Neurocomputing 151 (2015) 1086–1098

Contents lists available at ScienceDirect

Neurocomputing

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

Multi-scale local region based level set method for image segmentation in the presence of intensity inhomogeneity

Xiao-Feng Wang [a,b,*], Hai Min [b,c], Yi-Gang Zhang [a]

[a] Key Lab of Network and Intelligent Information Processing, Department of Computer Science and Technology, Hefei University, Hefei, Anhui 230601, China
[b] Intelligent Computing Lab, Hefei Institute of Intelligent Machines, Chinese Academy of Sciences, P.O.Box 1130, Hefei, Anhui 230601, China
[c] Department of Automation, University of Science and Technology of China, Hefei, Anhui 230601, China

ARTICLE INFO

Article history:
Received 25 October 2013
Received in revised form
28 November 2013
Accepted 29 January 2014
Available online 18 October 2014

Keywords:
Image segmentation
Intensity inhomogeneity
Level set
Local region
Multi-scale
Statistical analysis

ABSTRACT

Intensity inhomogeneity arising from the imperfect image acquisition process is a major challenge for image segmentation. Most of widely used image segmentation methods usually fail to segment the image with intensity inhomogeneity due to the assumption of intensity homogeneity. In this paper, an efficient multi-scale local region based level set method is proposed to segment the image with intensity inhomogeneity, which is based on the multi-scale segmentation and statistical analysis for intensities of local region. Firstly, the local region is defined in circular shape for capturing more local intensity information. The statistical analysis can be performed on intensities of local circular regions centered in each pixel by using multi-scale low-pass filtering. Then, the data term of level set energy functional can be constructed by approximating the normalized weighted image divided by multi-scale local intensity information in a piecewise constant way. In addition, the regularization term is built to control the smoothness of evolving curve and avoid the over-segmentation phenomenon and re-initialization step. Finally, the multi-scale segmentation is performed by minimizing the total level set energy functional by using the finite difference scheme. The experiments on synthetic and real images with slight or severe intensity inhomogeneity can demonstrate the efficiency and robustness of the proposed method. In addition, the comparisons with the recently popular local binary fitting (LBF) model and local Chan-Vese (LCV) model also show that our method has obvious superiority over the traditional local region based methods.

1. Introduction

Image segmentation has always been a fundamental and important task for image processing. Generally, it needs to be performed as long as the object needs to be detected in an image. A major challenge for image segmentation is the intensity inhomogeneity which arises from the imperfect factors of image acquisition process, such as non-uniform daylight, inhomogeneous artificial illumination and inhomogeneity of reception coil sensitivity, etc. The presentence of intensity inhomogeneity will greatly reduce the accuracy of image segmentation due to the overlaps in the intensity distributions of foreground and background. To solve this problem, many promising methods have been proposed [1]. Among them, the level set method proposed by Osher and Sethian [2] is the most popular and successful one in the recent years.

In the level set method, a deformable curve is represented by the zero level set of a higher dimensional smooth function, also called level set function, and driven by evolving the level set functions to approach the object boundary. Thus, the level set method can efficiently handle the topological changes of evolving curve in a natural way, which is a main advantage compared with the parametric active contour models [3]. Another advantage of level set methods is that it does not require parameterizing the evolving curve and the numerical computation can be implemented on a fixed Cartesian grid [4]. Generally, level set method can be divided into edge-based method and region-based method according to the features used in the level set energy functional.

Edge-based level set methods [5–9] usually depend on the image gradient information to drive the curve evolution and are efficient for segmenting image with sharp gradient of pixel intensity. Due to the intrinsic limitations of gradient dependence, they are not only sensitive to the noise but also difficult to detect the weak boundaries. The evolving curve may surround the noise region or even pass through the weak boundaries. Moreover, the capability of approaching object boundary of edge-based level set methods is weak. To obtain satisfying segmentation result, the initial contour is usually required to be placed near or in the target objects.

* Corresponding author.
E-mail addresses: xfwang@iim.ac.cn (X.-F. Wang), minhai361@gmail.com (H. Min), yxygz@sina.com (Y.-G. Zhang).

http://dx.doi.org/10.1016/j.neucom.2014.01.079
0925-2312/

Different from the edge-based methods, the region-based methods [10–16] utilize global region information to stabilize their responses to local variations and guide the evolving curve to approach the true object boundary. Consequently, they can achieve satisfying performance for segmenting images with strong noise and weak object boundaries, which are main drawbacks associated with the edge-based methods. In addition, the capability of approaching object boundary has been greatly enhanced so that the initial contour can be placed anywhere in the image to be segmented. Most of the region-based methods are to find the approximation of the Mumford-Shah functional minimization [10]. Among them, the Chan–Vese (CV) model [11] is the most representative and popular one, which approximates a given image with constant functions inside each region. Generally, these region-based methods [11–14] work on images with intensity homogeneity since they assume that the intensities in each region are homogeneous. As a result, they often fail to segment the images with intensity inhomogeneity. In [15,16], two similar models, namely PS models, were independently proposed by approximating the image with the piecewise smooth (PS) function. They did not insist on the assumption of intensity homogeneity and can be used for segmenting image with intensity inhomogeneity. However, the PS models suffer from the expensive computational complexity and sensitivity to contour initialization, which limit their application in practice.

To further improve the performance of region-based methods for images with intensity inhomogeneity, some efficient implementation schemes [17–23] have been proposed by adopting the local region information to guide the curve evolution. They can be called local region-based methods. The most popular methods include the local binary fitting (LBF) model [18,19], the localizing region-based (LRB) model [21] and the local Chan–Vese (LCV) model [23], etc. These methods generally rely on the assumption that the images with intensity inhomogeneity are intensity homogeneous in smaller local regions. By approximating the original image in terms of local regions rather than global regions, they can successfully segment the images with slight intensity inhomogeneity. In practical implementation, the local region-based methods usually examine the local region centered in each pixel by using certain statistical function with fixed scale. However, due to the non-linear and complicated intensity inhomogeneity, fixing scale for all local regions may result in the failed segmentation for image with severe intensity inhomogeneity. To improve the segmentation performance, the scales should be adaptively changed for each local region. However, it should be noted that to pre-define the precise scale for each local region can hardly be performed for practical segmentation. It needs to model the intensity inhomogeneity in advance which is still a complex problem in image processing field.

Recently, inspired by the multi-scale idea in wavelet transform, some multi-scale level set methods are proposed [24–26]. Lin et al. [24] applied the coarse scale to extract image boundary and then utilized the extracted coarse boundaries as initial contour to drive contour evolution at fine scale. Kim et al. [25] proposed using two evolving curves for level set evolution where one curve at the coarse scale tracked the object boundary and the other evolving curve at fine scale was used to smooth the object boundary. Sui et al. [26] decomposed the original image into several sub-images at different scale and performed level set evolution in sub-image with finer scale where the segmentation result of sub-image with coarse scale was regarded as the initial contour. Sun et al. [27,28] proposed using constrained ICA model and nonlinear least-squares model for depth estimation. These methods have achieved some good performance on echocardiographic, SAR and face images, etc.

In this paper, we shall propose a novel multi-scale local region based level set method to segment the image with slight or severe intensity inhomogeneity. The multi-scale segmentation idea and local statistical analysis are incorporated into the construction of level set energy functional. Firstly, the local region is defined in circular shape so as to approximate the non-uniform illumination and capture more local intensity information. Then, the statistical analysis shall be performed on intensities of the local circular regions centered in each pixel by using multi-scale low-pass filtering. Thus, the multi-scale local intensity information is extracted. The data term of energy functional can be constructed by approximating the normalized weighted image divided by multi-scale local intensity information, which is the key to improve the segmentation capability of our method on the images with severe intensity inhomogeneity. To further control the smoothness of the evolving curve and avoid the over-segmentation phenomenon and re-initialization step, the regularization term is included in the energy functional which consists of the arc length penalty term and re-initialization penalty term. Finally, the multi-scale segmentation is performed by minimizing the newly constructed level set energy functional. The experiments on the synthetic and real images have demonstrated that the proposed method is efficient and robust for segmenting image with slight or severe intensity inhomogeneity. In addition, we have also made some comparisons with the LBF model and LCV model to show the superiority of our method over the traditional local region based methods.

The rest of this paper is organized as follows: In Section 2, we briefly review the CV model, LBF model and LCV model. Our multi-scale local region based level set method is presented in Section 3. In Section 4, the proposed method is validated by experiments on several synthetic and real images with slight or severe intensity inhomogeneity. Finally, the conclusive remark is included in Section 5.

2. Related works

2.1. Chan–Vese model

The Chan–Vese (CV) model [11] is proposed by Chan and Vese, which is to minimize the following energy functional:

$$E^{CV}(c_1, c_2, C) = \lambda_1 \int_{inside(C)} \left|I(x) - c_1\right|^2 dx + \lambda_2 \int_{outside(C)} \left|I(x) - c_2\right|^2 dx + \mu Length(C), \quad (1)$$

where λ_1 , λ_2 and μ are positive constants, usually fixing $\lambda_1 = \lambda_2 = 1$. c_1 and c_2 are intensity averages of given image I inside and outside evolving curve C, respectively.

To solve the above minimization problem, the energy functional in (1) should be firstly reformulated in terms of the level set function $\phi(x)$ as follows:

$$\begin{aligned} E_\varepsilon^{CV}(c_1, c_2, \phi) = \lambda_1 &\int_\Omega \left|I(x) - c_1\right|^2 H_\varepsilon(\phi(x))\, dx \\ &+ \lambda_2 \int_\Omega \left|I(x) - c_2\right|^2 (1 - H_\varepsilon(\phi(x)))\, dx \\ &+ \mu \int_\Omega \delta_\varepsilon(\phi(x)) \left|\nabla \phi(x)\right| dx, \end{aligned} \quad (2)$$

where $H_\varepsilon(z)$ and $\delta_\varepsilon(z)$ are the regularized approximation of Heaviside function $H(z)$and Dirac delta function $\delta(z)$, respectively.

The minimization problem for (2) can be solved by taking the Euler-Lagrange equations and updating the level set function $\phi(x)$ according to the gradient descent method:

$$\frac{\partial \phi}{\partial t} = \delta_\varepsilon(\phi) \left[-\lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2 + \mu div\left(\frac{\nabla \phi}{|\nabla \phi|}\right)\right]. \quad (3)$$