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Comparitive Analysis of Image Segmentation Methods

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ABSTRACT

Image segmentation using active contour models have been widely used for the segmentation of deformed structures. They have wide applications in medical image segmentation. These methods may use either edge information or region information to segment and identify objects. All these methods have their own advantages and limitations in terms of computational time and performance. This paper presents a comparative evaluation of the recent and popular level set models using certain similarity criteria. The algorithms are tested on natural images and medical images of different modalities and the results are analysed.

Keywords :— Image segmentation, active contours, level set method, comparative analysis.

I. INTRODUCTION

Image segmentation refers to the process of partitioning an image into a set of contours or segments which have high correlation with real world objects. It is one of the most important steps which lead to the analysis of processed image data. Segmentation using active contour models [1]-[3], has been widely used for the segmentation of deformed structures. The basic principle is to evolve a contour to deform so as to minimize a given energy functional to achieve the desired segmentation. They generate smooth and closed contours as segmentation results and can be readily used for shape analysis and object recognition. They have wide applications in medical image segmentation for finding the size and shape of organs, abnormality detection, surgical planning and treatment progress monitoring.

The active contour models are classified into two types: parametric [3] and geometric models [1], [4-8]. In geometric deformable models, curves are evolved using only geometric computations independent of any parameterization. In this method a curve is represented as the level set of a higher dimensional function [2] called level set function (LSF). They have some advantages over parametric ones. They can handle topology changes easily. Areas inside and outside the contour can be easily determined.

The Level-Set models are categorized into edge based [4], [5], [9] and region based models [1], [6], [7], [8], [11]. Edge based models use local edge information for attracting the contour towards object boundaries. Region based models use statistical region information to find an energy optimum where the model best fits the image. Region based methods use global statistics [1] or local statistics [6], [7] for segmentation. The level set models may be whole domain [4], [7], [8] or narrow band [1], [5], [6], [10] based on the way the interface evolution is driven. The whole domain implementation develops new contours far from the zero level-set. The narrow band implementation develops contours only on a small region around its zero level-set.

In this paper, a comparative evaluation of the recent and popular level set methods is discussed. The class of input images include natural images and medical images of different modalities. The implemented level set models are discussed in Section 2. Section 3 defines the algorithm comparison criteria. The proposed methodology is discussed in section 4. Section 5 includes experimental results and their inferences. Section 6 and 7 deals with conclusion and references respectively.

II. IMPLEMENTED LEVEL SET MODELS

A. DRLSE Model

Li et al. [5] applied the Distance Regularized Level Set Evolution (DRLSE) formulation to an edge based active contour model and provided a narrow band implementation to reduce the computational cost.

For an image I(x,y) on the image domain, they propose to minimize the following energy:

$$E(\phi) = \mu P(\phi) + E_m(\phi) \tag{1}$$

where ϕ is the level set function (initialized as a binary step function) whose zero level set corresponds to the contour, μ >0 is a constant , $P(\phi)$ is the internal energy term and E_m is the external energy term.

The term $P(\phi)$ is the level set regularization term which characterizes the deviation of ϕ from the signed distance function. Thus the need for re-initialization procedure is completely eliminated.

$$P(\phi) = \int_{\Omega} \frac{1}{2}(|\nabla\phi|-1)^2 dxdy \tag{2}$$

The term $E_m(\phi)$ is the external energy term that depends upon the data of interest. This term is responsible for the contours to stop at the objects of interest.

$$E_m(\phi) = \lambda \int_{\Omega} g\delta(\phi)|\nabla\phi| dxdy + \nu \int_{\Omega} gH(-\phi)dxdy \tag{3}$$

where λ >0 and ν are constants, g is the edge indicator function, H is the heavy side function and δ is the dirac function. The function g takes smaller values at the object boundaries as

$$g = \frac{1}{1+|\nabla G_\sigma * I|^2} \qquad (4)$$

where G_σ is the Gaussian kernel with a standard deviation σ.

The gradient descent process for the minimization of E is

$$\frac{\partial\phi}{\partial t} = \mu\left[\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] + \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + \nu g\delta(\phi) \qquad (5)$$

Edge based models utilize image gradient and they work well for images having strong object boundaries. But they give poor performance for noisy images and images with weak and discontinuous object boundaries.

B. CV Model

CV (Chan and Vese) model [1] uses global region statistics instead of image gradient information. So it has better performance for noisy images and is also less sensitive to the initial location of contour. For an image I(x,y) on the image domain, Chan and Vese proposed the following energy functional :

$$F(C, c_1, c_2) = \lambda_1 \int_{inside(C)} |I(x) - c_1|^2\, dx + \lambda_2 \int_{outside(C)} |I(x) - c_2|^2\, dx + \nu|C| \qquad (6)$$

where inside(C) outside(C) represent the regions inside and outside of the contour respectively, the optimal constants c1 and c2 are global means which are the averages of the intensities in the entire regions inside(C) and outside(C). This energy is incorporated into a level set formulation with a level set function initialized as a signed distance function. From this a curve evolution equation is derived for energy minimization.

The CV model is based on the assumption that image intensities are statistically homogeneous (roughly a constant) in each region. So it is not ideal for segmenting heterogeneous objects. Thus region based models using global statistics may cause over segmentation when used to segment complex medical images with inhomogeneous intensities and many regions.

C. RSF Model

The Region Scalable Fitting (RSF) Model [7] use local region statistics for segmentation as it uses a kernel function to specify local regions. Thus this model is suitable for images having intensity in homogeneity (especially medical images).

Let Ω be the image domain Ω and C is a closed contour in Ω, which separates it into two regions, Ω_1 as inside(C) and Ω_2 as outside (C). The RSF energy for a given point x in Ω is defined as:

$$\varepsilon_x^{fit}(C, f_1(x), f_2(x)) = \sum_{i=1}^{2} \lambda_i \int_{\Omega i} K(x-y)|I(y) - f_i(x)|^2 dy \qquad (7)$$

where λ1 and λ2 are positive constants, $f_1(x)$ and $f_2(x)$ are two values that approximate the intensities in Ω_1 and Ω_2 (local equivalents of global means) and K is a kernel function. The kernel function can be chosen as a Gaussian kernel

$$K_\sigma(u) = \frac{1}{(2\Pi)^{n/2}\sigma^n} e^{-|u|^2/2\sigma^2}$$

with a scale parameter σ. The size of the region around the point x is controlled by the kernel function (value of σ in K). For smaller values of σ, the segmentation results will be more accurate, but the model will be highly sensitive to initialization. So for real images larger values for σ are chosen. The RSF energy is incorporated into a level set formulation with a level set regularization term. The LSF is initialized as a binary step function which speeds up contour evolution and allows new contours to emerge quickly. This model uses a whole domain implementation for interface evolution.

D. LUM Model

Localizing Uniform Modeling Energy (LUM) [6] is a localization of Chan and Vese Energy [1] using a region mask with localization radius as the scale parameter. An explicit analysis of the effect of localization radius on segmentation results is given in [6]. Let I be a given image defined on Ω and C be a closed contour represented as the zero level set of a signed distance function $\phi : \Omega \to R$ such that $C = \{x \mid \phi(x) = 0\}$. Then the Localizing UM Energy is defined as:

$$F = H(\phi(y))(I(y) - u_x)^2 + (1 - H(\phi(y))(I(y) - v_x)^2) \qquad (8)$$

where H is the heavy side function which specifies the interior of the contour and its derivative is the dirac function, u_x and v_x are the local equivalents of the global means. The local neighbourhood is specified by the following region mask with a localization radius parameter termed as r.

$$B(x, y) = \begin{cases} 1, & \|x - y\| < r \\ 0, & otherwise \end{cases} \qquad (9)$$

This model is ideal for the segmentation of heterogeneous objects. As the interface evolution is confined to a narrow band, it is not disturbed by the presence of bright regions far away from the contour. The method computes local statistics for every point of the evolving interface at each iteration. So the computation time is high. The model is also very sensitive to initialization.

TABLE I
PROPERTIES OF THE IMPLEMENTED LEVEL SET MODELS

Model	Energy type	Evolution	Level Set function
DRLSE	Contour based	Narrow band	Binary step function
CV	Region based	Narrow band	Signed distance function
RSF	Localized region based	Whole domain	Binary step function
LUM	Localized region based	Narrow band	Signed distance function

III. ALGORITHM'S COMPARISON CRITERIA

The criteria measure the closeness between the final segmented region and the corresponding reference region. Let R and S are the reference mask region and the segmented mask region of an algorithm. The following three criteria are used for comparison.

Dice criterion:

$$Dice = \frac{2(R \cap S)}{R + S} \tag{10}$$

The value of Dice coefficient ranges form 0 to 1. The value is when 1 the regions are identical and 0 when they are completely different. The acceptable value should be greater than 0.9.

Mean Squared Error:

$$MSE(R,S) = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} \| R(m,n) - S(m,n) \|^2 \tag{11}$$

where MN is the size of the image.

PSNR:

$$PSNR = 10\log_{10}\left(\frac{d}{MSE(R,S)}\right) \tag{12}$$

where d is the maximum possible value of the image.

TABLE II
VALUES OF THE SIMILARITY CRITERIA FOR THREE SITUATIONS

Criterion	Min value	Max value	Required value
Dice	0	1	>=0.9
PSNR	1	Infinity	>=20dB
MSE	0dB	0	Near to 0

IV. PROPOSED METHODOLOGY

The proposed work focuses on the comparison of the models mentioned in section 2 in order to analyze their performance on different classes of images. The general framework for the analysis of the implemented algorithms is given below.

1. Input the image.
2. Pre-process the input image (optional).
3. Input the reference mask region.
4. Initialize the LSF (ϕ).
5. Perform any one of the four algorithms (section 2) to update ϕ.
6. Continue step 5 till the required number of iterations is reached.
7. Display the final contour for ϕ.
8. Create the segmented mask region from the final ϕ. (Areas inside the contour ($\phi \le 0$) will be the segmented objects).
9. Measure the similarity between the segmented mask region and the reference mask region using the criteria mentioned in section 3.
10. Estimate the computation time needed for the algorithms.

V. EXPERIMENTAL RESULTS AND OBSERVATIONS

The analysis of the algorithms mentioned in Section 2 is performed in two classes of images.

a. Natural images.

b. Medical images of different modalities (Angiogram, XRay, CT, Microscopic, Ultrasound and MRI).

The following inferences are made from the analysis of natural images. The DRLSE model gives satisfactory results for natural images having well defined boundaries and less noise. But it is sensitive to initial location. CV model is suitable for real images having homogenous intensity profiles. RSF model is suited for real world images only when the size of kernel function is increased because for real world images, in homogeneity is not so severe. Otherwise it tends to over segment the image and is highly sensitive to initial contour location and parameters. As it uses whole domain implementation, evolution will spread to bright locations far from the initial contour. UM Model gives satisfactory results for natural images having heterogeneous objects. But it is highly sensitive to initial contour location as and it requires higher computation time.

Fig.1 shows an in-homogeneous real image of a T shaped object, its reference region and the results obtained using different models. The reference region can be created in the same way as the initial contour. The values of the three similarity criteria and CPU time for this image are listed in table 3. The following inferences are made from the table.

The values of the similarity criteria obtained for RSF and UM Model is in the acceptable range. This shows that these models are well suited for images having intensity in homogeneity. But the CPU time is higher compared to CV and DRLSE Model.

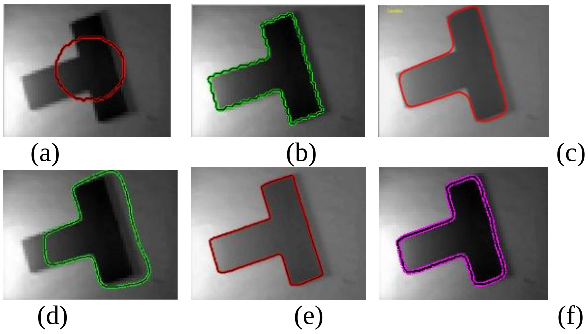

Fig. 1 An inhomogeneous real image of a T shaped object. (a) Shows the initial contour; (b) Reference contour; (c), (d), (e) and (f) shows the segmentation results of DRLSE Model, CV Model, RSF Model and LUM Model respectively. RSF and LUM Model give satisfactory results.

TABLE III
SIMILARITY CRITERIA AND CPU TIME FOR FIG.1

Criterion	**Dice**	**PSNR**	**MSE**	**Computation time**
DRLSE	0.9	16.79	0.0004	3.174s
CV	0.6	12.56	0.018	3.341s
RSF	0.97	Inf	3.1E-004	10.327s
UM	0.918	Inf	2.3E-004	7.488s

Fig.2 shows the results for a mushroom image. From the values in Table IV it can be inferred that LUM Model is appropriate for this image.

The level set methods in section II give proper results for medical images having severe intensity in homogeneity, poor contrast and noise. For some images pre-processing techniques like anisotropic diffusion, morphological operations, histogram equalization etc. are required to enhance the images.

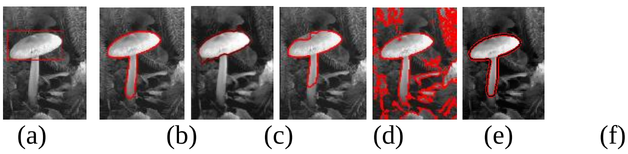

Fig. 2 Real image of a Mushroom. (a) Shows the initial contour; (b) Reference contour; (c), (d), (e) and (f) shows the segmentation results of DRLSE Model, CV Model, RSF Model and LUM Model respectively. LUM Model gives satisfactory results.

TABLE IV
SIMILARITY CRITERIA AND CPU TIME FOR FIG. 2

Criterion	**Dice**	**PSNR**	**MSE**	**Computation time**
DRLSE	0.60	6.38	0.04	8.114
CV	0.862	16.324	0.002	2.778s
RSF	0.517	6.33	0.043	28.504s
UM	0.98	23.006	0.0002	35.4 s

The vasculatures in angiogram images are very important in performing neuro surgery and cardiovascular surgery. But these images are inhomogeneous and the complex structures of the vessels makes the segmentation task challenging. The RSF Model gives proper segmentation of vessels in angiogram images.

For XRay, CT and Ultrasound images the choice of the algorithm depends on the segmentation results needed for the application. If the whole image need to be segmented, then RSF Model is chosen else LUM Model is appropriate. For microscopic images RSF and DRLSE model give proper segmentation of cells. MRI images of brain suffer from severe in-homogeneity. So RSF and LUM Model are appropriate for segmenting the different parts like white matter, grey matter, corpus callosum etc.

Fig.3 shows medical images of different modalities, their initial contour and final segmentation results. Table. V shows the suitable segmentation algorithms for the images in Fig.3

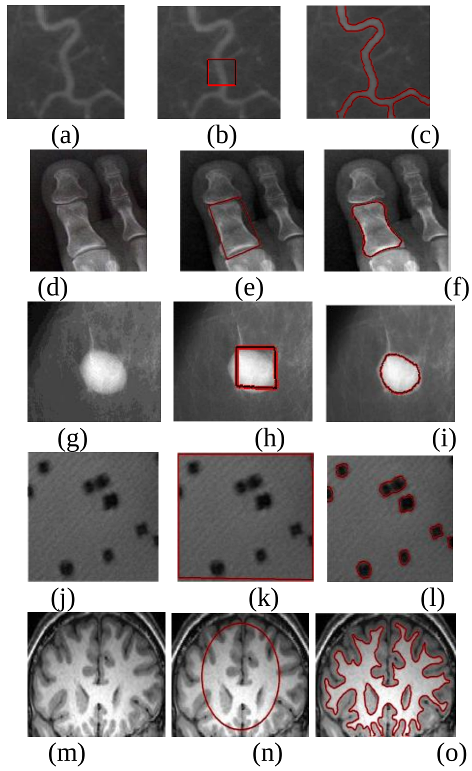

Fig. 3 Medical images. (a) Blood vessel (d) Arms XRay (g) Tumour (j) Confocal Microscopic cells (m) Brain-Axial View. (b), (e), (h), (k) and (n) show the initial contours and (c), (f), (i), (l) and (o) shows the of final segmented results of (a), (d), (g), (j) and (m) respectively.

TABLE V
SUITABLE MODELS FOR MEDICAL IMAGES

Image name	**Modality**	**Best algorithm**
Blood vessel	Angiogram	RSF
Arms XRay	XRay	LUM
Tumour	Ultrasound	LUM
Confocal Microscopic cells	Microscopic	RSF
Brain-Axial View	MRI	RSF

VI. CONCLUSION

This paper presents a comparative analysis of the popular level set methods for segmentation. The performance of the algorithms is evaluated from similarity measurements between the segmented region and a reference region. The results obtained for natural images and medical images of different modalities are discussed.

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