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A novel active contour model driven by local and global intensity fitting energies

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ABSTRACT

In this paper, we propose a novel hybrid active contour model for image segmentation. In our model, we define a new region-scalable fitting (RSF) energy functional which combines the local and the global image information. The RSF energy functional can not only attract the contour toward object boundaries, but also improve the robustness to initialization of the contours. In order to segment the image fast and accurately, the length term and regularization term is incorporated into the variational level set formulation. Finally, by adopting gradient descent method, the minimization of the energy equation can be given. Due to the new kernel function we defined, our model can cope with intensity inhomogeneity images and less sensitive to the initialization of the contour when compared with the other models. Experimental results demonstrated that the proposed model can also segment both the real and medical images accurately.

1. Introduction

Image segmentation is a basic and important operation in the fields of image analysis and computer vision. In the past two decades, a wide variety of image segmentation techniques have been proposed to solve the image segmentation problem, especially the active contour models [1], which are based on the theory of surface evolution. The fundamental idea of active contour models is to evolve a curve under some constraints from a given image to detect the desired objects in that image. Generally speaking, the existing active contour models can be categorized into two classes: edge-based models [2–6] and region-based models [7–11,16–21].

Edge-based models mainly use image gradient as an external force to stop the evolving contours on the object boundaries. However, edge-based models are often sensitive to noise and do not easily detect objects with weak boundaries. Region-based models do not depend on image gradient and use image region information, therefore can segment the image with weak boundaries. Moreover, they are less sensitive to the location of initial contours. One of the most popular region-based active contour models is the C–V model [7], which, as a special case of M–S model [12]. It has been successful for homogeneous image region. But, the C–V model can not applicable to images with intensity inhomogeneity.

To overcome these problems, several models have been developed and successfully applied to image segmentation. Recently, Li et al. [13,14] proposed the LBF (local binary fitting) model, which utilizes the local intensity information efficiently and incorporates the benefits of region-based techniques, can well segment objects with intensity inhomogeneities. Zhang et al. [15] proposed a local image fitting (LIF) model. It utilizes the local image information and can get the desired results. However, nearly all these models are sensitive to initial contours.

In this paper, we propose a novel hybrid active contour model for image segmentation. By defining a new RSF energy functional which combines the local and the global image information, our model can cope with intensity inhomogeneity images and less sensitive to the initialization of the contour when compared with the other models. Experimental results demonstrated that the proposed model can also segment both the real and medical images accurately.

The rest of the paper is structured as follows: In Section 2, we recall the general form of the C–V model and LBF model. Section 3 shows the new active contour model in details. Section 4, experimental results are given. Finally, conclusions are drawn in Section 5.

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2. Background

2.1. C–V method

Chan and Vese [7] proposed an active contour model by simplify the Munford–Shah model that divides the image into inside and outside region. They defined the following energy functional:

$$E(\phi) = \lambda_1 \int_{inside(\phi)} |I - c_1|^2 dxdy + \lambda_2 \int_{outside(\phi)} |I - c_2|^2 dxdy + \mu Length(\phi) \quad (1)$$

where $\mu, \lambda_1, \lambda_2$ are the fixed nonnegative parameters of each item and $I(x, y)$ is the origin image, c_1 and c_2 are average intensities inside and outside of the curve ϕ. By minimizing the energy functional (1), we obtain the following variational formulation:

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

where ϕ is the level set function, and c_1, c_2 are defined as:

$$c_1(\phi) = \frac{\int_\Omega I(x, y) H(\phi)\,\mathrm{d}x\mathrm{d}y}{\int_\Omega H(\phi)\,\mathrm{d}x\mathrm{d}y} \quad (3)$$

$$c_2(\phi) = \frac{\int_\Omega I(x, y)(1 - H(\phi))\,\mathrm{d}x\mathrm{d}y}{\int_\Omega (1 - H(\phi))\,\mathrm{d}x\mathrm{d}y} \quad (4)$$

Eq. (2) is the C–V level set evolution equation. The first term is the length term, which is necessary to maintain the regularity of the contour. The second term is the global image fitting force, which based on the inside and outside region of the contour to guide the contour evolution. C–V model has an important property that it is less sensitive to the initial contour. However, that is limited is that, it often leads to poor segmentation results for images intensity inhomogeneity.

2.2. The LBF model

In order to overcome intensity inhomogeneity, Li et al. [13,14] proposed the LBF model by exploiting the local image information. By introducing a kernel function, the model can accurately segment images with intensity inhomogeneities. The energy functional defined as follows:

$$E^{\mathrm{LBF}}(\phi, f_1, f_2) = \lambda_1 \int_\Omega \int_{\mathrm{inside}(\phi)} K_\sigma(y - x)\,|I(x) - f_1(y)|^2 \mathrm{d}y\mathrm{d}x + \lambda_2 \int_\Omega \int_{\mathrm{outside}(\phi)} K_\sigma(y - x)\,|I(x) - f_2(y)|^2 \mathrm{d}y\mathrm{d}x, \quad (5)$$

where λ_1, λ_2 are fixed parameters, K_σ is a Gaussian kernel with standard deviation σ, f_1 and f_2 are two smooth functions that locally approximate the intensities inside and outside the contour ϕ, respectively.

Using the level set function ϕ to represent the contour and minimizing the energy functional E^{LBF}, we have the gradient descent flow as follows:

$$\frac{\partial \phi}{\partial t} = -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) \quad (6)$$

where f_1, f_2, e_1, e_2 are as follows, respectively:

$$f_1 = \frac{K_\sigma \times (H_\varepsilon(\phi) I(x))}{K_\sigma \times (H_\varepsilon(\phi))} \quad (7)$$

$$f_2 = \frac{K_\sigma \times ((1 - H_\varepsilon(\phi)) I(x)}{K_\sigma \times (1 - H_\varepsilon(\phi))} \quad (8)$$

$$e_1 = \int K_\sigma(y - x)\,|I(x) - f_1(y)|^2 \mathrm{d}y, \quad (9)$$

$$e_2 = \int K_\sigma(y - x)\,|I(x) - f_2(y)|^2 \mathrm{d}y, \quad (10)$$

Due to the introduction of the kernel function, and the utilization of the local region information, the LBF model can obtain accurate segmentation results with the intensity inhomogeneity. However, the LBF model sensitive to the initialization of the contour.

3. Proposed method

In this section, we propose a novel hybrid active contour model which combines the local and the global image information. In Eqs. (7) and (8), f_1 and f_2 are two smooth functions that only utilization of the local region information, so we employ both the local and global intensity information by defining u_1 and u_2 as follow:

$$u_1 = \omega \times f_1 + (1 - \omega) \times c_1 \quad (11)$$

$$u_2 = \omega \times f_2 + (1 - \omega) \times c_2 \quad (12)$$

where ω is a positive constant $(0 \le \omega \le 1)$. The energy function of our model is defined as follow:

$$E(\phi, u_1, u_2) = \lambda_1 \int_\Omega \int_{\mathrm{inside}(\phi)} K_\sigma(y - x)\,|I(x) - u_1(y)|^2 \mathrm{d}y\mathrm{d}x + \lambda_2 \int_\Omega \int_{\mathrm{outside}(\phi)} K_\sigma(y - x)\,|I(x) - u_2(y)|^2 \mathrm{d}y\mathrm{d}x, \quad (13)$$

In order to obtain accuracy evolution of the level set function, we need a signed distance function (SDF) [12] to regularize the level set function. The SDF can be characterized as follows:

$$P(\phi) = \int\int \frac{1}{2}\left(\left|\nabla\phi\right|^2 - 1\right) \mathrm{d}x\mathrm{d}y \quad (14)$$

To regularize the level set contour, we need its length to derive a smooth contour during evolution:

$$L(\phi) = \int\int \left|\nabla H(\phi)\right| \mathrm{d}x\mathrm{d}y \quad (15)$$

Using the standard gradient descent flow method, we obtain the level set evolution equation as follows:

$$\frac{\partial \phi}{\partial t} = -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) + \nu\delta_\varepsilon(\phi) div\left(\frac{\nabla\phi}{|\phi|}\right) + \mu\left(\nabla^2\phi - div\left(\frac{\nabla\phi}{|\phi|}\right)\right) \quad (16)$$

where e_1, e_2 are as follows, respectively:

$$e_1 = \int K_\sigma(y - x)\,|I(x) - u_1(y)|^2 \mathrm{d}y, \quad (17)$$

$$e_2 = \int K_\sigma(y - x)\,|I(x) - u_2(y)|^2 \mathrm{d}y, \quad (18)$$

In this paper, we use the functions $H_\varepsilon s(\phi)$ and $\delta_\varepsilon(\phi)$ as follow:

$$H_\varepsilon(\phi) = \frac{1}{2}\left(1 + \frac{2}{\pi}\arctan\left(\frac{\phi}{\varepsilon}\right)\right) \quad (19)$$

$$\delta_\varepsilon(\phi) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + \phi^2} \quad (20)$$

4. Experimental result

In this section, synthetic images and real images have been tested on to evaluate the proposed model. The results are all carried out by Matlab2011a in the PC with Pentium CPU 2.50 and 4