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Automated segmentation of breast lesions in ultrasound images

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***Abstract*— Breast cancer is one of the leading causes of death in women. As a convenient and safe diagnosis method, ultrasound is most commonly used second to mammography for early detection and diagnosis of breast cancer. Here we proposed an automatic method to segment lesions in ultrasound images. The images are first filtered with anisotropic diffusion algorithm to remove speckle noise. The edge is enhanced to emphasize the lesion regions. Normalized cut is a graph theoretic that admits combination of different features for image segmentation, and has been successfully used in object parsing and grouping. In this paper we combine normalized cut with region merging method for the segmentation. The merging criteria are derived from the empirical rules used by radiologists when they interpret breast images. In the performance evaluation, we compared the computer-detected lesion boundaries with manually delineated borders. The experimental results show that the algorithm has efficient and robust performance for different kinds of lesions.**

I. INTRODUCTION

Breast cancer is one of the leading causes of death in women, and early detection improves prognosis and survival rate. During the last decades of clinical practice, ultrasound imaging has proved to be a valuable addition to mammography in the detection and classification of breast lesions.

Use of ultrasound can help to determine whether a mass is cystic or solid. Further ultrasound can help to characterize solid lesions as benign or malignant [1]. Accurate segmentation of a breast lesion is an important step to ensure accurate classification of a detected breast lesion as a benign or malignant lesion. Automated segmentation of breast lesions in ultrasound images can improve work flow by removing the manual segmentation step. Several approaches have been proposed to segment ultrasound breast images for automated diagnosis of breast lesions [2], [3]. However, given that ultrasound images comprise of speckle noise and tissue related textures, automated segmentation task remains as a challenge.

In this paper, we present a fully automated segmentation method for breast lesions using ultrasound images, as described in Fig.1. The system first takes an input ultrasound image with a potential abnormality, as shown in Fig.2 and outputs a detected boundary. In section IV, we present results of a set of clinical cases to evaluate the segmentation performance of the method. The performance is evaluated against manually drawn lesion boundaries.

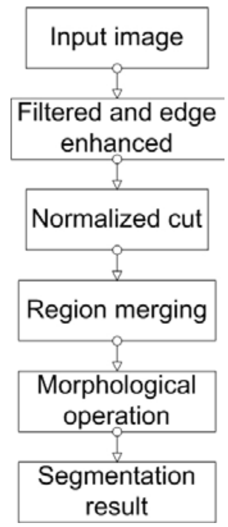
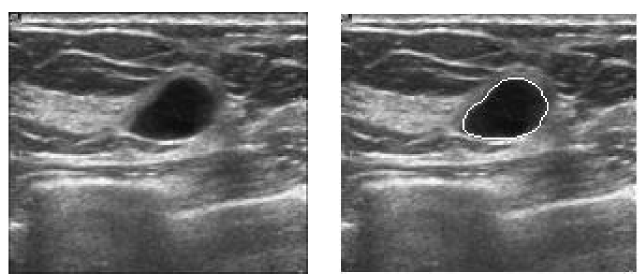


Fig. 1: System overview



a) (b)

Fig. 2: An example of a breast lesion in an ultrasound image

II. PREPROCESSING OF ULTRASOUND IMAGES

A. *Anisotropic diffusion technique*

Nonlinear filtering techniques are increasingly being used in image-processing applications. The advantage of nonlinear filters is that they can smooth the noise while being able to retain fine structure features. We applied the anisotropic diffusion nonlinear filter to the ultrasound images.

Anisotropic diffusion was first introduced by Perona and Malik [4]. Its basic idea is to obtain a family of filters of

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$I(x, y)$ as the solution for a suitable diffusion process, with $I_0(x, y)$ as the initial condition:

$$\begin{cases} I_t & = & div(c(|\nabla I|)\nabla I) \\ I(x,y,0) & = & I_0(x,y) \end{cases} . \quad (1)$$

where div indicates the divergence operator, $\bigtriangledown$ indicates the gradient operator with respect to the space variables, and $c(\cdot)$ is an "edge stopping" function. One of the functions introduced by Perona and Malik is:

$$c(x) = \frac{1}{1 + (x/k)^2}. \quad (2)$$

where k is the constant that depends upon the application.

B. Unsharp masking

Unsharp masking is a well-known technique to enhance the edges[5]. We applied unsharp masking after nonlinear filtering to improve the appearance of the edges of the breast lesions. An unsharp filter with a 3×3 kernel is constructed using the negative of a two-dimensional Laplacian filter. After this process the border details are enhanced accordingly.

III. SEGMENTATION: NORMALIZED CUT AND CLUSTERING

A. Image Segmentation Using Normalized Cut Technique

Shi and Malik [6] recently proposed a normalized cut (Ncut) technique. The normalized cut formulates segmentation as a graph-partitioning problem. It maximizes the total dissimilarity between the different groups and the total similarity within the groups. This segmentation technique readily admits combinations of different features such as brightness, position, windowed histograms, etc., thereby increasing the possibility of its use in applications of different imaging modalities.

Ncut is considered to be an unsupervised segmentation method and is based on a global criterion for a given image represented by $G = (V, E)$, with nodes V of the graph representing points in the feature space and E representing edges between any two nodes. To partition G into two disjoint sets A and B, the dissimilarity between A and B sets is calculated using (3).

$$cut(A, B) = \sum_{u \in A, v \in B} w(u, v). \quad (3)$$

where $w(u, v)$, the weight on each edge, is a function of the similarity between node u and node v. An optimal cut or partition of these nodes into two disjunctive sets A and B can be reached when $cut(A, B)$ reaches its minimum, as suggested by Wu and Leahy [7]. The normalized cuts method calculated in equation (4) was later proposed by Shi and Malik [6] to remove the bias for partitioning out small sets of isolated nodes in the graph when minimizing $cut(A, B)$.

$$Ncut(A, B) = \frac{cut(A, B)}{asso(A, V)} + \frac{cut(A, B)}{asso(B, V)}. \quad (4)$$

where $asso(A, V) = \sum_{u \in A, t \in V} w(u, t)$ is the total connection from node A to all nodes in graph V.

B. Region merging

To better detect the lesion region, we applied the Ncut method to partition an image into multiple small sets, as shown in Fig. 3(c). Adjacent sets were then merged into several bigger regions, shown in Fig. 3(d), based on the empirical rules of size, shape, margin, and texture features used by radiologists in diagnosing breast lesions [1]. With the prior knowledge that lesions tend to be located around the center of images and with low-average gray value on ultrasound images, we searched for the potential breast lesion region in each image. Shown in Fig. 3(e) is a binary image with the identified region after morphological operation (i.e., close operation) to smooth the border.

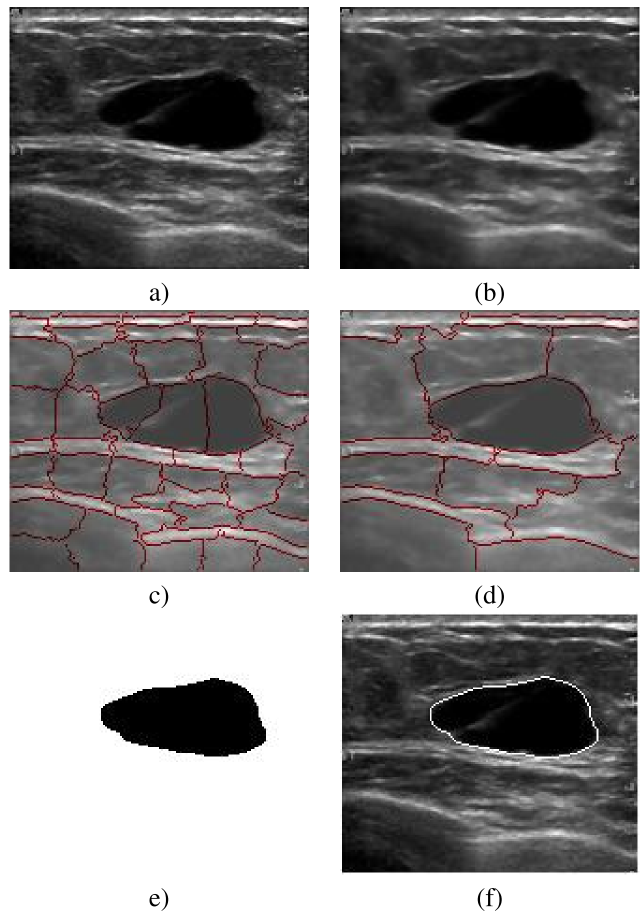


Fig. 3: . Examples of (a) the original image, (b) the image after filtering edge enhancement, (c) the image obtained from a normalized cut segmentation, (d) the image after region merging, (e) the smoothed region after morphological operation, and (f) final segmentation result.

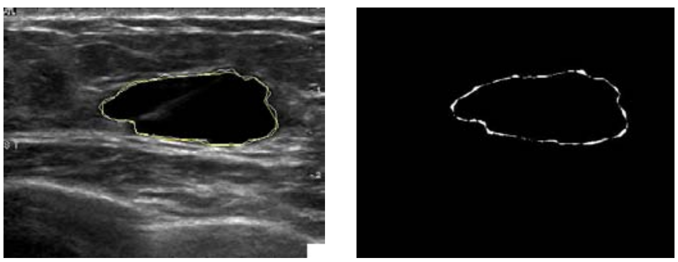
IV. EXPERIMENTAL RESULTS AND EVALUATION

To evaluate the performance of the above segmentation method, we tested it on a set of breast ultrasound images. The database consisted of 40 breast ultrasound images, each with a lesion. Among the database, 25 lesions are benign cysts, 15 lesions are solid malignant tumors. Fig. 4(a) shows the manually delineated and computer-detected boundaries of the same lesion.

A quantitative measure of the error between the manually and computer-detected borders was calculated to evaluate the segmentation accuracy[8]. The value of this error depends not only on the difference between the two borders, but also on the size of the underlying contour; therefore, a normalized error e is defined as

$$e = d/S \tag{5}$$

where d is the mismatched area shown in Fig. 4(b), and S is the perimeter of the manual contour. For the image shown in Fig. 4, its error e is 1.9934; the ratio of the matched area to the true area is 0.97.



a) (b)

Fig. 4: (a) Manually delineated border (white) and computer-generated border (yellow), (b) mismatched area.

Table 1 lists the experimental performance for cysts and malignant lesions separately. Fig. 5 gives more examples from which we can see that the approach presents robust performance for both benign cysts with well-defined borders and malignant lesions.

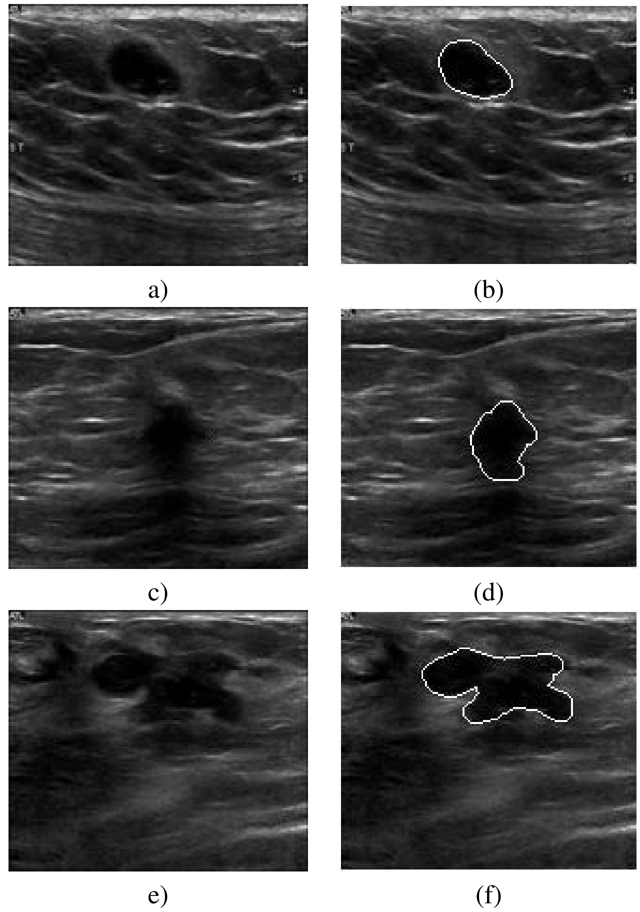


Fig. 5: Segmentation of breast lesions, left column: original images; right column: segmentation results

TABLE I: THE CALCULATION RESULTS

	Average Error (STD)	Average Ratio of Matched Area (STD)
Benign Cysts	2.314 ± 0.25	0.9625 ± 0.03
Malignant Solid Lesions	5.271 ± 0.49	0.923 ± 0.61

V. CONCLUSIONS

In this paper, we propose a promising algorithm for breast ultrasound image segmentation. It utilizes the advantage of the normalized cut theory in partitioning images into different parts and improves its performance on ultrasound images by incorporating a region-merging technique. Experimental results show that this algorithm is an effective segmentation approach for computer-aided diagnosis of breast diseases.

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