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A COMBINATION OF LOCAL AND DIFFERENTIAL IMAGE INFORMATION BASED ON HYBRID ACTIVE CONTOUR METHOD FOR IMAGE SEGMENTATION

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Abstract— Image segmentation is the actual scheme of partitioning an image into several regions and it has a big importance in image processing and computer vision. Until now, there is a variety of segmentation methods, and among them active contour model is a popular one widely studied and used in many applications. The fundamental idea of active contour model is to construct some constraints to the object and realize the segmentation process by curve evolution. Depending on the type of information used active contour method scan roughly be categorized into three categories: edge based, region based and hybrid active contour models. This research we proposed a hybrid active contour method combining the local and differential gray intensity information for inhomogeneous image segmentation.

Keywords-segmentation, level set method, inhomogeneous image, local image information, active contour model

Introduction:

Image segmentation is an essential part of the image processing and computer vision. It is a process that divides an image into its regions or objects that have similar features or characteristics. This is usually used to segregate the similar portions of an image and to find the boundaries of a particular image. Thus this part separates the region of interest from other parts of the image. There are a variety of Segmentation methods, and among them active contour model is a popular. The fundamental idea of active contour model is to construct some constraints to the object and realize the segmentation process by curve evolution. According to the property of constraints, the methods basically divide into three categories: edge based, region based and hybrid active contour models.

The edge based active contour model, such as snake and geodesics active contour (GAC) model utilizes image gradient based edge detector function to stop the contour evolution on object boundaries. But it is sensitive to noise and difficult to detect weak edges. This model based on the perception of shrinking/expanding a curve until it reaches the edges. Regions mostly rely on the property of the contours and on a stopping function which involves the magnitude and orientation of the edge.

The Region based models use the similarity amidst the regions in the image to segregate the image into different regions. This has overcome the drawbacks of most problems using edge based techniques and is therefore widely used. The Region competition method was the first and foremost model in the region-based Image Segmentation models. The Region Competition Method considers the Segmentation Problem as a Variation minimization problem based on Bayes Minimum Description Framework, with two segmentation models namely snakes and statistical growth method as its components.

A hybrid active contour model incorporates the geodesics active contour (GAC) model, which is an edge-based active contour model, and the Chan and Vese (CV) model, which is a region-based active contour model. The new-fangled model was known as geodesic intensity fitting (GIF) model. After some time it was extended to two models: i) global geodesic intensity fitting (GGIF) model and ii) local geodesic intensity fitting (LGIF) model. The GGIF model is basically used for images with intensity homogeneity. And the other LGIF model is used for images with intensity in homogeneity. It is able to segment images more accurately.

This paper presents a novel hybrid active contour model, which uses local and differential gray information to construct the level set function to control the direction of evolution contour. It can fast and accurately segment images with inhomogeneous intensity.

The Related Models

The Chan-Vese (CV) Model

This model is proposed for a particular case of the Mumford-Shah problem when the image u in the functional is a piecewise constant function, Chan and Vese generate a piecewise constant model called the CV model not including the image gradient. For an image I, they projected to minimize the following energy:

$$\mathcal{F}^{CV}(C, c_1, c_2) = \lambda_1 \int_{\text{outside}(C)} |I(\mathbf{x}) - c_1|^2 d\mathbf{x} + \lambda_2 \int_{\text{inside}(C)} |I(\mathbf{x}) - c_2|^2 d\mathbf{x} + \nu |C|,$$

where λ1, λ2, and ν are positive constants. outside(C) and inside(C) represent the regions outside and inside the contour C, respectively, and c1 and c2 are two constants that approximate the image intensity in outside(C) and inside(C). This energy can be represented by a level set formulation, and then the energy minimization problem can be converted to solve a level set evolution equation. A most attractive property of the CV model is that it is very less sensitive to the initialization.

Local Binary fitted Model

Li et al. proposed the (Local Binary fitted) LBF model in to segment images with intensity in homogeneity by using the local intensity information powerfully. The proposed energy functional is

$$E_{LBF}(C,f_1,f_2) = \lambda_1 \int_{\Omega} K_\sigma(x-y)|I(y)-f_1(x)|^2 H_\epsilon(\phi(y))dy + \lambda_2 \int_{\Omega} K_\sigma(x-y)|I(y)-f_2(x)|^2 (1-H_\epsilon(\phi(y)))dy$$

where Ω1 = outside(C) and Ω2 = inside(C). Kσ are a Gaussian kernel with the standard deviation σ. f1 and f2 are two local fitting functions that estimated the intensities outside and inside the contour C. The localization property of this kernel function acts a key role in segmenting images with intensity in homogeneity. But, these localization properties may also introduce many local minimums of the energy functional. therefore, the result is more dependent on the initialization of the contour.

Geodesic active contour (GAC) Model

GAC method is related to a standard active contour method which uses image gradient information from the boundary of the object. Let I: OR2 is an image domain, I: O!Ris an input image and C(q)is a closed curve. The proposed the energy functional:

$$E_{GAC}(C(q)) = \int_0^1 g(|\nabla I(C(q))|)C'(q)dq,$$

Where g is the edge stopping function. This model is edge based contour evolution that could only capture objects through edges defined by its gradient. Hence, this method doesn’t support regional information and fall into local minimum when the initial contour is not placed near object boundaries.

The BGFRLS Model Binary and Gaussian Filtering Regularized Level Set

The BGFRLS model is formulated by minimizing the following data fitting energy

$$E(C) = -\int_{in(c)} w(x) \frac{I(x) - \frac{c_1 + c_2}{2}}{c_1 - c_2} dx - \int_{in(c)} (1 - w(x)) \frac{I_0(x) - \frac{m_1 + m_2}{2}}{m_1 - m_2} dx + \lambda \int_c ds \tag{1}$$

where c_1 and c_2 are the mean values of the intensities of the image *I* inside and outside of the active contour C, w(x) is a weighted function, $I_0 = G_k * I - I$, G_k is an averaging convolution operator with $k \times k$ size window, m_1 and m_2 are the mean values of the intensities of the difference image I_0 inside and outside of the active contour C, λ is a positive constants.

The Proposed Model

In the previous introduced BGFRLS model, the region gray within the contour prefer being bigger than two means. The first one is the mean gray of original image inside and outside the contour. The second one is computed in the same way, but from the difference image. The first term in the right of (1) is a variety of the data fitting term of CV model. Such a global gray fitting is not proper for the inhomogeneous image. Thus, we use the local fitting term in LBF combined with the difference image information used in (1) to achieve the segmentation for inhomogeneous image. To strengthen their respective functions of different image information, we propose the following energy.

$$\begin{aligned} E(C) &= Ed(C + E2(C) + \lambda|C| \\ &= -\iint_{in(c)} \frac{I_0(x,y) - \frac{m_1 + m_2}{2}}{m_1 - m_2} dxdy \\ &+ \lambda_1 \int_{\Omega} \int_{in(c)} K_\sigma(x - y)|I(y) - f_1(x)|^2 dydx \\ &+ \lambda_2 \int_{\Omega} \int_{out(c)} K_\sigma(x - y)|I(y) - f_2(x)|^2 dydx + \lambda\,|C| \end{aligned} \tag{2}$$

where λ , λ1 and λ2 are positive constants. The first term in the right of above formula is the difference fitting term in (1) and the second is the local gray fitting energy used in LBF model. Added a curve normalization term, the total energy *E(C)* can be minimized by solving the following equation of the level set function ∅:

$$\frac{\partial \emptyset}{\partial \emptyset} = \left(\frac{I_0(x,y) - \frac{m_1 + m_2}{2}}{m_1 - m_2} - (\lambda_1 e_1 - \lambda_2 e_2) + \lambda div\left(\frac{\nabla \emptyset}{|\nabla \emptyset|}\right) \right) \delta\varepsilon(\emptyset) \tag{3}$$

In fact, δε can be replaced by |∇∅|, we draw upon the following equation for the level set evolution

$$\frac{\partial \emptyset}{\partial t} = \left(\frac{I_0(x,y) - \frac{m_1 + m_2}{2}}{m_1 - m_2} - (\lambda_1 e_1 - \lambda_2 e_2) + \lambda div \left(\frac{\nabla \emptyset}{|\nabla \emptyset|} \right) \right) |\nabla \emptyset| \tag{4}$$

The Heaviside function H is approximated by a smooth function Hε defined by

$$H_\varepsilon(x) = \frac{1}{2}[1 + \frac{2}{\pi} arctan \left(\frac{x}{\varepsilon}\right)] \tag{5}$$

The Hε is the following smooth function

$$\delta_\varepsilon(x) = \frac{dH_\varepsilon(x)}{dx} = \frac{1}{\pi} \cdot \frac{\varepsilon}{\varepsilon^2 + x^2} \tag{6}$$

In order to ensure stable evolution of the level set function $\emptyset$, we set the condition $|\nabla \emptyset| = 1$, then the (4) can be simplified as

$$\frac{\partial \emptyset}{\partial t} = \frac{I_0(x,y) - \frac{m_1 + m_2}{2}}{m_1 - m_2} (\lambda_1 e_1 - \lambda_2 e_2) + \lambda \Delta \emptyset \tag{7}$$

Or equivalently

$$\frac{\partial \emptyset}{\partial t} = \frac{1}{\lambda} \left[\frac{I_0(x,y) - \frac{m_1 + m_2}{2}}{m_1 - m_2} - (\lambda_1 e_1 - \lambda_2 e_2) \right] + \Delta \emptyset \tag{8}$$

which is a linear equation. Here, we split the evolution (21) into two parts: the first one is

$$\frac{\partial \emptyset}{\partial t} = \frac{1}{\lambda} \left[\frac{I_0(x,y) - \frac{m_1 + m_2}{2}}{m_1 - m_2} - (\lambda_1 e_1 - \lambda_2 e_2) \right] \tag{9}$$

And the second one is

$$\frac{\partial \emptyset}{\partial t} = \Delta \emptyset \tag{10}$$

Then, we use a simpler implemental step to solve the Laplacian equation, which is the Gaussian filtering process.

Conclusion and Fortune Scope

In this research, we propose an image segmentation method by constructing a novel hybrid level set function which consists of the local and differential intensity information. It keeps the property of local model that can overcome noise and inhomogeneous gray intensity, and combines the differential gray information to make the model robust to the initial position. Experimental results showed that our method can fast and accurately segment images with both homogeneous intensity and inhomogeneous intensity, especially, it is not sensitive to the initial curve. In present approach we had worked on a static image, in future the work can be done on a moving picture (video).

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