A Coastline Detection Method Based on Level Set

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Abstract. This paper proposes a level set based coastline detection method by using the template initialization and local energy minimization. It can complete the sea-land boundary detection in infrared channel image. This method is an improvement on the traditional level set algorithm by using the information of GSHHS to optimize the initialization procedure, which can reduce the number of iterations and numerical errors. Moreover, this method optimizes regional energy functional, and can achieve the rapid coastline detection. Experiments on the IR image of FY-2 satellite show that the method has fast speed and high accuracy.

Keywords: Edge detection, level set method, IR image processing.

1 Introduction

With the increase of the remote sensing satellite data, the preprocessing of satellite remote sensing data becomes more and more time consuming. Image navigation is the first step of preprocessing, which allows researchers to get the geographical latitude and longitude of each satellite image pixels. Automated image navigation makes satellite data processing efficiency improved significantly [1].The procedure of the automatic navigation of remote sensing images is as follows: firstly the real satellite image is matched with the template image to obtain the relative offset, and then adjust this satellite's attitude according to the offset . In the process, researchers usually realize the image matching using the satellite image coastline as features. Therefore, to achieve automatic navigation of remote sensing images, the first problem is: the automatic coastline detection of the remote sensing image.

The theory and technology of edge detection has made significant progress in recent years. Many new edge detection techniques have been developed, and they are based on neural networks, genetic algorithms, wavelet transform, morphology and partial differential equations (PDE) etc. Compared to other emerging methods, the method based on partial differential equations, has stronger local adaptability and higher flexibility [2]. PDE itself is based on the continuous image model, which makes the change at the current time of a pixel value in the image only depend on a

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near infinite small neighborhood of the pixel point. In this sense, PDE method has nearly infinite local adaptive capacity. Considering the characteristics of satellite remote sensing images and the advantages of the PDE method, we use a method based on level set.

2 Related Works

Currently, in many mature edge detection method based on PDE, level set method performs well when processing complicated images and multi-target images, and it is easy to expand, Level set method can be categorized into two major classes: edge-based geometric active contour models [3-5] and region-based geometric active contour models [6-11].

The earliest level set model is the geometric active contour model proposed in 1993 by Caselles[3]. Since the model depends on the edge gradient information, the edge detection result is not ideal due to the tiny gradient. Moreover, level set model is sensitive to noise. Therefore, the contours detected by the model are discontinuous. In order to solve the problems of edge-based models, Chan [6] proposed a region-based model based on a simplified Mumford-Shah energy functional, referred as CV model. The model combines edge information and regional information, and no longer depends on the gradient information on the edges. The model is not sensitive to noise and applies to fuzzy edges or discontinuous edges. Subsequently, a number of researchers have made some improvements on the basis of this model. Li [7] propose a level set method without re-initialization. Lee[8] propose a level set method with stationary global minimum. Both of two models are based on the fact that image intensities are statistically homogeneous (roughly a constant) in each region. Therefore, they are known as the piecewise constant (PC) models. In fact, the real images often show intensity inhomogeneity, and PC model is not available for these images. To address this issue, Tsai[9] and Vese[10] independently propose two improved scheme to overcome the shortcomings of the PC model by piecewise smooth function, and make the edge extraction range expandable to multi-phase images. These models are called piecewise smooth (PS) model. However, the PS model also has the disadvantage of the large amount of calculation.

To efficiently perform the edge detection of images with intensity inhomogeneity, a new class of models has been proposed which not only utilize region-based techniques but also incorporate the benefits of local information. Brox[12] propose the idea of incorporating localized statistics into a variational framework, which shows that segmentation with local means is a first order approximation of the piecewise smooth simplification of the Mumford–Shah functional. Sum et al [13] minimize the sum of a global region-based energy and a local energy based on image contrast, thus construct a new hybrid-based level set model for the edge detection of vascular images with intensity inhomogeneity. Lankton et al[14] propose a new curve evolution scheme based on the combination of the geodesic active contour model and region-based method, which allows the region-based energy to be localized in a fully variaional way so that edges of objects with intensity inhomogeneity can be successfully extracted with the localized energies. Li[15] propose a variational level set method by introducing a local binary fitting (LBF) energy with a kernel function. By drawing upon spatially varying local region information, the LBF model is able to deal with intensity inhomogeneity. Recently, Li et al[16] improve the above formulation, and propose a distance regularized level set evolution(DRLSE) method. The method has an intrinsic capability of maintaining regularity of the level set function, particularly the desirable signed distance property in a vicinity of the zero level set, thereby avoids reinitialization procedures and its induced numerical errors, greatly reduces the number of iterations.

In order to adapt to the characteristics and the processing requirements of the infrared image, on the basis of the LBF method, we propose a new level set formulation by combining the template initialization and local energy minimization. The method optimizes initialization procedure by optimization of the information of GSHHS, reduces the number of iterations and numerical errors, improves the stability of the algorithm; optimizes regional energy functional, and improves the efficiency of the algorithm.

3 Coastline Detection Method Based on Level Set

In order to adapt the intensity inhomogeneous in IR images, this paper proposes a novel level set initialization method by combining the template initialization and local energy minimization. As shown in Fig.1, the system is composed of two sections: object region selection and edge detection. In the region selection section, we select a plurality of regions with the relative position and the same size respectively in the IR image and the template image by certain rules. In the edge extraction section, firstly, we initialize the object regions by the coastline contours in the template, and then we complete edge detection for object region through many times of iteration calculation. The detection results are the coastline contours in IR images.

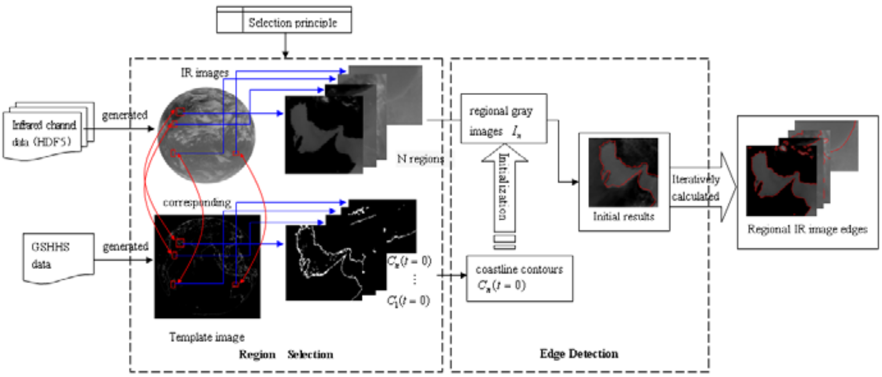

Fig. 1. Level set system based on template initialization

Object Region Selection. When selecting regions, we should pay attention to the exclusion of adverse factors, i.e. choosing the cloudless regions. At the same time, we should try to select the regions with better features too, such as the boundaries of selected regions with corners, continuous, not far away relative to the earth center.

Initialization Based on Template. Traditional level set algorithm is sensitive to the initialization conditions. Different initialization may lead to different evolution results. This paper generates the global coastline template images according to the Global Self-consistent Hierarchical High-resolution Shorelines (GSHHS) data, and then initializes level set by template images. In practice, we set the initial state to the coastline $C_n(t=0)$ in the evolution image I_n'. This means that the initial contour of the level set algorithm is consistent with template coastline. While matching, both the x-axis and y-axis offset of I_n relative to I_n' are no more than seven pixels. So we can find out, initial value of the level set algorithm is closed to the final evolution result, which can greatly reduce the number of iterations, thereby reduce the amount of computation. To some extent, this approach improves the accuracy and stability of the algorithm.

Region-Scalable Energy Model. In this section, we construct a region-scalable energy model [15] as the energy functional in level set method. Minimizing the energy functional can make the contour curves gradually approach the target boundary in the image, and thus achieve the purpose of the edge detection.

Consider a given vector valued image $I:\Omega \to \Re^d$, where $\Omega \subset \Re^n$ is the image domain, and is the dimension of the vector $I(x)$.Let C be a closed contour in the image domain Ω, which separates Ω into two regions: $\Omega_1 = outside(C)$ and $\Omega_2 = inside(C)$. For a given point $x \in \Omega$, we define the following local energy:

$$\begin{aligned} & e_x(C, f_1(x), f_2(x)) \\ & = \sum_{i=1}^{2} \lambda_i \int_{\Omega_i} K_\sigma(x-y)\,|\,I(y)-f_i(x)\,|^2\, dy \end{aligned} \tag{1}$$

where $K_\sigma(u) = \frac{1}{(2\pi)^{n/2}\sigma^n} e^{-|u|^2/2\sigma^2}$ is a Gaussian kernel, with a scale parameter $\sigma > 0$, λ_i is positive constant, and $f_i(x)$ is the approximation of image intensities in Ω_i.

In (1), the energy e_x is described by a weighted mean square error, with the weight $K_\sigma(x-y)$. Due to the localization property of the kernel function, the contribution of the intensity $I(y)$ to the energy e_x decreases increasingly as the point y goes away from the center point x. Therefore, only the points y in the neighborhood $\{y:|x-y|<3\sigma\}$ are, $I(y)$ is dominant in the energy e_x. The values $f_1(x)$ and $f_2(x)$ approximate the image intensities in a region centered at the point x, whose size can be controlled by the scale parameter σ. The energy e_x with a small σ only involves the intensities within a small neighborhood of the point x, while the energy e_x with a large σ involves the image intensities in a large region centered at x. Therefore, the energy e_x is region-scalable.

Given a center point x, the energy e_x can be minimized when the contour C is exactly on the object boundary and the estimated values f_1 and f_2 optimally approximate the local image intensities on the two sides of C. To obtain the entire object boundary, we must find a contour C that minimizes the energy e_x for all x in the image domain Ω. This can be achieved by minimizing the integral of e_x over all the center points x in the image domain Ω, namely, $\int e_x(C, f_1(x), f_2(x))dx$. In addition, it is necessary to smooth the contour C by penalizing its length. Therefore, we define the following energy functional for a contour C:

$$\begin{aligned} &E(C, f_1(x), f_2(x)) \\ &= \int e_x(C, f_1(x), f_2(x))dx + \upsilon |C| \end{aligned} \tag{2}$$

To handle topological changes, we will convert it to a level set formulation. Let the level set function ϕ take positive value outside the contour C and negative value inside C. Let H be the Heaviside function, then the energy functional $e_x(C, f_1(x), f_2(x))$ can be expressed as

$$e_x(C, f_1(x), f_2(x)) = \sum_{i=1}^{2} \lambda_i \int_{\Omega_i} K_\sigma(x-y)|I(y)-f_i(x)|^2 M_i(\phi(y))dy \tag{3}$$

Let $M_1(\phi) = H(\phi)$ and $M_2(\phi) = 1 - H(\phi)$ in (3). Thus, the energy E in (2) can be written as

$$\begin{aligned} &E(C, f_1, f_2) \\ &= \sum_{i=1}^{2} \lambda_i \int (\int K_\sigma(x-y)|I(y)-f_i(x)|^2 M_i(\phi(y))dy)dx + \upsilon \int |\nabla H(\phi(x))| dx \end{aligned} \tag{4}$$

Where the last term $\int |\nabla H(\phi(x))| dx$ computes the length of the zero level contour of ϕ, can be equivalently expressed as the integral $\int \delta(\phi(x)) |\nabla \phi(x)| dx \cdot$

In practice, the Heaviside function H is approximated by a smooth function H_ε defined by

$$H_\varepsilon(x) = \frac{1}{2}[1 + \arctan(\frac{x}{\varepsilon})] \tag{5}$$

The derivative of H_ε is

$$\delta_\varepsilon(x) = H_\varepsilon^{'}(x) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + x^2} \tag{6}$$

The energy functional $E_\varepsilon(C, f_1, f_2)$ can be approximately written as

$$\begin{aligned} & E_\varepsilon(C, f_1, f_2) \\ & = \sum_{i=1}^{2} \lambda_i \int (\int K_\sigma(x-y) \,|\, I(y) - f_i(x) \,|^2\, M_i^\varepsilon(\phi(y))dy)dx + \upsilon \int |\nabla H_\varepsilon(\phi(x))|\, dx \end{aligned} \tag{7}$$

Where $M_1^\varepsilon(\phi) = H_\varepsilon(\phi)$ and $M_2^\varepsilon(\phi) = 1 - H_\varepsilon(\phi)$. To preserve the regularity of the level set function ϕ, we add the last term for the energy functional, defined as

$$P(\phi) = \int \frac{1}{2}(|\nabla\phi(x)| - 1)^2 dx \tag{8}$$

Therefore, we construct the final energy functional as

$$F(\phi, f_1, f_2) = E_\varepsilon(\phi, f_1, f_2) + \mu P(\phi) \tag{9}$$

where μ is a positive constant.

We use the steepest descent method to minimize the energy functional (9). For a fixed level set function ϕ, the functions $f_1(x)$ and $f_2(x)$ that minimize $F(\phi, f_1, f_2)$ satisfy the following Euler–Lagrange equations

$$\int K_\sigma(x-y) M_i^\varepsilon(\phi(y))(I(y) - f_i(x))dy = 0, \quad i = 1,2 \tag{10}$$

From above (10), we obtain

$$f_i(x) = \frac{K_\sigma(x) * [M_i^\varepsilon(\phi(x))I(x)]}{K_\sigma(x) * M_i^\varepsilon(\phi(x))}, i = 1,2 \tag{11}$$

Keeping f_1 and f_2 fixed, we minimize the energy functional $F(\phi, f_1, f_2)$ with respect to ϕ using the steepest descent method as follows:

$$\begin{aligned}\frac{\partial\phi}{\partial t} &= -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) + \upsilon\delta_\varepsilon(\phi)div(\frac{\nabla\phi}{|\nabla\phi|}) \\ &+\mu(\nabla^2\phi - div(\frac{\nabla\phi}{|\nabla\phi|}))\end{aligned} \tag{12}$$

Where $e_i(x) = \int K_\sigma(y-x)|I(x) - f_i(y)|^2\, dy, i = 1,2$, the above (12) is the level set evolution equation to be solved in the proposed method.

Implementation. In PDE (12), all of the partial derivative can be discretized into a finite difference, and then the left side of the equal sign can obtain a forward time difference of ϕ, so we can achieve the desired iterations according to the PDE (12). During initialization, according to the information provided by template, the value of land areas is initialized to the -2.0, the value of marine areas is initialized to 2.

4 Experimental Results

In this section, we present the experimental results of our model, and compare with the experimental results of other commonly used methods, such as Sobel operator, Canny operator, and traditional level set method. The proposed model was implemented on a computer with Intel Core i7-2920XM 2.5GHz CPU, 2G RAM, and Windows XP operating system. For all the experiments referred later in this section, we use infrared channel images of FY-2 satellite as processing objects; the sizes of the images are 2288×2288. We used the same parameters of $\sigma = 3.0$, $\varepsilon = 1.0$, $\lambda_1 = 1.0$, $\lambda_2 = 2.0$, time-step $\Delta t = 0.1$, $\mu = 1$ and $\upsilon = 0.004 * 255 * 255$ for all the experiments in this section.

Comparison with Common Edge Extraction Algorithm. In different regions of the infrared image, the degree of cloud coverage is different. In order to test the effect and accuracy of the algorithm from the cloudy and cloudless regions respectively, we randomly select plurality of regions to experiment. The regional boundaries in figure.2 and figure.3 are less affected by cloud, have a higher definition. The detected edge is discontinuity by using Sobel operator, not conducive to the subsequent processing. Canny operator can extract edge accurately, but due to the influence of the selected threshold, double-edge phenomenon occurs in some place. The image edge after processing by our algorithm is continuous, smooth, and with a higher accuracy.

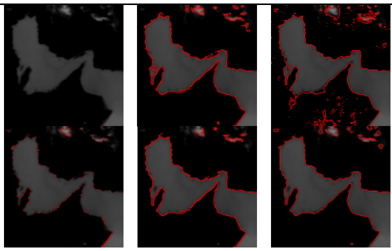

Fig. 2. Results of our method and common edge extraction methods for a regional IR image (cloudless-1). Column 1: up: Original image, and down: the result of Sobel operator; Column 2: up: the result of canny operator with the thresholds (43-129), and down: with the thresholds (87-261). Column 3: up: initial contours of our method, and down: final contours of our method.

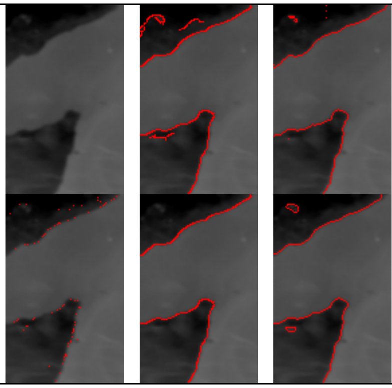

Fig. 3. Results of our method and common edge extraction methods for a regional IR image (cloudless-2). Column 1: up: Original image, and down: the result of Sobel operator; Column 2: up: the result of canny operator with the thresholds (32-96), and down: with the thresholds (63-189). Column 3: up: initial contours of our method, and down: final contours of our method.

The regional boundaries in Figure.4 and Figure.5 are affected seriously by cloud, have a lower definition. The detected edge is not continuity by using Sobel operator, even only individual edge points. The detected edge by using canny operator is also discontinuous and there exist more useless edges. Using our algorithm can maximally avoid the interference of cloud, and obtain accurate, continuous and smooth edges.

Comparison with Traditional Level Set Method. In the traditional level set algorithm, we use standard coastline as the initial state of contour evolution. From Figure.6 and Figure.7, we can see the detected sea-land boundary is still missing after 2000 iteration steps. By comparison, our algorithm can detect the sea-land boundary more accurately only after 20 iteration steps, thereby has a great advantage in the computation and accuracy.

Finally, in order to compare our method with the traditional level set method quantitatively, we randomly select 25 regional images, respectively by using the two methods for edge extraction experiments. The computational time and iteration number for these images are listed in Table 1.

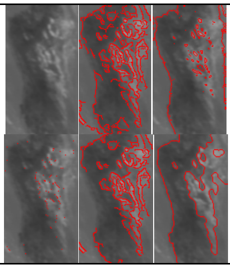

Fig. 4. Results of our method and common edge extraction methods for a regional IR image (cloudy-1). Column 1: up: Original image, and down: the result of Sobel operator; Column 2: up: the result of canny operator with the thresholds (16-48), and down: with the thresholds (22-66). Column 3: up: initial contours of our method, and down: final contours of our method.

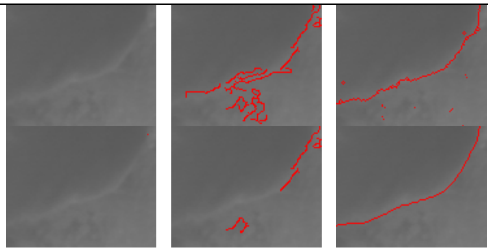

Fig. 5. Results of our method and common edge extraction methods for a regional IR image (cloudy-2). Column 1: up: Original image, and down: the result of Sobel operator; Column 2: up: the result of canny operator with the thresholds (11-33), and down: with the thresholds (12-36). Column 3: up: initial contours of our method, and down: final contours of our method.

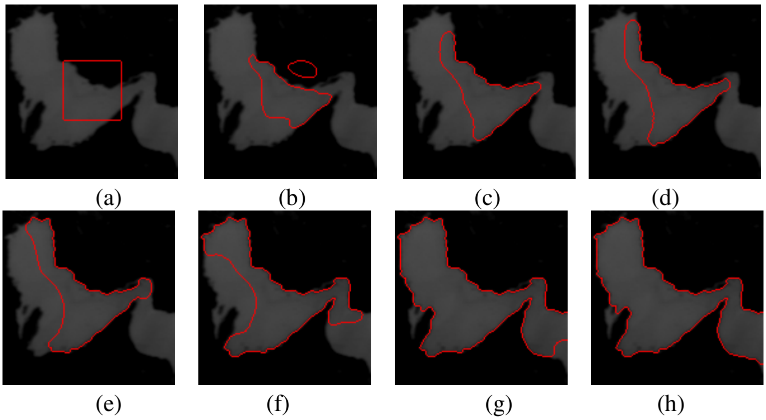

Fig. 6. Results of the traditional level set for a regional IR image. (a): Initial contours. (b): 20 iterations. (c): 100 iterations. (d): 200 iterations. (e): 400 iterations. (f): 800 iterations. (g): 1600 iterations. (h): Final contours, 2000 iterations.

Fig. 7. Results of our method for a regional IR image. Column 1: Initial contours. Column 2: Final contours, 20 iterations.

Table 1. The performance comparisons of our model and traditional level set model

	Our model	Traditional level set model
Average iteration number	21	2485
Average computational time (s)	2.16	273.35

5 Conclusions

With the increase of the remote sensing satellite data, the preprocessing of satellite remote sensing data becomes more and more time consuming. According to the characteristics of remote sensing images, we propose a new coastline detection method based on prior knowledge and level set method. This method uses the information of GSHHS to optimize the initialization procedure, and use an effective energy model, which is applicable to the infrared remote sensing image for sea-land boundary detection. The experiment results show that the proposed method can obtain satisfactory results, and can greatly reduce the computational complexity.

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