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A local region-based Chan–Vese model for image segmentation

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ABSTRACT

In this paper, a new region-based active contour model, namely local region-based Chan–Vese (LRCV) model, is proposed for image segmentation. By considering the image local characteristics, the proposed model can effectively and efficiently segment images with intensity inhomogeneity. To reduce the dependency on manual initialization in many active contour models and for an automatic segmentation, a degraded CV model is proposed, whose segmentation result can be taken as the initial contour of the LRCV model. In addition, we regularize the level set function by using Gaussian filtering to keep it smooth in the evolution process. Experimental results on synthetic and real images show the advantages of our method in terms of both effectiveness and robustness. Compared with the well-know local binary fitting (LBF) model, our method is much more computationally efficient and much less sensitive to the initial contour.

1. Introduction

Image segmentation is the process of dividing images into meaningful subsets that correspond to surfaces or objects. It is a fundamental problem in the field of computer vision, because recognition and reconstruction often rely on this information [1,2]. To solve the problem, many researchers have done great efforts and proposed a wide variety of methods for image segmentation [3–5].

The active contour model (ACM) that is proposed by Kass et al. is one of the most successful models for image segmentation [6]. The basic idea of ACM is to evolve a curve to extract the desired object based on an energy-minimizing method. An advantage of ACM for image segmentation is that it partitions an image into sub-regions with closed and smooth boundaries. In early works the explicit snake model with a standard parametric curve representation was used [6,7]. However, it cannot conveniently deal with topological changes like the merging and splitting of the evolving curve. To over this drawback, many methods have been proposed, in which the most important and successful one is the PDE-based level set method introduced by Osher and Sethian [8]. It generalizes the Euler–Lagrange equation and evolves the interface which is represented implicitly as the zero level set of a function. An outstanding characteristic of level set methods is that contours can split or merge as the topology of the level set function changes. Therefore, the level set methods can detect more than one boundary simultaneously, and multiple initial contours can be placed. This flexibility and convenience provide a means for an automatic segmentation by using a predefined set of initial contours.

Without loss of generality, most of the ACMs studied under the level set framework can be categorized into two types: edge-based [8–10] and region-based [11–18] ones. The edge-based models utilize image gradient to construct force to direct the contours toward the boundaries of desired objects. These models are not only very sensitive to the noise, but also difficult to detect the weak boundaries. Moreover, the segmentation result is highly dependent on the initial contour placement. The region-based models utilize the image statistical information to construct constraints, which have many advantages of region-based approaches when compared with edge-based methods. First, they do not depend on the image gradient, and can satisfactorily segment the objects with weak boundaries. Second, by utilizing the global region information, they are generally robust to the noise.

The Mumford–Shah model, as a general image segmentation model, is firstly proposed by Mumford and Shah [12]. In this model, the image is decomposed into some regions that each region is approximated by a smooth function. The optimal partition of the image can be derived by minimizing the Mumford–Shah functional. However, the functional is non-convexity in generality, which make it difficult to be minimized.

One of the most popular region-based models is the Chan–Vese (CV) model [14], which is based on a simplified Mumford–Shah functional for segmentation. The CV model has been successfully applied for images with two regions which have a distinct mean of pixel intensity. But, in the CV model, the image intensities are assumed to be statistically homogeneous in each

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region. However, the assumption does not hold for some general images, which limits its applications.

To solve the limitations of the CV model, Vese and Chan [15] and Tsai et al. [16] proposed two similar region-based active contour models by minimizing Mumford–Shah functional [12]. These models, widely known as piecewise smooth (PS) models, are based on a piecewise smooth description of the images. The PS models have exhibited certain capability of handling intensity inhomogeneity. However, the computational cost of the PS models is rather expensive due to the complicated procedures involved.

Recently, to solve the problem caused by intensity inhomogeneity, Li et al. proposed a local binary fitting (LBF) model [19]. Because of using local region information, specifically local intensity mean, the LBF model can cope with intensity inhomogeneity. Some related methods were recently proposed in [18,20] which have similar capability of handling intensity inhomogeneity as the LBF model. However, to some extent these methods are still sensitive to initial contour, which holds back their practical applications.

To improve the robustness to initialization, Wang et al. considered to combine the local intensity information and the global intensity information [21,22]. When the contour is far away from object boundaries, the force from the global intensity information is dominant and has large capture range. When the contour is close to the object boundaries, the force from the local intensity information becomes dominant, which attracts the contour toward and finally stops the contour at object boundaries. The technique of using global image information can improve the robustness to the initialization of contours. However, when the contour is close to the object boundaries, the interference from the global intensity force will result in the deviation of contour from the real object boundary.

In this paper, a new region-based active contour model, named local region-based Chan–Vese (LRCV) model, for image segmentation is proposed. By introducing the local image information into the proposed model, the images with intensity inhomogeneity can be effectively segmented. At the same time, to avoid the manually initialization, a degraded CV model is presented whose segmentation result is taken as the initial contour of the LRCV model. In addition, we use the Gaussian filtering to regularize our level set function, which keeps the level set function smooth. Experimental results on some synthetic and real images show the advantages of our method in terms of efficiency and robustness. Moreover, comparisons with the well-know local binary fitting (LBF) model also show that our method is more computationally efficient and robust to the location of initial contour.

The rest of this paper is organized as follows. In Section 2, we review some well-known region-based models and their limitations. The LRCV model is proposed in Section 3. The degraded CV model is introduced in Section 4. The implementation and results are given in Section 5. This paper is summarized in Section 6.

2. The review and discussion of related works

2.1. The Mumford–Shah model

The idea of Mumford–Shah function for image segmentation is to find an optimal contour C that partitions the image domain into disjoint sub-regions, and an optimal piecewise smooth function $u(x)$ that fits the original image $I(x)$ within each of the sub-regions. This can be formulated by minimizing the following energy functional:

$$E^{MS}(u,C) = \lambda \int_{\Omega} (I(x)-u(x))^2 dx + v \int_{\Omega \setminus C} |\nabla u|^2 dx + \mu \,\text{Length}(C) \tag{1}$$

where C is a smooth and closed curve, $I(x)$ is the observed image data, $u(x)$ represents the piecewise smooth approximation to with discontinuities only along C, and Ω denotes the image domain. The parameters λ, v and μ are positive constants. Usually, the first term in Eq. (1) is called the data fidelity term, which is taken as the measurement of $u(x)$; the second term is called the smoothness term, which is the prior model of $u(x)$given C; and the third term is called the prior model of C which penalizes excessive arc length. With these terms, the Mumford–Shah function based image segmentation can be performed by minimizing the energy functional over all the contours that fit $u(x)$. However, due to different nature of the two unknowns: the contour C and the function $u(x)$, and the non-convexity of the function as well, it is not easy to find the optimal solution to the above energy functional. For practical applications, many works [14,18–20] have been reported to simplify or modify the above Mumford–Shah functional, including the several well known approaches reviewed below.

2.2. The Chan–Vese (CV) model

Based on the special case of Mumford–Shah problem where the image $I(x)$ in the Eq. (1) is a piecewise constant function, Chan and Vese proposed an active contour approach for 2-phase image segmentation [14]. The basic idea is to look for a particular partition of a given image $I(x)$ into two regions, one representing the objects to be detected and the other representing the background. For a given image $I(x)$ on the image domain Ω, they proposed to minimize the following energy function:

$$E^{CV}(c_1,c_2,C) = \lambda_1 \int_{in(C)} (I(x)-c_1)^2 dx + \lambda_2 \int_{out(C)} (I(x)-c_2)^2 dx \tag{2}$$

where C represents the curve, the constants c_1 and c_2 denote the average intensities inside and outside the curve, respectively, and the coefficients λ_1 and λ_2 are fixed parameters.

In the Chan–Vese model, they also have a regularizing term, such as the length of C and the area inside C to control the smoothness of the boundary. Therefore, the energy $E^{CV}(c_1,c_2,C)$ is defined by

$$\begin{aligned} E^{CV}(c_1,c_2,C) = {} & \lambda_1 \int_{in(C)} (I(x)-c_1)^2 dx + \lambda_2 \int_{out(C)} (I(x)-c_2)^2 dx \\ & + \mu \,\text{Length}(C) + \upsilon \,\text{Area}(in(C)) \end{aligned} \tag{3}$$

Using the level set to represent C, that is, C is the zero level set of a Lipschitz function $\phi(x)$, we can replace the unknown variable C by the unknown variable $\phi(x)$, and the energy function $E^{CV}(c_1,c_2,C)$ can be written as

$$\begin{aligned} E^{CV}(c_1,c_2,\phi) = {} & \lambda_1 \int_{\Omega} (I(x)-c_1)^2 H(\phi(x)) dx + \lambda_2 \int_{\Omega} (I(x)-c_2)^2 (1-H(\phi(x))) dx \\ & + \mu \int_{\Omega} \delta(\phi(x)) |\nabla \phi(x)| dx + \upsilon \int_{\Omega} H(\phi(x)) dx \end{aligned} \tag{4}$$

where $H(\phi)$ and $\delta(\phi)$ are Heaviside function and Dirac function, respectively. Generally, the regularized versions are selected as

$$\begin{cases} H_\varepsilon(z) = \frac{1}{2}\left(1 + \frac{2}{\pi} \arctan\left(\frac{z}{\varepsilon}\right)\right) \\ \delta_\varepsilon(z) = \frac{1}{\pi} \frac{\varepsilon}{\varepsilon^2 + z^2} \end{cases} z \in R \tag{5}$$

Keeping $\phi(x)$ fixed and minimizing the energy $E^{CV}(c_1,c_2,\phi)$ with respect to the constants c_1 and c_2, we have

$$\begin{cases} c_1(\phi) = \frac{\int_{\Omega} I(x) H(\phi(x)) dx}{\int_{\Omega} H(\phi(x)) dx} \\ c_2(\phi) = \frac{\int_{\Omega} I(x)(1-H(\phi(x))) dx}{\int_{\Omega} (1-H(\phi(x))) dx} \end{cases} \tag{6}$$