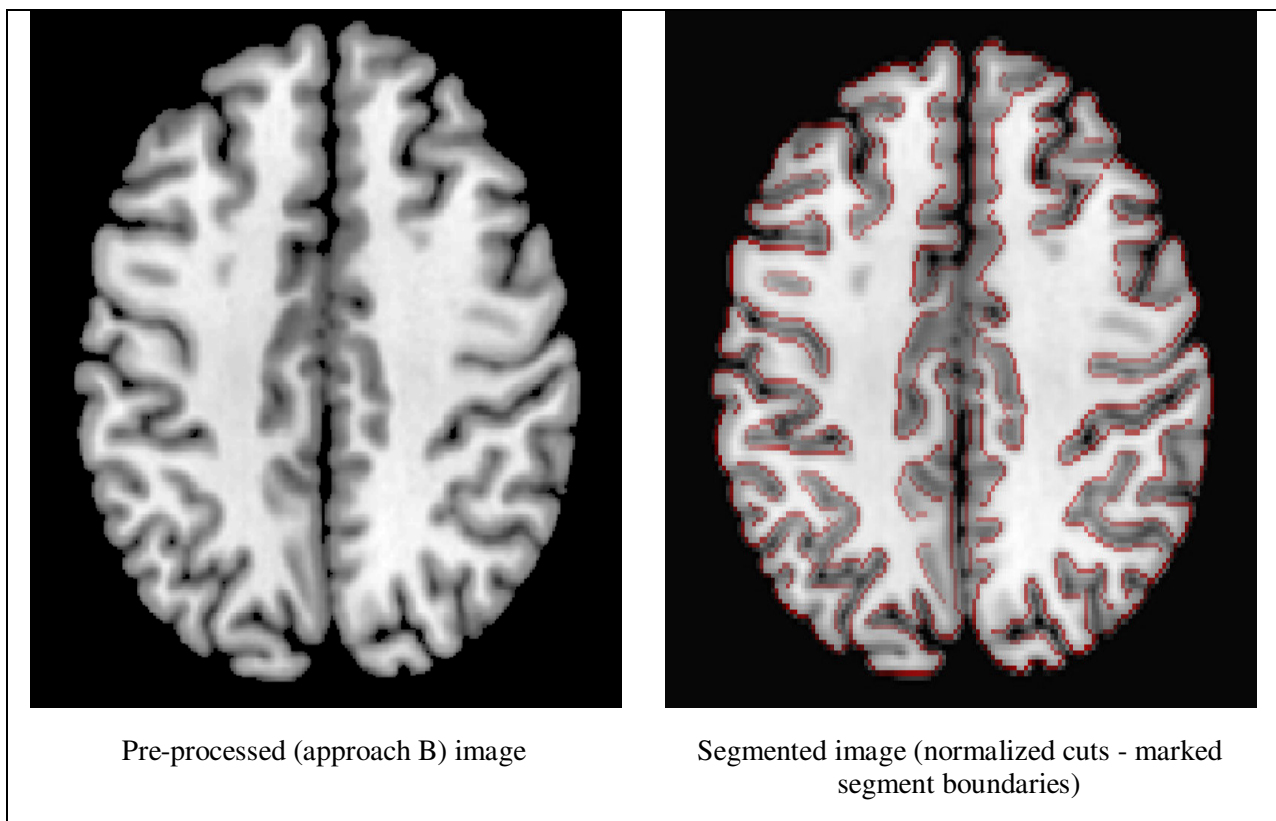
to find maximum flow of the connected regions. Minimum cut was achieved after finding the maximum flow using pixels' growth, augmentation and adoption in search trees S and T. Properties of image regions were investigated to attain min-cut and applying graph cuts segmentation. Computational time in second was checked for segmentation of each image slice in two algorithms. The number of segments was selected manually in the normalized cut algorithm whereas threshold values were selected manually for the min-cut/max-flow algorithm.

5.1 Brain image segmentation using the normalized cut algorithm in [18]

The normalized cut with prior application to graph cuts approach [18] has been used initially for our brain MR image segmentation experiment with the existing MATLAB simulation tools [25]. The normalized cuts approach aimed at extracting global impression of an image rather than focusing on local features and consistencies.

Based on the grouping algorithm in [25], brain MR image segmentation has been done with two main criteria viz. marked segment boundaries and segmentation numbers. The normalized cuts with marked segment boundaries technique has much complexity, computational time and the output segmentation visual quality is in the acceptable range. But the segmentation number for normalized cuts provide inacceptable visual quality image for brain MRI. If number of segmentation is increased, the quality becomes worse rather performing efficient segmentation.

The experimental results with some modifications of the MATLAB codes in tutorial of [25] are illustrated in the following Figure 18.

Pre-processed (approach B) image   Segmented image (normalized cuts - marked segment boundaries)

| Pre-processed (approach A) image | Segmented image (normalized cuts- marked segment boundaries) |
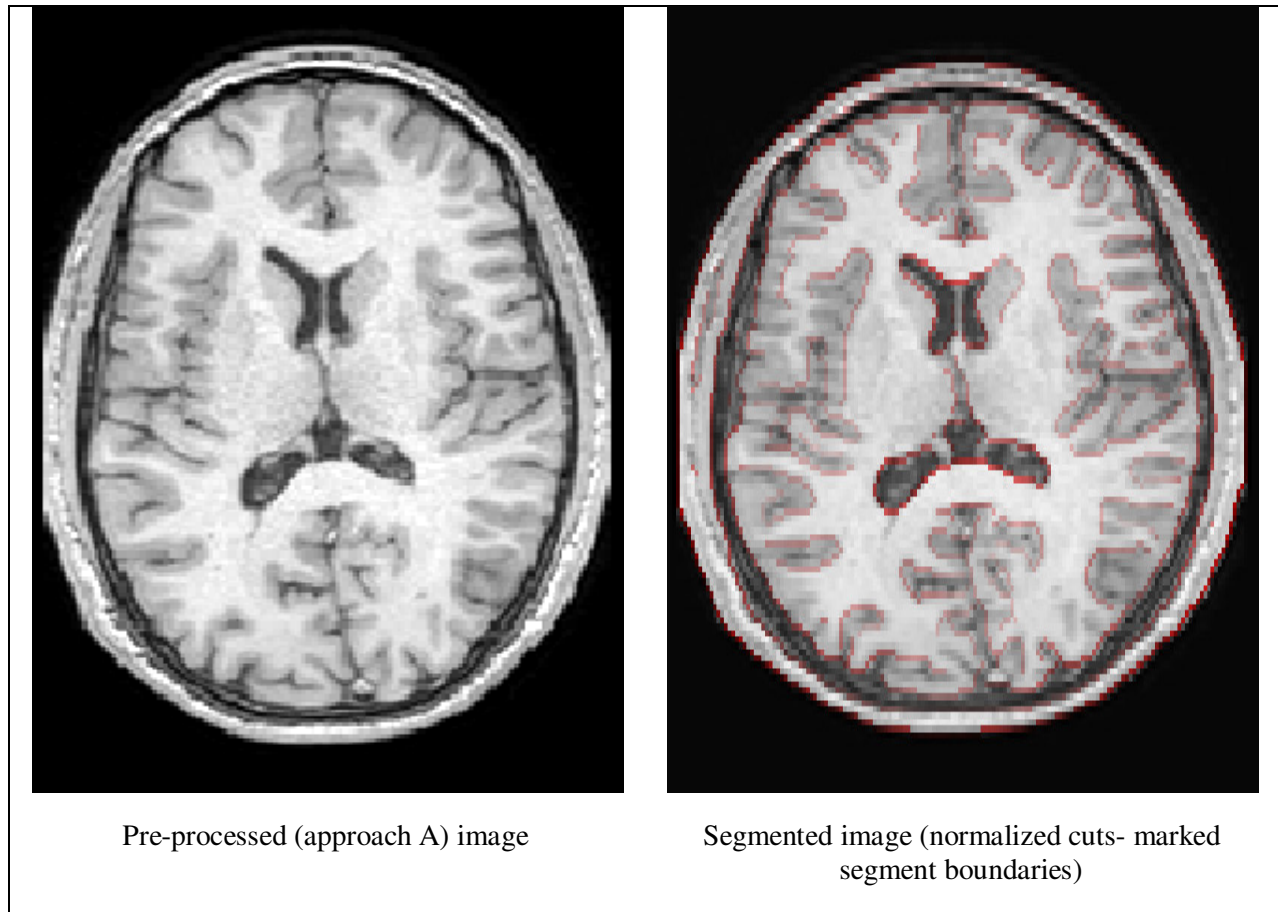
Figure 16. Pre-processed image (left) and segmented image (right) from using the normalized cuts [18] where the segment boundaries are marked (only segmented to 2 groups: white, gray-CSF regions.)

In Figure 18, the interpolated image has been obtained from the pre-processed brain MRI after resizing. Normalized cut algorithm with marked segment boundaries technique has been applied in the interpolated image. From the segmented image it can be visualized that the WM, GM and CSF are distinguishable with minimum quality. However, the segmentation can be improved with further investigation of this technique. Only two segmented groups were obtained like white matter region and gray matter-CSF region.

An original image has been segmented with varying segment numbers in Figure 19. When the segmentation number of the normalized cuts algorithm is low, the brain tissues- GM, WM and CSF can be differentiated to a little extent. But if the segmentation number is increased beyond 100 levels the quality of the segmentation becomes worse to identify. Basically, the area of the image is divided rather segmenting the brain tissues in this method.

Pre-processed (approach A) image

Segmented image (normalized cuts – different segment numbers): no. of segments (SN)= 30

SN=50
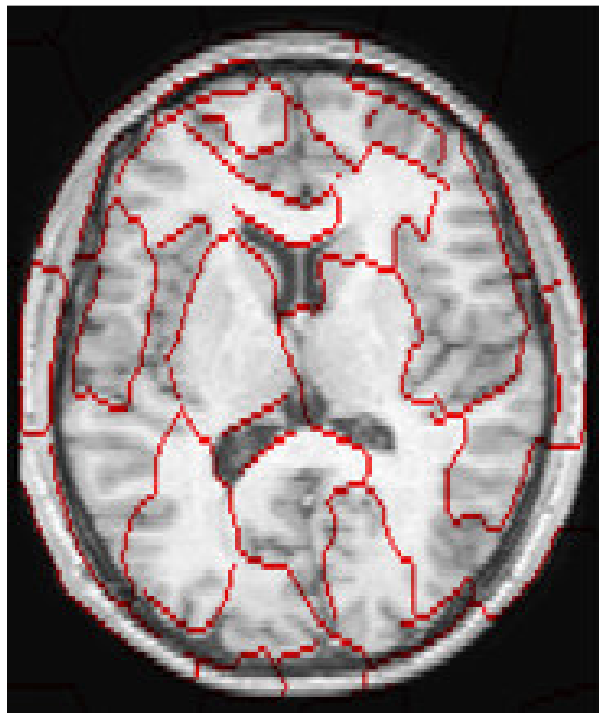
SN=70
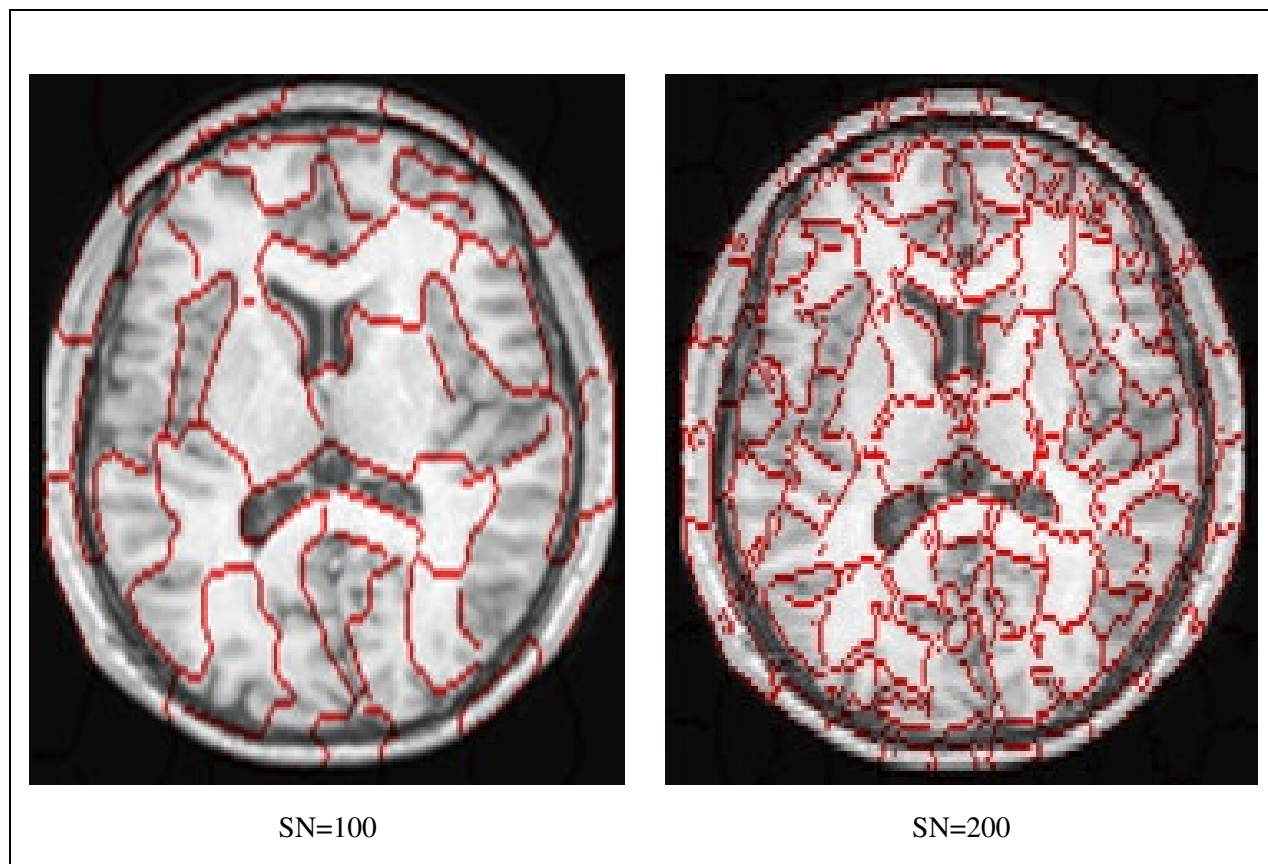
Figure 19. Segmented results from pre-processed image (approach A) using different segment numbers of normalized cuts [18].

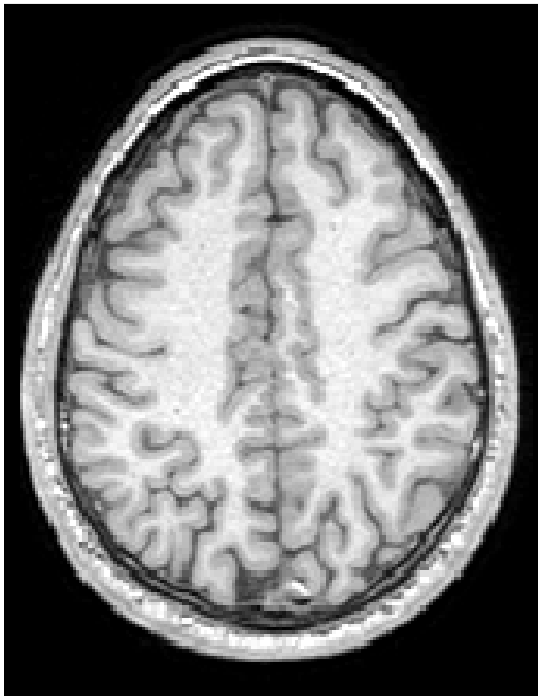## *5.2 Brain image segmentation using the min-cut/max-flow algorithm in [6]*

The minimum-cut/maximum-flow algorithm [10] for graph based image segmentation became very popular recently to minimize energy along with segmentation of connected components in vision and medical imaging applications. Various standard algorithms for graph-cuts segmentation prevail including push-relabel method, Ford-Fulkerson augmenting paths method etc. However, to implement in brain image segmentation we chose the min-cut/max-flow algorithm described in [6] as it provides faster, accurate and reliable output. We divided the whole process into two parts: brain MR image pre-processing with medical image analysis software and the MATLAB implementation of the min-cut/max flow algorithm in [6] for graph cuts based segmentation of brain soft tissues. These are described in the test systems analysis of earlier section. Figure 20 shows the experiment result on the synthetic images which are preprocessed using method A or B.

Pre-processed (approach B) image
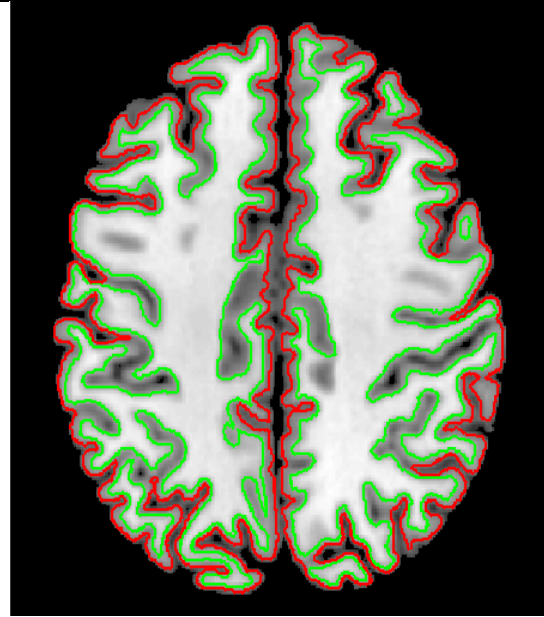
Segmented image: Thresholds (T1,T2) (white-gray, gray-CSF) = (166,115); connected regions (CR) (white-gray, gray-CSF)=(6,2)

Pre-processed (approach A) image
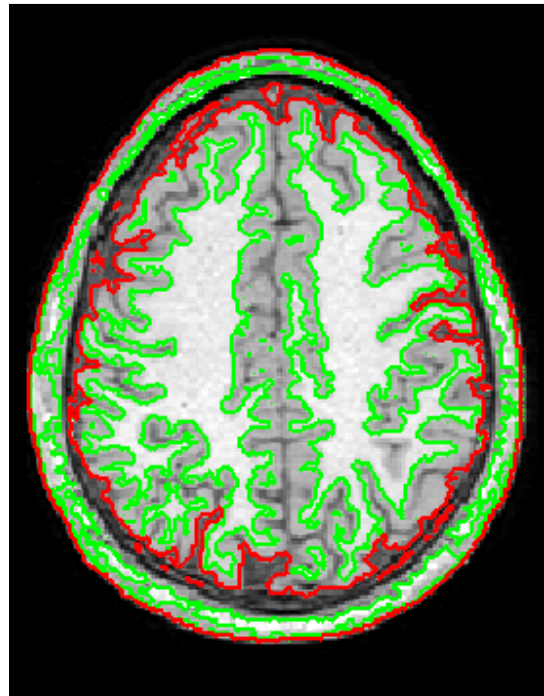
Segmented image: Thresholds (T1,T2) (white-gray, gray-CSF) = (191,115); connected regions (CR) (white-gray, gray-CSF)=(86,25)

Figure 17. Segmentation results from the min-cut/max-flow algorithm in [6] using pre-processed MRI images.

The normalized cut is performed after image interpolation and brightness minimization. It produced poor segmentation results for brain tissues (considering only GM) where much flexibility and accuracy are required. The graph cuts method applying the min-cut/max-flow algorithm produced significant outputs. The segmentation results found with the normalized cut algorithm using segmentation number 30 is compared with the min-cut/max-flow algorithm with threshold values (T1,T2)=(191,115) for pre-processing approach A in Figure 21 and (T1,T2)=(166,115) for pre-processing approach B in Figure 22.

Pre-processed (approach A) image

Segmented image (normalized cuts – different segment numbers): no. of segments (SN)= 30

Segmented image: thresholds (T1,T2) (white-gray, gray-CSF) = (191,115); CR=(79,26)

Figure 18. Comparing the segmentation results from two different algorithms. Top: Pre-processed (approach A) MRI image. Bottom left: segmented results from the normalized cuts with segmentation number allocation technique [18], [25]; Bottom right: segmented results from the min-cut/max-flow algorithm [6].

Pre-processed (approach B) image

Segmented image (normalized cuts – different segment numbers): no. of segments (SN)= 30
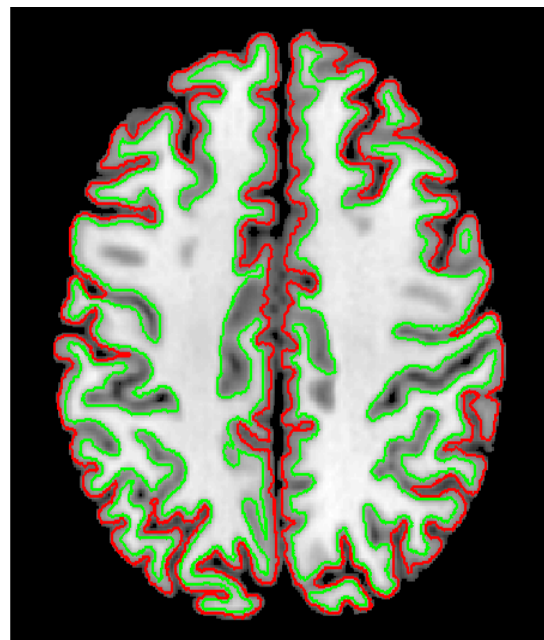
Segmented image: thresholds (T1,T2) (white-gray, gray-CSF) = (166,115); connected regions (CR) (white-gray, gray-CSF)=(6,2)

Figure 19. Comparing the segmentation results from two different algorithms. Top: Pre-processed (approach B) MRI image. Bottom left: segmented results from the normalized cut with segmentation number allocation technique [18], [25]; Bottom right: segmented results from the min-cut/max-flow algorithm [6].

In segmentation process, right partition for cost function, efficient optimization algorithm and time consumption are essential to achieve significant results. Minimum cut generally favors isolated nodes or connected components [18]; but the min-cut/max flow algorithm considers both the connected and non-connected nodes with the two search trees and finally the maximum connected nodes are segmented based on energy minimization of the pixels.

Computational time:

It took less time to segment the brain MR image into WM and GM by the min-cut/max-flow algorithm in MATLAB than the normalized cut with segmentation numbers technique, and the normalized cut with marked segment boundaries technique. Table 2 shows the average computational time required for segmenting 10 slices of two brain images from these algorithms.

Table 2. Segmentation time for different algorithms.

Algorithm	Average time consumption (in seconds)
Normalized cut with marked segment boundaries	6.47
Normalized cut with different segment numbers	5.89
Min-cut/max-flow	3.42

Evaluations:

Only viewing at the segmented images by different algorithms is not sufficient enough to evaluate the results. It is imperative to measure the quality of the segmented image applying the min-cut/max flow algorithm and existing normalized cut algorithm with different techniques in the graph cuts. GM and WM in the experimental MRIs were taken into account; other brain tissues including CSF and the skull were eliminated for experiment purpose. The results are compared with ground truth labeling in order to do quantitative evaluation as a standard segmentation benchmark. Four procedures- true positive fraction (TPF), false positive fraction (FPF), true negative fraction (TNF) and false negative fraction (FNF) are observed in the segmentation results for quality measurement [3]. These measuring parameters can be revealed in following way:

$$e_{TPF} = \frac{|A(T) \cap A(G)|}{|A(G)|}, \quad e_{FPF} = \frac{|A(T) - A(G)|}{|\overline{A(G)}|}$$

$$e_{TNF} = \frac{|\overline{A(T) \cup A(G)}|}{|\overline{A(G)}|}, \quad e_{FNF} = \frac{|A(G) - A(T)|}{|\overline{A(G)}|}$$

Here, $A(T)$ is for the area of segmented foreground in the test segmentation technique, $A(G)$ is indicates the area of the ground truth of foreground i.e. the entire image area except the background and $\overline{A(G)}$ represents the complement of $A(G)$ i.e. the background area of the image. Maximum connected nodes of the segmented images are obtained for each pre-processed image

for different threshold values. These values represent $A(T)$ and $A(G)$ which are obtained by MATLAB code and manual thresholding of T1 and T2. Three algorithms were tested over 10 slices of two brain MR images; the results are enlisted in Table 3.

Table 3. Quantitative evaluation of segmentation results by different algorithms based on four procedures- true positive fraction (TPF), false positive fraction (FPF), true negative fraction (TNF) and false negative fraction (FNF).

Algorithm	e_{TPF} (%)	e_{FPF} (%)	e_{TNF} (%)	e_{FNF} (%)
Normalized cut with marked segment boundaries	91.22	14.45	95.23	14.21
Normalized cut with different segment numbers	89.06	4.89	93.29	17.35
Min-cut/max-flow	89.35	3.31	94.01	3.07

It is obvious from Table 3 that the min-cut/max flow algorithm produces excellent results of FPF, TNF and FNF and supersedes other two mentioned algorithms. TPF index is the highest in the normalized cut with edge detection technique as larger segmentation area including background and foreground is involved. Interpolation and resizing of the image is also responsible of higher FPF in this method. The segmentation results are satisfactory if TPF and TNF indexes indicate the largest values and FPF and FNF present the smallest values. The relative parameter used in the growth and augmentation steps plays important role to achieve better TPF and TNF.

6. Discussions and Conclusions

6.1 Discussions

Three brain tissues- gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) are of interest to be segmented by different algorithms. It has been found from the literature study that the min-cut/max flow algorithm used in graph cuts is quite a new and potential method beside the normalized cut and other algorithms. Image smoothness and energy minimization are basis of this method. The purpose of this thesis was to conduct MRI brain image segmentation using two algorithms namely the min-cut/max-flow algorithm and the normalized cuts for graph cuts.

The thesis research work comprises the detail study of this method to implement using an MRI brain image. Pre-processing of the synthetic image, edges and boundaries detection after convolution, histogram thresholding and finally segmentation of GM, WM and CSF are the major steps in applying the min-cut/max flow algorithm. The segmentation of GM, WM and CSF are also done by the normalized cut using marked segmentation boundaries and segmentation number techniques. Existing simulations were used to apply these techniques in brain MRI. Quantitative evaluation of these algorithms provides a comparison view in a standard benchmark. 10 different slices of two brain images were pre-processed using approach A and B. In approach A, pre-processing was conducted through MRIcroN software and the output was a pre-processed image. A pre-processed image was generated using FSL software followed by MRIcroN software in approach B. The brain image slices are without bones and the tissues are segmented with less error in the pre-processing method B and therefore approach B was chosen for test systems.

In the normalized cut algorithm the slices of brain image are interpolated and resized by 160x160 grey levels for both the marked segment boundaries and different segment numbers techniques. Only WM tissue is segmented in the normalized cut with marked segment boundaries technique while the regions are separated by the normalized pixel values of image data in the different segment numbers technique. Therefore, it can be described that the marked segment boundaries provide slightly better output than the different segment numbers technique.

The min-cut/max flow algorithm provided result that was slightly faster and with less error. WM, GM and CSF are attempted to segment according to growth, augmentation and adaptation stages to obtain minimum cut and maximum flow of images data. Two threshold values have been set manually for each image that segregates the image pixel values in different regions based on energy. The pre-processed and experimental images are not reshaped.

6.2 Conclusions

Analysis of the processed image data is one of the hot topics in imaging field where segmentation plays vital role. Segmentation of medical images can be divided into two classifications: a) manual, semi-automatic and automatic, b) pixel based local method and region based global method [2]. Brain MR Image is a complex system to be segmented with efficient method for having variable kind of tissues. Graph based approaches like graph cuts produce

significant output in the automatic and pixel based segmentation of brain MRI. Finding the maximum flow from the source to the sink provides the solution of minimum cut in the graph cuts method which is proved in the min-cut/max flow algorithm. Growth, augmentation and adoption stages in this method with two search trees option for the connected nodes reveal the segmentation performance to a new direction [6].

For brain MR image segmentation 10 different slices of two brain images have been tested in our research for project simplicity and time constraints. The MR image segmentation experiments were performed using both the normalized cut algorithm and min-cut/max-flow algorithm. The preliminary test gives an impression that computational time and complexity are much less to segment the brain MR image into WM, GM and CSF by the min-cut/max-flow algorithm compared to the normalized cut algorithm. Furthermore, significant outputs for the segmentation of WM, GM and CSF were produced by min-cut/max-flow algorithm. On the other hand applying the normalized cut algorithm resulted in poor segmentation of WM, GM and CSF with minimum quality. FSL and MRIcroN softwares were used for the pre-processing of brain MR images. Extensive tests of various brain slices such as twenty brain images need to be conducted along with other image analysis softwares in order to verify and improve the present results.

Appendix

Three major steps of the minimum-cut/maximum-flow algorithm described in [6] and used to implement brain MR image segmentation are summarized as follows:

Pseudo codes:

Growth stage

$while\ A \neq \emptyset$
$\quad pick\ an\ active\ node\ p\ \in\ A$
$\quad for\ every\ neighbor\ q\ such\ that$
$\qquad RC(p \to q) > 0$
$\quad if\ Tr\ (q) = \emptyset$
$\quad then\ add\ q\ to\ search\ tree\ as\ an\ active\ node:$
$\qquad Tr\ (q) \coloneqq Tr\ (p), Pt(q) \coloneqq p,$
$\qquad A \coloneqq A \cup \{q\}$
$\quad if\ Tr(q) \neq \emptyset\ and\ Tr\ (q) \neq Tr(p)$
$\qquad return\ P = PATH_{s \to t}$
$\quad end\ for$
$\quad remove\ p\ from\ A$
$end\ while$
$return\ P = \emptyset$

Augmentation stage

$find\ the\ bottleneck\ capacity\ \Delta\ on\ P$
$update\ the\ residual\ graph\ by\ pushing\ flow\ \Delta\ through\ P$
$for\ each\ edge\ (p,q)in\ P\ that\ becomes\ staurated$
$if\ Tr\ (p) = Tr(q) = S\ then\ set$
$\quad Parent\ Pt(q) \coloneqq \emptyset\ and\ Orphan\ On \coloneqq On \cup \{q\}$
$if\ Tr(p) = Tr(q) = T\ then\ set$
$\quad Parent\ Pt\ (p) \coloneqq \emptyset\ and\ Orphan\ On \coloneqq On \cup \{p\}$
$end\ for$

Adoption stage

$while\ On\ \neq \emptyset$
$\quad pick\ an\ orphan\ node\ p \in On\ and\ remove\ it$
$\qquad from\ On$
$\quad process\ p$
$end\ while$

The operation "*process p*" consists of the following steps: First, a new valid parent for p among its neighbors is to be found. A valid parent q should satisfy $Tr(q) = Tr(p), RC(q \to p) > 0$ and the origin of q should be either source or sink. Note that the last condition is necessary because, during the adoption stage, some of the nodes in the search trees $S\ or\ T$ may originate from orphans.

If node p finds a new valid parent q then, we set $Pt(p) = q$. In this case p remains in its search tree and the active (or passive) status of p remains unchanged. If p does not find a valid parent, then p becomes a free node and the following operations are performed:

$Scan\ all\ neighbors\ q\ of\ p\ as\ Tr(q) = Tr(p):$
$if\ RC(q \to p) > 0, add\ q\ to\ the\ active\ set\ A$
$if\ Pt(q) = p,$
$add\ q\ to\ the\ set\ of\ orphans\ On\ and\ set\ Pt(q) := \emptyset$
$Tr(p) := \emptyset, \qquad A := A - \{p\}.$

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