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Breast Density Analysis in 3-D Whole Breast Ultrasound Images

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Abstract—The breast density information is one of important factors for estimating the risk in breast cancer detection and early prevention. In this paper, we present two methods, including threshold-based and proportion-based, to automatically analyze the breast density using whole breast ultrasound. The two algorithms are experimented with 32 cases which are scanned from 32 patients using the US machine SSD-5500 with a recent developed scanner ASU-1004 (Aloka, Japan). The experimental results are graded from 4 (extremely dense tissue) to 1 (almost entirely fat), and respectively compared with the majority grades of three radiologists. The accuracy of the threshold-based and proportion-based strategies is 88% and 84% respectively.

Keywords: breast density, whole breast ultrasound, ROI, Grandular, Fatty, Threshold, Proportionate, Performance

I. INTRODUCTION

Breast cancer is one of the leading causes for cancer mortality among women [1]. Breast cancer screening, which includes mammography and clinical examination, has long been established in Western countries [2]. The United States Preventive Services Task Force (USPSTF) had recommendations on breast cancer screening, which call for annual clinical breast examinations after 40 years of age, mammography every 1 to 2 years beginning at 50 years of age [3]. If women can take screening early, they will be earlier diagnosed having tumor or not and take the earlier cure so that the risk of the breast cancer will be decreased.

In general, many factors are used for estimating the risk in breast cancer detection and early prevention, and the breast density information is one of the strongest indicators. Breast density is assessed at the initial examination and classified as 'dense' (if > 25% of the breast was composed of density) or 'lucent' (< or = 25% density) [4]. The relative risk is estimated to be about 4 to 6 times higher for women that have parenchymal densities over 60% of the breast area, as compared to women with less than 5% of parenchymal densities [5]

Boyd *et al.* [6] determined the level of breast cancer risk associated with varying mammographic densities using quantitative grade of breast density. Investigation by Saha *et al.* [7] described an automatic and reproducible method to segment dense tissue regions from fat using scale-based fuzzy connectivity methods and compute different measures for characterizing mammographic density. Both of these researches showed high accuracy on the risk estimation of breast cancer using mammographic density calculation. However, screening mammography may be too expensive and its sensitivity declined significantly with increasing breast density. In the last decade, ultrasound imaging is an important tool for clinical examination in the further diagnosis of both palpable and impalpable breast abnormalities. It is used not only to detect breast abnormalities which can be found at mammographic examination but also to screen the women with dense breast that is difficult to do using mammography. Hou *et al.* [8] compared breast mammography, ultrasound and physical examination for 935 high-risk Asian women who usually have dense breasts. The experimented result shows the sensitivity of ultrasound was 90.4%, which was higher than mammography (52.4%) and physical examination (33.3%). We will analyze the breast density based on the ultrasound images. However, the conventional 2-D ultrasound, which only obtains the sectional image of partial breast region, is not enough to provide the whole breast imaging like mammography. Fortunately, the recently developed whole breast ultrasound could provide the whole breast image. The whole breast ultrasound may be useful for three reasons. First, the volumetric ultrasound data may be more enough to analyze the breast density than conventional 2-D ultrasound. Second, whole breast ultrasound can provide more data and better statistics more than 2-D mammograms. Third, it is considerably beneficial for its convenience, non-invasive and inexpensive modality. Hence, this paper will analyze the breast density based on the new whole breast ultrasound imaging technique.

In this paper, a novel breast density analysis system has been presented to measure the breast density automatically based on whole breast ultrasound images that offers radiologists a second quantification reading for prediction of breast cancer risk. Two quantification methods are proposed to measure the breast density. One is to calculate the proportion of glandular tissue and fat tissue, another one is based on the threshold algorithm. Finally, the two experimental results will be respectively compared with the radiologists' diagnoses based on the American College of Radiology Breast Imaging Reporting and Data System (BI-RADS) standard [9].

II. 3-D WHOLE BREAST ULTRASOUND ACQUSITION

The whole breast ultrasound images are scanned using the US machine SSD-5500 with scanner ASU-1004 (Aloka, Japan). The water proof probe is sunk in the water, and the breast is also sunk the bag of water. The conventional probe is moved under the water bag, as shown in Fig.1(a). One breast needs three passes with a 6-cm probe, and the overlapping between two passes is 1 cm. So, the scanning area is 16×16 cm^2. Because it needs three passes for scanning a whole breast, the three-pass frames should be merged into full-view images before analysis. The operation of ASU-1004 is shown in Fig.1(b). A full automatic mechanism is used to move the probe for scanning the whole breast. Then 252 images (84 images/per pass) are obtained, and the distance of each image is 2 mm.

All the acquired 252 images are first stored into a DICOM file. Hence, a DICOM reader is used to decompose the DICOM file into serial 2-D images with size 608 × 420 pixels. In each 2-D image, the actual useful US region is 261 × 390 pixels, and the pixel resolution of the US images is 44 pixels / 1 cm. These image slices S_n, $1 \le n \le 252$, are divided into right frames R_m (pass 1), left frames L_m (pass 3), and middle frames M_m (pass 2), $1 \le m \le 84$. Because the direction of pass 2 is the reverse direction of passes 1 and 3 as shown in Fig.1(b), the relation of L_k, M_k, and R_k to S_s is defined as

$$R_m = S_m,\ M_m = S_{169-m},\ L_m = S_{m+168},\ 1 \le m \le 84. \qquad (1)$$

The BI-RADS lexicon is a quality assurance tool designed to standardize mammography reporting, reduce differences between breast imaging interpretations, and facilitate outcome monitoring. In the BI-RADS classification scheme, it classifies the breast density into four categories: (1) almost entirely fat, (2) scattered fibro-glandular tissue, (3) heterogeneously dense tissue, or (4) extremely dense tissue. In this paper, before experimenting, all the experimental cases would be viewed by three radiologists and then graded from 4 to 1.

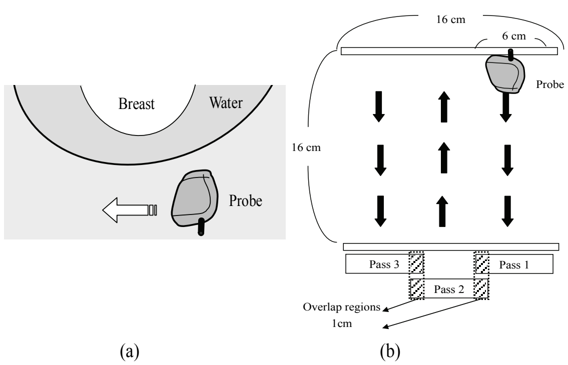


Fig.1. (a) ASU-1004 scanner. (b) ASU-1004 scanner system.

III. ALGORITHMIC ARCHITECTURE

In substance, the breast tissue roughly includes two tissue components. The first component is the glandular tissue (also called the mammary gland) which includes the stroma and parenchyma, and the second is adipose or fatty tissue. The breast density is the ratio of the mammary gland to the fat. Hence, the two regions should be separated before density measurement. In the system, we adopt two methods to measure the breast density. The first is based on thresholding, and the second is to calculate the sum of proportions of glandular tissue to the breast region for all frames.

A. Preprocessing

Before measuring the breast density, the images would be pre-processed through two stages. The first stage is to find the breast region from each US image and the second stage is used to remove the speckle noise.

A.1 Breast Region of Interest (ROI) Extraction

In fact, the non-breast areas like pectoral muscle and background usually exist in the experimental ultrasound images. Its inclusion would affect efficiency of the intensity-based methods in estimation of breast density.

In order to exclude these regions from the images, we present an algorithm described as follows to find the breast region. First, the inner boundary of the skin can be found by detecting the brighter pixel in the vertical orientation. This skin line can exclude both of the above black background and the skin layer from the image, which are not breast tissue in breast region. Then, a straight line called the chest line would be drawn. The left end position of the chest line is located by moving the left end position of the skin line down with the experimented constant (about 50 pixels), and the definition of the right end position is same as the left. The chest line can exclude the non-breast region under chest lines in each US image.

A.2 Adaptive Speckle Reduction

In the analysis system, due to the coherence of the backscattered echo signals, the US images have interference patterns called speckle. Speckle degrades the resolution and the object detectability and it increases the difficulty on segmentation and diagnosis. Therefore the speckle reduction is an important issue in the research of US image analysis. In this paper, the adaptive speckle reduction filter [10] is adopted for speckle noise removing.

The adaptive speckle reduction filter is an unsharp masking filter and based on the statistical analysis model called the *K*-distribution model. The *K*-distribution model has been used for speckle statistics and can provide the statistics of scattering media with arbitrary scatterer densities. With this statistic model, the unsharp masking filter Y is given by

$$Y = \overline{X} + c\left(X - \overline{X}\right) \qquad (2)$$

where X is the input of the filter, $\overline{X}$ is the local mean, and c is the local statistic. If the statistic c is limited to range [0, 1], the filter output will range from the maximal smoothing (mean) to no filtering. The statistic c is given by

$$c = 1 - \frac{\pi^2}{24}\frac{\hat{D}^2}{V} \qquad (3)$$

where $\hat{D}$ is the estimate of the logarithmic compression parameter of logarithm compression transfer function, which is used to transfer the ultrasound echo signal to a signal for displaying. The parameter $\hat{D}$ is given by

$$D = \frac{K}{R}\left(X_{\max} - X_{\min}\right) \qquad (4)$$

where $X_{\max}$ and X_{mix} are the maximum and minimum output values of display device, R is the input dynamic range of ultrasound echo signal, and K=20. V is the sample variance of the logarithm-compressed image, and it is defined by

$$V=\frac{1}{N-1}\sum_{i=1}^{N}\left(X_i-\overline{X}\right)^2 \qquad (5)$$

where X_i are the N samples of the echo envelope.

B. Tissue Classification

In order to diagnose without any manual interaction, we adopt an optimum thresholding method presented by Otsu [11] to automatically select a threshold value from the histogram of the processed image. It uses discriminant analysis to divide foreground and background by maximizing the discriminant measure function.

In an image with L gray levels, the number of pixels at level i is denoted as n_i, and the total number of pixels is denoted as $N=n_1+n_2+\ldots+n_L$. If we want to divide all pixels into two classes, C_1 and C_2, the sums of the probabilities with level 1-k and k-L should be calculated and represented as $w_1(k)$ and $w_2(k)$ respectively. Let μ_i be the gray-level mean of C_1 and μ_T be the gray-level mean of all pixels, and then the optimum threshold value can be measure by

$$\sigma^2(k)=\frac{[\mu_T w(k)-\mu_i(k)]^2}{w_1(k)\cdot w_2(k)} \qquad (6)$$

$$\sigma^2(k^*)=\max_{1\le k<L}\sigma^2(k)\,. \qquad (7)$$

When $\sigma^2(k)$ approximates to the maximum, the optimal threshold k^* will be produced (as represented by Eq. (7)).

C. The Analytic methods

After the above pre-processing, the desired breast region has been located and roughly divided into glandular tissue and fatty tissue. Then, two methods, threshold-based and proportion-based analyses, are proposed to measure the breast density.

In the threshold-based method, we use a statistics model to determine that each pixel belongs to glandular tissue or fatty. To focus on the breast region, N_g is the number of the corresponding pixels which are classified as glandular tissue in all images and can be calculated by

$$N_g=\sum_{i=1}^{M}C_i(x,y)$$
$$\begin{cases}C_i(x,y)=1 & \textit{if}\ \text{pixel}(x,y)\in G\\ C_i(x,y)=0 & \textit{otherwise}\end{cases} \qquad (8)$$

where $C_i(x, y)$ represents the category of the pixel (x, y) in the ith image, M (= 84) is the number of all merged images, and G represents the glandular tissue. Then, a threshold T_g is chosen to determine whether the pixel belongs to glandular tissue or fatty tissue. If $N_g > T_g$, the pixel (x, y) would be decided as glandular tissue; otherwise it would be decided as fatty tissue. In this paper, the T_g value is set to 30 empirically. After all the breast region pixels have been decided, the breast density ρ_B is calculated by

$$\rho_B=\frac{G}{B}\times 100(\%) \qquad (9)$$

where G and B are numbers of pixels within glandular tissue and breast region respectively.

Fig.2 illustrates that if more than 30 corresponding pixels are classified as glandular pixels, that position would be defined as glandular tissue.

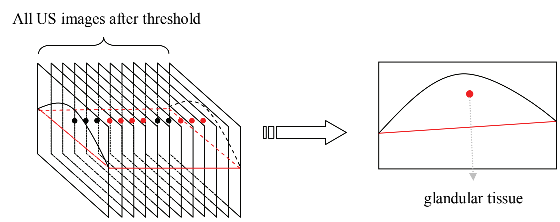


Fig.2. The category determination of the pixel.

In our second analytic method, the proportion-based analysis, the basic concept of this method is based on the 3-D viewpoint. By using the optimum thresholding, mentioned in section III.B, each image has been roughly divided into two categories, glandular and fatty tissues. Hence, the volume of the glandular tissue V_G can be calculated by accumulating the number of glandular pixels in all images, and so does the volume of breast region V_B. The breast density D_P is calculated as follows

$$D_P = V_G / V_B \qquad (10)$$

IV. EXPERIMENTAL RESULTS

The experimental cases were acquired from the 32 patients, and these patients were also examined to acquire the mammographic films. The experimental results are compared with three radiologists' results which are scored by observing the mammograms. We use the majority mammogram grades of three radiologists as the ground true for US images. Fig.3 shows the distribution of the grades for these cases by using the majority grades of radiologists' results for mammograms.

Fig.4(a) shows the result after applying the threshold-based method to the merged breast ultrasound with grade 2, and Fig.4(b) is its corresponding mammogram. For results of all experimental cases, T_{D1}, T_{D2} and T_{D3}, which are defined through training and shown in Table 1, would be used as the threshold values and classify them into the four categories. The distributions of 32 classified results is shown in Fig.5 (the triangle line represents the threshold-based method, the rectangle line represents the proportion-based one, and the straight line show the results of radiologists). In summarization, the threshold-based method has four false positives and the accuracy of it approximates to 87.5%, on the side, the proportion-based one has five false positives and the accuracy approximates to 84.4% (as shown in Table 2).

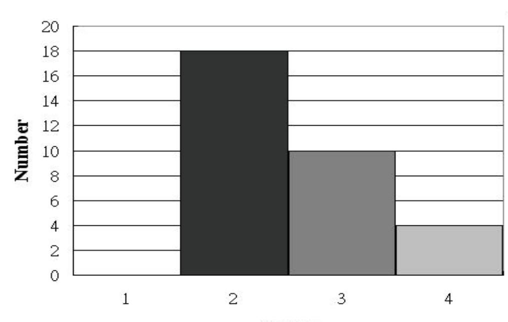
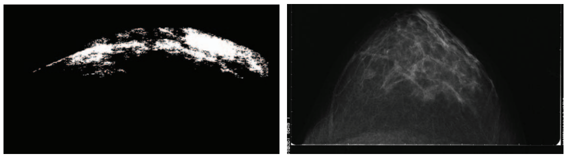


Fig.3. The distribution of grades for experimented breast cases.

applied on breast MR data, and this can be useful tool in breast CAD and improve its clinical performance.



(a) (b)

Fig.4. Whole breast ultrasound with grade 2. (a) The result of the threshold-based method. (b) The corresponding mammogram.

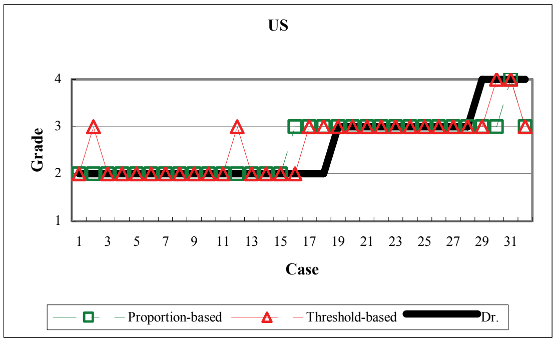


Fig.5. The distribution of the grade values of two proposed methods and radiologists.

Table 1 Three threshold values for two proposal methods.

	TD_1	TD_2	TD_3
Threshold-based	10	32	44
Proportion-based	13	31	38

Table 2 The summarized results with the two methods.

Density Grade	2		3		4		Total		Accuracy(%)
	T	F	T	F	T	F	T	F	
Threshold-based	16	2	10	0	2	2	28	4	87.5
Proportion-based	17	1	10	0	1	3	27	5	84.4

V. CONCLUSIONS

Breast density is an important factor in risk of breast cancer. When the patients perform the mammogramphic screening work with dense breast, there are many limitations, such as lower sensitivity and specificity. Hence, the breast US is quite useful for dense breast patients, especially the patients are young women or the Asian women with dense breast. In the conventional 2-D US, the data only obtains the sectional image of partial breast region, is not enough to provide the whole breast imaging like mammography. Therefore, in this paper, we use the whole breast US images, which are scanned using the US machine SSD-5500 with a recent developed scanner ASU-1004 (Aloka, Japan) to analyze the breast density. The US results of breast density can offer radiologists a second quantification reading for prediction of breast cancer risk.

In this paper, we provide two methods to analyze the breast density based on the new whole breast ultrasound imaging technique. The ultrasonic results are very encouraging and consistent with the radiologists' grading and it could provide an objective quantification of breast density. The future improvement is to use US images with better quality by registering the three passes in whole breast US images. Furthermore, the similar breast density analysis method can be applied on breast MR data, and this can be useful tool in breast CAD and improve its clinical performance.

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