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A Novel Image Segmentation Approach Based on Improved Level Set Evolution Algorithm

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Abstract: Image segmentation is a fundamental topic in image processing. And the method of level set based on curve evolving theory is widely applied in image segmentation. In this paper, we propose a novel region-based active contour model which bases on the region-scalable fitting (RSF) term and the new signed pressure force (SPF) term. The RSF term is responsible for attracting the contour toward object boundaries and is dominant near object boundaries, while the SPF term which utilizes structure tensor information can improve the robustness to initialization of the contours. The model can handle weak edge and provide desirable segmentation results in the presence of intensity inhomogeneity, and offers high efficiency and rapid convergence. Given these advantages, the proposed method can get good performance and experiments show promising segmentation results on both synthetic and real images. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Level set, Segmentation, Signed pressure force, Active contour.

1. Introduction

Image segmentation is a very important problem in the field of computer vision and pattern recognition. And the active contour based on segmentation techniques are being widely used in image segmentation. Generally, the existing active contour models can be broadly categorized as either region-based models [1, 2, 22-26] or edge-based models [3, 4, 17-21].

Edge-based models utilizes gradient of the image to perform contour extraction. Region-based active contour models have more advantage than edge-based ones. Region-based models utilize the global and/or local image statistics inside and outside the active contour to control the evolution. They generally have better performance for images with weak edges or discontinuous boundaries. In area of image segmentation, C–V model is one of the most popular region-based models [5], which had been successfully applied to binary phase segmentation.

Recently, Li et al. [6, 10] proposed the LBF (local binary fitting) model, which utilizes the local image information as constraint, and can well segment objects with intensity inhomogeneities. Wang et al. [32] improved the LBF model by using Gaussian distribution with different means and variances describing the local image intensities. It has a relatively high computational complexity. Zhang et al. [33] proposed a local image fitting (LIF) model. It utilizes Gaussian filtering to regularize the level set function, which is much more computationally efficient. However, nearly all these models are sensitive to initial contours.

The SBGFRLS model [16] utilizes the global statistical information to construct a region-based signed pressure force function, which is used in place of the edge stopping function of the GAC model. The model combines the merits of the GAC and C-V models, which is more efficient than the traditional level set methods, but its SPF is still based on global information. As a result, it is difficult to locate the exact object boundaries, especially for the images with intensity inhomogeneity.

In this paper, we propose a novel region-based active contour model which bases on the region-scalable fitting term and the new Signed Pressure Function term. The SPF term which utilizes structure tensor information can improve the robustness to initialization of the contours. The segmentation tests demonstrate that the proposed method is efficient, accurate, fast and robust, with better segmentation results compared with the other models.

The rest of the paper is structured as follows: In Section 2, we recall some classical models. Section 3 shows the new level set approach in details. In Section 4, experimental results are given. Finally, conclusions are drawn in Section 5.

2. Background

2.1. The Description of C-V Model

The Chan and Vese model, integrating the Mumford-Shah model and level set, utilizes the region information for segmentation. The level set formulation of the C-V mode, regarding the time evolution of the level set function ϕ, can be described as:

$$\begin{aligned}\frac{\partial\phi}{\partial t} &= \delta_\varepsilon(\phi)[\mu div(\frac{\nabla\phi}{|\nabla\phi|}) - \nu \\ &-\lambda_1(I(x)-c_1)^2 + \lambda_2(I(x)-c_2)^2]\end{aligned}, \qquad (1)$$

where $I(x)$ is the original image and μ, ν, λ_1, λ_2 are the positive constant of each item, and the $\delta_\varepsilon(\phi)$ is the Dirac function. The first term keeps the level set function smooth, while the third and fourth terms are the internal and external forces respectively that drive the contour towards the object boundaries. In C-V model, c_1 and c_2 are defined as follow:

$$c_1 = \frac{\int_\Omega I(x)H(\phi)dx}{\int_\Omega H(\phi)dx}, \qquad (2)$$

$$c_2 = \frac{\int_\Omega I(x)(1-H(\phi))dx}{\int_\Omega (1-H(\phi))dx} \qquad (3)$$

Although this algorithm works well for image segmentation, the obvious deficiencies also exist in the experiments. The main disadvantage is its efficient and the initialization problem.

2.2. The LBF Model

In order to overcome the problem of intensity inhomogeneity, Li et al. [6, 10] proposed the LBF model which is able to segment images with intensity non-uniformity and is much more efficient and accurate than the C-V model. The basic idea is to introduce a kernel function to define the LBF energy functional as follows:

$$\begin{aligned}&E^{LBF}(C, f_1, f_2) = \\ &\lambda_1\int\left[\int_{inside(C)} K_\sigma(x-y)\,|\,I(y)-f_1(x)|^2\,dy\right]dx \\ &+\lambda_2\int\left[\int_{outside(C)} K_\sigma(x-y)\,|\,I(y)-f_2(x)|^2\,dy\right]dx\end{aligned}, \qquad (4)$$

where λ_1, λ_2 are the fixed parameters, K_σ is the Gaussian Kernel function. In order to ensure stable evolution of the level set function ϕ, a distance regularizing term is added to penalize the deviation of the level set function ϕ from the SDF. On the other hand, a length term is used to regularize the zero level curve of ϕ. The total variational formulation of the model is as follows:

$$\begin{aligned}\frac{\partial\phi}{\partial t} &= -\delta_\varepsilon(\phi)((\lambda_1 e_1 - \lambda_2 e_2) \\ &+\nu\delta_\varepsilon(\phi)div(\frac{\nabla\phi}{|\nabla\phi|}) + \mu(\nabla^2\phi - div(\frac{\nabla\phi}{|\nabla\phi|})),\end{aligned} \qquad (5)$$

where e_i are the functions

$$e_i(\phi) = \int K_\sigma(y-x)\,|\,I(x)-f_i(y)\,|^2\,dy, \qquad (6)$$

where f_1 and f_2 are two values that approximate image intensities inside and outside the zero level set contours, they are formulated as follows

$$f_1 = \frac{K_\sigma * (H(\phi)I(x))}{K_\sigma * (H(\phi))}, \qquad (7)$$

$$f_2 = \frac{K_\sigma * ((1-H(\phi)I(x))}{K_\sigma * (1-H(\phi))}. \qquad (8)$$

Eq. (5) is the LBF level set evolution Equation. The first term is the data fitting term; it is responsible for driving the active contour toward object boundaries. The second term is the length term, which is necessary to maintain the regularity of the contour. The third term is a level set regularization term, since it serves to maintain the regularity of the level set function.

Although the model can be used to segment images with intensity inhomogeneity and weak object boundaries, its drawback is too slow and could not be performed on the segmentation of the noisy images. In order to overcome these problems, a novel region-based active contour model (ACM) for image segmentation is proposed.

2.3. The SBGFRLS Model

The SBGFRLS model [16] utilizes the global statistical information to construct a region-based signed pressure force function, which is used in place of the edge stopping function of the GAC model. The level set formulation of the model can be written as:

$$\frac{\partial \phi}{\partial t} = spf\,(I(x))\alpha\,|\,\nabla \phi\,|\,, \tag{9}$$

where α is the balloon force parameter and the spf is defined as

$$spf\,(I(x)) = \frac{I(x) - \frac{c_1 + c_2}{2}}{\max(|\,I(x) - \frac{c_1 + c_2}{2}\,|)}\,, \tag{10}$$

where c_1 and c_2 are defined in Eq. (2) and Eq. (3). The spf function in Eq. (10) is constructed using the region statistical information. As a result, the model has the global region segmentation property, and is difficult to deal with the images with intensity inhomogeneity.

3. Proposed Method

3.1. Structure Tensor

Structure tensor was propose in 1987 [9], which was a kind of low-dimensional features treated by space derivative of image. In the form of image gradient tensor product, structure tensor can be used to analyze the image structure and estimate local directional information. So far, it has been widely used for image segmentation in the image processing applications, especially in the algorithms of texture image segmentation based on geodesic active contour model. It is defined as follow:

$$T_\rho = K_\rho * (\nabla I \nabla I^T) = \begin{pmatrix} K_\rho * I_x^2 & K_\rho * I_x I_y \\ K_\rho * I_x I_y & K_\rho * I_y^2 \end{pmatrix}, \tag{11}$$

where ρ is the standard deviation.

When there are some gray differences between the target and background of the image, adding the gray information can improve the segmentation speed and accuracy. So gray information is considered into (11) to construct a new structure tensor:

$$T_\rho = K_\rho * (vv^T) = \begin{pmatrix} K_\rho * I_x^2 & K_\rho * I_x I_y & K_\rho * I_x I \\ K_\rho * I_x I_y & K_\rho * I_y^2 & K_\rho * I_y I \\ K_\rho * I_x I & K_\rho * I_y I & K_\rho * I^2 \end{pmatrix}, \tag{12}$$

where $v = \begin{bmatrix} I_x & I_y & I \end{bmatrix}^T$.

The mean of each component of T_ρ is regarded as the mean. It is as below:

$$T = \frac{T_\rho(11) + T_\rho(12) + T_\rho(13) + T_\rho(21) + T_\rho(22) + T_\rho(23) + T_\rho(31) + T_\rho(32) + T_\rho(33)}{9} \tag{13}$$

After the T is computed, our model can be adopted to address image segmentation by replacing the original grayscale image I.

3.2. Description of our Method

In order to avoid the drawbacks of related approaches, we propose a new segmentation model by modifying the LBF model. So in our model a new SPF function $spf(I(x))$ is developed to overcome these problems.

The SPF function defined in Ref. [16], has values in the range [-1, 1]. It modulates the signs of the pressure forces inside and outside the region of interest so that the contour shrinks when it is outside the object or expands when inside the object. By considering illumination and reflections of the image which will make segmentation complex, we derived T_1 and T_2 which are the mean intensities.

Based on this analysis, we construct the SPF functions as follows:

$$spf\,(I(x)) = \frac{I(x,y) - \frac{T_1 + T_2}{2}}{\max|\,I(x,y) - \frac{T_1 + T_2}{2}\,|}\,, \tag{14}$$

where $spf(I(x))$ is the new SPF function, T_1 and T_2 are similar to c_1 and c_2. They are defined as follows:

$$T_1 = \frac{\int_\Omega T(x)H(\phi)dx}{\int_\Omega H(\phi)dx}\,, \tag{15}$$

$$T_2 = \frac{\int_\Omega T(x)(1 - H(\phi))dx}{\int_\Omega (1 - H(\phi))dx}\,, \tag{16}$$

Now we define the SPF energy functional:

$$E^{SPF}(C, \mathrm{T}_1, T_2) = \eta \int spf\,(I(x))H(\phi)dx\,, \tag{17}$$

In our model, the local energy function with local image intensity information is the same as Eq. (4).

$$\begin{aligned} &E^{LBF}(C, f_1, f_2) = \\ &\lambda_1 \int \left[\int_{inside(C)} K_\sigma (x-y) \,|\, I(y) - f_1(x) \,|^2 \, dy \right] dx \\ &+\lambda_2 \int \left[\int_{outside(C)} K_\sigma (x-y) \,|\, I(y) - f_2(x) \,|^2 \, dy \right] dx \end{aligned} \quad , \qquad (18)$$

Then, the energy function is defined as:

$$E(C,\mathrm{f}_1, f_2, T_1, T_2) = E^{LBF}(C,\mathrm{f}_1, f_2) + E^{SPF}(C,\mathrm{T}_1, T_2)\,, \qquad (9$$

In order to obtain accurate evolution of the level set function, we need a signed distance function (SDF) [8] to regularize the level set function. The SDF can be characterized as follows:

$$P(\phi) = \int \frac{1}{2} (|\nabla \phi|^2 - 1) dx\,, \qquad (20)$$

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

$$L(\phi) = \int |\nabla H(\phi)| dx\,, \qquad (21)$$

Now, the novel model can be defined as:

$$F(\phi, f_1, f_2, c_1, c_2) = E(C, f_1, f_2 T_1, T_2) + P(\phi) + L(\phi)\,, \qquad (22)$$

By adopting the gradient descent method, the minimization of the energy functional given in Eq. (21) can be used the following equation:

$$\begin{aligned} \frac{\partial \phi}{\partial t} &= -\delta_\varepsilon(\phi)((\lambda_1 e_1 - \lambda_2 e_2) + \eta \delta_\varepsilon(\phi) spf(I(x)) \\ &+ v\delta_\varepsilon(\phi) div(\frac{\nabla \phi}{|\phi|}) + \mu(\nabla^2 \phi - div(\frac{\nabla \phi}{|\phi|})) \end{aligned} \quad , \qquad (23)$$

4. Experimental Result

In this section, the proposed method has been tested on synthetic images and real images. We compared our method with Selective Binary and Gaussian Filtering Regularized (SBGFR) method [16], local image fitting energy (LIF) method [33] and Local Binary Fitting (LBF) model [6]. The results are all carried out by Matlab2011a in the PC with Pentium CPU 2.50 and 4 GB of RAM. And the initial contours and the final contours are plotted as blue contours and red contours, respectively.

4.1. Application on Synthetic Images

Fig. 1 presents the results for two synthetic images which have inhomogeneity gray intensity with different initial contours. Original images are shown in first column and the other columns give the results of the proposed works. As can be seen, the proposed model obtains the satisfactory segmentation results for these images.

4.2. Application on Real Images

Fig. 2 presents the results for real-world images. The first row shows the result of rice image corrupted by intensity inhomogeneity. It can be seen that the new contours can emerge during the evolution to extract multiple object boundaries. The second row in Fig. 2 shows the result of our method on one infrared image, which includes some rather weak boundaries. Moreover, significant intensity variations exist in this infrared image, which renders a difficult task to recover the whole object boundary if it relies on local intensity means alone. The third and fourth rows in Fig. 2, show the results of our method on two biomedical images. Nevertheless, our method successfully extracts the object boundaries for these images.

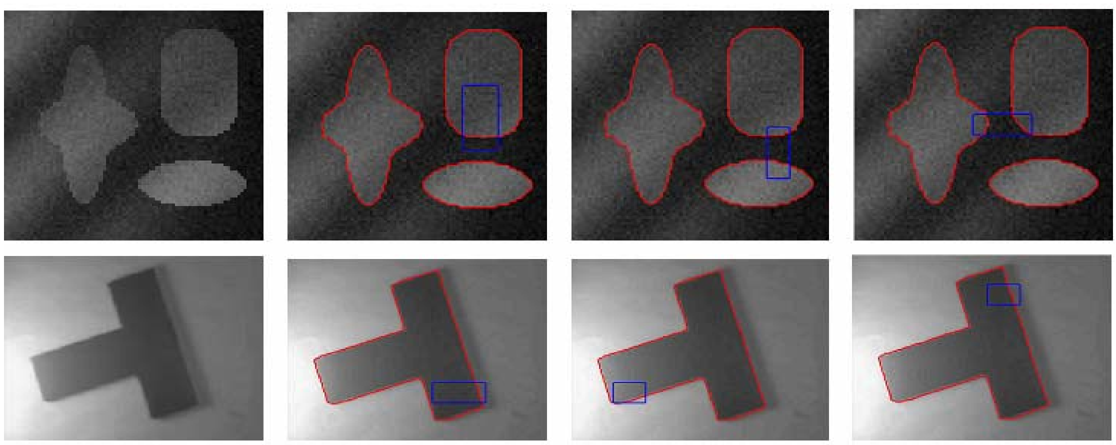

Fig. 1. Results of our method for synthetic images with different initial contours.

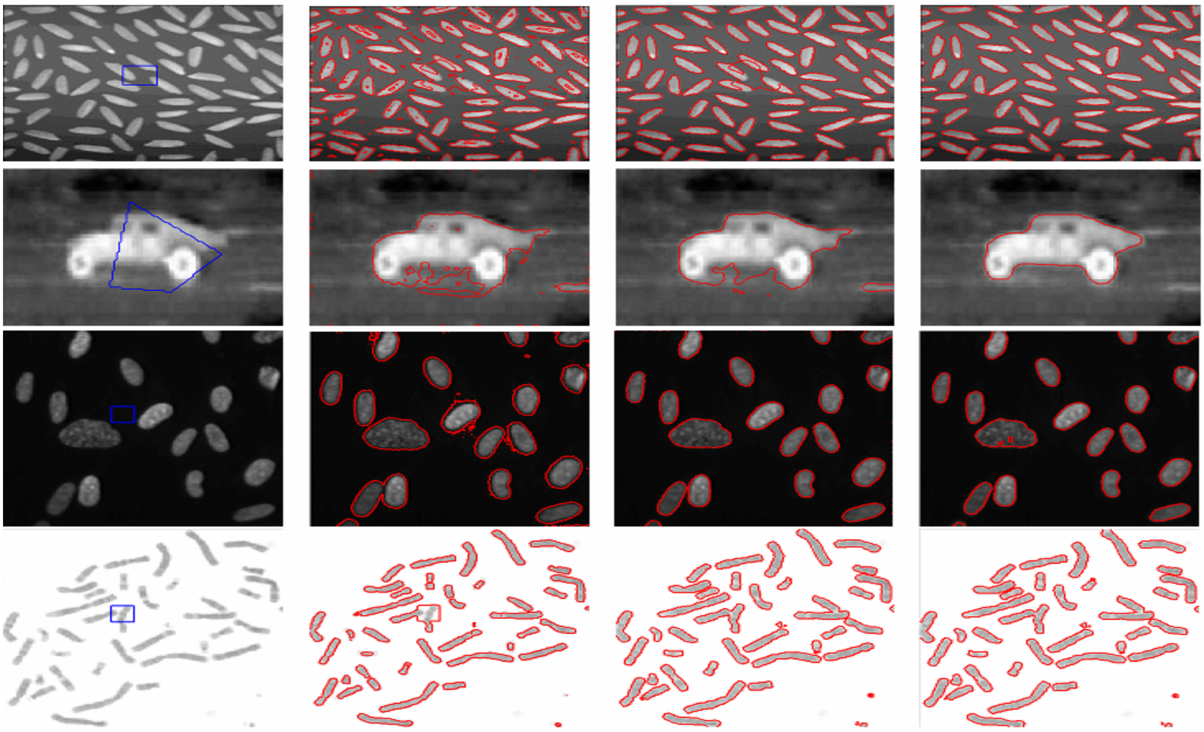

Fig. 2. Results of our method for real images. The curve evolution process from the initial contour (in the first column) to the final contour (in the fourth column) is shown in every row for the corresponding image.

4.3. Compare with the other Models

We apply our model to segment a vessel of intensity inhomogeneity shown in Fig. 3. All the images use SBGFR, LIF, LBF and our method with different initial contours. In these four different initializations, the first column is the original images, the second column is the results of SBGFR, the third column is the results of LIF, the fourth column is the results of LBF, and the last column is the results of our model. It can be observed that the SBGFR model and LBF model fail to segment vessel with these initializations. LIF model and our model always detect the object of interest with the initial contour being anywhere in the image.

In Fig. 4, it shows the result for brain MR image comparing our model with the other methods. As we can see from the figure, SBGFR model and LIF model can't segment the white matter accurately. And LBF model is sensitive to the initial contour, which leads to the inaccuracy segmentation result. From the segmentation result, our model has higher segmentation accuracy with various initial contours. It can be observed that the proposed model has more accurate results than other methods.

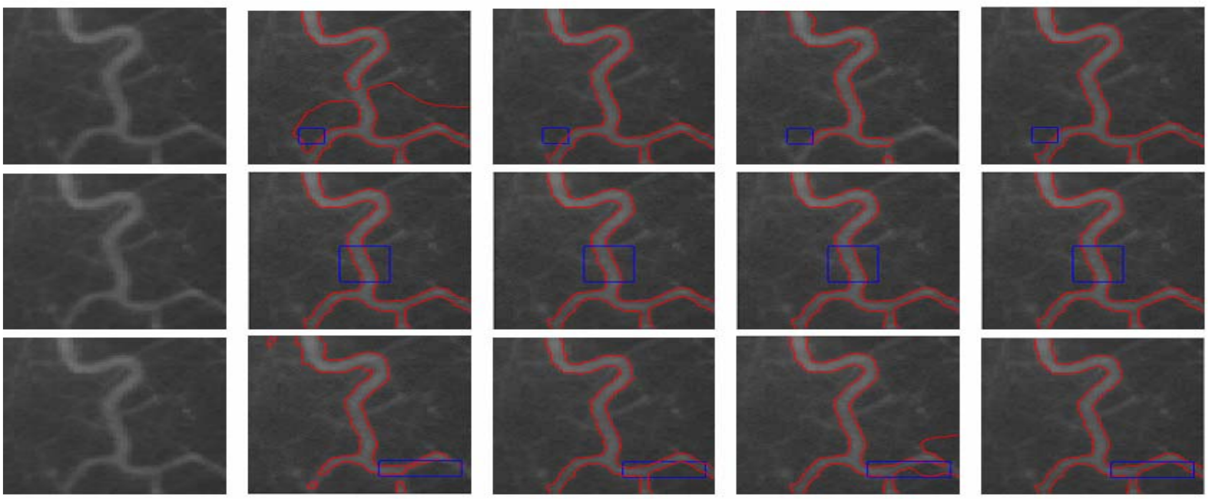

Fig. 3. Performances of SBGFR model, LIF model, LBF model and our model on a vessel image with different initial contour.

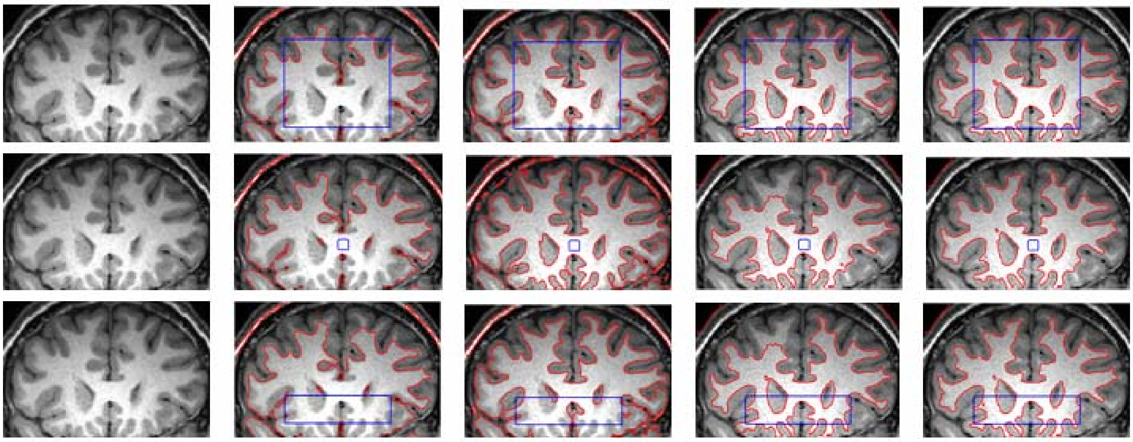

Fig. 4. Performances of SBGFR model, LIF model, LBF model and our model on a brain MR image with different initial contour.

5. Conclusions

In this paper, a novel region-based active contour model or image segmentation is proposed, which is built based on the techniques of curve evolution. The proposed method is based on a new signed pressure force function by taking the structure tensor into account. The segmentation tests demonstrate that the proposed method can achieve accurate segmentation results. So, we can safely draw the conclusion that our model is efficient, accurate, robust, with better segmentation results compared with the other models.

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