

Segmentation Of Cancer Cells In Mammogram Using Region Growing Method And Gabor Features

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Abstract

Breast cancer is one of the most common cause of cancer death in women. But the mortality rate can be greatly reduced by early detection. Early detection is efficiently performed by using Digital Mammograms. Sometimes manual reading will result in misdiagnosis, hence the performance will vary from 65% to 85%. Many Computer Aided detection techniques have been developed to improve the performance rate. Even then the detection rate is still not high. In the proposed method a new hybrid approach has been developed to segment the malignancy region in mammograms. Noise and artifact removal are performed in preprocessing. Alarm region generation process with region growing method is used to segment the suspicious region. The segmented region will be examined with Gabor filter in different angles and frequency levels.

Keywords: Computer Aided Detection, Gabor filter, Malignancy, Mammogram, Segmentation.

I.Introduction

Cancer is one of the most dangerous disease for which still proper treatment is not available. World Health Organization (WHO) mentioned that cancer accounted 13% of all death in the world in 2004. Cancer is a tumor that grows larger than 2mm in every 3 months and multiplies out of control. It also spreads to other parts of the body and destroys the healthy tissue. This process is called as metastasis. Most kind of cancer is named after the part of the body where it started. Breast cancer begins in the breast tissue, it may spread to lungs but still it is breast cancer not lung cancer. Breast cancer is the second most common cause of cancer death particularly for women in all over the world. It is rapidly becoming the number one cancer in females and pushing the cervical cancer to second place. The breast cancer has been diagnosed to occur in 1 woman out of 1000 during 1970's. But today it occurs 1 in 10 which shows the necessity of taking preventive steps against it. The root cause of breast cancer is still unknown. Hence the proper preventive measures are absent. However complete curing is sometimes possible if it is detected in its earlier

stages. Early detection will improve the survival rate of patient by 95%.

Masses and microcalcification are the confusing signs present in mammogram. Microcalcification is nothing but the collection of calcium cells. Mass will have different shapes and ill defined boundaries than microcalcification. Other confusing terms are benign and malignant. Benign is just the growth of tumor. It is not cancerous. So the main objective in breast cancer study is differentiating these factors. Mammography is the best available technique to detect cancer cell in its earlier stages. MRT, CT, Ultrasonic are some of the secondary methods. But the accordance rate between the above mentioned methods and histopathological feature is low, in the case of mammography the rate is quite high. Mammography is highly accurate and low cost detection method. In Digital mammography the images are displayed on a computer monitor and can be enhanced for efficient diagnosis.

Normally radiologists will perform the mammogram readings. It is difficult to provide accurate diagnosis due to variety of factors such as benign appearance of lesions, poor quality of image, eye fatigue factor, and deviation in brightness of objects in mammogram. Due to the above mentioned reasons the performance of manual reading varies from 65% to 85%. A variety of computer assisted detection techniques have been proposed to improve the detection accuracy. Developing CAD algorithm using extracted textures from breast profile region would reduce number of unnecessary biopsies in patients with benign disease. Thus CAD acts as a second reader and assists radiologist for accurate and efficient detection of cancer cells in the earlier stages. Thus the combination of CAD scheme with expert's knowledge will help to improve the detection accuracy. Many computer aided detection techniques have been proposed for the past two decades. Even then the detection rate is still not high. The general algorithm that can produce good result for all images is still not available. Although significant progress has been made over the last 20 years much works still needs to be done to develop more effective CAD system.

In this paper previous works in this field are discussed in section II. Section III explains the methodology of the proposed system. Section IV gives the results of the implementation. Finally conclusions are drawn in section V.

II. Literature Survey

Implementation of computer aided detection contains various fields such as enhancing the mammogram, identifying suspected region, feature extraction from segmented mammogram, classifying the mammograms and so on. Many algorithms have been proposed to improve the efficiency of the CAD system in the above mentioned fields. Some of those methods are discussed in this section.

Many attempts have been made by researchers to efficiently use the fuzzy logic and neural network methods to improve the diagnostic efficiency in cancer detection [17, 23, 24, 32]. Genetic algorithm was used with different combination of technologies for the effective diagnosis [16]. Jinshan et al. [26] provided an overview of recent advances in the development of CAD system. Maurice et al. [7] proposed a new algorithm based on the correspondence between MLO and CC views of mammograms.

Pectoral segmentation and artifact removal are the important preprocessing works. Jawad et al. [3] used morphological operation and seeded region growing method to segment the pectoral muscles. Contrast limited adaptive histogram equalization (CLAHE) and multiscale contrast enhancement algorithm are some of the effective methods in enhancing the mammograms [19, 22]. Arianna et al. [14] proposed a novel algorithm for denoising and enhancement based on dyadic wavelet processing.

Numerous segmentation algorithms have been proposed for segmenting the mass region. Each has its own advantage in some perspective. Farhang et al. [20] used mean shift algorithm to cluster the pixels in mammogram. Ka hu et al. [8] developed a combination of adaptive global and local thresholding to segment the multiresolution mammogram. Morphological component analysis was designed by xinbo gao et al. [13] to detect the suspicious region. Indra et al. [10] presented a combination of techniques that incorporates seeded region growing with ASB algorithm to isolate normal and abnormal regions in the breast tissue. Various algorithms based on Jacobi moments [12], SUSAN filter [14], vector quantization [28] have been tried to segment the mass from normal tissue. Yufeng zheng et al. [27] proposed a hybrid method in which Gabor feature is used with the combination of different methods to detect the cancer cells in mammogram. Mohd et al. [31] designed a method using gray level cooccurrence matrix to identify the mass region in mammogram.

After segmenting the suspected mass region, features of the segmented region should be examined to verify whether the extracted region contains mass or not. Various features like intensity histogram features, Gray level co-occurrence matrix features and intensity features are used for breast cancer diagnosis. In an comparative study Nithya et al. [4]

found out that GLCM outperformed the other two methods. Hence this method is used for the feature extraction process of the proposed method.

Classification is another most important process in CAD system design. Ju liu et al. [18] used improved local binary pattern operator for mass classification. Mohammad et al. [21], Fatima et al. [6], Leonardo de et al. [30] used support vector machine with combination of different techniques for the classification of masses. Naïve bayes classifier [19], K means classifier, fuzzy C means clustering [15, 29] are some of the common methods used in the previous work. Kemal et al. [5] designed least square support vector machine which provided effective classification compared to other methods.

III. Methodology

3.1 Data collection

The data used in the experiments of the proposed work was taken from Mammography Image Analysis Society database. MIAS is an organization of UK research groups. It contains left and right breast images of 161 patients. Totally 322 images are there which are selected from United Kingdom national screening programme..

3.2 Preprocessing

Mammograms are medical images that are difficult to interpret. Preprocessing is the essential thing to improve the quality of mammogram, So that the segmentation can be efficiently performed on the preprocessed mammogram than raw mammogram. Digitization noise and high frequency components are some of the unwanted regions present in the mammography images. These can be removed by using median filter. Edges are the more important factor in the segmentation process. The advantage of using median filter is, it can remove the noise without disturbing the edges. The film artifacts such as label and x-ray marks are removed using morphological operation in combination with thresholding methods. MATLAB functions are used to perform the above process.

3.3 Segmentation

The goal of segmentation is to extract the entire suspicious mass region from mammogram. A mass is space occupying lesion and usually appears as a bright region on a mammogram. We can ignore the darker regions. We need to concentrate only on the brighter region. Contrast enhancement is implemented in order to extract the brighter region alone from the mammogram.

3.3.1. Contrast enhancement

Contrast enhancement can be performed by increasing the brightness. Intensity values are added by using adaptive histogram equalization over different segments. It enhances the contrast of each pixel relative to its local neighborhood adaptively. As a result improved contrast can be produced

for all levels in the image. Adaptive histogram equalization also helps to reduce the noise produced in homogenous area.

3.3.2. Alarm pixel generation

Alarm pixels are produced by thresholding the contrast enhanced image. Alarm threshold is determined by histogram analysis. Segmentation through alarm pixel generation contains the following steps,

i. Histogram and accumulated histogram should be computed. H and AH.

ii. Using histogram gradient changes location of peaks in histogram should be found out. $(H_{g1}, H_{g2}, \dots, H_{gi})$ where H_{gi} are the gray levels.

iii. Candidate of alarm threshold is chosen by following condition,

$T_C = \{ H_{gi} \mid \text{When the selected alarm area} < 10\% \text{ of the entire region of interest} \}$, $C=p, p+1, \dots, q$. AH can be used to calculate the selected alarm area.

iv. Alarm threshold should be one of $\{T_C; C=p \sim q\}$ i.e $T_{AM} = T_1$ $p \leq 1 \leq q$, such that $H_{gi} - H_{gi-1}$ is maximum among $\{ |H_{gk} - H_{gi-1}| ; C=p \sim q \}$.

v. Mark pixel at (x, y) as a candidate of alarm pixel if $I_{Fm}(X, Y) > T_{Am}$ ($m=1, 2, 3$).

vi. A pixel at (x, y) is considered as alarm pixel if

$$\sum_{m=1}^4 I_{Am}(X, Y) \geq 3.$$

3.3.3. Region growing

Region growing method seeks group of pixels with uniform intensities. Seeded region growing performs a segmentation of an image with respect to set of points known as seed. Alarm pixel generated from the above process can be considered as seed point. Given the seed the region growing method finds the tessellation of the image into regions with property that each connected component of region meets exactly one of A_i . Each step of algorithm involves the addition of one pixel into above set. Let z be the unallocated pixel.

$$\alpha = \{x \notin U_{i-1} \cap A_i \mid n(x) \cap U_{i-1} \cap A_i \neq \Phi\} \quad (1)$$

Where, $n(x)$ is set of immediate neighbours of the pixel x . Consider the rectangular grid with immediate neighbours of 8 connected pixel x . if $x \in \alpha$ then $n(x)$ meets just one of A_i . Hence $i(x) \in \{1, 2, \dots, n\}$ to be the index such that

$$n(x) \cap A_{i(x)} \neq \Phi. \quad (2)$$

$$\delta(X) = |g(X) - \text{mean}_{g \in A_i(X)} [g(y)]| \quad (3)$$

Where $\delta(X)$ is measure of how different x is from the region it joins and $g(x)$ is the gray value of the pixel x . if $N(x)$ meets two or more values of A_i then A_i will be selected according to the lowest value

$$\delta(X) = \min_{x \in T} \{ \delta(X) \} \quad (4)$$

The above process is repeated until all the pixels have been allocated.

3.3.4. Gabor filter

Gabor filters have been used in many applications, such as texture segmentation, target detection, edge detection, retina identification, image coding and image representation. A *Gabor filter* can be viewed as a *sinusoidal* plane of particular frequency and orientation, modulated by a *Gaussian* envelope. It can be written as:

$$G(x, y) = e^{-\frac{1}{2}[\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}]} e^{-i2\pi(u_0x + v_0y)} \quad (5)$$

where in fourier frequency domain, filter's response consists of two 2D Gaussian function

$$G(u, v) = G_1 + G_2 = e^{-\frac{1}{2}[\frac{u^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}]} + e^{-\frac{1}{2}[\frac{u^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}]} \quad (6)$$

where $\sigma_u = 1/(2\pi\sigma_x)$ and $\sigma_v = 1/(2\pi\sigma_y)$ are the standard deviation along two orthogonal directions (which determines the width of the Gaussian envelope along the x - and y -axes in spatial domain), and assume that the origin of the Fourier transform has been centered. The intermediate variables are defined as following:

$$u_1 = (u - f \cos \theta) \cos \theta + (v - f \sin \theta) \sin \theta \quad (7)$$

$$v_1 = -(u - f \cos \theta) \sin \theta + (v - f \sin \theta) \cos \theta \quad (8)$$

$$u_2 = (u + f \cos \theta) \cos \theta + (v + f \sin \theta) \sin \theta \quad (9)$$

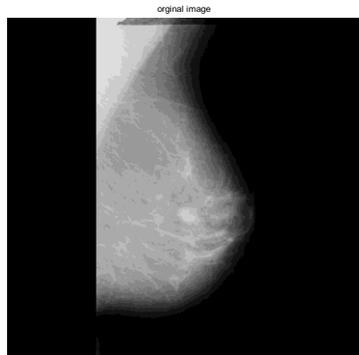
$$v_2 = -(u + f \cos \theta) \sin \theta + (v + f \sin \theta) \cos \theta \quad (10)$$

From each mammogram, a total of 20 Gabor filtered images (I_{Gmn} , $m = 1 \sim 5$, $n = 1 \sim 4$, in spatial domain) are produced with 20 Gabor filters distributed along five bands, located from low to high frequencies ($f=6, 12, 24, 48, 80$) and by four orientations (vertical, 45° , horizontal, and 135°).

IV. Results

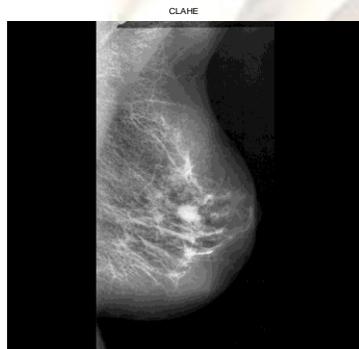
Experiments are conducted on the image taken from MIAS database. 250 mammograms have taken for experiments in which 125 are normal and 125 are abnormal. Results of three mammograms out of 250 mammograms are given in this section. "Fig 1" shows the segmentation result of the mammogram 'mdb010' "Fig 2" and "Fig 3" shows the result of implementation in mammograms 'mdb15' and 'mdb31'. In all the three figures a shows the original mammogram, b shows the mammogram after preprocessing

such as median filter and artifact removal process, c shows the image after contrast enhancement process, d shows image after alarm region generation process e shows the region after region growing and final segmentation process and finally f shows the image after application of gabor filter.



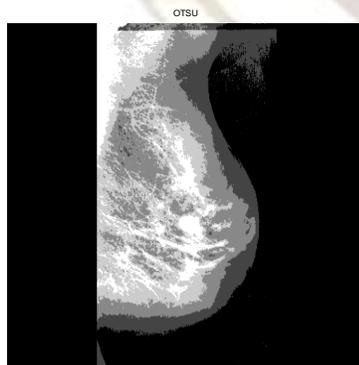
Pixel info(86, 274) 0

Fig 1a. Original mammogram (mdb 010).



Pixel info(4, 250) 22

Fig 1b. mammogram after noise and artifact removal process.



Pixel info(82, 298) 1

Fig 1c. mammogram after contrast enhancement process.

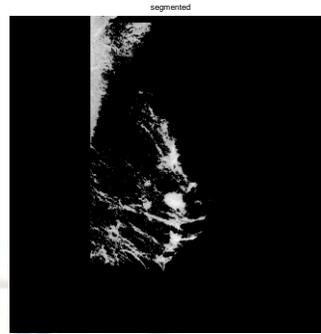


Fig 1d. mammogram after alarm region generation process.

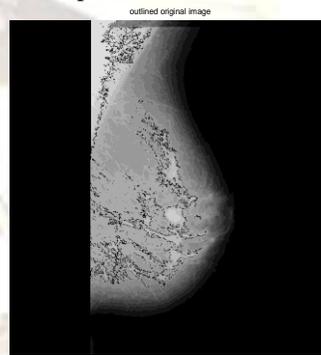
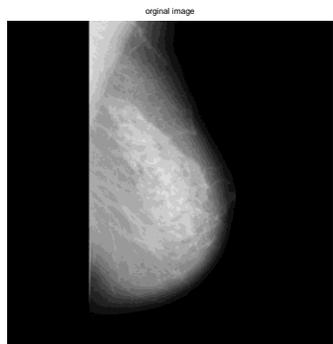


Fig 1e. mammogram after final segmentation.



Fig 1f. mammogram with gabor filter generation process

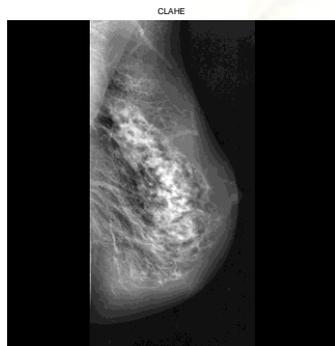


Pixel info (24, 262) 0

Fig 2a. Original mammogram(mdb 015).



Fig 2d. mammogram after alarm region generation process.



Pixel info (X, Y) Intensity

Fig 2b. mammogram after noise and artifact removal process.

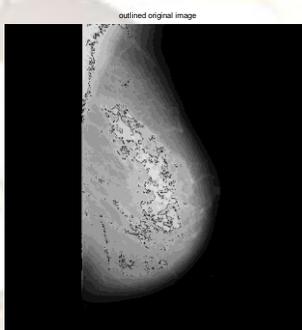
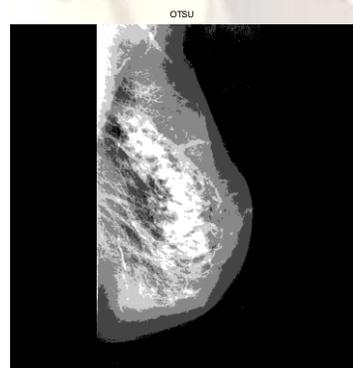


Fig 2e. mammogram after final segmentation.



Pixel info (X, Y) Intensity

Fig 2c mammogram after contrast enhancement process.

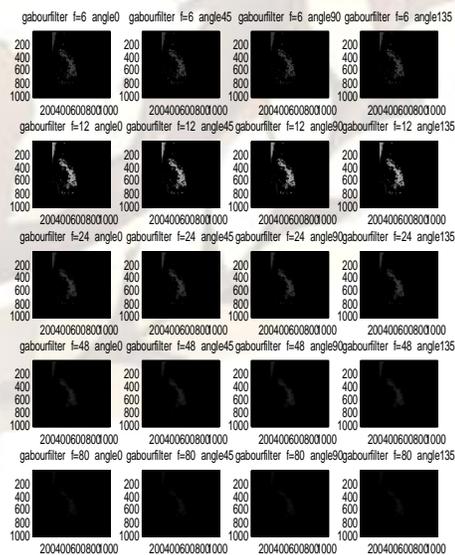
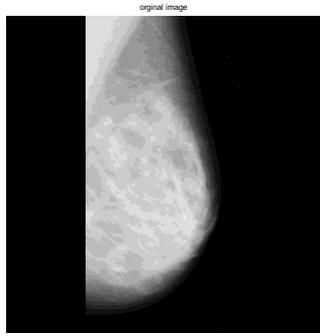


Fig 2f. mammogram with gabor filter generation process .



Pixel info (76, 258) 0

Fig 3a. Original mammogram (mdb 031).

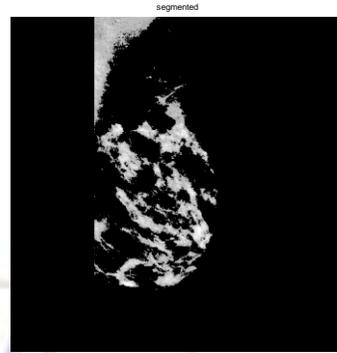
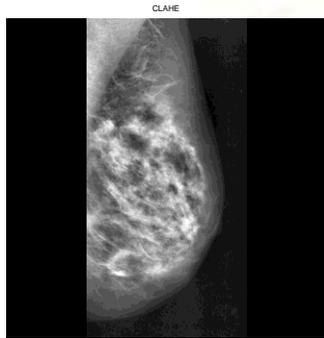


Fig 3d. mammogram after alarm region generation process.



Pixel info (28, 248) 22

Fig 3b. mammogram after noise and artifact removal process.

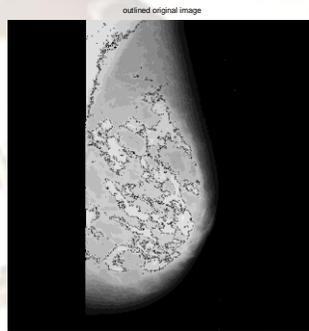
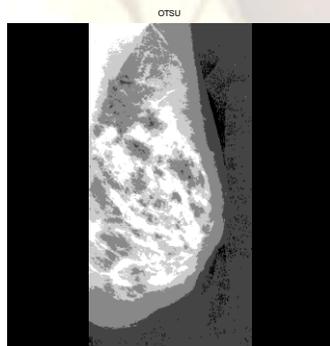


Fig 3e. mammogram after final segmentation.



Pixel info (98, 260) 1

Fig 3c mammogram after contrast enhancement process.



Fig 3f. mammogram with gabor filter generation process.

V. Conclusion

In the proposed work a new computer aided detection technique has been designed to detect the mass region automatically without any human interruption. Preprocessed image is segmented using alarm region generation process in combination with region growing method. The segmented region is examined thoroughly using Gabor filter which helps to study the segmented mammogram in all possible angles and frequencies. The segmented region from the proposed work can be used for further processing such as feature extraction and classification of mass region in future. Hence the proposed method is highly desirable in order to assist the radiologist in the detection of malignant region and to improve the diagnostic accuracy.

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