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An Efficient Segmentation of Magnetic Resonance Brain Image using Clustering Technique and Watershed Transform

Graduate School of Chosun University

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클러스터링 기술과 워터쉐드 변환을 이용한
MRI 영상의 효율적인 세션화

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바수카라 디바쉬의 석사학위논문을 인준함

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ACRONYMS

MRI	**Magnetic Resonance Imaging**
WM	**White Matter**
GM	**Gray Matter**
CSF	**Cerebrospinal Fluid**
CT	**Computed Tomography**
PET	**Positron Emission Tomography**
SPECT	**Single-Photon Emission Computed Tomography**
k**NN**	k**-Nearest Neighbor**
ML	**Maximum Likelihood**
EM	**Expectation-Maximization**
FCM	**Fuzzy** C**-Means**
GMM	**Gaussian Mixture Model**
E	**Expectation**
M	**Maximization**
ADNI	**Alzheimer's Disease Neuroimaging Initiative**
DRLSE	**Distance Regularized Level Set Evolution**
TP	**True Positive**
TN	**True Negative**
FP	**False Positive**
FN	**False Negative**

Abstract

An Efficient Segmentation of Magnetic Resonance Brain Image using Clustering Technique and Watershed Transform

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Watershed transformation is an effective segmentation algorithm that originates from the mathematical morphology. This algorithm is widely used in medical image segmentation because it produces complete division even under poor contrast. However, over-segmentation is its most significant limitation. Therefore, this thesis proposes a combination of watershed transformation and the clustering algorithm to segment magnetic resonance brain images efficiently. The clustering algorithm is used to form clusters. Then, the brightest cluster which contains gray matter (GM) and cerebrospinal fluid (CSF) is thus selected and converted into a binary image. A Sobel operator applied on the binary image generates the initial gradient magnitude image. Morphological image reconstruction is applied to find the foreground and background markers. The final gradient magnitude image is obtained using the minima imposition technique on the initial gradient magnitude along with markers. In addition, watershed segmentation applied on the final gradient magnitude generates effective GM and CSF segmentation. The results are compared with simple marker-controlled watershed segmentation, watershed segmentation combined with Otsu multilevel thresholding, and distance regularized level set for validation.

초록

클러스터링 기술과 워터쉐드 변환을 이용한 MRI 영상의 효율적인 세션화

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워터쉐드 변환은 수학적 형태학에서 유래한 효과적인 알고리즘이다. 이 알고리즘은 낮은 명암에서도 효과적으로 분할되어 의료 영상 분할에 폭넓게 활용된다. 하지만 의료 영상에서의 과분할은 가장 중요한 제한 사항이다. 제안하는 방법은 워터쉐드 변환과 클러스터링 알고리즘의 조합을 통한 자기 공명 뇌 영상의 효율적인 분할이다. 우선 클러스터링 알고리즘은 특징 집합을 형성하는데 사용된다. 이후, 높은 명암 부분의 클러스터에 포함되는 회백질(Gray-Matter, GM)과 뇌척수액(CerebroSpinal Fluid, CSF) 영역을 선택하여 이진 영상으로 변환한다. 변환 된 이진 영상은 Sobel 연산을 통해 초기 기울기 크기 영상을 생성하고 형태적(Morphological)영상 복원은 전경과 배경 마커를 찾기 위해 사용한다. 최종 기울기 크기 영상은 마커와 함께 얻어지며, 이는 초기 기울기 크기값에 최소값 부과 기법을 적용하여 얻을 수 있다. 또한 워터쉐드 분할에 최종 기울기 크기를 적용하여 회백질과 뇌척수액을 효과적으로 분할한다. 제안한 방법의 실험 결과는 심플 마커 제어 워터쉐드 분할, Otsu Multilevel 임계값과 결합된 워터쉐드 변환 그리고 거리 정규화 레벨 셋과 비교 분석하였다.

Chapter 1
Introduction

Image segmentation [1]- [3] is an essential step for many image analysis tasks. The main motive of image segmentation is to separate the image into meaningful, homogenous, and non-overlapping regions of similar characteristics such as intensity, texture, depth, and color. The result of segmentation is either an image which identifies each homogenous regions or a set of contours describing the boundaries of the region. It is essential for successful automated analysis of biomedical images and is a crucial step in numerous clinical and research applications, including three-dimensional visualization, volumetric measurement, image guided surgery, radiotherapy planning and detection of changes over time. Detection of lesions and abnormalities is important for medical diagnosis. Magnetic resonance imaging (MRI) is particularly used in medical image segmentation [4]- [6] because it generates tomographic images with high spatial resolution and contrast. Brain structure segmentation from MRI is predominant as it differentiate itself from other imaging modalities and can be applied in Alzheimers disease, schizophrenia, multiple sclerosis, cerebral atrophy, epilepsy involving volumetric analysis of brain tissues. However, what makes it more interesting is being a risk-free imaging modality. Accurate segmentation of the brain tissue is not a simple task [7] because of the presence of noise and intensity non uniformity among other effects.

Clustering is a method used to place a set of patterns into different clusters such that the patterns that are similar are assigned to one cluster. Each pattern describes a vector having many characteristics. The computation of a measure of similarity or distance between the respective patterns is the basis of clustering technique. Therefore, clustering technique aims to determine the intrinsic grouping in a set of unlabeled data.

Watershed algorithm has been widely used in medical image segmentation [8]- [10] due to its inherent advantages. Advantages of watershed transform in-

clude its fast approach, simplicity, and intuitive nature. It also produces complete division of the image into separated regions, even under poor contrast. As a result, there is no need to perform any post-processing work, such as contour joining.

1.1 Background

In image segmentation, the level of partitioning of an image into its constituent regions depends on the problem to be solved i.e. image segmentation should stop once the object of focus is separated. The primary aim of segmentation is to separate an image into parts that have strong correlation with areas of interest in the image. Image segmentation requires classification of pixels and hence can be treated as a pattern recognition problem [11].

Brain MRI segmentation is an important task in many clinical applications. It is because it affects the outcome of the entire analysis as many processing steps depends on accurate segmentation of anatomical regions. MRI segmentation is often used for brain development analysis, for measurement and development of varying brain structures, for delineating lesions, and for image guided interventions and surgical planning. In medical imaging, spaces of the brain automated delineation of various image components are used for dividing an entire image into different regions such as the white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF), for analyzing anatomical structures such as bones, tissue types, muscles blood vessels, multiple sclerosis lesions, and pathological regions such as cancer. In medical image processing field, segmentation of MR brain image is important as MRI is especially suitable for brain studies as it has non-invasive characteristic, excellent contrast of soft tissues, and a high spatial resolution. Various segmentation techniques of different accuracy and degree of complexity have been developed because of the diversity of image processing applications.

1.2 Problems and Challenges of Brain Image Segmentation

There are many techniques for the segmentation of an image into homogenous regions. All the techniques are not suitable for medical image analysis because of inaccuracy and complexity. For imaging applications like brain MRI, brain cancer diagnosis, there is no standard image segmentation technique, which can produce satisfactory results. The main obstacles for brain image segmentation are the optimal selection of features, tissues, brain and non-brain elements. The other problem is the accurate segmentation over the full field. Manual thresholding and operator supervision are another hindrance to segment brain image. Verification of results is another source of difficulty during the segmentation procedure.

1.3 Scopes and Objectives of the Thesis

Human brain is perceived differently by various medical imaging techniques such as computed tomography (CT) and MRI. Many segmentation techniques such as manual segmentation, region growing, classifiers, clustering algorithms, watershed, active contour, atlas guided approaches etc. are available for brain MRI in medical imaging.

The objective of this thesis is to develop a framework for a robust and accurate segmentation of MR brain images. We proposed a new method for the segmentation of MR brain images using the advantages of watershed transform and clustering algorithms. The thresholding values will be selected from the mean values of the clustering algorithms. In this regard, MATLAB simulations will be carried out. Results comparison of the proposed technique with the Otsu method and level set method will be accomplished to evaluate segmentation quality. Besides, Segmentation validation and quantitative analysis will also be performed to check the accuracy of segmentation.

1.4 Thesis Contribution

A new algorithm for the segmentation of the MR brain images has been presented in this thesis. We use the hybrid segmentation method using the combination of watershed transform and clustering algorithm for the effective segmentation of the MRI of the human brain. Already proposed algorithms have also been surveyed in this thesis. The main algorithms proposed in the literature for MR brain image segmentation are identified and explained in this thesis. The major contributions of this thesis are described below:

New Algorithm: A new algorithm is proposed for the effective segmentation of MR brain images.

Design Procedure: Important parameters of the proposed algorithm is given in design procedure. An engineer can follow this procedure to find the appropriate number of phases and important parameters in the proposed algorithm for a given application with its specifications and requirements.

Simulation: A simulation code was written in MATLAB R2014b to test the performance of the proposed algorithm and also to compare with other algorithms.

1.5 Thesis Outline

The remainder of this thesis is organized as follows. Chapter 2 provides the information about different kinds of imaging modalities in practice. Literature review of different segmentation techniques and various kinds of algorithms are discussed in Chapter 3. Chapter 4 describes the detailed explanation of the proposed method for the segmentation of MR brain images. Simulation results with MATLAB software applying the algorithm and the advantages of our proposed method over the other methods is presented in Chapter 5 followed by conclusions in Chapter 6.

Chapter 2
Imaging Modalities

The human body consists primarily of water and bones. Moreover, trace elements exist in different parts of human body, such as iodine in the thyroid, tellurium in the liver and iron in blood. Medical imaging techniques use different properties of these elements. The important modalities are CT, x-ray, single photon emission computed tomography (SPECT), positron emission tomography (PET), ultrasound and magnetic resonance imaging. The x-ray was invented by Wilhelm in 1895, and it measures the transmission of x-ray throughout the body. However, a disadvantage of x-ray is the high level of radiation emitted which can cause diseases such as cancer and eye cataract. In x-ray computer assistance tomography, reconstruction of image is done with a large number of x-rays. Radio nuclides are injected into the body of patients which is attached to a specific organ in case of PET. SPECT is a nuclear medicine tomographic imaging techniques which is able to produce true 3D image. It uses gamma rays. Ultrasound is used for the measurement of the reflection of ultrasonic waves, which is transmitted through the body and is the best modality for investigation of soft tissues.

2.1 Magnetic Resonance Imaging

MRI is a technique used to obtain high quality images of the inside of the human body. It is based on the radio-frequency waves that the protons in the examined tissues emit when exposed to an external magnetic field. Each signal is then processed by advanced computer programs, which transform it into high quality images. Unlike conventional x-ray systems and procedures of nuclear medicine, this kind of technique does not emit ionizing radiations.

MR imaging is one of the popular methods used in medical imaging and was invented in 1970. Unlike other medical imaging modalities, MRI scanning can be used as frequently as necessary because it is relatively safe. Moreover, it can

be adapted to image brain. MRI is based on the hydrogen nucleus because of the presence of a large amount in human body and also their magnetic resonance sensitivity. A large static magnetic field perturbs magnetic moments of proton, which exists in the hydrogen nucleus from their equilibrium and observing how perturbed moments relaxed back to their equilibrium, for image formation. The protons are oriented at random naturally. But in the presence of static magnetic field, they are lined up with the field and as a result, the net magnetization of protons tends toward the direction of the field. In existence of enough energy, it is possible to make the net magnetization zero. An induced electronic signal is recorded in the relaxation process. The strength and duration of the signal depend on three quantities:

1. ρ (proton density)

2. Spin-lattice relaxation time: It is the time which describes how fast the net magnetization takes to relax back to its equilibrium (T1).

3. Spin-spin relaxation time: Magnetization components decrease to zero (T2) with this time. Three different images of the same body can be obtained by setting different parameters while scanning a person's body, including T1-weighted, T2-weighted, and ρ-weighted. The images used in this thesis are T2-images.

Chapter 3
Segmentation Methods

This chapter gives a brief literature study of the different segmentation techniques commonly used in medical image analysis. Segmentation is the major analysis function in medical imaging for which numerous algorithms and methods have been built up [12]- [16]. In medical image processing, there is high variability of data for analyzing tissue types and anatomical structures. Hence, segmentation techniques that provide accuracy, flexibility and convenient automation are of prime importance.

MRI segmentation is an important task, because acquired MR images are not perfect and are often corrupted by image artifacts and noise. Different studies have been conducted in the field of MR brain image segmentation but no universally agreed best method exists. Segmentation problem is approached in different ways by various segmentation methods. Different methods base the segmentation on various features in the images such as intensity or gradient. The selection of the method should be based on the tissues being segmented as various methods are better suited for segmenting different tissues.

Segmentation methods can be categorized into different groups. Level of user interactivity is one of the aspects. The groups include manual methods requiring high level of user interactivity, computer-aided semiautomatic methods, and completely automatic methods. Segmentation methods also include region-based (segmentation) or voxel-based (classification).

3.1 Manual Segmentation

The most commonly used, and conceptually simplest, method is manual segmentation. Manual segmentation refers to the process where a human operator segments and labels an image by hand. This type of segmentation is performed in a “slice-by-slice” manner for 3D volumetric imagery. This requires that an ex-

pert performs the segmentation, i.e. someone who has detailed knowledge about the anatomy of the regions being segmented. The performance will depend on the complexity of the shapes being segmented. For example, it might be difficult to delineate the contours of the convolutions of the brain accurately. Manual segmentation is a region-based segmentation technique.

Manual segmentation is intensively used for defining a surrogate for true delineation (called "ground truth") and quantitative evaluation of automated segmentation methods because manual segmentation is believed to be the most accurate. Also, manual segmentation of different brain structures is a basic step in the formation of brain atlas and is used in atlas-based segmentation approaches. For manual delineation, editing tools such as ITK-SNAP normally display 3D data in the form of three synchronized 2D orthogonal views (axial, coronal, and sagittal) onto which the operator draws the contour of the target structure. Hence, the output data consists of a series of 2D contours from which a continuous 3D surface has to be extracted.

3.2 Region Growing

Region growing also known as region merging aims at finding regions sharing some common characteristics features. First a seed point is selected. The neighboring voxels are compared to the seed voxel and are added to the region if they fulfill some similarity criteria [17]. The neighboring voxels are then examined and compared until the growing stops. The stopping criteria could be gradient value or relative intensity value to the seed point. Similarity criteria and the selection of seed points both affect the final output of a region growing algorithm.

Cardiac images, kidney segmentation, extractions of brain surface, etc. are the areas where region growing technique can be applied in medical image segmentation. The capability of appropriate segmentation of the region having matching property and generating joined regions are the advantages of this segmentation method. Region growing is used within a set of image processing operations i.e. it is not used alone. Its main disadvantage is the requirement of manual inter-

action to obtain the seed point. A seed must be planted for every single region, which needs to be extracted. In addition to this, since the result of region growing depends on homogeneity criterion, failure in accurately choosing the criterion might result in adjacent areas or regions that do not belong to the object of interest. Region growing is also sensitive to noise, thereby extracted regions may be disconnected or even have holes.

3.3 Classifiers

Classifier methods partition a feature space that is derived from the image using data with known labels. A feature space is commonly the range space of any function of the image. Image intensities are the common feature space. Classifiers are also known as a supervised method as they require training data, which are manually segmented, and then it can be used as a reference for automatic segmentation of new data. Training data can be used in classifier methods in numerous ways.

Nearest-neighbor classifier is a simple classifier, where every single voxel or pixel is classified in the same class as the training datum having closest intensity. Generalization of this approach is the k-nearest-neighbor (kNN) classifier [18] where the pixel is classified in accordance to the majority vote of the closest training data. The kNN classifier is also considered to be a nonparametric classifier as it does not makes any underlying assumption about the statistical structure of the data.

Maximum likelihood (ML) or Bayes classifier are the most commonly used parametric classifier. The assumption made is that the pixel intensities are considered as independent samples from a mixture of probability distributions, which is usually Gaussian. This mixture, is known as a finite mixture model and is given by the probability density function,

$$f(y_j;\theta,\pi) = \sum_{k=1}^{K} \pi_k f_k(y_j;\theta_k) \tag{3.1}$$

Where y_j is the intensity of pixel j,f_k is a component probability density function parameterized by θ_k, and $\theta = [\theta_1, ..., \theta_k]$. The variables π_k are mixing coefficients that weight the contribution of each density function and $\pi = [\pi_1, ..., \pi_k]$. Training data is obtained by representative samples from each component of the mixture model and estimating each θ_k accordingly. This means estimation of K means, co-variances, and mixing coefficients in case of Gaussian mixtures. New data is classified by assigning every single pixel to the class having the maximum posterior probability. The ML classifier can perform really well when the data actually follows a finite Gaussian mixture distribution. Hence, it is capable of performing a soft segmentation comprising of the posterior probabilities.

The structures to be segmented must possess distinct quantifiable features in case of standard classifiers. It is because the training data can be labeled, classifiers can actually transfer these labels to a new data as long as the feature space differentiates each label as well. They are relatively computationally efficient as it follows non-iterative approach. They can also be applied to multi-channel images unlike thresholding methods. Training data is obtained by manual interaction which is the main disadvantage of the classifier methods. Training sets can be obtained for each image which needs to be segmented, but this can be laborious and time consuming. Also, the use of the same training set for huge number of scans can give biased results which do not take physiological and anatomical variability between different subjects.

3.4 Clustering Algorithms

Clustering algorithms perform the identical function as classifier methods. The only difference is that the clustering algorithms do not require training data. Hence they are termed as unsupervised methods. Clustering algorithms iterate between segmentation of the image and characterization of the properties of each class to compensate the lack of training data. In a way, clustering methods train themselves by using the available data. The most popular clustering meth-

ods are: the k-means clustering, the fuzzy C-means clustering (FCM), and the expectation-maximization (EM) method.

3.4.1 K-means Clustering Algorithm

K-means clustering [31]- [33] algorithm is a simple clustering method that partitions the input data into k classes by iteratively computing a mean intensity for each class (also known as centroid) and segmenting the image by classifying each pixel in the class with the closest centroid. It is also known as hard classification method as it forces each pixel to belong to only one class in each iteration.

The algorithm comprises of the following steps for classification of a data set say x_i, $i = 1, 2, 3.....n$ into k clusters.

1. At first we initialize the centroids with k random intensities.

2. The data point x_i is assigned to the group that has the closest centroid.

3. After assigning all the data points to any of the clusters, the position of k centroids is calculated.

4. Steps 2 and steps 3 are repeated until the cluster labels do not change anymore.

The main aim of this algorithm is to minimize the objective function given by,

$$F = \Sigma_{j=1}^{K} \Sigma_{i=1}^{n} ||x_i^{(j)} - c_j||^2 \tag{3.2}$$

where, $||x_i^{(j)} - c_j||^2$ is a measure of intensity distance between a data point x_i and the cluster center c_j.

The k-means clustering algorithm can be considered as a heuristic search algorithm to find the cluster assignments that minimizes the sum of the squared Euclidean distances from each of the data points to a cluster center. Also, the k-means clustering algorithm can be considered as a non-probabilistic alternative to Gaussian mixture. For better understanding of the concept of k-means clustering algorithm a flowchart is shown in Figure 3.1 which shows the working principle of k-means clustering algorithm.

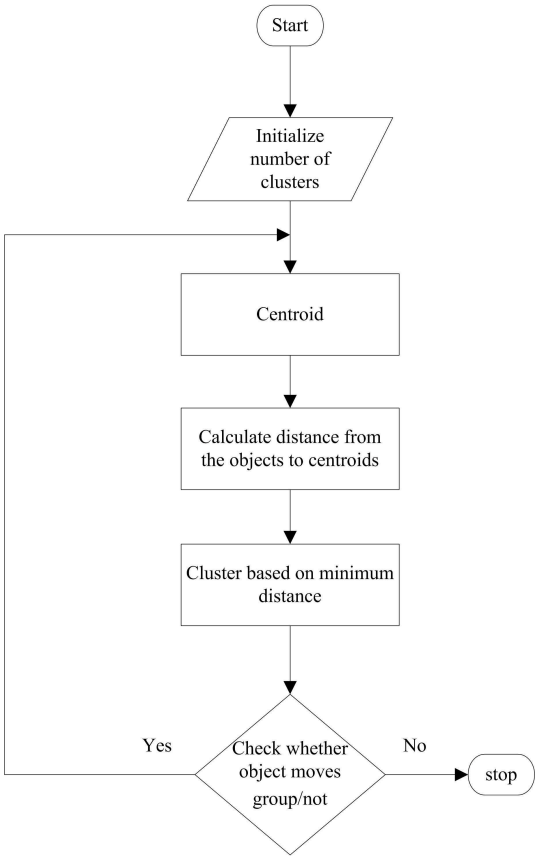


Figure 3.1: Flowchart of k means clustering algorithm.

3.4.2 Fuzzy C-Means Clustering

The FCM clustering is soft classification approach based on fuzzy set theory [34]. It is a generalization of the k means clustering because each pixel is allowed to belong to multiple classes in accordance to a certain membership value. FCM [35] is a clustering algorithm introduced by Bezdek based on minimizing an object function as follows,

$$J_q = \sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}^{q} d(x_i, \theta_j) \tag{3.3}$$

Where q controls the fuzziness degree of clustering, u is fuzzy membership of data x_i to cluster with center θ_j, and d is distance between data x_i and center

of the cluster j,θ_j. The u has the following conditions,

$$u_{ij} \in [0,1], \sum_{j=1}^{n} u_{ij} = 1 \& 0 < \sum_{j=1}^{n} u_{ij} < n \tag{3.4}$$

The membership function and center of each cluster are obtained as follow,

$$u_{ij} = \frac{1}{\sum_{k=1}^{m} (d(x_i,\theta_j)/d(x_i,\theta_k))^{2/q-1}} \tag{3.5}$$

$$\theta_j = \frac{\sum_{i=1}^{N} u_{ij}^q x_i}{\sum_{i=1}^{N} u_{ij}^q} \tag{3.6}$$

FCM optimize object function by continual update of the membership function and centers of clusters until optimization between iteration is more than a threshold.

FCM only considers intensity of image and in noisy images, intensity is not trustful. Hence, this algorithm does not produce a satisfactory result in inhomogeneity and noisy images. Many algorithms are introduced to make FCM robust against noise and inhomogeneity but most of them still are not flawless. Also that FCM clustering falls into local optimal solution easily.

We will describe about EM algorithm in the next chapter.

3.5 Watershed Transform

Watershed transform [25]- [26] is an efficient method for medical image segmentation based on mathematical morphology and was first proposed by Digabel and Lantuejoul. The watershed transformation is another region-based segmentation approach. In the watershed algorithm, the image is treated as a topographical surface in which the height of each point on the surface is given by its corresponding gray level. The set of pixels with the lowest regional elevation corresponds to

the regional minimum. The minima of an image are the groups of connected pixels whose gray levels are lower than those of their neighbors. There are two approaches to find watershed of an image which are described as follows:

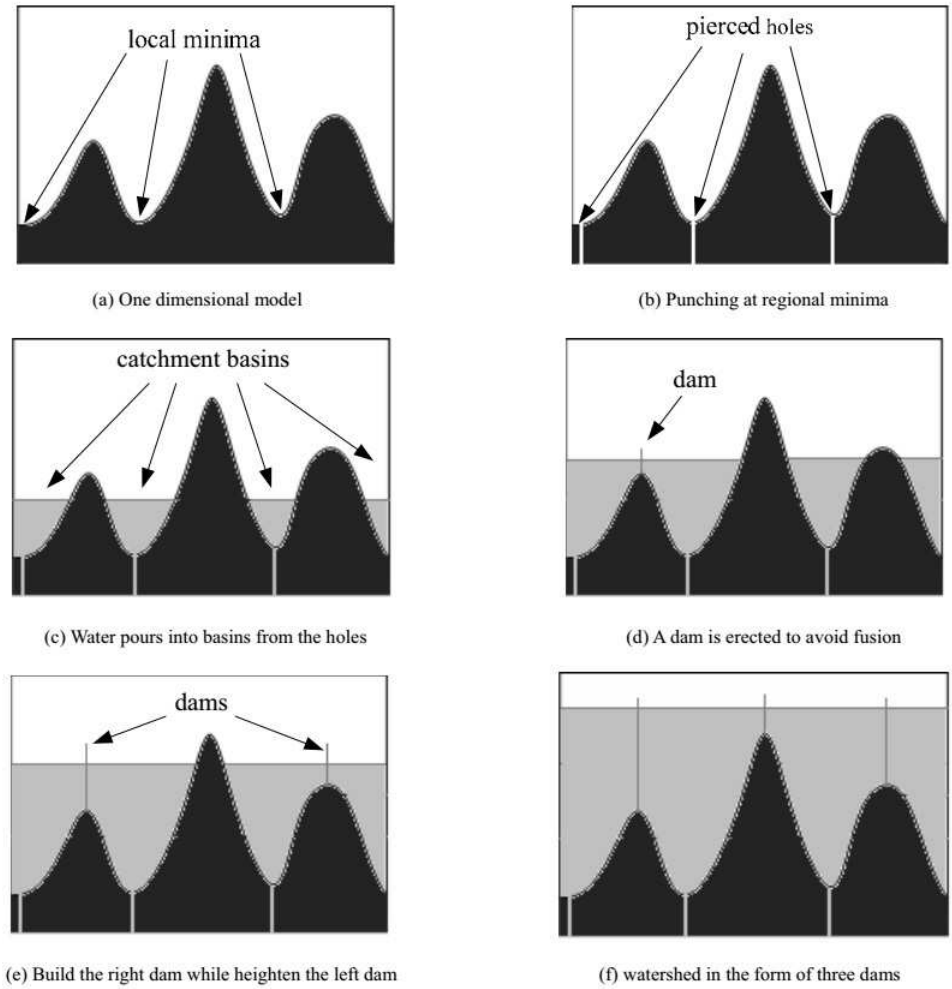
3.5.1 Rainfall Approach

In rainfall approach, the image is viewed as a landscape with valleys, hills, and plateaus. The intensity value of the image is then proportional to the altitude. Thus peaks are the high intensity values. Then assume that rainfalls on the landscape and flows downward along the path of steepest slope, eventually ending in a minimum and creates pools of water. This is the catchment basin. Watershed separates the two pools from meeting with each other. Thus, the watershed separates different objects from each other. The number of resultant objects from the segmentation is dependent on the number of local minima that exist in the image. Alternatively, water begins to collect at each local minimum, and every single local minimum gives rise to one different object in the segmentation result. Watershed transform is often performed on the gradient image [1].

3.5.2 Flooding Approach

In flooding approach, a hole is punched at each local minimum and then it is immersed in the water. The water rises until local maximums. A dam is built between them, when two bodies of water meet. The water rises until all points in the map are immersed. The image is segmented by the dams. The dams are known as watersheds while the segmented regions are referred as catchment basins. Figure 3.2 shows watershed algorithm based on Flooding approach.

However, watershed segmentation has several disadvantages when used on medical images. Firstly, over-segmentation is often a problem. Over-segmentation means that numerous objects have been segmented, which means the image is divided into numerous different regions. It occurs due to too many local minima in the image. Watershed transformation is sensitive to noise, thus there might be difficulty in finding thin structures, and also in finding the regions that are parti-



(a) One dimensional model

(b) Punching at regional minima

(c) Water pours into basins from the holes

(d) A dam is erected to avoid fusion

(e) Build the right dam while heighten the left dam

(f) watershed in the form of three dams

Figure 3.2: Immersion model for one dimensional watershed algorithm.

tioned by a boundary of lower contrast than the other boundaries in the proximity. Improvement of the watershed algorithm has been made to increase the performance. The concept of markers was introduced to remove over-segmentation [27]- [30].

3.6 Atlas-Guided Approaches

Atlas-guided approaches are strong and powerful tool used for medical image segmentation when a standard template or atlas is available. The atlas is generated by compilation of the information on the anatomy which needs to be segmented. Thus, this atlas is used as a reference frame for the segmentation of the new images. Atlas-guided approaches are very much similar to classifiers conceptually. However, the only difference is that the implementation of the atlas-guided approaches is done in the spatial domain than in a feature space. The standard atlas-guided approach treats segmentation as a registration problem..

Atlas-guided approaches are mainly applied in MR brain images. The benefit of atlas-guided approaches is that segmentation and labels both are transferred. Standard systems for studying morphometric properties are also provided by atlas-guided approaches. Accurate segmentation of complex structure is also tough due to anatomical variability even with non-linear registration methods. Anatomical variability can be modeled by using probabilistic atlases, but they require interaction to accumulate the data and additional time.

3.7 Active Contours

Active contours is a method to find the contours of objects. It can be carried out in 2D, which is called snakes, or also in 3D called as active surfaces. The idea is to place a contour, or snake, in the image. This snake is then supposed to find the contours of the searched object in an automatic way. Different forces also affect the snake so that its shape can be changed to fit the contours of the object that one desires to find. Rubber band that changes its size and shape to fit the contour of

an object can be imagined to picturize the snake.

External and internal forces affect the snake in the basic snake model. The internal force attempts to make the contour smaller while the external force counteracts the internal force. The external forces are the result of the image itself. It is generally the gradient image. Flexibility of the snake is determined by how much the different forces are affecting the snake. For example, it has to be very flexible if it should be able to delineate the convolutions.

The main difficulty in active contours is to find the optimal parametric contour $c(s)$.

$$c(s) = (x(s),y(s)) \quad s \in [0,1] \tag{3.7}$$

Internal and external forces both are affecting every point on the contour. The energy of a point on the contour is given by:

$$E(c(s)) = E_i(c(s)) + E_e(c(s)) \tag{3.8}$$

E_i and E_e are the energy due to the internal and external forces respectively. The total energy of the contour is:

$$E = \int_0^1 E(c(s))ds = \int_0^1 (E_i(c(s)) + E_e(c(s)))ds \tag{3.9}$$

The optimal snake is found by minimizing the total energy of the contour:

$$\hat{c}(s) = \arg\min_{c(s)}(E) \tag{3.10}$$

The contour actually changes its shape until a local minimum of the energy function E is reached, when using active contours.

The choice of the parameters is the main difficulty with active contours. It is because it decides how much the different forces should be affecting the contours is not always straight forward. To get the best outcome on various sets of images, fine tuning is needed from the user.

3.8 Multiphase Active Contours

The highly popular Chan Vese level set method [19] has been successfully used in image segmentation with two distinguishing regions (images having binary segmentation energies). In [20], binary segmentation energies were extended to a multiphase level set formulation by Vese and Chan. In this way, multiple non-overlapping regions with spatial consistency and varying characteristics (such as the mean intensities of regions) could be represented with multiple level set functions. Multiphase levelset approach was attractive for MR brain image segmentation because it consists of numerous region of interest with different characteristics. Starting from the Vese and Chan method, different extension to multiphase active contours had been developed [21]- [22]. Robustness to image variations, topological flexibility, adaptive energy functional, and accurate boundaries are the advantages of multiphase active contours in comparison to other approaches.

Active contours used a gradient descent formulation for implementing the non-convex energy minimization which can be stuck in undesirable local minima thereby leading to erroneous segmentations. Moreover, traditional level set implementation is prone to slower convergence because of re-initialization requirement and discretization errors. Recently, a lot of interest is being shown in techniques which can obtain a general convex formulation for active contours schemes based on energy minimization that can reduce the problem of local minima at the same time focusing on the computational complexity.

3.9 Hybrid Segmentation Methods

New application-specific MR brain image segmentation problems are emerging and new methods are continuously explored and introduced. Since appropriate technique selection for a given application is a difficult task, a combination of several techniques may be required to achieve the segmentation goal. Hence, hybrid which is also known as combined segmentation methods have been extensively used in different MR brain image segmentation applications [23]- [24].

The main idea is the combination of different segmentation methods into a hybrid approach to avoid the disadvantages of each method alone and thereby improving the accuracy of segmentation.

Increased complexity in comparison to single method is the main drawback of hybrid (combined) segmentation methods. This also includes a lower computational time and a large number of different parameters which needs to be tuned for a specific application. Hence, a hybrid segmentation method should be wisely and carefully designed to give a good and efficient quality of segmentation. The algorithm proposed in this thesis also belongs to the category of hybrid segmentation method.

Chapter 4
The Proposed Method

MR image segmentation conducted with marker-controlled watershed segmentation solves the problem of over-segmentation, but cannot mark GM and CSF properly. Therefore, a clustering process has been introduced. In our thesis work, we use the EM clustering algorithm, which is an unsupervised method and performs soft cluster assignments. A thresholding operation is conducted to perform binarization and edge detection is subsequently performed. Morphological image reconstruction and marker extraction are also performed before applying the watershed transformation. The combination of the EM clustering algorithm along with marker-controlled watershed segmentation provides effective segmentation results that can mark GM and CSF efficiently. The flowchart of the proposed method (algorithm) is shown in Figure 4.1.

4.1 Filtering Operation

Brain MRI was used for our experiment because MRIs produces detailed information on the internal parts of the human brain. However, MRIs are susceptible to various unwanted noise, such as Gaussian and, salt and pepper, which makes the results unfavorable. Hence, the MRI images must be preprocessed with the help of filtering operations to remove the noise [41]- [42]. In our experiment we used a Wiener filter. An optimal tradeoff between noise smoothing and inverse filtering is executed by Wiener filter. Also, additive noise is removed and the blurring is inverted simultaneously. The Wiener filter minimizes the overall mean square error in the process of noise smoothing and inverse filtering. The Wiener filtering performs a linear estimation of the original image.

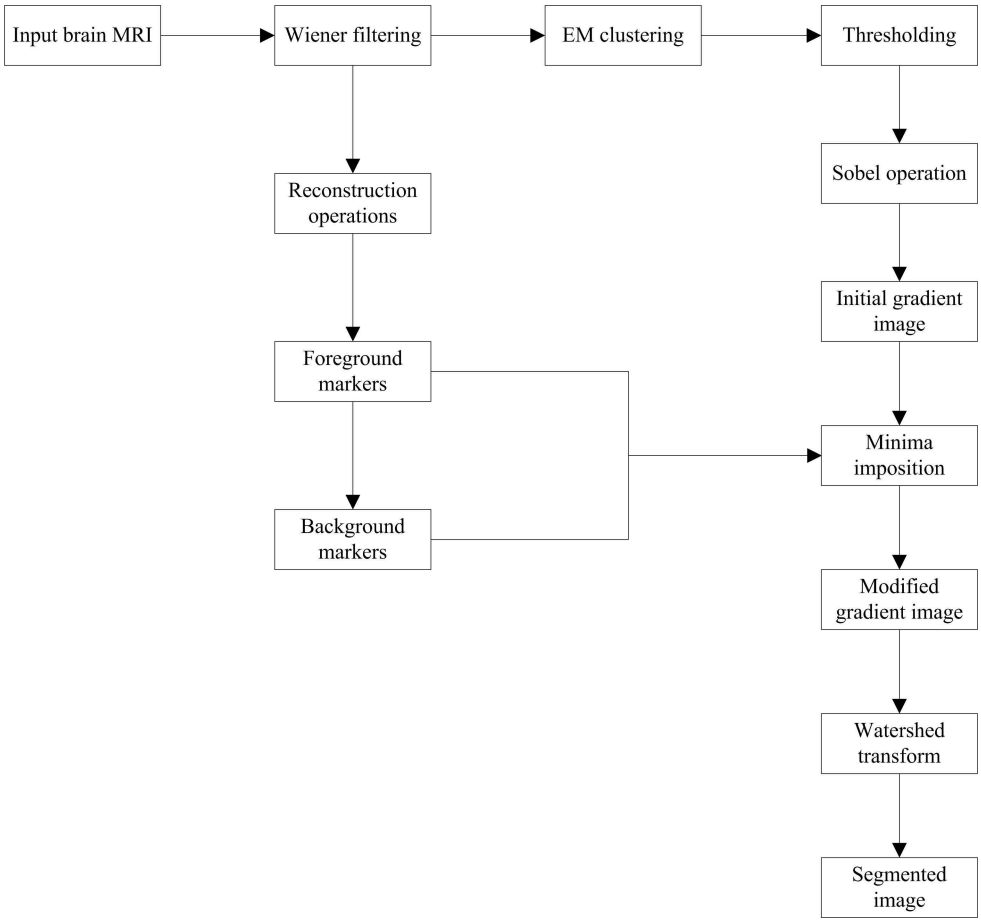


Figure 4.1: Flowchart of the proposed method.

4.2 Expectation-Maximization Algorithm

The EM algorithm [36]- [37] is a class of algorithm for finding the ML in an iterative manner and assumes that the data follows a Gaussian mixture model (GMM). The EM algorithm is a popular technique used for density estimation of data points in an unsupervised clustering. The EM algorithm performs alternating steps of Expectation (E) and Maximization (M) iteratively until the results converge. An expectation of the likelihood is computed on the E-step by including the latent variables, and the ML of the parameters is performed on the M-step based on the last E-step by maximizing the expected likelihood. Based on the pa-

rameters found on the M-step, another E-step starts, and the process is repeated until convergence is met.

The EM algorithm is used to divide the image into clusters. Data points are partially assigned to different clusters instead of assigning to only one cluster. Each cluster is modeled using a probabilistic distribution for the partial assignment. Hence, a data point is associated with a cluster with certain probability and it belongs to the cluster with the highest probability in the final assignment unlike k-means clustering. K-means clustering algorithm is simple but it is easy to get stuck in local optimal. On the other hand, the EM algorithm tends to get stuck less than k-means algorithm. Hence, we have decided to use EM algorithm as the clustering technique for our thesis.

The EM algorithm requires the initialization of model parameters of a Gaussian mixture. It is presumed that there is a finite number of gray-level probability density functions, say K, and each pixel distribution can be modeled by one Gaussian. The shape of the density of probability of this mixture is given by:

$$P(x|\psi) = \sum_{j=1}^{K} \pi_j P(x|\mu_j,\Sigma_j) \tag{4.1}$$

where, x is the characteristics vector, $\pi_j \geq 0$, and $\Sigma_{j=1}^{K}\pi_j = 1$. Similarly, parameter ψ consists of means μ_j, co-variances Σ_j, and mixing coefficients π_j for $j = 1, 2, ..., K$. Hence,

$$P(x|\mu_j,\Sigma_j) = \frac{1}{(2\pi)^{\frac{d}{2}}|\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu_j)^t\Sigma_j^{-1}(x-\mu_j)} \tag{4.2}$$

Steps:

1. Initialize means μ_j, co-variances Σ_j, and mixing coefficients π_j, and then evaluate the initial value of the log likelihood.

2. ***E-step***:

At the E-step, we evaluate the expectancy using the current parameter values.

$$S_{ij} = \frac{\pi_j P(x_i|\mu_j,\Sigma_j)}{\Sigma_{m=1}^{K}\pi_m P(x_i|\mu_m,\Sigma_m)}, \quad 1 \leq j \leq K, \quad 1 \leq i \leq N \tag{4.3}$$

3. ***M-step***:

At the M-step, we update the parameters.

The updated mean can be calculated as,

$$\mu_j^{new} = \frac{1}{N_j}\sum_{i=1}^{N} S_{ij}x_i\,, \quad 1 \leq j \leq K \tag{4.4}$$

The updated covariance can be calculated as,

$$\Sigma_j^{new} = \frac{1}{N_j}\sum_{i=1}^{N} S_{ij}(x_i - \mu_j^{new})(x_i - \mu_j^{new})^t\,, \quad 1 \leq j \leq K \tag{4.5}$$

The updated mixing coefficient can be calculated as,

$$\pi_j^{new} = \frac{N_j}{N}\,, \quad 1 \leq j \leq K \tag{4.6}$$

where, $N_j = \Sigma_{i=1}^{N} S_{ij}$

4. The log likelihood is evaluated by,

$$logl(\psi) = \sum_{i=1}^{N}\left(log\sum_{j=1}^{K}\pi_j P(x_i|\mu_j,\Sigma_j)\right) \tag{4.7}$$

The value of log likelihood is computed using Equation 6.7 to detect the convergence. If the convergence criterion is not fulfilled, the algorithm returns to the E-step.

4.3 Thresholding

Thresholding [38] is a widely used method for image segmentation because of its simplicity. Thresholding segment scalar images by creating a binary division of the image intensities. A thresholding procedure attempts to find an intensity value, called the threshold which partitions the desired classes. The segmentation by thresholding approach is achieved by grouping all pixels with intensity greater than the threshold into one class, and all other pixels into another class as shown in Figure 4.2(b) at the valleys of the histogram. Multi thresholding is the determination of more than one threshold value. In our thesis, we determine threshold

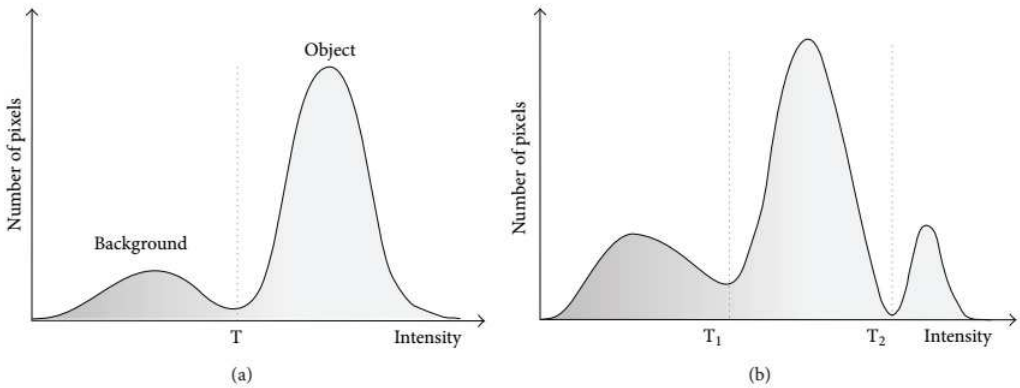


Figure 4.2: (a) Gray level histograms that can be partitioned by a single threshold. (b) Gray level histogram that can be partitioned by multiple thresholds.

value form the means obtained from the EM algorithm. The threshold value is selected as the mean of the brightest cluster consisting of GM and CSF.

Thresholding is fast and computationally efficient and also provides ease of implementation. Thresholding is a simple and effective means for obtaining the segmentation in images where different structures have contrasting intensities or other quantifiable features. Thresholding may be viewed as an operation that involves tests against a function T,

$$T = T[x,y,p(x,y),f(x,y)] \tag{4.8}$$

Where $f(x,y)$ is the gray level of point (x,y) and $p(x,y)$ denote some local property of this point, for example, the average gray level of a neighborhood centered on (x,y).

When T depends only on $f(x,y)$ i.e., only on gray level values the threshold is called global. If T depends on both $f(x,y)$ and $p(x,y)$, then the threshold is called local. If, in addition, T depends on the spatial coordinates x and y, the threshold is called dynamic or adaptive.

The actual part of thresholding consists of setting foreground values for pixels above a threshold value T and a different set of values for the background. A

thresholded image, $g(x, y)$ is then defined as,

$$g(x,y) = \begin{cases} 1 & if\ f(x,y) > T \\ 0 & if\ f(x,y) \leq T \end{cases} \tag{4.9}$$

The input to a thresholding operation is a grayscale or color image. In thresholding, the output is a binary image which represents the segmentation. White pixels correspond to foreground and black pixels correspond to background (or vice versa). In our thesis, if the pixel intensity is lower than the threshold, the pixel is set to black in the output. If it is higher than the threshold, it is set to white.

4.4 Edge Detection Method

In edge detection technique an edge or boundary on an image is defined by the local pixel intensity gradient. An approximation 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,

$$|G| = \sqrt{G_x^2 + G_y^2} \tag{4.10}$$

The direction of gradient is represented as,

$$D = \tan^{-1}(\frac{G_y}{G_x}) \tag{4.11}$$

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

Edge-based techniques are computationally fast and do not require a priori information about image content. In this technique, the direction and magnitude can be presented as images. A post processing step of grouping edges or linking is generally required to structure closed boundaries neighboring regions. There are many edge detection techniques in the literature for image segmentation. The most commonly used edge detection techniques are Roberts cross-gradient operators, Prewitt operators and Sobel operators.

Weighed summation of the pixel intensities in a small neighborhood can be represented as a numerical array in this method which is known as mask/window/kernel. The mask for different edge detection techniques are shown below:

Roberts Cross-Gradient Operators:

−1	0
0	1

0	−1
1	0

Prewitt Operators:

−1	−1	−1
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

Sobel Operators:

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

To compute G_x and G_y first and second mask are used respectively. Finally, joining G_x and G_y using Equation 6.10, gradient magnitude image is obtained. In our thesis, we use Sobel operator to get the gradient image. The Sobel operator works well at detecting the edges and it also provides differencing and smoothing effect.

4.5 Morphological Image Reconstruction

Before describing morphological image reconstruction, we need to know about dilation and erosion. Therefore, we describe dilation and erosion in brief.

4.5.1 Dilation

Dilation implies that object areas are expanded along the border to the background. This means that background pixels closer than a given distance, r, to an object pixel are converted into object pixels. An example of dilation is presented in Figure 4.3.

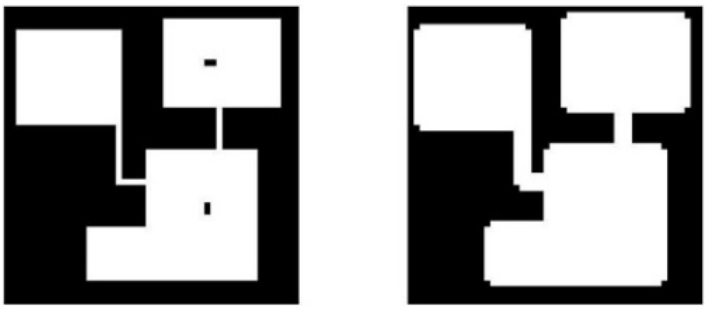


Figure 4.3: Example of dilation: (a) Original image and (b) dilated image.

4.5.2 Erosion

Erosion implies that object areas are shrunk along the border to the background. This means that all object pixels closer than a given distance, r, to a background pixel are converted into background pixels. An example of erosion is presented in Figure 4.4.

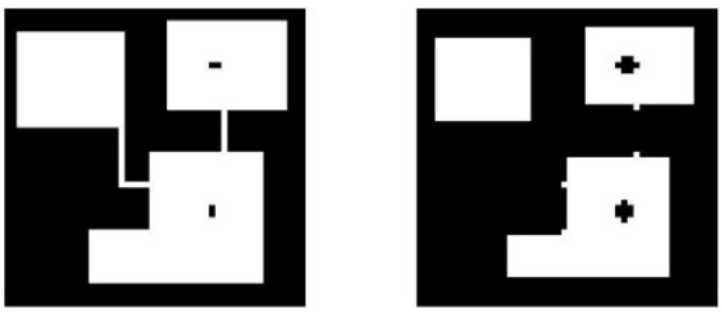


Figure 4.4: Example of erosion: (a) Original image and (b) eroded image.

4.5.3 Erosion Based Gray-Scale Image Reconstruction

Let us suppose that M and N are two gray-scale images defined on the same domain such that $M \leq N$. The reconstruction by erosion of N from M is obtained by iterating the gray-scale erosions of M "above" N until stability is reached.

$$\rho_N^*(M) = \bigwedge_{n \geq 1} \varepsilon_N^{(n)}(M) \tag{4.12}$$

The elementary erosion $\varepsilon_N^{(1)}(M)$ of gray-scale image $M \leq N$ is obtained as follows:

$$\varepsilon_N^{(1)}(M) = (M \ominus b) \vee N \tag{4.13}$$

where $\vee$ represents the point wise maximum and $(M \ominus b)$ is the erosion of M by the flat structuring element denoted by b.

4.5.4 Dilation Based Gray-Scale Image Reconstruction

Let us suppose that M and N are two gray-scale images defined on the same domain such that $M \leq N$. The reconstruction by dilation of N from M is obtained by iterating the gray-scale dilations of M "under" N until stability is reached.

$$\rho_N(M) = \bigvee_{n \geq 1} \delta_N^{(n)}(M) \tag{4.14}$$

The elementary dilation $\delta_N^{(1)}(M)$ of gray-scale image $M \leq N$ is obtained as follows:

$$\delta_N^{(1)}(M) = (M \oplus b) \wedge N \tag{4.15}$$

where $\wedge$ represents the point wise minimum and $(M \oplus b)$ is the dilation of M by the flat structuring element denoted by b. A detailed explanation can be found in [39]- [40].

4.6 Markers Extraction

As discussed earlier, direct application of watershed transformation on the gradient image creates over-segmentation because of noise and other irregularities contained in MRIs. Therefore, the EM clustering algorithm and reconstruction operators are applied to mark the brain tissues efficiently. Reconstruction operators, such as erosion-based and dilation-based grayscale image reconstruction, are performed. Both are the same, and the difference is simply that we change the erosion operation with dilation and vice-versa. Foreground markers within the region of interest and background markers contained within the background are obtained from the reconstruction operators. These markers are extremely important because they help in modifying the gradient image obtained from the EM clustering algorithm by the minima imposition technique. Watershed transformation performed on this modified gradient magnitude actually helps segment brain tissues efficiently.

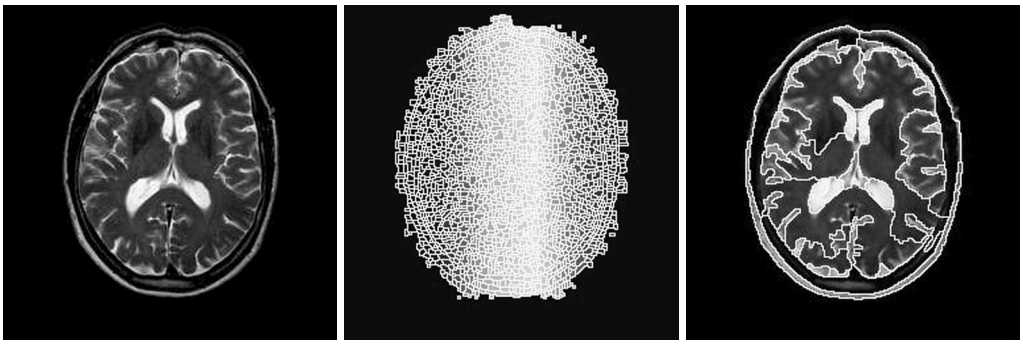
Chapter 5
Performance Evaluation

In this chapter, we present experimental results of evaluating the performance of the proposed algorithm using different brain MR images acquired from Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). We performed experiments with some existing algorithms used in the watershed method on the MR brain images. MATLAB simulation results with the proposed algorithm provides better segmentation outputs in comparison to the traditional watershed algorithm and marker-controlled watershed algorithm. This chapter is organized for the simulated results by the traditional watershed algorithm and marker-controlled watershed algorithm and then our approach to implement the EM clustering algorithm and thresholding technique along with marker-controlled watershed segmentation algorithm and finally comparison of our implementation with the combination of Otsu multilevel thresholding and watershed algorithm, and distance regularized level set evolution (DRLSE). The proposed algorithm was tested using MATLAB R2014b.

5.1 Subjective Quality

Conventional watershed algorithm on the gradient magnitude image results in severe over-segmentation and therefore the results are practically useless. There are several hundreds or thousands of over-segmented regions using traditional algorithm, for a given original image in Figure 5.1(a) which can be seen in Figure 5.1(b). When applied to the images, marker-controlled watershed segmentation alone cannot properly segment the GM and CSF. In fact, many objects are left without marking as seen in Figure 5.1(c). Hence, EM clustering algorithm and thresholding technique is used along with marker-controlled watershed algorithm to segment and mark brain tissues efficiently.

Noise present in the brain MRI generates several minima which is also one



(a) (b) (c)

Figure 5.1: (a) Original image (b) Result of traditional watershed algorithm, and (c) Result of marker-controlled watershed segmentation algorithm.

of the major causes of over-segmentation. Therefore, Wiener filter has been applied to remove the noise and artifacts present in the image and also to solve the problem of over-segmentation due to noise. Segmentation results with filtering technique gives better results. A filtered image has been shown in Figure 5.2(a).

MR image of the brain typically consists of three tissues: GM, WM, and CSF. Hence, the EM clustering algorithm is used with a cluster number of three. The clustered image is shown in Figure 5.2(b). Our goal is to segment GM and CSF, and through the clustered image, we find that they are contained in the brightest cluster. Therefore, the mean value of the brightest cluster is used as the threshold value. The threshold value used for the brain MR image is 71. The result is the binary image as discussed in earlier section. The initial gradient magnitude is thus obtained by using Sobel operator on the binary image and is shown in Figure 5.2(c).

Foreground and background markers are computed using morphological reconstruction operations, such as erosion-based and dilation-based, on the filtered image by selecting a proper structuring element. Square shaped structuring element is used in this case. Foreground markers and background markers are shown in Figure 5.2(d) and Figure 5.2(e) respectively. The final gradient magnitude image is thus obtained using the minima imposition technique based on the initial

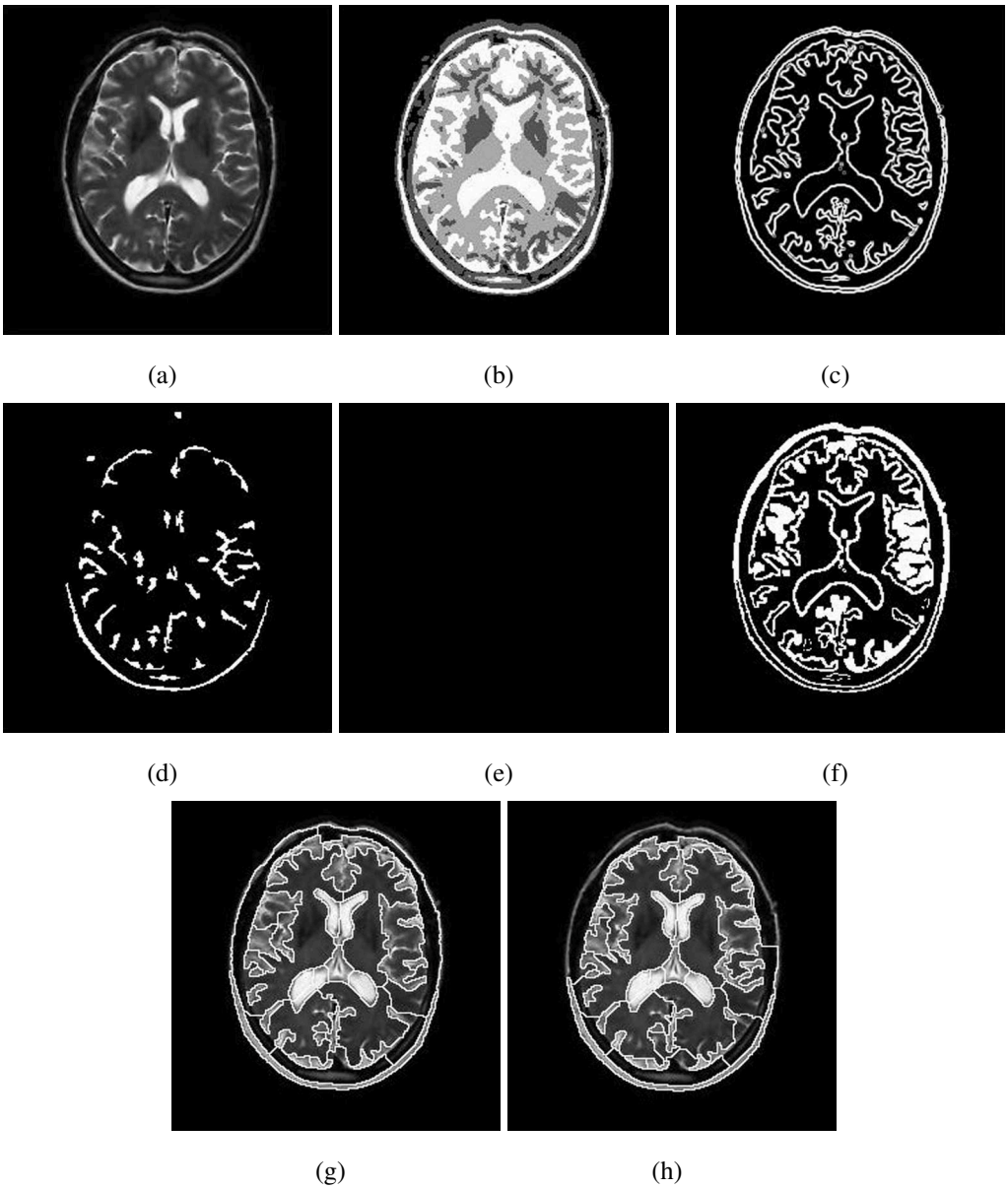
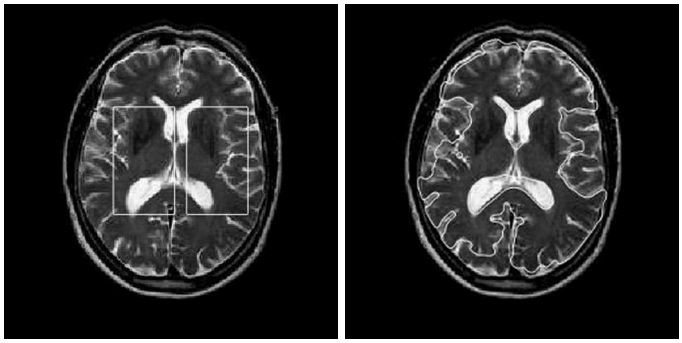


Figure 5.2: (a) Filtered image (b) Clustered image (c) Initial gradient magnitude image (d) Foreground markers (objects) (e) Background objects (f) Final gradient magnitude image (g) Result of our proposed method (h) Result of the combination of Otsu method and watershed segmentation.

gradient magnitude image and, foreground and background markers. The final gradient magnitude image is shown in Figure 5.2(f). Watershed transformation thus applied on the final gradient magnitude gives the effective segmented result as shown in Figure 5.2(g). Although, some over-segmented lines in the final result are obtained while segmenting the brain tissue, as seen in the Figure, the results are much better than the conventional watershed algorithm on the gradient image and simple marker-controlled watershed segmentation. The proposed methodology is capable of efficiently marking brain tissues.

The algorithm is also tested with Otsu multilevel thresholding for comparison [43]- [44]. Otsu thresholding is one of the most successful methods for image segmentation based on thresholding, and it is based on the criterion that minimizes the within-class variance. Because our aim is to segment GM and CSF, the threshold value we obtain from the Otsu multilevel thresholding for the MR brain image is 82. Binary image is thus obtained using these values. Watershed segmentation thus applied using the proposed algorithm gives the segmented result as shown in Figure 5.2(h). The result obtained looks comparable to the results obtained using our proposed method but our proposed method is actually performing better than the combination of Otsu multilevel thresholding and watershed segmentation (which will be explained in next section). Otsu method actually has disadvantage of being computationally inefficient. The inefficient formulation of between-class variance increases the computational cost of algorithm, especially in the multilevel threshold selection. The computational complexity of the algorithm grows exponentially with the number of thresholds. Similarly, the Otsu method requires the computation of gray-level histogram first.

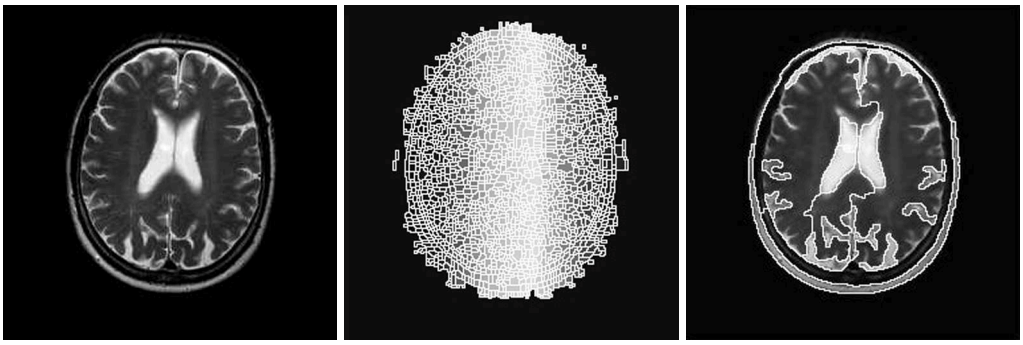
Similarly, our proposed method is also tested with DRLSE [45] for comparison. Figure 5.3 shows the initial contour and segmentation result using DRLSE on the MR brain image. An inspection of the result clearly indicates that the proposed method has superior performance than the DRLSE. It should also be noted that the DRLSE is sensitive to correct tuning of parameter values. Improper parameter values will result in inaccurate segmentation and longer computational time. Therefore, estimation of correct parameters is very important. Hence, our



(a) (b)

Figure 5.3: Results using DRLSE: (a) Initial contour (b) Segmented result.

method has superior hold on these areas as well.



(a) (b) (c)

Figure 5.4: (a) Original image (b) Result of traditional watershed algorithm, and (c) Result of marker-controlled watershed segmentation algorithm.

Figure 5.4(a) shows the original MR brain image. The results of using traditional watershed algorithm and marker-controlled watershed segmentation is shown in the Figure 5.4(b) and Figure 5.4(c) respectively. Conventional watershed segmentation algorithm resulted in severe over-segmentation while marker-controlled watershed segmentation could not mark all the objects. Fig. 11 shows the steps of using the proposed algorithm. Figure 5.5(a) shows the filtered image while the clustered image is shown in Figure 5.5(b). The threshold value used

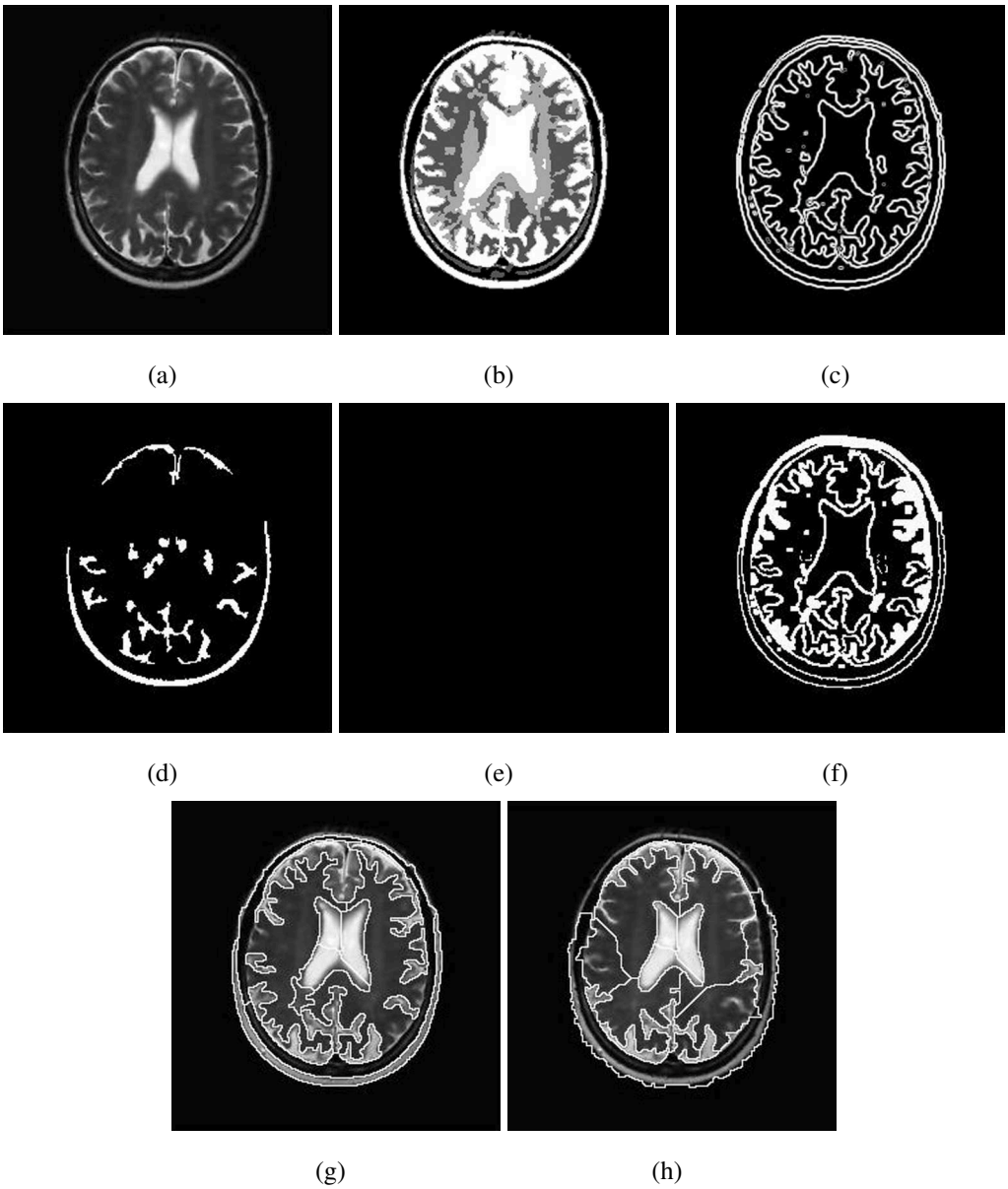
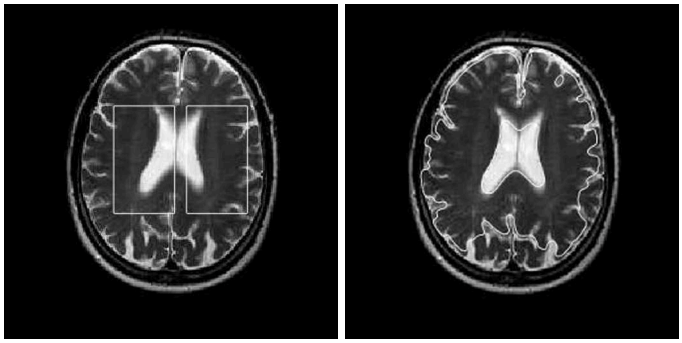


Figure 5.5: (a) Filtered image (b) Clustered image (c) Initial gradient magnitude image (d) Foreground markers (objects) (e) Background objects (f) Final gradient magnitude image (g) Result of our proposed method (h) Result of the combination of Otsu method and watershed segmentation.

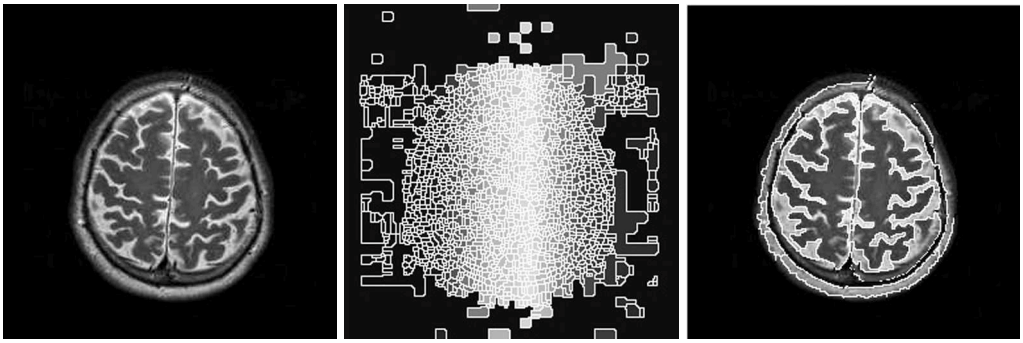


(a) (b)

Figure 5.6: Results using DRLSE: (a) Initial contour (b) Segmented result.

here is 61 for obtaining the binary image. Similarly, Figure 5.5(c) - 5.5(f) shows the initial gradient magnitude image, foreground markers, background markers, and final gradient magnitude image respectively. The result of the proposed method is seen in Figure 5.5(g) which is much better than the conventional watershed segmentation algorithm and marker-controlled watershed segmentation algorithm. Similarly, Figure 5.5(h) shows the result of the combination of the Otsu method and watershed segmentation. The threshold value obtained from Otsu multilevel thresholding for the segmentation of brain tissues is 85. Otsu method fails to segment the brain tissues efficiently. Besides, there are number of over-segmented lines as seen in the Figure. Also, Figure 5.6(a) shows an initial contour and Figure 5.6(b) shows the segmentation result using DRLSE. Inspection of the result shows that DRLSE is unable to segment and mark the brain tissues. Hence our proposed method is better than the watershed segmentation combined with Otsu method and DRLSE.

The original MR brain image is shown in Figure 5.7(a) along with the result of traditional watershed algorithm on the gradient image and marker-controlled watershed segmentation algorithm in Figure 5.7(b) and Figure 5.7(c) respectively. To overcome the drawbacks of these algorithms, the proposed methodology is applied which is shown in Figure 5.8 starting with the filtered image in Figure 5.8(a). The clustered image obtained using EM algorithm is shown



(a) (b) (c)

Figure 5.7: (a) Original image (b) Result of traditional watershed algorithm, and (c) Result of marker-controlled watershed segmentation algorithm.

in Figure 5.8(b). A threshold value of 90 is used for obtaining the binary image and thereby obtaining the initial gradient magnitude image as seen in Figure 5.8(c). Foreground and background markers are shown in Figure 5.8(d) and Figure 5.8(e) respectively. Watershed segmentation applied on the final gradient magnitude image as shown in Figure 5.8(f) gives the effective segmentation result given in Figure 5.8(g). Hence, the proposed algorithm successfully segments the GM and CSF. Result is compared with the combination of the Otsu multilevel thresholding and watershed transform with the threshold value of 98. The result can be seen in Figure 5.8(h) which clearly indicates that both the methods are comparable. However it should be taken into account that Otsu multilevel thresholding is computationally inefficient. Figure 5.9(a) shows the initial contour and Figure 5.9(b) gives the segmented result using DRLSE. The DRLSE method miserably fails to segment and mark the GM and CSF. Hence, our proposed method outperforms the DRLSE.

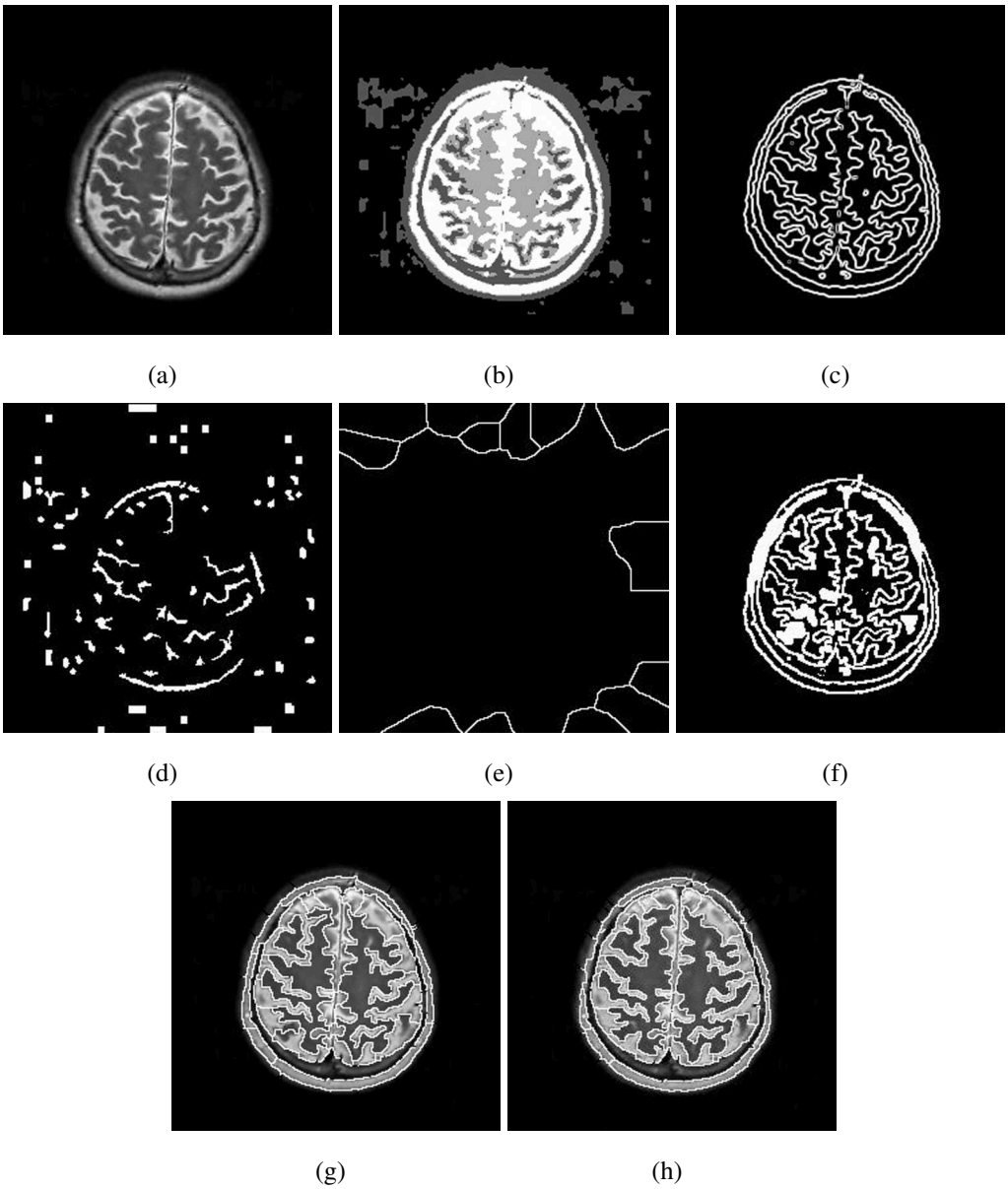
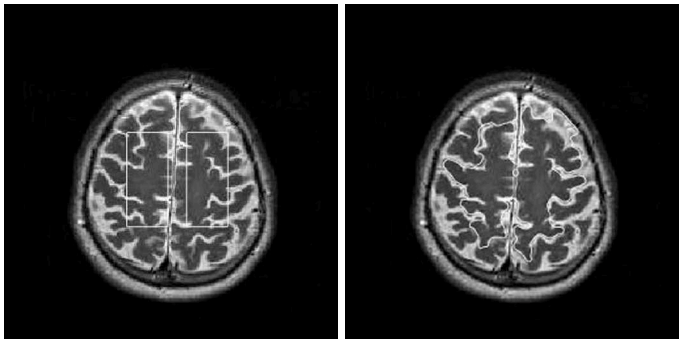


Figure 5.8: (a) Filtered image (b) Clustered image (c) Initial gradient magnitude image (d) Foreground markers (objects) (e) Background objects (f) Final gradient magnitude image (g) Result of our proposed method (h) Result of the combination of Otsu method and watershed segmentation.



(a) (b)

Figure 5.9: Results using DRLSE: (a) Initial contour (b) Segmented result.

5.2 Segmentation Validation and Quantitative Analysis

Quantifying the quality of the segmentation is difficult in the real patient image, as the ground truth is usually unknown. In the absence of ground truth images for the given set of medical images we have used the idea proposed by Chunming Li [46] and referred to it as ground truth or equivalent to manual segmentation result. The results of brain image segmentation using the proposed method, Otsu method combined with watershed segmentation, and DRLSE are compared with ground truth. In this thesis, we have used the common metrics for validation including success rates and similarity metrics. The success rates and similarity metrics compare the consistency between the ground truth and the proposed segmentation method. Let G and A denote the set of voxels labeled as segmented object from ground truth and from different methods respectively.

• True positive (TP) set of common labeled voxels between a ground truth and a proposed method $(TP = G \cap A)$

• True negative (TN) set of non-target-object labeled voxels between these two sets $(TN = \bar{G} \cap \bar{A})$

• False positive (FP) set as $FP = \bar{G} \cap A$

• False negative (FN) set as $FN = G \cap \bar{A}$

5.2.1 Success Rates

Success rates are usually defined by sensitivity and specificity. Sensitivity is also named as target overlap that is the intersection between two similarly labeled regions r in G and A over the extent of G volume. It can be represented as,

$$Sensitivity = \frac{|G_r \cap A_r|}{|G_r|} = \frac{|TP|}{|TP| + |FN|} = \frac{|TP|}{|G|} \tag{5.1}$$

Specificity is defined as the fraction of the non-target-object voxels over the non-ground-truth voxels. That is, the fraction of the negative samples which are also labeled as negative by the to-be-evaluated segmentation method. It can be represented as,

$$Specificity = \frac{|TN|}{|TN| + |FP|} = \frac{|TN|}{|\bar{G}|} \tag{5.2}$$

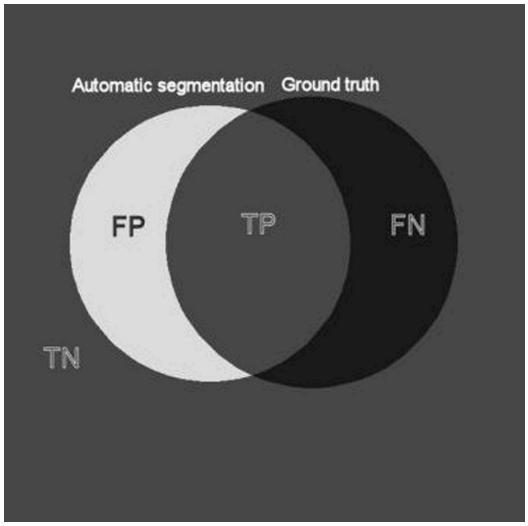


Figure 5.10: Schematic Venn diagram based on comparison between ground truth segmentation and automated segmentation.

5.2.2 Similarity Metrics

Similarity metrics measures how well two segmentation overlaps. Dice coefficient is commonly used similarity metrics which is used to measure the fraction of spatial overlap between two binary images. Dice is defined as the intersection between two similarity labeled regions r in G and A over the average volume of these two regions. Furthermore, Dice can be summed over a set of multiple labeled regions.

$$Dice = 2\frac{|G_r \cap A_r|}{|G_r| + |A_r|} = 2\frac{|TP|}{(|TP| + |FP| + |TP| + |FN|)} \tag{5.3}$$

The values obtained for sensitivity, specificity, and dice coefficient are listed in the Tables below for different MR brain images obtained from different methods.

Table 5.1: Comparative Results: Sensitivity

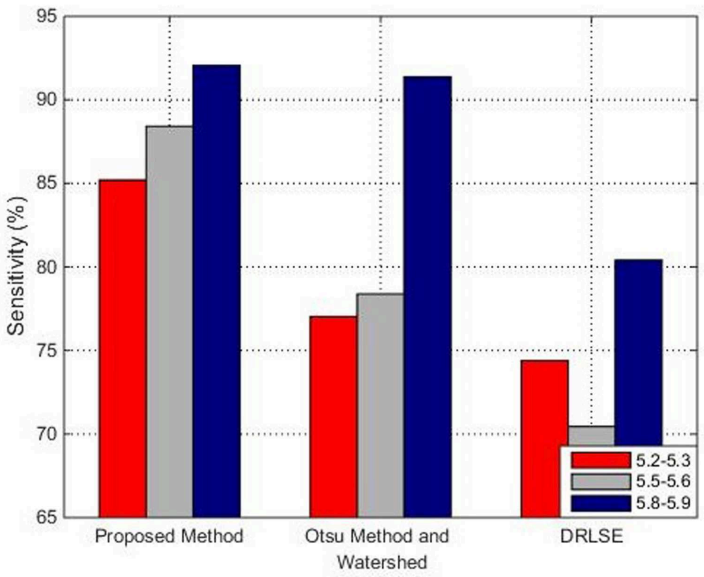
Image Index	Proposed Method (%)	Otsu Method and Watershed (%)	DRLSE (%)
5.2-5.3	85.2	77.03	74.39
5.5-5.6	88.42	78.38	70.45
5.8-5.9	92.06	91.38	80.41

Table 5.2: Comparative Results: Specificity

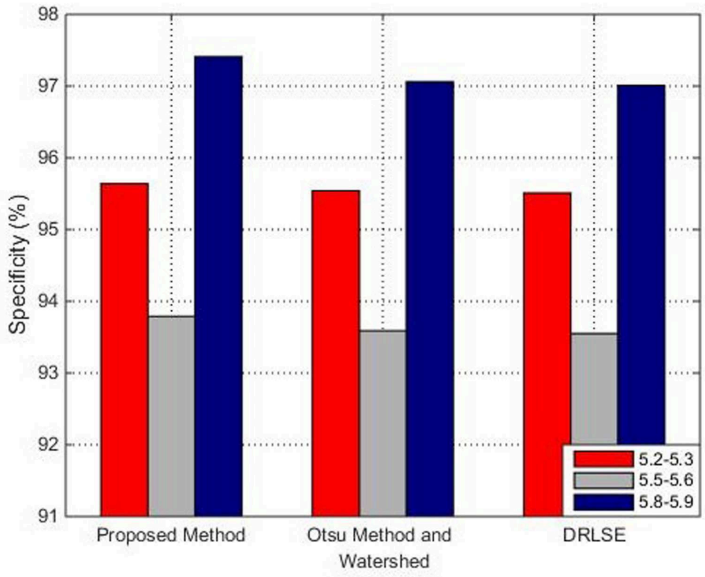
Image Index	Proposed Method (%)	Otsu Method and Watershed (%)	DRLSE (%)
5.2-5.3	95.64	95.54	95.51
5.5-5.6	93.79	93.59	93.55
5.8-5.9	97.41	97.06	97.01

Table 5.3: Comparative Results: Dice Coefficient

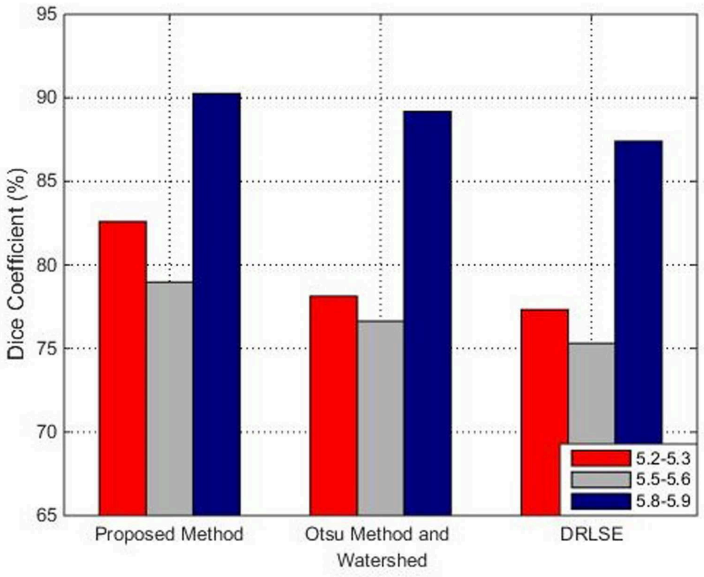
Image Index	Proposed Method (%)	Otsu Method and Watershed (%)	DRLSE (%)
5.2-5.3	82.59	78.13	77.32
5.5-5.6	78.97	76.63	75.31
5.8-5.9	90.25	89.18	87.40



(a)



(b)



(c)

Figure 5.11: Graphical comparisons in terms of Sensitivity, Specificity, and Dice Coefficient obtained from (a) Table 5.1, (b) Table 5.2, and (c) Table 5.3.

The proposed method uses sensitivity, specificity, and dice coefficient value for the objective analysis between the proposed method, combination of Otsu method and watershed segmentation, and DRLSE. Table 5.1 shows the comparative results in terms of sensitivity. For the images in Figure 5.2 - 5.3, the value of sensitivity using our proposed method is as high as 85.2% against 77.03% of the combination of Otsu method and watershed segmentation and 74.39% of the DRLSE. The high value of sensitivity is consistent for the images in Figure 5.5 - 5.6 with 88.42% for proposed method. Combination of Otsu method and watershed segmentation, and DRLSE resulted in 78.38%, and 70.45% respectively. The highest value of sensitivity for our proposed method is obtained for the images in Figure 5.8 - 5.9 with 92.06%. The other two methods resulted in the sensitivity value of 91.38%, and 80.41% respectively. The graphical representation of sensitivity is shown in Figure 5.11(a).

The value of specificity is demonstrated in the Table 5.2. The value for the images in Figure 5.2 - 5.3 is 95.64% for our proposed method, 95.54%, and 95.51% for the combination of Otsu method and watershed segmentation, and DRLSE respectively. Specificity value using our proposed method continues to dominate for the images in Figure 5.5 - 5.6 with 93.79% as opposed to 93.59% for Otsu method and watershed segmentation, and 93.55% for DRLSE. Similarly, our proposed method, Otsu method and watershed segmentation, and DRLSE resulted in specificity value of 97.41%, 97.06%, and 97.01% respectively for the given images in Figure 5.8 - 5.9. Our proposed method performs marginally better than the other two methods in terms of specificity but is should be noted that specificity is the fraction of the non-target-object voxels over the non-ground-truth voxels. The graphical representation of specificity is shown in Figure 5.11(b).

Table 5.3 illustrates the value of similarity metric using dice coefficient. Proposed method resulted in 82.59% over 78.13% and 77.32% for combination of Otsu method and watershed, and DRLSE respectively for the images in Figure 5.2 - 5.3. The proposed method, Otsu method and watershed segmentation, and DRLSE for the images in Figure 5.5 - 5.6 resulted the values of 78.97%, 76.63%,

and 75.31% respectively. 90.25% is calculated for the images in Figure 5.8 - 5.9 using our proposed method, against 89.18% for the combination of Otsu method and watershed segmentation and 87.40% for DRLSE. The graphical representation of dice coefficient is shown in Figure 5.11(c).

When we compare Figure 5.11(a), Figure 5.11(b), and Figure 5.11(c) the proposed method outperformed the combination of Otsu method and watershed segmentation, and DRLSE in all three validation techniques. Therefore, the proposed method is better than the other two methods.

Chapter 6
Conclusions

This thesis presented a class of algorithm for the effective segmentation of the brain from MR images. Segmentation plays a vital role in analyzing processed image data which is one of the hot topics in imaging field. Brain MR Image is a complex system to be segmented with efficient method for having variable kind of tissues. Watershed transformation is used in this thesis because of its inherent advantages including simplicity and ability to produce complete division of the image even under poor contrast. But, the conventional watershed algorithm on a gradient image resulted in heavily over-segmented results. Hence, marker-controlled watershed segmentation is applied, but it could not properly segment and mark brain tissues. Therefore, the EM clustering algorithm and thresholding operation is used along with marker-controlled watershed segmentation for the effective segmentation of brain MR images. The EM algorithm is introduced to divide the image into clusters. Sobel edge detection operator is used for obtaining the gradient magnitude image as it provides differencing and smoothing effect. Structuring elements must be selected as per the desired object. Foreground markers within the region of interest and background markers contained within the background are obtained from the reconstruction operators. Real brain MR images are used for the purpose of experiment over synthetic images. Experimental results prove the effectiveness of the proposed algorithm in terms of both subjective and quantitative analysis in comparison to other methods. Since, the final results of the proposed method over the different MR brain images are better than the other methods, our method can be used efficiently for the segmentation of the brain images.

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List of Publications

Jeong-Muk Kim, Ramesh Kumar Lama, **Dibash Basukala**, Suk-seung Hwang, Jae-Young Pyun and Goo-Rak Kwon, *Pedestrian detection using individual feature information from multiple pedestrian tracking process*, International Conference on Electronics, Information, and Communication (ICEIC), 2015.

Dibash Basukala and Goo-Rak Kwon, *Watershed algorithm based image segmentation using moment preserving bilevel thresholding and extended maxima transform for kernels*, Journal of KIIT, 2015.

Van Han Nguyen, Goo-Rak Kwon, **Dibash Basukala** and Jae Young Pyun, *An advanced watershed algorithm for image segmentation*, International Conference on Electronics, Information, and Communication (ICEIC), 2016.

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