Adaptive Edge Detection Technique Towards Features Extraction from Mammogram Images

Indra Kanta Maitra[1], Sangita Bhattacharjee[2], Debnath Bhattacharyya[3], Tai-Hoon Kim[4] and Samir Kumar Bandyopadhyay[2,*]

[1]*B.P.Poddar Institute of Management and Technology, Kolkata, WB, India*

[2]*Dept. of Computer Sc. and Engg, University of Calcutta, Kolkata, WB, India*

[3]*Bharati Vidyapeeth Deemed University College of Engineering, Pune, Maharashtra, India*

[4]*Sungshin Women's University, Dongseon-dong 3-ga, Seoul, Korea*

Abstract: Cancer is one of the most dreaded diseases of modern world. Breast cancer is the second most type of cancer & the fifth most common cause of cancer related death so it's a significant public health problem in the world especially for elderly females. Computer technology specifically computer aided diagnosis (CAD), relatively young interdisciplinary technology, has had a tremendous impact on medical diagnosis of cancer detection due to its accuracy and cost effectiveness. The accuracy of CAD to detect abnormalities on medical image analysis requires a robust segmentation algorithm. To achieve accurate segmentation, an efficient edge-detection algorithm is essential. The mammogram is a comparatively efficient and low cost diagnostic imaging technique for breast cancer detection. In this paper a robust mammogram enhancement and edge detection algorithm is proposed, using tree-based adaptive thresholding technique. The proposed technique has been compared with different classical edge-detection techniques yielding acceptable out come. The proposed edge-detection algorithm showing 0.07 p-values and 2.411 t-stat in one sample two tail t-test (α = 0.025). The edge is single pixeled and connected which is very significant for medical edge-detection.

Keywords: Mammogram, CAD, Edge Detection, Full and Complete Binary Tree, Adaptive Threshold, Histogram, Average Bin Distance (ABD), Maximum Difference Threshold (MDT), Prominent Bins, t-Test.

1. INTRODUCTION

Every year breast cancer is newly diagnosed in more than one million women worldwide and more than four lakh women die from it [1, 2]. The mortality incident ratio is much higher in developing countries than in developed countries. Only half of the global breast cancer are diagnosed in developing world but they account for three fourths of the total deaths from the disease [1]. Early and efficient detection, followed by appropriate diagnosis is the most effective way for treatment to reduce mortality. Mammography has been proven to be the most effective and reliable screening method for early breast tumor detection. The interpretation of medical images is still almost exclusively the work of humans but in the next decade this is expected to change. Computers will be used more often for image interpretation. This research area is known as CAD.

Computerized medical image analysis is critical in numerous bio medical applications such as detection of abnormalities, tissue measurement, surgical planning and simulation, and many more. In particular image segmentation is an essential step, which partitions the medical image into different non-overlapping regions such that each region is nearly homogeneous and ideally corresponds to some anatomical structure or region of interest (ROI). It is a main tool in pattern recognition, object recognition, image restoration, image segmentation and scene analysis.

Process of identification of sharp discontinuities of an image is called edge of an image i.e. edges are significant local changes of intensity. Here the discontinuities mean abrupt changes of pixel intensity of image. Thus, intensity causes basically geometric events and non-geometric events; geometric events basically discontinuity in entropy and/or color depth and texture i.e. object boundary and discontinuity in surface and/or color and texture i.e. surface boundary and non-geometric events basically direct reflection of light called specularity and inner reflection or shadow from other objects or same objects. In high level image vision, edge detection is used in the interpretation of 3D objects from 2D images obtained from an image occulation in radiological imaging. The goal of edge detection is to produce a continuous line drawing of a scene from an image of that scène. Important features can be extracted from an image and these features can be used by high level computer vision and decision making algorithms for analysis.

*Address correspondence to this author at the Depatment of Computer Sc. and Engg, University of Calcutta, JD Block, Sec III, Salt Lake, Kolkata 700098, WB, India; Tel: 919831030823; E-mail: skb1@vsnl.com

ISSN: 1929-2260 / E-ISSN: 1929-2279/16

The anatomical features of breast can be either at the surface or internal. The former include skin boundary [3] and nipple [4], while the later include the pectoral muscle, fibro-glandular tissue and vasculature. Imaging techniques provide an effective means of non-invasive mapping of the anatomy of an organ of a patient. The relative change in size, shape and spatial relationships between anatomical structures obtained from the intensity distributions provide important information in clinical diagnosis.

In this citation a new edge detection algorithm for gray scale mammogram images using DICOM format has been proposed. In the later part of this citation we have described some of the popular edge detection techniques. The material and method section contains description about dataset and proposed edge detection method, and in the third section results of the proposed method are discussed and analysed. Final section contains the conclusion of this citation.

1.1. Literature Review

It is found that edge detection operators depend on the response to the change in intensity values. So to choose an operator that will respond to changes in intensity values is a vital process, it is found that the wavelength-based method is useful to differentiate the edges in a medical image. To generalize, we can say that, most of the methods are based on gradients in all images, thus, all edge detection methods cans be categorized into three broad ways: (i) The maximum and minimum values derived from the first derivative is useful to obtain the edges by the gradient method, ii) the second order derivative has helped to find the zero crossings and detect the edges in an image by the Laplacian method and iii) other recent methods of edge detection used divergent techniques to derive the edge which is discussed in this section later.

In Sobel's operator [5, 6] method the direction of the edges is obtained from the direction of gradient. The magnitude of the gradient is obtained from both the kernels running, one from north-south direction and one from east-west direction. Whereas, Robert Cross's method [7] is similar to Sobel's as one kernel is perpendicular to the other but in this citation the gradients of each input image at a particular point determines the output pixel's gradient. Prewitt's operator [8] also has a subtle relation with Sobel's operator but here, the partial derivative is used for detecting the horizontal as well as vertical edges of an image.

The Laplacian of Gaussian [9] is the second order partial derivative of a 2D image. By the application of Gaussian smoothening operators the frequency of noise has been reduced in an image and then the Gaussian standard deviation is performed to detect the prominent edges in an image. In the optimal edge detection algorithm by Canny [10], first derivative of the Gaussian result is considered, then the result of the product between the ratio of signal -noise and localized edges after suppressing the edges which are not maximum, yields the final edges. Frei-Chen's [11] edge detector method has combined 4 pairs of wavelengths, two are first degree partial derivative of Gaussian smoothening function and other two are mixed partial derivative of Gaussian smoothening function which are found to be sensitive to step edges. The steps for Canny's edge detection are:

$$fx= \partial/\partial x(f*G), \text{ hence } fx=f*G_x$$

Similarly for y it is, $fy= \partial/\partial y(f*G)$, hence, $fy =f*G_y$

Therefore, the Gaussian functions i.e. G_x (x, y), G_y (x, y) is the derivate of G(x, y) with respect to x and y, respectively yielding:

$$G_x(x, y) = -x/\sigma^2\, G(x, y) \text{ and } G_y(x, y) = -y/\sigma^2\, G(x, y)$$

The performance of the Canny's algorithm [10] depends heavily on the adjustable parameters, σ, which is the standard deviation for the Gaussian filter, and the threshold values, 'T1' and 'T2'. σ also controls the size of the Gaussian filter. The greater the value for σ, the larger the size of the Gaussian filter.

The citation by Zhang [12], the Viterbi algorithm has shown the hidden state to map the estimation and evaluate the result of the edge detection algorithm based on the coefficient obtained at each step. Whereas F. Jassim [13] in his citation step by step edge detection on gray scale image preceded by denoising to smoothen the image pixel is followed. In this citation, the upper left pixel in the 2x2 window represents an edge and the differences observed visibly between the edges proposed and the standard edge detectors is shown. Instead of detectors for filtering purpose N.C Woods [14] used spammers to filter out the edges with the help of Optical Character Recognition. The global magnitudes of edges in an image are obtained from filtering the low level features which classified the image into spams.

If value of Gaussian filter is higher, than more blurring will be required to detect the edges ,also

Prewitt's filter is found to be sensitive to noise which acts as a hindrance in edge-detection. Canny's algorithm is highly complex compared to Sobel's, Robert's, and Prewitt's, whereas, it is found to be performing better than the others under all circumstances. In discussion section, a comparative study has been cited between the proposed method and other classical methods.

2. MATERIALS AND METHODS

2.1. Dataset

Three types of mammogram imaging techniques are most commonly practiced in clinical diagnosis. The first one is the traditional film mammography whereas remaining two techniques are computed radiography (CR) and digital radiography (DR) mammogram system. The latter two types of technique using electronic signals and returns back response to the requesting machine, therefore, CAD can be deployed on these two methods. The DICOM (Digital imaging and communication machine) image format is used by both CR and DR mammography. In CR 2^8 and in DR 2^{12} or 2^{16} gray scale color intensities values are used to represent the 8 bits or the 12/16 bits in the DICOM image format.

The proposed adaptive thresholding edge detection algorithm has been extensively tested with two well-known mammogram databases namely, MIAS (Mammographic Image Analysis Society) digital mammogram database with 322 mammogram images of 8 bit category and DEMS (Dokuz Eylul University Mammography Set) database with 485 mammogram images of 16 bit category. The MIAS database is 8 bit .png image whereas DEMS is 16 bit DICOM image. The DEMS database is based on DR mammography system. For experimental purpose CR images obtained from different medical institutes has been considered but due to ethical issues and anonymity of the patients, the results are not published here.

Any gray scale image is basically a 2D array of pixel intensities where intensities ranging from k=0 to n. In CR mammogram DICOM images the gray shade is ranging from k=0 to 255 whereas in DR it is k=0 to 2^{12} or 2^{16}. So the intensity of the image is the primary feature to determine the abnormality. The significant variation is observed in CR and DR mammogram images at the same time distinguishable variation of intensity can also be marked in different makes of mammographic machine of same type as well as version of the same make. Hence, a robust adaptive thresholding algorithm is required to determine the discontinuation in mammogram image for regional segmentation. The proposed method consists of three parts where the first part is to calculate the adaptive threshold i.e. maximum distance threshold (MDT), in subsequent part is to generate enhanced image and finally to determine the edge map of the original mammogram.

2.2. Calculation of Adaptive Threshold

In this research paper, a modified full and complete binary tree is used to accommodate both the intensity and frequency measures. A binary tree can be defined as a full binary tree if the entire node contains exactly two child nodes whereas complete means if all levels of tree except possibly the last are completely full. The objective in constructing such a tree is to obtain an image with reduced number of color, yet maintaining the full color palette; thus achieving color quantization at every tree level.

The proposed data structure, all the possible color of an image can be represented by the leaf nodes i.e. if the image contains 2^n number of distinct colors then the tree will have 2^n leafs at level n. The node structure of the said binary tree will contain pointers for left and right child along with image data. The data will have two components i.e. color intensity and its frequency present in the image. The frequency of intensity of left child node $f(L)$ and right child node $f(R)$ whichever is greater, will be the intensity of the parent node. The frequency for the node will be the summation of $f(L)$ and $f(R)$. As per the proposed algorithm the parent node will hold the intensity value of the child node that has a greater frequency among the two child nodes. To achieve the same the tree has to be traversed in postorder manner. According to the postorder traversal of tree the left child node and the right child node is traversed before the parent node, making it possible to compare the intensity frequencies of the child nodes. The intensity value of the parent node is updated based on the comparison results of the child nodes. This process is continued till the intensity value of the image data for root node is achieved.

The tree structure that is obtained by the above procedure contains the histogram of the original image with 2^n gray shades at level n and in every subsequent upper level contains 2^l number of gray shades. The intensity values of intermediate nodes can contain any gray shade values, thus preserving the original color

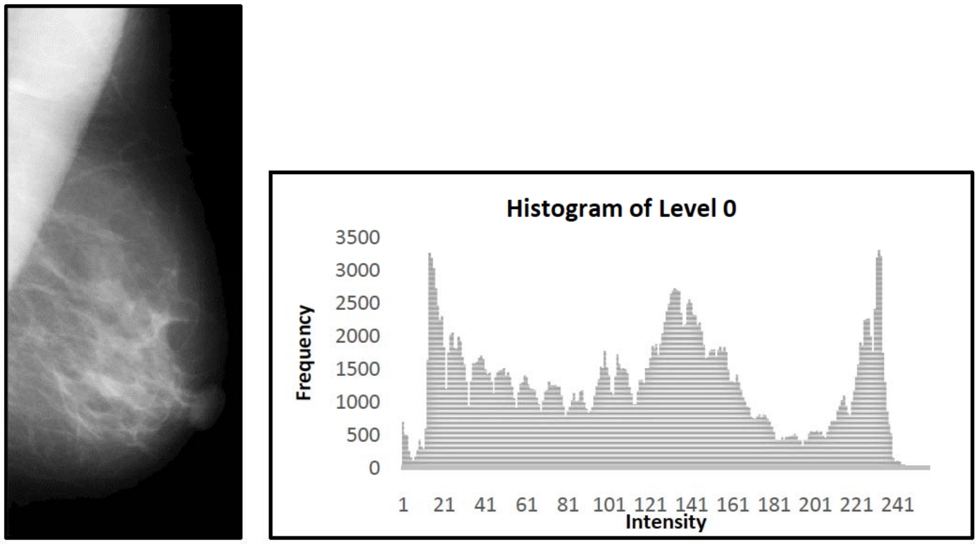


Figure 1: Original Flipped Mammogram Image (MIAS 047) along with Histogram of Level 0.

palette and performing uniform color quantization at every level. Appropriate level of the aforesaid data structure can be utilized to accommodate different cases depending on the intensity characteristics to obtain optimal result. Moreover, to highlight or segment out a portion of any image intensity, different parts of multiple levels can be utilized.

In this proposed method, color intensities and their frequencies are extracted from the original image color space to generate the histogram. A histogram is a function that counts the number of observations that fall into each of the disjoint categories. The extracted histogram data are stored in the leaf nodes of the proposed tree i.e. each leaf node representing individual disjoint intensity sequentially. By definition, total number of nodes (tNode) in a Complete Binary Tree of height h is 2^h-1, whereas, the number of terminal / leaf nodes (lNode) is 2^{h-1} in a Complete Binary Tree. Hence, the number of internal nodes (non-leaf nodes) is iNode = tNode – lNode. So, the propagation of histogram data will be started from iNode + 1 upto tNode. The complexity of this algorithm is that we have assumed the height = width = n, the running time of the algorithm is Θ (n^2) for all cases.

LEVEL-HISTOGRAM is an important process to generate color quantized histograms for each subsequent level of tree with reduced number of color i.e. half number of colors upto the root in bottom-up mode. The way LEVEL-HISTOGRAM works:

- It will work for all leaf nodes i.e. iNode (h) + 1 to tNode (h).
- Compare frequency count of Tree [i] with child nodes i.e. Tree[Left (i)] and Tree[Right (i)], intensity of the larger will be propagated to parent intensity and sum of frequency count of children will be the frequency count of parent.
- The iteration will be terminated when the parent node is the root of tree.

Whereas to generate quantize color space in different levels, the complexity found is to assume that the number of leaves is lNode (h) = 2^h, so, the outer loop will execute 2^h number of times. To traverse from a leaf to root, lg(h-1) number of iteration is required. The inner loop will be executed 2^hlg(h - 1) times. So, the running time of the algorithm is Θ (2^h. lg(h - 1)) for all cases.

In each level, half of intermediate colors bin are truncated depending on the condition stated above. This intermediate truncation will generate different bin distance in the histogram of particular level of the Tree. The process BIN-DISTANCE will calculate the average bin distance of that histogram. The Average Bin Distance (ABD) is the mean of different bin distance in the histogram. The way BIN-DISTANCE has been calculated.

- It will work for a particular height (h1) of the Tree.
- The iteration will start from first node i.e. iNode (h1) upto the last node i.e. tNode (h1) of particular height of the Tree.
- Summing the intensity distance between all adjacent nodes sequentially and calculate

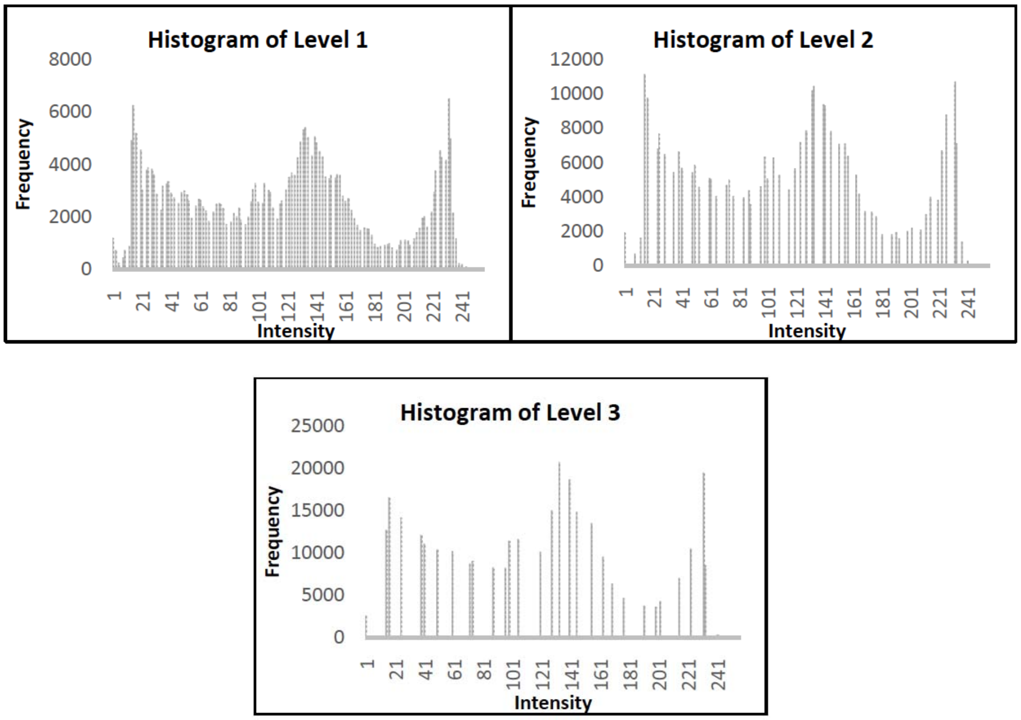


Figure 2: Level 1, Level 2 and Level 3 Histograms of Mammogram Image.

average bin distance (ABD) dividing by the number of bins.

Assuming that the Tree with height h, the complexity here is the number of node = tNode (h) - iNode (h), so, the loop will execute tNode (h) - iNode (h) number of times. Therefore, the upper bound of the running time will be O (2^h) in ABD.

CALCULATE-MDT process first segregates the bins into two categories namely, Prominent Bins and Truncated Bins. Prominent Bins are the points of histogram from where sharp change intensity values are recorded. Whereas, Truncated Bins has an insignificance difference of intensity with its adjacent bins. Prominent bins have a significant role to determine edges of an image. Using the prominent bins, CALCULATE-MDT process generates the Maximum Difference Threshold (MDT). The outline of CALCULATE-MDT:

- It will work for a particular height (h1) of the Tree.
- The iteration will start from first node i.e. iNode (h1) upto the last node i.e. tNode (h1) of particular height of the Tree.
- It will compare the intensity difference of a node with its previous node with ABD. If intensity difference is greater than the ABD, it will be marked as prominent node else it will be marked as truncated.

In MDT, the complexity is assumed as that of ABD but here the inner loop will be executed in maximum times for all leaf node of the Tree. For the leaf node of the Tree, loop will be executed in maximum times. For intermediate height of Tree loop will be executed in lesser number of times, rest is similar to ABD.

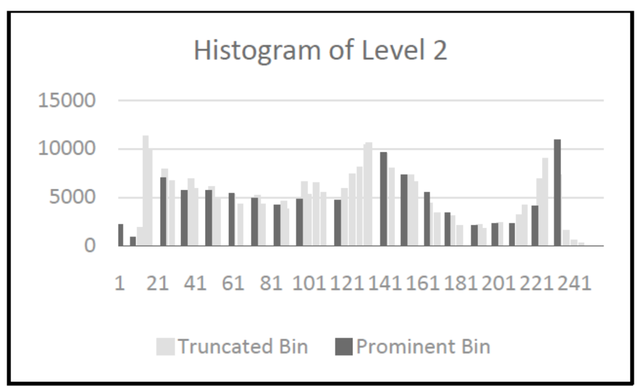


Figure 3: Histogram of Level 2 showing Prominent Bins in dark along with other bins.

2.3. Generation of Enhanced Image

In this phase, the ENHANCED-IMAGE will be generated from the original mammogram image. The derived Intensity of a particular pixel has been calculated using the truncated histogram from the tree

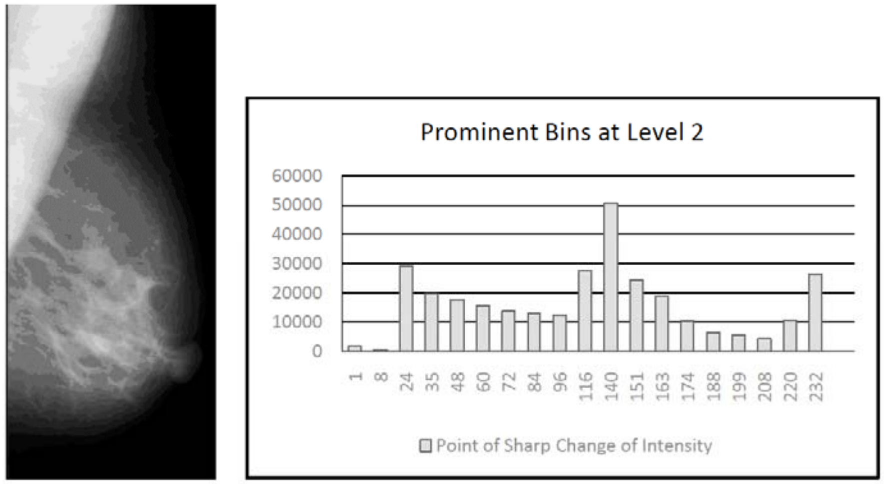


Figure 4: Enhanced Mammogram and Prominent Intensity Bins at Level 2 showing Point of Sharp Change.

of a particular level. Initially mapping between original histogram at level (h-1) and the desired level histogram at level h1 has been done. From mapping process a particular intensity has been selected from the level histogram and checking has been performed whether the obtained intensity is prominent or not. If the obtained intensity is prominent one then it will be propagated to the image pixel, else the next higher prominent intensity will be selected from the level histogram to propagate.

2.4. Generation of Edge Map

In the previous process, the enhanced image has been generated by using the level histogram of a desired level. In this part of the algorithms the HORIZONTAL-EDGE-MAP i.e. *f*(*h*) will be obtained using the aforesaid enhanced image. The process will scan the enhanced image in row major order. It will be started from the left most pixels from first row and terminated at the right most pixel of the last row. Here two consecutive pixels i.e. current Intensity and next Intensity respectively are compared. If the absolute value of the difference is greater than the MDT then the corresponding pixel position of the HozEdgeMapImage image will be set to 0 i.e. black else 255 i.e. white.

$$f(h) = \sum_{i=0}^{r}\sum_{j=0}^{c} P_{i,j} = \begin{cases} 0, & \left|P_{i,j} - P_{i+k,j}\right| > MDT \\ 255, & \left|P_{i,j} - P_{i+k,j}\right| < MDT \end{cases}$$

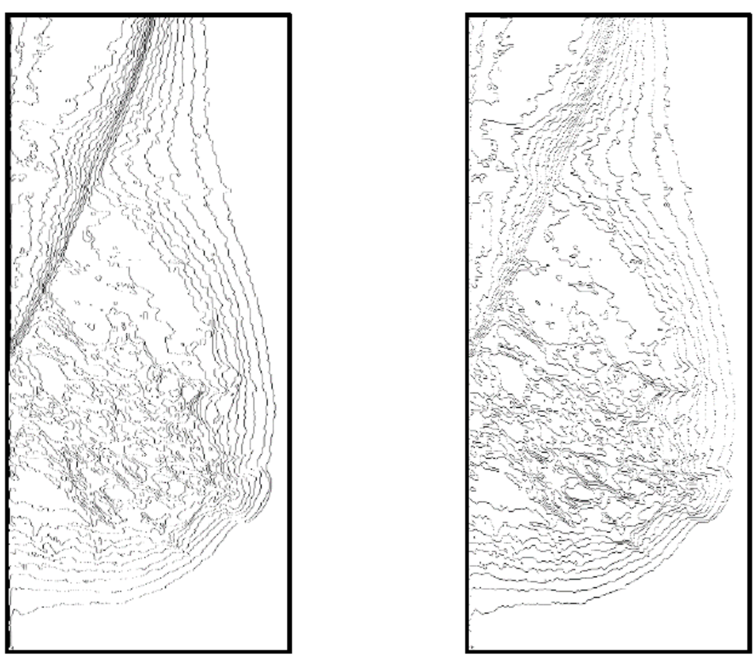


Figure 5: Horizontal and Vertical Edge Map in Level 2.

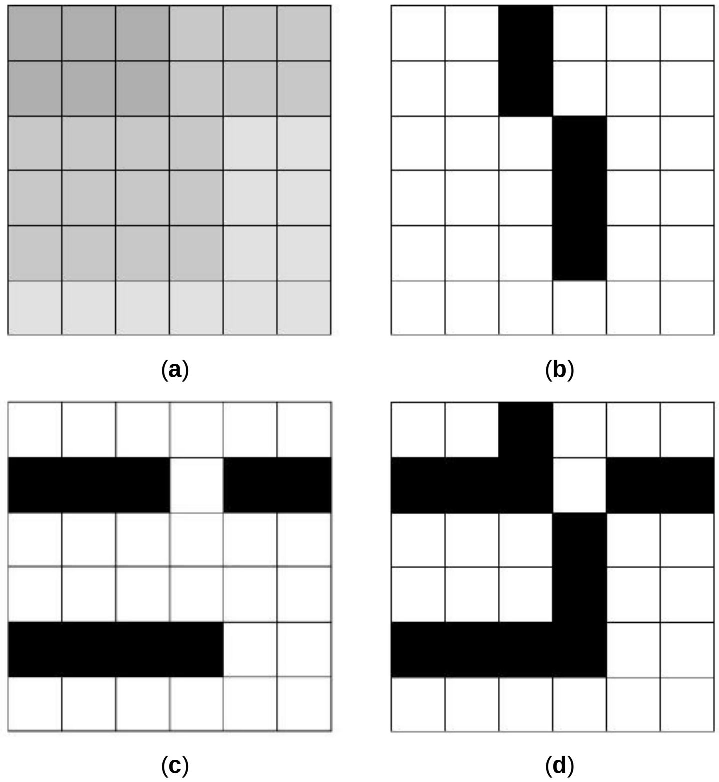


Figure 6: Edge detection steps (**a**) The 6X6 pixel 2-D array of original image, (**b**) The 6X6 pixel 2-D array of image after performing the horizontal edge map image, (**c**) The 6X6 pixel 2-D array of image after performing the vertical edge map image and (**d**) The 6X6 pixel 2-D array of image after performing the Union showing complete edge map image.

For VERTICAL-EDGE-MAP i.e. *f*(*v*) detection, algorithms is similar to the above horizontal edge detection algorithm except it sets pixels vertically i.e. in column major order rather thsan horizontally. Assuming that the height of the image is r and width of the image is c, the complexity in generating the horizontal and vertical edge map is the maximum number of iteration of loop is r*c. Thus if r = c = n then the complexity of the above algorithm is O (n^2).

In previous two methods horizontal edge map and vertical edge map images has been obtained. In this process the horizontal and vertical edge map are super impose in each other using logical OR operation.

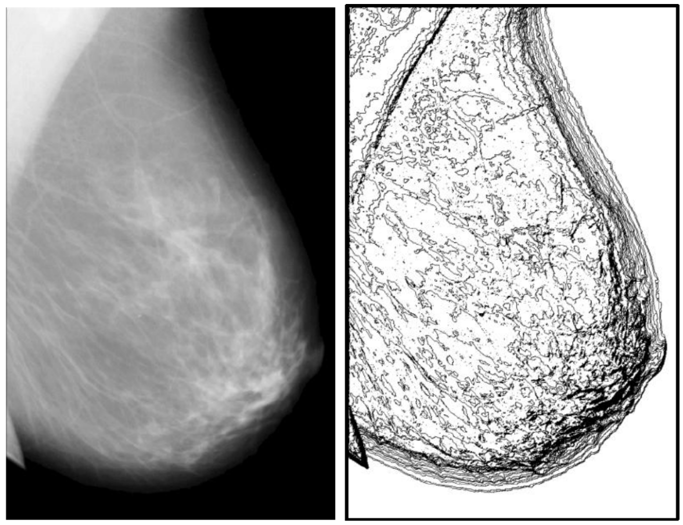
$$EdgeMap = f(h)\, V\, f(v)$$

The superimposed output image will be the obtained edge of the mammogram i.e., EDGE-MAP-IMAGE. It is the final outcome of the research paper which can be applicable to any mammogram.

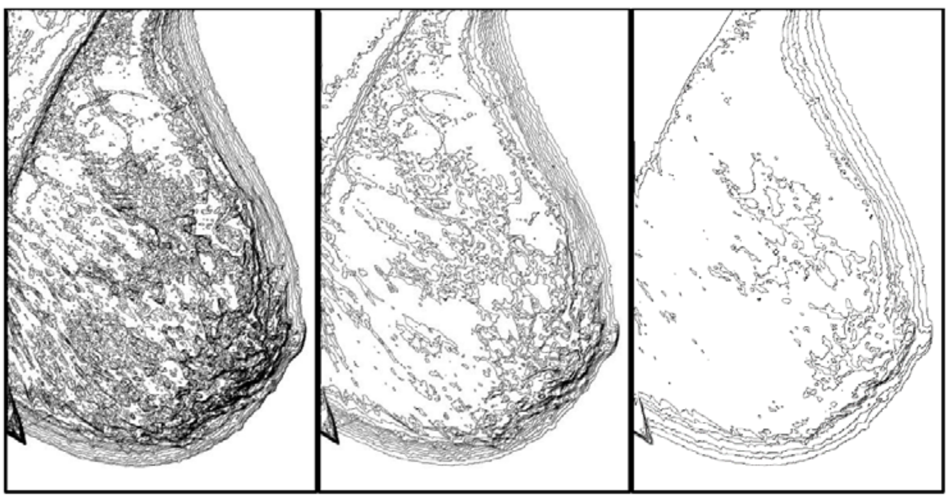
3. RESULTS

As mentioned earlier, the proposed adaptive thresholding edge detection algorithm has been extensively tested with two well-known mammogram databases namely, MIAS and DEMS mammographic databases along with CR images obtained from different medical institutes. The MIAS database is 8 bit

Figure 7: Derived Edge of the Mammogram Image at Level 2.



(a) (b)



(c) (d) (e)

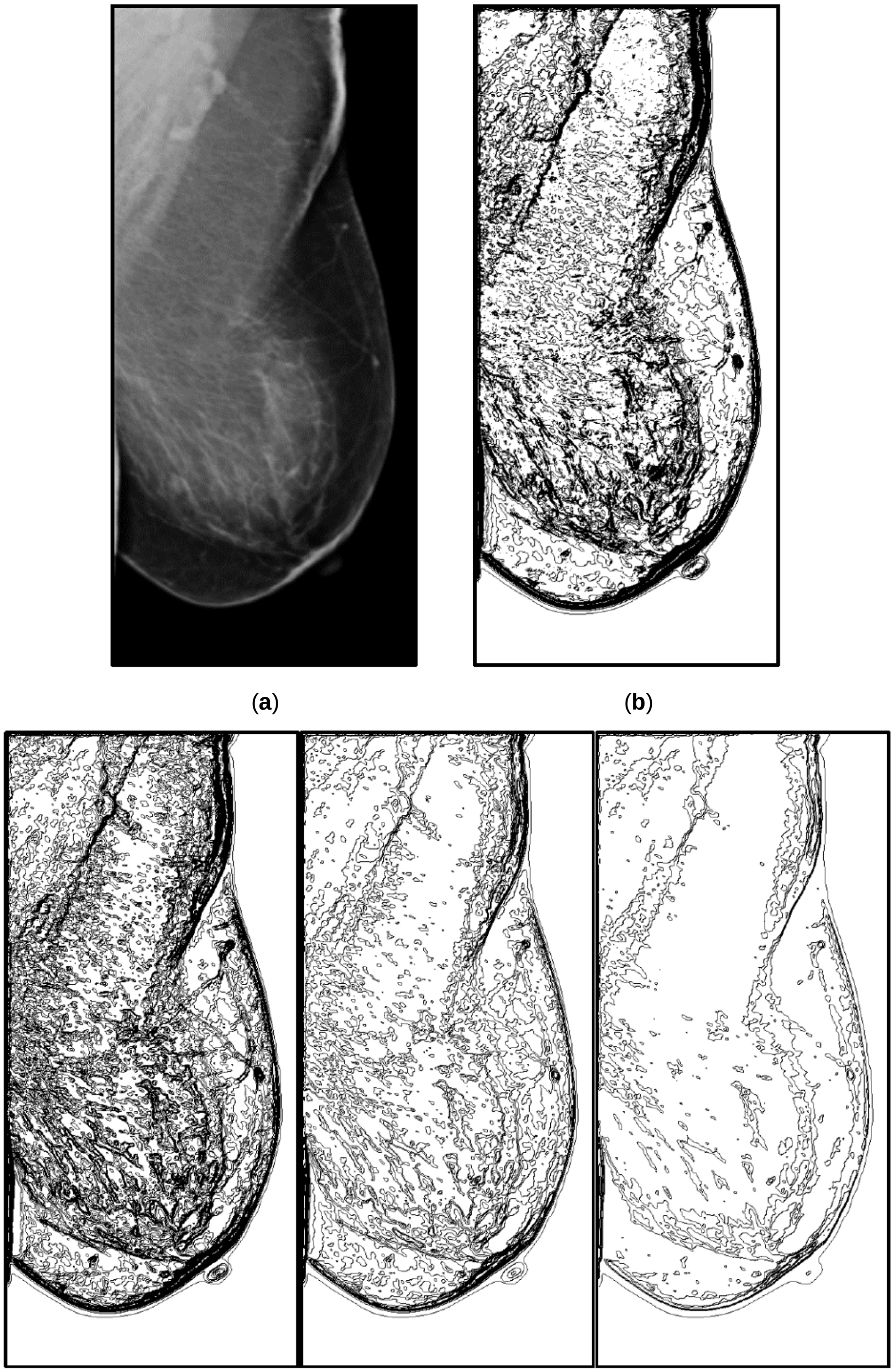
Figure 8: Mammogram Image from MIAS (mdb160L) – (**a**) Original Image, (**b**) Derived Edge at Level 0, (**c**) Derived Edge at Level 1 and (**d**) Derived Edge at Level 2.

.png image whereas DEMS is 16 bit DICOM image. Sample outputs of two different types are cited in Figures **8** and **9**. After consulting with medical experts and by observations, it has been recorded in general second level decomposition of 2^8 color bins and fifth level decomposition of 2^{16} can be treated as default level due to most of the important edges are preserved leaving behind the redundant edges. Over decomposition may lead to loss of information whereas under decomposition may cause presence of insignificant edges leads to false identification of feature extraction.

3.1. Result Evaluation

Performance evaluation in algorithm design is an important step that is commonly neglected. What constitutes an “acceptable” result differs significantly, and is often based on visual subjective opinion with very little quantitative endorsement [15]. So, it is needed to derive a quantitative measure to get the accuracy of the proposed segmentation method. The "masks" derived is compared with the Ground Truth (GT) to obtain the measures of "True Positive (TP)","False Negative (FN)" and "False Positive (FP)"."True Positive" denotes the intersection of obtained mask and GT indicating the actual match between the two. "False Negative" is the under-segmented region that is absent in "mask" whereas in "False Positive" it is the over segmented region that is absent in GT.

Using the Quantitative analysis parameters mentioned are applied on the obtained breast



(**a**) (**b**)

(**c**) (**d**) (**e**)

Figure 9: Derived Edge of DR Mammogram Image from DEMS (60 RMLO) - (**a**) Original Image, (**b**) Derived Edge at Level 8, (**c**) Derived Edge at Level 7, (**d**) Derived Edge at Level 6 and (**e**) Derived Edge at Level 5.

boundary/contour in comparison with the GT image. The GT image is obtained by manual segmentation and verified by radiologist. The accuracy test conducted on MIAS and DEMS database, the proposed algorithm has obtained the following average result of CR and DR images on different quality measures.

3.2. Comparative Analysis

The results obtained by the application of the proposed algorithm are compared with the results obtained from the six renowned classical methods namely, Roberts, Sobel, Prewitt, Kirsch, LoG and Canny. The mean value of the edge map pixel is

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

Common measures	Computation	Avg. Result
Accuracy (Percentage agreement)	|TN|+|TP|/|TN|+|TP|+|FP|+|FN|	0.9986
Dice similarity coefficient (DSC)	2×|TP|/2×|TP|+|FP|+|FN|	0.8571
Error rate	|FP|+|FN|/|FP|+|FN|+|TP|+|TN|	0.0014
Sensitivity (Percentage of Correct Estimation)	|TP|/|TP|+|FN|	0.9294
Specificity (True Negative Fraction/Rate)	|TN|/|TN|+|FP|	0.9168
False Positive Fraction/Rate	1 – Specificity	0.0832
Under estimation fraction (UEF)	|FN|/|TN|+|FN|	0.0007
Over estimation fraction (OEF)	|FP|/|TN|+|FN|	0.0008

obtained for all the methods by considering only the edge pixels that are present within the breast ROI. Table **2** shows the average relative frequencies of the detected edge pixels using the edge detection algorithms for the entire dataset. The ratio of edge pixels with respect to each other provides a definitive comparative statistics for the occurrence of edges.

These derived values are analyzed using one sample two tail T-Test where Alpha is 0.025. A t-test is used in statistical hypothesis testing for checking whether the null hypothesis can be supported. It is used to determine if two sets of data are significantly different from each other. The ratio of edge map pixels between each other as shown in the Table **3** is used to perform the one sample two tail t-test to show their relative acceptance.

Table **3** summarizes the t-test performed on the relative frequency for every method with other methods described. The result obtained show that there is no significant difference among Sobel, LoG, Canny and the proposed algorithm. The p-value of proposed algorithm shows a higher value in comparison with

Table 2: Average of Relative Frequency (RF) of Detected Edge Pixels

	Roberts	Sobel	Prewitt	Kirsch	LoG	Canny	Proposed Algorithm
Roberts	1	3.3216	7.2299	4.9079	3.9192	2.9313	2.6839
Sobel	0.3010	1	2.1766	1.4775	1.1799	0.8824	0.8080
Prewitt	0.1383	0.4594	1	0.6788	0.5420	0.4054	0.3712
Kirsch	0.2037	0.6767	1.4731	1	0.7985	0.5972	0.5468
LoG	0.2551	0.8475	1.8447	1.2522	1	0.7479	0.6848
Canny	0.3411	1.1331	2.4664	1.6743	1.3370	1	0.9156
Proposed Algorithm	0.3725	1.2376	2.6938	1.8286	1.4602	1.0921	1

Table 3: One Sample Two Tail T-Test Result where α is 0.025

	Roberts	Sobel	Prewitt	Kirsch	LoG	Canny	Proposed Algorithm
Mean (μ)	0.2686	1.2793	2.9807	1.9699	1.5395	1.1094	1.0017
SD (s)	0.0877	1.0407	2.1266	1.4942	1.2152	0.9230	0.8461
Std Err	0.0358	0.4248	0.8681	0.6100	0.4961	0.3768	0.3454
t-Stat	7.5006	3.0110	3.4333	3.2292	3.1032	2.9442	2.8999
p-value	0.0006	0.0297	0.0185	0.0232	0.0267	0.0320	0.0337
Significant Difference	Yes	no	Yes	Yes	No	no	No

Table 4: Comparison of the Classical Methods with the Proposed Method Based on Important Parameters

Edge Operators	Convolution	Sensitivity to Noise	Single Pixel edge	Edge Continuity	Algorithm	Computational Time
Sobel	Yes	Yes	No	No	Simple	Slow
Roberts	Yes	Yes	No	No	Simple	Slow
Kirsch	Yes	Yes	No	No	Simple	Slow
Prewitt	Yes	Yes	No	No	Simple	Slow
LoG	Yes	No	No	No	Complex	Slow
Canny	No	No	No	No	Multi-Stage	Fast
Proposed Algorithm	No	No	Yes	Yes	Simple	Fast

others. The t statistics value of the proposed algorithm is very close to Sobel, LoG and Canny methods. It may be inferred that the edge map obtained from newly proposed method is acceptable.

The edge map obtained by the proposed algorithm is though similar to Sobel, LoG and Canny statistically but significantly better than them, as it forms a single pixel connected edge map rather than discrete edge pixels. This is extremely important for the image segmentation in medical image analysis. So, the occurrence of edge pixels that are connected with least sensitivity to noise is a remarkable achievement for the algorithm proposed in this research paper. The generalized comparative analysis of all the methods described in this paper, is summarized in Table **4**.

4. CONCLUSION

The proposed method is an edge detection algorithm to accommodate both the CR and DR mammogram images. This edge detection method can be applied as pre-processing step towards feature extraction and abnormality detection. Due to its adaptive nature it is independent of common image properties like contrast, brightness etc. and produce same quality edge from diverse mammogram images from different make and version. In the above mentioned algorithm the abstraction of edge can also be determined by the use of the level of tree data structure. This feature, thus gives the freedom to the users in selection of the number of bins to achieve the most appropriate results/outcome. Another achievement of the proposed algorithm is faster execution time, least interference of noise to obtain the desired isolated region from the edge maps separated from the exterior regions. The sensitivity and specificity of the proposed method is 0.92 and 0.91 respectively. The statistical analysis has proved that the derived edge map of the proposed method is very similar to other classical methods namely, LoG and Canny but it is significantly better than them due to its single pixel connected edge map which is very important for medical imaging. Thus this proposed method stands out due to its flexibility, efficiency, accuracy and applicability to a diverse range of mammography.

ACKNOWLEDGEMENT

The authors are obliged to Mammographic Image Analysis Society (MIAS) and Dokuz Eylul University for their public mammographic dataset dedicated for research and development. They also thankful to Dr. Pradip Saha, MD, Radiology for his continuous participation in proposed work and Dr. Soma Chakraborty, MD, Radiology (Specialist in Mammography) for her expert opinions and comments. The authors are also appreciative to Mr. Sanjay Nag and Mr. Sumit Das for their contribution related to algorithm development, coding and documentation of the proposed work.

REFERENCES

[1] Stewart, *et al.* World Cancer Report, Lyon, France: IARC Press 2003.

[2] Ferlay, *et al.* GLOBOCAN 2002: cancer incidence mortality and prevalence worldwide, IARC Cancer Base, Lyon France: IARC Press, 2004.

[3] Ojala, *et al.* Accurate Segmentation of the Breast Region from Digitized Mammograms. Computerized Medical Imaging and Graphics 2001; 25(1): 47-59. http://dx.doi.org/10.1016/S0895-6111(00)00036-7

[4] Chandrasekhar, *et al.* A simple method for automatically locating the nipple on mammograms. The Institute of Electrical and Electronics Engineers Transactions on Medical Imaging 1997; 16(5): 483-494. http://dx.doi.org/10.1109/42.640738

[5] Gonzalez, *et al.* Digital Image Processing, 2nd edition, Prentice Hall, Upper Saddle River, NJ, 2002.

[6] Rosin, *et al.* Evaluation of global image thresholding for change detection. Pattern Recognit Lett 2003; 24: 2345-56. http://dx.doi.org/10.1016/S0167-8655(03)00060-6

[7] Roberts. Machine Perception of 3-D Solids, Optical and Electro-optical Information Processing, MIT Press, 1965.

[8] Prewitt. Object Enhancement and Extraction in Picture processing and Psychopictorics, Academic Press, 1970.

[9] Marr and Hildrith. Theory of Edge Detection. Proc Royal Society of London 1980; B207: 187-217.

[10] Canny. A Computational Approach to Edge Detection. IEEE Trans Pattern Analysis and Machine Intelligence 1986; 8: 679-714.

[11] Frei and Chen. Fast Boundary Detection: A Generalization and New Algorithm. IEEE Trans Computers 1977; C-26(10): 988-998. http://dx.doi.org/10.1109/TC.1977.1674733

[12] Zhang, *et al.* Image Edge Detection Using Hidden Markov Chain Model Based on the Non-decimated Wavelet. International Journal of Signal Processing and Image Processing and Pattern 2009; 2(1): 109-118.

[13] Jassim. Semi-Optimal Edge Detector based on Simple Standard Deviation with Adjusted Thresholding. International Journal of Computer Applications (0975 – 8887) 2013; 68(2): 43-48.

[14] Woods, *et al.* A Sobel Edge Detection Algorithm Based System for Analyzing and Classifying Image Based Spam. Journal of Emerging Trends in Computing and Information Sciences 2012; 3(4): 506-511.

[15] Maitra, *et al.* Automated Digital Mammogram Segmentation for Detection of Abnormal Masses Using Binary Homogeneity Enhancement Algorithm. IJCSE (0976-5166) 2011; 2(3): 415-427.

Received on 18-02-2016 Accepted on 21-03-2016 Published on 15-04-2016

DOI: http://dx.doi.org/10.6000/1929-2279.2016.05.02.2