Pectoral Muscle Segmentation on Digital Mammograms by Nonlinear Diffusion Filtering

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***Abstract*—The pectoral muscle represents a predominant density region in the most medio-lateral oblique (MLO) views of mammograms. Presence of pectoral muscle in the mammogram may affect the resulting of image processing and could bias the detection procedures. So during analysis, the pectoral muscle should preferably be excluded from processing. We proposed a new method for the identification of the pectoral muscle in MLO mammograms based on nonlinear diffusion algorithm which is an edge preserving smoother. The proposed method is applied to 90 mammograms from Mammography Image Analysis Society (MIAS) database. We compared our results by those recognized by two expert radiologists. To evaluate the accuracy of proposed method, HDM (Hausdorff Distance Measure) and MAEDM (Mean of Absolute Error Distance Measure) were used. Then we compared our results by two other pectoral muscle segmentation methods proposed by Karssemeijer and Ferrari. The first is based on Hough-Transform and the second is based on Gabor-Filters. Our proposed algorithm shows superior results in comparison**.

I. Introduction

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 interpreted and diagnosed by relatively few radiologists. It is considered that the use of computerized mammographic analysis is helpful to radiologists for higher precision detection [1]. However, before analyzing of digitized mammogram by computer, it is recommended to be segmented into its representative anatomical regions [2].

Segmentation in digital mammogram includes three stages: breast contour identification, nipple identification and pectoral muscle segmentation [2].

The pectoral muscle represents a predominant density region in the most medio-lateral oblique (MLO) views of mammograms, and can affect the results of image processing [3]. Existence of the pectoral muscle in the image data being processed may bias the detection procedures. Another important need to identify and segment the pectoral muscle lies in the possibility that the local information of its edge, along with an internal analysis of its region, may be used to identify the presence of abnormal axillary lymph nodes, which may be the only manifestation of occult breast carcinoma [4].

Karssemeijer [5] used the Hough transform and applied a set of threshold values to the accumulator cells in order to detect the pectoral muscle. Aylward et al. [6] used their gradient magnitude ridge traversal algorithm at small scale, and then solved the resulting multiple edges via a voting scheme in order to segment the pectoral muscle region, Ferrari et al. [7] presented a technique based on the Gabor wavelet representation proposed by Manjunath and Ma [8].

In this paper, we present a new approach for pectoral muscle segmentation based on nonlinear diffusion filtering.

The paper is organized as follows: In section II nonlinear diffusion method is introduced. Section III presents the proposed algorithm. Section IV discuses experimental results and conclusions.

II. NonLinear Diffusion

One of the most important problems in image processing is denoising. Usually the procedure used for denoising, is dependent on the features of the image, aim of processing and also post-processing algorithms [9].

Denoising by low-pass filtering not only reduces the noise but also blurs import edges. On the contrary nonlinear diffusion is smoother which is an edge preserving [10].

The nonlinear diffusion is based on an analogy of physical diffusion processes, like the temperature diffusion on a metal bar, or the diffusion between two fluids put together. These physical diffusion processes are modeled by the following differential equation [11]:

$$\frac{\partial U}{\partial t} = D\nabla.(\nabla U) \tag{1}$$

In (1) U is the concentration (temperature), constant D is the diffusivity (a conductance), $\nabla.$ is divergence operator and ∇ is gradient operator. Accordingly concentration variation will be faster where the concentration gradient is higher [11].

Equation (1) is linear and the procedure of diffusing acts on noise and edges at the same time. Thus using a linear diffusion would quickly destroy the borders [12].

To overcome this problem, nonlinear diffusion is introduced. The nonlinear diffusion makes the diffusivity parameter, D, no longer a constant value, but instead the diffusivity becomes a function of the concentration gradient which decreases for higher gradients as following [12]:

$$\frac{\partial U(x,t)}{\partial t} = \nabla.(D(x,t)\nabla U(x,t)) \qquad (2)$$

This new formulation allows to perform an image denoising while preserving the borders.

In order to implement (2) by computer, we wrote discrete form of left and right part of (2) as follows [13].

$$\frac{\partial U(x,t)}{\partial t} = \frac{U(x,t+\Delta t)-U(x,t)}{\Delta t} \qquad (3)$$

$$\begin{aligned}\nabla.(D(x,t)\nabla U(x,t)) &= \frac{\partial}{\partial x}(D(x,t)\frac{\partial}{\partial x}U(x,t)) \qquad (4)\\ &= \frac{\partial}{\partial x}\left\{D(x,t).\frac{1}{\Delta x}\left[U(x+\frac{\Delta x}{2},t)-U(x-\frac{\Delta x}{2},t)\right]\right\}\\ &= \frac{1}{(\Delta x)^2}\left\{D(x+\frac{\Delta x}{2},t)[U(x+\Delta x,t)-U(x,t)]\right.\\ &\left.\quad -D(x-\frac{\Delta x}{2},t)[U(x,t)U(x-\Delta x,t)]\right\}\end{aligned}$$

So we have:

$$\begin{aligned}U(x,t+\Delta t) = U(x,t) &+ \frac{\Delta t}{(\Delta x)^2}\times \qquad (5)\\ &\left\{D(x+\frac{\Delta x}{2},t)[U(x+\Delta x,t)-U(x,t)]\right.\\ &\left.-D(x-\frac{\Delta x}{2},t)[U(x,t)-U(x-\Delta x,t)]\right\}\end{aligned}$$

The discrete form of D is given by:

$$D(x,t) = F(\frac{1}{\Delta x}\left[U(x+\frac{\Delta x}{2},t)-U(x-\frac{\Delta x}{2},t)\right] \qquad (6)$$

By substation of x by $x \pm \frac{\Delta x}{2}$ we have:

$$D(x+\frac{\Delta x}{2},t) = F(\frac{1}{\Delta x}(U(x+\Delta x,t)-U(x,t)]) \qquad (7)$$

$$-D(x-\frac{\Delta x}{2},t) = -F(\frac{1}{\Delta x}[-U(x,t)+U(x-\Delta x,t)]) \qquad (8)$$

If we define $\nabla U1$ and $\nabla U2$ such that:

$$\begin{aligned}\nabla U_1(x) &\triangleq U(x+\Delta x,t)-U(x,t)\\ &= U(x-h_1,t)-U(x,t)\end{aligned} \qquad (9)$$

$$\begin{aligned}\nabla U_2(x) &\triangleq U(x-\Delta x,t)-U(x,t)\\ &= U(x-h_2,t)-U(x,t)\end{aligned} \qquad (10)$$

In which $-h_1 = \Delta x$ and $-h_2 = -\Delta x$. From (7)- (10) we have:

$$D_1(x) \triangleq D(x+\frac{\Delta x}{2},t) = F(\frac{1}{\Delta x}\nabla U_1(x)) \qquad (11)$$

$$D_2(x) \triangleq -D(x-\frac{\Delta x}{2},t) = F(\frac{1}{\Delta x}\nabla U_2(x)) \qquad (12)$$

Now (9) and (11) are substituted into (5):

$$\begin{aligned}U(x,t+\Delta t) = U(x,t) + \frac{\Delta t}{(\Delta x)^2}\times\\ \left[D_1(x)\nabla U_1(x)+D_2(x)\nabla U_2(x)\right]\end{aligned} \qquad (13)$$

Generally we can rewrite (13) as follows:

$$\begin{aligned}U(x,t+\Delta t) = U(x,t) +\\ \Delta T'\sum_{d=1}^{\Gamma} D_d(x,t)\nabla U_d(x,t)\end{aligned} \qquad (14)$$

Where Γ is the number of directions on U which diffusion occurs.

The interpretation of (14) is: At time $t=0$, $U(x,0)$ is equal to U. At a given time, t, $U(x,t)$ can be calculated by iterative method in (14).

When U is two dimension function like images, the algorithm is employed to rows and columns successively.

III. OVERALL ALGORITHM

In this section the overall method used for pectoral muscle detection is proposed. The flowchart of this method is shown in Fig. 1. Here a short description of each block is given.

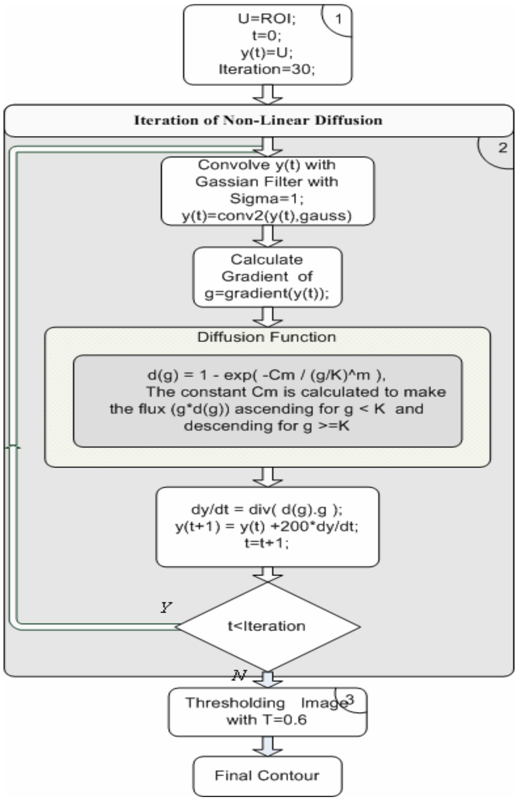


Figure 1. Flow chart of the procedure for identification of the pectoral muscle

A. Defenition of ROI

In order to define an appropriate region of interest (ROI) containing the pectoral muscle, it is needed to have an approximate breast border.

In this paper for extracting approximate breast border, global thresholding is used to convert image to binary image. In binary image, breast is the biggest nonzero region which helps us to extract an approximate breast border.

After obtaining breast border approximately, five control points are defined. These control points, *N1* to *N5*, which are used to define ROI are shown in Fig. 2 and defined as:

- *N1*: top-left corner pixel of the breast contour.
- *N2*: top-right corner pixel of the breast contour.
- *N5*: lowest pixel on the left edge of the boundary
- *N3*: mid-point between *N1* and *N5*;
- *N4*: the point that completes a rectangle with *N1*,*N2*, and *N3*.

B. Block of Nonlinear Diffusion

The diffusivity function, $D(x,t)$, that is used in this paper is given by:

$$D(x,t) = 1 - \exp(-\frac{C_m}{(\frac{\nabla U(x,t)}{\lambda})^m}) \qquad (15)$$

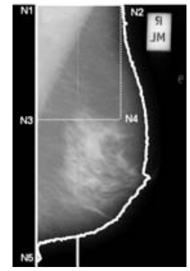


Figure 2. Approximate breast border and control points, *N1* to *N5* used to limit the region of interest (rectangle marked) for the detection of the pectoral muscle

The constant C_m is selected to make the flux, $\nabla U(x,t) * D(x,t)$, ascending for $\nabla U(x,t) < \lambda$ and descending for $\nabla U(x,t) > \lambda$, as can be seen in Fig. 3.

λ is the contrast parameter (if the gradient is inferior to λ, the flux is increasing with the gradient and if the gradient is larger then λ, the flux decreases as the gradient grows).

m defines the speed of the diffusivity (and the flux) changes for a variation in the gradient. Big values of m make the flux change quickly [11].

Usually in the region near the pectoral muscle, there are some abrupt changes, which should not be preserved as edge. So in order to smooth the abrupt changes of pectoral muscle, in the block of nonlinear diffusion, the image is denoised with Gaussian filter before calculating the gradient of image.

Implementing this algorithm for large number of mammogram shows that suitable λ and m for better enhancement of the region which contains pectoral muscle is 3 and 100 respectively.

C. Thresholding Image.

As it can be seen in Fig. 4(g), pectoral muscle region can be extracted by thresholding. This region has higher intensity compare with the other regions. The suitable threshold for extracting this region is selected as average intensity of the up-left pixels in the image which resulted from iteration of nonlinear diffusion.

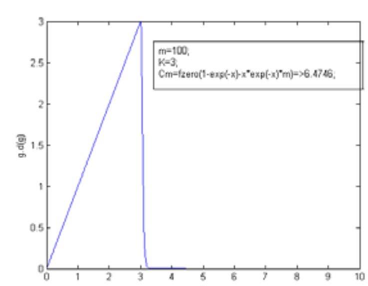
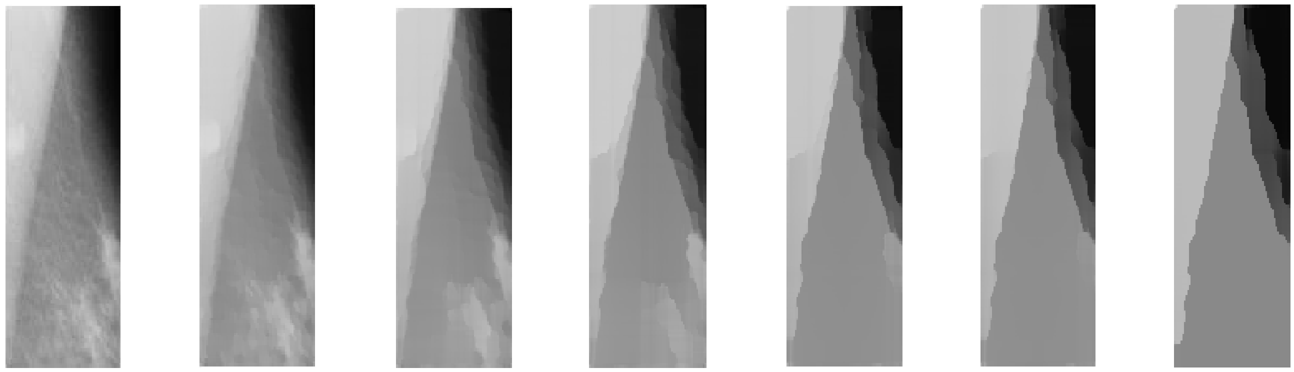


Figure 3. Flux $\nabla U(x,t) * D(x,t)$ for (15)



a b c d e f g

Figure 4. Results of iteration of nonlinear diffusion for detecting of the pectoral muscle on ROI for mdb012 from MIAS

IV. EXPERIMENTAL RESULTS AND CONCLUSIONS

The proposed method was applied to 90 mammograms from Mammography Image Analysis Society (MIAS) database [14]. We compared our results by those recognized by two expert radiologists. To evaluate the accuracy of proposed method, HDM (Hausdorff Distance Measure) [15] and MAEDM (Mean of Absolute Error Distance Measure) were used. Then we also compared our results with two pectoral muscle segmentation methods proposed in [5] and [7]. The first is based on Hough-Transform and the second is based on Gabor-Filters. Table 1 and Table 2 show a comparison of error between our method, Hough-Transform method and Gabor-Folter method for 90 mammograms with HD and MAED measures respectively. As it can be seen, our method outperforms both of them.

TABLE 1. RESULTS FROM HDM

Error / Method	Mean	Variance
Hough-Transform	27.1545	8.7909
Gabor -Filter	19.1185	7.8123
Nonlinear Diffusion	14.7585	7.7737

TABLE 2. RESULTS FROM MAEDM

Error / Method	Mean	Variance
Hough-Transform	8.5035	3.4005
Gabor -Filter	4.981	1.9189
Nonlinear Diffusion	2.5525	1.6343

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