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Detection of Tumor Using Image Segmentation

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Detection of Tumor using Image segmentation

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Recommendation

The undersigned certify that they have read and recommended to the Department of Electronics and Computer Engineering for acceptance, a thesis entitled **“Detection of Tumor Using Image Segmentation**”, submitted by **Durgaprasad Bhandari** in partial fulfillment of the requirement for the award of the degree of “**Master of Science in Information and Communication Engineering**”.

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Departmental Acceptance

The thesis entitled **"Detection of Tumor Using Image Segmentation",** submitted by **Durgaprasad Bhandari** in partial fulfillment of the requirement for the award of the degree of "**Master of Science in Information and Communication Engineering**" has been accepted as a bonafide record of work independently carried out by him in the department.

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Abstract

Image segmentation is an important and challenging factor in the medical image segmentation. Detection of cancer tumors has variety of segmentation problems. Filters are being used to remove the noise and generate effective features for segmentation purpose. Breast cancer is currently one of the leading causes of death among women worldwide. This thesis presents an approach for detecting breast tumor not only the detection, an early stage of tumors can also detectable. The difficulty of image segmentation found is the misclassified pixels which lead to ambiguity at correct detection of boundary. The effective classification is required to correct the error and fix the boundary to locate the exact spreading of Cancer Tumor and remove the boundary errors around it.

Selection of proper segmentation method is the prime purpose of this work. The thesis is totally concerned to the segmentation of Mammograms of breast and the analysis and performance of different segmentation technique that can be employed in the segmentation process. The different segmentation technique including edge based segmentation, thresholding, region-based approached, clustering are used to generate useful outcome.

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1. Introduction

The advances in medical imaging over the last three decades have been greatly improved the type and quality of medical care that is available to the patients. Medical images are rich in information that can be used for diagnosis and subsequent medical interventions. Imaging modalities such as mammograms, Computed Tomography (CT), Ultrasound and Positron Emission Tomography (PET) all provide different measures of the structure and function of internal composition and are of considerable use to the medical practitioner. These methods are still inherently limited because they provide images with information content limited by the physical characteristics of the imaging device and no imaging method in existence provide all the information that a doctor or surgeon might need to diagnose a condition or treat a patient .[2]

One of the successful applications of image processing technique is in the area of medical imaging or medical image processing. Introduction to sophisticated imaging devices coupled with advances in algorithms specific to medical image processing both for diagnostics and remedial planning is the key to wide popularity if image processing in this field . The earlier applications involve computer processing of X-rays, chromosome karyotyping, blood cell analysis and similar other computer analysis technique for laboratory testing, especially which involves human observation under microscopes. Advancement in radiographic imaging technique has considerably assisted the medical field. They have become important tool for diagnostics and also for pre-operative planning. [2]

In clinical diagnosis particularly in cancer detection, mammography system has become a standard tool for detecting a variety of tumors. Differing from other diagnostic techniques, mammography imaging systems can produce several images each of which emphasizes different fundamental parameters of internal anatomical structures in same body section with multiple contrasts .For the analysis of medical images, segmentation is considered as preliminary stage for the visualization, quantification and image interpretation. Manual segmentation could be more difficult and time consuming.

Tumor in breast is widely known as breast cancer which is one of the main causes of women death in Nepal. An early detection of tumor existence increases the chance of survival and overcoming the problem. There are various number of detection method which suffer from miss detection which in turn causes the damages of surrounding tissues. These limitations motivate the need of other method that can improve the miss detection ratio in cost effective manner.

In this thesis work image processing technique is proposed to detect the tumor in breast. Emphasis will be given to the edge detection method in the image processing to find the boundary of tumor. Thesis work is proposed to find the result using various methods i.e. edge based segmentation, thresholding, region-based approached, clustering, and the filters.

2. Objectives

This thesis work attempts to provide the algorithm by making use of image segmentation techniques to achieve better results i.e. Improve miss detection ratio of tumor boundary due to manual segmentation in the breast. Main objectives of this thesis work are as follows:

1. Segmentation of mammography images of breast using different segmentation techniques including edge based segmentation ,local and global segmentation ,clustering methods

2. Implementation of bi-level and multi-level thresholding techniques.

3. Implementation and analysis of different types of clustering methods

4. Performance evaluation of segmentation techniques.

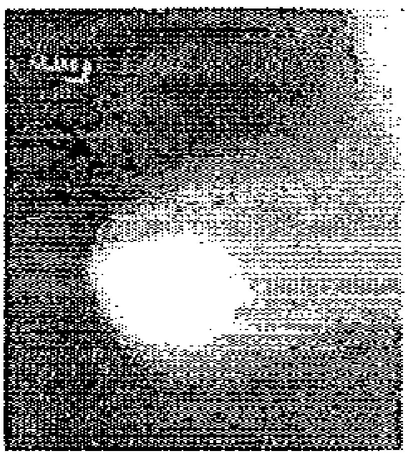
3. Scope of the work

This thesis work will be useful to understand the advantages if image processing methods and its application for the very useful application of early breast cancer detection to save women life in the future. Image Segmentation is the key process if image analysis and it helps significantly in the image interpretation and pattern recognition. The manual analysis and interpretation of mammography images are insufficient for the efficient use of mammography. For the reason, automatic or semi-automatic techniques of computer aided analysis are necessary.

4. Research Methodology

4.1 Introduction to X-Ray Mammography

X-Ray Mammography is commonly used in clinical practice for diagnostic and screening purposes. Screening mammography has been recommended as the most effective method for early detection of breast cancer. Singapore Health Promotion Board (HPB) has launched Breast Screen Singapore (National breast cancer screening programme) on 17 January 2002 to encourage women aged 40 years and above to go for regular mammography. [3]



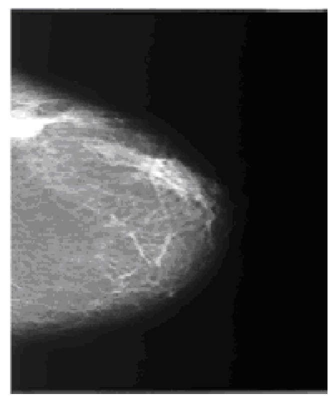


Figure 4-2: The mammography images[4][1] [4] [3].

Mammography provides high sensitivity on fatty breast and excellent demonstration of micro calcifications [3]. It is highly indicative of an early malignancy. Due to its low cost, it is suitable for mass screening program. Mammography has its limitations. It is less reliable on dense breast of young women or women underwent a surgical intervention in the breast because glandular and scar tissues are as radiopaque as abnormalities. Furthermore, there is low dose X-Ray radiation [3].

4.2 MRI of the Breast

Magnetic Resonance Imaging is the most attractive alternative to Mammography. MRI is sensitive for detecting some cancers which could be missed by mammography. In addition, MRI can help radiologists and other specialists determine how to treat breast cancer patients by identifying the stage of the disease. It is highly effective to image breast after breast surgery or radiation therapy. To be effective, contrast-enhanced breast MRI is carried out by injecting in the patient's body of a paramagnetic contrast agent. This method is based on the hypothesis that, after the injection of the agent, abnormalities enhance more than normal tissues due to their increased vascularity, vascular permeability and interstitial spaces [9] MRI forms 3D uncompressed image. It can perform with all women including who are not suitable for mammography, such as young women with dense breast and women with silicone-filled breast implants. Since it uses magnetic fields, MRI has no harmful effects on human bodies [3].

However, MRI takes rather long time to perform and has high cost which is more than ten times greater than mammography. Its low resolution limits its application to very small lesions or micro calcifications.

4.3 Image processing tools (Segmentation) for tumor detection in Mammograms:

Image segmentation is one of the important steps in image analysis. It is the process of partitioning the image into meaningful regions. Segmentation subdivides an image into its constituent regions or objects. The level to which the subdivision is carried depends on the problem being solved. A good segmentation is typically one in which

- Pixels in the same categories have similar selected property

- Neighboring pixels that ate in different categories have dissimilar selected property.

Fig 4.2: Segmentation Procedure

Segmentation has a long history in the image processing tools and many methods have been proposed with various degrees of complexities. Segmentation methods can be broadly divided into three categories:

1. Edge based segmentation

2. Thresholding based segmentation

3. Clustering and Region based segmentation

Accuracy of segmentation determines the success and failure of computerized analysis procedures. Image segmentation algorithms depend on the two properties of intensities values, discontinuity and similarity [2]. The partition is done based on the abrupt changes in intensity in the first approach, the example is edge detection. While the principle approaches in the secondary category are based on the partitioning of an image into regions that ate similar. Thresholding, region growing, clustering are similarity based approaches.

5.Segmentation Algorithms

5.1 Edge Based Segmentation

To detect the boundary of cancer tumors in digital mammograms the edge based segmentation techniques are the first and second order provides an effective segmentation to detect boundary profiles. Edge detecting an image significantly reduces the amount of data and filters out useless information while preserving the important structural properties in an image. Edge detectors are a collection of very important local image pre-processing methods.[1]

Edge detection is the process to characterize the intensity changes in the image in terms of the physical process that have originated them. The goal of edge detection is the detection and characterization of significant intensity changes i.e. the detection of meaningful discontinuities in gray level. Edge based segmentation represents a large group of methods based on information about edge in the image. These methods rely on edges found in an image by edge detecting operators which mark the edge in the image locations of discontinuities in gray level, color, texture etc.[2]

An edge is a set on connected pixels that lie on the boundary between two regions. A reasonable definition of edge requires the ability to measure gray-level transitions in a meaningful way. An ideal edge is a set of connected pixels, each of which is located at an orthogonal step transition in gray level. The image affected by the acquisition imperfections yields the blurred image resulting the edge with “ramp-like” profile. [2] The slope of the ramp is proportional to the degree of blurring in the edge and thickness of the edge is determined by the length of the ramp resulting blurred textures to have thick edge and sharp textures to have thin edge.

The biggest drawback to edge detection methods of image segmentation is the sensitivity to the size and type of smoothing and derivative convolution masks applied to the original image [1]. Their weakness in connecting together broken contour lines them which prone to failure in the presence of blurring. The main disadvantage of the edge detectors is their dependence on the size of objects and sensitivity to noise. Further, since conventional boundary finding relies on changes in the grey level, rather than their actual values, it is less sensitive to changes in the grey scale distributions over images as against region based segmentation [1]. In some cases these two masks are not parameterized and are therefore not under user control. This limits the applicability of these algorithms to different types of images. Most edge detection algorithms are very sensitive to noise and can yield edge information that is not a boundary between regions in an image. Furthermore, edges that are computed are often not linked where contiguity exists in the image Edge linking algorithm can be used for this purpose.

Edge detection techniques like the Kirsch, Sobel, and Prewitt operators are based on convolution in very small neighborhoods and work well for specific images only. An edge detection technique, based on the zero crossings of the second derivative explores the fact that a step edge corresponds to an abrupt change in the image function. The first derivative of the image function should have an extreme value at the position corresponding to the edge in the image, and so the second derivative should be zero at the same position. [11]

5.1.1 Canny Edge Detector

Canny edge detector is known as the optimal edge detector. The application of this algorithm for the detection of the edges of mammography images is the matter of interest to be discussed. This algorithm was suggested by J. Canny in 1986. He defined edges as a set of points where the gradient magnitude assumes a maximum in the gradient direction. He also suppressed noise by saying that only those weak edge points that are connected to strong edge points are interesting [14]. The method includes following step:

1. Gaussian smoothing: it is performed to filter out any noise in the original image before trying to locate and detect any edges. The Gaussian mask is convoluted to the image on the pixel by pixel basis. The Gaussian mask is calculated in two dimension as follows:

The Gaussian distribution in 1-D has the form:

$$\mathbf{G(x)} = \frac{\mathbf{1}}{\sqrt{\mathbf{2\Pi\sigma}}}\ \mathbf{e}^{\frac{-\mathbf{x}^2}{\mathbf{2\sigma^2}}} \qquad \text{Equation (2.1)}$$

where σ is the standard deviation of the distribution. We have also assumed that the distribution has a mean of zero (*i.e.* it is centered on the line *x*=0)

In 2-D, an isotropic (*i.e.* circularly symmetric) Gaussian has the form:

$$\mathbf{G(x,y)} = \frac{\mathbf{1}}{\sqrt{\mathbf{2\Pi\sigma^2}}}\ \mathbf{e}^{\frac{-(\mathbf{x}^2+\mathbf{y}^2)}{\mathbf{2\sigma^2}}} \qquad \text{Equation (2.2)}$$

Where, x and y are image coordinates and σ is the standard deviation of the associated probability distribution of the image. The standard derivation σ is the only parameter of the Gaussian filter which is proportional to the size of neighborhood on which the filter operates. Pixels more distant from the center of the operation have smaller influence and pixels more distant from the center of the operator have smaller influence and pixels further than 3σ from the center have negligible influence.

The larger the width of the Gaussian mask, the lower the detector's sensitivity to noise. The Gaussian mask used is [14] :

$$\frac{1}{115}\begin{bmatrix} 2 & 4 & 6 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 6 & 12 & 15 & 12 & 6 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 6 & 4 & 2 \end{bmatrix}$$

2. After smoothing the image and eliminating the noise, the edge strength is calculated by estimating the gradient magnitude of the image. Sobel operator can be used to estimate the spatial gradient measurement at each point. The sobel operator masks in the both direction x and y are:

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

The gradient magnitude is then approximated by $|G| = |Gx| + |Gy|$

The orientation of the edge normal in each pixel is approximated by

$$eo\ (x,y) = \arctan\ (Gy/Gx)$$

3. Every pixel has two neighbors along the direction of edge normal. If the magnitude of the gradient at a pixel is smaller than the magnitude of the gradient of one of its neighbors it is not considered as an deep point. The output is an image of thinned edge points still with a specific magnitude of the gradient. This is called Non-Maximum Suppression [9] as it traces along the edge in the edge direction and suppress any pixel value that is not considered to be an edge.

5.1.2 Laplacian of Gaussian

The image is first blurred with a Gaussian smoothing operator and then the laplacian operator is applied to it. The alternate way to perform this is to convolute the Gaussian smoothing operator with the laplacian operator to form a single edge-finding operator . The smoothing operation serves two purposes. First, it reduces the effect of noise on the detection of intensity changes. Second, it sets the resolution or scale at which intensity changes are detected. Smoothing of the intensities can remove the minor fluctuation due to noise [2].

Gaussian smoothing function G(x,y) is given by,

$$\mathbf{G(x,y)} = \frac{\mathbf{1}}{\sqrt{\mathbf{2\Pi\sigma^2}}}\ \mathbf{e}^{\frac{\mathbf{-(x^2+y^2)}}{\mathbf{2\sigma^2}}}$$

The laplacian of G(x,y) is

$$\nabla^2 G(x,y) = \frac{1}{2\pi\sigma^6}\left[x^2 + y^2 - \sigma^2\right]e^{-\frac{x^2+y^2}{2\sigma^2}}$$

The application of LoG operator to the image generates the zero crossings which can be used to establish the location of edges. Zero thresholding of resulting image f(x,y) in the following manner gives better edge detection .

Output image, g(x,y) = L-1 if f(x,y)>0

= 0 otherwise

Where, L-1 is the maximum intensity level.

5.2 Thresholding based Segmentation

Thresholding is the powerful method for segmentation. Gray level thresholding is the simplest and oldest segmentation process and is still widely used in simple applications. Moreover, it is computationally inexpensive and fast [2]. Many objects or image regions are characterized by constant reflectivity or absorption of their surface. The application of thresholding technique is based on the assumptions that object and background pixels in a digital image can be distinguished by their gray level values. [14]

For a thresholding algorithm to be really effective, it should preserve logical and semantic content. There are two types of main thresholding algorithms:

1. Global thresholding algorithms
2. Local or adaptive thresholding algorithms

In global thresholding a single threshold for all the image pixels is used. When the pixel values of the components and that of background are fairly consistent in their respective values over the entire image, global thresholding could be used. In adaptive thresholding different threshold values for different local areas are used.

Thresholding may be viewed as an operation that determines the parameter T known as threshold which transforms the input image f(x,y) to an output (segmented) image g(x,y) such that the segmented image consists of set of segments or regions. If the image is segmented into two regions then it is termed as binary thresholding otherwise multilevel thresholding [2]. The threshold parameter might be the function of spatial location (x,y), f(x,y) the gray level of point (x,y) and some local property of this point, p(x,y).

$$T = f[x, y, p(x,y), f(x,y)]$$

In the multilevel thresholding, T can have more than two threshold values. When T depends only on gray-level values, the threshold is called global. If it depends on both f(x,y) and p(x,y) then the threshold is called local and it is termed as dynamic or adaptive threshold if it depends on the spatial coordinates x and y.

Binary or bi-level thresholding is the simplest thresholding technique. With the help of histogram it is possible to determine the optimal threshold segmenting images into two brighter regions. Resulting image consists of two brighter levels. Bi-level thresholding follow the techniques to determine the threshold value T such that the g(x,y) of the segmented image is an object pixel if f(x,y)>=T, and is a background pixel otherwise.

Global thresholding can be applied only those images where clear foreground and background relationship exists. These methods use same threshold for every pixel in an image. Difficulties arise when the illumination of a scene varies across the image. Moreover, for the complex images with different objects with varying brightness level, such methods are inappropriate to segment the image into the segments where each segment represents different object. In such cases, multilevel thresholding techniques are used. To determine multiple thresholds is not a simple task. In multi-object image, there are several difficulties for selection of multiple thresholds which are associated with the gray level distributions of the objects and overlapping of the objects. Some binary thresholding techniques can be adapted to function with more than two segments or clusters [4].

Adaptive or local segmentation techniques are useful for the images which are affected by uneven illumination [14]. Adaptive threshold could be based on the histogram of an appropriately sized sub-image encompassing each pixel. Obviously, any global thresholding technique could be used for determining each local threshold. Local segmentation can only utilize a small number of pixels belonging to fragments of larger segments. Thus a local segmentation algorithm differs in that it has less data and fewer contexts to work with. Smaller windows increase the chance of obtaining a uni-modal histogram, corresponding to a homogeneous or extremely noisy region. If a method is unable to detect this situation, the threshold it computes could be non sensible. It is important to determine the no. of segments present in a local window.

Thresholding is best applied to image of relatively homogeneous areas which are contrasted against a uniform background. For example, in case of binary thresholding a suitable application is extraction of text from a printed page. Well known histogram modification and manipulation techniques are applied in image thresholding. There are however, inherent shortcomings present in all thresholding techniques. Primarily there is the problem of threshold selection which usually requires some priori knowledge of the images being segmented. As well, valleys and peaks in the histogram used to segment the images are often not well defined and are difficult to differentiate. Multi-level thresholding methods can be more useful for the segmentation of the mammography images [2].

In this study, different thresholding based on histogram of the image and adaptive thresholding techniques will be discussed in detail.

5.2.1 Local Thresholding

Thresholding methods cannot enhance and segment all the edges and do not provide detail information. Global thresholding methods use the same threshold for every pixel in an image. Difficulties arise when the illumination of the varies across the image.

Algorithm for Basic Global Thresholding

This thresholding method is the simple and optimum thresholding method. The algorithm for this method is given by:

1. Select an initial estimate for To.

2. Segment the image using T . This will produce two groups of pixels. G1 consisting of all pixels with gray level values > T and G2 consisting of pixels with values<=T.

3. Compute the average gray level values m1 and m2 for the pixels in the region G1 and G2

4. Compute a new threshold values

$$T = (m1+m2) / 2$$

5. Repeat step2 through 4 untill the difference in T in successive iterations is smaller than a predefined parameter To.

6. g (x,y) = L-1 for f(x,y) >=T

= 0 for f(x,y) <T

5.2.2 Simple Local Thresholding

In this method, the procedure is to define a square or rectangular neighborhood or window and move the centre of this area from pixel to pixel. At each location the local mean of the points in the neighborhood is computed. For each window, local mean of the pixels within the window is considered as the threshold for that window. If the intensity value of each pixel is greater than the local mean, intensity of centre pixel is assigned as one level otherwise other intensity level is assigned. Another way to estimate the local threshold for a window is as follows [2]:

1. Set min-range
2. Set window
3. For each pixel repeat

   Find minimum and maximum under a selected window

   Range=maximum- minimum

   If range> min_ range then

   T= (maximum+ minimum) / 2

   Else

   T= maximum + min_ range / 2

   Or

   T= minimum + min_ range / 2

End if

Until all pixels are processed.

5.2.3 Multi-thresholding

Gray –level reduction in an image is an important task for segmentation. In most cases, it is easier to process and understand an image with a limited no. of gray levels. Usual technique for reduction in gray level is multi-thresholding [14]. Using only the values of the image histogram, multi-thresholding determines appropriate threshold values that limit the gray levels classes of the image. The application of multi-thresholding is based on the assumption that objects and background pixel in a digital image can be well distinguished by their gray level values. Therefore in complex images and multi-object images, multi-thresholding techniques may give satisfactory result [2].

5.2.4 Multi-level Thresholding based on optimal thresholding

This method exploits the technique to determine the multiple threshold recursively until certain stopping criteria is met [2]. The threshold between two consecutive intensity levels is determined using the same principle used in the determination of threshold in bi-level optimal thresholding (algorithm is given below):

The algorithm is described as follows:

1. Determine the no. of thresholds and variance threshold

2. Threshold T is determined as in optimal thresholding method, considering all the gray levels from 0 to L-1 , L-1 is the maximum intensity level.

3. Calculate the variance of the intensities that fall between 0 and T (Group G1) and , T and L-1 (group G2) , if the variance is smaller than VarThreshold in any group , stop determining threshold in that particular group , else determine the threshold of that group.

4. Repeatedly follow step 3 for each subgroup until the no. of threshold is below the specified threshold no. N or each subgroup has the variance less than VarThresold.

6. Clustering

Clustering can be considered the most important *unsupervised learning* problem; so, as every other problem of this kind, it deals with finding a *structure* in a collection of unlabelled data. A simple definition of clustering can be "the process of organizing objects into groups whose members are similar in some way". A *cluster* is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters. We can show this with a simple graphical example:

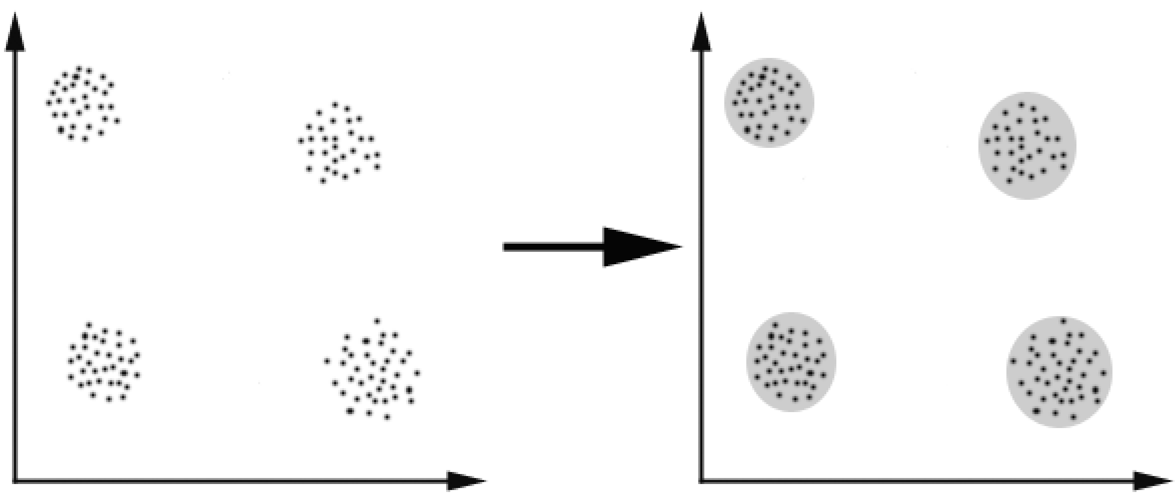


Fig 6.1 Clustering

In this case we easily identify the 4 clusters into which the data can be divided; the similarity criterion is *distance*: two or more objects belong to the same cluster if they are "close" according to a given distance (in this case geometrical distance).This is called distance-based clustering.
Another kind of clustering is *conceptual clustering*: two or more objects belong to the same cluster if this one defines a concept *common* to all that objects. In other words,

objects are grouped according to their fit to descriptive concepts, not according to simple similarity measures.

Clustering can be classified in two ways:

1. Hierarchical Clustering
2. Partitional Clustering

Hierarchical algorithms find successive clusters using previously established clusters. These algorithms usually are either agglomerative ("bottom-up") or divisive ("top-down"). Agglomerative algorithms begin with each element as a separate cluster and merge them into successively larger clusters. Divisive algorithms begin with the whole set and proceed to divide it into successively smaller clusters. [15].

Partitional algorithms typically determine all clusters at once, but can also be used as divisive algorithms in the hierarchical clustering.

6.1 Hierarchical Clustering

Hierarchical clustering refers to a clustering that organizes the data into large group, which contain smaller groups .This type of clustering structure provides a comprehensive description of the data. The size of clusters depends on the criterion which is chosen to split or merge clusters. Mainly there are two types of hierarchical clustering, agglomerative clustering and divisive.

The agglomerative algorithm starts with an initial partition of a given image into N segments and sequentially reduces the number of segments by merging the best pairs of segments among all possible pairs in terms of a given criterion .The merging process is repeated until the required number of segments is obtained.[2]

Divisive clustering employs top down procedure for recursively splitting clusters. The algorithm starts from a single cluster and sequentially increases the number of clusters by partitioning the cluster based on some given criterion. The division process continues until the required number of segments is obtained.[2]

6.2 Partitional clustering

Partitional algorithms typically determine all clusters at once, but can also be used as divisive algorithms in the clustering. The purpose of the partitional clustering is to create set of clusters that partitions the data into similar groups. In many of the partitional algorithms, the no. of clusters to be constructed is specified in advance.

The main advantage of this algorithm is that only the top of the tree, which shows the main groups and possibly their subgroups, may be required, and there may be no need to complete the tree structure.

6.2.1 Forgy's Algorithm

This is the simplest partitional clustering algorithm. For the k clusters, k seed point is chosen randomly or some knowledge of the desired cluster structure could be used to guide their selection.

1. Initialize the clusters centroids to the seed points
2. For each sample, find the cluster centroid nearest to it and put the sample in the cluster identified with this nearest cluster.
3. If no sample changes clusters in step 2 , stop
4. Compute the centroid of the resulting clusters and go to step 2

6.2.2 K-Means algorithm

This is the improved version of Forgy's algorithm. In this the centroid of the clusters is recomputed as soon as a sample joins clusters.

Given a set of observations ($\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_n$), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k sets ($k \leq n$) $\mathbf{S} = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS):

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in S_i} \left\| \mathbf{x}_j - \boldsymbol{\mu}_i \right\|^2$$

where $\boldsymbol{\mu}_i$ is the mean of points in S_i.

Standard algorithm:

The most common algorithm uses an iterative refinement technique. Due to its ubiquity it is often called the ***k*-means algorithm**; it is also referred to as Lloyd's algorithm, particularly in the computer science community.[15]

Given an initial set of k means $\mathbf{m}_1^{(1)},\ldots,\mathbf{m}_k^{(1)}$, which may be specified randomly or by some heuristic, the algorithm proceeds by alternating between two steps:[15]

> **Assignment step**: Assign each observation to the cluster with the closest mean i.e. partition the observations according to the Voronoi diagram (In mathematics, a **Voronoi diagram** is a special kind of decomposition of a metric space determined by distances to a specified discrete set of objects in the space, e.g., by a discrete set of points generated by the means).

$$S_i^{(t)} = \left\{ \mathbf{x}_j : \left\| \mathbf{x}_j - \mathbf{m}_i^{(t)} \right\| \leq \left\| \mathbf{x}_j - \mathbf{m}_{i^*}^{(t)} \right\| \text{ for all } i^* = 1, \ldots, k \right\}$$

Update step: Calculate the new means to be the centroid of the observations in the cluster.

$$\mathbf{m}_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{\mathbf{x}_j \in S_i^{(t)}} \mathbf{x}_j$$

The algorithm is deemed to have converged when the assignments no longer change.

6.3 Watershed algorithm

The watershed transform is a well established tool for the segmentation of images. However, watershed segmentation is often not effective for textured regions that are perceptually homogeneous. Such regions are usually inaccurately over-segmented with no reference to any texture changes. A novel marker location algorithm is subsequently used to locate significant homogeneous textured or non textured regions. A marker driven watershed transform is then used to properly segment the identified regions. The combined algorithm produces effective texture and intensity based segmentation for the application to content based retrieval of images.[12]

A grey-level image may be seen as a topographic relief, where the grey level of a pixel is interpreted as its altitude in the relief. A drop of water falling on a topographic relief flows along a path to finally reach a local minimum. Intuitively, the **watershed** of a relief correspond to the limits of the adjacent catchments basins of the drops of water.[15]

Morphological watershed segmentation is a simple yet powerful image segmentation method picturing the image as a landscape with valleys (local minima) and peaks/ridges (local maxima), the watershed lines (i.e. dividing lines) between the valleys are found by flooding the valleys, using one source or *marker* in each valley, and building dams where the waterfronts meet. The dams together constitute the watershed lines. It is well known that the direct use of watersheds on a natural image almost always leads to over segmentation, due to the large number of spurious extreme present in the image. Consequently the input image is filtered using a reconstructive alternating open/close sequential filter prior to watershed segmentation. This filter flattens small details while keeping larger structures relatively unaltered. One important feature of the filter is that the edges of the remaining structures are preserved. Assuming that objects of interest have relatively sharp edges, the object edges can be found as the morphological gradient of the simplified image. This results in an image in which the valleys are the interior of the objects and the ridges are the object edges. It is this image that is flooded during the watershed segmentation.[13]

Since most objects of interest (i.e. tumors) have relatively high intensity, the markers (i.e. sources) used in the flooding are the regional maxima in the image. Only maxima with contrast larger than a certain *dynamics threshold* are used. In this manner only regions with relatively large contrast with respect to their background are segmented.[13]

6.4 Result analysis of Segmentation Algorithms

Image segmentation algorithms are application specific and the efficiency of the algorithms depends on the judgment of the person assessing the segmented images. The same segmentation approach could be proven the best for some task but may not suit to the other kind of image .In this section study and result of different algorithm will be discussed and presented.

6.4.1 Edge based segmentation

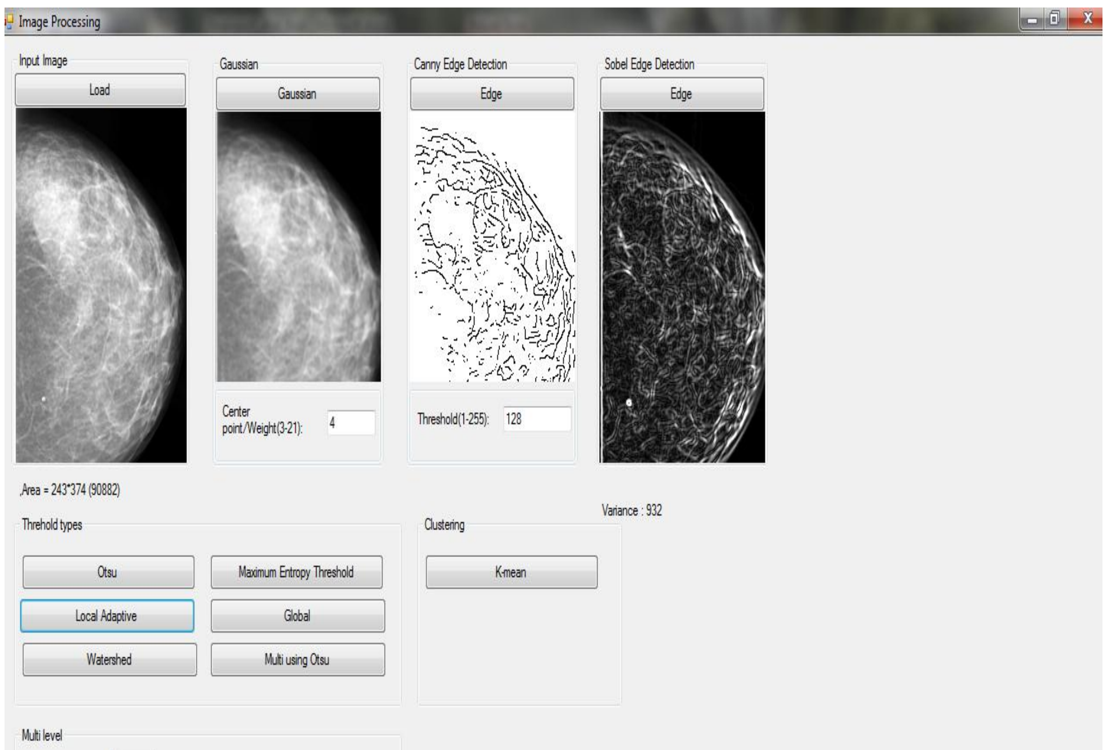


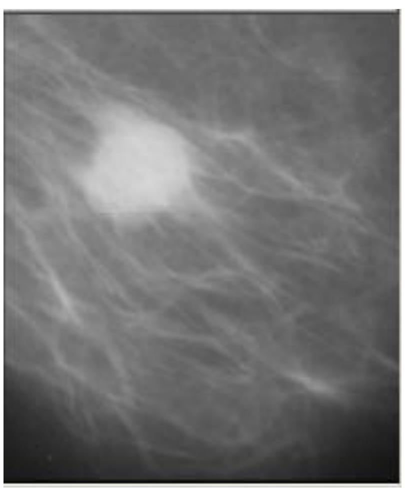
Figure 6.2: Programming snapshot

The edges are the representation of the discontinuities of image intensity function. There could be various reasons for the discontinuities. Different kind of algorithms is being presented for the detection of these discontinuities.

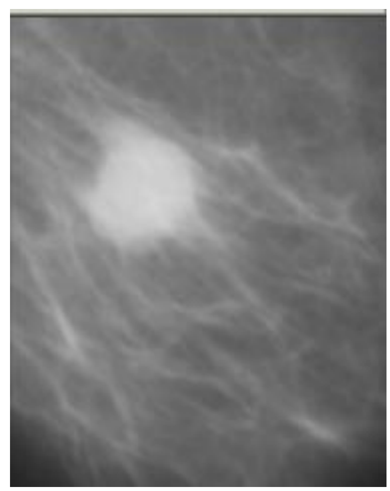
Edge based segmentation methods are suitable to find the edges of the image which has clear intensity variation between two objects i.e in our case it will be tumor and non-tumor section. The transition in intensities in grey scale image is relatively smooth in nature than abrupt as in the case of segmented or binary image

Canny edge detector has improved performance on detecting the boundaries in most of the images which consist of discontinuities of the pixel intensities in the edges Use of Gaussian Filter and Canny edge detector is shown in the figure. Gaussian Filter is used to remove the noise introduced due to image acquire and image transmission. Then the filter image is classified through Canny algorithm.

Use of Gaussian Filter and Canny edge detector is shown in the figure.

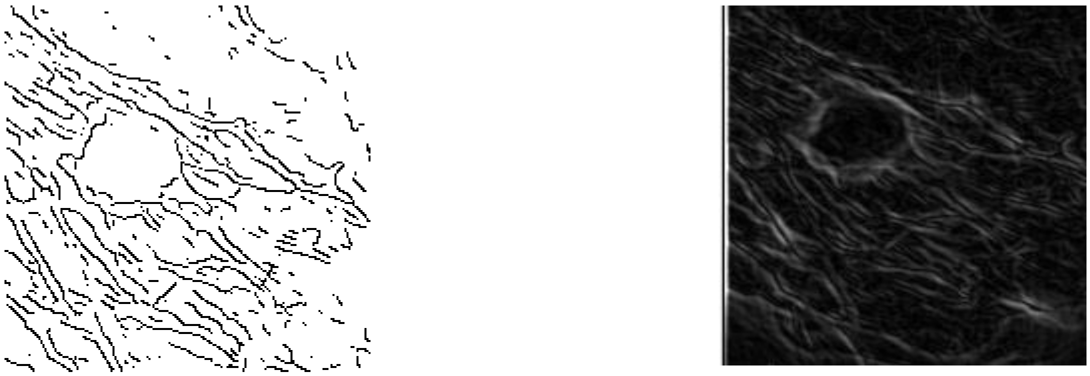


(a)



(b)

Figure 6.3 a) Original Image [1]   b) After Gaussian filter

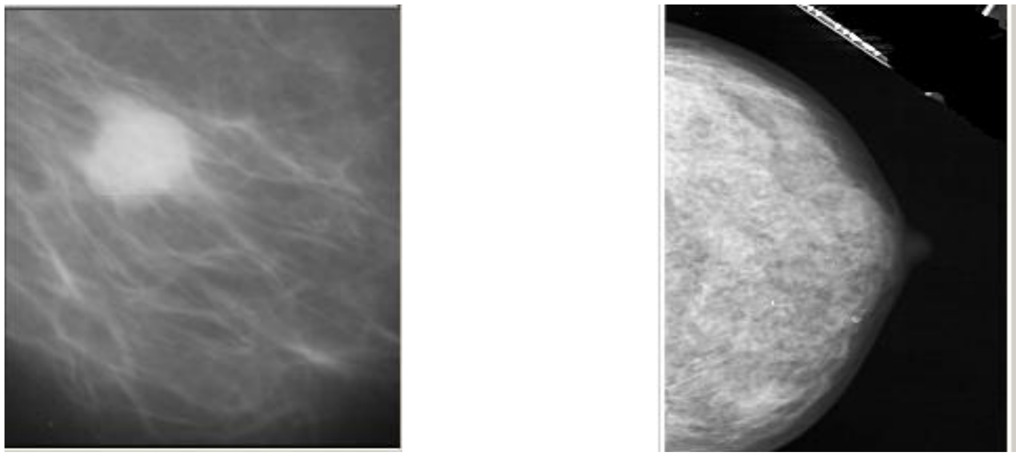


(a) (b)

Figure 6.4 a) After Canny edge detection b) After Sobel operator

6.4.2 Thresholding approaches

Thresholding methods application is useful in the cases where images consist of distinct objects and intensity levels of the objects are quite separable. The digitized mammography images consist of breast structure which is difficult to distinguish manually. For the comparison purpose different algorithms are being implemented for the two types of images which consist of tumor and without tumor. The result of application of different threshold techniques is illustrated below.



(a) (b)

Figure 6.5: a) Original Image with tumor [1] b) Normal image*

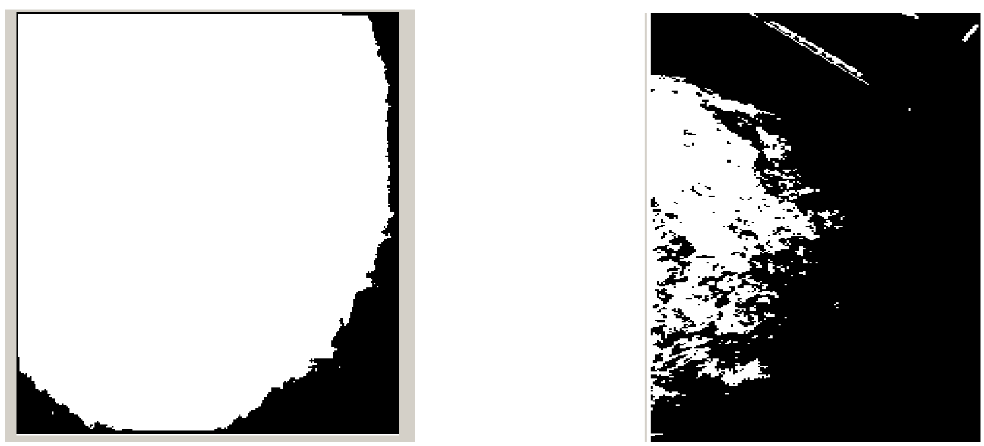
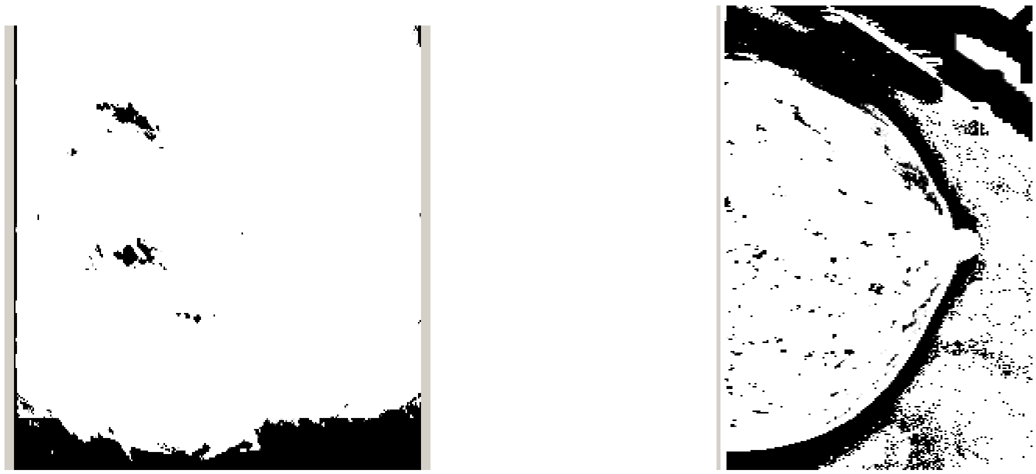


Fig 6.6: After Maximum Entropy Thresholding

(Left figure is output figure of 6.5 ‘a’ and right figure is of figure 6.5 ‘b’)

(* Image samples are taken from the Digital Database for Screening Mammography (DDSM) established by University of South Florida)



(a) **(b)**

Fig 6.7: After Local adaptive thresholding (Left figure is output figure of 6.5 ‘a’ and right figure is of figure 6.5 ‘b’)

(a) **(b)**

Figure 6.8 After Global thresholding (Left figure is output figure of 6.5 ‘a’ and right figure is of figure 6.5 ‘b’)

(a) (b)

Figure 6.9: After OTSU thresholding (Left figure is output figure of 6.5 ‘a’ and right figure is of figure 6.5 ‘b’)

In thresholding application sometimes loosing too much of the region and sometimes getting too many unrelated background pixels has been observed. For breast tumor application among the above thresholding approaches Global thresholding object is observed the significant one in which clear foreground and object pixel is defined due to its proper segmentation of grey level. From the following results it is observed that optimum and adaptive thresholding technique can separate the brightest objects from the dark object but in breast tumor detection application it could not be the appropriate one. Local adaptive thresholding approaches could be useful for multiple object detection in the mammograms.

Few snapshot outcomes from the programming tool is listed in the coming pages.

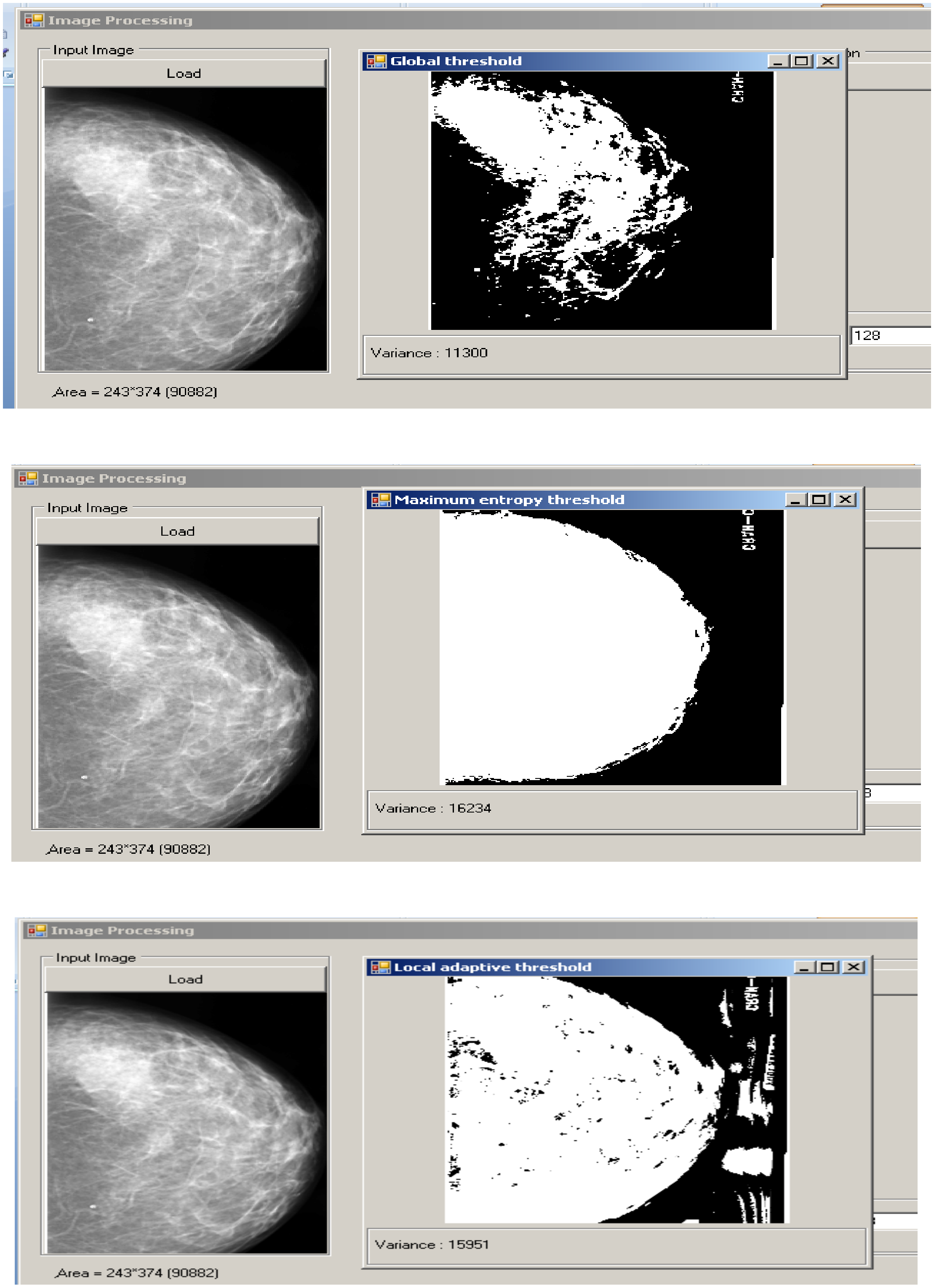


Figure 6.10: Snapshots outcome of some Thresholding algorithm

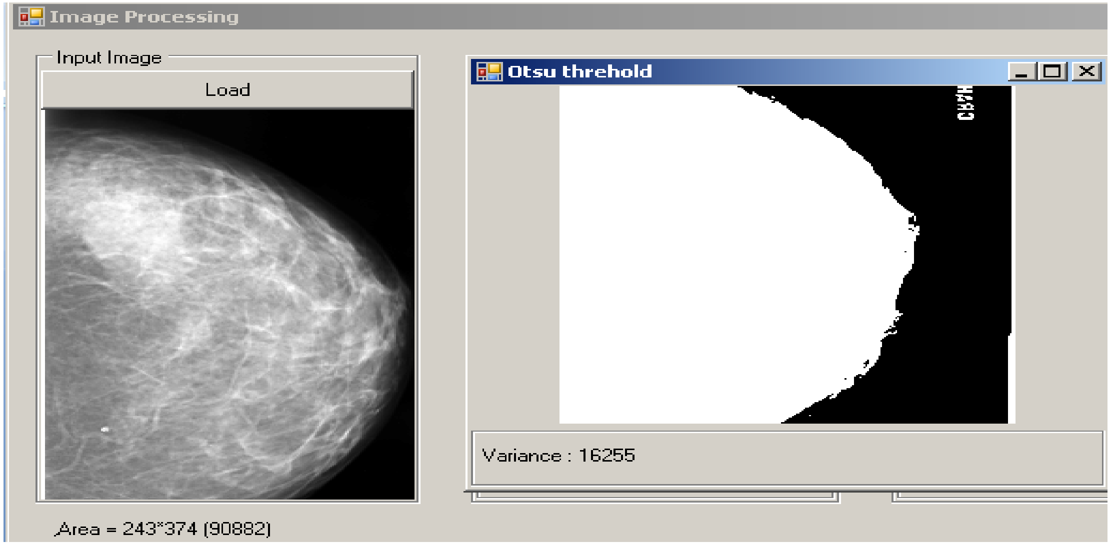


Figure 6.11(a) : OTSU snapshot

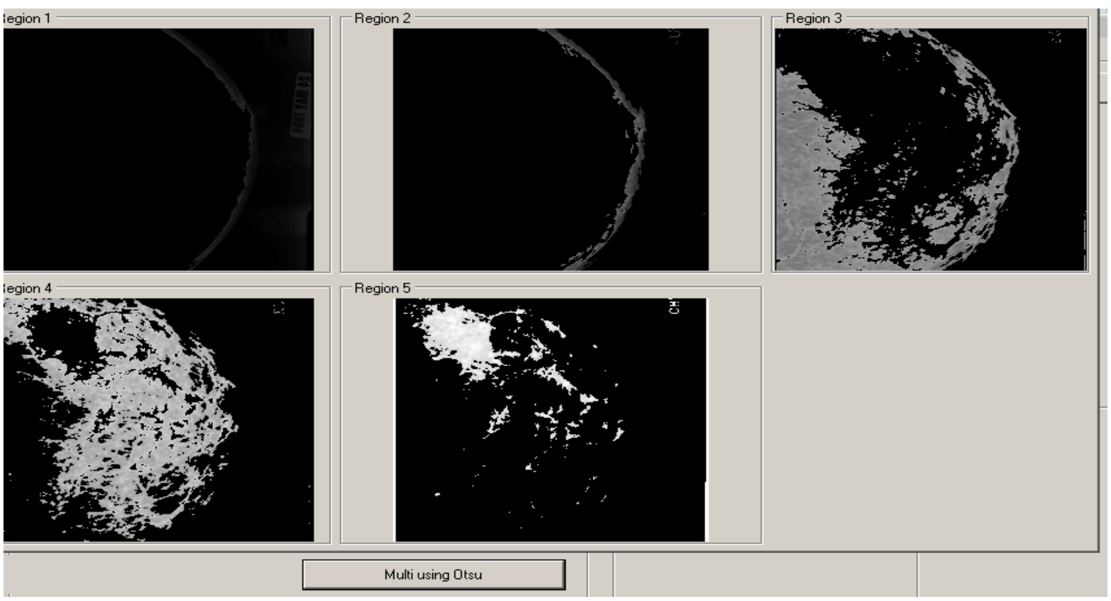
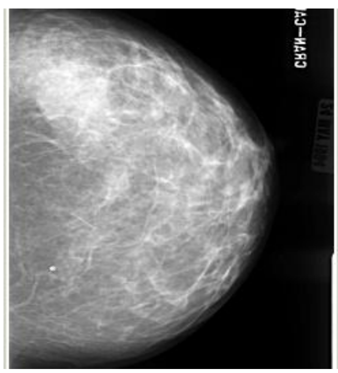


Figure 6.11(b): Multi Thresholding (Using OTSU), (same input image in figure 6.11(a) is used as input).

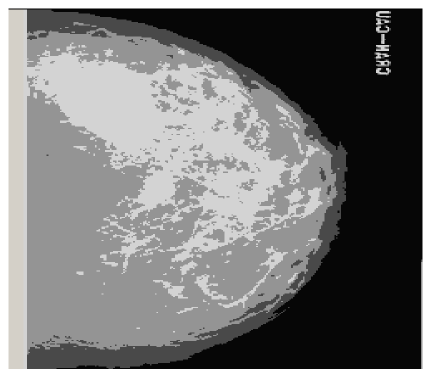
6.4.3 Clustering Algorithms

Clustering referees to classification of image into different sub regions based on certain characteristics of feature of the image. In this thesis K-mean clustering algorithm is implemented. From the following observations it is observed that for breast tumor location K-mean could be better than other thresholding technique.

If the numbers of clusters is increased tumor detection becomes more easy .Hence observation is recorded depend upon the number of clusters and output image is brighter.



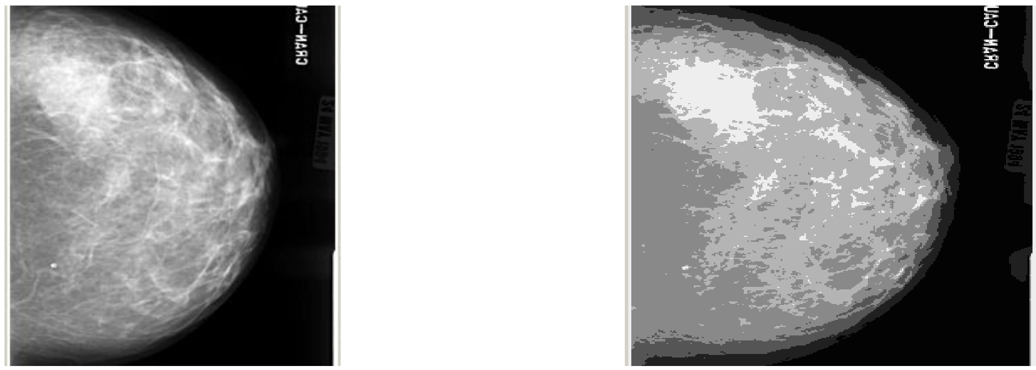
(a)



(b)

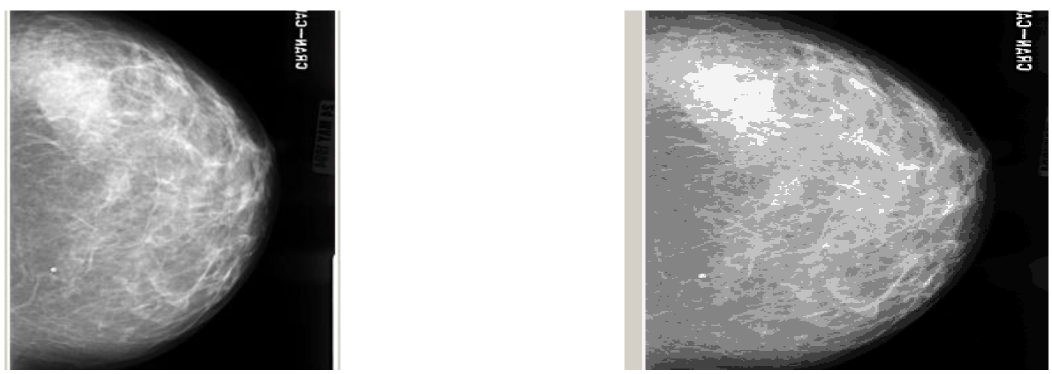
Figure 6.12(a) Original image *   (b) After K-mean clustering with no. of clusters = 4

(*Samples image are taken from the Digital Database for Screening Mammography (DDSM) established by University of South Florida)



(a) **(b)**

Figure 6.13: a) Original image* b) After K-mean clustering with no. of clusters = 6



(a) **(b)**

Figure 6.14(a) Original image * (b) After K-mean clustering with no. of clusters = 10

Some more results are listed in the coming pages.

(*Samples image are taken from the Digital Database for Screening Mammography (DDSM) established by University of South Florida)

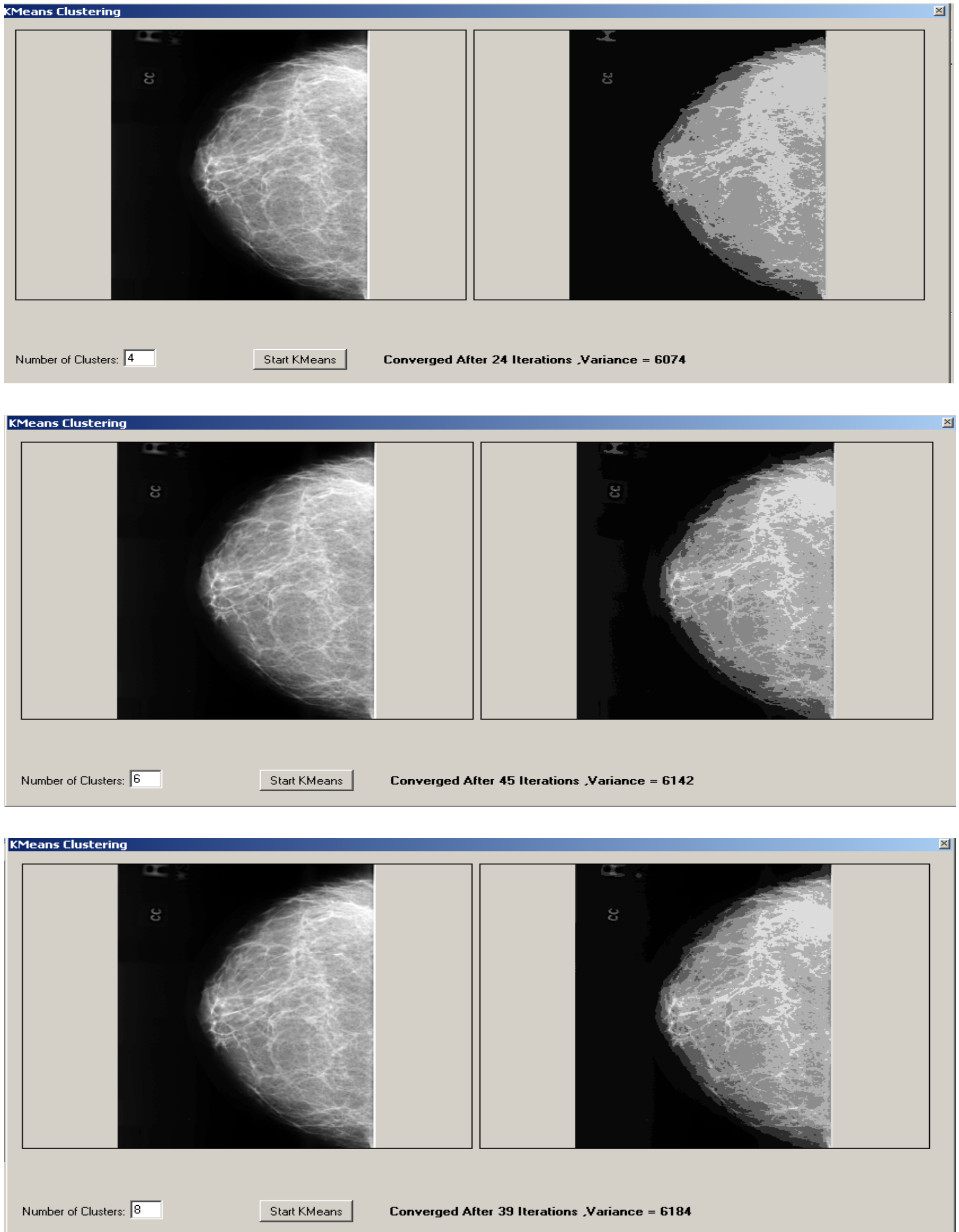


Figure 6.15: Snapshots of k-mean clustering algorithm using different no. of clusters.

7.Performance Evaluation of segmentation algorithm

The performance of the segmentation algorithm is evaluated by judging the quality of segmented image. The performance evaluation of segmentation is very challenging job due to ad hoc nature of segmentation. It is highly dependent on the judgment of the person assessing the segmented images. The same segmentation approach could be proven the best for some task but may not suit to the other kind of image. The segmented image should be able to demonstrate the required necessity of the data for the specific application effectively. To assess the applicability of any segmentation algorithm for the particularly application the segmented data should be compared with the requirements. Most of the segmented images can be evaluated under the basis of human perception and it is very difficult to quantify the efficiency and applicability of segmentation algorithm in general.

In this study for the comparison purpose different algorithm to the same image have been applied. The different breast images which consisting of tumor and non-tumor breast images taken consider for the study. The edge detector algorithm Canny's algorithm could identify the strong edges but the weak edges are difficult to identify.

Thresholding algorithm can segment the image into two regions, however optimum thresholding, adaptive thresholding, entropy based thresholding and Otsu thresholding play significant role in identifying object and background. In our application as the requirement is to find out clear boundary the global thresholding approaches meet the requirement where clear foreground and object is defined.

Among clustering approaches, K-mean clustering approach has been implemented in this thesis work. It is observed that K-mean clustering has superior performance over other segmentation but the selection of centroid becomes the significant otherwise improper selection may lead to the undesired result.

Algorithm	Area	Variance
Gaussian	90882	526
Canny	90882	185
Sobel	90882	932
Otsu	90882	8245
Max. entropy	90882	8517
Local adaptive	90882	7306
Global	90882	8778
Watershed	90882	7984

Table 7.1 Result of applying different segmentation approaches for the image

In the above table 7.1 to evaluate segmentation algorithms the variance calculated in the output images in the chapter 6 is shown. Area is calculated based on total width and height of the breast image and variance is calculated on the basis of white portion. From the table it shows that Local & Global thresholding algorithm meet the highest variance, some variation in the performance of algorithms to the different images is due to the difference of local properties of image. In some cases the actual performance of the algorithms depends upon the visual assessment and is judged according to the requirement of the application in which the image is used.

Furthermore few samples were tested and the variance is also calculated based upon the white parameter in the digitized mammograms as listed below:

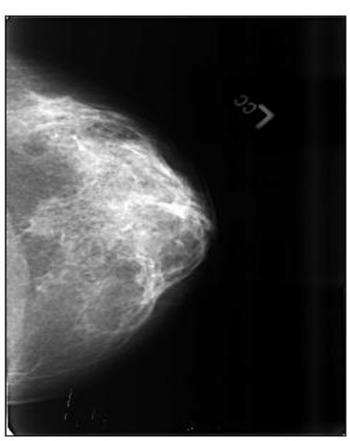
Sample Image *	Algorithms	Variance
	Gaussian	4832
	Canny	2725
	Sobel	908
	Otsu	13585
	Max. entropy	995
	Local adaptive	16013
	Global	6364
	Watershed	8023
	Multi level	Level(3) = 4358
	K-mean	Cluster(4)=4762
		Cluster(6)=6142

Table 7.2 (a) Result of applying different segmentation approaches

Sample Image *	**Algorithms**	**Variance**
	Gaussian	4660
	Canny	2891
	Sobel	1154
	Otsu	16144
	Max. entropy	16142
	Local adaptive	13520
	Global	3630
	Watershed	8156
	Multi level	Level(3) = 5569
	K-mean	Cluster(4)=4566, Cluster(6)=4745,

Table 7.2(b) Result of applying different segmentation approaches

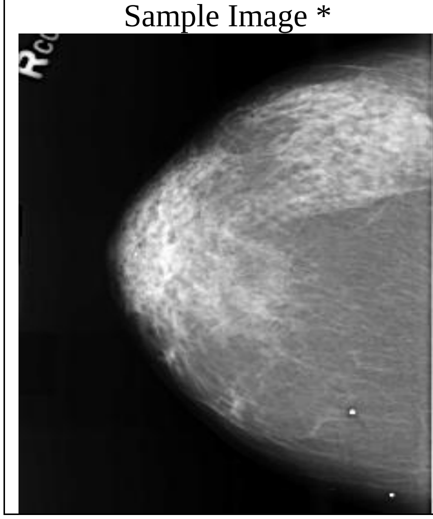
Sample Image *	**Algorithms**	**Variance**
	Gaussian	4654
	Canny	2190
	Sobel	1118
	Otsu	15663
	Max. entropy	15123
	Local adaptive	14596
	Global	5363
	Watershed	8212
	Multi level	Level(3) = 4344
	K-mean	Cluster(4)=4637, Cluster(6)=4727,

Table 7.2(c) Result of applying different segmentation approaches

(* Samples image are taken from the Digital Database for Screening Mammography (DDSM) established by University of South Florida)

8. Conclusion and recommendations

8.1 Conclusion

This study endeavors to justify the use of image processing based approach in the segmentation of images. This thesis has empirically investigated the different type of segmented approaches for the segmentation of digital mammogram images of the breast. Different type of samples normal and cancer images were taken for the testing purpose.

Overall, this thesis work comprises of the analysis and discussions on the application of different segmentation approaches for the segmentation of mammogram images of breast. However the methods discussed in this thesis can be implemented to any images of other kind

8.2 Limitation

In this study mammograms from the Digital Database for Screening Mammography (DDSM) established by University of South Florida are used to evaluate the effectiveness of the processing methods. This database contains approximately 2600 mammography exams. They are cataloged into normal, cancer and benign classes.

Mammography has its limitations, it is less reliable on dense breast young women or women underwent surgical intervention [3]. For the effective evaluation of the segmentation algorithm on the recent mammography, local hospitals including Bhaktapur Cancer hospital, Teaching hospital were visited but unable to get the same due to various problems. Due to this limitation database images as mentioned above only were considered for the study.

In some cases the actual performance of the algorithms depends upon the visual assessment and is judged according to the requirement of the application in which the image is used. It is observed that the methods study in this study don’t determine the mass of the tumor to separate the malignancy of the tumor.

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