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Automated Breast Profile Segmentation for ROI Detection Using Digital Mammograms

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***Abstract*—Mammography is currently the most effective imaging modality used by radiologists for the screening of breast cancer. Finding an accurate, robust and efficient breast profile segmentation technique still remains a challenging problem in digital mammography. Extraction of the breast profile region and the pectoral muscle is an essential pre-processing step in the process of computer-aided detection. Primarily it allows the search for abnormalities to be limited to the region of the breast tissue without undue influence from the background of the mammogram. The presence of pectoral muscle in mammograms biases detection procedures, which recommends removing the pectoral muscle during mammogram pre-processing. In this paper we explore an automated technique for mammogram segmentation. The proposed algorithm uses morphological preprocessing and seeded region growing (SRG) algorithm in order to: (1) remove digitization noises, (2) suppress radiopaque artifacts, (3) separate background region from the breast profile region, and (4) remove the pectoral muscle, for accentuating the breast profile region. To demonstrate the capability of our proposed approach, digital mammograms from two separate sources are tested using Ground Truth (GT) images for evaluation of performance characteristics. Experimental results obtained indicate that the breast regions extracted accurately correspond to the respective GT images.**

***Keywords*—Breast cancer, Mammogram segmentation, Seeded region growing, Pectoral muscle, Region of interest.**

I. INTRODUCTION

Breast cancer is a type of cancer with highest incidence rates in women. It is the most common cause of cancer death in women in many countries [1]. Recent statistics show that breast cancer affects one of every ten women in Europe and one of every eight in the United States [2]. It has been shown that early detection and treatment of breast cancer are the most effective methods of reducing mortality [3].

Mammography is the most widely used method to screen asymptomatic women for early detection of breast cancer. The large number of mammograms generated by screening of population must be diagnosed by relatively few radiologists [4]. Retrospective studies have shown that radiologists can miss the detection of a significant proportion of abnormalities in addition to having high rates of false positives. The estimated sensitivity of radiologists in breast cancer screening is only about 75% [5]. Double reading has been suggested to be an effective approach to improve the sensitivity. In order to improve the accuracy of interpretation, a variety of Computer-Assisted Detection (CAD) techniques have been proposed [6].

Interpretation of mammograms mainly involves two major processes: Computer-Aided Detection (CADe) and Computer-Aided Diagnosis (CADi) [7], [8]. It would be valuable to develop a CAD algorithm using extracted features from the breast profile region; region of interest (ROI). This would reduce the number of unnecessary biopsies in patients with benign disease and thus avoid patients' physical and mental suffering, with a bonus of reducing healthcare costs [9].

Before CAD algorithms can be applied for the task of classification and identification, mammograms need to be pre-processed. Preprocessing steps include: (a) noise removal, (b) radiopaque artifact suppression, (c) pectoral muscle removal, which are mainly related to the problem of mammogram image processing and segmentation.

In this paper we propose an automated technique for mammogram segmentation. The proposed algorithm uses morphological preprocessing and seeded region growing (SRG) to remove digitization noises, suppress radiopaque artifacts and remove the pectoral muscle to accentuate the breast profile region for use in CAD algorithms.

II. LITERATURE SURVEY

Mammogram segmentation usually involves classifying mammograms into several distinct regions, including the breast border [10], the nipple [11] and the pectoral muscle. The edge of the pectoral muscle is useful in determining mammogram adequacy [12], mammogram-pair registration and comparison [13] and for restricting the searching space for calcification and lesion detection [14]. The pectoral muscle represents a predominant density region in most mediolateral oblique views of mammograms, which affects the results of image processing [15]. Thus, it is recommended that the pectoral muscle should be removed during mammogram segmentation [8].

There have been various approaches proposed to the task of segmenting the breast profile region in mammograms. Some of these have focused on using thresholding [16] [17], gradients [18], modelling of the non-breast region of a mammogram using a polynomial [19], or active contours [7].

One of the earliest approaches to segmentation of the breast contour was presented by Semmlow *et al.* [20], who used a spatial filter and Sobel edge detector to locate the breast boundary on xero-mammograms. The most obvious approach would seem to be the use of thresholding [16] [17], however since there is usually a certain amount of overlap between the breast region and background, such partitions will inevitably result in the misclassification of some background pixels as breast region and vice versa.

Recent efforts, such as that of Masek *et al.* [21] using local thresholding have shown more promising results. Abdel-Mottaleb *et al.* [22] use a system of masking images with different thresholds to find the breast edge. Méndez *et al.* [18] found the breast contour using a gradient based method. They first use a two-level thresholding technique to isolate the breast region of the mammogram. The mammogram is then divided into three regions using a number of automatically determined reference points and a tracking algorithm is applied to the mammogram to detect the border.

The global segmentation approach proposed by Bick *et al.* [16] incorporates aspects of thresholding, region growing and morphological filtering. The mammogram is initially filtered to reduce noise and then features are extracted using a texture operator. A histogram is then constructed for all pixels whose local range was minimal. This histogram was then used to classify pixels as belonging to either the breast or non-breast regions. Region growing is then used to label the different regions, while morphological filtering is used to eliminate irregularities along the breast contour and contour tracing extracts the breast contour.

An interesting algorithm was described by Lou *et al.* [23]. It is based on the assumption that the trace of intensity values from the breast region to the air-background is a monotonic decreasing function. The algorithm first searches for an initial boundary using a clustered image. For each initial boundary point a corresponding point is estimated with an extrapolation method. Through a refinement process, a contour point is derived from the extrapolated point, and by linking all the boundary points, the breast contour is defined.

There have also been various attempts to use active contours, such as that of McLoughlin and Bones [24]. They first derive an approximate separation of the breast region and background using a global threshold. Pixels below this threshold are used to obtain a model of the background of the mammogram using Poisson approximation. The threshold found by the Poisson model is used to form a binary mask from which an initial contour is extracted and is smoothed using the *greedy snake algorithm*.

A semi-automated method based on the concept of *united snakes* is described by Ojala *et al.* [25]. It uses an interactive boundary tracing technique called livewire to initialize the snake. The united snake compactly unifies the most significant snake variants, allowing the user to choose the most appropriate snake. The algorithm is tested on mammograms from databases using the "basic snake" as defined by Kass *et al.* [26]. Ojala *et al.* [27] later describe an active contour method for smoothing breast contours in mammograms as part of a comparison with two other methods, namely Fourier smoothing and BSpline approximation.

The method, as described by Chandrasekhar *et al.* [19], involves modelling the non-breast region (background) of a mammogram as a polynomial and subtracting it from the original mammogram. An initial threshold is used to approximate the breast region. This region includes the whole breast region, a small portion of the breast contour, and the non-breast region, included in the region being modelled. This modelled background is then subtracted from the original mammogram, yielding a difference image which, when thresholded, results in a binary mammogram. A connected components algorithm is then used to identify and merge related regions, followed by morphological operations to smooth irregularities to yield a labelled binary mammogram representing the breast/non-breast association.

One of the inherent limitations of these methods is the fact that very few of them preserve the skin or nipple in profile. Despite the numerous techniques that have been proposed in pursuit of an adequate segmentation method in the field of digital mammography there is still no exact solution to this complex problem. The complexity of mammograms comes from inherent blurring caused by round anatomical feature shapes in the direction of X-ray beam and superimposed boundaries resulting from overlapping features in the path of each X-ray beam [10].

III. Seeded Region Growing

Seeded region growing (SRG) performs a segmentation of an image with respect to a set of points, known as *seeds*. Consider a number of seeds which have been grouped into n sets, say $A_1, A_2, \ldots, A_n$. Sometimes individual sets will consist of single points. It is in the choice of seeds that the decision of what is a feature of interest and what is irrelevant or noise is embedded. Given the seeds, SRG finds a tessellation of the image into regions with the property that each connected component of a region meets exactly one of the A_i and, subject to this constraint; the regions are chosen to be as homogenous as possible. The description of the SRG method as applied to grayscale images is presented below [29].

The process evolves inductively from the seeds, namely, the initial state of the sets, $A_1, A_2, \ldots, A_n$. Each step of the algorithm involves the addition of one pixel to one of the above sets. Considering the state of the sets A_i after m steps. Let T be the set of all as-yet unallocated pixels which border at least one of the regions:

$$T = \{x \notin \cup_{i=1}^{n} A_i | N(x) \cap \cup_{i=1}^{n} A_i \neq \emptyset\} \qquad (1)$$

where $N(x)$ is set of immediate neighbours of the pixel x. In this correspondence as an example, consider the use of a rectangular grid with immediate neighbours being those which are 8-connected to the pixel x. If for, $x \in T$ we have that $N(x)$ meets just one of the A_i, then we define $i(x) \in \{1,2,\dots,n\}$ to be that index such that $N(x) \cap A_{i(x)} \neq \emptyset$ and define $\delta(x)$ to be a measure of how different x is from the region it joins. The simplest definition for $\delta(x)$ is:

$$\delta(x) = \left| g(x) - \mathrm{mean}_{g \in A_{i(x)}} [g(y)] \right| \quad (2)$$

where $g(x)$ is the gray value of the image point x. If $N(x)$ meets two or more of A_i, $i(x)$ is taken to be a value of i such that $N(x)$ meets A_i and $\delta(x)$ is minimized. Alternatively, in this circumstance x can be classified as a boundary pixel, which is appended to the set B of already-found boundary pixels. Flagging such boundary pixels is useful for display purposes. Then taking $z \in T$ such that,

$$\delta(x) = \min_{x \in T} \{\delta(x)\} \quad (3)$$

by appending z to $A_i(z)$. This completes step $m+1$. The process is repeated until all pixels have been allocated. The process commences with each A_i being just one of the seed sets. The definitions in (1) and (2) ensure that the final segmentation is into regions as homogenous as possible given the connectivity constraint.

IV. Methodology

A. Data Collection

The framework proposed for automated mammogram segmentation is indicated in Figure 1, which is implemented in MATLAB. Digital mammogram images were acquired from Malaysian patients treated at the Universiti Malaya Medical Centre (UMMC), Kuala Lumpur and the mini-MIAS database [30]. Images acquired consist of left and right breast images of fatty, fatty-glandular and dense-glandular breasts. The acquired mammogram images are classified into three major cases: *malignant*, *benign* and *normal*, all of which are subdivided into five categories as follows:

1) Circumscribed masses
2) Spiculated masses
3) Ill-defined masses
4) Architecturally distorted masses
5) Asymmetrical masses

The images are digitized at 200 micron pixel edge and clipped (padded) in order to obtain all images with a size of 1024 × 1024 pixels in Portable Greymap (PGM) format. Each pixel in the images is represented as an 8-bit word, where the images are in grayscale format with a pixel intensity of range [0, 255]. For the acquired mammogram images the *Ground Truth Markings* (locations where abnormalities are present for benign and malignant cases) were also obtained from diagnosis conducted by radiologists and clinicians at UMMC.

B. Digitization Noise Removal

Digitization noises such as straight lines (see Figure 2(a)) present in the majority of acquired mammogram images are filtered using a two-dimensional (2D) *Median Filtering* approach in a 3-by-3 neighbourhood connection. Each output pixel contains the median value in the 3-by-3 neighbourhood around the corresponding pixel in the input images. The edges of the images however, are replaced by zeros (total absence or black colour). Figure 2(a) shows the digitization noise present in a mammogram image and Figure 2(b) shows the same image after noise removal.

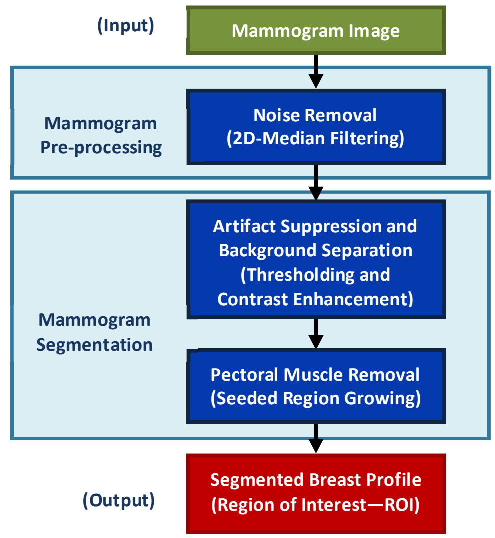
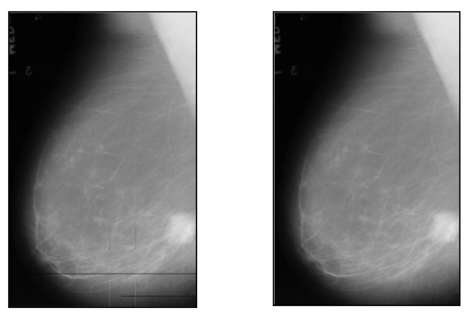


Fig. 1. Proposed framework for mammogram segmentation

C. Artifact Suppression and Background Separation

Radiopaque artifacts such as wedges and labels in the mammograms images are removed using thresholding and morphological operations. Figure 3(a) shows a mammogram image acquired from the UMMC mammogram database with a radiopaque artifact present. Through manual inspection of the all mammogram images acquired, a global threshold with a value of $T = 18$ (normalized value, $T_{norm} = 0.0706$) is found to be the most suitable threshold for transforming the grayscale images into binary [0, 1] format.



(a) (b)

Fig. 2. Mammogram digitization noise removal using 2D median filtering. (a) Original image (b) Filtered image after noise removal

After the grayscale mammogram images are converted into binary, as shown in Figure 3(b) for the image in Figure 3(a), morphological operations such as *dilation*, *erosion*, *opening* and *closing* are performed on the binary images. The algorithm used for suppression of artifacts, labels and wedges is given as follows:

1. All objects present in the binary image in Figure 3(b) (thresholded using, $T = 18$) are labeled using the $bwlabel$ function in MATLAB. The binary objects consist of the radiopaque artifacts and the breast profile region as indicated in Figure 3(b).
2. The 'Area' (actual number of pixels in the region) of all objects (regions) in Figure 3(b) is calculated using the $regionprops$ function in MATLAB.

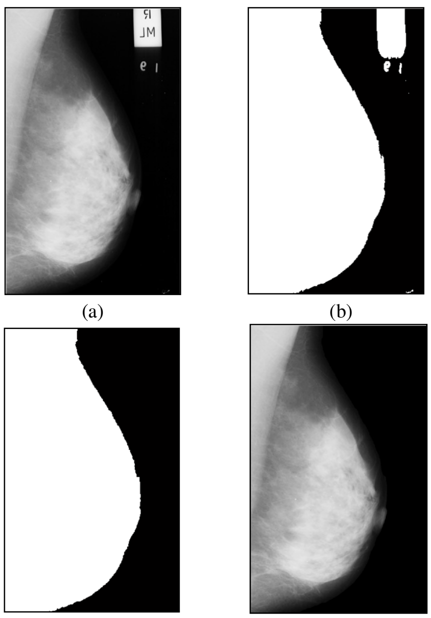


Fig. 3. Suppression of artifacts, wedges and labels from a mammogram
(a) Original image (b) Thresholded image using $T = 18$
(c) Largest area (object) selected from thresholded image 3(b)
(d) Mammogram image with radiopaque artifacts suppressed

3. From all of the binary objects in the mammogram image (Figure 3(a)), the largest object—breast profile (Figure 3(c)), in each image is selected by using the $bwareaopen$ function in MATLAB, using the object with the largest Area (calculated in Step 2). This process morphologically opens a binary image and removes all objects in the binary image, except the largest object (breast profile). This operation uses an 8-connected neighbourhood.
4. Next, a morphological operation to reduce distortion and remove isolated pixels (individual 1's surrounded by 0's) is applied to the binary images using the $bwmorph$ function in MATLAB with parameter 'clean'.
5. Another morphological operation is applied the binary images to smoothen visible noise using the $bwmorph$ function in MATLAB with the parameter 'majority'. This algorithm checks all pixels in a binary image and sets a pixel to 1 if five or more pixels in its 3-by-3 neighbourhood are 1's, otherwise, it sets the pixel to 0.
6. The binary images are *eroded* using a flat, disk-shaped morphological structuring element (STREL) using the MATLAB $strel$ and $imerode$ functions. The radius of the STREL object used is $R = 5$.

Fig. 4. Separation of breast profile region from background
(a) Largest area (object) selected from thresholded image 3(b)
(b) Breast profile separated from the background

7. Next, the binary images are *dilated* using the same STREL object in Step 6. Morphological dilation is performed using the MATLAB $imdilation$ function.
8. The holes in the binary images are filled using the $imfill$ function in MATLAB with the parameter 'holes'. This algorithm fills all holes in the binary images, where a *hole* is defined as a set of background pixels that cannot be reached by filling in the background from the edge of the image.
9. The resulting binary image obtained from Step 8 is multiplied with the original mammogram image using the MATLAB $immultiply$ function to form the final grayscale image in Figure 4(b).

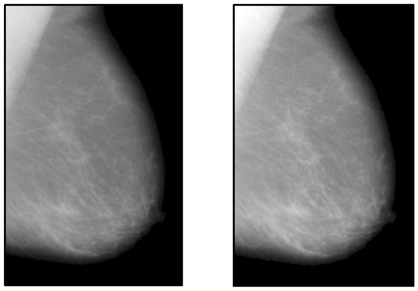
During artifact, wedge and label suppression the breast profile region is also segmented from the background (see Figure 3(c)), as indicated in Figure 4(b).

D. Pectoral Muscle Segmentation

The algorithm applied for pectoral muscle segmentation using Seeded Region Growing (SRG) is illustrated in the following steps:

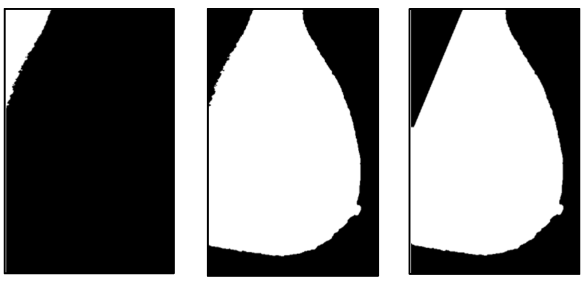
1. The breast orientation in each mammogram image needs to be determined prior to performing Seeded Region Growing (SRG). In order to determine the breast profile orientation (left or right) using an automated procedure, the binary image in Figure 3(c) is used. The binary image is cropped left to right and then cropped top to bottom, such that the breast profile touches all four borders (left, right, top and bottom) of the image. Then the sum of the *first* and *last* 5 columns of the binary values in the cropped binary images is calculated. The breast profiles are classified using a simple if-else logic, such that, if $sum_{first} > sum_{last}$ then the breast is right orientated else it is left-orientated.
2. Contrast enhancement is performed on the breast-profile images using the MATLAB $imadjust$ and $stretchlim$ functions. The $stretchlim$ function finds limits to

contrast stretch an image. Since the $imadjust$ function maps the values in an intensity image to newer values, the output limits from the $stretchlim$ function are used as the input into the $imadjust$ function. Figure 5 illustrates the contrast enhancement technique applied to the breast profile images.



(a) (b)

Fig. 5. Contrast enhancement of a mammogram image
(a) Original image (b) Image after contrast enhancement



(a) (b) (c)

Fig. 6. Pectoral muscle segmentation
(a) Segmented pectoral muscle
(b) Segmented pectoral muscle in the breast profile
(c) Straightened pectoral muscle boundary of breast profile in Figure 6(b)

3. After the breast orientation in determined in Step 1 and the breast profile contrast is enhanced in Step 2, the pectoral muscle is segmented using the Seeded Region Growing (SRG) technique. In order to implement automated SRG a *seed* needs to be placed inside the pectoral muscle of the grayscale mammogram image. Using results obtained from Step 1, if the breast profile is right-orientated a seed is placed inside the first 5th column and 5th row of the mammogram image, while if the breast profile is right-orientated a seed is placed inside the last 5th column and 5th row. The following four steps (a to d) are applied in the SRG process:
   a. The region is iteratively grown by comparing all unallocated neighboring pixels to the region.
   b. The difference between the pixel of interests' intensity value and the region's mean used as a measure of similarity.
   c. The pixel with the smallest difference measure is allocated to the respective region.
   d. The process stops when the intensity difference between the region mean and the new pixel become larger than the threshold value (maximum intensity distance).

   Based on inspection of all acquired mammogram images a SRG *threshold* value of $S = 32$ is identified as the optimum threshold satisfying all mammogram images to reliably segment the pectoral muscle from the breast profile. After SRG is complete, a binary image of the segmented pectoral muscle is obtained as indicated in Figure 6(a), which is subtracted from Figure 4(a) using the MATLAB $imsubtract$ function in order to obtain Figure 6(b).
4. There is normally only one binary object (Figure 5.16(b)) present in the binary images after the suppression of the pectoral muscle. However in some mammograms, other smaller objects, i.e. parts of the pectoral muscle near the segmented pectoral muscle border are retained. In order to cater for this situation, Steps 1 to 8 in Section C (Methodology) are evaluated for Figure 5.16(b).
5. Four points are found from the segmented pectoral muscle x_1, x_2, y_1 and y_2, and the straight line equation $y = mx + c$ is used to construct a straight line in order to remove the rough edges (produced after SRG) of the pectoral muscle boundary, as shown in Figure 6(c).
6. The binary images in Figure 6(c) are *eroded* and *dilated* using a flat, disk-shaped morphological structuring element (STREL) with radius of $R = 3$.
7. The resulting binary image obtained in Step 6 is multiplied with the grayscale image in Figure 4(b) using the MATLAB $immultiply$ function. This step produces the final grayscale mammogram image with the segmented pectoral muscle as shown in Figure 7(a).

(a) (b)

Fig. 7. Mammogram image obtained after automated segmentation
(a) Segmented breast profile region
(6) Ground Truth performance indices: TP, TN and FP

The qualitative performance measures indicated in Figure 7(a) are used to evaluate the accuracy of automated mammogram segmentation algorithm. The pixels in the breast profile region (mask in Figure 6(c)) which match the Ground Truth (GT) image in Figure 7(b) are denoted as a true positive (TP). Pixels shown in the GT but not shown in the mask (Figure 6(c)) are defined as false negative (FN). Conversely, the pixels not in the GT, but in the mask are defined as false positive (FP) pixels.

EXPERIMENTAL RESULTS & CONCLUSION

Finding an automated algorithm capable of segmenting the breast region in mammograms has proven to be a difficult task. We have approached the problem from a morphological image processing and seeded region growing (SRG) perspective.

There are a number of factors which make it difficult to postulate the exact effect digital mammograms on a particular segmentation algorithm. The first of these relates to acquisition parameters, such as exposure time and energy level, which influence the quality of the image registered on film. These factors introduce imaging artifacts, in the form of noise, scratches, labels and wedges, which may interfere with the interpretation process. Secondly, segmentation of the breast region (ROI) from the background is further hampered by the tapering nature of the breast.

There are two key contributions of the work presented in this paper. The first of these is a fully automated segmentation algorithm which provides a breast contour representation of the breast profile region. The second contribution is the algorithm's performance evaluation. This algorithm has been tested using mammogram images of differing densities from multiple databases and has shown results with high accuracy. Our future work will involve the development of a computer-aided detection (CAD) system using the results presented in this paper.

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