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Identifying Contours with Selective Local or Global Segmentation Using a Naïve Formulation and Level Set Method

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ABSTRACT

A novel region-based active contour model (ACM) is proposed in this paper. It is implemented with a special processing named Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) method, which first selectively penalizes the level set function to be binary, and then uses a Gaussian smoothing kernel to regularize it. The advantages of our method are as follows. First, a new region-based signed pressure force (SPF) function is proposed, which can efficiently stop the contours at weak or blurred edges. Second, the exterior and interior boundaries can be automatically detected with the initial contour being anywhere in the image. Third, the proposed ACM with SBGFRLS has the property of selective local or global segmentation. It can segment not only the desired object but also the other objects. Fourth, the level set function can be easily initialized with a binary function, which is more efficient to construct than the widely used signed distance function (SDF). The computational cost for traditional re-initialization can also be reduced. Finally, the proposed algorithm can be efficiently implemented by the simple finite difference scheme. Experiments on synthetic and real images demonstrate the advantages of the proposed method over geodesic active contours (GAC) and Chan–Vese (C–V) active contours in terms of both efficiency and accuracy.

Keywords : Active Contours, Geodesic Active Contours, Chan Vese Model, Image Segmentation, Level Set Method

I. INTRODUCTION

Image segmentation is a fundamental problem in image processing and computer vision. Extensive study has been made and many techniques have been proposed [1,2], among which the ACM [1,3–6] is one of the most successful methods. The basic idea of ACM is to evolve a curve under some constraints to extract the desired object. According to the nature of constraints, the existing ACMs can be categorized into two types: edge-based models [1,3,4,6,10,12,18,20] and region-based models [5,7,8,11,14–17].

II. METHODS AND MATERIAL

This paper is based on the following models:

1. GAC model

Let Ω be a bounded open subset of R^2 and I: [0, a] [0, b] → R^+ be a given image. Let C(q): [0, 1] → R^2 be a parameterized planar curve in Ω. The GAC model is formulated by minimizing the following energy functional:

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

2. C–V Model

Chan and Vese [5] proposed an ACM which can be seen as a special case of the Munford–Shah problem [8]. For a given image I in domain Ω , the C–V model is formulated by minimizing the following energy functional:

$$E^{CV} = \lambda_1 \int_{inside(C)} |I(x) - c_1|^2 dx + \lambda_2 \int_{outside(C)} |I(x) - c_2|^2 dx, \quad x \in \Omega,$$

The Proposed Model

The SPF function defined in [9] has values in the range [-1, 1]. It modulates the signs of the pressure forces inside and outside the region of interest so that the contour shrinks when outside the object, or expands when inside the object. Based on the analysis in Section 2, we construct the SPF function as follows:

$$spf(I(x)) = \frac{I(x) - \frac{c_1+c_2}{2}}{\max\left(\left|I(x) - \frac{c_1+c_2}{2}\right|\right)}, \quad x \in \Omega,$$

III. RESULTS AND DISCUSSION

Our algorithm is implemented in Matlab 7.0 on a 2.8-GHz Intel Pentium IV PC. In each experiment, we choose q = 1, e = 1.5, r = 1, K = 5, and time step Dt = 1. The values of a were set according to the images.

Fig. 4 shows the segmentation results of a synthetic image with objects having weak edges and interior holes. The GAC model with the traditional level set method is used in the comparison. The size of the test image is 250 x 250 pixels. The left column in the first row of Fig. 1 shows the initial contour of our model, which is not around or inside the objects, while all of the objects are surrounded by the initial contour of the GAC model (see the right column in the first row of Fig. 1). The second row shows the corresponding segmentation results of our method and the GAC model, respectively.

For our method, the evolution of the level set function converges in 30 iterations and takes only 0.25 min, while for the traditional GAC model, the evolution converges in 7000 iterations and takes for 45 min. Our method accurately detects the exterior and interior boundaries of the objects, as well as the weak edge object, whereas the traditional GAC model fails to detect the interior boundary of the object and the weak edge object.

Fig. 1 demonstrates the global segmentation property of our method. The initial contour is far from the objects, as shown in the first row of Fig. 1. The second row shows the segmentation results of the C–V model, which fails to extract all the objects, whereas our method could accurately extract all the objects, as shown in the third row of Fig. 1.

Fig. 2 shows the segmentation results of two galaxy images by the proposed method. The first row shows the initial contours which are around the objects. The second row shows the segmentation results. We see that the contours of the galaxies are accurately detected.

Fig. 3 demonstrates the selective segmentation property of the proposed method. The size of the test image is 60 x 80 pixels.

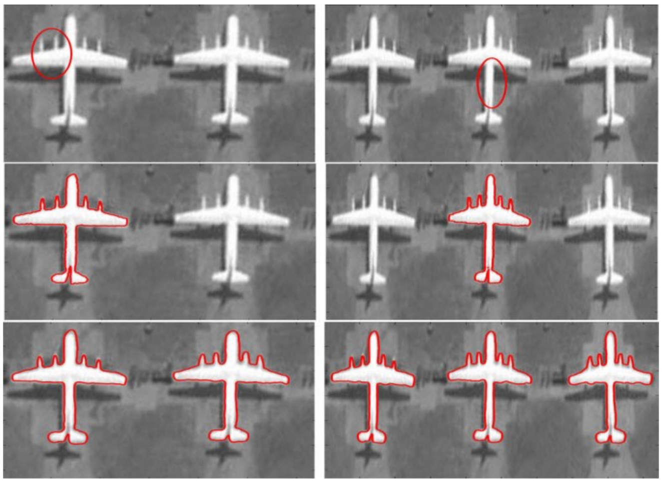

Figure 1. Comparisons of the global segmentation property between the C–V model and the proposed method. The first row shows the initial contours, the second row shows the segmentation results of C–V model, and the third row shows the segmentation results of the proposed method. The parameter α=20.

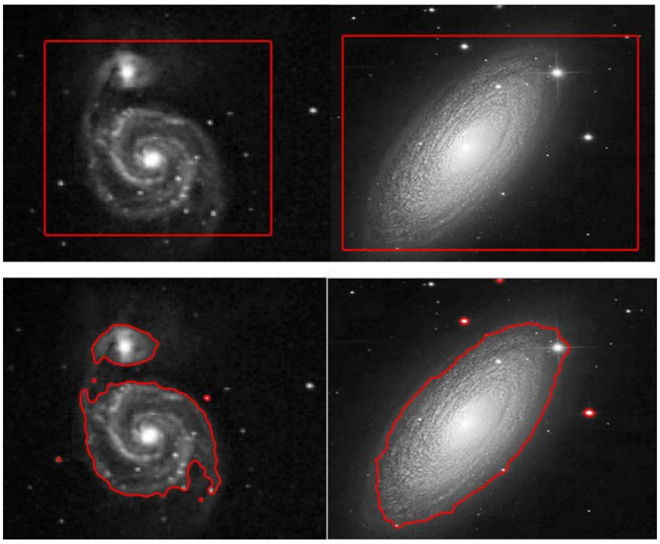

Figure 2. Segmentation results of the galaxy images. The first row shows the initial contours and the second row show the segmentation results. The parameter α =20

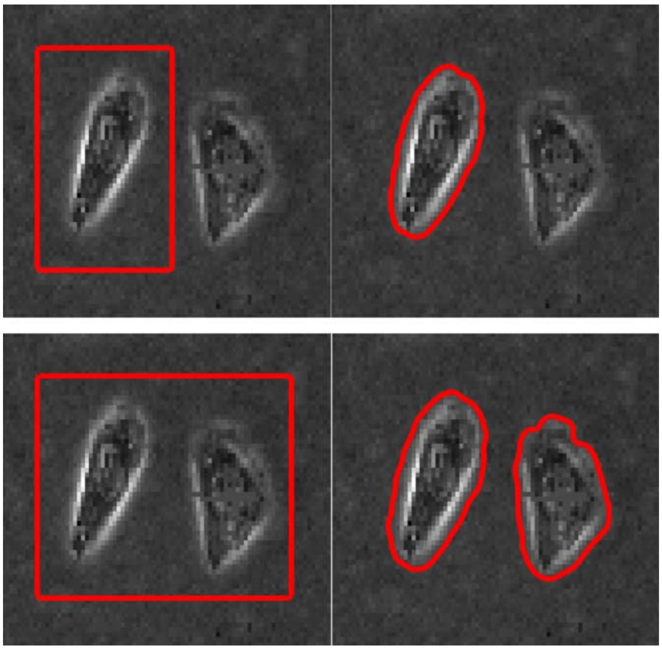

Figure 3. Selective segmentation results for a real microscope cell image. The left column shows the initial contours, and the right column shows the corresponding segmentation results. The parameter α = 20.

IV. CONCLUSION

In this paper, we proposed a novel region-based ACM for image segmentation which is implemented with a new level set method named SBGFRLS method. The SBGFRLS method reduces the expensive re-initialization of the traditional level set method to make it more efficient. The proposed model implementing with the SBGFRLS method combines the merits of the traditional GAC and C–V models, which possesses the property of local or global segmentation. Extensive experiments on synthetic and real images demonstrated the advantages of the proposed method over the classical ACMs with the traditional level set methods, such as the GAC and C–V models. Our proposed SBGFRLS method is general and robust which can be applied to implementing the algorithms of some classical ACMs, such as GAC model [3, 4], C–V model [5], PS model [14, 15], LBF model [11, 24], and so on.

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