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Three Comparative Approaches for Breast Density Estimation in Digital and Screen Film Mammograms

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Abstract—In general, several factors are used for risk estimation in breast cancer detection and early prevention, and one of the important factors in risk of breast cancer is breast density. The mammography is important and effective adjunct in diagnosing the breast cancer. The radiologists would analyze visually the breast density with the BI-RADS lexicon on mammograms. However, this usually causes a large inter-observer variability among the different experienced radiologists. In this paper, we individually adopt three methods, including pixel-based, region-based, and physics-based, to analyze the breast density on mammograms, and the results can offer radiologists a second quantification reading for predicting the risk of breast cancer. The three methods are tested on 208 digital and conventional film mammograms which are scanned from both breasts of 104 patients respectively. The experimental results show that the accuracy of the proposed region-based method, which is more consistent with the radiologists' viewpoint, is 88% more than other two conventional methods.

Keywords—breast density, grandular, fatty, hentrogeneous, dense, pixel, region, physics-based, digital, screen-film, mammography

I. INTRODUCTION

The American Cancer Society (ACS) indicated that one in every eight women will develop breast cancer at some point in their lives. In the United States during 2005, an estimated 212,240 new cases of invasive breast cancer and about 40,870 (19%) deaths are expected to occur among women [1]. Although the death rates of breast cancer have continued to increase since 1980, the mortality rates have declined by 2.3% per year from 1990 to 2001. This situation is due to increased awareness, earlier detection through screening, and improved treatment.

In general, many factors are used for risk estimation in breast cancer detection and early prevention, and the breast density information is one of the important indicators. Breast density was assessed at the initial examination and classified as 'dense' (if > 25% of the breast was composed of density) or 'lucent' (< or = 25% density) [2]. The relative risk is estimated to be about 4 to 6 times higher for women whose have parenchymal densities over 60% of the breast area, as compared to women with less than 5% of parenchymal densities [3]. Mandelson *et al.* [4] investigated whether the high breast density increased interval cancer risk in a large group of women with interval and screening detected cancers.

In the clinical practice, X-ray mammography is the most effective method in helping radiologists to recognize breast lesions and evaluate the breast density [5]. The BI-RADS lexicon [6] which is recommended by the American College of Radiology was proposed many years ago to identify breast density groups of women at high risk for breast cancer. However, there is a large inter-observer variability in the BI-RADS ratings even among the experienced radiologists that analyze visually the breast density on mammograms. Thus, a computerized method is required to be a supplement for analyzing the breast density. The computer-aided diagnosis (CAD) system is a useful tool in the examination of medical images and gives radiologists a second diagnosis opinion in clinical use. Many studies [7-10] have investigated methods for providing quantitative measures in the assessment of breast density patterns on mammograms. Boyd *et al.* [7] studied the relation between the breast cancer risk and the breast density on the mammographic images. Although it developed a computer-assisted measurement based on interactive pixel-based density threshold, the method needs to define two thresholds manually rather than automatically. The paper by Wang *ea al.* [10] presented a physics-based model method to recover the compressed breast tissue composition information by considering mammographic attenuation.

In this paper, a novel breast density analysis system is proposed to measure the breast density automatically based on mammograms for offering radiologists a second quantification reading for prediction of breast cancer risk. We adopt three methods, pixel-based, region-based, and physics-based, individually. The first two methods individually use the optimal thresholding [11] and the watershed segmentation [12] to separate the glandular tissue from the breast region, and then calculate the mammographic breast density. The third method uses the compressed tissue of mammograms to recover the tissue composition information. Finally, all of the three experimented results will be compared with the radiologists' diagnosis.

The rest of the paper is organized as follows: Section II presents the data acquisition and brief discussion on databases. The three algorithmic approaches are presented in section III. Results of our experimental protocol are discussed in section IV and the paper concludes in section V.

II. DIGITAL AND SCREEN FILM MAMMOGRAPHY

In this paper, the experimental dataset consists of 208 cases which are scanned from 104 patients. Each case contains the craniocaudal (CC) view of both breasts of the patient. The first 144 cases of 72 patients belong to digital mammography screening and are selected from lots of files in the Changhua Christian Hospital, Changhua, Taiwan, from September to October, 2004. These digital mammograms are obtained by using the machine Senographe 2000D (GE) with the pixel size of 100μm × 100μm and the active area of 19cm × 23cm. The gray scale of the processed images is 12 bits (4096 intensity levels). Other 64 cases are conventional film mammograms and obtained from the Dokkyo University, Mibu, Japan, from January to June, 2003. These conventional films were scanned into the digital computer files in the resolution 300 dot per inch.

In this paper, digital and conventional mammograms are analyzed and graded from 4 to 1 according to the American College of Radiology Breast Imaging Reporting and Data System (BI-RADS). BI-RADS lexicon is a quality assurance tool designed to standardize mammography reporting, reduce differences between breast imaging interpretations, and facilitate outcome monitoring. The four categories of BI-RADS classification scheme are: (1) almost entirely fat, (2) scattered fibro-glandular tissue, (3) heterogeneously dense tissue, or (4) extremely dense tissue.

III. ALGORITHMIC ARCHITECTURE

The definition of breast density is the ratio of the glandular tissue to the fat. The breast density should be analyzed within the breast region, therefore, we use the Laplacian operator [13] to separate the breast region from the background. Then, we use three methods including pixel-based, region-based, and physics-based, on the breast region for recognizing glandular and fatty tissues.

A. Pixel-based Analysis

Most of the conventional pixel-based methods need the operators to select a threshold to separate different tissue for each image. Different operators would select different threshold values and the analytic results are to be affected. Hence, 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 $N=n_1+n_2+\ldots+n_L$. Hence, the probability distribution of level i can be computed by

$$P_i = n_i / N \tag{1}$$

The pixels of an image are divided into two classes, C_1 and C_2, which include pixels with level 1 - k and k - L, respectively. The sum of the probabilities of classes C_1 and C_2 are calculated by

$$w_1(k) = \sum_{i=1}^{k} P_i \quad \text{and} \tag{2}$$

$$w_2(k) = \sum_{i=k}^{L} P_i \tag{3}$$

where $w_1 + w_2 = 1$. Let μ_i be the gray-level mean of C_1 and μ_T be the gray-level mean of all pixels. Then, the optimum threshold k^* is obtained by the following formulas.

$$\sigma^2(k) = \frac{[\mu_T w(k) - \mu_1(k)]^2}{w_1(k) \cdot w_2(k)} \tag{4}$$

$$\sigma^2(k^*) = \max_{1 \le k < L} \sigma^2(k) \tag{5}$$

When $\sigma^2(k)$ is the maximum of all, the optimal k^* will be produced.

After applying optimum thresholding algorithm, the processed mammogram is converted to a binary image. Then, the breast density ρ_B can be calculated by

$$\rho_B = \frac{G}{B} \times 100(\%) \tag{6}$$

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

B. Region-based Analysis

On radiologists' viewpoint, the glandular tissue is grouped into several regions and the total area of glandular regions is used to decide the density. Hence, we propose the region-based analysis method with the similar principle. A well-known region-based segmentation method called watershed segmentation is used to segment the breast region and then a thresholding value is selected to find the glandular regions out.

B.1 Noise Removing

Prior to segmentation process, we remove the system noise by enhancing the mammograms and preserving the edges. Traditionally, a number of linear or nonlinear low-pass filters are proposed to smooth the image and reduce the noise. The linear filter like the mean filter blurs the image by replacing the pixel value with the average value of neighboring pixels. It can achieve the objective of noise suppression, but it causes the loss of edge information. The non-linear filter like the median filter can successfully preserve the edges, but it still loses the small details of the image. Hence, the anisotropic diffusion filtering, proposed by Perona and Malik [14] , is used not only to smooth image, but also to preserve the edge information. The diffusion operator is similar to the averaging operation. It evaluates the diffusion by using the relationship between the center pixel and its neighborhood and controls the anisotropic diffusion by employing the local image gradient, represented as the formula

$$\frac{\partial I(x,y,t)}{\partial t} = div\left[g\left(\|\nabla I\|\right) \cdot \nabla I\right] \tag{7}$$

where g(.) is the diffusivity function or the edge stopping function, $\|\nabla I\|$ is the gradient of image I. For example, the diffusion or smoothing decreases monotonically as the gradient strength increasing, and the diffusion stops crossing the edge when the gradient magnitude is close to infinity. Then the discontinuities will be preserved successfully.

B.2 Watershed Segmentation

The watershed transform has been widely used in many fields of image processing, including medical image segmentation, and it segments a whole image into several separated regions even if the contrast is poor, thus avoiding the need for any kind of contour joining. The intuitive idea underlying this method comes from geography and it regards the gradient magnitude image as a relief map where the intensity value corresponds to the contour line. The area where a rain drop would drain to the same minimum is denoted as a catchment basin, and the line separating adjacent catchment basins is denoted as the watershed. On the viewpoint of gradient values, the catchment basins have low-gradient values and the watershed lines have high-gradient values, as shown in Fig.1.

After the watershed procedure, the images have been divided into lots of closed regions, and the gray values of all the pixels in the same region could be replaced by the mean of these gray values. The optimum thresholding (as described above) is employed to select a suitable threshold value to distinguish the glandular tissue from the segmented regions, and then the breast density is calculated by the Eq. (6).

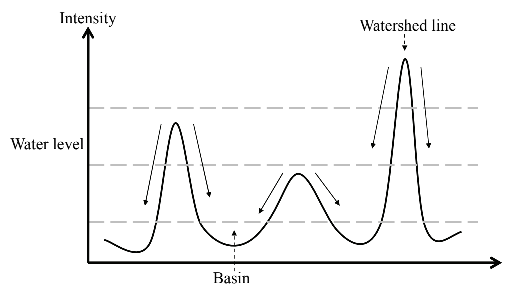


Fig.1. Illustration of the watershed segmentation.

C. Physics-based Analysis

The third method in the analysis system is based on the physics model of X-ray attenuation, and employed to recover the tissue composition information from mammograms with compressed tissues. This method proposed by Wang et al. [10] quantitatively derives tissue composition from adjusted pixel values, as tailored to mammography, which enabled us to estimate the fraction of glandular tissue, for each pixel, over the entire breast region.

In the mammography, the tissue thickness and the internal pixel values are in an inverse proportion; that is to say, while the thickness of the tissue increases the pixel values would be decreased. If a beam of X-ray doesn't pass through any tissue, the corresponding value is assigned to 255 but would be displayed as the black pixel on the mammogram. The relationship between the pixel value and the total attenuation of the tissue is approximated as

$$D = D_0 - k\Sigma\mu_i x_i \tag{8}$$

where D_0 is the intensity of film's background (i.e., non-attenuated exposure), μ_i is the attenuation coefficient of one of the tissue types, x_i is the thickness of that tissue type, and $\Sigma\mu_i x_i$ is the total attenuation of the tissue. If $D_{(fat)}$ is the pixel intensity corresponding to the pure fatty tissue, x_{fat} which is the relative thickness of fatty tissue becomes 1, and then $D_{(fat)}$ can be defined as

$$D_{(fat)} = D_0 - k\mu_{fat} \tag{9}$$

By referring to [10], the background intensity D_0 is calculated as the mean pixel value in a 15 × 15 mask without the breast region. The $D_{(fat)}$ is measured as the mean value of the 15% of the highest pixel values within the breast region, as the pure fatty tissue. Then, the thickness of the fat tissue x_{fat} is calculated by

$$x_{fat} = \frac{\left(\dfrac{D_0 - D}{D_0 - D_{(fat)}}\right) - R}{1 - R} \tag{10}$$

where R is the ratio of the glandular attenuation coefficient $\mu_{glandular}$ to the fat attenuation coefficient μ_{fat} [15]. The final tissue composition is the proportion of glandular tissue to the entire breast region, and represented as the following formula

$$\rho_B = \frac{\sum_{breast\_region}(1 - x_{fat})}{B} \tag{11}$$

where ρ_B is the breast density, and B is numbers of pixels within breast region.

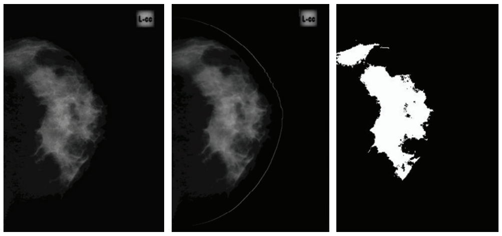
IV. Experimental Results

In this paper, the 208 digital and conventional film mammograms of 104 patients are used for the development of the density analysis method. According to the BI-RADS, each case was graded as four categories, almost entirely fat (n=2), scattered fibro-glandular tissue (n=43), heterogeneously dense tissue (n=52), and extremely dense tissue (n=7), by three radiologists. For experiments, a ground truth is needed to evaluate the analysis accuracy. We would use the majority grades of three radiologists as the ground true. In order to obtain the BI-RADS categories, three thresholding values, T_{D1}, T_{D2} and T_{D3}, need to be defined for classifying the evaluating density values into four grades, and are listed in Table 1.

Fig.2 shows the separating result using the pixel-based method. Fig.2(a) is the original mammogram and Fig.2(b) shows the breast region detected by Laplacian operator. In Fig.2(c), the breast region is divided into glandular tissue (the white region) and fatty by using the thresholding algorithm. The result of region-based method is shown in Fig.3. Fig.3(a) is the original image, Fig.3(b) is the result with applying watershed segmentation, and then the glandular tissue can be separated out by using thresholding, as shown in Fig.3(c). Through the experiment, the pixel-based, region-based, and physics-based methods respectively have 15, 12, and 24 false positives, and the accuracy for three proposed methods is shown in Table 2. The result shows that the region-based watershed method has higher accuracy than the pixel-based and physics-based methods. Additionally, we also use the mean square error (MSE) to evaluate the variation between the analyzed grades of three methods and the ground true. The formula of the MSE is defined as follows

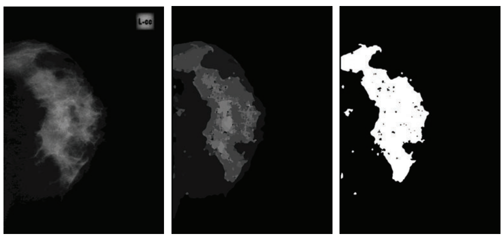
$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X(i) - I(i))^2 \tag{12}$$

where $X(i)$ is the grade value estimated by our system for the i-th case, and $I(i)$ is the ground true grade value estimated by three radiologists. In Table 3, the MSE of pixel-based method is 0.1574, and the MSE of the physics-based method is 0.2963, and the region-based method has the lowest MSE value 0.1111. Thus, the region-based method has good result on the breast density analysis because of its lowest MSE.



(a) (b) (c)

Fig.2. (a) The original image. (b) Applying Laplacian operator to detect the skin line. (c) Applying the optimum thresholding to find the glandular tissue.



(a) (b) (c)

Fig.3. (a) The original image. (b) Applying watershed segmentation. (c) Applying the optimum thresholding.

Table 1 The three breast category thresholds for three proposed methods.

	T_{D1}		T_{D2}		T_{D3}	
	Digital	Film	Digital	Film	Digital	Film
Pixel-based	15	-	26	27	40	45
Region-based	13	-	24	28	39	46
Physics-based	19	-	25	25	39	39

Table 2 The accuracy of the three methods.

	True Cases		Accuracy (%)	
	Digital	Film	Digital	Film
Pixel-based	60 of 72	29 of 32	83.3	90.6
Region-based	63 of 72	29 of 32	87.5	90.6
Physics-based	57 of 72	23 of 32	79.2	71.9

Table 3 The MSE of three methods.

	Method		
	Pixel-based	Region-based	Physics-based
MSE	0.1574	0.1111	0.2963

V. CONCLUSIONS

Breast density is an important factor in risk of breast cancer. The mammography is important adjunct in the detection of breast cancer. The mammographic results of breast density can offer radiologists a second quantification reading for prediction of breast cancer risk.

In this paper, we provide three methods to analyze the breast density based on the mammographic images. The three automatic mammographic methods, including pixel-based, region-based and physics-based, are used to calculate the breast density individually. The experimental results for mammographic images show that the accuracy of our proposal region-based method is 88% more than other two conventional methods. That is to say, the region-based results are more consistent with the radiologists' viewpoint. Besides, the similar breast density analysis method can be applied on breast MR data, and the density results are included in a computer-aided diagnosis system to enhance the diagnosis performance.

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