Segmentation And Characterization Of Masses In The Digital Mammograms

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Article ID: WMC00726

Article Type: Research articles

Submitted on:24-Sep-2010, 05:29:08 AM GMT **Published on:** 24-Sep-2010, 05:29:25 PM GMT

Article URL: http://www.webmedcentral.com/article_view/726

Subject Categories:BREAST

Keywords: Breast cancer, Malignant Breast Masses, Digital Mammograms, MGMRGT and Watershed Segmentation.

How to cite the article: Dubey R , Hanmandlu M , Gupta S . Segmentation And Characterization Of Masses In The Digital Mammograms . WebmedCentral BREAST 2010;1(9):WMC00726

Source(s) of Funding:

Not applicable.

Competing Interests:

N.A.

Additional Files:

total manuscript

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Abstract

Breast tumor segmentation is needed for monitoring and quantifying breast cancer. However, automated tumor segmentation in mammograms poses many challenges with regard to characteristics of an image. A comparison of two different semi-automated methods, viz., modified gradient magnitude region growing technique (MGMRGT) and watershed method is undertaken here for evaluating their relative performance in the segmentation of breast tumor. A set of 6 mammogram images is used to validate the effectiveness of the segmentation methods. The MGMRGT segmentation shows better results than those due to watershed approach. The present application is intended to assist the radiologist in performing an in-depth examination of the breast at considerably reduced time.

Introduction

Breast cancer is the most common female cancer and the second leading cause of cancer death among women in America. A mammogram is an X-ray examination of the breast. Mammography is the only effective and viable techniques to detect breast cancer. It is proved that early stages of breast cancer are well treatable. X-ray mammography is the current, clinical Gold Standard for the detection of breast cancer. It is a well understood and standardized procedure, it works fairly well in postmenopausal women and it is inexpensive [1- 3]. The early stages of breast cancer may only have subtle indications which can be varied in appearance, making physical examination ineffective and making diagnosis difficult even for experienced radiologist [4, 10].

A mammogram mainly contains two regions: the exposed breast region and the unexposed non-breast region. It is necessary to first identify the breast region for the reduction of the subsequent processing calculation and the removal of the non-exposed breast region. Bick et al. [5] have explored a segmentation method for the breast region based on the morphological gradient calculation and the modified global histogram analysis. Ball et al. [6] present an automated mammographic computer aided diagnosis system to detect and segment spicules. Mendez et al. [7] have described an automatic algorithm that computes the gradient of gray levels. Wirth et al. [8] make use of the snakes and fuzzy approach [9] for the purpose of segmentation.

Elter and Horsch [11] focused their view on approaches for mass and micro-calcification diagnosis, covering the segmentation of region of interests for extracting shape and contour features and their posterior classification [12]. In particular neural network have demonstrated their efficacy in the clinical domain with diseases such as cancer where there is a weak relationship between the classes forming a benign or malignant diagnosis [13-14]. Hassanien [15] proposed a hybrid scheme that combines the advantages of fuzzy sets and rough sets in conjunction with statistical feature extraction techniques. An application of breast cancer imaging has chosen and hybridization scheme have been applied to see their ability and accuracy to classify the breast cancer images into two outcomes: cancer or non-cancer. Du et al. [16] presented a framework for improvement of mammogram classification, which includes a new preprocessing methodology for segmenting, a unique associative rule discovery based algorithm for classification and an evaluation of efficacy of raw derived features using fuzzy K-nearest neighbor and agglomerative clustering of associative features. A co–occurrence analysis is applied to identify statistically significant differences in pathology co-occurrence patterns between premenopausal and postmenopausal women [17, 18].

This paper explores the comparison of the MGMRGT and morphological watershed approach for segmentation.

Methods

Modified gradient magnitude region growing technique (MGMRGT)

In the first step proper threshold is chosen in order to distinguish the interior area from other organs in the MR image dataset. Then modified gradient magnitude region growing algorithm is applied, in which gradient magnitude is computed by Sobel operator and employed as the definition of homogeneity criterion. This implementation allowed stable boundary detection when the gradient suffers from intersection variations and gaps. By analyzing the gradient magnitude, the sufficient contrast present on the boundary region that increases the accuracy of segmentation [19].

To calculate the size of segmented tumor the relabeled method based on remaps the labels associated with object in a segmented image such that the label numbers are consecutive with no gaps between the label numbers used. Any object can be extracted from the relabeled output using a binary threshold. Here, the algorithm is adjusted to extract and relabeled the tumor and then find its size in pixels. The algorithm works well in two stages. The first stage is to determine the input image labels and the number of pixels in each label. The second stage is to determine the output requested region to get total number of pixels accessed. Segmented areas are automatically calculated and to get desired tumor area per slice [19-20].

Fig. 1: (a) Original image, (b) segmented mage, (c) extracted tumor after MGMRGT and ROI.

Watershed Segmentation (WS)

A watershed line is defined as the line separating two catchment's basins, as shown in Fig. 2. The rain that falls on either side of the watershed line will flow into the same lake of water. The image gradient can be viewed as terrain. The homogeneous regions in the image usually have low gradient values which represent valleys, while edge represents the peaks having high gradient values. Vincent et al. [21] propose the immersion simulation algorithm for the calculation of watershed lines.

Fig. 2: Watershed line with catchment basins.

The watershed transform detects intensity valleys in the image and the image is enhanced by highlighting the intensity valleys. The enhanced image is used to convert the objects of interest into intensity valleys. We detect all intensity valleys below a particular threshold with output as a binary image. Then imposed minimum function will modify the image to contain only valleys. The imposed minimum function will also change a valley's pixel values to zero. All regions containing an imposed minimum will be detected by the watershed transform. The segmentation of the imposed minima image is accomplished with the watershed function. Watershed function returns a label matrix containing non-negative numbers that correspond to watershed regions. Pixels that do not fall into any watershed region are given a value of zero. The label matrix is to convert it to a color image. In the colored version of the image, each labeled region is displayed in a different color and the pixels that separate the region are white. We specify a polygonal region of interest of the objects in binary image. Total area is a scalar whose value corresponds roughly to the total number of pixels in the image.

Morphological Operations

Morphology is an operation of image processing based on shapes. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, we can construct a morphological operation that is sensitive to specific shapes in the input image [22-24]. Dilation and erosion are two fundamental morphological operations. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels from the object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image.

Contrast Enhancement

First image is dilated and then eroded using matlab functions. Now, to minimize the number of valleys found by the watershed transform, we maximize the contrast of the objects of interest. A common technique for contrast enhancement is the combined use of the top hat and bottom-hat transforms. The top-hat transform is defined as the difference between the original image and its opening. The opening of an image is the collection of foreground parts of an image that fit a particular structuring element.

The top-hat image contains the peaks of objects that fit the structuring element. The bottom-hat transform is defined as the difference between the closing of the original image and the original image. The closing of an image is the collection of the background parts of an image that fit a particular structuring element [22-24]. To maximize the contrast between the objects and the gaps that separate them from each other we add the top-hat image to the original image and then subtract the bottom-hat image from the result. Top-hat image contains the peaks of objects that fit the structuring element. In contrast, the bottom-hat image shows the gaps between the objects of interest. To maximize the contrast between the objects and the gaps that separate them from each other, the bottom-hat image is subtracted from the original and top-hat image. The various processes involved in watershed segmentation are shown in Fig. 3.

Fig. 3 (a-k): Various steps involved during watershed segmentation.

Results

The mammograms that are positive for the malignant mass are collected for this study from the mammography image analysis (MIAS) database. The total number of cases is 6. Mammograms come up with labels and contain noise and irregularities that need to be eliminated prior to the segmentation. This can be achieved by using several denoising techniques, viz. morphological open-close reconstruction filter and morphological top and bottom hat filtering.

The algorithm is implemented on personal computer (1.8GHz CPU, 2GB RAM). The proposed algorithms have been tested on 6 mammograms containing malignant masses. Expert-segmented data in all the images are provided in Table 1. All images are semi-automatically segmented and the results are compared with the corresponding expert-segmented ones.

We introduce two segmentation approaches for mammogram images and investigate its application to the detection of region of interest (ROI), which includes both masses and the pectoral muscles. In the mammograms, masses are assumed to be distinctive regions that are relatively brighter than the surrounding background, while the pectoral muscles appear to be more uniformly bright making their presence at a predictable location. Different tumor area obtained after MGMRGT and watershed segmentation are tabulated in Table 3 and the results are validated with manually segmented expert radiologist.

Table 1: Comparison of tumor area with an expert radiologist.

Conclusion(s)

Two semi-automated approaches are presented for the segmentation of a tumor. These overcome the accuracy and sensitivity limitations of the current solutions. Our goal here is to compare two popular techniques: MGMRGT and watershed with an expert's manual segmentation. Recently attention is being paid to the semi-automatic segmentation methods on tumor measurements in order to avoid the observer variability and therefore to increase the accuracy. In the study of the reliability of the breast tumor area measurements, we quantitatively compare the expert manual trace method with semi-automatic segmentation methods. The semi-automatic segmentation techniques require very less time to generate tumor area measurements than the manual method. Manual method is highly labor intensive and requires more concentration than the semi-automatic method. Both methods have been tested extensively and results are validated numerically. The result shows that MGMRGT segmentation better than the watershed approach.

Authors Contribution(s)

Tested two methodology

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Illustrations

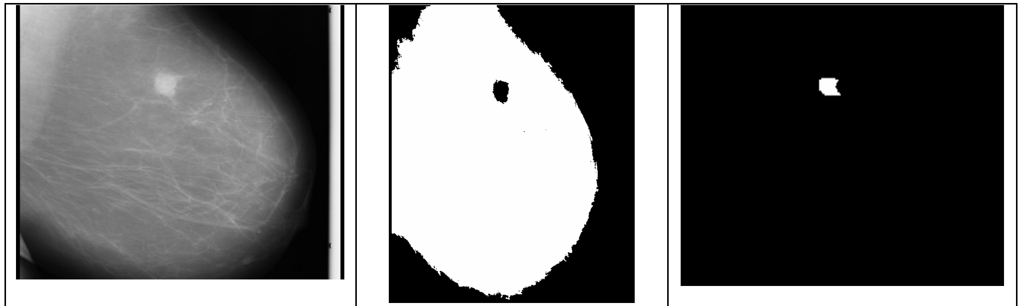
Illustration 1

Table 1: Comparison of tumor area with an expert radiologist.

Sample No.	Expert radiologist Area (mm^2)	MGMRGT Method Area (mm^2)	WS Method Area (mm^2)	Relative Error (%) (MGMRGT)	Relative Error (%) (WS)
1	1000.00	1090.78	900.32	8.32	9.07
2	85.70	78.36	70.10	7.75	8.56
3	1000.60	989.76	900.54	1.08	10.06
4	20000.30	20758.66	18684.43	3.79	6.58
5	2800.89	2758.13	2271.19	1.53	18.91
6	900.00	855.08	805.00	4.99	4.91

Illustration 2

Fig. 1: (a) Original image, (b) segmented mage, (c) extracted tumor after MGMRGT and ROI.



1 (a)	1(b)	1(c)

Illustration 3

Fig. 2: Watershed line with catchment basins.

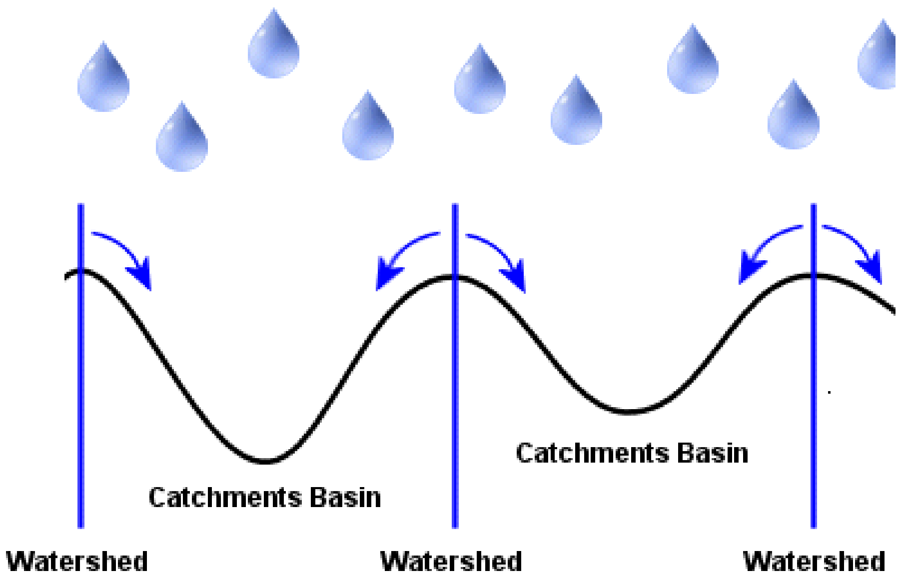


Illustration 4

Fig. 3 (a-k): Various steps involved during watershed segmentation.

Fig. 3 (a): Original image.

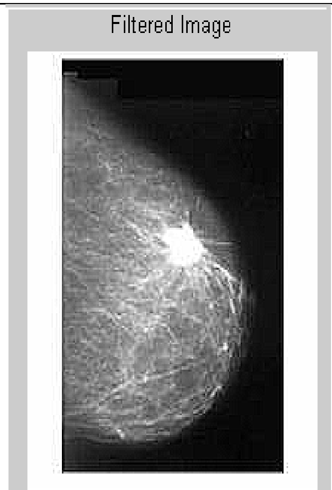


Fig. 3(b): Filtered image.

Illustration 5

continue..

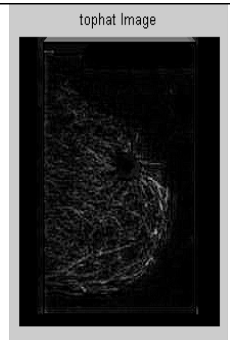
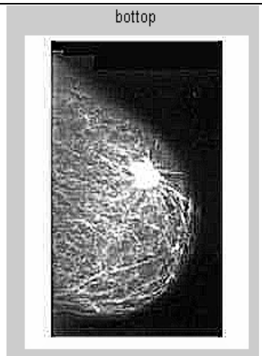
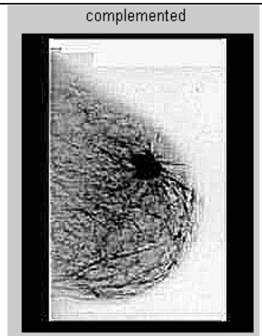
 Fig. 3 (c): Eroded image	 Fig. 3 (d): Dilated image	 Fig. 3 (e): Top-hat image
 Fig. 3(f): Original+tophat-bottomhat image.	 Fig.3(g): Complemented image.	 Fig. 3 (h): Imposed minima.

Illustration 6

continue..

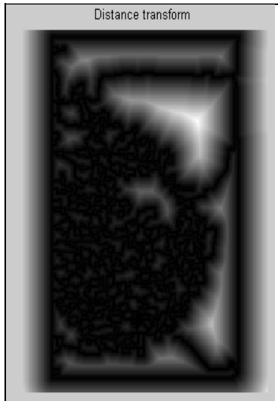


Fig. 3(i): Distance transformed image.

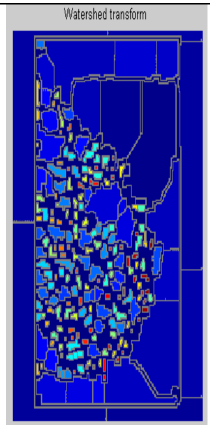


Fig.3(j): Watershed segmented image.

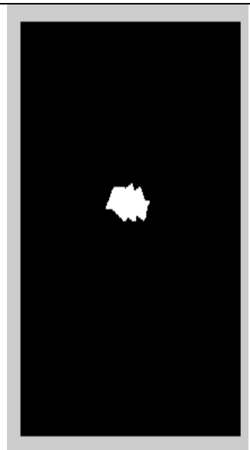


Fig. 3(k): detected tumor location.