A Level Set Image Segmentation Method Using Prior Region Information

Dai Yuan-ming, Wei Wei, Lin Yi-ning

College of Electrical Engineering, Zhejiang University, Hangzhou, China

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Abstract

Image Segmentation is a promising technology and very important for image retrieval, target tracking and image analysis applications. The existing region-based level set image segmentation methods which obey a criterion of maximizing the statistic distance of sub-region are mostly on the assumption of dimidiate image, often leading to unsatisfied segmentation results. In order to overcome this deficiency, this paper presents a novel level set image segmentation method using prior region information to improve the segment accuracy. The paper firstly introduces how the prior information is adopted into curve evolution energy function. Then the associated Euler-Lagrange equation which is the most important step is deduced. Finally, the implementation details for the proposed novel method are presented. Extensive experimental results show that the novel level set image segmentation method using prior region information presented in this paper has achieved higher accuracy compared with existing methods.

1 Introduction

Image segmentation is the technique to partition the image into meaningful sub-areas which refers to different objects areas and background area. From a more application perspective, the object could be a pedestrian on street, a diseased organ in medical imaging, a vehicle in navigation system, a gesture of a human been, or a target in military applications.

A large variety of segmentation algorithms have been proposed over the last few decades. Among them, curve evolution technique receives most attentions due to its flexibility. It could be classified into two categories depending on whether the methods use a parameterized contour (represented by Snake [1]) or a nonparameterized contour (represented by Level Set [2]). By contrast, the level set method has advantages in dealing with topological changes and contour representation of an arbitrary shape. Furthermore, the region-based cost functional of level set method tends to have less local minima for most realistic images. Thus, the region-based level set methods are more robust to noise and to varying initialization.

Many region-based level set active contour image segmentation algorithms were presented. Chan and Vese [3] proposed active contour without edge. The object region is segmented to make the mean intensities of object region and background region differ the most. If the object region and the background region have approximately mean values, second-order moments could be used by a similar method [4]. Further on, Michailovich et al. [5] presented a method which uses the entire shapes of probability distributions. Kim et al. [6] presented a method using information theory to segment image by maximizing mutual information between two regions' labels. These region-based methods take the whole image plane into consideration, without prior information, and obey a criterion of maximizing the statistic distance of sub-region, such as intensity means, Bhattacharyya distance and so on. For the relatively simple images, they work well. But if the images are more complex, segmentation results may not so satisfied.

A reasonable objection may be raised: why not incorporate prior information, either photometric or geometric? This is the eventual goal of this research program; the active contour image segmentation method using prior region information is presented in this paper. The outline of this paper is as follows: Section 2 gives a brief review of level set method, and points out the deficiency of existing methods. Section 3 introduces our methods, including how the prior information be adopted into curve evolution energy function, the deduced associated Euler-Lagrange equation, and the implementation details. Section 4 shows the experiment results of using proposed method for segmenting several images, and compares these results with those obtained using existing methods. Finally, Section 5 concludes.

2 Level Set Segmentation

Level set method used the zero-level set of a Lipschitz function: $C = \{x \mid \phi(x) = 0\}$ to represent the contour curve C. A segmentation of the image is evolving the boundary C by locally minimizing a specific energy functional $E(\phi)$ based on image information. The main idea is to evolve the boundary C in direction of the negative energy gradient from some initialization. The energy gradient descent equation is as follow:

$$\frac{\partial \phi}{\partial t} = -\frac{\partial E(\phi)}{\partial \phi} \tag{1}$$

The classical active contour models [7-10] depend on edge defined by the image gradient to stop the curve evolution. These models are limited to detect only objects with positive edges. In practice, the active contour would be easily trapped in undesired local minima due to image noise and complicated background. The isotropic Gaussian filter which is used to smooth the noise would also blur the true edge. Moreover, the stopping function can never be zero on the edges due to the discrete gradients. As a result, the curve may pass through the boundary.

Aimed this, many region-based level set active contour image segmentation algorithms were presented [3-6]. However, as mentioned in section 1, the inherent shortcoming of these methods lies in the fact that the real images are always multifarious and the assumption of having exactly two regions in the image often leads to unsatisfied segmentation results, as shown in fig. 1. This leads us to segment the object region by using prior information which would be elaborated in the next section.

a. Initial Curve b. Chan and Vese's Method [3] c. Michailovich's Method [5]

Fig.1 Region-based Level Set Image Segmentation Results

3 Level Set Using Prior Information

Unlike two-phase level set segmentation methods aforementioned, our method is more akin to object seeking from a practical perspective rather than pixel classification from a pure image processing perspective. For a particular target to be segmented from image plane, prior information could be provided. For example, a diseased organ in medical imaging is darker; a pedestrian on street is humanoid; a vehicle in navigation system gets specific shape; a target in military applications is red and so on. These are semantic descriptions. To incorporate prior information into level set framework, the semantic description should be interpreted to analytical description, such as color, texture, motion and so on. In this paper, the color distribution (which is easily understood) is incorporated into level set segmentation as the prior information.

3.1 Energy Functional

Assume that the target region's color distribution is known beforehand, the goal of image segmentation is to find the most similar region. To define the similarity, here, the Bhattacharyya distance is employed due to its better performance in defining distribution distance as compared to other measures. Besides, the Bhattacharyya distance also has a technical advantage of having an extraordinarily simple analytical form. Specifically, the Bhattacharyya coefficient between two probability densities $p_1(z)$ and $p_2(z)$ is defined as

$$B(p_1, p_2) = \int \sqrt{p_1(z) p_2(z)}dz \tag{2}$$

Let q represents target's prior color distribution, and p represents segmentation area's color distribution, then the similarity energy is defined as

$$E_{\text{Similarity}}(\phi) = B(p(z;\phi), q) \tag{3}$$

Besides, the energy function should take into consideration some plausible properties of the optimal solution. Therefore, some regularizing terms should be added to the total energy functional. Like the length of the curve energy $E_{\text{Length}\{\phi=0\}}(\phi)$, and deviation penalizing of ϕ from a signal distance function $E_{\text{Penalizing}}(\phi)$ [11], which allows level set evolution can work without reinitialization. And the total energy functional defined as

$$E(\phi) = \mu \cdot E_{\text{Length}\{\phi=0\}}(\phi) + \lambda \cdot E_{\text{Penalizing}}(\phi) - \gamma \cdot E_{\text{Similarity}}(\phi) \tag{4}$$

Where μ, λ, γ are fixed positive parameters. Therefore, the level set segmentation could be considered as the minimization problem:

$$\phi^*(x) = \arg\inf_{\phi(x)} E(\phi(x)) \tag{5}$$

3.2 Variational Level-Set Formulation

Using the Heaviside function H and the one-dimensional Dirac measure δ, the terms in the total energy functional are expressed in the following way:

$$\begin{aligned} E_{\text{Length}\{\phi=0\}}(\phi) &= \int \left|\nabla H(\phi(x,y))\right| dxdy \\ &= \int \delta(\phi(x,y)) \left|\nabla \phi(x,y)\right| dxdy \end{aligned} \tag{6}$$

$$E_{\text{Penalizing}}(\phi) = \int \frac{1}{2}(|\nabla \phi(x,y)| - 1)^2 dxdy \tag{7}$$

$$E_{\text{Similarity}}(\phi) = B(p(z;\phi), q) = \int \sqrt{p(z;\phi) q(z)} dz \tag{8}$$

Where $p(z;\phi) = \dfrac{\int \delta(z - Z(x)) H(\phi(x,y)) dxdy}{\int H(\phi(x,y)) dxdy}$ and $q(z)$ is known priorly. Then the total energy can be written as

$$E(\phi)=\mu\int\delta(\phi(x,y))\left|\nabla\phi(x,y)\right|dxdy+\lambda\int\frac{1}{2}(|\nabla\phi(x,y)|-1)^2dxdy$$
$$-\gamma\int\sqrt{\frac{\int\delta(z-Z(x,y))H(\phi(x,y))dxdy}{\int H(\phi(x,y))dxdy}q(z)}dz \tag{9}$$

The associated Euler–Lagrange equation for ϕ was deduced to minimizing $E(\phi)$ with respect to ϕ . Parameterizing the descent direction by an artificial time t, the equation in $\phi(x,y,t)$ (with $\phi(x,y,0)=\phi_0(x,y)$ defining the initial contour) is

$$\frac{\partial\phi}{\partial t}=\mu\delta(\phi)\mathrm{div}(\frac{\nabla\phi}{|\nabla\phi|})+\lambda[\nabla\phi-\mathrm{div}(\frac{\nabla\phi}{|\nabla\phi|})]$$
$$-\frac{\gamma\delta(\phi)}{\int H(\phi)dxdy}\left[\frac{q^{1/2}(Z(\phi))}{p^{1/2}(Z(\phi)}-B(p,q)\right] \tag{10}$$

3.3 Implementation

During implementation, the Dirac function $\delta(x)$ in (10) is smoothed and defined by $\delta_\varepsilon(x)$:

$$\delta_\varepsilon(x)=\begin{cases}0, & |x|>\varepsilon\\ \frac{1}{2\varepsilon}[1+\cos(\frac{\pi x}{\varepsilon})], & |x|<\varepsilon\end{cases} \tag{11}$$

The regularized Dirac $\delta_\varepsilon(x)$ with ε = 1.5 was used for all the experiments in this paper. The approximation of (10) can be simply written as

$$\frac{\phi(x,y,t+1)-\phi(x,y,t)}{t}=F(x,y,\phi(x,y,t)) \tag{12}$$

Where $F(x,y,\phi(x,y,t))$ is the approximation of the right hand side in (10). The difference equation (12) could be iteratively expressed as following:

$$\phi(x,y.t+1)=\phi(x,y,t)+tF(x,y,\phi(x,y,t)) \tag{13}$$

A stop criterion is needed while the segment method iterately evolves the contour curve. Our method uses the similarity between prior color distribution and segmented region's color distribution, and sets a similarity threshold B_{thr}. During iteration, if the similarity reaches to B_{thr}, then stop the curve evolution.

4 Experiments and Analysis

To verify the effectiveness of the proposed method, a series of image segmentation experiments carried out. The level set image segmentation method using prior color information was used for segmenting targets from complicated image. The other two region-based segmentation method also used as a comparison. The segmentation results show in Figure 2.

Initial iteration 50th iteration

200th iteration 450th iteration

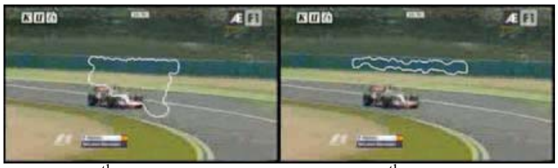
a. Using prior information method

Initial iteration 50th iteration

500th iteration 2000th iteration

b. Chan and Vese's Method

Initial iteration 50th iteration



200th iteration 550th iteration

c. Michailovich's Method

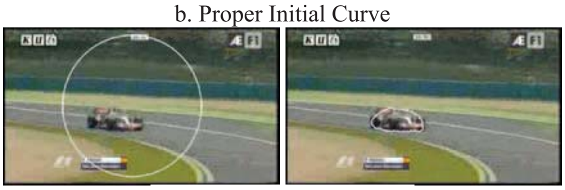
Fig.2 Racing Car Segmentation Results

From the segmentation results, it can be seen that the segmentation results based on Chan and Vese's Method [3] and Michailovich's Method [5] are unsatisfied due to their undirectional and complicated background. Chan and Vese's Method segments the image into lighter part and darker part; Michailovich's Method shows much more instability which would lead to segmentation result of a vacuous region. On the contrary, the segmentation results based on level set image segmentation method using prior information show greater accuracy of target region which we want. Furthermore, the proposed method needs less iteration to reach the final result.

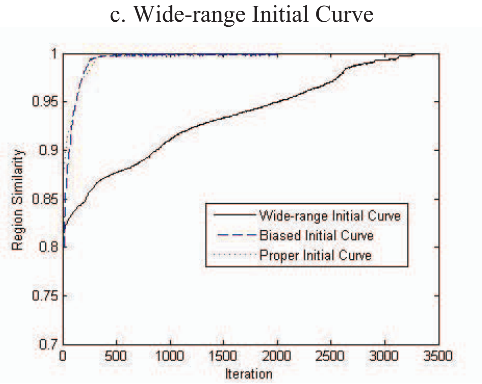
The initial curve could largely affect the image segmentation results. Therefore, several experiments using proposed method under varying initial curve were carried out to illustrate the effects. The segmentation results show as Figure 3.

a. Biased Initial Curve

b. Proper Initial Curve



c. Wide-range Initial Curve



d. Segmentation Progress

Fig.3 Segmentation Results under Varying Initial Curve

From the experimental results, the segmentation results have more accuracy when the target is inside the initial curve. And between two initial curves both contain the target, the one contain less background data needs less running time. As a conclusion, the initial curve should set to contain the target as well as set a proper scale.

5 Conclusion

In this paper, a level set image segmentation method using prior information was presented. The presented method inherits the merit of region-based level set methods and overcomes the limitation of two-phase segmentation meanwhile. Experimental results show that the proposed method can precisely segment the target region from whole image although the background is complicated and has similar statistical features.

In future work, we will devote to speed up the runtime of the algorithm in order to improve the real-time ability of the method, thus to expand the application of method with superior accuracy and real-time ability.

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