Object Segmentation in Color Images using Distance Regularized Level Set

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Abstract

Segmenting objects in images is an important problem of image processing and computer vision. There have been various level set methods applied on gray scale images. However, in practice, these methods will give negative effects to color images such as the distortion when using its gray-scale gradient information. In this paper, object segmentation based on a modification of a new type of level set method named distance regularized level set evolution (DRLSE) in color images is proposed. The speed function here will be designed to use color gradient information of the image. Finally, experimental results are provided to show the accuracy of this method when applying to different color images.

Keywords: Object segmentation, level set method, color images

1. Introduction

In recent research of image processing and computer vision, segmentation via the level set method becomes an important problem applied widely to many applications using both gray-scale images and color images. The level set method was introduced by Osher and Sethian [1] in 1988 as the first time. For segmenting dynamic shapes of objects in an image, Kass, Witkins, and Terzopoulos [2] introduced active contours in 1987. Its basic idea is to describe an active contour as the zero level set of a level set function (LSF) to control the evolution of this contour for reaching the final boundary of objects by various external forces, such as gradient or gradient vector flow of the image, embedded in a speed function [3,4,5,6,7,8]. There are two active contour models classified as parametric active contour models and geometric active contour models.

There are expected advantages of active contours implemented through level set methods. One of them is to be suitable for handling complex and changeable topology, such as splitting and merging a contour. Another is its ability to perform numerical computations on Cartesian grid without concerning the parameterization of points on a contour. For these reasons, our work here also uses an active contour applied in level set framework shown by a new method called distance regularized level set evolution (DRLSE) developed in [9].

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The segmentation of these methods into meaningful areas of images can be driven by various criteria, such as edge, color, texture, or motion information. Among these criteria, edge information is used the most by computing many types of gradient value of both gray-scale images and color images to identify the intensity changes appearing at edges or corners in images. The original DRLSE method is only proposed to segment objects in gray-scale images. To apply this method into color images, there will be some effects on not only slowing down processing time if the size of general images is large but also decreasing computing accuracy if the intensity of pixels is converted to gray value as well as the way to calculate gradient value is chosen.

In this paper, we suggest a modification of speed function of DRLSE method to improve the segmenting results on color images. Its speed function in level set equation is changed to use color gradient information rather than traditional gray-scale gradient. The image can also be subsampled during its implementation to speed up the program. So, the paper is organized as follows. In Section II, a necessary background of level set method is provided. In section III, we briefly introduce distance regularized level set evolution (DRLSE) method as well as our improvement based on color gradient function. The experimental results of applying our proposed method to different color images are given in section IV. Finally, section V is our conclusions to remark our improvement.

2. Background

Early active contours (or fronts) are modeled as a dynamic parametric active contour $C(s,t):[0,1]\times[0,\infty)\rightarrow\Re^2$ with a spatial parameter *s* which describes the points in the contour, and a temporal parameter *t*.

The basic idea of level set method is represented by formulating a contour $C(s,t)$ on the plane as the zero level set of a higher dimensional function $\phi(\vec{x},t)$, called level set function, in the space of $\Re^3$. Its evolution equation can be described as

$$\frac{\partial\phi}{\partial t}+F|\nabla\phi|=0 \tag{1}$$

The function *F* is called a speed function and controls the motion of the contour. For image segmentation, the speed function can be separated into two terms, an external term which forces the contour toward the desired object boundaries based on image data and an internal term which smooths out the contour in areas of high curvature. To improve the highly inaccurate computation made by some problems of the traditional level set methods during the evolution [5,6], the function ϕ is initialized as a signed distance function

$$\phi(\vec{x},t)=\begin{cases}-d(\vec{x}) & \text{inside } C\\ 0 & \text{on } C\\ d(\vec{x}) & \text{outside } C\end{cases} \tag{2}$$

where $d(\vec{x})=\min(|\vec{x}-\vec{x}_i|)$ for all $\vec{x}_i$ on the contour *C*. Although this scheme gives good results due to its main property $|\nabla\phi|=1$, it still has weak points such as the periodically complicated reinitialization process of the signed distance function as well as an undesirable side effect of moving the zero level set away from its original location [6,11].

3. Distance regularized level set evolution applied in color images

3.1 Color gradient

Color space is the way in which colors are expressed. In digital images, RGB color space is widely used the most. However, converting RGB color images into grayscale ones would usually lead to negative effects. Using only gray gradient information can appear the distortion in color images. Some information to distinguish different colors can also be lost if they have the same gray value. In this case, sometimes the boundary between objects and background cannot be separated clearly. Moreover, converting RBG color space into others (such as HSV, Lab, etc.) is usually time-consuming if the image has large size due to its complex computation. In order to apply the original DRLSE method, which uses gray gradient information to control the movement of the contour, in color images, we use the color gradient information itself because of its richness of information in RGB color space directly.

Before extracting color gradient information, the color image I is convolved with a Gaussian kernel G with a specific standard deviation σ as

$$I_\sigma = G_\sigma * I \tag{3}$$

After that, the color gradient components in X and Y direction are computed by choosing the maximum gradient value among three color channels of convolved image I_σ in each direction respectively. Therefore, the edge indicator function is defined by

$$g = \frac{1}{1 + \left|\max\left(\nabla I_\sigma^i\right)\right|^2} \tag{4}$$

for all color channels $i = \overline{1,3}$.

3.2 DRLSE

The proposed distance regularized level set evolution (DRLSE) by Li et al. in [11] introduces the following energy functional

$$\varepsilon(\phi) = \mu R_p(\phi) + \varepsilon_{ext}(\phi) \tag{5}$$

where $R_p(\phi)$ is the level set regularization term to characterize how close the level set function ϕ is to a signed distance function, μ is a constant controlling this deviation, and $\mathcal{E}_{ext}(\phi)$ is a certain external term depending on the desired image feature.

Let Ω be the image domain. The regularization term is defined as

$$R_p(\phi) = \int_\Omega p(\nabla\phi)dx \tag{6}$$

where p is chosen as a double-well potential function [11] provided by the below construction

$$p(s) = \begin{cases} \frac{1}{(2\pi)^2}\left(1 - \cos(2\pi s)\right) & \text{if } s \le 1 \\ \frac{1}{2}(s-1)^2 & \text{if } s \ge 1 \end{cases} \tag{7}$$

The external term in (5) is defined as

$$\varepsilon_{ext}(\phi) = \lambda\int_\Omega g\delta(\phi)|\nabla\phi|dx + \nu\int_\Omega gH(-\phi)dx \tag{8}$$

where g is the edge indicator function described by (4), $\lambda > 0$ and $\nu \in \Re$, H is the Heaviside function, and δ is the univariate Dirac function defined by $\delta(\phi) = H'(\phi)$. In this term, the first component computes the length of the zero level contour of ϕ. This energy is minimized when the zero level contour of ϕ is located at the object boundaries. And the second component computes the weighted area of the region inside the contour ϕ as well as is able to speed up the motion of the zero level contour of ϕ.

By taking the derivative of the level set function with respect to t, the energy functional $\mathcal{E}(\phi)$ can be minimized by solving the following gradient flow

$$\frac{\partial\phi}{\partial t} = \mu\left(\Delta\phi - \mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) + \lambda\delta(\phi)\mathrm{div}\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + \nu g\delta(\phi) \tag{9}$$

To implement this equation in numerical scheme, the univariate Dirac function and Heaviside function in (9) are approximated by the following smooth functions

$$\delta_\varepsilon(x) = \begin{cases} \frac{1}{2\varepsilon}\left[1 + \cos\left(\frac{\pi x}{\varepsilon}\right)\right] & |x| \le \varepsilon \\ 0 & |x| > \varepsilon \end{cases} \tag{10}$$

$$H_\varepsilon(x) = \begin{cases} \frac{1}{2}\left[1 + \frac{x}{\varepsilon} + \frac{1}{\pi}\sin\left(\frac{\pi x}{\varepsilon}\right)\right] & |x| \le \varepsilon \\ 1 & x > \varepsilon \\ 0 & x < -\varepsilon \end{cases} \tag{11}$$

where ε is a constant chosen by implementing experiment. Moreover, the narrow band algorithm [9, 12] is also chosen to reduce complexity cost during the implementation since it only computes pixels around the zero level set of contour, not whole images.

4. Experimental results

Our implementation of DRLSE method in color images has been carried out by using various types of images. A PC of Core^{TM}2 6700 2.67GHz and 2GB RAM is used to run Matlab 2011a. In numerical implementation, all experiments are tested based on two different approaches, a full domain and a narrow band algorithm [11].

The initial function ϕ_0 can be a signed distance function or a binary step function defined by

$$\phi_0(x) = \begin{cases} -c_0 & \text{if } x \in R_0 \\ c_0 & \text{otherwise} \end{cases} \tag{12}$$

where R_0 is a region in image domain and $c_0 > 0$ is a constant. Then, the discretization of evolution equation (9) is followed by the difference equation

$$\phi_{i,j}^{k+1} = \phi_{i,j}^k + \tau L\left(\phi_{i,j}^k\right) \tag{13}$$

where $L\left(\phi_{i,j}^{k}\right)$ is the approximation of the right hand side in (9) by the spatial difference scheme approximated by the central difference for partial derivatives and the forward difference for temporal derivative.

Fig. 1 shows the result of our improvement of DRLSE applied in a color image by narrow band implementation, with parameters λ =5.0, μ =0.02, v =3.0, and time step τ =10. Fig. 1(a) describes the original image whose size is 480 x 320. After 500 iterations, the computing time to segment the object is nearly 92.5 seconds.

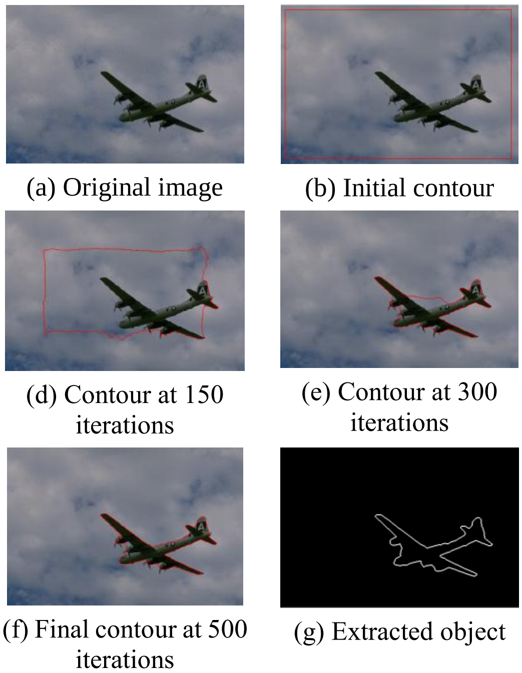

Fig. 1. Evolution of the zero level set and the final extracted result for a color image

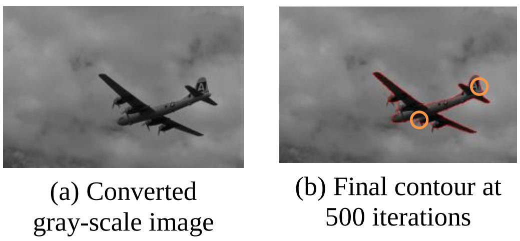

Fig. 2. The final zero level set of contour for a converted gray-scale image

In **fig. 2**, the picture used in **fig. 1** is converted to gray-scale value before evolving the zero level set of contour. Compared with the final result in **fig. 1**, we see that the final contour in **fig. 2** is not quite fit as fig. 1(f) and has some small distortion (shown by orange circles).

Fig. 3 is given by trying our improvement of DRLSE in different type of color images. The zero level set of contour is described by a red curve bounding the object. The last two fig. 3 (e,f) shows weak points of our method. All color images should be assumed that color intensity of the background is at least nearly homogeneous. Moreover, the difference of color intensity between segmented object and others in images should also be large enough to be able to distinguish mutually. Finally, in this paper, the contour has to be initialized completely inside or outside segmented objects.

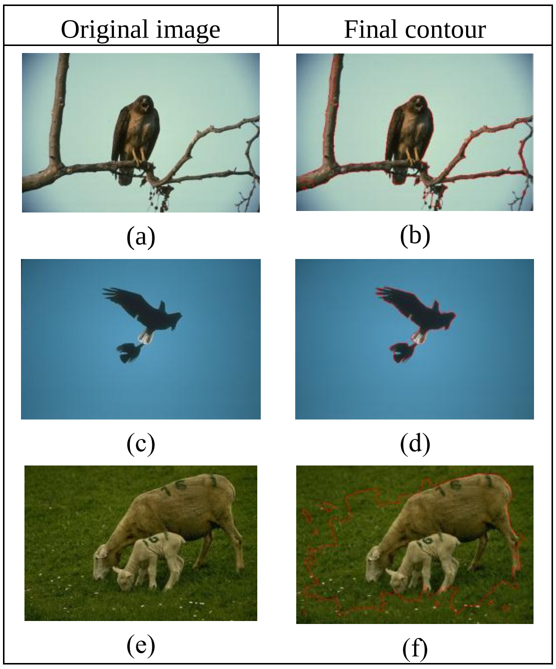

Fig. 3. Results of DRLSE in different images

Table 1 compares the computation time (in seconds) taken by narrow band algorithm and the full domain approach with or without subsampling color images. We can remark that the narrow band implemetation runs faster than the full domain approach. Thus, using more and more image subsampling can speed up the evolution. However, it may cause errors in the boundary location if the size of original images is decreased too much. There should be a tradeoff between subsampling image and accuracy in boundary location.

Table 1. Comparison of computation time two implemeting approaches with different size of images

#Iters	Narrow Band		Full Domain	
	100% size	80% size	100% size	80% size
50	8.8	5.6	14.3	8.2
200	34.7	22.6	53.5	32.7
400	70.6	44.5	107.3	65.3
500	92.5	53.8	130.9	81.5

5. Conclusions

In this paper, we modified the edge indicator function used in DRLSE method based on the color gradient aiming to color images to replace the original method based on gray gradient. The experiments show that the resulting contour in color images can be fit mostly the boundary of an object more than in gray-scale images. Besides, this method with narrow band implementation and subsampling method decreases its computation time. So, it has acceptable performance in terms of accuracy and efficiency. Besides, there are disadvantages of this method which should be improved as mentioned in section IV. Our future research is to continue focusing on general color images. Not only the final zero level set of contour is able to fit the boundary of objects more exactly even if there exists the presence of weak boundaries, but also the contour is initialized more flexibly.

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