Computers in Biology and Medicine 43 (2013) 1827–1832

Contents lists available at ScienceDirect

Computers in Biology and Medicine

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

A novel region-based level set method initialized with mean shift clustering for automated medical image segmentation

Pei Rui Bai *, Qing Yi Liu, Lei Li, Sheng Hua Teng, Jing Li, Mao Yong Cao

College of Information and Electrical Engineering, Shandong University of Science and Technology, Qing'dao 266590, PR China

ARTICLE INFO

Article history:
Received 16 January 2013
Accepted 31 August 2013

Keywords:
Medical image segmentation
Mean shift clustering
Level set methods
Global region information
Local region information

ABSTRACT

Appropriate initialization and stable evolution are desirable criteria to satisfy in level set methods. In this study, a novel region-based level set method utilizing both global and local image information complementarily is proposed. The global image information is extracted from mean shift clustering without any prior knowledge. Appropriate initial contours are obtained by regulating the clustering results. The local image information, as extracted by a data fitting energy, is employed to maintain a stable evolution of the zero level set curves. The advantages of the proposed method are as follows. First, the controlling parameters of the evolution can be easily estimated by the clustering results. Second, the automaticity of the model increases because of a reduction in computational cost and manual intervention. Experimental results confirm the efficiency and accuracy of the proposed method for medical image segmentation.

1. Introduction

In computer vision and medical image analysis fields, it is crucial to conduct exact segmentation to acquire high-level information from images. Therefore, separating interesting image components from their backgrounds effectively is a considerable problem. The classic segmentation methods have limitations in application to medical images. For example, application of thresholding or region growing algorithms usually exhibits poor performance because of the presence of noise, artifacts and intensity inhomogeneity [1]. Recently, level set methods have become increasingly popular for use in medical image segmentation [2–4]. Level set methods have several desirable characteristics such as sub-pixel accuracy, ease of formulation and flexible incorporation of prior knowledge. The existing level set methods can be classified into two types: region-based models and edge-based models. The region-based level set models fit the intensity of certain image regions using statistical models [5] and tend to rely on the intensity homogeneity in each image region. The edge-based level set models use local edge information to attract an active contour towards the object boundaries [6]. Desirable criteria of the level set methods are appropriate initialization and stable curve evolution, no matter what information is utilized to drive the level set function. In the traditional level set methods, a signed distance function is commonly used as the initial level set function. An obvious shortcoming of the signed distance function is periodical re-initialization, which is necessary to maintain a stable evolution of the zero level set curves. The re-initialization of the level set function has an intensive computational cost and a side effect of numerical inaccuracy. In addition, it is difficult to determine when and how to re-initialize the level set function.

Recently, a new variational level set formulation which avoids the re-initialization of the signed distance function has been proposed [7]. An internal energy term was introduced to penalize the deviation of the level set function from the signed distance function. To keep the stability of the curve evolution, several modifications of the variational level set formulation have been proposed [8–11]. The most interesting issues are how to represent the local region information and how to combine the local intensity information with the global intensity information. Among the proposed modifications, the region-scalable fitting (RSF)-level set method is an important method which introduces a RSF energy function to enhance the function's ability to cope with intensity inhomogeneity [8,9]. The RSF-level set method also employs a binary step function to act as the initial level set function, but this is not an optimal initial scheme. Thus, to obtain more appropriate initial contours and to reduce the necessary manual intervention of the RSF-level set method, it is preferable to adopt some intelligent search methods.

In this study, we propose a novel region-based level set method that integrates mean shift clustering with the RSF-level set method (MS-RSF level set method) based on the following considerations. First, the clustering result of the mean shift is utilized to approximate the genuine boundaries of objects. It is an advantage that mean shift clustering can decide the number of

* Corresponding author. Tel./fax: +86 532 80681195.
E-mail address: bprbjd@163.com (P.R. Bai).

0010-4825/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.compbiomed.2013.08.024

subclasses automatically without any prior knowledge. Second, the mean shift clustering procedure can be implemented numerically with an effective scheme. Third, the RSF-level set method is a region-based level set model which is robust and can cope well with intensity inhomogeneity. It is also less sensitive to the location of the initial contours.

The remainder of this paper is organized as follows. Section 2 describes the background of the proposed method. The MS-RSF level set method is introduced in Section 3. Experimental results are presented in Section 4 followed by discussion in Section 5. Our work is summarized in Section 6.

2. Background

2.1. The RSF-level set method

Level set methods embed active contours into a time-dependent partial differential equation (PDE). They approximate the evolution of active contours by tracking the zero level set curves. The evolution of the level set function $\phi(t,x,y)$is generally expressed as follows:

$$\begin{cases} \frac{\partial\phi(t,x,y)}{\partial t}+F|\nabla\phi|=0 \\ \phi(0,x,y)=\phi_0(x,y) \end{cases} \tag{1}$$

where F denotes the speed function. F is usually regularized by an edge indication function to stop the level set evolution near the optimal solution. $\phi_0(x,y)$ is the initial contour and $|\nabla\phi|$ denotes the normal direction of the initial contours. To solve Eq. (1), traditional level set methods usually adopt the Eulerian formulation (also termed pure PDE driven level set methods) [6]. In contrast, the variational level set methods derive the PDE directly from the minimization of a certain energy function [5,7]. The most desirable advantage of the variational methods exists in their capability to incorporate additional information. Recently, a region-based active contour model, called the RSF-level set method, based on the new variational formulation in a previous study [7] has been proposed. By introducing a region-scalable fitting energy, the method enhances the ability to cope with image intensity inhomogeneity. In the RSF-level set method, the local intensity fitting energy is defined as follows [9]:

$$E_X^{Fit}(C,f_1(X),f_2(X))=\sum_{i=1}^{2}\beta_i\int_{\Omega_i}K_\sigma(x-y)|I(y)-f_i(X)|^2dy \tag{2}$$

where C is a contour in the image domain Ω. $\Omega_1=$ outside (C) and $\Omega_2=$ inside (C) are the two regions separated by C, and β_1 and β_2 are the two positive constants. K_σ denotes a kernel function that controls the size of the local region centered at the point $X\in\Omega$. For any point X, $f_1(X)$ and $f_2(X)$ are two values that approximate the image intensities in Ω_1 and Ω_2, respectively. Compared with the popular piecewise constant models (PC) which approximates the image intensity outside and inside C using two constants, the RSF-level set method better approximates these image intensities using two functions, $f_1(X)$ and $f_2(X)$. The RSF-level set formulation is expressed as follows:

$$\frac{\partial\phi}{\partial t}=\mu\left[\Delta\phi-\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right]+\lambda\delta(\phi)\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)-\delta(\phi)(\beta_1e_1(X)-\beta_2e_2(X)) \tag{3}$$

where $e_1(X)$ and $e_2(X)$ are the local information outside and inside C, respectively.

The first term on the right side of Eq. (3) is responsible for the regularization of the zero level set function during the evolution procedure. The second term, called the arc length term, is used to smooth the zero level curves. The third term, called the data fitting term, drives the active contour towards the object boundaries. Clearly, the RSF-level set method uses local region information as the main external force that drives the zero level set curves. This is the reason why the RSF-level set method is classified as a region-based level set model.

2.2. Mean shift clustering

Mean shift clustering is a general nonparametric technique used to analyze multimodal feature space, and it is widely used in the computer vision field and medical image analysis [12–15]. A desirable advantage of the mean shift is that the mean shift vector consistently moves towards in the direction of maximum increase in the density. In addition, mean shift clustering can be implemented effectively through an iteration procedure without any prior knowledge.

Given a sample set X_i ($i=1, 2, \ldots, n$) in a d-dimensional Euclidian space R^d, the density gradient can be estimated from the gradient of the kernel $k(X)$ with the bandwidth h (where $h>0$ denotes the bandwidth parameters) as follows [12]:

$$\nabla\hat{\rho}_{h,k}(X)=\frac{2c_{k,d}}{nh^{d+2}}\left[\sum_{i=1}^{n}g\left(\left\|\frac{X-X_i}{h}\right\|^2\right)\right]\left[\frac{\sum_{i=1}^{n}X_ig(||(X-X_i)/h||^2)}{\sum_{i=1}^{n}g(||(X-X_i)/h||^2)}-X\right] \tag{4}$$

where X is a d-dimensional stochastic variable. $c_{k,d}$ is a positive normalization constant that makes $k(X)$ integrate to 1. $g(x)=-k'(x)$.

The third term in Eq. (4) is the popular mean shift vector

$$m_{h,G}(X)=\frac{\sum_{i=1}^{n}X_ig(||(X-X_i)/h||^2)}{\sum_{i=1}^{n}g(||(X-X_i)/h||^2)}-X \tag{5}$$

where $G(X)$ is the weight kernel. The mean shift vector represents the difference between the weighted mean and the center of the kernel. It is proportional to the normalized density gradient obtained with kernel $k(X)$ at location X.

The mean shift procedure can be implemented by a recursive iteration which computes the mean shift vector first and then modifies the kernel. If $k(X)$ is the Epanechnikov kernel, the robustness and convergence of the mean shift procedure are guaranteed [16]. Actually, the mean shift can be used to segment images directly, but it usually gives rise to over-segmentation, especially when applied to medical images [12,13]. Therefore, we adopted the mean shift procedure to extract global image information which can be used to obtain appropriate initial contours which are close to the genuine boundaries. Then, the details of the objects can be searched for and determined by the RSF-level set method.

3. The proposed method

The desirable advantages of the RSF-level set method are its flexible initialization and effective solving scheme. But, it is inconvenient to set the initial contour and evolution controlling parameters manually. To optimize the initialization and to stabilize the contour evolution, we propose to use the MS-RSF level set method, which includes integrating mean shift clustering with the RSF-Level set method.

Benefitting from the flexible initialization of the RSF-Level set method, the initial function $\phi_0(x,y)$ can be defined as follows:

$$\phi_0(x,y)=\begin{cases} -D & (x,y)\in\Omega_0-\partial\Omega_0 \\ 0 & (x,y)\in\partial\Omega_0 \\ D & (x,y)\in\Omega-\Omega_0 \end{cases} \tag{6}$$