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An efficient level set method based on multi-scale image segmentation and hermite differential operator

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ABSTRACT

In this paper, an efficient and robust level set method is presented to segment the images with intensity inhomogeneity. The multi-scale segmentation idea is incorporated into energy functional construction and a new Hermite differential operator is designed to numerically solve the level set evolution equation. Firstly, the circular shape window is used to define local region so as to approximate the image as well as intensity inhomogeneity. Then, multi-scale statistical analysis is performed on intensities of local circular regions centered in each pixel. So, the multi-scale local energy term can be constructed by fitting multi-scale approximation of inhomogeneity-free image in a piecewise constant way. To avoid the time-consuming re-initialization procedure, a new double-well potential function is adopted to construct the penalty energy term. Finally, the multi-scale segmentation is performed by minimizing the total energy functional. Here, a new differential operator based on Hermite polynomial interpolation is proposed to solve the minimization. The experiments and comparisons with three popular local region-based methods on images with different levels of intensity inhomogeneity have demonstrated the efficiency and robustness of the proposed method.

1. Introduction

Image segmentation is a process to partition given image into homogeneous regions associated with different objects. It is equivalent to find the contours corresponding to the object boundaries. To achieve this goal, image segmentation can be reformulated as a minimization problem. The predefined energy functional determines the segmentation criterion where the unknown variables represent the deformable contours. The most representative and successful method within this context is the level set method (LSM) which was originally proposed by Osher and Sethian [1]. LSM adopts an implicit parameterization of the contours so that the contours can be described by the zero level set of a high dimensional function (also called level set function, LSF). Thus, the motion of the contours is formulated as the evolution of level set function. Correspondingly, the deformable contours can be driven to approach the object boundaries along with the minimization of the energy functional. The popularity and success of level set method owe to its ability to easily deal with complex topological changes of contours (merging or splitting) on the condition that no additional functions are used. Besides, extensive numerical solution schemes based on Hamilton–Jacobi equations can provide stable contour evolution for level set method.

In general, the existing level set methods can be classified into edge-based methods and region-based methods according to the image property incorporated in the energy functional. The energy functional of edge-based methods [2–7] is designed based on the image gradient. Therefore, edge-based methods can easily segment object whose boundary is defined by sharp gradient. However, there are some intrinsic disadvantages associated with these methods. Their segmentation performance is quite sensitive to noise existed in images as a result of the strong dependence of gradient. Moreover, the robustness to initial parameter setting and initial contour placement are both weak. Particularly, they may produce serious boundary leakages in the position of weak

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boundary. Evolving contour may mistakenly pass through the boundary due to the weak gradient. Different from edge-based methods, region-based methods [8–13] construct the energy functional by measuring the variance of region information inside and outside the evolving contour. They assume that the image domain consists of several homogeneous regions and aim to find an energy optimum for best fitting the image. In comparison with edge-based methods, they have a better performance on segmenting images with weak object boundaries and are less sensitive to initial conditions. Nonetheless, due to the holding intensity homogeneity assumption, the presence of intensity inhomogeneity will greatly affect the segmentation performance of these region-based methods. To solve this problem, some region-based methods [14,15] abandon the intensity homogeneity assumption and attempt to utilize multiple level set functions to find the minimizer of image with intensity inhomogeneity. Although they can obtain much precise segmentation results, the expensive computational complexity and sensitivity to contour initialization restrict their practical application [16].

Recently, local region-based methods have been proposed [16–21] where local region information are extracted and incorporated into the energy functional. The representative methods include local binary fitting (LBF) model [16], local image fitting (LIF) model [17], local Chan-Vese (LCV) model [18] and local intensity clustering (LIC) model [19], etc. Just like the methods in [13,14], local region-based methods agree that the intensities are inhomogeneous in global region of image with intensity inhomogeneity. Meanwhile, they assume that the intensity homogeneity assumption still stands in local regions. In other words, the intensities are homogeneous in local regions of image with intensity inhomogeneity. By fitting the image in terms of local regions rather than global regions, the above methods are advantageous in segmentation of image with intensity inhomogeneity. For extracting the local region information, these methods usually examine local region centered in each pixel by using statistical method. Theoretically, to obtain the best segmentation result, the optimal scale should be assigned to each possible local region. It means that scale may vary for different local region. However, it is hardly performed for practical segmentation since modeling the intensity inhomogeneity is a difficult problem to solve in image processing field. For convenience, the scale of local region is usually fixed in the existing local region-based methods. This measure is efficient for segmenting image with slight intensity inhomogeneity. For images with moderate or severe intensity inhomogeneity, unsatisfying segmentation may appear since the existent intensity distribution of image is non-linear and complicated. No matter what scale is used, intensities may be inhomogeneous in some local regions while intensities are homogeneous in the other local regions. To solve this problem, we consider incorporating the multi-scale idea into the local region-based method.

It should be noted that the multi-scale idea have already been referred by several level set methods [22–29]. Many of them [22–26] adopt the hierarchical coarse-to-fine strategy to perform segmentation. The original image is generally decomposed into several images at different scale. Certain level set model is used to perform coarse segmentation on coarse-scale image and the final segmentation result is regarded as the initial contour of next fine segmentation. Then, the same model or another model with higher accuracy is applied on fine-scale image, thus gradually driving the evolving contour to reach the true object boundary. Although these methods achieve good performance on segmenting medical and SAR images, the related computational complexity has been increased due to the hierarchical segmentation manner. Some other methods [27–29] proposed extracting the local intensity information in a multi-scale way and construct the multi-scale local region-based method. The corresponding segmentation accuracy for images with severe intensity inhomogeneity can be greatly improved while no significant computational burden is introduced. Particularly, some good idea about linear and nonlinear information extraction in [30–37] can also be introduced into level set method to address the intensity inhomogeneity problem.

In this paper, we propose an efficient and robust level set method by introducing the multi-scale segmentation idea into the local region-based method. In addition, a new Hermite differential operator is constructed to solve the level set evolution equation. Here, we utilize the circular shape window to define the local region so as to approximate the given image as well as the existent intensity inhomogeneity. Then, multi-scale statistical analysis is performed on intensities of local circular regions centered in each pixel. Further, the multi-scale local energy term can be constructed by approximating the average of inhomogeneity-free images at each scale in a piecewise constant way. In addition, a new double-well potential function is used to construct the penalty energy term to enforce level set function to maintain a signed distance function near the zero level set. Finally, the multi-scale segmentation is performed by minimizing the overall energy functional. To solve the level set evolution equation, a new differential operator based on Hermite polynomial interpolation is proposed to replace the traditional differential operators. The experiments can demonstrate that the proposed method is efficient and robust for segmenting image with different levels of intensity inhomogeneity.

The rest of this paper is organized as follows: In Section 2, we briefly discuss some background knowledge. The proposed multi-scale level set method is presented in Section 3. In Section 4, the proposed method is validated by experiments on several images with intensity inhomogeneity. Finally, the conclusive remark is included in Section 5.

2. Background

2.1. Local region-based methods

Let $\Omega \subset \Re^2$ be the two-dimensional image domain and $I : \Omega \to \Re$ be the given grayscale image. In level set methods, the image segmentation is equivalent to find an optimal contour C which can separate the image domain Ω into several disjoint regions. This problem can be formulated as the minimization of predefined level set energy functional where contour is implicitly represented by the zero level set of level set function $\phi : \Omega \to \Re$. Local region-based methods generally employ certain statistical function to extract the local region information and drive the level set evolution based on extracted information. The most representative method is local binary fitting (LBF) model which was proposed by Li et al. [16]. By introducing the Gaussian kernel function into energy functional, LBF model successfully used two smooth functions f_1 and f_2 to describe the local intensities inside and outside evolving contour C. The related energy functional is described as follows:

$$\begin{aligned} E^{LBF}(f_1, f_2, \phi) &= \lambda_1 \int [\int K_\sigma(x-y)|I(y)-f_1(x)|^2 H(\phi(y))dy]dx \\ &+ \lambda_2 \int [\int K_\sigma(x-y)|I(y)-f_2(x)|^2 \cdot (1-H(\phi(y)))dy]dx \\ &+ \mu \cdot \int_\Omega \frac{1}{2}(|\nabla\phi(x)|-1)^2 dx \ + \nu \cdot \int_\Omega \delta(\phi(x))|\nabla\phi(x)|dx, \end{aligned} \tag{1}$$

where λ_1, λ_2, μ and ν are fixed parameters. $H(x)$ and $\delta(x)$ are Heaviside function and Dirac delta function, respectively. K_σ denotes the Gaussian kernel function with standard deviation σ. f_1