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Analysis of Active Contour Techniques for Digital Mammogram Images.

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ABSTRACT

Mammograms images are used as a powerful tool to identify the breast cancer. However, the presence of the noise and intensity variation makes segmentation process crucial one. In this paper we implement three methods for the segmentation of mammogram images: one based on region based, second based on the level set and the other based on the Chan-Vese active contour model. Three methods are analyzed based on the accuracy, no of iterations and efficient segmentation and the accuracy of identification.
Keywords: Mammograms, segmentation, region based segmentation, level set based segmentation, Chan-Vese active contour Model , Accuracy, iterations.

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INTRODUCTION

Breast cancer is one of the most deadly and devastating diseases among women in the whole world [1]. Mammography is the effective method of screening for breast cancer [2]. It uses to detect a disease up to two years before a lump can be felt. But in certain cases mammography can directly delay or prevent early detection and can adversely affect the woman's chances of surviving breast cancer. Computer based approach is the important one to overcome the problems stated above. However, locating the edges of the abnormalities is a complex process because of the varying thickness of the tissues in the breast. Computer-aided diagnosis and detection (CAD) can be used on the digital images to help your doctor to analyze the flag areas that need closer study. CAD can discover tumors that a radiologist might not identify. Once a CAD analysis has been done, a radiologist will decide how serious the mass may actually be.

The objective of this investigation is to address the needs of Active Contour algorithms that are designed to aid in locating abnormalities in digital mammograms. Specifically, this dissertation seeks to provide and improve tools that are considered essential to identify the abnormalities in mammogram images. This includes Active Contour Segmentation algorithm, a method for identifying the weak edges of a mammogram image, and a method for testing and comparing results from different Contour algorithms. In addition to functioning properly, the methods must be computationally efficient, i.e., their performance is feasible for use in a clinical environment.

Previously, an algorithm that effectively segments mammogram images into major sub-components and also meets the goals of efficiency and generality has been lacking. This investigation accomplishes this by creating an algorithm that segments a general mammogram image into its distinct components. This algorithm is computationally efficient and works on a general set of mammogram images without the need of "training sets." Also, effective image segmentation is required for focused and adaptive computer analysis of separate image components.

EXPERIMENTAL METHODS

In Active Contour Model, The basic idea is to start with a closed curve in two dimensions (or a surface in three dimensions) and allow the curve to move perpendicular to itself at a prescribed speed [3].The approach is very similar to the parametric method used in snakes.

M. Kass, A. Witkins, and Terzopoulos replaced the bottom up approach [4] proposed by canny using top down approach at the year of 1987[5].Contour is a time evolving curve which moves internally and externally over time. External forces and internal forces are used to reach equilibrium when energy is minimized. Image forces and external constraints are the external forces make the movement in curve evolution. Image intensity, image edges and image features act as the image forces. Cohen et all [6] added balloon force to eliminate the absence of a close feature.

Snakes algorithm failed to handle the topological changes as well as it requires the control to push the snake towards edge. To overcome this problem osher and sothian [7] introduced a PDE based method called level set method. The operation involves minimization of energy by the computation of minimal distance curves. The basic Idea of the level set method is to represent a closed curve on the plane as a zero level set of higher dimension function [8].

The surface is divided into internal regions and external regions of the curve define a signed distant function (SDF) on the surface

$$\phi(x,y,t=0)=d \quad (1)$$

The common movement formula of the level set is

$$\phi_t+F\left|v\varphi\right|=0 \quad (2)$$

Where F denotes a constant speed term to push or pull the contour.

The level set method based on the mean curvature motion is given by the equation [8];

$$\phi_t = \frac{|v\phi|}{(\varepsilon k\phi + v)} \qquad (3)$$

Where v is the correction term which is carefully chosen to keep the quantity ($\varepsilon k\phi + v$) to a positive value and k denotes the mean curvature of the level set function given by

$$k = div(\frac{v\phi}{|v\phi|}) \qquad (4)$$

Where v is a constant and it denotes correction value. It should be chosen to the quantity ($\varepsilon k\phi + v$) remains always positive. Mean curvature of the level set function is given by

$$k = \frac{\phi_{xx}\phi_y^2 - 2\phi_x\phi_y\phi_{xy} + \phi_{yy}\phi_{xx}^2}{(\phi_x^2 + \phi_y^2)^{3/2}} \qquad (5)$$

Where ϕ_x and ϕ_{yy} denote first and second order partial derivative of ϕ_x .

Caselles et all [5] proposed geometric active contours

$$\phi t = g(I(x,y)\frac{k\phi + v}{|v\phi|} + vg(I(x,y) \qquad (6)$$

Where g(I(x,y)) denotes the stopping functions.

Region base active contour techniques were proposed to reduce the noise sensitivity [9][10]."Descriptors" is the word used to represent the mathematical expressions of region of interest is extracted from the background images by boundary based hybrid techniques [11][12][13][14].The general form of including both region based and boundary based term is

$$J(\Omega in) = \int_{\Omega in} kin(\Omega in, x)dx + \eta \int_{\Gamma} kb(x)dx \qquad (7)$$

Where Ωin is the domain inside Γ and η is positive constant. An example of descriptor K_{in} is

$$kin(\Omega in, x) = (\mu(\Omega in) - I(x))^2 \qquad (8)$$

Where μ denotes the mean intensity;

$$\mu(\Omega m) = \frac{\int_{\Omega in} I(x)dx}{\int_{\Omega in} Idx} \qquad (9)$$

Region based active contour model is implemented by three process. First process is to convert parametric to implicit form. Basic operation in the conversion is legrangian approach. However the management of topological changes is not simple. Spline is the second approach used in the implementation of region based segmentation. Advantage of spline implementation is less time consumption compared to level set techniques. Final operation in the implementation is smoothening. It is an approximation technique performed by balancing the tradeoff between interpolation error and smoothness [15,16].

Computational speed is the main drawback of the level set method .varying nature of the contour requires many computational steps to keep ϕ in the region of interest. The complexity is reduced by initializing the ϕ on the region where ϕ(x) ≈ 0. This has led to proposals of various narrow-band algorithms that reduce the computational complexity by only performing calculations near the zero level set [17].Chan-Vese method remains as the efficient technique for the accurate representation of ϕ. Level sets are redefined in order to minimize the segmentation process. One of the best redefined models is chan –vese active contour model. Energy function is given as

$$E = \int (I - \mu_1)^2 + \int (I - \mu_2)^2 \qquad (10)$$

Force function is derived from the equation

$$F = (I - \mu_1)^2 - (I - \mu_2)^2 \qquad (11)$$

Here F should be normalized such that || F || < 0.5 at each iteration. Chan-vase model is based on the Mumford-Shah Framework [18-21].

RESULTS AND DISCUSSION

A mammogram picture is chosen to validate the performance of the active contour models. Input mammogram image with the size of 425 x 282 is shown in figure 1.

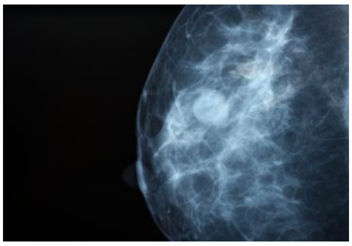


Figure 1: Input Mammogram Image

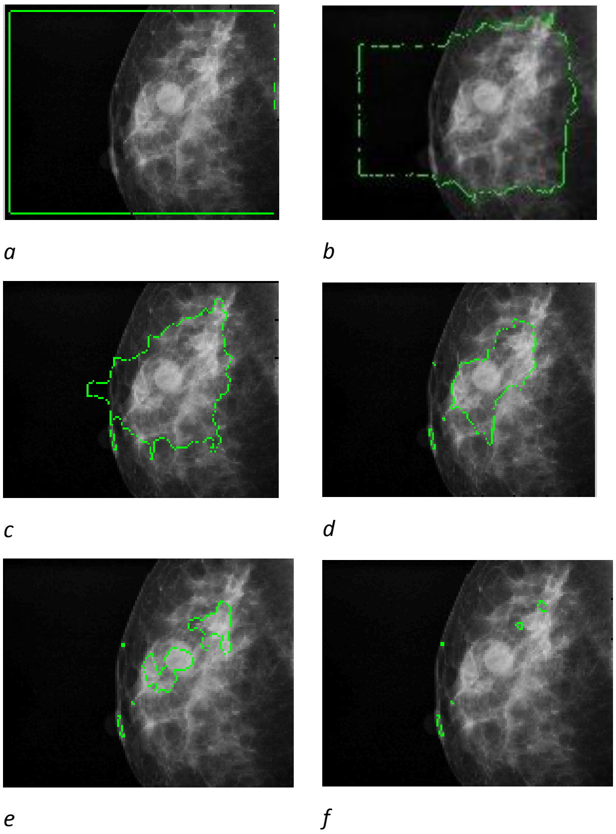


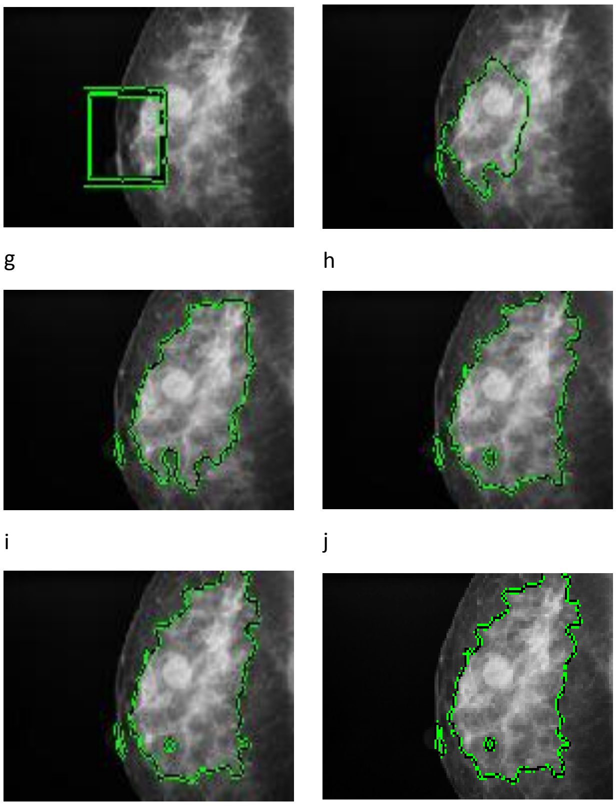
Figure 2: Level Set Based Active Contour Segmentation

(a) **Iteration=1** (b) **Iteration=100** (c) **Iteration=250**
(d) **Iteration=500** (e) **Iteration=750** (f) **teration=1000**

Level set active contour model comprises many steps. The noisy input image is smoothening by Gaussian convolution by defining Gaussian kernel smooth parameter. After defining edge indicator and step function, coefficient for the internal energy term, weighted length term and weighted area term are specified. Initial level set function is chosen on the outside on the boundary and inside of region. Level set Evaluation is done by passing the parameter and it should satisfy the Neumann boundary condition. The result of the level set active contour model is shown in figure 2.By inspecting the result for different iterations the curve shrinks as the no of iterations increases. Result for the iteration 1 shows the initial contour. In iteration 1, entire image is taken as initial contour Initial contour move towards inside as the iteration increases. Main problem of level set active contour mode is the over segmentation problem. It clearly observed by validating the result shown in the figure 2 for the iterations 750 and 1000.

In region Based segmentation Selected input image is reduce in size for faster computation. After resizing, initialization mask is specified based on the region of interest. Figure 3(b) shows the initialization mask for the selected mammogram image based on the region of interest. After getting the intermediate result the given image is converted into 2D matrix. Signed distance map (SDF) is calculated from 2D matrix mask Force is calculated by finding interior and exterior points in the image. Final step in the segmentation is the curve evaluation towards region of interest. In the force analysis the abnormalities are identified by means of external and internal forces. As the iteration increases the contour line moves closely to the affected region. Result for the various iteration is shown in the figure. Finally it identifies the abnormality region as a line evolving curve. From this curve we can easily identify the affected region and make necessary decision.

In Chan-Vese Active Contour Segmentation After specifying the masking regions, the input picture is reduced in size. Front and Background indexes are calculated. Based on the index, image components are calculated inside and outside of phi region. In Chan-vese model based on the initialization mask the curve is evolved internally or externally according to the contour forces. Output for the Chan-vesa model is shown in figure 4. If



g h i j k l

Figure 3: Region Based Segmentation

(a) **Iteration=1** (b) **Iteration=100** (c) **Iteration=250**
(d) **Iteration=500** (e) **Iteration=750** (f) **Iteration=1000**

The iteration increases the curve is moved towards the user's region of interest. Fig 4 a shows the user defined initialization mask. Figure 4 b, c, d, e, f shows the output for the iteration level 100,250,500,750 and 1000. For the maximum iteration output is more accurate. From the fig itself we say that it doesn't affected by the Over segmentation problem and it's clearly identify the defective area.

CONCLUSION

In this paper we demonstrate the effectiveness of three Active Contour models; Region based Active Contour Models, Level set methods and Chan-vese Active Contour Models. Level set methods are not sensitive to the light variation of the intensity and also affected by over segmentation problem. In case of Region based segmentation the regions are identified with the less run time compared to the Level set method and it is susceptible to the Over segmentation. But the accuracy of identifying the defective area is not a prominent one. Similar to region based Active contour model, Chan Vese model is also susceptible to the over segmentation problem and the outputs are obtained with in less runtime over than the region based method. Finally segmentation results Shows that the Chan-Vese Active Contour model is the promising model for the mammogram Images. In future we can apply this algorithm for the different computer tomography images .This will be very

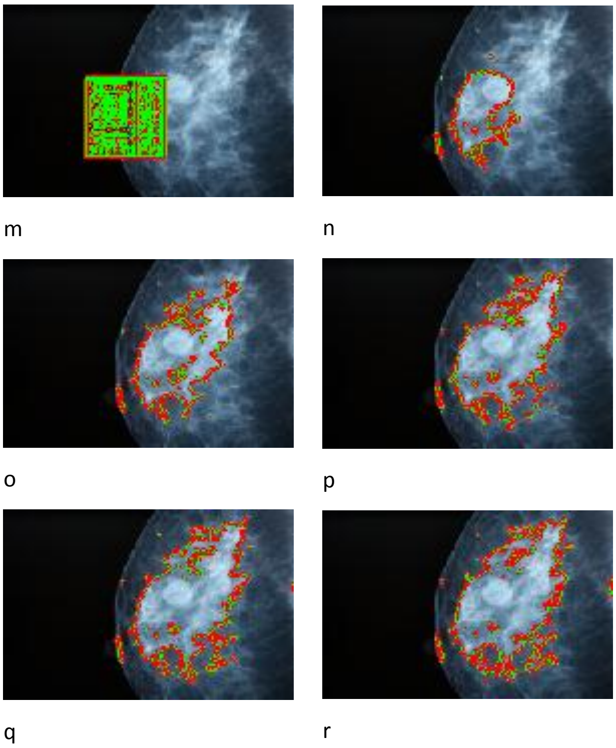


Figure 4: Chan-vese Active Contour Segmentation

(a) **Iteration=1** (b) **Iteration=100** (c) **Iteration=250**
(d) **Iteration=500** (e) **Iteration=750** (f) **Iteration=1000**

Useful method for the diagnostics for their accurate assistance. By using this algorithm diagnostics valuable time to spend to identify the disease is reduced. Within few minutes diagnostics know the cancer level and treatment level. This algorithm has better scope in the medical area.

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