3D RECONSTRUCTION OF MAMMOGRAM IMAGES USING ICP ALGORITHM WITH TWO VIEWS

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report titled is the bonafide work of **"3D RECONSTRUCTION OF MAMMOGRAM IMAGES USING ICP ALGORITHM WITH TWO VIEWS " KAYALVIZHI S[Reg. No. 15MCO004]** 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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ABSTRACT

The 3D reconstruction of mammogram images is the process of combining the preprocessed mammogram images into a 3D image for the purpose of finding the exact location of the abnormal growth in the breast. This is achieved by ICP algorithm. The pre-processing of mammogram images is an important aspect in the reconstruction of mammogram images in the field of mammography. The Mammogram images are obtained by number of views in order to combine it for reconstruction. But many views may lead to over dosage of radiation. Hence two views CC (Cranio Caudal view)and MLO (Medio Lateral Oblique view) only are used. Here the Mammogram images obtained from CC and MLO view should be pre-processed in order to obtain vivid information about the Mammogram images. Hence the mammogram images undergo three steps in the pre-processing stage. In the first step, mammogram images are made noise free by Median filtering de-noising algorithm. In the second step, the de- noised mammogram images undergo image enhancement using CLAHE (Contrast Limited Adaptive Histogram Equalization). In the third step, the mammogram images undergo pectoral muscle identification and segmentation by using Adaptive K-means algorithm. Finally the segmented tumour images are taken for 3-D reconstruction using ICP algorithm.

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LIST OF ABBREVIATIONS

ABBREVATION	NOMENCLATURE
CC	Carnio Cardial
MLO	Medio Lateral Oblique
CLAHE	Contrast Limited Adaptive Histogram Equalisation
DDSM	Digital Database For Screening Mammography
BI-RADS	Breast Imaging Reporting And Data System
HE	Histogram Equalisation
PSNR	Peak Signal To Noise Ratio
MSE	Mean Square Error
ICP	Iterative Closest Point
KD TREE	K Dimensional tree

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CHAPTER 1

INTRODUCTION

The complete objective of this project is the finding of the breast cancer in the early stage. The joining of information from two views of the breast may upgrade the execution of examination. The combination of data from two mammogram images improves the accuracy of the breast cancer detection. The normal pre-preprocessing stage includes: Noise reduction, image enhancement, background exclusion, orientation homogenization and pectoral muscle identification, Segmentation of tumor, and 3D -Reconstruction of tumor.

1.1BREAST CANCER

Breast cancer starts when cells in the breast begin to grow out of control. These cells usually form a tumor that can often be seen on an x-ray or felt as a lump. The tumor is malignant if the cells can grow into surrounding tissues or spread to distant areas of the body. Breast cancer occurs almost entirely in women, but men can get it too. Most breast lumps are not cancer, they are benign. Benign breast tumors are abnormal growths, but they do not spread outside of the breast and they are not life threatening. But some benign breast lumps can increase a woman's risk of getting breast cancer.

Breast cancer occurs almost entirely in women, but men can get it too. Breast cancer is the second leading cause of cancer death in women. (Only lung cancer kills more women each year). The chance that a woman will die from breast cancer is about 1 in 36 (about 3%).Death rates from breast cancer have been dropping since about 1989, with larger decreases in women younger than 50. These decreases are believed to be the result of finding breast cancer earlier through screening and increased awareness, as well as better treatments.

1.2 MAMMOGRAPHY

Mammography is a specific type of breast imaging that uses low-dose x-rays to detect cancer early – before women experience symptoms – when it is most treatable. It plays a central part in early detection of breast cancers because it can show changes in the breast up to two years before a patient or physician can feel them. It can also be used if you have a lump or other sign of breast cancer. A **mammogram** is an x-ray picture of the breast. Screening mammograms simply look for signs of cancer. These procedures are x-ray exams of the breasts done yearly in women who have no breast symptoms or changes in their breast exam. Two types of mammograms are take into considerations

1. Screening mammogram
2. Diagnostic mammogram

Screening mammogram:

The goal of a screening mammogram is to detect breast cancer as early as possible. In a screening mammogram, each breast is X-rayed in two different positions: from top to bottom and from side to side. When a mammogram image is viewed, breast tissue appears white and opaque and fatty tissue appears darker and translucent.

Diagnostic mammogram:

When something is abnormal or difficult to determine, a woman may be referred for a diagnostic mammogram. For example, a woman with a breast problem a lump or an abnormal area found on a routine screening mammogram would get a diagnostic mammogram. Diagnostic mammograms are also done in women who need short interval, follow-ups exams as a result of a prior diagnostic exam. Also, women that were previously treated for breast cancer may get a diagnostic exam. On average, mammography will detect about 80–90% of the breast cancers in women without symptoms.

1.3 MAMMOGRAM RECONSTRUCTION

Mammograms taken in two views : cranio caudal (CC) and medio lateral oblique (MLO) to give just 2D projections of the abnormal growth, which do not have the depth data. Imagining the relative **wroth size stranger** mammograms is a **hard assignment** for radiologists. In order give the exact point location of the abnormal growth, reconstruction is essential for the radiologists.

1.4 MAMMOGRAM PRE-PROCESSING

- Digital mammograms are medical images that are difficult to be interpreted, thus a preparation phase is needed in order to improve the image quality and make the segmentation results more accurate.
- Mammogram pre-processing techniques are necessary, in order to find the orientation of the mammogram, to remove the noise and to enhance the quality of the image .
- Before any image-processing algorithm can be applied on mammogram, preprocessing steps are very important in order to limit the search for abnormalities from background of the mammogram.
- The main objective of this process is to improve the quality of the image to make it ready to further processing by removing the unrelated and surplus parts in the back ground of the mammogram.
- Breast border extraction and pectoral muscle suppression is also a part of preprocessing. It is used in mammogram orientation, label and artifact removal, mammogram enhancement and mammogram segmentation.
- Preprocessing may also involve in creating mask for pixels with highest intensity, to reduce resolutions and to segment the breast.

1.5 BREAST CANCER STATISTICS

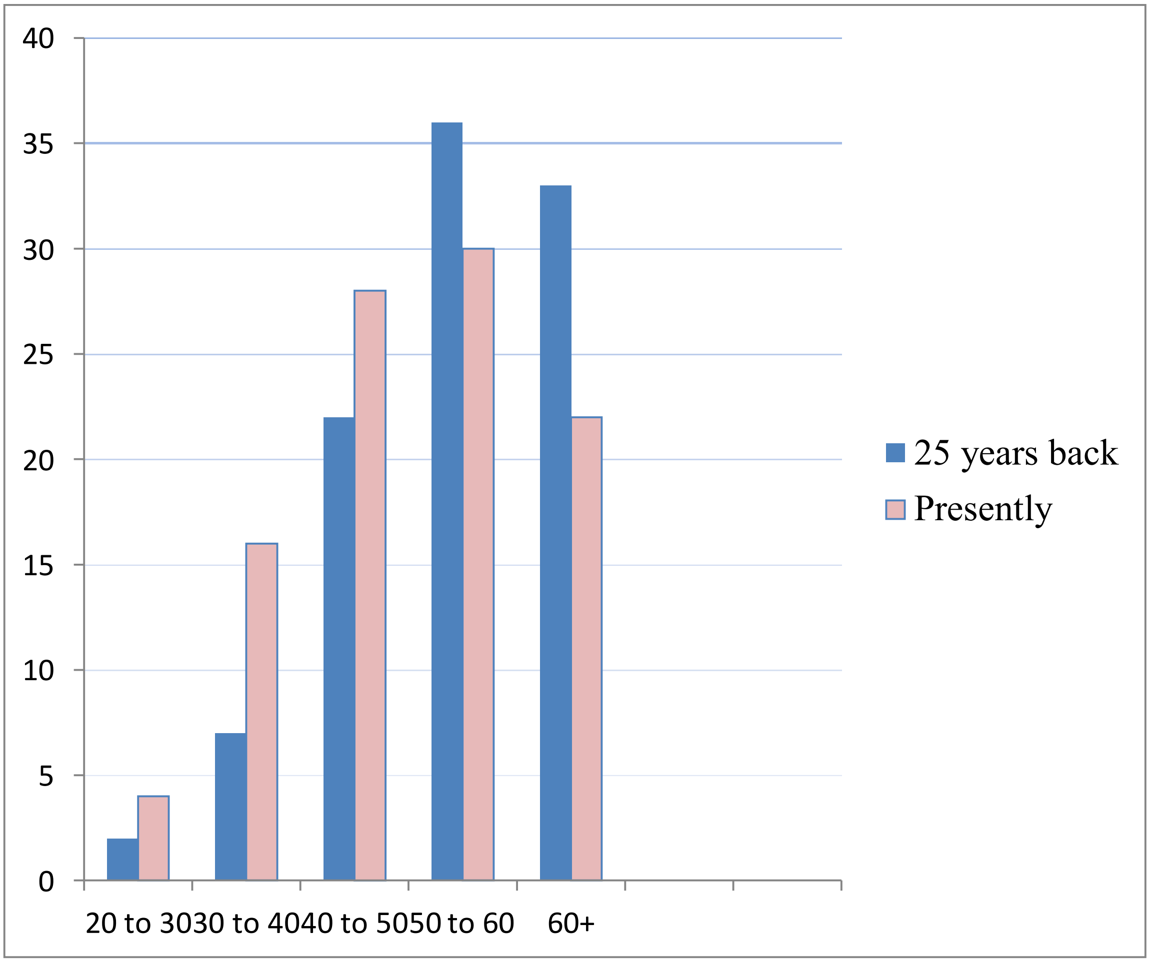


Fig.1.1 breast cancer statistics in India

In Fig.1, the x axis represents the age and the y axis represents the percentage of the affected people.

SOFTWARE USED

MATLAB R2014b

CHAPTER 2

LITERATURE SURVEY

This survey deals with pre-processing of mammogram images. Pre-processing is very important to change and adjust the mammogram image for further study and processing. This may include noise reduction, image enhancement and image segmentation.

2.1 NOISE REDUCTION

FILTERING

Median Filtering

Median filtering is a nonlinear method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges[2][3]. It is particularly effective at removing 'salt and pepper' type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixels. The median is calculated by first sorting all the pixel values into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

Max and Min filter

Minimum and maximum filters, also known as erosion and dilation filters, respectively, are morphological filters that work by considering a neighborhood around each pixel. From the list of neighbor pixels, the minimum or maximum value is found and stored as the corresponding resulting value[7]. Finally, each pixel in the image is replaced by the resulting value generated for its associated neighborhood.

Mid Point Filter

In the midpoint method, the color value of each pixel is replaced with the average of maximum and minimum (i.e. the midpoint) of color values of the pixels in a surrounding region.

A larger region (filter size) yields a stronger effect[4][5][8]. The midpoint filter is typically used to filter images containing short tailed noise such as Gaussian and uniform type noise.

Adaptive median filter:

`Adaptive median filter works on a rectangular region . It changes the size during the filtering operation depending on certain conditions .Each output pixel contains the median value in the 3-by-3 neighbourhood around the corresponding pixel in the input images. The edges of the images however, are replaced by zeros. Adaptive Median filtering has been found to smooth the non repulsive noise from two-dimensional signals without blurring edges and preserve image details. This makes it particularly suitable for enhancing mammogram images.

SALT-PEPPER IMPULSE NOISE DETECTION AND REMOVAL USING MULTIPLE THRESHOLDS

A novel decision-based filter, called the multiple thresholds switching filter, is proposed to restore images corrupted by salt-pepper impulse noise. The filter is based on a detection- estimation strategy. The impulse detection algorithm is used before the filtering process, and therefore only the noise-corrupted pixels are replaced with the estimated central noise-free ordered mean value in the current filter window. An impulse detector that classifies the input pixels as either noise-corrupted or noise-free, and a noise reduction filter that modifies only those pixels that are classified as noise-corrupted[25].The new impulse detector, which uses multiple thresholds with multiple neighborhood information of the signal in the filter window, is very precise, while avoiding an undue increase in computational complexity. The new impulse detection approach based on multiple thresholds considers multiple neighborhood information of the filter window to judge whether impulse noise exists. The new impulse detector is very precise without, while avoiding an increase in computational complexity. The impulse detection algorithm is used before the filtering process starts, and therefore only the noise-corrupted pixels are replaced with the estimated central noise-free ordered mean value in the current filter window.

2.2 IMAGE ENHANCEMENT

Image enhancement is to process a given image so that the result is more suitable than the original image for a specific application. It accentuates or sharpens image features such as edges, boundaries, or contrast to make a graphic display more helpful for display and analysis. The enhancement doesn't increase the inherent information content of the data, but it increases the dynamic range of the chosen features so that they can be detected easily. Image enhancement methods can be based on either spatial or frequency domain techniques.

CREATE NEGATIVE OF AN IMAGE

The major task involved in the image enhancement technique is the creation of the negative of the image. Those pixel faint qualities would modified with register those negative of a picture[4][5]. It might make seen that each pixel regard starting with those initial picture is subtracted from the 255. Those resultant picture gets with a chance to be negative of the initial picture. Negative portraits are important for enhancing white alternately faint point of interest introduced to faint areas of a picture**.**

LOGARITHMIC TRANSFORMATIONS

The general type of the log change is

$$\mathbf{s = c * \log (1 + r)}$$

where C is a constant and it is assumed that $r \geq 0$

- This transformation maps a narrow rang of low level grey scale intensity into a wide range of output values.
- similarly maps the wide range of high level grey scale intensity into a narrow range of high level output values.
- This transformation is used to expand values of dark pixels and compare values of bright pixels

POWERS-LAW TRANSFORMATIONS

$$s = cr^{\gamma}$$

- The nth power and root bends can be given by the expression it is called as gamma expression.
- For various levels of Gamma different levels of enhancement can be obtained.
- This technique is quite commonly called as Gamma corrections

WAVELET-BASED TEXTURE-CHARACTERISTIC MORPHOLOGICAL COMPONENT

wavelet-based texture characteristic morphological component analysis (WT-TC-MCA) to enhance the textural differences in the luminance channel of the colour image. The image enhancement method is intended to be the preprocessing method prior to the use of the colour image segmentation. The input colour image is firstly transformed to CIELab colour space to separate the luminance channel from the chromatic channels. Then only the luminance channel is enhanced by the WT-TC-MCA method to enhance the textural differences between different textures.[18]Therefore, the colour image is enhanced with more differentiate textures while preserving the chromatic information. The experimental results show that the proposed method can enhance different colour image segmentation algorithms more than the state-of-the-art colour image enhancement method.

The WT-TC-MCA based shading image enhancement is executed as takes after:

1. change the information picture I from RGB shading space to CIELab shading space;
2. upgrade the L segment by the WT-TC-MCA strategy so that diverse in l channel are adjusted to be commonly more extraordinary to get the upgraded segment L;
3. supplant the L part with L' , then change the shading picture back to the RGB shading space, yielding the surface improved shading picture I.

2.3 IMAGE SEGMENTATION

DYNAMIC CONTOUR MODELS

Dynamic contour model model is a set of connected vertices. With a minimum of interaction, an initial contour model can be defined, which is then automatically modified by an energy minimizing process. The internal energy of the model depends on local contour curvature, while the external energy is derived from image features[5]. Solutions are presented to avoid undesirable deformation effects, like shrinking and clustering, which are common in existing active contour models. The deformation process stops when a local minimum of the energy function is reached. The final shape of the model is a reproducible approximation of the desired contour. Results of applying the method to computer-generated images, as well as clinical images, are presented.

TYPICAL VESSELNESS FILTERS

Filters which can enhance vessel-like structures have played an important role in the vessel segmentation problems [26].

The three most influential filters are

- Eigen value-Based Filter

This filter is based on eigenvalues of the Hessian matrix For each pixel of a 2D image with intensity ,the Hessian matrix can be formed by its 3 second derivatives and from which two eigenvalues can be computed.

- Isotropic Undecimated Wavelet Filter

The good accuracy and computational efficiency is of the higher percentage in vessel segmentation by Isotrophic Undecimated Wavelet Filter. Applied to a signal , subsequent scaling coefficients are calculated by convolution with a filter.

- Local Phase-Based Filter

The structural information such as the lines and edges of an image can be measured accurately by means of the Local Phase-Based Filter. It has recently be shown that this information can be used to enhance vessels in a more precise way and produce promising segmentation results.

MASS SEGMENTATION ALGORITHM

The mass segmentation algorithm is to segment the mass region roughly, and then a level set is used to refine the segmentation. It aims to preserve the transition between masses and normal tissue to segment the mass boundary[17]. It can deal with complex and changing shapes of the segmentation of the mammograms well and get high segmentation accuracy. Mass segmentation is a more challenging problem than the detection of micro-calcifications, not only for the large variation in size and shape in which masses can appear in a mammogram but also because masses often exhibit poor image contrast.

2.4 ICP ALGORITHM:

The ICP(Iterative Closest Point) algorithm was introduced in 1991 by Chen and Medioni and independently by Besl and McKay and it was further developed by various researchers. The ICP algorithm has become the dominant method for aligning three dimensional models and sometimes colour of the meshes. ICP is used to align partially-overlapping point clouds. The mesh that is used as reference for the alignment is called the model and the mesh that is transformed is called the Scene. The algorithm performs the alignment by finding a correspondence between the model and scene points and calculating the distance between those points, and then finding and applying a rotation and translation to the scene such that the error is minimized. Many researchers have proposed solutions to address the issues of the ICP algorithm. This has led to several different variants of the ICP algorithm. As the two meshes are not aligned, unless specified the correspondence of points between the two meshes is not known. The algorithm makes an assumption that there are equal number of points on both the meshes. There are different ways of finding the correspondence:

- Closest point
- Normal Shooting
- Projective

The closest point approach is used in this project. The ICP algorithm uses four distinct stages:

1.Selection
2. Matching
3. Error metrics
4. Minimization of error metric

CHAPTER 3
IMAGE DATABASE

Two image databases are used for this work. They are

1. DDSM
2. INBREAST

3.1 DDSM

The purpose of this resource is to provide a large set of mammograms in a digital format that may be used by researchers to evaluate and compare the performance of algorithms.It contains about 2500 studies.Each study includes two images of each breast along with some associated patient information and image information.. A case is a collection of images and information corresponding to one mammography exam of one patient. A volume is the collection of cases collected together for the purpose of the distribution. Normal volumes contain mammograms from screening exams that were read as normal and had a normal screening exam four years later (plus or minus 6 months). Benign volumes contain cases in which something suspicious was found and the patient was recalled for some additional work-up that resulted in a benign finding. Cancer volumes contain cases in which a histologically proven cancer was found. Each volume may contain cases that include less severe findings in addition to the more severe findings that resulted in the assignment of a case to a particular volume.

3.2 INBREAST DATABASE

In breast has images from screening, diagnostic, and follow-up cases. Screening is made according to national and regional standards. Diagnostic is made when screening shows signs of anomaly. In follow-up images, cancer was previously detected and treated. . A total of 115 cases were 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. According to BI-RADS, a mass is defined as a three-dimensional structure demonstrating convex outward borders. Benign calcifications are usually larger than calcifications associated with malignancy and are often round with smooth margins and are much more easily seen. Calcifications associated with malignancy are usually very small.

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 4

PROPOSED WORK

In proposed work, the overall work includes the following: 1) the noises from the Mammogram images are reduced using Daubechie 4 wavelet method. 2)The resultant image is enhanced by using CC and MLO views. 3) From the mammogram images, the pectoral muscle is removed using Morphological operations. 4) Cancer and other calcifications are detected. 5) Finally the 3D reconstruction is made using ICP algorithm. In phase 1, noise removal and segmentation of the pectoral muscle had cleared. In phase 2, the 3D reconstruction of tumor is achieved by using ICP algorithm.

4.1 PROPOSED WORK

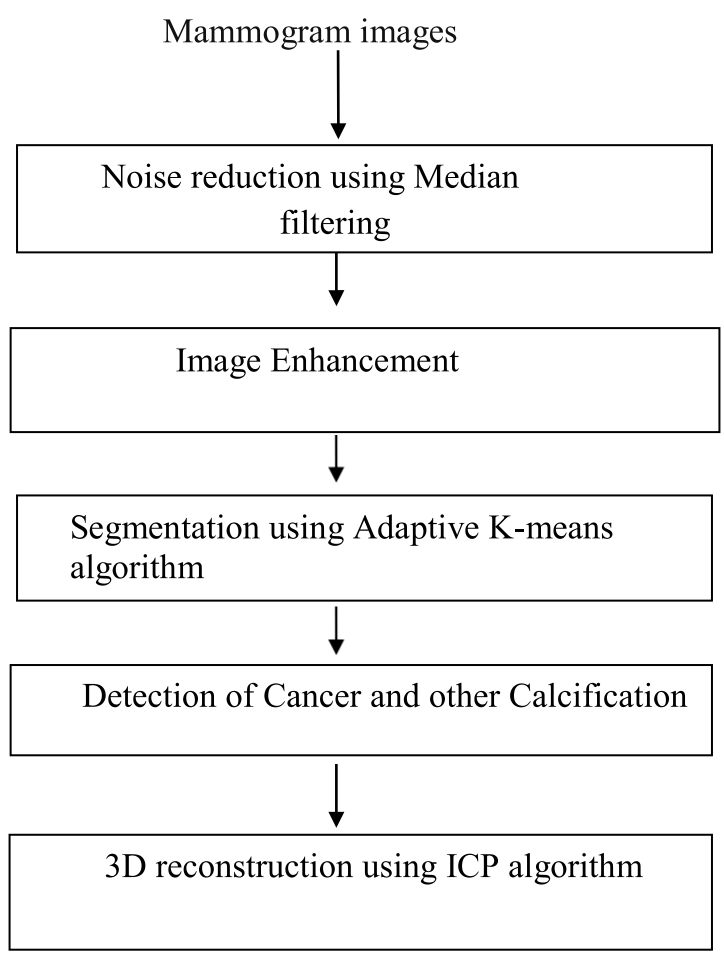


Fig 4.1 proposed work

The description of the figure 4.1 is as follows:

From the mammogram images, the noise is reduced by wavelet multilevel thresholding by using the Daubechie 4 method and then the image is get enhanced. The segmentation of pectoral muscle from the Mammogram image is by means of morphological operations such as complementing and subtracting. from the resultant image the detection of cancer and the calcifications are get identified. Finally the 3D reconstruction is made using ICP algorithm.

4.2 NOISE REDUCTION

Wavelet thresholding de-noising is introduced to preserve sharpness of the edges because of its localized nature in time & space domain and performs denoising with edge preservation. Wavelets have various advantages like no redundancy and efficient implementation. There is no redundant information stored, as wavelet functions are orthogonal.

The **Daubechie 4 wavelet** method is used in order to remove the noise. It provides excellent performance in image compression. It has four wavelet and scaling function coefficient. The Daubechie 4wavelet limit denoising involves the following steps:

1. First step involves computation of the wavelet transform of the Mammogram noisy image.
2. Second step is used to apply thresholding on noisy wavelet coefficients.
3. Finally computing inverse wavelet transform of modified wavelet coefficients.

THRESHOLDING

The purpose of thresholding is to extract those pixels from some image which represent an object (either text or other line image data such as graphs, maps). Though the information is binary the pixels represent a range of intensities. In this project for mammograms, thresholding usually involves selecting a single gray level value from an analysis of the grey-level histogram, to segment the histogram into background and breast tissues. All the pixels with grey level value less than the threshold are marked as background and the rest as breast Thresholding uses only grey level value and no spatial information is considered .Therefore, the major shortcoming of the threshold is that there is often an overlap between grey levels of the objects in the breast and the background. The thresholding can be represented as:

If f(x,y)>T then f(x,y)=0 else

f(x,y)=25 Hard and Soft thresholding are get taken into the

considerations

HARD THRESHOLDING

Hard thresholding is a “keep or kill” procedure and is more intuitively appealing . The choice of the threshold is a very delicate and important statistical problem. Hard thresholding sets any coefficient less than or equal to the threshold to zero. The formula for hard thresholding is

$$\tilde{w}_{j,k} = \begin{cases} w_{j,k} & \left|w_{j,k}\right| \geq \lambda \\ 0 & \left|w_{j,k}\right| < \lambda \end{cases}$$

where lambda is the threshold.

SOFT THRESHOLDING

Soft thresholding shrinks coefficients above the threshold in absolute value. Soft tresholding not only smooths the time series, but moves it toward zero. The formula for soft thresholding is

$$\tilde{w}_{j,k} = \begin{cases} \operatorname{sgn}(w_{j,k})(\left|w_{j,k}\right| - \lambda) & \left|w_{j,k}\right| \geq \lambda \\ 0 & \left|w_{j,k}\right| \geq \lambda \end{cases}$$

4.3 IMAGE ENHANCEMENT

HISTOGRAM EQUALISATION

This technique corresponds to redistribution of gray levels in order to obtain uniform histogram. In this case every pixel is replaced by integral of the histogram of the image in that pixel. Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to get better contrast. Histogram equalization accomplishes this by efficiently spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed . In mammogram images, Histogram equalization is used to make contrast adjustment so that the image abnormalities will be better visible.

CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALISATION(CLAHE)

The contrast enhancement phase is done using the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique, which is a special case of the histogram equalization technique that functions adaptively on the image to be enhanced. In the case of CLAHE, the contrast limiting procedure has to be applied for each neighbourhood from which a transformation function is derived. The CLAHE method seeks to reduce the noise and edge shadowing effect produced in homogeneous areas and was originally developed for medical imaging.

4.4 IMAGE SEGMENTATION:

PECTORAL MUSCLE IDENTIFICATION USING THRESHOLDING:

The thresholding strategy may be utilized for identifying the pectoral muscle in the mammogram images. The pre transformed mammogram images are thresholded toward utilizing the mid pixel worth in the breast range. Since those mammogram images would grayscale images, they need aid thresholded by setting a esteem. Dissimilar to hard and delicate thresholding, it changes over every one of the pixels to either dark or white. The pectoral muscle since it is a thick tissue package, it shows up as white pixels in the thresholded picture. Similarily a portion of the thick tissues and anomalous development like tumor, calcification masses, and so forth., are shown as white pixels.

4.5 PECTORAL MUSCLE REMOVAL AND SEGMENTATION OF TUMOUR USING ADAPTIVE K- MEANS ALGORITHM

This method divides the mammogram into clusters according to the mean of the vectorised datas. It divides the number of clusters on its own rather than depending on manual works.

ALGORITHM

- Vectorise all data.
- Initialize iteration count (i=0, j=0).
- Find data points.
- Data point= mean(data)
- Initialize data point , increment count for each iteration(i=i+1).
- Find distance between data and data points.

$$Dist = \sqrt{(data - datapoint)^2}$$

- Find bandwidth for each cluster center.

$$BW = \sqrt{(\sum(data - datapoint)^2/\text{numel(data)})}$$

- The qualified bandwidth is selected based on

Distance < bandwidth

- The new data points are found by

new data point = mean (new data)

- Store center of cluster.

- Check maximum number of cluster.
- Sort center.
- Find the difference between two consecutive center.
- Find minimum distance between two cluster center.
- Discard cluster center less than distance

4.6 3D RECONSTRUCTION USING ICP ALGORITHM

The segmented tumor from CC and MLO images are taken for the 3D Reconstruction using ICP algorithm. The ICP algorithm includes several stages for the reconstruction of tumor. The stages are as follows:

a. Selection of some set of points in CC or MLO.
b. Matching these points to samples in the other mesh(either CC or MLO).
c. Assigning an error metric based on the point pairs.
d. Minimizing the error metric.

ICP is used to align partially-overlapping point clouds of CC and MLO tumor. The mesh that is used as reference for the alignment is called the model and the mesh that is transformed is called the Scene. The algorithm performs the alignment by finding a correspondence between the model and scene points and calculating the distance between those points, and then finding and applying a rotation and translation to the scene such that the error is minimized.

CENTRE OF MASS:

The center of mass of the two point sets are given by,

$$\mu_x = \frac{1}{N_x} \sum_{i=1}^{N_x} x_i \qquad\qquad \mu_p = \frac{1}{N_p} \sum_{i=1}^{N_p} p_i$$

Subtract the corresponding center of mass from every point in the two point sets before calculating the transformation.

FINDING ROTATION AND TRANSLATION:

Once the distances between all the chosen points from CC and MLO are calculated, the rotation and translation of the scene is calculated such that the distances are reduced.

$$\mathbf{MLO = (R * CC) + T}$$

Where R = rotation, T=Translation.

SELECTION OF POINTS :

It may be beneficial to consider only some of the model and data points before applying the ICP algorithm. For instance outliers may be filtered on both the tumor images based on some threshold. Or to reduce computational complexity, the amount of points may be reduced by random or uniform sub sampling. The idea behind random sampling is to sample differently in every iteration of the algorithm in order to prevent any bias. This will speed up computations.

Let M be a model point set.

Let S be a scene point set

$N_M = N_S$.

CALCULATING DISTANCE:

The algorithm uses simple Euclidean distance for calculating the separation between the points. Given two corresponding points rm and rs in the CC and MLO respectively, the distance is given by:

$$d(r_m,r_s)=\sqrt{}(x_m-x_s)^2+(y_m-y_s)^2+(z_m-z_s)^2$$

The sum of all distances between corresponding points is to be mini-mized.

MATCHING:

Matching accounts for the pairing of points from the data point cloud to the model point cloud. Finding the nearest neighbours is usually the most computational intensive step in the ICP algorithm. The scene shape S (CC) is aligned to be in the best alignment with the model shape M(MLO). The distance of each point S of the scene from the model M is :

$$d(s, M) = \min_{m \in M} d\|m - s\|$$

To find closest point, there are 3 methods,

- ✓ Bruteforce triangulation,
- ✓ K-D tree nearest neighbouring search,
- ✓ Delaunay triangulation.

BRUTEFORCE ALGORITHM:

A basic idea is to calculate distances to all points in P and choosing the one with the shortest distance. This is called brute-force search, exhaustive search or the naive approach. The method is simple, but scales only linearly with the number N of points in P. Expressed in Big O notation, this is O(N). If many nearest neighbour searches are performed within P, it is advisable to
represent P in a structure that allows for more efficient searches.

The Bruteforce Algorithm is to compute the distance between every pair of distinct points and return the indexes of the points for which the distance is the smallest. The Brute Force Steps are as follows:

1. Compute all the distances between the query point and reference points.
2. Sort the computed distances.
3. Select the k reference points with the smallest distances.
4. Classification vote by k nearest objects.
5. Repeat steps (1 to 4) for all query points.

The weakness of the algorithm are as follows:

- Rarely yields efficient algorithms
- Some brute-force algorithms are unacceptably slow

- Not as constructive as some other design techniques.
- The brute-force algorithm is inefficient: as the number of vertices increases, the amount of work we have to do to find the answer increases very rapidly.

K-D TREE NEIGHBOUR SEARCH:

K-D tree was Invented in 1970s by Jon Bentley. It is Named originally as "3d-trees, 4d-trees. Now, people say "kd-tree of dimension d". In order to hold points in a kD tree, the set P is split by finding the median of all points first coordinates. The one point corresponding to the median becomes the root of the tree. Next, the two resulting subsets are split based on the median of their second coordinates[22].The process is known as binary space paritioning. By using kD trees the computation time for finding nearest neighbours can be greatly reduced. The K-D tree can be done in the following algorithmic way:

1. Move down the tree starting at the root comparing coordinates according to the actual splitting dimension until a leaf node is reached.
2. Mark the point at the located leaf node as current best, and calculate the distance d between q and current best.
3. Move up one level in the kD tree and determine the distance from q to this node. If the distance is shorter than d, define this node as current best and the distance to it as d. If the distance from q to the current nodes' splitting plane is longer than d, exclude this nodes' other side branch and continue moving upwards until the root is reached. Otherwise the nodes' other side branch is searched through just like the whole tree.
4. When the top node is reached and all necessary side branches have been searched, choose the shortest of all candidates from the main search and eventual sub branch searches.

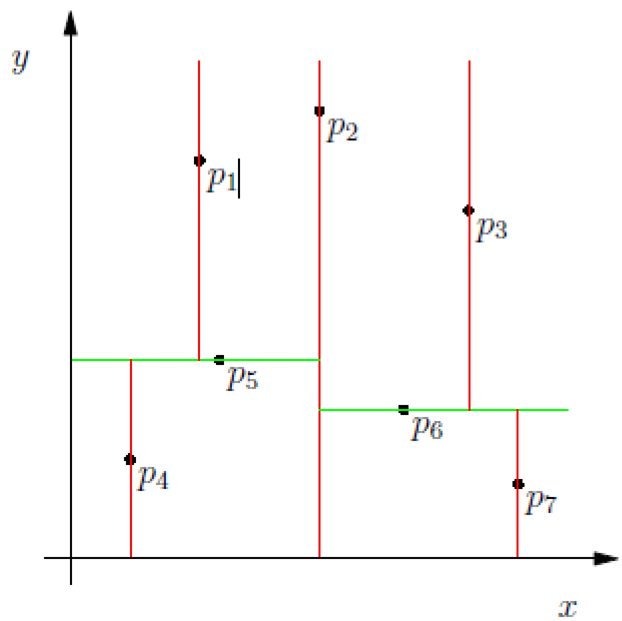


Fig 4.2 A two dimensional point cloud which has been divided using binary space partitioning.

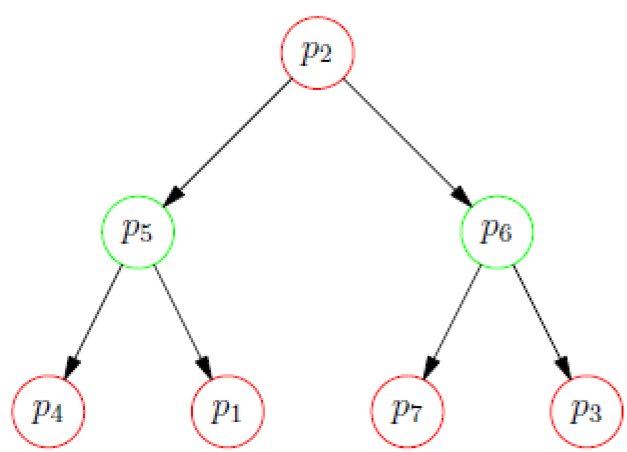


Fig 4.3 The correspoding k D-tree

Depending on the sparsity of P, very large or only smaller parts of P can be excluded from the nearest neighbour search. The reason is that if the distance to the first encountered leaf node is shorter than the distance to its parents splitting planes, then we are at the right node, and all other branches can be excluded[30]. In this case, only a single distance calculation was done, and the complexity is O(1). The expected complexity of the search algorithm is O(log2 N) . In the worst case, no point can be excluded from the search, and the algorithm will perform like the naive approach - that is O(N).

In performing k-nearest neighbour searches, the location algorithm will keep track of not only the nearest neighbour but a given number of nearest neighbours. We avoid to denote this number of neighbours k, since this variable is also used to denote the number of dimensions of the search space.

K-NEAREST NEIGHBOURS - DRAWBACKS

- It is computationally expensive to find the k nearest neighbours when the dataset is very large.
- Performance depends on the number of dimensions that we have.

DELAUNAY TRIANGULATION:

The Delaunay triangulation of a point set V, introduced by Boris Nikolaevich Delone in 1934, is a triangulation of V whose triangles are particularly nicely shaped. The Delaunay triangulation is performed as follows: Three points form a valid triangle if the following condition is met .The circumcircle of the triangle must not contain any other points from the point set (points are allowed to be on the rim of the circumcircle). Delaunay triangulation actually consists of tetrahedrons each of which is defined by four points that are uniquely circumscribed by a sphere.

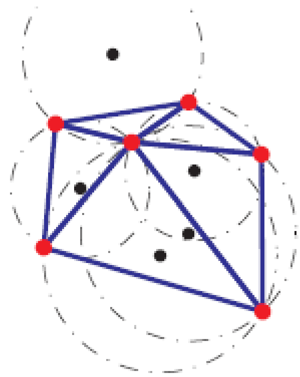


fig 4.4 A triangulation of six random points

The dual graph of a 2-D Delaunay triangulation connects the centers of the circumscribing circles to a new diagram called the Voronoi diagram.

VORONOI DIAGRAM:

It is named after Geori voronoi and is also called a Voronoi tessellation, a Voronoi decomposition, a Voronoi partition, or a Dirichlet tessellation. A Voronoi diagram is a partitioning of the plane into regions based on distance to points in a specific subset of the plane. Given a set of n points, the Voronoi diagram consists of all the Voronoi polygons of these points. E.g. A Voronoi diagram of 6 points:

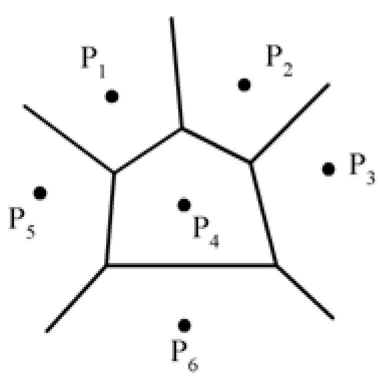


Fig 4.5 the voronoi diagram

The vertices of the Voronoi diagram are called Voronoi points and its segments are called Voronoi edges. The voronoi diagram images are represented as the patches.

ASSIGNING AND MINIMISING ERROR METRIC:

The error metric denotes the objective function that is minimized in every iteration of the algorithm. The metric commonly used is Point to point minimization. To minimise error, RMS value is calculated for every iteration.

POINT TO POINT MINIMIZATION:

The following describes least squares minimization of the alignment error using point to point minimization. Let p_i and q_i denotes the N matched point pairs. The normals corresponding to the model points are denoted as n_i.

$$\bar{p} = \frac{1}{m}\sum p \qquad \bar{q} = \frac{1}{n}\sum q$$

where m and n are the number of model points and data points respectively.

The points deviations from the centroid are given by

$$p_i' = p_i - \bar{p} \qquad q_i' = q_i - \bar{q}$$

The derivations of the point to point minimization requires knowledge of a popular matrix matrix factorization called singular value decomposition (SVD). The SVD is commonly met in linear minimization problems. The SVD is given by

$$\mathbf{M} = \mathbf{U\Sigma V}^{\mathrm{T}}$$

where U and V are orthogonal matrices of size m and n respectively.

3D RECONSTRUCTION :

The patches acquired from the dealunay triangulation are reconstructed using ICP algorithm. To display images, the image command is used .Then adjust axis scaling, and install the MRI colormap, which was loaded along with the data. Use contourslice to display a contour plot of a slice of the volume. To create a contour plot, adjust the y-axis direction set the limits , and the data aspect ratio. we can use isosurfaces to display the overall structure of a volume. When combined with isocaps, this technique can reveal information about data on the interior of the isosurface. First, smooth the data , then use isosurface to calculate the isodata. Use patch to display this data as a graphics object. Add lighting and recalculate the surface normals based on the gradient of the volume data, which produces smoother lighting. Increase the ambient strength property of the isocap to brighten the coloring without affecting the isosurface. Set the specular color reflectance and the specular exponent of the isosurface to make the color of the specular reflected light closer to the color of the isosurface and then reduce the size of the specular spot. The isocap uses interpolated face coloring, which means the figure colormap determines the coloring of the patch. This example uses the colormap supplied with the data. To display isocaps at other data values, try changing the isosurface value or use the subvolume command.

CHAPTER 5

PERFORMANCE MEASURES

5. 1 MEAN SQUARE ERROR:

The mean-squared error (MSE) between two images *g*(*x*,*y*) and g^(x,y) is:

$$e_{MSE} = \frac{1}{MN}\sum_{n=1}^{M}\sum_{m=1}^{N}\left[\hat{g}(n,m) - g(n,m)\right]^2$$

5.2 PEAK SIGNAL TO NOISE RATIO

Peak Signal-to-Noise Ratio (PSNR) avoids this problem by scaling the MSE accoding to the image range

$$\text{PSNR} = -10 log_{10}\frac{e_{MSE}}{S^2}$$

5.3 STRUCTURED SIMILARITY INDEX MEASURE

SSIM is used for measuring the middle of two portraits. The SSIM rundown is a full reference metric; during the conclusion of the day, those estimation or desire about picture personal satisfaction relies once a underlying uncompressed or curving free picture .SSIM may be planned on improve accepted techniques. The SSIM index can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. peak signal to noise ratio (PSNR) and mean squared error (MSE), which have turned out to be conflicting with human visual observation.

PERFORMANCE MESURES:

Peak signal to noise ratio values for various mammogram images:

HISTOGRAM EQUALISATION	CLAHE
11.5983	15.3254
9.8962	14.9685
11.384	15.206

11.853	13.8956
10.864	14.862
9.956	15.0598
10.465	14.5689

Structured similarity index measure for various mammogram images:

HISTOGRAM EQUALISATION	CLAHE
0.3880	0.2693
0.5967	0.2589
0.2569	0.2023
0.5698	0.3566
0.4589	0.401
0.359	0.298
0.2963	0.265

Mean square error for various mammogram images:

HISTOGRAM EQUALISATION	CLAHE
0.058	6.0596
0.096	7.9865
0.0986	5.9688
0.1566	12.054
0.1056	5.4579
0.039	6.2579
0.069	7.598

CHAPTER 6

CODING

```
clc;
clear all;
close all;
[m,n]=uigetfile('*');
[I]=dicomread([n,m]);
I=imresize(I,[256,256]);figure,imshow(I,[]);

I=medfilt2(I);
[mu,mask]=k_means(I,4);
figure,imshow(mask,[]);title('K MEANS SEGMENTATION ')
pect = mask;
[x y] = size(mask);
thres=2;
for i=1:x
   for j=1:y
      if (pect(i,j)<4)
         pect(i,j)=255;
      end
   end
end
seg1=pect;
figure,imshow(seg1,[]),,title('SEGMENETED IMAGE')
[m,n]=uigetfile('*');
[I1]=dicomread([n,m]);
I1=imresize(I1,[256,256]);
I1=medfilt2(I1);
[mu1,mask1]=k_means(I1,4);
figure,imshow(mask1,[]);title('K MEANS SEGMENTATION ')
pect1 =mask1 ;
[x y] = size(mask1);
thres=2;
for i=1:x
   for j=1:y
      if (pect1(i,j)<4)
         pect1(i,j)=255;
      end
   end
end
seg2=pect1;
```

```
figure,imshow(seg2,[]),title('SEGMENETED IMAGE')
A= imadd(seg1,seg2);
figure,imshow(A,[]);title('add');
matchLoc1=double(seg1);
matchLoc2=double(seg2);
[m,n]=size(matchLoc1);
for i=1:m
   x(i,1)=matchLoc1(i,1)/50;
   y(i,1)=matchLoc1(i,2)/50;
   z(i,1)=(((matchLoc1(i,1)-matchLoc2(i,1))/(0.1305))-(matchLoc1(i,1) * (0.0655)))/50;
end
k=[x y z];
D=transpose(k);
j=[x y z];
M=transpose(j);
[Ricp Ticp ER t] = icp(M, D, 15);
Dicp = Ricp * D + repmat(Ticp, 1, n);
figure;
plot3(M(1,:),M(2,:),M(3,:),'bo',D(1,:),D(2,:),D(3,:),'r.');
axis equal;
xlabel('x'); ylabel('y'); zlabel('z');
title('Red: z=sin(x)*cos(y), blue: transformed point cloud');
% Plot the results
figure,
plot3(M(1,:),M(2,:),M(3,:),'bo',Dicp(1,:),Dicp(2,:),Dicp(3,:),'r.');
axis equal;
xlabel('x'); ylabel('y'); zlabel('z');
title('ICP result');
b=seg1;
b1=seg2;
c(:,:,1)=b;
c(:,:,2)=b;
c(:,:,3)=b;
[m,n]=size(b);
d1=b1;
c1(:,:,1)=d1;
c1(:,:,2)=d1;
c1(:,:,3)=d1;
c1=imresize(c1,[m,n]);
c(:,:,1)=0;
c1(:,:,2)=0;
c1(:,:,3)=0;
dd=c+c1;
Y=dd;
```

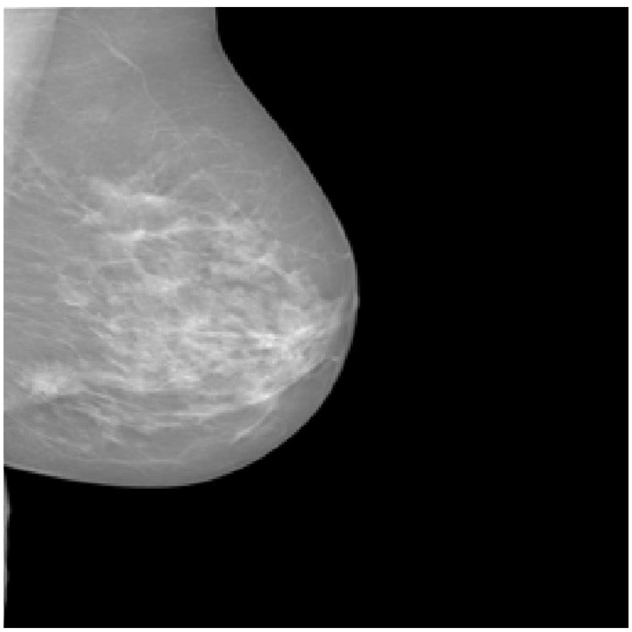
```
i1= uint8(Y);
i1= rgb2gray(i1)
figure,surf(double(i1));
figure,
I1=uint8(dd);
XR = I1;
Ds = smooth3(XR);
hiso = patch(isosurface(Ds,5),'FaceColor',[1,.75,.65],'EdgeColor','none');
hcap = patch(isocaps(XR,5),'FaceColor','interp','EdgeColor','none');
colormap(maps)
daspect(gca,[1,1,.4])
lightangle(305,30);
set(gcf,'Renderer','zbuffer');
lighting phong
isonormals(Ds,hiso)
set(hcap,'AmbientStrength',.6)
set(hiso,'SpecularColorReflectance',0,'SpecularExponent',50)
set(gca,'View',[215,30],'Box','On');
axis tight
title('3D reconstruction')
```

CHAPTER 7

RESULTS AND SIMULATION

DE-NOISING USING MEDIAN FILTERING

ORIGINAL IMAGE



DENOISED IMAGE- MLO

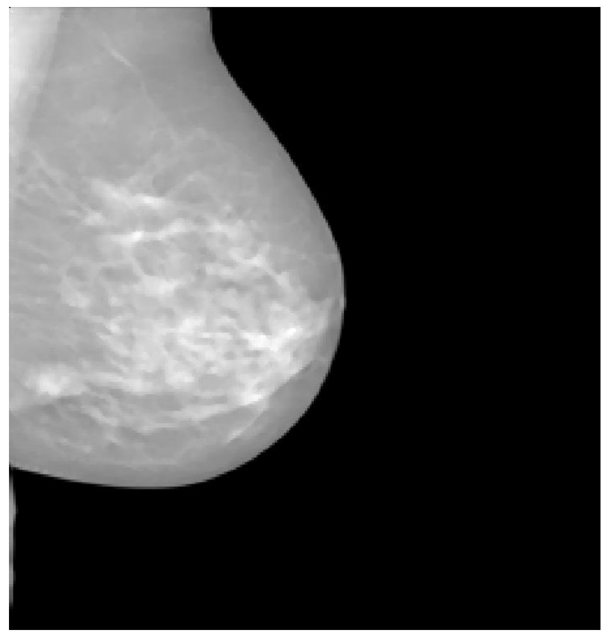


Fig 7.1 Median filtering de-noising

IMAGE ENHANCEMENT :

ORIGINAL IMAGE AND ITS HISTOGRAM

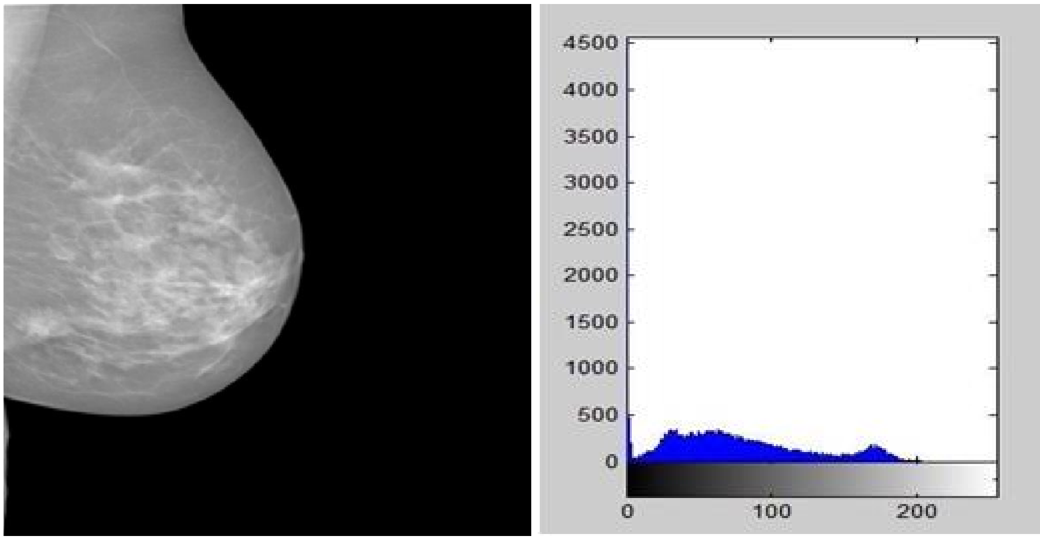


Fig 7.2 original image and its histogram

HISTOGRAM EQUALISATION

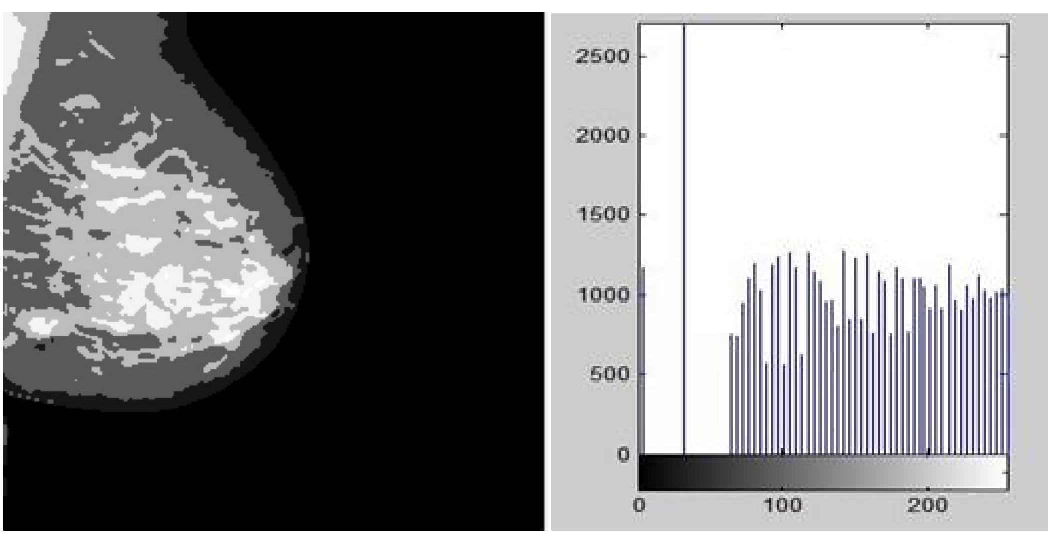


Fig 7.3 histogram equalisation

CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALISATION(CLAHE)

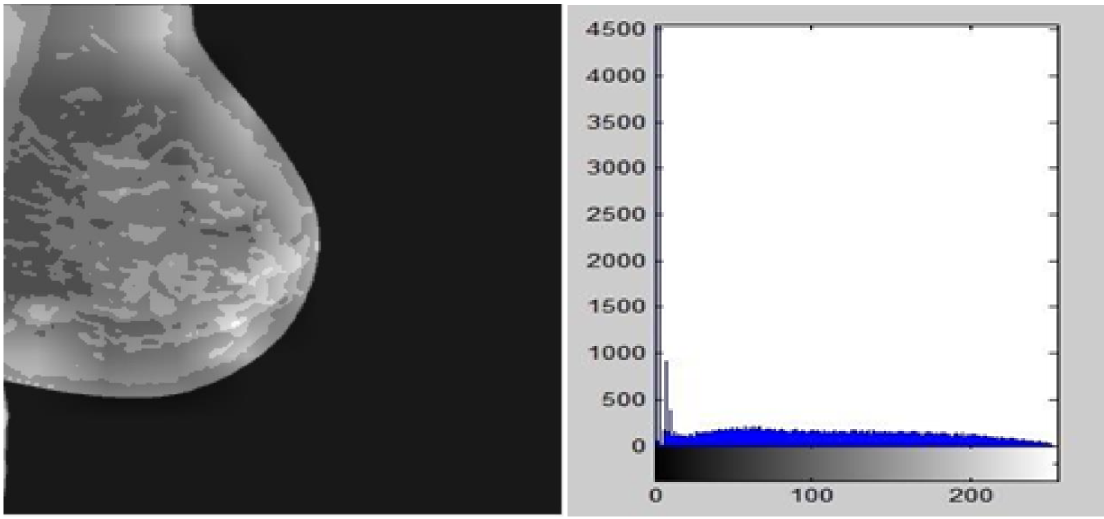
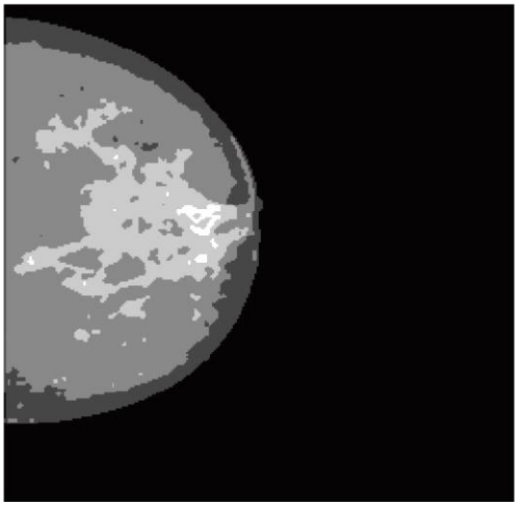


Fig 7.4 contrast limited adaptive histogram equalization(CLAHE)

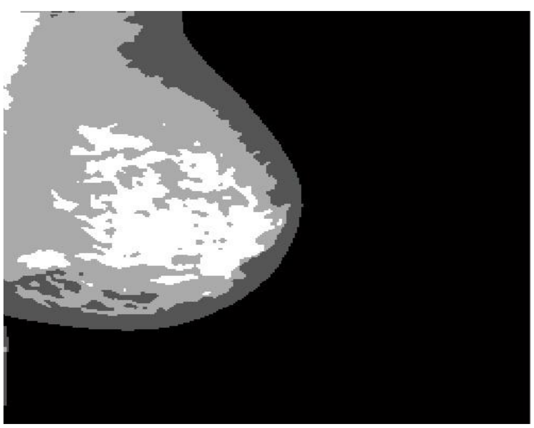
PECTORAL MUSCLE REMOVAL AND IDENTIFICATION OF TUMOUR

SEGMENTED MAMMOGRAM
CC- VIEW



SEGMENTED TUMOR-CC

SEGMENTED MAMMOGRAM
MLO- VIEW



SEGMENTED TUMOR -MLO

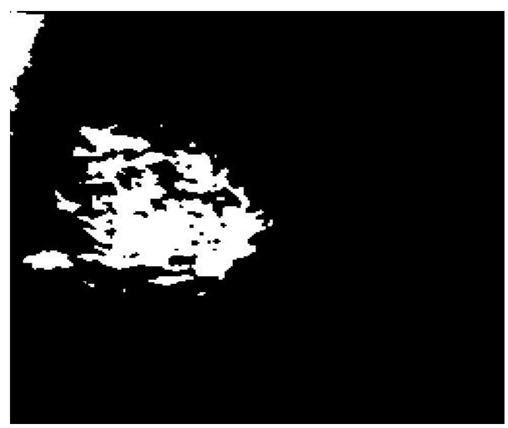
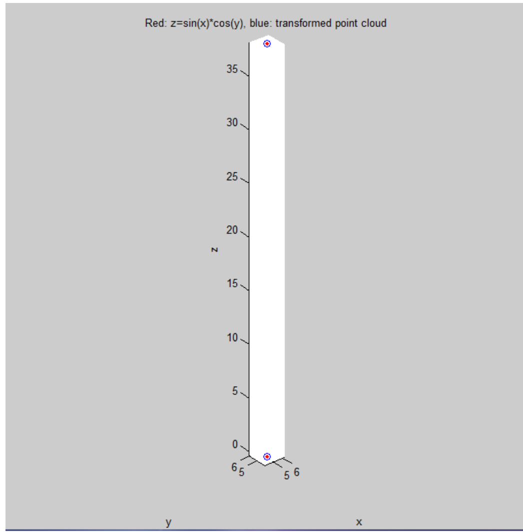


Fig 7.5 pectoral muscle identification and removal

TRANSFORMED POINT CLOUD OF CC AND MLO TUMOR



i

Fig 7.6 transformed point cloud of CC and MLO tumor

ICP RESULT

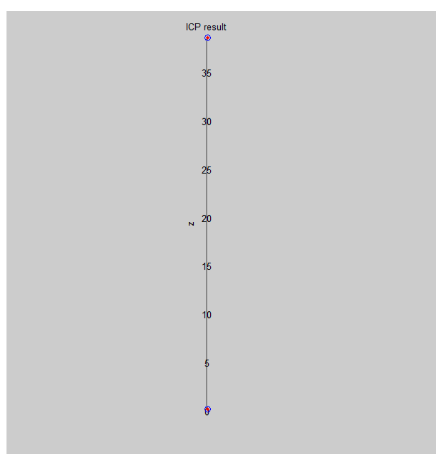


Fig 7.7 Icp result

SURFACE RECONSTRUCTION

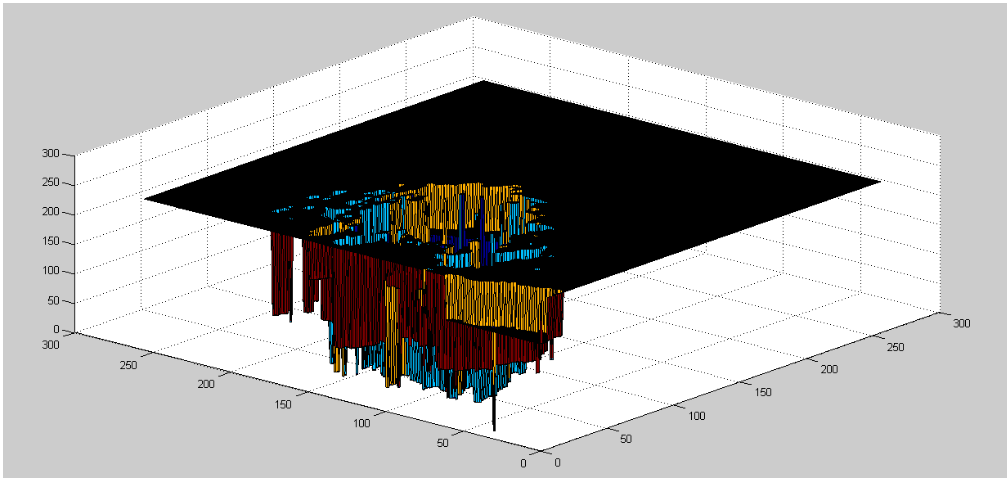


Fig 7.8 surface reconstruction

3D RECONSTRUCTION OF TUMOR

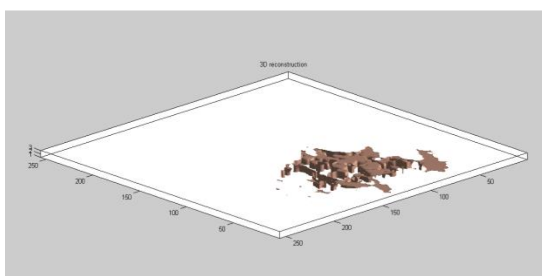


Fig 7.9 3d reconstruction of tumor

CHAPTER 8
CONCLUSION AND FUTURE WORKS

The preprocessing and segmentation of tumor from the mammogram images and 3-D reconstruction of tumor are achieved in this project. Median filtering is used to eliminate the noises in the images. Histogram equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization) is used for achieving the Image Enhancement and the comparison had been done by means of low contrast mammographic images. The image brightness was altered by HE. The image details cannot be clearly viewed, whereas the image contrast is get maintained by CLAHE during the equalization of the histogram. Better enhancement results are produced by the CLAHE techniques. The Adaptive K-means clustering algorithm plays a vital role in the segmentation of tumor from the mammographic images. The segmented tumor is taken for 3D reconstruction using ICP algorithm.

FUTURE WORKS

The future works include the following :

- Nipple point detection.

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