3D RECONSTRUCTION OF BREAST MASSES USING MAMMOGRAM

PROJECTREPORT

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BONAFIDE CERTIFICATE

Certified that this project report titled **"3D RECONSTRUCTION OF BREAST MASSES USING MAMMOGRAM"** is the bonafide work of **VIVITADURGA.R [Reg. No. 13MCO24]** who carried out the research under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

Radiologists have only the 2D mammographic reports to detect the abnormalities like mass, tumor, micro calcification present, which do not give the feel that how the abnormalities exactly look like. Hence there is a need of representing the abnormalities in 3D to increase the accuracy in detection. The accuracy greatly depends on how the segmentation of the abnormalities is carried out. Before the segmentation, the images are preprocessed to remove the unwanted portions in the mammographic images. The segmentation step uses Watershed algorithm for detecting the abnormalities. Then, the work involves the extraction of the texture features of the suspicions from the segmented images. The method uses Gray Level Co-occurrence Matrix (GLCM) for extracting the texture features. Then, this method classifies the suspicions into normal, benign or malignant tumor based on the texture features of the suspicions. It uses Back Propagation Neural network (BPN) for the classification of the suspicions. The classification step has two parts. The first part involves the usage of single views i.e. considering the CC (Cranio Caudal) and MLO (Medio Lateral Oblique) views individually for classification. The second part uses two views i.e. both CC and MLO views for classification. Then, this method compares the classification results obtained for individual CC, MLO views and combined CC and MLO views. Finally, the masses are reconstructed in three dimensions using the triangular mesh model.

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LIST OF ABBREVIATIONS

2D	Two Dimensions
3D	Three Dimensions
ALOE	Analysis of Local Oriented Edges
BIRADS	Breast Imaging-Reporting and Data System
BPN	Back Propagation Neural network
CAD	Computer Aided Designing
CC	Cranio Caudal
CLAHE	Contrast Limited Adaptive Histogram Equalization
CT	Computer Tomography
DDSM	Digital Database for Screening Mammography
DICOM	Digital Imaging and Communications in Medicine
GLCM	Gray Level Co-Occurrence Matrices
MLO	Medio Lateral Oblique
MPGS	Modified Projective Grid Space
MRI	Magnetic Resonance Imaging
PET	Positron Emission Tomography
US	Ultrasound
VRMLV	Virtual Reality Modeling Language Viewer

CHAPTER I

INTRODUCTION

Breast cancer has become one of the main causes of cancer deaths among women in the world. In 2013, an estimated 232,340 new cases of invasive breast cancer will be diagnosed among women, as well as an estimated 64,640 additional cases of in situ breast cancer. Approximately 39,620 women are expected to die from breast cancer. More than 2.9 million US women with a history of breast cancer were alive on January 1, 2012. Some of these women were cancer-free, while others still had evidence of cancer and may have been undergoing treatment.

After slowly increasing for many years (0.4% per year from 1975- 1990), breast cancer death rates decreased by 34% from 1990 to 2010. The decline has been faster among women younger than 50 (3.1% per year) than women 50 and older (1.9% per year).From 2001 through 2010, breast cancer death rates declined annually by 1.8% in non-Hispanic whites, 1.7% in Hispanics/Latinas, 1.6% in African Americans, and 1.0% in Asians/Pacific Islanders, but remained unchanged among American Indians/Alaska Natives. The drop in breast cancer mortality has been attributed to both improvements in breast cancer treatment and early detection. However, not all segments of the population have benefited equally from these advances.

In India, according to GLOBACCON (WHO), for the year 2012,144,937 women were newly detected with breast cancer, 70,218 women died of breast cancer. So roughly, in India, for every 2 women newly diagnosed with breast cancer, one lady is dying of it. India is experiencing an unprecedented rise in the number of breast cancer cases across all sections of society. There is no way we can prevent breast cancer, but we can definitely detect it early and treat adequately. Only with early detection, can we achieve a longer survival.

1.1 CAUSES & SYMPTOMS

The breast part of the body is made of fibro glandular and fatty tissue. Malignant tumors arise from the glandular tissues. The causes of cancer may be due to family history, late pregnancy, childlessness, short lactation and overweight. Breast cancer symptoms include lumps, swelling, and changes in the nature of skin. Sometimes these symptoms may be due to any infection. Most of the breast cancers do not have any explicit symptoms. Such cancers are identified by doctors through medical imaging techniques like mammography, magnetic resonance imaging (MRI), positron emission tomography (PET), and ultrasound.

1.2MAMMOGRAPHY

Mammography is a method used for detecting breast cancer. It is an X-ray examination used for detecting any abnormalities present. The image produced is called as the mammogram. Mammography plays an important role in detecting cancer before the tumor become visible clinically.

Mammograms have more advantage when we compared with X-rays because X-ray uses a high dose of radiation when compared to mammograms. Also diagnosis of breast using X-rays doesn't provide the best information as mammograms do. Since, the radiation cannot spread deeply into the breast tissues.

Mammograms are efficient than CT. It is because CT uses the x ray tubes in a circular arc with high level of radiation and it makes difficult to distinguish the micro calcification or the calcium clusters. Mammograms provide the more accurate images than the x rays and CT. High dose of radiation exposure can also be avoided in the mammogram. Also the BIRADS(Breast Imaging-Reporting and Data System) category that defines the stages of breast cancer cannot be obtained in CT. Thus, mammogram is the best option for examining the breast tissues with low dose of radiation.

Mammograms are better when compared to ultrasound (US) because US can detect the lumps or the suspicious that can be felt physically whereas mammograms can diagnose all the lumps that cannot be felt physically. Also studies prove that mammograms are more suitable for both older and younger ages, but US are suitable only for the younger cases. This proves that mammograms are good for the early diagnosis of the breast cancer.

The Cochrane Collaboration states that the mortality rate is best reduced by regular screening of mammograms.

The chances of curing the cancer greatly depend on the early detection of it. Early detection reduces the mortality rate and increases the survival rate. For this, mammography is the mostly used technique. Using this, micro calcification of size from 0.1mm diameter and tumors from 5mm diameter can be detected. It is approved by the U.S. Food and Drug Administration (FDA) to help screen for breast cancer in women who show no signs of the disease explicitly. A mammogram can show calcifications, masses or other rare conditions. Early detection of these abnormalities results in a higher chance of recovery from the cancer. Mammogram shows these indications even in the early stage and improves the chance of curing.

A mammogram allows the doctor to have a closer look for changes in breast tissue that cannot be felt during a breast exam. In fact, most of these changes are not cancer and are called “benign,” but only a doctor can know for sure.

There are two kinds of mammograms:

1. Screening mammogram
2. Diagnostic mammogram

1.2.1. Screening mammogram

Screening Mammograms are done for women who have no symptoms. It usually involves two X-rays of each breast. Screening mammograms can detect lumps or tumors that cannot be felt. They can also find micro calcifications or tiny deposits of calcium in the breast, which sometimes mean that breast cancer is present.

1.2.2. Diagnostic mammogram

Diagnostic mammograms are used to check for breast cancer after a lump or other symptom or sign of breast cancer has been found. Signs of breast cancer may include pain, thickened skin on the breast, nipple discharge, or a change in breast size or shape. This type of mammogram also can be used to find out more about breast changes found on a screening mammogram, or to view breast tissue that is hard to see on a screening mammogram. A diagnostic mammogram takes longer than a screening mammogram because it involves more x-rays in order to obtain views of the breast from several angles. The technician can magnify a problem area to make a more detailed picture, which helps the doctor make a correct diagnosis.

A digital mammogram also uses X-rays to produce an image of the breast, but instead of storing the image directly on film, the image is stored directly on a computer. This allows the recorded image to be magnified for the doctor to take a closer look.

The goal of mammography is the early detection of breast cancer, typically through detection of characteristic masses and/or microcalcifications. There are several views in mammography but the Cranio-Caudal (CC) view and Medio-Lateral Oblique (MLO) view are commonly used for cancer detection analysis. MLO view covers a larger area than a CC view. The X-ray image which is taken from “head to toe” is CC view whereas MLO is taken from “shoulder to the opposite hip”.

The MLO view allows visualization of the largest amount of breast tissue. A technically adequate exam has the nipple in profile, allows visualization of the inframammary fold and includes the pectoral is muscle extending down to the posterior nipple line (an oblique line drawn straight back from the nipple).

The Cranio Caudal **(CC)** view is the other standard view used in every screening exam. A technically adequate CC view will include as much breast tissue as possible. If we measure straight back from the nipple, the value we get should be within 1cm of measuring the posterior nipple line on the MLO view.

Computer based image analysis aids to detect the abnormal changes in the breast tissues from mammograms. The digital mammogram provides two dimensional images. The 2D view does not give the accurate position of the masses. Hence, a 3D view of the masses gives a better result for the analysis. 3D visualization is one of the most important aspects of image processing.

3D reconstruction of the tumor allows locating the masses reliably before surgery. It increases the efficiency of diagnosis for breast cancer. The 3D reconstruction reduces the chances of false needle biopsy.

CHAPTER II

LITERATURE SURVEY

PARTIAL VOLUME COMPENSATED RECONSTRUCTION OF THREE-DIMENSIONAL MASS SHAPES IN MAMMOGRAPHIC IMAGES

Ling Shao

In this paper, a partial volume compensated reconstruction technique for mass shapes is presented. The two-dimensional shapes of the masses are first automatically segmented using a region growing approach. Region growing begins by locating a set of seeds and attempts to merge neighboring pixels into this growing region until no more pixels can be added to it. The 3D mass shapes are then iteratively refined according to an algebraic reconstruction technique.The initial 3D mass shape, which is represented by a binary volume image, is reconstructed based on an algebraic reconstruction technique. Partial volume estimation is applied on the boundary to get a smoother 3D shape.

3D LOCALIZATION OF CLUSTERED MICRO CALCIFICATIONS USING CRANIO-CAUDAL AND MEDIO-LATERAL OBLIQUE VIEWS

Sheng-Chih Yang, Hsian-He Hsu, Giu-Cheng Hsu, Pau-Choo Chung, Shu-Mei Guo,Chien-Shen Lo, Ching-Wen Yang, San-Kan Lee, Chein-I Chang

This paper presents a 3D localization method to register clustered micro calcifications on mammograms from cranio-caudal (CC) and medio-lateral oblique (MLO) views. The method consists of three major steps: registration of clustered micro calcifications in CC and MLO views, 3D localization of clustered micro calcifications and 3D visualization of clustered micro calcifications.The registration is performed based on three features, gradient, energy and local entropy codes that are independent of spatial locations of micro calcifications in two different views and are prioritized by discriminability in a binary decision tree. The 3D localization is determined by a sequence of coordinate corrections of calcified pixels. Finally, the 3D visualization implements a virtual reality modeling

language viewer (VRMLV) to view the exact location of the lesion as a guide for needle biopsy. In order to validate the 3D localization system, a set of lesions, which appear both in mammograms and in MR Images is used for experiments where the depth of clustered micro calcifications are verified with the MR images.

IDENTIFICATION OF MASSES IN DIGITAL MAMMOGRAM USING GRAY LEVEL CO-OCCURRENCE MATRICES

A Mohd.Khuzi,R Besar, WMD Wan Zaki, NN Ahmad

The extraction of the textural features of ROIs is done by using gray level co-occurrence matrices (GLCM) which is constructed at four different directions for each ROI. The results show that the GLCM at 0º, 45º, 90º and 135º with a block size of 8X8 give significant texture information to identify between masses and non-masses tissues. Analysis of GLCM properties i.e. contrast, energy and homogeneity resulted in receiver operating characteristics (ROC) curve area of *Az*= 0.84 for Otsu's method, 0.82 for thresholding method and *Az*= 0.7 for K-means clustering. ROC curve area of 0.8-0.9 is rated as good results.

USE OF EDGEFLOW BASED ALOE FEATURES IN JOINT ANALYSIS OF MULTIPLE MAMMOGRAPHIC VIEWS

Zoltan Ludanyi

This paper performs analysis on mammographic views for detecting the masses. It is based on the experiences that masses and calcifications are present on both CC and MLO views. If a mass/calcification seen in one view is not in other view, it is noted as false positive. Edgeflow algorithm is used for image segmentation, which uses an energy propagation technique before thresholding. This technique allows shifting in energy of edges in each iteration. The shifting direction is based on probabilities. For the mass detection step, ALOE texture feature is used. Once the mass is identified in one view then a strip is assigned parallel to the pectoral muscle in the other view. It is assumed that the position of

a mass from a tangent drawn parallel to pectoral muscle is same in both the CC and MLO views. There are some variances in the position of the masses. To compensate, the width of the stripe is adjusted. The limitation of this method is that a malignant mass missed in one view would be unnoticed. It gives a loss of false positive hits of 31%.

ESTIMATING THE TUMOR-BREAST VOLUME RATIO FROM MAMMOGRAMS

J. Rodríguez , P. Linares, E. Urra, D. Laya ,F. Saldivia ,A. Reigosa

This method allows interaction of the specialist for detecting the tumors in mammograms. The specialist segments the breast portion and tumor portion from the mammogram using a contour connection strategy (Intelligent scissors). It gives a semi-automatic segmentation of tumor in which the mouse movement, by the specialist on the image, gets adjusted according to the borders of the object. Because of this, a person doesn't need to have a good drawing skill to segment the tumor. The mammogram and contour are projected on two orthogonal planes. They are then adjusted to get a match of the tumors position. On getting a match, each curve (representing the mammogram) and its contour (representing the tumor) are plotted in XZ and YZ planes. The elliptical base of the breast is obtained by projecting the curves on the XY plane. A triangular mesh is generated from the appropriate surface of breast. For the tumor volume, a contour estimationis made. A bounding box of different shapes is used instead of exact tumor shape.

BREAST CANCER SEGMENTATION AND DETECTION USING MULTI-VIEW MAMMOGRAM

S.M. Vijayarajan

In this work, the masses identified in both MLO and CC image in 2-D view are then merged into 3-D view. To detect the masses, the co-ordinate values of mass tissue are calculated. This method has the stages viz., segmentation and pre-processing, initial detection of suspect image locations, region segmentation and final single-view

classification. Multi-view CAD schemes is to match corresponding regions in Medio Lateral Oblique (MLO) and Cranio Caudal (CC) views. This study focused on development of a CAD scheme for the detection of masses and architectural distortions that utilizes correspondence between MLO and CC views. The region detected images are mapped into original MLO and CC mammograms. Features are extracted from the region detected images. These features extracted make the feature sets.Finally 3D mammogram with mass is generated from the 3D feature set and the mass value. The combined features gives the better understanding of the breast mass location in both left projected and right projected MLO and CC images.

PECTORAL MUSCLE REMOVAL AND DETECTION OF MASSES IN DIGITAL MAMMOGRAM USING CCL

T.S.Subashini, V. Ramalingam, S. Palanivel

Mammogram images are initially preprocessed to remove the artifacts and for smoothening the image. The second module performs binarization to create a binary image. Binary image undergoes edge detection and segmentation to remove unwanted background region, which will reduce the processing time in subsequent image analysis. Then gray level manipulation is performed toimprove the contrast of suspected masses so that mass detection can be done effectively. Global thresholding is performed to find the exact region of interest form the manipulated image. This is followed by global thresholding which detects the masses and connected component labeling step to detect masses. Once all groups have been determined, each pixel is labelled with a gray level according to the component it was assigned to. The largest component in the image is extracted. The resulting image contains tumor image.

THREE-DIMENSIONAL RECONSTRUCTION OF MICROCALCIFICATION CLUSTERS FROM TWO MAMMOGRAPHIC VIEWS

Margaret Yam, Michael Brady, Ralph Highnam, Christian Behrenbruch, Ruth English, and Yasuyo Kita

Margaret Yam et al developed a method for the classification of micro calcification clusters into benign or malignant. It is done by finding the shape of the clusters. After preprocessing, the registration is done for matching of the clustered points in the CC and MLO views. The suspicions are segmented using the area constraint of the size of micro calcifications. The non-calcifications are distinguished from the calcifications using the thresholding. After locating the positions, the shape of the individual calcification is generated based on the shadow of their regions in CC and MLO views.

A CAD SYSTEM FOR THE 3D LOCATION OF LESIONS IN MAMMOGRAMS

Yasuyo Kita, Eriko Tohno, Ralph P. Highnam, Michael Brady

Yasuyo Kita et al proposed a method of locating lesions in CC and MLO views. It also allows specialist to point on a lesion in one view (CC/MLO). The corresponding epipolar line is then found. The same lesion is searched in the other to get a match. The CAD system proposed in this method displays the epipolar lines for the match as soon as the lesion in one view is clicked. The 3D location of the lesion is estimated from these inputs. It is assumed that the mammogram has no undesirable deformations. Presence of deformation results in errors in the results obtained. The error achieved is reported as 10-20 mm in the estimation of lesion location and mostly these errors result in the variation in depth direction.

CHAPTER III

IMAGE DATABASES

Three image databases are used for the project. They are

1. DDSM
2. INBREAST

3.1 DDSMDATABASE

The Digital Database for Screening Mammography (DDSM) is a resource for useby the mammographic image analysis research community. Primary support for this project was a grant from the Breast Cancer Research Program of the U.S. Army Medical Research and Materiel Command. The DDSM project is a collaborative effort involving at the MassachusettsGeneral Hospital, the University of South Florida, and Sandia National Laboratories. Additional cases from Washington University School of Medicine were provided by Peter E. Shile, MD, Assistant Professor of Radiology and Internal Medicine. Additional collaborating institutions include Wake Forest University School of Medicine Departments of Medical Engineering and Radiology, Sacred Heart Hospital and ISMD, Incorporated. The primary purpose of the database is to facilitate sound research in the development of computer algorithmsto aid in screening. Secondary purposes of the database may include the development ofalgorithms to aid in the diagnosis and the development of teaching or training aids.

The database contains approximately 2,500 studies. Each study includes two images of each breast, along with some associated patient information (age at time of study, ACR breast density rating, subtlety rating for abnormalities, ACR keyword description of abnormalities) andimage information (scanner, spatial resolution) Images containing suspicious areas have associated pixel-level "groundtruth" information about the locations and types of suspiciousregions. Also provided is software both for accessing the mammogram and truth images and for calculating performance figures for automated image analysis algorithms.

The Digital Database for Screening Mammography is organized into "cases" and "volumes." A "case" is a collection of images and information corresponding to onemammography exam of one patient. A "volume" is simply a collection of cases collected together for purposes of ease of distribution. All volumes are available on 8mm tape. Normallyall (or almost all) volumes are also available on-line.

Each volume is a collection of cases of the corresponding type. Normal cases are formed from a previous normal screening exam (pulled from a file) for a patient with a normal exam atleast four years later. A normal screening exam is one in which no further "work-up" was required. Cancer cases are formed from screening exams in which at least one pathology proven cancer was found.

Benign cases are formed from screening exams in which something suspicious was found, but was determined to not be malignant (by pathology, ultrasound or some other means).The term benign without callback is used to identify benign cases in which no additional films or biopsy was done to make the benign finding. These cases, however, contained somethinginteresting enough for the radiologist to mark. A small number of cancer cases may contain, in addition to one or more regions that are path-proven malignant, one or more regions that areunproven. These are suspicious regions for which there is no path result.

3.2 INBREAST DATABASE

The image matrix was 3328 x 4084 or 2560 x3328 pixels, depending on the compression plate used in the acquisition (according to the breast size of the patient). Images were saved in the DICOM format. All confidential medical information was removed from the DICOM file, according to Supplement 55 of the DICOM standard; the correspondence between images of the same patient is kept with a randomly generated patient identification and collected from which 90 have two images (MLO and CC) of each breast and the remaining 25 cases are from women who had a mastectomy and two views of only one breast were included. This sums to a total of 410 images. Eight of the 91 cases

with 2 images per breast also have images acquired in different timings. The database includes examples of normal mammograms, mammograms with masses, mammograms with calcifications, architectural distortions, asymmetries, and images with multiple findings and their bi-rads rating.

BI-RADSis an acronym for Breast Imaging-Reporting and Data System, a quality assurance tool originally designed for use with mammography.

BI-RADS Assessment Categories are:

Category 0: Incomplete
Category 1: Negative
Category 2: benign findings;
Category 3: probably benign findings;
Category 4: suspicious findings;
Category 5: a high probability of malignancy; and
Category 6: proved cancer
In case of categories 4 and 5, a biopsy is needed to exclude or confirm malignancy.

CHAPTER IV

PROPOSED WORK

4.1. PROCESS FLOW

The proposed work has the following process flow:

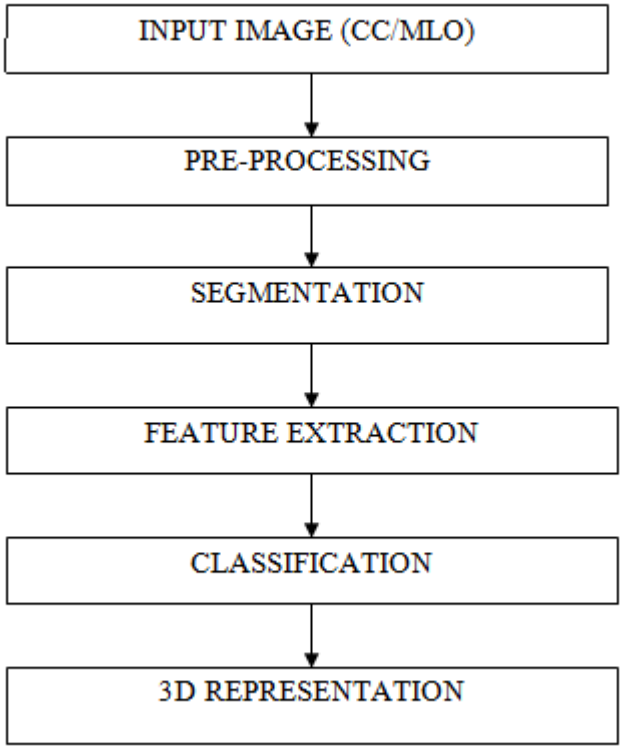


Figure 4.1 Process flowchart

The work consists of five steps viz., preprocessing, segmentation, feature extraction, classification and 3d reconstruction of mass.

4.2. PREPROCESSING

Mammograms are difficult images to interpret, and a preprocessing phase is necessary to improve the quality of the images and make the feature extraction phase more reliable. In order to limit the search for abnormalities by computeraided diagnosis systems

to the region of the breast without undue influence from the background of the mammogram, removal of artifacts and removal of pectoral muscle is necessary.

Preprocessing stage consists of three steps.

1. Contrast enhancement
2. Label removal
3. Pectoral muscle removal

4.2.1. Contrast enhancement

The first part involves the contrast enhancement of the images in CC and MLO views, if required.The DDSM database has low contrast images and is in need of contrast enhancement.

4.2.2. Label removal

The next part is the removal of labels from the images. Labels are small regions in the image and provide information regarding the mammogram projections, scanning equipment etc. It does not contribute anything in the classification of masses. Removal of labels from the images gives better result for the analysis. They are removed on the basis of area constraint of the label. Initially, the individual components in the image are labelled. Then, area is calculated for each labelled component. The breastpart has the largest area compared to all other individual components in the image. Based on this area constraint, the labels with smaller area are blacked out.

4.2.3. Pectoral muscle removal

The pectoral muscle lies on the left or right edge of the image. It has an inverted triangle structure.It hasthe brightest pixels. It must be removed before detecting the masses. Initially, the image is converted to binary image to find the pectoral boundary. To detect the position of the pectoral muscle, nonzero pixels are searched from the left and right top corner of the binary image. If the right width is smaller than the left width, then the

pectoral muscle is on the right side of the image else it is on the left side of the image. The start and end point of the detected pectoral muscle are then joined by a line. The area above the line has the pectoral muscle. It is then removed to get the required region for the analysis.

4.3. SEGMENTATION

The masses in the mammograms are then segmented using the Watershed algorithm. It is used to separate the touching objects in the mammogram. It uses watershed transform which works better if the foreground objects and background can be identified.

The procedure involves

1. Computation of a segmentation function. This is an image whose dark regions are the objects that are to be segmented.

2. Computation of foreground markers. These are connected blobs of pixels within each of the objects.

3. Computation of background markers. These are pixels that are not part of any object.

4. Modification of the segmentation functions so that it only has minima at the foreground and background marker locations.

5. Computation of the watershed transform of the modified segmentation function.

6. Visualization of the result.

CHAPTER V

FEATURE EXTRACTION

Feature Extraction is a method of capturing visual content of images for indexing & retrieval. Primitive or low level image features can be either general features, such as extraction of color, texture and shape or domain specific features. It involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved.

Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent them in some simpler but unique form, so that they can be used for robust, accurate classification and segmentation of objects.

Texture features are extracted from the segmented image. Texture analysis helps in determining a unique way of representing the characteristics of textures. It is used for robust, better classification of objects. Initially, the segmented image is divided into tiles of same size. The size chosen for the tile is 128x128. Mean is chosen as the preliminary measure of detecting the masses. Mean is calculated for each tile. The tile with the suspicion has the maximum mean. Texture features are then extracted for this tile.

This work uses gray level co-occurrence matrix (GLCM) to extract second order statistical texture features. In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics.

The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. The approach has been used in a number of applications. Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty.

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. It is obtained by calculating how often a pixel with gray-level (p (i,j)) value 'i' occurs horizontally adjacent to a pixel with the value 'j'. Each element (i,j) in GLCM specifies the number of times that the pixel with value 'i' occurred horizontally adjacent to a pixel with value 'j'. If `the image` is a binary image, `GLCM` scales the image to two gray-levels. If `the image` is an intensity image, `GLCM` scales the image to eight gray-levels as shown in Figure 5.1.

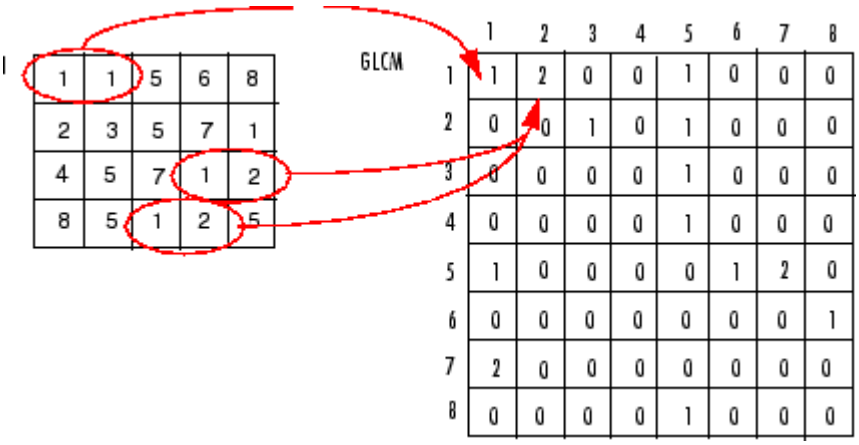


Figure 5.1 GLCM generation

The co-occurrence matrix is often formed using a set of offsets sweeping through 180 degrees (i.e. 0, 45, 90 and 135 degrees) at the same distance to achieve a degree of rotational invariance. Transforming the input data into the set of features is called feature extraction. Almost 18 parameters are considered for feature extraction. It includes contrast, correlation, energy and homogeneity, autocorrelation, contrast, correlation, cluster Prominence, cluster shade, dissimilarity energy, entropy, homogeneity, homogeneity positive, maximum probability, sum of squares, sum of squared variance , Sum average,

sum variance, sum entropy, difference variance, Difference entropy, information measure of correlation1, information measure of correlation2, inverse difference, Inverse difference normalized and Inverse difference moment normalized are also calculated.

Correlation

It returns a measure of how correlated a pixel is to its neighbor over the whole image.

```
Range = [-1 1]
```

Correlation is 1 or -1 for a perfectly positively or negatively correlated image. It is given by

$$\text{Correlation} = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)p(i,j)}{\sigma_i \sigma_j} \quad (1)$$

Energy

It returns the sum of squared elements in the GLCM. Range is between [0 1]. Energy is `1` for a constant image. It is given by

$$Energy = \sum_{i,j} p(i,j)^2 \quad (2)$$

Homogeneity

It returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Range is between [0 1]. Homogeneity is 1 for a diagonal GLCM. It is given by

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1 + |i - j|} \quad (3)$$

Autocorrelation

It resembles to the information provided by the GLCM correlation.

Entropy

Entropy is a measure of the uncertainty associated with a random variable. Entropy in an information sense is a measure of unpredictability. It is given by

$$Entropy = -\sum_{i}\sum_{j} p(i,j)\log(p(i,j)) \quad (4)$$

Cluster Prominence

Cluster Prominence is a measure of asymmetry is given by

$$Cluster\ Prominence = \sum_{i=0}^{Ns-1}\ \sum_{j=0}^{Ns-1}\ \left(i + j - u_x - u_y\right)^4 p(i,j) \quad (5)$$

Cluster shade

Cluster shade is a measure of skewness of the matrix is given by

$$Cluster\ shade = \sum_{i=0}^{Ns-1}\ \sum_{j=0}^{Ns-1}\ \left(i + j - u_x - u_y\right)^3 p(i,j) \quad (6)$$

Dissimilarity

The dissimilarity measure weights increase linearly (0, 1, 2, 3 etc.). Dissimilarity equation is

$$Dissimillarity = \sum_{i,j=1}^{N}\ P_{i,j}|i - j| \quad (7)$$

Sum Average

The sum Average is found by

$$Sum\ Average = \sum_{i=1}^{2G-2} iP_{x+y}(i) \quad (8)$$

Sum Entropy

The sum Entropy is found by

$$Sum\ Entropy = \sum_{i=1}^{2G-2} i\, P_{x+y}(i) \log i\, (P_{x+y}(i)) \quad (9)$$

Difference Entropy

The Difference Entropy is found by

$$Difference\ Entropy = -\sum_{i=1}^{G-1} P_{x+y}(i) \log(P_{x+y}(i)) \quad (10)$$

Inverse Difference Moment

It is also called the Homogeneity positive. If weights decrease away from the diagonal, the result will be larger for windows with little contrast.Its equation is

$$IDM = \sum_{i=1}^{G}\sum_{j=1}^{G} \frac{P(i,j|\Delta x, \Delta y)}{1+(i-j)^2} \quad (11)$$

Sum of variance

The Sum of variance is calculated by

$$SOV = \sum_{i=1}^{G}\sum_{j=1}^{G} (i-\mu)^2 P(i,j) \quad (12)$$

Contrast

It returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. Contrast is 0 for a constant image.

It is given by

$$Contrast = \sum_{i,j} |j|^2 p(i,j) \quad (13)$$

Correlation Maximum

It is initialized as zero. It is given by

$$corm(k) = \sum_{k}\sum_{i}\sum_{j} corm(k) \; + \left(\left((i) - \; u_{x(k)}\right) * \left(j) - \; u_{y(k)}\right) * glcm(i,j,k)\right) \qquad (14)$$

Correlation Positive

It is initialized as zero. It is given by

$$corrp(k) \; = \sum_{k}\sum_{i}\sum_{j} (corrp(k) \; - \; u\_x(k) * u\_y(k))/(s\_x(k) * s\_y(k)) \qquad (15)$$

CHAPTER VI

CLASSIFICATION

Backpropagation, an abbreviation for "backward propagation of errors", is a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent. The method calculates the gradient of a loss function with respects to all the weights in the network. The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function.

Backpropagation requires a known, desired output for each input value in order to calculate the loss function gradient. It is therefore usually considered to be a supervised learning method, although it is also used in some unsupervised networks such as autoencoders. It is a generalization of the delta rule to multi-layered feedforward networks, made possible by using the chain rule to iteratively compute gradients for each layer. Backpropagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable.

The goal of any supervised learning algorithm is to find a function that best maps a set of inputs to its correct output. An example would be a simple classification task, where the input is an image of an animal, and the correct output would be the name of the animal. Some input and output patterns can be easily learned by single-layer neural networks (i.e. perceptrons). However, these single-layer perceptrons cannot learn some relatively simple patterns, such as those that are not linearly separable.

A single-layer neural network however, must learn a function that outputs a label solely using the intensity of the pixels in the image. There is no way for it to learn any abstract features of the input since it is limited to having only one layer. A multi-layered network overcomes this limitation as it can create internal representations and learn different features in each layer. The first layer may be responsible for learning the orientations of lines using the inputs from the individual pixels in the image. The second

layer may combine the features learned in the first layer and learn to identify simple shapes such as circles. Each higher layer learns more and more abstract features such as those mentioned above that can be used to classify the image. Each layer finds patterns in the layer below it and it is this ability to create internal representations that are independent of outside input that gives multi-layered networks their power. The goal and motivation for developing the backpropagation algorithm was to find a way to train a multi-layered neural network such that it can learn the appropriate internal representations to allow it to learn any arbitrary mapping of input to output.

The backpropagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
2. Backward propagation of the propagation's output activations through the neural network using the training pattern target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight update

For each weight-synapse follow the following steps:

1. Multiply its output delta and input activation to get the gradient of the weight.
2. Subtract a ratio (percentage) of the gradient from the weight.

This ratio (percentage) influences the speed and quality of learning; it is called the *learning rate*. The greater the ratio, the faster the neuron trains; the lower the ratio, the more accurate the training is. The sign of the gradient of a weightindicates where the error is increasing; this is why the weight must be updated in the opposite direction.Phase 1 and 2 are repeated until the performance of the network is satisfactory.

As the algorithm's name implies, the errors propagate backwards from the output nodes to the input nodes. Technically speaking, backpropagation calculates the gradient of the error of the network regarding the network's modifiable weights. This gradient is almost always used in a simple stochastic gradient descent algorithm to find weights that minimize the error. Often the term "backpropagation" is used in a more general sense, to refer to the entire procedure encompassing both the calculation of the gradient and its use in stochastic gradient descent. Backpropagation usually allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

Backpropagation networks are necessarily multilayer perceptrons (usually with one input, one hidden, and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers: a multilayer network using only linear activation functions is equivalent to some single layer, linear network. Non-linear activation functions that are commonly used include the logistic function, the softmax function, and Gaussian function.

The backpropagation algorithm for calculating a gradient has been rediscovered a number of times, and is a special case of a more general technique called automatic differentiation in the reverse accumulation mode.

6.1 CLASSIFICATION OF MASSES USING BPN

Based on the features extracted, the massesare classified as benign, malignant or normal tissue. The proposed work uses Back Propagation Neural network (BPN) for the classification of the suspicions. Back propagation algorithm is a supervised learning method for multilayer network. It is used as a learning method in feed forward multilayer neural networks and classification problems.

In the training, the input pattern and the corresponding target output are applied to the input layer of BPN. The input produces a response to the neurons of the first layer, which in turn produce a response to the neurons of the upper hidden layer, and so on, until

a response is produced at the output layer. The obtained response is then compared with the target output and the error is computed. The weights between the last hidden layer and the output layer are recalculated using the error value obtained so that the output error is reduced. This process is repeated up to the input layer. Now, the weights are updated to new value. When the weights have reached a steady state, the algorithm takes the next set of input-target patterns and repeats the above steps. The testing is done with different set of inputs.

The classification is done in two stages. The first stage is done considering the features obtained from either of the two (CC, MLO) views. The second stage is done using the features obtained from both views. The obtained results are compared in terms of accuracy as shown in Table 9.3. Accuracy gives the efficiency of the classification process. It is calculated using the equation (16).

6.2 PERFORMANCE MEASURE

6.1.1 Accuracy

The obtained results are compared in terms of accuracy as shown in Table I. Accuracy gives the efficiencyof the classification process. It is calculated using the equation (16).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (16)$$

Where,

TP - True Positive; FP - False Positive

TN - True Negative; FN - False Negative

From Table 9.3, it is clear that the combined CC and MLO views have the largest accuracy compared to the individual CC and MLO views.

CHAPTER VII

3D REPRESENTATION

Radiologists have only the 2D mammographic reports to detect the abnormalities present, which do not give the feel that how the abnormalities exactly look like. Hence there is a need of representing the abnormalities (like mass, tumor, micro calcification) in 3D to increase the accuracy in detection.A mass is intrinsically a three-dimensional (3-D) entity and its projection onto a 2-D image results in a loss of depth information. Accurately reconstructing the three-dimensional mass shapes in mammographic images is important for classifying the abnormality into malignant or benign. It is believed that an accurate 3D reconstruction contains more information for classification of masses into benign or malignant and is valuable to the clinician by visualization.

The segmented mass is represented in three dimension by using a triangular mesh model. Let v(i, j, k) be the 3-D reconstructed object image, i=1, ..., n, j=1, ..., n, k=1, ..., n, which is a discrete three-dimensional image that represents a binary object. An isosurface is created to represent the mass 3-D coordinates by connecting points that have the specified value much the way contour lines connect points of equal elevation. A patch object is created by taking the faces and vertices information of the mass. The 3-D object is obtained by creating a mesh model made of triangles. It can be rotated so that the shape of the mass can be fully seen. The entire process is done using MATLAB R2013a.

CHAPTER VIII

MATLAB

MATLAB (**mat**rix **lab**oratory) is a numerical computing environment and fourth-generation programming language. Developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and FORTRAN. Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing capabilities. An additional package, Simulink, adds graphical multi-domain simulation and Model-Based Design for dynamic and embedded systems.

MATLAB Compiler compiles a MATLAB application into a standalone application or software component. The act of compiling this code is sometimes referred to as building. Building with MATLAB Compiler enables we to run our MATLAB application outside the MATLAB environment. It reduces application development time by eliminating the need to translate our code into a different language. If we are building a standalone application, MATLAB Compiler produces an executable for our end users. If we integrate into C or C++, MATLAB Compiler provides an interface to use our code as a shared library. If we integrate into other development languages, MATLAB builder products (available separately) let us package our MATLAB applications as software components. We are able to use Java classes, .NET components, or Microsoft Excel add-ins. It provides good platform for performing image processing operations.

Image Processing Toolbox provides a comprehensive set of reference-standard algorithms and graphical tools for image processing, analysis, visualization, and algorithm development. We can perform image enhancement, image deblurring, feature detection, noise reduction, image segmentation, spatial transformations, and image registration. Many functions in the toolbox are multithreaded to take advantage of multicore and multiprocessor computers. Image Processing Toolbox supports a diverse set of image types, including high dynamic range, giga pixel resolution, ICC-compliant color, and

tomographic images. Graphical tools let us explore an image, examine a region of pixels, adjust the contrast, create contours or histograms, and manipulate regions of interest (ROIs).

With the toolbox algorithms we can restore degraded images, detect and measure features, analyze shapes and textures, and adjust the color balance of images.

Key Features

- Image enhancement, filtering, and deblurring
- Image analysis, including segmentation, morphology, feature extraction, and measurement
- Spatial transformations and image registration
- Image transforms, including FFT, DCT, Radon, and fan-beam projection
- Workflows for processing, displaying, and navigating arbitrarily large images
- Modular interactive tools, including ROI selections, histograms, and distance measurements
- ICC color management
- Multidimensional image processing
- Image-sequence and video display
- DICOM import and export

MATLAB supports standard data and image formats, including JPEG, JPEG-2000, TIFF, PNG, HDF, HDF-EOS, FITS, Microsoft Excel, ASCII, and binary files. It also supports the multiband image formats BIP and BIL, as used by LANDSAT for example. Low-level I/O and memory mapping functions enable us to develop custom routines for working with any data format.

CHAPTER IX

RESULTS

9.1. ORIGINAL IMAGES

The proposed work uses two databases viz., Digital Database for Screening Mammography (DDSM) and INBREAST database. It uses an image set of 170 images from these two databases. These image databases have both the CC and MLO view images with normal, benign and malignant categories.

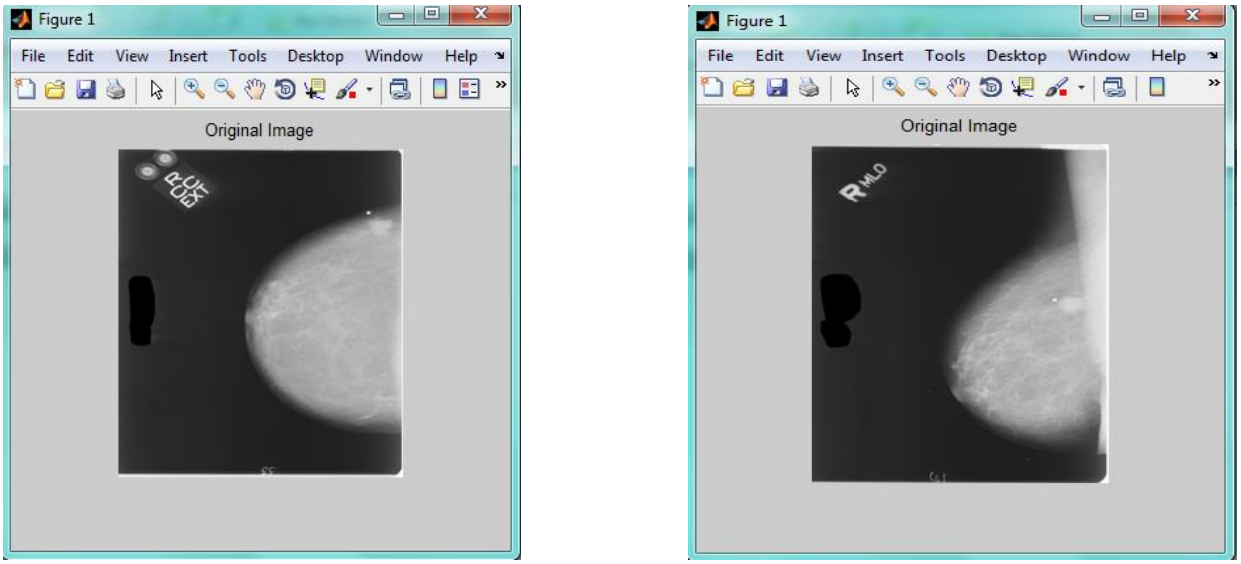


Figure 9.1 Original images

The mammograms are low contrast images. Hence, contrast enhancement is needed in order to improve the image quality and make the segmentation results more accurate.

9.2. PREPROCESSING - Label removal

The next part is the removal of labels from the images. The labels occupy only smaller portion in the image. Based on the area calculation, the desired part occupying larger area is separated out.

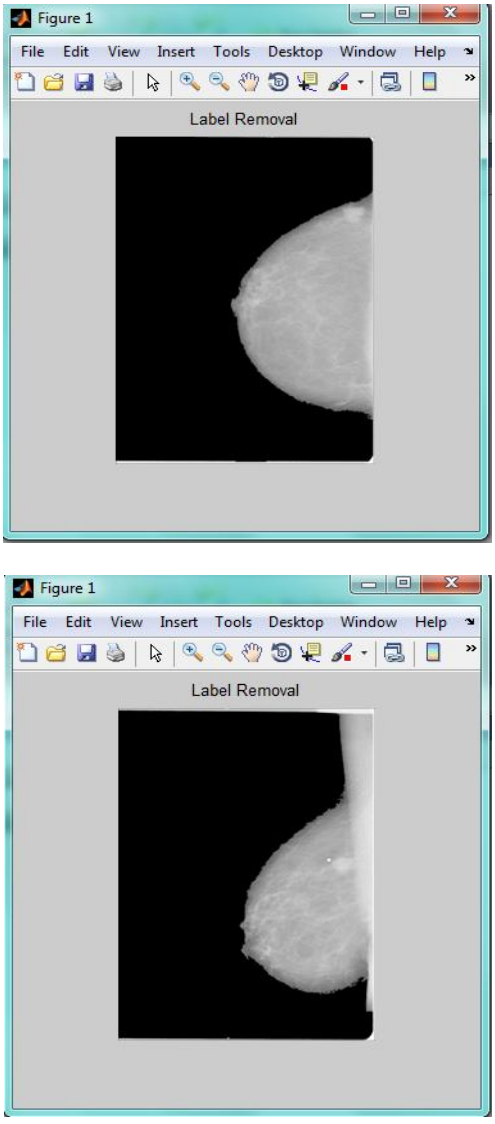


Figure 9.2 Label removed images

9.3. PREPROCESSING - Pectoral muscle removal

The next step is the removal of pectoral muscle in the mammograms. It doesn't contribute to the analysis of the masses in the mammograms. The images without pectoral muscle are as shown in Figure 9.3

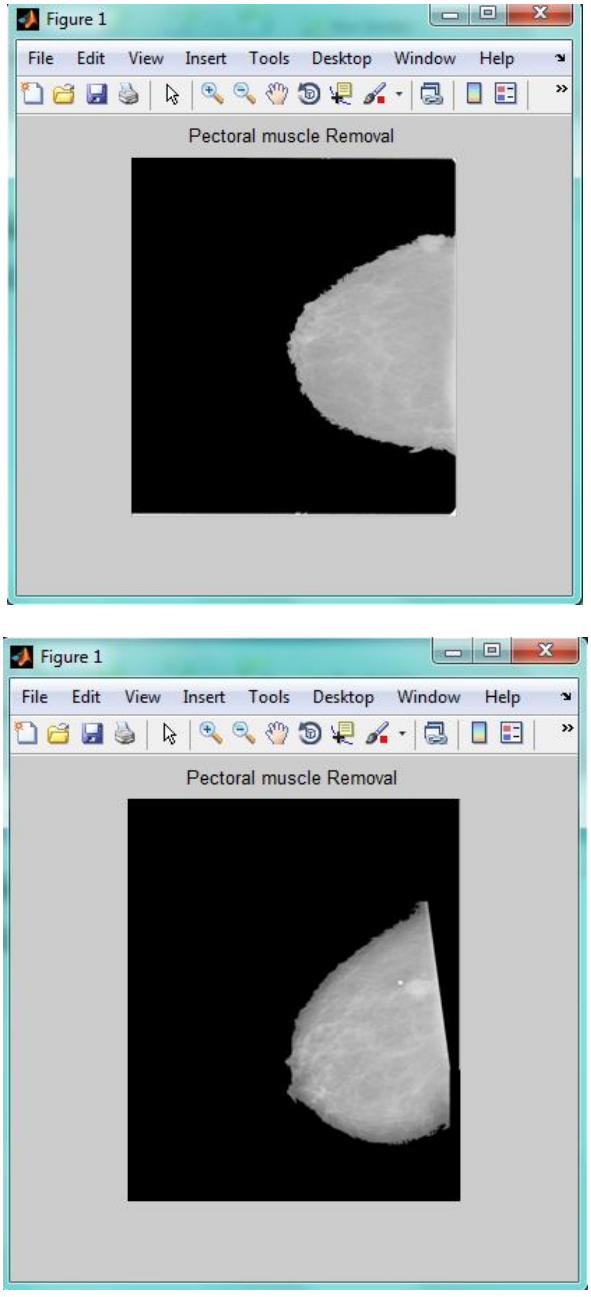


Figure 9.3 Pectoral muscle removed images

9.4. SEGMENTATION

The proposed method uses Watershed algorithm to segment the suspicions in the images. The segmentation step detects the suspicions in the image and segments it. The gradient magnitude is used as the segmentation function. This gives an image whose dark regions are the masses that are to be segmented. The foreground marker is calculated which is connected blob of pixels within the mass. The background markers is calculated which are pixels that are not part of the mass. The segmentation function is modified to get minima at the foreground and background marker locations. The watershed transform is then applied to get the mass in the image.

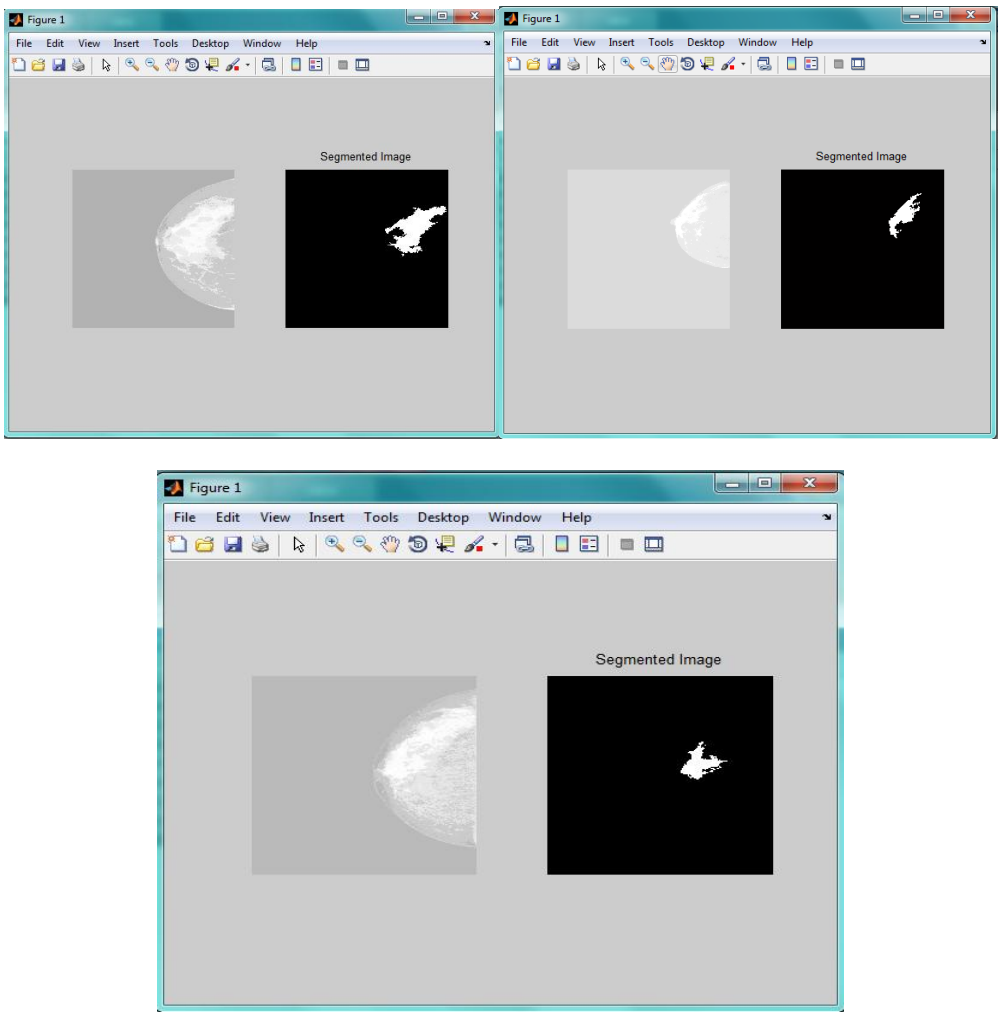


Figure 9.4 Mass segmented from images

9.5. TEXTURE FEATURES OF DDSM DATABASE

Features	Benign	Malignant
Contrast	0.041093	0.18344
Correlation	0.995731	0.978879
Energy	0.44743	0.305749
Homogeneity	0.983637	0.969611
Autocorrelation	1715.501	2827.615
Correlation maximum	0.203323	0.227812
Correlation Positive	0.203323	0.227812
Cluster Prominence	5273797	13779128
Cluster Shade	-9544.78	22858.45
Dissimilarity	47.76686	42.49147
Entropy	8.660527	9.166383
Sum Entropy	5.043947	5.274412
Homogeneity Positive	0.021559	0.023291
Sum Average	92.20082	107.8579
Sum Variance	9188.62	12888.29

Table 9.1 Texture features extracted from DDSM Database

9.6 TEXTURE FEATURES OF INBREAST DATABASE

Features	Benign	Malignant
Contrast	0.015317	0.016486
Correlation	0.976368	0.984314
Energy	0.46615	0.443879
Homogeneity	0.992341	0.991757
Autocorrelation	4052.983	4088.093
Correlation maximum	-0.00216	-0.02233
Correlation Positive	-0.00216	-0.02233
Cluster Prominence	17812856	17690964
Cluster Shade	1922.638	2183.966
Dissimilarity	42.80553	43.61005
Entropy	9.700954	9.701548
Sum Entropy	5.350778	5.347318
Homogeneity Positive	0.023847	0.023325
Sum Average	127.4022	128.3909
Sum Variance	17619.28	17837.43

Table 9.2 Texture features extracted from INBREAST Database

Texture features are extracted from the segmented image. Texture analysis helps in determining a unique way of representing the characteristics of textures. It is used for robust, better classification of objects. GLCM is used to calculate thesetexture

features.Totally 15 features are extracted for each image. The features so obtained are normalized for getting better results in the classification.

9.7. CLASSIFICATION

Based on the features extracted, the masses are classified as benign, malignant or normal tissue. The proposed work uses Back Propagation Neural network (BPN) for the classification of the suspicions. Back propagation algorithm is a supervised learning method for multilayer network. It is used as a learning method in feed forward multilayer neural networks and classification problems.

The obtained accuracy results are compared in CC, MLO and combined CC&MLO views.

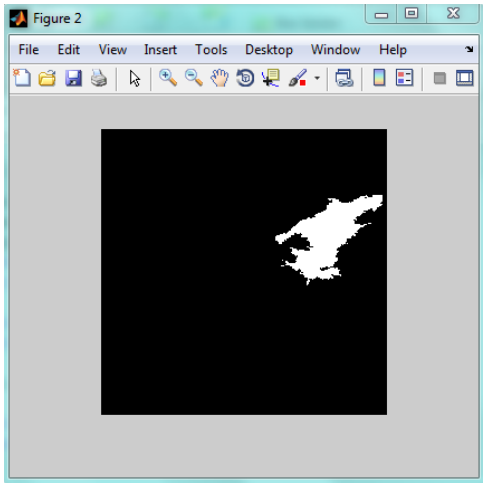
Mammographic Views used in Classification	**Accuracy**	
	INBREAST DATABASE	**DDSM DATABASE**
CC view	88%	88.88%
MLO view	91%	92.307%
CC & MLO view	95%	94.73%

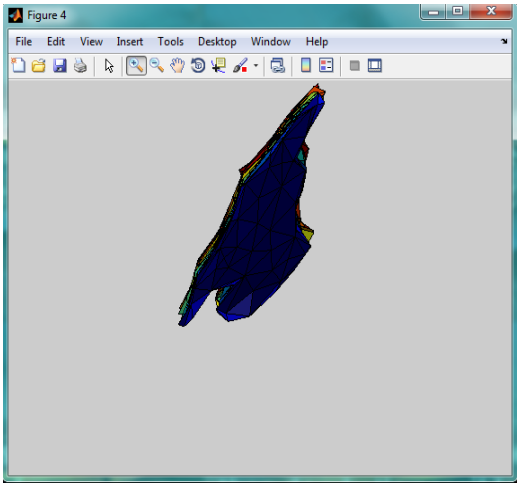
Table 9.3 Accuracy obtained in the classification of Masses

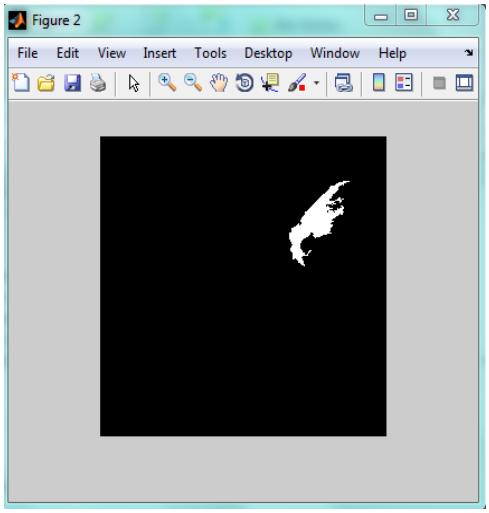
9.8. 3D RECONSTRUCTION

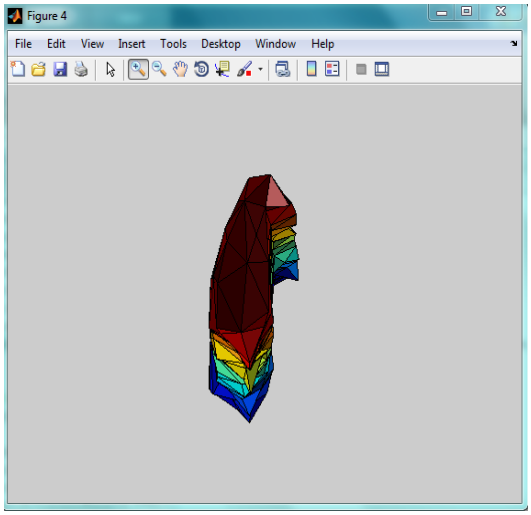
Finally, the masses are reconstructed in three dimensions using triangular mesh model. Radiologists can use the reconstructed three-dimensional mass coupled with the two-dimensional masses in the CC and MLO views to classify the lesion into malignant or benign. The reconstructed mass shapes can be also used as a visualization tool for medical education.

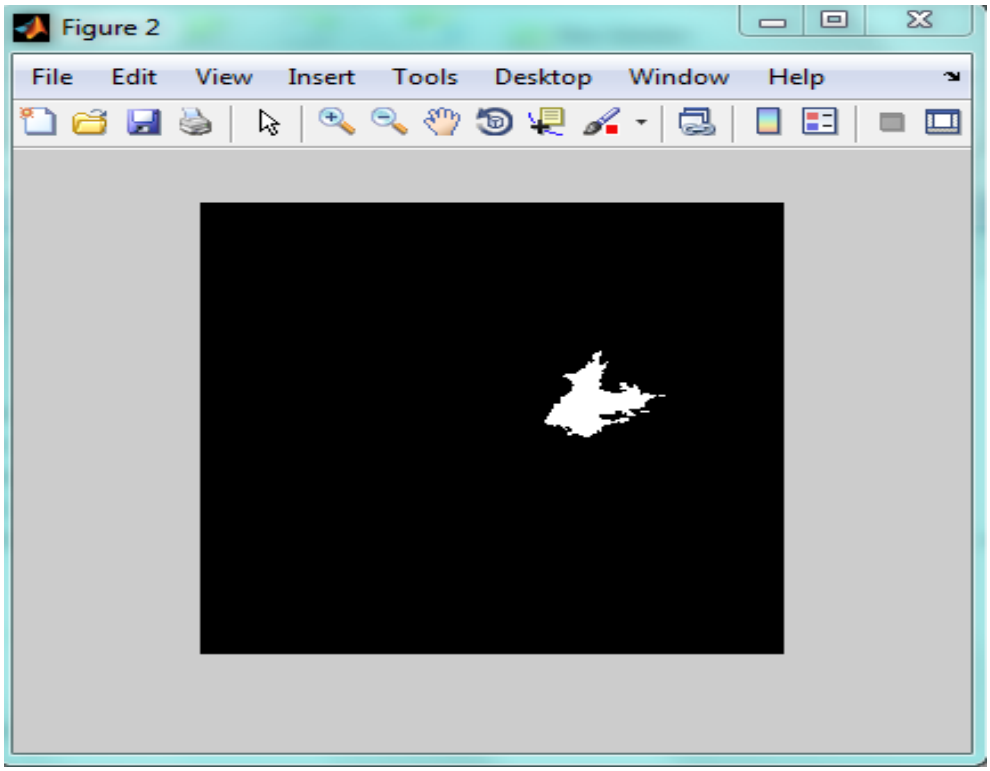
The segmented masses are represented in 3d by converting the volume of the segmented mass into a triangular mesh.











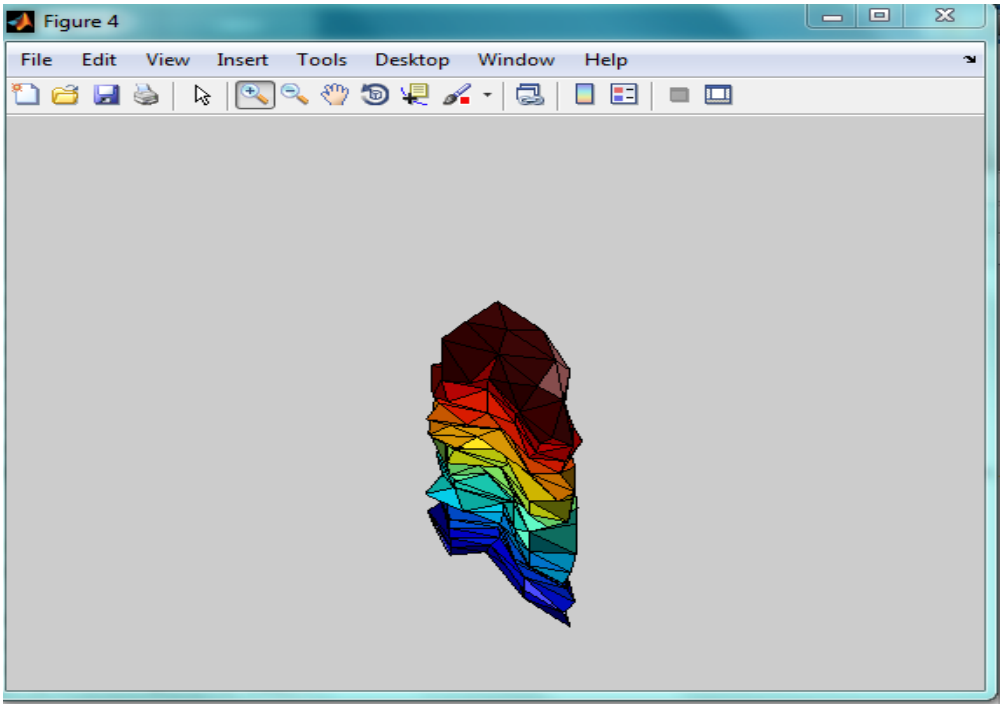


Figure 9.5 3d model of segmented mass

CHAPTER X

CONCLUSION AND FUTURE WORK

First, the proposed method preprocesses the input images. The preprocessing process removes the unwanted artifacts from the images. These artifacts do not contribute anything in the analysis of the breast cancer. Then, the proposed method uses Watershed algorithm to segment the suspicions in the images. Then, it extracts the texture features of the suspicions from the segmented images. The method uses Gray Level Co-occurrence Matrix (GLCM) for extracting the texture features. Then, this method classifies the suspicions into normal, benign or malignant tumor based on the texture features of the suspicions. It uses Back Propagation Neural network (BPN) for the classification of the suspicions. The classification step has two parts. The first part involves the usage of single views i.e. considering the CC and MLO views individually for classification. The second part uses two views i.e. both CC and MLO views for classification. Then, this method compares the classification results obtained for individual CC, MLO views and combined CC and MLO views. Finally, the masses are reconstructed in three dimensions using triangular mesh model. The future work can be extended to locate the exact position of tumor. Features can be extracted from the 3d mass and be used for the classification.

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LIST OF PUBLICATIONS

JOURNAL

- Published a paper "**Detection and 3D Reconstruction of Tumor Based on Mammographic Images: A Survey"** in **International Journal of Applied Engineering Research,** ISSN 0973-4562, Volume 9, Number 20, 2014.

CONFERENCE

- Presented a paper titled "**Detection and 3D reconstruction of tumor based on mammographic images: A Survey**" in **International Conference on Pattern Recognition and Multimedia Signal Processing** at Annamalai University, Chidambaram.