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# Mass Auto-detection in Mammogram based on Wavelet Transform Modulus Maximum

Li Ke*, Wei He, and Yan Kang

*Abstract*—**High accurate detection of mass in mammogram is critical for improving the performance and efficiency of computer-aided diagnosis (CAD) system. In this paper, we propose a novel approach to enhance the detection performance of mass in mammograms using Wavelet Transform Modulus Maximum (WTMM). First, hunt the region of interest (ROI) through the whole image and the ROI was approximately located by multi-threshold method. Then the contour of the ROI was extracted from the modulus image acquired by Wavelet Transform Modulus Maximum (WTMM) method .The region of interest was finally refined by the contour extracted. Experimental results indicate that the proposed method is able to detect not only isolate masses, but also the masses connected with the glandular tissues successfully. This technique could potentially improve the performance of CAD system and diagnosis accuracy in mammograms.**

## I. INTRODUCTION

Breast cancer is one of the leading causes of death in women. Among the imaging modalities and detection tools, mammogram is considered one of the most cost-effective methods for cancer detection in early stage. Generally, the main indicants of breast cancer in mammograms are the presences of micro calcifications and masses [1], and the automated computerized diagnose can be useful in assisting radiologists, thus reduce the number of unnecessary biopsies in patients.

The procedures of computer-aided diagnosis (CAD) system for the detection of masses can be described as three steps: (1) Detect the regions of interest that likely to be massive lesions. (2) Segment the region of interest (ROI) (3) Classification. Moreover, the efficient of classification is strongly based on the result of segmentation. Commonly used technique for masses segmentation in mammograms are based on methods such as adaptive threshold method [2], region grow method [3], Markov random field [4], fuzzy clustering [5], and segmentation based on wavelet transform [6]. Among these methods, the detection of masses immerged in glandular tissues have not resulted effectively, because the mass has a very low contrast with the glandular tissues and ill-defined margins [7], because massive lesions exhibit a very low contrast with the glandular tissue and ill-defined margins.

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Li Ke is with Institute of Biomedical and Electromagnetic Engineering, Shenyang University of Technology, Shenyang, Liaoning 110178, China, e-mail: amykeli@hotmail.com
Wei He is with School of Postgraduate, Shenyang University of Technology, Shenyang, Liaoning 110178, China, e-mail: ivyhe@live.cn
Yan Kang is with Sino-Dutch Biomedical and Information Engineering, Northeastern University, Shenyang, Liaoning, China

Fig.1 shows a series of mammograms with massive lesions. Fig.1 (a)-(c) illustrated the kind of mammogram with mass immerged in (or connected with) glandular tissues, while (d)-(f) are the cases with masses isolated to the background. As is shown in Fig.1, massive lesions are immerged in glandular tissues without clear margin. It's hard to find an effective criterion to segment the regions from the glandular tissues since massive lesions in mammograms exhibit different intensity, shape, and contrast. Therefore, it is necessary to develop more effective for mass detection in mammogram.

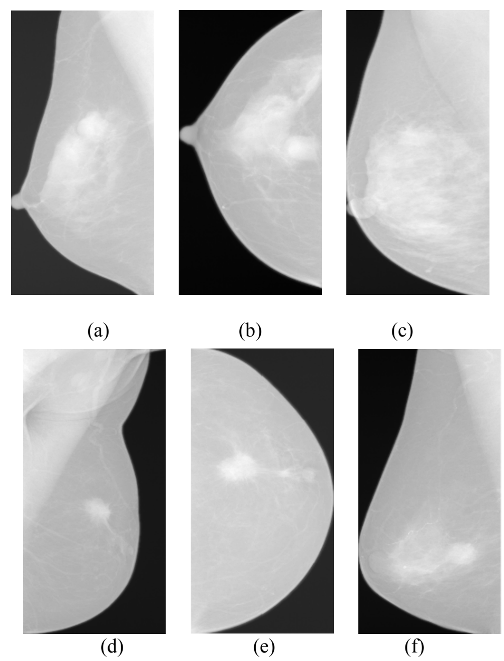
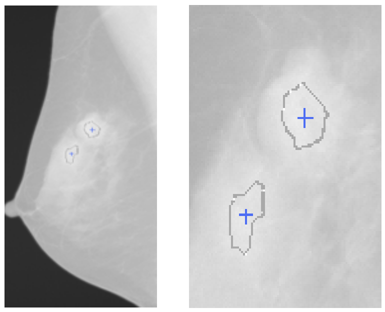



Fig. 1 Mammograms with massive lesion

In this paper, a novel segmentation method by contour extraction was proposed, basing on two steps: detection of ROI, region segmentation.

## II. DETECTION OF ROI

Massive lesions, which are similar to the glandular tissues in anatomy, exhibit different in intensity, shape, and contrast in mammogram [8-9]. Generally, the massive lesion exhibits high gray intensity comparing to the surroundings [10]. First, the region of interest are detected in the image, the goal of this step is to locate the regions that are likely to be massive lesions in the background initially. Dispose the mammogram by a series threshold; detect the region of interest (ROI) in the images acquired. Fig. 2 shows the results of the processing, while the pixel marked in blue "+" is the central of ROI detected.



(a) (b)

Fig. 2 ROI in mammograms and the central of the regions

This procedure provides the location of ROI in mammogram, only selected regions are stored for the next processing steps, rather than the whole mammogram shown in Fig.2 (a). The region of interest (ROI) detected should be refined to improve the result of segmentation in order to keep stable features such as the area, gray value and roundness of each region. The consecutive contour of the ROI will be extracted from the modulus image in the following steps to refine the region of interest segmented initially by multi-threshold method.

## III. MASS SEGMENTATION METHOD

### A. Edge detection based on WTMM

In the segmentation step, wavelet modulus maximum method was used to detect the edge due to its excellent time-frequency characteristic [11]. Extract the contour of the ROI from the modulus image, and then the region refined by the consecutive contour extracted to improve the accuracy of segmentation algorithm. Considering the smoothing function $\phi(x,y)$ , let $\iint_{R^2}\phi(x,y)dxdy = 1$ . Compute the gradient in direction x and y separately.

$$\psi^{(x)}(x,y) = \frac{\partial\phi(x,y)}{\partial x} \tag{1}$$

$$\psi^{(y)}(x,y) = \frac{\partial\phi(x,y)}{\partial x} \tag{2}$$

Equation (1) and (2) can be written as:

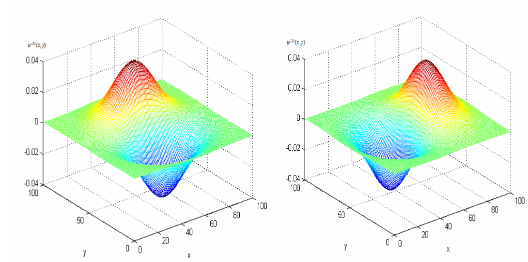
$$\tau_s(x,y) = \frac{1}{s^2}\tau\left[\frac{x}{s},\frac{y}{s}\right] \tag{3}$$

where $s$ is the scale. $\psi^{(x)}(x,y)$ and $\psi^{(y)}(x,y)$ was treated as the wavelet bases of the wavelet transform, the 3-D illustration of $\psi^{(x)}(x,y)$ and $\psi^{(y)}(x,y)$ was shown in Fig3.

The directional wavelet transform of image $f(x,y)$ is defined as:

$$\left.\begin{aligned} W_S^{(x)}(x,y) &= f(x,y)\Theta\psi_S^x(x,y) \\ W_S^{(y)}(x,y) &= f(x,y)\Theta\psi_S^y(x,y) \end{aligned}\right\} \tag{4}$$

Where $W_S^{(x)}$ and $W_s^{(y)}$ describe the gray gradients of the image in direction $x$ and $y$ respectively.



(a) (b)

Fig 3 (a)The wavelets in direction $x$; (b) The wavelets in direction $y$

The wavelet transform of image $f(x,y)\in L^2(R)$ has two components and can be expressed in a vector form:

$$\begin{bmatrix} W_s^{(x)}(x,y) \\ W_s^{(y)}(x,y) \end{bmatrix} = s\bullet\begin{bmatrix} \frac{\partial}{\partial x} f\otimes\psi_s(x,y) \\ \frac{\partial}{\partial y} f\otimes\psi_s(x,y) \end{bmatrix} \tag{5}$$
$$= s\bullet(f\otimes\psi_s)(x,y)$$

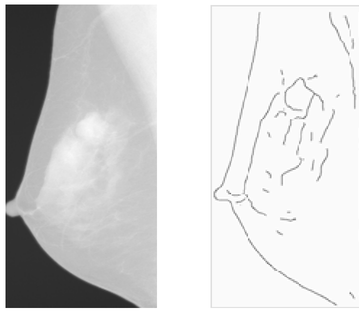
In the Equations (4), $s$ is the scale, $\phi(x,y)$ is smoothing function. The edge of the image is the inflexion of $(f\otimes\phi_S)(x,y)$ . It can be seen that, the modulus value at scale $s$ is the edge of the image. So, the modulus of wavelet transform at scale $s$ is defined as:

$$M_S(x,y) = \sqrt{\left|W_S^{(x)}(x,y)\right|^2 + \left|W_S^{(y)}(x,y)\right|^2} \tag{6}$$

the phase angel is written as:

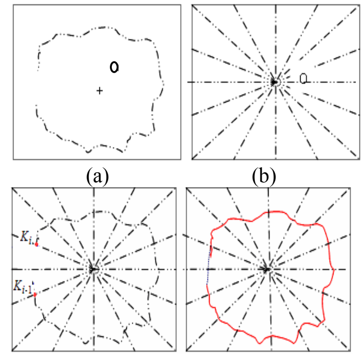
$$A_s(x,y) = tg^{-1}\frac{\left|W_S^{(y)}(x,y)\right|^2}{\left|W_S^{(x)}(x,y)\right|^2} \tag{7}$$

In Eq. (5) and (6), $X=\{(x,y):\left|M_2^j f(x,y)\right|\neq 0\}$ describes the feature of the edge. $M_S(x,y)$ is the gray gradient at point $(x,y)$; while the points with the maxim modulus in direction $A_2^j$ is the mutation points of $f(x,y)$. Fig.4 shows the edge detection result of the image shown in Fig. 4 (a).



(a) (b)

Fig. 4 (a) The initial image; (b) Edge detection result based on WTMM



(a) (b) (c) (d)

Fig. 6 Edge-point linking

*B. Contour extraction*

As we know the edge acquired by 2D-WTMM method can not be used in segmentation algorithm since there are so many segments on the contour [12], as is shown in Fig. 4. So it is necessary to delete the segments irrelevant in case that they are treated as the contour of the region.

There are some small breaks in the edge image acquired by-2D WTMM in Figure 5, so the first step is to delete the edge in case they are treated as the contour of the region. Then the edge-points are linked as in Figure 4 [8]. The purpose of this processing is to find the edge–points isolated by scanning the edge-points in a 3×3 neighborhood in the edge image.

If there is only one point in the neighborhood of $P(x,y)$ , $P(x,y)$ is an isolated point, as is shown in Figure 5 (a). While in Figure 5 (b), $P(x,y)$ is a breaking point on the edge if the two points in the neighborhood are adjacent. On the contrast, the points are consecutive as is show in Figurer 5 (d) and (e), and Figurer 5 (e) depicts the pixel on the crossing of two or more edge lines.

| | | |
|---|---|---|
| 1 | 0 | 0 |
| 0 | ① | 0 |
| 0 | 0 | 0 |

(a)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 0 | ① | 0 |
| 0 | 0 | 0 |

(b)

| | | |
|---|---|---|
| 1 | 0 | 1 |
| 0 | ① | 0 |
| 0 | 0 | 0 |

(c)

| | | |
|---|---|---|
| 1 | 0 | 0 |
| 0 | ① | 0 |
| 0 | 0 | 1 |

(d)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 0 | ① | 0 |
| 0 | 1 | 0 |

(e)

Fig.5 Edge points

Link the breaking points with close distance on the contour, while the breakings with relevant remote location are linked as follows (as in Fig.6):

1) Considering that the massive lesions are approximately round in shape, the central of the massive lesions in the mammogram are almost the pixel with high intensity. Hence, we treat the pixel 'O' as the center.

2) A set of radial lines are depicted from the center 'O' of the region to the boundary, as is shown in Fig. 6(b).

3) Scan the pixels along the radial line from the center of the region to the boundary to find the pixels $K_1, K_2 \cdots, K_i$ with the maximum modulus [Fig.6 (c)].

4) If there is no consecutive segment between the two points $K_i$ and $K_{i-1}$ , then $K_i$ and $K_{i-1}$ are connected on modulus image as a part of the contour [Fig.6 (d)], thus, the consecutive contour of the massive lesion was extracted by the linking procedure.

5) Segment the massive region by the contour extracted from the modules image in mammogram, Fig.7 shows the result of the segmentation algorithm.

(a) (b) (c)

Fig.7 (a) Edge detection result; (b) the edge of ROI

## IV. Results and Discussion

The mammograms used in this study were obtained by GE's digital mammography product, Senographe 2000D, collected in collaboration with Liaoning Tumor Hospital, with a pixel resolution of 100×100μm and 12 bit per pixel. The digitized mammographic images used in this study contains 52 ROIs, with 32 massive lesion immerged in (or connected with) glandular tissues such as in Fig.1 (a)-(c), and 20 cases with mass isolated to the background as in Fig.1 (d)-(f).

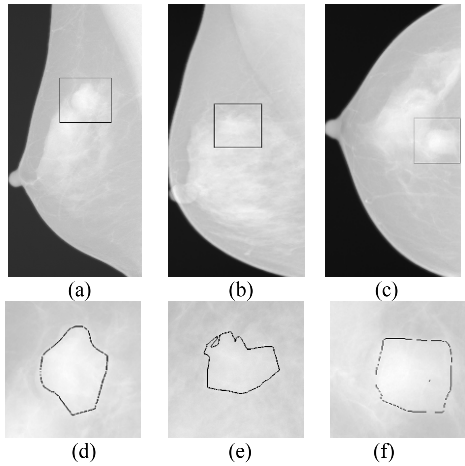


Fig.8 (a)-(c) the mammograms with immerged mass; (d)-(f) The results of the auto-detection algorithm

The massive lesions are immerged in glandular tissues without clear margin. Fig.8 (a)-(c) are the mammograms with immerged mass, and the "blocks" is given by the physician's diagnosis. While (d)-(f) shows the results of mass auto-detection using the methods described above.

As is shown in Fig.8, the massive lesions immerged in the glandular tissues with similar intensity are segmented from the background successfully. Results of 32 cases with the kind of mass immerged in background with glandular tissues show that the algorithm could segment the massive lesion exactly to its geometric boundary condition. The algorithm is also effective to the kind of masses isolated to the background, as is shown in Fig.9, (a)-(c) are the mammograms with the physician's diagnosis, while (d)- (f) showed the segmentation results of the algorithm proposed.

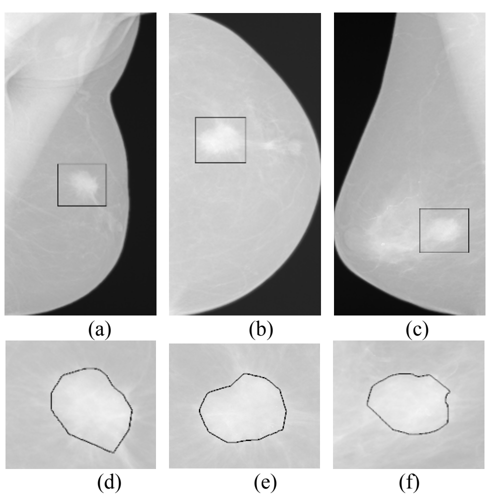


Fig.9 (a) -(c) The mammograms with isolated mass; (d)-(f) The results of the auto-detection algorithm

## V. CONCLUSION

In this paper, an algorithm for mass detection has been presented. The method relies on an edge-based extraction strategy, for the segmentation of masses. Hunt the region of interest by multi-threshold method in the whole image, then the wavelet transformation modulus maximum was introduced to refine the region detected in mammograms by extracting the contour. Experiment results show that the segmentation algorithm is able to extract the massive lesion from surroundings efficiently with initial geometric features. The work could potentially improve the accuracy of the computer aided diagnose.


## VI. ACKNOWLEDGEMENTS

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