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Segmentation Approach for Detecting Micro-Calcified Region in Bosom

Ms.Jayashree R.Parate[1],Prof.R.K.Krishna[2]
[1] Reasearch Scholar, Rajiv Gandhi College Of Engg And Research Chandrapur.
[2] Asst Prof., *Rajiv Gandhi College Of Engg And Research Chandrapur*

Abstract:- An image processing application was developed in C++ for the improvement of mammographic images. Wavelet-based image enhancement was implemented by processing the DWT detail coefficients with a sigmoid function. Mammography is the most effective method for the early detection of breast diseases. However, the typical diagnostic signs such as micro calcifications and masses are difficult to detect because mammograms are low-contrast and noisy images. .images are of low contrast so here require denoising and the process is called preprocessing. Coarse segmentation is the first step which can be done by using wavelet based histogram thresholding where, the thereshold value is chosen by performing 1-D wavelet based analysis of PDFs of wavelet transformed images at different channels. These wavelet were applied to 130 digitized mammograms. The mammograms gone under processing were blind-reviewed by an expert radiologist. A number of mammographic image parameters, such as definition of masses, vessels, microcalcifications, etc. were checked. Filter performances were assessed by thresholding analysis of the physician's evaluation. Processing time was less than 3s for the wavelet-based and hyperbolic filters in a typical desktop.

Keywords :- wavelet based Thresholding, breast cancer,mammography, window based Thresholding, segmentation.

I. INTRODUCTION

Breast cancer is now a days is one of the major cause of death in women worldwide. Breast cancer currently affected for more than 38% of cancer incidence and a significant percentage of cancer mortality in both developing and developed countries. It has been shown that early detection and treatment of breast cancer are the most effective methods of reducing mortality .manual checking for this disease is labour intensive . mammography is the method of choice for early breast cancer detection [6]-[8]. Although automated analysis of mammograms cannot fully exchange the concept of radiologists, an accurate computer-aided analysis method can help radiologists to make more accurate and efficient decisions .Tumors and other disabilities present in the mammograms are of area interests that need to be segmented and extracted in mammograms . Some of the grey scale based segmentation methods are good to extract the exact edges of same characteristics grayscale regions. They are ever not so good to extract the desired affected areas in mammograms with complex structure because of the complex distribution of the grayscale. However, the appearances of breast cancers are very substle and unstable in their early stages. Therefore, doctors and radiologists can miss the abnormality easily if they only diagnose by experience. The computer aided detection technology can help doctors and radiologists in getting a more reliable and effective diagnosis. There are numerous tumour detection techniques have been used by many authors to solve the queries related to cancer. Wavelet transform-based methods offer a normal original framework for providing multiscale image representations that can be separately explored .by using multiscale decomposition, almost of the gross intensity distribution can be merged in a large scale image, while the information about details and single characteristics, such as edges and textures, can be used in mid- to small scales. Here 1-D wavelet-based analysis is performed to find the Power density function and adaptively selected proper thresholds for segmentation by searching for the local minima of the 1-D wavelet transformed PDF. This method is simple, fast, and effective for segmenting tumors in mammilla. However, the method is not very good when the target and the background regions having little difference in gray-level values. According to the neighboring windows around the pixel a threshold is computed for each pixel of the image. It did not consider the case where a mass contains the small window, the center region of a suspicious lesion is not detected, and it gives an empty area in the segmentation result. In other words, the algorithm can obtain good detection results on one type of lesions, but it may generate unreasonable detection results on other types of lesions. An approach is used to segment the suspicious mass regions by a local adaptive thresholding technique after the mammograms are enhanced with a linear transformation filter. For each pixel of the image, a threshold is calculated according to the next placed windows around the pixel. Next, a decision is made to classify the pixel whether it belongs to a suspicious lesion or a normal region by the threshold. From the experimental results, we can see that this algorithm works best in mammographic mass detection. At the same scene, experiments show that the algorithm has a drawback that It did not consider the case where a mass contains the small window, the center region of a suspicious lesion is not detected, and it gives an empty area in the segmentation result.

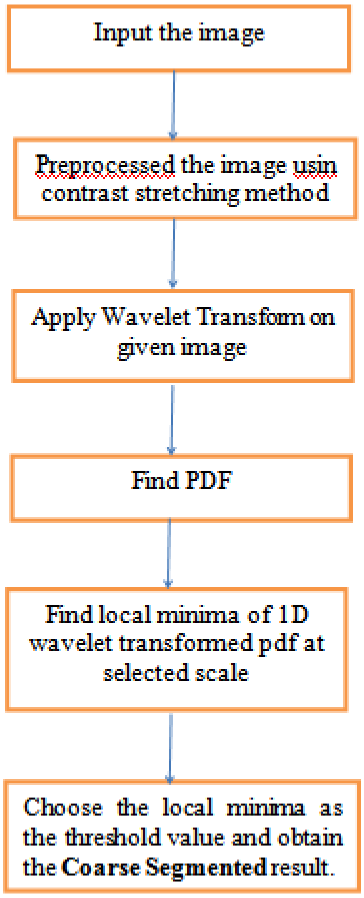


Fig-1. Flow chart for working of algorithm

Global thresholding is one of the most declared techniques for image segmentation. It is based on the global information, such as histogram. The fact that masses usually have greater intensity/density than the surrounding masses can be used for finding global threshold value. On the histogram, the regions with an abnormality create extra peaks while a healthy region has only a single peak. After finding a threshold value the regions with abnormalities can be segmented. Global thresholding is not a best method to identify ROI (Region of Interest) because masses are often superimposed on the tissue of the same intensity level.

Over the past few years, wavelet-based techniques have been enhanced and applicable in many areas of image processing. Image enhancement is an area that wavelet-based techniques have proven to perform successfully.In this study, a systematic evaluation of a wavelet-based enhancement filter and five histogram equalization filters were performed to X-ray mammographic images. An experienced radiologist assessed 11 mammographic image quality parameters for all the processed mammograms, in order to investigate the accuracy A survey on different preprocessing techniques, segmentation techniques have been covered in paper Comparative study of Wavelet Adaptive Windowing method an effective technique for tumor detection in mammilla (bosom).[1] and how to implement preprocessing to improve image quality is discussed in paper preprocessing method a first stage for detection of cancer in mammographic images.[2].this paper contain how to done segmentation to get spotted area in mammograms.paper contain total four section .section2 contain working section 3 contain expected output and section 4 contain conclusion of paper.

II. WORKING

Flow chart for given processing is shown in fig.1.which describe the working of algorithm. Working for detecting micro-calcified region in bosom are containing two stages :

A. Preprocessing

The aim of pre-processing is to enhance the image data by suppressing the undesired distortions or enhances some image features relevant for further processing and analysis task. In this paper, linear contrast stretching is used as a preprocessing step. This is the simplest contrast stretch algorithm. The gray values in the original image 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 whiteThe remaining pixel values are distributed linearly between these extremes. The features that were obscure on the original image will be clear in the contrast stretched image. The pixel values are changed to new values after applying pre processing.

B. Coarse Segmentation

Segmentation decompo an image into its same size but in number of regions or objects that have similar features according to a set ofgiven 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.

- **Brief of Wavelet Transform**

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image creation. The Discrete wavelet transform can be interpreted 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

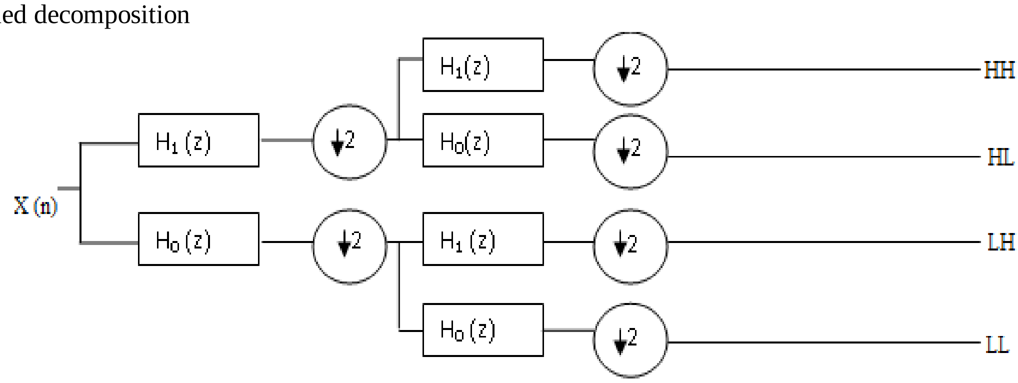
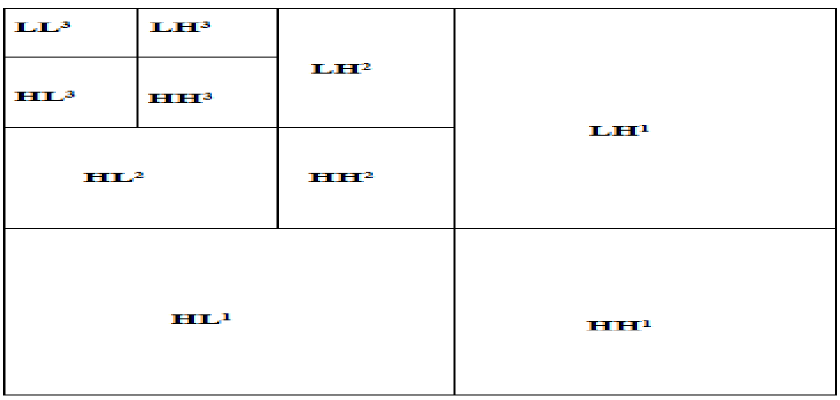


Fig. 2 Area wise distribution of filters iterated for the DWT standard

Fig.2 shows the area of filters iterated for the 2D-DWT. The components can be gain back into the original signal without loss of information. This process is called reconstruction . The mathematical manipulation, 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 namely, LL, LH, HL and HH as shown in Fig.3.



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

The second level of wavelet transform is applied to the low level frequency sub band image LL only. 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. 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.

1. Wavelet based 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 minima 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) Criteria 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) Criteria 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) Criteria 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. Thesethreshold values were chosen after experimenting with the images in the database.

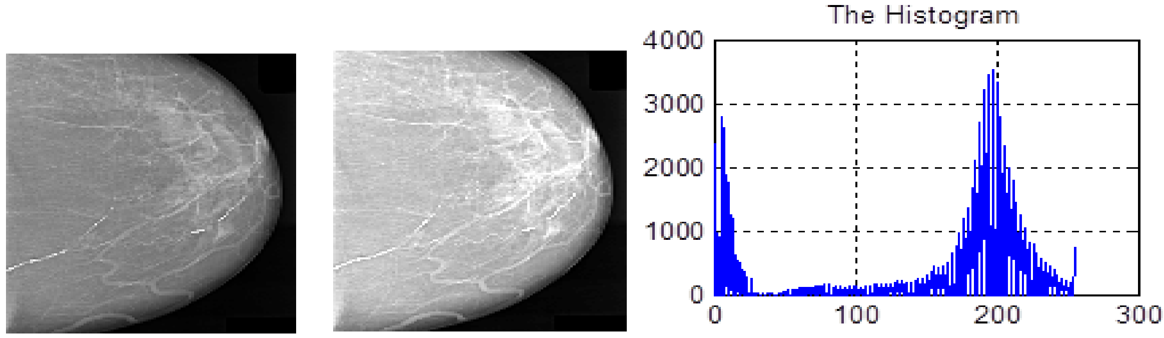
Background	**Threshold Value Tm**
Fatty	160 < Tm< 170
Glandular	171 < Tm< 180
Dense	Tm> 181

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

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.

III. EXPERIMENTAL RESULT

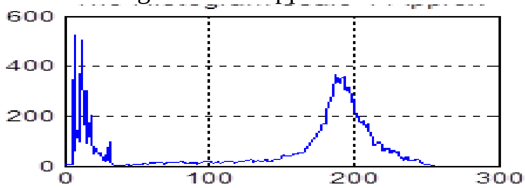
In this processed work, Mini-MIAS database for mammogram is used. This work has been done using matlab 2011 environment. All images are digitized at the resolution of 1024 × 1024 pixels and 8-bit accuracy (gray level).The original image is shown as Fig.4(a). The preprocessing is done by linear contrast stretching which is shown in Fig.4(b). and histogram of linear contrast stretching in Fig.4(c). Daubechies 6-point wavelet is selected to process the image. Fig.5 (a)-(d) indicates the histograms (PDFs) of these four transformed images respectively. The image in scale 2 is used for segmentation since it can effectively detect the tumours present in the digital mammograms. Next, 5-scale wavelet transforms for the histogram of the image in scale 2 is taken. By taking the local minima of the curve at recursively selected scale, four local minima are created. Using the largest local minima as the final threshold, the coarse segmented areas are obtained. In order to show the goodness or effectiveness of the proposed method it is compares with global thresholding and window based adaptive thresholding method. Global threshold methods suffer from drawback as threshold value is fixed manually. Some of them can be segmented accurately and part the tumour cannot be detected correctly.the wavelet segmented image and its histogram are shown in fig.6 The final coarse segmented region result is shown in Fig. 7.



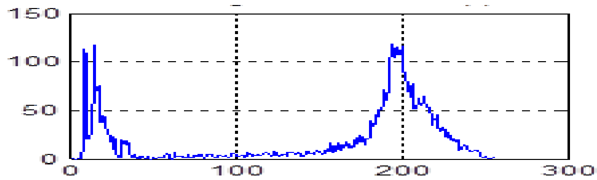
A)Original Image B)preprocessed image by linear contrast stretching C) The Histogram
Fig.4 Original image and Preprocessed Image and its Histogram

IV. CONCLUSIONS

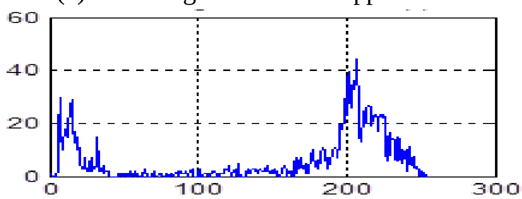
Wavelet based adaptive windowing method is presented for the coarse segmentation of bright targets in an image. Coarse segmentation is proposedby using wavelet based histogram thresholding where,the thereshold value is chosen by performing 1-D wavelet based analysis of PDFs of wavelet . transformed images at different channels. Final segmented result is obtained by choosing threshold by using windowing method. The simulation results show that the proposedmethod is effective to segment the tumours in mammograms and it can also be used in other segmentation applications.



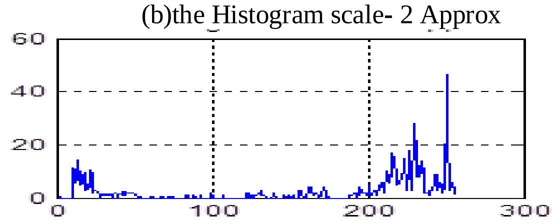
(a)the Histogram scale- 1 Approx



(b)the Histogram scale- 2 Approx

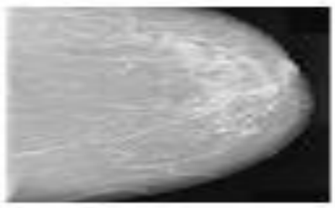


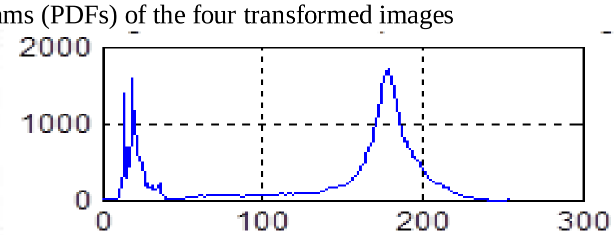
(c) the Histogram scale- 3 Approx



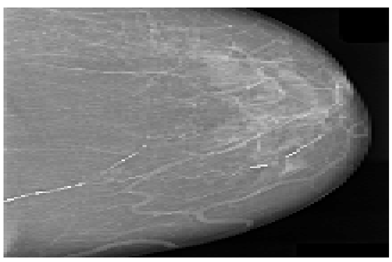
(d)the Histogram scale- 4 Approx

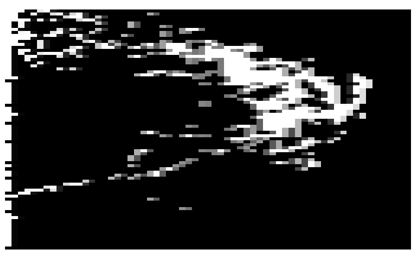
Fig.5(a-d) Histograms (PDFs) of the four transformed images



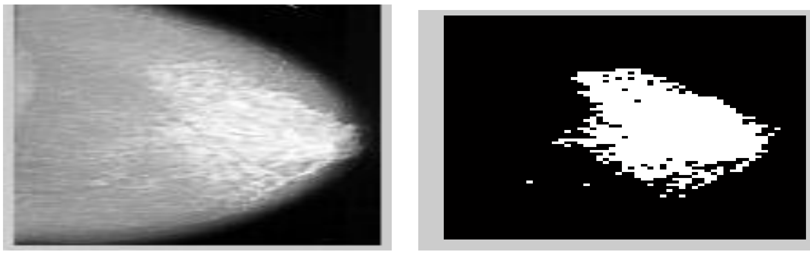


(a) wavelet segmented image (b)histogram of wavelet processed image
Fig .6 (a-b) wavelet transformed output





Original image Coarse Segmented image



Original image Coarse Segmented image

Fig.7 final output of segmentation

REFERENCES

[1]. [1] Comparative study of Wavelet Adaptive Windowing method an effective technique for tumor detection in mammilla (bosom) .

[2]. [2] preprocessing method a first stage for detection of cancer in mammographic images.

[3]. [3].R.Mata, E.Nava,F. Sendra, "Microcalcifications detection using multi resolution methods, pattern Recognition,"2000,proceeings,15th International Conference.4,344-347,2000.

[4]. [4].X. P. Zhang, "Multiscale tumor detection and segmentation in mammograms," in Proc. IEEE Int. Symp. Biomed. Imag., pp. 213–216, Jul. 2002.

[5]. [5].F. Fauci, S. Bagnasco, R. Bellotti, D. Cascio, C. Cheran, F. De Carlo, G. De Nunzio, M. E. Fantacci, G. Forni, A. Lauria, E. Lopez Torres, R.

[6]. Magro, G. L. Masala, P. Oliva, M. Quarta, G. Raso,

[7]. [6] .T.C.Wang, N.B. Karayiannis, "Detection of microcalcifications in digital mammograms using wavelets, Medical Imaging," IEEE Transactions, 17 , 498 -509, 1998.

[8]. [7] [2].H. Kobatake, M. Murakami, H. Takeo, and S. Nawano, "Computerized detection of malignant tumors on digital mammograms," IEEE Trans.Med. Imag., vol. 18, no. 5, pp. 369–378, May 1999.

[9]. [8] A. Retico, and S. Tangaro, "Mammogram segmentation by contour searching and mass lesions classification with neural network," IEEE

[10]. Trans. Nucl. Sci., vol. 53, no. 5, pp. 2827–2833,Oct. 2006.

[11]. [9] Celia Varela, Pablo G. Tahoces, Arturo J. Mendez, Miguel Souto, and Juan J. Vidal, "Computer detection of breast masses in digitized mammograms", *Computers in Biology and Medicine*, vol. 37, pp. 214- 226, 2007.

[12]. [10] A. Mencattini, M. Salmeri, R. Lojacono, M. Frigerio, and F. Caselli,

[13]. "Mammographic images enhancement and denoising for breast cancer

[14]. detection using dyadic wavelet processing," *IEEE Trans. Instrum. Meas.*,

[15]. vol. 57, no. 7, pp. 1422–1430, Jul. 2008.

[16]. [11] S. Liu, C. F. Babbs, and E. J. Delp, "Multiresolution detection of speculated lesions in digital mammograms," *IEEE Trans. Image Process.*,

[17]. vol. 10, no. 6, pp. 874–884, Jun. 2001.

[18]. [12] S. Liu, C. F. Babbs, and E. J. Delp, "Multiresolution detection of speculated lesions in digital mammograms," IEEE Trans. Image

[19]. Process., vol. 10, no. 6, pp. 874–884, Jun. 2001.

[20]. [13] G. M. te Brake and N. Karssemeijer,"Segmentation of suspicious densities in digital mammograms," Med. Phys., vol. 28, no. 2, pp. 259–266, Feb. 2001. [14]Shengzhou Xu & Hong Liu & Enmin Song "Marker-Controlled Watershed for Lesion Segmentation in Mammograms," J Digital Imaging

[21]. 24:754–763, 2011.

[22]. [15]M. Grgic et al. (Eds.): Rec. Advan. in Mult. Sig. Process. And Communication., SCI 231, pp. 631–657, 2009.

[23]. [16]Umesh Adiga et al" High Throughput Analysis of Multispectral Images of Breast Cancer Tissue,"IEEE Trans on image processing, vol.15,No.8,August 2006.