

Analysis of Level set methods for Lesion Segmentation on Breast Ultrasound Images

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Abstract

Detection of Breast cancer which is growing fast is crucial. Mammography procedures are uncomfortable involving ionizing radiation. Ultrasound, a broadly popular medical imaging modality which is non invasive, real time, convenient and of low cost is preferable. But speckle noise corrupts, diminishing the excellence of ultrasound image. Wavelet based on soft threshold method is a prerogative to reduce the speckle noise and enhance signal to noise ratio (SNR) and contrast resolution of the image before segmentation. Analysis of a recently developed method of image segmentation using a lower sensitivity to contour initialization and noise with enhanced ability capturing a structured configuration is under taken in this paper, proposing an accurate and robust algorithm for detection of breast lesion, namely LEVEL SET

METHOD.

Key Words Breast Ultrasound Image, Speckle reduction and Segmentation, Levelset Method.

1 Introduction

The limitations of mammography in the detection of breast cancer that involves ionizing radiation was subsequently replaced by ultrasonography a popular tool imaging soft tissues in the body due to its non invasive, real time convenient and low cost [1]. Denoise algorithms are developed subsequently for such images to tackle speckle reduction anisotropic diffusion, preserving edges for images on speckle noise reduction in homogeneous region [. Anisotropic diffusion equation providing a technique for selective smoothing was later proposed. The use of wavelet threshold to reduce speckle noise has of late posed many challenges [8]. Later efforts have been taken for Breast ultrasound image (BUS) segmentation. Some of them are Threshold [9], Region growing [10, 11], Markov random fields (MRF) , active contours , neural networks , watershed [19], cell competition [20]. However these methods have their own drawbacks such as Region of Interests (ROI) are determined manually and they could segment the ROI's only. The location of ROI in the BUS images is complicated as its structure has different kinds of tissues with changing sizes and positions. In all the many speckle noise removing methods , distinguishing noise suppression and feature preserving remains a problem, as general speckle noise blurs BUS images where as speckle patterns reflect local echo of the underlined scatters . MRF based methods , Active contour model based methods are found convenient for image segmentation and useful in processing noisy BUS images. Success of Model based methods is dependent on initial contour conditions which are easily effected by noise resulting in poor segmentation. Different automatic breast ultrasound lesion segmentation methods, consisting of speckle reduction method and region and edge based active contour model are explored in this paper for obtaining good initial condition to solve segmentation task. First initially wavelet soft threshold technique is used for the reduction of

speckle noise. Once speckle is removed the image is segmented using region based and edge based level set methods, active contour with Otsu and active contour with region growing method. The results of the experiment carried out are presented for discussion and evaluate the merits of the conclusions arrived at.

2 Materials and Methods

Data base acquisition

In this work, the Breast ultrasound (BUS) images are acquired with an ultrasound scanner GE Healthcare LOGIQ E9, using linear transducer array of frequency 5 to 10 MHz. The algorithms are applied to benign and malignant masses of breast.

Speckle reduction by Wavelet soft thresholding

Breast ultrasound image consists of high frequency component which is called multiplicative noise named as speckle. To reduce this noise wavelet soft threshold technique [24] is used in this paper. In this technique the wavelet coefficients are logarithmically transformed of breast ultrasound image. This technique is based on the generalized Gaussian distributed modeling of sub-band coefficients and Bayes-Shrink method used in this.

Level Set Segmentation

Active Contour method is fast evaluation method but it is difficult to handle if there are any topological changes [25]. Even though it has the advantage of giving fast evaluation, there is a drawback that is difficult to handled topological changes. Besides that one more drawback is a typical external energy coming from the image which is positive on homogeneous regions and near zero on the sharp edges. A level set method embeds the contour into a higher dimensional space [26]. It overcomes the drawback of active contour method that means automatically handles the topological changes but it has slower evaluation. Level set segmentation, can be divided into region and edge-based image patterns.

a) Region -Based Active Contour Model (RBACM)

Region based active contour method primarily separates the image into the regions based on intensities. In this method, the position of the initial contour can be anywhere in the image, and it does not necessarily surround the objects to be detected. This method minimizes an energy which can be seen as a particular case of the minimal partition problem. [27, 28].

b) Edge-Based Active Contour Model in Distance Regularized Level Set Formulation (EBACM-DRLS)

Distance regularized level set is called edge based level set method in which the regularity of the level set is intrinsically maintained throughout the function. Level set evolution is resulting due to the gradient flow that minimize the energy function by a distance regularization term and an external energy that drives the movement of the zero level set near desired locations. The distance regularization effect eliminates the call for re-initialization and thereby avoids its induced numerical errors. In the numerical implementation, relatively large time steps can be used in the finite difference scheme to reduce the number of iterations, to ensure sufficient numerical accuracy. So the distance regularized level set evolution formulation has an intrinsic facility of maintaining regularity of the level set function [29].

c) Region -Based Active Contour Model with Otsu (RBACM-O)

i) Global image threshold using Otsu's method

An optimal threshold is based on the integration means global property of the histogram. It does not depend on the probability density functions. Segmentation is based on "region homogeneity". It means Region homogeneity is able to measured using variance. Regions with high homogeneity will have low variance. Otsu's method selects the threshold by minimizing the variance [12].

ii) Proposed method (Active Contour with Otsu)

In the proposed method, first step is the global threshold is used then second step is region-based active contour approach used. Now combine first and second methods those are global threshold approach and region-based active contour approach

to get better segmentation result and analysis. To emphasize the segmentation results TP, TN, FP and HD by the proposed method is used to quantitatively analysis the performance of the RBACM-O algorithm.

c) Region -Based Active Contour Model with Region Growing(RBACM-RG)

The method summarized as below

1) First we reduced the speckle noise by wavelet soft threshold technique.

2) Speckle removal of the image can be segmented by alone active contour model. Observed that still some irrelevant regions present in the output of alone active contour model are easily affected by speckle noise, and the local edge information is not considered in active contour model.

3) Now apply region growing algorithm to the output of active contour model. To remove these irrelevant regions. In Region growing we used Trace region boundaries technique by using region growing algorithm [31]. In region growing algorithm we used the Moore-Neighbour tracing algorithm modified by Jacob's stopping criteria, for 8 connected neighbourhoods. The threshold value is range of pixel intensities.

4) This technique applied to the output of ACWE model to achieve better segmentation with region boundary.

3 Results and Discussion

Speckle reduction by Wavelet soft thresholding

To reduce the speckle noise in breast ultrasound image we used wavelet soft threshold technique which gives better performance than remaining filter methods. Figure. 1 (a) shows that the Original image and Figure. 1 (b) shows that the Speckle noise reduced by Wavelet based soft threshold with the PSNR of 76.67 dB.

Performance and Analysis of Levelsets Segmentation

The segmentation methods are tested on the images in the breast ultrasound image database. Here, simulation results are presented to demonstrate the performance of the region and edge based active contour methods. For validating the overall performance of the segmentation methods, used three Area error metrics, one Boundary Error Metrics and CPU Execution time.

Error metrics are true-positive ratio (TP), false-negative ratio (FN) and false-positive ratio (FP) [11]. One boundary error metrics is Hausdorff distance (HD) is to analyze the difference between the contours generated by the segmentation method and the marked by the radiologist. Hausdorff (HD) distance means it measures the worst point-distance between two contours between the manually determined areas and the automatically located lesions. When the TP ratio is higher and the FN ratio is lower, more real tumor regions are classified as breast lesion regions and when the FP ratio is lower, fewer normal tissue regions are classified as 'breast lesion' regions. Let A_a be the pixel set of the ROIs determined by the computer segmentation and A_m be the pixel set of the ROIs determined manually by the radiologist the three error metrics are calculated as:

$$TP = \frac{|A_m \cap A_a|}{|A_m|} \quad FP = \frac{|A_m \cap A_a - A_m|}{|A_m|} \quad FN = \frac{|A_m \cap A_a - A_a|}{|A_m|} \quad (1)$$

Figure. 1 shows that the lesion segmentation with the RBACM and EBACM-DRLS methods. Fig. 3 and 4 shows that the lesion segmentation with the RBACM-O and EBACM-DRLS methods. The performance of the region and the edge based active contour methods is shown in Table 1.

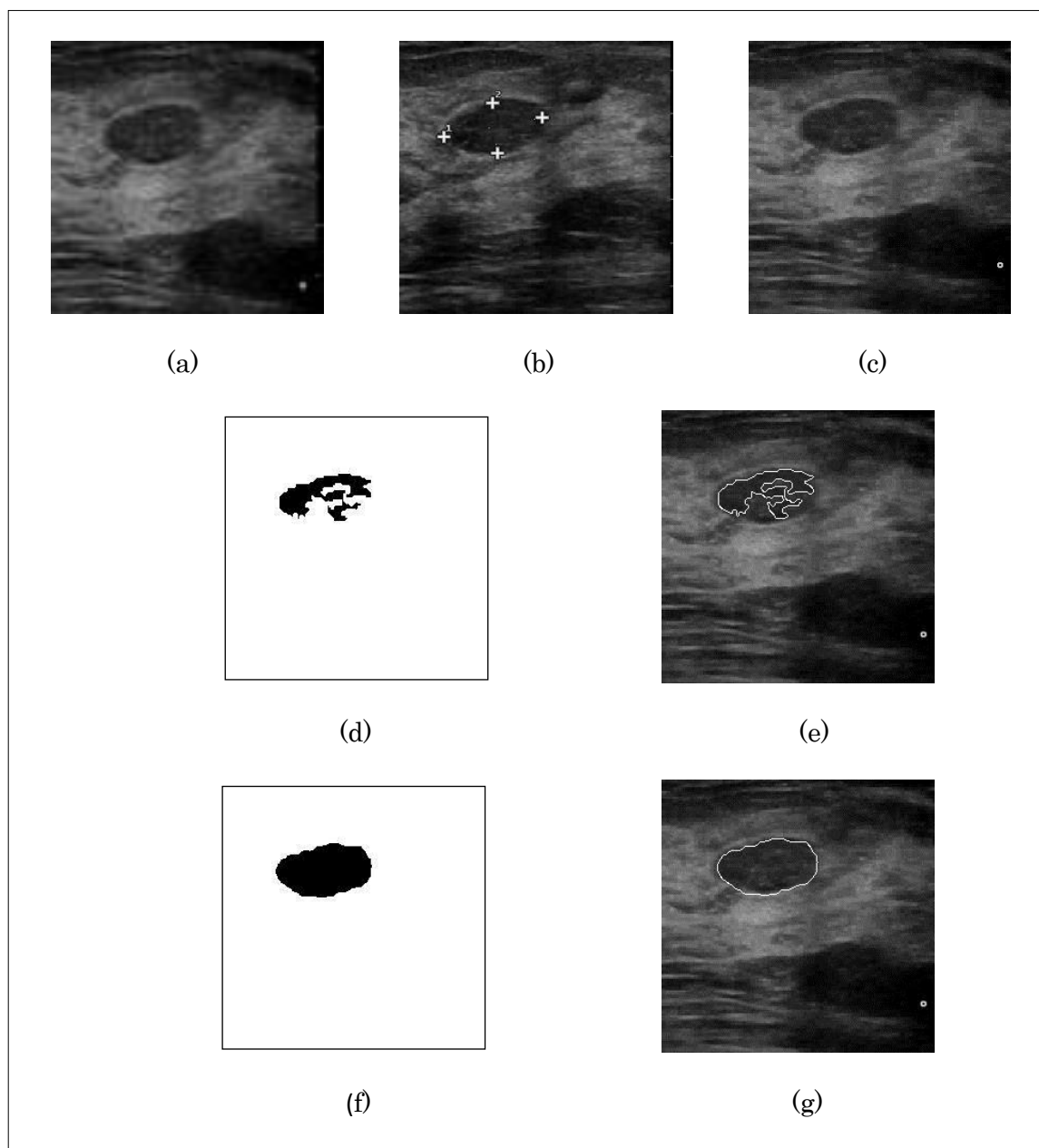


Figure.1. Results of Lesion segmentation in BUS image
 (a) Original image (b) manually description by the radiologist. (c) Speckle noise reduced by Wavelet based soft threshold (d) Binary image for RBACM. (e) Segmentation result produced by RBACM. (f) Binary image for EBACM-DRLS. (g) Segmentation result produced by EBACM-DRL

The TP ratio of the RBACM is 83.83% , EBACM-DRLS is 89.54%, RBACM-O is 93.54% and RBACM-RG is 97.72% indicating that the RBACM-RG method is effectively covers the real breast lesion regions well, however, there are still some real breast tumor regions 2.28% that are not covered for RBACM-RG method. This is because the boundaries between breast tumors and normal tissues are very blurry.

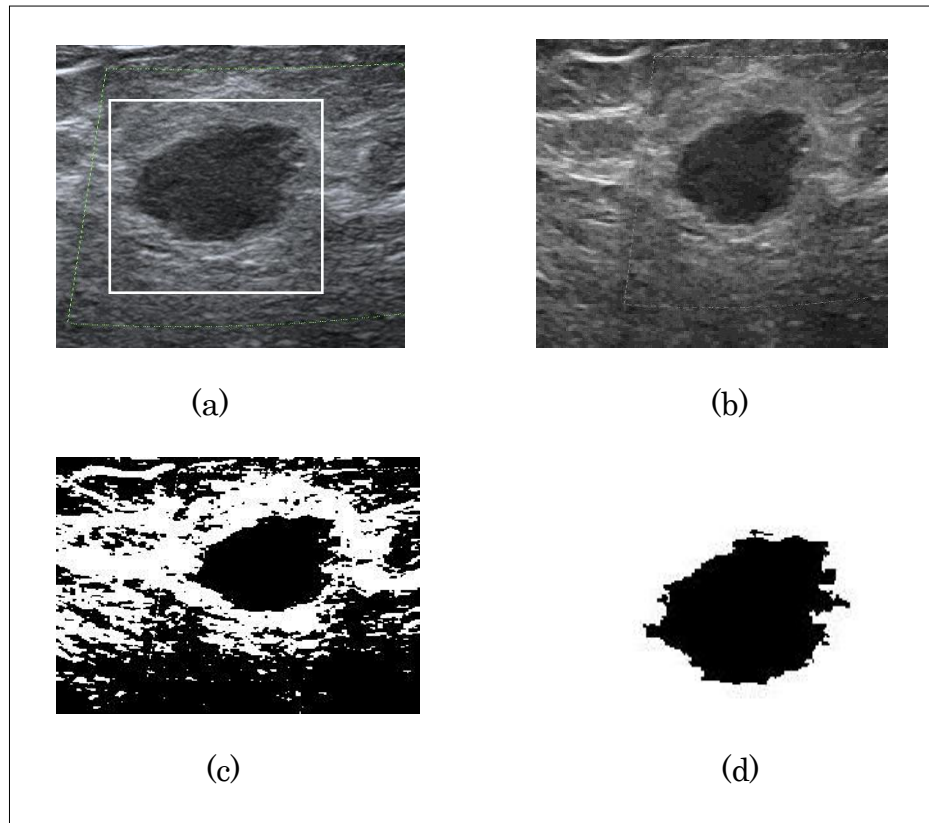


Figure .2 Region Based Active contour model with Otsu segmentation result in BUS Image.

- (a) Original image and manually description by the radiologist. (b) Speckle noise reduced by Wavelet based soft threshold (c) Threshold image by Otsu's method. (d) Segmentation result produced by Region Based Active contour model with Otsu method (RBACM-O).

The FP ratio of the region RBACM is 52.91% and for the RBACM-RG is 29.63% it is low when compared to the RBACM i.e., the segmentation result was accurate and credible, and few surrounding tissue regions are covered. For RBACM, HD distance is 13.73 pixels and for the RBACM-RG method is 6.08 pixels. So the HD value is reduced for the edge method.

TABLE I.
THE PERFORMANCE AND ANALYSIS OF LEVEL SETS SEGMENTATION

Level Set Methods	Area error metrics			Boundary error metrics	CPU Execution time/case (seconds)
	TP ratio (%)	TN ratio (%)	FP ratio (%)	HD (pixels)	
RBACM	83.83	16.17	52.91	13.73	12.12
EBACM-DRLS	89.54	10.46	30.07	11.81	9.38
RBACM-O	93.34	6.66	34.26	9.85	7.60
RBACM-RG	97.72	2.28	29.63	6.08	1.65

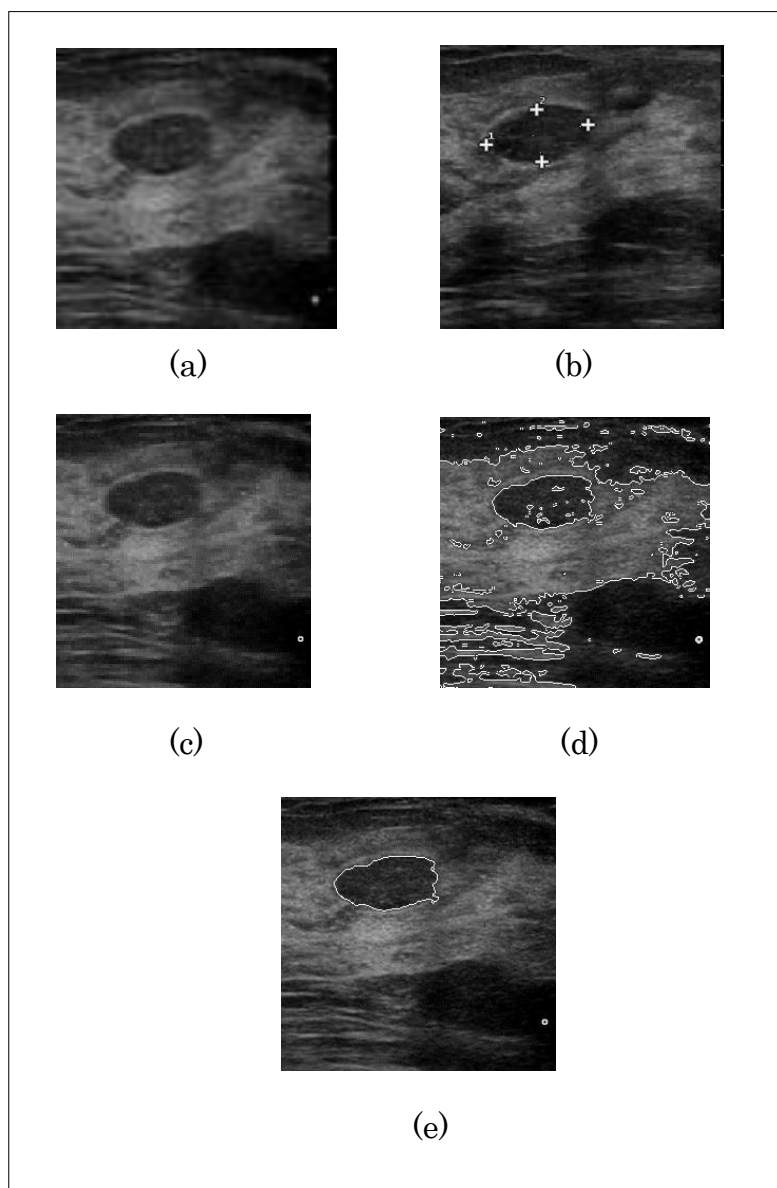


Figure.3. Active contour model with Region growing segmentation result in BUS image

- (a) Original image (b) manually description by the radiologist. (c) The segmentation produced by the Region Bbased Active contour model (RBACM) (d) Segmentation result produced by Region Based Active contour model model with Region growing (RBACM-RG).

The FP ratio of the region RBACM is 52.91% and for the RBACM-RG is 29.63% it is low when compared to the RBACM i.e., the segmentation result was accurate and credible, and few surrounding tissue regions are covered. For RBACM, HD distance is 13.73 pixels and for the RBACM-RG method is 6.08 pixels. So the HD value is reduced for the edge method. The execution time per case is 12.12 sec for RBACM and 1.65 sec for RBACM-RG method. So RBACM-RG gives better results like fast processing, less HD distance and less FP ratio than RBACM,EBACM-DRLS and RBACM-O.

4 Conclusion

The Region of Interest (ROI) can be segmented by using level set methods. The methods based on regions and edge based intensities. Initially the speckle noise is reduced using wavelet based soft threshold. RBACM-RG method minimizes trivial regions raised in RBACM, EBACM-DRLS and RBACM-O methods for ultrasound image. This is because of the pre processing method is wavelet based soft threshold technique which reduces the speckle noise greatly. This approach could be helpful in detecting the breast cancer more accurately and this will help the radiologist to identify the lesion boundary automatically. This process computation speed is moderate. In future; ultrasound image can be segmented with high computation speed technique it may be improved for better diagnosis.

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