Breast Ultrasound Image Segmentation to Detect Tumor by Using Level Sets

G. R. Byra Reddy and H. Prasanna Kumar

Abstract Common cancer among the women is breast cancer that develops in either the lobules or the ducts of the breast. Identifying the tumor shapes in ultrasound images is still a challenging job because of speckle noise, poor contrast, and image intensity variations. A multiphase level set strategy is proposed in this research to efficiently segment the ultrasound image. Speckle noise of ultrasound images is reduced by using speckle reducing anisotropic diffusion (SRAD) filter. This proposed model demonstrates that it outperforms the Chan-Vese (CV) method and handles noisy, low contrast images better. This proposed approach is more robust to intensity inhomogeneities. Experiments show that the suggested method extracts more precise tumor boundaries than the CV method. This proposed approach is validated with different performance measure metrics such as Jaccard coefficient, Dice coefficient, and Hausdorff distance.

Keywords Breast cancer · Hausdorff distance · Jaccard similarity · Level set · Ultrasound

1 Introduction

Breast cancer is the most common cancer among women worldwide [1, 2]. Early identification of signs and symptoms of breast cancer helps to decrease the mortality [3, 4]. Breast ultrasound (BUS) imaging is popular since it is non-invasive and does not use radiation [4]. However, in order to achieve the correct diagnosis, clinical knowledge and competence are required [5]. Currently time-consuming and tedious manual segmentation methods are replaced by automated segmentation process that requires little or no user intervention. Automatic segmentation of the BUS image remains a difficult task for two primary reasons. First, the BUS images show speckle

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noise, local intensity changes, and low contrast. Secondly, breast tumors vary widely in shape, size, and location. Numerous researchers have segmented the image of the BUS using active contour methods.

In this paper, the preprocessing of ultrasound images has been done by using speckle reducing anisotropic diffusion (SRAD) to minimize speckle noise. Most frequently used region-based active contour method has been shown homogeneous regions. However, they fails with inhomogeneity of the image. To overcome this, paper proposes multiphase level set formulations to segment the inhomogeneous images in order to detect the more precise tumor boundaries in low contrast regions. The following is the structure of the paper: Sect. 2 describes related works for ultrasound image segmentation. Section 3 explains the preprocessing, Chan-Vese (CV), and level set approaches, and Sect. 4 describes data collection, experimental results, and discussion accompanied by the works conclusions.

2 Related Work

Many popular segmentation methods rely on [6–8] intensity homogeneity but they are ineffective for inhomogeneous images. Based on task specific constraints, a quantitative survey of low-quality ultrasound image segmentation is conducted [9]. Region-based active contour model with Ostu thresholding technique can be applied for homogeneous images [10]. The threshold will be selected by minimizing the variance. The snake model [11, 12] was widely used for BUS images. The snake deformation procedure is a very time-consuming and manual generation of initial contour. The smoothing process [13] to reduce the effect of noise will make weak edges to disappear.

To handle the speckle noise robustly, phase-based level segmentation [14] is proposed. This method considers the local orientation and phase from the monogenic signal. An efficient despeckling method called Bayesian non-local means filter (OBNLM) [15] is used to ultrasound images to minimize speckle noise. The speckle noise will be removed by using SRAD filter for sonography images. Edge-based active contour model [16] which will robustly mange the speckle noise and uses the phase information for better edge map.

3 Proposed Multiphase Level Set Approach

Ultrasound images are generally affected by speckle noise [17, 18]. SRAD filter is used to reduce the speckle noise and the preservation and enhancement of the edges. In the Chan-Vese active contour [6, 19] method, for given US image $f(x, y)$ in domain Ω, the energy functional given by (1)

$$F(c1, c2, C) = \mu \cdot \text{length}(C) + v \cdot \text{Area}(\text{inside}(C))$$

$$+ \lambda 1 \cdot \int\limits_{\text{inside}(C)} (|f(x, y) - \ c1|)^2 \, \mathrm{d}x, \mathrm{d}y$$
$$+ \lambda 2 \int\limits_{\text{outside}(C)} (|f(x, y) - c2|)^2 \, \mathrm{d}x, \mathrm{d}y \tag{1}$$

where μ, v, and $\lambda 1 \lambda 2$ are fixed parameters having the value greater or equal to zero. Smoothness controlled by μ, propagation speed increased by v, and inside and outside forces of the image contour controlled by $\lambda 1 \lambda 2$. Inside and outside of the C, image intensity are approximated by $c1$ and $c2$ energy functions, respectively.

CV method requires a complex differential method for numerical stability and relays on intensity homogeneity. This proposed technique overcomes the segmentation difficulty for intensity heterogeneous images. Multiphase level set method is used in this technique to segment the US image into 2^{m} sections. The US images can be segmented with more than two objects. For two phase segmentation, image domain Ω is divided into two $\Omega 1$ and $\Omega 2$ sections and can be shown as membership functions represented by $M1\ (\phi) = H(\phi)$ and $M2\ (\phi) = 1 - H(\phi)$. Hence, the level set formulation [20] for the energy is given by Eq. (2)

$$\varepsilon = \int \left(\sum_{i=1}^{N} \int K(y - x)|f(x, y) - b(y)c_i|^2 M_i((\phi)(x)) \mathrm{d}x \right) \mathrm{d}y \tag{2}$$

Here, $K(y - x)$ is positive window function. Such that $K(y - x) = 0$, $b(y)$ is the slowly varying bias field. By simplification, Eq. (2) can written as Eq. (3)

$$\varepsilon = \int \left(\sum_{i=1}^{N} \int K(y - x)|f(x, y) - b(y)c_i|^2 \mathrm{d}y \right) M_i((\phi)(x)) \mathrm{d}x \tag{3}$$

Hence, rewriting the energy $\varepsilon((\phi), c, b)$ for multiphase level set Eq. (4)

$$\varepsilon((\phi), c, b) = \int \sum_{i=1}^{N} \mathrm{e}_i(x) M_i((\phi)(x)) \mathrm{d}x \tag{4}$$

Multiphase level set approach detects the region of interest in inhomogeneous better than the CV method, and also the position of the initial contour is independent of the object need to be detected in the given image. The multiphase level set not only gives us intensity information, but it also tells us where and how picture features are located.

4 Results and Discussion

Experiments are performed on the ultrasound (US) image dataset of Baheya [21] hospital. MATLAB 2018b is used to implement the proposed approach and validated with CV method results for the dataset of 100 images. In Fig. 1a, it shows four despeckeled ultrasound images are illustrated to evaluate the effectiveness of the method. The segmented results of CV method and proposed approach are shown in Fig. 1b and c. The CV method's accuracy is determined by the initial contour's location. The CV method curves boundaries are not smooth, as can be seen in the figure, but the proposed strategy can detect the tumor boundary with very smooth contours, independent of the starting contour's position. Experiments show that the proposed method extracts more precise tumor boundaries than the CV method. Figure 1d shows the segmented part of the tumor for the proposed approach.

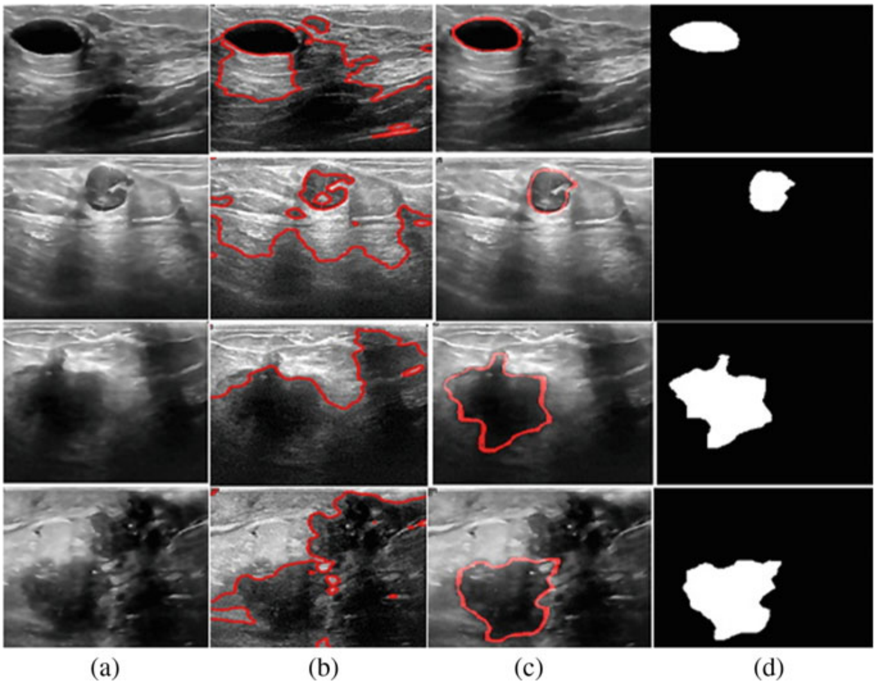

Fig. 1 **a** Despeckled image, **b** CV method contour, **c** proposed method contour, **d** segmented

Table 1 Performance analysis of two segmentation methods

S. No.	Ultrasound database images	Performance metrics					
		CV method			Proposed method		
		Jaccard	Dice	HD	Jaccard	Dice	HD
1	Benign	0.864	0.901	1.949	0.9264	0.9171	1.641
2	Benign	0.844	0.897	3.241	0.8894	0.9071	2.692
3	Benign	0.837	0.893	2.242	0.8935	0.9325	1.644
4	Benign	0.873	0.878	2.132	0.8777	0.8981	1.667
5	Malignant	0.906	0.907	2.193	0.9364	0.8967	1.949
6	Malignant	0.899	0.897	2.262	0.841	0.943	2.041
7	Malignant	0.873	0.831	2.126	0.885	0.9125	2.001
8	Malignant	0.837	0.847	2.671	0.877	0.9178	1.679
	Avg of 100 images	**0.861**	**0.895**	**2.542**	**0.891**	**0.9254**	**1.962**

4.1 Performance Metrics

To evaluate the accuracy of the proposed segmentation approach, the performance measures [22] Dice coefficient (DC), Jaccard coefficient (JC), and Hausdorff distance are represented in Eqs. (5), (6), and (7), respectively, were used. The Hausdorff distance (HD) [23] measures the max distance between two contours. Comparison of performance metrics for CV and proposed method is shown in Table 1. For tumor region between two label sets L and S, let L is the ground truth and S is the automated contour from segmentation. J(L, S) and D(L, S) get values ranging from 0 to 1. Larger value implies the better segmentation. Optimal value of HD(L, S) is 0. DC measures the segmentation result's overlap with the ground truth.

$$\mathrm{DC} = D(L, S) = 2\frac{|L \cap S|}{|L| + |S|} \tag{5}$$

$$\mathrm{JC} = J(L, S) = \left|\frac{L \cap S}{L \cup S}\right| \tag{6}$$

$$\mathrm{HD}(L, S) = \max\left\{\max_{a\in L}\min_{b\in S} a - b \max_{b\in S}\min_{a\in L} b - a\right\} \tag{7}$$

5 Conclusion

Currently, ultrasound is the best imaging modality in conjunction with mammography for detecting and diagnosing breast abnormalities. In this paper, level set-based

US image segmentation is proposed. First, low contrast and speckled US images are denoised by SRAD filter and proposed method has been validated by performing experimentation on 100 images. The experiments demonstrate that the CV method is fails in case inhomogeneity images, and boundaries are not smooth. In contrast, this proposed approach can detect the tumor boundary with very smooth contours. The metrics such as JC, DC, and Hausdorff distance have been used to assess the recommended method's efficacy for better segmentation. Further, these findings can be used in feature extraction and classification of ultrasound images to detect breast cancer.

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