ROBUST ACTIVE CONTOURS FOR MAMMOGRAM IMAGE SEGMENTATION

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ABSTRACT

In this paper a new region based active contour method is proposed for mammogram image segmentation. In the formulated energy function, a characteristics function limits the contour evolution inwards. A new SPF function is defined using phase shifted Heaviside function that helps to attain optimum solution in fewer number of iterations. The proposed method is tested on several mammogram images from mini-MIAS database. Quantitative evaluations will demonstrate the efficiency of the proposed method and shows that our method yield better segmented results with high accuracy compared to previous state of art methods.

***Keywords*—** Segmentation, Active contours, SPF function, Mammogram image analysis.

1. INTRODUCTION

Image segmentation is a well-known problem in the areas of computer vision and image processing in which an image is segregated into non-overlapping regions. In order to accurately detect and segment tumors in mammogram images the radiologists need to carefully analyze the regions of interest. In manual detection, distraction and fatigue can cause high number of false positives [1]. Therefore, a computer aided diagnosis (CAD) system is needed, which can help doctors and radiologists to accurately segment tumor tissues. Active contour method is one of the numerous segmentation techniques used for mammogram image analysis. It partitions an image by evolving a curve towards the object boundaries. Active contour methods are divided into two major categories: edge-based [2–4] and region-based [5–9] models. Edge-based models integrate an edge stopping function by utilizing image edge information, which deforms towards the object boundary. These models do not perform accurately on images with weak edges, noise and blurred boundaries. On the other hand, region-based model exploits image statistical information and build region growing force term, which restricts the contour at different regions.

Chan and Vese (CV) [5] is regarded as most extensively used model for the region-based image segmentation. However, this model is not suitable for the images with intensity inhomogeneity. Zhang et al. proposed region-based active contours with selective local and global (ACSLG) segmentation method [9]. This model uses a region-based function by utilizing global and local information of an image in order to handle intensity inhomogeneity across regions. In traditional region-based active contour models, different optimization techniques are used on the proposed energy functional to minimize the energy. However, it has been reported that regardless of their numerical stability, smoothness and adaptability, their energy functional do not yield fast convergence for global minimum. In order to solve this issue, Lee and Seo [10] proposed a new level-set based bimodal segmentation model which converges rapidly to global minimum.

This paper presents a new region-based image segmentation model by accumulating the advantages of level set evolution without re-initialization (LSEWR)[4], Lee and Seo [10], and ACSLG [9] models. The proposed method uses modified energy minimization technique, which converges to global minimum. It converges faster than previous models and detects desired objects efficiently. Furthermore, it incorporates image statistical information to formulate a region-based SPF function. Moreover, an energy penalizing term is used to maintain level-set function as signed distance function (SDF), which also helps to remove computationally expensive re-initialization.

Rest of the paper is organized as follows. The proposed method is presented in section 2. Experimental results and comparisons are shown in section 3. Discussion about the quantitative analysis with other state-of-the-art methods is placed in section 4. Finally, conclusion is given in section 5.

2. PROPOSED METHOD

Chan and Vese [5] proposed an energy formulation based on Mumford and Shah model [6], which does not necessarily rely on gradient based information in the segmentation process. Let $I:\Omega \subset R$ be an input image, $\phi:\Omega \subset R$ a level set, then the CV energy formulation is defined as:

$$\begin{aligned} E_{CV}(c_1,c_2,C) &= \lambda_1 \int_\Omega |I(x)-c_1|^2 H_\varepsilon(\phi(x))dx \\ &+ \lambda_2 \int_\Omega |I(x)-c_2|^2 (1-H_\varepsilon(\phi(x)))dx \\ &+ \mu \mathrm{Length}(C) + \nu \mathrm{Area}(in(C)) \end{aligned} \tag{1}$$

where $\mu \geq 0$, $v \geq 0$, $\lambda 1$ and $\lambda 2 > 0$ are constants. Length term regularize the contour C. $H_\varepsilon(\phi)$ is a smoothed approximation of Heaviside function, which is defined as:

$$H_\varepsilon(\phi) = \frac{1}{2}\left(1 + \frac{2}{\pi}\arctan\left(\frac{\phi}{\varepsilon}\right)\right) \tag{2}$$

ε is a constant, which controls the smoothness of the Heaviside function. In (1), c_1 and c_2 represent image intensities inside and outside of curve C, respectively.

CV model has been a prominent method for segmenting noisy images and images whose boundaries cannot be delineated by gradient. However, it does not work well on images with intensity inhomogeneity. Moreover, the variational formulation of the model is not guaranteed to converge to the global minimum and sometimes points to the local minimum [10]. In order to make solution converge at global minimum Lee and Seo proposed a modified CV model known as bimodal segmentation model, whose energy functional is defined as:

$$\begin{aligned} E_{LS}(\phi, c_1, c_2) &= \lambda_1 \int_\Omega | I(x) - c_1 |^2 \phi(x) H_\varepsilon(s + \phi(x)) dx \\ &+ \lambda_2 \int_\Omega | I(x) - c_2 |^2 \phi(x) H_\varepsilon(s - \phi(x)) dx \end{aligned} \tag{3}$$

where $H_\varepsilon(s \pm \phi(x))$ is the phase shifted Heaviside function with small arbitrary value s. It creates a region of competition $\{x | -s \leq \phi(x) \leq s\}$ between first and second term of (3) to check if the minimizer converges towards s or $-s$. c_1 and c_2 represent image intensities with phase shifted Heaviside function both inside and outside of curve C, respectively.

A new energy functional E_{pro} is defined by introducing a contour direction restricting characteristics term M^k from E_{LS} as:

$$\begin{aligned} E_{prop}(\phi, c_1, c_2) &= \int_\Omega | I(x) - c_1 |^2 \phi(x) H_\varepsilon(s + \phi(x)) M^k(x) dx \\ &+ \int_\Omega | I(x) - c_2 |^2 \phi(x) H_\varepsilon(s - \phi(x)) M^k(x) dx \end{aligned} \tag{4}$$

where $H_\varepsilon(s \pm \phi(x))$ is the phase shifted Heaviside function with small arbitrary value s. Multiplication of ϕ inside energy functional detects the changes in ϕ even in the absence of sign change. It prevents the contour from stopping at the local minimum [10]. M^k characteristic function restricts the contour inwards as defined:

$$\begin{aligned} M^k &= \phi > 0, \\ M^0 &= \Omega \to -1 \end{aligned} \tag{5}$$

In the proposed method, Heaviside function is shifted with small arbitrary value s. The shift in the Heaviside function gives a rapid boost to the level-set value towards the optimum solution within few number of iterations. Moreover, shifted Heaviside function restricts the value of ϕ and finds a stationary solution at global minimum.

By minimizing energy functional E_{prop} from (4) with respect to c_1 and c_2, the intensities c_1 and c_2 with phase shifted Heaviside and directional control characteristics term are defined as:

$$c_1 = \frac{\int_\Omega I(x)\phi(x) H_\varepsilon(s + \phi(x)) M^k dx}{\int_\Omega H_\varepsilon(s + \phi(x)) M^k dx} \tag{6}$$

$$c_2 = \frac{\int_\Omega I(x)\phi(x) H_\varepsilon(s - \phi(x)) M^k dx}{\int_\Omega H_\varepsilon(s - \phi(x)) M^k dx} \tag{7}$$

We define an energy functional which drives zero level-set curve ϕ towards the object boundary as follows:

$$E_{spf}(\phi) = \lambda L_{spf}(\phi) + v A_{spf}(\phi) + \alpha P(\phi) \tag{8}$$

where $L_{spf}(\phi)$ is region-based length term and $A_{spf}(\phi)$ is region based area term, which are defined as follows:

$$L_{spf}(\phi) = \int_\Omega spf(I) \delta_\varepsilon(\phi) | \nabla \phi | dx \tag{9}$$

$$A_{spf}(\phi) = \int_\Omega spf(I) \phi(x) H_\varepsilon(s - \phi) dx \tag{10}$$

In (8), $P(\phi)$ is energy penalization term [4], which stops energy leakage and regularize the level set and it is defined as:

$$P(\phi) = \int_\Omega \frac{1}{2}\left(| \nabla \phi | - 1\right)^2 dx \tag{11}$$

In (9) and (10), $spf(I)$ is newly formulated SPF function which is defined as:

$$spf(I) = \frac{(I(x) - I_{GFI}(x)) M^k}{\max\left(\left| I(x) + I_{GFI}(x) \right|\right)} \tag{12}$$

I_{GFI} is a newly constructed two phase bimodal global fitted image which is defined as follows:

$$I_{GFI} = c_1 H_\varepsilon(s + \phi) + c_2 H_\varepsilon(s - \phi) \tag{13}$$

where c_1 and c_2 are intensity means defined in (6) and (7), respectively.

By the calculus of variations [11], the Gateaux derivative (first variation) of the functional E_{spf} in (8) can be defined as:

$$
\begin{aligned}
\frac{\partial \phi}{\partial t} &= \lambda \mathrm{div}\left(spf(I) \frac{\nabla \phi}{|\nabla \phi|} \right) \delta_\varepsilon(\phi) \\
&+ vspf(I)\big(\phi \delta_\varepsilon(s-\phi) - H_\varepsilon(s-\phi)\big)\delta_\varepsilon(\phi) \\
&- \left(\Delta \phi - \mathrm{div}\left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right)
\end{aligned} \tag{14}
$$

where $\delta_\varepsilon(\phi)$ is a smoothed approximation of Dirac function, which is defined as:

$$
\delta_\varepsilon(\phi) = \frac{\varepsilon}{\pi(\phi^2 + \varepsilon^2)} \tag{15}
$$

ε is a constant, which controls the width of Dirac function.

Mathematically SPF function has the value in the range of [-1,1] inside and outside of the contour. It modulates the sign of pressure force within the area of interest, such that contour contracts if it is outside of object and expands when it is inside of object. This paper introduces a new shifted Heaviside SPF function, which uses global fitted image restricted with mask term to enforce level set evolution inwards. If mask term set to 1 then it start modulating its signs inside and outside of regions of interest.

For outmoded level set methods, it is very important to set initialization of ϕ as signed distance function (SDF). The proposed formulation completely eliminates computationally expensive re-initialization procedure by using the penalizing energy from LSEWR method [4]. Initial level set function for the proposed method is defined here as:

$$
\phi(x, t=0) = \begin{cases} -\rho & x \in \Omega_0 - \partial\Omega_0 \\ 0 & x \in \partial\Omega_0 \\ \rho & x \in \Omega - \Omega_0 \end{cases} \tag{16}
$$

where ρ > 0 is constant. Finally, the subsequent steps of the method are summarized as follows:

i. Initialize M^k by and $M^0 \phi$ by ϕ_0 using (5) and (16), respectively at t = 0.

ii. Compute c_1 and c_2 using (6) and (7).

iii. Compute *spf(I)* from (12).

iv. Solve PDE of ϕ using (14) to get solution.

v. Check the solution if it is stationary. Otherwise, move to step (ii) and repeat.

This paper presents a fast and effective method for detecting high intensity regions in mammograms. These regions correspond to the regions of interest (ROI). In Fig. 1 different regions of interest in a mammogram image are identified with arrow markers. The top arrow points to the pectoral muscle. While, other arrows are pointing to the dense tissues with probable inclusion of tumors are our regions of interest.

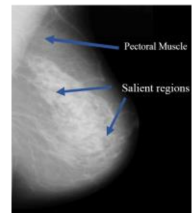
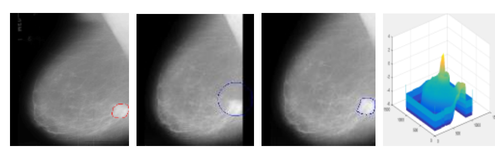


Fig. 1 Mammogram image showing high intensity regions

3. EXPERIMENTAL RESULTS

The proposed method is tested on 116 mammogram images with tumor tissues from mini-MIAS database [12]. Following parameters are selected for all experiments: $\lambda=1$, $\mu=200/2552$, $v=15$, $\Delta t=1.0$, $\rho = 4$, $\varepsilon = 1.5$ *and* $s=1.5$.
The ground truths of salient regions are not given in the mini-MIAS database only their location and diameter information is given in the supplementary files. Therefore, in the first stage ground truths are drawn manually by using hand based polygonal tool. Fig. 2 illustrates the detection and segmentation of tumor region using the proposed method. The proposed method has accurately segmented abnormal regions from the mini-MIAS database. Meaningful dense regions and masses are detected within 5 iteration steps. Fig. 3 presents more results of tumor segmentation and their ground truths using mini-MIAS database.



(a) (b) (c) (d)

Fig. 2 Segmentation result of mammograms mdb184 (first row) and mdb 271 (second row) from mini-MIAS database. (a) Original image with ground truth shown in red contour. (b) Initial Contour. (c) Final Contour after 5 iterations. (d) Final level set

4 DISCUSSION

In Fig. 4, segmentation results of proposed method are compared with other state-of-the-art methods. The first column shows mammogram images with ground truth, the second column shows the initial contour, the third column shows the results using Chan-Vese model [5], the fourth column shows results using Zhang et al. model [9] and the last column shows results using the proposed algorithm. It can be seen that the proposed method yields better segmentation results visually. Table 1 shows a quantitative analysis of the proposed method with the discussed state-of-

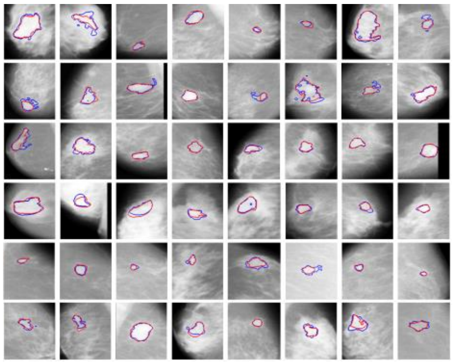


Fig. 3 Examples of detected masses from mini-MIAS database using the proposed method. The ground truth contour is shown in red and computed segment is shown in blue.

the-art methods in terms of precision, recall and number iterations. It shows that Zhang et al. method yields best precision first case. In turn, the proposed method yields best precision in both remaining cases. Chan-Vese methods yields best recall, however, it cannot properly segment regions of interest in all cases. On the other hand, recall of all other methods is also close to 1 with better segmentation accuracy. The proposed method converges faster to attain optimum solution converges in few numbers of iterations with high accuracy.

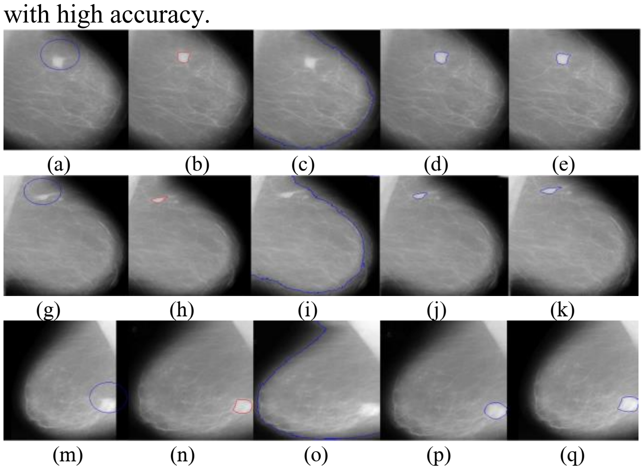


Fig. 4 Segmentation results comparison with other methods. (a), (g) and (m) Original images with ground truth. (b), (h) and (n) Initial contour. (c), (i) and (o) Chan-Vese method. (d), (j) and (p) Zhang et el. method. (e), (k) and (q) Segmentation results using the proposed method.

5. CONCLUSION

In this paper a new region-based image segmentation method based on bimodal level-set formulation is proposed, which detects high intensity regions in mammograms. The proposed method is based on region-based SPF function with level-set formulation of Lee-Seo model. The introduction of phase shift in the Heaviside function converges the level set fast to attain an optimum solution. Therefore, it is able to segment useful information in very small number of iterations with high accuracy compared to other state of art algorithms.

Table 1 Quantitative analysis based on Fig. 4.

Method	*Fig*	*Precision*	*Recall*	*Iterations*
Chan-Vese model	(a)	0.0061	**1**	100
	(g)	0.0033	**1**	100
	(m)	0.0222	**1**	100
Zhang et al. model	(a)	**0.9986**	0.9926	80
	(g)	0.8030	0.9852	90
	(m)	0.8275	0.9907	60
Proposed model	(a)	0.9285	0.9865	04
	(g)	**0.9387**	0.9664	04
	(m)	**0.9672**	0.9722	06

5. Acknowledgment

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