A Combined Approach for Building Detection in Satellite Imageries using Active Contours

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Abstract - *This paper presents a combined approach for detecting building rooftops in satellite images. The proposed method is an active contour based approach combined with local texture and edge information for curve evolution. This method allows extraction of multiple buildings simultaneously. Verification for accepting or rejecting rooftop hypotheses is performed based on the existence of shadow evidence along the sun direction in the immediate surrounding neighborhood of each hypothesis. Experimental results for QuickBird satellite imageries confirm the efficiency and accuracy of the proposed method in identifying building structures with complicated rooftops.*

Keywords: active contour, rooftop detection, 3D city map generation, satellite image processing

1 Introduction

Automatic extraction of building profiles from satellite images is one of the most challenging problems in applications of remotely sensed image processing including 3D building reconstruction and 3D map generation. In recent years, various roof detection approaches are proposed using edge/line/corner features, graph and learning methods, and active contour techniques.

Due to the complexity of automatic building detection, many researchers integrate satellite images with height information provided by Digital Elevation Maps (DEM), Lidar-based height data or stereo images. Brunn and Weidner [1] employed a Digital Surface Model (DSM) to apply a classifier based on Bayesian net to detect building profiles. Some researchers incorporated line-based approaches to detect rooftops with polygonal profiles [2]. Others have employed active contours [3-6]. Ahmady et. al. proposed a method for building extraction using active contour without edge [3]. In their method a series of circles were distributed homogenously over the entire image as initial curves. The boundaries were detected by evolving the initial curves. While their method had the advantage of automatic initialization, it could suffer from inefficiency due to the homogenous distribution of the initial curves. Moreover the method could be confused in identification of true buildings from areas with similar spectral information such as asphalt streets. Peng et. al. [4] proposed an improved snake model for building detection with a shape recovery score of 83.6%. Their method was based on radiometric and geometric behaviors of buildings. Mayunga et. al [5] proposed a semi automatic approach using radial casting algorithm to initialize snake based contours. Ruther et. al. [6] reported a semi-automatic approach with a shape accuracy of 80% using DSM to generate the initial raised structure hypotheses which were refined later using active contour and dynamic programming.

This paper presents a hybrid approach for detecting building rooftops including curved or polygonal profiles in satellite images. The proposed method utilizes the active contour approach with a curve evolution process that relies on both texture and edge information. Figure 1 shows the flow diagram of the proposed approach.

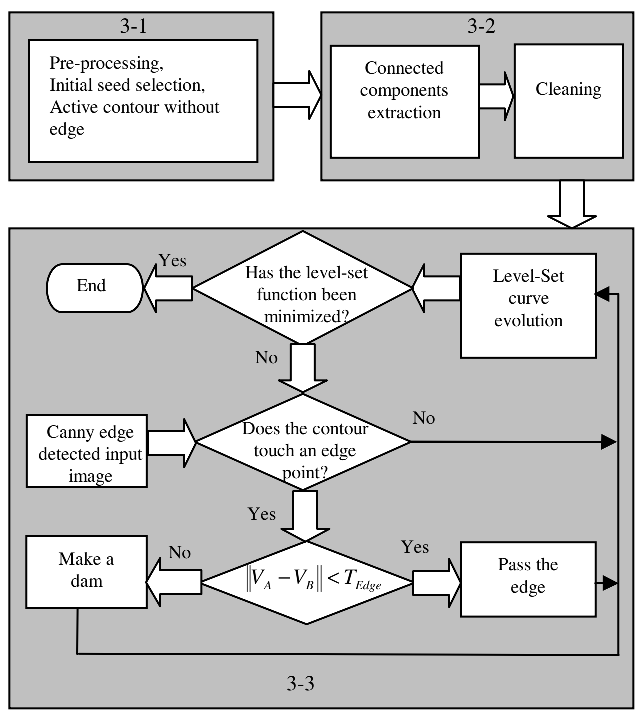


Figure 1. Outline of the proposed method. The numbers 3-1 to 3-3 specify the processing steps in the proposed algorithm.

Specific features of the proposed method are as following:

- The use of local texture in the edge-based contour evolution,
- Extracting multiple buildings simultaneously,
- Less computational complexity compare to methods based on line grouping and graph search.

2 Background

Active contouring (Snakes) is a curve based approach that moves within an image to segment various image regions. The contour moves under the influence of two internal and external forces. The internal energy depends on the contour's shape, and it controls the elasticity and stiffness of the contour. The external energy depends on the local property of the image region and it affects the contour's evolution. Minimization of these two energies is the main concept behind the active contour method. Methods based on active contours can be divided into two groups: (1) region-based and (2) boundary-based.

1) Chan and Vese [7] proposed a region-based active contour method called Active Contour without Edge. Their method could detect objects whose boundaries were not defined by gradient. For a given image $I: \Omega \rightarrow R$ where $\Omega \subset R2$, they proposed the following energy function:

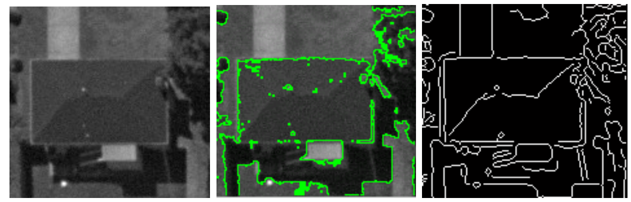
$$F(c_1, c_2, C) = \mu.Length(C) + \upsilon.Area(inside(C)) + \lambda_1 \int_{inside(c)} |I(x,y) - c_1|^2 \, dxdy + \lambda_2 \int_{outside(c)} |I(x,y) - c_2|^2 \, dxdy \quad (1)$$

here $\mu, \upsilon > 0$ and $\lambda_1, \lambda_2 > 0$ are constants. C is the contour and c_1, c_2 are two constants that represent image intensities inside and outside of contour C.

2) The boundary-based active contours are based on image gradient information. Here one way to minimize the energy function is to employ Level Set algorithm proposed by Osher and Sethian [8]. In the level set formulation, the contour C is presented by the zero level set $C(t)=\{(x,y)|\phi(t,x,y)=0\}$ of the level set function $\phi(t,x,y)$. The evolution equation of the level set function ϕ is defined by:

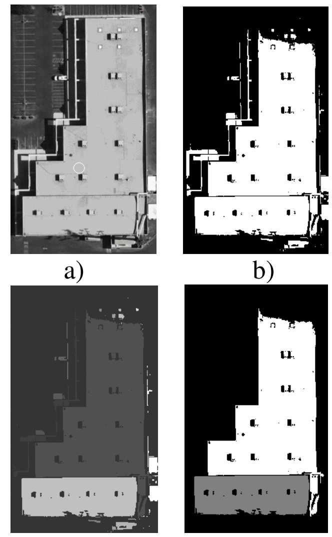
$$\frac{\partial \phi}{\partial t} + F |\nabla \phi| = 0 \quad (2)$$

here F is the speed function and could be a function of $|\phi|$.



a) b) c)

Figure. 2. a) Input image. b) Segmentation by [1] . c) Edge image (Canny).



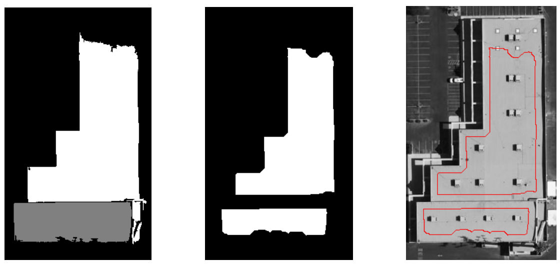
a) b) c) d)

Figure 3. a) Original Image. b) Active Contour without Edge Level Set (white circle in (a) is the initial seed). c) Detected connected components. d) Resultant segments.

3 Proposed Method

Figure 2a shows the rooftop of a building in a satellite image. Figure 2b depicts the resultant segmented image using Active Contour without Edge [7], which in this case fails to identify rooftop boundaries properly. Figure 2c displays the edge information. Clearly edge details include substantial amount of information that could be used in identification of rooftop's boundaries. In the proposed method, we incorporate both texture and edge information in the active contour concept to detect and identify buildings' rooftops. Following steps describe the proposed method in this paper:

3-1) First a seed point (called building seed) is identified on a building. The active contour without edge is applied on the image then. In this step, all areas with the same gray level values and at the same level set (could be from other buildings) are automatically selected. In the urban areas the color of rooftops are not widely variants. In fact many of the neighboring buildings have similar colors. This enables the algorithm to automatically select multiple buildings using only one building seed. There might be more than one building seed required, if there are a variety of buildings with various rooftop intensity values.



a) b) c)

Figure 4. Main components: a) After filling the holes. b) After eroding. c) Automatic contour initialization.

3-2) A connectivity test is run on the resultant regions. The area of each region is inspected and component with small areas are eliminated. A threshold of 20% of the largest component is chosen in this work. This threshold is scene dependent. However, we found that for all urban scenes tested in this work such value works well. The main assumption is that the background in the image is the largest connected component. The background is removed then by eliminating the largest (in area) component. Figure 3d shows the two main components of the image shown in Figure 3a. The boundaries of each one of these main components are used as the initial contours for the edge-based active contour. The detected components are processed using a morphological reconstruction hole filling process [9]. This process is followed by an erosion to ensure that the initial contours stay inside the rooftop definition (Figure 4).

3-3) The boundaries of the main components, from the previous step, are extracted and fed into the edge-based active contour as the initial contours. Here the edge-based active contour with level set evolution [10] is employed. The level set algorithm has several attractive properties comparing to the traditional active contour based methods. One of its main properties is that the level set function could break and yet merge naturally during the evolution process and this is a useful property as many buildings include small objects like air conditioners, satellite dishes and ventilation openings on their roofs. The breaking and merging properties of the level set can help the contour to pass such objects without compromising the accuracy of the detected contours.

The level set method by Li [10] does not require re-initialization. Li surmounted the need of re-initialization by defining a distance regularizing term to penalize for the deviation of the level set function ϕ from a signed distance function defined by:

$$P(\phi)=\int_{\Omega}\frac{1}{2}(|\nabla\phi(x)-1|^2\ dxdy \tag{3}$$

They proposed the following total energy function:

$$\mathcal{E}(\phi)=\mu.P(\phi)+\mathcal{E}_m(\phi) \tag{4}$$

here μ (>0) is a constant that controls the effect of penalizing term (P). ε_m is an external energy that drives the zero level set towards the true object boundaries.

$$\mathcal{E}_m=\lambda.L(\phi)+\upsilon.A(\phi) \tag{5}$$

$$L(\phi)=\int_{\Omega}g.\delta(\phi)|\nabla\phi|dxdy \tag{6}$$

$$A(\phi)=\int_{\Omega}g.H(-\phi)dxdy \tag{7}$$

Here λ is greater than zero (set to 5 for this work) and υ is a constant. L in equation (6) is the length of the contour ϕ, and A in equation (7) is the weighted area inside the curve ϕ. δ and H are variant Dirac and Heaviside functions and g is the edge indicator:

$$g=\frac{1}{1+|\nabla G_\sigma*I|^2} \tag{8}$$

$$\delta(z)=\frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2+z^2} \tag{9}$$

$$H(z)=\frac{1}{2}(1+\frac{2}{\pi}\arctan(\frac{z}{\varepsilon})) \tag{10}$$

I represens the image and G_σ is the Gaussian function with standard deviation σ. For minimizing the $\mathcal{E}$, the following evolution equation is solved:

$$\frac{\partial\phi}{\partial t}=-\frac{\partial\varepsilon}{\partial\phi} \tag{11}$$

Since the initial contour is located inside the building, parameter υ in equation (5) is set to a negative value (-2.5), which naturally enforces the contour to expand and grow outwardly. The initial contours grow until reaching the true boundaries of rooftops. The main emphasize in the edge-based active contour approach is on incorporating the edge values into the contour evolution stopping condition. The existence of noise and the poor quality of some edges in satellite images could make the true boundaries of buildings too weak to be used for stopping the contour evolution. To address this issue additional condition is introduced in the curve evolution procedure. During the curve evolution, as soon as a contour touches an edge point, the length of that edge is computed. The edge will be ignored if its length is too

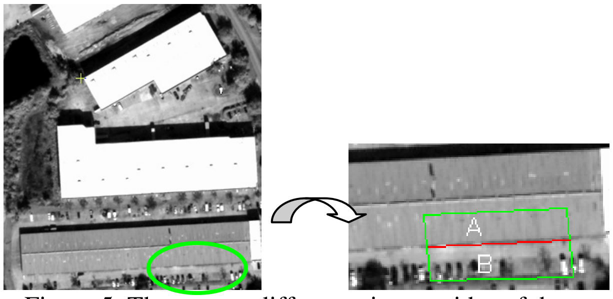


Figure 5. The texture difference in two sides of the contour helps to choose the edge at the rooftop boundary.

small. If the length of the edge is large, statistical features of the image on the two sides of the edge will be calculated to assess whether the edge should be ignored and the evolution should be continued, or the evolution must be stopped.

The statistical information computed here are two vectors V_A and V_B:

$$V_A = [\mu_{1A}, \mu_{2A}, \mu_{3A}], \quad V_B = [\mu_{1B}, \mu_{2B}, \mu_{3B}] \qquad (12)$$

$$m_A = \sum\nolimits_A I_i p(I_i), \quad m_B = \sum\nolimits_B I_i p(I_i) \qquad (13)$$

$$\begin{aligned} \mu_{rA} &= \sum\nolimits_{i=0}^{n_A-1} (I_{iA} - m_A)^r \, p(I_{iA}), \\ \mu_{rB} &= \sum\nolimits_{i=0}^{n_B-1} (I_{iB} - m_B)^r \, p(I_{iB}) \end{aligned} \qquad (14)$$

here m is the local mean, I_{iA} and I_{iB} are A's and B's i^{th} intensity value, $i_A=0,1,\ldots,n_A-1$ and $i_B=0,1,\ldots,n_B-1$ with n_A and n_B the number of discrete gray levels. μ_{rA} and μ_{rB} are the r^{th} moment of A and B about their means. $P(I_i)$ is the local amplitude histogram. μ_1 and μ_2 are the local mean and variance respectively. μ_3 is the third moment that measures the skewness. In most cases rooftops has a uniform and symmetric texture near their boundaries. Therefore, the variance and the skewness values are expected to be small for true rooftops. The vector V encapsulates the local texture information based on the gray level distribution in the local area. After computing V_A and V_B the following rules are enforced:

$$\begin{cases} \text{Force the curve to pass the edge} & \text{if } \|V_A - V_B\| < T_{Edge} \\ \text{Make a dam along the edge} & \text{otherwise} \end{cases} \qquad (15)$$

To make a dam along an edge, the corresponding area in g, equation (8), is set to zero so the contour cannot pass through that area. Figure 5 displays a typical case in which the texture and moment information has allowed the correct identification of the rooftop boundary.

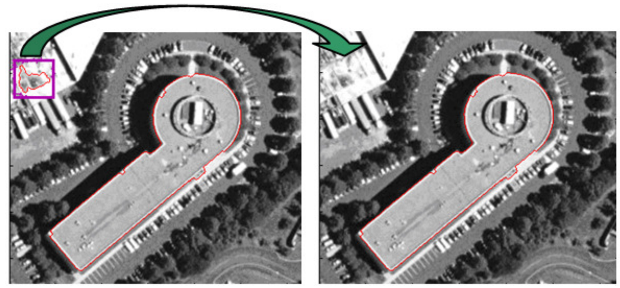
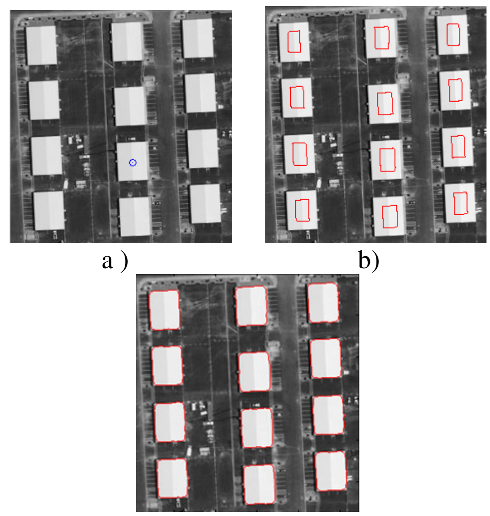


Figure 6. Removing the wrong detected hypothesis using shadow



a) b) c)

Figure 7. a) Clicking on one building as the initial seed for the region-based active contour (the blue circle). b) Automatic initialization for all similar buildings. c) Final results.

Occasionally there are flat patterns or structures in the scene that are not corresponding to real rooftops but their intensity and shape characteristics are similar to one. To ensure that such structures are not identified as buildings, a verification process is employed in which for each detected hypothesis the presence of shadow evidence is assessed. Here it is assumed that every building has shadows on the ground. So, those hypotheses that do not project shadows on the ground are removed. For each hypothesis the location of the expected shadow is estimated based on the acquisition geometry that is provided in the satellite image's metadata file. To estimate the location of the expected shadow corresponding to each rooftop hypothesis, Izadi and Saeedi's algorithm [11] is used. Also to segment the input image into shadow and non-shadow regions the following equation is employed [12]:

$$k=(H+1)/(I+1) \qquad (16)$$

here H is the hue and I shows the intensity in the HIS color space. In the k image, pixels corresponding to shadow areas have higher values. Each hypothesis with detected shadows in the regions that are predicted by the acquisition geometry will be announced as rooftop. The hypotheses that do not have shadow correspondences are filtered out from the remaining process. Figure 6 shows an example where an outlier without a shadow is identified and removed. Figure 7 highlights the multiple extraction property of the proposed method. Note that if there are several buildings with different gray levels in a scene, it is necessary to click on more than one building to detect all buildings.

4 Experimental Results

The proposed method was tested on 20 different satellite images. Figure 8 displays the performance of the system for some of these images.

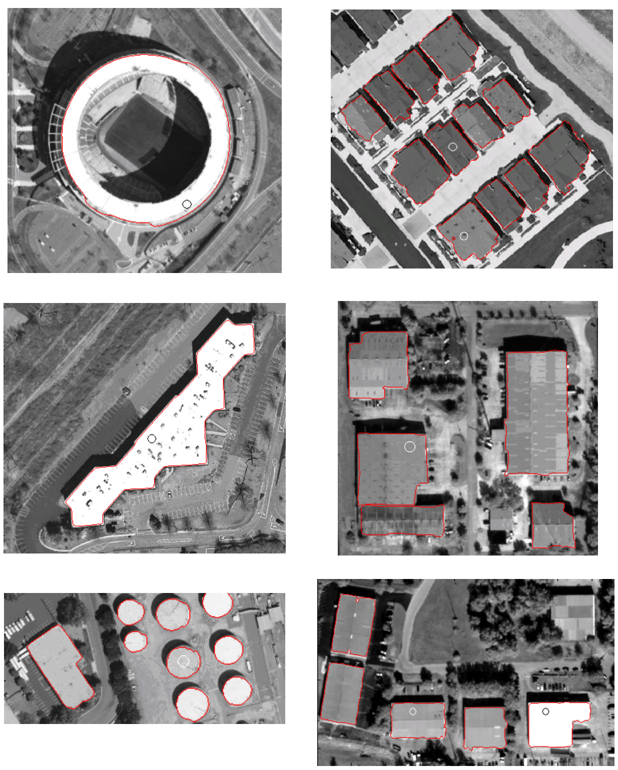


Figure 8. Experimental results (QuickBird Imagery)

The small circle(s) in these images depicts the location of the initial building seed at the first stage (Active Contour without Edge). The average detection rate for the proposed method is 90.62%. McKeown's factor [13] is used to measure the quality of segmentation. To calculate the McKeown's factor, the areas of buildings in the manually prepared ground truth (A_{GT}) are compared against the areas of the automatically detected buildings by the proposed algorithm (A_{DB}).

$$shape\ accuracy = 1 - \frac{\left|A_{GT} - A_{DB}\right|}{A_{GT}} \qquad (17)$$

Table 1 compares the shape accuracy measure of the proposed method with those of Peng et. al [4] and Ruther et. al [6] methods.

Experimental results show good performance in extracting the multiple flat rooftops. However, it was noted that the algorithm has a tendency to perform incompletely for gabled rooftops with large variation in the intensity values on the two sides (for instance the circled rooftops in Figure 9). This issue should be addressed in the future work by incorporating methods that could identify gabled rooftops and adjust the intensity values based on the sun direction and rooftop slopes.

Table 1. Comparing the shape accuracy

Method	Peng et. al [4]	Ruther et. al [6]	Proposed method
Average Shape Accuracy	83.63%	80%	92.5%

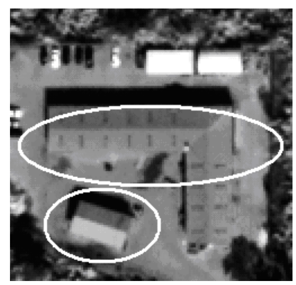


Figure 9. A scene that the presented algorithm failed for.

5 Conclusion

This paper proposed a combined approach for rooftop detection in satellite images using active contour with texture and edge information. By identifying class representatives of image rooftops, all potential rooftop hypotheses are extracted using active contour without edge. These hypotheses are further refined and used for initializing contours that are processed by an edge-based level set. During curve evolution, the local texture information is processed to determine whether the contours should pass the edge or stop the contour by generating a dam along the edge.

Using the proposed method multiple buildings with similar characteristics are detected simultaneously.

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