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Original contribution

A fast and reliable noise-resistant medical image segmentation and bias field correction model☆

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ABSTRACT

In recent years, with the rapid development of modern medical image technology, the medical image processing technology is becoming more important. In particular, the accurate segmentation of medical images is significant for doctors to diagnose and analyze the etiology. However, the false contours appearing in medical images due to fuzzy image boundary, intensity inhomogeneity and random noise, may lead to the inaccurate segmentation results. In this paper, an improved active contour model based on global image information is proposed, which can accurately segment images disturbed by intensity inhomogeneities and serious noise. We give the two-phase energy functional and multi-phase energy functional of our model, and apply it to segment magnetic resonance (MR) images, ultrasound (US) images and synthetic images. Experimental results and comparisons with other models have shown that our model has the advantages of higher accuracy, higher efficiency and robustness in dealing with the intensity inhomogeneity and serious noise in image segmentation.

1. Introduction

The main mission for image segmentation is to divide an image into disjoined sub-regions without overlapping each other. Theoretically, all pixels in the same region should possess the same image feature. Due to the limitation of equipments, intensity inhomogeneity and noise often occur in medical images, such as X-ray images, magnetic resonance images, radionuclide images and ultrasonic images, which makes the image segmentation more difficult.

In recent years, the image segmentation based on the partial differential theory and the level set method has made great progress. In particular, by applying the active contour model (ACM) to image segmentation, the level set method has solved some difficulties in segmentation successfully. The basic principle of this method is to use a horizontal section of the surface in a high-dimensional space to represent a closed evolution curve. The level set method extends the segmentation problem to the fields of partial differential equations and differential geometry. The numerical research in this direction is much easier. By using the level set formulation, the ACM method has been applied widely to the edge-based models and region-based models.

In general, edge-based active contour models [1-6] utilized an edge detection factor which is associated with the image gradient to guide the boundary to approach the target object. The geodesic active contour (GAC) and snake model proposed originally in [1,3,4] are typical edge-based active contour models. In those models, an edge-based stopping term and a balloon force term are both calculated to control the movement of the contour curve. The edge-based stopping term computed by the gradient of the image is used to stop the curve on the desired object boundary, while the balloon force term mainly attracts the active contour to move from a position far away the object boundary to a closer position. Although the snake model and the GAC model have overcome some shortcomings of the traditional segmentation models, they also show many limitations including the sensitivities to the initial position, high risk falling into a local optimum and incorrect segmentation results of inhomogeneity images. Taking these shortcomings into consideration, the gradient vector flow (GVF) model [5] improves the snake model, which has performed a large attracting range in segmentation and can converge to the target boundary of the depression regions.

The region-based active contour models [7-16] generally use the characteristic that the same region approximately shares the same gray value to guide the boundary contour approximation to the target one. The Chan-Vese(CV) model [8], an active contour model based on the Mumford-Shah model [7], is a famous region-based image segmentation model to segment images with two regions. The CV model was extended to the multi-phase level set segmentation model [10] to solve

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the multi-phase image segmentation problem. In general, the images suitable to be segmented by CV model have special features that each region in the image has an average of the gray values of different pixels. However, only a few of images are in this situation, and a majority of the gray images are with intensity inhomogeneities. The piecewise smooth model [9] can handle the problem of intensity inhomogeneity, but it needs massive calculation, which leads to poor practicality. The local image fitting (LIF) model [11] and the region scalable fitting (RSF) model [13] can effectively segment the images with intensity inhomogeneity by using the local intensity information of the image. But the LIF model and the RSF model are more dependent on the shape and position of the initial contour. Besides, the characteristic of the local intensity information makes the segmentation result easy to fall into the local minimum. The local and global intensity fitting (LGIF) model [17] combines the local intensity information and global intensity information of the image, and adjusts the weight of the two parts of the information in the energy functional to balance the effects of the local information and global information of the image. The LGIF model is better to segment image with intensity inhomogeneity, and the sensitivity to the shape and position of the initial contour is significantly reduced. But it is difficult to choose the approximate weight, which limits the application of the LGIF model in practice.

Recently, the clustering-based active contour models [18-22] are a new important class of methods for image segmentation and bias correction. Different from previous two classes of models, the clustering-based models decompose the real image into the ideal image and the bias field that accounts for the intensity inhomogeneity. The local intensity clustering (LIC) model [18] is a classical clustering-based active contour model and the optimal bias field is estimated by minimizing the energy functional. Li et al. [19] also used the local clustering criterion to propose the multiplicative intrinsic component optimization (MICO) model, in which the bias field is described by a series of linear functions. Tu et al. [20] added a total variation of the membership functions as a regularization term into energy functional to extend the MICO model. Different from the former one, Gao et al. [21] extended the MICO model into the multi-channel formulation and introduced a non-local means technique to perform spatially regularized segmentation.

Many problems in the field of image processing can be transformed into the L1 regularization problems, and the split Bregman method has become an efficient technique for solving these types of problems. Goldstein et al. [23,24] proposed the split Bregman method with high efficiency and applied it into the CV model. Then Yang et al. applied the split Bregman method into the RSF model and the LGIF model and proposed improved active contour models [25,26]. Furthermore, the authors also applied the split Bregman method in [27,28] and proved the efficiency.

In this paper, we reconstruct the CV model by combining the bias field correction method with the LIC model, and we give the two-phase energy functional and the multi-phase energy functional of our model. Meanwhile, we introduce an edge detector function in the energy functional to detect the image boundaries. We also apply the split Bregman method to minimize the energy functionals to obtain the final segmentation results efficiently.

The remainder of this paper is organized as follows. In Section 2, we review the CV model, the LIC model and the split Bregman method. In Section 3, we propose an improved active contour model based on global image information, including the two-phase and multi-phase energy functionals, and apply the split Bregman method to minimize those energy functionals. We apply our model to segment medical images and synthetic images, and the segmentation results are shown in Section 4. Finally, this paper is concluded in Section 5.

2. Preparations

In this section, we will introduce the CV model and the LIC model, which will be used to optimize our energy functional. And we also introduce the split Bregman method which will be used to minimize our energy functional.

2.1. The CV model

The CV model is a piecewise constant image segmentation model. Let I: $\Omega \subset \mathbb{R}^2 \to \mathbb{R}$ be the image domain, for the image I, the energy functional of the CV model is proposed as:

$$\begin{aligned} E_{CV}(\phi, u_1, u_2) &= \nu \int_\Omega |\nabla H(\phi(x, y))|\, dxdy + \mu \int_\Omega H(\phi(x, y))dxdy \\ &+ \lambda_1 \int_\Omega |I(x, y) - u_1|^2 H(\phi(x, y))dxdy \\ &+ \lambda_2 \int_\Omega |I(x, y) - u_2|^2 (1 - H(\phi(x, y)))dxdy, \end{aligned} \tag{1}$$

where $\lambda_1,\lambda_2,\nu,\mu > 0$ are parameters. ϕ is the level set function whose zero level set contour partitions the image domain Ω in two disjoint regions $\Omega_1 = \{(x,y) : \phi(x,y) > 0\}$ and $\Omega_2 = \{(x,y) : \phi(x,y) < 0\}$. $H(z)$ is the Heaviside function defined as:

$$H(z) = \begin{cases} 1, & z \geq 0, \\ 0, & z < 0. \end{cases} \tag{2}$$

Besides, u_1 and u_2 are the intensity averages of the two disjoint regions Ω_1 and Ω_2. Keeping ϕ fixed and minimizing the energy function E_{CV} (ϕ,u_1,u_2) with respect to u_1 and u_2, it is easy to express them as functions of ϕ [8].

2.2. The LIC model

In order to deal with the problem of segmenting the image with intensity inhomogeneity, the LIC model considers that the bias field is one of reasons for the inhomogeneity of the image intensity. It shows that the intensity of the pixel at the same level exhibits a slow and uniform change along the direction of the spatial. So the following model for the real image is given:

$$I = BJ + n, \tag{3}$$

where I is the real observed image, J is the ideal image with intensity homogeneity, B is the bias field, and n is the noise. J is measured the intrinsic physical property of the object, so J is assumed to be approximately piecewise constant. Then J is approximated by N different constant values $c_1,\ldots,c_N$ in different regions $\Omega_1,\ldots,\Omega_N$, where $\Omega_i|_{i=1}^N$ forms a partition of the image domain Ω, i.e. $\Omega = \bigcup_{i=1}^N \Omega_i$ and $\Omega_i \bigcap \Omega_j = \varnothing$ for $i \neq j$. This model assumes that the bias field B changes slowly, and the additional noise n is assumed to be a Gaussian noise with zero mean.

The data term of the energy functional in the LIC model is:

$$\varepsilon_{LIC}(\phi, c_1, c_2, B) = \int_\Omega \sum_{i=1}^N \left(\int K(\mathbf{y} - \mathbf{x}) |I(\mathbf{x}) - B(\mathbf{y}) c_i|^2 d\mathbf{y} \right) M_i(\phi(\mathbf{x})) d\mathbf{x}, \tag{4}$$

where $\mathbf{x},\mathbf{y} \in \Omega$, $\mathbf{x} = (x_1,x_2)$ and $\mathbf{y} = (y_1,y_2)$. And for each point $\mathbf{y}$ as a center, there is a circular neighborhood with a radius of ρ, defined by $O_\mathbf{y}$, then $O_\mathbf{y} = \{\mathbf{x} : |\mathbf{x} - \mathbf{y}| \leq \rho\}$. $K(\cdot)$ is the kernel function, such that $K(\cdot) = 0$ for $\mathbf{x} \notin O_\mathbf{y}$. For the case of $N = 2$, the membership functions $M_1(\phi) = H(\phi)$ and $M_2(\phi) = 1 - H(\phi)$.

Next we give the energy functional of the LIC model:

$$E_{LIC}(\phi, c_1, c_2, B) = \varepsilon_{LIC}(\phi, c_1, c_2, B) + \nu\zeta(\phi), \tag{5}$$

where the length term is

$$\zeta(\phi) = \int_\Omega |\nabla H(\phi(\mathbf{x}))|\, d\mathbf{x}, \tag{6}$$

and $\nu > 0$ is the weight of the length term. Details about this model can be referred to [18].