A building roof detection method using snake model in high resolution satellite imagery

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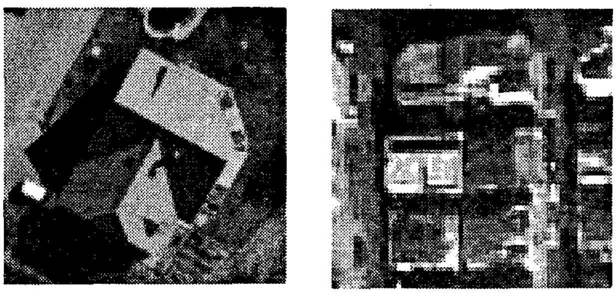
ABSTRACT:
Many building detection methods mainly rely on line segments extracted from aerial or satellite imagery. Building detection methods based on line segments, however, are difficult to succeed in high resolution satellite imagery such as IKONOS imagery, for most buildings in IKONOS imagery have small size of roofs with low contrast between roof and background. In this paper, we propose an efficient method to extract line segments and group them at the same time. First, edge preserving filtering is applied to the imagery to remove the noise. Second, we segment the imagery by watershed method, which collects the pixels with similar intensities to obtain homogeneous region. The boundaries of homogeneous region are not completely coincident with roof boundaries due to low contrast in the vicinity of the roof boundaries. Finally, to resolve this problem, we set up snake model with segmented region boundaries as initial snake's positions. We used a greedy algorithm to fit a snake to roof boundary. Experimental results show our method can obtain more correct roof boundary with small size and low contrast from IKONOS imagery.

KEY WORDS: Snake algorithm, building roof detection, watershed segmentation, edge-preserving filtering

1. INTRODUCTION

There have been many researches on building detection using high resolution aerial imagery. Many building detection methods use line segments or corners extracted from aerial imagery. Building roofs are detected by grouping extracted line segments and corners. In the case of high resolution satellite imagery such as IKONOS imagery, however, building detection is difficult task mainly due to building's size and low contrast between building roof and its background. Though the sizes of buildings in real world are same, buildings in IKONOS imagery are represented smaller than those in aerial imagery due to spatial resolution differences as shown in Figure 1).



(a) (b)

Figure 1. (a) Avenches aerial sample imagery(spatial resolution: 7.5cm, 25% zoom out) (b) IKONOS sample imagery(spatial resolution: 1m, 200% zoom in)

We proposed an efficient building detection algorithm based on snake model, which is able to detect and group building roof segments simultaneously. As initial contour for snake model, watershed region boundary is used. Watershed is an useful region-based segmentation method to detect small size of homogeneous regions in high resolution satellite imagery, for the pixels with similar intensity are grouped into a region.

2. SNAKE MODEL

Traditional snake model (kass etl al, 1988; Xu, 1998; Gao, 1998) where the snake is an ordered set of discrete points, is used to represent and fit a general, closed curve of arbitrary shape. Starting from the initial position, we find the deformable contour which fits the target image contour best by minimizing the following energy functional.

$$E = \sum_{i=1}^{N} (\alpha_i E_{continuity} + \beta_i E_{courvature} + \gamma_i E_{image}) \qquad (1)$$

where $E_{continuity} = x'(s) = | x(s_i) - x(s_{i-1}) |$

$E_{curvature} = x''(s) = | x(s_{i+1}) - 2x(s_{i-1}) + x(s_{i-1}) |$

$E_{image} = - | \nabla I(x(s_i)) |^2$

$\alpha_i, \beta_i, \gamma_i =$ weight constants of energy terms.

$E_{continuity}$ is continuity term encouraging equally spaced points on the contour, $E_{courvature}$ is smoothness term penalizing high contour curvatures and E_{image} is image energy term (magnitude of the gradient) attracting the deformable contour towards the desired image contour. Edge-based image energy can give a good localization of the contour near the boundaries, but it has a small basin of attraction, thus requiring a good initialization or a balloon force.

3. PROPOSED SNAKE MODEL

We set up snake's initial position on the region boundary extracted from watershed segmentation. Boundary pixels as well as inner pixels of watershed region have homogeneous intensity. The assumption of homogeneous intensity region of building roof gives the snake a good guideline to detect roof's boundary concerning snake's initial position and stopping criteria.

3.1 Image Segmentation

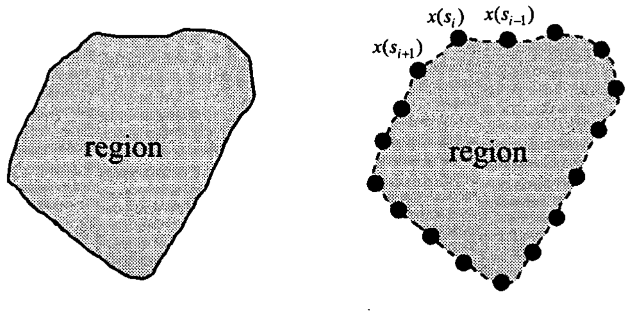
It is important for snake model to have close initial position to desired contour, i.e., roof boundary. Watershed segmentation is an efficient method to obtain good initial snake position. Watershed segmentation generally causes over-segmentation problem, however, which need more post-processing such as region merging. We employed edge preserving filtering and region merging method to reduce over-segmentation. Mean curvature diffusion (MCD) where image diffusion is controlled according to the mean curvature of the image surface, shows good noise reduction result preserving edge information (Malladi and Sethian, 1996; Ye and Lee, 2001). After edge preserving filtering using MCD, we segment image by watershed algorithm (Ye and Lee, 2002), which segments image into watershed pixels with high gradient magnitude and catchment basins with low gradient magnitude. Each segmented region is labelled to identify it during following the boundary of the region. The similar pair of regions among over-segmented regions are merged using region adjacency graph (RAG). This method provides one-pixel wide, closed contours.

3.2 Snake initial position

Though we can reduce over-segmentation of watershed by applying edge preserving filtering and region merging, the boundaries of watershed region are not completely coincident with roof boundaries due to low contrast in the vicinity of the roof boundaries. We set up initial snake position using segmented region boundary as follows. For each region in the labeled image, initial snake position is obtained by following the boundary of the region according to 8-directional chain code in a counterclockwise direction. We assign initial snake pixels to the pixels with some interval as shown in Figure. 2.

3.3 Unified image energy term

Traditional snakes mainly rely on edge-based energy and recently some algorithms use region-based energy as image energy term. Edge-based energy approach is usually based on the magnitude of the gradient.



(a) (b)

Figure 2. (a) Region extracted by watershed algorithm (b) initial snake pixels on the region boundary.

Edge-based energy can give a good localization of snake contour near the building boundaries, but it has a small basin of attraction, thus requiring a good initialization or a balloon force. On the contrary, region-based energy has a large basin of attraction and can converge even if explicit edges are not present. It does not give, however, as good as a localization as the edge-based energy at the image boundaries (Jacob et al, 2004).

We used unified image energy term by including region-based energy into the energy functional equation (1), considering the observation that small homogeneous building regions are very often detected in satellite imagery. One can observe that many small buildings have similar intensities in its roof region in IKONOS imagery as shown in Figure 3.

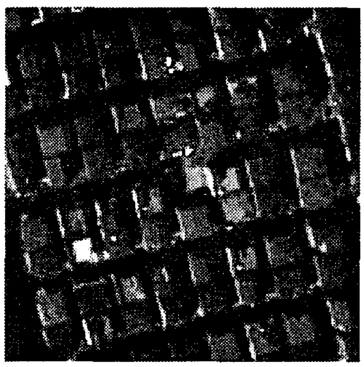


Figure 3. IKONOS sample image. Most small building shows similar intensities on its roof.

We add new intensity energy $E_{intensity}$ as region-based energy, into the equation (1) as follows:

$$E = \sum_{i=1}^{N} (\alpha_i E_{continuity} + \beta_i E_{courvature} + \gamma_i E_{image} + \delta_i E_{intensity} + \varepsilon_i E_{balloon}) \tag{2}$$

where

$$E_{intensity} = -\exp\left(\frac{-|I_{mean} - I(x(s_i))|}{K}\right)$$

$$I_{mean} = \frac{1}{2}(I(s_{i-1}) + I(s_{i-1}))$$

K = constant

$$E_{continuity} = (L_{mean} - |(x(s_i) - x(s_{i-1}))|)^2$$

$$L_{mean} = \frac{1}{N}\sum_{i=1}^{N} |x(s_i) - x(s_{i-1})|, (s_0 = s_N)$$

$\alpha_i, \beta_i, \gamma_i, \delta_i, \varepsilon_i$ = weight constants of energy terms.

If the intensity $I(x(s_i))$ of snake pixel $x(s_i)$ is similar to the mean intensity I_{mean} of adjacent snake pixels $x(s_{i-1})$ and $x(s_{i+1})$, total energy E becomes small. If the difference between $I(x(s_i))$ and I_{mean} is large, $E_{intensity}$ makes little influence on total energy E. The intensity energy encourages snake pixels move easily within homogeneous region and prevent them from moving beyond homogeneous region. After all, intensity energy makes all snake pixels remain within homogeneous region. We also modified $E_{continuity}$ term to have the snake pixels more equally spaced between two pixels.

A balloon energy is used to force the snake to expand until it nears the object boundary (Chalana et al, 1995). The balloon energy is scaled to the ragne [0, 1], then adapted to the image gradient intensity:

$$E_{balloon} = \frac{C(x(s_i)) - C_{\min}(x(s_i))}{C_{\max}(x(s_i)) - C_{\min}(x(s_i))}\left(1 - \frac{|\nabla I(x(s_i))|}{|\nabla I|_{\max}}\right)$$

$$C(x(s_i)) = n_i \cdot (x(s_i) - N_{neighbor}(x(s_i)))$$

where n_i is the outward unit normal of $x(s_i)$ and $N_{neighbor}(x(s_i))$ is the point in the neighbourhood of $x(s_i)$. $|\nabla I|_{\max}$ is the maximum gradient magnitude in the entire image. Therefore, balloon force is strong in homogeneous regions and weak near object boundary. The energy functions $E_{continuity}$, $E_{curvature}$ and E_{image} are also adjusted to the ragne [0, 1].

3.4 Energy Minimization

Greedy algorithm is used to minimize the energy functional defined in equation (2). Let $N(x(s_i))$ be a small neighbourhood of snake pixel $x(s_i)$ as shown in Figure 4. For each $i = 1, 2, ..., N$, we find the location of $N(x(s_i))$ for which the energy functional E defined in equation (2) is minimum, then move the snake pixel $x(s_i)$ to that location. We repeat the previous minimization process until the energy functional E reaches a minimum.

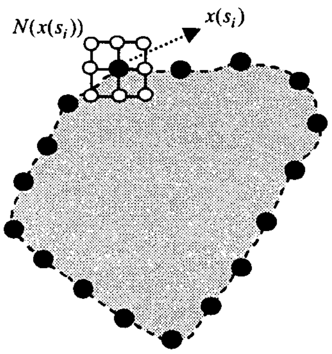


Figure 4. Small neighbourhood of snake pixel $x(s_i)$.

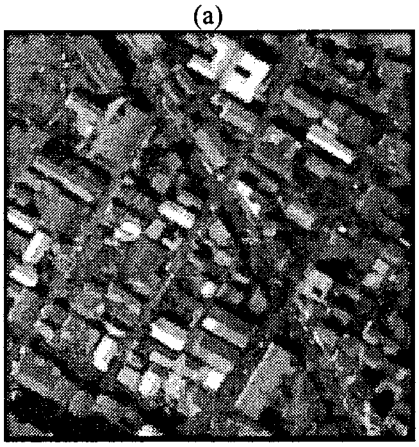
4. EXPERIMENTAL RESULTS

For the experiment, we used IKONOS imagery over Taejeon, which was acquired on 2 February, 2002. We show in Figure 5a sample image where various buildings are contained. The segmented image by watershed method is shown in Figure 5b. From the segmented image, we extracted some regions whose boundaries are used as initial points of snake algorithm. We imposed two constraints on the minimum size and mean intensity of building roof (Figure 5c). The size and mean intensity of each extracted region are over 40 pixels and 129 grey levels, respectively. Although some regions are not belonging to building roofs, we were able to detect 68 buildings from 71 observed buildings in Figure 5a by imposing the previous constraints. The shapes of some building roofs are, however, partially distorted through segmentation or thresholding processes. Figure 5d shows the result of detected region boundaries by applying proposed snake algorithm. We can find many region boundaries are correctly recovered from partially distorted region boundaries. Compared to the edge detection result using Canny edge filer as shown in Figure 5e, roof boundaries with small size and low contrast were correctly detected. Although there are some building roofs consisting of more than two regions due to over-segmentation, we can describe building roof by using the region boundary.

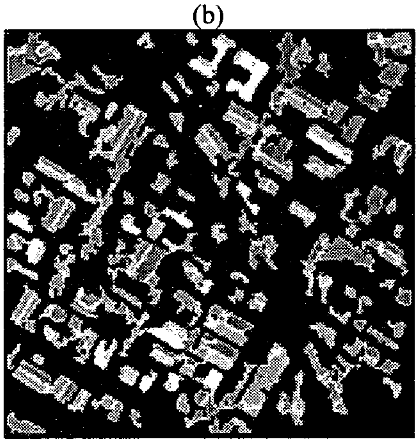
5. CONCLUSIONS

In this paper, we proposed an efficient building detection algorithm using watershed segmentation and snake model. The major contribution of proposed method is that we provided a method to detect and group roof boundaries with small size and low contrast simultaneously. Future work will explore how to merge the over-segmented regions into one roof region and improve position accuracy of roof boundary.

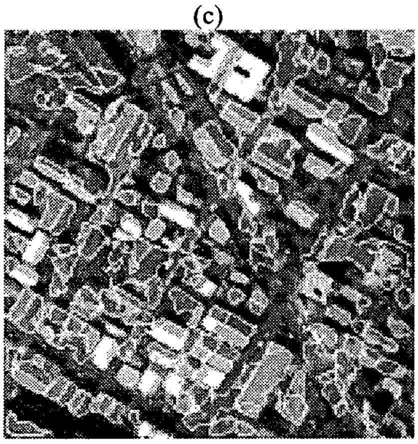
(a)



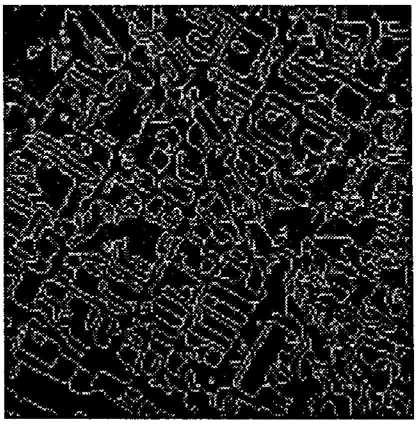
(b)



(c)



(d)



(e)

Figure 5. (a) Sample IKONOS image (b) segmented image by watershed method (c) extracted some regions used as initial points of snake algorithm (d) detected region boundaries by applying proposed snake algorithm ($\alpha_i = 1$, $\beta_i = 1$, $\gamma_i = 1$, $\delta_i = 1$, $\varepsilon_i = 1$, $K = 128$, number of iteration = 20) (e) edge detection result using Canny edge filer (σ =1).

REFERENCES

C. Xu and J. L. Prince, "Snakes, shapes, and gradient vector flow," IEEE Trans. Image Processing, vol. 7, pp. 359–369, 1998.

C.S. Ye and K.H. Lee, "Anisotropic diffusion for building segmentation form aerial imagery," in Proc. of International Symposium on Remote Sensing, EMSEA and KSRS, Seogwipo, Korea, Oct. 31-Nov. 2, pp. 599-604, 2001.

C.S. Ye and K.H. Lee, "Remote sensing image segmentation by a hybrid algorithm," Journal of KSRS, vol. 18, no.2, pp. 107-116, 2002.

J. Gao, A. Kosaka, and A. Kak, "A deformable model for human organ extraction," in Proc. Int. Conf. Image Processing, Chicago, IL, pp. 323–327, 1998.

Jacob, M., Blu, T. and Unser, M., "Efficient energies and algorithms for parametric snakes," IEEE transactions on image processing, v.13, no.9, pp.1231-1244, 2004.

M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," Int. J. Comput. Vis., vol. 1, pp. 321–332, 1988.

R. Malladi and J.A. Sethian, "A unified approach to noise removal, image enhancement, and shape recovery," IEEE Trans. Image Processing, vol. 5, no. 11, pp. 1554-1567, 1996.

Vikram Chalana, Wendy Costa, and Yongmin Kim. "Integrating region growing and edge detection using regularization," In Proceddings of the SPIE Conference on Medical Imaging. SPIE, vol. 2434, pp. 262-271, 1995.