Abstract

In this paper, we propose a novel active contour method for image segmentation, which utilizes the advantages of the GAC and the LRAC methods. We consider the smoothing force of the GAC method and local region-based force of the LRAC method. The advantages of our method are as follows. First the proposed method a new region-based signed pressure force function, which can efficiently stop the contours at weak boundary. Second the proposed method can handle the heterogeneous texture objects and able to reach into deep concave shapes. Finally, the proposed formulation can be easily implemented by simple finite difference scheme and is computationally more efficient and accurate. The proposed method has been applied to both synthetic and real images.

1. Introduction

Image segmentation is a fundamental problem of image processing and computer vision. The active contour is one of the popular models, which are based on the theory of surface evaluation and geometrics flows. Generally speaking, the existing active contour models can be classified into two types: edge-based model and region-based model.

The edge-based models [1,5,9,10] utilize image gradient as an additional constraint to proposed to stop the contours on the boundaries of desired objects. Many methods have been proposed to improve the active contour models performance. One interesting method is geodesic active contour (GAC) by Caselles et al.[1]. They often have boundaries leakage problems where the object is occluded or has weak boundaries and sensitive to image noise, but one advantage of these flow types is the fact that on global constraints are placed on the image.

Region-based models [2,4,11,12,13,14] utilize the image statistical information to construct constraints and have many advantages over edge-based models. They can successfully segment object with weak boundaries or even without boundaries including less sensitive to image noise. There are many active contour models that take into account the region-based models. For instance, Chan and Vese [2] proposed active contour without edge (ACWE). They integrated the level set method [3] and the Mumford-Shah model [4] to obtain an energy function. That was based on the average intensities of the pixels within the object and background areas. Their energy was optimized when the average pixel intensities of the interior and exterior of the contour were well separated. In the case where the object or the background are of heterogeneous textures, the region-based models with such global constrain may not perform effectively. To overcome the limitation of the global region-base models in segmenting image, where the object or the background or both are of heterogeneous textures. However, several methods attempt to utilize local regional information as a constrain to the active contour. One interesting method is the localizing region-based active contour (LRAC) by Lankton and Tannenbaum [5]. This method uses the local regional information within the circles that are around the contour. The centers of these circles are the pixels on the contour, as shown in figure 1. The LRAC model superiority of localizing regional information to global region one is an ability to handle heterogeneous texture problem.

![Figure 1. Region descriptions of LRAC model.](image-url)
Zhang et al.[6] proposed active contours with selective local or global segmentation: a new formulation and level set method. It's implemented with a special processing named selective binary and Gaussian filtering regularized level set (SBGFRLS) method, which shared the advantages of GAC and ACWE models. However, the SBGFRLS cannot handle heterogeneous texture problem. We propose a novel method to handle segment heterogeneous textures utilizing advantages of GAC and LRAC models.

This paper is organized as follows: we review the GAC and LRAC models in Section 2. The proposed model describes the formulation of our method in Section 3. Experimental results are given in Section 4. Lastly, conclusion is made in Section 5.

2. The GAC and LRAC models

2.1. The GAC model

The GAC model which utilizes image gradient to construct an edge stopping function as follows:

\[
g(|\nabla I|) = \frac{1}{1 + |\nabla G_{\sigma} * I|}, \tag{1}
\]

where \( I \) is input image, \( G_{\sigma} \) is Gaussian kernel and standard deviation is \( \sigma \). Let \( C(q) : [0,1] \rightarrow \mathbb{R}^2 \) be a parameterized planar curve in \( \Omega \). They introduce formulated by minimizing the following energy functional \( E \) :

\[
E = \int_0^1 g \left( |\nabla I| \right) \left| C'(q) \right| dq. \tag{2}
\]

In the calculation of variation [7], they could get the Euler-Lagrange equation and added increase the propagation speed term \( \alpha \), can be written as:

\[
C = g \left( |\nabla I| \right) (\kappa + \alpha) \vec{N} - \nabla g \cdot \vec{N} \right) \vec{N}. \tag{3}
\]

Let \( \kappa \) is the curvature of the contour and \( \vec{N} \) is the inward normal to the curve. The derivative of Eq. (3) becomes as follows:

\[
\frac{\partial \phi}{\partial t} = g |\nabla \phi| \left( \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) + \alpha \right) + \nabla g \cdot \nabla \phi. \tag{4}
\]

2.2. The LRAC model

The LRAC model analyzes the local energies at each point along the curve. In order to optimize these local energies each point is considered separately and moved to minimize the energy computed in its own local regional information. The energy optimization is done by fitting a model to each local region. This model is based on theory curve evolution implemented via level set technique. The contour \( C \) is embedded as the zero level set of a signed distance function \( \phi(x, y) \), i.e., \( C = \{ (x, y) \in \Omega : \phi(x, y) = 0 \} \), where \( \Omega \) is the image spatial domain. They introduce the energy function in terms of a generic force function as follows:

\[
E(\phi) = \int_\Omega \delta(\phi) \beta \cdot F(I, \phi) dydx
+ \lambda \int_\Omega \delta(\phi) |\nabla \phi| dydx. \tag{5}
\]

Using \( \beta \) to mask local region, the function \( F \) is a generic internal energy measure used to represent local adherence to a given model at each point along the contour, \( \delta(\phi) \) is a smooth delta function and \( \nabla \) is the gradient operator. Chan-Vese [2] energy function relies on the assumption that the object and background are statistically homogeneous. This energy is minimized when constant intensities of their averages approximate the region optimally is as follows:

\[
F = H_{\varepsilon}(\phi)(I - u)^2 - (1 - H_{\varepsilon}(\phi))(I - v)^2, \tag{6}
\]

where \( H_{\varepsilon}(\phi) \) is a smooth regularized Heaviside function, \( u \) and \( v \) represent local intensity averages of the two regions, written as:

\[
u = \frac{\int_{\Omega} \beta \cdot 1 \cdot (1 - H_{\varepsilon}(\phi)) dydx}{\int_{\Omega} \beta \cdot (1 - H_{\varepsilon}(\phi)) dydx}, \tag{7}
\]

\[
u = \frac{\int_{\Omega} \beta \cdot 1 \cdot (1 - H_{\varepsilon}(\phi)) dydx}{\int_{\Omega} \beta \cdot (1 - H_{\varepsilon}(\phi)) dydx}. \tag{8}
\]

By taking the derivative of Eq. (6) with respect to \( \phi \), can be written as:

\[
\nabla(\phi) F = \delta(\phi) \left( (I - u)^2 - (I - v)^2 \right). \tag{9}
\]
The derivative and inserting Eq. (9) into Eq. (5) they obtain the curvature flow for the localized energy as follows:

$$\frac{\partial \phi}{\partial t} = \delta(\phi) \int_{\Omega} \beta \cdot \delta(\phi) \cdot \left( (I-u)^2 - (I-v)^2 \right) dy dx + \lambda \delta(\phi) \text{div} \left( \frac{\nabla \phi}{\sqrt{\nabla \phi}} \right).$$

The uniform modeling flow finds its minimum energy when the interior and exterior are best approximated.

### 3. Proposed method

In this section, the novel active contour method is explained. The signal pressure force function is defined in [8], which modulates the signs of the pressure forces interior and exterior the region of interest. So that the signal pressure force function is the local region-based energy functional. The first term in Eq.(10) is the local region-based force, the second term is the smoothing force to control the elasticity of the contour during the deformation, which the local region-based force is as follows:

$$F_{LR} = \delta(\phi) \int_{\Omega} \beta \cdot \delta(\phi) \cdot \left( (I-u)^2 - (I-v)^2 \right) dy dx. \quad (11)$$

We can substitute the signal pressure force function for edge stopping function in Eq.(4), the level set formulation of the proposed model is as follows:

$$\frac{\partial \phi}{\partial t} = F_{LR} \left( \text{div} \left( \frac{\nabla \phi}{\sqrt{\nabla \phi}} \right) + \alpha \nabla \phi \right) + F_{LR} \cdot \nabla \phi. \quad (12)$$

In the traditional level set methods, the curvature based term $\text{div} \left( \frac{\nabla \phi}{\sqrt{\nabla \phi}} \right) \nabla \phi$ is usually used to regularize the level set function $\phi$, this is smoothing force. However, we can removed and used term $\alpha \nabla \phi$ to regularize the level set function, this term is crucial for convex initial curves to capture non-convex shapes, which is the smoothing force as well. In addition, the term $\nabla \phi \cdot \nabla \phi$ can be removed, because our method utilizes the local region-based information. Lastly, the active contour formulation of the proposed model can be written as follows:

$$\frac{\partial \phi}{\partial t} = F_{LR} \cdot \alpha \nabla \phi. \quad (13)$$

The overall process of our active contour method as follows:

1. **Step1**: Initialize $\phi$, where contour $C$ is embedded.
2. **Step2**: Initialize the radius parameters of all circles around the contour, which default size is set to be approximately $1/10$ of the input image size.
3. **Step3**: Compute $u$ and $v$ using Eqs. (7) and (8), respectively, which are the average intensity value of the intensity region of the circle inside and outside the contours.
4. **Step4**: Evolve the level set function as according Eq.(13).
5. **Step5**: Check whether the evolution of the level set function has converged. If not, return to step 2.

### 4. Experimental results.

We test the performance of our active contour method proposed to compare the SBGFRLS method and LRAC method. Fig. 2 shows the results of segmentation. In column (a) are the initial contours, column (b)-(c) are the final contours of the SBGFRLS method, LRAC method and in the last column are the results of using the method which we have proposed.

We can see in the first row of Fig. 2 the heterogeneous texture objects both LRAC method and our proposed method can segment correctly, while the SBGFRLS method fails to segment. In these images, the intensity of both object and background areas is non-uniform. Since the SBGFRLS method attempts to separate the dark region of both object and background are grouped together as one and the light regions of both areas are considered as the other object. However, LRAC method and our proposed method can distinguish the difference in intensity locally. Therefore, it can find the true object boundary successfully even though the object and the background are of non-uniform intensities. In the second row of Fig. 2, the image of monkey has heterogeneous texture, SBGFRLS method cannot segment completely. It can extract the boundary of the monkey correctly but includes some background region because this region has almost the same intensity as the monkey region. On the other hand, LRAC method and our proposed method extract only the monkey boundary, but LRAC method cannot segment U shape region between both legs of monkey image, while our proposed method can segment this region completely. We can see clearly that in the third row of Fig.2, the leaf image, LRAC method cannot segment V shape region boundary object. However, SBGFRLS method and our proposed method can segment the leaf image completely. From the fourth...
row of Fig. 2, it is found that the proposed method can segment the image of the airplane pretty much better in the heterogeneous texture object and V shape than both SBGFRLS method and LRAC method. For the left ventricle of human’s heart shown in the fifth row of fig. 2, it is found that SBGFRLS method cannot segment well only region but it includes nearby boundary due to utilize global region-based force information. LRAC method cannot segment into the real boundary image as the result of U and V shapes. Therefore our proposed method as shown in column (d) can successfully segment the images.

![Segmentation Results](image)

**Figure 2.** The segmentation results of our method and other method. (a) Initial contour. (b) SBGFRLS method. (c) LRAC method. (d) Our method.

5. **Conclusion**

We proposed a novel active contour which utilizes the advantages of GAC method and LRAC method. The smoothing force of GAC method and local region-based force of LRAC method are used. Experiments results the advantages of our proposed method over the SBGFRLS method and LRAC method. The new proposed method can segment perfectly for both the heterogeneous texture object and handle U and V shapes region, which be able to reach into deep concave shape. The comparison of the active contours between SBGFRLS method, LRAC method and our proposed method. Shows that our proposed method performs better in segmentation.

**References**