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Object Segmentation with Active Contours Driven by Weight Matrix

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ABSTRACT

Active contour model is one of the most popular image segmentation technique. In active contours model a curve is evolve under the constraints of image forces which evolve the contour towards region of interest. These methods use image statistical information to deform the curve towards object boundaries. There are two types of active contour models: edge-based models and region-based models. Both models have their own advantages and disadvantages, and their usage depend on the characteristics of the image. Some researchers proposed hybrid energy functional which use region force and edge term together. Edge-based active contour models use image gradient information. Edge-based methods utilize edge stopping function to enforce the contour to the desired boundaries. Alternatively, region-based models use image statistical information to control the contour evolution. Their major advantage over edge-based models is, they perform well over noisy and blurred images. Moreover, the location of initial contour has less significance in region-based models. Li et al. present a local region-based model to overcome the problem of intensity inhomogeneity. They introduced a gaussian kernel with local image information which is called local binary fitting energy (LBF) to segment the inhomogeneous regions.

This thesis presents an improved local active contour by introducing weight matrix into local energy term. Weight matrix is constructed on optimal threshold which removes weak intensities and enhance the weight of the desire objects. Weight matrix plays an important role for contour evolution in severe inhomogeneous regions. It helps to extract region of interest and eliminates some unimportant information from the image. The proposed method is less sensitive to initialization position as compared to other local models. For the regularization of level set function, a Gaussian kernel is computed which also helps to eliminate the costly re-initialization. Proposed method is evaluated on real and medical images. Experiment results were performed on PH2 skin lesion database and Caltech database for the quantitative validations. Quantitative analysis reveals the efficiency and robustness of our method.

Keywords: Weight matrix, Image segmentation, Level set, Active cont.

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Chapter 1
Introduction

1.1 Image Segmentation

In computer vision and image processing, image segmentation is the technique of dividing the image into different representation that is easier to analyze. After segmentation we extract region of interest or important features of an image. Basically, image segmentation is the technique of locating the object boundaries, lines and curves in images. Segmenting the region of interest is the challenging task as it depends on the simplicity of the algorithm, accuracy, computational cost, parametric selection and sensitivity of the algorithm. Intensity inhomogeneity occurs due to the reason of defects in capturing device and influence of the outer interfaces. Intensity inhomogeneity is the condition of varying intensity so smoothly that it is difficult to extract the object boundaries from the background. Over the years, many methodologies have been presented for inhomogeneous image segmentation including level set method [1]. Each of it has its own advantages and disadvantages regarding to image type. Most famous image segmentation techniques are based on clustering, thresholding, graph partitioning, histogram based, probabilistic cuts and active contours.

1.2 Active Contours

In 1980s. Sethian and Osher [1] proposed level set methods which are widely used in image processing related fields applications (e.g., image segmentation, Iris tracking and medical image segmentation [2, 3]). In late 1980, Kass et al. [4] developed an active contour method, which is useful to identify the region of interest (ROI) in image recognition, image detection and segmentation [5, 6]. In active contour model, a curve is evolved under constraints from a given image. In snakes or active contour model an edge detector is used to stop the curve at the object boundary, which depends on the image gradient. There are two types of active contour models: edge-based [4, 7] models and region-based models [8, 9]. Both models have their own advantages and disadvantages, and their usage depend on the characteristics of the image. Some researchers proposed hybrid energy functional [10] which use region force and edge term together.

Edge-based active contour models use image gradient information to stop the curve evolution on the object boundaries [11, 12]. Edge-based methods utilize edge stopping function to enforce the contour to the desired boundaries. Usually, a balloon force is deployed into the edge function to control the motion of the contour. Balloon force controls the contour evolution that's why the choice of appropriate balloon force [13] is sometimes difficult. Moreover, they do not achieve desired result on the images with low contrast, blurred edge and severe noise. Alternatively, region-based [8, 9] models use image statistical information to control the contour evolution. Their major advantage over edge-based models is, they perform well over noisy and blurred images. Moreover, the location of initial contour has less significance in region-based models. One of the most popular region-based method is the Chen-Vese method [8]. This model is very successful for binary phase segmentation, but it has limitation on images with multiple regions[14]. Chen-Vese extended their earlier work and proposed piece-wise constant (PC) models[15], in which they utilize multilevel set formulation to represent multiple regions. However, chan-vese methods do not work on the images with intensity inhomogeneity as they operate on the assumption that the given image is inhomogeneous.

Vese and Chen [16] and Tsai et al. [17] introduced two similar models to solve the problem of intensity inhomogeneity, which are called piecewise smooth (PS) models. They work well over inhomogeneous images, but their computational cost is very expensive. Li et al. [18] proposed a local region-based model to overcome the problem of intensity inhomogeneity. They introduced a gaussian kernel with local image information which is called local binary fitting energy (LBF) to segment the inhomogeneous regions. LBF successfully able to overcome the limitation of piecewise smooth function (PS). In comparison with PS model, LBF model can properly segment the images with intensity inhomogeneity with computational efficiency and give us more accurate segmentation. However, LBF model is very sensitive to initialization, which limits its applications. Zhang et al.[19] also proposed an active contour model for images with intensity inhomogeneity. The used image local information which is called local image fitting energy (LIF) for image segmentation. The use Gaussian kernel to regularize level set method which avoid the expensive reinitialization. Gaussian smoothing filter increases its computation efficiency as compared to LBF model. However, due to the usage of smoothing filter, the LIF model ignores the small details during segmentation. Therefore, it gives us insufficient segmentation in inhomogeneous regions.

Both LBF[18] and LIF[20] models have limited segmentation performance performances in the presence of high severe inhomogeneity. Lei et al[20] proposed a local hybrid image fitting energy to overcome this issue. He integrated the local image fitting energy in a variational level set framework to enforce the contour evolution towards the object boundaries. Local Hybrid energy fitting functional (LHIF)[20] combined the strength of both LBF and LIF models. In their functional they approximate the square of local image in square fitted image (SFI) which proves to be an optimal way to drive the contour curves toward the boundaries of desirable objects.

(b)

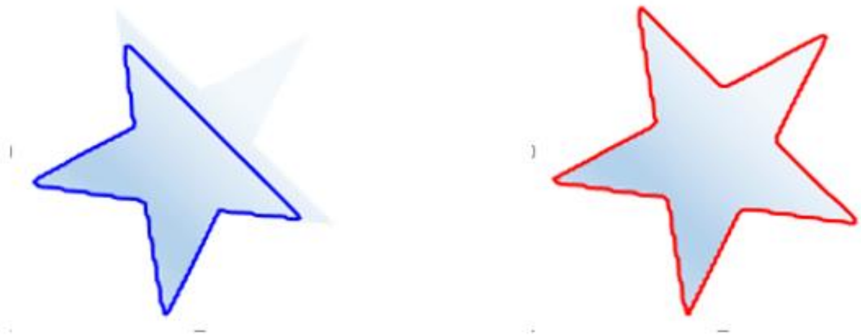


Figure 1: Image segmentation on inhomogeneous images using (a) chan vese (b) LBF

1.3 Motivation

Object boundaries are always very important for the computer vision[21] and pattern recognition. During segmentation our main concern is to find the bojects of interest than the other parts of given image. Sometimes, due to illumination, noise, blurred edges and unwanted shadows in each image, which results in erroneous segmentation. In this theis, we proposed an active contour model by utilizing weighted matrices to detect objects of interest. It relies on the LIF model and proposes a local weighting factor of the mean region intensity in the data driven term. The basic idea is to embed weighted matrices into local image fitting model, so that the active contours can detect region of interest in inhomogeneous regions and ignore the trivial or weak parts. We used Otsu's [22] method for threshold detection. Furthermore, for more accurate segmentation, we can use different threshold technique to find the more precise threshold value according to given image.

1.4 The proposed method

We proposed and improved local active contour by introducing weight matrix into local energy term. Weight matrix is constructed on optimal threshold which removes weak intensities and enhance the weight of the desire objects. Weight matrix plays an important role for contour evolution in severe inhomogeneous regions. It helps to extract region of interest and eliminates some unimportant information from the image. In this method, we are using Otsu's algorithm [22] to acquire the optimal threshold automatically.

The LIF model use Gaussian smoothing filter which increase its computation efficiency as compared to LBF model. However, due to the usage of smoothing filter, the LIF model ignores the small details during segmentation. Therefore, it gives us insufficient segmentation in inhomogeneous regions.

Inspired by the work of chen at el.[24] we proposed an active contour model by introducing a weight matrix into local image fitting energy. Weight matrix in LIF [19] enhance the values of foreground region and lower the effect of background region in a given image. Therefore, it differentiates the foreground and background pixels which helps the contour evolution towards the object of interest.

1.5 Thesis Organization

This thesis has five chapters. Chapter 2 contains the background and related work about image segmentation with active contour. In chapter 3 we explained about the energy formulation of proposed method. All the mathematical steps to implement the proposed method are also discussed in algorithm section. In chapter 4 we showed the experiment results of proposed method as compare to other state of art methods. Iterations and CPU time table are also presented for qualitative analysis in chapter 4. For quantitative analysis we compared our method on some medical images. In chapter 5 we concluded our contribution with some future work.

Chapter 2

Related Work

There are two type of active contour models: Edge based and region-based models. Edge based active contours model use image gradient information to detect the boundaries of the object. Edge function is used in edge based active contour model. It becomes zero at the boundary of an object which stop the further movement of the evolving curve. They have one major disadvantage that they are very sensitive to noise and give very poor segmentation results on images with blurry or no clear boundaries. On the other hand, region based active contour models use image statistical information to evolve the curve and use stopping function to stop the contour between the regions. These methods are fast and have better results in noisy and inhomogeneous regions. Region based active contours further categorize into local and global based active contour models.

2.1. Mumford-shah model

In [9], Mumford and Shah proposed a methodology for region-based image segmentation. Their method focuses on finding the optimal piece-wise smooth approximation function u of image I, and this function keep changing smoothly within each sub-region of image domain $I:\Omega \to R^2$. They proposed the following energy functional:

$$E_{MS} = \lambda \int_{\Omega} \left| I(x) - u(x) \right|^2 dx + v \int_{\Omega / C} \left| \nabla u(x) \right|^2 dx + \mu L(C) \qquad (1)$$

Where | C | is contour's length, and $\mu, v \geq 0$ are fixed parameters.

However, minimization of above function is very difficult because of unknown set C and non-convex behavior of energy functional. Over the years, many alternative methods have been proposed to simplify the above functional, including one very popular one reviewed below.

2.2. Chan-Vese model

Chan-Vese (CV) [8] suggested a simplified model grounded on the concept of Mumford-Shah model [9]. This method approximated an image intensity of every region inside and outside of curve called u_1 and u_2 respectively. Assume I: $\Omega \subset R^2$ is image, Φ: $\Omega \subset R^2$ a level set function and C an enclosed curve relating to the zero-level set: C = {x ∈ Ω|Φ(x) = 0}. The Chan-Vese energy function is defined as:

$$E_{CV}(C,\mu_1,\mu_2) = \lambda_1 \int_{\Omega} |I(x)-\mu_1|^2 H_\varepsilon(\phi(x))\,dx + \lambda_2 \int_{\Omega} |I(x)-\mu_2|^2 (1-H_\varepsilon(\phi(x)))\,dx + \mu \int_{\Omega} |\nabla H_\varepsilon(\phi)|^2 dx + v \int_{\Omega} H_\varepsilon(\phi) \tag{2}$$

$\mu \geq 0$, $v \geq 0$ and $\lambda_1, \lambda_2 \geq 0$ are constants parameters, where $\mu \geq 0$ controls the Euclidian length of the contour and v is the constant that controls the area term inside the contour C. H_ε (Φ) is regularized Heaviside function explained as:

$$H_\varepsilon(\phi) = \frac{1}{2}\left(1 + \frac{2}{\pi} arctan\left(\frac{\phi}{\varepsilon}\right)\right) \tag{3}$$

Where ε manages the smoothness of Heaviside function. In Eq (2), u_1 and u_2 are average global force terms inside and outside of curve C, respectively. Minimization of Eq (2), with respect to Φ by gradient descent method [23], we have the corresponding level set formulation:

$$\frac{\partial \phi}{\partial t} = \left(-\lambda_1 (I-\mu_1)^2 + \lambda_2 (I-\mu_2)^2 + \mu div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) - v \right) \delta_\varepsilon(\phi) \tag{4}$$

Where δε(Φ) is a smooth form of a Dirac delta function, explained as:

$$\delta_{\varepsilon}(\phi) = \frac{\varepsilon}{\pi(\phi^2 + \varepsilon^2)} \tag{5}$$

Beside controlling the smoothness of a Heaviside function, ε also handles the size of the Dirac function in Eq (5). Minimizing energy in Eq (2) with respect to c_1 and c_2, we get:

$$c_1 = \frac{\int_{\Omega} I(x) H_{\varepsilon}(\phi(x)) dx}{\int_{\Omega} H_{\varepsilon}(\phi(x)) dx} \tag{6}$$

$$c_2 = \frac{\int_{\Omega} I(x)(1 - H_{\varepsilon}(\phi(x))) dx}{\int_{\Omega} (1 - H_{\varepsilon}(\phi(x))) dx} \tag{7}$$

Chan-Vese segmentation strategy is associated with only global characteristics of an image and this method is able to segment only homogeneous regions. Thus, this method yields undesirable outcome if the image has intensity variation or inhomogeneous regions.

2.3. LBF model

Li et al. [18] proposed the local binary fitting (LBF) model for intensity inhomogeneity. The LBF [18] model works well for intensity inhomogeneity due the usage of image local energy information. They introduce the kernel function which defines the energy function as below:

$$E^{LBF}(C, f_1, f_2) = \lambda_1 \int\int_{inside(C)} K_\sigma(x-y)\left|I(y) - f_1(x)\right|^2 dydx$$
$$+\lambda_2 \int\int_{outside(C)} K_\sigma(x-y)\left|I(y) - f_2(x)\right|^2 dydx \tag{2.12}$$

where $\lambda_1, \lambda_2 > 0$ are fixed parameters. K_δ is a Gaussian kernel having standard deviation σ. f_1 are the average intensity value inside the contour C and f_2 are the average intensity values outside of contour C. f_1 and f_2 are defined as:

$$f_1(x) = \frac{K_\sigma * [H_\delta(\phi)I(x)]}{K_\sigma * H_\delta(\phi)} \tag{2.13}$$

$$f_2(x) = \frac{K_\sigma * [(1 - H_\delta(\phi))I(x)]}{K_\sigma * (1 - H_\delta(\phi))} \tag{2.14}$$

For the Lipchitz function ϕ, the curve C is represented by the zero level set, and the minimization of the energy functional E^{LBF} gives the gradient descent flow as follows:

$$\frac{\partial\phi}{\partial t} = -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) \tag{2.15}$$

where e_1 and e_2 are defined as:

$$e_1 = \int K_\sigma(y-x)\left|I(x) - f_1(y)\right|^2 dy \tag{2.16}$$

$$e_2 = \int K_\sigma(y-x)\left|I(x) - f_2(y)\right|^2 dy \tag{2.17}$$

Due to the introduction of kernel function and local information LBF [18] have accurate segmentation as compared to global methods. However, LBF model is very sensitive to contour initialization.

2.4. LIF Model

Zhang et al. [19] proposed a region-based active contour model that uses image local information. They presented local fitting energy to estimate imagen local information and achieved better segmentation as compared to LBF [18].

They defined the following energy functional:

$$E^{LIF}(\phi, m_1, m_2) = \frac{1}{2}\int_\Omega \left|I - I^{LFI}\right|^2 dx \tag{8}$$

$$I^{LFI} = m_1 H(\phi) + m_2(1 - H(\phi))$$

Where m_1 and m_2 are defined by

$$m_1 = mean\left(I \in \left(x \in \Omega \middle| (x) < 0 \cap W_k(x)\right)\right)$$
$$m_2 = mean\left(I \in \left(x \in \Omega \middle| (x) > 0 \cap W_k(x)\right)\right)$$

They used ractangual guassian window function in their method which is represtend with $W_k(x)$ in above equation. In their functional they approximate the weighted the intensities values inside that window. m_1 are the avarage intensity values inside contour C and m_2 are the average intesity value outside contour C in that guassain window.

Chapter 3

Local active contour driven by weight matrix

In this chapter we briefly explained about an improved active contour model with weight matrix based on a level set formulation. The proposed energy function uses image local energy with mathematically constructed weight matrix to force the contour towards the object of interest and stop them at boundaries. Weight helps to extract region of interest by eliminating some unimportant information from the image. Weight matrix in LIF model enhance the values of foreground region and lower the effect of background region in a given image. The proposed method gives better result as compared to other local methods and give better results even in the presence of complex background.

3.1. Otsu's Method

Otsu [22] is automatic clustering-based image thresholding method which convert the gray level image to a binary image. Otsu's method works on the assumption that image has two classes of pixels which means histogram and images are bimodal (foreground and background pixels). Algorithm then finds the optimal threshold differentiating the both classes that minimizes the intra-class variance, or which is same as maximizing the inter-class variance. By applying otsu's method, we exhaustively search for the optimal threshold that minimizes the inter class variance:

$$\sigma_{\omega}^{2}(T)=\min_{t}(\varpi_{1}(t)\sigma_{1}^{2}(t))+\varpi_{2}(t)\sigma_{2}^{2}(t)) \quad (9)$$

Where σ_i^2 (i = 1,2) is the variances of the two classes and weights ω_i are the probabilities of these two classes separated by a threshold t. In this paper, we are using Otsu's method [22] to search the optimal threshold t that we will utilize to construct the weight matrix.

3.2. Prosed Method Formulation

Weight matrix is defined as:

$$\begin{aligned} w_1 &= (I-t)(I_{\max}-I_{\min}) \\ w_2 &= 1-w_1 \end{aligned} \quad (14)$$

Where I is a given image, I_{max} and I_{min} are the maximum and the minimum intensities of the image I respectively calculated by Otsu's method. t is an optimal threshold value of image I which can be calculated by many threshold detection algorithms. In this paper, we used Otsu's [22] method to calculate the optimal threshold t, which is then used to construct the weight matrices w_1 and w_2 in Eq (14). let's assume that region of interest has an average intensity m1 and background has average intensity m_2; and $m_1 > m_2$. when the optimal threshold t < m_1, it means that

$w_1 > 0$ for the region of interest which will enhance the values of first term in Eq (10). On the other hand, the background influence will be reduced due to weight ($1 - w_2$) while we minimize Eq (10). So, high intensity region and low intensity region can be separated with help of Eq (14).

Eq (14), shows that w_1 will enhance the value of every pixel which has intensity greater than optimal threshold t. On the contrary, the influence of every other pixel which has intensity value less than threshold t will be reduced in curve evolution. Thus, the weight matrix affects the curve evolving force to a great extend.

Weight matrix into local fitted image (LFI) is defined as follow:

$$I^{LFI} = w_1 m_1 H(\phi) + w_2 m_2 (1 - H(\phi)) \qquad (11)$$

Where w1 and w2 are the weight matrices Eq (14), m1 and m2 are defined

By

$$m_1 = mean\left(I \in \left(x \in \Omega \middle| (x) < 0 \cap W_k\left(x\right)\right)\right)$$
$$m_2 = mean\left(I \in \left(x \in \Omega \middle| (x) > 0 \cap W_k\left(x\right)\right)\right)$$

Where I^{LFI} (Local Fitted Image) is the approximation value of image I inside local region. W_k is a Gaussian window of radius K and m1 and m2 are average intensity values inside that window; it has standard deviation of σ.

The proposed method uses zhang et al [19] local fitting energy functional. In

Zhang's local fitting model the minimization of the difference between fitted image Eq (10) and the original image give us new local image fitting energy functional. The formulation is as follows:

$$E^{LIF}(\phi) = \frac{1}{2}\int \left| I(x) - I^{LIF} \right|^2 dx, \quad x \in \Omega \tag{12}$$

The following is the corresponding gradient descent ow with weight matrix. It is obtained by minimizing the $E^{LIF}(\Phi)$ with the help of the calculus of variation and the steepest descent method [23].

$$\frac{\partial \phi}{\partial t} = \left(I - I^{LFI}\right)\left(w_1 m_1 - w_2 m_2\right)\delta_\varepsilon\left(\phi\right) \tag{12}$$

In above equation $\delta_\varepsilon(\Phi)$ is the regularized Dirac function defined in Eq (5) and w1 and w2 are the weight matrices given in Eq (14).

The level set formulation is as follows:

$$\frac{\partial \phi}{\partial t} = \mu\left(\delta^2\phi - div\left(\frac{\nabla \phi}{|\nabla \phi|}\right)\right) + v\delta_\varepsilon(\phi)\, div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \left(I - I^{LFI}\right)\left(w_1 m_1 - w_2 m_2\right)\delta_\varepsilon(\phi) \tag{13}$$

3.3. Implementation

In the traditional level set methods, level set function Φ is initialized to signed distance function (SDF) to prevent it from being too at. Level set function need to re-initialize during contour evolution to reshape the level set function as an SDF. Li et al. [25] proposed a variational formulation which uses a penalizing term, but it is computationally very expensive. To avoid the expensive re-initialization, proposed method uses a gaussian filter to regularize the level set function. The initial level set function Φ_0 is defined as:

$$\phi(x,t=0)=\begin{cases}-\rho & x\in\Omega\setminus\partial\Omega\\ 0 & x\in\partial\Omega\\ \rho & x\in\Omega\setminus\Omega\end{cases} \tag{15}$$

Where $\rho \geq 0$ is a constant, Ω_0 is a subset of initial contour $\partial\Omega_0$, Ω is the image domain. The main implementation steps of the proposed method can be summarized with the following algorithm:

Algorithm

1. Find threshold value using Eq (9).

2. Calculate weight matrix with Eq (14).

3. Initialize the level set function Φ from Eq (15).

4. Solve level set function Φ using Eq (13).

5. $\Phi = G0_{\xi} * \Phi$, Utilize Gaussian kernel to regularize the level set function.

6. If evolution is not stationary return to step 4.

7. Output: Final and accurate segmentation result, final Φ.

Chapter 4

Results Analysis and Comparison

The comparative analysis and efficiency of the proposed method is examined in this section. All experimental results are conducted in MATLAB 9.0 (R2016a) on a Personal Computer with Intel Core i7, 3.4 GHz CPU and 16 GB RAM. Standard values of parameters used for all the experiments are given in Table 1.

Table 1: Default Parametric values used by all experiments

Method	Force Constant		Length Term constant	Gaussian Kernel/ radius constant	Initial level set constant	Dirac constant	Time Step
	λ_1	λ_2	υ	σ	ρ	ε	Δ
CV	1	1	0	-	2	1	-
LBF	1	1	0.001*255*255	3	2	1	0.1
LIF	1	1	-	3	1	1	0.025
LHIF	1	0.1	0.001*255*255	3	1	0.1	0.1
Proposed	1	1	-	3	1	1	0.025

4.1. Results on different kind of images

Fig. 1 shows that experiment results of proposed method for inhomogeneous and noisy synthetic images. These results illustrate that proposed method achieved satisfactory results on typical noisy and inhomogeneous synthetic images.

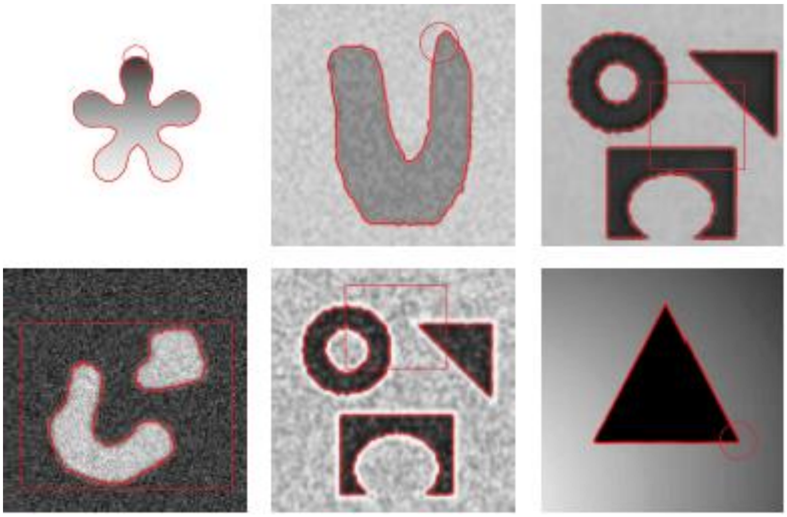


Figure 2: Segmentation of inhomogeneous and noisy synthetic images with proposed method.

4.2. Comparison with traditional methods

For comparative evaluation we compared our method with CV model, LBF model, LIF model and local hybrid image fitting model (LHIF) [20]. Fig. 2 shows a comparison of CV, LBF, LIF, LHIF and proposed method on inhomogeneous images. Column (a) shows the original images with initial red contour. Column (b) to (f) are the segmentation results of CV, LBF, LIF, LHIF and proposed method. CV model has the worst segmentation results in which background and object of interest are mixed with each other. It demonstrates that the CV model give us inadequate segmentation in inhomogeneous regions. LBF and LIF models are able to find the object of interest but had a lot of undesired parts included in segmentation. LHIF and proposed method has best segmentation accuracy among all methods which is shown in the last two columns.

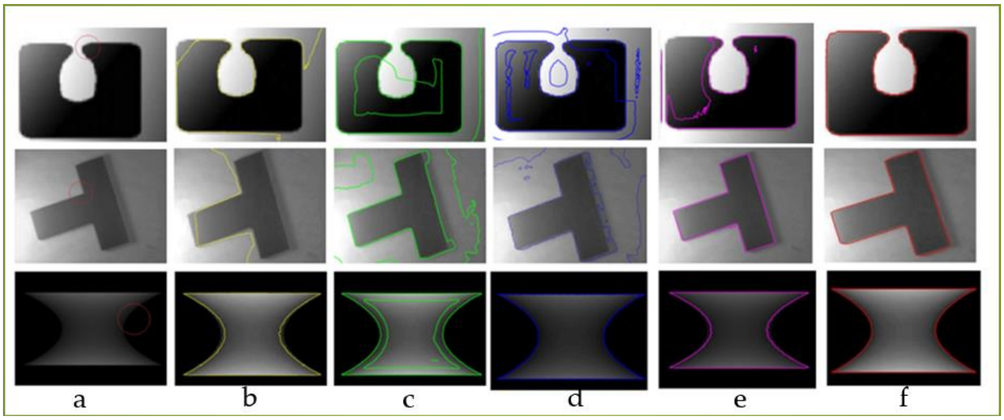


Figure 3: Column a shows original image with initial contour. Column b to f are results of CV, LBF, LIF, LHIF and proposed method, respectively.

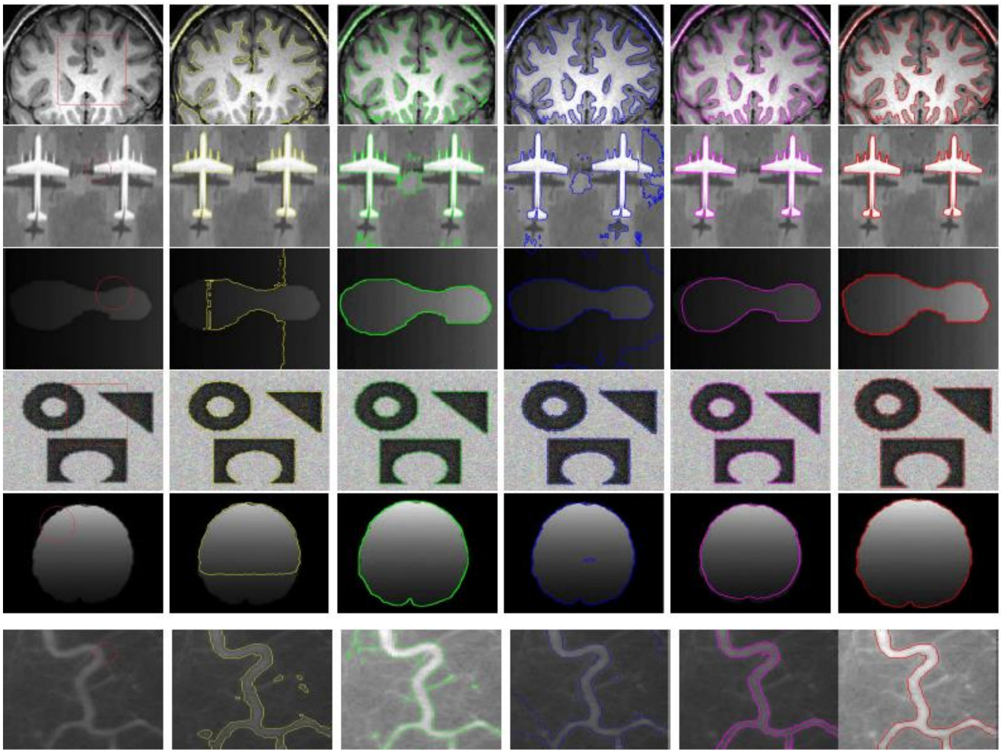
The Local active contour models [18, 19] are very efficient for the extraction of small intensity changes in images. Therefore, local model's suitability is eminent for inhomogeneous images. But, they tend to struggle in contour initialization. There is no established technique to overcome this problem. However, in proposed method, inclusion of weight matrix into local model reduce the initialization problem by distinguishing the background and foreground regions. Table 2 shows the time and iterations taken by each method for figure 3. CV model consumed less time and iterations but give us undesired segmentation.

Table 2: CPU time and iterations taken by each method in Fig 3.

Methods		Image 1	Image 2	Image 3
CV	Iterations	20	20	20
	CPU time	1.664	0.919	1.302
LBF	Iterations	50	50	50
	CPU time	9.82	9.23	7.02
LIF	Iterations	150	200	80
	CPU time	10.02	13.11	8.30
LHIF	Iterations	45	40	55
	CPU time	7.01	6.98	7.42
Proposed Method	Iterations	30	35	50
	CPU time	6.39	4.59	8.21

4.2.1. Comparison for real images

The robustness of proposed method to segmentation has also been tested on real and synthetic images which contains complex regions. Fig. 3 shows the segmentation results of proposed method and other state-of-art methods.



(a) (b) (c) (d) (e) (f)

Figure 4: Segmentation results of CV, LBF, LIF, LHIF and our method from column b to column f respectively. Column a show the original image with same initial contour for each method.

Column (a) shows the original images with initial contours used for all methods. Columns (b), (c), (d) and (e) are the segmentation results of CV [8], LBF [18], LIF [19] and LHIF [20]. From the last column, we can see that proposed method is able to get the segmentation results accurately.

Table 3 shows the computational time taken by the CV, LBF, LIF, LHIF and purposed method to segment the image. We can see from the table; purposed method gives more accurate results in less time taken by CPU as compare to other state of art methods.

Table 3: CPU time(in seconds) and iterations of each method in Fig 4.

Methods		Image1	Image2	Image3	Image4	Image5	Image6
CV	Iterations	30	30	30	30	30	30
	CPU time	4.65	3.42	4.72	2.69	3.27	3.82
LBF	Iterations	96	50	100	140	60	55
	CPU time	25.64	13.32	26.13	18.12	12.40	11.13
LIF	Iterations	300	300	300	300	300	300
	CPU time	50.36	48.90	53.89	48.13	58.36	54.29
LHIF	Iterations	60	65	45	40	35	45
	CPU time	6.12	6.18	5.32	5.54	5.96	5.59
Proposed Method	Iterations	40	60	26	30	35	40
	CPU time	5.58	5.75	4.96	5.32	6.82	5.84

We have also tested our method on real world images taken for Caltech database [26]. Figure 4 shows the segmentation results of proposed method on real images. Column (a) to column (e) are, respectively, original images with initial contour, segmentation results of CV [8], LBF [18], LIF [19], LHIF [20] and proposed method. We can observe that with the help of weight matrix our method is able to ignore the undesired regions easily. In Table 4, we have listed the number of iterations and CPU time taken by each method in Fig 4. Although, proposed method did not take the least number of iterations, but it is able to get the required segmentation accurately.

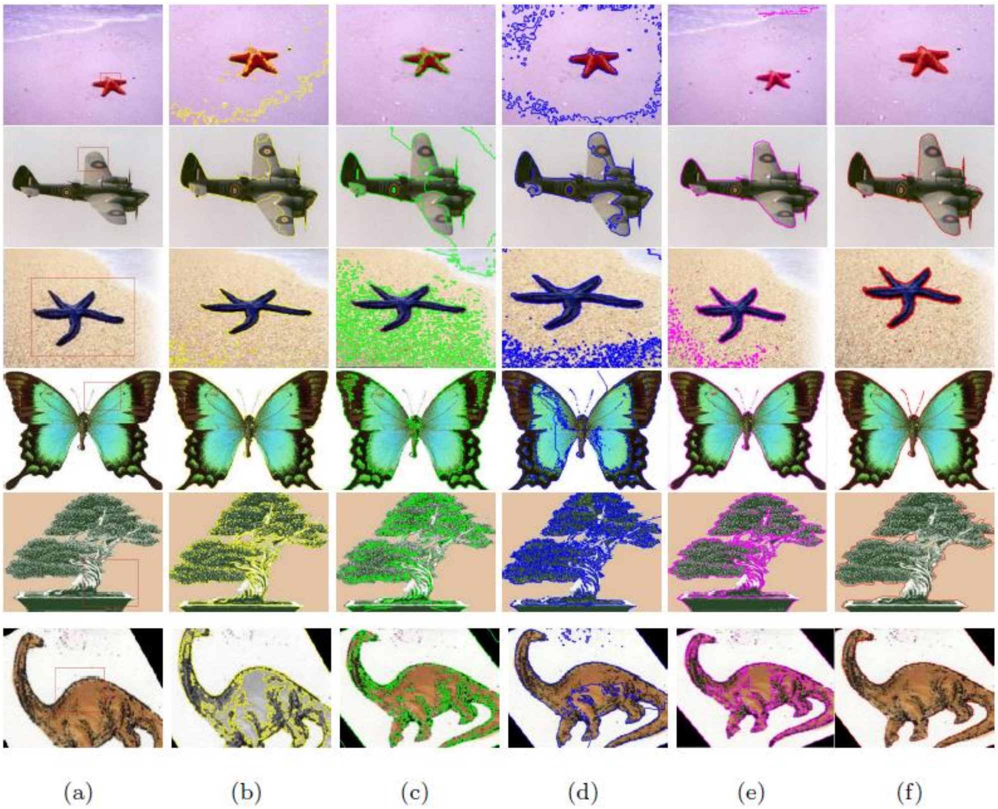


Figure 5: Segmentation Comparison between CV, LBF, LIF, LHIF and Proposed method. Column a is original image with initial contour and b to f are results of CV, LBF, LIF, LHIF and our method, respectively

4.3. Quantitative Analysis on PH² database

In recent years, the spreading rate of skin cancer has been consistently extending. Melanoma is one of its deadliest kind which can spread to other organs in the body. Early detection and proper treatment help the patients to cope with the disease. Image segmentation of melanoma [27] with active contours have received an immense attention of researchers. Therefore, for quantitative analysis, we evaluate our method on skin lesion images and compared results

with other state-of-the-art methods. We used publicly available skin lesion dataset named as PH^2 database [28]. It contains more than 400 images of skin lesion disease with manually annotated ground truths. Fig 5 illustrates the results over PH^2 database, where red contour represents the segmented part with proposed method and green contour represents the true segmentation respectively.

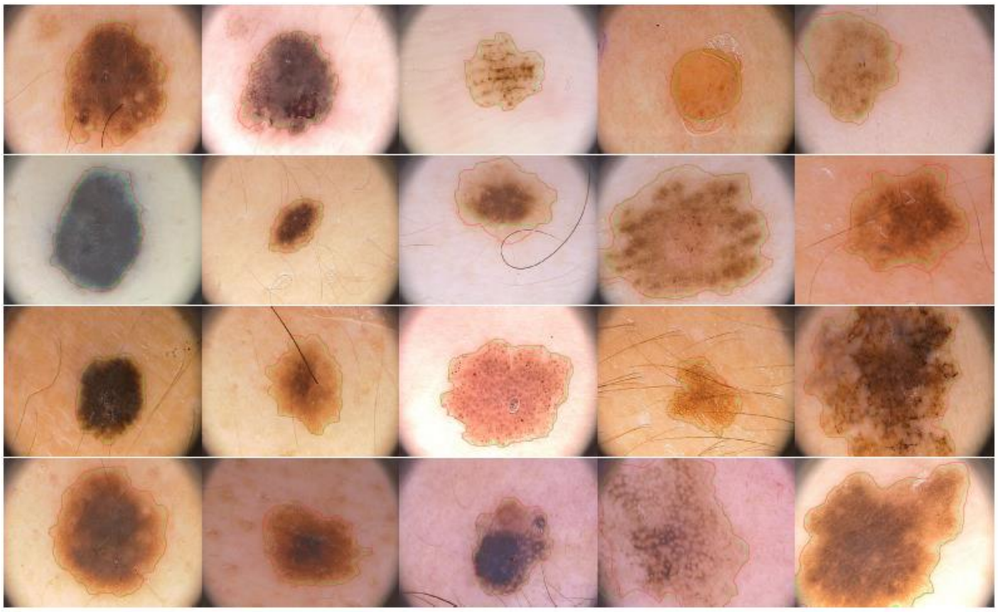


Figure 6: Segmentation results of proposed method on PH2 database; result of proposed method (red contour) and ground truth (green contour)

Fig 6 shows the experimental results of our method on skin lesion database. Accuracy term shows the accuracy of methods across the whole image domain. TP is the sum of all true positives, TN is the sum of true negatives, FP and FN represents the sum of false positives and false negatives as given in Eq. (16)

$$\text{Accuracy} = \frac{TN + TP}{TP + FP + TN + FN} \qquad (16)$$

Specificity determines the ignorance of true negatives during segmentation.

Sensitivity shows the accuracy of methods without considering false positives.

Specificity and sensitivity are defined as:

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{17}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{18}$$

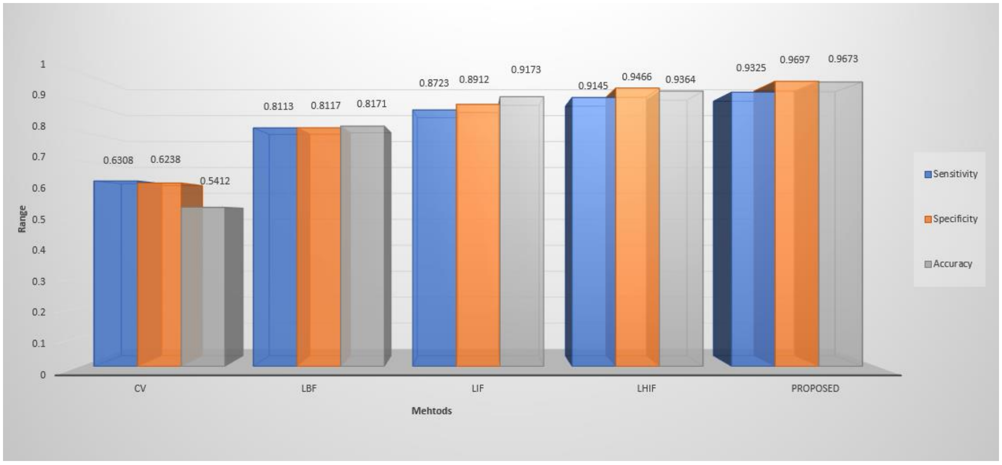


Figure 7: Accuracy of Chen-Vese, LBF, LIF and our methods. The second column: LBF model. The Third column: LIF model. The fourth column: shows the accuracy of Proposed Method.

Chapter 5

Conclusion and future work

In this thesis we proposed an improved local active contour model by combining threshold algorithm with local image fitting model. Threshold based weight matrix distinct the region boundary from background pixels which enhance the curve driving force towards the object of interest. By reducing the influence of undesired region, it increases the accuracy of segmentation. After calculating the accurate threshold our method is able to detect the object of interest more accurately as compared to other local region base models. we used the Otsu's method to calculate the optimal threshold automatically. For complex inhomogeneous region we need more precise threshold value. As new techniques developing over the years we can use more accurate threshold technique to find the perfect segmentation. Gaussian kernel is used for smoothness regularization of level set function and which also eliminate the re-initialization cost. At first, the proposed method has been verified on synthetic images to validate the results. Secondly, the experiments have been carried out on Caltech database. At last, for quantitative analysis we tested our method on publicly available PH2 database.

Experimental results show that the proposed method give better segmentation results on real and medical image as compared to other local models. Furthermore, time computation and efficiency comparison with other method as well as DSC comparison on PH^2 database prove the robustness of our method.

Global region-based methods are computationally very efficient and give good results when intensities are homogeneous throughout the whole image. Due to their assumption that image is bimodal these methods perform poorly on image with intensity inhomogeneity. On the contrary, local region-based model use image local energy information that's why they give better segmentation results in inhomogeneous regions. But these methods are very sensitive to contour initialization. So, if we can apply the threshold value on every truncated gaussian window we can construct the accurate weight matrix for that window. Which will give us more prefect segmentation.

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국문 초록

가중치 매트릭스를 이용한 능동 윤곽 기반 객체 분할

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능동 윤곽 모델은 가장 널리 사용되는 이미지 분할 기법 중 하나이다. 능동 윤곽 모델에서 관심 영역으로 윤곽선을 전개하는 이미지 힘의 제약 하에서 곡선이 전개된다. 이 방법은 이미지 통계 정보를 사용하여 곡선을 오브젝트 경계쪽으로 변형한다. 능동 윤곽 모델에는 두 가지 유형이 있다 : 엣지 기반 모델과 영역 기반 모델. 두 모델 모두 장점과 단점이 있으며 사용법은 이미지의 특성에 따라 다르다. 일부 연구자들은 지역 힘과 가장자리 용어를 함께 사용하는 하이브리드 에너지 기능을 제안했다. 엣지 기반 능동 윤곽 모델은 이미지 그라디언트 정보를 사용한다. 엣지 기반 방법은 원하는 경계에 윤곽을 적용하기 위해 엣지 정지 기능을 사용한다. 대안으로, 영역 기반 모델은 이미지 통계 정보를 사용하여 윤곽 진

화를 제어한다. 엣지 기반 모델에 비해 장점은 시끄럽고 흐릿한 이미지를 훨씬 능가한다는 것이다. 또한 초기 윤곽의 위치는 영역 기반 모델에서 덜 중요하다. Li et al. 강도 불균일성의 문제를 극복하기위한 지역 기반 모델을 제시한다. 그들은 불균일 영역을 분할하기 위해 LBF (local binary fitting energy)라고 불리는 로컬 이미지 정보가있는 가우시안 커널을 도입했다.

이 논문은 지역 에너지 용어로 가중치 행렬을 도입함으로써 개선 된 지역 능동 윤곽을 제시한다. 가중치 행렬은 약한 강도를 제거하고 원하는 객체의 가중치를 높이는 최적의 임계 값으로 구성된다. 무게 매트릭스는 심한 비 균질 영역에서 윤곽선 진화에 중요한 역할을 한다. 관심 영역을 추출하고 이미지에서 중요하지 않은 정보를 제거한다. 제안 된 방법은 다른 로컬 모델에 비해 초기화 위치에 덜 민감하다. 레벨 집합 함수의 정규화를 위해 비용이 많이 드는 재 초기화를 제거하는 데 도움이되는 가우시안 커널이 계산된다. 제안 된 방법은 실제 및 의료 영상에서 평가된다. 실험 결과는 양적 검증을 위해 PH2 피부 병변 데이터베이스와 Caltech 데이터베이스에서 수행되었다. 정량 분석은 우리 방법의 효율성과 견고성을 보여준다.

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