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A local Gaussian distribution fitting energy-based active contour model for image segmentation☆

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ABSTRACT

Intensity inhomogeneity and the bias field often occur in real-world images, which cause considerable difficulties in image segmentation. This paper presents a local region-based active contour model for segmentation of images with intensity inhomogeneity and simultaneous estimation of the bias field. In our model, the local image intensities and the bias field are described by the Gaussian distributions with different means and variances. A local Gaussian distribution fitting energy functional is defined on the image region, which combines the level set function and the bias field. Then, gradient flow equations and the bias field are derived for energy minimization. Due to the definition of local image intensities and the bias field, the proposed model is able to deal with intensity inhomogeneity and estimate the bias field. Experimental results on real images demonstrate that the proposed model has advantages over the other classical methods.

1. Introduction

Image segmentation problem is fundamental and important in image analysis and computer vision [1,2]. Its goal is to separate the image domain into several regions in each of which the intensity is homogeneous. A wide variety of image segmentation methods have been presented [3]. Active contour model is one of the most successful methods for image segmentation and boundary detection. The basic idea is to derive a curve under some constraints to extract the desired object. A popular way to implement such a curve evolution numerically is through the level set framework of Osher and Sethian [4]. According to the nature of constraints, the existing active contour models studied under the level set can be categorized into two groups: the edge-based models [5,6] and the region-based models [7–9].

The edge-based active contour models [6] utilize some edge detectors, which are depending on image gradient, to construct a force to stop the curve evolution on the desired object boundaries. The main drawbacks of these models are its sensitivity to the initial curve placement and the difficulties to detect the weak boundaries.

Unlike edge-based level set models using image gradient, region-based models [10,11] usually utilize the image statistical information to construct constraints, that have more advantages over the edge-based models. First, they do not depend on the image gradient, and can satisfactorily segment the objects with weak edges or without edges. Second, by using the global region information, they are less sensitive to noise. One of the most popular region-based models is the Chan–Vese

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(C-V) model [7], which is the curve evolution implementation of a piecewise constant case of the Mumford–Shah (M-S) model [12]. This model has been successfully used in binary phase segmentation with the assumption that each image region is statistically homogeneous. However, the C-V model leads to poor segmentation results for the images with intensity inhomogeneity. In order to segment images with intensity inhomogeneities, two similar active contour models were proposed in [13,14]. These models, widely known as piecewise smooth (PS) model, have exhibited certain capability of handling intensity inhomogeneity. However, these models are computationally expensive.

Intensity inhomogeneity is often apparent in images obtained by different imaging modalities, such as microscopy, computer tomography, ultrasound, and magnetic resonance (MR) imaging. The intensity inhomogeneity usually refers to the slow, nonanatomic intensity variations of the same tissue over the image domain. Although intensity inhomogeneity is hardly noticeable to a human observer, many medical image segmentation methods are highly sensitive to the spurious variations of image intensities. This is why segmentation of such medical images usually requires intensity inhomogeneity correction as a preprocessing step.

In order to handle directly intensity inhomogeneity, the local statistical information of intensity is widely employed in the region-based active contour models to approximate the images. Especially, Li et al. [8] proposed a local binary fitting (LBF) energy in a region-based model. The LBF model draws upon intensity information in spatially varying local regions depending on a scale parameter, so it is able to deal with intensity inhomogeneity accurately and effectively.

More recently, based on a generally accepted model of images with intensity inhomogeneities and a derived local intensity clustering property, Li et al. [15] proposed a variational level set method for image segmentation and bias correction. Wang et al. [11] proposed a novel local Gaussian distribution fitting energy with different means and variances. These above methods were evaluated on a few images to show a certain capability of handling intensity inhomogeneity.

In this paper, a novel local Gaussian distribution fitting energy-based active contour for image segmentation and bias field correction is presented. Firstly, in order to improve performances of segmentation for images with intensity inhomogeneity and bias field correction, a local Gaussian fitting energy with a bias field is defined. Then, combining level set and gradient descent method, a gradient flow equation is obtained. Finally, a image with intensity inhomogeneity is segmented and the bias field is estimated by using the finite difference method. Experiments on real and MR images demonstrate the advantages of the proposed model over the current method.

The remainder of this paper is organized as follows. In Section 2, three well-know region-based models are briefly reviewed. In Section 3, a local Gaussian fitting energy for image segmentation and estimation of bias field is proposed. Section 4 presents experimental results, followed by some discussion in Section 5. The paper is summarized in Section 6.

2. Background

2.1. The C-V model

In order to segment a image without edge, Chan and Vese [7] proposed an active contour model based on the special case of M-S model. Let $\Omega \subset R^2$ be the image domain, $I : \Omega \longrightarrow R$ be an input image and C be a closed contour. The energy functional is defined by

$$E^{CV}(c_1, c_2, C) = \lambda_1 \int_{inside(C)} |I(\mathrm{x}) - c_1|^2 d\mathrm{x} + \lambda_2 \int_{outside(C)} |I(\mathrm{x}) - c_2|^2 d\mathrm{x} + \mu \cdot length(C) + \nu \cdot area(inside(C)), \mathrm{x} \in \Omega \tag{1}$$

where μ, ν, λ_1 and λ_2 are parameters larger than zero, and c_1 and c_2 are two constants which are the average intensities of I inside and outside of the contour, respectively.

To solve this minimization problem, the level set method [4] is used to represent the contour C with the zero level set function $\phi(\mathrm{x})$, $\mathrm{x} \in \Omega$. The level set function $\phi(\mathrm{x})$ is defined as follows:

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

Thus, the energy functional $E^{CV}(c_1, c_2, C)$ can be reformulated as follows:

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

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

The minimization problem in Eq. (3) is solved by the Euler-Lagrange equations and the corresponding variational level set formulation can be obtained as follows:

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