Image Segmentation Algorithm of Improved C-V Model Based On Multi-Scale Wavelet

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Abstract
On the basis of the multi scale wavelet transform analysis framework, this article proposes an image segmentation algorithm of improved C-V model. The method first uses wavelet transform to decompose image into a low frequency subband and three high frequency sub bands, and then uses the good signal noise separation ability of wavelet transform in each scale space to extract the local edge information, integrate the extracted information to the energy function of the C-V model, thus to improve local control ability of the model. Meanwhile, add the internal deformation energy to the energy function and constraint level set function approximation distance function to avoid the reinitialization process of the level set function thus propose an improved C - V model. On the basis of this, from the top layer of low frequency subband image of wavelet transform, the improved C-V model is used to segment image layer by layer, and by interpolation, the segmentation results is transferred to the next layer wavelet low-frequency sub-band image as the initial contour of the subband image segmentation of this layer. By repeating the steps, segmentation of the original image can be realized.
Key words: C-V MODEL SEGMENTATION MULTI-SCALE INTERPOLATION

1. Introduction

Image segmentation has always been a difficult task in image processing and computer vision, the goal of which is to divide images into some meaningful subsets. In recent years, active contour models implemented via level set methods have been successfully used in image segmentation. The basic idea of the level set method is to embed the two-dimensional curve in the image space to the three-dimensional surface as its zero Level set. When the surface evolves, the zero level set curve embedded into the three-dimensional surface also changes. Therefore, the determination of the zero level set can finally determine the results of the moving surface evolution, handling with the weak boundaries. One of the most famous set level models is the CV model [1]. Based on the characteristic of global optimization of image region information of C - V model, segmentation is not limited by the position of the initial closed evolution curves and has the advantages of good anti noise performance. The C-V model is not sensitive to noise [2], and the model is very effective to the edge blur image and image containing inner contour [3]. But the C-V model also has some shortcomings. First of

all, since C-V model does not use the image edge information, the local control ability is weak [4], so in the segmentation of some non-uniform gray image, the effect is not good [5]; secondly, the C-V model needs a constant reinitialization of level set function in the iteration process, so the amount of calculation is great [6].Then this article proposes an image segmentation algorithm of improved C-V model on the basis of the multi-scale wavelet transform analysis framework. The main advantage of this algorithm is to make full use of the image edge information, and cut fewer iteration times.

2. The improved C-V model

C-V model is proposed by Chan and Vese in 2001, a regional level set method, which uses the internal and external image gray mean to promote the evolution of the level set curve. The C-V model of the energy functional is shown as follows:

$$E(c_1,c_2,C)=\alpha\int_{inside(C)}|u_0(x,y)-c_1|^2dxdy+\beta\int_{outside(C)}|u_0(x,y)-c_2|^2dxdy+\mu\cdot Length(C) \quad (1)$$

Where C denotes a smooth closed contour curve, u_0 is the source image, c_1 and c_2 are internal and external image gray value of the curve C, under normal circumstances, $\alpha=\beta=1$, μ is a positive constant. The introduction of the level set function $\varphi(x,y)$ to replace the evolution curve C, and regulations when the point (x,y) in the interior of the C, $\varphi(x,y)>0$; when the point (x,y) outside of C; $\varphi(x,y)<0$; when when the point (x,y) on C, $\varphi(x,y)=0$. Thus the energy functional can be written as follows:

$$E(c_1,c_2,C)=\mu\int_\Omega\delta_\varepsilon(\varphi(x,y))|\nabla\varphi(x,y)|dxdy+\int_\Omega|u_0(x,y)-c_1|^2H_\varepsilon(\varphi(x,y))dxdy+\int_\Omega|u_0(x,y)-c_2|^2(1-H_\varepsilon(\varphi(x,y)))dxdy \quad (2)$$

Where $H_\varepsilon(z)$ and $\delta_\varepsilon(z)$ are egularization forms of Heidegger's function and Dirac function, and $H(z)=\begin{cases}1, z\ge 0\\ 0, z\le 0\end{cases}$, $\delta(z)=\frac{d}{dz}H(z)$,

Ω represents the image domain. The energy function minimization problem can be achieved by solving the corresponding Euler equation of the energy functional, so as to get the following level set evolution equation:

$$\frac{\partial\varphi}{\partial t}=\delta_\varepsilon(\varphi)[\mu\cdot div(\frac{\nabla\varphi}{|\nabla\varphi|})-(u_0-c_1)^2+(u_0-c_2)^2] \quad (3)$$

Among them $\varphi(0,x,y)=\varphi_0(x,y)$ in Ω.

Gray value in the formula and can be updated by the following ways in each iteration, respectively:

$$c_1(\varphi)=\frac{\int_\Omega u_0(x,y)H_\varepsilon(\varphi(x,y))dxdy}{\int_\Omega H_\varepsilon(\varphi(x,y))dxdy},$$

$$c_2(\varphi)=\frac{\int_\Omega u_0(x,y)(1-H_\varepsilon(\varphi(x,y)))dxdy}{\int_\Omega(1-H_\varepsilon(\varphi(x,y)))dxdy}$$

However, C - V model is lack of local edge information of the image, so the the local control ability of the image is weak . On the basis of this, an improved model,based on the C-V model ,is put forward which joins the edge information and needs no reinitialization. First, because the level set function is usually the signed distance function generated by the initial contour, and level set function degradation often occurs in the iteration, which ceased to be a signed distance function, after several times of iteration, the level set function must be re initialization, make its restore to the signed distance function of the current zero level set [7]. But the calculation of re initialization is large, which leads to the low efficiency of segmentation. In order to avoid the re initialization, a lot of literature proposes an improved scheme[8], namely to increase an internal energy constraint on the level set function of the energy functional:

$$E(\varphi)=\int_\Omega\frac{1}{2}(|\nabla\varphi|-1)dxdy$$

The gradient descent flow:

$$\frac{\partial\varphi}{\partial t}=\Delta\varphi-div(\frac{\nabla\varphi}{|\nabla\varphi|})$$

Secondly, the traditional C-V model only considers the information of the global area of the image, without considering the edge gradient information of image, the evolution speed and edge information detection of the level set will be affected, resulting in the evolution is often easy to fall into local minima. So consider the introduction of edge detection function in the energy functional to replace in the last $\delta_\varepsilon(\varphi)$ [9]. Firstly the original image multi-scale decomposition, calculation the high frequency componen H_i of the layer i, which is composed of horizontal, vertical and diagonal part, and then construct the edge detection function $g(H_i)=\frac{1}{1+|\nabla H_i|^2}$,

and get the improved C-V level set evolution equation as follows:

$$\frac{\partial\varphi}{\partial t} = g(H_i)[\mu \cdot div(\frac{\nabla\varphi}{|\nabla\varphi|}) - (u_0 - c_1)^2 + (u_0 - c_2)^2] + \Delta\varphi - div(\frac{\nabla\varphi}{|\nabla\varphi|}) \quad (4)$$

3. Image segmentation algorithm of improved C-V model based on multiscale wavelet decomposition

3.1. Multi-scale wavelet set level segmentation algorithm principle

First, the original image is multiscale decomposed through wavelet transform, then the image is segmented with the improved C-V model layer by layer from the coarse scale low frequency subband image, and by interpolation, the segmentation results is transferred to the next layer wavelet low-frequency sub-band image as the initial contour of the subband image segmentation of this layer. By repeating the steps, segmentation of the original image can be realized. The advantages of this algorithm are that at coarse scale the image is smaller in size and with less control points of contour line, which only needs a small amount of calculation; and at coarse scales smooth components, part of the noise is suppressed, the complex details are smoothed, so relatively less times of iteration are needed to terminate curve evolution; in addition, with evolution of curve layer by layer, in the image of fine scale, the initial position of contour has been close to target contour, which can effectively avoid the iteration falling into local minimum value.

3.2. Steps of algorithm

(1) Adapt multi scale wavelet transform to the original image.

(2) From the coarsest scale J, use the image center of wavelet low frequency domain as the center, half the size of the image as the radius of a circle , as the initial contour, according to equation (1) calculate the scale J values c_1 and c_2 and determine the value of each parameter, then according to the formula (2) level set evolution, to find the target boundary C in the scale of the sub image.

(3) interpolation operation on C (interpolation process as shown in Figure 1), the initial contour line 1 to get J - scale, determine the value of each parameter before the j- 1 scales of sub images on the curve evolution, get the j 1 scales on the segmentation contour line.

(4) repeat steps (3), until it achieves the final segmentation of the original image.

4. Numerical experiment and results

In experiment one, first segmentation with the C-V model, it needs 30 iterations, and takes 4.226 seconds(Figure 3); then adapts two scale decomposition to original image, and segmentation with this method, it only needs 14 iterations to get the final segmentation results and only takes 3.028 seconds (Figure 5). In Experiment two, which is about the segmentation of a satellite cloud image, first segmentation with the C-V model, it needs 34 iterations, and takes 4.782 seconds(Figure 7); then two scale decomposition is adapted to the image, and with the method mentioned, only 18 iterations are needed to get results of segmentation, taking 3.125 seconds (Figure 9).

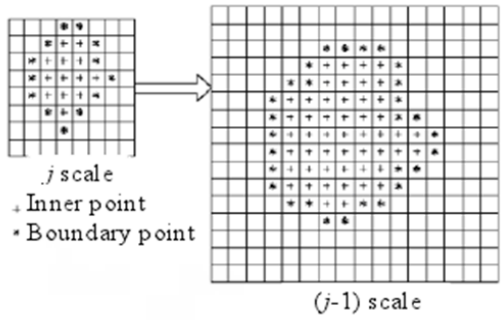

Figure 1. Interpolation process

Figure 2. The original image

Figure 3. The segmentation results of C-V model

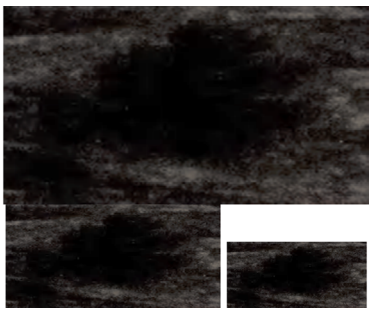

Figure 4. The original image and the two scale decomposition sub image

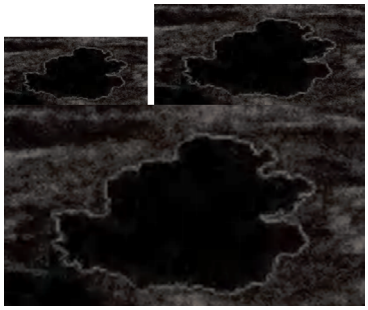

Figure 5. The segmentation results of this method

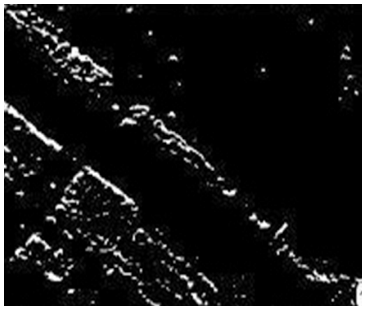

Figure 6. The original image

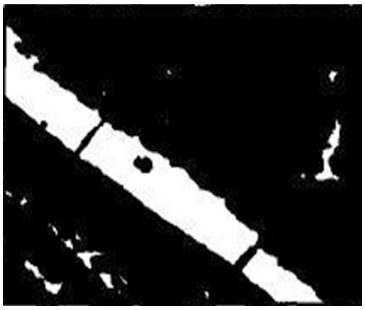

Figure 7. The segmentation results of C-V model

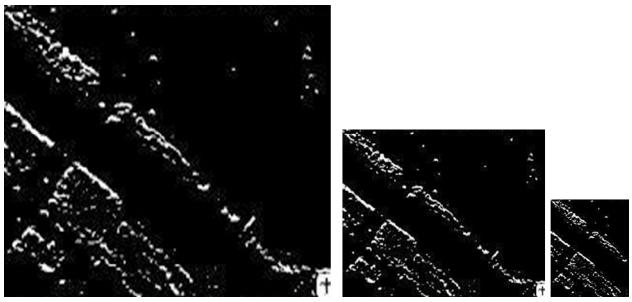

Figure 8. The original image and the two scale decomposition sub image

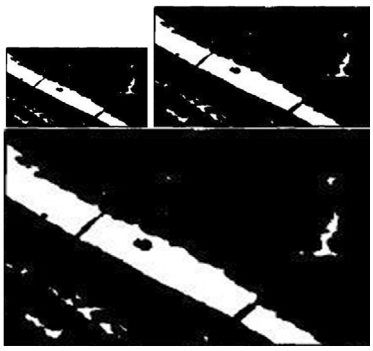

Figure 9. The segmentation results of this method

5. Conclusion

In image segmentation, the traditional C-V model only considers the global information of the image. This paper proposes a multi-scale wavelet level set segmentation model which is with image edge information and does not need re-initialization. The image edge information is constructed by the high frequency component decomposed by wavelet, which has a very good performance on boundary detection. And verified by experiments, the model is better than the traditional C-V model with fewer iterations, better stability and faster convergence speed, and easier to segment the image with noise and fuzzy edge. The combination of this method and other segmentation methods can further improve the efficiency of image segmentation which is the direction of next research.

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An Improved k-Nearest Neighbor Classification Algorithm Using Shared Nearest Neighbor Similarity

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