

**Ochotona Curzoniae Image Segmentation Based on Improved CV Model**

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**Keywords:** Ochotona curzoniae, Chan-Vese (CV) model, Mean filtering, Rectangular dirac delta function, Quadtree, Otsu.

**Abstract.** Ochotona curzoniae image possessed the characteristics of low contrast, intensity inhomogeneity and complex background. This paper proposed an improved Chan-Vese (CV) model. This model is combined image mean filtering information with object fitting term. As CV model has a problem with easily falling to segment image with object’s intensity inhomogeneity. In addition, to suppress the effects of background interference by using rectangular dirac delta function, to reduce the calculation of initialization of the evolving level set function by using Quadtree, to automatically obtain the initial contour by using Otsu. Tests and comparisons show that the new model has a better effect for Ochotona curzoniae image segmentation in autumn and winter season.

**Introduction**

Ochotona curzoniae images possess the characteristics of low contrast, intensity inhomogeneity and complex background. The image segmentation method based on level set can segment the image by using global information, local information and edge information, this method has strong universality, and it can solve the problem of curve topology change. However, the traditional image segmentation method, such as threshold method and regional growth method can’t segment the image of low contrast, and edge-based image segmentation method can’t segment the image of complex background. In summary, we segment the Ochotona curzoniae image by using image segmentation method based on level set.

Geometric Active Contour (GAC) model[1] and Chan-Vese (CV) model[2] are classical image segmentation model based on level set. GAC model not suitable for Ochotona curzoniae image of complex background, because it is built on the edge of the image segmentation model. CV model promotes the evolution of active contours by using the image global information, so this model has a better segmentation effect for weak edges image. CV model segmentation result is stable and high universality, so it has been widely used. But CV method can’t be adapted to the intensity inhomogeneity image segmentation, and the initialization level set function causes great redundancy calculation. In 2007, Li et al proposed Local Binary Fitting (LBF) model[3], Gaussian kernel function is added to CV model energy functional, so that the calculation is limited to the image local region. In 2014, Jiang et al proposed Region-scalable Fitting (RSF) model[4], the local fitting information is added to CV model. LBF model and RSF model can segment the image of intensity inhomogeneity well. However, these two methods are the global image segmentation methods which can not achieve the local image segmentation. In 2009, Zhang[5] et al constructed the Signed Pressure Force (SPF) function using the fitting information of CV model, SPF function substituted the edge stop function in GAC model, so adding the region information to GAC model, and the local segmentation of the image can be realized by the improvement of level set function, but this method is only suitable for intensity homogeneity image.

In this paper, we proposed an improved CV model to improve the adaptability of CV model for the image of intensity inhomogeneity. Adding the local mean information to internal fitting value in CV model, which plays the key role in changing of the buffer fitting values in the intensity inhomogeneity, the new model can segment the image of intensity inhomogeneity. In addition, Quadtree boundary description is used to remove part of the background region. The initial contour
can be automatically obtained with Otsu method. Ochotona curzoniae images are segmented by improved CV model, and compared with CV model and with the method in literature [5].

**Improved CV Model**

CV model segments image according to the intensity difference between the foreground and the background. However, this model is under the premise of intensity homogeneity, the energy function of CV model is defined as follows.

\[
E(C) = \mu \cdot \text{Length}(C, c_1, c_2) + \lambda_1 \int_{\text{outside}(C)} |u_0(x, y) - c_1|^2 \, dx \, dy + \lambda_2 \int_{\text{inside}(C)} |u_0(x, y) - c_2|^2 \, dx \, dy
\]

(1)

where \( C \) is active contours, \( \mu > 0 \), \( \lambda_1 > 0 \), \( \lambda_2 > 0 \) are fixed parameters, \( \mu \) controls the length of active contours, \( \lambda_1, \lambda_2 \) control the image data driven force inside and outside the contour respectively. \( u_0 \) is the image pixel value, \( c_1 \) and \( c_2 \) are the average intensities in inside(\( C \)) and outside(\( C \)) respectively, and by adding the level set function \( \phi \), can be written as equation (2),

\[
E(\phi, c_1, c_2) = \mu \int \delta_x(\phi(x, y)) \nabla \phi(x, y) \, dx \, dy + \lambda_1 \int |u_0(x, y) - c_1| H_x(\phi(x, y)) \, dx \, dy
\]

\[
+ \lambda_2 \int |u_0(x, y) - c_2| (1 - H_x(\phi(x, y))) \, dx \, dy
\]

(2)

where \( \nabla \) is gradient operator, \( H_x(\phi) \) is regularized Heaviside function and \( \delta_x(\phi) \) is regularized dirac delta function. Regularized Heaviside function and regularized dirac delta function are given by equation (3),

\[
H_x(\phi) = \frac{1}{2} \left( 1 + \frac{2 \arctan(\phi / \varepsilon)}{\pi} \right), \quad \delta_x(\phi) = \frac{1}{\varepsilon^2 + \phi^2}
\]

(3)

\( c_1 \) and \( c_2 \) can be obtained using \( \phi \).

\[
c_1 = \frac{\int u_0(x, y) H_x(\phi) \, dx \, dy}{\int H_x(\phi) \, dx \, dy}, \quad c_2 = \frac{\int u_0(x, y) (1 - H_x(\phi)) \, dx \, dy}{\int (1 - H_x(\phi)) \, dx \, dy}
\]

(4)

Then minimization with respect to \( \phi \) leads to the following equation.

\[
\frac{\partial \phi}{\partial t} = \delta_x(\phi) \left[ \mu \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - \lambda_1 (u_0 - c_1)^2 + \lambda_2 (u_0 - c_2)^2 \right]
\]

(5)

\( \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \) is a contour curvature. In this paper, regularized dirac delta function is replaced by rectangular dirac delta function. Regularized dirac delta function is a globally function that the segment results include background disturbances of Ochotona curzoniae image. Rectangular dirac delta function can be used to limit the partition in a local area, effectively suppressing the background interference and improving the segmentation accuracy.

Rectangular dirac delta function can be written as:

\[
\delta_x(x) = \begin{cases} 
1 & -1 < x < 1 \\
0 & \text{other}
\end{cases}
\]

(6)

CV model can’t segment the image of object with intensity inhomogeneity, because of CV model is proposed under the premise of intensity inhomogeneity. This paper draws on the idea of the literature[6], mean value of the image is added to the fitting value. The internal fitting value of improved model is as follow.

\[
c_2 = \alpha \cdot \text{ave}(u_0(x, y)) + (1 - \alpha) \cdot \frac{\int u_0(x, y) (1 - H_x(\phi)) \, dx \, dy}{\int (1 - H_x(\phi)) \, dx \, dy}
\]

(7)
where, \( \text{ave}(u_h(x, y)) \) is the mean filtered image; \( \alpha \) is a weight value and the value is in \([0,1]\). We can draw the following conclusions from the new interior fitting values, the difference between \( c_2(x) \) and pixel intensity \( x \) is minimal when pixel \( x \) is located within the object’s intensity homogeneity or intensity inhomogeneity. The pixel intensity changes slowly in this region. The difference between pixel \( x \) and mean filter pixel \( x \) position value is smaller, so the pixel \( x \) is fitted by \( c_2(x) \), the difference between fitting value \( c_2(x) \) and the pixel \( x \) is larger when the pixel \( x \) is at the edge of the image. Due to the dramatic change in the intensity values of the local pixel, so that the fitting value \( c_2(x) \) and the pixel \( x \) value is large, the difference between the fitting value \( c_2(x) \) and the pixel \( x \) is very larger when the pixel \( x \) is at the background region, because the intensity of the background pixel is different from the mean value of the object’s pixel. In summary, improved internal fitting value can flexible, completely represent of the image within the pixel information of object, but can not represent the image of background pixel information. So the new model can segment the image of intensity inhomogeneity of object by applying new internal fitting value.

**Algorithm Implementation**

The image is filtered by morphological methods\(^7\). Morphological filtered image has the object’s edges information but removes the fine texture and some noise. Then, we can more accurately and easily to segment the image. In order to reduce the redundancy calculation of the level set initialization, a binary image of the boundary is obtained by Quadtree image boundary description method. The original image corresponding to the minimum rectangle of the boundary description point is used as the segmented image to improve the segmentation efficiency. In addition, this paper make up for CV model’s shortcomings that it need to set the initial contour by Otsu.

In summary, this method has three steps to segment image.

a. Image segmentation preprocessing

(1) Image filtering using morphological methods. (2) Image removal part of the background using the Quadtree method. (3) The initial contour is determined by the Otsu method that has been removed part of the background.

b. Image segmentation with improved CV model

(1) Initialize level set function, \( \phi = 0 \). (2) \( c_1 \) and \( c_2 \) are calculated and substituted into the curve evolution equation. Then update the level set function \( \phi \). (3) To determine whether the level set function converges, if the convergence, iteration stop, otherwise continue to step(2).

c. Embed the segmented image into the original image. The specific process is shown in Figure 1.

![Figure 1. The flow char of this proposed method.](image)

**Experiment and Analysis**

This experiment with Matlab code run on a Lenovo Thinkpad E40 PC (Inter (R) Pentium (R) CPU P6100 @ 2.00GHz) with Matlab 2013a on windows 7. The images of the Ochotona curzoniae in the autumn and winter season obtained in Gannan grassland of the northeastern Qinghai-Tibet Plateau (1013536 , 1025815 , 335821 344848) are selected as the experimental data. The image size are 256 pixels×256 pixels. In this environment, the Ochotona curzoniae image possesses the characteristics of low contrast, intensity inhomogeneity, complex background and mach noise.
Four images of Ochotona curzoniae were segmented by using the method proposed in this paper, the method of CV model and the method in literature [5]. In this paper, we select the circular structure element with size 3 in the morphological filtering process. The threshold value in the Quadtree image decomposition function is 0.27, the average filter template size is 3, constant value $\alpha = 0.1$, rectangular dirac delta function is used to replace regularized dirac delta function, the constant value of proposed method in this paper and in CV model is $\mu = 0.01 \times 255 \times 55$. $\lambda_1$, $\lambda_2$ are equal to 1. The time step satisfies the CFL condition of $dt = h / v$, and $h$ is the grid interval and $h = 1$, $v$ is the evolution speed. The initial contour position of the three methods is the same. Figure 2 shows the images of the Ochotona curzoniae collected in the autumn and winter season. Figure 3 shows the segmentation results of CV model. Figure 4 shows the segmentation results of the method in literature [5]. Figure 5 shows the segmentation results of the proposed method in this paper.

In this paper, we use DSC (Dice Similarity Coefficient) [8], FPVF (False Positive Volume Function) [9], FNVF (False Negative Volume Function) [9], and the Jaccard (J) [10] to quantify the quantitative results. The results are shown in Table 1.

As can be seen from Table 1 and Figures 2 to Figure 4, the segmentation results of CV model cause very serious over-segmentation. CV model’s dirac delta function is global and the image background is complex, then the results of CV model have serious over-segmentation. The method in literature [5] can be segment image in local but can’t segment image of intensity inhomogeneity. So, the segmentation of Ochotona curzoniae’s belly, chest and leg are not complete in Figure 3(b). Ochotona curzoniae’s buttock is not segmented in Figure 3(c). Ochotona curzoniae’s legs, ears and mouth information are missing in Figure 3(d). The results of this paper’s method are relatively complete because this method can segment image of intensity inhomogeneity.

| Image index | Image | CV model | the literature [5] | This paper’s model |
|-------------|-------|-----------|-------------------|-------------------|
| (a) | DSC | 0.0531 | 0.8439 | 0.8891 |
| | FPVF | 33.2179 | 0.0341 | 0.1487 |
| | PNVF | 0.0840 | 0.2452 | 0.0806 |
| | J | 0.0273 | 0.7300 | 0.8004 |
| (b) | DSC | 0.1093 | 0.8306 | 0.9007 |
| | FPVF | 13.5984 | 0.0380 | 0.0370 |
| | PNVF | 0.1563 | 0.2627 | 0.1503 |
| | J | 0.0578 | 0.7103 | 0.8194 |
| (c) | DSC | 0.0432 | 0.8313 | 0.8822 |
| | FPVF | 41.0638 | 0.0615 | 0.1141 |
| | PNVF | 0.0705 | 0.2450 | 0.1208 |
| | J | 0.0221 | 0.7113 | 0.7892 |
| (d) | DSC | 0.2319 | 0.7936 | 0.8711 |
| | FPVF | 5.3677 | 0.0110 | 0.0299 |
| | PNVF | 0.1647 | 0.3439 | 0.2054 |
| | J | 0.1312 | 0.6579 | 0.7716 |

Note: the figure of (a),(b),(c),(d) of table 1 is belong to Figure 2.
Table 2 shows the time-consuming comparison of CV model and the method (all iterations 100 times).

| Image | (a)  | (b)  | (c)  | (d)  |
|-------|------|------|------|------|
| CV model | 32.65958s | 28.34239s | 37.55901s | 23.8928s |
| Our method | 2.961108s | 2.905626s | 2.821545s | 3.956364s |

Note: the figure of (a),(b),(c),(d) of table 1 is belong to Figure 2.

Summary

It can be seen from Table 2 that the average iteration time of the proposed method in this paper is much smaller than that of CV model. (1) The computation of level set initialization is greatly reduced due to a part of background image has been removed. (2) The computation of contour evolution is reduced because of rectangular dirac delta function is a local function.

Image segmentation of Ochotona curzoniae is one of the key technologies in the intelligent monitoring of Ochotona curzoniae. In this paper, we have improved CV model to segment the image of intensity inhomogeneity. This goal is achieved by adding image mean filtering information to internal fitting values. In addition, background disturbances are suppressed by using rectangular dirac delta function, efficiency of segmentation is improved through removing part of the background by the Quadtree method. The initial contour is automatically given by using the Otsu method. Compared with CV model and the method in literature [5], the experimental results show that the proposed method has high precision and low running time, and has a better effect in background suppression and object area initial contour location. This method has laid a good foundation for the follow-up identification, monitoring and tracking of Ochotona curzoniae.

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