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# Segmentation of Circumscribed Masses in Mammograms using Improved Homomorphic Filter and Adaptive Thresholding

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**Abstract**

Early breast cancer detection is necessary to decrease mortality rate. In this paper, an improved algorithm for detection and multilevel segmentation of suspicious lesions from mammograms is proposed. Initially, non-decimated wavelet transform (NDWT) is applied on selective scale of input mammograms. For first level segmentation, decimated wavelet transform is applied to NDWT sub-image, thereafter multiscale analysis of image probability distribution function is used. In order to improve morphological characteristics of first level segmented image, morphological filter is applied to NDWT transformed sub-image and convolved with first level segmented output. Final segmented image is obtained by applying linearly enhanced homomorphic filter and then local adaptive thresholding method. The proposed algorithm is tested on 22 circumscribed mammograms in the Mammographic Image Analysis Society database. The results of proposed algorithm show 90% sensitivity and .1429 false positives per image. Use of NDWT and enhanced homomorphic filter improves false positive per image performance.

***Key Words*:**Segmentation; adaptive thresholding; homomorphic filter; mammograms; breast cancer.

# 1 Introduction:

Main cause of early mortality in women is breast cancer.Mammography is the best radiographic technique for accurate diagnosis of breast cancer [1-2].Digital mammograms are classified as normal, benign andmalignant,last two categories are considered as abnormal.In addition, abnormal cases are further categorised ascircumscribed masses(CIRCS), speculated masses, micro classification, ill-defined masses, architectural distortion, asymmetricetc. [3-4].

However, shape features are used for characterization and classification of CIRCS masses, but lesions are also characterized by gray value and gray-level features.To detect suspicious lesion and site number,many techniqueshave been reported [5-12].A two stage adaptive density weighted contrast enhancement filtering technique along with edge detection and morphological texture classification for automatic segmentation of potential masses has been presented in [6], [14-15]. Detecting speculated tumours based on local edge characteristics and law texture features has been reported in [7]. Mass detection using adaptive thresholding has also been presented in [8-10].Wavelet transform-based methods offer a natural framework for providing multiscale image representation that can be separately analysed. In [8], [14-15]multiscale analysis of the input mammograms which made gray-level probability distribution function (PDF) approach to Gaussian distributionhave been introduced. They choose the threshold adaptively, by looking for global local minima of PDFs of wavelet transformed images. This algorithm is not effective when there is little difference between background and target regions.To overcome this problem a technique oflinear transformation filter for enhancement of mammogram and adaptive thresholding based segmentation has been reported in [9].This algorithm did not consider masses with small window and it also gives an empty area in segmentation results. In [10] combination of adaptive global and local thresholding for segmentation of sub images of wavelet transformed image has been reported. Schemes for contrast enhancement of mammogram images using homomorphic filter in wavelet domain have also been reported [11-12].

Due to low contrast of mammogram images detection and segmentation methods have a trade-off between false positive detection and sensitivity. Different features are used to detect different type of abnormalities. Hence, single algorithm cannot be applied to detect all types of abnormalities optimally. Therefore,in this paper an algorithm for detection and segmentation of circumscribed masses in mammograms using improved multiresolution based local adaptive thresholding and homomorphic filter is presented.NDWT used in proposed scheme provide improved multiresolution characteristics due to non-sparse sampling grid and removes singularities from image. Improved homomorphic filter improves contrast and intensity of image in order to discriminatethe masses from high dense mammograms without losing the details [11-13]. The combination of shape feature and gray-level feature is used for classifying between CIRCS and healthy tissue among various parenchymal tissue patterns. Mammographic Image Analysis Society (MIAS) database is tested in proposed algorithm.

Rest of this paper is presented as Section background theory of multiscale based adaptive thresholding method and local adaptive thresholding using homomorphic filtering technique. In Section III proposed algorithm is described in detail. In Section IVresults and discussion are shown and discussed. Section V concludes the work.

# 2 Background Theory

## 2.1 Multiscale Adaptive Thresholding

The distribution of gray-values between bright target and background region in images approaches to Gaussian distribution [6]. Background region would have lower gray-level than bright target.

PDFs of background$x_b$(m) and target$x_t$ (m) is as follows[10]:

$$x_b(m) = \frac{1}{\sqrt{2\pi\sigma_b}} exp\{-\frac{(m-\mu_b)^2}{2\sigma_b^2}\}$$

$$x_t(m) = \frac{1}{\sqrt{2\pi\sigma_b}} exp\{-\frac{(m-\mu_b)^2}{2\sigma_b^2}\}, \mu_t > \mu_b \quad (1)$$

where $_t$and $_b$ are the means of background and target of image, pixel value is m and standard deviation of background and target of image is $_t$and $_b$ ,respectively.

Let I(m) is the PDF of image and$X_b$ and $X_t$ be the prior probabilities of background and target image.

where I(m) is given by

$$I(m) = X_b x_b(m) + X_t x_t(m) \quad (2)$$

Due to prior probabilities information of both classes are unknown so Bayes threshold cannot be computed. The performance of Bayes threshold is close to the adaptive threshold, which is selected by looking at global local minima of PDFs curve (histogram) of wavelet transform of image. Image is segmented according to adaptive threshold $_1$.Let W be the segmented binary image

$$W(j,k) = \begin{cases} 0, & Y(j,k) < T_1 \\ 1, & Y(j,k) > T_1 \end{cases} \quad (3)$$

where (j,k) is the coordinates of Y image and Y(j,k) is the pixel value compared to threshold $T_1$.

## 2.2 Homomorphic Filtering

Homomorphic filter is used to control illumination and reflectance components. The filter *Homo(u,v)* is used to control specification, affecting high and low frequency component of the Fourier transform in different ways. The image Im(w,x) can be expressed as the product of illumination and reactance component[13].

$$Im(w,x) = i(w,x)r(w,x) \quad (4)$$

After taking log on both sides, convert image into frequency domain using Fourier transform. It is processed by means of a filtered function *Homo(u,v)*.Take the Fourier transform of filtered image. In order to separate illumination and reflectance component, spatial domain of filtered image is obtained by taking inverse Fourier transform.Finally, enhanced image is $HI_1(w,x)$is obtain by

$$HI_1(w,x) = i_m(w,x)r_m(w,x) \tag{5}$$

The filter function is given by

$$Homo = (\beta_h - \beta_l)[1 - e^{-g(\frac{D(u,v)}{D_0})^2}] + \beta_l \tag{6}$$

where g is constant is used to control steepness of the slope as it transitions between $\beta_h$ and$\beta_l.D_0$ and D(u,v) are the cut-off frequency and distance from the centre frequency coordinates (u,v) respectively.Fig.1 shows process of homomorphic filtering.

## 2.3 Local Adaptive Thresholding

Local adaptive thresholdingreported in [7,8],is used in the proposed scheme. In this threshold computed by local windows[9].

Subtracted image Sub(u,v) is obtain by subtracting original image from enhanced image.

If Aveg> $\eta.Sub_{diff}$(u,v)and

$$(\frac{|Aveg - Sub(u,v)|}{Aveg}) < 1 - \eta \tag{7}$$

and threshold is calculated as

$$Thres(u,v) = \begin{cases} \eta.Aveg, & if Aveg > Sub(u,v) \\ Aveg, & otherwise \end{cases} \tag{8}$$

else
Thres(u,v)=Aveg+$\kappa Sub_{diff}$
with

$$Sub_{diff} = Sub_{max}(u,v) - Sub_{min}(u,v) \tag{9}$$

Here (u,v) are the pixel value,Aveg is the average pixel intensity in small neighbourhood around Sub(u,v) pixel. $\eta$ and $\kappa$ are thresholding bias coefficients.$\kappa$ is set to 0.5 for better results and $\eta$. The second level segmentation would give more prescribe results.

# 3 Proposed Scheme

In this section the proposed scheme for detection and segmentation of CIRCS masses is described. Fig.1. shows the block diagram of proposed method.The following are the steps involved in the process of detection of suspicious lesions site in mammograms using proposed method:

1. Non-decimated wavelet transform (NDWT) (Daub6) is being performed on normalised image $M_0$ at scale J=1,2,3,4, for better localization of pixels and improved multiresolution characteristicsdue to non-sparse sampling grid.

2. Again 2-D discrete wavelet transform(DWT)(db6) is being performed on image$M_2$ at scale J=1,2,3,4,5, using prior information of approximated size of target image is selected at scaling channel J=2. At large scaling channel J=1,2,3.., the singularities are removed and made it suitable for target segmentation and distribution of masses are smoothen.

3. The adaptive threshold is selected byhistogram (PDF curves) of wavelet-transformed sub-images. Wavelet transform of PDF curves are aligned at every scale according to their largest local minimum and weighted to select final threshold value forfirst level segmentation. Here,$M_1$is the sub image of 2D-DWT. $M_seg^j$ is the segmented areas of transformed image at scale J by using selected threshold value, thenmapped from wavelet domain to original domain.

   (x,y) and (m,n) are the pixel value of original domain and spatial domain respectively. Time delay of FIR filter is given by$D_l$, occur due to spatial shift. Length of scaling filter is given by$D_J = (2^J - 1)D - 2^J + 2.M_seg$is the adjusted segmented areas in the original image using the segmented areas $M_seg^J$ (m,n) .Then$M_seg$ is obtain by multiplying with masked image M as shown equation (9).

$$M_{seg}(m,n) = \begin{cases} 1, & if M^J_{seg}(m,n) = 1 \\ and(x,y) \in [(m - D_l, & n - D_l), \\ (m - D_l + D_J - 1, & n - D_l + D_J - 1)] \\ 0, & otherwise \end{cases}$$

$$M_{seg} = M_{seg}.M + M \tag{10}$$

4. After first level segmentation,higher resolution inverse mapping is applied. For better resolution, first-level segmentation$F_1^{'}$ corresponds to 2×2 matrix in$F_1$ as shown in equation (10)

$$F_1^{'}(2e + r, 2d + f) = F_1(e, d) \tag{11}$$

where r,f∈{-1,0}

5. Simultaneously morphological filter is applied on$M_2$(sub-image of NDWT) for removing the structural noise and make it suitable for target segmentation.Filtered image $EI_1$is obtained from morphological enhancement technique.

6. After enhancement, image $C_1$ is obtained by convolution of $F_1 and EI_1$

$$C_1 = conv(F_1, EI_1) \tag{12}$$

7. Linearly Enhanced Homomorphic (LEH)Filteringis applied on convoluted image, for obtaining enhanced image.This novel filter normalises the intensity and increases the contrast of image and enhancing the boundaries of lesions by increasing the high frequency and lowering the low frequency. Firstly, logarithm function enhances dark areas and inverse of it enhances bright areas using equation (13).For better results λ=0.3 and a=10000 are chosen to obtain enhanced image. $a^{'}$ and $b^{'}$ are two real number and $g^{'}$ is said to be maximum gray-value,255.

$$b^{'} = \frac{1 - exp(\frac{g'}{a'})}{g'} \tag{13}$$

To obtain final enhanced image by using equation (13)

$$Enhc = \begin{cases} a^{'}.\log[1 + b^{'}.c_1(i_1, j_1)]c_1(i_1, j_1) > \lambda \\ ([exp[c_1(i_1, j_1)/\lambda] - 1])c_1(i_1, j_1) < \lambda \end{cases} \tag{14}$$

Secondly, homomorphic filtering is applied on enhanced image for improving the segmentation. Using equation (5) and (6) homomorphic filter is implemented.

8. After taking complement for filtered image, local adaptive thresholding is implemented for second level segmentation.Enhc(i,j) is processed using with homomorphic enhancement filter to obtain $HI_1(i, j)$.

$$HI_1 \leftarrow exp \leftarrow idft \leftarrow Homo(u, v) \leftarrow DFT \leftarrow\leftarrow Enhc \quad (15)$$

Subtracted image Sub(i,j)obtain as shown below

$$Sub(i, j) = C_1(i, j) - HI_1(i, j) \quad (16)$$

In order to define smaller and larger window, boundary pixel of Sub(i,j) is padded by symmetric method.Threshold is computed for each pixel of breast area is computed, whether it lie in normal area or suspicious area.$Sub_{diff}(i, j)$ and Aveg and Thres(i,j) is calculated as shown in equation (8) and (7) and used for final segmentation as shown in Fig.1.

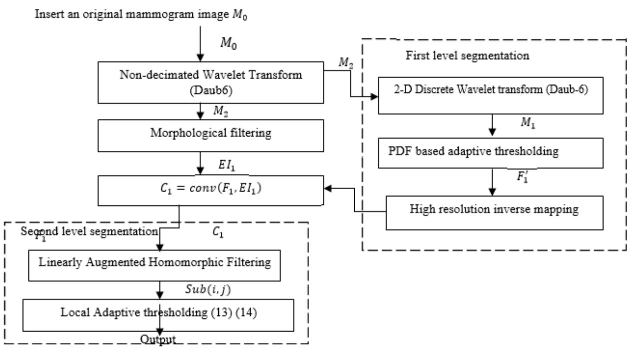


Fig.1 Block diagram of proposed method

In this section simulation results of the proposed scheme implemented using MATLAB are presented. The proposed algorithm is tested on the 22 CIRC mammogram images of 1024×1024 size acquired from mini-MIAS database. Among these, 22 CIRCSimages there are 24 lesions. Number of false positive per image(FP/I) and sensitivity is used for evaluating results of proposed algorithm.The results of the proposed scheme are compared with [10], with same mammogram images. Comparison results are summarised in table I

TABLE I Comparison Results of CIRCS Lesions

| Scheme | Class of abnormality | Lesions/images | Lesions Detected | Sensitivity(%) | FP/I |
|---|---|---|---|---|---|
| Proposed method | CIRCS | 22/24 | 27 | 90% | .1429 |
| [10] | CIRCS | 22/24 | 23 | 95% | .71 |

Initially NDWT using (‘db6’) is applied to the input mammogram image at scale 4. Then 2DDWT (‘db6’) is performed on sub-image of NDWT, to remove the singularities at selective

scale and $L_vH_v$ scaling channels will maintain greyscale information. Histograms (PDF curves) is used for removing the fluctuation and select global local minima, which is used as adaptive threshold for first-level segmentation. Simultaneously, morphological filter is applied on sub-image of NDWT transformed sub-images for enhancing the suspected lesions and reduced texture noise. To extract texture in transformed image morphological structuring element disk of diameter 7 pixel is chosen. For, background correction disk with diameter of 75 pixels is chosen.

In order to increase intensity gradient of convoluted image novel filter technique (LEH) filter is applied. This filter normalises the intensity and increases the contrast of image and enhancing the boundaries of lesions. A homomorphic filter uses approximation coefficients$\beta_H = 0.5$ and $\beta_L = 1$. Finally, local adaptive thesholding technique is applied for second level segmentation.

Fig.2. shows results of proposed detection algorithim. Fig.2.(a) shows the input mammograms of cases mdb002, mdb15, mdb21, mdb23,mdb25, mdb028,respectively.Fig.2.(b) shows the results of first level segmentation using PDF based thresholding.Fig.2.(c) shows LEH filtred images.Fig.2.(d) shows the results of second segmentation. The detection results of proposed scheme are also compared with ground truth results provided by MIAS and shown in table-II.

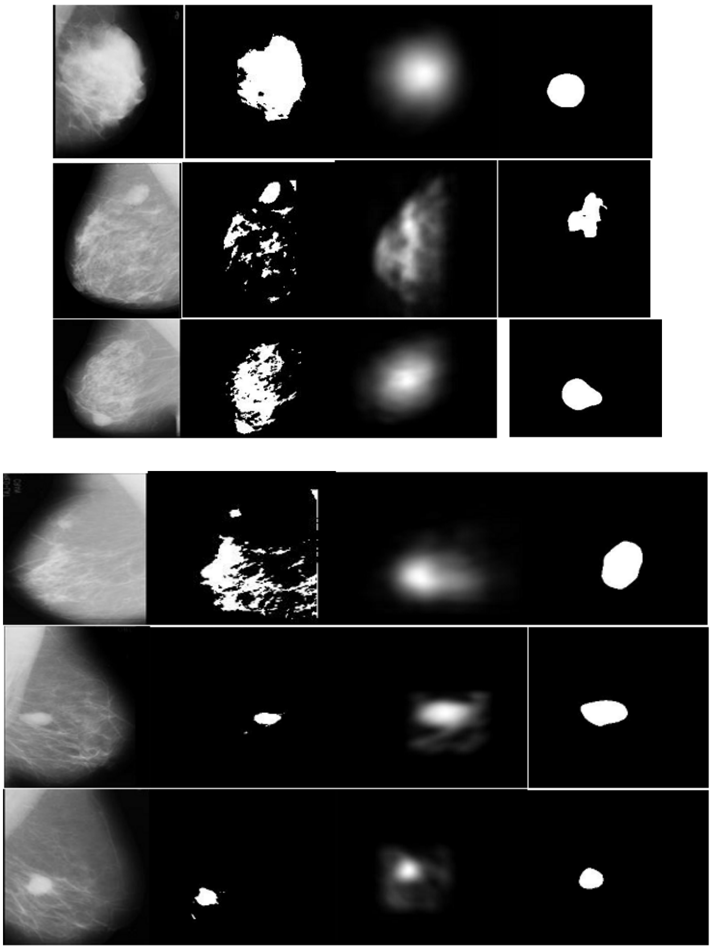

Fig.2 Results detection of CIRCS lesions. The cases from top to bottom mdb002, mdb15, mdb21, mdb23,mdb25, mdb028,respectively.(a) Input mammogram.(b)First level segmentation(c)LEH filtered image(d)Second level segmentation.

Table II COMPARISON OF DETECTION RESULTS OF SUSPICIOUS LESION PER IMAGE BETWEEN PROPOSED ALGORITHM AND GROUND TRUTH PROVIDED BY MIAS.

| Mammograms | Our method | Ground truth |
|---|---|---|
| mdb001 | 1 | 1 |
| mdb002 | 1 | 1 |
| mdb005 | 4 | 2 |
| mdb012 | 1 | 1 |
| mdb015 | 1 | 1 |
| mdb017 | 1 | 1 |
| mdb019 | 2 | 1 |
| mdb021 | 1 | 1 |
| mdb023 | 1 | 1 |
| mdb025 | 1 | 1 |
| mdb028 | 1 | 1 |
| mdb069 | 1 | 1 |
| mdb080 | 1 | 1 |
| mdb091 | 1 | 1 |
| mdb132 | 2 | 2 |
| mdb141 | 1 | 1 |
| mdb142 | 1 | 1 |
| mdb244 | 1 | 1 |
| mdb270 | 1 | 1 |
| mdb290 | 1 | 1 |
| mdb315 | 1 | 1 |
| Total | 27 | 24 |

# 4 Conclusion

In this paper an improved algorithm for automatic detection and segmentation of suspicious lesion from CIRCS images is presented. Proposed algorithm uses NDWT for enhancing the multiresolution capability and improved homomorphic filter is used to enhance the contrast of the mammograms. Morphological properties are improved by morphological filtering.

Shape and gray value features are used for automatic detection of suspicious lesions. Morphological filtering provides enhanced shape feature while linearly enhanced homomorphic filter provide improved gray feature. Simulation results shows that proposed scheme is having low false positive per image and sensitivity comparable to the scheme compared.

# References

[1] A.G Hauss, M J Yaffe, A categorical course in physics: technical aspects of breast imaging, in: 78th Scientific Assembly and Annual Meeting of RSNA (Radiological Society of North America),1994.

[2] K. Bovis and S. Singh, Detection of masses in mammograms using texture features, in Proc. 15th International Conference Pattern Recognition., 2000, vol. 2, pp. 267270.

[3] G. Cardenosa, Mammography: Anoverview, inProcessing3rdInt.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, and P. Taylor, Mammographic Image Analysis Society MiniMammographic Database,2005.

[5] A Mencattini, M. Salmeri R. Lojacono, M. Frigerio, and F. Caselli, Mammographic images enhancement and de-noising for breast cancer detection using dyadic wavelet processing, IEEE Trans. InstrumentaionMeasurement Society, vol. 57, pp. 7, pp. 1422-1430, Jul. 2008.

[6] H. Li, Y. Wang, K.J. Ray Liu, B.L. Shih-Chung, M.T. Freedman, Computerized radiographic mass detection. Part I: lesion site selection by morphological enhancement and contextual segmentation,IEEE Transactions on Image Processing, vol. 20, no. 4, pp. 289-300, Apr. 2001.

[7] N.Petrick, H.P. Chan, B. Sahiner,D. Wei, An adaptive density-weighted contrast enhancement filter for mammographic breast mass detection,IEEE Transactions on Medical-Imaging, vol. 15, no. 1, pp.59-67, Feb. 1996.

[8] X. P. Zhang and M. D. Desai, Segmentation of bright targets using wavelets and adaptive thresholding, IEEE Transactions on Image Processing., vol. 10, no.7,pp. 1020-1030, July 2001.

[9] G. Kom, A. Tiedeu, and M. Kom, Automated detection of masses in mammograms by local adaptive thresholding, Computer inBiology andMedicine, vol.37, no.1, pp.37-48, Jan. 2007.

[10] Kai Hu, Xieping Gao, and Fei Li, Detection of suspicious lesions by adaptive thresholding based on multiresolution analysis in mammograms,IEEE Transactions on Instrumentation and Measurement, vol.60, no. 2, pp.462-472,Feb.2011.

[11] J.H. Yoon and Y.M. Ro, Enhancement of the contrast in mammographic images using the homomorphic filter method, IEICE Transactions on Information and Systems, vol. 85, no.1, pp. 298-303, 2002.

[12] J. Tang, X. liu and Q. Sun, A direct image contrast enhancement algorithm in the wavelet domain for screening mammograms, Selected Topics in Signal Processing, IEEE Journal of, vol. 3, no. 1, pp. 74-80, Feb. 2009.

[13] Gonzales, R., and Woods, R., Digital image processing. Prentice Hall, USA, pp. 191-193,2002. Total page:793, chapter 4.

[14] Sakellaropoulos, P., Costaridou, L., and Panayiotakis, G., An adaptive wavelet-based method for mammographic image enhancement, Digital Signal Processing vol. 17, pp. 453456, 2002.

[15] P.S. Vikhe and V. R. Thool, Mass detection in mammographic images using wavelet processing and adaptive threshold technique, Journal of Medical Systems, vol. 40, no. 4, pp. 116, 2016.