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FULLY AUTOMATED FIBROGLANDULAR TISSUE SEGMENTATION AND BIAS CORRECTION IN BREAST MR IMAGES USING LEVEL SET METHOD

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ABSTRACT

In this paper an image processing method is proposed for bias correction and fibroglandular tissue segmentation from Magnetic Resonance Images (MRI) of human breast. The proposed method is based on level sets and includes three steps. In the pre-processing step, a chest wall line detection method is applied to separate the chest wall from the breast region in the MR images of breast. In the next step, a new level set algorithm is employed to estimate the bias field. The bias field estimation is used for intensity inhomogeneity correction, which leads to an efficient segmentation of the fibroglandular tissue. Finally, in the post-processing step, the skin layer is detected using morphological operations, and the fibroglandular tissue is extracted after skin layer subtraction. The proposed method has been validated on 2D images of an MR scan of the human breast. The implementation results show efficient performance of this method in tissue segmentation of MR images with the presence of intensity inhomogeneity.

INTRODUCTION

Breast MRI is a powerful imaging technique, which is used for breast tumor staging, disease progress monitoring or treatment progress assessment [1]. This imaging modality provides good contrast between fatty tissue and fibroglandular tissue of breast. According to different studies, the percentage of the fibroglandular tissue (FT%) extracted from breast MRI is a factor related to breast cancer risk [2]. Fully automated and accurate segmentation of fibroglandular tissue is needed to compute FT%. However, there are different challenges in this segmentation process. The fibroglandular tissue varies in shape, location, pattern, and size. Another major challenge in breast MRI segmentation is intensity inhomogeneity or bias field. Bias field is a multiplicative component of the MR images and causes smooth intensity variation in the image, which causes misclassification [3].

Different methods can be used to remove the bias field artifact, such as filtering, surface fitting, histogram-based, and segmentation-based techniques [4]. Segmentation-based methods are the most attractive bias field correction methods. These methods use one algorithm to do the segmentation and bias field estimation at the same time. Level set method is one of the proposed segmentation-based methods for segmentation, and bias field correction in MRI images of the brain [4].

The purpose of this paper is to develop a fully automated algorithm for bias correction and fibroglandular tissue segmentation in MR breast images. This algorithm includes a pre-processing step, level set segmentation method, and a post-processing and image refinement step to extract the fibroglandular tissue.

The rest of this paper is organized as follows. In section II the proposed segmentation methodology is explained. Section III describes the results and section IV concludes the paper.

METHODOLOGY

Step 1: Pre-processing

The first step in the segmentation of the breast regions is to separate the breast from chest in the MR image. In order to do this separation, the line between breast and chest wall should be detected. In this paper, the description of the CWL method is adapted from [5].

The CWL detection method initially extracts the gray level information (L_{air}) of the pixels corresponding to air from a thin vertical strip with width of Δ, positioned at the extreme left of an MR image. With pixels denoted as $I(x_1, x_2)$ and the image dimension of $M \times N$, the following expression is used:

$$L_{air} = \frac{1}{M\Delta} \sum_{x_1=1}^{M} \sum_{x_2=1}^{\Delta} I(x_1, x_2) \qquad (1)$$

After computing L_{air}, the image is scanned from left to right to find the average number of pixels corresponding to air. The location of the CWL is determined by finding the position x_2 for which the average number of air pixels is minimum. After determining the location of the CWL, the chest part of the image is removed from the original MR image.

Step 2: Segmentation

In order to segment the fibroglandular tissue as well as bias correction of the image, the level set approach proposed in [6] is used. In this method, the intensity inhomogeneity b, which varies slowly, is modeled as a multiplicative component of the image I:

$$I = bJ + n_I \qquad (2)$$

In this model, J is the true image, which is assumed to be piecewise constant, and n_I is additive zero-mean Gaussian noise.

I is assumed to be a function $I : \Omega \to \Re$ on continuous domain Ω. The bias field, b, is assumed as a constant in a neighborhood of each point in the image domain. The image J takes N distinct constant values $c_1, \ldots, c_N$ in sub-regions $\Omega_1, \ldots, \Omega_N$, respectively, where $\Omega = \cup_{i=1}^{N} \Omega_i$ and $\Omega_i \cap \Omega_j = 0$ for $i \neq j$. This level set method estimates the regions $\{\Omega_i\}_{i=1}^{N}$, the constants $\{c_i\}_{i=1}^{N}$ and the bias field b. Using these estimations, the bias correction and region segmentation are achieved simultaneously.

To consider the local intensity, a circular neighborhood $O_y = \{x : |x - y| \leq \rho\}$ with radius ρ is defined at each point $y \in \Omega$. The values $b(x)$ for all x, which was defied as (x_1, x_2), in the circular neighborhood O_y are close to $b(y)$. Thus, in each sub-region $O_y \cap \Omega_i$, $I(x) \approx b(y)c_i + n_I(x)$. So, the intensities in this sub-region form a cluster with cluster center $m_i = b(y)c_i$. This local intensity clustering property shows that the intensities in the neighborhood O_y can be classified into N clusters, which leads to applying the K-means clustering algorithm for classification and minimization of the following criterion [6]:

$$\varepsilon_y = \sum_{i=1}^{N} \int_{\Omega_i} K(y - x)|I(x) - b(y)c_i|^2 dx \qquad (3)$$

where $K(y - x)$ is a kernel function, such that $K(y - x) = 0$ for $x \notin O_y$. This local clustering function should be minimized for all y in Ω. Therefore, the energy $\varepsilon = \int \varepsilon_y dy$ is defined as:

$$\varepsilon = \int \left(\sum_{i=1}^{N} \int_{\Omega_i} K(y - x)|I(x) - b(y)c_i|^2 dx \right) dy \qquad (4)$$

Different functions can be used for K. In this paper, a truncated Gaussian function is chosen as kernel function.

In order to perform minimization, this energy is converted to a level set formulation with two disjoint regions Ω_1 and Ω_2. The energy can be written as:

$$\varepsilon(\phi, \boldsymbol{c}, b) = \int e_1(x)H(\phi) + e_2(x)(1 - H(\phi))dx \qquad (5)$$

where H is the Heaviside function and:

$$e_i(x) = \int K(y - x)|I(x) - b(y)c_i|^2 dy \qquad (6)$$

The energy function $\varepsilon(\phi, \boldsymbol{c}, b)$ is used as the data term in the energy of the variational level set formulation proposed by Chan and Vese [7] :

$$F(\phi, \boldsymbol{c}, b) = \varepsilon(\phi, \boldsymbol{c}, b) + \nu L(\phi) + \mu R_p(\phi) \qquad (7)$$

where ν and μ are weight parameters and, $L(\phi)$ and $R_p(\phi)$ are regularization terms and defined as $L(\phi) = \int |\nabla H(\phi)| dx$ and $R_p(\phi) = \int p|\nabla\phi| dx$. p is the potential function and based on the definitions in [6] is defined as $p(s) = (1/2)(s-1)^2$. The energy minimization is performed in an iterative process. In each iteration, the energy $F(\phi, \boldsymbol{c}, b)$ is minimized with respect to ϕ, $\boldsymbol{c}$, and b, using the standard gradient descent method. These variables are computed as follows:

$$\frac{\partial\phi}{\partial t} = -\delta(\phi)(e_1 - e_2) + \nu\delta(\phi)\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \mu\,\mathrm{div}\left(\frac{p'(|\nabla\phi|)}{|\nabla\phi|}\nabla\phi\right) \quad (8)$$

$$c_i = \frac{\int (b * K) I M_i dy}{\int (b^2 * K) M_i dy} \qquad i = 1,\ldots,N \qquad (9)$$

$$b = \frac{(I \sum_{i=1}^{N} c_i M_i) * K}{(\sum_{i=1}^{N} c_i^2 M_i) * K} \qquad (10)$$

where ∇ is the gradient operator and $\mathrm{div}(.)$ is the divergence operator.

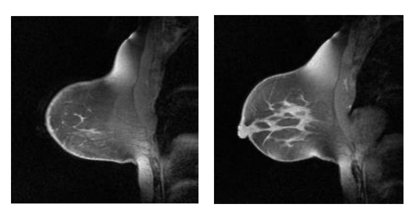
Step 3: Post-processing

After bias correction and segmentation, the fibroglandular tissue should be extracted. However, the segmented image contains the breast skin, which should be removed. In order to subtract the breast skin from the image, several morphological operations are applied to the segmented image. First, the breast contour should be extracted. This contour is extracted by applying the binary thresholding technique to separate the whole breast region from the background. The edge of the obtained binary contour is determined as the skin layer in the breast image. A simple morphological operation, called erosion, is applied to the binary image to detect the edge. The skin layer is the result of subtracting the eroded binary image from the binary contour image. Finally, by skin subtraction, which is subtraction of skin layer image from the segmented breast image, the fibroglandular tissue is extracted.

RESULTS AND DISCUSSION

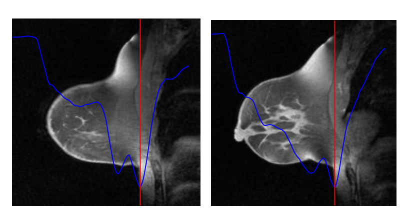
We evaluate the performance of our proposed method for bias correction and fibroglandular tissue segmentation. The MR images are 2D slices of a 3D sagittal breast MR scan. The images are pre-contrast and obtained with a T1-weighted sequence (Gradient Echo VIBE with variant SP/OSP) under study E-22121 (approved by the Conjoint Health Research Ethics Board, University of Calgary). Two MR slices are selected from the beginning and middle of the 3D MR image, containing small and larger amounts of fibroglandular tissue, respectively, as shown in Figure 1. These images contain pixels corresponding to air, skin layer, fatty tissue, fibroglandular tissue, and the chest wall.

Figures 2(a) and (b) illustrate the process of chest wall line detection. In the next step, the level set method is applied on the cropped images. Bias field b should be slowly varying. As Figures 3 (a) and (d) show, a Butterworth low pass filter is applied to the original images to obtain the initial value of the bias field. Figures 3 (b) and (e) illustrate the initial contour for the level set function. The final contour, which segments the fibroglandular tissue, is shown in Figures 3 (c) and (f). Another result of the level set segmentation method is bias field estimation, which is shown in Figures 4 (a) and (c). Bias corrected images, in which the intensity inhomogeneity has been removed, are shown in Figures 4 (b) and (d). The post-processing part of the algorithm is shown in Figure 5, including detection of the breast contour, obtaining the skin layer, and extracting the fibroglandular tissue by subtracting the skin layer.



(a) (b)

Figure1: MR slices of breast image



(a) (b)

Figure 2: Chest wall line detection

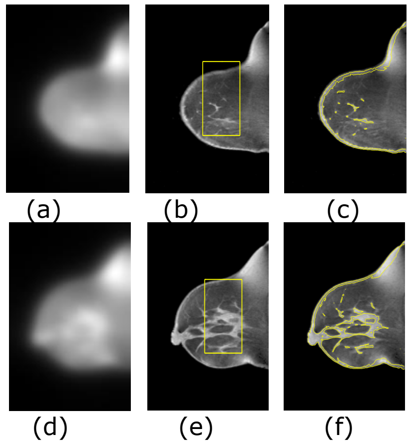


Figure 3: (a) Initial value of bias field, (b) Initial contour, (c) Final contour of the first image; (d) Initial value of bias field, (e) Initial contour, (f) Final contour of the second image.

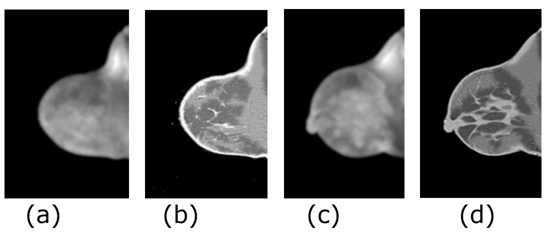


Figure 4: (a) Bias field estimation, (b) Bias correction in the first image; (c) Bias field estimation, (d) Bias correction in the second image.

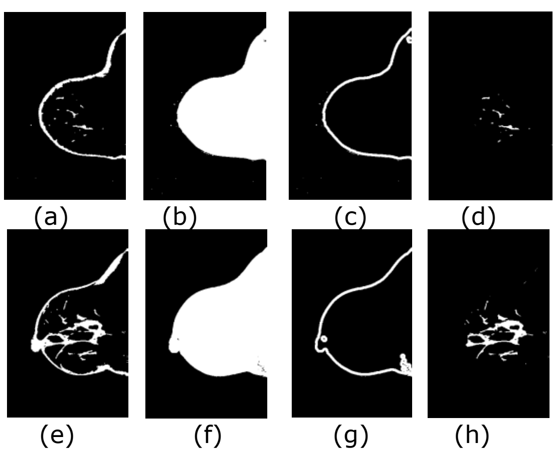


Figure 5: (a) Result of level set segmentation, (b) Breast contour, (c) Skin layer, (d) Result of segmentation after skin subtraction for the first image; (e) Result of level set segmentation, (f) Breast contour, (g) Skin layer, (h) Result of segmentation after skin subtraction for the second image.

CONCLUSION

This paper presented an image processing method in order to perform bias correction and fibroglandular tissue segmentation on MRI scans of the human breast. In the first step of the proposed scheme, the chest wall line was detected and cropped from the breast image. In the segmentation step, level set algorithm was applied for bias field estimation and correction, as well as segmentation of fibroglandular tissue. In the final step the skin layer was detected using morphological operations, and the fibroglandular tissue was extracted after skin layer subtraction. The proposed method was applied to 2D images obtained from an MR scan of the human breast. The implementation shows promising results in tissue segmentation of MR images with the presence of intensity inhomogeneity.

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