NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

Study of Segmentation Techniques for Medical Images

by

Sachin Kumar Sethi

A thesis submitted in partial fulfillment for the
degree of Bachelor Of Technolgy

under the guidance of
Prof. Ratnakar Dash
Department Of Computer Science and Engineering

May 2013

Computer Science and Engineering
National Institute of Technology Rourkela
Rourkela-769 008, India. www.nitrkl.ac.in

Prof.Ratnakar Dash
Assistant Professor

May 13, 2013

Certificate

This is to certify that the work in the project entitled "*Study of Segmentation Techniques for Medical Images*" by *Sachin Kumar Sethi* is a record of their work carried out under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of *Bachelor of Technology* in *Computer Science and Engineering.*

Ratnakar Dash

Abstract

Segmentation techniques are widely used in for the application of Medical Images. These techniques play a crucial role by automating or facilitating the delineation of anatomical structures and other regions of interest . Image Segmentation is particularly difficult due to restrictions imposed by biological variation and image acquisition . Goal of medical image segmentation is to perform operations on medical images to identify patterns in the use of interaction and develop qualitative criteria to evaluate interactive segmentation methods and extract information from it .Techniques available for segmentation are specific to application and the segment of biological detail to be studied . Number of techniques require wide use of Algorithms specifically for certain segmentation procedure of medical images . From the Medical Image processing point of view the classification of segmentation techniques is on gray level and texture based techniques. Approaches have been proposed to segment CT and MR Images. In the following chapters we discuss the reviewed methods with respect to all information provided by the user and the parameters for the computational part. Medical image segmentation techniques require some form of expert supervision to provide accurate and consistent identification of anatomic structures. A novel segmentation technique was developed that combines a knowledge-based segmentation system with a contour model. This method exploits the guidance of a higher level process to robustly perform the segmentation of kind of anatomic structures. Knowledge about the anatomic structures to be segmented is defined statistically in terms of probability density functions of parameters of location, size, and image intensity. The active contour based technique outperform the standard segmentation methods due to its capacity to fully enforce the available a priori knowledge concerning the anatomic structure of interest. The active contour algorithm is suitable for integration with high-level image understanding frameworks, and providing a robust low-level segmentation tool. Studies are required to determine whether the proposed algorithm is indeed capable of providing consistently superior segmentation.

Acknowledgements

I take this opportunity to express my profound gratitude and deep regards to my project supervisor Prof.Ratnakar Dash for his exemplary guidance, monitoring and constant encouragement throughout the course of this thesis. The blessing, help and guidance given by him time to time shall carry me a long way in the journey of life on which I am about to embark. I also take this opportunity to express a deep sense of gratitude to Prof. Bansidhar Majhi, for his cordial support, valuable information and guidance, which helped me in completing this task through various stages. Lastly, I thank almighty, my parents and friends for their constant encouragement without which this assignment would not be possible.

Sachin Kumar Sethi

Contents

List of Figures

Chapter 1

Introduction

Image segmentation is the process labeling every pixel in an image such that pixels with the same label share certain visual characteristics. The different Image segmentation algorithms are Feature-Space Based Techniques, Clustering (K-means algorithm Fuzzy k-means algorithm), Histogram thresholding , Image-Domain or Region Based Techniques , Fuzzy Techniques and Physics Based Approaches . With the increasing size and number of medical images, the use of computers in facilitating their processing and analysis has become necessary. In particular, computer algorithms for the delineation of anatomical structures and other regions of interest are a key component in assisting and automating specific radiological tasks. These image segmentation algorithms have a vital role in numerous biomedical imaging applications such as the quantification of tissue volumes , diagnosis , localization of pathology , study of anatomical structure , treatment planning, partial volume correction of functional imaging data , and computer integrated surgery. Methods for segmentations vary widely depending on the specific application, imaging modality, and other factors. For instance, the segmentation of brain tissue has different requirements from the liver image segmentation. There is currently no single segmentation method that yields acceptable results for every medical image. Methods that are specialized to particular algorithms can often achieve better performance by taking into account prior knowledge. Selection of an appropriate approach to a segmentation problem can therefore be a dilemma. This chapter provides a brief of current methods used for computer assisted or computer automated segmentation of anatomical images. Methods and algorithms that have appeared in the recent literature are briefly described. Description of segmenting methods is beyond the scope of this chapter and the readers are referred to references for additional details. We focus instead on providing the reader an introduction to the different applications of segmentation in medical imaging and the various issues that must be confronted.

Although a number of algorithms have been proposed in the field of medical image segmentation , but continues to be a complex and challenging problem. Researchers have done the classification of segmentation techniques in one or another way . At present, from the medical image processing point of view we have done the classification of segmentation techniques on the basis of gray level based techniques and textural feature based techniques. Artificial intelligence techniques to achieve accurate segmentation results.

Thus, the broad classification of techniques available for segmentation of an image classified into two classes- Methods based on gray Level features Methods based on texture features[10]. For application of thresholding based segmentation method, the correct threshold values is required to be applied in order to achieve proper segmentation results. The histogram of an image is particularly used to determine the value of threshold. Edge based segmentation is the most common method based on boundaries which separate distinct regions i.e detection of edges . Edge detection method is based on the discontinuities markings in gray level, color etc., where these edges represent boundaries between objects. on the basis of boundaries this method divides as.

- Edge relaxation,
- Border detection method,
- Hough transform based

1.1 Region based segmentation

Region based method is based on the principle of homogeneity i.e.pixels with similar properties are clustered together to form a homogenous region.[11]
Region based segmentation is also classified into three types based on the principle of region growing:

1. Region merging
2. Region splitting
3. Split and merge

1.2 Region merging

To initialize the process seeding points are required, the segmentation results are dependent on the choice of seeds.Regions are grown iteratively by merging the neighboring pixels depending upon the merging criteria.Continue the process till all pixels are assigned to their respective regions as per merging criterion.

1.3 Region splitting

just opposite to the principle of region merging and whole image is continuously split until no further splitting of a region is possible.

1.4 Split and merge method

This is the combination of splits and merges utilizing the both the methods. This method is based on quadrant tree representation of data whereby image segment is split into four quadrants provided the original segment is non-uniform in properties. Next, the four neighboring squares are merged depending on the uniformity of the region . This split and merge process is continued until no further split and merge is possible.

1.5 Method based on the textural features

Textural features of image are important from image segmentation and classification point of view. Researchers use these features to achieve both image segmentation as well as classification. The texture based segmentation method aims to subdivide the image into region having different texture properties and to classify the regions which have already been segmented by one or other method.

1.5.1 Definition of texture:

Texture is defined as something consisting of mutually related elements.A texture can be fine,smooth,coarse, or grained depending upon its tone and structure. A tone is based on pixel intensity properties and the structure defines the spatial relationship between pixels.Further texture can be defined as the spatial arrangements of texture primitives or texture elements, arranged in more or less periodic manner. Texture property is set of pixels representing the simplest or basic sub pattern.
Medical image segmentation techniques require some form of expert supervision to provide accurate and consistent identification of anatomic structures[11]. A novel segmentation technique was developed that combines a knowledge-based segmentation system with a sophisticated active contour model. This method exploits the guidance of a

higher level process to robustly perform the segmentation of kind of anatomic structures. Knowledge about the anatomic structures to be segmented is defined statistically in terms of probability density functions of parameters of location, size, and image intensity. Preliminary results suggest that the performance of the algorithm at chest and abdominal CT is comparable to that of more traditional segmentation techniques like region growing and morphologic operators. The active contour based technique outperform the standard segmentation methods due to its capacity to fully enforce the available a priori knowledge concerning the anatomic structure of interest. The active contour algorithm is suitable for integrating with frameworks high-level image understanding, providing robust and controlled low-level segmentation application. Further study is required to determine the capability of proposed algorithm to provide consistently superior segmentation.

Chapter 2

Fast Medical Image Segmentation

Image segmentation algorithms classes- region growing and fast level matching algorithm programmed for the speed of segmentation of region-growing algorithm is fast. The fast matching algorithm handle the geometry of complex topological structures. Adaptibility of segmentation algorithm in form of region based which take advantage of the uniformity of same area to identify various areas of the image. The second method is the edge based method which take advantage of the discontinuity of gray regions to segment the borderline of two regions.

2.1 Image Segmentation by Region Growing Algorithm

Three Components for followith the algorithm of Region-Growing method.

1. Seed Point Selection.
2. The principle of growth.
3. The terminating conditions.

The Seed point selection needs human-computer interaction method and the principle of growth tells about the pixel value of pixels in neighbor is less than the threshold[2].Lastly the terminating conditions will continue until it has no pixels left to complete the need of the step 2.

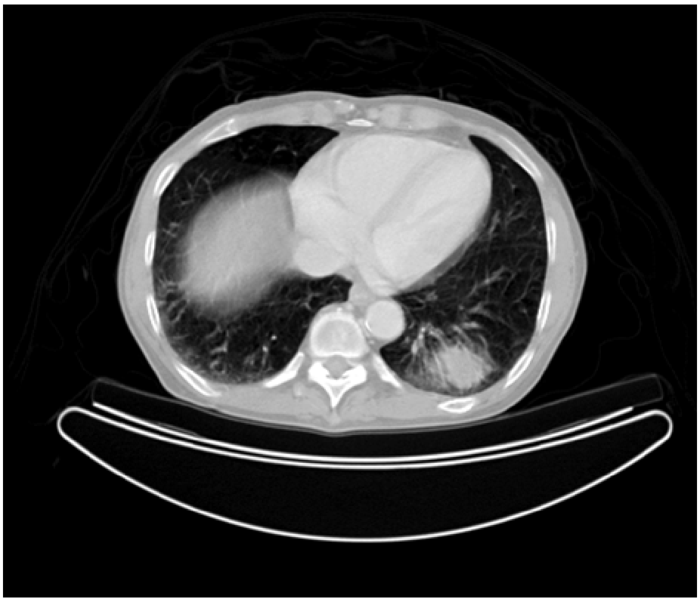


FIGURE 2.1: Original Image MRI

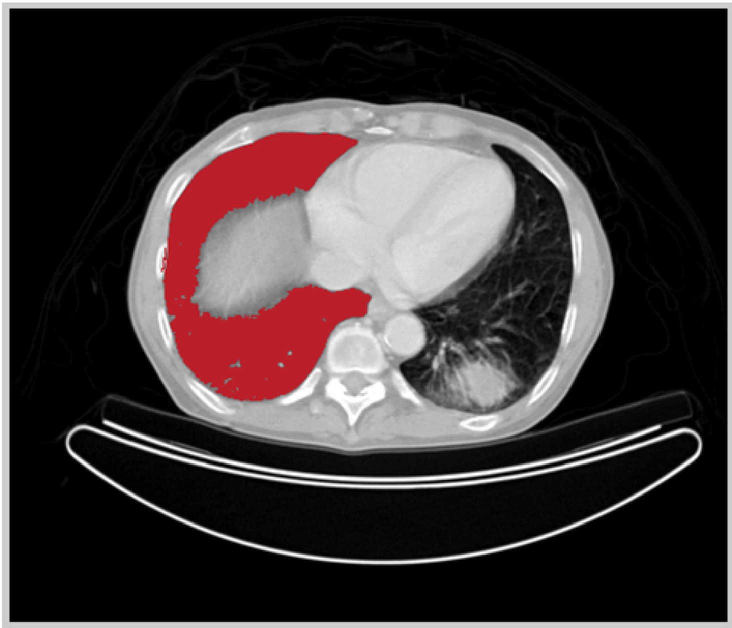


FIGURE 2.2: Image after Segmentation

2.2 Fast Matching Level Set Method

This method focus on transforming the motion of curve into the deformation of surface.The critical problems in the application of level set method for image segmentation are the velocity and the setting of stopping criteria.

$F = e^(- a|I(x, y)|), a > 0$

Where F(x,y) is the velocity item. The fast matching algorithm will follow the procedures: Setting the assembled points as-

1. alive points ; initial points defined.
2. close points ; one pixel distance between close points and alive points.
3. far points ; except alive points and close points other points are defined.

Now we track the boundary contour :

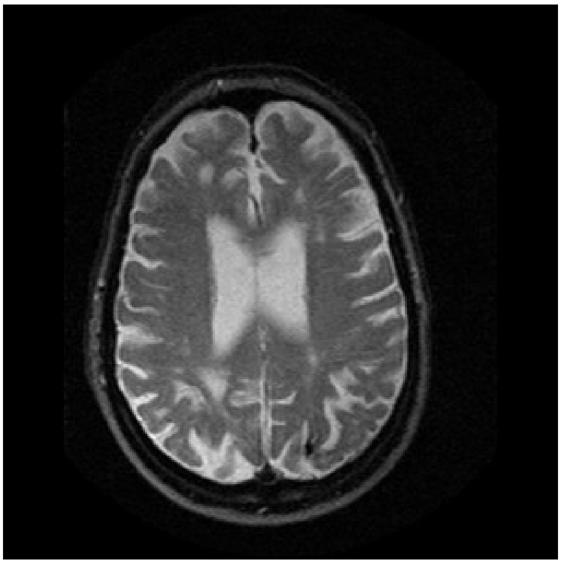
1. set trial points : points with smallest T value among close points are defined.
2. trial points are changed to alive points and they are deleted from the close points.
3. realizing the transformation from far to close.
4. The T value is recalculated of all neighbor points.
5. return step 1
6. (6)the boundary contour is constituted by aggregating all trial points.[2]

2.3 Improving the Fast matching Algorithm

Above experiments proved that the gray part of image is lower and the transition of edge is slower.using the fast matching algorithm , the problem of edge leakage caused by small boundary is solved.

$F = 1/(1 + a|I(x, y) * 255|I(x, y)||)$
Where F is the velocity function which is improved.
The improved algorithm enhanced the segmentation effect and prevented the edge leakage of the medical image.

2.3 and **??**

Original MRI Image 

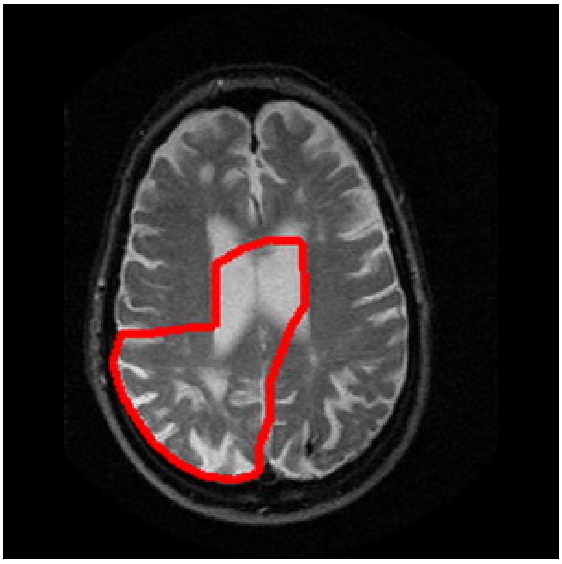
Segmented Image 

FIGURE 2.3: Segmented Image of the Original MRI

Chapter 3

Medical Image Segmentation using Genetic Algorithms

Genetic algorithms are effective in the domain of medical image segmentation, as the problem is mapped to one of search in a complex landscape. Medical image segmentation face challenges due to bad image contrast resulting missing or diffuse tissue/part boundaries. The resulting search space is therefore often noisy with a multitude of local optima. The Genetic algorithmic only prove to be effective in coming out of local optima but also brings considerable flexibility into the segmentation procedure[3]. In this chapter, an attempt has been made to study and understand the applications of GAs to the domain of medical image segmentation.

3.1 Overview of GA's

GAs being efficient, adaptive, and robust techniques of search and optimization guided by the principles of evolution and natural genetics and have implicit parallelism.

The essential components of all Genetic Algorithms are :

(a) A representation strategy called of chromosomes;

(b) A population of chromosomes;

(c) mechanism for evaluating each string (fitnessfunction);

(d) selection/reproduction procedure; and

(e) genetic operators.

The different steps of a GA process are as follows:

(a) Initialize the population.

(b) Decode the strings and compute their fitness values.

(c) If (termination criterion is attained), then stop the process.

(d) Reproduce/select strings to create new mating pool.

(e) Generate new population by crossover and mutation.

(f) Go to Step 2.

3.2 GA's for Segmentation of medical Images

Genetic Algorithm is a search technique used in computing to find approximate solutions to optimization and search problems[6].Genetic algorithms as a search strategy have been applied successfully in many fields. This chapter describes the genetic algorithms evolution process.Then describes the active contours to detect the boundaries of the object of undefined boundaries. Then it describes the use of genetic algorithm with active contours in image segmentation.

3.2.1 Contour Based Technique

Contours are the boundaries of regions in an image. Contour based image segmentation is generally computationally efficient, but for real images often lack robustness due to their sensitivity to noise and data variability. The reliability of such methods can be improved by using techniques based on data driven elastic models, such as snakes and deformable surface models , which have been applied successfully in the field of medical imaging . However, there are a number of problems associated with contour-based techniques in extracting the region of interest (ROI), such as initialization, existence of multiple minima, and selection of elastic parameters. GAs can alleviate typical deformable model weaknesses pertaining to model initialization and deformable parameter selection through the simultaneous evolution of a large number of models. The GA has been used in to evolve a segmenting contour by incorporating both texture and shape information. Each chromosome (of length k + 4) represents a vector of k shape and four pose parameters[3]. The pose parameters are incorporated using an affine transform which is the product of the translation, the scaling, and the rotation matrix.

Segmentation of the cardiac chambers is the first step for almost any kind of automatic high-level analysis of heart shape and its function. Due to the presence of noise and defects like masking structures, tissue inhomogeneity, imaging-chain anisotropy, biological shape variability etc., segmenting these images is difficult.

In order to overcome these problems, most researchers have adopted the strategy of exploiting anatomical knowledge about the image structure. Artificial neural networks (ANNs) with supervised training have been found to be particularly suited to implement this strategy.

3.2.2 Texture Based Technique

GA with specific adaptation include texture analysis as part of its evaluation module, for medical image segmentation. Here, GA-based optimization algorithm is used to produce a population of individual subimages that are tested via a quantitative objective function and rank using a linear fitness and decrement scheme, and modified using crossover. GA has been used in for designing texture filters for regular/structured patterns with rotational invariance, angular discrimination, and sensitivity to scale and intensities. An extension of the study is found where the GA approach extend to real texture and the task of image classification and segmentation. It exploits the well-established Fourier spectral properties of the texture. During the training phase, for a given number of pattern classes, each with an arbitrary number of members, a mask is designed. This is configured to determine different classes of texture by response of its correlation with the Fourier spectrum of training image templates. GA is used as the optimization tool for evolving a proper mask over all possible sets of masks. A further extension of the study is provided in where two GA-based pattern detection techniques, one involving structured texture and other random noise, have been described. The objective in both these cases is to discriminate between regions based on their texture properties. Both these methods have been formulated as large-scale optimization problems and GAs are used to solve them. For structured texture, the approach followed is the same as the one described in . For random texture, the proposed technique starts from a groundtruth image and a corresponding image corrupted with a specific type and level of noise. Training is performed by selecting a window (taken to be 1/16th area of the full image in) over which to configure a stack filter. For this purpose, GA is used to determine the sequence of rank-order functions to use in the stack filter design which minimizes an objective function over the training window[3]. The objective function that has been used in is due to, which measures the mean absolute error (MAE) between the noise-free image I0 and the restored image I1 and is defined as
$MAE = (1/n) * image|I0(i,j) - I1(i,j)|$

where n is the number of pixels over which the calculation is performed.

3.2.3 Knowledge based Technique

Knowledge about the human anatomy and imaging parameters can often be effectively incorporated in the segmentation process to improve its efficiency. In and , a CT image segmentation technique based on template matching and knowledge-based approach has been developed. Region growing technique along with knowledge-based classification , and edge-based technique along with knowledge-based interpretation have been proposed by researchers for MRI segmentation. While the performance of the aforesaid automatic segmentation techniques is generally good for images with high contrast-to-noise ratio, they are not suitable for segmentation of insufficiently delineated, low-contrast neuro-anatomic structures, such as globus pallidus ,thalamus, putamen, etc., in the human brain. In order to overcome this limitation, A GA-based method is proposed that utilizes a priori knowledge about the human brain anatomy. Initially an edge-based region growing method is adopted which use the edge information to specify boundaries between homogeneous regions accurately. In the primary segmentation step, an intentionally over-segmented image is generated such that further processing only deals with merging primary regions[3]. Subsequently, a region adjacency graph (RAG) is constructed, to describe region properties and region interrelationships in the primary regions resulting from primary image segmentation. At the beginning of the segmentation/interpretation process, each primary region in the RAG is numbered and a one-to-one correspondence between primary regions and the position in a chromosome used by the GA is established. The objective function used by the GA represents a priori knowledge about human brain anatomy and imaging parameters.

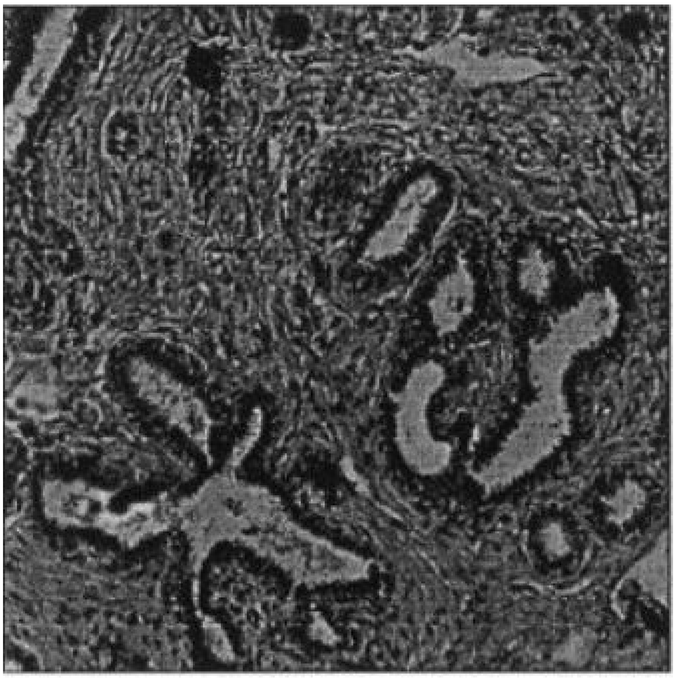


FIGURE 3.1: Original Image MRI

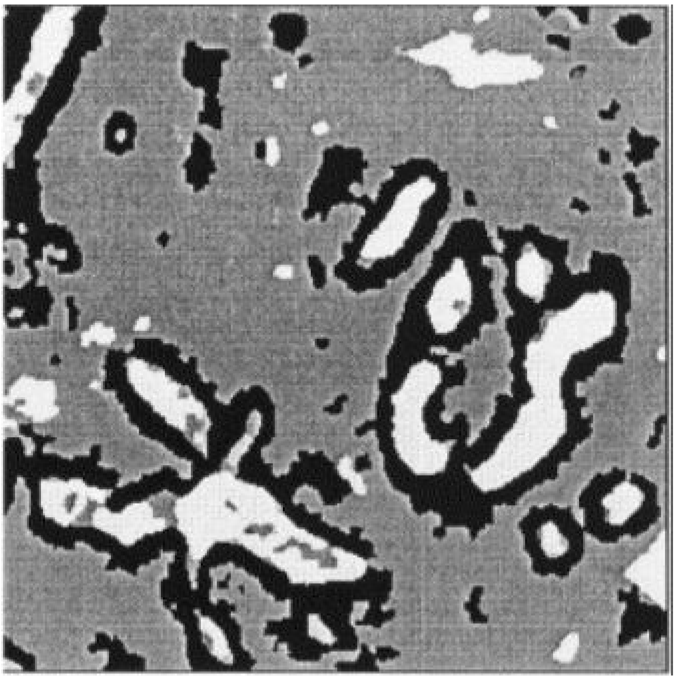


FIGURE 3.2: Image after Segmentation using Contour Based Technique

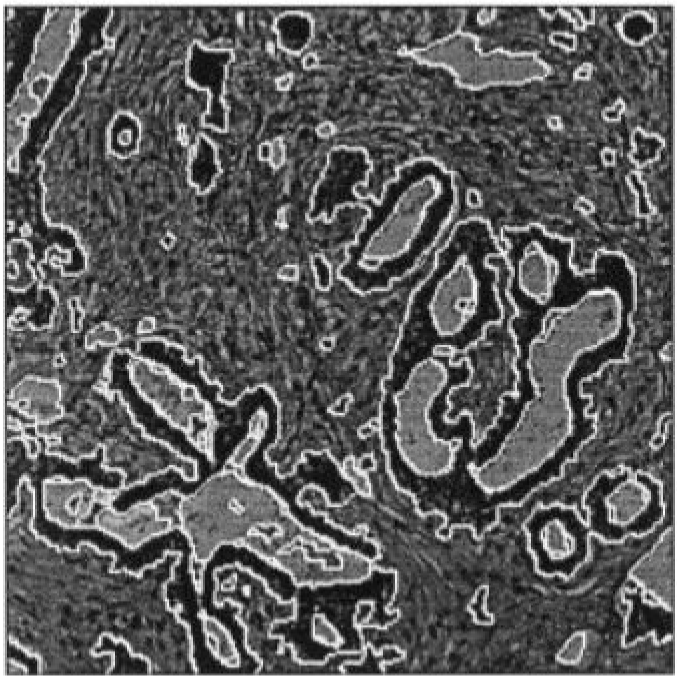


Figure 3.3: Image after Segmentation using Texture based Technique

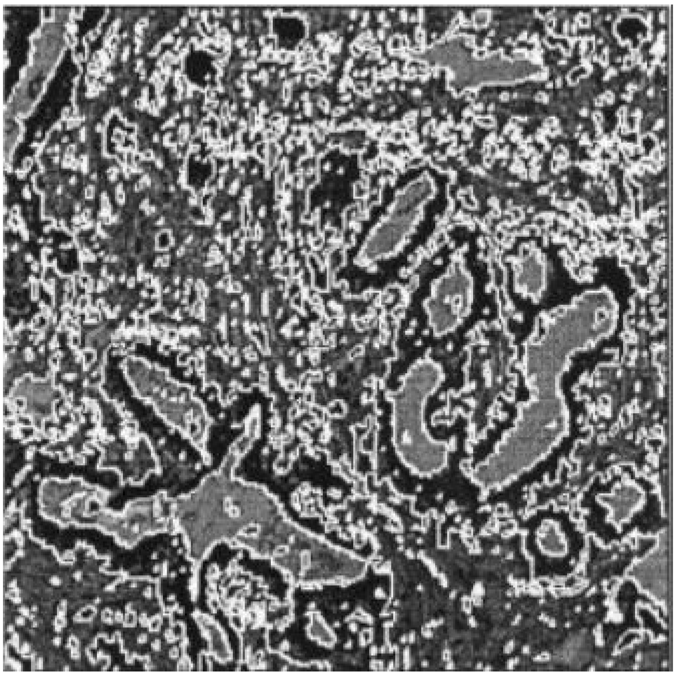


Figure 3.4: Image after Segmentation using Knowledge based Technique

Chapter 4

Novel Segmentation Algorithm in Segmenting Medical Images

The aim of this chapter is to develop an effective fuzzy c-means (FCM) technique for segmentation of Magnetic Resonance Images (MRI) which is seriously affected by intensity inhomogeneities which are created by radio-frequency coils. A weighted bias field information is employed in this work to deal with these intensity inhomogeneities in the segmentation of MR images. In order to segment the general shaped MRI dataset which is corrupted by intensity inhomogeneities and the effective objective function of fuzzy c-means is constructed by replacing the Euclidean distance with kernel-induced distance. In this chapter, the initial cluster centers are assigned using the proposed center initialization algorithm for executing the effective FCM iteratively. FCM has been widely used in applications of MR image segmentation. However, the standard FCM algorithm is noise sensitive, because of not considering the spatial information in the image. To overcome the above problem,many researchers recently introduced many modified fuzzy c-means algorithms for MRI segmentation[4]. A bias-corrected FCM (BCFCM) is developed by normalizing the objective function of FCM with a spatial neighborhood regularization term and then the proposed technique successfully applied in the segmentation of MRI dataset.

4.1 Formulation of Proposed method

4.1.1 Kernel method

A number of powerful kernel-based learning machines were proposed and have found successful applications such as pattern recognition and image processing[4] . A common philosophy behind these algorithms is based on the following kernel (substitution) trick, that is, a nonlinear map which is defined from the data space to the higher dimensional feature space S is used to have the proper structure for nonlinear dataset. Kernel method studies often employ a high-dimensional feature space S for having nonlinear boundary classification.

For this purpose a mapping : RpS
is used where an object x is mapped into S: $(x) = (1(x), 2(x), ...)$

4.1.2 Notion of Kernelized fuzzy c-means with weighted bias field information

FCM is effective only in clustering those crisp, spherical, and non-overlapping data. When dealing with non-spherical shape and much overlapped data, such as the Ring dataset , FCM cannot always work well. In this chapter, the kernel method to construct the nonlinear version of FCM, and propose a kernel-based fuzzy C-means clustering algorithm [7]. The basic ideas of KFCM is to first map the input data into a feature space with higher dimension via a nonlinear transform and then perform FCM in that feature space. Thus the original complex and nonlinearly separable data structure in input space may become simple and linearly separable in the feature space after the nonlinear transform. So we desire to be able to get better performance. Another merit of KFCM is, Unlike the FCM which needs the desired number of clusters in advance, it can adaptively determine the number of clusters in the data under some criteria.The image for segmentation is provided as input. Mostly, the number of successive centers and results of fuzzy c-means and other soft clustering depends on initial centers of clusters. In general the clustering algorithms choose the initial centers in random manner , which are affect the results of clustering.

(a) Providing the kernels for the input image.

(b) Evaluation of memberships of pixels using the equation for computing

(c) Evaluation of successive centers.

(d) Repeat the steps iteratively until no new cluster centers are found.

The image for segmentation is provided as input[7]. Mostly, the number of successive centers and results of fuzzy c-means and other soft clustering depends on initial centers of clusters.

4.1.3 Bias Field

A novel segmentation algorithm is achieved in order to segment or differentiate the tissue classes in given medical images. Intensity inhomogeneity or bias field in MRI images affects the process of differentiating different tissue classes during medical image segmentation. So, in order to deal the bias field in the brain MRIs, this section proposes additive bias field to the novel fuzzy c-means of this chapter. There are three commonly used bias models of how the bias interacts with noise. The bias filed model was used is defined by:

$yi = xi + wiii1, 2, ..., n$ where xi and yi are the true and observed log-transformed intensities at the ith voxel.

4.2 Proposed Method

Effective kernelized fuzzy c-means with bias field information
Kernelized FCM algorithms (KFCM) that could improve magnetic resonance imaging (MRI) segmentation. The proposed KFCM method is implemented with some spatial constraints on the objective function. The spatial information is incorporated into the membership function and the clustering for validitating procedure using these algorithms. Intra-cluster distance is used to measure the median distance between a point and its cluster center. Increase in the number of the cluster in accordance of the intra-cluster value .For example when a cluster is obtained, to evaluate intra-cluster of the next cluster it uses the previously obtained cluster as input to the KFCM and so on and stops only when intra-cluster is smaller than the desired value[9]. The most important use of the algorithms proposed is to work automatically. Other way is to improve automatic image segmentation process.
Kernel fuzzy c-means (KFCM) was used to generate an initial contour curve which overcomes leaking at the boundary during the curve propagation.Initially the KFCM algorithm computes the fuzzy membership values for each and every pixel. The edge indicator function was redefined on the result out basis of KFCM[7,9]. Using the edge indicator function the segmentation of medical images which are added with salt and pepper noise was performed to extract the regions of interest for further processing.

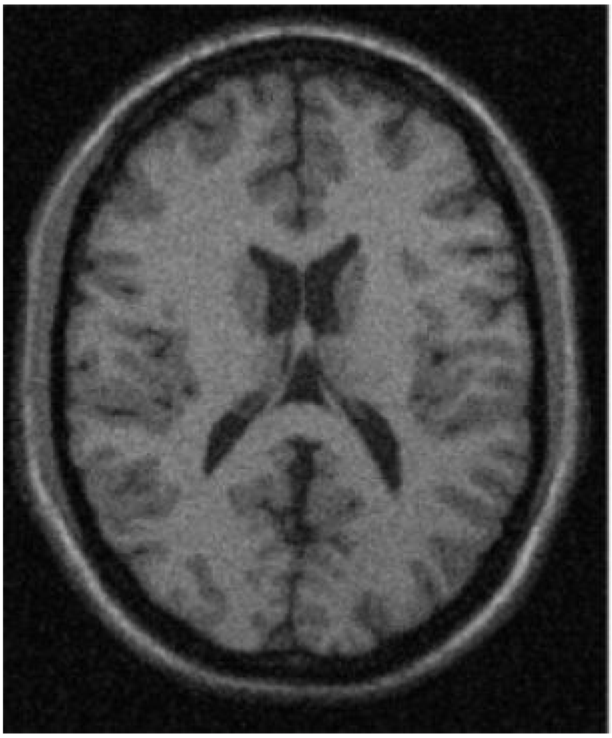


Figure 4.1: Original Image MRI

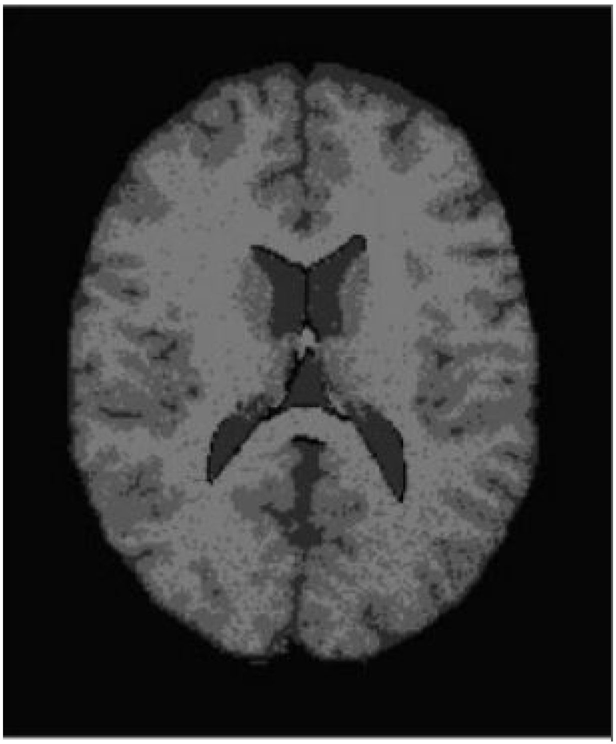


Figure 4.2: Image after Segmentation using Kernel Method

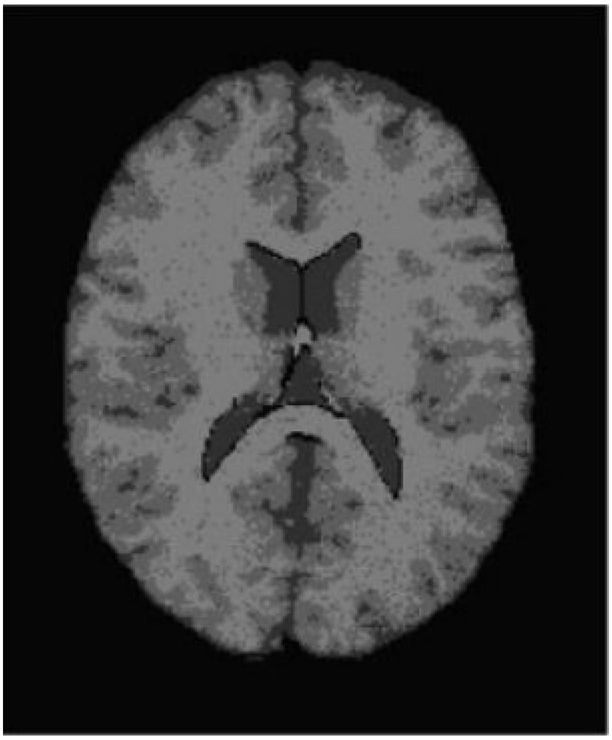


Figure 4.3: Image after Segmentation using FCM c-means Kernelized Technique

Figure 4.4: Proposed Method Segmentation Result

Chapter 5

Conclusion

The image segmentation is a relevant technique in image processing. Many number of methods exist for many and each type of application. Now that we have reviewed and studied the algorithms, we compared the outputs and check which type of segmentation technique is better for a particular function and section of segmentation. It is believed that there are two key factors which allow for the use of a segmentation algorithm in a larger object detection system: correctness and stability. On an average parameter set of the edge detection techniques,. The same is reflected by higher value of entropy after segmentation.
Histogram based methods are found to be very efficient in terms of computation complexity when compared to other image segmentation algorithms. If distinguishable graphically peaks and valleys are identified properly and proper thresholding is fixed, this technique yields good result.
Region-grow technique operates well over all formats of images provided proper seed point is selected and range of threshold is properly defined. This method performs well even when noise is present and it is reflected with a reasonably good value of entropy. The clustering algorithm is guaranteed to converge but optimal solution is not guaranteed. The quality of the result depends on the initial set of clusters and value of k. An inappropriate choice of K yields very poor result. This algorithm can be directly applied for color images.
Surveying of the applications of Genetic Algorithms to medical image segmentation is reported. The classical image segmentation technique use information regarding texture, shape, contours, etc., perform well when the images are simple, less noisy, and the problem can be described in some closed mathematical form that can be solved analytically. However, in the domain of medical images, it is found that the objective function is usually much complex, multimodal, and discontinuous. As a result, application of GAs and other evolutionary techniques become attractive and is also quite effective. The main challenges and issues in

integrating GAs for solving the optimization problems in medical image segmentation are manifold. First, the encoding strategy must be suitably defined so that it conforms to the building block hypothesis. Any adhoc encoding strategy may not follow this hypothesis, and GAs may often yield poor result in such situations.The choice of the different genetic operators as well as the termination criteria are also important issues in GAs. Often, these are tuned manually, and require a large amount of expertise as well as experience. Alternatively, the parameters can be kept variable and/or adaptive so as to be able to self-modify in response to the population statistics. Ways of avoiding premature convergence are also critical in any application of GAs. A common approach in this regard is fitness scaling . Another important consideration in medical image analysis is the reduction of the computation time of GAs, which is, usually, timeconsuming in nature. Incorporation of expert knowledge and integration with local search are ways to enhance the convergence rate.

Studying and Experimenting each methods have their variety of Applications in the Real World.Using these techniques based on the Survey at the beginning it is always possible to have optimized and Efficient methods to adapted and develop for better scope of study and wide use in applications and problem solving.

Bibliography

[1] Dzung L.Pham,Chenyang Xu , Jerry L.Prince. *A Survey of Current Methods in Medical Image Segmentation* , Technical Report JHU/ECE 99-01 Annual Review of Biomedical Engineering ,January 19,1998.

[2] Dai Junfeng , YAN Yunyang . *The fast Medical Image Segmentation of target Region based on Improved FM Algorithm.*2012 International Workshop of Information and Electronics Engineering.

[3] Ujjwal Maulik , Senior Member ,IEEE. *Medical Image Segmentation Using Genetic Algorithms* . IEEE Transactions of information Technology in Biomedicine , VOL.13 , NO.2 , March 2009.

[4] S.R.Kannan , A.Sathya , S.Ramathilagam , R.Devi .*Novel Segmentation algorithm in segmenting medical images.*The Journal of systems and Software , July 15 2010.

[5] H.S.Prasantha , Dr.Shashidhara.H.L. , Dr.K.N.B.Murthy , madhavi Lata.G.*Medical Image Segmentation.*International Journal on Computer Science and Engineering Vol. 02 , No. 04,2010.

[6] Poonam Panwar , Neeru Gulati .*Genetic Algorithms for Image Segmentation using Active Contours.*Journal of Global Research in Computer Science, Volume 4 , No.1 ,January 2013.

[7]Saritha A K , Ameera P.M .*Image segmentation based on kernel fuzzy C means clustering using edge detection method on noisy images.*International Journal of Advanced research in Computer Engineering and Technology , Volume 2 , Issue 2 , February 2013.

[8] Dao-Qiang Zhang , Song-Can Chen . *A novel kernelized fuzzy C-means algorithm with application in medical image segmentation.*Artificial Intelligence in Medicine in China , Volume 32 , Issue 1 , September 2004.

[9]EA Zanaty , S Aljahdali , N Debnath.*A kernelized fuzzy c-means algorithm for automaticmagnetic resonance image segmentation.*Journal of Computational Methods in Science and Engineering.Volume 9, 2009.

[10]Neeraj Sharma , Amit K. Ray , Shiru Sharma , K.K. Shukla .*Segmentation and classification of medical images using texture primitive feaatures.*Journal of Medical Physics July-September; 33(3).

[11]Neeraj Sharma , Lalit M. Aggarwal.*Automated medical image Segmentation techniques.*Journal of Medical Physics.2010 January-March; 33(3).