Pattern Recognition Letters 104 (2018) 29–36

Contents lists available at ScienceDirect

Pattern Recognition Letters

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

Active contours driven by local pre-fitting energy for fast image segmentation

Keyan Ding[a], Linfang Xiao[b], Guirong Weng[a,*]

[a] School of Mechanical and Electric Engineering, Soochow University, Suzhou 215021, China
[b] College of Biosystems Engineering and Food Science, Zhejiang University, Hangzhou 310058, China

ARTICLE INFO

Article history:
Received 25 August 2017

Keywords:
Image segmentation
Active contour model
Level set method
Robust initialization
Local pre-fitting

ABSTRACT

Local fitting-based active contour models can segment images with intensity inhomogeneity effectively, but they are time-consuming and often fall into local minima. In this paper, we present an active contour model using local pre-fitting energy for fast image segmentation. The core idea of local pre-fitting energy is to define two pre-fitting functions by computing average image intensities locally before the evolution of curve. Experiments have shown that the proposed model is robust to initialization, which allows the initial level set function to be a small constant function. And it costs less segmentation time compared to other local fitting-based models. In addition, the proposed local pre-fitting method can be applied to other local fitting-based models to improve the robustness of initial contours and reduce the computational costs.

1. Introduction

Image segmentation is a fundamental problem in the field of image processing and computer vision. Over the past decades, many famous image segmentation methods have been presented, such as region grow, watershed algorithm and graph cut [1,2]. Active contour models have been widely applied in image segmentation since the presentation by Kass et al. [3]. Existing active contour models can be roughly categorized into two basic classes: edge-based models [4–11] and region-based models [12–27,29]. Edge-based models often use an edge indicator to drive the curve towards the object boundaries, such as GAC model [4,5]. Region-based models often use a certain region descriptor to find a partition on the image domain. Chan–Vese (CV) model [13] is a well-known region-based model and has been widely used in practice applications. But the CV model cannot work well for images with intensity inhomogeneity due to the assumption that the image intensities are statistically homogeneous. To handle the intensity inhomogeneity which is often occurred in medical and natural images, Chan and Vese [14] proposed a piecewise smooth (PS) model. It has exhibited certain capability of segmenting images with intensity inhomogeneity. However, the computational efficiency is much low.

Li et al. [16] presented an active contour model based on region-scalable fitting (RSF) energy. The RSF model draws upon the local image information by a kernel function. With the information of local image intensities, the RSF model can effectively segment images with intensity inhomogeneity. But when the initial contour is set inappropriately, the RSF model will be stuck in local minima because the energy functional is non-convex [28,29]. In addition, the time cost is relatively large due to the computation of four convolutions in each iteration. Zhang et al. [18] presented an active contour model driven by local image fitting (LIF) energy. By extracting the local image information, it is able to segment images with intensity inhomogeneity. Compared to the RSF model, the computational cost of LIF model is smaller because only two convolutions are computed in each iteration. However, the problem of initial contours has not been solved. Liu et al. [19] proposed a local region-based Chan–Vese (LRCV) model. Similarly, it can segment images with intensity inhomogeneity, and the computational cost is lower than the RSF model. But it is sensitive to initial contours. Wang et al. [20] presented an active contour model based on local Gaussian distribution fitting (LGDF) energy. It defines a local Gaussian distribution fitting energy by using local means and variances as variables. The LGDF model is able to distinguish regions with similar intensity means but different variances. But the problem of initialization is still unsolved and the segmentation speed is low due to the extra computation of variances. Considering that the object and background in many real-world images are hard to be described by a predefined distribution, Liu et al. [21] proposed a nonparametric active contour model driven by the local histogram fitting (LHF) energy. It defines two fitting histograms that approximate the distribution of object and background locally. The

* Corresponding author.
E-mail address: wgr@suda.edu.cn (G. Weng).

https://doi.org/10.1016/j.patrec.2018.01.019

LHF model can segment the regions whose distribution is hard to be predefined. However, it has much high computational costs because the histogram distribution of each grey value needs to be calculated. Likewise, it is sensitive to initialization.

In summary, active contour models based on local information fitting energy [16–24] can segment images with intensity inhomogeneity effectively. However, an inappropriate initial contour will cause a wrong segmentation. Moreover, the segmentation cost of these models is high in general.

In this paper, we present an active contour model driven by local pre-fitting energy for image segmentation, which is robust to initialization and has low computational costs. First, we define two pre-fitting functions by computing average image intensities locally before the evolution of curve. Next, an energy based on local pre-fitting functions is proposed, and then incorporated into the variational level set formulation with a length constraint term and a distance regularized term. The steepest descent method is used to minimize the energy functional. Experiments have shown that the proposed model can efficiently segment images with intensity inhomogeneity. As an application, the proposed model can be used for denoising and improving image contrast. In addition, the proposed local pre-fitting method can be easily applied to other local region fitting-based models to improve the segmentation speed and the robustness against initialization.

The remainder of this paper is organized as follows. Section 2 briefly reviews some well-known local fitting-based models, including the RSF model [16], the LIF model [18] and the LGDF model [20]. Section 3 introduces our model using local pre-fitting energy. Section 4 shows some experimental results of the proposed model. Section 5 presents some discussions. Last, Section 6 concludes this paper.

2. The related works

2.1. Region-scalable fitting model

Li et al. [16,17] proposed a region-scalable fitting (RSF) model for segmenting images with intensity inhomogeneity. They define the following energy functional:

$$\begin{aligned} E^{RSF}(\phi, f_1, f_2) &= \lambda_1 \int_\Omega \left(\int_\Omega K_\sigma(x-y)|I(y)-f_1(x)|^2 H_\varepsilon(\phi(y))dy \right) dx \\ &+\lambda_2 \int_\Omega \left(\int_\Omega K_\sigma(x-y)|I(y)-f_2(x)|^2 [1-H_\varepsilon(\phi(y))]dy \right) dx \\ &+\upsilon \int_\Omega \delta_\varepsilon(\phi(x))|\nabla\phi(x)|dx + \mu \int_\Omega \frac{1}{2}(|\nabla\phi(x)|-1)^2 dx \end{aligned} \tag{1}$$

where, x, $y \in \Omega$, λ_1, λ_2, v and μ are positive constants. K_σ is a Gaussian kernel function with standard deviation σ. $f_1(x)$ and $f_2(x)$ are two smooth functions that approximate the intensities of image outside and inside the contour C in a local region, respectively. $H_\varepsilon(x)$ and $\delta_\varepsilon(x)$ are regularized Heaviside and Dirac function defined by

$$\begin{cases} H_\varepsilon(x) = \frac{1}{2}\left(1+\frac{2}{\pi}\arctan\left(\frac{x}{\varepsilon}\right)\right) \\ \delta_\varepsilon(x) = \frac{\varepsilon}{\pi(\varepsilon^2+x^2)} \end{cases} \tag{2}$$

The method of steepest descent is used to minimize the energy functional (1). Keeping level set function ϕ fixed and minimizing E^{RSF} with respect to f_1 and f_2, the following formulations can be obtained:

$$\begin{cases} f_1(x) = \frac{\int_\Omega K_\sigma(x-y)[H_\varepsilon(\phi(y))\cdot I(y)]dy}{\int_\Omega K_\sigma(x-y)H_\varepsilon(\phi(y)dy} \\ f_2(x) = \frac{\int_\Omega K_\sigma(x-y)[(1-H_\varepsilon(\phi(y))\cdot I(y)]dy}{\int_\Omega K_\sigma(x-y)[1-H_\varepsilon(\phi(x))dy} \end{cases} \tag{3}$$

Keeping f_1 and f_2 fixed and minimizing E^{RSF} with respect to the level set function ϕ, the following gradient descent flow can be obtained:

$$\begin{aligned} \frac{\partial\phi}{\partial t} &= -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) + \nu\delta_\varepsilon(\phi) div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) \\ &+\mu\left(\nabla^2\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right) \end{aligned} \tag{4}$$

where e_1 and e_2 are

$$\begin{cases} e_1(x) = \int_\Omega K_\sigma(y-x)|I(x)-f_1(y)|^2 dy \\ e_2(x) = \int_\Omega K_\sigma(y-x)|I(x)-f_2(y)|^2 dy \end{cases} \tag{5}$$

2.2. Local image fitting model

Zhang et al. [18] presented an active contour model driven by local image fitting (LIF) energy. This energy functional is defined by minimizing the difference between the fitted image and the original image:

$$E^{LIF}(\phi, m_1, m_2) = \frac{1}{2}\int_\Omega \left|I(x) - I^{fit}(x)\right|^2 dx \tag{6}$$

where $I^{\rm fit}$ is the local fitting image defined as follows:

$$I^{fit}(x) = m_1(x)H_\varepsilon(\phi(x)) + m_2(x)[1-H_\varepsilon(\phi(x))] \tag{7}$$

with

$$\begin{cases} m_1(x) = mean(I(x) : x \in \{\phi(x) < 0\} \cap \Omega_w(x)) \\ m_2(x) = mean(I(x) : x \in \{\phi(x) > 0\} \cap \Omega_w(x)) \end{cases} \tag{8}$$

where $m_1(x)$ and $m_2(x)$ can be seen as the weighted averages of the image intensities in a Gaussian window Ω_w outside and inside the contour, respectively. Thus,$m_1(x)$ and $m_2(x)$ are totally the same to $f_1(x)$ and $f_2(x)$ in the RSF model. Similarly, the steepest descent method is used to minimize the energy functional (6). By introducing the local image information, the LIF model is able to segment images with intensity inhomogeneity and the computational cost is lower because only two convolutions are computed in each iteration, which is about half of that in the RSF model. However, it is sensitive to initialization, like the RSF model.

2.3. Local Gaussian distribution fitting model

Wang et al. [20] presented an active contour model based on local Gaussian distribution fitting (LGDF) energy. It defines a local Gaussian distribution fitting energy by using local means and variances as variables:

$$\begin{aligned} &E^{LGDF}(\phi, p_{1,x}, p_{2,x}) \\ &= \int_\Omega \left(\int_\Omega K_\sigma(x-y)\log p_{1,x}(I(y))H_\varepsilon(\phi(y))dy \right) dx \\ &\quad + \int_\Omega \left(\int_\Omega K_\sigma(x-y)\log p_{2,x}(I(y))[1-H_\varepsilon(\phi(y))]dy \right) dx \end{aligned} \tag{9}$$

where $P_{1,x}$ and $P_{2,\,x}$ are

$$p_{i,x}(I(y)) = \frac{1}{\sqrt{2\pi}\sigma_i(x)} \exp\left(-\frac{u_i(x)-I(y)}{2\sigma_i{}^2(x)}\right), i = 1, 2 \tag{10}$$

where $u_1(x)$ and $u_2(x)$ can be seen as the weighted averages of the image intensities in a Gaussian window outside and inside the contour, respectively. $\sigma_1^2(x)$ and $\sigma_2^2(x)$ can be seen as the weighted variances of the image intensities in a Gaussian window outside and inside the contour, respectively. Note, $u_1(x)$ and $u_2(x)$ are also the same to $f_1(x)$ and $f_2(x)$ in the RSF model, and the LGDF model will be the same as the RSF model if $\sigma_i^2(x) = 0.5$. By computing both the first order and second order statistics of local intensity information, the LGDF model can better handle intensity inhomogeneity and noise, and differentiate regions with similar intensity means but different intensity variances. But the problem of initialization is still unsolved and the computational cost is large due to the extra computation of variances.