J. Vis. Commun. Image R. 39 (2016) 100–106

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

A multi-object image segmentation C–V model based on region division and gradient guide ☆

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ARTICLE INFO

Article history:
Received 20 December 2015
Revised 24 April 2016
Accepted 19 May 2016
Available online 20 May 2016

Keywords:
Multi-object image segmentation
C–V model
Gradient guide
Region division

ABSTRACT

The Chan–Vese (C–V) model is an ineffective method for processing images in which the intensity is inhomogeneous. This is especially true for multi-object segmentation, in which the target may be missed or excessively segmented. In addition, for images with rich texture information, the processing speed of the C–V is slow. To overcome these problems, this paper proposes an effective multi-object C–V segmentation model based on region division and gradient guide. First, a rapid initial contour search is conducted using Otsu's method. This contour line becomes the initial contour for our multi-object segmentation C–V model based on a gradient guide. To achieve the multi-object segmentation the image is then converted to a single level set whose evolution is controlled using an adaptive gradient. The feasibility of the proposed model is analyzed theoretically, and a number of simulation experiments are conducted to validate its effectiveness.

1. Introduction

Image segmentation is the technique of separating the "target" area from the "background," and is a fundamental component of image processing and analysis. However, because of the ill-posed nature of many image segmentation problems [1], different methods bring about different segmentation effects. At the same time, different images contain different information characteristics, and so the segmentation results for the target regions are not the same. To date, it has been difficult to find an effective method that can adapt to all kinds of image segmentation. The image segmentation problem based on the Partial Differential Equation (PDE) is represented as an energy minimization problem and the objective functional is solved by variational methods. In recent years, methods based on the active contour model (ACM) have made good progress [2–4]. The ACM control mobilization for initial contour to stop on the edge of the target by energy function. Image segmentation methods based on the ACM mainly include edge-based and region-based segmentation techniques. The edge-based models utilize an edge descriptor as additional constraint to stop the evolving curve on the object boundaries. Usually, a stopping function is used to attract the curves to the desired boundaried. For example, the GAC model [5] utilizes image gradient to construct an edge stopping function to stop the evolving curve on the object boundaries. Generally speaking, edge-based models have been successfully used for segmenting general images with strong object boundaries, but they are usually sensitive to noise and weak edges. Instead of utilizing image gradient as an edge descriptor, region-based methods take the global characteristics of the image into account and identify each region of interest by using a certain region descriptor, such as intensity, color, texture or motion, to guide the motion of the evolving curve. Therefore, region-based models generally have better performance of noise and weak object boundaries [6]. The Chan–Vese (C–V) is a widely used segmentation method. The C–V model is fairly robust in regions that have no (fuzzy) edges [7], and is an effective image segmentation tool under certain instances of local noise. However, using the C–V model, it is difficult to process objects of inhomogeneous intensity effectively, especially for multi-object segmentation in which the target may be missed or excessively segmented. In addition, for images with rich texture information, the evolution of the C–V model is slow. These difficulties in processing multi-target image segmentation effectively, have led to the development of improved algorithms based on multi-level sets. Among them, piecewise smooth and piecewise constant models have been proposed [8] based on the model of Mumford and Shah. These solve the problem

☆ This paper has been recommended for acceptance by M.T. Sun.

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http://dx.doi.org/10.1016/j.jvcir.2016.05.011

of inhomogeneous intensity to some extent, but their computational efficiency is too poor to be adapted to actual image segmentation, Cao et al. [9] constructed the corresponding image area through multiple level set equations, which improved the segmentation efficiency to a certain extent. However, the segmentation result is heavily reliant on the initial curve position, so this approach can easily become trapped in a local optimum. Wang and Li [10] proposed a level set image segmentation model based on dual contours by setting both inside and outside contour lines. The difference between these contours is then minimized to approach the target with the aim of achieving better segmentation results. However, this model is still computationally expensive. Wang et al. [11] defined a local Gaussian distribution fitting energy with a level set function and local means and variances are variables. Although this model (LGD) is able to distinguish regions with similar intensity means but different variance, it is weak in segment multi-object images. It is clear that, although multi-level set solutions can achieve good multi-object segmentation to a certain degree, their high complexity, over-reliance on initial contour lines, and other weaknesses usually present difficulties to their practical application. Thus, achieving effective multi-object segmentation with level sets has become an issue of great concerns.

This paper presents a multi-object C–V segmentation model based on region division and gradient guide. First, the model rapidly determines the target boundary outline, and then uses this initial contour to commence the evolution of the ACM based on a contour gradient guide. The multi-object segmentation is then converted into a single level set evolution process, and the evolution of the contour line level set is controlled using an adaptive gradient. Based on the consideration of global image information, the model takes the local characteristics of each target into account through the broad contours to avoid missing the target. The accuracy and efficiency of target segmentation are further improved through the evolution of the gradient guide for the adaptive control contour line.

2. Analysis of the C–V model

According to the gray level differences between the background and the target, the C–V model takes a controlled closed curve and considers the difference between its internal and external energy, ultimately leading the control curve toward the edge of the target. The energy function of C–V model is:

$$E(C,C_1,C_2) = \mu\, length(C) + \lambda_1 \int_{I_1} |I(x,y) - C_1|^2 dxdy + \lambda_2 \times \int_{I_2} |I(x,y) - C_2|^2 dxdy \tag{1}$$

where I_1 and I_2 are the background and target of the image, respectively, and C_1, C_2 are the average gray values of the background and target. This energy function includes three parts: the length term of the evolution curve $\mu\, length(C)$, the energy value deviation controlling the evolution of the background region $\lambda_1 \int_{I_1} |I(x,y) - C_1|^2 dxdy$ (set to E_1), and the energy value deviation controlling the evolution of the target region $\lambda_2 \int_{I_2} |I(x,y) - C_2|^2 dxdy$ (set to E_2). These three terms vary with the current position of the evolving curve, with the next, iteration controlled by the deviation between E_1 and E_2. Eventually, when E_1 and E_2 both approach 0, the evolving curve reaches the boundary of the target. The control process for the evolution of the curve according to E_1 and E_2 is shown in Fig. 1. The evolving curves demonstrated by white lines.

The ability of the C–V model to segment images effectively is based on the large gray differences between the target and the background. These two gray distributions are assumed to be homogeneous. In addition, the model is sensitive to the initial contour line. However, for images containing multiple-objects this assumption is rarely true, because the gray in different target regions will usually have significant differences. The model's sensitivity to the initial contours makes it difficult to use traditional methods to set a suitable initial curve for multi-object segmentation. The model falls into local minima very easily during the evolution process, meaning that some targets cannot be segmented.

3. Adaptive level set C–V model for region division

Because of the sensitivity of the C–V model to the initial contour line and the complexity of the multiple level set schemes for multi-object image segmentation, this paper proposes a single level set segmentation scheme that can determine the initial contour line based on the prior division of image object regions.

3.1. Rapid region division based on object

In general, regions those are closer to the edge of the image exhibit greater changes in gray levels. Thus, the connection between the target and the background (i.e., the edge of the target) usually has a large gradient. Hence, a number of edge detection methods search the whole image for the maximum gradient position to determine the image edge location. However, target edge is obtained by this method usually exist the following problems: (1) the largest gradient threshold value is difficult to define and (2) the boundary points determined by this method are generally not closed contours. For this reason, we propose a method of determining the broad contour of the target boundary quickly to lay the foundation for the evolution of synchronized curves around multiple objects. The specific process is as follows.

Binary processing based on Otsu's method [12] is applied to approximately distinguish the target from the background region. As shown in Fig. 2, "0" represents the general background regions and "1" represents the general target regions. Target a1 and a2 are show in Fig. 2.

(2) After this binary processing step, the gray value differences between each pixel and its four adjacent pixels (above, below, left, and right; see Fig. 3) determine the broad contours of the target region. Namely, if one of the four difference values is zero, the current pixel lies on the rough contour. Fig. 4 shows the broad contour corresponding to Fig. 2, 1 represents the contour points of the target a1 and a2.

3.2. Adaptable multi-object evolution model based on region partitioning

Based on this region division method, we now present an ACM based on the gradient edge to control the level set.

Assume that region Ω of image I is segmented into N mutually disjoint target regions Ω_i^m $(i = 1, 2, \ldots, N)$ and a background region Ω^b. After the target region partition, $\Omega = \Omega_1^m \cup \Omega_2^m \cup \cdots \cup \Omega_N^m \cup \Omega^b$. Furthermore, suppose that the initial curve C is composed of the contour lines C_i^m for the target regions. The average gray values of Ω_i^m and Ω^b are c_i^m and c^b, respectively.

The counter C is represented by the zero level set of the Lipschitz function $\phi: \Omega \rightarrow R$ as follows: $C = \{(x,y) \in \Omega : \phi(x,y) = 0\}$.

Define functions $H_\varepsilon(\phi)$ and $\delta_\varepsilon(\phi)$ as follows:

$$\begin{cases} H_\varepsilon(\phi) = \frac{1}{2}\left[1 + \frac{2}{\pi}\arctan\left(\frac{\phi}{\varepsilon}\right)\right] \\ \delta_\varepsilon(\phi) = H'_\varepsilon(\phi) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + \phi^2} \end{cases} \tag{2}$$