

A completely automatic segmentation method for breast ultrasound images using region growing

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Abstract

In this paper, we propose a fully automatic segmentation algorithm of masses on breast ultrasound images by using region growing technique. First, a seed point is selected automatically from the mass region based on both textural features and spatial features. Then, from the selected seed point, a region growing algorithm based on neutrosophic logic is implemented. The whole algorithm needs no manual intervention at all and is completely automatic. Experiment results show that the proposed segmentation algorithm is efficient in both selecting seed point and segmenting region of interests (ROIs).

Keywords: Seed point selection, region growing, segmentation, neutrosophic logic.

1. Introduction

Ultrasonography has been one of the most powerful techniques for imaging organs and soft tissue structures in human body [1]. It has been used for breast cancer detection in recent years because of the advantages of ultrasound (US) imaging such as no-radiation, sensitive to dense breast, low false positive rate, portable and cheap cost. Therefore, US imaging becomes one of the most important

diagnostic tools for breast cancer detection.

However, due to the nature of US imaging, the images always suffer from the poor quality caused by speckle noise, low contrast, blurred edge and shadow effect. It takes considerable effort for radiologists to extract the contours of lesions and the manual extraction is not reproducible. Therefore, a computer aided diagnosis (CAD) technique for segmentation is needed. One of the frequently used segmentation methods is region growing [2, 3]. The crucial techniques for region growing method are how to select a seed point and how to set the growing stop criteria. A correct seed point selection is the basic requirement for region growing and good growing stop criteria are the guarantee of promising segmentation results. [8] calculated a fuzzy connectedness map and thresholded the map using a threshold selection mechanism to segment the lesion. [4] adopted the image gradient magnitude as the region growing control criterion. Intensity values based criterion such as the region mean are also used to test if a pixel should belong to the region or not [5]. Some region growing methods discussed how to select a seed point automatically [4, 5, 6], while most others focused on the region growing process but left the seed point was selected manually. In this paper, we propose a completely automatic region growing method to segment the lesion regions on breast

ultrasound images. Not only the region growing process is automatic, but the seed point selection is automatic as well. Furthermore, to make the segmentation accurate and efficient, we incorporate the neutrosophic logic into the region growing method and the new method shows promising segmentation result.

We describe the automatic seed point selection algorithm in section 2. The region growing algorithm is discussed in section 3. Section 4 shows experiment results and section 5 draws conclusions.

2. Automatic seed point selection

A seed point is the starting point for region growing and its selection is very important for the segmentation result. If a seed point is selected outside the region of interests (ROIs), the final segmentation result would be definitely incorrect. Due to the low quality of US images, most of the region growing methods require the seed point be selected manually in advance. In order to make the region growing segmentation fully automatic, it is necessary to develop an automatic and accurate seed point selection method for US images. In this paper, we develop a new automatic seed point selection method for breast US images. The method not only considers the texture features of a lesion, but also incorporates the spatial characteristics of a lesion. The seed point selection method is composed of 5 steps. They are described as below.

2.1. Speckle reduction

We employ the speckle reducing anisotropic diffusion (SRAD) [7] as the de-speckle method. SRAD can iteratively process the noisy image with adaptive weighted filters, reduce noise and preserve edges. The diffusion coefficient is determined by

$$\alpha(q) = \frac{1}{1 + [q^2(x, y; t) - q_0^2(t)] / [q_0^2(t)(1 + q_0^2(t))]}$$

and the instantaneous coefficient is

$$q(x, y; t) = \sqrt{\frac{(1/2)(|\nabla I|/I)^2 - (1/4^2)(\nabla^2 I/I)^2}{[1 + (1/4)(\nabla^2 I/I)^2]}}$$

The initialized $q_0(t)$ is given by

$$q_0(t) = \frac{\sqrt{\text{var}[z(t)]}}{z(t)}, \text{ where } z(t) \text{ is the most}$$

homogeneous area at t . In our experiments, we set the iteration times as 5.

2.2. Iterative threshold selection

To threshold the image into background and foreground, the algorithm iteratively selects thresholds until the most proper one is found. It needs no human interaction to tune a reasonable threshold value. Only the information of the US image is needed to determine the proper threshold.

The procedure is described below:

1. Calculate all the local minimums of the image histogram.
2. Let t equal to the current local minimum of the histogram (from smallest to biggest local minimum). Binarize and reverse the de-speckled image using threshold t (lesion becomes white and background is black) to get I_b . If the ratio of the number of foreground points and the number of background point is less than 0.1, let t equal to the next local minimum. Continue until the ratio is no less than 0.1.
3. Perform dilation and erosion on I_b to remove noise.
4. Find all the connected components in I_b . If none of the connected components has intersection with the image center region (a window about 1/2 size of the whole image and centered at the image center), let t equal to the next local minimum and go to step 2.
5. Continue until there is a connected component has intersection with the cen-

ter window. Use the current local minimum t as the threshold to binarize the image into background and foreground.

Because the iterative threshold chosen process starts from the smallest local minimum and increases gradually based on the possible lesion to image ratio, it can avoid the problems that foreground is too large (lesion is connected with other tissues) or too small (lesion is not included into the foreground).

2.3. Delete the boundary-connected regions

After image binarization, we find all the connected components. Each connected component represents a possible lesion region. Besides the real lesion region, there are some regions connected with the boundary and such kind of boundary-connected regions always have a big area. We cannot simply delete all the regions connected with boundary of the image because sometimes the lesion region is also connected with the boundary. Therefore, we use the center window in section 2.2 to evaluate every boundary region. If a region has no intersection with the center window and it is connected with any of the 4 image boundaries, we delete this region from the lesion candidate list.

2.4. Rank the regions

Now the left regions are either not connected with the boundary or having intersection with the image center window. We use the following score formula to rank each left region. The one with the highest score is considered as the lesion region.

$$S_n = \frac{\sqrt{Area}}{dis(C_n, C_0) \cdot \text{var}(C_n)}, n = 1, \dots, k$$

where k is the number of regions, $Area$ is the number of pixels in the region, C_n is the center of the region, C_0 is the center

of the image, and $\text{var}(C_n)$ is the variance of a small circular region centered at C_n . In the implementation, we slightly moved the image center C_0 to the upper part of the image (around row/4) based on our observation that a lesion frequently appears in the upper part of an image and shadow frequently appears in the lower part of an image.

2.5. Determine the seed point

Suppose the minimum rectangle contains the winning region $[x_{\min}, x_{\max}; y_{\min}, y_{\max}]$. For most cases, the center of the winning region $((x_{\min}+x_{\max})/2, (y_{\min}+y_{\max})/2)$ could be considered as a seed point. However, there are cases that the lesion shape is irregular and thus the center point might be outside the lesion. For these special cases, we choose a seed point by the following rule:

$$x_{seed} = (x_{\min} + x_{\max}) / 2,$$

$$y_{seed} = \{\forall y | (x_{seed}, y) \in \text{lesion region}\}.$$

3. Region Growing

A logic, in which each proposition is estimated to have the degree of truth in T , the degree of indeterminacy (neither true nor false) in I , and the degree of false in F , is called neutrosophic logic, where T , I , F are called neutrosophic components. The advantage of neutrosophic logic over fuzzy logic or $[0, 1]$ logic is that it brings the degree of indeterminacy I and I can be used to evaluate how much valuable the T and F is. In our region growing algorithm, for simplification, we define the degree of false $F = I - T$. Thus, for every pixel we need to calculate the degree of truth T and degree of indeterminacy I respectively, and make the final decision that if the pixel belong to the region or not based on the value of T and I . The for-

mulas for degree of truth T and degree of indeterminacy I are given as:

$$\begin{cases} T(i, j) = 1 - \frac{|f(i, j) - \bar{f}_R|}{\bar{f}_R} \\ T'(i, j) = 1 - \frac{|\bar{f}_{ij} - \bar{f}_R|}{\bar{f}_R} \\ I(i, j) = 1 - e^{-\frac{\text{var}(f_{ij})}{100}} \end{cases} \quad (1)$$

where $f(i, j)$ is the intensity value of pixel (i, j) , \bar{f}_R is the intensity mean of all the pixels in the current lesion region, \bar{f}_{ij} and $\text{var}(f_{ij})$ are the intensity mean and variance of a small circular region centered at pixel (i, j) , respectively.

Because $T(i, j)$ and $T'(i, j)$ can evaluate the difference between the current pixel and the current lesion region's mean, they can be used as the region growing criteria to decide if the current pixel should be added into the region or not. In a homogeneous region, we can use criterion $T(i, j)$ confidently to justify if the pixel belongs to the lesion region. However, in a noisy region, criterion $T(i, j)$ is not that confident because the current pixel's intensity might vary in a big range due to the noise effect. In such a case, we need another criterion $T'(i, j)$ to decide if the current pixel belongs to the region or not, which is based on the difference between the intensity mean of the current lesion region and intensity mean of a small circular region centered at pixel (i, j) .

Based on the above analysis, we find that the degree of indeterminacy is low if the pixel is in a homogeneous region and high if the pixel is in a noisy region. Thus, we use the variance of a small circular region centered at the pixel (i, j) to evaluate the indeterminacy degree $I(i, j)$ of a pixel and when the indeterminacy degree is low, we use criterion $T(i, j)$ and when the indeterminacy degree is high, we use criterion $T'(i, j)$. The whole region growing algorithm is described in Fig. 1.

```

Input Image M and Seed Point Pij
Output Binary segmented image J
Variables
Stack: S
Pixel: CP /*current pixel*/
      Q /*temporary pixel*/
Matrix: T, T', I and J /*same size as M*/
Begin
Initialize_stack(S)
Push pixel Pij into the stack S
Set J(Pij) = 1 and J(x) = 0 for all x ≠ Pij
Set region_mean = intensity of Pij
Repeat
Pop pixel CP from the stack S
For every pixel Q in the 8-connectivity
neighborhood of pixel CP Do
If Q is not in the current region
Calculate T(Q), T'(Q) and I(Q) by eq.(1)
If I(Q) < t1 && T(Q) >= t2 or
I(Q) >= t1 && T'(Q) >= t3
Push pixel Q into stack S
Set J(Q) = 1
/*Include Q in the region*/
Update current region_mean
End
End
End
Until the stack S is empty
Return the binary matrix J
End

```

Fig. 1: The region growing algorithm

4. Experimental Results

The test image used in this research comes from our breast US image database and the lesion's boundary is manually outlined by radiologist. Fig. 2 (a) shows the original US image used as input to our algorithm. Fig. 2(b) shows the output after SRAD preprocessing. Fig. 2(c) shows the seed point selected by our algorithm. Fig. 2(d) shows the binary output image of the region growing algorithm. Fig. 2(e) shows the final segmentation result of the proposed method and Fig. 2(f) shows the manually outlined lesion by radiologist.

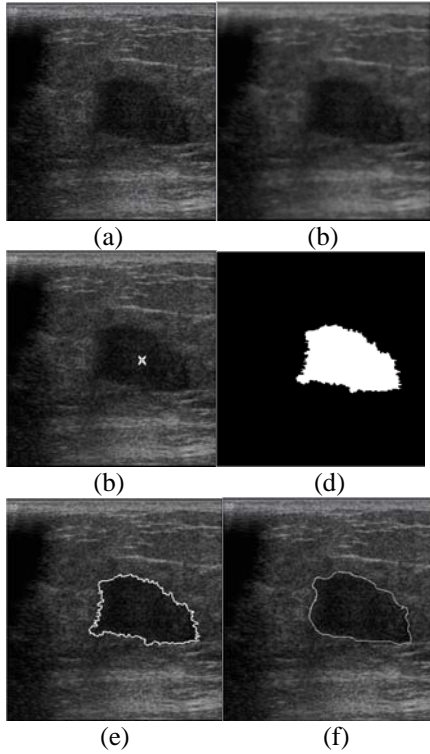


Fig. 2 Experiment results: (a) original image; (b) preprocessed image; (c) seed point selected; (d) binary output; (e) final segmented image; (f) manually outlined lesion image

To evaluate the result of our segmentation algorithm, the following formulas are used:

$$\text{OverlapRate} = \frac{\#of\{x \in \text{Area}_a \ \& \ x \in \text{Area}_m\}}{\#of\{x \in \text{Area}_m\}}$$

$$\text{MistakeRate} = \frac{\#of\{x \in \text{Area}_a \ \& \ x \notin \text{Area}_m\}}{\#of\{x \in \text{Area}_m\}}$$

where Area_a is the automatic segmented lesion region obtained by the algorithm, Area_m is the manually outlined lesion region by radiologists and x is a pixel in the image. OverlapRate can evaluate the percentage of correctly classified pixels and MistakeRate can evaluate the percentage of misclassified pixels. The result of our segmentation method gives OverlapRate = 0.938 and MistakeRate = 0.061 with $t_1 = 0.5$, $t_2 = 0.2$ and $t_3 = 0.99$.

5. Conclusions

In this paper we proposed a completely automatic segmentation algorithm using region growing technique. Seed point selection is based on textural and spatial information and region growing process uses both the degree of truth and degree of indeterminacy to classify each pixel. Experiment results show that our proposed method provides a considerable estimation of the breast lesion contours in US images.

6. References

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