Middle-East Journal of Scientific Research 23 (6): 1257-1261, 2015
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2015.23.06.22318

Study of Mammographic Lesions Decomposition Using Gabor Filter

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Abstract: This research describes a mammographic lesions using wavelet based active contour model. The sensitivity of the breast cancer detection was analyzed by mammography. Wavelet based decomposition techniques are used and tested for decomposing the noise present in the mammographic lesions. Gabor filtering method is used to reduce the unwanted noise obtained in the mammographic lesions by automated segmentation. The experimental results are tested with the MATLAB and proved reliable and cost effective.

Key words: Mammogram · Wavelet · Decomposition

INTRODUCTION

Various methods are being developed to improve the sensitivity of the breast cancer detection. Mammography is currently used to detect early breast cancer. It contains four images two of each breast, one is craniocaudal and another is mediolateral oblique views. If a suspicious is detected then the radiologist first diagnostic workup to be performed the abnormality malignant, because the malignant lesions finding is a very challenging task for radiologists. This research indicates that the sensitivity of breast cancer detection on mammograms is only 70 to 80 percentages. In this research reviewed mammograms taken from the breast cancer patients before the test in which the cancer was detected. The CAD (Computer Aided Diagnosis) is the predetermined [1] research efforts in this area. Many computer vision techniques have been developed in various areas of CAD for mammography used by many researchers. It is very difficult to compare the performance of detection because the performance based on the data used for testing the mammogram. The effect of CAD is to reduce the cancers are ongoing research. It is expected that digital mammography detectors will provide good solution [2, 3].

Image Properties: Mammography depends on the size and density of the breast. Most sign of breast [4] pathology are either in the form of soft tissue masses that are not very different from the surrounding tissue or in the form of very small (micro) calcification.

Picture visualization [5] of these very challenging conditions requires imaging procedure with special characteristics. When there is a suspected image quality problem a first step is to identify which one of the five characteristics is the source.

- Artifacts
- Blur
- Contrast sensitivity
- Noise
- Geometry

These are three sets of objects. Within the phantom to simulate structure and objects that might be within a breast. These are mass, fibers, specks [6, 7].

Analysis of Image: The breast is a sweet gland to produce and secrete milk during lactation. The female breast is undergoing a number of changes which lead to a wide spectrum of appearances on mammogram. This [8, 9] appearance is affected by the factors such as age, menstrual cycle, pregnancy, hormone replacement therapy. The breast can divide into fatty tissue and glandular tissue together with lymphatic system and blood vessels. Young women typically have a large glandular tissue; this is gradually replaced by fatty tissue as the women get older in a process known as involution. There is a wide verity of breast diseases depends on sensitivity of breast tissues.

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Sensitivity is a fundamental characteristic of an imaging system and the imaging procedures with each system. The different imaging testing's are radiography, CT, MRI etc., have different contrast of their design and physical principles. For the radiographic imaging methods, mammography is designed to have much higher contrast sensitivity than the other radiographic procedures [10].

Characteristics of Lesions: On the body, a lesion is an area with is an abnormality or alteration in the tissues lesions. Breast lesions [9] usually come in the form of lumps or swellings in or around the breast area and they are frequently felt during a self breast examination or when examined by a physician. Some breast lesions, however, may be present but not felt. They are called non-palpable lesions and they are mostly detected during a screening mammogram test.

MATERIALS AND METHODS

The proposed method is Active contour modeling with wavelets. Original image is filtered through a family of db4 and Gabor filter with different resolution. Then the Gabor filter is applied to the db4 filtered image to produce noiseless image.

Proposed Method Flow Chart

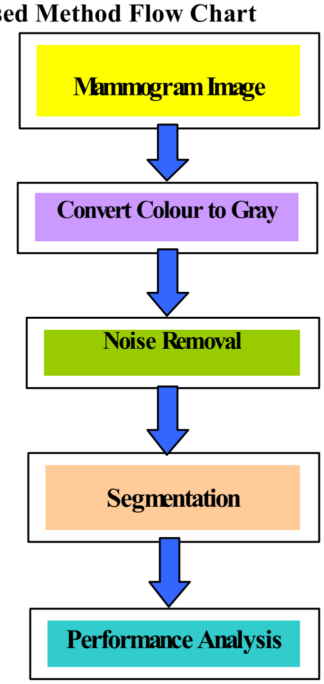

Fig. 1: Flow chart of the proposed stages

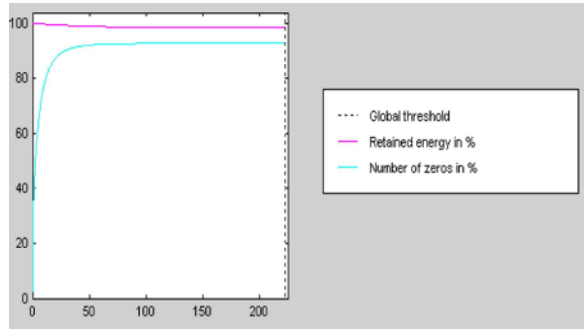

Fig. 2: Fixed thresholding

Thresholding: The concept of thresholding from being used as segment a two region image to segment an image with many intensity regions. It is used to divide thresholded image into sub image for further application. It introduces a program for valuating the image and document extracted from a mammogram at varies steps. The most important approximations are the breast boundary and separation of background noise [11].

In this Figure (2) fixed threshold is called global threshold. In fixed (or global) thresholding, the threshold value is held constant throughout the image and to determine a single threshold value by treating each pixel independently of its neighborhood.

Fixed thresholding is in the form of

$$g(x,y) = \begin{cases} 0 \, f(x,y) \langle T \\ 1 \, f(x,y) = T \end{cases} \tag{1}$$

Compare with the local thresholding and adoptive thresolding this is used to extract an object from its background by assigning intensity value T (threshold) for each pixel such that each pixel is either classified as an object point or a background point.

Noise Removal: To remove the noise from the original image, we have to use a Gabor filtering technique. From this result we get a noiseless image

The horizontal and vertical derivatives are used to determine the direction of intensity in the near skin tissue. The derivatives are obtained by filtering the image. The number of pixel values is taken into the chest wall.

Thresholding usually involves analyzing the histogram. Different features give rise to distinct features in a Histogram. In general the histogram peaks corresponding to two features will overlap. The degree of overlap depends on peak Separation and peak width.

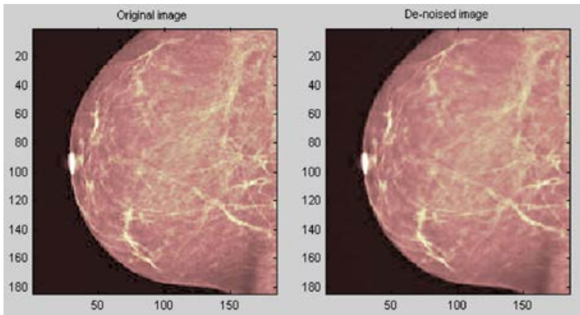

Fig. 3: (a) Original image (b) Denoised using Gabor filter

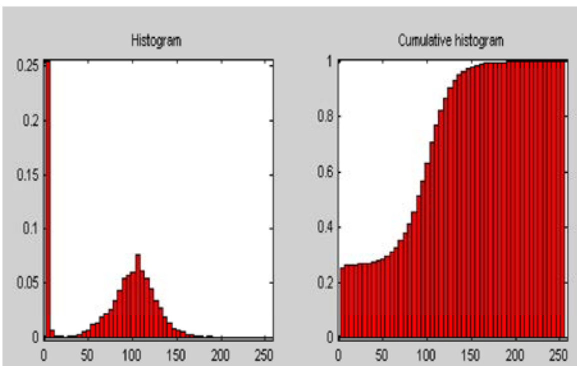

Fig. 4: Status of Histogram

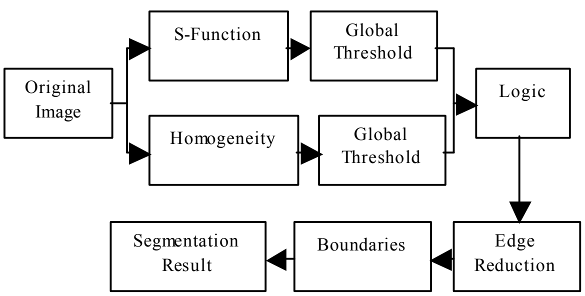

Fig. 5: Block diagram of segmentation results

Table 1: Statistics

S. No	Statistical parameter	Statistical data
1	Mean	76.81
2	Median	92.00
3	Mode	03.55

The statistical histogram is shown in the Figure. 3 and calculated Mean, Median, Mode are tabulated.

Here we used the wavelet 2-D toolbox and testing the De-Noising results of original image and statistical data, histogram.

Segmentation: Breaking an image is called segmentation. It deals with basically separating the background and foreground of images. Snakes or active contours [1] [2] provide the effective way of segmentation. Active contours [3] are extensively used in the field of digital image processing to find the contour of an object by forming a snake around the boundary. Gray level thresholding is common approach to the breast segmentation. Two thresholds are generally required. The first rejects pixels with low grey-levels, assuming them to belong to non-breast [5] radiolucent objects. The second discards pixels with high grey-levels, assuming them to belong to non-breast radiopaque objects.

Adoptive window method of matrix equation is applied in this segmentation as followed by

$$\begin{bmatrix} C_0 & C_{+1} & C_{+2} & 0 & 0 & C_{-2} & C_{-1} \\ C_{-1} & C_0 & C_{+1} & C_{+2} & 0 & 0 & C_{-2} \\ C_{-2} & C_{-1} & C_0 & C_{+1} & C_{+2} & 0 & 0 \\ 0 & C_{-2} & C_{-1} & C_0 & C_{+1} & C_{+2} & 0 \\ 0 & 0 & C_{-2} & C_{-1} & C_0 & C_{+1} & C_{+2} \\ C_{+2} & 0 & 0 & C_{-2} & C_{-1} & C_0 & C_{+1} \\ C_{+1} & C_{+2} & 0 & 0 & C_{-2} & C_{-1} & C_0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} + \begin{bmatrix} \partial E_{ext}/\partial x_1 \\ \partial E_{ext}/\partial x_2 \\ \partial E_{ext}/\partial x_3 \\ \partial E_{ext}/\partial x_4 \\ \partial E_{ext}/\partial x_5 \\ \partial E_{ext}/\partial x_6 \\ \partial E_{ext}/\partial x_7 \end{bmatrix} = 0$$

Active Contour and Mammograms: In this research we focus on general parametric snakes [6-7]due to its computational advantages and simplicity. There are many different images energy terms that are used in practice. Most of the commonly used [11] approaches fall into two methods. They are broadly defined as

- Edge-based method (gradient information)
- Region-based method (statistical formulation)

Total energy of the active contour is written as

$$e_{contour}\Theta = e_{image}\Theta + e_{\text{int}}\Theta + e_c\Theta \tag{2}$$

Edge maps are derived from the following equation.

$$E_{edge} = \int_s \nabla . e_f(s)ds \tag{3}$$

In this paper active contour model based method for segmentation of the lesions. There are some disadvantages related to the original model. Many improved active models have been proposed based on the original model. The GVF (Gradient Vector Flow) model is one of them. GVF model is designed to overcome one of the disadvantages of original model which can be implemented by minimizing the following energy function [13]

$$E_{GGVF}(u,v) = \frac{1}{2}\iint g(|\nabla f|)(u_x^2 + u_y^2 + v_x^2 + v_y^2) + (1 - g(|\nabla f|))((u - f_x)^2 + (v - f_y)^2)dxdy, \tag{4}$$

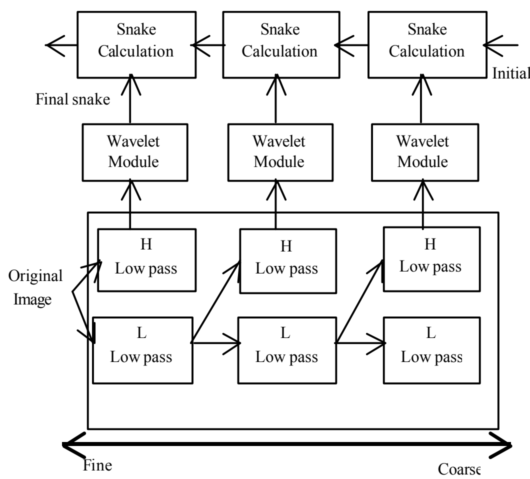

Fig. 6: Flow chart of the wavelet-based active contour model

where g is a decreasing function of edge-force magnitude

$$g(|\nabla f|) = \exp\left(-\left(\frac{|\nabla f|}{k}\right)\right) \tag{5}$$

There are several reasons why active contours offer a suitable approach to the process of breast region extraction. The major foundation is that the breast is a well defined curve and as such is pleasurable to the curve approximation characteristics of active contours. In addition, the background in most mammograms is a low intensity, low gradient region and as such can be avoided by the active contour in its search for a local minimum. However it is predictable that there will be several issues to resolve before using active contours with mammograms

- Medium intensity noise may unconsciously attract the active contour away from the breast region if it is too close to the initial contour.
- The breast-air boundary is typically a medium gradient, so any energy functional based on edges will need some preprocessing.
- The initial contour will have to be placed moderately close to the desired breast contour.

This wavelet based snake model is employed in many experiments on mammogram images. The flow chart of utilized model is shown in Figure.

RESULT AND DISCUSSION

By the iterative process energy function for each point in the local area is calculated, the point is moved to the next point with lowest energy function. This process is repeated for every point. Iteration is done until termination condition met. Defined number of iterations gives stability of the position of the points.

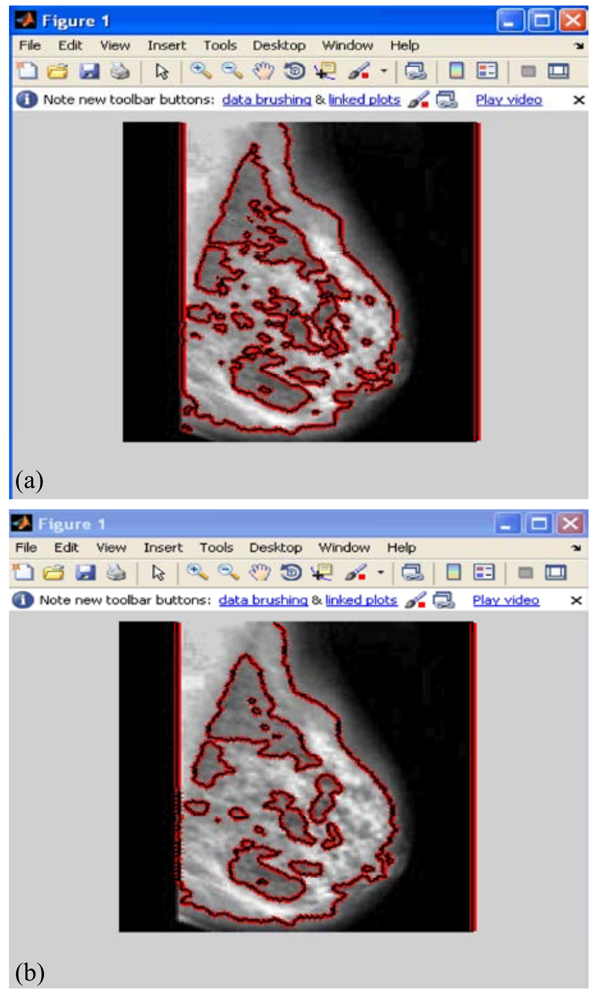

Fig. 7: First and last iterative image segment by active contour model

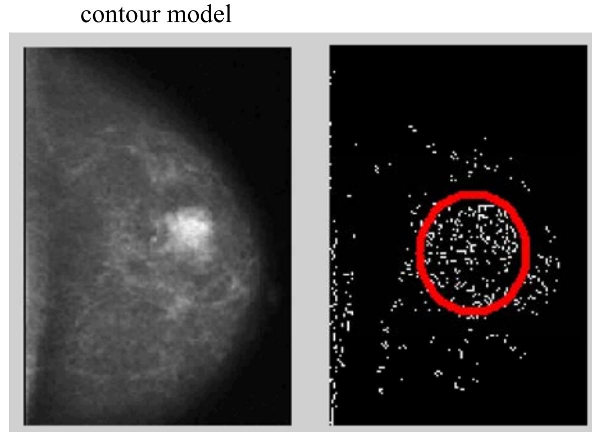

Fig. 8: (a) Original image (b) Calcification image with lesion

Analysis of Lesion: The mammogram report shows some white spots on mammogram it has been recorded as breast cancer. This original image shows the abnormal tissues change is called lesion. In the 100th iteration process where by calcium salt is deposited in an organic matrix and then it has been indicated in red marked portion

CONCLUSION

The method has been described for applying active contours to the assignment of segmenting the breast region in mammograms and extracting the breast contour. It uses from the mammogram problem domain to automate the initial placement of the snake and process the image into a suitable input for an active contour. Preliminary results indicate that, in terms of the amount of the mammogram classified as breast region, it is comparable to existing techniques. One of the significant shortcomings of this method is the lack of ability of the snake to recognize when it is inside the breast. If such a situation occurs, the snake will segment on subcutaneous tissue instead of the breast contour. Future work will focus on couture snake parameters and extending the concept on active contours to develop neural networks in an algorithm we term it as neural snakes.

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