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Breast Skin Line Segmentation on Digital Mammogram using Fractal Approach

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Abstract

Objective: To develop an algorithm for the identification of breast skin line in mammographic images and evaluate its performance against ground truth images. **Methods/Analysis:** A three stage processing pipeline was developed to segment the breast skin line. The first part of the segmentation used a pre-processing stage to remove artifacts and reduce image noise. The second stage employed a fractal based approach for segmentation and the third step detects the border region from the segmented image. **Findings:** The performance of the method has been evaluated using bench mark datasets from MIAS and DDSM. The results of the findings reveal that fractal based approach is an effective method to improve the skin line segmentation from mammogram images in the computer aided diagnosis. The algorithmic results of the segmentation were validated against the ground truth generated by manual segmentation. **Improvement:** The proposed method shows the importance of fractal analysis for breast skin line segmentation.

Keywords: Density, Fractal Modeling, Mammogram, Skin Line, Segmentation

1. Introduction

Breast cancer is the second most deadly form of cancer in women. American Cancer Society (ACS) estimated that there will be more than 246,660 cases of invasive breast cancer diagnosed in US women and about 40,450 death during 2016[1,2]**.** The diagnosis of breast cancer in its initial stage of development is very important since there is no method devised for preventing it. Mammography is the standard approach for preliminary examination wherein, if a suspicious lesion is found then other method such as biopsy is used for detection of breast cancer. During this procedure, the patient undergoes a surgical intervention, where breast tissues are sampled for examination. To avoid this at the initial stage people widely depends on mammography.

Mammography is the most reliable screening technique used for the early detection of breast cancer. The procedure depends on a specific type of imaging unit that uses X-ray to examine the breast region. An X-ray is a non-invasive medical test that helps the radiologist to diagnose and treat medical patients[3]. For close examination, accurate identification of breast boundary from a mammogram image is required, but presents several challenges due to the artifacts and noises in the image. Correct representation of breast tissues is closely related to skin line. Failure to detect these lines leads to misclassification. Therefore, many active research groups proposed different approaches for breast skin line segmentation[4,5]**.** In[6,32] developed an algorithm based on contour modeling, morphological filtering and histogram thresholding. The method was tested on both high and low quality mammogram images and achieved a satisfactory result. Earlier work for the breast skin line segmentation was based on histogram thresholding. In[7] proposed fully automated algorithm based on a combination of modified global histogram analysis, region growing and a gray value range operator. Here 97% of the results were acceptable for computer aided diagnostic purposes. In[8] developed a segmentation method by considering feature sets generated

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by the monogenic signal. The derived local phase gives structural information like edges and ridges. The information about local brightness and contrast is provided by local amplitude. This method can be applicable not only for 2D but also for 3D and can be scaled up to 4D spatiotemporal data. In[9] proposed a method, that can automatically extract information like orientation of the breast region from mammograms and identify the breast regions. The limitation of this approach is that the accuracy depends on the image quality. If the image has noises, then the expected results will be below marginal. To demonstrate this, the histogram of the four images in Figure 2 clearly shows the variation in their intensities from Figure 1. Gradient based approach for breast border and nipple extraction presented by[10], achieved an accuracy of about 89%. Modified fast marching algorithm for estimating breast skin line was demonstrated by[11]. The mentioned methodology combines information like intensity and gradient on fast marching speed function and introduces end point constrain, that ensures that given boundary expands within the intended region and stops when the boundary reaches its end-point. An important feature of breast region is its contour. Extracting the contour is an important step for finding abnormalities in the image. In[12] proposed an algorithm for segmenting the breast region from its background. Initially they used a self organization map for the initial segmentation and applied the K-means algorithm for clustering the map. In[13] proposed a fuzzy reasoning and active contour based approach for segmenting the breast region. This method is fully automatic and preserves both skin line and nipple. It uses morphological preprocessing to suppress artifacts in the breast region. Identification of pectoral muscles proved to be more challenging in mammogram image segmentation. The presence of pectoral muscle can influence the tumor cell detection. In[14] applied wavelet decomposition for segmenting the pectoral muscle and breast border. The method achieved good success rate for detecting the accurate skin-line interface. The system was tested with 40 good quality mammogram images. [15] Proposed a modified active contour model to obtain the breast skin line. This method starts with modifying the contrast in the original image, and then a binarization procedure was applied followed by chain coding algorithm to find the appropriate breast contour from the given image. The database considered for the work was from Mini-MIAS and DDSM. The main objective of this paper is to propose a new skin line segmentation approach for mammogram images using fractal properties. Fractal is a mathematical object that is self similar with a fractional dimension. This phenomenon was clearly explained by Mandelbrot[16]. In[17] different fractal models were explained, among which Fractal Brownian motion (fBm) was considered as the useful model for natural fractal phenomena. It was later applied by[18] for segmenting the images using fractal dimension. To calculate the fractal dimension they applied the fast Fourier transform on the image, considering rows/columns as a series. And the limitation is that, it requires significant computational power. In[19] used fractal approach for analyzing the X-ray medical images. Fractals can be used to measure the irregularities of boundary regions under successive magnifications. Consequently, this approach can be applied to circumscribe the scale problem of texture. In[20] proposed a modified box counting approach to compute the fractal dimension of images. To segment the image into number of classes,

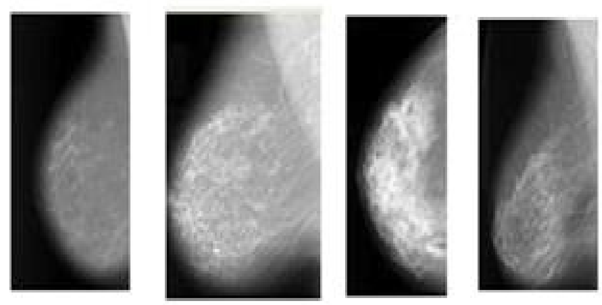

Figure 1. Example of mammograms with different breast densities.

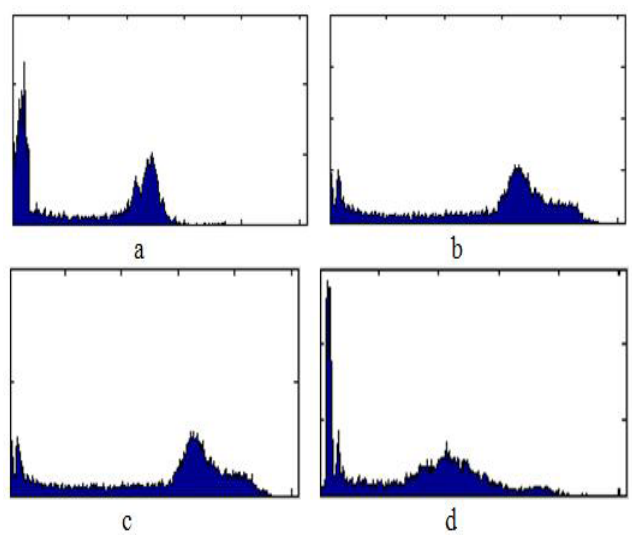

Figure 2. Histogram for the image from Figure 1.

an unsupervised K-means clustering approach was used. Fractal based image analysis method was studied[21]. They proposed that fractal dimension can be applied for edge enhancement and detection by calculating the fractal dimension of each pixel by a 7x7 pixel block. In[22] used fractal for the analysis and classification of textures based on scale varying surface area. This change in scale proved to be helpful in characterizing the texture. Considering all these features, we propose a new identification method for skin line extraction in mammographic images.

2. Materials and Methods

The proposed approach developed for breast skin line segmentation is based on fractal analysis. The algorithm mainly consists of three stages: Pre-processing to remove the artifacts, segmentation and detection of border region from the segmented image. First, the artifacts removal is done using a connected component labeling algorithm. Then the image is segmented using fractal approach. Finally, the border region is extracted from the segmented image. Figure 3 illustrates different steps in the proposed method. The following sections give the details of the above mentioned stages.

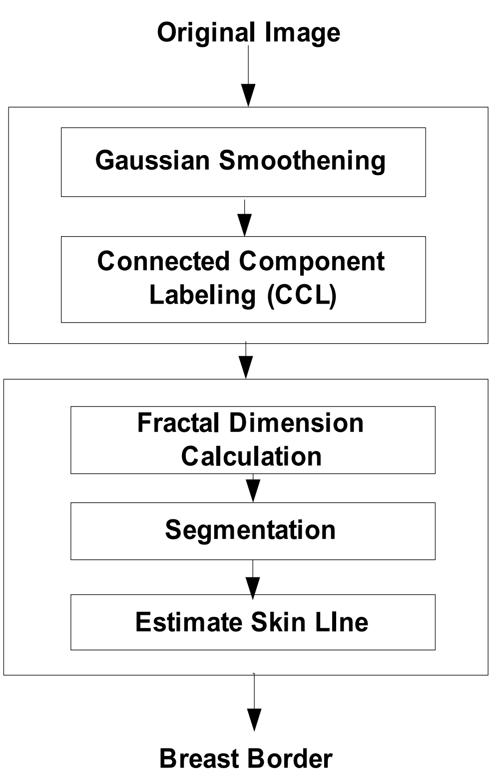

Figure 3. Flow-chart of the proposed method.

2.1 Pre-Processing

Improving the quality of the image to preserve the region boundaries is an important task in image segmentation. Several linear and non-linear filtering techniques have been proposed to enhance the quality of the image[23]. We have adopted the Gaussian filter algorithm as it is well known for reducing the image noise, as given in Equation (1).

$$G(x,y) = \frac{1}{2\pi\sigma^{2^{\varepsilon}}} - \frac{x^2 + y^2}{2\sigma^2} \tag{1}$$

The variable x denotes the distance from the origin in horizontal axis and y denotes the distance from the origin in vertical axis; σ is the standard deviation of the Gaussian distribution. Normally mammogram images contain artifacts such as markers and labels. If these artifacts are found near the border of the breast region, it may lead to a decrease in the precision of extracting the border region. To avoid this[24,25] used different approaches to remove these artifacts. We have adopted the connected component labeling method for finding the largest region, where the breast region is obtained from the filtered image. This approach is considered best for finding the non-connected components in mammographic images. Every image is represented as a grid of image elements. The algorithm then assigns labels to the black region so that adjacent black image pixels are grouped by the same label. One can choose the adjacent as 4 or 8-connected adjacency. By using any of these connected adjacencies, it scans an image, pixel by pixel to identify the connected pixel regions. The artifacts removal from a mammogram images is shown by Figure 4. Figures 4(a) and 4(b) are the

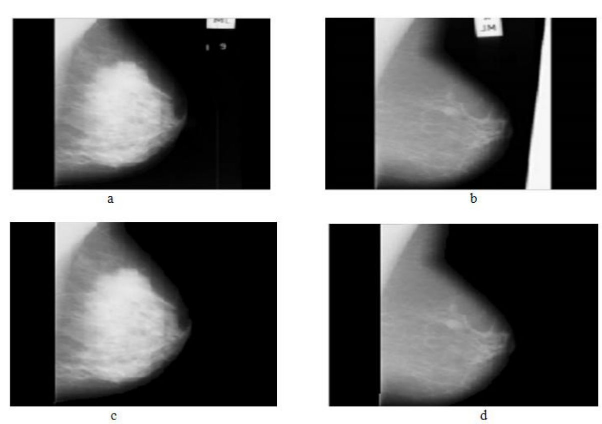

Figure 4. Example of artifact suppression. **(a)**, **(b)** Original image. **(c)**, **(d)** After applying connected component labeling algorithm.

two images, and Figures 4(c) and 4(d) shows the results after applying the CCL algorithm.

2.2 Fractal Methodology

Fractals have been used extensively in the medical field[26–28]. The boundaries of specific masses give rise to non-fractal intensity surface and this leads to an effective methodology for detecting the edge points from a given image. In this work we applied box-counting method for calculating the pixel wise Fractal Dimension (FD) of the image. The modified variation method was considered in this paper for the evaluation of FD of an image. Modified variation method is an enhanced form of variation method. This method has been proved to be robust and accurate for the estimation of the FD[29]. Consider an image I of size R x R, FD can be calculated in all the different region of size R x R. Once the FD is calculated for each pixel location, it is then mapped to its original pixel position of the original image for segmentation. The algorithm first calculates E_ε, the average of the intensity values computed over a window size T that surrounds the pixel. This will repeat for all pixels of the image for $\varepsilon = 1, 2, 3 \dots \varepsilon_{max.}$ The size of the window T is estimated by $T = 2\varepsilon + 1$ and the maximum value of $\varepsilon_{max} <$ (image size)/2. Then the slope obtained by fitting a line of log (R/ε) versus $\log(R/\varepsilon)^3$ E_ε. E_ε is the average of V_ε.

Algorithm 1: Fractal Dimension

Input: Image [N∗N], T=Mask Size
Output: Slope of the Image (FD)

```
for each pixel in an image I( i , j) do
  for ε= 1,2,3,… ε max do
    compute a window T= 2ε+ 1
    compute M_ε= max(T)
    compute N_ε= min (T)
    compute D_ε= M_ε-N_ε
  end for
end for
for each pixel in an image I( i , j) do
  construct a window of suitable size P
    for ε= 1,2,3,… ε max do
      E_ε= avg(D_ε)
    end for
Do a line fit of (log(R/ε)), log(((R/ε³)E_ε)
where R is a window of suitable size
end for
```

2.3 Detection of Breast Boundary using Fractal Dimension

In our approach, modified variation method calculates the fractal dimension value from the down sampled images. And we obtained a transformed image in which each pixel location has a fractal dimension value. We then applied the threshold method for skin line segmentation. The selection of the threshold is based on the histogram analysis of the fractal values. We have considered the threshold to be the peak value for segmenting the image. Morphological operators are then applied to the resultant image for smoothing the breast area. Finally a binarization step followed by chain coding as a post processing to extract the breast contour. Figure 5 shows one example for breast skin line segmentation by our approach.

3. Results and Discussion

We have evaluated our proposed methodology with two globally available databases: Mini-Mammographic Image Analysis Society database[30] and Digital Database of Screening

Mammography[31,32]. We have considered and tested 90 images which were randomly chosen in our experiment from MIAS and DDSM databases. All these images are Medio Lateral Oblique (MLO) views. Normally the breast consists of fibro glandular tissues and fat. The fatty region appears to be darker and brighter region is associated with fibro glandular tissue. The images were displayed on a computer monitor (21.6" with wide screen size 1680x1050 and dot pitch of 0.276 having image aspect ratio 16:10)

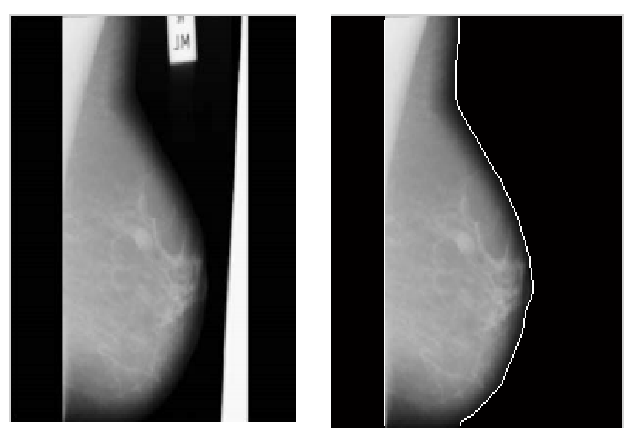

Figure 5. Segmentation of mammogram. **(a)** Original image. **(b)** Breast boundary detected automatically and superimposed on original image.

which helps the person to see the breast border areas in detail. For reducing the computation times, all the images were down sampled to 256 x 256 pixels. The results produced by the down sampled images are later resized to its original image size. Using the Gimp and Graphire 4 A6 (CTE-440) we draw each image border manually. Graphire 4 pen tablet gives us a detailed precision with an accuracy of ±0.5 mm with pressure sensitivity 512 levels which makes the person to draw the border without much effort. This ground truth image was verified under the supervision of radiologist. An acceptable skin line was segmented using fractal dimension approach. Figure 6 is the results obtained from test examples for breast skin line segmentation by our proposed approach.

The original images are illustrated in Figure 6(a) Figure 6(b) shows the overlays of breast boundary obtained by the fractal approach superimposed into the preprocessed image. It can be observed that the results obtained by the proposed method have good accuracy, robustness and was visually evaluated by a radiologist. We could achieve satisfactory results for nipple extraction from the proposed method. The development of new methods for skin line segmentation has greatly increased for the enhancement of mammographic features for computer aided diagnosis of digital mammograms. Due to noisy and artifacts in mammogram image, it is not an easy task to extract the skin line. It is mandatory to extract the skin line for profound understanding for the characteristic of the breast region, to control the growth of tumors. For example, distinguish the tumors between malignant and benign. Several techniques have been introduced to increase the accuracy of breast skin line segmentation. As most of the work were based on histogram analysis, which can be limited to image noise and threshold value selection. In our present study, a hybrid approach has been adopted to segment the breast skin line using fractal properties. This approach is simple and robust, and has limitation: capability to extract the nipple region partially. But, this limitation do not disprove the main objective of our study: To show how fractal methodology can be used for the study of skin line segmentation in mammograms. It is important to mention here that, the different approaches by other researches also show a similar limitation to nipple extractions[15]. And this paper attempts to address the skin line segmentation using fractal. To evaluate the performance of our proposed algorithm, we compared our test result with deformable model. The images taken from MIAS database were considered for the performance testing. Figure 7 shows the comparing result of fractal dimension approach with deformable model. The result shown by the fractal dimension approach is the binary mask of the resultant image. Ground truth boundary coordinate and deformable model boundary coordinate are superimposed into the binary mask of the fractal dimension approach. The skin line obtained by our approach has very close matching with the ground truth image, and has significant improvement. The estimated lines are seen to be much smoother. We have also done a quantitative comparison between fractal approach and the deformable model. Using Hausdorff Distance method, we calculated the distance between fractal detected border with ground truth image verified by the radiologist. Also we did the

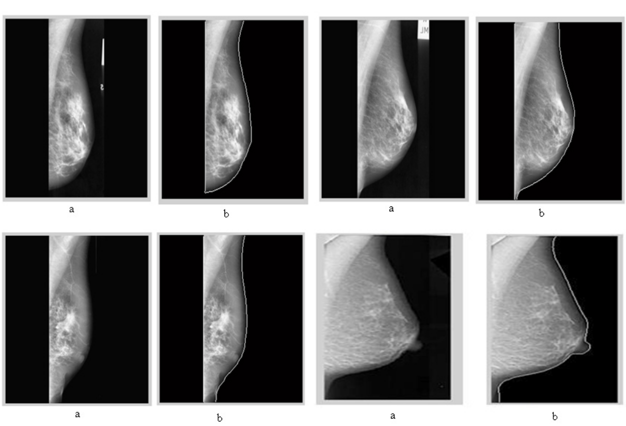

Figure 6. Segmentation of mammogram. **(a)** Original image. **(b)** Breast boundary detected automatically and superimposed on original image.

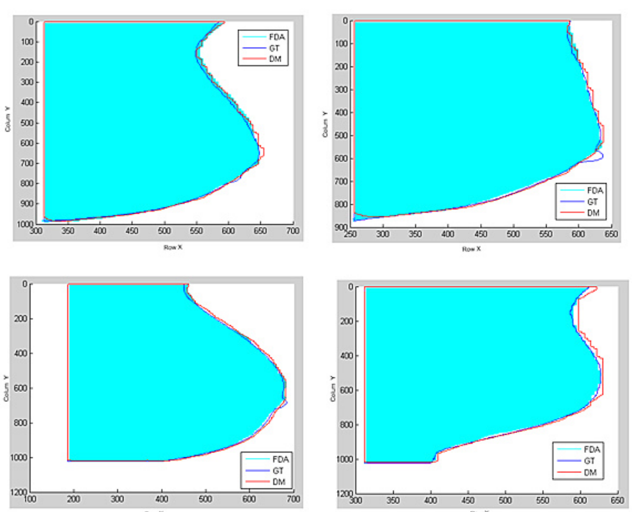

Figure 7. Two examples, comparing the result of fractal dimension approach with deformable model.

Table 1. Hausdorff distances

Distances	Range	Mammogram Numbers
Hausdorff Distances	H ≤ 10	05
(FDA)	10 < H ≤ 20	64
	20 < H ≤ 30	18
	30 < H ≤ 45	03

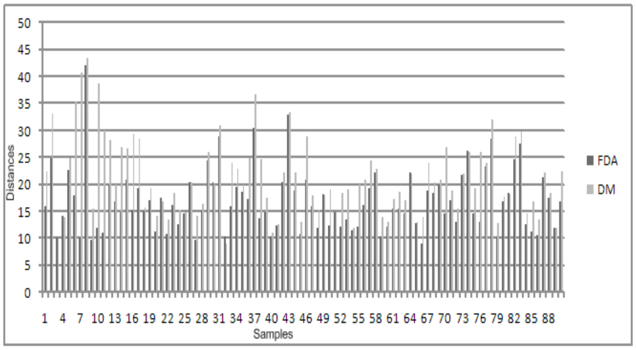

Figure 8. Hausdorff Distance between FDA(Fractal Dimension Approach) and DF (Deformable Approach).

same with deformable approach. Table 1 illustrate its Hausdorff distances. Figure 8 shows the graphical representation of the two different distance approaches for a set of 90 samples from the two databases. This Figure shows that the proposed method accuracy is acceptable and has minimum Hausdorff distances. This significance is due to the fractal properties which make smooth extraction of breast border from the given image. We executed the same image several times for testing the statistical efficiency of the proposed design.

4. Conclusion

Using MIAS and DDSM, we proposed a system for the segmentation of breast skin line from the mammographic images. In this study, fractal based approach is considered and the results reveals the proposed method is computationally efficient and good for skin line segmentation. As a future work we will consider new algorithms for the removal of pectoral muscle from the breast border.

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