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A robust patch-statistical active contour model for image segmentation

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ABSTRACT

This paper proposes a novel region-based active contour model (ACM) for image segmentation, which is robust to noise and intensity non-uniformity. The energy functional of the proposed model consists of three terms, i.e., the patch-statistical region fitting term, the improved regularization term, and the intensity variation penalization term. The patch-statistical region fitting term computes the local statistical information in each patch as the basis for driving the curve accurately with resist to intensity non-uniformity and weak boundaries. And the regularization term coupling with the gradient information improves the ability of capturing the boundaries with cusps and narrow topology structures. Furthermore, an intensity variation penalization term is proposed to make sure that the segmentation result is robust to the irregular intensity variation. Experiments on medical and natural images show that the proposed model is more robust than the popular active contour models for image segmentation with noise and intensity non-uniformity.

1. Introduction

Active contour model (ACM) is one of the most successful methods for image segmentation, which plays an important role in the computer vision. The basic idea is to drive a contour under some constraints to the desired object. According to the nature of constraints, the existing ACMs can be categorized into two groups: the edge-based models (Kass et al., 1991; Caselles et al., 1997; Kichenesamy et al., 1996; Mishra et al., 2011) and the region-based models (Chan and Vese, 2001; Chan et al., 2006; Bresson et al., 2007; Qin and Clausi, 2010; Ni et al., 2009; Aubert et al., 2003; Jehan-Besson et al., 2003; Herbulot et al., 2006; Lecellier et al., 2006; Meziou et al., 2011). The latter ones are less sensitive to noise, as well as the location of the initial contour, and have better performance with weak boundaries. Hence these models can efficiently detect the exterior and interior boundaries simultaneously. There are several successful region-based models such as the Mumford–Shah functional (Mumford and Shah, 1989) and the Chan–Vese (CV) model (Chan and Vese, 2001). The CV model, implemented by the level set method (Osher and Sethian, 1988), has been successfully applied in binary phase segmentation under the assumption that each image region is statistically homogeneous. Vese and Chan extended their work (Vese and Chan, 2002) to represent multiple regions utilizing multiphase level set functions. These models are referred to as piecewise constant (PC) models. However, both the CV and the PC models often lead to poor segmentation results for images with intensity non-uniformity due to their underlying assumption that the intensities in each region always keep constant.

In order to segment images with smooth intensity non-uniformity, the local statistical information of intensity is widely employed in the region-based active contour models to approximate the images (Yezzi et al., 1999; Li et al., 2008a,b; Zhang et al., 2010; Brox and Cremers, 2010; Aubert et al., 2003; Ni et al., 2009). Li et al. (2008a,b) proposed a local binary fitting (LBF) model, which embedded the local statistical information of intensity into a region-based active contour model by a Gaussian kernel with a scale parameter. The LBF model superiorly segments the images with spatially smooth intensity non-uniformity. However, with a too small scale parameter, the model would output undesirable contours due to noise and unsmooth intensity non-uniformity. Moreover a large scale parameter induces very few of undesired contours, it may be computationally expensive and lead to inaccurate segmentation results. The reason is that these models extract the local statistical information by assuming that the distribution of intensity is uniform. Nevertheless, the intensities of images are not necessarily described by one specific distribution because the intensity non-uniformity also varies spatially. Hence it will be inaccurate to partition each region by the statistical information of intensity using a fixed-scale estimation method. In order to solve this problem, the region-based contour models were proposed in recent literature (Aubert et al., 2003; Jehan-Besson et al., 2003; Ni et al., 2009), by using the histogram of the intensity in a

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local region to drive the evolution of the contour. Not only are these methods insensitive to noise, but also can effectively extract the objects with textures.

On the other hand, generally in region-based active contour models, e.g. Chan–Vese model (Chan and Vese, 2001), the regularization term is implemented by a total variation (TV) norm with respect to the level set function. This term is used for capturing boundaries between sub-regions and keeping the contour smooth. However, it induces undesired over-smoothing to the sharp features of the boundaries, especially in corners, because the traditional regularization term only keeps the zero level set contour smooth during the evolution without considering gradient information of the image. Bresson et al. (2007) used a weighted TV-regularization term with an edge detector function to improve the ability of capturing the boundaries with large gradient. However, this improved regularization term is limited to deal with the images with weak boundaries.

As in previous works (Li et al., 2008a,b), an image can be decomposed into a "cartoon" component depicting the inter-object difference of physical property and a variation field formed by the intensity spatial variations. The first component is an ideal image formed purely by the physical property of the objects (surfaces or body tissues). For simplicity, we usually assume each object is characterized by a uniform physical property. However, because of the intensity variations introduced by the intensity non-uniformity and noise, this assumption of piecewise constancy on an ideal image cannot be satisfied anymore. The second component, i.e., the variation field including intensity non-uniformity and noise, is treated as the image artifacts and therefore its effectiveness should be reduced necessarily.

In this paper, we propose a novel patch-statistical region fitting energy, composed of the local image information in each patch. Noise and unsmooth intensity non-uniformity are both induced by irregular intensity variation in a small area, so it is necessary to take the image information into consideration in such region. Inspired by the work of (Li et al., 2008a,b), an image is assumed to be composed of small patches with fixed size, and each observed pixel is on the center of this patch. Since the patch is small, we assume that each patch is homogeneous. For simplicity, the probability of a pixel belonging to the patch is referred to the membership. The statistical information is extracted from each patch to compute the membership of the observed pixel. Generally, the memberships of two adjacent pixels may be similar to each other. Consequently, a weighted kernel is introduced to measure the similarity between the memberships of two adjacent pixels in each patch, and then the Nadaraya–Watson estimator (Nadaraya, 1964) is adopted to estimate the membership in each patch. With this treatment, the membership of each observed pixel is robust to noise and unsmoothed intensity non-uniformity.

Furthermore, we investigate an intensity variation penalization term to control the curve evolution according to the variation field. The variation field, consisting of noise or intensity non-uniformity usually induces inaccurate evolution. It can be considered as some fluctuation compared to the ideal image. The intensity variation is measured by the divergence of the variation field, since it plays a role for shock calculation measuring the magnitude of this fluctuation. Also the divergence of image intensity describes intensity variation. On one hand, it is obvious that these divergences are both close to zero where the variation field vanishes. In that case, the image is equal to an ideal image. And the difference between these two divergences is also close to zero when the observed pixel is on the edge of the image, according to definition of the two divergences. On the other hand, both of the divergences are large when the variation field is strong, as well as the difference between them. Therefore, we use the penalization term with respect to these divergences to control the curve evolution. In the case that the intensity variation is strong, the penalization will accelerate the evolution process; while the observed pixel is on the edge in the opposite situation, the term may have less impact on the evolution.

In the proposed model, the gradient information of intensity is utilized as the weight coefficient to compute the total variation of the level set function, which is then normalized by the magnitude of intensity gradient, to form a regularization term. With this new regularization term, the curve is driven by the image gradient effectively.

This paper is organized as follows. First we review the previous work in Section 2. Then we describe our model and the algorithm in Section 3. In Section 4, we show the experimental results and demonstrate the effectiveness and efficiency of the proposed method. Finally in Section 5, we end the paper by a brief conclusion.

2. Previous work

2.1. The Chan–Vese model

Chan and Vese (2001) proposed an active contour model based on Mumford and Shah (1989). Let $I:\Omega\to R$ be an input image and C be a close contour. The energy functional is defined by:

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

where μ, λ_1 and λ_2 are positive parameters. The Euclidean length term is used to regularize the contour. c_1 and c_2 are the average intensities of I inside and outside of the contour C, respectively.

To solve this minimization problem, the level set method (Osher and Sethian, 1988) is used which replaces the unknown curve C by the level-set function $\phi(x)$, $x\in\Omega$. Assuming

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

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

$$E_\varepsilon^{CV}(\phi,c_1,c_2)=\mu\cdot\int_\Omega\delta_\varepsilon(\phi(x))|\nabla\phi(x)|dx+\lambda_1\int_{inside(C)}(I(x)-c_1)^2H_\varepsilon(\phi(x))dx+\lambda_2\int_{outside(C)}(I(x)-c_2)^2(1-H_\varepsilon(\phi(x)))dx, \tag{3}$$

where $H_\varepsilon(z)$ and $\delta_\varepsilon(z)$ are, respectively. The regularized approximation of Heaviside function $H(z)$ and Dirac delta function $\delta(z)$ are defined as:

$$H(z)=\begin{cases}1 & \text{if } z\geqslant 0\\ 0 & \text{if } z<0,\end{cases}\quad \delta(z)=\frac{d}{dz}H(z). \tag{4}$$

The minimization problem is solved by taking the Euler–Lagrange equations and updating the level set function $\phi(x)$ by the gradient descent method

$$\frac{\partial\phi}{\partial t}=\delta_\varepsilon(\phi)\left[\mu div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)-\lambda_1(I-c_1)^2+\lambda_2(I-c_2)^2\right], \tag{5}$$

where at each iteration, c_1 and c_2 are, updated by

$$c_1(\phi)=\frac{\int_\Omega I(x)\cdot H(\phi)dx}{\int_\Omega H(\phi)dx},\quad c_2(\phi)=\frac{\int_\Omega I(x)\cdot(1-H(\phi))dx}{\int_\Omega(1-H(\phi))dx}. \tag{6}$$