



Performance Comparison Between Balloon Active Contour and Seed Based Region Growing Methods in Segmenting Breast Ultrasound Images

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Abstract

Segmentation images have been widely used in the medical field, especially in detecting breast cancer. Ultrasound images can be used as modalities in early detection of breast cancer. However, the detection becomes difficult due to speckle noise and unwanted information in the ultrasound images. In this study, performance comparison between Balloon Active Contour (BAC) and Seed-Based Region Growing (SBRG) methods in segmenting breast ultrasound images was carried out. The performance of segmentation results for both methods was measured in terms of accuracy and sensitivity. Results obtained showed that the accuracy for SBRG and BAC methods was 90.55% and 87.41%, respectively. In addition, sensitivity for both methods was 83.3 and 79.0, respectively. This implies that the SBRG method has better performance compared to the BAC method in segmenting breast cancer in ultrasound images.

Keywords: Segmentation; Breast Cancer; Ultrasound Images

1. Introduction

Breast cancer is one of the main causes of death among women worldwide. In Malaysia, a woman has 1 in 19 chances of getting breast cancer in her lifetime. Out of 100 women who are suffering from cancer, 30 are breast cancer patients. The National Cancer Registry of Malaysia stated that in 2011, there were 18,206 cases registered among women which accounted for 32.1% per 100,000 populations (National Cancer Registry, 2016). The highest incidence of breast cancer in Malaysia is among Chinese, followed by Indians and Malays.

Currently, early detection of breast cancer is an initiative to reduce the number of deaths among women. Generally, an ultrasound image is an alternative modality that can be used in detecting breast cancer at the early stages. This modality is suitable for pregnant and breast-feeding women as it has no ion radiation; hence, can protect their foetuses. These modalities are safer and suitable compared to mammograms (Guo, 2010).

However, ultrasound images have limitations in detecting abnormalities due to speckle noise and blurry edges (Malek *et al.*, 2017). Speckle noise is a type of multiplicative noise causing the ultrasound images difficult to be observed. The radiologist requires more time to detect the abnormalities due to speckle noise. Besides, misinterpretation by the radiologist may affect in detecting the cancer. It is important for them to make diagnostic decisions correctly because these rely on the radiologist's abilities and experiences.

Therefore, segmentation method is used to help the radiologist determine the exact abnormalities of ultrasound images. Awcock and Thomas (1996) defined segmentation as a process of dividing an image into regions that can be described into something meaningful and easy to understand within the scene. Among various segmentation methods, region-based and edge-based segmentations are widely used in many applications. Region based segmentation is separating an image into some regions while edge based is the process of locating its boundary using an image gradient (Malek *et al.*, 2010).

The Balloon Active Contour (BAC) is one of the edge based methods introduced by Cohen (1991) to overcome the problems of the traditional snake, which refer to the difficulties in progressing the concavity of the boundary. This method is extensively used in the segmentation of many medical images. Cohen (1991) found that the BAC can be used to segment the cavity of the human heart in both 2D and 3D of ultrasound and magnetic resonance images in order to find the boundary of the cavity. Nithila and Kumar (2016) proposed the lung nodule segmentation in CT data by using the Active Contour model to eliminate partitions in CT image, aside from the lesion of the lung due to pulmonary nodules, which have small tissues and are mostly cancerous. Jumaat *et al.* (2011) also used this method in segmenting and classifying masses in ultrasound images.

The Seed Based Region Growing (SBRG) method can be classified as a region based segmentation technique. The central goal of this technique is to divide an image into regions. To date, SBRG has been widely developed in segmentation for early detection of breast

cancer. Nagi et al. (2010) proposed Seeded Region Growing and Morphological Preprocessing in digital mammograms to eliminate noises, cover the radiopaque artefact, spread out background area from the breast profile area and to eliminate pectoral muscle. In addition, Malek et al. (2010) enhanced the Region Growing segmentation method in mammogram images by developing an initial seed point automatically based on morphology operations. Moreover, the SBRG method can be used in various images such as the segmentation of the lung computed tomography image and retinal image (Kumar & Kumar., 2014).

In this paper, the performance of BAC and SBRG methods was compared in segmenting masses of ultrasound images. The performances were measured based on the erroneous area and sensitivity of segmentation results against the reading by a radiologist.

2. Approaches and Methods

A. Balloon Active Contour (BAC)

In this paper, we focused on the parametric active contour which is a vector valued function, closed curve in the spatial domain of an image and parametrically. This can be represented by $v(s) = (x(s), y(s))$ where the parameters x and y are the coordinate of the vertices and are functions of the normalised arc length $0 \leq s \leq 1$ (Jumaat et al., 2011).

Active Contour Method was proposed by Kass et al. (1988), which is an energy minimising curve that solves the problems within an image and, consists of a unique approach. The energy minimisation system establishes the difference between traditional contour modelling approaches which involved edge detection, followed by subjective interpretation and edge connection. The action of the snake is classified as an energy-minimisation process, where total of energy, E_V defined as

$$E_V = \int_0^1 [E_{\text{int}}(v(s)) + E_{\text{ext}}(v(s))] ds \quad (1)$$

where $E_{\text{int}}(v(s))$ and $E_{\text{ext}}(v(s))$ are the internal and external energy function respectively.

The E_{int} was computed based on the local shape of the curve $v(s)$ and helped us to determine the continuity and the smoothness of the curve. It can be represented as

$$E_{\text{int}} = \frac{1}{2} \left[\alpha |v'(s)|^2 + \beta |v''(s)|^2 \right] \quad (2)$$

where the first order term was controlled by the parameter α and the second order term measured by parameter β . Also, the parameters α and β are the function coefficient of the E_{int} characterised as the elasticity function and rigidity function respectively. Therefore, the general form of the energy function (1) can be arranged to be

$$E_V = \int_0^1 \left(\frac{1}{2} \left[\alpha |v'(s)|^2 + \beta |v''(s)|^2 \right] + E_{\text{ext}}(v(s)) \right) ds \quad (3)$$

for a large value of α , the curve became straight between two points. Similarly for the large value of β , it will produce a smooth curve.

On the other hand, the E_{ext} attracts the deformable curve to the boundary of the image and uses the sum of pressure energy and image energy. Since the E_{ext} is derived based on the image information and it drives the curve to the boundary of object, therefore different types of active contour uses different types of E_{ext} . According to Cohen (1991), the E_{ext} is defined as:

$$E_{\text{ext}} = -k \frac{F_{\text{image}}}{\|F_{\text{image}}\|} + k_{\text{pressure}} n(s) \quad (4)$$

where F_{image} is image energy and k is the image energy weighting.

The parameter k_{pressure} is the pressure energy and its positive or negative sign causes the active contour to inflate or deflate respectively.

B. Seed Based Region Growing (SBRG)

The SBRG is a method of extracting a region of image based on the homogeneity criteria (Adam & Bischof., 1994). These homogeneity criteria can be determined by the intensity information in the image. The parameters of SBRG include initial seed point and stopping criteria. Starting with an initial point, the similarity of the region will be obtained by comparing the minimum difference of four connected neighbourhoods, $N(p)$ with the region mean, $\mu(p)$ defined as (Malek et al., 2017):

$$\delta(p) = \min |N(p) - \mu(p)| < T \quad (5)$$

where T is the threshold value for stopping criteria, and mean of the region is defined by Pitas (2000) as:

$$\mu(p) = \frac{1}{n+1} \left[\delta(p) + n^* \mu(p) \right]_{p \in A_i} \quad (6)$$

where n is the number of pixels and A_i is the set of iterative seed points. These processes are recursive until no more pixel can be added to the region.

3. Implementation

A total of 24 ultrasound images are provided from National Society Cancer Malaysia (NCSM). The implementation was done by using MATLAB R2014a software. The segmentation processes are illustrated in Figure 1 below.

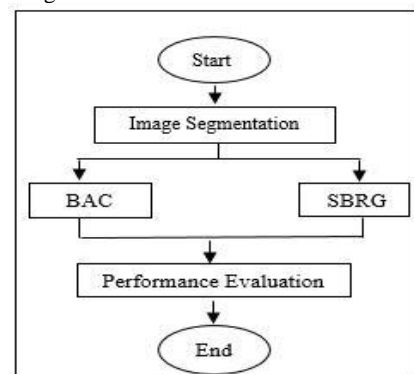


Figure 1. The Segmentation Process

Based on Figure 1, the first process is a segmentation of masses in ultrasound images using BAC and SBRG methods. Initial point is one of the parameters required in both methods. For SBRG, this

point is very important as starting point for the region to grow, whereas BAC used this point as a centre of radius in initialisation contour process. This study used the same value of initial point. In addition, the values of α and β in equation (3) were set as 0.5 for all images. The number of iteration in BAC must be chosen properly because it significantly affected the completion of the segmentation process. The number of iterations used in this study was 75 for all images. Finally, all the segmented results were

evaluated using percentage relative error of area to measure the accuracy and sensitivity between both methods, as well as area traced by the radiologist.

4. Results and Discussion

Figure 2 shows sample of segmentation results obtained from both methods.

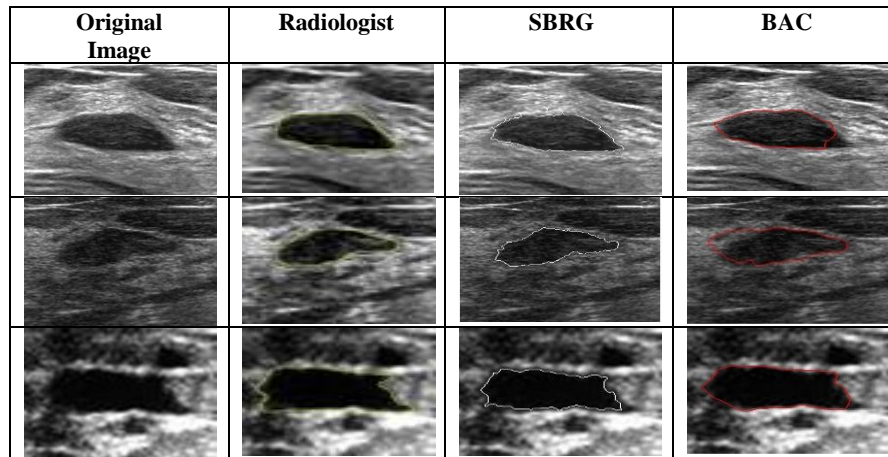


Figure 2. Segmentation Results of BAC and SBRG Methods

Based on the above figure, both methods were able to segment masses successfully. However, BAC method was more sensitive to noise, hence produced under and over segmented image. The performance of segmentation results was measured based on accuracy and sensitivity. The erroneous of area was calculated between both methods and the area was manually drawn by the radiologist. The experimental results showed that the average percentage errors of BAC and SBRG were 12.59% and 9.45% respectively. This implies that the accuracy of the methods had been

87.41% and 90.55% respectively. In addition, the sensitivity was defined based on the detection of true positive area over the real number of positive area (Jaffery et al.,2013). Masses area that had a relative error lower than 15% of the area provided by the radiologist was detected as true positive otherwise known as false positive. Table 1 provides sensitivity classification based on relative error of the segmented images. It shows that SBRG method achieved 4.3% higher sensitivity than the BAC method.

Table 1. Comparative Analysis of Methods using Statistical Data

Recognition Statistics	BAC	SBRG	Relative Error Range (%)
Very good	4	12	0 – 4.99
Good	7	3	5 – 9.99
Average	8	5	10 – 14.99
Below Average	2	1	15 – 19.99
Poor	3	3	≥ 20
Sensitivity (%)	79	83.3	

5. Conclusion

In this paper, we compared the performances of both SBRG and BAC methods. As a conclusion, the SBRG method displayed exceptional segmentation results with high sensitivity and a maximum number of segment with extensive accuracy, in comparison the BAC method.

Acknowledgements

This research was supported by the Universiti Teknologi Mara (UiTM) under the Geran Dalam Pemudayaan Penyelidikan (iRAGS),600-MI/DANA5/3/iRAGS(23/2015). The author(s) would like to acknowledge Prof. Dr. Rozi Mahmud (radiologist) and Abdul Kadir Jumaat for the support and contribution.

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