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## *Pectoral Muscle Identification in Medio-Lateral Oblique View Mammograms*

**Jayasree J Das<sup>1</sup>**

Electronics Engineering  
Collage of Engineering Cherthala  
Cherthala – India

**Vinu Thomas<sup>2</sup>**

Electronics Engineering  
Collage of Engineering Cherthala  
Cherthala – India

*Abstract: Mammograms are X-ray images of breasts which are the first line of defence for breast cancer. The pectoral muscle (PM) is a mass tissue that covers chest wall on which the breast resides. During routine mammographic screening, in Medio-Lateral Oblique (MLO) Views, the pectoral muscle turns up in the mammograms along with the breast tissues. The omission of pectoral muscle from the mammogram is required for an effective automated Computer Aided Diagnosis (CAD). This is due to the similar intensities and texture resemblance of pectoral muscles to that of abnormal breast tissues which can result in awry CAD results. So removal of PM region can be considered as a prerequisite step for early breast cancer detection using mammographic images. In this method, a region of interest of the mammogram is considered based on an optimum threshold. The principal component of pectoral muscle Boundary component is extracted by defining search area for pectoral muscle edge by approximating the PM boundary as a straight line from canny edge detected components of coarse mammographic image obtained after a multi-scale decomposition technique using Laplacian Pyramid (LP). The principal component of PM boundary is extended to top and left boundaries using nearest neighbour approach. PM boundary coordinates thus obtained are used to delineate Pectoral muscle. The algorithm is tested on images from the Mammographic Image Analysis Society (MIAS) database.*

*Keywords: Pectoral Muscle, Laplacian Pyramid, Canny Edge Detector, Mammogram, Breast Cancer.*

### I. INTRODUCTION

According to statistics of American cancer society Breast cancer is a leading cause for increased fatality rate among women. To reduce the death rate, early detection of cancer is required. X-ray mammography or Mammographic screening is used widely for early detection of breast cancer. Factors affecting Mammographic screening are different level of radiologist's expertise and high volume of cases. The double reading improves accuracy but it is deployed because of high cost, intra-observer variability and manpower limitation.

A CAD system in the diagnosis of breast cancer potentially provides a consistent and reproducible second opinion to a radiologist whose major role is to localize suspicious regions and characterize them into benign or malignant. Among the various types of breast abnormalities that are visible in mammograms, the most important indications of malignancy on mammograms are the presence of micro-calcifications and masses. A CAD system are to assist radiologist's detection with increased speed and accuracy avoiding false diagnoses caused by intra-observer discrepancies but it is a tough to analyze mammograms automatically using computers. Difficulties arise mainly from the inherently complex, variable, and ambiguous nature of mammograms. The breast anatomy is intrinsically complex and causes mammographic images to have heavily textured patterns. Mammograms are highly variable not only between women, but also within the same individual due to varying imaging conditions, such as aging and variations due to hormonal cycles. And mammogram is a 2-D projection of a compressed 3D breast introduces complexity in differentiating internal structures.

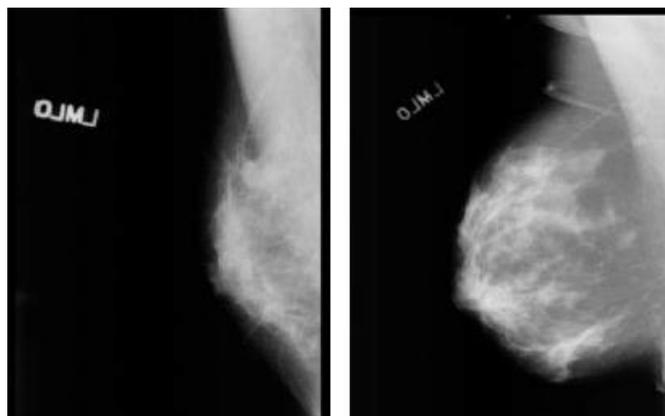
In this paper, it is proposed an automatic method for removing pectoral muscle from MLO view of mammographic images to get region of interest (ROI). This ROI helps to reduce false positive results which may occur in pectoral muscle region thereby improving the accuracy of computer aided methods for detecting breast cancer in its early stage. The PM boundary is estimated using the Canny edge detector [6] on a contrast enhanced coarse view of the mammographic image, to extract the principal PM boundary component. A histogram based contrast enhancement technique; Gray Level Grouping (GLG) [7] is utilized to enhance the contrast of mammographic image. In order to remove background labels and other artifacts, a morphological operation is performed on the mammogram which is initially preprocessed with a Weiner filter and thresholding operation. The images from MIAS database [21] is considered for experimental analysis. Automatically detected PM boundaries are compared with a manually marked segmentation line by a specialized radiologist. Qualitative as well as quantitative analyses are performed based on these results.

## II. PROBLEM FORMULATION

Automatic computer aided methods for removing pectoral muscle have great significance in early breast cancer detection using mammograms. The similarity in densities and texture of PM and dense breast tissues may lead to inefficacy of detection methods. Inaccurate detection may in turn lead to an increase in false negative and false positive rates. Challenges for Automatic detection of PM, the pectoral muscle boundary on a mammogram can be complicated. Depending on anatomy and patient positioning during image acquisition, the pectoral muscle could occupy as much as half of the breast region, or as little as a few percent of it. The curvature of the muscle edge is usually convex, but it can also be concave, or a mixture of both. Although the pectoral muscle boundary is perceived to be visually continuous by humans, there are large variations in edge strength and texture. Here describes examples of four typical pectoral muscle patterns observed that are challenging for

Automatic PM Detection.

- Dense breast containing large area of dense fibro-glandular tissue overlapping the pectoral muscle that makes it difficult to reliably characterize the pectoral muscle image region
- Skin fold located in the upper region of the breast mimicking pectoral muscle boundary fuzzy pectoral edges in the lower region of the pectoral muscle
- There is a high variability of region surface; the most tedious cases are met when the pectoral muscle covers a very small area or is completely missing.
- The small bright triangle region in the upper-right corner which is not the pectoral muscle, but may be detected mistakenly by the computer because of its strong and straight edge and location.[22]



(a) (b)

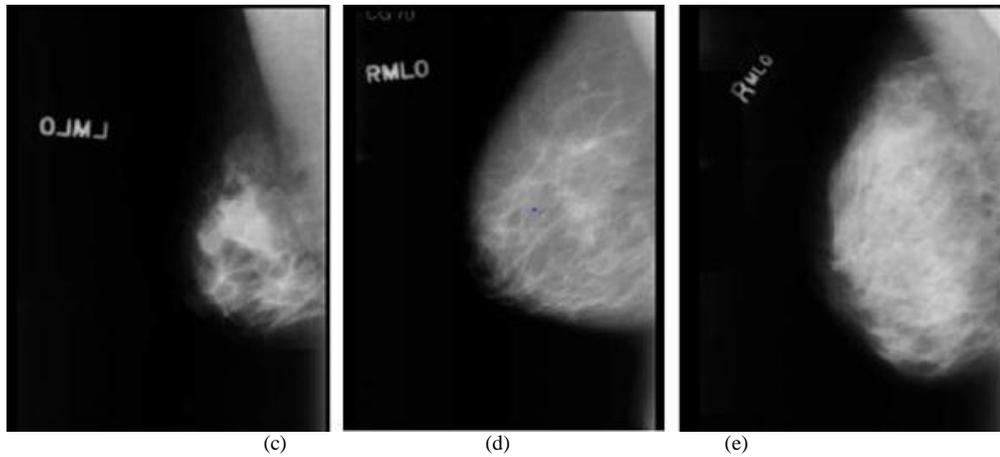


Fig 1. Examples of different patterns of pectoral muscle on the mammograms that are challenging for automated pectoral muscle detection. (a) Dense breast containing large area of fibro-glandular tissue overlapping the pectoral muscle; (b) skin fold located in the upper region of the breast mimicking pectoral muscle boundary; (c) fuzzy pectoral edges in the lower region of the pectoral muscle; (d) small pectoral muscle; (e) small bright triangle region in the upper-right corner which is not the pectoral muscle

The complicated and varied patterns cause the difficulties for computerized pectoral muscle detection. A large number of studies on CAD methods for mammography have been reported in the literature; however, few studies evaluated the performance of a specific automated pectoral muscle identification method using a large data set in comparison to radiologist's manual segmentation as a reference standard. It is not clear whether the published methods are robust against the difficult situations demonstrated above. Although the difficult cases may only constitute a small fraction of all cases, they are major hurdles to the full automation of advanced CAD techniques.

### III. PROPOSED METHOD

The expedience of the proposed algorithm is its simplicity, novelty and accuracy. The proposed method for PM boundary detection exploits the following properties of pectoral region and its boundary.

1. PM boundary need not be a straight line, margin can be concave, convex or mixture of both.
2. And PM boundary line can be approximately considered as straight line
3. There are sharp intensity discontinuities at PM boundary.
4. PM lies at the upper left corner of mammographic image if it is right oriented.
5. PM boundary component of left oriented image lies within 300 to 800[2].
6. PM boundary is visually separable but difficult to segment from breast tissues.
7. PM region is roughly approximated as a triangular region.
8. PM boundary is visible in the approximation image in a multi-resolution decomposition.

The flowchart of the proposed figure is depicted as Fig. 2.

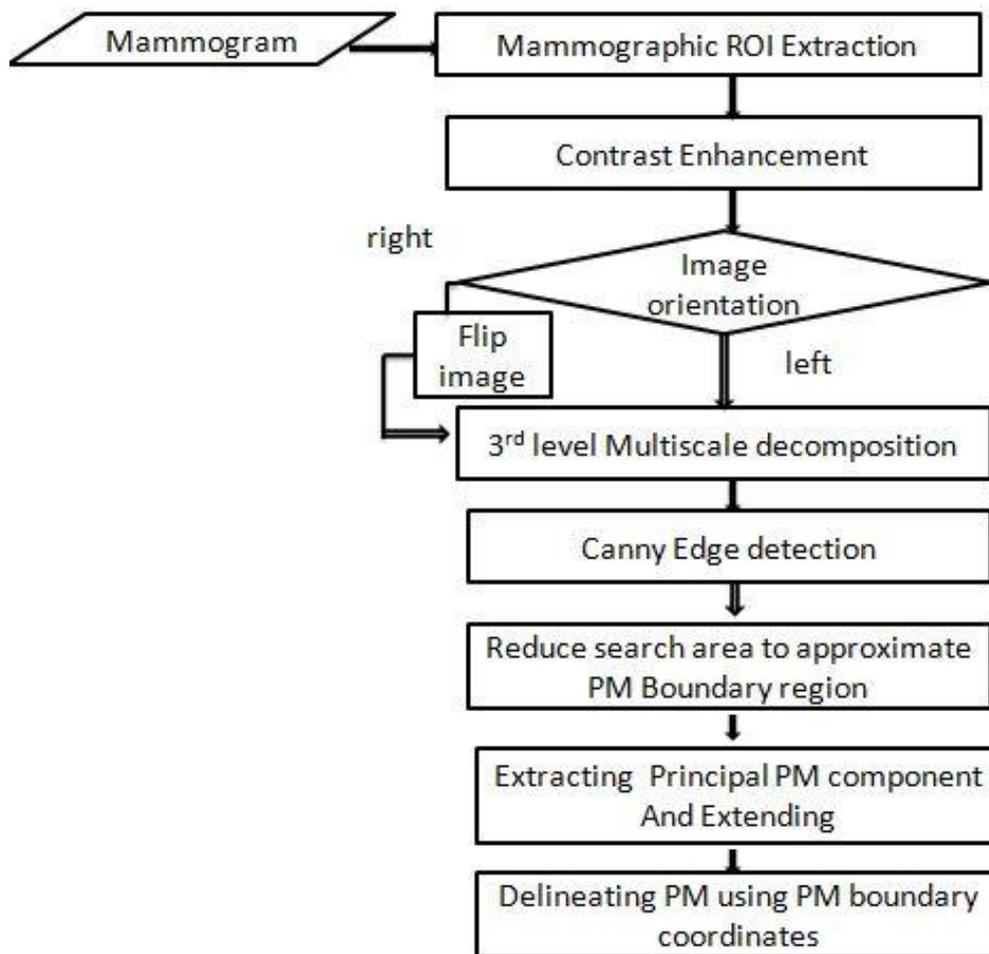


Fig.2. Flowchart of the Proposed Method

The first stage of the algorithm, Region of Interest (ROI) extraction by removing noise, labels, and other artifacts, consists of three steps: noise reduction using Weiner filtering, thresholding and large area detection using morphology. The threshold employed here, TH is computed as

$$TH = (I_{min} + I_{max}) * 0.05$$

Where  $I_{min}$  and  $I_{max}$  are respectively the minimum and maximum intensity values of the image, I. The connected component with the largest area is selected as mammographic area. In most methods, it is found difficult to separate the PM boundary from dense tissues. The reason for the inadequacy is mainly due to the low contrast between breast and PM tissues. Hence we have considered a histogram based efficient contrast enhancement method, GLG [7, 13] which is better for medical images. Average pixel distance between pixels on a grayscale is a contrast measure used for this purpose

Average Pixel Distance,  $D_{n-1} =$

$$\frac{1}{Npix(Npix - 1)} * \left[ \sum_{i=0}^{M-2} \sum_{j=i+1}^{M-1} H_{n-1}(i)H_{n-1}(j)(j - 1) \right]$$

For  $i, j \in [0, M-1]$ , where  $[0, M-1]$  is the gray level range of the grayscale, and Npix is the total number of pixels in the image and  $H_{n-1}(\cdot)$  is the histogram of the processed image.

Orientation of mammographic image was detected by checking the total number of pixels in the left and right boundary. For a left oriented mammographic image, the number of pixels in the column corresponding to the left boundary of the breast

region is more than the number of pixels in the column corresponding to the right boundary of the breast region. The analysis of the mammographic image at different resolutions using a multi-scale decomposition aids in extraction of relevant edge features. The coarse scale representations of the image will carry edge features of larger objects such as the pectoral region, while smoothing out some of the finer information from other tissue structures. Discontinuities at the edge of PM can be captured more efficiently at coarser levels. A multi-scale decomposition is performed using a three level Laplacian Pyramid (LP) [14]. Sharp discontinuities indicating PM boundary can be detected by employing Canny edge detection of the approximation image. Canny edge detector is selected because of its good localization feature and minimal response [6]. The PM region is roughly triangular shape.

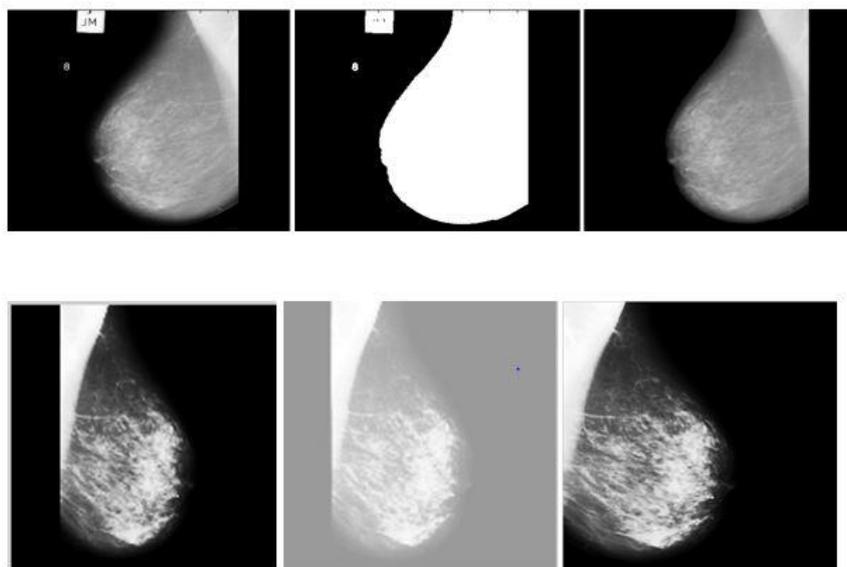
A region of interest of the mammogram is considered which includes the region of pectoral muscle and then it is thresholded based on mean and approximated the pectoral muscle boundary as a straight line. Defining an area in between lines drawn parallel with respect to approximated straight line. And from the reduced area search is used so principal PM component can be easily extracted. The principal PM boundary component can be extended to the top and left boundary of mammographic image by selecting pixels based on the assumption that the PM region is roughly of triangular shape. From the reference pixel, the neighboring pixel to be included for extension of the Principal PM Boundary Component can be vertical, horizontal or diagonal. The neighboring pixel having intensity value closest to that of the reference pixel is selected for extension. For extending upwards, the neighboring pixel in the outward direction is considered while an inward extension direction is utilized in the case of extensions towards left boundary. PM boundary coordinates thus obtained can be used to delineate Pectoral Muscle region from the ROI of mammographic image.

#### IV. EXPERIMENTAL SETUP AND PERFORMANCE MEASURES

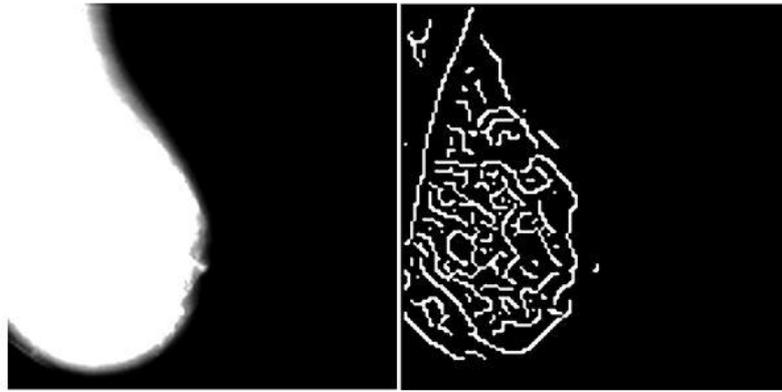
The Images in the MLO view from the Mammographic Image Analysis Society, London, U.K. (MIAS) [21] were considered for experimental analysis. The images in the MIAS database have been digitized with 200  $\mu\text{m}$  sampling interval and 8-bit gray-level quantization. It is preferred the coordinates of same images and the results were compared with the ground-truth contours as described by Ferrari et al. [4] for analyzing the performance of the proposed method. Performance evaluation and comparison of the proposed method were conducted using performance measures including the false positive average, false negative average, row normalized error and Hausdorff distance [4, 10, 11, 16].

#### V. RESULTS AND DISCUSSIONS

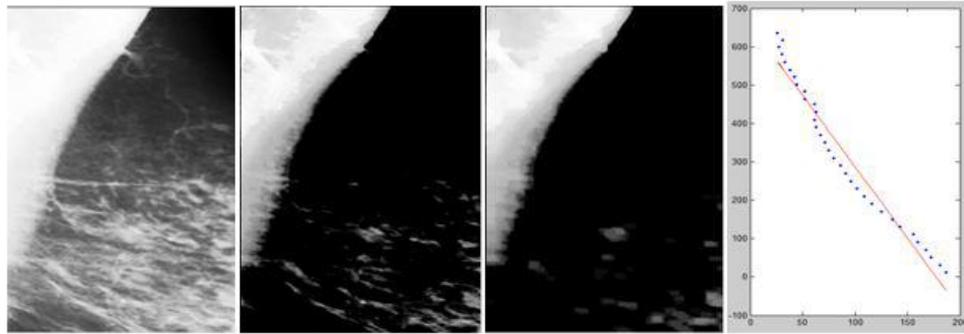
Preprocessing steps



(f)



(g)



(h)

Fig.3.(f) Preprocessing of mammographic image by the proposed method;(g) Laplacian Decomposition and Canny edge detection;(h) Finding approximate PM boundary coordinates,which can be used to define search area.



(i)

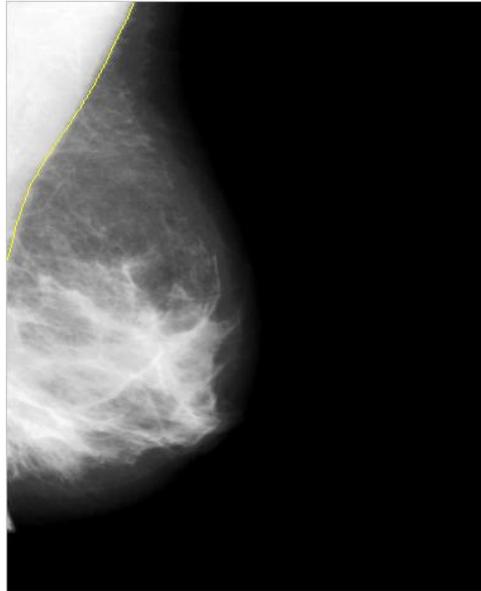


Fig: 4 (i) Defining mask and Extracting Principal boundary component and edge coordinates; (j) Plotted Identified PM edge coordinates

## VI. CONCLUSION

Research in Computer Aided Diagnosis (CAD) for automatic detection of breast cancer has been going on for a long time now. But, from the research papers, it is seen the topic of pectoral muscle segmentation, which is a preliminary step for CAD in detection of breast cancer is really low. Also, the techniques followed in the available literature are very limited and has tremendous scope to be expanded, wherein several new theories can be applied to the problem in hand. And there is not one specific method which works perfectly well for the problem of pectoral muscle segmentation. In most cases, the solution provided is more targeted towards a particular set of data or a particular problem in hand.

There are few generic solutions available for the pectoral muscle detection. The proposed method for the extraction of PM boundary component will show immense potential to be used as a pre-processing CAD technique for early breast cancer detection using MLO mammographic images. The MIAS mammographic database [21] is employed to validate the algorithm. The orientation property and reduced region search were utilized to obtain the principal PM boundary component. Extension of the principal PM boundary component is possible by determining minimally varying adjacent pixels. Accuracy of the proposed method will be validated using performance measures such as false positive average, false negative average, and Hausdorff distance. The obtained performance measure values for the proposed method indicate that the ground truth is closely met by the algorithm.

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