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Segmentation of Breast Regions Based on Anatomical View

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Abstract
The accurate interpretation of various regions of mammogram is one of most important step to detect abnormalities in breast. In this paper segmentation of regions of mammogram is proposed on Medio-lateral oblique (MLO) view of mammograms.

Key Words: MLO View, Gland, Anatomical View and MIAS Database

Introduction

The mature women's breast, the milkproducingsystem, is made up of 15 to 20 irregular lobes of branched tubuloalveolar glands. The gland is surrounded bysubcutaneous connective tissue that forms septa between lobes and lobules, providing asupport for the glandular elements. All macroscopic breast structures can be easily imaged [1-3]. The breast can be divided into fourregions skin, nipple, sub-areolar tissues; subcutaneous region contains fat and lymphatics; parenchyma region, a triangular shape between the subcutaneous and retromammary regions, with the apex towards the nipple and retromammary region consists of retromammary fat, the pectoral muscle, ribs, intercostal muscles and the pleural reflection[4-6,15].

The accurate interpretation of mammogram is one of most important step to detectabnormalities[7-10]. On mammogram images, breast masses appear as white regions. Fat appears as black regions on the images. Allother components of the breast like glands, connective tissue, tumours, calcium deposits etc. appear as different shades of white on a mammogram. In general, the younger woman has denser breasts [11-14]. As a woman ages, her breasts become less dense and the space is filled with fatty tissue shown as dark areas on mammogram.

The proposed algorithm for Anatomical Segmentation of Breast is applied to differentiate various regions within the breast which is the primary objective of the paper. The proposed method has been implemented and applied to Mammographic Image Analysis Society (MIAS), one of the most well-known mammographic databases consisting of 322 MLO view and other mammographic database in public domain. To demonstrate the capability of the segmentation algorithm, it was extensively tested on different types and categories of mammograms within the database.

Literature Review

Some researchersfocus on improving segmentation accuracy and identifyingeffective image features. They suggested that improving the accuracy ofmass and non-mass region segmentation could also significantly improve the performanceof Computer Aided Diagnosis (CAD) based breast region detection and characterization.

Automated and semi-automated methods include using a density-weighted contrast enhancement algorithm thatcombines adaptive filtering and edge detection [16], an adaptive multilayer topographicregional growth algorithm [17], a grey-level–based iterative and linear segmentationalgorithm [18], a dynamic programming approach [19], and dynamic contour modelling[20] to segment mass and non-mass lesions from surrounding breast tissue. Numerous other techniques have been developed to segment lesions from surroundingtissues in digital mammograms. Petrick et al. [16] employed density-weighted contrastenhancement (DWCE) segmentation algorithm to extract lesions and potential lesions fromtheir surrounding tissues. Comer et al. [21] and Li et al. [22] used Markov random fieldsto classify the different regions in a mammogram based on texture. A lesion segmentationalgorithm was developed by Sameti et al. [23] used fuzzy sets to partition themammographic image data.

Although significant research effort hasmadefor developing computerized methods todetect abnormal masses of various types. Some researchers classify them for detecting breast contour, identify nipple position, pectoral muscle isolation etc., but the research on anatomicalregions identification and isolation is very uncommon.

Proposed Method

Digital Mammograms requires a preparation phase in order to improve the image. Theobjective during this process is to improve the quality of the image for better segmentation results. Any anatomical regions of living beings are of closed structure and bounded by a periphery. Breast is also consisting of bounded anatomical regions. Hence, the edge map indicates various closed structures within the breast region that corresponds to the different anatomical regions of the breast namely, the fatty tissues, ducts, lobules, glands, irregular mass and calcifications. The objective of process is to clearly identify these regions on the mammogram image and erase all other unwanted edges, lines and dots from the edge map for further processing and analysis.In this paper Anatomical Segmentation of breast is proposed. The process is started by identifying the left baseline i.e. chest wall of the breast image from the edge map and draw a line vertically from top to bottom of the edge map identifying the left boundary or the horizontal reference of the breast. In the next step, the breast boundary is scanned on the right side to locate the rightmost pixel on the breast contour. After the rightmost pixel is identified, another vertical line is drawn from top tothe image horizontally into N number of distinct segments, like a ladder as shown in Figure 1. All complete paths are then plotted on another image thus providing the anatomical regions of the breast.

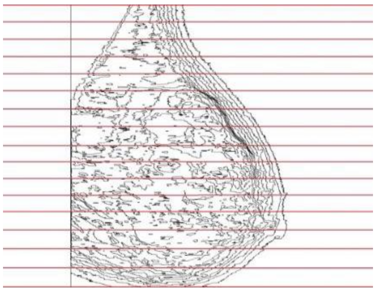
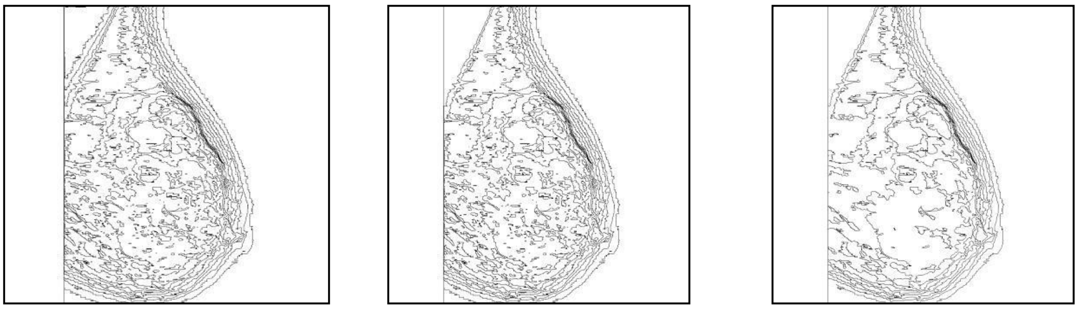


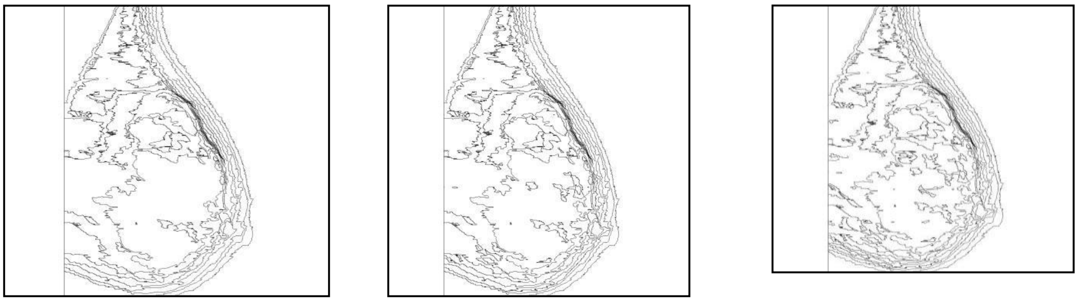
Figure 1 Proposed Ladder to Extract the Anatomical Segmentation

If the value of N is higher it will identify smaller regions but running time will be higher, at the same time the value of Nislesser, the running time will reduce but there is a chance to loss of some smaller region which has got high importance like calcifications inbreast. Figure 2 and figure 3 shows edge map and anatomical Region of Interest (ROI).

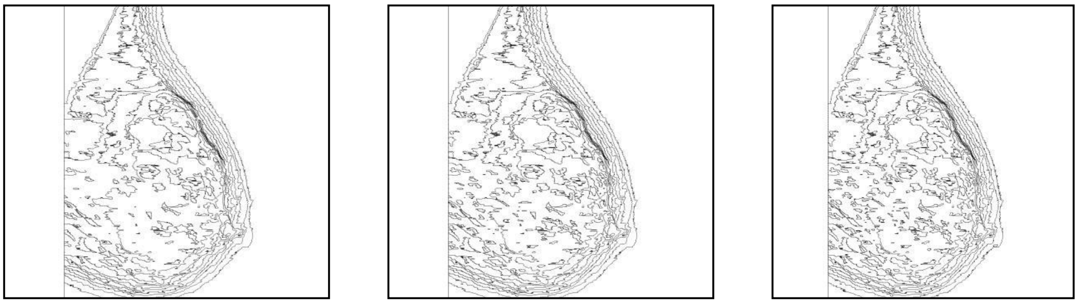


(a) (b) (c)

Figure 2(a)The Edge Map, (b)Edge Map within ROI and (c)Anatomical Regions of ROI



(a) (b) (c)



(d) (e) (f)

Figure 3. Anatomical Regions of ROI with (a) 4 segments, (b) 8segments, (c) 16 segments, (d) 32 segments, (e) 64 segments and (f) 128 segments

Algorithm for Anatomical Segmentation of Breast ROI

Step 1. Locate the leftmost pixel of the breast region by scanning the image from left side.

Step 2. Draw a vertical line along this pixel from top to bottom representing the Left baseline or chestwall.

Step 3. Locate the rightmost pixel of the breastregion by scanning the image from right side.

Step 4. Draw a right vertical line along this pixel from top tobottom.

Step 5. Partition the obtained rectangle horizontally into N number of segments and start with the first row of the firstsegment.

Step 6. Locate the enclosed rectangle from the right side to left, from the first row of the segment.

Step 7. Consider the pixel with the highest priority after considering surrounding pixels in a clockwise.

Step 8. The pixels that surrounded the edge pixel, but are of lower priority are stored in a Backtrack Stack to be used only if the traversal process reaches a deadend.

Step 9. Pop out from the Backtrack stack a lesserpriority pixel after dead end reached and continue with the traversalprocess.

Step 10. Pixels traversed are stored in a Plotting List for plotting.

Step 11. Continue the process to the next pixel till it reaches the left baseline or the bottom of the image or the start position is reached.

Step 12. The plotting list is erased if traversal is terminated and continues from Step7

Else draw pixels from the Plotting List.

Step 13. Same process is continue from Step6 till all black pixels, indicating an edge path, is traversed.

Step 14. Move to the first row of the next segment and continue from Step6.

Complexity Analysis of Algorithm

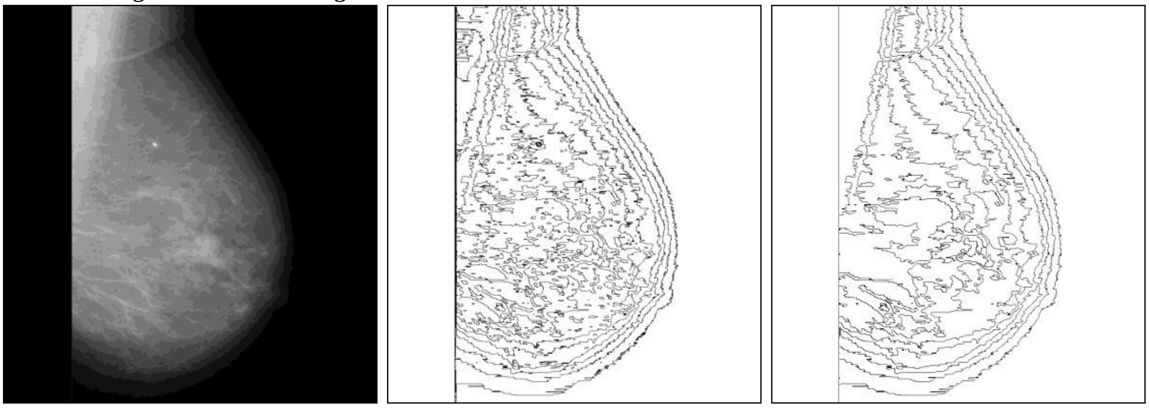
The algorithm is consisting of two iterations. The outer loop is for the N numbers of segments and the inner loop is to search the edge path which are originated or within a segment. Here outer loop is invariant. At start of every iteration of outer loop, eachsegment of the edge map image x = 1, 2, …, N. Initially x = 1 i.e. it is at first segment of the image before the first iteration of the outer loop, so, the invariant is initially true. It is at the position Image[1][y]. In each successive iteration loop invariant moves to next segment by incrementing x. Loop works by moving Image [x + Δ][y], Image [x + 2Δ][y], Image [x + 3Δ][y] and so on. The outer loop ends when x > image height, i.e. all the segment of the image is already traversed. Assuming the height=n and width=m from left vertical line to right vertical line, the running time of the algorithm is O(n*m) i.e.$O(n^2)$.

Results Analysis

The proposed algorithm is used in different test cases readily available in the public domain for academic research like MIAS. According to presence of percentage of fatty tissue, breasts are divided into three types, namely Fatty, Fatty-Fibro Glandular and Dense-Fibro Glandular. All the aforesaid types are considered and some of the examples are cited here considering all the types.

Experiment: FattyTissue

Results obtained by applying the proposed segmentation algorithm on mammogram comprising of Fatty tissues are shown in figure 4 and figure 5.



(a) (b) (c)

Figure 4 (a) Original Mammogram, (b) the Edge Map within ROI and (c) Anatomical Regions of ROI with 16 segments

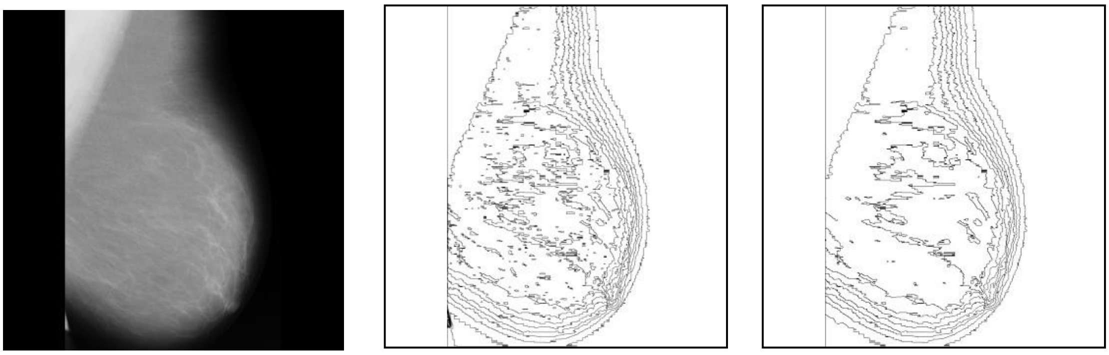


Figure 5 Original Mammogram, the Edge Map within ROI and Anatomical Regions of ROI with 16 segments

Experiment: Fatty-Fibro Glandular Tissue

Results obtained by applying the proposed segmentation algorithms on mammogram with Fatty-Fibro Glandular tissues are shown in figure 6 and figure 7.

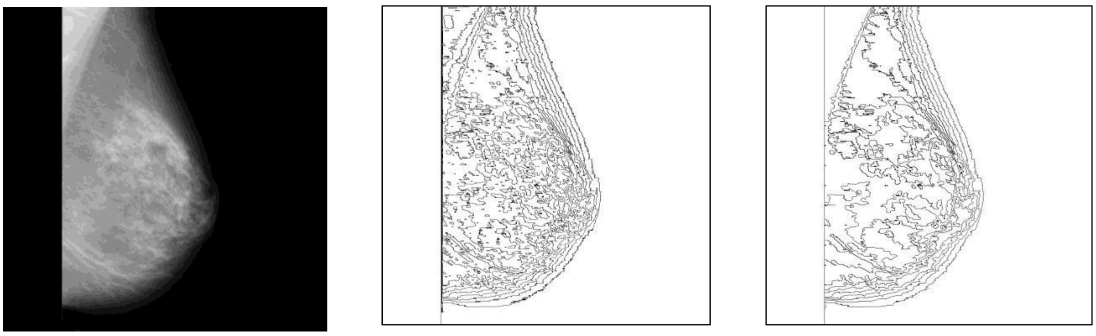


Figure 6 Original Mammogram, the Edge Map within ROI and Anatomical Regions of ROI with 16 segments

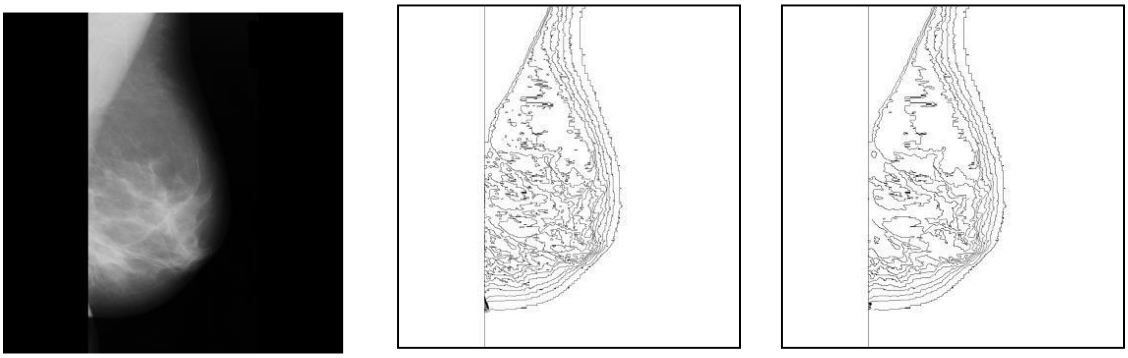


Figure 7 Original Mammogram, the Edge Map within ROI and Anatomical Regions of ROI (MIAS 052.L) with 16 segments

Experiment: Dense-Fibro Glandular Tissue
Results obtained by applying the proposed segmentation algorithms onmammogram with Dense-Fibro Glandular tissues are shown in figure 8 and figure 9.

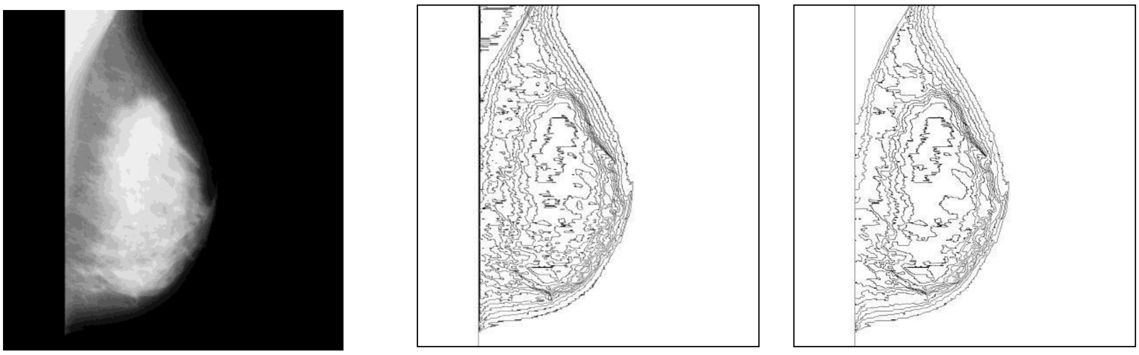


Figure 8 Original Mammogram, the Edge Map within ROI and Anatomical Regions of ROI with 16 segments

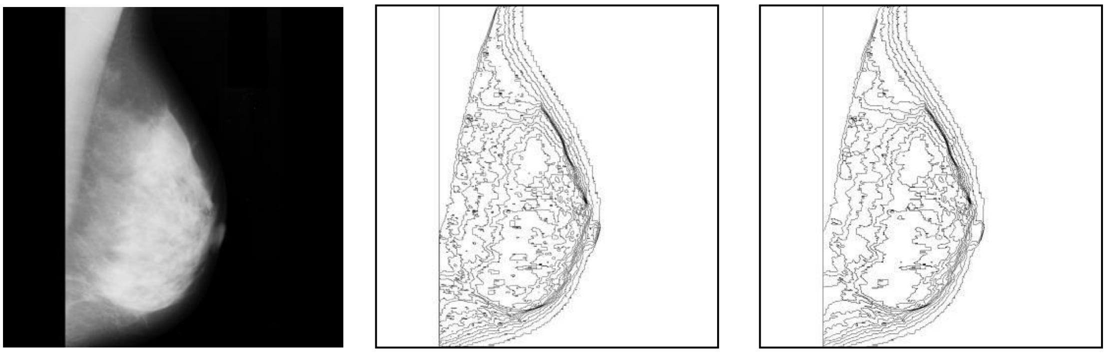


Figure 9 Original Mammogram, the Edge Map within ROI and Anatomical Regions of ROI with 16 segments

Quantitative Analysis
Using the Quantitative analysis parameters already mentioned reapplied on the obtained ROI in comparison with the Ground Truth(GT) image. The GT image is obtained by manual segmentation and verified by radiologist. The accuracy test conducted on all the 322 mammogram images in MIAS database, the proposed algorithm has obtained the following average result on different quality measures. These results are shown in figure 10, figure 11, figure 12 and Table 1.

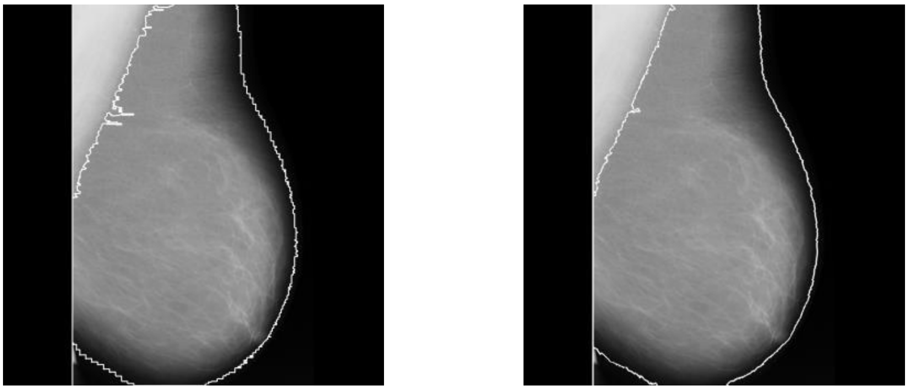


Figure 10 Derived Outline of ROI and Ground Truth of Mammogram Predominantly Comprised of Fatty Tissues

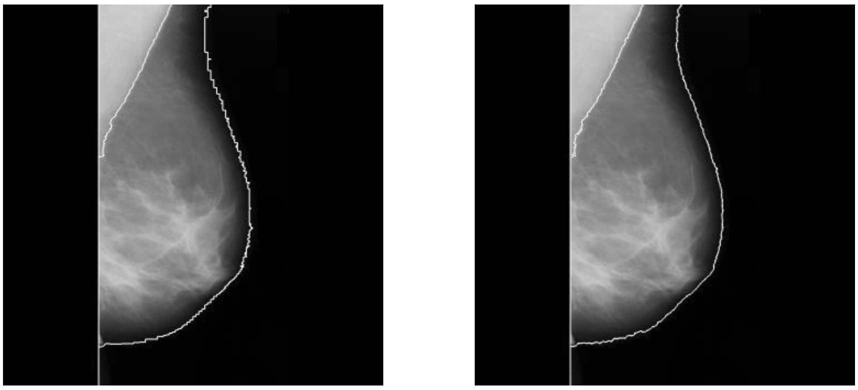


Figure 11 Derived Outline of ROI and Ground Truth of Mammogram Predominantly Comprised of Fatty-Fibro Glandular Tissue

Figure 12 Derived Outline of ROI and Ground Truth of Mammogram Predominantly Comprised of Dense-Fibro Glandular Tissue

Table: 1 Common Measures Used in the Evaluation of the Proposed Method

Common measures	Computation	Mean Result
Accuracy (Percentage agreement)	(|TN|+|TP|)/(|TN|+|TP|+|FP|+|FN|)	0.9944
Dice similarity coefficient (DSC)	(2×|TP|)/(2×|TP|+|FP|+|FN|)	0.9838
Error rate	(|FP|+|FN|)/(|FP|+|FN|+|TP|+|TN|)	0.0055
Sensitivity (Percentage of Correct Estimation) / Completeness (CM)	|TP|/(|TP|+|FN|)	0.9944
Correctness (CR)	|TP|/(|TP|+|FP|)	0.9892
Specificity (True Negative Fraction/Rate)	|TN|/(|TN|+|FP|)	0.9892
False Positive Fraction/Rate	1 – Specificity	0.0107
Under estimation fraction (UEF)	|FN|/(|TN|+|FN|)	0.0028
Over estimation fraction (OEF)	|FP|/(|TN|+|FN|)	0.0055

The outcome of the method described in this chapter is the anatomical differentiation of breast region and obtaining the ROI of the breast. An accuracy analysis has already been done on the Pectoral Isolation and Breast contour detection as described in the earlier chapters. The result on ROI obtained confirms the effectiveness of the methods described. Anatomical Segmentation is a pre-requisite step for further detection of mass and other abnormalities. The effectiveness of the segmentation algorithm can only be analysed through the results obtained in the methods that use the segmented image as the input for their algorithm. A detailed statistical analysis has been described in the next chapter where tumour detection has been performed.

Conclusions

The proposed method has been implemented producing anatomically segmented breast regions. Results of the proposed methods show are liable ROI detection and differentiation of breast region. Furthermore, due to its simple procedure the methods executes faster than other complicated methods. The segmentation algorithms have been tested extensively.Theproposedmethodhasbeentestedwithcommonlyavailablemammogram databases.

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