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A two-stage image segmentation via global and local region active contours

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ABSTRACT

Based on popular active contours, this paper proposes a novel two-stage image segmentation method, which incorporates the global and local image region fitting energies. In the first stage, according to the global region active contour, we preliminarily segment the image by globally using the Gaussian distribution, which can rapidly get a coarse segmentation result. Subsequently, by employing a window function, we further segment the image by using the local region active contour, where we use the final active contour of the first stage as the initialization. Compared with the first stage, the local object details are accurately segmented in the second stage, which can be considered as an accurate segmentation result. Due to the suitable initialization from the first stage, the second stage works well in accurately segmenting the image, especially in local details. To regularize the level set function, we introduce a Laplace operator, which efficiently eliminates the expensive re-initialization process of traditional level set methods. Compared with the state-of-the-art methods, experiment results demonstrate the effectiveness and performance of the proposed method with applications to synthetical and real-world images, which usually contain noise, blurry boundaries, and intensity inhomogeneities.

1. Introduction

Image segmentation is defined as the problem of partitioning an image into its constituent components, which has a wide range of applications, such as the ultrasound image [1] and magnetic resonance imaging [2]. As one of the major problems in image analysis and computer vision, image segmentation is and always has been an active research area. As one can see, great efforts have been made in recent years to investigate the image segmentation, such as the famous normalized cut [3] and recent probabilistic graphlet cut [4]. As a kind of approach, active contour models [5–8] have been continuously studied and widely used in the field of image segmentation. The original active contour model was presented in [8], in which a parametric representation of the contour was used. As it is now well-known, this kind of model has some intrinsic disadvantages, especially in handling topological changes. To overcome this difficulty, the level set method [9], firstly proposed by Osher and Sethian, was then effectively used to handle topological changes by employing the representation of curves or surfaces as the zero level set of a high dimensional function. Starting from its introduction, the level set method has become a more and more popular approach in many fields of image processing and analysis, and peculiarly it is worth noting its application to image segmentation.

Most active contour models can be mainly classified into two different classes: edge-based models [6,10–13] and region-based models [7,14–18]. Edge-based models mainly rely on the edge information to drive the active contour toward the object boundaries and stop it there, of which the geodesic active contour model is a famous example. Nevertheless, edge-based models are very sensitive to initial conditions, and especially for those images with weak or fuzzy boundaries. Region-based models work without any dependence on the edge and gradient information of the image, and thus these models are more robust against the noise and clutter. By exploiting the global region information of the image statistics, the region-based models are usually less sensitive to the initialization. Up to now, there exist a large variety of region-based models and their related implementations. Among these models, one of increasingly popular methods is the introduction and application based on statistical methods [19], such as the Gaussian distribution [20–23], the Wishart distribution [24], the Rayleigh distribution [17], the Weibull distribution [25] and the Gamma distribution [26]. These models are mainly derived by maximizing a likelihood estimation or maximizing a posteriori probability, which can be transformed to minimizing the problem

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of an equivalent energy functional. Sometimes, these models presented above make strong statistical assumptions on the image intensity distributions of the subsets to be segmented. In such cases, one could also employ active contour models that use self-organizing neural networks, such as [27]. In the early years, one of the most famous region-based models was the Mumford–Shah model [28]. Later, as one of its special cases, the Chan–Vese (C–V) model [7] was proposed. Such a model minimizes a suitable energy functional to obtain a piecewise-constant approximation of the image. On the other hand, its vector-form [29] was also developed to segment color images. In the past ten years, the C–V model has been very often cited as a famous example of global region active contours. Even so, the C–V model supposes that the image intensity is statistically, respectively, inside and outside the region to be segmented, which limits its practical applications. As can be seen, intensity inhomogeneous images widely exist in the real world, such as medical images whose intensity inhomogeneity is due to technical limitations or artificial factors. Further, Vese and Chan [30] proposed a multi-phase level set framework for image segmentation, which is able to segment images with intensity inhomogeneity. However, its implementation is complex, especially because this model requires a periodic re-initialization of the level set function. Later on, Li et al. incorporated local region information into active contour models and proposed the famous Region-Scalable Fitting (RSF) model [15], which is usually considered as a typical example of local region active contours. The RSF model can be more effective than the C–V model on segmenting images with intensity inhomogeneity. However, there exists an intrinsic drawback that the RSF model is sensitive to the initialization of the contour. Besides, there exist some active contour models that incorporate the local region information of the image, such as [23,31–34]. In [35–37], the local and global region information are used together inside an active contour framework.

In this paper, inspired by the advantages of the global and local region fitting energies, respectively, we propose a two-stage segmentation method via global and local region active contours. The proposed method is divided into two stages. Similar to [21], the first stage employs a global region-based active contour model, in which the image intensities are globally modeled by Gaussian distributions. That is, in this stage, a coarse segmentation result is obtained by minimizing a global region fitting energy functional. The second stage employs a local region-based active contour model. By employing a window function, local region information of the image is incorporated into a local region fitting energy functional. By minimizing this energy functional, the local details of the image are effectively segmented, which is considered as an accurate segmentation. This kind of active contours considers the local intensities to be modeled by Gaussian distributions. With the evolution of the active contour, its local neighbor region is also gradually changed by the action of the window function. Thus, the local means and variances are gradually updated, which is of help in segmenting the local details of the image. More importantly, the second stage uses the final active contour of the first stage as the initialization, which effectively avoids the popular difficulty about finding a good choice for the initial contour in existing local region-based active contour models [15,23]. By the combination of the first and second stages, the object boundaries can be extracted satisfactorily. On the other hand, the re-initialization procedure of traditional level set methods is time-consuming, and sometimes it may move the location of the zero level set. Even if some distance regularized level set evolution methods [38–40] were presented to eliminate this troublesome procedure, this kind of methods cannot be easily extended to other level set methods based on partial differential equations [41]. Inspired by the works [32,41], we introduce the Laplace operator to regularize the level set function during its evolution process, which efficiently eliminates the costly re-initialization procedure.

The rest of this paper is organized as follows. In the next section, we present the global region-based active contour model and the region-based active contour model in detail. In Section 3, we propose a novel two-stage segmentation method. Section 4 presents some numerical experiments to demonstrate the effectiveness and satisfactory performance of the proposed method. Finally, we summarize and discuss the paper in Section 5.

2. Global and local region active contour models

2.1. Global region active contour model

Similar to the previous works [7,21], we globally consider the image as the Gaussian distribution. For each point $\mathbf{x}$ in the image domain Ω, we define $I:\Omega\subset R^2\to R^M$ to be either a gray-scale ($M=1$) or a color image ($M=3$). For $\mathbf{x}\in\Omega$, the pixel intensity $I(\mathbf{x})$ is denoted as a random variable, with a probability density function which is defined as follows:

$$F(I(\mathbf{x}))=\sum_{k=1}^{K}\gamma_k p(I(\mathbf{x}),u_k,\sigma_k^2), \quad (1)$$

where p is the Gaussian probability density function with mean u_k and variance σ_k^2 and K is the number of Gaussian probability density functions. Here, we consider $K=2$ for two-phase segmentation problem. Let $C(s):[0,1]\to R^2$ be a closed parameter curve, then it divides Ω as the two subregions Ω_1 and Ω_2. An optimal segmentation for the image I can be found through the maximum likelihood estimation method. Based on the works [22,37], one can easily see that the energy maximization problem of the maximum likelihood problem can be translated into a corresponding minimization problem. From a statistical point of view, the fitting energy of the global region active contour is directly described by two Gaussian distributions with different means and variances as follows:

$$F_g(C,u_1,\sigma_1^2,u_2,\sigma_2^2)=-\int_{\Omega_1}\log\ p_1(I(\mathbf{x}),u_1,\sigma_1^2)d\mathbf{x} -\int_{\Omega_2}\log\ p_2(I(\mathbf{x}),u_2,\sigma_2^2)d\mathbf{x}. \quad (2)$$

In order to regularize the length of the curve C, similar to [7], the energy (2) is further extended as follows:

$$E_g(C,u_1,\sigma_1^2,u_2,\sigma_2^2)=\nu_1 length(C)-\int_{\Omega_1}\log\ p_1(I(\mathbf{x}),u_1,\sigma_1^2)\,d\mathbf{x} -\int_{\Omega_2}\log\ p_2(I(\mathbf{x}),u_2,\sigma_2^2)d\mathbf{x}, \quad (3)$$

where $\nu_1\geq 0$ is a constant to be used to control the length regularization of C. Concretely, the two Gaussian probability density functions are defined as follows:

$$p_i(I(\mathbf{x}),u_i,\sigma_i^2)=\frac{1}{\sqrt{2\pi}\sigma_i}\exp\left(-\frac{(I(\mathbf{x})-u_i)^2}{2\sigma_i^2}\right), \quad (4)$$

where $i=1,\ 2$ correspond to the inside and outside regions of C, respectively. That is, the inside and outside intensities are globally described by two Gaussian probability density functions, respectively. In detail, u_1 and σ_1^2 are the mean and the variance of the inside region, respectively. Similarly, u_2 and σ_2^2 are the mean and the variance of the outside region, respectively.

In the level set method, a Lipschitz function $\phi:\Omega\to R$ is introduced to represent the curve C as $C=\{\mathbf{x}\in\Omega:\phi(\mathbf{x})=0\}$. Correspondingly, we assume $\Omega_1=\{\mathbf{x}\in\Omega:\phi(\mathbf{x})>0\}$ and $\Omega_2=\{\mathbf{x}\in\Omega:\phi(\mathbf{x})<0\}$. By employing the Heaviside function H and the Dirac function δ, the energy functional (3) is rewritten as