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Pattern Recognition 39 (2006) 1391 – 1395
PATTERN RECOGNITION
THE JOURNAL OF THE PATTERN RECOGNITION SOCIETY
www.elsevier.com/locate/patcog

Rapid and Brief Communication

GACV: Geodesic-Aided C–V method

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Received 5 October 2005; accepted 24 January 2006

Abstract

A novel algorithm for image segmentation is proposed. The proposed method incorporates geodesic curves and C–V method to raise active contours' performance on image segmentation. Moreover, we extend our method to color images. By practical experiments, it is verified that our model obtains better results than original methods, especially with respect to images within holes, complex background, weak edges, and noise.

Keywords: Image processing; Image segmentation; Deformable model; Active contour; C–V method; Geodesic active contours

1. Introduction

Recently, geometric active contours [1], based on the theory of surface evolution and geometric flows, are more and more focused due to their richness and power in image processing. And Geodesic active contours [2], and C–V method [3], are representatives of them. In the model of geodesic active contours, gradient flow is used as a stopping operator to get accurate boundaries with high variation in gradient, and a new term is incorporated to attract the curve to object boundary, while C–V method is a two-class segmentation model, relying on the global information of homogeneous regions instead of the local gradient of the image. In this paper, we first cover associated shortcomings of C–V method and geodesic curves, and discuss preliminary solutions of them, and then, we present our novel active contour model, which modifies the original C–V formulation to achieve better performance. Moreover, the proposed model is extended to vector-valued images. The experiments and results demonstrate that our method is promising.

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2. Problems of C–V method and geodesic active contours

C–V method depends on the image information derived from homogenous regions; therefore it can obtain favorable results in fuzzy or discrete cases. Besides, a process of denoising is not necessary in this model. However, in spite of these advantages, C–V method has an unavoidable restriction. That is, there are only two classes, the objects and the background, which are considered in this model, resulting in problems in detecting more than two objects or multiple objects with complex background. The multiphase level set framework [4] is proposed to solve this problem, but it is very time consuming. Additionally, the original C–V method's global property is not satisfactory enough, which makes C–V method fail when detecting images with holes. Another deficiency is that the precise boundary usually cannot be obtained, because C–V method is based on information of homogeneous regions instead of local information.

Geodesic active contours are based on gradient and curvature to detect boundary, in which only local information of boundary is used, thus it is difficult to get ideal results dealing with fuzzy edge and discrete edge. Furthermore, because of the local attributes and the dependence on gradient, geodesic active contours are heavily affected by noisy inputs.

0031-3203/$30.00
doi:10.1016/j.patcog.2006.01.017

3. Geodesic C–V method

In order to raise C–V method's performance on multiple objects and complex background (which is just the advantage of geodesic curve), while keeping the advantages of C–V method in dealing with discreet edges and regions, we suppose to synthesize the two algorithms in a reasonable way, and the new synthesized method is called "Geodesic C–V method".

The original C–V method's PDE formulation is

$$\frac{\partial \phi}{\partial t} = \delta_\varepsilon(\phi)\Big[\mu \cdot \nabla \cdot (\nabla\phi/|\nabla\phi|) - v - \lambda_o[I(x, y) - c_o]^2 + \lambda_b[I(x, y) - c_b]^2\Big], \tag{1}$$

where $I(x, y)$ denotes the pixels in image, ϕ is the value of level set, c_o and c_b are the means of pixel values inside the curve and outside the curve respectively, v is assumed to be 0. Firstly, as the effective range of $\delta_\varepsilon(\phi)$ is very small, we replace it by $|\nabla\phi|$, which has an effective range of the whole image, to strengthen the global property of C–V method. Secondly, with the aim of adding geodesic curves' advantages in C–V model, we replace $\mu\nabla \cdot (\nabla\phi/|\nabla\phi|)$ in Eq. (1) as $\mu\nabla \cdot (g \cdot \nabla\phi/|\nabla\phi|)$, defining a new Riemannian Space as in geodesic curves (g is the local gradient defined in Ref. [2]). In this way, we synthesize the C–V method and geodesic curves. Then, the formulation becomes

$$\frac{\partial \phi}{\partial t} = |\phi|\left[\mu\nabla \cdot \left(g\frac{\nabla\phi}{|\nabla\phi|}\right) - v - \lambda_o[I(x, y) - c_o]^2 + \lambda_b[I(x, y) - c_b]^2\right].$$

By the identical transform

$$\nabla \cdot \left(g\frac{\nabla\phi}{|\nabla\phi|}\right) = g\nabla \cdot \left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \nabla g \cdot \frac{\nabla\phi}{|\nabla\phi|},$$

the formulation become

$$\frac{\partial \phi}{\partial t} = g|\nabla\phi|\left[\mu \cdot div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - \lambda_o[I(x, y) - c_o]^2 + \lambda_b[I(x, y) - c_b]^2\right] + \tau \cdot \nabla g \cdot \nabla I(x, y), \tag{2}$$

where $\tau = 1$, μ, λ_o and λ_b are assumed to be 1, τ can be adjusted. In Eq. (2), there are two terms in right, and we call the first as "region detector" and the second as "local detector". The region detector, as in original C–V model, uses curvature and statistic information of the homogenous regions, $-\lambda_o[I(x, y) - c_o]^2 + \lambda_b[I(x, y) - c_b]^2$ as image information, while multiplying $g|\nabla\phi|$ as the controller of evolution speed. Multiplying $g|\nabla\phi|$ can control the speed of evolution and the weight of region detector, and make possible the local property in order to obtain accurate boundaries. The second term $\nabla g(I) \cdot \nabla I(x, y)$ functions as an attractive detector, which attracts the evolving curve to the real boundary of objects (more details in Ref. [2]). In conclusion, in the proposed model, the attractive term cooperates with the gradient flow to form the local detector, while the region detector is based on the image information derived from the homogeneous regions in the image. On the one hand, when the gradient variation is very high, according to the definition of the gradient flow described in Ref. [2], the gradient flow becomes very little, making the first term on the right-hand side of Eq. (2) becomes little too. As a result, the sum of the right-hand side of Eq. (2) would be mainly decided by the attractive term. In this case, the function of the attractive term turns to be obvious, which makes the evolving curve be able to find the definite boundary automatically. Undoubtedly, this style is helpful in obtaining accurate boundary and ensuring the detection of boundary with high variation in gradient, which may possibly be neglected in the original C–V method, which is based on region information solely. On the other hand, when the gradient flow is not very little, the information of homogeneous regions acts as the main force to attract the curve to the boundary, and our model functions as the original C–V model The region detector is contributive in detecting holes, fuzzy boundary and discrete edges, and it is not affected by noisy inputs. In our model, the result of segmentation is mainly affected by region detector too.

In sum, the new method can adjust the weight of the two detectors automatically, and it synthesize the advantages of geodesic active contours and C–V method. When the gradient flow become very little, which means there might be some sharp edges, the local detector functions mainly, to get the accurate edges of objects, otherwise, the region detector functions mainly, and the method turns to be original C–V method, keeping its advantages in evolving speed, robustness against noise, and detecting discreet edges.

4. Extension to color case

Now we describe the way to extend our method to color image. From Eq. (2), we can find that the extension focuses on two points: how to decide the color gradient flow and how to use the color information of homogenous regions. In this paper, we obtain the color gradient flow in the way described in Ref. [2], and synthesize the color information in Euclidian space by replacing the scalar distance $I - c_o$, $I - c_b$ in Eq. (2) by Euclidian distance. Then the final formulation of color geodesic C–V method turns out to be

$$\frac{\partial \phi}{\partial t} = g_{color}|\nabla\phi|\left[\mu \cdot div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - \frac{1}{3}\sqrt{\sum_{i=1}^{3}\lambda_{io}(u_{0,i} - c_{io})^2} + \frac{1}{3}\sqrt{\sum_{i=1}^{3}\lambda_{ib}(u_{0,i} - c_{ib})^2}\right] + \nabla g_{color} \cdot \nabla I(x, y).$$