

## Research Article

### Region-based Method of Adaptive Distance Preserving Level Set Evolution

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**Abstract:** The effect of image segmentation is directly affected by the selection of image dependent weight coefficient and the edge stopping function in the traditional method of adaptive distance preserving level set evolution. For its shortage, a novel adaptive varying stopping function Region-based is designed. The algorithm improves image dependent weight coefficient and designs a region-based method of adaptive distance preserving level set evolution. Experimental results show that the method effectively solves the problem that the level set cannot continue to evolve in equal area for gray value and inaccurate segmentation of target due to dramatic change of image gradient reduces noise sensitivity for model and improves robustness of the algorithm.

**Keywords:** Adaptive varying edge stopping function, distance preserving level set method, geometric active contour mode, image dependent weight coefficient, image segmentation, level set method

## INTRODUCTION

Image segmentation as a key technology of image analysis and computer vision field has become the hot spot in the field of medicine, nature and remote sensing (Wang *et al.*, 2008; Ji *et al.*, 2007; Ma *et al.*, 2012). Geometric active contour model as one of the main direction is based on the curve evolution theory and level set method. It is usually divided into the boundary model (Caselles *et al.*, 1997; Li *et al.*, 2010; Li and Fox, 2005) and regional model (Li *et al.*, 2008; Zhang *et al.*, 2010) two categories. The former mainly use image gradient information as the driving force of the curve evolution, which make the level set function in the control of a partial differential equation evolution until the target boundary, This has obvious advantages for the image of the edge of the fracture, but often fall into the local minimum and stop the evolution at the noise. The latter mainly use the level gray information of the contour inside and outside the region. It has a good effect on the image of the gray-scale uneven and has a strong anti-noise. Although the level set method based on curve evolution has the advantages of free topological transformation and provide high-precision closed partition curve, but the disadvantages of the level set function is that it need repeatedly initialize and a lot of calculation. In order to overcome these shortcomings, Li et in the energy functional by adding the internal energy functional method provide the distance preserving level set method (Li and Fox, 2005), which make the traditional level set method obtain a major breakthrough. For these shortcomings of

evolution in one-way and the external energy functional invariance of the weight coefficient, the proposed adaptive distance level set evolution, which introduce image dependent weighting coefficient  $v(I)$ . We can use it to adapt itself according to the image information to determine the direction and speed of curve evolution and define a new stop function  $g(s)$ . This can accelerate the evolution speed and the segmentation results of the algorithm are improved. But this model has the following limitations:

- In the areas where gray value are equal, the image gradient  $|\nabla (G \times I)|$  is 0, which will make  $v(I)$  be 0, the level set cannot evolution to the edge of the target object.
- In the larger region of the intensity change, due to the rapid change of image gradient,  $v(I)$  is too large or too small which can cause the boundary to leak or is unable to effectively separate the image.
- Because of the large gradient in the uneven distribution of image gray non-edge part, leaving the edge of the stop function to close to zero, resulting in the split are not allowed.
- In the noise because of the large image gradient, edge stopping function may reach a local minimum which leading to that the model is sensitive to the noise.

In response to the above-mentioned shortcomings, In this study, the image dependent weighting coefficient are corrected, We also combined the regional information to design the adaptive changing stop

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function and proposed adaptive distance maintain the level set method of integration of regional information.

**BACKGROUND KNOWLEDGE**

**The method of adaptive distance preserving level set evolution:** Aiming at the inadequacies of distance preserving level set evolution model (Li *et al.*, 2005) without re-initialization, based on the distance preserving level set evolution method, reference (He *et al.*, 2008) introduces weight coefficient associated with image information and designs adaptive distance preserving level set evolution method. The energy functional  $E(\phi)$  is expressed by:

$$E(\phi) = \mu P(\phi) + E_m(\phi) = \frac{1}{2} \int_{\Omega} (|\nabla \phi| - 1)^2 dx dy + \lambda \int_{\Omega} g(\nabla \phi) \delta(\phi) |\nabla \phi| dx dy + \int_{\Omega} v(I) g(\nabla \phi) h(-\phi) dx dy \tag{1}$$

where,  $P(\phi)$  is the internal energy functional of the level set function ( $\Omega$  is the image zone), Which quantitatively expresses the extent of offset between the signed distance function and the level set function and can be used to correct the deviation between the level set function and the sign.  $\mu$  is the weight coefficient.  $E_m(\phi)$  is an external energy functional, which is used to drive the zero level set to move toward target boundary in the image,  $\lambda$  is a constant and  $\lambda > 0$ .

Using the Euler-Lagrange equation, the energy functional (1) can be minimized by solving the following gradient flow:

$$\frac{\partial \phi}{\partial t} = \mu \left[ \Delta \phi - \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \right] + \lambda \delta(\phi) \text{div} \left( g(\nabla \phi) \frac{\nabla \phi}{|\nabla \phi|} \right) + v(I) g(\nabla \phi) \delta(\phi) \tag{2}$$

where,  
 $\delta(x)$  : Dirac function  
 $H(x)$  : The Heaviside function  
 $I(x, y)$ : The image function  
 $v(I)$  : Variable weights  
 $g(x)$  : The edge stopping function which are defined by:

$$v_n(I) = c \cdot \text{sgn}(\Delta G_{\sigma} \times I) |\nabla G_{\sigma} \times I| \tag{3}$$

$$g(\nabla I) = \exp(-|\nabla G_{\sigma} \times I|/m) \tag{4}$$

where,  
 $\text{sgn}(\cdot)$  = The sign function  
 $\Delta G_{\sigma} \times I$  = The results of effect which Laplace operator has on the Gaussian filtered image  
 $\nabla G_{\sigma} \times I$  = Gradient after image gets through Gaussian filter  
 $c, m$  = A constant

**Analysis of variable weight coefficient:** The nature of the level set evolution is to use the image edge characteristics to make the evolution curve move towards the minimization of the energy functional. Therefore, in the method of distance preserving level weight coefficient  $v_n(I)$  not only controls the evolutionary direction of the zero level set, but also directly affects the magnitude of the stopping function  $g$ , to a certain extent, determines the ability of the zero level set to capture the multi-contours of the object (He *et al.*, 2008). Therefore,  $v_n(I)$  is very important.

When the movement of level set evolves to the area with equal gray value its gray value in (3) is still equal after the Gaussian filtering, the image gradient  $|\nabla(G_{\sigma} \times I)|$  is 0, the weighting coefficient  $v(I)$  is 0 and the level set will stop the evolution, making it impossible to segment the image.

When the level set moves into the uneven gray area the image gradient  $|\nabla(G_{\sigma} \times I)|$  changes greatly, resulting in that weight coefficient  $v(I)$  changes greatly, Thus boundary leak may happen. When the curve evolves to the deeply recessed area with flat image  $v(I)$  is smaller, so that the curve cannot penetrate the deeply recessed area to reach the boundary of target object, which cannot effectively detect the outline of the target object.

**Analysis of the stopping function:** Figure 1 is the case that in literature (He *et al.*, 2008) the edge stopping function  $g(s) = e^{-s/m}$  changes with the parameter  $m$  and the image gradient,  $g(s)$  is an monotone decreasing positive function regarding to image gradient. With  $m$  under certain conditions, the stopping conditions of the level set evolution depend only on the gradient and its speed of converging to 0 is too fast. Thus:

The edge stopping function  $g$  is close to zero for the image gradient is larger in the non-edge portion with intensity in homogeneity, leading to the curve evolution rather than continue to stay in the evolution, unable to reach the target boundary.

The edge stopping function may fall into the local minimum value for larger gradient at the noise. For example, if the gradient of a noise in Fig. 1 is 20 and  $m = 2$ , then  $g(s) = 4.5 \times 10^{-5}$ , it approximate to 0, the evolution curve will stop evolution at this noise, which cannot effectively separate the target object.

**THIS PAPER MODEL**

**The definition of the variable weight coefficient:** To solve the problem above, we can take it into consideration that modifying the variable weight coefficient mentioned in the literature (He *et al.*, 2008), in order to make it satisfy two conditions:

- Ensure that level set can continue to evolve to boundary where the gray is equal to each other.
- We can not only detect the contour of the target, but also has the ability to capture the multi-layer profile where the gray change is comparatively large.

Based on the above considerations, this study defines that:

$$v_n(I) = \text{sgn}(\Delta G_\sigma \times I) (\alpha |\nabla(G_\sigma \times I)| + \beta) \quad (5)$$

where,  $\alpha > 0$ ,  $\beta > 0$  and they are both constant, the analysis of the variable weight coefficient  $v_n(I)$  is following as follows:

- Where the pixel value is equal to each other, The mode of the image gradient  $|\nabla(G_\sigma \times I)|$  is 0. Then the value of  $v_n(I)$  is  $\beta$ , to ensure that the zero level set can continue evolving until it reach the contours of the target area. Typically, the value of  $\beta$  is between 0.5 and 1.3.
- Take the place of  $|\nabla(G_\sigma \times I)|$  in the literate (He *et al.*, 2008) with  $\alpha |\nabla(G_\sigma \times I)| + \beta$ , then  $v_n(I)$  is determined by  $|\nabla(G_\sigma \times I)|$  and constants  $\alpha$  and  $\beta$ . As to the recessed area boundary or the boundary where the pixel value is relatively flat, If the mode of the image gradient is relatively small,  $\alpha$  and  $\beta$  can be properly adjusted to increase  $v_n(I)$ , ensure that the curve penetrate the depth of depression area to reach the target object boundary. With regard to those target object boundary whose gray scale changes greatly, although the image gradient mode are relatively large,  $\alpha$  and  $\beta$  can still be properly adjusted to decrease  $v_n(I)$  to ensure that the zero level set stay at the target boundary and not to generate boundary leak.
- In this way, by introducing the parameters of  $\alpha$  and  $\beta$  to control the different needs of the target boundary by different environments. If you need to detect the depth of depression boundary, the value of  $\alpha$  is usually between 1.3 and 4.2, while  $\alpha$  is usually between 0.5 and 1.8, If you need to detect contours of objects target whose gray scale change is relatively great, the value of  $\beta$  is usually between 0.7 and 2.8, the value of  $\beta$  usually ranges from 0.3 to 1.8.

**The design of edge stopping function:** In the adaptive distance to maintain the level set evolution method, the

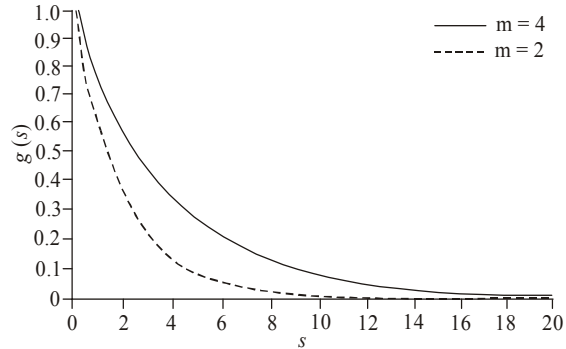


Fig. 1: The  $g(s)$  with the gradient of image

value of edge stopping function  $g(s) = \exp(-s/m)$  is determined by the value of image gradient modulus. The speed it converges to 0 is high. (As is shown in Fig. 1), which make it possible that the value may reach local minimum at the image noise or at the non-boundary where the gradient is relatively large, So that the model is not segmented accurately on the uneven gray image, poor at anti-noisy as well.

Therefore, an adaptive edge stopping function  $g$  was proposed by introducing a coefficient  $M_\rho$  with regional information (Zhou *et al.*, 2012), to ensure that the function  $g(I, M_\rho)$  adaptively change according to the image area information (Zhou *et al.*, 2012) and level set evolution. In this respect we define stopping function  $g$  by:

$$g(I, M_\rho) = \frac{1}{1 + \left| \frac{\nabla(G_\sigma \times I)}{M_\rho} \right|^2} \quad (6)$$

where,

$G_\sigma$  = A Gaussian kernel with a standard deviation, a new adaptive varying coefficient  $M_\rho$  was defined by:

$$M_\rho = \rho \left| I - \frac{c_1 + c_2}{2} \right| + \theta \quad (7)$$

where,

$c_1$  = The average value of those in the evolution curve in the image

$c_2$  = The average value of those out of the evolution curve in the image  $\rho$ ,  $\theta$  are constants whose values are rang from 0 to 1.2.

The edge stopping function  $g(I, M_\rho)$  is analyzed as follows:

- When the level set surrounds the object and is far away from the boundary,  $\rho \left| I - \frac{c_1 + c_2}{2} \right| + \theta \gg \theta$ , thus  $M_\rho \gg \theta$ ,  $g(I, M_\rho) \approx 1$ , despite the image

$|\nabla(G\sigma \times I)|$  is bigger in place with noises and great change in gray scale,  $M\rho \gg \theta$ , so that  $g(I, M\rho)$  becomes larger, this conclusion ensures  $g(I, M\rho)$  does not fall into local minimum in the non-boundary, which increases the robustness of the algorithm.

- When the level set evolve to the object boundary,  $|I-(c1+c2)/2| \approx 0$ ,  $M\rho = \theta$ , as the gradient mode in the boundary is larger, if  $\theta$  is close to 0,  $g(I, M\rho)$  will converge to 0 rapidly in the boundary of the object, to make sure the model fall into a global minimum value and improve the accuracy of the image segmentation.

The parameters  $\rho$  and  $\theta$  are respectively used to control the noise sensitivity and the convergence speed to 0 of  $g(I, M\rho)$ , generally  $\theta$  is in the range of 0 to 1.2. Take a larger  $\rho$ -value to accelerate the evolution speed when there is no noise or little gray-scale change and make the evolution curve stay in the object boundary as soon as possible, generally  $\rho$  is between 0.7 and 2.8. If the noise level is higher, a relatively smaller  $\rho$ -value is supposed to be taken to ensure the evolution curve skip the noise point and continue to evolve until it reaches the boundary of the object, generally between 0.3 to 1.8.

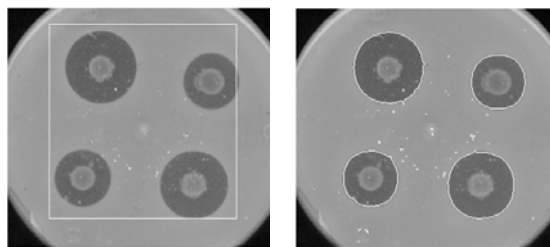
### THE EXPERIMENT AND ANALYSIS

Level set model compared to the experimental method proposed in this study and literature (He *et al.*, 2008), to verify the proposed method:

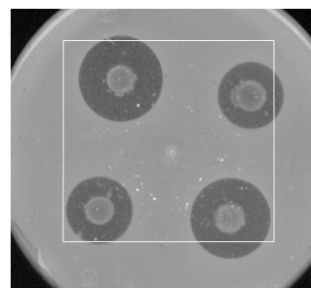
- The zero level set in the gray value equal area can continue to evolve until the detected target object contour.
- Solve problem that non-edge gradient larger target objects boundary detection is not accurate and edge leakage cause by severe intensity change.
- Avoid the level set in the noise falling into local minimum and improve the noise resistance of the model.

Experiments use three groups with different patterns of the target boundary image. Experimental environment: MATLAB 7.10, the operating system is Windows XP. In this experiment, in this study we set  $\sigma = 2.0$ ,  $\mu = 0.04$ ,  $\lambda = 7.8$ , time step  $\tau = 5.5$  and the method in (He Chuanjiang *et al.*, 2008):  $\sigma = 2.0$ ,  $\mu = 0.04$ ,  $\lambda = 8.2$ , time step  $\tau = 5.0$ .

#### Experiment 1 test whether zero level set can evolutes from the gray value equal area to the object



(a) Initial contour (b) The proposed (100 iterations)



(c) The method in He Chuanjiang *et al.* (2008) (900 iterations)

Fig. 2: Segmentation results in region with the same gray value

**boundary or not:** As shown in Fig. 2 for 297×272 microbial antibacterial circle image, gray value almost equal on the inside and outside of the target contour. We set  $\alpha = 1.8$ ,  $\beta = 1$ ,  $\rho = 0.8$ ,  $\theta = 1$ , the method in this study based on the formula (5) makes weight coefficient  $V_n(I)$  approximation for  $\beta$ ,  $g(I, M\rho)$  is also close to  $\theta$ , experiments show that level set in a gray value equal area can continue to evolve and get the outline of the object. The speed of curve evolution was adjusted by setting up appropriate  $\beta$  and  $q$  in  $V_n(I)$ . In method of literature (He *et al.*, 2008) ( $c = 1.8$ ,  $m = 1$ ), the regional weighting coefficient value of  $V_n(I)$  is approximately equal to 0 as the image gradient approximation 0, so that the level set cannot effective evolve and get the outline of the target area.

**Experiment 2 test segmentation to image with intensity in homogeneity:** Figure 3 is a pair of real medical ultrasound images (167×133); the whole image gray scale is strongly uneven and has a depth of concave contour. Although the most large internal gradient of the outline is not the real target boundary, a adaptive changes  $M\rho$  based on regional information is set in  $g(I, M\rho)$  of this study ( $\rho = 0.6$ ,  $\theta = 0.8$ ), the initial gradient value at the maximum is are very large and the appropriate value of  $\alpha$  and  $\beta$  in  $V_n(I)$  is set

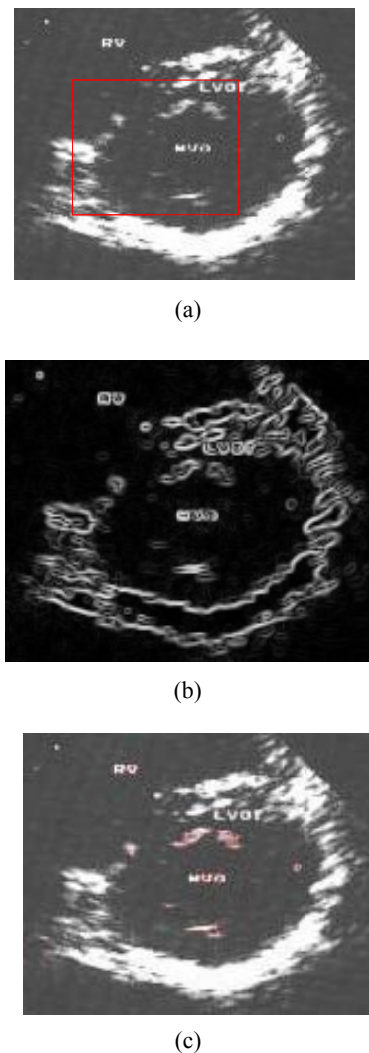


Fig. 3: Segmentation results to image with intensity in homogeneity, (a) initial contour, (b) the proposed (600 iterations), (c) the method in He Chuanjiang *et al.* (2008) (15000 iterations)

( $\alpha = 1.8, \beta = 1$ ), as shown in Fig. 3 that it does not fall into local minimum in the maximum gradient, segmentation effect is good. Resulting programs of literature (He Chuanjiang *et al.*, 2008) ( $c = 3, m = 4$ ) fall into local minimum in the maximum gradient, segmentation target is not ideal.

**Experiment 3 inspection the influence of noise on the performance of the algorithm:** Figure 4 is  $116 \times 103$  Gaussian noise image (mean is 0.5, the variance is 0.05). Figure 4 (b) shows that in reference (He Chuanjiang *et al.*, 2008) ( $c = 2.8, m = 4$ ), the value of the stop function at big noise condition is similarly equal to 0, so that zero level set curve that stays in some

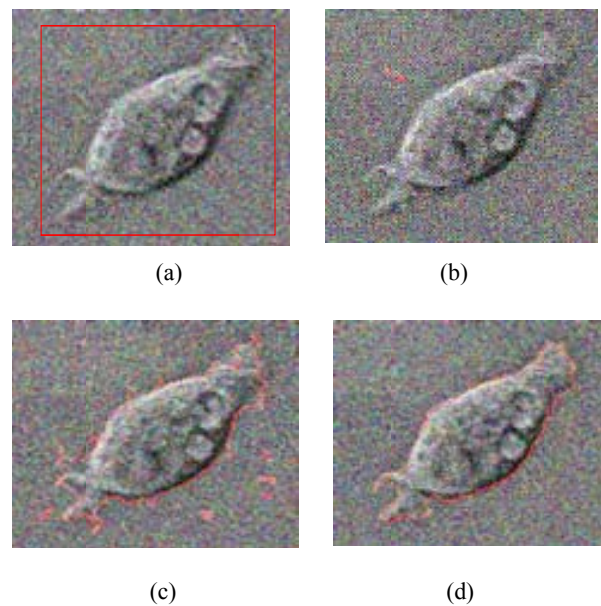


Fig. 4: Segmentation results the image with noise (a) initial contours (b) the method in He Chuanjiang *et al.* (2008) (1000 iterations) (c) the proposed (d) the proposed (60 iterations) (300 iterations)

noise point can't continue evolve to target boundary. And with algorithm ( $\alpha = 1.5, \beta = 2$ ) in this study, due to the introduction of the adaptive change coefficient  $M\rho$  ( $\rho = 0.8, \theta = 1.2$ ), avoiding the stop function  $g(I, M\rho)$  in the noise place falling into the local minimum, the number of iterations is more, the segmentation effect is better.

## CONCLUSION

Aiming to the defects of the traditional adaptive distance preserving level set evolution method; the adaptive distance preserving level set evolution based on region is presented. The algorithm improves image dependent weight coefficient and edge stop function. Experiments show that the method ensures level set in area of equal gray values can continue to evolve until it detects target boundary; solves inaccurate segmentation of target due to dramatic change of image gradient; avoids the level set in the noise hardly segment image caused by local minimum for stop function, enhances the robustness of the algorithm.

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