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A new active contour remote sensing river image segmentation algorithm inspired from the cross entropy

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ABSTRACT

The CV (Chan–Vese) model is a piecewise constant approximation of the Mumford and Shah model. It assumes that the original image can be segmented into two regions such that each region can be represented as constant grayscale value. In fact, the objective functional of the CV model actually finds a segmentation of the image such that the within-class variance is minimized. This is equivalent to the Otsu image thresholding algorithm which also aims to minimize the within-class variance. Similarly to the Otsu image thresholding algorithm, cross entropy is another widely used image thresholding algorithm and it finds a segmentation such that the cross entropy of the segmented image and the original image is minimized. Inspired from the cross entropy, a new active contour image segmentation algorithm is proposed. The region term in the new objective functional is the integral of the logarithm of the ratio between the grayscale of the original image and the mean value computed from the segmented image weighted by the grayscale of the original image. The new objective functional can be solved by the level set evolution method. A distance regularized term is added to the level set evolution equation so the level set need not be reinitialized periodically. A fast global minimization algorithm of the objective functional is also proposed which incorporates the edge term originated from the geodesic active contour model. Experimental results show that, the algorithm proposed can segment images more accurately than the CV model and the implementation speed of the fast global minimization algorithm is fast.

1. Introduction

Image segmentation is one of the most fundamental problems in image processing and computer vision. Among various image segmentation algorithms, level set based image segmentation algorithms have several advantages and various image segmentation algorithms based on level set have been proposed [1–4]. The image segmentation problem is represented as an energy minimization problem and the objective functional is solved by variational methods. The Euler–Lagrange equation of the objective functional can be obtained which guides the evolution of the level set function. The object contour is embedded as the zero level set of an implicit higher dimensional level set function and the evolution of the object contour is realized through the evolution of the level set function. The topology changes can be handled naturally by this method and the segmentation result is achieved when the object functional is minimized.

The existing level set based image segmentation algorithms can roughly be divided into three categories: the edge based level set image segmentation algorithms [1–5], the region based level set image segmentation algorithms [6–11] and the hybrid level set image segmentation algorithms [12–14]. The most typical edge based method is geodesic active contour model [2]. The level set evolves according to an edge indicator function and stops at high contrast image gradients. There are obvious disadvantages of the edge based method such that it is very sensitive to the initial level set position and the level set can easily leak through weak edges. The region based method is thus proposed and the most typical region based method is the CV model [7]. It approximates the original image with two regions with constant grayscale so it is also called piecewise constant model. The region based method is not sensitive to the initial level set position and since the objective functional does not depend on image gradients, it can segment regions with weak edges. The evolution speed is also faster than

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edge based method. The hybrid method combines the two previous methods and the objective functional depends both on image gradients and region homogeneity.

The basic assumption of CV model is that each segmented region has constant grayscale. The objective functional of CV model can be divided into two parts which contain a smoothness constraint term and a region term. The region term measures the integral of the squared difference between the mean value of the current segmented regions and the grayscale of the original image inside the current segmented regions. When this objective functional gets its minimum, the integral of the squared difference between the mean value and the grayscale of the two segmented regions is minimized. Actually, the integral of the squared difference between the mean value and the grayscale is the variance of that region. The variance of each region must get its minimum when the objective functional is minimized. This procedure is quite similar to the Otsu image thresholding algorithm. The Otsu image thresholding algorithm [15] is also known as maximum between-class variance thresholding algorithm or minimum within-class variance thresholding algorithm which means that a threshold is chosen such that the two segmented regions have maximum between-class variance or minimum within-class variance. From the above analysis, we can see that both methods aim to minimize the variance of the segmented regions and the only difference is the method of determination of the region. In CV model, the method of determination of the region is through a level set function and in Otsu thresholding algorithm, the determination is through a threshold. Through numerical experimentation, we also find that the segmentation results of the two methods are very similar. Since CV model also takes into consideration of the smoothness of the level set and Otsu method does not, their segmentation results are not exactly the same but are very similar. The segmentation results of CV model are always better than those obtained by Otsu method because of the smoothness constraint considered.

In the image thresholding community, there is another widely used image thresholding algorithm which is called cross entropy based image thresholding algorithm [16]. The cross entropy measures an information theoretic distance between two probability distributions. The cross entropy image thresholding algorithm measures the probability distributions of the original image and segmented image. A threshold is chosen such that the distance is minimized. The cross entropy based image thresholding algorithm is similar to Otsu image threshold algorithm. In many cases, to minimize the distribution between the original image and the segmented image is more accurate than minimizing the variance of each segmented regions. The measurement of the distribution can be incorporated in the level set based framework. Inspired from the cross entropy, a new level set image segmentation algorithm is proposed where the region term is based on the measurement of the probability distribution. This new segmentation model can get similar results with cross entropy based image segmentation algorithm but better results can be obtained since the smoothness constraint is taken into consideration in the proposed level set based segmentation model. During the evolution of the level set function, the level set can deviate from the signed distance function and reinitialization is usually needed. To avoid reinitialize the level set function periodically, a distance regularized term [17, 18] is added to the objective functional and level set function will tend to be a signed distance function during evolution. Another global minimization algorithm of the objective functional based on a dual formulation of the TV norm [19] is also proposed and the geodesic edge term can be incorporated naturally in the objective functional. Thus this formulation not only measures the probability distributions but also considers image gradient based energy. The implementation speed of the fast global minimization algorithm is very fast compared to the level set based method [20].

The rest of the paper is organized as follows: Section 2 introduces CV model and its relationship with Otsu image thresholding algorithm. Section 3 describes a new image segmentation algorithm and its relationship with cross entropy based image thresholding algorithm. The fast global minimization algorithm of the proposed method is introduced in Section 4. Some experiments applying the proposed method and some closely related level set based methods including CV model [7], minimization of region-scalable fitting energy level set model [8], bias field correction level set model [9], fast global minimization of the geodesic active contour model [20] and fast global minimization of the CV model [20] in segmenting remote sensing river images are presented in Section 5 followed by some concluding remarks in Section 6.

2. Piecewise constant active contour model (CV model) and its relationship with Otsu image thresholding algorithm

2.1. Otsu image thresholding algorithm

Suppose a given $N_x \times N_y$ image has L grayscale levels represented by $[0, 1, \dots, L-1]$. The number of pixels whose grayscale intensity value equals i is h_i and $\sum_{i=0}^{L-1} h_i = N_x \times N_y$. h_i is called the occurring frequency of grayscale i and $\{h_i\}_{i=0,\dots,L-1}$ is the grayscale histogram of the given image. The probability of a pixel whose grayscale intensity value equals i is p_i and $p_i = \frac{h_i}{N_x \times N_y}$. $\{p_i\}_{i=0,\dots,L-1}$ is the normalized grayscale histogram of the given image. Suppose that we segment the pixels into two classes C_0 and C_1 (background and objects, or vice versa) by a threshold at level t_{Otsu}; C_0 denotes pixels with levels $[0, \dots, t_{\text{Otsu}}]$, and C_1 denotes pixels with levels $[t_{\text{Otsu}} + 1, \dots, L-1]$. Then the probabilities of class occurrence and the class mean values, respectively, are given by

$$\omega_0 = \sum_{i=0}^{t_{\text{Otsu}}} p_i \tag{1}$$

$$\omega_1 = \sum_{i=t_{\text{Otsu}}+1}^{L-1} p_i \tag{2}$$

and

$$\mu_0 = \sum_{i=0}^{t_{\text{Otsu}}} i p_i / \omega_0 = \sum_{i=0}^{t_{\text{Otsu}}} i p_i \Big/ \sum_{j=0}^{t_{\text{Otsu}}} p_j \tag{3}$$

$$\mu_1 = \sum_{i=t_{\text{Otsu}}+1}^{L-1} i p_i / \omega_1 = \sum_{i=t_{\text{Otsu}}+1}^{L-1} i p_i \Big/ \sum_{j=t_{\text{Otsu}}+1}^{L-1} p_j \tag{4}$$

are the zeroth-order and the first-order cumulative moments of the normalized histogram up to the t_{Otsu}th level, respectively.

The class variances are given by

$$\sigma_0^2 = \sum_{i=0}^{t_{\text{Otsu}}} (i - \mu_0)^2 p_i / \omega_0 = \sum_{i=0}^{t_{\text{Otsu}}} (i - \mu_0)^2 p_i \Big/ \sum_{j=0}^{t_{\text{Otsu}}} p_j \tag{5}$$

$$\begin{aligned} \sigma_1^2 &= \sum_{i=t_{\text{Otsu}}+1}^{L-1} (i - \mu_1)^2 p_i / \omega_1 \\ &= \sum_{i=t_{\text{Otsu}}+1}^{L-1} (i - \mu_1)^2 p_i \Big/ \sum_{j=t_{\text{Otsu}}+1}^{L-1} p_j \end{aligned} \tag{6}$$