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An improved active contours model for image segmentation by level set method

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ABSTRACT

The variational level set approaches are widely used in image segmentation. To extract the objects from the inhomogeneity image, an improved local and global binary fitting active contours model is presented in this paper. The energy functional has been defined by a local intensity fitting term and a global intensity fitting term. The generalized Gaussian distribution has been used as the kernel function of the local binary fitting information. The experiment results of the homogeneity images, artificial and real inhomogeneous images have shown the advantages of LGBF model in terms of accuracy and robustness.

1. Introduction

In the field of computer vision researches, the traditional image segmentation methods have enormous challenges, which are image noise, low contrast and intensity inhomogeneity. In particular, intensity inhomogeneity image segmentation is a difficult problem to classical techniques such as edge detection and threshold segmentation.

The well-known parametric active contours model (Snake model) was proposed by Kass et al. [1]. Many researchers have done a lot of works, and improved the active contours models which are applied to many fields, such as edge detection, image segmentation [2,3], object tracking and image reconstruction. The parametric curves are smooth and closed, but this model cannot control the curves' topological changes adaptively, furthermore, the object image with hollow area is difficult to be segmented clearly.

Many researchers have proposed the improved methods for the shortcoming of the Snake model. The classical models are as follows: Osher and Sethian [4] proposed geometric active contour model using the level set method; Caselles et al. [5–8] proposed geodesic active contour model (GAC); according to regional-based level set ideas and Mumford–Shah functional, Chan and Vese [9] proposed piecewise constant variational level set model (CV). The different image segmentation methods can segment different images, and each method has its own advantages and disadvantages. Especially, there are many intensity inhomogeneity medical images, such as X-ray image, MR image and CT image.

Subsequently, Vese and Chan [10,11] put their CV model extended to the multiphase level set model, which has a large amount of computation, and the initial contour needs close to the object's boundary. Li et al. [12] introduced the penalty energy functional to measure the distance between the level set function and the sign function, which can avoid the re-initialization of the evolution curve. Li et al. [12,13] proposed the local binary fitting active contours model (LBF), which can accurately segment the inhomogeneity image object. However, there will be redundant segmentation while the image is more complex. Subsequently, Wang et al. [14] improved the active contours model with the local and global intensity fitting energy (LGIF). In this model, the image information has been fitted by the Gaussian function, and achieved the accurate segmentation for the inhomogeneity image.

According to the problems of the CV model and LBF model, an effective improved scheme is proposed in this paper, which considers the global and local information of the inhomogeneity image based on the generalized Gauss distribution function. The local and global binary fitting (LGBF) model consists of three parts: the global term, the local term and the regularization terms. The LGBF model can segment the inhomogeneity image with fewer iteration times by using the local image information. The global image information plays a major role with the evolution curves, while the curves are far away from the target edge. In addition, the re-initialization of the evolution curves can be avoided by the punitive energy functional, and the calculation time is reduced.

Compared with experiment results of the CV model and LBF model, it is concluded that the LGBF model can segment the inhomogeneity images with accurate and effective results. The

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proposed method is not sensitive to the location of the initial contours, and the iteration times are fewer.

2. Background

2.1. The CV model

Chan and Vese proposed an active contour model without edges which based on Mumford–Shah model. The input gray level image is $I:\Omega\to R$, C is a closed curve, energy functional is defined as follows:

$$E^{CV}(C,c_1,c_2)=\mu\cdot\text{length}(C)+\nu\cdot\text{area}(\text{inside}(C))$$
$$+\lambda_1\int_{\text{inside}(C)}\left|I-c_1\right|^2dx+\lambda_2\int_{\text{outside}(C)}\left|I-c_2\right|^2dx,\quad x\in\Omega \quad (1)$$

where $\mu\geq0$, $\nu\geq0$, $\lambda_1,\lambda_2\geq0$. The first item is the Euclidean length of the closed curve C, the second item expresses the area of the inside curve C. The image area Ω is divided into two homogeneous regions which are target (inside(C)) and background (outside(C)), c_1 and c_2 are two constants that represent the average intensity in inside(C) and outside(C), respectively. When the contour C lies in the target boundary, the above energy functional reaches the minimum.

The contour curves are expressed by level set ϕ, $C=\{x\in\Omega\,|\,\phi(x)=0\}$. According to the variational method [12,13], Euler–Lagrange equation is received, then get the partial differential equations with gradient descent method as follows:

$$\begin{cases} c_1(\phi)=\dfrac{\int_\Omega IH(\phi)d\Omega}{\int_\Omega H(\phi)d\Omega}, \quad c_2(\phi)=\dfrac{\int_\Omega I[1-H(\phi)]d\Omega}{\int_\Omega [1-H(\phi)]d\Omega} \\ \dfrac{\partial\phi}{\partial t}=\delta(\phi)\left[\mu\cdot\text{div}\left(\dfrac{\nabla\phi}{|\nabla\phi|}\right)-\nu-\lambda_1(I-c_1)^2+\lambda_2(I-c_2)^2\right] \end{cases} \quad (2)$$

In the curve evolution, the data fitting term $-\lambda_1(I-c_1)^2+\lambda_2(I-c_2)^2$ is very important. Usually, set $\lambda_1=\lambda_2$, $\nu=0$, μ is the scale parameter. Apparently, in Eq. (2), c_1 and c_2 represent the global information of internal and external contours. However, if the input image with intensity inhomogeneity in the internal and external contour, the global image information is not accurate.

2.2. The LBF model

The LBF model is proposed by Li et al. that embedded the local image information, can deal with the intensity inhomogeneity images, the basic idea is the introduction of kernel function to define the energy functional as follows:

$$E^{\text{LBF}}(C,f_1,f_2)=\lambda_1\iint_{\text{inside}(C)}K_\sigma(x-y)\left|I(y)-f_1(x)\right|^2dydx$$
$$+\lambda_2\iint_{\text{outside}(C)}K_\sigma(x-y)\left|I(y)-f_1(x)\right|^2dydx,\quad x,y\in\Omega \quad (3)$$

where $\lambda_1,\lambda_2>0$ are fixed parameters, $I:\Omega\to R$ is an input image, K_σ is a Gaussian kernel with standard deviation σ, f_1 and f_2 are two smooth functions that approximate the local image intensities inside and outside the contour C, respectively.

With variational level set method, the curve C is represented by the zero level set of for the Lipschitz function ϕ, and minimize the energy functional to get the gradient descent flow as follows:

$$\frac{\partial\phi}{\partial t}=-\delta_\varepsilon(\phi)(\lambda_1e_1-\lambda_2e_2) \quad (4)$$

When parameters are fixed ($\lambda_1=\lambda_2$), e_1 and e_2 are defined as follows:

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

Function f_1 and f_2 are defined as follows:

$$\begin{cases} f_1(x)=\dfrac{K_\sigma*[H_\varepsilon(\phi)I(x)]}{K_\sigma*H_\varepsilon(\phi)} \\ f_2(x)=\dfrac{K_\sigma*[1-H_\varepsilon(\phi)I(x)]}{K_\sigma*(1-H_\varepsilon(\phi))} \end{cases} \quad (6)$$

The standard deviation of Gaussian kernel function σ is a scale parameter to control the mensurability from the image smaller neighborhood to the whole image area. The larger bandwidth is more likely to result in the fuzzy boundary, however, smaller bandwidth cannot characterize the image local information, and result in redundant contours. Apparently, the functions f_1 and f_2 in Eq. (6) represent the image average intensity both inside and outside of the curve C under Gaussian window, respectively.

In the above equations, the regularized versions of Heaviside function H and Dirac function δ are utilized as follows:

$$\begin{cases} H_\varepsilon(z)=\dfrac{1}{2}\left[1+\dfrac{2}{\pi}\arctan\left(\dfrac{z}{\varepsilon}\right)\right] \\ \delta_\varepsilon(z)=\dfrac{1}{\pi}\cdot\dfrac{\varepsilon}{\varepsilon^2+z^2},\quad z\in R \end{cases} \quad (7)$$

3. The improved local and global binary fitting active contours model

In this paper, the local and global binary fitting model is proposed based on the curve evolution theory and the variational level set approach. In order to enhance the differentiation and self-adaptability of the model, this paper introduces the generalized Gaussian distribution function as the kernel function. In the LGBF model, the energy functional is composed of three parts: the global term, the local term and the regularization terms, which can be expressed as:

$$E^{\text{LGBF}}=\omega E^L+(1-\omega)E^G+E^R \quad (8)$$

where $0\leq\omega\leq1$. When the image intensity is inhomogeneous, the parameter ω should be large, as a major force the local information has promoted the evolution curve closed to the real contour.

3.1. The global term

The input gray image is $I:\Omega\to R$, C is a closed curve, the energy functional of the global fitting term is defined as follows:

$$E^G(c_1,c_2,C)=\lambda_1\int_{\text{outside}(C)}\left|I-c_1\right|^2d\mathbf{x}$$
$$+\lambda_2\int_{\text{inside}(C)}\left|I-c_2\right|^2d\mathbf{x},\quad \mathbf{x}\in\Omega \quad (9)$$

where $\lambda_1,\lambda_2\geq0$. The closed curve C divides the image area Ω into two parts that are target area (inside the curve C) and the background area (outside the curve C), c_1 and c_2 are two constants that represent the average intensity inside and outside the curve C, respectively.

In Fig. 1(a), it is shown that the energy functional inside the curve C is larger than zero from Eq. (9), and the outside energy functional is close to zero; in Fig. 1(b), when the curve C is surrounded by the real contour C^*, the inside energy functional is near to zero, and the