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Interactive geospatial object extraction in high resolution remote sensing images using shape-based global minimization active contour model

Ge Liu [a,b,*], Xian Sun [a], Kun Fu [a], Hongqi Wang [a]

[a] *Key Laboratory of Technology in Geo-spatial Information Processing and Application System, Institute of Electronics, Chinese Academy of Sciences, Beijing, China*
[b] *University of Chinese Academy of Sciences, Beijing, China*

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ABSTRACT

In this work, we propose a novel algorithm to extract geospatial objects with regular shape in remote sensing images, using shape-based global minimization active contour model (SGACM). Specially, we define a new energy function combining both image appearance information and object shape prior, and minimize it with an iterative global minimization method. In the proposed energy, not only image edge and color information are utilized, but also a new shadow region term is introduced to obtain more accurate extraction result; moreover, a new shape energy term in which we use kernel principle component analysis (KPCA) to model shapes is defined in our method, which provides good constraint on the extraction process and makes results more robust with respect to disturbances. In the energy numerical minimization process, Split Bregman method is used to get a global solution which overcomes the drawback of running into local minimum for the traditional level set method. Experiment results demonstrate more robustness and accuracy of our proposed method compared with others without shape constraint.

1. Introduction

Object extraction is one of the most challenging tasks for high resolution remote sensing images, and plays important roles in image interpretation and object recognition. As the spatial resolutions of sensors increase, more abundant spatial and contextual information is provided in images. So the extraction of geospatial objects even with complex structure and surrounded by disturbing background, e.g. aircraft, is becoming considerable and feasible.

Generally, object extraction can be seen as a two-phase segmentation problem. It aims to segment out the interested target under various situations. As for remote sensing images, object extraction often suffers from several problems, including intensity variation, various background disturbances, complex structure of object, shadow, bad image quality such as blur, poor contrast and so on.

Despite these challenges, many approaches have been achieved in recent years. Among them, active contour model gives a flexible segmentation strategy and attracts much attention. It provides a convenient framework to utilize various information such as image edge and region intensity, and has been widely used in many remote sensing applications, e.g. water and land separation (Silveira and Heleno, 2009), contour extraction (Jing et al., 2011; Xu et al., 2011).

Until now, many works have explored image appearance information and concentrated on objects in remote sensing that have little regularity on shape. Whereas there are also many other objects in remote sensing with regular or somewhat fixed shapes, for example, house roof, aircraft, ship, oilcan, and so on. Extractions of these targets should be well constrained on shape to obtain better results. In other words, segmentation should combine both image appearance and object shape information. So far, a lot of researches have been achieved on this issue in the processing of natural images (Cremers et al., 2006; Malcolm et al., 2007; Plissiti et al., 2011; Liu et al., 2011a; Alessandrini et al., 2011), while in remote sensing images, only a few works have been done. Existing works in remote sensing include the extraction of rectangular objects by imposing shape constraint (Korting et al., 2011), circular objects detection through shape parameters (Han and Fu, 2012), building contour extraction using active contour model (Ahmadi et al., 2010), and so on. These shape prior based methods have greatly improved the effect of detection and segmentation. Beside these works, more researches are still needed in remote sensing to extract objects with regular shape e.g. aircraft which has complex structure.

In this paper, we continue to focus on extracting geospatial objects with regular shape in remote sensing images. And a new algorithm that combines both image appearance information and object shape prior is proposed in our method. There are two novelties as follows.

First, we propose a new energy function based on active contour model. This new energy function consists of three complementary parts. One is edge weighted regular term, with which the

* Corresponding author. Address: No. 19, North 4th Ring Road West, Haidian District, Beijing 100190, China. Tel.: +86 010 58887208 8933; fax: +86 010 58887200.
E-mail address: liuge86@163.com (G. Liu).

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segmentation contour tends to the boundary location and small noises would be removed. The second part contains three region terms. In the first term, intensity probability distribution is used to model fore/background. Shadow is one kind of important information in remote sensing images, whereas it is rarely used in previous studies. Here we utilize shadow information in the second region energy term to get more accurate extraction result. An interactive bounding box needs to be provided in our method to give initialization of intensity distribution like that in grab cut (Rother et al., 2004), and it is used as a strong constraint in the third region term. The last part is a new defined shape prior based energy term. In our method, KPCA is used to construct the shape prior considering its excellent effect on shapes modeling (Dambreville et al., 2008). With this shape energy term, our method shows more resistance to background disturbances compared with other segmentation methods without shape constraint.

Second, we minimize the proposed energy function with a global minimization method – Split Bregman method in an iterative way. This avoids the problem of local minimum in the conventional level set method, and also provides much faster calculation in optimization compared with other global minimization approaches (Goldstein et al., 2010). Experiments on two classes of geospatial objects show that our proposed method, compared with many others, exhibits much better robustness with respect to various disturbances and produces more accurate segmentation results.

The rest of this paper is organized as follows. Section 2 briefly reviews the active contour model. Section 3 gives detail description and analysis on our proposed algorithm and presents the iterative global minimization process. Experiments results and evaluations are illustrated in Section 4. Section 5 concludes this paper.

2. Overview of active contour model

2.1. Theoretical model

The active contour model, based on the theory of surface evolution and geometrics, has been extensively applied to image processing field, such as image denoising and segmentation. The general energy form for any two-phase active contour model is given as follows (Bresson, 2009):

$$F_{ACM}(C) = \int_C g_b(C,s)ds + \lambda_1 \int_{C_{in}} g_r^{in}(C_{in},x)dx + \lambda_2 \int_{C_{out}} g_r^{out}(C_{out},x)dx \tag{1}$$

where $\lambda_1 \geqslant 0, \lambda_2 \geqslant 0$ are constants. C is the closed segmentation contour; C_{in} and C_{out} are the inside and outside region, respectively; g_b is a boundary function and ds is the arc length element of contour; g_r^{in} and g_r^{out} are two defined region functions. The first term is the integration along contour, and the last two are region energies. An optimal segmentation contour is considered to be obtained by minimizing the above energy function.

According to the energy form, existing active contour models are classified into two categories: edge-based models and region-based models. Edge-based models mainly take use of local edge information, and evolve contours towards desired boundaries. The most popular one is the geodesic active contours (GAC) method (Caselles et al., 1997), which is defined by the following formula:

$$E_{GAC}(C) = \int_0^{L(C)} g(|\nabla I(C(s))|)ds \tag{2}$$

where $L(C)$ is the length of C, ds is the Euclidean element of length, and g is an edge indicator function as follows:

$$g(|\nabla I(C(s))|) = \frac{1}{1+|\nabla I(C(s))|^2} \tag{3}$$

where ∇ is the standard gradient operator. This edge indicator function ranges from 0 to 1, and takes large values on smooth region while small values on edges. So the minimization of (2) will attract contours to be located on object boundaries.

Compared with edge-based models, region-based models utilize statistic information of image region to guide the motion of contours, and are more robust with respect to noises and weak edges. One of the most popular region-based models is the two-phase, piecewise-constant Mumford–Shah (PCMS) model (Chan et al., 2006; Chan and Vese, 2001) with the following energy:

$$F(c_1,c_2,C) = \mu \cdot Length(C) + \lambda \int_{inside(C)} |u_0(x,y)-c_1|^2 dxdy + \lambda \int_{outside(C)} |u_0(x,y)-c_2|^2 dxdy \tag{4}$$

where $\mu \geqslant 0, \lambda \geqslant 0$ are fixed parameters, u_0 denotes the test image. PCMS is based on the assumption that image intensities in each of the two regions are statistically homogeneous, as denoted by c_1 and c_2 in (4). Further, many other methods are proposed to address the problem of intensity inhomogeneous, such as piecewise-smooth model (PSM) (Vese and Chan, 2002) and Region-Scalable Fitting (RSF) (Li et al., 2008), which reformulate the region functions. However, how to choose the region functions is application dependent, for example, finite mixture of lognormal densities for water and land in SAR images (Silveira and Heleno, 2009) and RSF in oil slick infrared images (Jing et al., 2011).

2.2. Minimization of ACM

A very popular method of minimizing all the above energy functions is the level set method. In the level set formulation, contour C is represented as the 0-level set of a function $\phi : R^N \to R$, which is $\{x \in R^N : \phi(x) = 0\}$, and the inside and outside regions are denoted by $\{x \in R^N : \phi(x) > 0\}$ and $\{x \in R^N : \phi(x) < 0\}$, respectively. With this representation, the above energy, taking PCMS for example, can be expressed as follows:

$$F(c_1,c_2,\phi(x,y)) = \mu \int_\Omega |\nabla H_\varepsilon(\phi)|dxdy + \lambda \int_\Omega |u_0(x,y) - c_1|^2 H_\varepsilon(\phi)dxdy + \lambda \int_\Omega |u_0(x,y) - c_2|^2 (1-H_\varepsilon(\phi))dxdy \tag{5}$$

where $H_\varepsilon(\phi)$ is a smooth approximation to the Heaviside function (Chan and Vese, 2001). Iterative scheme and variational method are used to minimize (5). In specific, the following two steps are repeated until converge:

(1) ϕ being fixed, the optimal values of c_1 and c_2 are:

$$c_1 = \frac{\int_\Omega I(x,y)H_\varepsilon(\phi(x,y))dxdy}{\int_\Omega H_\varepsilon(\phi(x,y))dxdy}, \quad c_2 = \frac{\int_\Omega I(x,y)(1-H_\varepsilon(\phi(x,y)))dxdy}{\int_\Omega (1-H_\varepsilon(\phi(x,y)))dxdy} \tag{6}$$

(2) c_1 and c_2 being fixed, ϕ is calculated using the Euler–Lagrange equation:

$$\frac{\partial \phi}{\partial t} = \delta_\varepsilon(\phi)\left\{\mu \cdot div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - \lambda(u_0(x,y)-c_1)^2 + \lambda(u_0(x,y)-c_2)^2\right\} \tag{7}$$

Variational calculation is a gradient descent method. However, for fixed c_1 and c_2, the function (5) is non-convex, and may have more than one minimizer. So the gradient descent based optimization easily runs into local minimum. This is a common difficulty in many variational image processing models, and it makes the initialization critical to get satisfactory result. To solve this problem,