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Boundary Extraction of Breast Ultrasonic Images

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Abstract— **The accurate boundary extraction is an essential preprocessing step for computerized analysis of a breast ultrasonic image. In this study, a novel approach based on the wavelet transform and the dynamic programming is proposed to extract tumor boundaries from breast ultrasonic images. Firstly, a rectangular region-of-interest (ROI) is manually selected from the ultrasonic image, followed by the ROI-based preprocessing for the noise reduction and image enhancement. Then an initial boundary of the tumor is obtained using the wavelet transform. To achieve a more accurate result, a dynamic programming algorithm based on the active contour model is applied to adjust the initial boundary. Experiments on 45 breast ultrasonic images have shown that this proposed method is a promising technique for the boundary extraction of breast tumor on ultrasonic images.**

I. Introduction

BREAST cancer is one of the most frequently diagnosed forms of cancer among Chinese women. Recent statistics show that the incidence of breast cancer in Shanghai has increased significantly in the last two decades, and now ranks first among new cancer cases in women [1]. The best way to decrease the mortality rate of breast cancer is to treat the disease as early as possible. Currently, physical examination, mammography and ultrasonographic technology are the most frequently adopted methods for early detection of breast tumors. However, physical examination often fails in the palpation of small tumors and multi-focuses. The sensitivity of mammography is reduced in Asian women with small and dense breasts [2], and young women are more sensitive to X-ray which may induce breast cancer [3]. Compared with the above two approaches, ultrasound technology, without any cost of traumatism, provides a method for real-time imaging of local tissue motion. Hence, it has been playing a leading role in the detection of breast tumors.

The ultrasonic diagnosis of breast tumors is usually based on the sonographic features of breast tumors such as shape, border, internal echo structure, echogenic rim and architecture of the surrounding tissue, among which an accurate tumor boundary is a prerequisite for high-level image analysis. The traditional manual delineation of the tumor boundary is both time-consuming and operator-dependent, so it is quite necessary to extract the breast tumor boundary by computer.

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Many segmentation algorithms for medical images with minimal manual involvement have been proposed in the last decade [4]-[5]. Considering the different database they used, it is hard to compare these algorithms. On the other hand, the poor quality of ultrasonic images, for instance, the low signal-to-noise-ratio (SNR), poor contrast and shadowing artifacts, makes the absolutely automatic image segmentation still a challenging task in spite of the recent advances in ultrasonic imaging.

The proposed method mainly focuses on the wavelet transform and dynamic programming. The wavelet transform, as a powerful approach to local and multiresolution analysis, has been widely used in image processing. When the wavelet transform is applied to image segmentation, the object boundary is detected by tracking along the wavelet coefficients for local extrema. However, taking the above-mentioned defects the ultrasonic images possess into account, the traditional wavelet-based algorithm cannot yield a satisfying result when used in boundary extraction for breast ultrasonic tumors; hence some modifications have to be made to improve the practicability of the wavelet-based boundary detection.

The proposed method consists of three steps. First, a region-of-interest (ROI) preprocessing based on a fuzzy domain enhancement algorithm and an implementation of a recursive and separable low-pass filter [6] is applied for the purpose of noise reduction and image enhancement. Then a multilevel 1-D wavelet analysis is performed both in the horizontal and vertical direction to extract an initial tumor boundary line by line. Finally, the dynamic programming is applied to adjust the initial boundary for a more accurate result.

II. Methods

A. Image Preprocessing

1) ROI Selection: An original breast ultrasonic image contains both the tumor and some non-tumor regions which possess similar intensity distribution and texture characteristics, such as posterior acoustic shadowing. In order to avoid the interference of these regions as well as to reduce the image processing time, a rectangular ROI is manually selected for each image according to the locations marked by an experienced physician: the tumor region is roughly located by marking the tumor's four border points, which are the upmost and undermost points in vertical direction and the corresponding point pair in horizontal direction. Then the ROI is outlined with an area that extends beyond the tumor region by a 15-pixel-distance in all directions.

2) Noise Reduction: On account of the considerable speckles in ultrasonic images, a separable Butterworth low-pass filter [6] is adopted to remove the speckles before image enhancement. The advantage of this filter lies in its low computational complexity and fast realization compared with the kernel-based methods, such as an averaging operator or a Gaussian operator. Moreover, this filter allows the speckle removal of ROI without an extensive loss of image details.

3) Image Enhancement: Fuzzy domain enhancement algorithm proposed in [6] is used in the step, with the basic idea of reducing the fuzziness of an image to adjust the image contrast and highlight the edge sharpness. Both the dynamic range and the local gray level variations of the original ROI are transformed to the fuzzy domain where they are assigned with fuzzy membership values between [0,1] by the transformation functions. After that, the enhancement function is applied in the fuzzy domain to adjust the dynamic range and enhance the image details. Finally, the fuzzy domain data are inversely transformed to obtain an enhanced ROI. Performance comparisons between this algorithm and other enhancement methods, for instance, unsharp masking and local statistic-based enhancement, are provided in [6], where the fuzzy-logic-based algorithm excels in terms of computational complexity, the possibility of real-time realization, and the property of being locally adaptive.

B. The Wavelet Transform

The traditional 2-D wavelet transform detects the edge point by tracking along the wavelet coefficients for the local extrema. Nevertheless, the hypoechoic inhomogeneity in internal density distribution of the breast tumor, for instance, the scattered calcification, can also cause the local extrema in wavelet coefficients, which may cause over segmentation of the tumor. Therefore, the method proposed here simplifies the edge detection by deciding only one boundary point for every row or column in each of the four overlapping sub-images of the ROI. The ROI is first split into four overlapping sub-images by dashed lines in Fig.1. Each sub-image is half of the original ROI size. For the upper and lower sub-images, the boundary points are detected column by column while a row-by-row detection is used in the left and right sub-images (shown as the solid lines in Fig. 1). If there exists more than one edge point in one line, for instance, the dash line in Fig.2 with four boundary points on it, only the outmost point from the tumor center will be saved, which is point A and D. Point B and C will be searched in the corresponding columns where they are situated. Here we do not search the edge points along the radial lines outward from the tumor center, so that the interpolation of the boundary can be avoided and a consecutive contour is guaranteed. In addition, the gray levels of the ROI are inversed (0 represents the lightest and 255 the darkest) for the sake of the following best-fit boundary detection.

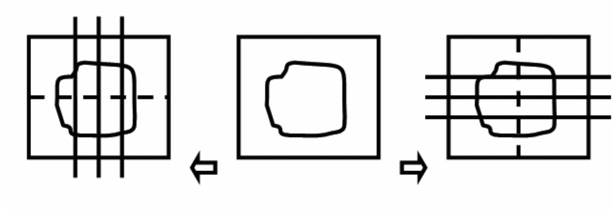


Fig. 1. The illustration of ROI division (dashed line) and line-by-line detection of edge points (solid line).

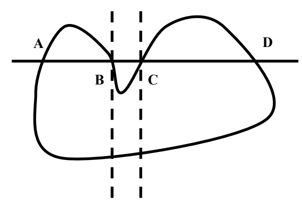


Fig. 2. The inter-compensation of the row-by-row and column-by-column detections.

As far as the line-by-line detection of the edge point is concerned, the 1-D wavelet decomposition of the signal at level N is performed by convolving each column vector in the upper part with a set of quadrature filters associated with wavelet bases and downsampling afterwards, according to Mallat's pyramid algorithm. The edge point is searched along the approximation coefficients $f(i)$ (i=1,2,…,n, n is the length of $f(i)$)at level N with the following definition:

$$s(i)=\begin{cases} f_{\min}, & if\ f(i)<SV \\ f_{\max}, & if\ f(i)\geq SV \end{cases},SV\in[f(1),f(n)] \quad (1)$$

$$p(SV)=\arg\left\{\frac{\min\int_{i=1}^{n}abs\left[f(i)-s(i)\right]di}{n}\right\} \quad (2)$$

where $s(i)$ is a step function used to fit $f(i)$, $f_{\min}$ and $f_{\max}$ are the minimum and maximum values of the current coefficient vector, SV is the sliding value of the threshold which ranges from $f(1)$ to $f(n)$, and the edge point is decided in position p which satisfies the minimum value of (2).

After detecting all the edge points at level N, we search for their positions at the original scale. As a result, two rough outlines of the breast tumor in ROI can be obtained, one from the set of edge points detected in the upper and lower sub-images and the other from the left and right parts. In order to remove some incorrect edge points lying far from the actual tumor boundary, two binary ROIs are created based on both sets of edge points respectively and a morphologic filtering is applied to smooth the outlines. The initial boundary is extracted from the "and" result of the two filtered binary ROIs with the sobel operator applied.

C. Dynamic Programming

As the edge points are detected line by line, the connectivity of these points and the smoothness of the boundary are unconsidered. Furthermore, density variations from inside a malignant tumor to the outside are usually smooth and gradual, which may result in a deviation of the edge points from the actual ones; hence the dynamic programming algorithm is used to adjust the initial boundary.

Dynamic programming is an energy optimization algorithm. It ensures global optimality of the solution by setting up the optimization problem as a discrete multistage decision process. Here, dynamic programming is applied on the discretization of the energy-minimizing active contour model [7], and the boundary extraction is regarded as a process of minimizing the energy of the active contour. The energy of the active contour is defined as follows:

$$E_{total} = \sum_{i=0}^{n-1} [E_{\text{int}}(v_i) + E_{ext}(v_i)] \quad (3)$$

where

$$E_{\text{int}}(v_i) = \alpha |v_i - v_{i-1}|^2 + \beta |v_{i+1} - 2v_i + v_{i-1}|^2 \quad (4)$$

$$E_{ext}(v_i) = -\gamma |\nabla I(v_i)|^2 \quad (5)$$

Here, E_{int} represents the internal energy that constrains the curve to be smooth, and E_{ext} denotes the external force pushing the active contour towards salient image features, $\{v_i=(x_i,y_i)\}$ represents the pixel position on the initial boundary, α and β control the membrane and thin-plate term respectively, $\nabla I(v_i)$ is the image gradient attracting the contour to image points with high gradient values, and γ controls the contour movement. It is obvious that α, β and γ in different values will certainly affect the time for convergence, and the final position of the active contour.

Now that the contour energy minimization can be viewed as a discrete multistage decision process, E_{total} can be redefined as

$$E_{total}(v_1, v_2, ..., v_n) = E_1(v_1, v_2, v_3) + E_2(v_2, v_3, v_4) + ... + E_{n-2}(v_{n-2}, v_{n-1}, v_n) \quad (6)$$

$$E_{i-1}(v_{i-1}, v_i, v_{i+1}) = E_{ext}(v_i) + E_{\text{int}}(v_{i-1}, v_i, v_{i+1}) \quad (7)$$

where v_i corresponds to the state variable in the ith decision stage, and it is only allowed to take m possible values according to the adopted searching mode, v_{i-1}, v_i, and v_{i+1} are the control points in each decision stage. Here we use the normal searching direction with m equal to seven for a relatively high computing efficiency. More specifically, given three consecutive points, for example v_{i-1}, v_i, and v_{i+1} in the ith decision stage, the state variable v_i should be able to move roughly perpendicular to the straight line connecting v_{i-1} and v_{i+1}.

The dynamic programming involves generating the sequence functions of one variable $\{S_i\}_{i=1}^{n-1}$ (the optimal value function). For each S_i, the minimization is carried out in accordance with the following equation:

$$S_i(v_{i+1}, v_i) = \min_{v_i - 1} S_{i-1}(v_i, v_{i-1}) + E_{\text{int}}(v_{i-1}, v_i, v_{i+1}) + E_{ext}(v_i) \quad (8)$$

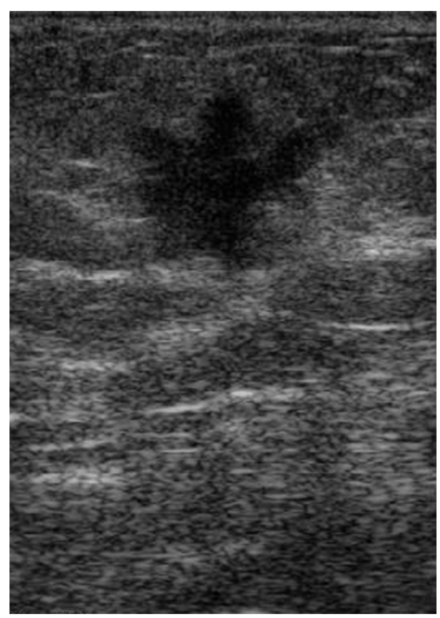
The optimal value of S_i in the ith decision stage is stored in the energy matrix, while the corresponding v_i is stored in the position matrix. The minimal energy of the active contour is

$$E_{\min} = \min S_{n-1}(v_n, v_{n-1}) \quad (9)$$

When $E_{\min}$ is obtained, the backward search is applied to trace back in the position matrix to find the optimal contour, which is the final boundary of the breast tumor.

III. Results

45 ultrasonic breast images are used for the verification of our method. All of the 45 images are captured from ATL HDI-3000 with an 8-MHz linear real-time transducer. No acoustic stand-off pad is used with any of the cases. The parameters in our method are set as follows: N is 3 for 1-D wavelet transform; the wavelet bases used are Symlets with length 6; as the initial boundary has already located near the actual tumor boundary, the values of α, β and γ remain constant when applied to different images: α=0.5, β=2, γ=30; the length of the searching list m is 5, which means the normal has two pixels on either side of the initial boundary, besides the point on the initial boundary.



(a)

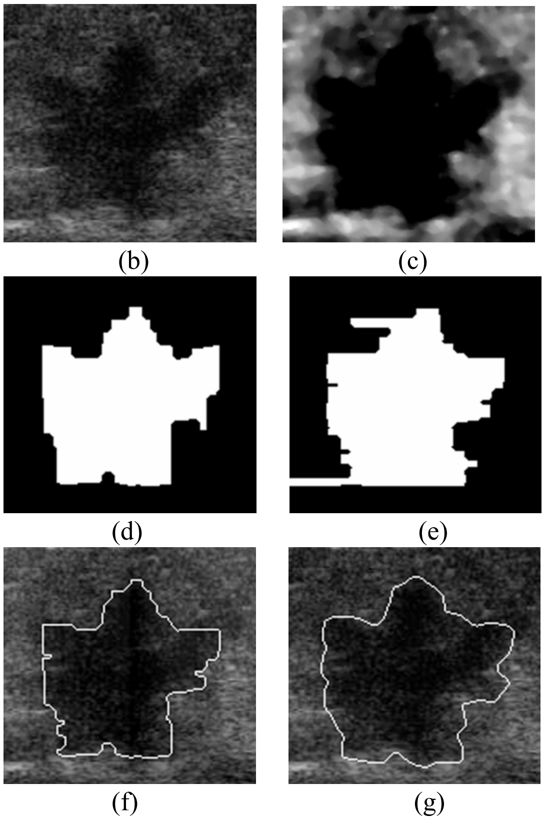


Fig. 3. Boundary extraction for a malignant breast tumor in ultrasonic images. (a) Ultrasonic image of a malignant breast tumor; (b) ROI of the malignant breast tumor; (c) preprocessed ROI; (d) binary ROI based on the edge points detected in the upper and lower sub-images; (e) binary ROI based on the edge points detected in the left and right sub-images; (f) initial boundary in ROI; (g) final boundary in ROI.

Experimental results show that boundaries extracted from 40 cases are reasonable whereas the results of the other 5 cases need manual modification. Fig. 3 illustrates an example of the boundary extraction for a malignant tumor. Fig. 3(b) and (c) gives us a comparison between the original ROI and the preprocessed ROI. From the image we can see that the speckle noise in the original ROI has been greatly reduced without extensive loss of image details. The image contrast has been greatly enhanced so that the breast tumor is emphasized after preprocessing. From Fig. 3(f) we can find that the initial boundary has already located near the tumor boundary. However, the boundary is rather coarse compared with the final boundary in Fig. 3(g), and the initial boundary seems a bit more constrictive than the actual tumor boundary we find. Fig. 3(g) illustrates the final result of boundary extraction after dynamic programming. It is clear that the final boundary is more smooth and accurate than the initial one.

IV. Conclusions

A semi-automated boundary extraction method is proposed to segment the breast tumor from ultrasonic images. The method is composed of three parts, which are the preprocessing module, the initial boundary detection and the final boundary adjustment.

An important step here is the manual ROI selection before the application of our method. Although various algorithms aim at segmenting breast tumor from its surrounding tissues automatically, it is unavoidable to introduce manual help into segmentation due to the low quality of ultrasonic imaging. This is why the manual ROI selection is still widely used in many approaches to boundary extraction of breast tumor.

The main advantage of our method lies in its simple principles and easy realization. Comparison between our experimental results and the manual delineations of an experienced physician shows that our method is a promising technique for boundary extraction of breast tumors in ultrasonic images. However, the quantitative evaluation of the boundary extraction is not included in this paper, for the lack of a definitive gold standard. Such a comparison will be considered and developed in the further improvement of our method in the near future.

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