Mathematical Problems of Computer Science 35, 109--115, 2011.

Segmentation of Mammography Images Enhanced by Histogram Equalization

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Abstract:

The mammography is the most effective procedure for an early diagnosis of the breast cancer. In this paper, a technique for detecting masses in mammographic images will be presented. Image enhancement techniques, based on histogram equalization, are shown and used before image segmentation. Threshold technique is proposed for an image segmentation which is a very critical task in any image processing. Enhancement methods are implemented on a mammogram and accordingly, a comparison between the methods for better threshold is carried out.

1. Introduction

Breast cancer stays in the first place among women malignant neoplasia structures list (about 30%). According to Worldwide Health Corporation it is being #1 of the fundamental reasons of the women's average age mortality. The National Cancer Institute estimates that one out of eight women develops breast cancer at some point during her lifetime [1]. Year after the year indexes of the morbidity with breast cancer are growing [2]. The same image is viewed in many countries: USA, European Union, Russian Federation and North America, as well as in Armenia.

The goal of mammography is to provide early detection of breast cancer through low-dose imaging of the breast. Mammography is considered to be the most efficient technique for identifying lesions when they are not palpable and when there are structural breast modifications [3]. It shows to the physician differences in breast tissue densities and these differences are fundamental to a correct diagnosis. At present, there are no effective ways to prevent breast cancer, because its cause remains unknown [4, 5]. Therefore urgency and importance of mammography image processing is obvious.

Computer-Aided Detection and Diagnosis systems are continuously being developed aiming to help the physicians in early detection of breast cancer. These tools may call the physician's attention to areas in the mammography that may contain radiological findings. In digital mammography, segmentation is the process of partitioning mammograms into regions, aiming to produce an image that is more meaningful and easier to analyze [6]. A physician has to previously select a region of interest that contains one suspicious region in a mammogram. After being segnented, the mammogram or the mass lesion region can be further used by physicians, helping them to take decisions that involve their patients' health.

This paper is organized as followed. Section 2 reviews some enhancement algorithms based on histogram equalization. Section 3 describes an image segmentation technique using threshold. In Section 4 there are shown experimental results of described techniques. In the next section the conclusion and future work are given.

2. Image Enhancement Methods

The visual quality of mammographic images can be improved by collecting more image data at the data acquisition stage or enhancing images during the post image processing stage in medical imaging systems. However, the former method on the acquisition stage significantly increases the overall acquisition time, the amount of radiation that a patient is exposed to and hardware costs [7]. Mammographic enhancement based on the post image processing stage utilizes different image enhancement techniques to enhance the contrast of mammograms. The goal is to improve the visual quality of mammograms without affecting the acquisition process or increasing the hardware costs. This offers radiologists more accuracy and efficiency for analyzing and recognizing breast cancer, evaluating the effectiveness of treatment, and predicting the development of breast cancer.
In this section some enhancement methods based on histogram equalization are described.
There are two types of histogram equalization: global and local [8].

2.1.Global Histogram Equalization

Global histogram equalization (GHE) techniques acquire the scale factor from the normalized cumulative distribution of the brightness distribution of the original image and multiply this scale factor to the original image to redistribute the intensity. Consider a discrete grayscale image $\{r\}$. The probability of occurrence of gray level r_k in an image is approximated by

$$p_r(r_k)=\frac{n_k}{n}, \quad k=0,1,2,...,L-1, \tag{1}$$

where n is the total number of pixels in the image, n_k is the number of pixels that have gray level r_k, and L is the total number of possible gray levels in the image. Transformation function is

$$s_k=T(r_k)=\sum_{j=0}^{k} p_r(r_j)=\sum_{j=0}^{k} \frac{n_j}{n}, \quad k=0,1,2...,L-1.. \tag{2}$$

A processed (output) image is obtained by mapping each pixel with level r_k in the input image into a corresponding pixel with level s_k in the output image via Eq. (2). A plot of $p_r(r_j)$ versus r_k is called a *histogram.* The transformation (mapping) given in Eq. (2) is called *histogram equalization* or *histogram linearization.*

The histogram processing methods discussed above is *global*, in the sense that pixels are modified by a transformation function based on the gray-level content of an entire image.

2.2. Local Histogram Equalization

Although this global approach is suitable for overall enhancement, there are cases in which it is necessary to enhance details over small areas in an image. The number of pixels in these areas may have negligible influence on the computation of a global transformation whose shape does not necessarily guarantee the desired local enhancement. The solution is to devise transformation functions based on the gray-level distribution or other properties in the neighborhood of every pixel in the image.
The histogram processing techniques described above are easily adaptable to local enhancement. The procedure is to define a square or rectangular neighborhood and move the center of this area from pixel to pixel. At each location, the histogram of the points in the neighborhood is computed and either a histogram equalization or histogram specification transformation function is obtained. This function is finally used to map the gray level of the pixel centered in the neighborhood. The center of the neighborhood region is then moved to an adjacent pixel location and the procedure is repeated. Instead of using the image histogram directly for enhancement, we can use instead some statistical parameters

obtainable directly from the histogram [8] Let r denote a discrete random variable representing discrete gray-levels in the range $[0, L-1]$, and let $p(r_i)$ denote the normalized histogram component corresponding to the ith value of r. As indicated previously in this section, we may view $p(r_i)$ as an estimate of the probability of occurrence of gray level r_i. The nth moment of r about its mean is defined as

$$\mu_n(r)=\sum_{i=0}^{L-1} r_i p(r_i), \tag{3}$$

where m is the mean value of r (its average gray level):

$$m=\sum_{i=0}^{L-1} r_i p(r_i). \tag{4}$$

It follows from Eqs. (3) and (4) that $\mu_0=1$ and $\mu_1=0$. The second moment is given by

$$\mu_2(r)=\sum_{i=0}^{L-1}(r_i-m)^2 p(r_i). \tag{5}$$

We recognize this expression as the variance of r, which is denoted conventionally by $\sigma^2(r)$. The standard deviation is defined simply as the square root of the variance. In terms of enhancement we are interested primarily in the mean, which is a measure of average gray level in an image, and the variance (or standard deviation), which is a measure of average contrast.

We consider two uses of the mean and variance for enhancement purposes. The *global* mean and variance are measured over an entire image and are useful primarily for gross adjustments of overall intensity and contrast. A much more powerful use of these two measures is in local enhancement, where the *local* mean and variance are used as the basis for making changes that depend on image characteristics in a predefined region about each pixel in the image.

Let (x, y) be the coordinates of a pixel in an image, and let S_{xy} denote a neighborhood (subimage) of specified size, centered at (x, y). From Eq. (4) the mean value $m_{S_{xy}}$ of the pixels in S_{xy} can be computed using the expression

$$m_{S_{xy}}=\sum_{(S,t)\in S_{xy}} r_{S,t}\, p(r_{S,t}),$$

where $p(r_{S,t})$ is the gray level at coordinates (s, t) in the neighborhood, and $p(r_{S,t})$ is the neighborhood normalized histogram component corresponding to that value of gray level. Similarly, from Eq. (5), the gray-level variance of the pixels in region S_{xy} is given by

$$\sigma^2_{S_{xy}}=\sum_{(S,t)\in S_{xy}}[r_{S,t}-m_{S_{xy}}]^2\, p(r_{S,t})$$

The local mean is a measure of average gray level in neighborhood S_{xy}, and the variance (or standard deviation) is a measure of contrast in that neighborhood

Adaptive Histogram Equalization (AHE) computes the histogram of a local window centered at a given pixel to determine the mapping for that pixel, which provides a local contrast enhancement. However, the enhancement is so strong that two major problems can arise: noise amplification in "flat" regions of the image and "ring" artifacts at strong edges [9, 10].

A generalization of AHE, adaptive histogram equalization has more flexibility in choosing the local histogram mapping function. By selecting the clipping level of the histogram, undesired noise amplification can be reduced [11].

The contrast-limited adaptive histogram equalization (CLAHE) [12] is a well-known technique of adaptive contrast enhancement. The normal and adaptive histogram equalization may over-enhance the noises and sharp regions in images due to the integration operation. It yields large values in the enhanced image for high peaks in the histogram of the nearly uniform regions in the original image. To solve this problem, the CLAHE uses a clip level to limit the local histogram in order to limit the amount of contrast enhancement for each pixel. This clip level is a maximum value of the local histogram specified by users. An interactive binary search process is used to redistribute the pixels which are beyond the clip level. The

CLAHE algorithm has following steps: 1) divide the original image into contextual regions; 2) obtain a local histogram for each pixel; 3) clip this histogram based on the clip level; 4) redistribute the histogram using binary search; 5) obtain the enhanced pixel value by histogram integration.

3. Segmentation

In Section 2 some enhancement techniques for image enhancement were shown. After enhancement - the segmentation of the image will be easier. In this section thresholding technique for image segmentation is described.

Suppose that the gray-level histogram shown in Fig. 1(a) corresponds to an image $f(x, y)$, composed of light objects on a dark background, in such a way that object and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold T that separates these modes. Then any point (x, y) for which $f(x, y) > T$ is called an *object point*; otherwise, the point is called a *background point*.

Figure 1(b) shows a slightly more general case of this approach, where three dominant modes characterize the image histogram (for example, two types of light objects on a dark background). Here, *multilevel thresholding* classifies a point (x, y) as belonging to one object class if $T_1 < (x, y) \le T_2$, to the other object class if $f(x, y) > T_2$, and to the background if $f(x, y) \le T_2$.

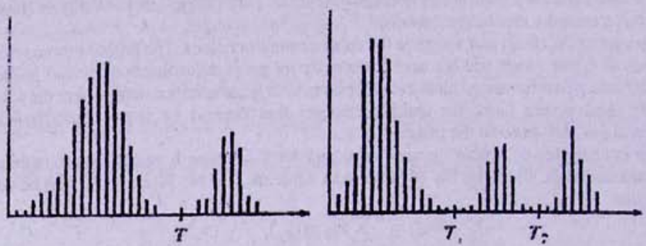


Fig.1: (a) Gray-level histograms that can be partitioned by (a) a single threshold, and (b) multiple thresholds.

Based on the preceding discussion, thresholding may be viewed as an operation that involves tests against a function T of the form

$$T = T[x, y, p(x, y), f(x, y)],$$

where $f(x,y)$ is the gray level of point (x, y) and $p(x, y)$ denotes some local property of this point for example, the average gray level of a neighborhood centered on (x, y). The thresholded image $g(x, y)$ is defined as

$$g(x,y) = \begin{cases} 1, & if \; f(x,y) > T \\ 0, & f(x,y) \le T \end{cases}.$$

Thus, pixels labeled 1 (or any other convenient gray level) correspond to objects, whereas pixels labeled 0 (or any other gray level not assigned to objects) correspond to the background.

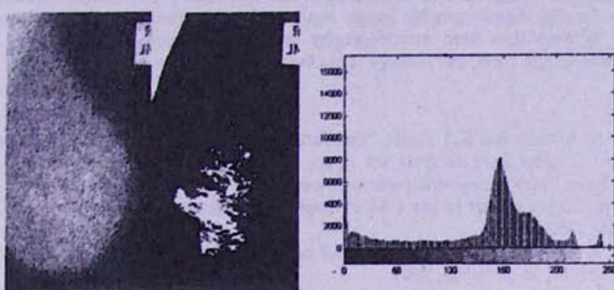
When T depends only on $f(x, y)$ (that is, only on gray-level values) the threshold is called *global*. If T depends on both $f(x, y)$ and $p(x, y)$, the threshold is called local.

The key parameter in the thresholding process is the choice of the threshold value. Several different methods for choosing a threshold exist; users can manually choose a threshold value, or a thresholding algorithm can compute a value automatically, which is known as automatic thresholding [8]. A simple method would be to choose the mean or median value, the rationale being that if the object pixels are brighter than the background, they should also be brighter than the average. In a noiseless image with uniform background and object values, the mean or median will work well as the threshold, however, this will generally not be the case. A more sophisticated approach might be to use the method described below, which is relatively simple, does not require much specific knowledge of the image, and is robust against image noise:

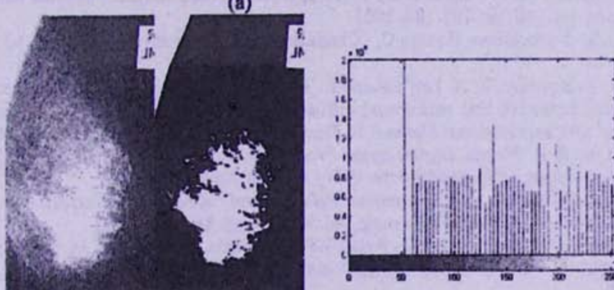
1. An initial threshold (T) is chosen; this can be done randomly or according to any other method desired.
2. The image is segmented into object and background pixels as described above, creating two sets:
   a. $G1 = \{f(m,n) : f(m,n) > T\}$ (object pixels).
   b. $G2 = \{f(m,n) : f(m,n) \le T\}$ (background pixels) (note, f(m,n) is the value of the pixel located in the mth column, nth row)
3. The average of each set is computed.
   a. $m1$ = average value of $G1$
   b. $m2$ = average value of $G2$
4. A new threshold is created that is the average of $m1$ and $m2$
   a. $T' = (m1 + m2)/2$
5. Go back to step two, now using the new threshold computed in step four, keep repeating until the new threshold matches the one before it (i.e. until convergence has been reached).

4. Results

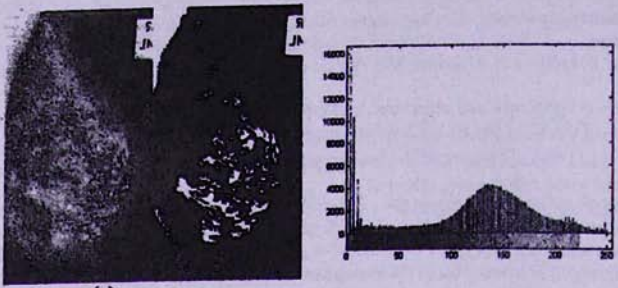
In this section results of image enhancement and segmentation using methods described in Section 2 and Section 3 are shown. For testing images from 'The mini-MIAS database of mammograms.' internet resource (http://peipa.essex.ac.uk/info/mias.html) were selected.



(a)



(b)



(c)

Fig.2 Mammogram, threshold result image and histogram, a) original mammogram, b) mammogram enhanced by GHE, c) mammogram enhanced by CLAHE.

5. Conclusion and Future Works

As we can see from the results, mammography segmentation using threshold is more efficient when images are enhanced before the segmentation. As an enhancement method, CLAHE showed better results, which means that using CLAHE enhancement and threshold segmentation techniques together give good results for the mammography image analyze. For the future work it is planned lesion classification and its extraction from mammography image. Also discovering and right analysis of calcificats place, sizes, count, form, morphology is planned.

References:

[1] L.-M. Wun, R. M. Merrill, and E. J. Feuer, "Estimating Lifetime and Age-Conditional Probabilities of Developing Cancer," *Lifetime Data Analysis*, vol. 4, pp. 169-186, 1998.

[2] "WHO Cancer Facts," *http://www.who.int/cancer/en/*, 2009.

[3] G. M. Swanson, "Breast cancer in the 1990's", *Journal of American Medical Women's Association*, vol. 47, pp. 140-148, 1992.

[4] D. E. Stewart, et al., "Attributions of cause and recurrence in long-term breast cancer survivors", *Psycho-Oncology*, vol. 10, pp. 179-183, 2001.

[5] H. D. Cheng and H. Xu, "A novel fuzzy logic approach to mammogram contrast enhancement", *Information Sciences*, vol. 148, pp. 167-184, 2002.

[6] Shapiro, Linda G. & Stockman, George C, "Computer Vision", Prentice Hall. ISBN 0-13-030796-3, 2002.

[7] I. Larrabide, A. A. Novotny, R. A. Feij'oo, and E. Taroco, "A medical image enhancement algorithm based on topological derivative and anisotropic diffusion". *in Proceedings of the XXVI Iberian Latin-American Congress on Computational Methods in Engineering*, Guarapari, Esp'ırito Santo, Brazil, 2005.

[8] R. C. Gonzalez and R. E. Woods, *Digital Image Processing, 3 ed.*: Pearson Prentice Hall, 2007.

[9] W. K. Pratt, *Digital Image Processing*. John Wiley & Sons, New York, 2001.

[10] J. Alex Stark, "Adaptive image contrast enhancement using generalizations of histogram equalization" *IEEE Trans. On Image Processing*, vol. 9, no. 5, pp. 889-896, 2000.

[11] Jin, Yinpeng; Fayad, Laura M.; Laine, Andrew F., "Contrast enhancement by multiscale adaptive histogram equalization". *Proc. of Wavelets: Applications in Signal and Image Processing IX*, no. 4478, pp. 206-213, 2001.

[12] S. M. Pizer, et al., "Adaptive histogram equalization and its variations", *Computer Vision, Graphics, and Image Processing*, vol. 39, pp. 355-368, 1987.

Մամոգրաֆիկ պատկերների սեգմենտարման բարելավումը սյունապատկերային հավասարեցման եղանակով

Ա. Սահակյան

Ամփոփում

Մամոգրաֆիան կրծքի քաղցկեղի վաղ ախտորոշման համար արդյունավետ եղանակներից է: Աշխատանքում ներկայացվում է մամոգրաֆիկ պատկերներում կուտակումների հայտնաբերման մեթոդը: Ուսումնասիրվում են հիստոգրամային հավասարեցման վրա հիմնված պատկերների բարելավման մեթոդներ: Այս մեթոդները օգտագործվում են մինչ պատկերի սեգմենտավորումը, որի համար առաջարկվում է շեմային մեթոդը: Բերված են իրական մամոգրամների բարելավման փործնական արդյունքները և շեմային արդյունքների համեմատությունը: