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A coupling segmentation method based on CV model for high-noise image

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Abstract. For image segmentation methods, a clear image is often the object. High-quality segmentation is possible in many experiments. However, in the actual image, noise is inevitable. Many segmentation methods for high-noise images are not satisfactory. This paper puts forward a method of image coupling denoising and segmentation for high-noise image. A new variational model is adopted, then the denoised image is segmented using the improved CV model. The numerical calculation uses multiple directions difference to approximate the partial derivative, obtaining a rapid and stable effect. The experimental results show that the proposed coupling denoising and segmentation method could demonstrate validity. Where the image's, high noise is concerned, segmentation is obviously superior to the Li's[15] model.

Keywords: image segmentation; high noise; denoising; coupling model; CV model.

1. Introduction

In brief, image segmentation serves to separate the background and objective of an image. It is a key technology in image processing. Since the 1970s, it has been a subject of great interst. Thousands of algorithms have been proposed in relation. Image segmentation methods can be divided into four categories: threshold segmentation methods, edge detection methods, region extraction methods and methods based on specific theories. Threshold segmentation involves determining a threshold value in the range of the image gray value, then comparing the threshold with each of the pixel gray values in the image, moreover, the pixels are divided into two categories[2-5]. The most basic feature of the image is its edge, which is the result of a discontinuity in the local characteristics. Edge detection uses the first-order derivative of the image of the extreme value or the two-order derivative of the zero-point information to provide the basic basis for judging the edge point[6]. We use the first-order differential operators such as Roberts Operator, Sobel Operator, Prewitt Operator in practical work, the second-order differential operators Laplacian Operator, and Krish Operator. The advantages of the differential operator method are that it is fast and easy to calculate, and the disadvantage is sensitive to noise. The essence of region segmentation is to link up the pixels with some similar properties to form the final segmentation region. It uses the local spatial information of the image, which can effectively overcome the shortcomings of image segmentation in other ways, but it usually leads to over-segmentation of the image. In recent years, people have put forward a lot of segmentation technology combined with some specific theories, methods, and tools. Image segmentation based on mathematical morphology, image segmentation based on fuzzy theory, and image segmentation based on neural network[7-12] are proposed and so on. The active contour model has become a research hotspot in the field of image segmentation. It can effectively deal with variable topology. The variable level set method not only has the above advantages, but also can effectively integrate multiple model components. It is widely used in image segmentation, motion tracking, 3D reconstruction and so on. Experts have proposed many different manifestations of the active contour model: Mumford and Shah[13] proposed the MS model; Chan and Vese put forward the CV model[14].

This article will focus on high-noise images using the improved PM model to deal with the noise of the image; the variational model is obtained by Euler-Lagrang equation and gradient descent flow, differential equation with finite difference approximation of the pixels each direction derivative, makes full use of its local information. Using improved CV model segmentation, increase the punishment term, make maintain throughout the image area keep the property of signal distance, to avoid the cyclical to initialize, get a optimal segmentation image.

2. CV model and improved model

In 2001, Chan and Vese put forward the CV model based on M-S model. The CV model considers the simplest of segmentation, namely the image is divided into two parts, the background and target, the target and the background of gray level distribution constant values. The CV model of energy functional is obtained:

$$E(C,c_1,c_2) = \mu Length(C) + \lambda_1 \int_{inC} |I(x,y)-c_1|^2\, dxdy + \lambda_2 \int_{outC} |I(x,y)-c_2|^2\, dxdy \tag{1}$$

Among these, $I(x,y)$ is for image segmentation, C is evolution curve, and $\mu \ge 0, \lambda_1, \lambda_2$ is weight coefficient. In the energy functional, the first term corresponds to the length of the curve evolution, a regular role, after the two as binary fitting. Get the energy function level set representation:

$$\begin{aligned} E(\phi,c_1,c_2) = \; & \mu \int_\Omega \delta_\varepsilon(\phi)|\nabla(\phi)|\,dxdy + \lambda_1 \int_\Omega |I-c_1|^2 H_\varepsilon(\phi)dxdy \\ & + \lambda_2 \int_\Omega |I-c_2|^2 (1-H_\varepsilon(\phi))dxdy \end{aligned} \tag{2}$$

In the functional,

$$\delta_\varepsilon(\phi) = H_\varepsilon{}'(\phi) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2+\phi^2} \tag{3}$$

is regularization form of the $\delta(\phi)$ function. So $\delta_\varepsilon(\phi)$ is not zero, makes the energy functional drive equation play a role in all levels, it has nothing to do with the curve of the initial position of the global minimum. In addition, this will help automatically detect the target of internal and external contours. Given the evolution curve corresponding to the level set function of ϕ, minimise the energy functional $E(\phi,c_1,c_2)$ available c_1, c_2 expression.

$$c_1 = \frac{\int_\Omega I(x,y)H(\phi(x,y))dxdy}{\int_\Omega H(\phi(x,y))dxdy}, c_2 = \frac{\int_\Omega I(x,y)(1-H(\phi(x,y)))dxdy}{\int_\Omega (1-H(\phi(x,y)))dxdy} \tag{4}$$

Make the c_1, c_2 remains invariant, according to the variational method and the steepest descent method, the partial differential equation of the controlled level set evolution is as follow:

$$\frac{\partial\phi}{\partial t} = \delta(\phi)[\mu div(\frac{\nabla\phi}{|\nabla\phi|}) - \lambda_1(I-c_1)^2 + \lambda_2(I-c_2)^2] \tag{5}$$

The CV model involves comprehensive utilisation of the global information of the image and gets the global optimal result of image segmentation. The model also has obvious defects because of inherent characteristics: (1) can't deal with gray inhomogenous images; (2) have to periodically to initialize level set function; (3) although the segmentation result is insensitive to the initial position of natural evolution, the evolution speed is obviously dependent on the initial position of the evolution curve; (4) despite the reduced sensitivity to noise, can't split images of the noise pollution seriously; antinoise ability is still not strong. To overcome the defect of the re-initialisation, Li et al[15] proposed the LBF(local binary fitting) method, namely the level set function ϕ , adding the term

$$P(\phi) = \iint_\Omega \frac{1}{2}(|\nabla\phi|-1)^2 dxdy \tag{6}$$

Obviously, minimising $P(\phi)$ means that requires $|\nabla\phi|=1$, which is then required in the evolution of the level set function, always staying as the signal distance function in the process. By the variational method and gradient descent method, we can obtain its gradient descent of flow.

$$\frac{\partial\phi}{\partial t} = \Delta\phi - div(\frac{\nabla\phi}{|\nabla\phi|}) = div[(1-\frac{1}{|\nabla\phi|})\nabla\phi] \tag{7}$$

This is a nonlinear heat equation, its conductivity rate

$$\alpha = 1 - \frac{1}{|\nabla\phi|} \tag{8}$$