Proceedings of the 2007 IEEE Symposium on Computational Intelligence in Image and Signal Processing (CIISP 2007)

AN ADAPTIVE APPROACH TO THE SEGMENTATION OF DCE-MR IMAGES OF THE BREAST: COMPARISON WITH CLASSICAL THRESHOLDING ALGORITHMS

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Abstract-**The segmentation of MR images has been playing an important role to improve the detection and diagnosis of breast cancer. Main problem in breast images is the identification of the boundary between chest wall and breast tissue. Minimizing the effects of patient motion is also important step in segmentation process. In image processing, there are many different segmentation algorithms. The most common used method among them is thresholding. However, classic thresholding methods are not effective for axial MR breast images completely because of the fact that the sequence artifacts in axial MR breast images are very high. For this reason, we have proposed a regional thresholding algorithm to segment MR images successfully. The outstanding problem is how to obtain an automatic procedure for detecting boundary between breast tissue and chest wall.**

I. INTRODUCTION

The segmentation of MR images is an important step to improve the detection and diagnosis of breast cancer. If the breast tissue is not segmented, it takes more time to extract needed information from breast images in computer aided diagnosis systems. Main problem in breast images is the identification of the boundary between chest wall and breast tissue. Minimizing the effects of patient motion is also important step in segmentation process. There are many different segmentation algorithms. The most common method is thresholding because of its usability and high level performance. In this study, we have examined and tested common thresholding methods such as Otsu's thresholding method, and Fuzzy C Means based thresholding for dynamic contrast enhanced MR breast images. This paper proposes a regional thresholding algorithm to segment MR breast images successfully. The outstanding problem is how to obtain an automatic procedure for detecting boundary between breast tissue and chest wall.

This study also provides comparisons of the quality of segmentations among the proposed method and others. Extending this approach, the goal of this study was to evaluate the success of thresholding based method without binarization in the segmentation of DCE-MR breast images. The remaining part of this paper is organized as follows: Thresholding methods used in the segmentation problem of this study and the proposed algorithm are described in Section 2, the steps of the proposed algorithm is developed in Section 3, results with other methods are discussed in Section 4 and finally, conclusions are presented in Section 5.

II. METHODS

This study considers image data from dynamic contrast enhanced breast MR images. In background of MR breast images, there are little free protons which produces a near-zero regions. While crossing from the background region, a great increase in the pixel values appear and this means that the boundary of the breast begins to be identified in MR image. Since the breast has non-rigid structure and the sequence artifacts which are being resulted from patient motion, segmentation is very complicated.

Firstly, so to reduce the noise effect of sequence artifacts, a 3 x 3 x 3 median filter is applied to the image and the near-zero intensity values in the background are set to zero intensity value.

Secondly, a proper threshold value is estimated from the histogram of the filtered image. One of the well-known methods is Otsu's thesholding method among thresholding based methods. [1] This method is described as follows:

To examine the formulation, start by treating the normalized histogram as a discrete probability density function, as in

$$p_r(r_q) = \frac{n_q}{n} \qquad q = 0,1,2,......, L-1 \tag{1}$$

n : Total number of pixels in the image

n_q : Number of pixels that have intensity level r_q

L : Total number of possible intensity levels in the image.

A threshold k is chosen such that C_0 is the set of pixels with levels [0, 1, ……, k-1] and C_1 is the set of pixels with levels [k, k+1,….., L-1].
Threshold value k maximizes the between-class variance σ_b^2, which is defined as

$$\sigma_b^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \tag{2}$$

Where

$$\omega_0 = \sum_{q=0}^{k-1} p_q(r_q) \tag{3}$$

$$\omega_1 = \sum_{q=k}^{L-1} p_q(r_q) \tag{4}$$

$$\mu_0 = \sum_{q=0}^{k-1} q p_q(r_q) / \omega 0 \tag{5}$$

$$\mu_1 = \sum_{q=k}^{L-1} q p_q(r_q) / \omega 1 \tag{6}$$

$$\mu_T = \sum_{q=0}^{L-1} q p_q(r_q) \tag{7}$$

Fuzzy C-Means based thresholding method finds the optimum threshold by using fuzzy c-means clustering method which which finds number of clusters in the data set. Fuzzy c-means clustering method (developed by Dunn in 1973[3] and improved by Bezdek in 1981[4] is frequently used in pattern recognition. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^m \| x_i - c_j \|^2 \tag{8}$$

where m is any real number greater than 1, μ_{ij} is the degree of membership of x_i in the cluster j, x_i is the i_{th} of d-dimensional measured data, c_j is the d-dimension center of the cluster, and || * || is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership μ_{ij} and the cluster centers c_j by:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\| x_i - c_j \|^2}{\| x_i - c_k \|^2} \right)^{\frac{2}{m-1}}}, \qquad c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^m x_i}{\sum_{i=1}^{N} \mu_{ij}^m} \tag{9}$$

This iteration will stop when $\max_{ij}\left\{ \left| \mu_{ij}^{(k+1)} - \mu_{ij}^{(k)} \right| \right\} < \varepsilon,$ where ε is a termination criterion between 0 and 1, whereas k is the iteration steps. This procedure converges to a local minimum or a saddle point of j_m.

The algorithm is composed of the following steps:

Initialize $U = \lfloor \mu_{ij} \rfloor$ matrix, $U^{(0)}$;

At k-step: calculate the centers vectors $C^k = [c_j]$ with u_k;

$$c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^m x_i}{\sum_{i=1}^{N} \mu_{ij}^m} \tag{10}$$

Update $U^{(k)}, U^{(k+1)}$,

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\| x_i - c_j \|^2}{\| x_i - c_k \|^2} \right)^{\frac{2}{m-1}}}, \tag{11}$$

If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$ then stop; otherwise return to step 2.

III. THE STEPS OF THE PROPOSED ALGORITHM

Main objective of our proposed method is to partition MR breast images into two regions. Boundaries in each region are found by evaluating the discontinuities in intensity levels depending on the threshold value.

Let R represent the image area. R is divided into sub regions, R1 & R2 such that

$$R = \bigcup_{i=1}^{2} R_i \quad , \quad R1 \cap R2 = \varnothing \tag{12}$$

R1 and R2 are connected to each other as shown in Figure1. The most significant aspect of this method is to analyze the segmentation problem in smaller problem domains. Therefore, the discontinuity and similarity of the grey levels of an image can be tested in more detail.

The proposed algorithm is summarized as follows:

In this study, we take the threshold value for our proposed method using Otsu's thresholding method. But, the proposed method uses the thresholding value in different manner. The threshold value, which is calculated by using Otsu's method, is called "level".

Step 1. Middle point is determined as a reference point in the image. Image is scanned vertically from reference point. First point, which its intensity value is greater or equal to level, is identified and called b. Then, image is scanned vertically from that point. Second point, which its intensity value is smaller than level, is identified and called c. Average of these points are calculated and set as splitting reference point. This point is called a. Figure 1 illustrates these points.

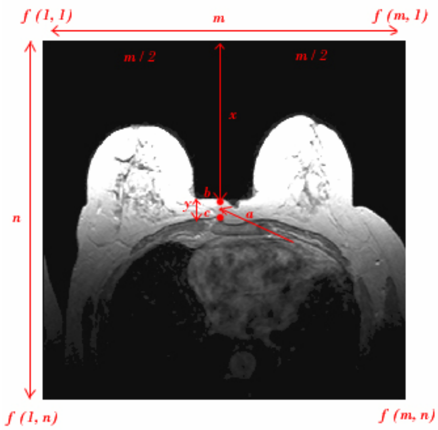


Fig. 1. Splitting reference point

level	: threshold value
m	: row dimension
n	: column dimension
reference point	: m/2
x	: distance from reference point to b.
y	: distance from point b to point c.
first point	: b
second point	: c
splitting ref. point	: a

$$y = c - b \,, \qquad a = \frac{y}{2} + x \tag{13}$$

Step 2. Image is divided into two regions (R1 & R2), by taking splitting reference point a as reference. It is shown in Figure 2.

R1 region is segmented easily by using classical segmentation methods. Segmentation problems appear due to the contrasted different intensity values on a uniform background and different non-trivial structures in R2 region. So, third step is for R2.

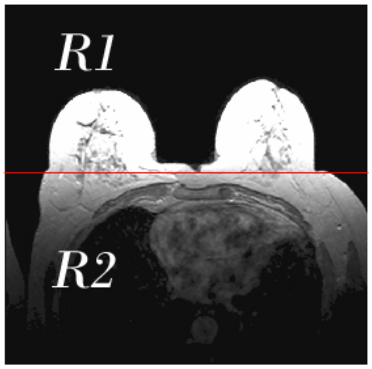


Fig. 2. Divided regions

Step 3. Two different procedures are applied in R2. Following steps are for these procedures.

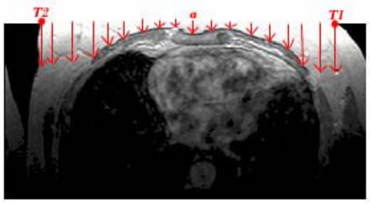


Fig. 3. Step 3.1 of the algorithm

3.1) R2 image is scanned from point a to the right while the intensity values are greater than "0" value horizontally. Automatically, first point, which its intensity value is equal to "0", is identified and called "T1". Figure 3 shows scanning process which is explained in step 3.1. R2 image is scanned again from point a to the left while the intensity values are greater than "0" value horizontally. Automatically, second point, which its intensity value is equal to "0", is identified and called "T2". After determining T1 and T2 points, the image is scanned from point a to point T1and from point a to T2 vertically. Intensity values which are greater than or equal to level are identified. Pixels below these points are set to "0" value and the regions which include "0" pixel values become a part of background.

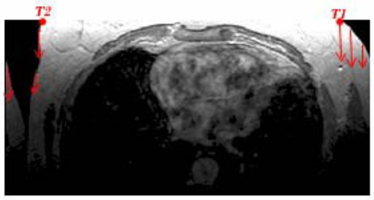


Fig. 4. Step 3.2 of the algorithm

3.2) R2 image is scanned from point T1 to the end of row (on the right) and from T2 point to the end of row (on the left) vertically. Because of the fact that the intensity values of top points on the right and on the left are "0", first set of points which includes intensity values that are greater than "0" is identified. Image is scanned again vertically from the points in the first set to determine the points which their intensity values that are greater than or equal to level. Pixels which are standing below these points in the second set are set to "0" value and the regions which include these pixel values become the part of background. Figure 4 shows scanning process which is explained in step 3.2.

Step 4. Regions (R1 & R2) are merged into one region. Noise reduction methods are applied to merged image. Merged image is shown as in Figure 5.

Fig. 5. Merged regions

IV. RESULTS

The thresholded and segmented images using the proposed method and other two methods are shown vertically in Figure 6.

We have compared our method with two others: Otsu's thresholding method (Otsu, 1979), and Fuzzy C Means based thresholding method. In general, gray level images can be easily segmented by using thresholding methods which are used to segment MR images in the study. However, they are not effective for axial breast images completely because of the fact that the breast has non-rigid structure and the sequence artifacts in axial MR breast images are very high.

In this study, Otsu's method calculates threshold value better than fuzzy c-means based thresholding method on MR breast images. While Otsu's method and Fuzzy C Means based thresholding method and the rest of all other thresholding methods create a binary image (binarization), our method does not produce a binary image. Therefore, segmentation process does not require binary mask image to represent the thresholded image. It creates segmented image directly. For this reason, the number of operations to segment a MR breast image is decreased and any data loss, which can be caused by morphological operations, is prevented because of the fact that our method does not consist of any morphological operations. This property shows that the representation of the segmented boundary is same as the boundaries of the breast in the proposed method. In other methods, approximate boundary to the breast wall is represented and the segmentation is realized according to this approximation.

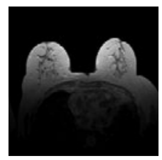
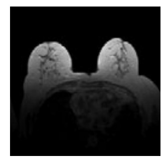
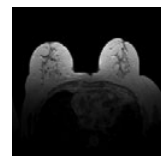
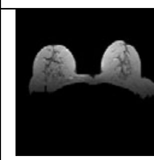
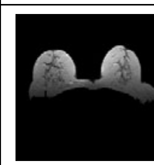
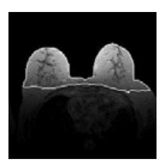
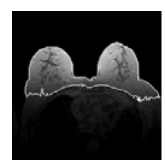
	Otsu's Thresoding	*Fuzzy C Means based Thresholding*	*The Proposed Method*
a	 Original	 Original	 Original
b	 Thresholded	 Thresholded	 Thresholded
c	 Morph. Closing	 Morph. Closing	 Noise Reduction
d	 Segmented	 Segmented	 Segmented

Fig. 6. Segmentation process for MR breast images. Row *a* shows *Original* images. Row *b* shows *Thresholded* images. Row *c* shows *Operations* on the thresholded images. Row *d* shows *Segmented* images.

According to expert opinions, segmentation by the proposed method appears to be better than the others as shown in Figure 6.

V. CONCLUSIONS

This paper proposes a region based thresholding method which is applicable to axial MR breast images. The algorithm of the proposed method is based on evaluating the discontinuity and similarity of pixel values within each region dependent on the threshold value. The experimental results show that proposed technique produces segmented image successfully.

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