Development of Unsupervised methods for medical image segmentation

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Certificate

This is to certify that the work in the entitled *Development of unsupervised methods for medical image segmentation* by *Anupama Deo & Nupur Jha* is a record of an original research work carried out by them under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Electrical Engineering during the session 2011-2012 in the department of Computer Science and Engineering, National Institute of Technology, Rourkela. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

NIT Rourkela	**Prof. Dipti Patra**
14 May 2012	EE dept of NIT Rourkela

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We express our heartfelt sincere gratitude to all those people who helped us in getting this thesis done. We would like to gratefully acknowledge the enthusiastic supervision and guidance of Prof. Dipti Patra, NIT Rourkela during this work. She is our source of inspiration. Our sincere thanks goes to Subhrajeet Mohapatra, Research Scholar, for his continuous encouragement, help and support. We are also grateful to Smita Pradhan, Research Scholar, for providing us with MRI images from CWS Hospital, Rourkela. We must acknowledge the academic resource that we have got from NIT Rourkela.

Anupama Deo & Nupur Jha.

Abstract

Image segmentation is the process of partitioning an image into meaningful parts. Image segmentation is used to locate objects and boundaries in images. It is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.[1]

The need for accurate segmentation tools in medical applications is driven by the increased capacity of the imaging devices. Due to high resolutions and a large number of image slices CT and MRI generated images cannot be examined manually. Furthermore, it is very difficult to visualize complex structures in three-dimensional image volumes without cutting away large portions of, perhaps important, data. Tools, such as segmentation, can aid the medical staff in browsing through such large images by highlighting objects of particular importance. In addition, segmentation in particular can output models of organs, tumors, and other structures for further analysis, quantification or simulation. We have used k means, fuzzy c means for better performance we map the input space onto a self-organising map and then the low dimensional input is clustered using the above methods.

A self-organising map (SOM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map. This thesis is devoted to medical image segmentation techniques and their applications in clinical and research settings.

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CHAPTER 1

INTRODUCTION

The theme of this thesis is various methods of image segmentation applied on medical images. This chapter will begin by outlining the basic problem of segmentation and motivate its importance in many applications. Modern medical imaging modalities like MRI and CT scans generate larger and larger images which cannot be analysed manually. This drives the necessity for more efficient and robust image analysis methods, tailored to the problems encountered in medical images. The aim and motivation of this thesis are directed towards the problem of segmenting blood vessels, liver and brain MRI images.

Image segmentation is the problem of partitioning an image into meaningful regions on the basis of grey-level, color, texture. This implies the generality of the problem- segmentation can be found in any image-driven process, e.g. fingerprint/text/face recognition, tracking of moving people/cars/airplanes, etc. For many applications, segmentation reduces to finding an object in an image. This involves partitioning the image into two class of regions - either object or background. It is simply not feasible in practice to manually process all the images (like MRI and CT scan), because of the overwhelming amount of information it provides. So we design algorithms which look for certain patterns and objects of interest and put them to our attention. For example, are cent popular application is to search and match known faces in your photo library which makes it possible to automatically generate photo collections with a certain person. An important part of this application is to segment the image into “face” and “background”. This can be done in a number of ways, and it is well accepted that no general purpose segmentation algorithm exists, or that it ever will be invented. Thus, when designing a segmentation algorithm, the application is always of primary focus: Should we segment the image based on edges, lines, circles, faces, cats or dogs?

1.1 Literature Survey

Diagnostic imaging is an invaluable tool in medicine today. The technologies like magnetic resonance imaging (MRI), computed tomography (CT), and other imaging modalities have eased knowledge of normal and diseased anatomy for medical research and are a crucial component in diagnosis and treatment planning.[2]

The potential of intelligent data analysis techniques has risen with the increasing amount of data available digitally. With improvements in computer performance and development of the digital devices opportunities have been created to use multimedia data, such as images and voice. In existing storage systems, a quantity of data that our system is able to store and an index entry is made when information is stored. When users want to retrieve some item of information, they use the index to find the required item. It is difficult to find something accurately and quickly from among the many complex items in a database because of the huge index space for the data being searched.[3]

Methods for performing the segmentation vary widely depending on the specific application, and several factors. For example, the segmentation of brain tissue has different requirements from the segmentation of the liver and the segmentation of the blood images. General factors such as noise, partial volume effects, and motion can also have significant consequences on the performance of segmentation algorithms.[2] Furthermore, every imaging modality has its own features with which to contend. At present, there is no single segmentation method which is capable to give satisfactorily results for every medical image. But, methods do exist that are more general and also can be applied to a variety of data. However, different methods that are specialized to particular applications can often achieve better performance. Selection of an appropriate approach to a segmentation problem can therefore be a difficult problem.[2]

The segmentation method can be divided roughly into the following categories: (1) thresholding approaches,(2) region growing approaches, (3) classifiers, (4) clustering approaches, (5) Markov random field models, (6) artificial neural networks, (7) deformable models, and (8) atlas guided approaches. Other notable methods also exist. Of the different approaches stated above; thresholding, classifier, clustering, and Markov random field approaches can be considered pixel classification methods.[2]

Three commonly used clustering algorithms are the k-means, the fuzzy c-means algorithm, and the expectation-maximization (EM) algorithm. In the k-means clustering algorithm clusters mean is iteratively computed and a mean intensity for each class is assigned and image is segmented the by assigning each pixel in the class with the closest mean. The fuzzy c-means algorithm generalizes the k–means algorithm, allowing for soft segmentations based on fuzzy set theory. Training data is not required by clustering algorithms, but they do require an initial segmentation (or equivalently, initial parameters). Therefore, unlike classifier methods, clustering algorithms can be sensitive to noise and intensity inhomogeneities. This lack of spatial modelling, however, can provide significant advantages for fast computation.[2]

K-means clustering algorithm is also an unsupervised method for the segmentation of the image. In a MR image of the head there are many regions which are of similar intensities, which result in many local minima that increases over-segmentation. The coarse areas are smoothened in the segmentation by k-means method. K-means clustering is used because it is simple and has relatively low computational complexity. In addition, it is suitable for biomedical image segmentation as the number of clusters (K) is usually known for images of particular regions of human anatomy.[4]

The shape, volume, and distribution of brain tissue are altered by many neurological conditions; magnetic resonance imaging (MRI) is the preferred imaging modality for examining these conditions. Consistent measurement of these alterations can be implemented by using image segmentation. Several investigators have developed methods to automate

such quantities by segmentation. Fuzzy c-means (FCM) clustering is an unsupervised technique that has been successfully applied to clustering, feature analysis and classifier designs in fields such as medical imaging, image segmentation, astronomy, target recognition, and. There are various feature spaces in which an image can be represented, and the FCM algorithm categorizes the image by combination of similar data points in the feature space into clusters. This clustering is achieved by iteratively minimizing a cost function. This cost function is dependent on the distance of the pixels to the cluster centres in the feature domain. The pixels on an image are highly correlated, i.e. the pixels in the immediate neighbourhood possess nearly the same feature data. Therefore, the spatial relationship of neighbouring pixels is an important characteristic that can be of great help in imaging segmentation. However, the spatial relationship between pixels is seldom utilized in FCM.[5]
The SOM is an unsupervised neural network mapping a set of n-dimensional vectors to a two-dimensional topographic map displaying in such a way that similar data items are located close to each other on the map. However, the basic SOM lacks the ability to extract the hierarchical structure of the data. A quality measure based on the variance of the data together with threshold parameters are used to decide which granularity is appropriate for a specific SOM, and which areas of the SOM are promising candidates for further hierarchical expansion.[5] It can be seen that the number of output units used in a SOM influences its applicability for clustering.[5]

1.2 Motivation

The motivation is to devise a better segmentation method for medical images such as liver, brain, blood cell for detection of malignant tissue. Image segmentation has been identified as the key problem of medical image analysis and remains a popular and challenging area of research. Image segmentation is increasingly used in many clinical and research applications to analyse medical imaging datasets; which motivated us to present a snapshot of dynamically changing field of medical image segmentation.[6]

CT (Computed Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography) etc. generate a large amount of image information. With the improved technology, not only does the size and resolution of the images grow but also the number of dimensions increases. In the future, we would like to have algorithms which can automatically detect diseases, lesions and tumors, and highlight their locations in the large pile of images. But another complication arises is that we also have to trust the results of these algorithms. This is especially important in medical applications as we do not want that the algorithms to give false signal alarms, and we certainly do not want them to miss fatal diseases.

Therefore, developing algorithms for medical image analysis requires thorough validation studies to make the results usable in practice. This adds another dimension to the research process which involves communication between two different worlds - the patient-centered medical world, and the computer-centered technical world. The symbiosis between these worlds is rare to find and it requires significant efforts from both sides to join on a common goal.

1.3 Problem Formulation

The algorithms of image segmentation play a vital role in the numerous biomedical imaging applications such as quantification of the tissue volumes, diagnosis, localization of the pathology, study of the anatomical structure, treatment planning, partial volume correction of the functional imaging data, and computer-integrated surgery. There is currently no single segmentation method that yields acceptable results for every medical image. Methods do exist that are more general and can be applied to a variety of data.

However, some of these methods do not exploit the multispectral information of the MRI signal. There are many regions with similar intensities in a MR image of the head, which result in many local minima that increases over-segmentation.

Thus we have to devise a new method which is capable of segmenting various medical images and is computationally less complex.

1.4 Contribution

In the proposed method two-level approach is being adopted. In the first level a classifier is being developed using the SOMs. The input data set which are the pixel values are fed into this classifier. The SOM classifier classifies the input data set into various classes (according to the size of the SOM used). In the second level of the approach, the output from the SOM classifier is then segmented with the help of the image segmentation methods. Here, we used both k-means and fcm as the segmentation methods at the level two approaches. The output of the various methods are compared and the method giving the best result is analysed.

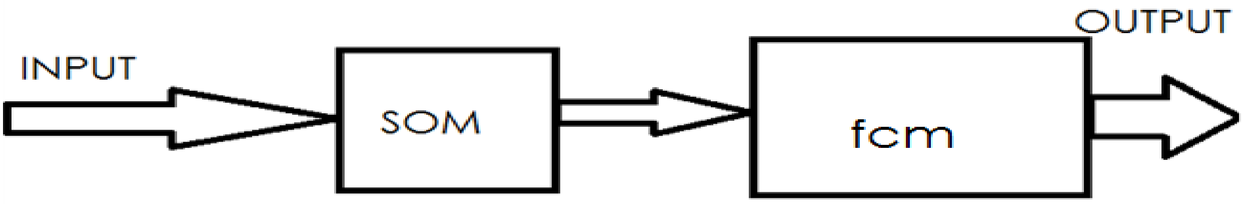


Figure 4.1: BLOCK DIAGRAM OF THE PROPOSED METHOD

DATABASE:

3 MRI brain images with tumor : collected from CWS hospital, Rourkela

3 liver MR images from:

http://www.mrtip.com/serv1.php?type=img&img=Anatomic%20Imaging%20of%20the%20Liver

3 blood sample microscopic images from :

http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3055951/figure/F3/

PROGRAMMING SOFTWARE:

Matlab version 2009

PROCESSOR:

Windows 7 32-bit

Chapter 2

IMAGE SEGMENTATION

Image segmentation can be classically defined as the partitioning of an image into non-overlapping, constituent regions which are homogeneous with respect to some characteristic such as intensity or texture. If the domain of the image is given by I, then the segmentation problem is to determine the sets whose union is the entire image I.[2]

Clustering (or cluster analysis) aims at organizing a collection of data items into clusters, such that these items which are within a cluster are more "similar" to each other than they are to the items in the other clusters. There are two types of machine learning algorithms. These are supervised and unsupervised learning.

1. Clustering is usually performed when no information is available concerning to the membership of data items to predefined classes. For this reason clustering is traditionally seen as a part of unsupervised learning. Unsupervised learning refers to the problem of trying to find the hidden structure in unlabelled data. However unsupervised learning also encompasses many other techniques that seek to review and explain key features of the data. Many methods employed in unsupervised learning are based on the data-mining methods used to pre-process data. Approaches to unsupervised learning include: clustering (e.g., k-means, fuzzy c-means clustering, hierarchical clustering). Among the neural network models, the self-organizing map (SOM) and adaptive resonance theory (ART) are commonly used unsupervised learning algorithms.[7]
2. Supervised learning is the machine learning task of inferring a function from training data. The training data consist of a set of training examples. In supervised learning, each example is a pair consisting of an input object (typically a vector) and a desired

output. A supervised learning algorithm analyzes the training data and produces an inferred function, which is called a classifier (if the output is discrete). The inferred function should predict the correct output value for any valid input object.[7]

2.1 k-means

K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their intrinsic distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them.[8]

The algorithm which follows for the k-means clustering is given below:

The cluster centres are obtained by minimising the objective function

$$V = \sum_{i=1}^{k} \sum_{xj \in Si} (xj - \mu i)^2$$

where there are k clusters S_i , i= 1,2,….,k and μ_i is the centroid or mean point of all the points $x_i \in S_i$

1. Initialise the centroids with k random values.

2. Repeat the following steps until the cluster labels of the image does not change anymore.

3. For each data point, we calculate the Euclidean distance from the data point to the mean of each cluster.

$c^{(i)} = \arg\min ||x^{(i)}-\mu_j||^2$

If the data point is not closest to its own cluster, it will have to be shifted into the closest cluster. If the data point is already closest to its own cluster, we will not shift it.

4. Compute the new centroid for each of the clusters.

$$\mu_i = \sum_{i=1}^{m} l\{c_{(i)} = j\}x^{(i)} / \sum_{i=1}^{m} l\{c_{(i)} = j\}$$

where k is a parameter of the algorithm (the number of clusters to be found), i iterates over the all the intensities, j iterates over all the centroids and $\mu_i$are the centroid intensities.

2.2 Fuzzy c means

Fuzzy c-means (FCM) clustering is an unsupervised technique that is used for feature analysis, clustering, in fields such as medical imaging, target recognition, and image segmentation. There are various features spaces in which an image can be represented, and the FCM algorithm categorizes the image by assembling similar data points into clusters. This clustering is achieved by iteratively minimizing a cost function that is dependent on the distance of the pixels to the cluster centers in the feature domain.

The FCM algorithm assigns pixels to each category by using fuzzy memberships.

We use the following algorithm:

Let $X=(x_1, x_2,.,x_n)$ denotes an image with N pixels to be partitioned into c clusters, where x_i represents the data. The algorithm is an iterative optimization that minimizes the cost function defined as follows:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^{m} \|x_j - v_i\|^2$$

Where u_{ij} represents the membership of pixel x_j in the i^{th} cluster, v_i is the i^{th} cluster center, and m is a constant. The parameter m controls the fuzziness of the resulting partition, and m=2 is used in this study. The cost function is minimized when pixels close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to pixels with data far from the centroid. The membership function represents the probability that a pixel belongs to a specific cluster. In the FCM algorithm, the probability is dependent solely on the distance between the pixel and each individual cluster center in the feature domain. The membership functions and cluster centers are updated by the following:

$u_{ij} = 1/\sum_{k=1}^{c}(||x_j - v_i||/||x_j - v_k||)^{2/(m-1)}$

and

$v_i = \sum_{j=1}^{N} u_{ij}^{m} x_{jb} / \sum_{j=1}^{N} u_{ij}^{m}$

Starting with an initial guess for each cluster centres, the FCM converges to a solution for v_i representing the local minimum of the cost function. Convergence can be detected by comparing the changes in the membership function or the cluster center at two successive iteration steps.[5]

2.3 Disadvantages of fcm and k-means

FCM is complex in computation and the fact that its performance degrades significantly with increased noise. It is because each data point has a membership with every cluster.K-means clustering algorithm on the other hand, is a simple clustering method with low computational complexities as compared to FCM. The clusters produced by K-means clustering do not overlap. However, a cluster number *k* must be determined before cluster processing. This method cannot be used to classify data when the value of *k* is inadequate. If input data comes from an unknown probability distribution, it is difficult to decide a suitable value for *k.* Some parameters must be provided before cluster processing, and they strongly affect the results.

These methods use the minimum distance clustering algorithm as a clustering system. In these methods, input data is treated as multi-dimensional vectors, the degree of similarity between input data is expressed as a distance (e.g.,the Euclidean distance), and the classification of the input data is done using these distances.

2.4 SOM (Self Organizing Map)

The self-organizing maps (SOM) is one of the best known unsupervised neural networks. It belongs to the class of vector coding algorithms. It defines a mapping from the input data space onto an output layer by using a learning algorithm.[9]

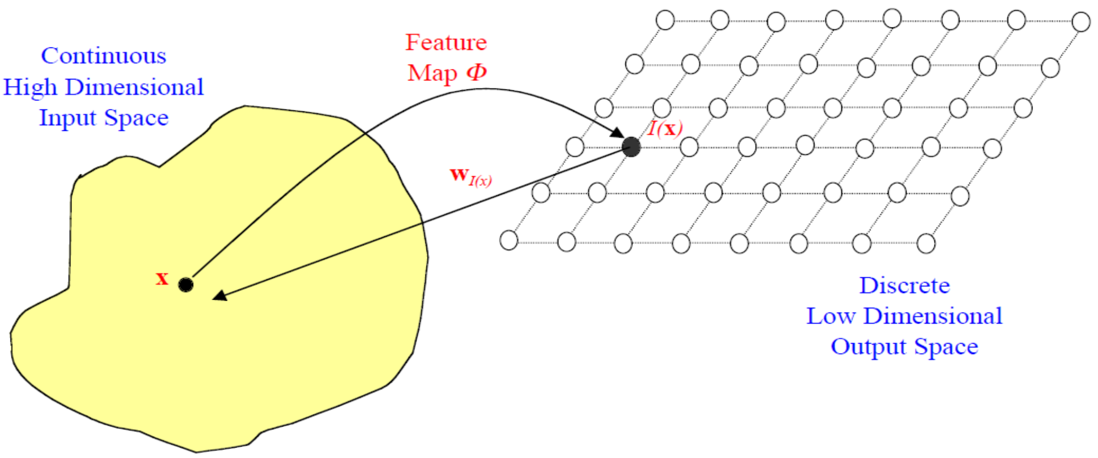


Figure 5.1: mapping of x points in input space to I(x) points in outer space [10]

The SOM model is defined as follows :

1. Let $x_i \in R^n (i=1,2,...d)$ be an input feature vector and $X=\{x_i\}$ be the set of all input vectors. The output layer of the SOM consists of a two dimensional array of nodes where a parametric reference vector $m_j \in R^n$ $(j=1,2,...k)$ is associated with every node j.
2. Chose initial values randomly for all the reference vectors.
3. For each input feature vector x_i , do steps (4) and (5)
4. Find the best matching node c according to

$$\| x_i - m_c(t)\| = \min_j \|x_i - m_j(t)\|$$

where $\|x_i - m_j\|$ is the Euclidean distance between x_i and m_j.

5. For each node of the output layer, adjust the feature vectors of all the nodes according to $m_j(t+1) = m_j(t) + \alpha(t) \times N_{c,j}(t) \times (x_i - m_j(t))$

Where $\alpha(t)$ is the gain factor and $N_{c,j}(t)$ is a neighbourhood function. We used a neighbourhood function equal to 1 for neighbour of c and 0 elsewhere.

2.4.1. ADVANTAGES OF SOM OVER FCM AND K-MEANS

We have used self-organizing map (SOM) and a method of image processing to create a clustering mechanism that efficiently classifies image objects having an unknown probability distribution without requiring the determination of complicated parameters. This clustering mechanism is fast and highly reliable. The clustering method using the SOM promises to be a valuable tool for classifying large numbers of objects as it reduces the large data set by mapping it to a low dimensional map. It speeds up cluster processing.

Chapter 3

SIMULATION AND RESULTS

Size of the images taken are :

- Brain1 : 270X219
- Brain2 : 200X163
- Brain3 : 215X180
- Liver1 : 169X243
- Liver2 : 189X269
- Liver3 : 186X274
- Blood1 : 170X190
- Blood2 : 170X190
- Blood3 : 170X190

The structure of the neural network used for the SOM topology has the size of 4X4 neurons.

The simulation of the programs for the clustering using SOM topology clusters different samples together according to the position of the neurons. One such image is shown below:

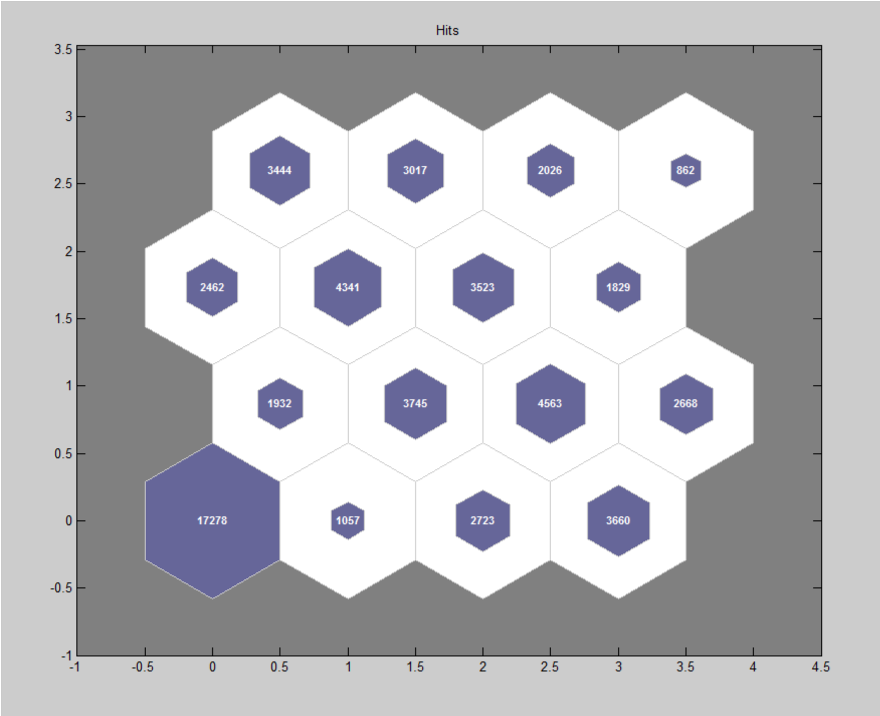


Figure 6.1: SOM sample hits for the brain2 image for a network of size 4 X 4 neurons

The ouptuts for the various simulations utilizing the different methods analysed are given in the following pages.

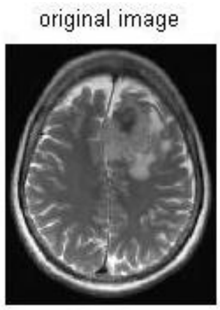


Figure 3.2: brain1 original image

Figure 3.3: 4 clusters segmented using k-means

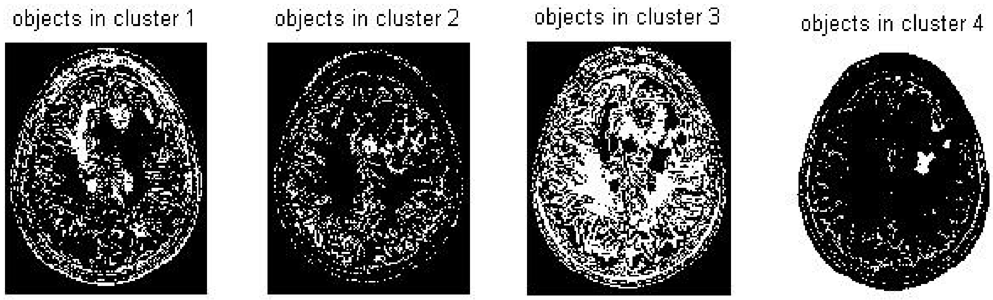
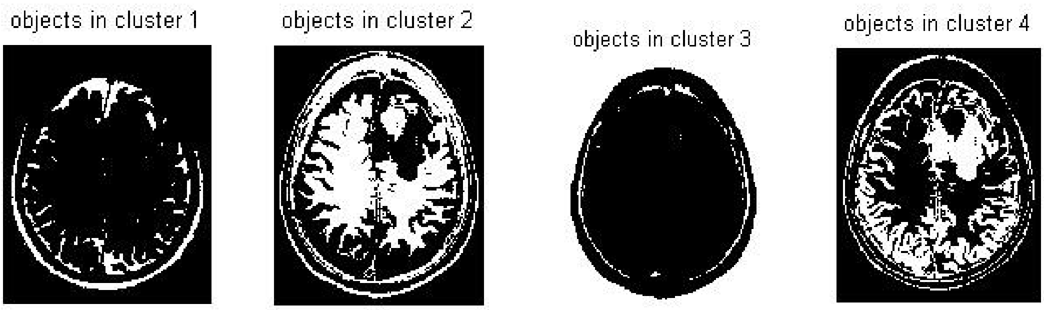


Figure 3.4: 4 clusters segmented image using fcm



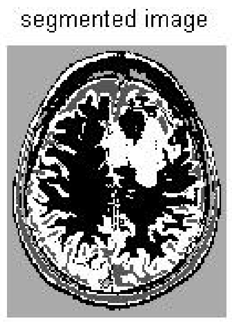


Figure 3.5: 4 clusters segmented image using SOM

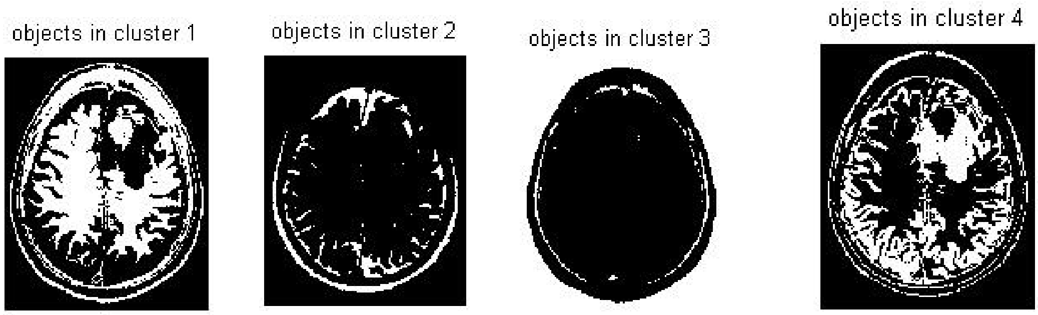
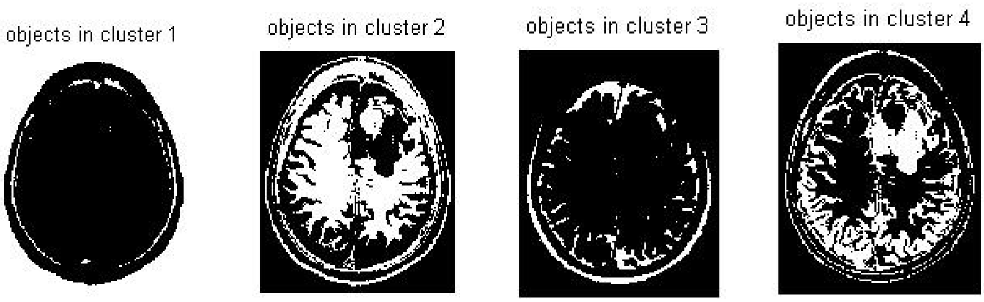


Figure 3.6: 4 clusters segmented image using SOM followed by fcm



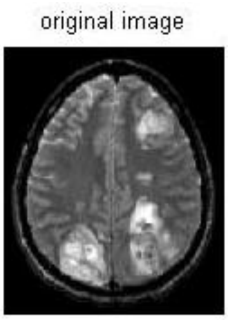
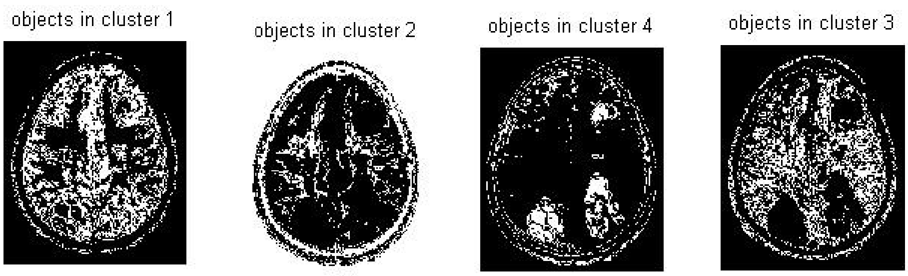


Figure 3.7: brain2 original image

Figure3.8: 4 clusters segmented image using k-means



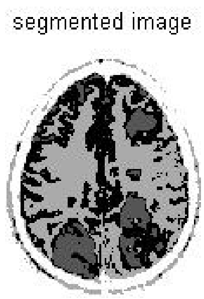
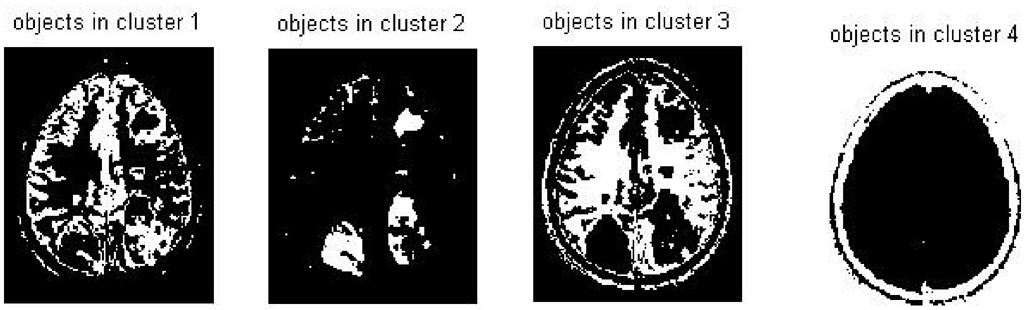


Figure 3.9: 4 clusters segmented image using fcm



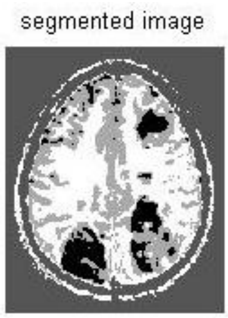
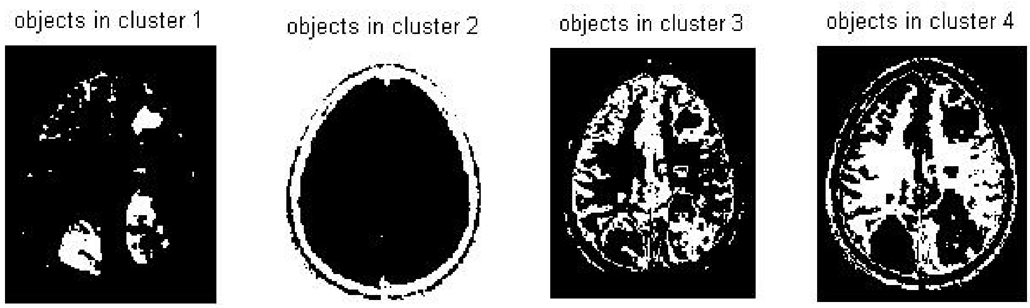


Figure 3.10: 4 clusters segmented image using SOM



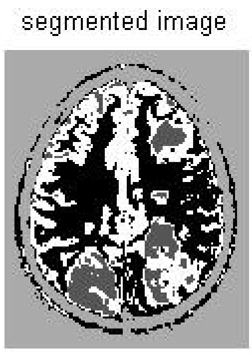
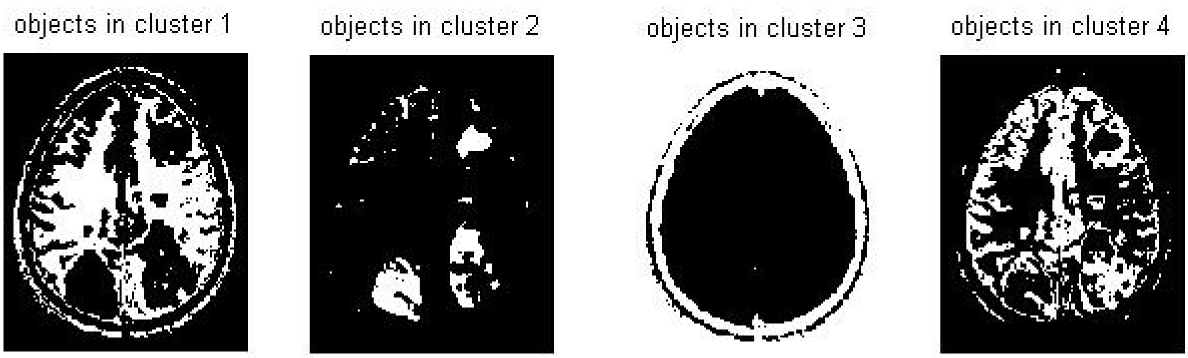


Figure 3.11: 4 clusters segmented image using SOM and fcm



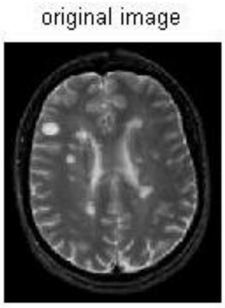
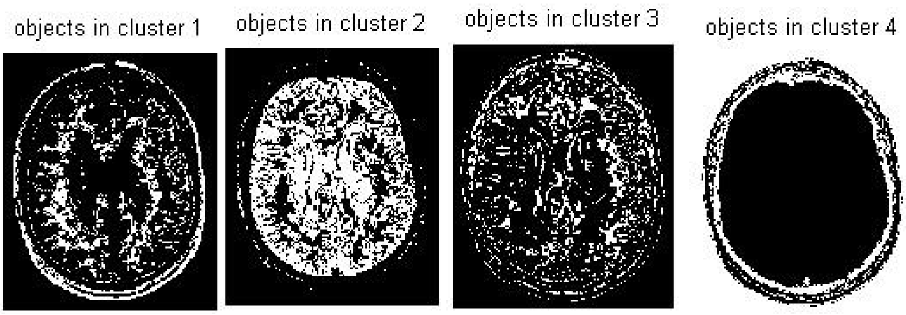


Figure 3.12: brain3 original image

Figure 3.13: 4 clusters segmented output using k-means



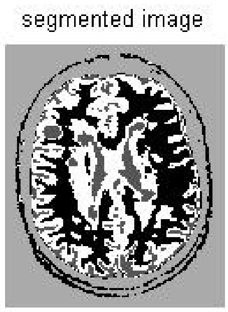


Figure 3.14: 4 clusters segmented image using fcm

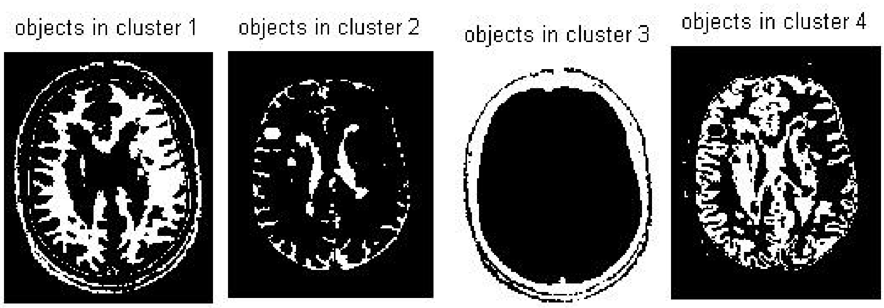


Figure 3.15: 4 clusters segmented image using SOM

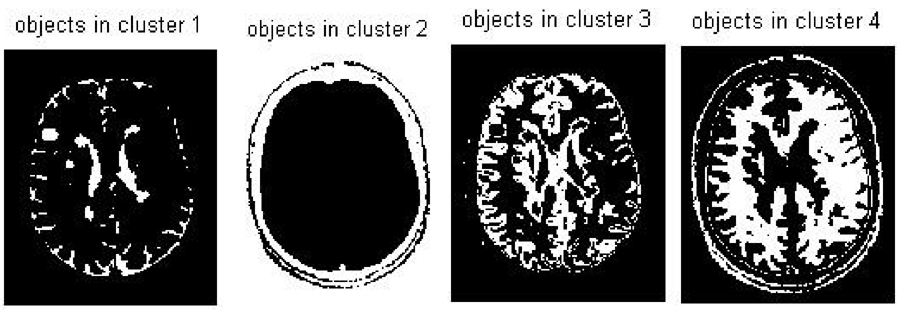
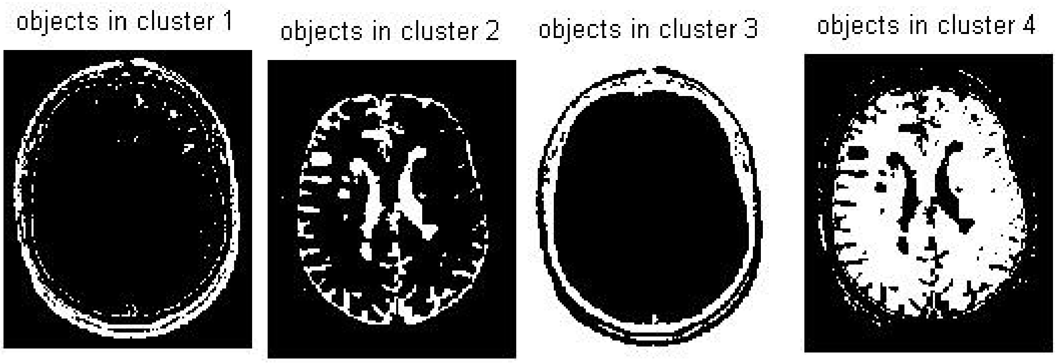


Figure 3.16: 4 clusters segmented image using SOM and fcm



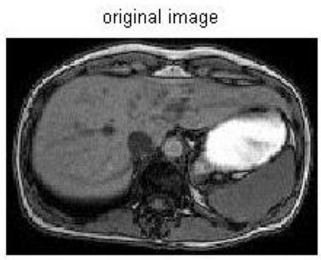


Figure 3.17: liver1 original image

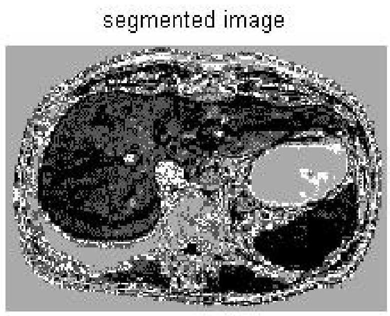
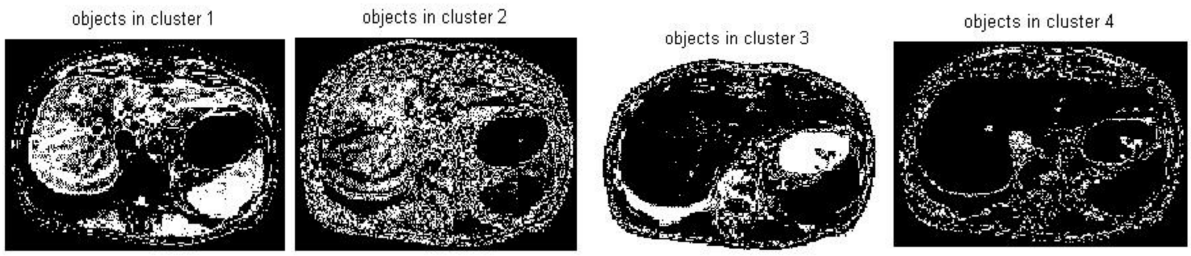


Figure 3.18: 4 clusters segmented image using k-means



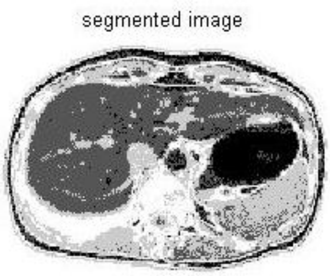
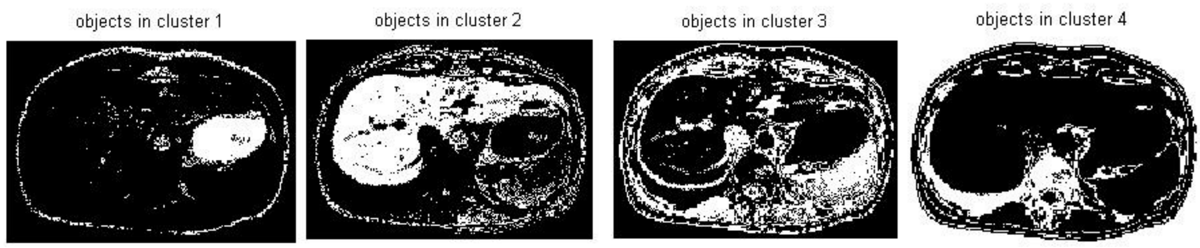


Figure 3.19: 4 clusters segmented image using fcm



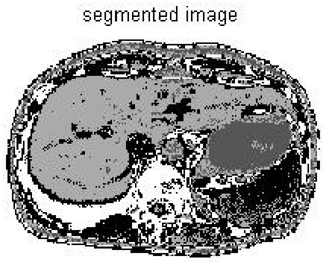
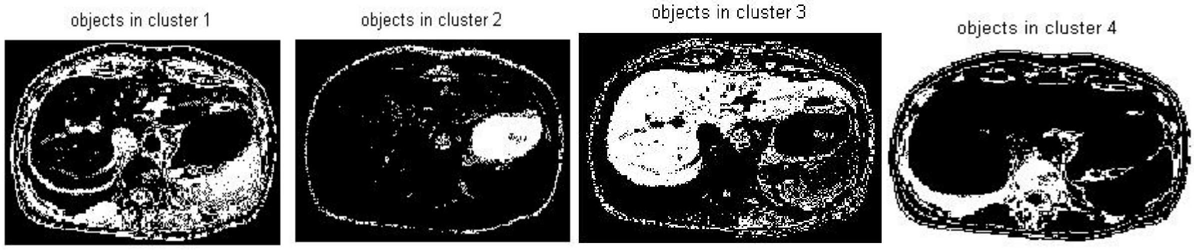


Figure 3.20: 4 clusters segmented output using SOM



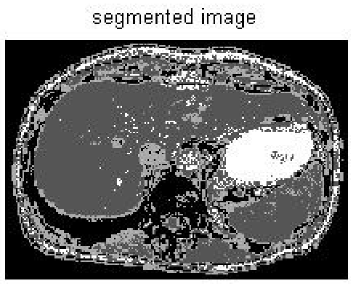
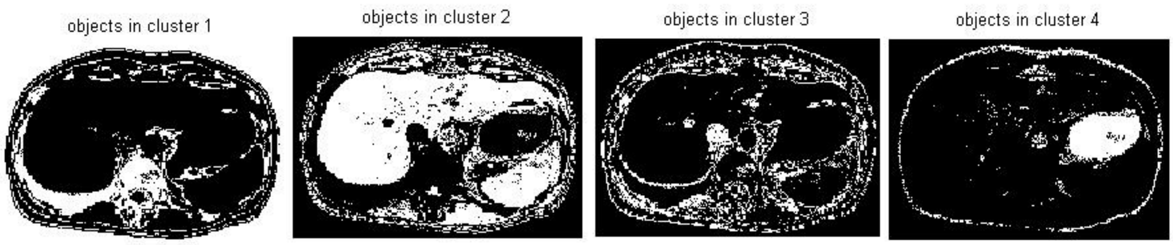


Figure 3.21: 4 clusters segmented output using SOM and fcm



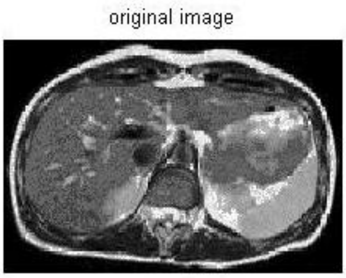
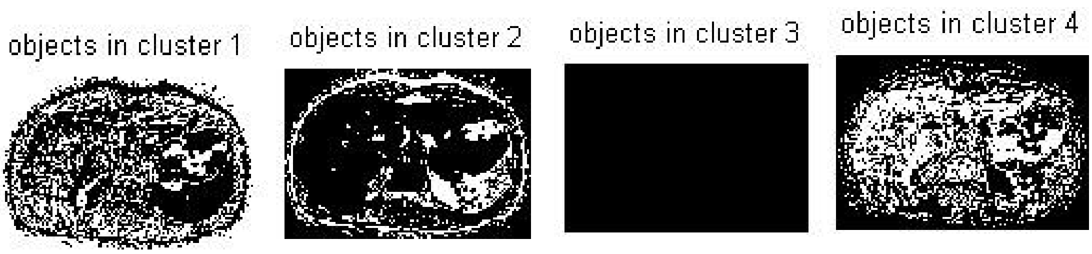


Figure 3.22: liver2 original image

Figure 3.23: 4 clusters segmented image using k-means



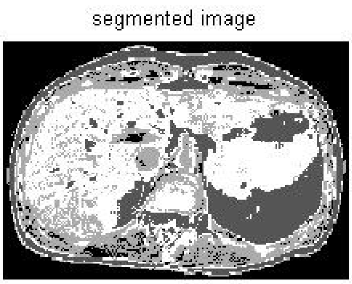
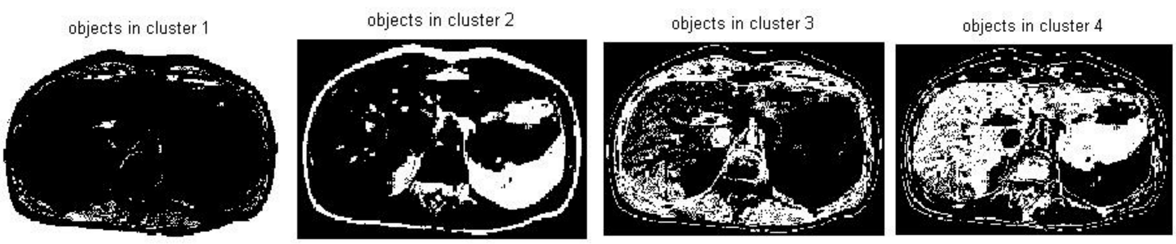


Figure 3.24: 4 clusters segmented output using fcm



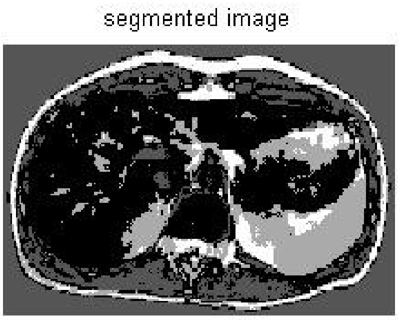
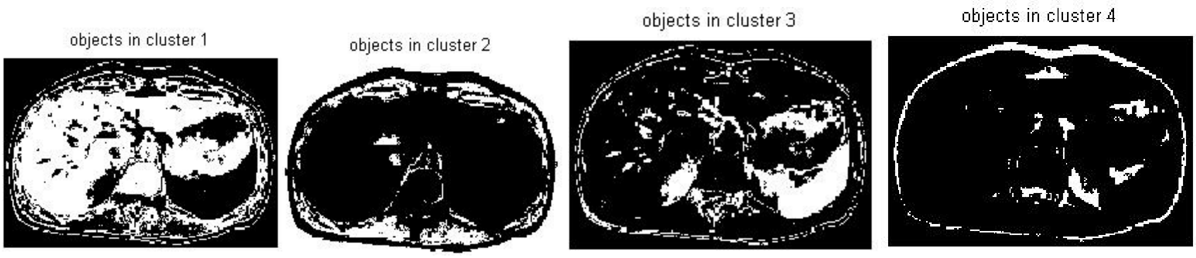


Figure 3.25: 4 clusters segmented image using SOM



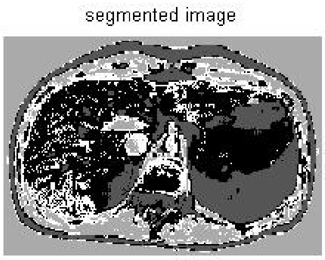
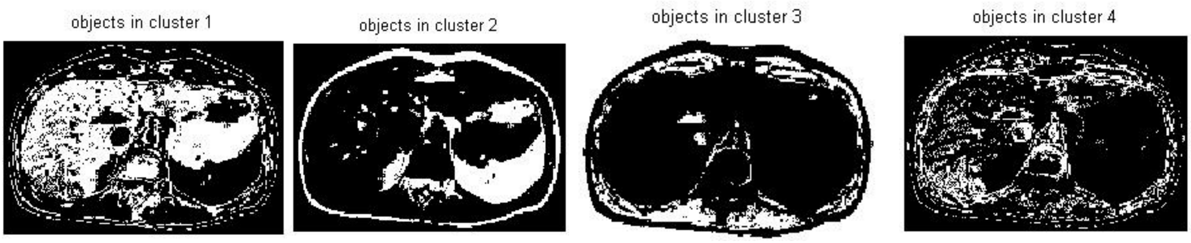


Figure 3.26: 4 clusters segmented image using SOM and fcm



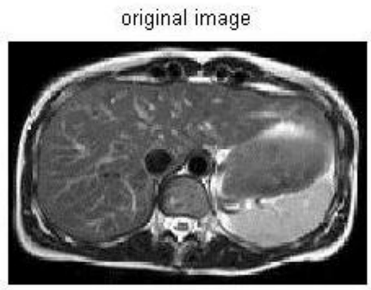


Figure 3.27: liver3 original image

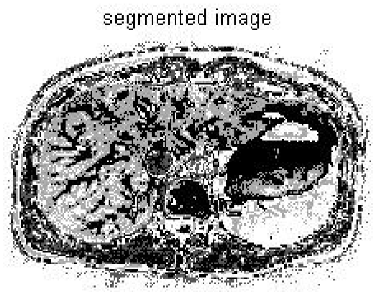
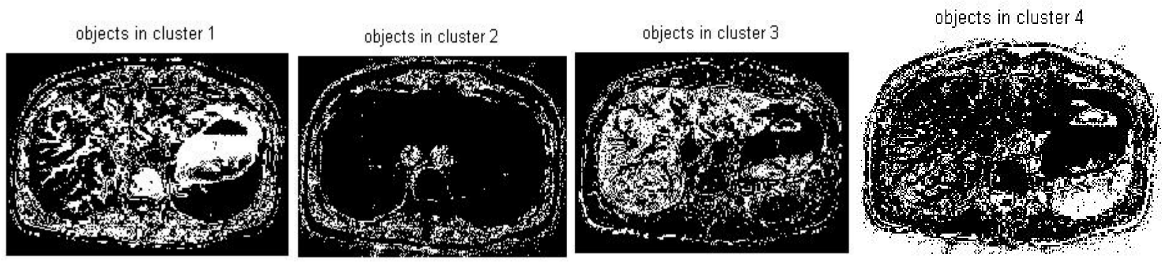


Figure 3.28: 4 clusters segmented image using k-means



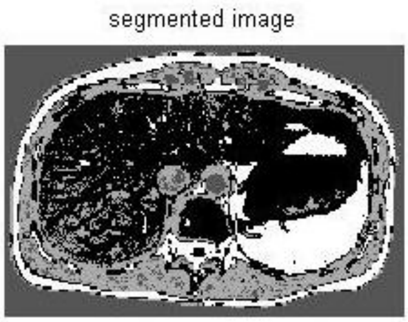
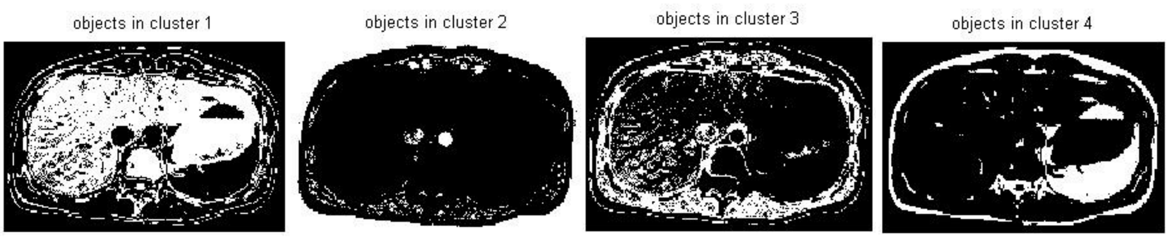


Figure 3.29: 4 clusters segmented output using fcm



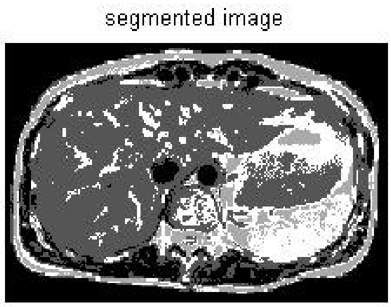
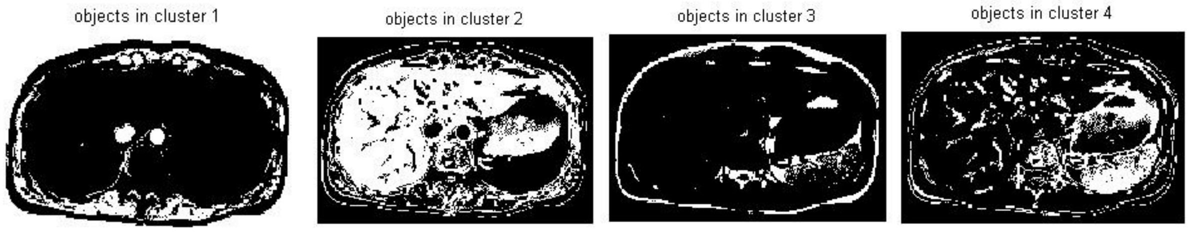


Figure 3.30: 4 clusters segmented output using SOM



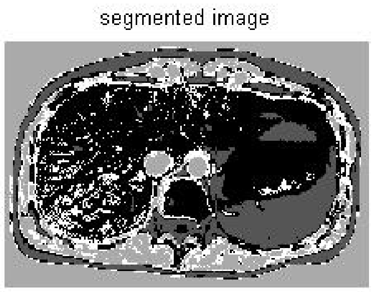
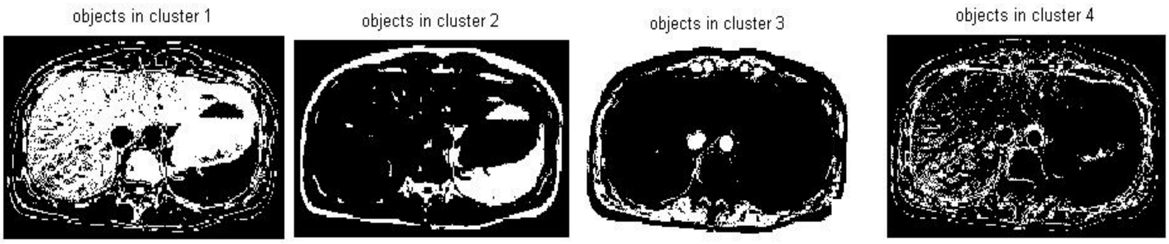


Figure 731: 4 clusters segmented output using SOM and fcm



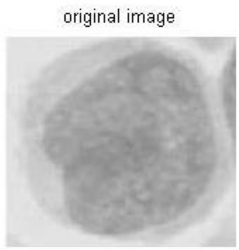


Figure 3.32: Blood1 sample image

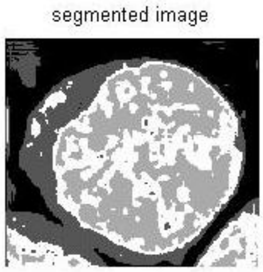
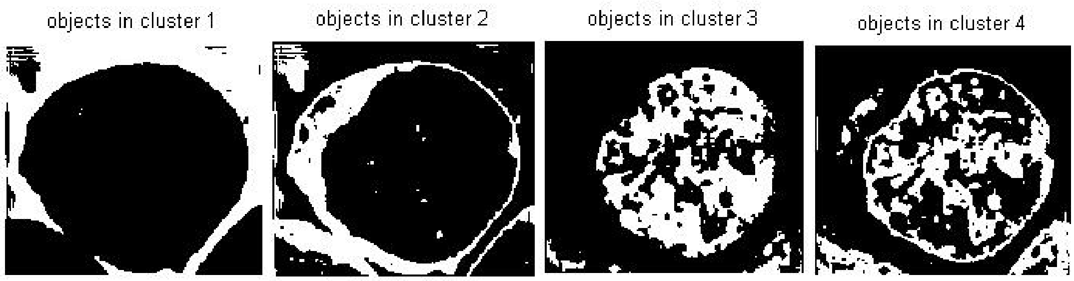


Figure 3.33: 4 clusters segmented image using k-means



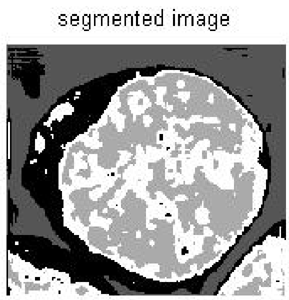
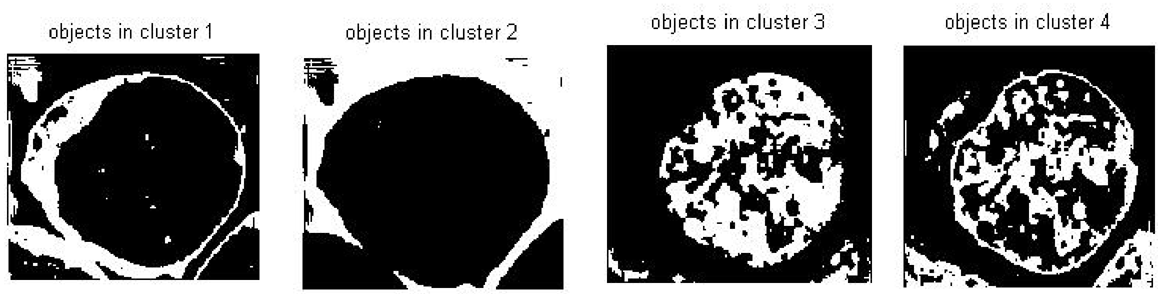


Figure 8: 4 class segmented output using fcm



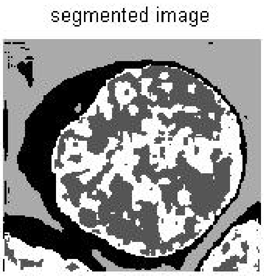
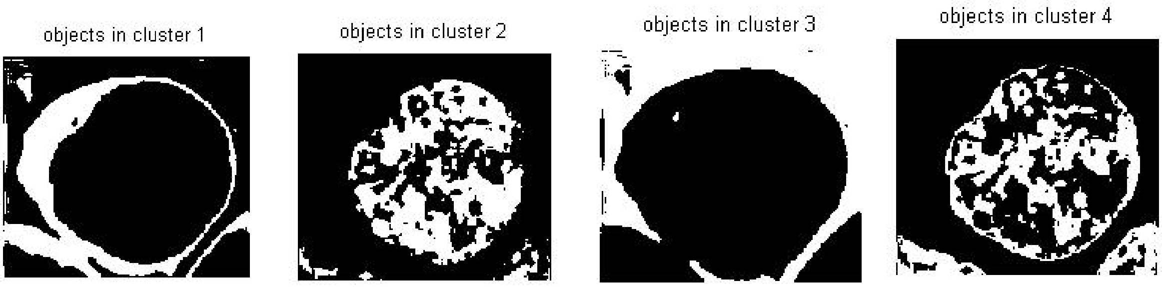


Figure 9: 4 clusters segmented image using SOM



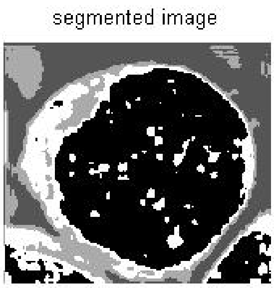
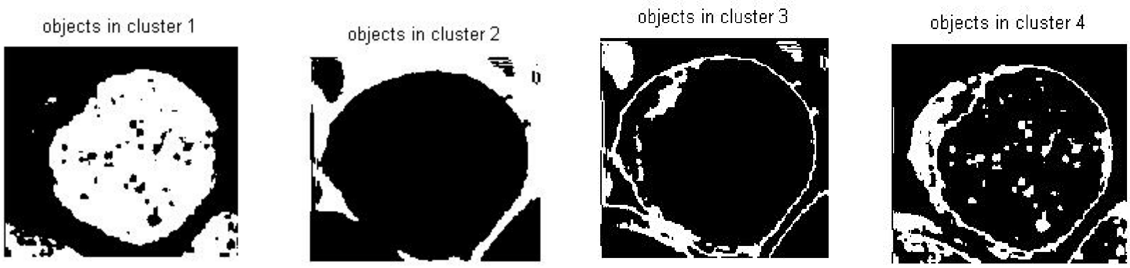


Figure 10: 3 class segmented output using SOM and fcm



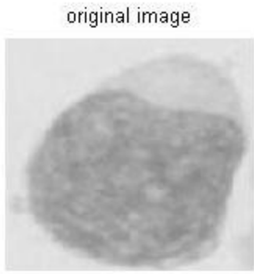


Figure 11: blood2 original image

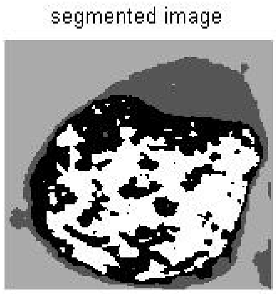
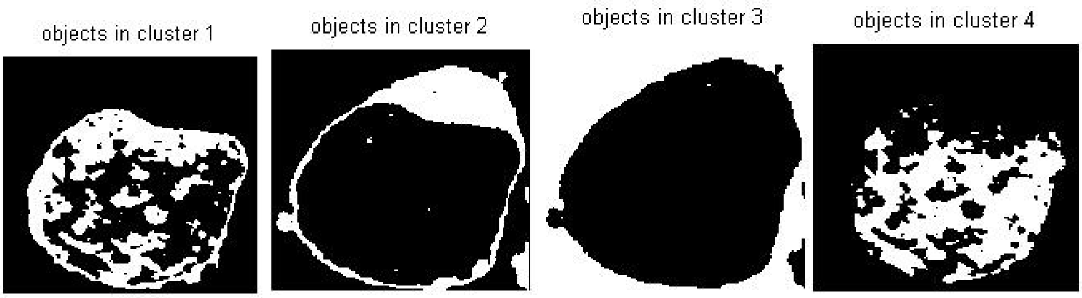


Figure 3.38: 4 clusters segmented image using k-means



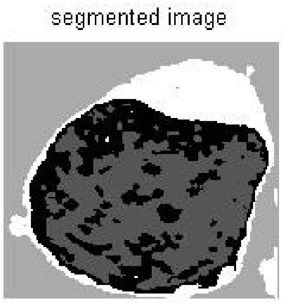
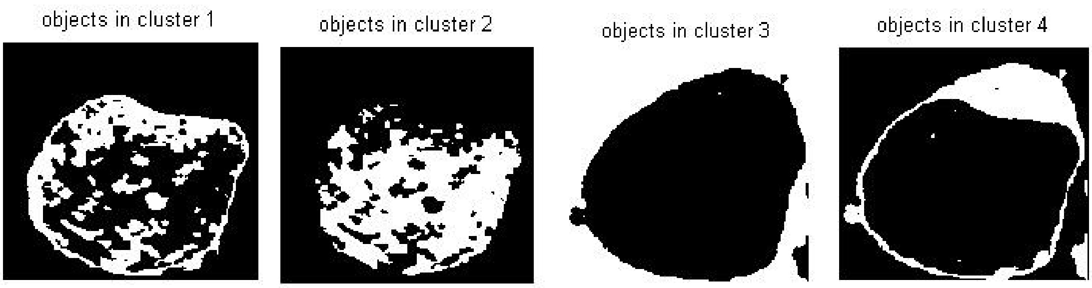


Figure 3.39: 4 clusters segmented image using fcm



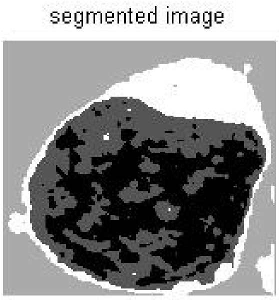
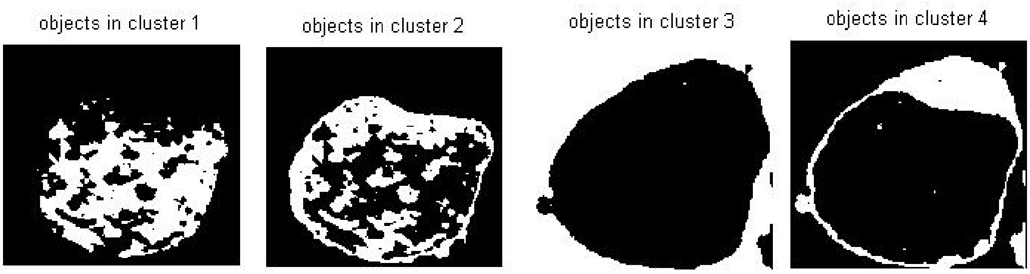


Figure 3.40: 4 clusters segmented image using SOM



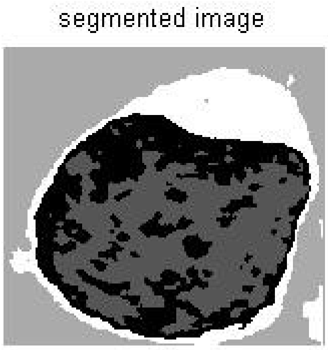
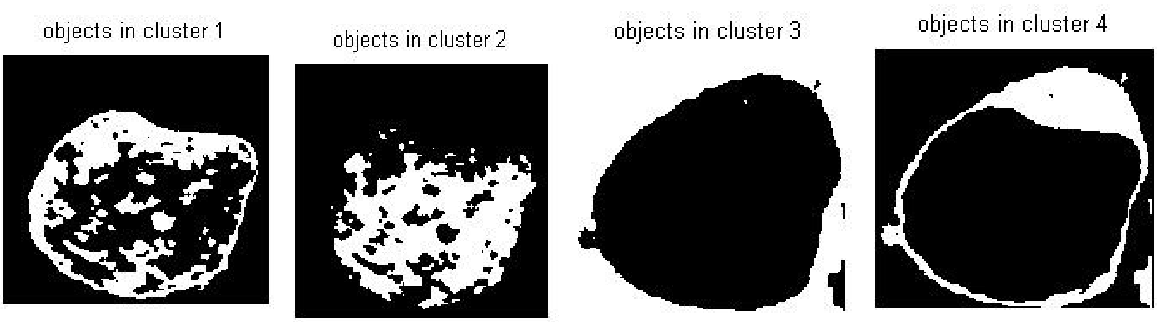


Figure 3.41: 4 clusters segmented output using SOM and fcm



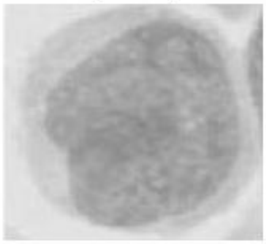
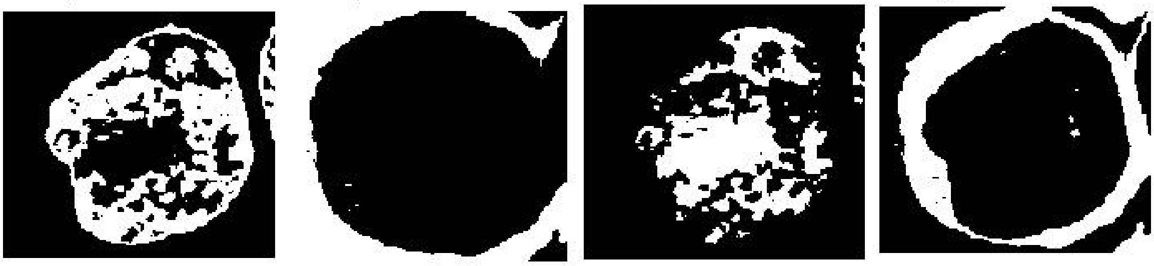


Figure 3.42: blood 3 original image

Figure 3.43: 4 clusters segmented image using k- means



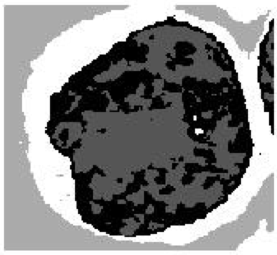
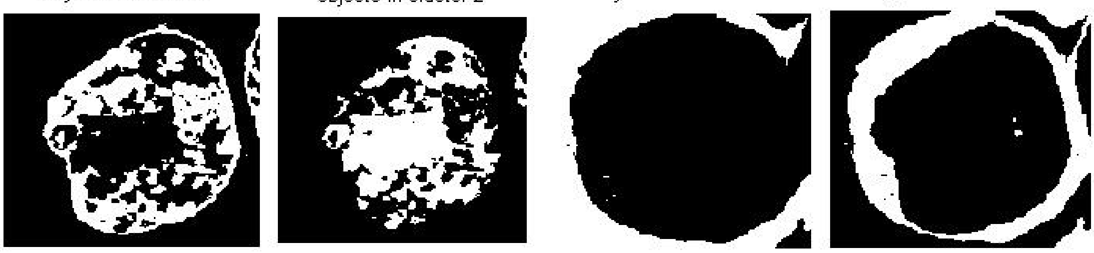


Figure 3.44: 4 clusters segmented image using fcm



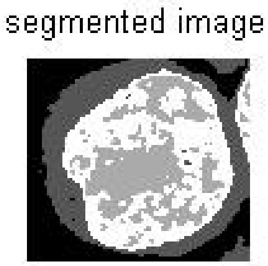
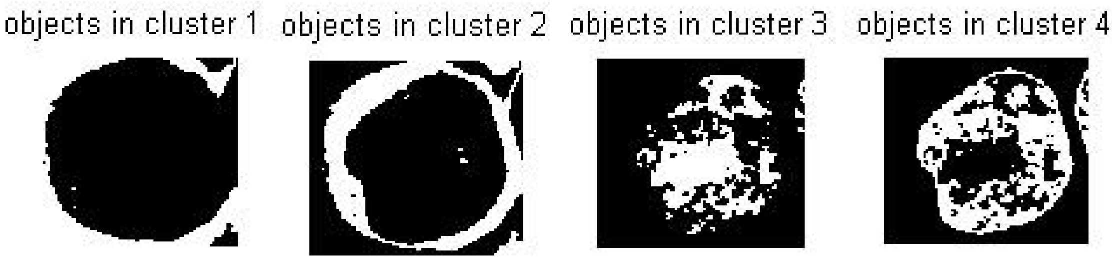


Figure 3.45: 4 clusters segmented image using SOM



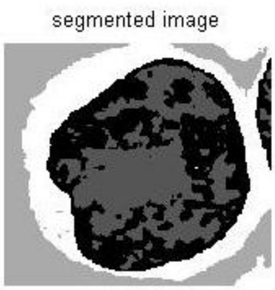
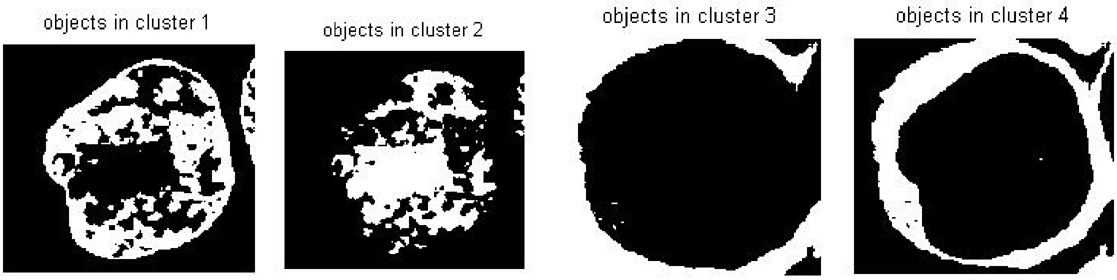


Figure 3.46: 4 clusters segmented output using SOM and fcm



Chapter 4

CONCLUSION AND FUTURE SCOPE

Following conclusions were drawn from the thesis::

- When only SOM is used for the clustering, the output image is not segmented properly as compared to the fcm or k-means but the edge detection of the images is better than the latters.
- Using fcm alogwith the SOM gives better segmented image as compared to SOM alone or fcm or k-means in terms of smooth clusters.
- In some images (Liver2 and Liver3), because of noise the outputs are not so accurate when compared to the outputs of Liver1.
- The two-layered method proposed uses a large variable set and various inputs are required during the simulation, but the average overall time taken to run the simulation is less when compared to fcm alone for clustering.

Future research in the segmentation of medical images will strive towards improving the accuracy, precision and computational speed of segmentation methods, as well as reducing the amount of manual interaction. Computational efficiency will be particularly important in real time processing applications.

Possibly the most important question surrounding the use of image segmentation is its application in clinical settings. Computerized segmentation methods have already demonstrated their utility in research applications and are now increasingly in use for computer aided diagnosis and radiotherapy planning. It is unlikely that automated image segmentation methods will ever replace physicians but they will likely become crucial elements of medical image analysis. Segmentation methods will be particularly valuable in areas such as computer integrated surgery, where visualization of the anatomy is a critical component.

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