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A global and local active contour model based on dual algorithm for image segmentation

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ABSTRACT

Most of local region-based active contour models in terms of the level set approach are able to segment images with intensity inhomogeneity. However, these models do not utilize global statistical information and are quite sensitive to the initial placement of the contour. This paper presents a new global and local region-based active contour model to segment images with intensity inhomogeneity. First, in order to reduce number of iterations, the global energy functional of the Chan–Vese (C–V) model is used as the global term. Then, the local term is proposed to incorporate both local spatial information and local intensity information to handle intensity inhomogeneity. Moreover, to increase robustness of the initialization of the contour and reduce number of iterations, a convex energy functional and the dual algorithm are designed in the numerical implementation. Experimental results for synthetic and medical images have shown the efficiency and robustness of the proposed method.

1. Introduction

Image segmentation is one of most important techniques for detecting objects and analyzing images in image processing and computer vision [1–3], whose aim is to partition a given image into a finite number of semantically important regions. During the last few decades, various partial differential equations (PDEs)-based methods have been proposed to extract regions of interest in images such as active contour model (ACM), initially proposed by Kass, Witkin and Terzopoulos [4].

According to the nature of constraints, most of active contour models can be categorized into two classes: the edge-based models [4–10] and the region-based models [11–18]. The edge-based models utilize image gradient information and make an edge-based stopping term to control the contour evolution. Although many good numerical results can be obtained with these models, these models are highly sensitive to the initial contour. Actually, the initial contour needs to be placed near the desired object, otherwise, these models may trap into a local minimum. This main drawback limits their applications in practice.

In contrast to the edge-based models, the region-based models utilize image region information instead of image gradient to construct constraints to stop the curve evolution on the object boundaries. Therefore, these models are less sensitive to the initial contours and have better performance for the images with discrete or blurred edges. One of the most wide region-based models is the Chan–Vese (C–V) model [11,19]. However, the C–V model generally gets satisfactory results for the

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images with intensity homogeneity since it assumes that image intensities maintain constant in each region. Thus, it fails to segment the images with intensity inhomogeneity.

In fact, intensity inhomogeneity caused by the imperfection of imaging devices often occurs in real images. In order to overcome the limitations of the C–V model, Vese et al. [20] and Tsai et al. [21] independently proposed two similar piecewise smooth(PS) models. Under the framework of minimization of the Mumford-Shah functional, these models, which cast image segmentation as a problem of finding an optimal approximation of the original image by a piecewise smooth function, can deal with intensity inhomogeneity to some extent. However, the computational cost of the PS models is rather expensive.

In order to handle intensity inhomogeneity, some local region-based active contour models [12,13,15–17,22,23] had been proposed. Typically, Li et al. [12] proposed a Local Binary Fitting (LBF) energy with Gaussian kernel function. The LBF model locally approximates the image intensities on the two sides of the contour to guide the evolution of the level set function. Similarly, Lankton et al. [13] proposed a localization framework that can be used to localize any region-based energy. Although the localization can handle the intensity inhomogeneity, the loss of global characteristics results in the increase of the sensitivity to the initial contour placements.

Recently, some global minimization active contour models had been proposed to avoid the problem of trapping into the local minima [24–28]. Chan et al. [24] proposed a convex relaxation method of the C–V model. Bresson et al. [25] further established theorems to determine the existence of a global minimization of the active contour/snake model. Jing et al. [26] proposed a novel global minimization active contour model, which is based on the LBF model for oil slick segmentation with promising results. However, this model only employs the local means of image intensities. By considering the statistical distribution of each local region, Song et al. [27] proposed a globally statistical active contour model. In addition, Wang et al. [28] proposed a novel global minimization hybrid active contour model.

In this paper, we propose a new active contour model driven by the global and local statistical information for image segmentation. The main contributions of this paper as follows:

(1) Intensity range kernel function, which depends on the difference of intensity, is utilized, and a new local energy functional is proposed.
(2) The global convex method is incorporated into the global and local active contour model. The global convex method guarantees the efficiency of the proposed model.

The remainder of this paper is organized as follows. In Section 2, we briefly review the C–V model, the LBF model and the globally convex segmentation method. The proposed model is described in Section 3. The implementation and results of the proposed model are given and discussed in Section 4. Finally, the paper is summarized in Section 5.

2. Background

2.1. The C–V model

Let $\Omega \subset R^2$ be the image domain, and $I : \Omega \to R$ be a given image. The C–V model is formulated by minimizing the following energy function [19]:

$$E^{CV}(c_1, c_2, C) = \lambda_1 \int_{inside(C)} |I(x) - c_1|^2 dx + \lambda_2 \int_{outside(C)} |I(x) - c_2|^2 dx + \mu \cdot |C|, \tag{1}$$

where λ_1, λ_2 and μ are positive constants, and c_1 and c_2 are the intensity averages of $I(x)$ inside C and outside C, respectively.

Using the level set method, we assume

$$\begin{cases} C &= \{x \in \Omega | \phi(x) = 0\} \\ inside(C) &= \{x \in \Omega | \phi(x) > 0\} \\ outside(C) &= \{x \in \Omega | \phi(x) < 0\}. \end{cases} \tag{2}$$

Thus, the energy functional $E^{CV}(c_1, c_2, C)$ can be reformulated in terms of the level set function $\phi(x)$ as follows:

$$E^{CV}(c_1, c_2, \phi) = \lambda_1 \int_\Omega |I(x) - c_1|^2 H(\phi(x)) dx + \lambda_2 \int_\Omega |I(x) - c_2|^2 (1 - H(\phi(x))) dx + \mu \int_\Omega \delta(\phi) |\nabla \phi| dx, \tag{3}$$

where $H(\phi)$ and $\delta(\phi)$ are Heaviside function and Dirac function, respectively.

Minimizing the above energy functional by using the steepest descent method, the variational level set formulation is obtained as follows:

$$\frac{\partial \phi}{\partial t} = \delta(\phi) \left[\mu \mathrm{div} \left(\frac{\nabla \phi}{|\nabla \phi|} \right) - \lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2 \right] \tag{4}$$

where c_1 and c_2 can be, respectively, updated at each iteration by

$$\begin{cases} c_1(\phi) &= \dfrac{\int_\Omega I(x) \cdot H(\phi) dx}{\int_\Omega H(\phi) dx} \\ c_2(\phi) &= \dfrac{\int_\Omega I(x) \cdot (1 - H(\phi)) dx}{\int_\Omega (1 - H(\phi)) dx}. \end{cases} \tag{5}$$