AUTOMATIC ROI GENERATION FOR LESION SEGMENTATION OF BREAST ULTRASOUND IMAGE USING DIRECTIONAL GRADIENT

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Abstract- In case of ultrasound image, lesion boundary suffers due to their peculiar nature, shadow**, low resolution** and the variance in shape. Automatically detecting tumors and extracting lesion boundaries become very difficult due to those problems. Many algorithms are proposed for automated segmentation of lesion from ultrasound image. Most of them are facing problem due to **the diversity of whole** ultrasound image. Automatic Region of Interest (ROI) selection is a good choice to execute the automated segmentation more specifically. **The specific region should have lower variations and specific algorithm can be applied.** In this paper we propose a novel technique to select the ROI **for breast** ultrasound image concentrating to the lesion boundaries. The images are prepossessed to detect the approximate boundary. On the basis of that boundary ROI is selected for automated segmentation of lesion boundaries. The proposed algorithm is also implemented to real patient data and shown as result at the later part of the paper.

Keywords- Breast Ultrasound Image, Automatic Segmentation, ROI Generation

I. INTRODUCTION

Breast cancer is the most common cancer encountered by women and one of the leading causes of women's death all over the world. It is a leading cause of cancer death, second only to lung cancer [1]. In 2013, an estimated 232,340 new cases of invasive breast cancer were expected to be diagnosed among US women, as well as an estimated 64,640 additional cases of in situ breast cancer and approximately 39,620 US women were expected to die from breast cancer [2]. Breast cancer is most effectively treated when detected at an early stage [3]. Computer Aided Diagnosis (CAD) acts an important agent in early detection of breast cancer.

Among different CAD analysis present for breast cancer detection, Ultrasound imaging is gaining an edge over others such as Digital Mammography and Magnetic resonance imaging (MRI) due to its lower expense and non-invasive nature. Automatic early detection of cancer using low expense material such as ultrasound seems to be a potential improvement in the cancer diagnosis for developing and underdeveloped countries.

The segmentation of breast ultrasound (BUS) images is an essential and critical step in CAD systems [4]. Efficientsegmentation will further ensure the accuracy of the CAD system. However, due to the inherent nature of US imaging, the images always suffer from the poor quality caused by speckle noise, low contrast, and blurred edge and shadowing effect. These impose potential challenges in segmentation of the BUS images.

The segmentation problem of BUS image can be divided into two parts:

i) Region of Interest (ROI) Generation and
ii) ROI Segmentation.

In this paper, we will be focusing on ROI Generation problem. A successful ROI has a very high possibility to have a good segmented data. The rest of the paper is organized as follows: in section 2, we briefly provide background and past works in ROI generation; in section 3, we present our proposed method, in section 4, we show some of our experimental results and in section 5 the conclusion.

II. BACKGROUND

Segmentation is a fundamental problem in ultrasound image processing and has numerous important clinical applications, including anatomic modeling, change quantification and image-guided interventions/therapy [5]. Several techniques exist to solve the BUS segmentation problem. The existing methods are: region growing [6], Markov random fields (MRF) [7], Active contours [6, 8], Neural networks [9, 10], Watershed [9] etc. These methods suffer some major problems in ROI generation phase. These are:

i) The most common problem is that the regions-of-interest (ROIs) were determined manually [11];
ii) The decision whether to consider speckles as noise or to treat them as features [4];
iii) Varying size and location of the contours together with shadowing artifacts make the ROI generation problem a complicated one.

There are many existing methods which aim to achieve automation in the ROI generation phase. Some of these are: Automatic ROI production by a supervised texture classification method [11], ROI generation using texture features and spatial characteristics [12], ROI generation using self-organizing map neural network [13] etc. In next section we propose a novel ROI generation method of BUS image.

III. PROPOSED METHOD

In the proposed method**,** texture information as well as spatial characteristics of BUS image is considered. The automatic ROI generation method involves three major steps:

1. Horizontal Cut based on Entropy Filtering
2. Seed Generation for Gradient Calculation
3. ROI Finalization using Directional Gradient

A. Horizontal Cut based on Entropy Filtering

First entropy filtering is applied on wholeBUS image. Entropy is a textural feature and can be defined as a measure of randomness:

$$Entropy = -\sum_{i=0}^{L-1} p(x_i)\log_2 p(x_i) \qquad (1)\ [13]$$

In equation (1), x is a random variable, p(x) is the histogram of the intensity levels, L is the number of possible intensity levels.

It is observed that the entropy values are different for different regions. The entropy values in the dark (anechoic) region inside the lesion vary from 3 to 5. The white (hyper-echoic) region found near the boundary of the lesion has very high entropy values ranging from 6 to 7.5. The rest of the image with mostly gray regions (hypo-echoic) has values from 5 to 6.5. We observed that always the lesion is surrounded by hyper-echoic boundary region with high entropy value. With this information, the entropy filtered image is divided into three horizontal blocks and the block with minimum entropy is deleted to have smaller region for further processing.

B. Seed Generation for Gradient Calculation

Binary Image Formation

For binary image formation from the entropy filtered image, a threshold value is set. It is observed that a fixed universal threshold yields to poor performance in the next subsequent steps. Therefore, an adaptive threshold selection process is adopted which will set different threshold value for different images.

For threshold selection, the histogram of the entropy filtered and horizontally cut image is taken into account. From the histogram, the maximum frequency is determined. Then entropy value whose frequency of appearance corresponds to 60% of the maximum frequency is used as the threshold value to generate the binary image. The reason behind choosing the entropy value whose frequency of appearance corresponds to 60% of the maximum frequency is because it visually gives satisfactory result in the binary image formation. The process of threshold selection can be summarized in Figure 01. Using this threshold, we form our binary image.

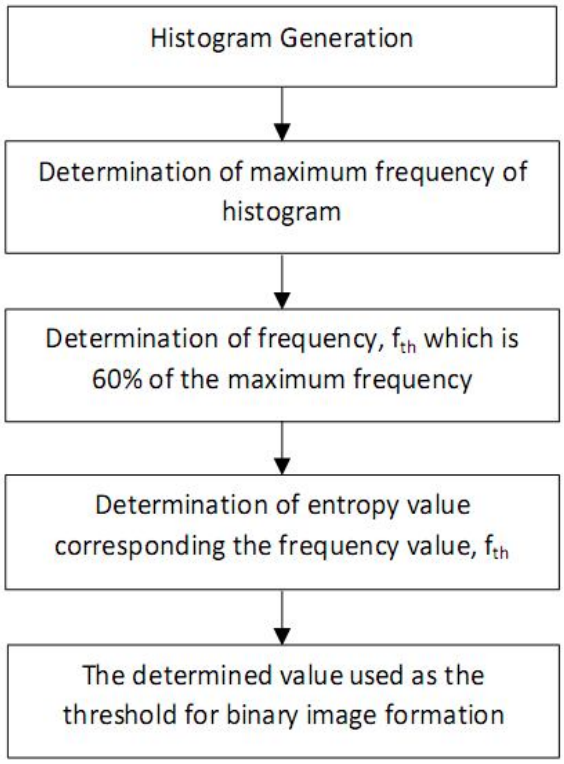


Figure 01: Flow chart of threshold selection process

Deleting Boundary Connected Region

Subcutaneous fat, glandular tissue and skin typically appear in the upper portion of the image [5]. Also, the shadowing region appears in the posterior part of the image [14]. It is observed that these regions are generally boundary connected. Thus eliminating boundary connected region will leave us potential lesion region. In this step, the technique mentioned in [15] is used. In this technique, a center window is used to evaluate every boundary region. If a region has no intersection with the center window and it is connected with any of the 4 image boundaries, this region is deleted from the lesion candidate list.

Ranking the rest regions

Then the rest regions are ranked which are potential candidates of the lesion region. Two arguments are considered such as the region with highest area and the regionnearest to the image center.We used to following ranking function from [15] with slight modifications:

S_n=(Area of the n^{th} region) / d(Cn,Co); (2)

Here, n=1,2,3…….k; k=number of regions; d(Cn,Co)=distance between center of the nth region, Cn to the center of the image, Co. The region with the maximum value from the ranking function marks our winning region for lesion.

A. ROI Finalization Using Directional Gradient

In this section, ROI is finalized by calculating directional gradient. The gradient of an image f in the location (x, y) is defined as

$$\nabla f \equiv grad(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} \equiv \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (3)$$

Thus the gradient of an image requires computing the partial derivatives at every pixel location of the image. Since we are dealing with digital images, a digital approximation of the partial derivatives over a neighborhood about a point is required. The equation 3 can be discretely approximately as follows:

$$g_y = \frac{\partial f(x,y)}{\partial y} = f(x,y+1) - f(x,y) \quad (4)$$

$$g_x = \frac{\partial f(x,y)}{\partial x} = f(x+1,y) - f(x,y) \quad (5)$$

Using equation 4 and 5 in a modified way, directional gradient along 360 degrees is calculated taking seed point as center for finalizing our ROI.

Gradient Calculation along 360 degree

Usually derivative calculation provides good result in boundary detection in noise-free image which is a very deviant case from ultrasound image. Here, derivative is used to obtain a preliminary contour serving as the intermediate result for ROI generation. Before derivate calculation, median filtering is applied on the image to suppress speckle noise. In the next step, the target of the proposed method is only to approximate the boundary rather than segmenting it. Therefore much attention is not paid in the noise suppression from the image.
To determine gradient of a pixel, grad(j) for in a direction Ø(i) we have used the following equation:

$$grad(j) = |q1(j) - q2(j)| \quad (6)$$

In equation 6,j= number of pixels of the image;
q1(j) = sum of next n no. of pixel intensities from the pixel under consideration, p(j);
q2(j)= sum of previous n no. of pixel intensities from the pixel under consideration, p(j);
n = number of pixels considered for the calculation.

In the proposed algorithm, n=8 yielded good outcome. This technique of pixel summation is used to suppress the noiseeffect of the ultrasound image. Then, 1st, 2nd and 3rd maximum values of gradients are determined in all directions. Finally a rough boundary is achieved by calculating medians among the top three gradients in each direction.

Final ROI Cut
For final ROI cut, image is divided into four quadrants as shown in Figure 02. Generally, it is observed that the irregularity in the shape of breast lesion can be closely correlated with oval shape. This is the motivation behind choosing such quadrants as depicted in Figure 02.

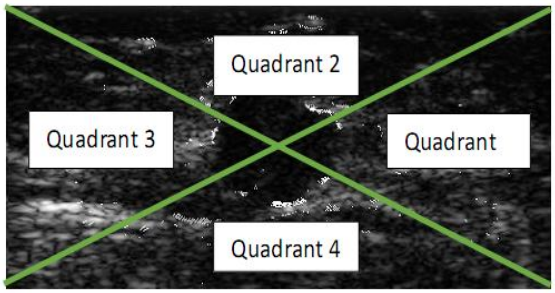


Figure 02: Quadrant Selection for radius calculation

From the set of gradient points in quadrant 1, the average among those points is determined and used the value as the radius of ROI in positive x direction. An offset of 15 pixels is purposefully added in order to make sure that the lesion is completely covered by ROI. The same procedure is repeated for other three quadrants. Thus the average radius of ROI is determined centering from the original seed point.
Using this radius in four directions, the final Region of Interest is selected.

IV. EXPERIMENTAL RESULT

For our experiment, we have used a database consisting of 80 BUS images. Among them, the proposed method successfully generated ROI for 75 images with a success rate of 93.75%. The figure 03 shows the result of the proposed method

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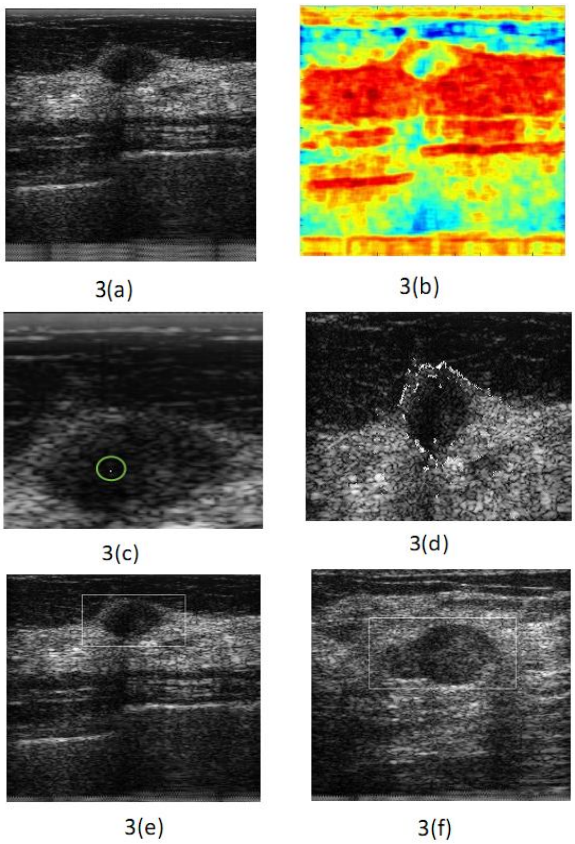


Figure. 03 (a) Original Image (b) Entropy Image (c) Generated Seed Point (d) Boundary Delineated Image (e) Final ROI marked with a rectangle (f) ROI of Speclked Image

CONCLUSION

A novel automatic seed and ROI generation algorithm is proposed in this paper for better segmentation of BUS. From the experimental result, it can be concluded that our algorithm works well for a large set of BUS image. Moreover, many segmentation algorithm requires manual seed selection. Those semi-automatic methods can be fully automated using the seed generated from the proposed method.
However, the method suffers from challenges such as multiple node ROI detection, less efficiency in highly shadowed image. Future work focuses on solving these problems and efficient automatic segmentation of the breast lesion using generated ROI.

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