STOCHASTIC MOTION AND THE LEVEL SET METHOD IN SEMI-AUTOMATIC BUILDING DETECTION

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ABSTRACT:

Image segmentation is defined as partitioning an image into non-overlapping regions based on the intensity or texture. The active contour methods with comes from the basic ideas of Stochastic Motion and the Level Set Method provide an effective way for segmentation, in which the boundary of an object usually with large image gradient value is detected by an evolving curve. But, these methods have limitations due to the fact that real images may have objects with complex geometric structures and shapes, and are often corrupted by noise. Developing more robust and accurate active contour methods has been an active research area since the idea of the methods was proposed. In this paper, we propose a new active contour method and apply the method to remote sensing image segmentation. This new method uses combination of boundary-based modelling and region-based modelling. The new method is more efficient and effective, especially in detecting structures with noise.

1. INTRODUCTIO

Extraction of geospatial semantic information from digital images is one of the most complex and challenging tasks faced by computer vision and photogrammetry communities. Semantic information such as buildings.in particular is required for varieties of applications such as urban planning, creation of urban city models.

For decades, manual extraction of semantic information in urban areas has been by conventional photogrammetry using aerial photos. This method is tedious, expensive, and requires well-trained people.

In recent years we have experienced the lots of emergence of high-resolution space borne images, which have disclosed a large number of new opportunities for large-scale for urban areas topographic mapping, and high efficiently extraction of semantic information is a key technology problem, the most potential way to deal with it is semi automatic reorganization.

The insight which we brought here is that there are many foreknow information about semantic information, especially about buildings, roads ect. We can use them to make recognition.

Based on recent work on Stochastic Partial Differential Equations (SPDEs), this paper presents a simple and well-founded method to implement the stochastic evolution of a curve to detect structured and unstructured urban settlements areas from high-spatial resolution panchromatic imagery.
In this paper we focus on building detection on high resolution remote sensing image, leading to what we call Stochastic Active Contours. The active contour method (ACM) for image segmentation was proposed in late 1980's. In ACM, a curve is evolved towards the object boundary under a force, until it stops at the boundary in which the curve moves to minimize the energy. These various energy functions used in ACM can be roughly categorized as boundary-based modelling, region-based modelling or a combination of both.

In boundary-based modelling, boundaries are characterized by a so-called "descriptor":

$$J(\Gamma) = \int_{\Gamma} k(s)ds$$

The key idea is to find contour minimizing cost function J , at mean time the curve has the minimum length in the metric defined by function k . As the J is a line integral in the curve Γ so it only uses the information along the Γ .

In region-based modelling region is characterized by a "descriptor":

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$$J(\Omega) = \int_{\Omega} k(x, y)dxdy$$

J is a region integral , all the information inside region Ω is used, so it much more "global" than boundary-based modelling, but it has a weak point: Sensitivity to initial segmentation.
There is an effort to integrate boundary-based with region-based approaches. Pair wise similarities or dissimilarities between points are also introduced into cost functions. Graph partitioning methods (GPM) is one of the popular tools for minimizing pair wise similarity based cost functions. A general advantage of GPM is its global minimization techniques, which are desirable for the segmentation problem.

In this paper, we introduce novel weighted Graph partitioning methods. Main contributions of this paper include:

Introduction of a new variation cost functions which are based on weighted pair wise similarities. Weight changes according to the pointers' positions. Different kind of similarity can be defined for different images.

An efficient computing strategy is proposed. The hybrid boundary-based modelling and region-based modelling method frameworks for pair wise similarity based cost functions requires excessive memory size and CPU computing ability, and naïve implementations are not practical even on high end workstations. We introduce novel pre-segmentation methods for efficient implementation of the curve evolution techniques that are derived for the minimization of pair wise dissimilarity based cost functions.

2. WEIGHTED GRAPH PARTITIONING ACTIVE CONTOURS

2.1 Graph Partitioning Active Contours

This insight of graph theoretic is as following. Assume is a representation of an undirected graph, where V are the vertices and E are the edges between these vertices. V corresponds to pixels in an image or small regions (set of connected pixels). $\omega(u,v)$ is a function of the dissimilarity between nodes u and v . Suppose V is divided into two disjoint sets, A and B , $V = A \cup B$, $A \cap B = \varnothing$, by simply removing edges connecting the two parts, cut of A and B can be defined as:

$$cut(A,B) = \sum_{u \in A, v \in B} \omega(u,v) \qquad (1)$$

Then image segmentation problem is formulated as minimum cut technique which is a graph partitioning method. In continuous domain, the equivalent energy functional of (1) can be written as:

$$E = \iint_{R_{in(C(t))}} \iint_{R_{out(C(t))}} \omega(u,v)dudv \qquad (2)$$

To the minimization problem given in (2), a graph partitioning active contours (GPAC) method is introduced, in tis method, a steepest descent method, in which a curve is instantiated and evolved towards the minimum, can be used to solve this minimization problem. The following theorem can be derived:

Theorem: Let N be the outward normal of the curve C. The curve evolution equation that corresponds to the steepest descent minimization of (2) is:

$$\frac{\partial X}{\partial t} = \left[\iint_{R_{in}(C(t))} \omega(X,p)dp - \iint_{R_{out}(C(t))} \omega(X,p)dp \right] N \qquad (3)$$

Where X is point on the contour C , $R_{in}(C(t))$ and $R_{out}(C(t))$ are the regions inside and outside of the contour C .

2.2 Weighted Graph Partitioning Active Contours

In GPAC model, the contributions of the pixels in the different regions are all the same. We will extend the model to suppose the condition in which the pixels in the different regions have different contribution in the cost function. For example, in some images with blur boundary, there is very little difference between the pixels at the different side of boundary, so the dissimilarities between the pixels at the different side of boundary have little contribution to the cost function.

Further more, region-based models are sensitive to initial segmentation and have little local properties. In order to enhance the model's local properties, we introduce dissimilarity weight into GPAC according to the pixels' positions. With dissimilarity weight, pixels at different regions have different contributions to the cost function. We refer this novel model as Weighted Graph Partitioning Active Contours(WGPAC).

In the definition of (1), dissimilarity function unction $\omega(u,v)$ is a function independent of time t , and the (2) is also based the fact that $\omega(u,v)$ is independent of t . In WGPAC, we add weight function $f(u.,v)$ to $\omega(u,v)$, so the cost function is:

$$E = \iint_{R_{in}} \iint_{R_{out}} f(u,v,t)w(u,v)dudv \qquad (4)$$

Let $W(u,v) = f(u,v)\omega(u,v)$, then (4) becomes:

$$E = \iint_{R_{in}} \iint_{R_{out}} W(u,v)dudv \qquad (5)$$

Here $W(u,v)$ is symmetric function .In order to minimize (5), We introduce Heave function and Dirac function:

$$H(\phi) = \begin{cases} 1 & (\phi \geq 0) \\ 0 & (\phi < 0) \end{cases} \qquad (6)$$

Suppose $C(t)$ is the active contour and ϕ is its level set function, the integration of function $f(p)$ in the region inside $C(t)$ is:

$$\iint_{R_{in}(C(t))} f(p)dp = \iint_{\Omega} f(p)H(\phi(p))dp \qquad (7)$$

Similarly, the integration of function $f(p)$ in the region outside $C(t)$ is：

$$\iint_{R_{out}(C(t))} f(p)dp = \iint_{\Omega} f(p)(1-H(\phi(p)))dp \quad (8)$$

Then, the energy function is:

$$\begin{aligned} E(W) &= \iint_{R_{in}} \iint_{R_{out}} W(u,v,t)dudv \\ &= \iint_{\Omega} \iint_{\Omega} W(1-H(\phi(u)))(H(\phi(v)))dudv \end{aligned} \quad (9)$$

In this way, the problem changes to find a level set function ϕ with which (6) gets its minimum. A simplified form of this problem is depicted as below function:

$$\begin{aligned} &\frac{\partial \phi(v)}{\partial t} = \delta(\phi(v)) \\ &[\frac{\iint_R \omega(v,u) w(\phi(u)) H(\phi(u) du}{\iint_R w(\phi) H(\phi(u)) du} \\ &- \frac{\iint_R \omega(v,u) w(\phi(u))(1-H(\phi(u))) du}{\iint_R w(\phi(u))(1-H(\phi(u))) du}] - \gamma\kappa |\nabla\phi| \end{aligned} \quad (9)$$

where $w(.)$ is weight function, and then $w(\varphi(p))$ is the dissimilarity weight of the pixel p and k is curvature of ϕ.

2.3 Watershed –based GPAC

The computation of the dissimilarities possesses most of memory and CPU resource during the WGPAC method. As for a image of M*N, a dissimilarity matrix W of size $MN \times MN$ should be calculated. Although W is a symmetric matrix, it requires very large memory resource.

We introduce a watershed pre-segmentation algorithm. First, we segment the image into m regions $A_k (k = 1,...,m)$ by watershed methods. Let $F(x, y)$ is the property of pixel (x, y). As for region A_k, the average property F'_k is:

$$F'_k = \frac{1}{Area(A_k)} \int_{A_k} F(x,y)dxdy \quad (10)$$

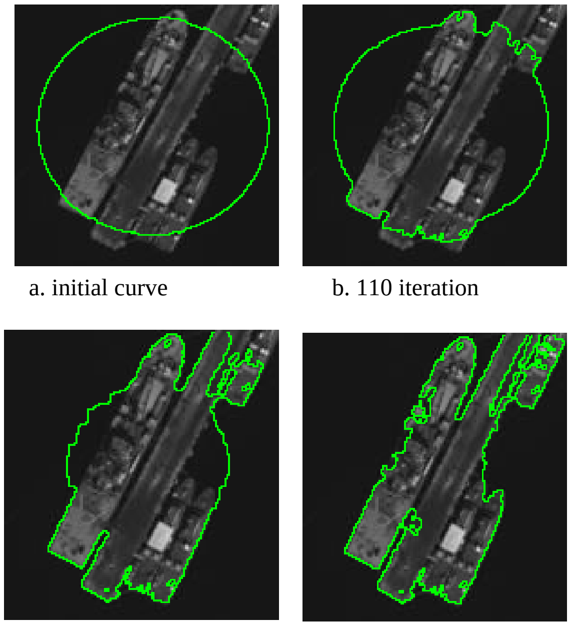
Where $Area(A_k)$ is area of A_k. The dissimilarities matrix W becomes a new dissimilarities matrix W' of $MN \times m$, where the dissimilarity between pixel (x, y) and region i is:

$$\omega'(x, y, i) = \|F(x, y) - F'_i\| \quad (11)$$

In order to reduce the number of regions, first we minify the original image n times and get a result image I_1, second I_1 are segmented into S_1 by watershed method, last we magnify S_1 n times and the magnification result S_0 is the target regions.

3. RESULTS AND DISCUSSION

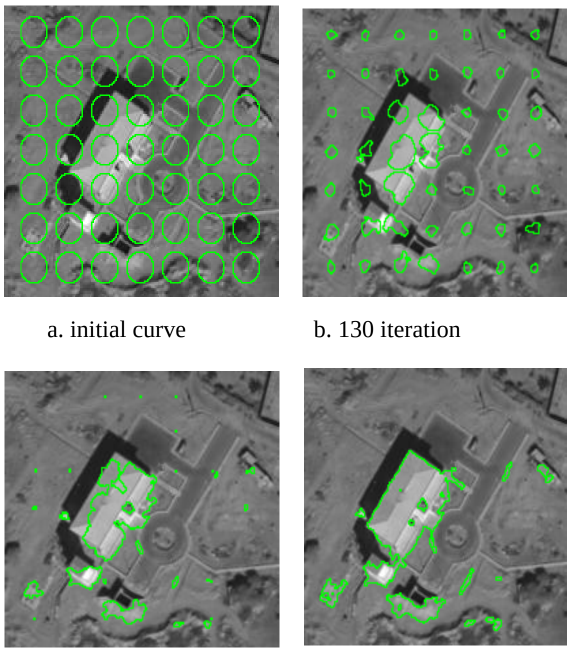
In Fig.1 and 2, we applied our method on a real high resolution remote sensing images, Fig.1 is an image of a harbour and ships, and Fig.2 is an image of a buildings, after 500 iteration a reasonable good segmentation results were gotten.



a. initial curve b. 110 iteration

c. 370 iteration d. 490 iteration

Figure 1 harbour and ships



a. initial curve b. 130 iteration

c. 380 iteration d. 510 iteration

Figure 2 buildings

In this paper, we introduce a weighted and hybrid active contour model. The problem of image segmentation is converted into minimization problem of the total dissimilarities between the pixels by defining different dissimilarity metrics. Our algorithm is flexible because the dissimilarity is easy to change. A watershed pre-segmentation is taken to accelerate the algorithm. We can adapt the weight to get better segmentation results according to the segmented image property.

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