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Breast Cancer Segmentation and Detection Using Multi-View Mammogram

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Abstract: A methodology that detects the breast mass from MLO and CC projection of mammogram images was proposed. It involves feature extraction from the given image set and find the component location value. Then breast mass in single view is figured out which is then merged to get a 3D view of the location breast mass in the mammogram image.

Key words: MLO Mammogram · CC Mammogram · Breast Mass · Segmentation

INTRODUCTION

Cancer causes an alarming effect in today's world. Statistics from World Health Organization (WHO), 13% of world death is due to cancer [1]. Among various cancers, breast cancer has been a major concern for women. Prevalence of cancer in women is relatively high when compared to men [2]. Cancer has become a major health problem in both developed and developing countries. Early detection of breast cancers can help women to reduce breast cancer morality.

Breast cancer screening is generally based on two-view mammography in which Medio Lateral oblique (MLO) and a Cranio Caudal (CC) projections are obtained from both breasts. When reading mammograms, radiologists combine information from all available views. They compare MLO and CC views, look for asymmetry and evaluate changes with respect to prior mammograms. Computer-aided detection (CAD) systems are nowadays widely used in breast cancer screening. These include sensitive algorithms for the detection of masses.

MLO projection taken from patients by capturing pectoral muscle's sides with an angle less than 45 degree. CC projection taken from patients by capturing pectoral muscle's contra lateral view. MLO projection gives the vertical 2-D view of pectoral muscle, while CC projection gives the Horizontal 2-D view of pectoral muscle. In MLO projection Y-Z Axis co-ordinates are measured and CC projection X-Z Axis co-ordinates are measured. Breast masses identified in both MLO and CC image in 2-D view can then be merged into 3-D view. To detect breast masses, we need to calculate co-ordinate value of mass tissue in both images.

In this work, single-view detection scheme is used to develop a multi-view scheme. Single-view detection system invokes both MLO and CC mammogram images separately. Single-view detection scheme consists of the following stages: 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 of the breast. Extended linking method is used for this purpose.

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. Radiologists compare the two mammographic views to decide whether or not a suspicious lesion is present. Specifically, we investigate how multi-view analysis can be made more effective for improving case-based performance. Fig. 1 shows the overall architecture of the system.

Related Work: Since 66% of women in the age group of 25-50 years suffer from breast cancer [2], an automatic detection of breast cancer form mammogram helps the doctors and radiologists.

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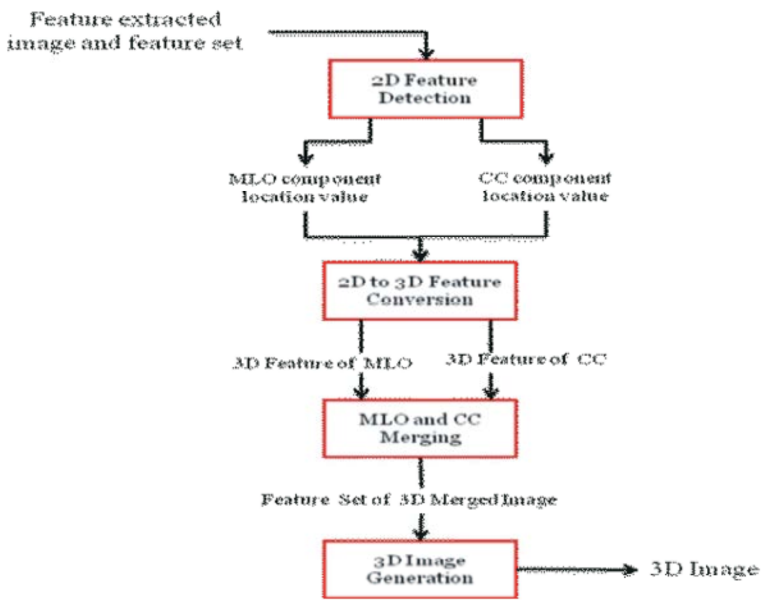

Fig. 1: Overall architecture of the proposed system

A study made on 800 young women reveal that benign breast lumps were changing from fibroadenomas to adenosis and fibrocystic disease [3]. No dietary pattern was found among the patients. Mammography is a technique for detecting breast tissue lumps using a low dosage of X-ray. The X-ray image of the breast tissue is captured and the image is thoroughly read by experienced radiologists and specialist mammogram readers [4]. Mammography is a specific type of imaging that uses a low-dose X-ray system [5], high-contract and high-resolution film for examination of the breasts. Computer-aided detection or diagnosis (CAD) systems [6] can play a key role in the early detection of breast cancer and can reduce the death rate among women with breast cancer. Adaptive Fuzzy C means clustering can be used to segment the images. The adaptive FCM clustering is just the modification of classical FCM clustering technique [7].

We can also use fuzzy neural networks in detecting the abnormalities in mammograms [8]. The dynamic method of updating pixel compactness based on the change in pattern of neighbor areas also helps in finding the breast and abnormalities edges separately. Wavelet transform based neural networks can also aid in medical imaging involving mammograms [8].

CAD system for digital mammogram classification involves ROI extraction, feature extraction and classification process [9]. Feature extraction can be done using statistical method and signal processing method [10]. The signal processing method can be categorized into two types namely, filters in space area and filters in frequency area [10]. Early detection of breast cancer can be done by segmentation of the masses followed by extraction of mass's border using morphological operation [11]. CAD algorithms operate at a level of one or two false positives [12] per four view case (MLO and CC views of the right and left breast), there are still a few hundred false positives for every true positive in a screening setting. An important step in multiview CAD schemes is to match corresponding regions in MLO and CC views of the breast. Because the breast is compressed to reduce the X-ray dose administered to the beast tissue, it is difficult to relate locations of potential mass regions in the MLO view to those in the CC view [13]. Specifically, we investigate how multi-view analysis can be made more effective for improving case-based performance. Modification of the learning rules of the CAD system using the class probabilities from our linking method and the inclusion of correspondence features [14] are useful. In the detection scheme, the mammogram is segmented into breast tissue, pectoral muscle (if the image is a MLO view) and the background area. Background pixels are classified by using thresholding [15].

The pectoral muscle represents a predominant density region in most MLO views of mammograms [16]; its inclusion can affect the results of intensity- based image processing methods or bias procedures in the detection of breast cancer. The co-ordinate transform can be used to extract Gaussian derivative [17] features so that the feature positions and orientations are registered and extracted without nonlinearly deforming the images. The coordinate system provides both the relative position and orientation information on the breast region from which the features are derived. In addition, the coordinate system can be used in temporal studies to pinpoint anatomically equivalent locations between the mammograms of each woman. Active contours [18], which are widely used in image segmentation, are deformable curves that can be used to delineate structures in an image using gradient (edge) information and global region-based information. Many false positives arise in normal dense tissue in the breast. When the likelihood scores assigned to normal tissue are relatively large compared to the candidate mass score [19], it is more likely that the candidate mass is a false positive. Therefore, we believe that CAD performance can be improved by including normal tissue context in the assignment of a malignancy score to the candidate region.

R. Hupse *et al*., developed a method to extract three-dimensional (3D) information [19] about breast lesions from two mammographic views. Their technique was based on a breast model to estimate the deformation of the canonical breast representation under compression [3]. Assessing the breast cancer risk on the basis of a 2-D mammogram [6] is a difficult but important problem in medical imaging.

In the detection scheme, the mammogram is segmented into breast tissue, pectoral muscle (if the image is a MLO view) and the background area [15]. Background pixels are classified by using thresholding in combination with a sequence of morphological operators. The pectoral muscle is segmented from the breast region in two steps. The first is based on straight line estimation [15, 20] using a modified Hough transform as described. In a second step, the boundary is determined more accurately by an optimal path search near the initial estimate using the dynamic programming method [15, 20]. A thickness equalization algorithm [15] is applied to enhance the periphery of the breast. This algorithm is used in MLO images to equalize the background intensity in the pectoral muscle, to facilitate detection of masses located on or near the pectoral boundary.

Finally, the nipple location [20] was estimated by a procedure that assumes that the nipple is the point on the skin contour with the largest distance to the chest in the CC view or pectoral muscle in the MLO view. In multiview CAD schemes is to match corresponding regions [21] in Medio Lateral Oblique (MLO) and Cranio Caudal (CC) views of the breast. Because the breast is compressed [3] to reduce the X-ray dose administered to the beast tissue, it is difficult to relate locations of potential mass regions in the MLO view to those in the CC view.

Two main methods of triangulating a lesion in two projections have been described in textbooks and journal articles. The arc-based [15] method and the straight-line based [15] method. The arc-based method is based on the idea that the distance between the nipple and lesion remains fairly constant during breast compression [3]. The straight line-based method is based on the general concept that the chest wall constrains the deformation during breast compression in such a way that points in the breast move forward with displacement of similar distances under the two views. Yu-qian, Zhao, *et al*. [22] presented a novel mathematical morphological edge detection algorithm to detect the edge of image with salt-and-pepper noise. It makes use of the basic theory of morphology including erosion, dilation, opening and closing operation and the synthesization operations to get clear image edge.

Candidate mass regions are detected by performing an initial detection as described [21]. In the interpretation stage, the candidate masses are classified into normal or malignant tissue by computing a set of features for each segmented region. By applying a threshold [21] on the output of this classifier, the number of false positive detections is reduced without a large reduction in sensitivity. Besides extracting contextual information [19] from the image in which the candidate region is located, also other views of the same case can be used. One case contains a maximum of four views: the medial lateral oblique (MLO) projection and the cranio caudal (CC) projection for the left and right breast.

Breast Mass Detection from Multi-View Images: Initially, Medio Lateral Oblique (MLO) and Cranio Caudal (CC) Mammogram images are given as the input for single view classification. The Medio Lateral Oblique (MLO) and Cranio Caudal (CC) mammogram images are segmented in segmentation and pre-processing module and then mass regions are calculated in both MLO and CC mammogram images. This forms the region detection of single-view region classification. The region detected images are mapped into original MLO and CC mammograms. Features are extracted from the region detected images. These feature extracted image makes the feature sets.

From the feature extracted images and the feature set, 2D feature detection is made for each MLO and CC images. MLO component location value and CC component location value are calculated. From the component values, 3D features are extracted for both images and then merged to get the 3D feature set. Breast masses identified in both MLO and CC image in 2-D view are then merged into 3-D view.

The methodology consists of four major parts, which are 2D feature detection, MLO and CC feature mapping in 3D, MLO and CC component merge and 3D image generation. Medio lateral oblique (MLO) and Cranio Caudal (CC) mammogram images are given as inputs. Mass detection is the output of both views like Medio Lateral Oblique (MLO) and Cranio Caudal (CC) views in single view classification and it will merged into 3D view. The following section explains in detail all the four sections.

Initially the input images MLO and CC images are converted into binary images. The parabolic boundary is detected by joining all the detected points. The noises are removed and then the pectoral boundary is calculated by joining the start and end positions of parabolic boundary. The nipple position is also calculated. This forms the first part 2D feature detection and its algorithm is detailed below.

Hence, the output will be the parabolic boundary, the pectoral boundary and nipple positions of Medio Lateral Obilque (MLO) mammogram or Cranio Caudal (CC) mammogram images. Fig. 2 shows the diagram of 2D feature detection.

Algorithm 1: 2D Feature Extraction

Input: Feature extracted value.
Output: Boundaries.
Begin
Normalize image to binary mode.
Detect modified region from normalized image.
Join all detected pixel positions, to form multiple continuous boundaries.
Remove interior boundaries with low frequency of pixels.
Connect parabolic boundary.
Calculate start and end position of parabolic boundary.
Connect start and end point of last step, to get plane of pectoral boundary.

End

The nipple position will be the peak position in the parabolic curve. So, we need to get the representation of the parabolic curve and find the maximum distance point from the pectoral line which makes the nipple position. It is calculated for both MLO and CC images. The values are exchanged between the various representations. The 3D co-ordinates are generated using the parabolic, pectoral and nipple features. The procedure is repeated for MLO and CC separately along with the mass values. Hence we will get the feature set of 3D image with mass regions coordinates. The algorithm for both MLO and CC feature mapping and merging is presented below. Fig. 3 shows the process of MLO and CC feature mapping and Fig. 4 shows the MLO and CC image component merging.

Algorithm 2: Mapping and Merging of MLO and CC

Input: Pectoral and Parabolic boundaries.
Output: Nipple position, 3d co-ordinates.
Begin
Calculate nipple position
Begin
Find the representation of mammogram (Either left or right).
Find peak position of boundary in parabolic curve (either low or high).
Find maximum distanced point in parabolic curve from pectoral line.
Match both cases and retrieve coincident point.
End
Calculate nipple position for MLO and CC image separately from above algorithm.
Pass MLO feature set to CC and vice versa.
Plot a 3D matrix of pixel values with MLO and CC feature sets multiplied dimensions.
Store matched position of primary axis value with calculated third axis value.
Find multiple instance of third axis value for all primary axis values.
Combine 3D feature set both mammograms.

End

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. Fig. 5 shows the diagram of 3D image generation.

Algorithm 3: 3D Image Generation

Input: 3D co-ordinates.
Output: 3D Image.
Begin
Combine mass features with 3D features to form finalized 3D image.

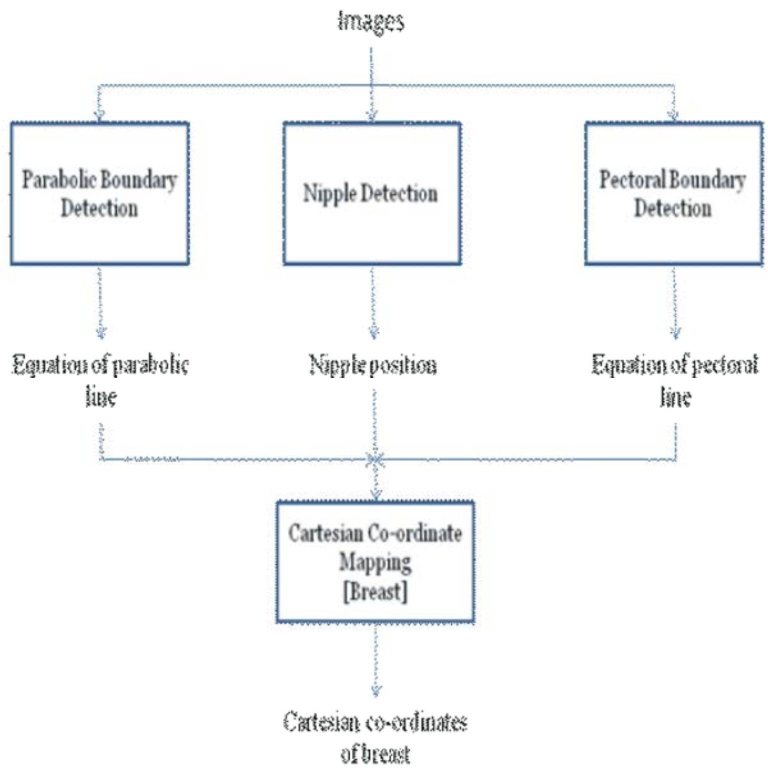

Fig. 2: 2D feature detection

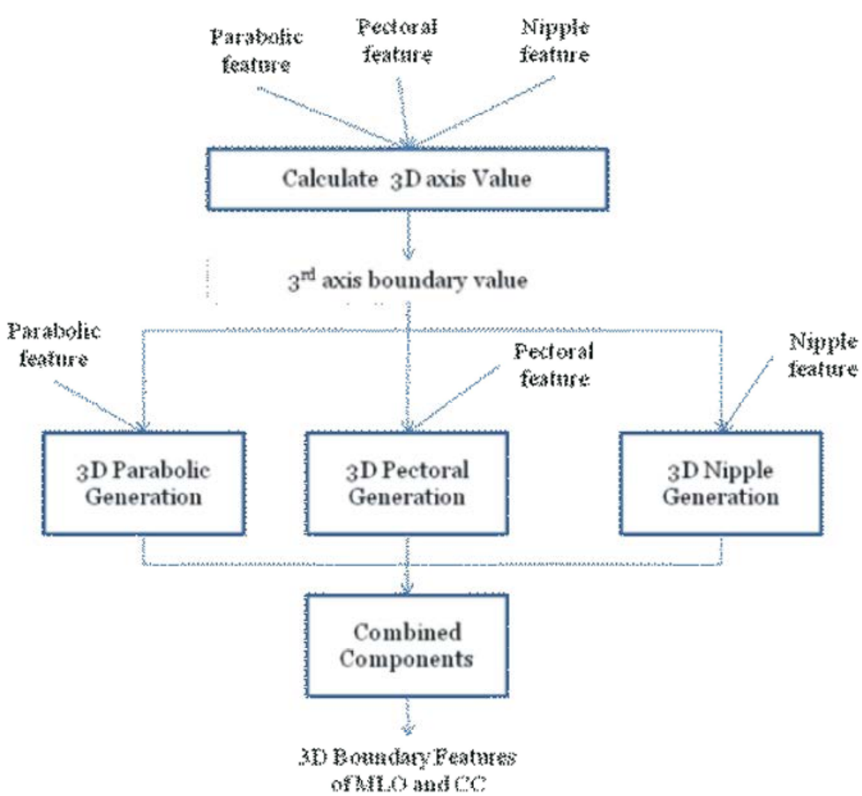

Fig. 3: MLO and CC feature mapping in 3D

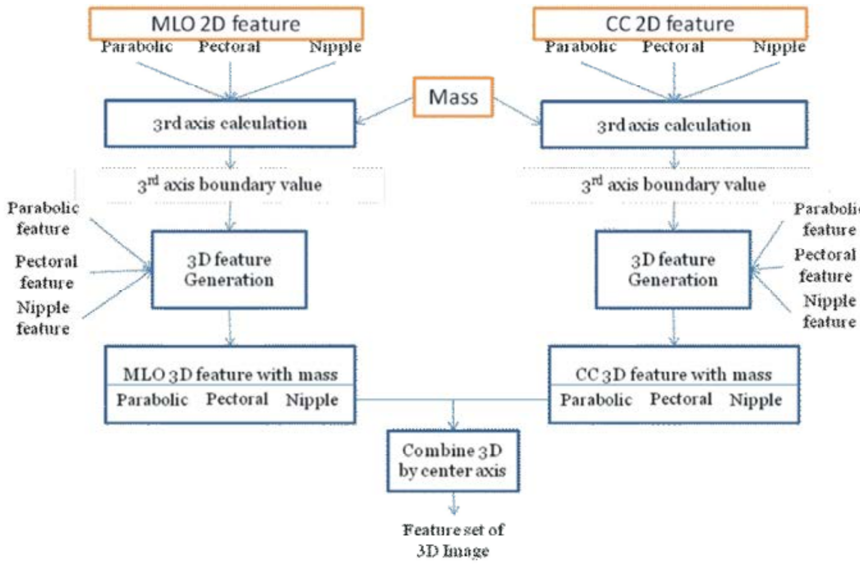

Fig. 4: MLO and CC component merging

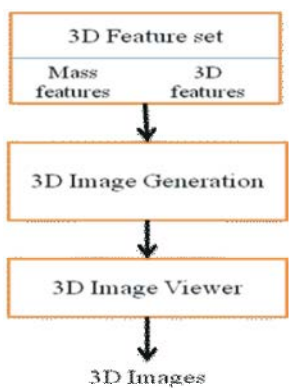

Fig. 5: 3D image generationm.

Construct 3D image from combined 3D feature set.
View 3D image in 3D image viewer
End

RESULTS AND DISCUSSION

The input dataset consists of 30 set of Medio Lateral Oblique(MLO) mammogram image and Cranio Caudal (CC) mammogram images. We trained our system to study the performance of the system using accuracy parameter. The experimented result of each algorithm is followed by performance evaluation of the overall system.

2D Feature Detection: In 2D feature detection, the Medio lateral Oblique(MLO) and Cranio caudal (CC) mammogram image's feature sets are given as the input. Output will be the parabolic boundary, the pectoral boundary and nipple positions of Medio Lateral Obilque (MLO) mammogram or Cranio Caudal (CC) mammogram images. In this module the MLO and CC mammogram images are normalized into binary mode. We have to detect the modified region from the normalized mammogram images. All detected pixels positions are joined to form the continuous boundaries. Then we have to calculate the start and end positions of the boundaries and draw the boundaries. Fig. 6 shows the boundary detection of Cranio Caudal (CC) mammogram image and Fig. 7 shows the boundary detection of Medio Lateral Oblique (MLO) mammogram image.

MLO and CC Feature Mapping in 3D: In MLO and CC feature mapping in 3D module, parabolic boundary features, pectoral boundary features and nipple features of Medio Lateral Oblique (MLO) and Cranio Caudal (CC) mammograms are given as the input. Output will be the 3D boundary features of Medio Lateral Oblique (MLO) Cranio Caudal (CC) mammogram images.

MLO and CC Component Merging: In MLO and CC component merging module 2D feature of parabolic boundary, pectoral boundary, nipple position and mass regions of both Medio Lateral Oblique (MLO) and Cranio Caudal (CC) mammogram images are given as the input. Output will be the feature set of 3D image with mass regions coordinates.

In both MLO and CC Feature Mapping in 3D module and MLO and CC component merging module, first we have to calculate the nipple position of both Medio Lateral Obilique (MLO) and Cranio Caudal (CC) mammogram images.

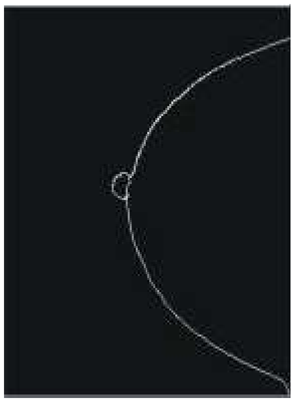

Fig. 6: Boundary detected CC mammogram

Fig. 7: Boundary detected MLO mammogram

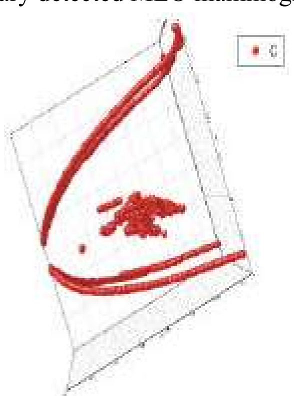

Fig. 8: 3D mammogram image with mass

3D Image Generation: In 3D image generation model, Feature set of 3D image with mass region coordinates are given as the input. Output will be the mass detected 3D mammogram image. The 3D mammogram image will be generated by using the application Origin 9.0. Fig. 8 shows the 3D mammogram image with mass.

Fig. 9 shows the right focused Cranio Caudal (CC) mammogram image. Fig. 10 shows the right focused Medio Lateral Oblique (MLO) mammogram image. Fig. 11 shows the right focused 3D mammogram image with mass.

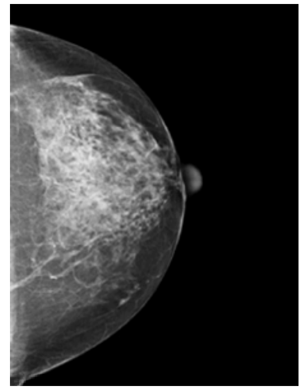

Fig. 9: Right focused CC mammogram

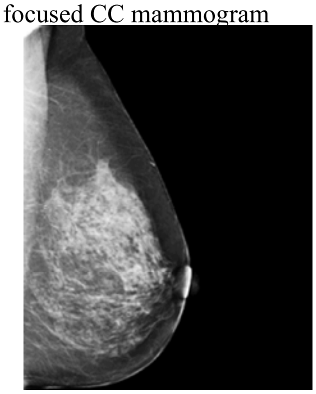

Fig. 10: Right focused MLO mammogram

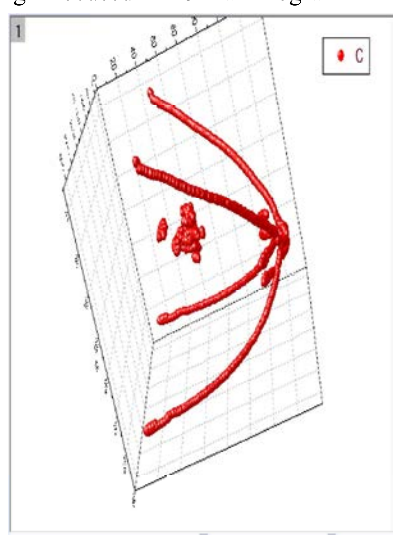

Fig. 11: Right focused 3D mammogram with mass

Fig. 12 shows the left focused Cranio Caudal (CC) mammogram image. Fig. 13 shows the left focused MedioLateral Oblique (MLO) mammogram image. Fig. 13 shows the left focused 3D mammogram image with mass.

This section gives you a sample input image and it's corresponding output image which highlights the detected portion of breast masses. Fig. 15a shows the input image.

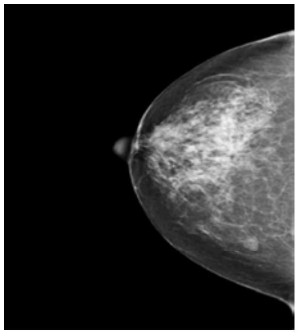

Fig. 12: Left focused CC mammogram

Fig. 13: Left focused MLO mammogram

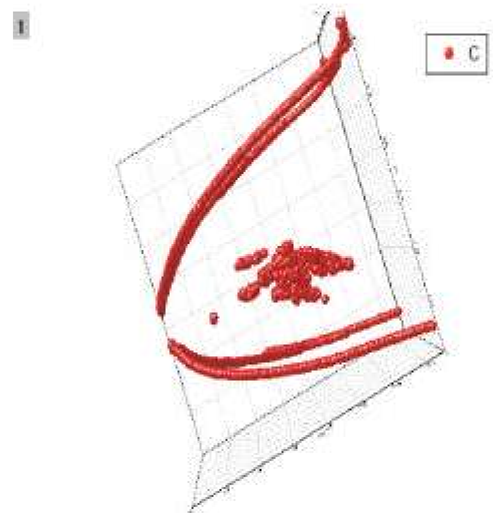

Fig. 14: Left focused 3D mammogram with mass

The circled portion of Fig. 15b shows the mass region which is detected. Rarely very small portions are not detected. It is because of the noise removal procedure done earlier.

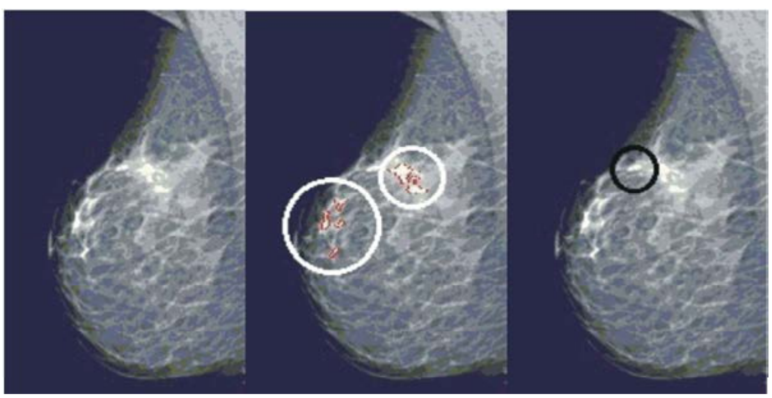

Fig. 15: a. Input mammogram image
b. Output image with detected portion highlighted
c. Input mammogram image with undetected portion highlighted

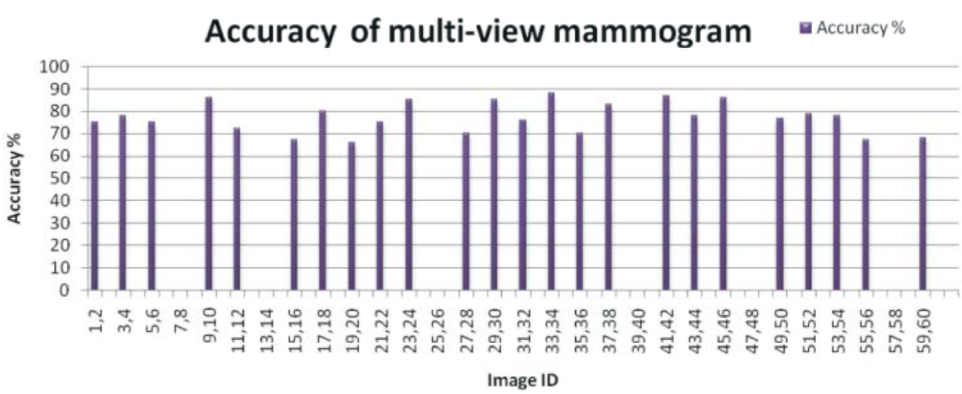

Fig. 16: Accuracy of multi-view mammogram

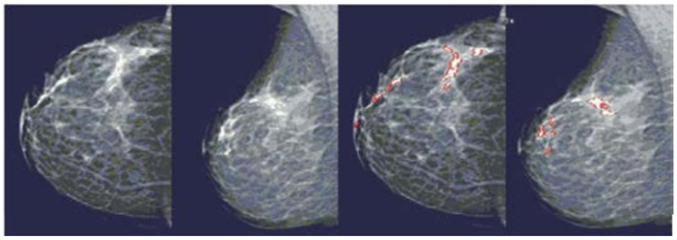

Fig. 17: a Input MLO and CC mammogram images with breast mass detected output (Output of 88% accuracy)

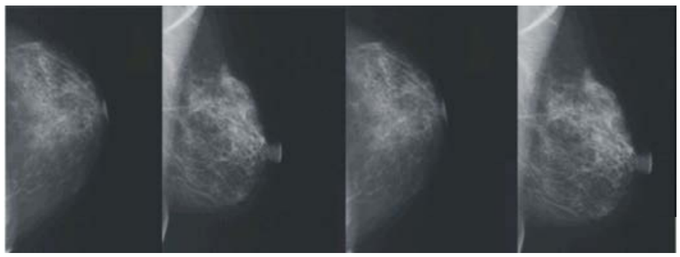

Fig 17: b Input MLO and CC mammogram images with corresponding output (Output of 0% accuracy)

Performance Evaluation: To find Accuracy, true positive, false positive and false negative values are needed. True positive (TP)is frame chosen as key frame both manually and by the technique. False positive (FP) is frame chosen as key frame by the technique but not manually. False negative (FN) is frame chosen as key frame manually but not by the technique.

The main objective of the CAD system is to obtain a high level of true positives detection rate even for small cells and a low number of false positives. Here True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN) are measured to find the accuracy of the CAD system.

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Accuracy} = \frac{TP+TN}{TP + FN + TN + FP}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

The evaluation is done using the region of mass detected in mammogram images along with the performance parameters like true positive (TP), false positive (FP), true negative (TN) and false negative (FN). Results are close to one which is good measure for absolute key frame extract algorithm. Fig. 16 represents the accuracy percentage across 30 sets ofmulti-view mammogram images. The detected mass tissue with 88% and 0% accuracy is shown in Fig. 17.a and b respectively.

CONCLUSION

We have developed a multi-view (3D view) detection scheme to improve the computerized detection of breast cancer tissue or masses from two views of the mammograms. A new method was used to identify the cancer tissue from the Cranio Caudal (CC) mammogram image and Medio Lateral Oblique (MLO) mammogram image. A multi-view detection scheme was designed to identify the shape of the cancer tissue from the Medio Lateral Oblique (MLO) and Cranio Caudal (CC) mammogram images.

The nipple location is identified by hand-extracted i.e., peak position of the mammogram's parabolic boundary is represented as the nipple position. In future we can develop a new method to automatically identify the nipple locations in multi-view CAD system.

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