International Journal of Modern Engineering Research (IJMER)
www.ijmer.com Vol.3, Issue.2, March-April. 2013 pp-908-914 ISSN: 2249-6645

Breast Cancer Detection Using Histogram Based Decomposition

Ms. Jayashree R. Parate, [1] Prof.R.K.Krishna[2]
[1]Department of Computer science, Rajiv Gandhi college of Eng. and research, chandrapur, R.T.M.N.U, Nagpur
[2]Department of ETC, Rajiv Gandhi college of Eng. and research, chandrapur, R.T.M.N.U, Nagpur

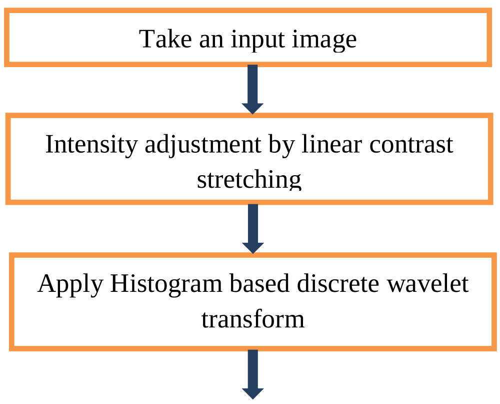
Abstract: *Breast disease are continues to be a common health problem in the world for womens. The mammographic diagnostic method is very famous method for detecting breast cancer. But sometimes in some cases, it is not so easy for the radiologist for detecting the typical diagnostic symptoms, such as masses and micro calcifications on the mammograms. Compact region in digital mammographic images are usually contain noisy and have very low contras and the infected regions are very difficult to recognize by radiologist. In this paper, we develop a Histogram base adaptive thresholding to detect suspicious cancerous location in mammograms. The algorithm consumes the combination of adaptive histogram thresholding segmentation and adaptive wavelet based thresholding segmentation on a multiresolution representation of the original mammogram. At last it shows adaptive wavelet techniques to produce the best denoised mammographic image using efficient thresholding algorithm. The algorithm has been checked with different types of around 100 mammograms in the Mammographic Image Analysis Society. Mini Mammographic database the experimental results show that the detection method has a Shows 94% correct result with exact micro calcified area.*

Keywords: *Breast, CAD, Speculated masses, Thresholding, Segmentation, Cancer detection.*

I. Introduction

A journey of Cancer begins with cells, after those building blocks that create tissues starts. Normal cells grow and divide to form new cells as the body needs them.in case of normal body, regular cells grow old or get damaged, after that they expire, and new cells take their place. Sometimes the process not working properly because of some reason New cells continue their production when the body doesn't need them, and old cells don't die as they are still in working situation. The continually formation of extra cells often forms a mass of tissue called a tumor. Cancer that forms in the tissues of breast, usually in the pectoral and in the duct is the breast cancer. Breast cancer is the famous and common disease in women and the second major cause of death [1]. For minimizing morbidity and mortality, it forcefully need an early detection of breast cancer. Breast cancer is one of the most affected disease in the female specially in India. The average affected rate varies from 22-28 per 1, 00,000 women per year in highly developed area settings to 6 per 100,000 women per year in rural areas. Due to rapid changing in lifestyles, The previous study proves that the early detection can reduces the chances of death as well as detect it n very early stages will help women to taking proper care of breast so that the chances reduced effectively also if someone is affected by it can easily curable. Mammography is now a days the best technique for reliable detection of early non curable breast cancer [3]. But the symptoms of breast cancer is very unstable in their early stages which is not easily understand by any radiologist or doctors and therefore, doctors can miss the abnormality very easily if they only diagnose by experience. Manual diagnosis is required laborious work because it need number of attempt to check the output of one image. Mammography is the most usefull modality for the detection of breast cancer. Because mammograms are projection images, they suffer from the superimposition of tissues, which may produce false alarms or hide lesions. The computer aided detection technology can help doctors to getting a more exact and effective result, since it checks the mammograms as the "second reader," thus giving to doctors and radiologists a favorable advice. Usually, a detection algorithm consists of two main steps:

- The first step is to detect suspicious lesions with segmentation.
- Second is detecting through fine segmentation.



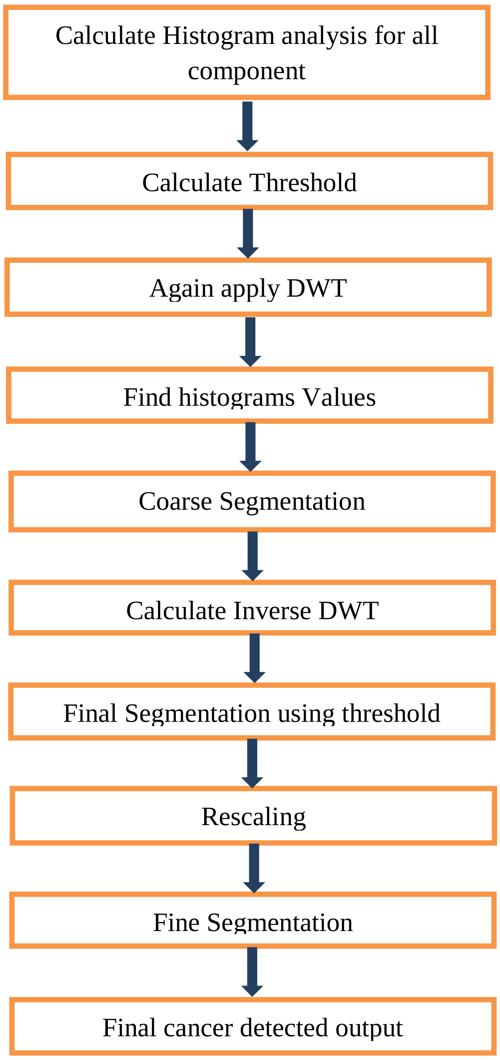


Fig-1 Flow chart for the proposed technique

Different kinds of methods was proposed for detecting Lesion in digital mammograms such as morphological approach[6],neural network analysis[7],wavelet based techniques[5],fuzzy logic based analysis[8],except the fact, all these techniques are usefull but still not detecting cancer easily. Different kinds of lesions are introduced habing different properties like star shape, oblique shape some of them are shown in fig 2. But still technology is not acceptable particularly for premenopausal women with dense breast tissue. it still required extra efforts to improve detection accuracy and reduce false positive rate. In the last surveyed works it is noticed that the thresholding based segmentation has outstanding advantages for detection of micro calcification. Mammograms contain structures with a wide range of sizes and contrasts. For example, a mammograms may contain masses, as well as micro-calcifications.

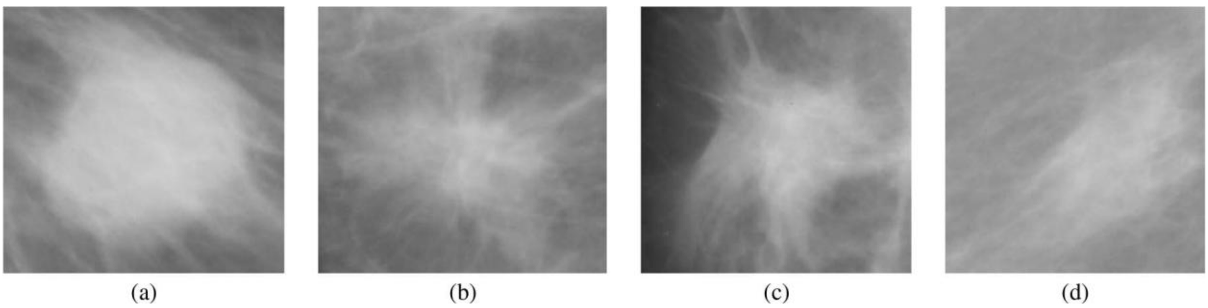


Fig.2 Typical example of different types of LESION A) CIRC, B)SPIC, C)ARCH , D)MISC.

These suspicious regions are surrounded by normal dense tissue that may make the radiologists' identification very difficult; multi threshold analysis is needed to distinguish these different structures. Wavelet based adaptive thresholding is an ideal tool for analyzing images with such a combinational patterns; it can decompose mammograms into different scale components. This property is quite helpful for micro-calcifications detection. this paper is organized as follows: section 2 describes the theories and methods used section 3, the mammogram images used through result together with the tests carried out in order to assess the performance of the methods; finally, conclusions are drawn in section 4.

II. WORKING

histogram based tumour detection can be achieved by using wavelet based adaptive thresholding value in which multiple threshold are taken to calculate calcified location in breast. Flow chart for the proposed technique is given in Fig.1.The following are the main stairs of computation used to segment the tumours in digital mammograms:

1.1 Intensity adjustment:

Intensity adjustment is used to improve the quality of image data by suppressing the un-useful distortions or enhances some image features necessary for next processing and analyse different task. In this paper, linear contrast stretching is used as intensity adjustment step. This is the simplest contrast stretch algorithm. The gray values in the input image and the modified image continuing to use linear relation in this algorithm. A value in the low range of the original histogram is assigned to extremely black and a value at the high end is assigned to extremely white. Block diagram or preprocessing using CAD system is shown in Fig-3. Image pre-processing techniques are necessary; in order to find the representation of the mammogram, to remove noise and to modified the quality of the image. before any image-processing algorithm can be applied on mammogram, pre -processing steps are very important in order to minimize the search for affected without removing influence from background of the mammilla .digital mammograms are medical images that are difficult to be calculated, thus a preparation stage is needed in order to maximize the image quality and make the segmentation results more accurate. The main objective of this process is to improve the quality of the image to make it ready for further processing by removing the unrelated and unwanted parts in the back ground of the mammogram.

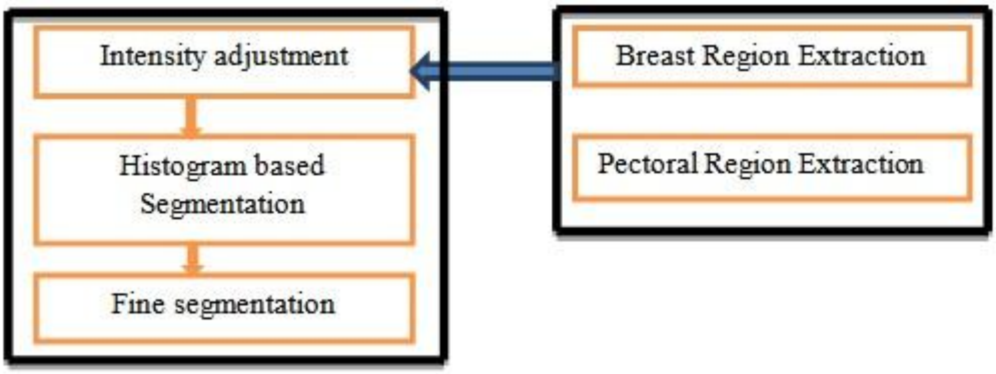


Fig.3 Block diagram of preprocessing using CAD system

There are methods of linear contrast enhancement ie Minimum-Maximum Linear Contrast Stretch.when applying this technique, the original minimum and maximum values of the data are assigned to a newly specified set of values that utilize the full range of available brightness values. The original minimum and maximum values of the data are assigned to a newly specified set of values that utilize the full range of available brightness values. Consider an picture with a minimum brightness value of 45 and a maximum value of 205. When such an image is digitised without enhancements, the values of 0 to 44 and 206 to 255 are not focussed. Important spectral differences can be detetected by stretching the minimum value of 45 to 0 and the maximum value of 120 to 255. As shown in fig4

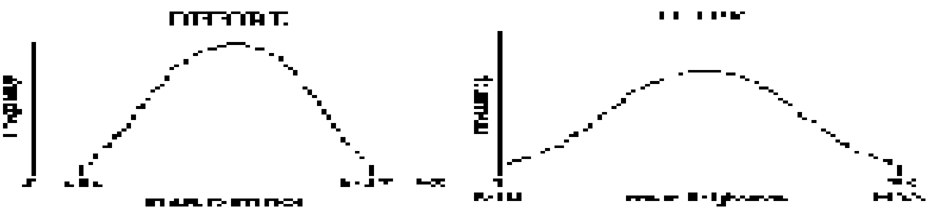


Fig 4: Minimum–Maximum Linear Contrast Stretch.

An algorithim can be used that relates the old minimum value to the modified minimum value, and the old maximum value to the modified maximum value. All the old intermediate values are placed exactly between the new minimum and maximum values. Many digital image processing systems have built-in capabilities that automatically expand the minimum and maximum values to optimize the full range of available brightness values. This is the simplest contrast stretch algorithm. The gray values in the original picture and the modified image follow a linear relation in this algorithm. A value in the low range of the original histogram is assigned to extremely black and a value at the high end is assigned to extremely white. noise may be of various type and according to the intensity value the noise can be removed.

1.2 Histogram based segmentation:

Segmentation subdivides an image into its same size but in number of regions or objects that have similar features according to a set of given criteria. In this paper, the random segmentation is done by using wavelet based histogram thresholding where, the thereshold value is selected by performing 1-D wavelet based analysis of PDFs of wavelet transformed images at different channels.

- **Introduction of different types of Wavelet transform**

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better global and spectral region of image creation. The DWT can be taken as signal dividation in a set of independent, spatially oriented frequency path. The signal is passed through two complementary filters and emerges as two signals, approximation and details. This is called decomposition. Fig.2. shows the bank of filters iterated for the 2DDWT standard. The components can be assembledback into the original signal without loss of information. This process is called reconstruction.The components can be gain back into the original signal without loss of information. This process is called reproduction of signals.

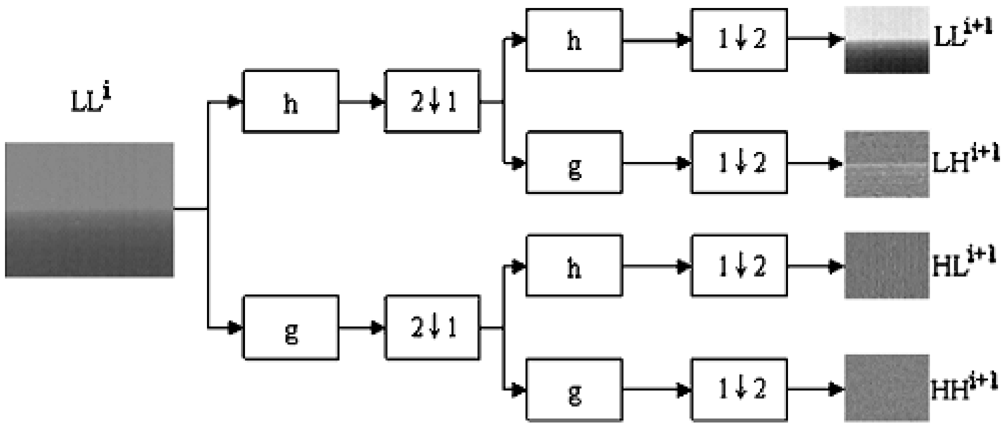
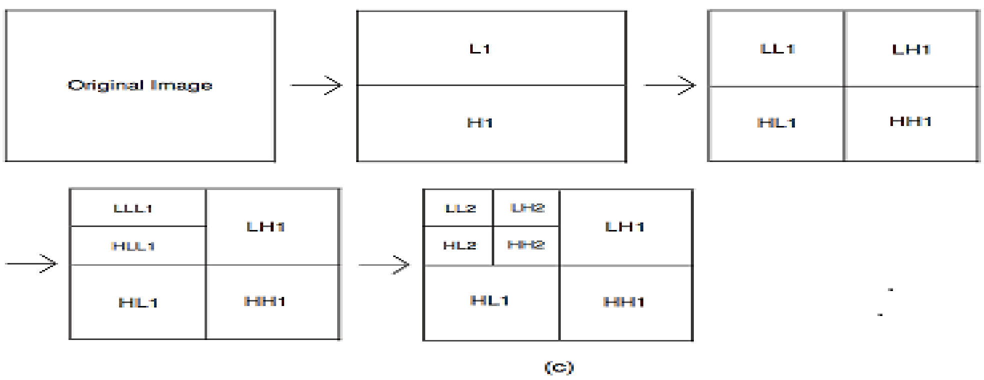


Fig.5 bank of filters iterated for DWT standard

The mathematical calculation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform. An image can be divided into a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands. The second level of wavelet transform is applied to the low level frequency sub band image LL only. The 2D-DWT with 3-level decomposition is shown in figure 6. The Gaussian noise almost averaged out in low frequency wavelet coefficients and hence only the wavelet coefficients in the high level frequency need to be thresholded In this paper, the concepts of Daubechies 6 wavelet transform are discussed. The Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a max number of removing moments for some given support .With each wavelet type of this class, there is a scaling function which generates an eight sided multi resolution analysis. Daubechies wavelets are widely used in solving a big range of problems, e.g. self-similarity properties of a signal or fractal problems, signal discontinuities, etc.



1, 2, 3 --- Decomposition levels
H --- High Frequency Bands,L --- Low Frequency Bands
Fig.6. 2D-DWT with 3-level decomposition

The decomposition of the image into different resolution levels which are sensitive to different frequency bands. By choosing an appropriate wavelet with a right resolution level, tumours can be detected effectively in digital mammogram. Experimental results show that the Daubechies wavelet achieves the best detecting result.

- **Wavelet based histogram Thresholding**

With the fulfilment of preprocessing, the daubechies wavelet transform is applied to a preprocessed image. Proper scaling channel is selected using prior information of appropriate size of the destination. After applying wavelet transform, find the histogram. Then perform 5 scale (on given LL, HL, LH, HH) 1-D db-6 wavelet transform. Calculate the local minimum of the 1-D wavelet transformed pdf at the selected scale .then threshold value t is calculated that retains bright pixels in the image. Pixels with values greater than **t** are set to white (1) and values less than **t** are set to black (0).related characteristic component labeling is applied to the binary image using eight pixel connectivity to indicate each discrete region in the binary segmented image. These discrete regions are subjected to following criteria given below which select the most important candidate regions that strongly resemble a suspicious mass in terms of their area and their statistical characteristics such as their pixel's intensity, higher order moments, etc.

***(a)* Requirent 1:** From the data given in the database, it is noticed that area of the mass ranges between 900 to 5000 pixels. So the region whose area lies between 900 pixels and 5000 pixels is considered to be suspicious. This rule is applied to each segmented region and this reduces the number of the candidate regions to Ri , i = 1, ..,M. Regions that don't meet this requirement are rejected.

***(b)* Requirement 2:** Each remaining region is considered a suspi-cious region if its third order moment (skewness) is negative in nature otherwise they are rejected.

***(c)* Requirement 3:** Each remaining region is still considered suspicious if its mean intensity is greater than a threshold value Tm. The regions that do not satisfy this criterion are cancelled. the threshold value is selected accordingly the character of the behind breast tissue is given in table 1. These threshold values were chosen after experimenting with the images in the database.

This selected threshold value is used to calculate local minima value. Then segmentation is done by using threshold value to obtain the coarse segmented areas. This course segmented result is then send to fine segmentation processing to get super fine output. Coarse segmentation gives good output on given database available.

Background	**Threshold Value Tm**
Fatty	160 < Tm< 170
Glandular	171 < Tm< 180
Dense	Tm> 181

Table 1: Threshold values for different types of back-ground tissue

2.3 Fine-Segmentation:

In fine segmentation first of all small window is selected which are use to calculate suspicious area in given mammograms and then large window is selected for calculating main highlighted area on breast. The procedures contain two phases:

- **Small Window Selection**

A small window is the first step in fine segmentation. Here the entire image is partitioned into a fixed number of large regions where R1, R2,……, Rm.Then this window is taken inside the next window Ri and which are use to calculate threshold for each window.normally the smaller the window size will better the result. However, when the window size becomes too small, it may produce the problem of same properties windows, i.e., windows contain only background or object pixels,Therefore, there is a strong need to develop a correct window size in order to get the optimal result. Final segmentation depends on the proper selection of initial window size.

- **Window based histogram Thresholding**

Fig.1 shows the flowchart of the proposed method for tumor detection. Histogram based segmentation is considered For each pixel P (i, j), a decision is fixed to detect the potential suspicious lesion pixel or a normal pixel by the following rule. If the neighborhood P [i,j] is having smaller value than T threshold ,Then convert pixel to background i.e. '0' Otherwise declare the pixel as suspicious. In this rule, T (i, j) is an adaptive Threshold value calculated by histogram based segmentation output. Each step is described further below.

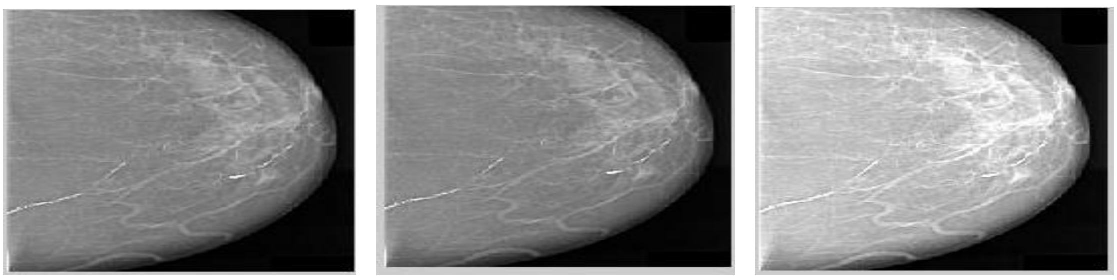
1. Set threshold in middle of window sum.[11*11].
2. Check the neighbourhood pixels position
3. If the neighbourhood addition is not greater than threshold value, change pixel to '0' Otherwise define it as '1' which makes it suspicious region.

    If
        P [I, j] <T
    Then
        Change pixel to '0'.
    Else
        Define it as suspicious area.

4. Repeat steps (2)-(3) till the whole image is checked.

III. OUTPUT

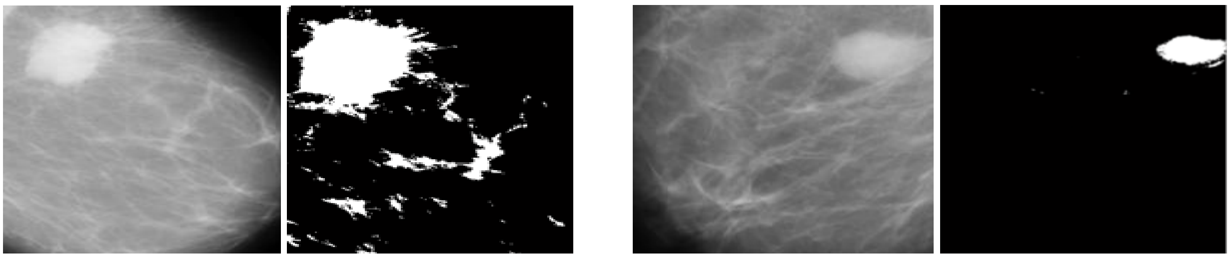
The data used in given experiments are taken from the mini- MIAS database of mammograms [4]. The same collection of database has also been used by other researcher for their studies in different fields, such as automatic mammogram classification, mass segmentation, and micro calcification detection. All images are covered at the resolution of 1024 ×1024 pixels and 8-bit accuracy (for gray level). The proposed algorithm was implemented in a MATLAB environment on acomputer (Intel Pentium IV, 3.0-GHz CPU, and 512-MB (RAM). It has been licenced with 170 mammograms in the mini-MIAS database. The testing images include some normal images and out of this some are real space-occupying lesion images, with 100 lesions in total. To calculate the accurate output throught computer-aided diagnosis, we adopted the following criteria given in [10], a computer aided system searching considered as a correct result if its area is covered by at least 50% of a true defects. The detection results are evaluated by terms of sensitivity and the number of false positives per image (FP/I).The original image is shown as Fig.7 (a). The intensity adjustment is done by linear contrast stretching which is shown in Fig.7 (b). Daubechies 6-point wavelet is selected to process the image.



a)original image b)grey scale image c)intensity adjust image

Fig.7 original image and preprocessed image

Then wavelet transforms applied on the input image from scales 1 to 4. Then histogram is taken for transformed images.Next, 5-scale wavelet transforms applied for the histogram of the image in scale 2. By selecting the local minima at adaptively selected scale, four local minima are calculated using the top most local minimum as the threshold value, the histogram segmented areas are obtained. there are some example images which are collected from minimias databases for locating good result for segmentation this output shows how this histogram based hresholding is superior then other thresholding(ex.local or global thresholding)

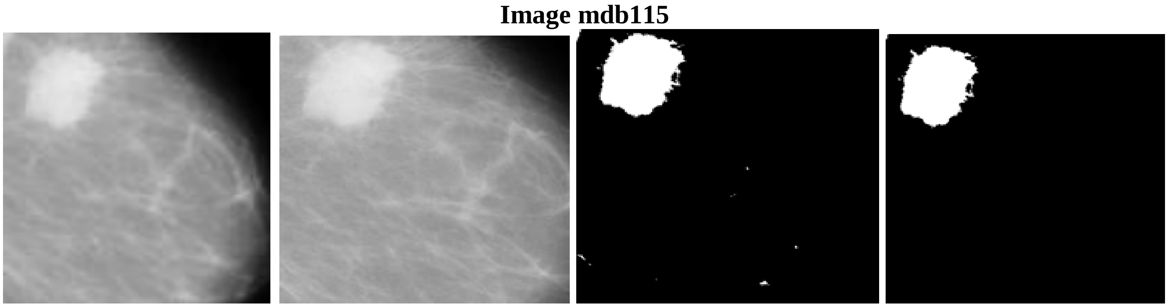


(a) Original image (b) Segmented image (a) Original image (b) Segmented image

Fig 8. Example of segmentation results by the histogram based decomposition

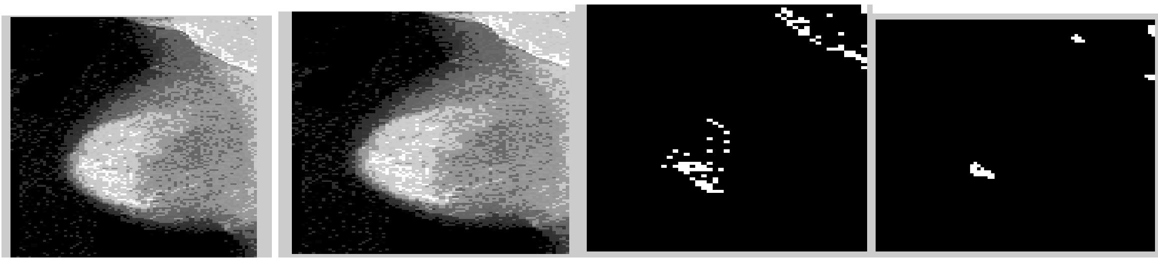
Fig.9 (a) shows the original mammilla picture, then Fig.9 (b) shows the intensity adjusted image output. Fig.9(c) shows the histogram based segmented result. Fig.9 (d) shows the fine segmented result. The exact result can be obtained with small window size as 15*15 and large window size as 128*128 which is shown in Fig.9 (d). hence the given histogram based decomposition algorithm obtained a good detection result.

Image mdb115



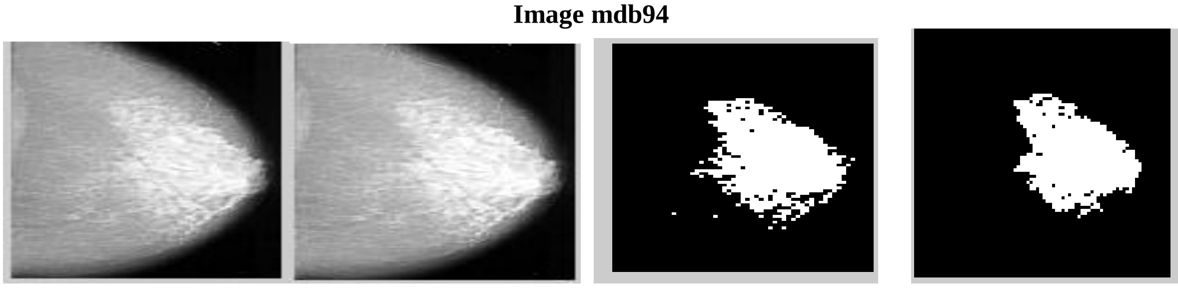
(a) Original image (b) Preprocessed image c) histogram based segmented result (d) Fine segmented result

Image mdb184



(a) Original image (b) Preprocessed image c) histogram based segmented result (d) Fine segmented result

Image mdb94



(a) Original image (b) Preprocessed image c) histogram based segmented result (d) Fine segmented result

Fig 9. Example of segmentation results by the wavelet based adaptive windowing method of thresholding

IV. CONCLUSION

Hence at the end we, conclude that a new algorithm based on the histogram based wavelet decomposition method is used for the segmentation of bright targets in an image. Histogram based segmentation is proposed by using wavelet based histogram thresholding in which thereshold value is chosen by performing 1-D DWT analysis of Power Density Functions of wavelet transformed images at different channels. Final segmented result is found by choosing threshold by using windowing method. The main feature of this method, with respect to the other techniques proposed is its adaptability and convenience to the different nature of solve a problem relevant to the nature in the image under analysis, allowing the use of the same basic algorithm for both micro-calcifications and mass detection. Many computerized results prove the suitability and availability of this approach to maximize both i.e. micro calcifications, and very low-contrast structures, such as masses. The improving quality of the processed images has been considered by radiologists as a true significant aid for the early detection of breast cancer.

REFERENCES

[1] S. Liu, C. F. Babbs, and E. J. Delp, “Multiresolution detection of spiculated lesions in digital mammograms,” IEEE Trans. Image Process.,vol. 10, no. 6, pp. 874–884, Jun. 2001.

[2] K. Bovis and S. Singh, “Detection of masses in mammograms using texture features,” in Proc. 15th Int. Conf. Pattern Recog., 2000, vol. 2, pp. 267–270.

[3] G. Cardenosa, “Mammography: An overview,” in Proc. 3rd Int. Workshop Digital Mammography, Chicago, IL, Jun. 9–12, 1996, pp. 3–10.

[4] J. Suckling, S. Astley, D. Betal, N. Cerneaz, D. R. Dance,S.-L. Kok, J. Parker, I. Ricketts, J. Savage, E. Stamatakis, andP. Taylor, Mammographic Image Analysis Society MiniMammographic Database, 2005. [Online]. Available: http://peipa.essex.ac.uk/ipa/pix/mias/

[5] Kai-yang Li, Zheng Dong, “A Novel Method of Detecting Calcifications from Mammogram Images Based on Wavelet and Sobel Detector,” ICMA. June 2006.

[6] Diyana, W.M., Besar, R., “Methods for clustered microcalcifications detection in digital mammograms,” ISSPIT, Dec.2004.

[7] Songyang Yu, Ling Guan, “A CAD system for the automatic detection of clustered microcalcifications in digitized mammogram films” IEEE Transactions on Medical Imaging, Vol 19, Issue 2, pp. 115 - 126, Feb. 2000

[8] Auephanwiriyakul, S., Attrapadung, S., Thovutikul, S., Theera- Umpon N., “Breast Abnormality Detection in Mammograms Using Fuzzy Inference System,” Fuzzy Systems, May. 2005, pp. 155-160 conclusion might elaborate on the importance of the work or suggest applications and extensions.