Abstract—In this paper, a novel model for intensity inhomogeneous image segmentation is proposed. The proposed model uses the local information of the image to be segmented; concurrently, it incorporates the geodesic active contour (GAC) model into Chan-Vese (C-V) model in energy function. Thus, the proposed model is effective when dealing with intensity inhomogeneous images. Practical experiments prove that the proposed model can obtain exact segmented results, especially with the intensity inhomogeneous images even with hole, noise and complex background.

Keywords—Image Segmentation; Active Contour; Level Set Method; Chan-Vese Model, Geodesic Active Contour model.

I. INTRODUCTION

Active contour models (ACM) have been widely used in image processing, especially in image segmentation [1-4], [5]. In general, ACM can be classified into two types: edge-based method [6-9] and region-based method [10-15]. The edge-based method uses the gradient of segmented image as a constraint condition to stop the contour at the boundaries of the interested object. Geodesic Active Contour (GAC) is one of famous models in this class. Though GAC has some advantages such as giving the precise results when detecting the object with high variation in gradient at the boundaries, and ability of detecting both exterior and interior contours, it meets difficulty when dealing with the object having blur/discrete boundary. In addition, it hardly detects the object corrupted by noise.

Region-based method utilizes the image statistical information to drive the initial contour toward the boundary of interested object. Chan-Vese (C-V) model is one of the most popular region-based methods. Unlike the GAC model based on the local gradient information, this model relies on the global information of homogeneous regions. C-V model can automatically detect the object, no matter where the initial curve starts in the segmented image. In addition, it can work well with the object having blur boundary. However, it cannot completely segment the images with intensity inhomogeneity. Another disadvantage is that the C-V model usually cannot obtain the exact boundary since this model uses the global information region instead of local information because in some cases, the global information is not enough to completely segment the image.

In this paper, we propose a new ACM model which takes the advantages of the C-V as well as the GAC model into account. In addition, the proposed model uses the local information; therefore it can deal with intensity inhomogeneous images.

This paper is organized as follows. In Section 2, we review the classical GAC and C-V methods. Section 3 describes the formulation of the proposed model. Experimental results are shown in Section 4. Finally, conclusions are given in Section 5.

II. BACKGROUND

A. The GAC model

The Geodesic active contour (GAC) model was introduced in [9]. This model can automatically change the topology by using the level set method [16]. The geodesic active contour method is briefly given as following:

Let $\Omega$ be a bounded of a open subset of $\mathbb{R}^2$ and $I: [0, a] \times [0, b] \rightarrow \mathbb{R}^+$ be a given image. Let $C(s): [0, 1] \rightarrow \mathbb{R}^2$ be a parameterized planar curve in $\Omega$. The GAC model is formulated by minimizing the following function [9]

$$E_{GAC}(C(s)) = \int_0^L g(\|\nabla I(C(s))\|) ds$$

where $g$ is a positive decreasing function, and $ds$ is the Euclidean arc-length and $L$ is the Euclidean length of $C(s)$. Using calculation of variation, one can get the Euler-Lagrange equation of Eq. (2) as follows

$$C_t = g(\|\nabla I\|) (\kappa + \alpha) \vec{N} - \left(\nabla g \cdot \vec{N}\right) \vec{N}$$

where $\kappa$ is the curvature of the contour, $\vec{N}$ is the inward normal to the curve, and $\alpha$ is constant which is added to increase the propagation speed. If, we represent the contour $C$ with the zero level set, i.e. $C = \{ x \in \Omega | \phi(x) = 0 \}$, we can obtain the level set formulation as follows:

$$\frac{\partial \phi}{\partial t} = g(\kappa + \alpha) \nabla \phi + \nabla g \cdot \nabla \phi$$

This motion equation shows that each point in the active contour $C$ should move along the normal direction in order to decrease the weight length of $C$. In other words, the initial curve $C_0(t)$ should evolve towards the object boundary to minimize $E(C(s))$. 

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B. The C-V model

Chan and Vese [12] proposed an active contour without edges model. Unlike other level set based active contours models i.e. GAC, the C-V model does not rely on the gradient of the image as the stopping term when the initialization curve is evolving. The C-V model utilizes the homogeneity information of the object to obtain the energy function. The C-V model is formulated by minimizing the following energy functional

\[ E^{CV}(c_1,c_2,\phi) = \mu \cdot \text{Length}(C) + \nu \cdot \text{Area}(\text{inside}(C)) + \lambda_1 \int_{\text{inside}(C)} |I(x) - c_1|^2 \, dx + \lambda_2 \int_{\text{outside}(C)} |I(x) - c_2|^2 \, dx \]

where \( c_1 \) and \( c_2 \) are two constant which are the average intensities inside and outside the curve \( C \), and \( \mu, \nu, \lambda_1 \) and \( \lambda_2 \) are positive parameters. The level set formulation of the C-V model can be expressed as:

\[ \frac{\partial \phi}{\partial t} = \delta_\phi(\phi) \left[ \mu \kappa - \nu - \lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2 \right] \]

where \( \kappa \) is the Euclidean curvature of the curve \( C \) and \( \delta_\phi(\cdot) \) is the slightly regularized version of one-dimensional Dirac measure defined by:

\[ \delta_\phi(z) = \frac{d}{dz} H(z) \]

and

\[ H(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{if } z < 0 \end{cases} \]

The Geodesic aided Chan-Vese model (GACV)

Chen et al. [17] introduced GACV model by incorporating the GAC and C-V model. The formulation of this hybrid model is expressed as follows:

\[ \frac{\partial \phi}{\partial t} = g|\nabla \phi| \left[ \mu \kappa - \lambda_1 (I - c_1)^2 \right] + \lambda_2 (I - c_2)^2 + \tau \cdot \nabla g \cdot \nabla I \]

where \( c_1, c_2, \mu, \lambda_1 \) and \( \lambda_2 \) as pointed out in section II.B, and \( \tau \) is an adjusted constant. Though having some advantages when segmenting images with weak edge, noise and holes, the GACV model hardly gives exact result with intensity inhomogeneous images. This can be explained as follows: in this model \( c_1 \) and \( c_2 \) are the constants, respectively representing the average intensity value of image \( I \) inside and outside the initial curve \( C \), respectively. Obviously, \( c_1 \) and \( c_2 \) are related to the global properties of the image intensity inside and outside the contour \( C \), respectively. However, if the image is inhomogeneous, such global image information is not accurate. Accordingly, the model does not work well. In order to overcome this drawback, in this paper, we introduce two smooth functions that approximate the local image intensities inside and outside the contour \( C \), and then embed them into the energy function of the model in section II.C.

III. THE PROPOSED MODEL

Let \( f_1(x) \) and \( f_2(x) \) be two smooth functions that approximate the local image intensity inside and outside the contour \( C \), respectively. \( f_1(x) \) and \( f_2(x) \) are defined as follows [18]:

\[ f_1(x) = \frac{I(x)H_\epsilon(\phi)*W}{H_\epsilon(\phi)*W} \]

\[ f_2(x) = \frac{I(x)(1-H_\epsilon(\phi))*W}{(1-H_\epsilon(\phi))*W} \]

where \( H_\epsilon(\phi) \) is the slightly regularized version of Heaviside function which is defined in Eq. (6), \( \phi \) is the level set function of the curve \( C \), \( W \) is Gaussian window, and ( \( * \) ) is the convolution operator.

Embedding \( f_1(x) \) and \( f_2(x) \) into the GACV model, we can get the new hybrid formulation. The level set function of the proposed model can be written as follows:

\[ \frac{\partial \phi}{\partial t} = g|\nabla \phi| \left[ \mu \kappa - \lambda_1 (I - f_1(x))^2 \right] \\
+ \lambda_2 (I - f_2(x))^2 + \tau \cdot \nabla g \cdot \nabla I \]

where \( f_1(x) \) and \( f_2(x) \) are defined in (8) and (9), \( g(\cdot) \) is the edge detection, \( I(x) \) is the segmented image, \( \kappa \) is the curvature of the curve \( C \) and parameters \( \mu, \lambda_1, \lambda_2 \) and \( \tau \) have been pointed out in section II.C.

Compared with the model in [9], this model can work well with the intensity inhomogeneous images because it uses the local image intensities. In addition, it takes the advantages of the C-V and GAC models. In the following section, we validate this model by extensive experiments on synthetic and real images.

IV. EXPERIMENTAL RESULTS

The experiments in this section illustrate the effectiveness of the proposed active contour model as well as demonstrate the advantages of this model over the GACV method in [17]. Experiments are conducted using Matlab on a PC with Intel Pentium Dual-Core CPU 2.80 GHz and 2 GB of RAM.

Fig. 1 compares the results of the GACV model and the proposed model in segmenting a synthetic image with intensity inhomogeneity. We can see form Fig. 1 (a) that, the GACV model fails to detect this image. This is because in this image both object and background are inhomogeneous. With the same initial contour one can get the satisfactory result when using the proposed model, as shown in Fig. 1(b).
Fig. 2 shows the segmentation results on a real image with strong inhomogeneity in intensity. In addition, the background of this image is complex. From Fig. 2(a), we can see that the GACV model totally fails when dealing with this image, whereas the proposed model gives exact result as shown in Fig. 2(b).

The experiment in Fig. 3 validates the proposed method in one medical image. The image used here is one human vein image with weak boundary and inhomogeneity in intensity. As can be seen from this image, the GACV model cannot work well with this image and the received result is unsatisfied as shown in Fig. 3(a). With the same image and initialization, the proposed model achieves satisfied segmentation result as shown in Fig. 3. (b)

V. CONCLUSION

This paper proposed a novel active contour model for intensity inhomogeneous image segmentation. The proposed model takes the advantages of the two well-known methods, GAC and C-V. Moreover, by using the local intensity of image in energy function, the model can work with the heterogeneous images which cannot be achieved by the original C-V or GAC model. The experimental results in synthetic and real images demonstrate the advantages of the proposed model over the GACV model.

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