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A new approach for Classification and Detection of Suspicious Lesions in Mammograms based on AdaptiveThresholding

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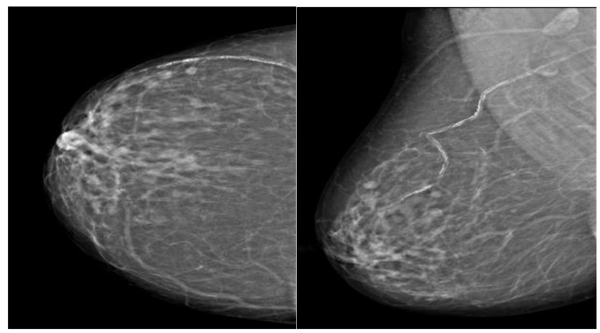
***Abstract*—Breast cancer has become one of the most dangerous carcinomas for middle-aged and older women in all over the world recently [2]. Early detection of breast cancer increases the survival rate and increases the treatment options. Mammography is the most reliable detection method used in the clinic, and computer-aided diagnosis (CAD) could assist the radiologists in reading the mammograms [4]. In this paper, a new algorithm based on adaptive thresholding for classification and detection of suspicious masses in mammograms is described. The related work was implemented using image processing tools, and using the MATLAB.**

Keywords-breast cancer, mammograms, masses, lesions, thresholding.

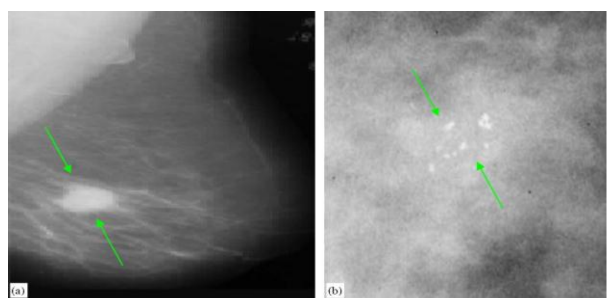
I. introduction

Breast cancer is considered a major health problem in all over the world, since it constitutes the most commoncancer among women [5]. Recently, with the high increment speed of the incidence, it has exceeded the lung cancer and been the first killer of women among all the caner, There is a rising incidence of breast cancer in India. According to The International Agency for Research on Cancer, which is part of the World Health Organization, there were approximately 78,000 women per year affected by breast cancer in India in 2001 and over 80,000 women in 2002.Detection and diagnosis of breast cancer in its early stage increases the chances for successful treatment and complete recovery of the patient. Mammography is the most effective and reliable detectionmethod of breast cancer, and is applied most widely in theclinic. With digital mammography the breast image is capture during a special electronic x-ray detector which converts the image into a digital mammogram for viewing on a computer monitor. Each breast is imaged separately in two type of views,craniocaudal (CC) view and mediolateral-oblique (MLO) view shown inFigure 1(a) and Figure 1(b), respectively.



(a) (b)
Fig. 1 Two basic views of mammographic image: (a) craniocaudal (CC) view, (b) mediolateraloblique (MLO) view

Breast cancer can be divided into two types, (a) masses and (b)microcalcifications, shown in fig 2respectively.



(a) (b)
Fig.2. Examples of mammograms: (a) arrows indicate mass area; (b) microcalcifications area

Masses are defined as space-occupying lesions that aredescribed by their shapes and margin properties. According to the shape and boundarycharacteristics of masses, it can be further divided into speculated masses (SPIC), circumscribed masses (CIRC), and other masses (MISC) [5]. Microcalcifications are tiny deposits of calcium that appear as small bright spots in the mammogram. Although they have higher inherent attenuation properties, they cannot be distinguished from the high-frequency noise because of their small size. The average size of microcalcifications is about 0.3 mm.

Many algorithms have been developed for detection and classification of suspicious lesions in mammograms. Each is having its advantages and disadvantages. The related work described in this paper is on mass type cancer. Here a new algorithm is described based on adaptive thresholding for classification and detection of mammograms. The method is tested on more than 80 images from mini MIASdatabase.

Mammogram databases [4]: The following are the list of the databases that are commonly being used

MIAS: Mammographic Image Analysis Society Database images scanned at a resolution of 50 um *50 um, at 8 bits/ pixel. A Small subset with lower resolution can be downloaded for research purpose.

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LLNL/UCSF database: Lawrence Livermore national laboratories (LLNL) and university of California at san Francisco (UCSF) radiology dept. has developed a 12 volume CD library of digitized mammogram features micro calcification. For each digitized image, two associated 'truth' images(full sized binary images) that shows the extent of calcification clusters and the counter and area of a few individualcalcification in each cluster, and contain 198 films from 50 patients [9].

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II. literaturereview

A. Window-Based Adaptive Thresholding Method

Local segmentation is expected to give more precise results since the global segmentation finds a coarse localization of the suspicious lesions. In [12], for each pixel $SI(i, j)$, a decision is made to classify it into a potential suspicious lesion pixel or a normal pixel by the following rule. If $SI(i, j) \geq TH(i, j)$ and $SI_{\text{dif}} \geq M_{voisi}P$, then $SI(i, j)$ belongs to the suspicious area; else, $SI(i, j)$ belongs to the normal area. In this rule, $TH(i, j)$ is an adaptive threshold value calculated by

$$TH(i, j) = M_{voisi}P + \gamma\, SI\text{dif}$$

With $SI\text{dif} = SI\max(i, j) - SI\min(i, j)$.

$M_{voisi}P$is an average of pixel intensity in a small window around the pixel $SI(i, j)$; $SI\max(i, j)$ and $SI\min(i, j)$ are the maximum and minimum intensity values in the large window as shown in Fig. 5. $\gamma$is a thresholding bias coefficient. Its value ranges from zero to one.

B. Histogram-Based Adaptive Thresholding Method

According to Zhang and Desai [8], after the mammogramsare wavelet transformed the gray-level distribution of the targetand the background regions of the images approaches toGaussian distribution. Moreover, the target has higher graylevel than the background. That is, if $p_b(x)$ and $p_t(x)$ denotethe PDFs of the background and the target, respectively, then

$$p_b(x) = \frac{1}{\sqrt{2\pi\sigma_1}} \exp\{-(x-\mu_1)^2/2\sigma_1^2\}$$

$$p_t(x) = \frac{1}{\sqrt{2\pi\sigma_2}} \exp\{-(x-\mu_2)^2/2\sigma_2^2\}$$

$$,\mu_2 > \mu_1$$

Where x is a pixel value, ,σ_1 and σ_2 are the standard deviations of the background and the target of image, And µ1 and µ2 are the means of the background and the target of image respectively.

Let $p_I(x)$ be the PDF of image I, and let $p(B)$ and $p(T)$ be the *a priori* probabilities of the background and the target of mage I, respectively. We have

$$p_I(x) = p(B)p_b(x) + p(T)p_t(x)$$

The Bayes threshold λ_1 [15] is the intersection of two solid lines that satisfy $p(B)p_b(\lambda_1) = p(T)p_t(\lambda_1)$. In fact, segmentation according to threshold λ_1 is a process of classifying pixels. Let binary image R be the segmentation result; then

Zhang and Desai have proved that, when the overlap between $p_b(x)$ and $p_t(x)$ is not significant, λ_2 is often close to λ_1. Hence, it is reasonable to carry out segmentation according to λ_2.

$$R(i,j) = \begin{cases} 0 & SI(i,j) < \lambda_1 \\ 1 & SI(i,j) < \lambda_2 \end{cases}$$

Where (i, j) denote the pixel coordinates and $SI(i, j)$ denotes the pixel value of (i, j). Usually, the Bayes threshold λ_1 cannot be calculated because $p_b(x)$, $p_t(x)$, and the *a priori* probability of each class are unknown. Assume that λ_2 is the minimum value in $pI(x)$.

III. proposed algorithm

The algorithm discussed in this paper for classification and detection of suspicious lessons in mammograms is based on adaptive thresholding, consists two parts:

1) Classification of mammograms.
2) Detection the suspiciouslesions in mammograms.

This algorithm is based on adaptive thresholding for classification and detection of cancer in mammograms. The related work is implemented using MATLAB and tested on more than 80 mammograms and the results are 90 % accurate. The flowchart of algorithm is shown in fig 3. It consists of mainly 5 steps. Firstly input the imageand normalized the image. The normalized image is then filtered and normalized again. The produced image is binary segmented and then the output is morphed. In the last step Boolean expression is checked for suspicious lessons.

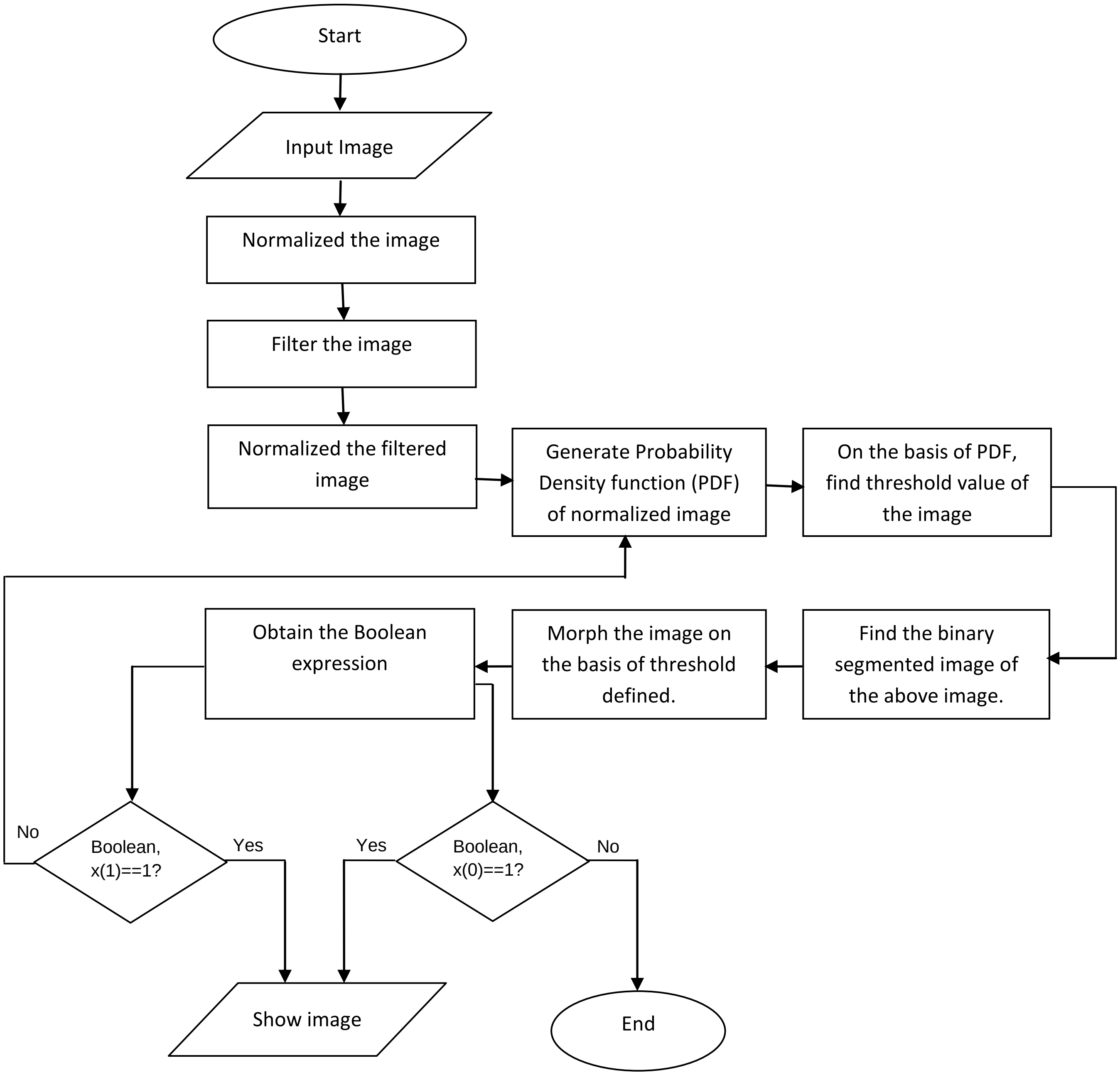

Fig3 Flow chart for new approach for classification & detection of suspicious lesions

IV. Experimental results and discussions

The data used in this workis obtained from the mini- MIAS database of mammograms [4]. The test was done on more than 80 images;all images are digitized at the resolution of 1024×1024 pixels and 8-Bit accuracy (gray level). The proposed algorithm was implemented in a MATLAB environment. Image (a), (d) and (g) are original mammograms images, image (b), (e) and image (h) are classified images and images (c), (f) and (i) are showing the detected cancer.

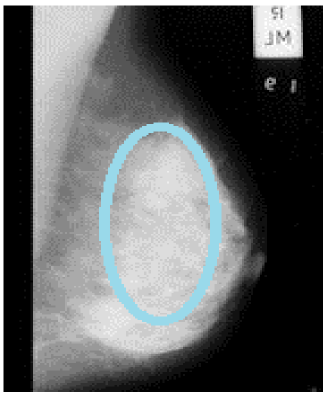
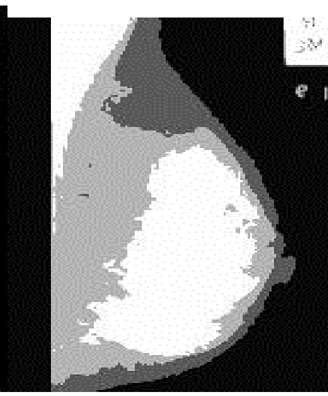
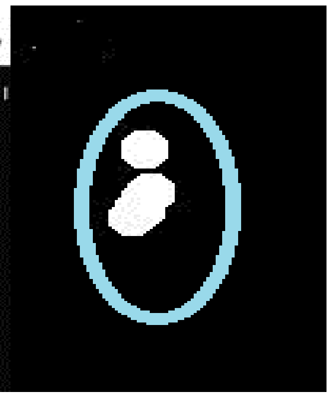

Image (a) original image image (b) classified image image (c) cancer detected

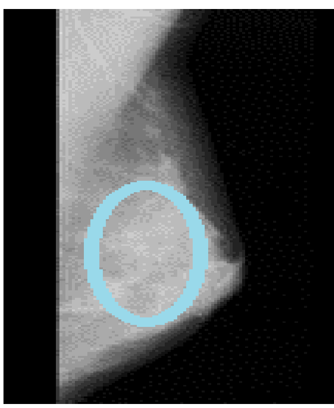
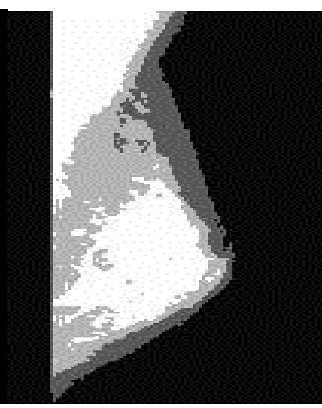
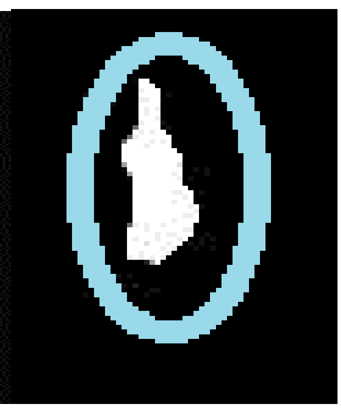

Image (d) original image image (e) classified image image (f) cancer detected

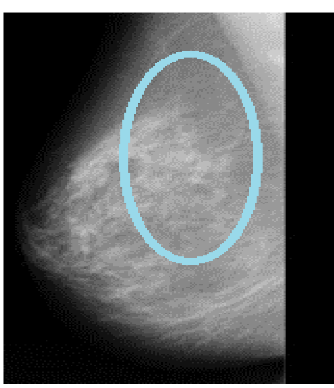
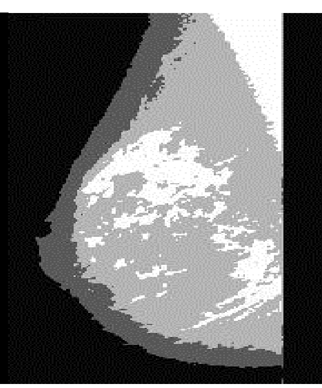


Image (g) original image image (h) classified image image (i) cancer detected

The image (a) is original mammogram image and image (b) is the classified image of image (a) and in image(c) the white portion shows the detection of suspicious lesions. The image (d) is original mammogram image and image (e) is the classified image of image (d) and in image (f) the white portion shows the suspicious lesions.The image (g) is original mammogram image and image (h) is the classified image of image (g) and in image (i) the white portion shows the suspicious lesions detection.

V. conclusion

In this paper a new algorithm is presented for the detection of suspicious lesions in mammograms. Adaptive Thresholding is used in the proposed method.Experimental results using the mini-MIAS image database have shown that the proposed detection system is capable of detecting suspicious lesions of different types at low false positive rates with low complexity and in minimum time. Furthermore, the detection results for some types of lesions mainly characterized by texture feature can be improved if other combinations of lesion features are taken into account in the proposed method. So this method can be used in the hospitals for detection of breast cancer in the earlier stages.

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