ARTICLE IN PRESS

Neurocomputing xx (xxxx) xxxx–xxxx

Contents lists available at ScienceDirect

Neurocomputing

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

Hybrid level set method based on image diffusion

Xiao-Feng Wang*, Le Zou, Li-Xiang Xu, Gang Lv, Chao Tang

Key Lab of Network and Intelligent Information Processing, Department of Computer Science and Technology, Hefei University, Hefei, Anhui 230601, China

A R T I C L E I N F O

Keywords:
Image segmentation
Level set
Hybrid method
Nonlinear diffusion
Homomorphic unsharp masking

A B S T R A C T

In this paper, a new hybrid diffusion-based level set method is proposed to efficiently address the complex image segmentation problem. Different from the traditional methods, the proposed method is performed on image diffusion space rather than intensity space. Firstly, the nonlinear diffusion based on total variation flow and additive operator splitting scheme is performed on the original intensity image to obtain the diffused image. Then, the local diffusion energy term is constructed by performing homomorphic unsharp masking operation on diffused image so as to implement a local piecewise constant search. To avoid trapping into local minimum produced by local energy, the global diffusion energy term is formed by approximating diffused image in a global piecewise constant way. Besides, the regularization energy term is included to have penalization effect on evolving contour length and maintenance of level set function being signed distance function. By minimizing the overall energy functional which is a linear combination of local energy, global energy and regularization energy, the evolving contour can be driven to approach the object boundary. The experiments on different characteristics of complex images have shown that the proposed method can achieve satisfying segmentation performance accompanied with some good properties, i.e. the robustness to initial parameter and contour setting, noise insensitivity, quick and stable convergence.

1. Introduction

Generally, image segmentation aims to partition a given image into some non-overlapping regions where the internal pixels are homogeneous with respect to intensity, color, texture, motion or semantics, etc. The biggest challenge for image segmentation is to segment the complex image which refers to the coherent image acquired in complicated environment, consisting of the background with complex space distribution and the scattered disturbances. Over the past decades, a lot of new research achievements come out where a particular group of methods called active contour models (ACMs) attract tremendous attentions. The fundamental idea of ACM is to apply the partial differential equation to deform a curve towards the object boundary. Due to the incorporation of different image features into contour evolution, ACMs have been successfully used in various image segmentation applications. According to the representation form of contour, ACMs can be roughly divided into two categories, i.e. parametric ACM and geometric ACM. The former one generally uses parametric equation to explicitly represent the evolving contour [1]. On the contrary, the geometric ACM implicitly represents contour as the zero level set of a higher dimensional function (level set function) and then compute a time-dependent equation to obtain a deforming surface [2]. Thus, the geometric ACM is usually called level set method (LSM). LSM has several advantages. Firstly, it can segment the object with complicated shape since the evolving contour implicitly represented by the zero level set can naturally change its topological structure. Secondly, it can avoid the track procedure for closed evolving contour and further transform the contour evolution problem to the numerical solution to partial differential equation. Thirdly, its numerical solution scheme is easily realized since the level set function always maintains being a function in the process of evolution.

According to the image feature incorporated in the energy functional, the early level set methods can be classified into edge-based methods [3–7] and global region-based methods [8–13]. Edge-based methods generally utilize the edge indicator depending on image gradient to attract evolving contour toward the object boundary, whereas global region-based methods utilize global image information inside and outside the evolving contour, e.g. the distribution of intensities, colors, textures and motions, to drive the level set evolution. Compared with edge-based methods, global region-based methods have a better performance on segmenting images with weak boundaries and are less sensitive to initial conditions and the existence of noise. Among them, the Chan-Vese (CV) model [9] is the most representative one which increases the contour convergence range by utilizing the image statistical information. Hence, it is particularly efficient for images containing homogeneous regions with distinct

* Corresponding author.
E-mail address: xfwang@iim.ac.cn (X.-F. Wang).

http://dx.doi.org/10.1016/j.neucom.2016.09.079
Received 28 December 2015; Received in revised form 27 March 2016; Accepted 8 September 2016
Available online xxxx
0925-2312/

Please cite this article as: Wang, X-F., Neurocomputing (2016), http://dx.doi.org/10.1016/j.neucom.2016.09.079

intensity means. However, CV model still has some intrinsic limitations. Firstly, if intensities inside and outside the evolving contour are not homogeneous, CV model often produce poor segmentation results due to the wrong movement of the evolving contour. Secondly, the placement of initial contour and setting of initial parameters irrelevantly determine the final segmentation especially in complex images. The problems associated with CV model can also be found in most of global region-based methods.

To improve the performance of global region-based methods, some methods (also called local region-based methods) were proposed to utilize local image features to guide the contour evolution instead of global image features. The representative ones include the region-scalable fitting (RSF) model [14], the local Chan-Vese (LCV) model [15], the local image fitting (LIF) model [16] and the local intensity clustering model (LIC) [17], etc. To extract the local region information, these methods usually examine local region centered in each pixel by using certain statistical method. As a result, they can efficiently segment inhomogeneous objects. Recently, some hybrid methods [18–21] combined the global and local image information to stabilize and speed up the evolution convergence. Moreover, some methods [22–24] proposed extracting the local intensity information in a multi-scale way. The corresponding segmentation accuracy for inhomogeneous images can be greatly improved while no significant computational burden is introduced. Some good linear and nonlinear information extraction and integration ideas proposed in [25–35] can also be introduced to further improve the segmentation performance of existing methods [36,37]. However, it should be mentioned that contour evolutions of most of existing methods are performed on intensity space. For complex image, the over-segmentation phenomenon may appear, i.e. evolving contours tend to surround the cluttered background and scattered disturbances, whereas the object can not be solely separated. The reason is due to that the intensities of cluttered background and scattered disturbances are similar to that of object. As a result, the complex image segmentation is still a problem for these intensity-based methods. In our former work [15], we proposed segmenting image on structure tensor space and achieved satisfying performance in the presence of obvious disturbance. Inspired by this work, we consider constructing level set energy functional on diffusion space rather than intensity space.

The diffusion idea is borrowed from physical phenomena. It is a physical process that balances the concentration differences but not to create or destroy mass [38]. Generally, the balance property can be expressed by Fick's law where the concentration gradient causes a flux to compensate itself. The relation between gradient and flu can be described by a positive definite symmetric matrix, i.e. diffusion tensor. Hence, the diffusion process can be easily modeled in mathematical formulation by constructing continuity equation and incorporate Fick's law into the continuity equation. In image processing filed, the diffusion can evolve the image as a dynamic system to reduce the random variation and restore the image by identifying concentration with the pixel intensity. Here, the diffusion tensor is of prime importance for image diffusion. If diffusion tensor is constant over image, the image diffusion is isotropic. If it is space-dependent, diffusion is anisotropic. From another perspective, the diffusion is nonlinear if diffusion tensor is a function of differential structure of evolving image. Diffusion being independent on the evolving image is called linear. Linear diffusion is equivalent to convolving image with a Gaussian kernel. However, due to the Gaussian smoothing property, some serious drawbacks are associated with linear diffusion, i.e. edge blurring and even losing when moving from finer to coarser scales. Unlike linear diffusion, nonlinear diffusion can produce some impressive results on image by applying a process which itself depends on local properties of the image. The earliest work was from Perona and Malik [39] where an inhomogeneous process is applied to reduce the diffusivity at those locations with a larger likelihood to be boundaries. Therefore, boundaries remain well localized and can even be enhanced. In many nonlinear diffusion methods, the diffusion tensor is replaced by a positive scalar-valued diffusivity function which makes these methods isotropic. However, it is sometime suggested that the flux is biased towards the orientation of interesting features. This requirement cannot be satisfied by using the diffusivity. Thus, diffusion tensor leading to anisotropic diffusion is introduced by applying spatial regularization strategies [38]. Anisotropic diffusion can be classified into two categories, i.e. edge-enhancing anisotropic diffusion which offers advantages at noisy edges and coherence-enhancing one which is well-adapted to process one-dimensional features. Due to the good property, nonlinear diffusion has been successfully applied in many image processing areas, such as images filtering [40,41], image segmentation [42,43], and image enhancement [44,45].

To capture the real boundaries and overcome the aforementioned problems of exiting level set methods in complex image segmentation, we proposed performing the level set evolution on diffusion space instead of intensity space. Besides, we consider combining the advantages of the local region-based method and the region-based method by taking both local and global information into account. Firstly, the nonlinear diffusion is performed on the intensity image so as to obtain the diffused image. Then, the local diffusion energy term is constructed by implementing a local piecewise constant search on diffused image. To avoid trapping into local minimum, the global diffusion energy term is introduced by approximating diffused image in a global piecewise constant way. The local term and global term are then combined in a linear form. Further, the regularization energy term is included to have penalization effect on evolving contour length and signed distance function maintenance. As a result, the total energy functional consists of three energy terms and the image segmentation can be implemented by minimizing the overall energy functional.

The remaining of this paper is organized as follows: Section 2 introduces some related knowledge about level set method and nonlinear diffusion. In Section 3, we shall discuss the energy functional construction of the proposed method in detail. Then, our method is validated by experiments on some complex images in Section 4. Finally, some conclusive remarks are provided in Section 5.

2. Related works

2.1. Chan-Vese model

As a representative global region-based method, Chan-Vese (CV) model [9] has been widely used in image segmentation field. Let $\Omega \subset \Re^2$ be the two-dimensional image domain and $I: \Omega \to \Re$ be the intensity image. By using the zero level set of a Lipschitz function $\phi: \Omega \to \Re$ to implicitly represent the evolving contour, the energy functional of CV model can be described as the following:

$$E^{CV}(c_1, c_2, \phi) = \lambda_1 \cdot \int_\Omega |I(x) - c_1|^2 H(\phi(x))dx + \lambda_2 \cdot \int_\Omega |I(x) - c_1|^2 (1 - H(\phi(x)))dx \ + \mu \cdot \int_\Omega \delta(\phi(x))|\nabla\phi(x)|dx, \tag{1}$$

where λ_1 , λ_2 and μ are nonnegative constants. c_1 and c_2 are the intensity means inside and outside evolving contour. $H(z)$ and $\delta(z)$ respectively denote Heaviside function and Dirac delta function. The minimization of (1) can be solved by taking the Euler-Lagrange equations and updating $\phi(x)$ according to the gradient descent method:

$$\frac{\partial\phi}{\partial t} = \delta(\phi)\left[-\lambda_1(I - c_1)^2 + \lambda_2(I - c_2)^2 + \mu div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right], \tag{2}$$

At each iteration, c_1 and c_2 can be computed as follows:

$$c_1(\phi) = \frac{\int_\Omega I(x)H(\phi(x))dx}{\int_\Omega H(\phi(x))dx}, \ c_2(\phi) = \frac{\int_\Omega I(x)(1 - H(\phi(x)))dx}{\int_\Omega (1 - H(\phi(x)))dx} \tag{3}$$

Since CV model is independent of image gradient information, it