Computerized Medical Imaging and Graphics 48 (2016) 21–29

Contents lists available at ScienceDirect

Computerized Medical Imaging and Graphics

journal homepage: www.elsevier.com/locate/compmedimag

A novel level set model with automated initialization and controlling parameters for medical image segmentation

Qingyi Liu [a], Mingyan Jiang [a,*], Peirui Bai [b], Guang Yang [a]

[a] School of Information Science and Engineering, Shandong University, Jinan 250100, China
[b] College of Electronic, Communication and Physics, Shandong University of Science and Technology, Qingdao 266590, China

ARTICLE INFO

Article history:
Received 25 December 2014
Received in revised form 6 November 2015
Accepted 9 December 2015

Keywords:
Medical image segmentation
Adaptive mean shift clustering
Level set method
Automated initialization
Reaction diffusion method

ABSTRACT

In this paper, a level set model without the need of generating initial contour and setting controlling parameters manually is proposed for medical image segmentation. The contribution of this paper is mainly manifested in three points. First, we propose a novel adaptive mean shift clustering method based on global image information to guide the evolution of level set. By simple threshold processing, the results of mean shift clustering can automatically and speedily generate an initial contour of level set evolution. Second, we devise several new functions to estimate the controlling parameters of the level set evolution based on the clustering results and image characteristics. Third, the reaction diffusion method is adopted to supersede the distance regularization term of RSF-level set model, which can improve the accuracy and speed of segmentation effectively with less manual intervention. Experimental results demonstrate the performance and efficiency of the proposed model for medical image segmentation.

1. Introduction

The purpose of medical image segmentation is to separate the components of the interested region from their background. The result can be used to assist doctors to treat their patients by making a diagnosis. Since the real medical image is mostly limited by poor resolution, weak contrast and intensity inhomogeneity [1], it is difficult to segment accurately by traditional segmentation method, such as the threshold or region growing method. In recent years, level set methods have become increasingly popular for medical image segmentation [2,3]. There are several advantages of the level set method [4]. For example, its numerical computations involving curves and surfaces can be performed on a fixed Cartesian grid. Moreover, it is able to represent contours with complex topological changes [5].

The level set methods can be categorized into edge-based models and region-based models [6,7]. Edge-based models use the local edge information to drive the active contour toward the object boundaries. However, the edge-based models are usually quite sensitive to the initial conditions and easily suffer from boundary leakage problems in images with weak object boundaries [8]. Region-based models aim to identify each interested region by using a certain region descriptor to guide the motion of the active contour [9]. Nevertheless, defining a certain region descriptor is difficult for images with intensity inhomogeneity or weak contrast. Being different from classical methods based on assumption of intensity homogeneity, a level set model based on local region information, which is called region-scalable fitting (RSF) level set model, was proposed by Li et al. [13]. It uses RSF energy term to guide the motion of the contour. This method is able to segment the images with intensity inhomogeneity. However, all these methods are sensitive to the initialization of the contour and need to set controlling parameters manually.

In traditional level set models, the periodical re-initialization is necessary to maintain stable evolution of the zero level set curves [10]. However, it may cause undesirable results for image segmentation and add unnecessary computation cost. Then, Li et al. proposed a classical method which is called distance regularized level set evolution (DRLSE) [11] which regularizes the level set function during evolution. Therefore, the re-initialization procedure can be eliminated. Subsequently, this method is used in many new or classical level set models [12,13]. However, DRLSE method still has the drawbacks such as limited anti-leakage capability for weak boundaries and sensitivity to noise. Recently, a new method was proposed for remit the re-initialization of the level set evolution, which is called reaction-diffusion (RD) method. This method has much better performance on weak boundary anti-leakage, and the implementation of the RD equation is very simple and it is more

* Corresponding author. Tel.: +86 13361073798.
E-mail address: jiangmingyan@sdu.edu.cn (M. Jiang).

http://dx.doi.org/10.1016/j.compmedimag.2015.12.005

robust to noise. These advantages of RD method have been verified by applying it to the classical level set model, geodesic active contours (GAC) model and Chan–Vese (C–V) model.

In this paper, we propose a novel level set model for medical image segmentation. Compared to some previous models, our model has significant contributions in the following aspects. First, we improve the mean shift clustering method by a new adaptive bandwidth algorithm which makes the clustering more accurate and faster. Furthermore, this improvement also solves the problem that the previous mean shift algorithm is quite sensitive to the setting of bandwidth. Second, the novel mean shift clustering method is used to obtain the initial contour of RSF-level set evolution close to the genuine boundaries of objects and estimate the controlling parameters of the level set model. Third, we apply the reaction diffusion method instead of the previous distance regularized method to avoid the re-initialization of RSF-level set evolution. It makes this algorithm's iteration faster and more robust to noise.

This paper is structured into the following sections. Section 2 describes the background and related works. Section 3 presents the novel level set model. Experimental results and the relevant discussions are shown in Section 4. The final section of the paper offers some conclusions.

2. Background and related works

2.1. Mean shift clustering

Mean shift clustering is a simple iterative procedure that shifts each data point to the mean of data points in its assigned neighborhood [14], and it is widely used in computer vision and image processing field [15,16].

The image segmentation with mean shift clustering is a straightforward extension of the discontinuity preserving smoothing algorithm. Each pixel associates with a significant mode of the joint domain density located in its neighborhood [17].

Given n data points $\mathbf{X}_i\,(i = 1, 2, \ldots, n)$ in a d-dimensional Euclidian space $\mathbf{R}^d$ and a symmetric positive definite $d \times d$ bandwidth matrix $\boldsymbol{H}$, which is proportional to the identity matrix, i.e., $\boldsymbol{H} = h^2\mathbf{I}$, where $h > 0$ is a bandwidth parameter. The multivariate kernel density estimator with bandwidth matrix $\boldsymbol{H}$ is given by the following equation:

$$\hat{f}_{h,K}(\mathbf{X}) = \frac{c_{k,d}}{nh^d}\sum_{i=1}^{n}\kappa\left(\left\|\frac{\mathbf{X}-\mathbf{X}_i}{h}\right\|^2\right) \tag{1}$$

where $c_{k,d}$ denotes a positive normalization constant, $\kappa(x)$ indicates the function called the profile of the kernel, only for $x \geq 0$.

We define a function $g(x) = -\kappa'(x)$. Then, we assume the derivative of the kernel profile $\kappa(x)$ exists for all $x \in [0, \infty)$, except for a finite set of points, the kernel $G(x)$ can be redefined as:

$$G(x) = c_{g,d}\,g\left(\|\mathbf{x}\|^2\right) \tag{2}$$

where $c_{g,d}$ denotes the corresponding normalization constant.

According to the linearity of Eq. (1) and introducing $g(x)$ into it, the density gradient estimator is obtained as the gradient of the density estimator as follows:

$$\hat{\nabla}f_{h,G}(\mathbf{X}) = \frac{2c_{k,d}}{nh^{d+2}}\left[\sum_{i=1}^{n}g\left(\left\|\frac{\mathbf{X}-\mathbf{X}_i}{h}\right\|^2\right)\right] \times \left[\frac{\sum_{n}^{i=1}\mathbf{X}_i g\left(\left\|(\mathbf{X}-\mathbf{X}_i)/h\right\|^2\right)}{\sum_{n}^{i=1} g\left(\left\|(\mathbf{X}-\mathbf{X}_i)/h\right\|^2\right)} - \mathbf{X}\right] \tag{3}$$

where $\sum_{i=1}^{n} g\left(\left\|(\mathbf{X}-\mathbf{X}_i)/h\right\|^2\right)$ is assumed to be a positive number. This condition is easy to satisfy for all the profiles met in practice. From Eq. (3), the first term is proportional to the density estimate at $\mathbf{X}$ computed with the kernel:

$$\hat{f}_{h,G}(\mathbf{X}) = \frac{c_{g,d}}{nh^d}\sum_{i=1}^{n}g\left(\left\|\frac{\mathbf{X}-\mathbf{X}_i}{h}\right\|^2\right) \tag{4}$$

and the second term is the popular mean shift vector:

$$m_{h,G(\mathbf{x})} = \frac{\sum_{i=1}^{n}\mathbf{X}_i g\left(\left\|(\mathbf{X}-\mathbf{X}_i)/h\right\|^2\right)}{\sum_{n}^{i=1} g\left(\left\|(\mathbf{X}-\mathbf{X}_i)/h\right\|^2\right)} - \mathbf{X} \tag{5}$$

Eq. (5) shows that the mean shift vector computed with kernel $G(x)$ is proportional to the normalized density gradient obtained with kernel $K(x)$ at location X. The mean shift vector always points to the direction of maximum increase in the density. The first step of the mean shift procedures is to compute the mean shift vector $m_{h,G(\mathbf{x})}$. Then, translate the kernel $G(x)$ by $m_{h,G(\mathbf{x})}$. At the end of the procedure, it is guaranteed to converge at a nearby point until some convergence criterions are satisfied.

2.2. Reaction diffusion method

The evolution of the classical level set function $\phi(t, x, y)$ can be expressed as follows:

$$\begin{cases} \dfrac{\partial\phi}{\partial t} + F\left|\nabla\phi\right| = 0 \\ \phi(t = 0, x, y) = \phi_0(x, y) \end{cases} \tag{6}$$

where F indicates the speed function that controls the motion of the contour. $\left|\nabla\phi\right|$ denotes the normal direction, and $\phi_0(x, y)$ is the initial contour.

During evolution, the traditional level set function may become too flat or too steep near the zero level set, causing serious numerical errors. Therefore, a procedure called re-initialization is periodically employed to keep it to be a signed distance function (SDF). Unfortunately, this re-initialization method is very time-consuming and may fail when the LSF deviates much from SDF.

To eliminate the re-initialization procedure, some formulations have been proposed in recent years. One of the most common methods is distance regularized level set evolution [10,11]. The authors propose a signed distance penalizing energy term as follows:

$$P(\phi) = \frac{1}{2}\int_{\Omega}\left(\left|\nabla\phi(x)\right| - 1\right)^2 dx \tag{7}$$

Recently, a novel means has been put forward to avoid re-initialization by reaction diffusion function [18].

By adding a diffusion term $\varepsilon\Delta\emptyset$ into the level set equation in Eq. (6), RD function for level set model can be defined as:

$$\begin{cases} \phi_t = \varepsilon\Delta\emptyset + \dfrac{1}{\varepsilon}F\left|\nabla\phi\right| \\ \phi(0, x, \varepsilon) = \phi_0(x) \end{cases} \tag{8}$$

where ε represents a small positive constant, and Δ indicates the Laplacian operator. The diffusion term $\varepsilon\Delta\emptyset$ gradually regularizes the LSF to be a piecewise constant in each segment domain, and the reaction term $(1/\varepsilon)F\left|\nabla\phi\right|$ forces the final stable solution of Eq. (8) to $F\left|\nabla\phi\right| = 0$.

The equilibrium solution of Eq. (8) is a piecewise constant as $\varepsilon \to 0^+$, which is the characteristic of phase transition. However, RD equation has the intrinsic problem of phase transition, which is the