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An improved edge-based level set method combining local regional fitting information for noisy image segmentation

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ABSTRACT

Level set methods (LSMs) have been widely used in image segmentation because of their good properties which provide more smooth and accurate segmentation results. The edge-based LSMs use the gradient information of images through edge stop functions (ESFs) to guide the contour curve approaching to object edges. The traditional edge-based LSMs cannot obtain satisfactory segmentation results for noisy images because their regional coefficients are constant and their ESFs are easily influenced by noises. To solve the problems, this paper analyzes the different properties between noise points and object edge points and uses the local regional properties of images points to distinguish noises and object edge points. Based on the local regional properties, we introduce a variable regional coefficient and an improved ESF to overcome shortcomings of the constant regional coefficient and the traditional ESFs. Then we propose an improved edge-based level set method combining local regional fitting information by applying the proposed variable regional coefficient and the improved ESF to the energy function of level set function. The experimental results show that our method obtains accurate segmentation results for noisy images with insensitive to noises and without missing object edges and prove that the method is efficient and robust.

1. Introduction

Image segmentation is of great significance in image processing and computer vision. Various methods have been proposed to solve this problem [1–6]. In these methods, active contour models (ACMs, also named snake or deformable models) are widely used because of their excellent properties which can provide smooth and accurate segmentation results [3–6].

Kass et al propose the original ACM in [7], which is also named parametric ACM. However, it is difficult in handling the topological changes of contour curve since it implements the explicit curve to extract object edges. Osher and Sethian propose the level set method in [8], in which a contour curve is implicitly represented as the zero level set of a high dimensional function (also called level set function, LSF), and easily handle the topological changes of contour curve in the level set evolution.

Existing level set methods for image segmentation can be categorized into two groups: edge-based level set methods [9–12] and region-based level set methods [13–17].

Through edge stop functions, edge-based level set methods use the gradient information of images to guarantee the contour curve locating at object edges. Due to using the gradient information as stopping criteria, edge-based level set methods can segment images without any priority of the number of heterogeneous objects. However, the gradient information is sensitive to noises, thus the traditional edge-based level set methods are sensitive to noises.

Geodesic active contour (GAC) model proposed by Caselles et al. in [9] is a classical edge-based level set method, which uses the intrinsic geometric measure of images to drive the contour curve toward object edges in its segmentation. Distance regularized level set evolution (DRLSE) method proposed by Li et al. in [10,11] is another classical edge-based level set method, which uses the external energy term to drive the contour curve toward object edges during its evolution.

Through regional descriptors, region-based level set methods use the regional information of images to guarantee the contour curve locating at object edges. Due to using the regional information as stopping criteria, the region-based level set methods can be insensitive to noises.

C-V model proposed by Chan and Vese in [14] is a classical region-based model, which uses the global regional information to segment images. It can segment the images whose object and background regions have homogeneous intensity but cannot

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segment the images whose object and background regions have heterogeneous intensity. Local binary fitting (LBF) model proposed by Li et al. in [17] is another classical region-based model, which uses the local region information to segment images. It can segment the images with heterogeneous intensity but is very sensitive to initialization and easily gets stuck into local minima.

Noise is always inevitably introduced into images through a variety of ways and brings great challenges in image segmentation [18]. The major problem of edge-based level set methods for noisy images is that noise may make the contour curve prone to passing through object edges or falling into local minima which lead to unsatisfactory segmentation results.

When the initialization of contour curve is far away from object edges, it is necessary for edge-based level set methods to use the external force term to guarantee the contour curve converging at object edges [11]. For this end, the GAC model introduces a balloon force term to shrink and expand the contour curve [9]. And the DRLSE method uses an external energy term including a length energy term and an area energy term to solve it [10,11]. Based on the edge stop function, the length energy term ensures the contour curve has the shortest length, which regularizes the contour curve and makes it smooth; and the area energy term ensures the contour curve has the smallest area, which controls the speed of the contour curve converging to object edges.

Edge stop functions are essential for edge-based level set methods which guarantee the contour curve locating at object edges; however, the traditional edge stop functions are sensitive to noises since they are merely based on the gradient information. In addition, since the area energy term controls the convergence properties of contour curve, it is not suitable to set its coefficient as a constant in noisy image segmentation, which we will offer a detailed analysis in Section 3.2. Therefore, the traditional edge-based level set methods usually cannot obtain satisfactory segmentation results for noisy images.

In this paper, we analyze the properties of noise points and object edge points, and use the local regional property to distinguish them. Based on the different local regional properties between them, we propose a variable regional coefficient and an improved edge stop function. The variable regional coefficient solves the problem that the constant regional coefficient may lead the contour curve easily falling into local minima or missing object edges in segmentation of noisy image. The improved edge stop function overcomes the shortcoming that the traditional edge stop functions are easily influenced by noises. By applying the variable regional coefficient and the improved edge stop function to the energy function of level set function, we propose an improved edge-based level set method combining local regional fitting information to better segment noisy images. The experimental results show that our method obtains accurate segmentation results for noisy images with insensitive to noises and without missing object edges, which prove the robustness and the effectiveness of our method to noises.

2. Principle of level set method

Based on the curve evolution theory [19], the evolution equation of curve can be expressed as

$$\begin{cases} \dfrac{\partial C(p,t)}{\partial t} = F\vec{N} \\ C(p,t=0) = C_0(p) \end{cases} \tag{1}$$

where $p \in [0,1]$ is the spatial parametric, $t \in [0,\infty]$ is the temporal parametric, $C(p,t)$ is the parametric equation of curve, F is the speed function, $\vec{N}$ is the inner normal vector of curve.

Let the parametric equation $C(p,t)$ of contour curve as the zero level set embedded in the level set function $\varphi(x,y,t)$ [20], the zero level set equation can be expressed as

$$\varphi(C(p,t),t) = 0 \tag{2}$$

and the full differential equation of the zero level set can be expressed as

$$\frac{\partial \varphi}{\partial t} + \nabla\varphi \cdot \left(\frac{\partial C}{\partial t}\right) = 0 \tag{3}$$

where ∇ is the gradient operator.

Assuming that the values outside contour curve are positive and the values inside are negative, the inner normal vector is

$$\vec{N} = -\frac{\nabla\varphi}{|\nabla\varphi|} \tag{4}$$

and the level set evolution equation of contour curve [21] can be expressed as

$$\begin{cases} \dfrac{\partial \varphi}{\partial t} = F|\nabla\varphi| \\ \varphi(x,y,t=0) = \varphi_0(x,y) \end{cases} \tag{5}$$

The level set evolution equation of the classical GAC method in [9] is defined as:

$$\frac{\partial \varphi}{\partial t} = |\nabla\varphi|\left(div\, g\left(\frac{\nabla\varphi}{|\nabla\varphi|}\right) + \upsilon g\right) \tag{6}$$

where υ is a constant coefficient, $div(\bullet)$ is the divergence operator, g is an edge stop function which is defined as

$$g = \frac{1}{1+f} = \frac{1}{1+|\nabla G_\sigma * I|^2} \tag{7}$$

where f is the gradient information of the given image I, G_σ is the Gaussian kernel function with standard deviation σ.

In the variational level set methods [10,11,22–24], the evolution problems of contour curve are converted to the minimization problem of the energy functions including different image feature information, and then are solved by the gradient descent flow method and the variational method. Therefore, the level set evolution equation of contour curve can be obtained as

$$\frac{\partial \varphi}{\partial t} = -\frac{\partial E}{\partial \varphi} \tag{8}$$

The energy function $E(\varphi(\mathrm{x}))$ of the classical DRLSE method in [10,11] is defined as

$$\begin{aligned} E(\varphi(\mathrm{x})) &= \mu R_p(\varphi(\mathrm{x})) + \lambda L_g(\varphi(\mathrm{x})) + \upsilon A_g(\varphi(\mathrm{x})) \\ &= \mu \int_\Omega p(|\nabla\varphi(\mathrm{x})|)d\mathrm{x} + \lambda \int_\Omega g\delta_\varepsilon(\varphi(\mathrm{x}))|\nabla\varphi(\mathrm{x})|d\mathrm{x} \\ &\quad + \upsilon \int_\Omega gH_\varepsilon(-\varphi(\mathrm{x}))d\mathrm{x} \end{aligned} \tag{9}$$

where $\mu>0, \lambda>0, \upsilon \in R$ are the coefficients of penalty energy function $R_p(\varphi(\mathrm{x}))$, length energy function $L_g(\varphi(\mathrm{x}))$ and area energy function $A_g(\varphi(\mathrm{x}))$ respectively, $p(|\nabla\varphi(\mathrm{x})|)$ is the potential function of $R_p(\varphi(\mathrm{x}))$, which is defined as

$$p(|\nabla\varphi(\mathrm{x})|) = \begin{cases} \dfrac{1}{(2\pi)^2}\left(1-\cos(2\pi|\nabla\varphi(\mathrm{x})|)\right), & \text{if } |\nabla\varphi(\mathrm{x})| \le 1 \\ \dfrac{1}{2}\left(|\nabla\varphi(\mathrm{x})|-1\right)^2, & \text{if } |\nabla\varphi(\mathrm{x})| \ge 1 \end{cases} \tag{10}$$

$\delta_\varepsilon(\cdot)$ and $H_\varepsilon(\cdot)$ are the Dirac function and the Heaviside function