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Local Chan-Vese Model for Segmenting Nighttime Vehicle License Characters

Shangbing Gao[1, 2+], Lanfang Wang[1]

[1] The School Computer Engineering, Huaiyin Institute of Technology, Huai'an, 223003, P.R.China
[2] The School of Computer Science and Technology, Nanjing University of Science and Technology, Nanjing, 210094, P.R.China

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Abstract. Aiming at the gray uneven distribution in the night vehicle images, a new local Chan–Vese (LCV) model is proposed for image segmentation. The energy functional of the proposed model consists of three terms: global term, local term and regularization term. By incorporating the local image information into the proposed model, the images with intensity inhomogeneity can be efficiently segmented. Finally, experiments on nighttime plate images have demonstrated the efficiency and robustness of our model. Moreover, comparisons with recent popular local binary fitting (LBF) model also show that our LCV model can segment images with few iteration times.

Keywords: license character segmentation; CV model; intensity inhomogeneity; LBF

1. Introduction

A typical Automatic License Plate Recognition system[1] consists of three major phases: license plate detection, geometric correction, character segmentation, size or aspect ratio normalization, character recognition and application of grammatical rules [2], [3], [4]. Among them, a very critical step is the license plate location and character segmentation, which directly affects the overall system performance. Here, we pay attention to the character segmentation. The characters are most susceptible to the environment, especially in nighttime. Because of low visibility at night, uneven illumination of street lamps and so on, the intensities of license plate image are not evenly distributed. Thus, it is difficult to set a global threshold of accurate and effective segmentation of license plate characters. Here, we choose the active contour model to overcome this problem.

Active contour model proposed by Kass et al.[5] has been proved to be an efficient framework for image segmentation. Level set method is based on active contour model and particularly designed to handle the segmentation of deformable structures. Chan-Vese(CV) model [6] has achieved good performance in image segmentation task due to its ability of obtaining a larger convergence range and handling topological changes naturally. However, it still has the intrinsic limitation, i.e., it generally works badly for images with intensity homogeneity. The reason is due to that the intensities in each region are assumed to maintain constant.

In this paper, we propose a local Chan-Vese model which utilizes both global image information and local image information for character segmentation. The energy functional for the proposed model consists of three parts: global term, local term and regularization term.

2. The review of the CV model and intensity inhomogeneity

2.1. Chan-Vese model

Chan and Vese [6] proposed an active contour model which can be seen as a special case of the Mumford–Shah problem [7]. For a given image I in domain Ω, the CV model is formulated by minimizing the following energy functional:

+ Corresponding author. Tel.: +86 25 8431 7297
E-mail address: luxiaofen_2002@126.com.

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$$E(C,c_1,c_2)=\lambda_1\int_{inside(C)}\left|I(x,y)-c_1\right|^2dxdy+\lambda_2\int_{outside(C)}\left|I(x,y)-c_2\right|^2dxdy,\ (x,y)\in\Omega \tag{1}$$

where c_1 and c_2 are two constants which are the average intensities inside and outside the contour, respectively. With the level set method, we assume

$$\begin{cases}C=\{(x,y)\in\Omega:\phi(x,y)=0\},\\ inside(C)=\{(x,y)\in\Omega:\phi(x,y)>0\},\\ outside(C)=\{(x,y)\in\Omega:\phi(x,y)<0\},\end{cases} \tag{2}$$

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

By incorporating the length and area energy terms into Eq. (1) and minimizing them, we obtain the corresponding variational level set formulation as follows:

$$\frac{\partial\phi}{\partial t}=\delta(\phi)\left[\mu div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)-\nu-\lambda_1(I-c_1)^2+\lambda_2(I-c_2)^2\right] \tag{4}$$

where $\mu\geq0,\nu\geq0$, $\lambda_1>0$, $\lambda_2>0$ are fixed parameters, μ controls the smoothness of zero level set, ν increases the propagation speed, and λ_1 and λ_2 control the image data driven force inside and outside the contour, respectively. ∇ is the gradient operator. $H(\phi)$ is the Heaviside function and $\delta(\phi)$ is the Dirac function.

CV model can segment all the characters of the plate well for the located homogenous plate images. It can be seen from Fig. 2. But for the nighttime plate, due to the uneven illumination, the segmentation results are not desired.

(a) homogenous plate image (b) the segmentation result of CV model

Fig. 1: The segmentation result by CV model for homogenous plate image

(a) inhomogeneous plate image (b) the segmentation result of CV model

Fig. 2: The segmentation result by CV model for inhomogeneous plate image

2.2. Intensity inhomogeneity

Intensity inhomogeneity often occurs in real images from different modalities. For nighttime images, intensity inhomogeneity is usually due to the illumination is not homogenous (see Fig. 3 for example).

Fig .3 the inhomogeneous nighttime plate image

Our method is based on the model commonly used to describe images with intensity inhomogeneity [8]:

$$I = bJ + n \tag{5}$$

where I is the measured image intensity, J is the true signal to be restored, b is the the intensity inhomogeneity field, and n is additive noise. To simplify the computation, the noise is often ignored. The generally accepted assumption on the bias field is that it is smooth (or slowly varying)[8].

These inhomogeneities are known to appear in images as systematic changes in the local statistical characteristics of object. Since the intensity inhomogeneity is slowly varying in the image domain, its spectrum in frequency domain will be concentrated in the low-frequency area. Thus, the intensity inhomogeneity effect mainly influences the non-contour pixels in the image, whereas for the pixels belonging to contour, this influence is less. Motivated by this observation, we propose adding the local information into the level set method to segment the images with intensity inhomogeneity. Due to the complexity that causes the intensity inhomogeneity, it is difficult for one models the intensity inhomogeneity under a variety of image acquisition conditions. So it should be stressed that we do not try to eliminate the intensity inhomogeneity from the images which is still not a completely solved problem [9].

3. Local Chan-Vese model

In this Section, we shall present and discuss the details of our proposed local Chan-Vese model and its numerical implementation. The overall energy functional consists of three parts: global term E_G, local term E_L and regularization term E_R. E_G corresponds to $E(C, c_1, c_2)$ in equation (1).

3.1. The global term

Accordingly, the global term in (1) can be rewritten so as to evaluate the level set function ϕ on the domain Ω:

$$E^G(c_1, c_2, C) = \int_\Omega |I(x,y) - c_1|^2 H(\phi(x,y))dxdy + \int_\Omega |I(x,y) - c_2|^2 (1 - H(\phi(x,y))dxdy \tag{6}$$

3.2. The local term

Here, the local term is introduced in (7) which uses the local statistical information to improve the segmentation capability of our model for the images with intensity inhomogeneity.

$$E^L(d_1, d_2, C) = \int_{inside(C)} |g_k * I(x,y) - I(x,y) - d_1|^2 dxdy + \int_{outside(C)} |g_k * I(x,y) - I(x,y) - d_2|^2 dxdy \tag{7}$$

where g_k is an averaging convolution operator with $k \times k$ size window, d_1 and d_2 are the intensity averages of difference image ($g_k * I(x,y) - I(x,y)$) inside C and outside C, respectively.

The assumption behind the proposed local term is that smaller image regions are more likely to have approximately homogeneous intensity and the intensity of the object is statistically different from the background. It is significative to statistically analyze each pixel with respect to its local neighborhood. The most simple and fast statistical information function is the average of the local intensity distribution, the rationale being that if the object pixels are brighter than the background, they should also be brighter than the average. By subtracting the original image from the averaging convolution image, the contrast between foreground intensities and background intensities can be significantly increased. Note that the difference image ($g_k * I(x,y) - I(x,y)$) with higher image contrast is still not easily to be segmented due to the weak object boundaries and complicated topological structure. It needs under a level set evolution for obtaining better segmentation result. In the same manner as global term, the local term (7) can also be reformulated in terms of the level set function $\phi(x,y)$ as follows:

$$\begin{aligned} E^L(d_1, d_2, C) = & \int_\Omega |g_k * I(x,y) - I(x,y) - d_1|^2 H(\phi(x,y))dxdy \\ & + \int_\Omega |g_k * I(x,y) - I(x,y) - d_2|^2 (1 - H(\phi(x,y))dxdy \end{aligned} \tag{8}$$

3.3. The regularization term

It is crucial to keep the evolving level set function as an approximate signed distance function during the evolution, so in the MCV model, re-initialization is used as a numerical remedy for maintaining stable curve evolution as follows [10]:

$$\frac{\partial \phi}{\partial t} = sign(\phi_0)(1-|\nabla \phi|) \tag{9}$$

But it leads very complicated process and side effects, so we use the following integral [11]:

$$p(\phi) = \int_\Omega \frac{1}{2}(|\nabla \phi(x,y)-1|^2) \tag{10}$$

The above expression is formulated as a metric to characterize how close the function ϕ is to the signed distance function. By minimizing the above expression, $|\phi|$ can be made to converge to 1, so that the level set function is made close to the signed distance function.

According to the above words, the regularized term is expressed as follows:

$$E^R(C,c_o,c_{bi}) = \int_\Omega \frac{1}{2}(|\nabla \phi(x,y)-1|^2)dxdy + \mu \cdot Length(C)$$

$$= \int_\Omega (\frac{1}{2}(|\nabla \phi(x,y)-1|^2) + \mu \cdot \delta_\varepsilon(\phi)|\nabla \phi|)dxdy \tag{11}$$

3.4. Level set Formulation

In the level set formulation, the curve C is represented by the zero level set of a Lipschitz function ϕ. The overall energy functional can be described as follows:

$$F(C,c_0,c_{b_i},d_0,d_{b_i})$$

$$=\alpha E^G(C,c_o,c_{bi}) + \beta E^L(C,d_o,d_{bi}) + E^R(C,c_o,c_{bi})$$

$$=\int_\Omega \alpha |I(x,y)-c_1|^2 H_\varepsilon(\varphi)dxdy + \int_\Omega \alpha(|I(x,y)-c_2|^2)(1-H_\varepsilon(\varphi))dxdy$$

$$+\int_\Omega \beta |g_k * I(x,y) - I(x,y) - d_1|^2 H_\varepsilon(\varphi)dxdy$$

$$+\int_\Omega (\beta|g_k * I(x,y) - I(x,y) - d_2|^2)(1-H_\varepsilon(\phi))dxdy$$

$$+\int_\Omega (\frac{1}{2}(|\nabla \phi(x,y)-1|^2) + \mu \cdot \delta_\varepsilon(\phi)|\nabla \phi|)dxdy \tag{12}$$

where α and β are two positive parameters which govern the tradeoff between the global term and the local term. For images without intensity inhomogeneity, the value of α is set to be 1 and β is set to be 0. If images present distinct intensity inhomogeneity, the value of α should be selected less than that of β.

Generally, the regularized version is selected as follows:

$$\delta_\varepsilon(\phi) = \frac{1}{\pi} \cdot \frac{\varepsilon}{\varepsilon^2 + z^2}, \quad z \in R \tag{13}$$

As shown in Fig. 4, if ε is too small, the values of $\delta_\varepsilon(z)$ tend to be near zero to make its effective range small, so the energy functional has a tendency to fall into a local minimum. The object may fail to be extracted if the initial contour starts far from it. However, if ε is large, although $\delta_\varepsilon(z)$ tends to obtain a global minimum, the finial contour location may not be accurate. So in this paper, we choose $\varepsilon = 1.5$.

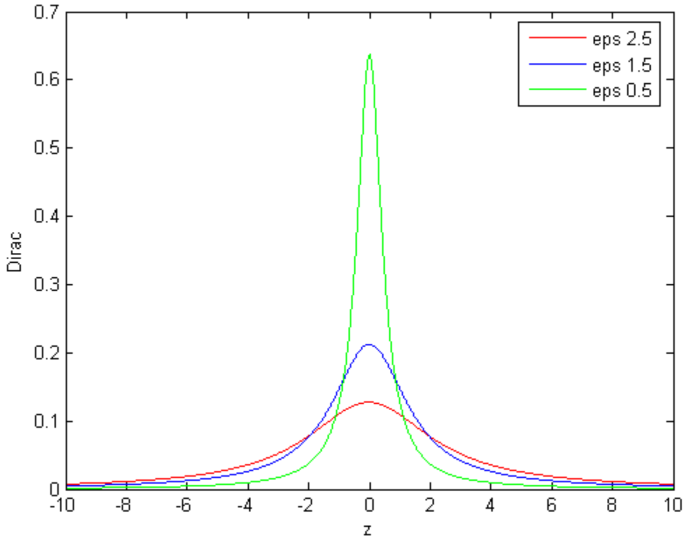

Fig. 4: The Dirac function w.r.t different epsilon values.

4. Experimental results

Our algorithm is implemented in Matlab 7.0 on a 2.8-GHz Intel Pentium IV PC. In each experiment, we choose ε = 1.5, $\mu = 0.01*255^2$, the window size of averaging convolution operator k = 15, time step Δt = 0.1 and $\beta = 1$, $\alpha = 0.1$.

Fig. 5 shows the segmentation result by our model for inhomogeneous plate image. Fig. 5(a) is exactly Fig. 2(a). From Fig. 5(b), we can see that our model can segment the inhomogeneous plate image accurately, while CV model can't.

(a) inhomogeneous plate image (b) the segmentation result of our model

Fig. 5: The segmentation result by our model for inhomogeneous plate image

We choose 1000 nighttime plate image to experiment by our method and the classical LBF [12] model. Their average number of iterations and processing time for segmenting images are presented in Table 1. It can be seen from Table 1 that the iteration number and processing time for the LCV model are both less than that of the LBF model for all three image segmentation. Note that the LCV model only needs to perform one convolution operation before level set evolution. Considering that the parameters and initial contours of the LBF model are selected elaborately, so our model is proved to be more efficient in segmenting the images with the intensity inhomogeneity.

Tabel1 The average number of Iterations and processing time for the LBF model and proposed LCV model

Algorithm	The average number of Iterations	The average Processing time(s)
LBF	200	16.5
Our method	120	9.6

5. Acknowledgements

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