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B-Spline based globally optimal segmentation combining low-level and high-level information

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ABSTRACT

Image segmentation is an important step for large-scale image analysis and object recognition. Variational-based segmentation methods are widely studied due to their good performance, but they still suffer from incapability to deal with images bearing weak contrast, overlapped noise and cluttered texture. To tackle this problem, we propose a new statistical information analysis based multi-scale and global optimization method for image segmentation. This multi-scale processing which is consistent with human's cognition mechanism enables us identify target at coarse scale. The high-level prior is obtained by the multiple Gaussian kernel gray equalization and used as shape constraint in following fine-scale. An efficient energy functional is proposed with convexity and improved TV regularization in order to segment inhomogeneous target from noisy background. A convex relaxation function is explicitly represented by cubic B-Spline basis for fast convergence and intrinsic smooth segmentation. Finally, the energy functional is minimized by standard methods of Split Bregman, Gradient Descent Flow and the corresponding Euler–Lagrange Equation. Experimental results on synthetic and real world images validate the robustness and high accuracy boundaries detection for low contrast, noisy and texture images.

1. Introduction

Image segmentation, crucially bridging low-level and high-level vision, is a fundamental problem in image processing. Almost trivial to human vision, image segmentation still remains one of the most challenging problems due to various imaging artifacts, e.g., weak contrast, noise and texture.

The literature on image segmentation is vast. Many simple and classical segmentation methods group pixels according to the intensity or texture uniformity of image regions. But these methods often get unsatisfactory results or even failure to segment objects from background. To tackle this issue, active contour models (ACM), based on the principle of smoothness and continuity, have been proposed. They are successful variational-based models and have been extensively studied in image segmentation because of the sub-pixel accuracy and closed object boundary.

According to the means of representation and implementation of contours, the existing ACM can be broadly classified as parametric active contour models (PAC) and geometric active contour models (GAC). PAC represent contour as an explicit (parametric) way corresponding to the Lagrangian formulation [1]. The typical methods are Snake [2,3]. These methods are sensitive to noise and initial positions, and the evolving contour cannot change the topology (split and merge). GAC were firstly proposed by Caselles et al. [4] and Malladi et al. [5], independently. Different from PAC, GAC represent contour by the zero level set of an implicit [6] or explicit [7] level set function (LSF) which allows the evolving curve to develop cusps, corners, and topological changes. Generally, segmentation models based on level set method can be categorized into two classes: edge-based models and region-based models.

Edge-based models use edge stopping function to stop the evolving contours. The Geodesic Active Contours [8], the popular edge-based one, constructed an edge stopping term and a balloon force term to control the evolution of contours. Such edge-based models are usually sensitive to noise and prone to different local minimum with different initial contours.

Compared with edge-based models, region-based models mainly use the region statistical information on intensity or texture, to control the evolution of contours. These models tend to have less local minima which show more advantages in the case of noisy, weak and blurred images. Chan–Vese model (CV) [9] is the most popular region-based one. But it does not work for image regions with statistically inhomogeneous regions. A general model of CV was originally proposed by Mumford and Shah (MS) [10]. However, it isn't widely used because of its non-convex property and

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expensive computational cost. For image regions with non-smooth (texture) structures, image patches model based on MS was proposed by Wang et al. [11] and Jung et al. [12]. Gaussian Markov random fields based texture feature extraction method was studied in [13].

For images with region inhomogeneity, many methods have been extensively studied, such as region-scalable-fitting (RSF) [14], local-Gaussian-distribution-fitting (LGDF) [15], regularized gradient flux flows [16] and piecewise-smooth model with approximately explicit solutions [17]. These models are usually sensitive to initialization. To couple global region information with local region information, based on RSF models, Wang [11,18] introduced the Gaussian distribution into their fitting energy. Simultaneously bias correction and segmentation with intensity inhomogeneity using Gaussian distribution was proposed in [19,20]. Pixel inhomogeneity factor (PIF) was proposed by Dai et al. [21] to segment region inhomogeneous natural images. Alternative strategies for inhomogeneity are multi-scale segmentation models [22,23].

Over the past few decades, many promising level set segmentation models have been introduced by combining edge, region or shape information. The first survey on image segmentation integrating region with edge information was introduced in [24]. Paragios and Deriche [25,26] introduced the exemplary work coupling active contour model with boundary and region information. Leventon et al. [27] and Paragios et al. [28] employed LSF to construct prior shape. The shape comparison term, in general cases, permitting translation, scaling and rotation of prior shape was proposed by Chan et al. in [29]. Many segmentation methods based on these models can be found in [30]. These studies show that combining low-level and high-level information is an effective way to decrease the limitations of level set formulation.

These methods are usually limited by local minimum [31]. Recently, globally convex segmentation models [32–35] have been introduced to improve these non-convex deformable models. But they usually neglect the expectation of smooth target contour.

In this paper, we present a novel statistical based global optimization method combining low-level and high-level information for low contrast, noisy and texture image segmentation. Intertwined low-level and high-level information are used to build an energy functional. For the low-level information, the intensities are described by the Gaussian distribution and the improved TV regularization is proposed to use the edge information of image. For the high-level information, the prior shape of object is obtained using the multiple Gaussian kernel gray equalization and image pyramid method without train a set of prepared shapes and no shape deformation between scale. This prior shape is updated by up-sampling during the coarse-to-fine segmentation. Otherwise, the global relaxation characteristic function is explicitly represented by cubic B-Spline basis functions. This representation contributes to fast convergence and intrinsic smooth segmentation results. We demonstrate this formulation using different kinds of images. In contrast to the existing implementation of the level set methods, the contributions of this work are summarized as follows:

(1) The low-level and high-level information are combined to build an energy functional using multi-scale. Rough contour achieved at coarsest scale by multiple Gaussian kernel gray equalization is used as the prior shape of object. This shape is updated and used as the constraint of evolving contour in following fine-scale.
(2) A new edge stopping function based on the TV regularization is proposed. This term can be very beneficial to both global-based method and fast decrease of energy minimization.
(3) Different from [35], we proposed a statistical based globally optimal segmentation model. Cubic B-Spline basis functions are used to explicitly represent the relaxation characteristic function which contributes to fast convergence and intrinsic smooth globally optimal segmentation results.

The rest of this paper is organized as following. In Section 2, we discuss the related background. Section 3 presents our energy model combining low-level and high-level information and the B-Spline based global relaxed model. In Section 4, we provide numerical computation and evaluate the performance of the proposed segmentation method. Finally, this paper is summarized and concluded in Section 5.

2. Background

2.1. Variational models

Let $\Omega \in \mathbb{R}^n (n = 2, 3)$ is an image domain, and $I : \Omega \to \mathbb{R}^n (n = 1, 3)$ is a given image. In [10], the MS segmentation method was formulated as follows:

$$\mathcal{F}^{MS}(u, C) = \int_\Omega |I(\boldsymbol{x}) - u|^2 d\boldsymbol{x} + \mu \int_{\Omega\setminus C} |\nabla u|^2 d\boldsymbol{x} + \nu|C| \tag{1}$$

where $|C|$ is the length of contour, μ and ν are positive weight parameters. That is to say, given an image I, MS method found a contour C to divide the image into non-overlapping regions and an function to approximate the image. The function u is smooth within each region inside or outside the contour C. The minimization of functional $\mathcal{F}^{MS}$ results in an optimal (usually is the local optimal) contour C which separates the image into object and background regions. In practice, because of the non-convex of the energy functional, it is difficult to find the global minima.

To tackle this difficulties, Chan and Vese (CV) [9] formulated a simplified MS image segmentation model based on the homogeneous of different regions:

$$\begin{aligned}\mathcal{F}^{CV}(c_1, c_2, C) = &\int_{inside(C)} |I(\boldsymbol{x}) - c_1|^2 d\boldsymbol{x} \\ &+ \int_{outside(C)} |I(\boldsymbol{x}) - c_2|^2 d\boldsymbol{x} + \nu|C|\end{aligned} \tag{2}$$

where $inside(C)$ and $outside(C)$ represent the object and background regions and $\Omega = inside(C) \cup outside(C)$. Intensity of each region is approximated by c_1 and c_2 respectively. The first two terms in Eq. (2) are global binary fitting energy driving contours toward the true boundaries of objects. Consequently, the CV model generally fails to segment images with inhomogeneity and suffer from local minima.

To overcome the failure in handling of image inhomogeneity, in [36], the Piecewise-Smooth (PS) models were proposed:

$$\begin{aligned}\mathcal{F}^{PS}(u^+, u^-, \phi) = &\int_\Omega \left|I(\boldsymbol{x}) - u^-\right|^2 (1 - H(\phi)) d\boldsymbol{x} \\ &+ \int_\Omega \left|\nabla u^-\right|^2 (1 - H(\phi)) d\boldsymbol{x} \\ &+ \int_\Omega \left|I(x) - u^+\right|^2 H(\phi) d\boldsymbol{x} \\ &+ \int_\Omega \left|\nabla u^+\right|^2 H(\phi) d\boldsymbol{x} + \nu \int_\Omega |\nabla H(\phi)| d\boldsymbol{x}\end{aligned} \tag{3}$$

where ϕ is a LSF which has the following properties:

$$\begin{cases} \phi(\boldsymbol{x}) = 0, \boldsymbol{x} \in C \\ \phi(\boldsymbol{x}) > 0, \boldsymbol{x} \in inside(C) \\ \phi(\boldsymbol{x}) < 0, \boldsymbol{x} \in outside(C) \end{cases} \tag{4}$$