An Automatic-Pre-processing Method For Mammographic Images

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Abstract

Screening mammography represents the technique adopted to detect breast cancer at an early stage. However the presence of artifacts and pectoral muscle can disturb the detection of breast cancer and reduce the rate of accuracy in the computer aided analysis (CAD). For this reason, the pre-processing of mammogram images is very important in the process of breast cancer analysis because it reduces the number of false positive. It also allows radiologists to help in the comparison between mammograms. The aim of this paper is to propose a method of pre-processing on medio-lateral oblique-view (MLO) mammograms that is composed of two stages: the first step helps to extract the breast region from the rest of the image (background.), while the second aims at the suppression of the pectoral muscle. To extract the breast region, we used a method based on automatic thresholding (Otsu's) and Connected Component Labelling algorithm. Identifying the pectoral muscle has been done using the Hough transform and active contour. We evaluated our pre-processing method on a set of 80 images obtained from the DDSM database and we found that breast region extraction gave an excellent success rate that reached 100%. The success rate in the removal of the pectoral muscle was 92.5% with the use of Hough transform and active contour.

Keywords: *Pectoral muscle extraction, Breast region extraction, Segmentation, Mammogram, Thresholding, Connected Component Labelling, Hough Transform, Active contour, Computer aided analysis*

1. Introduction

Breast cancer is considered one of the major causes for the increase in mortality among women. More specifically, breast cancer is the second most common type of cancer and the fifth most common cause of cancer related to death [1]. Screening mammography is currently the best available radiological technique for early detection of breast cancer [2]. However, the large number of mammograms generated by population screening must be interpreted by the relatively small number of expert radiologists [3]. In order to reduce the workload on radiologists, a variety of CAD systems (computer-aided diagnosis (CADi) and computer-aided detection (CADe)) have been proposed. These systems are used to identify a suspicious lesion (masse, calcification, etc) and to decrease the number of false positives cases. To accomplish those goals, most of the CAD systems used a typical block diagram, given by figure 1, composed of successive steps: pre-processing, segmentation, feature extraction, feature selection and classification. The first step in screening mammography (pre-processing step) has to be done to remove the background area (High intensity rectangular label, Tape artefact and noise) as shown in figure 2 and to remove the pectoral muscle from the breast region if the image is a MLO view [4]. Generally, pre-processing step is composed of two stages: breast region and pectoral muscle extraction.

Breast region extraction is a fundamental step in mammogram pre-processing that is important to find the skin-air interface, or the breast boundary. The aim of this step is to separate the breast from the rest of objects that could appear in a digital mammography: the black background, labels and tape artifacts [5]. To extract the breast region, many approach based upon histogram are proposed. In this context, J. Byng et al. [7] used a simple thresholding to extract the breast region from the background. U. Bick et al. [8] presents an approach that combines local thresholding and region growing. In recent work of H. Mirzaalian et al. [9], a thresholding based upon cumulative histogram is used after a step of normalization by Histogram Equalization and convolution of the image with a low-pass mask. In final step, they used a labelling procedure to select the largest region that represents the breast region. Recently, S. K. Kinoshita et al. [10] have used an approach that starts after filtering the image in order to remove the noise. They applied a variety of thresholding methods (maximum-entropy principle, Otsu's method, etc) for each mammogram image. The best result returned by the thresholding methods was selected for each image by one of the radiologists involved in the study. In their approach, an additional step based upon morphological opening and closing operations was used to remove small artifacts in the image and to smooth the contour of the breast region.

In many approaches, active contour model was applied as a refinement step in order to ameliorate the identification of the boundary of the breast region. In this context, K. McLoughlin et al. [11] used a global threshold to obtain an initial segmentation. After, they used a snake algorithm to obtain the final boundary that represents the contour of the breast region. R.J. Ferrari et al. [12] have proposed a method that started with the enhancement of the image by the logarithmic transformation. After, the authors used a binarization procedure (Lloyd-Max least-squares) and the chain-code algorithm to determinate a first approximation of the breast contour. In a final step, the identification of the final breast boundary was determined by using a traditional active deformable contour model (or snake). In their recent work, R.J. Ferrari et al. [13] have modified their approach used in [12] by replacing the traditional snake model by an adaptive active deformable contour model (AADCM). This modification resolves the problem of the no robustness of the snake model in the presence of noise and artifacts.

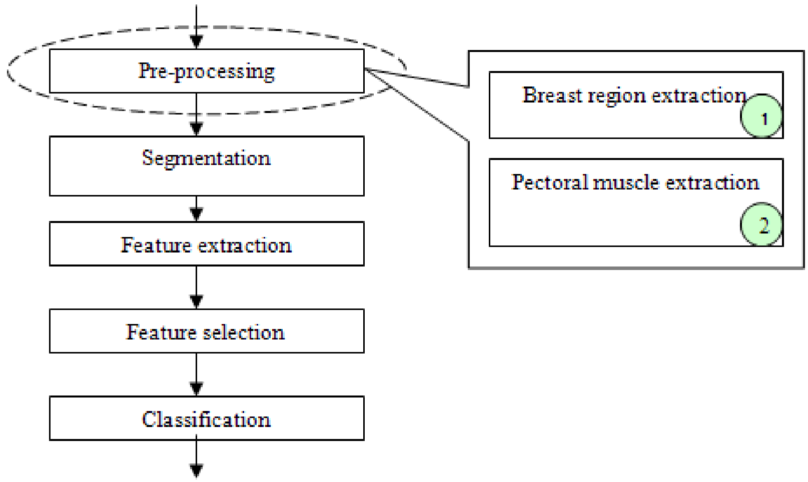
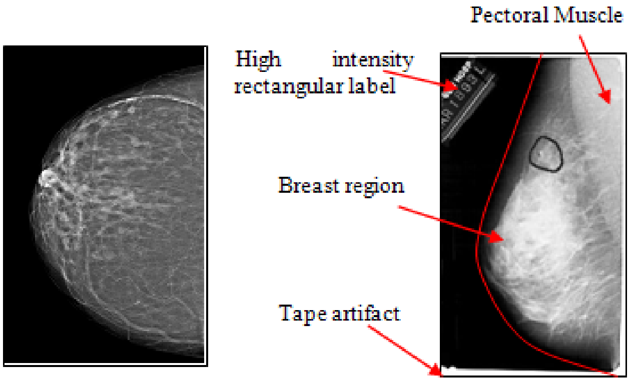


Figure 1. Typical block diagram used by CAD systems [6]

Automatic pectoral muscle extraction on MLO view mammograms is an important step in the pre-processing process. It can be useful in the reduction of the false positives of mass detection procedure, because of the similarity between the pectoral region and the mammographic parenchyma. Also, it is important to find some key-points in mammography image, so that it can be registered afterwards. Registration can help in some auto detect procedures such as finding bilateral asymmetry [14]. To identify the pectoral muscle, many different approaches have been used in the literature. In this context, N. Karssemeijer et al. [15] used Hough transform and a set of thresholds to identify the pectoral muscle. This method assumes that the edge of the pectoral muscle is approximately a straight line oriented in a certain direction. To ensure that the correct peak is selected in the Hough space, gradient magnitude and orientation, length of projected line and corresponding pectoral area are taken into account. Inspired by this work of N. Karssemeijer et al. [15], R.J. Ferrari et al. [12] identified the pectoral muscle by using geometric and anatomical constraints in order to reduce the number of unlikely pectoral lines instead of using threshold value.

However, the Hough transformation has a limitation. It identifies the pectoral muscle as a straight-line, whereas in several cases the pectoral muscle boundary is curved. Therefore, we will have a missed detection of the pectoral muscle. To ameliorate the pectoral muscle detection, many works used an additional step of optimization after detection. In the work of M. Yam et al. [16] Hough transform is used, in first step, to approximate the pectoral muscle boundary. In a second step, the boundary is refined with dynamic programming. In a recent work of X. Weidong et al. [17], after a first segmentation of pectoral muscle by an iterative thresholding technique, the authors used two straight-lines to fit the pectoral muscle boundary based on Hough transform and polygon approaching techniques.



(a) (b)

Figure 2. Two basic views of mammographic image: (a) craniocaudal (CC) view and (b) medio-lateral oblique (MLO) view

The Radon Transform, another identical method of Hough Transform, has been used for the identification of a straight-line approximating the edge of the pectoral muscle. In this context, S. K. Kinoshita et al. [10] applied the Radon transform to binary image (after application of a thresholding method) for the detection of straight-line candidates. For the selection of a straight-line that represents the edge of the pectoral muscle, two criteria are used. In a recent work, A. Boucher et al. [18] have used an approach based on the active contour to generate a curve separating the pectoral muscle from the breast region. However, the problem of the use of the active contour is that it is bound to an initialization. The initialization is a very important phase and can greatly have an influence on the result of segmentation.

In this paper, we are interested in the pre-processing step. In this context, a fully automated method is proposed. Breast region is determined by using an approach based upon Otsu's thresholding and Connected Componed Labelling algorithm. For pectoral muscle detection two approaches, Hough transform and Active contour, are proposed to overcome the limitations of the straight-line representation.

This paper is organized as follows: in section 2 the mammographic image database used is presented. Section 3 describes the proposed pre-processing method. Section 4 presents the results obtained by our method. The discussions and the conclusions are summarized in section 5.

2. Image data set

The Digital for Screening Mammography (DDSM) [19] is the largest publicly available database of mammographic data. It contains approximately 2620 screening mammography cases. From the total number of images included in the DDSM database, a total of 80 images randomly chosen, were used in this work. All the images were medio-lateral oblique (MLO) views.

3. Proposed pre-processing method

The pre-processing process is based on a segmentation step of the breast region in the mammogram. When mediolateral-oblique (MLO) mammograms are used, an additional step to identify the pectoral muscle is desirable because this region appears at approximately the same density as the dense tissues of interest in the image of the breast [10]. To achieve the pre-processing step we propose a classical based method shown at figure 3. It is composed of two stages: a breast region extraction approach to separate the breast from the background (first stage), and a pectoral muscle extraction approach (second stage) to eliminate the pectoral muscle from the breast region.

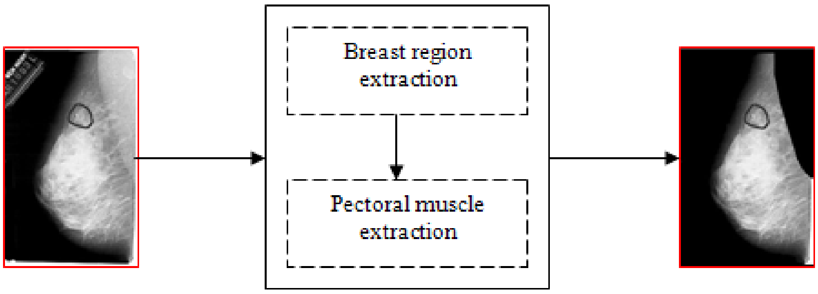


Figure 3. Proposed pre-processing method for MLO mammogram

In the following subsections, we will illustrate each stage included in the pre-processing procedure.

3.1. Breast region extraction

To identify the breast region, we used successive steps given by the block diagram shown at figure 4. In this section a short description of each step is presented.

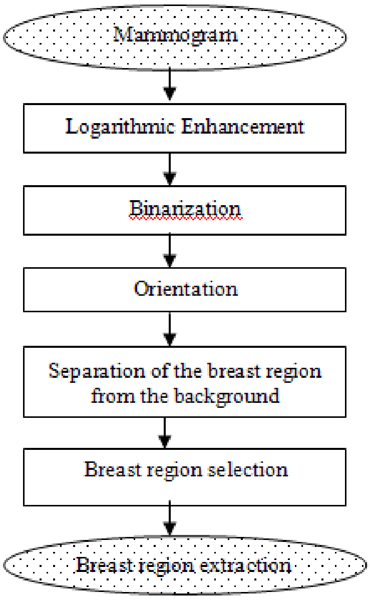


Figure 4. Block diagram of breast region extraction

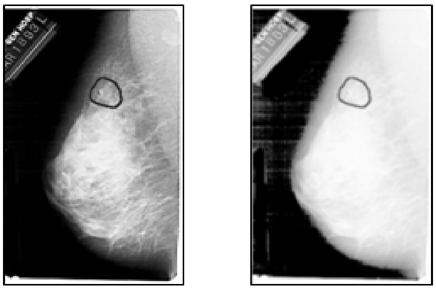
3.1.1. Logarithmic enhancement

In mammography, the application of the logarithmic transform to the whole image significantly enhances the contrast of the regions near the breast boundary in mammograms, which are characterized by low density and poor definition of details [20], [21]. In our approach the logarithmic transform of pixel I(x,y) has the form [22]:

$$G(x,y) = \left(c * \log\left(I(x,y) - s_{\min} + 1\right)\right) + 1 \qquad \text{Eq. (1)}$$

Where

- $c = \dfrac{-2}{\log(s_{max} - s_{min} + 1)}$ is a normalization factor
- S_{min} and S_{max} are the minimum and the maximum pixel values of the input image.
- G(x, y) is the transformed pixel.



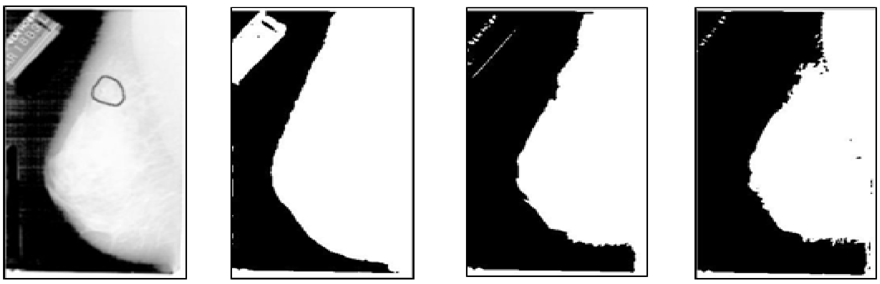
(a) (b)

Figure 5. Logarithmic enhancement result: (a) original image; (b) enhanced image

The objective of the application of the logarithmic transform to the mammogram image (figure 5) is to determine an approximate breast contour as close as possible to the true breast boundary [13].

3.1.2. Binarization

In this step, we use an automated thresholding method to obtain a binarization of the enhanced image. In this context, we used three thresholding methods for applying on each image in order to choose the best: the maximum-entropy principle [15], Otsu's method [23], and a method based on the maximum correlation criterion [24]. After the application of each method, we found that the best result was given by Otsu's method. In figure 6, we present an example of the result of binarization given by each method mentioned above.



(a) (b) (c) (d)

Figure 6. Binarization result: (a) Enhanced image; (b) Otsu'method; (c) Maximum-entropy principle method; (d) Maximum correlation criterion method

3.1.3. Orientation

This step permits to identify the orientation of the breast region. It is necessary for the next step and pectoral muscle extraction. For that, we divide the image into two equal parts (figure 7) and we calculate the number of pixels of each part: if the number of white pixels is big in left part, the direction of breast region is from left to right (respectively, if the number of white pixels is big in the right part, the direction of breast region is from right to left).

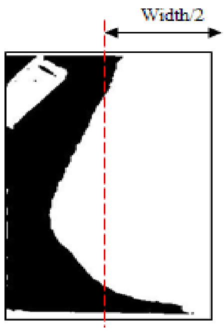
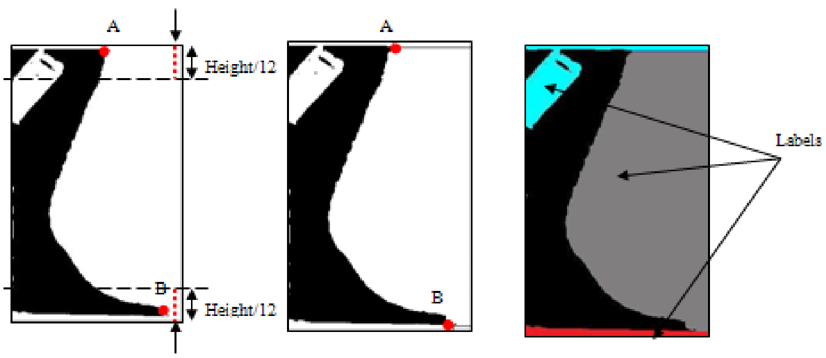


Figure 7. Image divided into two equal parts

3.1.4. Separation of the breast region from the background

In most images, the breast region is connected with tape artifact. For this reason, this step is used to separate the breast region from the background (tape artifact and labels). In the first phase (figure 8(a)), we search the two points (A and B) that coincide with the breast region: we take two parts from the mammogram image; a part at the top and another part at the bottom of the image (each part has as height the 1/12 of the image height). We travel the image vertically (from top to bottom); we start from the beginning of the image and we check if all pixels are white. We stop when we encounter the first black pixel, that is the searched point (noted A). Similarly to the research of the point B, except that we cross the image inversely (bottom to top).



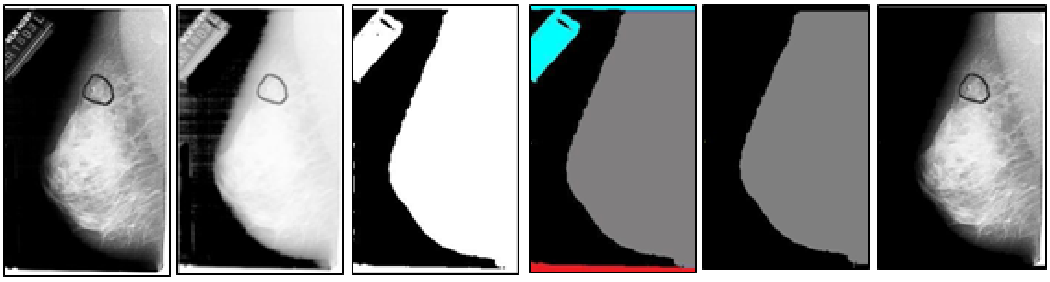
(a) (b) (c)

Figure 8. Separation of the breast region from the background: (a) Identification of top and bottom points; (b) Drawing of two lines for separation; (c) the use of the Connected Component Labelling algorithm

In the second phase, after the localization of two points, we draw two lines: the first point is between the beginning of the image (from left to right or from right to left) and the point A, while the second is between the beginning of the image and the point B (figure 8(b)). Finally, we use the connected component labelling algorithm [25] to divide the binary image into different labels (figure 8(c)).

3.1.5. Breast region selection

Looking at the image generated by the last step, we note that breast region has the largest area. For this reason, we use the area criteria to select the label that represents the breast region and to eliminate the unlikely labels (tape artifacts and high intensity labels). Finally, to obtain the effective breast region, the result of this step was multiplied with the original mammogram. Figure 9 shows the results of the various steps in the breast extraction stage.



(a) (b) (c) (d) (e) (f)

Figure 9. Breast region extraction: (a) Original image; (b) Logarithmic enhancement; (c) Binarization with Otsu's thresholding; (d) Separation of the breast region; (e) Selection of the largest label; (f) Final result of segmentation

3.2. Pectoral muscle extraction

To extract the pectoral muscle, we proceed with the process given by the Block diagram in figure 10: we begin by identifying the region of interest containing the pectoral muscle.

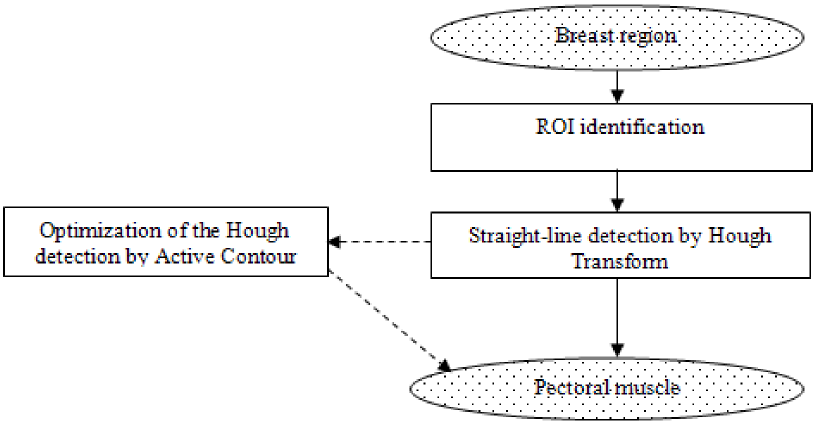


Figure 10. Block diagram of pectoral muscle extraction

After, we apply the Hough transform to identify the line separating the pectoral muscle from the breast region. We can apply an optimization step, using the active contour, when the Hough transform did not give a better identification. The decision to use this optimization step is left as a choice for the radiologist.

3.2.1. Region of interest identification

After extracting breast border, we use four points (ABCD) to represent the polygon containing the pectoral muscle. These points are shown in figure 11 where A represent the top-left corner pixel, B the top-right corner pixel, C the bottom-right corner pixel and D the bottom-left corner pixel of the breast border.

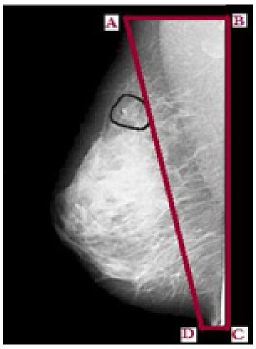


Figure 11. Region of interest identification

3.2.2. Straight-line detection by Hough Transform

Hough transform is used for the detection of lines, circles, ellipses, etc. In this paper, we are interested in detecting the straight-line that represents the boundary of pectoral muscle in mammogram images. The representation of a straight-line for the Hough transform computation is specified as [26]:

$$\rho = (x - x_0)\cos\theta + (y - y_0)\sin\theta \qquad \text{Eq. (2)}$$

where (x_0, y_0) is the origin of the coordinate system of the image located at the center of the image, and ρ and θ represent, respectively, the distance and the angle between (x_0, y_0) and the coordinates of the pixel being analyzed, as shown in figure 12.

For any given point (x, y), we can obtain lines passing through that point by solving for ρ and θ. A line in the image is represented as a point in the polar coordinates (ρ , θ). Conversely, a point in the image is represented as a sinusoid in the polar coordinates since infinitely many lines pass through this point. Hough transform is based on an accumulator (ρ , θ). Each cell of the accumulator is the number of occurrence (ρ , θ) for points of the perpendicular line [22].

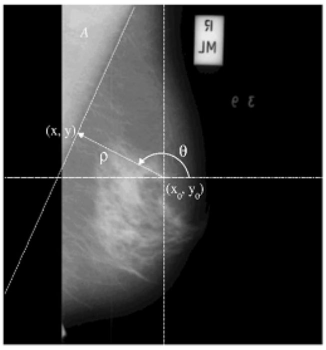


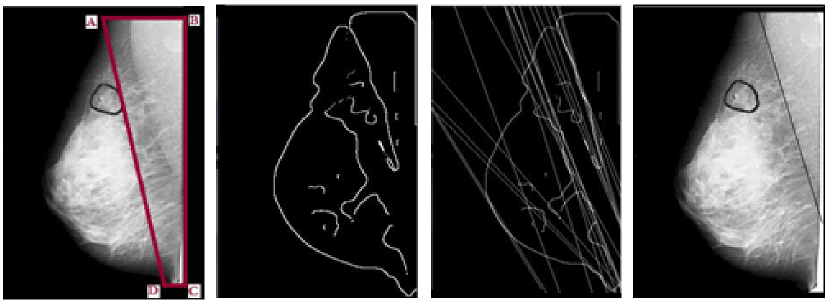
Figure 12. Detection of the pectoral muscle line [26]

In our Approach we proceed with the following steps in the implementation of the Hough transform:

- Initialize the accumulator
- Increment the accumulator (ρ , θ) for each possible line that passes through (x, y).
- For the number of wanted lines:
    1. Find maximum in the accumulator.
    2. Return the line.

3. Remove the maximum in the accumulator.

Before the use of the Hough transform, we applied the Canny edge detection [27] to detect the edge of the image (figure 13 b). The set of straight-line candidates were detected by applying the Hough transform in the angle interval between 135° and 165° for right breast images and between -165° and -135° for left breast images (figure 13 c). To detect a straight line that represents the edge of the pectoral muscle region we use two criteria: First, we focus only on lines included in the region of interest containing the pectoral muscle. Among the selected lines, we choose the one that coincides with the maximum number of pixels belonging to the contour (Figure 13 d).



(a) (b) (c) (d)

Figure 13. Pectoral muscle identification: (a) Region of interest; (b) Canny edge detection; (c) Hough lines detection; (d) Straight-line selection

3.2.3. Optimization of the Hough detection by Active Contour

The active contour model, or snake, is used to detect region of interest (ROI) or contour in image and particularly in identification of the pectoral muscle border in mammography [18]. It is an energy-minimizing spline. The result of this minimization is guided by two terms; the first term controls the aspect of the curve: it is often called internal energy. The second term attracts the curve C towards object which one seeks the borders: it is often called external energy. The detail of this method is illustrated in [28]. The principal concepts are given:

The snake is parametrically defined as:

$$v(s) = \big(x(s), y(s)\big), \text{ with } s \in [0\ 1] \qquad \text{Eq. (3)}$$

The energy is defined by:

$$E = \underbrace{\int_0^1 (\alpha|v'(s)|^2 + \beta|v''(s)|^2)ds}_{E\text{int}} \underbrace{- \lambda\int_0^1 |\nabla I(v(s))| ds}_{Eext} \qquad \text{Eq. (4)}$$

Where

- α , β and λ are real constants, respectively coefficients of elasticity, rigidity and contraction (or dilation) from the curve. In practice, shown in section 4, we used α =0.5, β =0.2 and λ =0.5.
- $\nabla I(v(s))$: is the gradient of image in s.

The phase of active contour is used in our approach as a refinement step to improve the identification of the contour representing the pectoral muscle: the radiologist chooses to use this phase to obtain a more precise identification of the pectoral muscle when the border between the region and the muscle has a form of curvature.

4. Experimental results

The evaluation of our proposed method of pectoral muscle extraction (respectively for breast region extraction) is based on the opinion of radiologists: The mammograms were viewed by a radiologist who drew a polygon representing the pectoral muscle, which noted Arad, as shown in Figure 14 (a) (respectively for breast extraction in figure 15(a)). The proposed method of pectoral muscle permits to produce a closed polygon, which noted Aseg, indicated in figure 14(b) (respectively for breast extraction in figure 15(b)) includes the contour that is completed by the edges of the image.

Evaluation of results was measured by the percentage of correct segmented region (Eq. 5) used in [18]. We consider that the extraction of pectoral muscle is correct (respectively for extracting the breast region) when we have:

$$\frac{A_{rad} \cap A_{seg}}{A_{rad} \cup A_{seg}} \rangle 0.8 \qquad \text{Eq. (5)}$$

where

- Arad : area of breast region (or pectoral muscle) defined by an radiologist.
- Aseg : area of breast region (or pectoral muscle) defined by our proposed method.

As shown in table 1, our proposed method for breast region extraction gave excellent results with a rate equal to 100 % for the set of 80 images used in our work. On the other hand, evaluation of the extraction of the pectoral muscle by using the Hough transform or by the combination between it and the active contour has yielded good results with a success rate that exceeds 92%, as shown in table 2.

Table 1. Breast region result

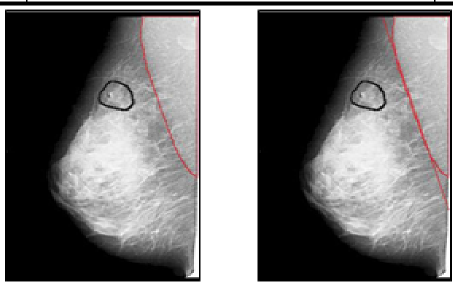
Breast region extraction	Acceptable	Unacceptable
Percentage	100 %	0 %

According to the found results we can see that extraction of the breast region gave the best result compared to the identification of the pectoral muscle. This can be explained by the fact that the separation between the breast region and the background is easier than the separation between the pectoral muscle and the breast region. In addition, pectoral muscle is not well differentiated from the surrounding breast. For this reason, the segmentation of the pectoral muscle is more difficult.

For evaluating the effectiveness of proposed method for pectoral muscle segmentation, we compared our results by other method, based on Active contour, which is proposed by A. Boucher et al. [18]. As it can be seen in Table 3, our method is better in relation to the other.

Table 2. Pectoral muscle result

Pectoral muscle extraction method (Hough transform only or Hough transform+Snake)	Acceptable	Unacceptable
Percentage	92.5 %	7.5 %

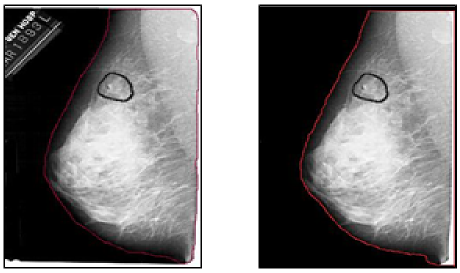


(a) (b)

Figure 14. Pectoral muscle identification: (a) by a radiologist and; (b) our proposed method (Hough Transform + Active Contour)

Table 3. Comparison with another result

Pectoral muscle extraction	Our method	Method presented in [18]
Percentage	92.5 %	91 %



(a) (b)

Figure 15. Breast border identification: (a) by a radiologist and; (b) our proposed method

5. Conclusions

In this paper, a pre-processing method for extraction of breast region and pectoral muscle is presented. The breast region extraction is based upon automated thresholding method and Connected Component Labelling algorithm. The pectoral muscle extraction in mammograms, based upon Hough transform and active contour, overcomes the limitation of the straight-line of the representation of the pectoral muscle. Our proposed method was evaluated on 80 MLO mammograms obtained from DDSM database: the first stage (breast border extraction) gave a rate of 100% in detecting the correct border while the second stage (pectoral muscle extraction) gave a rate of 92.5% for the correct pectoral muscle segmentation.

During this work, we found good results concerning the pre-processing step. Further development, concerns the addition of the detection of the Nipple in mammography images and the application of our pre-processing approach in the computer aided analysis (CAD).

Detection phase is the most difficult step in a CAD system. For this reason, the future work will be dedicated to the automation of detection by using of our approach of mass detection, based on Level Set, presented in [29] and using of our approach of mammograms pre-processing indicated in this paper.

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