Inhomogeneous Image Segmentation using Hybrid Active Contour Driven by Saliency Detection

Qurat Ul Ain[1], Shahnawaz Talpur[1], Asif Aziz Memon[1], Mahaveer Rathi[1]
Department of Computer Systems Engineering,
Mehran University of Engineering & Technology, Jamshoro

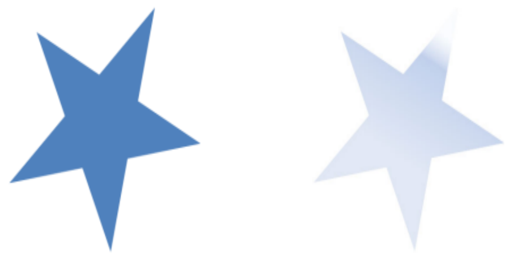
Abstract

In Image analysis, image segmentation is an important process that recognizes and removes ROI for postprocessing, including image identification. But Image segmentation isn't always an easy task as image attributes such as color, texture, and intensity have a major effect on segmentation accuracy. The performance of image segmentation models is severely impacted by image inhomogeneity and the outcomes are strongly dependent on the initial positioning of the contour. By the combination of Saliency Map and Signed pressure force, a hybrid ACM is proposed. An image's saliency map changes its representation, making it much more visible and significant and SPF is used to segment the images with a low gradient or to obscure the blurred images. The proposed approach is independent of the initial contour position and provides greater accuracy in comparison with other models. This model was evaluated using a publicly available dataset.

Index Terms: Image segmentation, ACM, SPF, Saliency map, level set.

Introduction

In computer vision, the most fundamental and significant problem is segmenting the images [1]. Image segmentation is used for a variety of purposes, including object identification, object recognition, and image analysis [2][3]. The image segmentation technique aims to separate ROI from the background of an image. Certain features, such as intensity, texture, or color, are used to classify the item or region of interest [4]. Other issues that can impact the segmentation process include noise, poor resolution, and rapid intensity variations. Image inhomogeneity is the term for this rapid intensity variation, which is more often appears in images. The most common cause of image inhomogeneity is spatial variances caused by errors in imaging technologies. Figure 1 shows examples of homogeneous and inhomogeneous images. Depending on image characteristics and segmentation methods, many techniques have been developed but ACM is an unsupervised method that had enormous success in the image segmentation field. A useful way for obtaining smooth closed boundaries around an object of interest is given by. Kass et al



(a) (b)

Figure 1. Examples of Images. (a) Homogeneous Image (b) In-Homogeneous Image

ISBN # 978-969-23372-2-9

The two main types of active contour models are Parametric ACM which is also called Snake and the other one is Geometric active contour which is based on level set [7]). Parametric ACM is reliant on the initial contour position and is unable to manage a dramatic change in curve structure. Whereas the geometric active contour model's curve movement is determined by geometric characteristics rather than expression factors. As a result, these models are better able to deal with abrupt changes in curve shape and can expand the scope of the implementation. Other models are less effective than geometric ACM which is based on the level set method [8,]. For segmenting images various dimensions such as color, intensities as well as textures are used. Those models are further divided into edge-based ACMs [9] and this model relies on the corners/edges of an object to segment [10] and cannot segment images with weak edges of the object. The other one is Region ACM which segments images with unclear borders. The contour is evolved toward the borders using both internal and external energies. For images with weak boundaries, region-based segmentation produced better results, but this model relies on the postulation that ROI is only made of uniform intensity, which restricts the model's usefulness when dealing with inhomogeneous images. It's difficult to deal with image intensity inhomogeneity and develop an effective technique for segmenting inhomogeneous images [12]. A hybrid strategy based on a saliency map and the SPF function can help solve some of these issues. An image's saliency map alters its representation, making it more visual and meaningful. The SPF function removes the initial contour position and captures inhomogeneous objects in images and increases segmentation accuracy by capturing weak edges of the object.

Related Studies

Various Geometric ACM relies on a level set formulation each contains its own set of limitations. A hybrid active contour driven by Saliency detection is proposed to overcome the limitations of several image segmentation models including the CV model, LBF, LIF, as well as SDREL models.

A. The Chan-Vese (CV) Method

The CV method [13] was presented by Chan and Vese, and it handles that segmenting image objects are homogeneous. Let C be a random curve and let $I\colon \Omega \to R^2$ be the original image. Because it is unchanged by object borders and the object with weak boundaries and low gradients this model cannot segments the image. This CV model is among the finest ACM for regions. As a result, the following is how the energy of CV is calculated:

$$E^{CV}(C, x_1, x_2) = vArea(Inside(C)) + \mu Length(C) + \lambda_1 \int_{inside(c)} |I(x) - x_1|^2 dx + \lambda_2 \int_{outside(c)} |I(x) - x_2|^2 dx -- (1)$$

where x_1 and x_2 represents inside and outside C, that indicate the average grey value, λ1, λ2, ν, μ show the related coefficients.

ISBN # 978-969-23372-2-9

B. LBF Method

Li et al. [14], [15] suggested a local binary fitting method that includes the information of a local image to produce local fitting energy with the help of the Gaussian kernel function to solve the constraint of extracting features with intensity inhomogeneity. Images with inhomogeneous intensities can be segmented using this approach, however, each iteration includes 4 convolution operations, increasing the computational cost. The following is the complete LBF energy function:

$$E_{LBF}(C, z_1, z_2) = \lambda_1 \int_\Omega K_\sigma(x-y)|I(y) - z_1(x)|^2 H_\epsilon(\phi(y))dy + \lambda_2 \int_\Omega K_\sigma(x-y)|I(y) - z_2(x)|^2 \left(1 - H_\epsilon(\phi(y))\right) dy \quad --(2)$$

C. LIF Method

The local image fitting (LIF) energy model was presented to reduce the difference between the fitted and input images [16]. With the help of a piece-wise smooth assumption, the internal and external regions can recreate input images I in a small region. The following is the concept of the LIF energy model:

$$\mathrm{E_{LIF}} = \frac{1}{2}\int_\Omega |\mathrm{I(x)} - \mathrm{I_{LIF}(x)}|^2 \mathrm{dx} \quad --(3)$$

The accuracy of this model is the same as that of the LBF [17] model. But, due to the Gaussian filter, the LIF [18] model ignores significant characteristics of small objects, resulting in insufficient image segmentation.

D. SDREL Method

In this, a map that is called a Saliency Map is combined with a global ACM in the Saliency-driven region edge-based top-down level set evolution model (SDREL) [19] to segment grayscale and colored images. SDREL's segmentation results are good, and the contour grows closer to the object boundaries in less time. Images with intensity inhomogeneity will not provide significant results because SDREL employs a saliency map in association with an ACM based on global image information. SDREL's level set equation is as follows:

$$\frac{d\varphi}{dt} = g[-\lambda_1.(I - c_1)^2 + \lambda_2.(I - c_2)^2 \beta_1(S - a_1)^2 + \beta_2(S - a_2)^2] \quad --(4)$$

Here, λ_1, λ_2, β_1, β_2 are constant positive parameters; S is the saliency map; and a_1 and a_2 are the average saliency of the contour's internally and externally regions.

The Proposed Method

In this research, for the segmentation of inhomogeneous images, the ACM driven by the energies of LSF as well as SPF is proposed. An input image's saliency map is calculated first. Then, using the saliency map, LSF energy is calculated, and finally, a novel energy functional that combines SPF and LSF is proposed. In most images, foreground and background regions are inherently inhomogeneous. To solve the problem, a hybrid ACM based on Saliency Map with signed pressure force is proposed that effectively segments inhomogeneous,

ISBN # 978-969-23372-2-9

noisy images and remains independent of the contour's starting position.

The main strategy of the SPF function is to create a primary cause that is based on the region's information. The region function uses area information to adjust the sign of the forces of the pressure, so the contour contracts when it's outside the object of interest and expands when it's inside

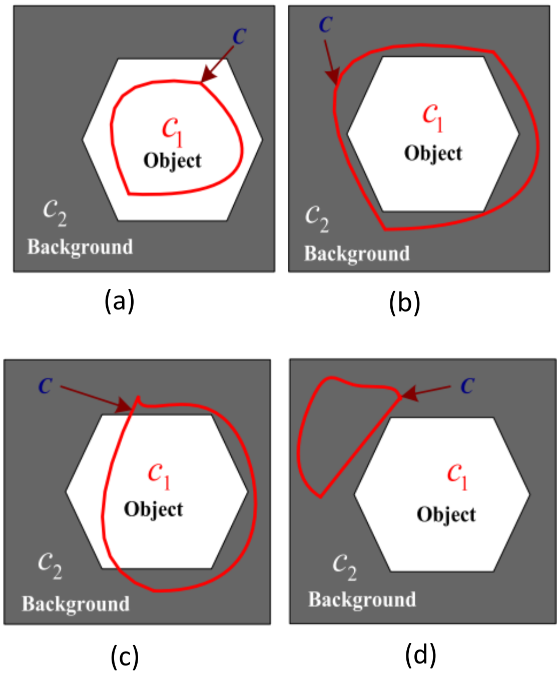


Figure 2: Various starting points. (a) The expanding curve is entirely within the object region; (b) The growing curve is entirely contained within the object region; (c) The increasing curve intersects the object region; (d) The emerging curve is entirely outside the object region. region.

Proposed Model

1: The level is put as zero and the constant function is set as the initial contour.

$$\emptyset_{t=0} = \begin{cases} q, x \in \Omega - \Omega_o \\ -q, x \in \Omega_o - \partial\Omega_o \\ 0, x \in \partial\Omega_o \end{cases}$$

Here, q represents the constant parameter, Ω_o is a subset of the image Ω, and $\partial\Omega_o$ represents boundary of Ω_o.

2: Compute the saliency map of the given image using the formulas below:

$$S(x,y) = |I_u - I_g(x,y)|$$

3: Calculate H_ϵ (φ) and δ_ϵ (φ) using the below formulas:

$$H_\epsilon(\varphi(x)) = \frac{1}{2}(1 + \frac{2}{\pi}\arctan(\frac{\phi}{\epsilon}))$$

$$\delta_\epsilon(\phi) = \frac{\epsilon}{\pi(\phi^2 + \epsilon^2)}$$

4: Observe image means m_1 and m_2 and the saliency means L_{s1} and L_{s2}.

$$m_1 = mean(I \in ((x \in \Omega | \phi(x) < 0 \cap W_k(x)))$$

$$m_2 = mean(I \in ((x \in \Omega | \phi(x) > 0 \cap W_k(x)))$$

and

$$L_{S1} = mean(S \in ((x \in \Omega | \phi(x) < 0 \cap W_k(x)))$$

$$L_{S2} = mean(S \in ((x \in \Omega | \phi(x) > 0 \cap W_k(x)))$$

5: Calculate S_{LSF} and SPF(I) using the below Equations:

$$S_{LSF} = L_{s1}(x)H_1 + L_{s2}(x)H_2$$

ISBN # 978-969-23372-2-9

$$SPF(I) = \begin{cases} \dfrac{(I(x) - I_{GFI})M^K}{\max(|I(x) - I_{GFI}|)} & I(x) \neq 0 \\ 0 & I(x) = 0 \end{cases}$$

6: To remove re-initialization and smooth the level set function a penalizing term is used.

$$L(\phi) = \int_{\Omega} \delta\emptyset(x)|\nabla\emptyset(\mathrm{x})|dx$$

7: Calculate final evolution.

Results

The presented method was tested using a Mini-MIAS dataset as well as on Microscipic Cells [26]. The intensity range in all images is 0 to 255, and the dimension of the image in pixels length and width (length x width) is 1024 x 1024. This model is tested on the in-homogenous images. The analysis was done on MATLAB.

Below are the results that are tested on Mini-MIAS Dataset in comparison with other models.

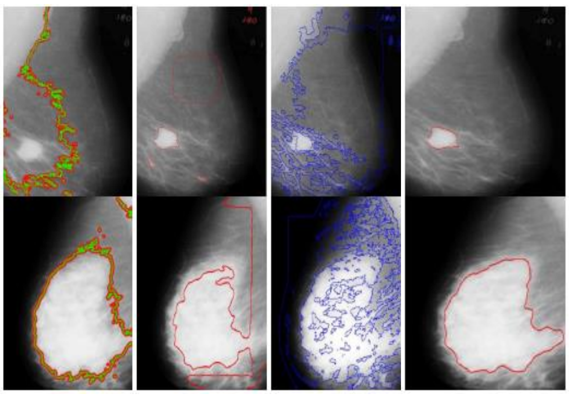
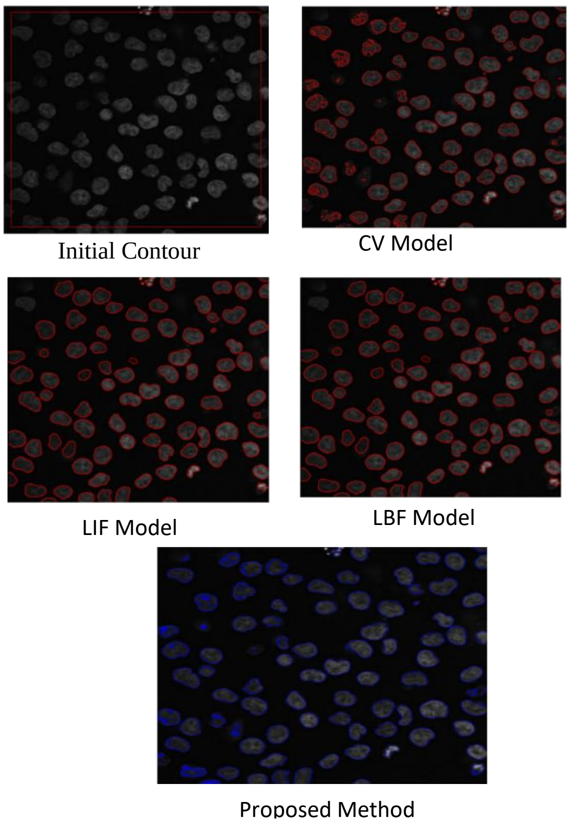


Figure 3: Result of various models in comparison of the Proposed method is given (col 1) C-V, (col 2) LBF, (col 3) LIF, and (col 4) proposed method

The results of various models are shown in Figure 3. Figure 3 (col 1) presents the CV model findings, which show that it can improve segmentation results for homogeneous images but not for inhomogeneous images. Figure 3(col 2) illustrates LBF findings, which yield superior segmentation results for inhomogeneous images. However, it is dependent on the initial position of the contour, the above results are inferior. Figure 3 (Col 3) depicts the LIF Model, which produces unsatisfactory results as well. Because the LIF model ignores some object features. The proposed model results are shown in figure 3 (col 4). The proposed model, which is a Hybrid ACM with Saliency Map and SPF function, works better for segmenting images and is independent of the initial contour position, as seen on the image. Saliency Map with SPF function works better for image segmentation and it is not dependent on the initial contour position.

This Model is not only tested on Mini-MIAS Dataset but also tested on different images. It also gives satisfactory results on microscopic Cells. In Figure 5, shows the better segmentation results in comparison with different models.



ISBN # 978-969-23372-2-9

Table 1. Performance summary for the considered methods

Parameter	CV	LBF	LIF	Proposed Method
Accuracy	0.675	0.85	0.87	0.94
Sensitivity	0.69	0.79	0.83	0.92
Dice Index	0.51	0.78	0.88	0.94

The contour evolution over inhomogeneous is independent of the original contour. The DI (Dice index) examines ROI duplicates with ground truth. Accuracy involves segmented results. proximity to ground truth. Sensitivity considers ROI detection, and accuracy necessitates segmented results' proximity to ground truth.

$$\text{Dice Index}=\frac{2*TP}{2*TP+FP+FN}$$

$$\text{Accuracy}= \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Sensitivity}=\frac{TP}{TP+FN}$$

The TP is true positive rate segments the regions of breast cancer. TN represents a True negative rate that cannot segment the non-tumor regions; whereas FP denotes a false positive rate in which the non-tumor regions are wrongly categorized as tumors, and FN is a false-negative rate in which the tumor tissues are incorrectly classified as non-tumor tissues.

Conclusion

Early breast cancer detection requires accurate breast mass identification. As a result, the research work presents a strategy for dealing with intensity inhomogeneity in mammography images. In malignant mass ROIs for breast imaging, the modified hybrid function delivers effective and efficient contour fitting. Re-initialization computations were avoided since they were computationally costly. In terms of detecting potential breast cancer regions, qualitative and quantitative studies confirmed the suggested method's superior effectiveness, efficiency, and resilience when differentiate from existing methods. As a result, the proposed model offers a valuable tool for detecting breast cancer in women.

References

[1] Elnakib, G. Gimel'farb, J. S. Suri, A. El-Baz, ''Medical image segmentation: A brief survey,'' in Multi Modality State-of-the-Art Medical Image Segmentation and Registration Methodologies. New York, NY, USA: Springer, 2011, pp. 1–39

[2] R. Chakraborty, R. Sushil, and M. L. Garg, ''An improved PSO-based multilevel image segmentation technique using minimum cross-entropy thresholding,'' Arabian J. Sci. Eng., vol. 44, no. 4, pp. 3005–3020, Apr. 2019.

[3] X. Zhang and S.-G. Zhao, ''Cervical image classification based on image segmentation preprocessing and a CapsNet network model,'' Int. J. Imag. Syst. Technol., vol. 29, no. 1, pp. 19–28, Mar. 2019.

[4] E. Karami, M. S. Shehata, and A. Smith, ''Adaptive polar active contour for segmentation and tracking in ultrasound videos,'' IEEE Trans. Circuits Syst. Video Technol., vol. 29, no. 4, pp. 1209–1222, Apr. 2019

[5] M. Kass, A. Witkin, and D. Terzopoulos, ''Snakes: Active contour models,'' Int. J. Comput. Vis., vol. 1, no. 4, pp. 321–331, Jan

ISBN # 978-969-23372-2-9

[6] M. Kass, A. Witkin, and D. Terzopoulos, ‘‘Snakes: Active contour models,’’ Int. J. Comput. Vis., vol. 1, no. 4, pp. 321–331, Jan. 1988.

[7] T. F. Chan and L. A. Vese, ‘‘Active contours without edges,’’ IEEE Trans. Image Process., vol. 10, no. 2, pp. 266–277, 2001

[8] S. Osher and J. A. Sethian, ‘‘Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton–Jacobi formulations,’’ J. Comput. Phys., vol. 79, no. 1, pp. 12–49, Nov. 1988.

[9] C. Liu, W. Liu, and W. Xing, ‘‘A weighted edge-based level set method based on multi-local statistical information for noisy image segmentation,’’ J. Vis. Commun. Image Represent., vol. 59, pp. 89–107, Feb. 2019

[10] S Pramanik, D. Banik, D. Bhattacharjee, M. Nasipuri, M. K. Bhowmik, and G. Majumdar, ‘‘Suspicious-region segmentation from breast thermogram using DLPE-based level set method,’’ IEEE Trans. Med. Imag., vol. 38, no. 2, pp. 572–584, Feb. 2019

[11] N Paragios and R. Deriche, ‘‘Geodesic active contours and level sets for the detection and tracking of moving objects,’’ IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 3, pp. 266–280, Mar. 2000

[12] M. Li et al. "Minimization of region-scalable fitting energy for image segmentation," IEEE transactions on image processing, vol. 17, no. 10, pp. 1940–1949, 2008.

[13] T. Chan and L. Vese, ‘‘Active contours without edges,’’ IEEE Trans. Image Process., vol. 10, no. 2, pp. 266–277, Feb. 2001.

[14] C. Li, C. Xu, C. Gui, and M. D. Fox, ‘‘Level set evolution without reinitialization: A new variational formulation,’’ in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., Jun. 2005, pp. 430–436.

[15] C. Li, C.-Y. Kao, J. C. Gore, and Z. Ding, ‘‘Minimization of region-scalable fitting energy for image segmentation,’’ IEEE Trans. Image Process., vol. 17, no. 10, pp. 1940–1949, Oct. 2008

[16] K.-h. Zhang, H.-h. Song, and L. Zhang. "Active contours driven by local image fitting energy," Pattern recognition, vol. 43, no. 4, pp. 1199–1206, 2010.

[17] C.-m. Li et al. "Minimization of region-scalable fitting energy for image segmentation," IEEE transactions on image processing, vol. 17, no. 10, pp. 1940–1949, 2008

[18] K.-h. Zhang, H.-h. Song, and L. Zhang. "Active contours driven by local image fitting energy," Pattern recognition, vol. 43, no. 4, pp. 1199–1206, 2010.

[19] X.-H. Zhi and H.-B. Shen, ‘‘Saliency driven region-edge-based top-down level set evolution reveals the asynchronous focus in image segmentation,’’ Pattern Recognit., vol. 80, pp. 241–255, Aug. 2018

ISBN # 978-969-23372-2-9