An Automatically Initialized Level Set Method for Ochotona Curzoniae Image Segmentation

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Abstract. In order to effectively solve this problem that that the traditional level set method needs to mark the initial contour manually, a novel method that automatic initialization by utilizing deep learning is proposed in this paper. Firstly, a target detection network based on Faster-RCNN is used for target detection of ochotona curzoniae. Secondly, the detected target boxes are regarded as the initial contour of level set models, and ochotona curzoniae images are segmented by level set models, by which the problem of manually plotting the initial contour required by traditional level set models is solved. The experimental results of ochotona curzoniae image segmentation show that there is little difference between the level set segmentation method in which the inital contour of the target is automatically generated by deep learning(LSECA) is used to automatically target initial contour and the level set segmentation method where initial contour needs to be manually plotted. Therefore, the experimental results prove that it is feasible to automatically obtain the target initial contour through deep learning.

1. Introduction
Ochotona curzoniae image segmentation is of great significance to study the life habits of ochotona curzoniae, effectively grasp their population changes and prevent them from destroying environment. In nature, ochotona curzoniae images are characterized by complicated background, intensity inhomogeneity, loud noise and weak edges. It makes ochotona curzoniae image segmentation even more challenging. Level set models (LSMs) have already been widely used in image segmentation. It especially achieved excellent results in the medical field. The ochotona curzoniae images and medical images share a lot of similar characteristics, so LSMs are used for ochotona curzoniae image segmentation in this paper.

LSMs can be divided into two categories: edge-based LSMs and region-based LSMs[1]. The region-based LSMs are to use region information instead of boundary information, to derive the equation of evolving curve. Thus, they can be better applied to segment images with weak edges or loud noise[2]. In view of the characteristics of ochotona curzoniae, the commonly used region-based LSMs are applied for ochotona curzoniae image segmentation in this paper. However, the initial contour is required to be manually plotted in all these models.

Recently, numerous methods have been proposed for solving the problem that the initial contour needs to be manually plotted in traditional LSMs. Bai et al proposed an adaptive definition of the initial contour based on the prior shape of the image[3], but the target in the complex background image cannot be accurately located through this method. Guo et al proposed a way to locate the initial contour of the target through quaternary tree method[4]. But this method is only applicable to square images. Zhang et al proposed a method to locate the initial contour of target by using the temporal information of video sequences and background subtraction[5]. However, this method took advantage
of the temporal information while there was no temporal information in static images.

Faster-RCNN has the characteristics of high detection accuracy and fast detection speed, therefore, in this paper, a target detection network based on Faster-RCNN is proposed to automatically plot the initial contour of the target, so as to overcome the problem that the initial contour needs to be manually plotted in the LSMs. Firstly, target detection network based on Faster-RCNN is used for target detection of ochotona curzoniae. Secondly, the detected target boxes are regarded as the initial contour of LSMs, by which ochotona curzoniae images are segmented.

2. Proposed Methodology

2.1. CV Model
CV model divided the image area into background area and target area, and the difference between these two regions was further used for image segmentation[6]. The energy function of CV is defined as equation (1):

\[
F(c_1, c_2, \varphi) = \mu \int_{\Omega} \delta_1(\varphi) |\nabla \varphi| dxdy + \nu \int_{\Omega} H(\varphi) dxdy
+ \lambda_1 \int_{\Omega} |I(x,y) - c_1|^2 H_\varepsilon(\varphi) dxdy + \lambda_2 \int_{\Omega} |I(x,y) - c_2|^2 (1-H_\varepsilon(\varphi)) dxdy
\]

(1)

Where \( \varphi \) is the level set function, \(|\nabla \varphi|\) is divergence of \( \varphi \), \( \Omega \) is image region. \( c_1 \) and \( c_2 \) are the means of intensities in the interior and exterior, respectively. \( I(x,y) \) signifies the intensity value of a local region centered at point \((x,y)\). \( H_\varepsilon(\varphi) \) is Heaviside function, \( \delta_1(\varphi) \) is the derivative of \( H_\varepsilon(\varphi) \). The items 1 and 2 are terms of length and area, respectively, representing internal energy, and their functions are to ensure the smoothness of contour. The items 3 and 4 are the external energy, and their functions are to attract the contour \( C \) toward the object in image. The positive constants \( \mu, \nu, \lambda_1, \lambda_2 \) are the weight coefficients of the corresponding terms.

Zhang et al. proposed a novel method to resolve the problem that images with intensity inhomogeneity cannot be segmented in traditional CV[7]. The method was: (a) original images are convolved with Laplace Operator to highlight the edge of the target and overcome the intensity inhomogeneity. (b) The global functions \( H_\varepsilon(\varphi) \) are modified as local functions \( H_\varepsilon \), and as shown in equation (2).

\[
H_\varepsilon = \begin{cases} 0 & (x < -1) \\
-\frac{x^2}{2} + x + \frac{1}{2} & (-1 \leq x < 0) \\
-x^2 + 2x + \frac{1}{2} & (0 \leq x < 1) \\
1 & x \geq 1 \end{cases}
\]

(2)

The zero level set function \( \varphi \) is used to represent the curve \( C \), so the energy function of improved CV model is shown in equation (3).

\[
F(c_1, c_2, \varphi) = \mu \int_{\Omega} \delta_1(\varphi(x,y)) |\nabla \varphi(x,y)| dxdy + \nu \int_{\Omega} |I(x,y) - c_1|^2 H_\varepsilon(\varphi(x,y)) dxdy
+ \lambda_1 \int_{\Omega} |I(x,y) - c_2|^2 (1-H_\varepsilon(\varphi(x,y))) dxdy - \alpha \int_{\Omega} |\nabla^2 \varphi(x,y)(1-H_\varepsilon(\varphi(x,y))) dxdy
\]

(3)

Where \( \delta_1 \) is the derivative of \( H_\varepsilon \). The ways of calculating \( c_1 \) and \( c_2 \) are indicated in equation (4).

\[
c_1 = \frac{\int_{\Omega} I(x,y) H_\varepsilon(\varphi) dxdy}{\int_{\Omega} H_\varepsilon(\varphi) dxdy}, \quad c_2 = \frac{\int_{\Omega} I(x,y)(1-H_\varepsilon(\varphi)) dxdy}{\int_{\Omega}(1-H_\varepsilon(\varphi)) dxdy}
\]

(4)

Through gradient descent method, evolution equation of equation (4) can be obtained, as shown in
equation (5).

\[
\frac{\partial \phi}{\partial t} = \delta_i(\varphi)[\mu \text{div}(\nabla \varphi)\\nabla \varphi] - \lambda_1(1-c_1)^2 + \lambda_2(1-c_2)^2 - \alpha \sqrt{\lambda_1^2 + \lambda_2^2} \nabla^2 I[\delta_i^2(\varphi) - \delta_i(\varphi)(1-H_i(\varphi))]
\] (5)

2.2. Target Detection Model

Faster-RCNN has the advantages with faster calculation speed and higher detection accuracy et al[8]. Therefore, a two-stage detection model based on Faster-RCNN was adopted for target detection of ochotona curzoniae in this paper.

In the two-stage detection model, firstly, on the basis of extracting the low-level features, the high-level convolutional layer is used to extract the semantic features, and semantic features are further used to generate suspected target areas. Secondly, semantic features of suspected target areas are mapped into fixed area, and the foreground target is further extracted to obtain the target area.

In this model, loss function is adopted in the first stage, and its formula is shown in equation (6).

\[
L(p_i, t_i) = \frac{1}{N_{\text{cls}}} \sum_i L_{\text{cls}}(p_i, p_i^*) + \lambda \frac{1}{N_{\text{reg}}} p_i^* L_{\text{reg}}(t_i, t_i^*),
\] (6)

Where \(L_{\text{cls}}\) is Log-likelihood Loss function. \(L_{\text{reg}}\) is Smooth \(L_1\) loss function. \(N_{\text{cls}}\) and \(N_{\text{reg}}\) are two hyper-parameters, representing the amount of candidate region boxes on the entire training batch and the amount of candidate region boxes participating in the training on the entire training batch. \(p_i^*\) is the type of the target in \(i\)-th boundary box. \(p_i\) is the classified prediction output of the \(i\)-th boundary box.

In the second stage, the candidate boxes of the suspected target regions that are detected in the first stage are further extracted for target features through pooling layer and full connection layer, and the real target regions were obtained through regression and category prediction, and the coordinates of the candidate region boxes were returned.

2.3. Algorithm Implementation

In view of complex background and large noise interference of ochotona curzoniae images, the morphological filtering of the detected ochotona curzoniae images is carried out to eliminate the interference caused by noise and to enhance the edge of the target in this paper. And then the detected target area by Fast-RCNN is used as the initial contour of the level set, and the level set is used to segment the images of ochotona curzoniae.

3. Experimental Results and Analysis

All images used in this paper were taken in Gannan grassland of Gansu province in China (East longitude 101°35′36″~102°58′15″, West longitude 33°58′21″~34°48′48″). The format of data set in this experiment is same as Pascal VOC. The images of ochotona curzoniae are segmented through the LSECA, and then the result of LSECA is compared with the level set segmentation method in which the initial contour is manually plotted (LSECM).

3.1. Qualitative Analysis

In the experiment, 800 ochotona curzoniae images in data set are used to train the network, and 330 ochotona curzoniae images in data set are used to test the network. After 1,000 times of iterations, the model fits the training data, and training ends. After 100 times of training, the accuracy of detection tends to be stable, and 330 images with the information about target position are obtained, as shown in Figure 1.
The segmentation results of LSECA and LSECM are compared and analyzed. The manually plotted initial contour is shown in Figure 2. The parameter of level sets are set as: \( \mu = 1, \lambda_1 = \lambda_2 = 1, \alpha = 1.5 \).

The segmentation results of Figure 1 and Figure 2 are shown in Figure 3. From Figure 3, These two methods can effectively segment the ochotona curzoniae images.

3.2. Quantitative Analysis
In order to quantitatively analyze the performance of LSECA, the dice similarity coefficient (DSC), false positive volume function (FPVF), false negative volume function (FNVF) and Jaccard index (J) are used to analyze the experimental results. Pearson correlation coefficients [9] are often used to measure the correlation between two sequences, so, in this paper, Pearson correlation coefficients is used to measure the similarity of DSC, FNVF, FPVF, J obtained by LSECA and LSECM.

As shown in Table 1, the values of the Pearson correlation coefficients of DSC, FNVF, FPVF, and J of these two segmentation methods are all greater than 0.6, indicating that the correlation of between LSECA and LSECM is very high, and that DSC, FNVF, FPNF, and J are similarly distributed.

| Indicators | DSC   | FNVF  | FPVF  | J     |
|------------|-------|-------|-------|-------|
| Values     | 0.8293| 0.8651| 0.6497| 0.8135|

Figure 2. The ochotona curzoniae images whose initial contours are manually plotted.
For comparing and analyzing the segmentation results of LSECA and LSECM, the means, variances and standard deviations of DSC, FNVF, FPVF, J are calculated, respectively, as shown in Table 2.

Table 2. Comparison of means, variances and standard deviations.

| Indicators/Model | LSECA     | LSECM     | Variance | LSECA     | LSECM     | Standard Deviation |
|------------------|------------|------------|----------|------------|------------|-------------------|
| DSC              | 0.513141   | 0.579426   | 0.043882 | 0.045418   |            | 0.209479          |
| FNVF             | 0.319121   | 0.323327   | 0.069269 | 0.045418   |            | 0.263191          |
| FPVF             | 1.222189   | 0.820458   | 1.389879 | 1.445023   |            | 1.178931          |
| J                | 0.372566   | 0.438794   | 0.038868 | 0.043458   |            | 0.197151          |

From Table 3, the differences of means of DSC, FNVF, FPVF, J of these two methods are less than 0.1, and the differences of variances and standard deviations are less than 0.06, showing that the performances of LSECA can be similar to LSECM.

4. Conclusions

In order to solve the problem that the initial contour needs to be manually plotted in traditional level set mode, a new level set method in which the initial contour of the target is automatically plotted by deep learning is proposed. Firstly, the Faster-RCNN is used to detect the target of ochotona curzoniae images and obtain the position of the target. And then the position is used as the initial contour of level set, and level set is further used to segment the images of ochotona curzoniae. The experimental results show that this model can realize the segmentation of ochotona curzoniae images, which proves the effectiveness of this method.

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6. References

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