BUILDING BOUNDARY DETECTION USING TOPOLOGICAL GRADIENT ANALYSIS

Chao-yuan Lo[1] and Liang-Chien Chen[2]
[1]PhD Candidate, Department of Civil Engineering, National Central University,
300 Jhongda Rd., Jhongli, Taoyuan 32001, Taiwan; Tel: +886-3-4227151#57623;
Email: freezer@csrsr.ncu.edu.tw

[2]Professor, Central for Space and Remote Sensing Research, National Central University,
300, Jhongda Rd., Jhongli, Taoyuan 32001, Taiwan; Tel: + 886-3-4227151#57622;
E-mail: lcchen@csrsr.ncu.edu.tw

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ABSTRACT: Completeness and localization are the two major requirements in many applications such as image matching and 3D reconstruction. To fulfill the requirements, this paper presents a topological gradient analysis to detect building boundaries for digital images. Traditional methods strive to select appropriate thresholds. Their results have good performance for some targets within specific areas; however, different aerial images and targets may bring difficulties in threshold selection due to dynamic spectral conditions. To overcome this problem, the proposed method analyzes gradient geometries instead of thresholding operation. The scheme includes three stages: (1) grayscale refinement, (2) gradient computation, and (3) topological analysis. The first stage uses the Gaussian to smooth target images. Then, the second stage computes directional gradients to estimate local extrema. The last stage analyzes the topological criteria to identify connected extrema and delineate linear features. In the validation, we select different aerial images to extract building boundaries and compare with a reference data set, i.e., Canny's edges. Since Canny's results are employed as the reference, thresholds are manually selected to reach the best possible performance. Experimental results indicate that, without setting any parameter, detected boundaries are more complete than Canny's edges in building areas.

1. INTRODUCTION

Building boundary detection is the bridge to image matching and 3D reconstruction. Image boundaries reflect object shapes with the distribution of grayscales in the spectral domain; thus, to detect complete boundaries is necessary. One boundary may have different gradients as the result of illumination, reflectance, and shadow. To analyze the spectral distribution, many methods have been proposed with varied strategies such as the gradient-based (Prewitt, 1970; Canny, 1986; Sobel, 1990; Smith & Brady, 1997; Laligant & Truchetet, 2010), scale multiplication (Bao et al., 2005; Tanaka et al., 2010), segmentation (Arbelaez et al., 2011), vector flow (Ma & Manjunath, 2000), neuro network (Lu et al., 2003), statistic (Rakesh et al., 2004), and universal gravitation (Sun et al., 2007). Among them, gradient-based methods directly identify edges with analyzing the differences of grayscales. This first-derivative concept is intuitive, but suffered by noises. To overcome this problem, Canny (1986) first proposed two important criteria: good localization and good detection (Demigny, 2002). Canny operator implements the Gaussian smoothing and hysteresis thresholds to increase the signal-noise-to-ratio (SNR) and feature identification. However, Canny operator depends on the scale and hysteresis thresholds to detect edges under specific image conditions. For the improvement on Canny operator, the noise filter and threshold selection are two research directions.

Bao et al. (2005) based on Canny operator to implement scale multiplication with double scales to improve localizations of detected edges. Dual scales and hysteresis thresholds could help to restrict false edges which are caused from noises. Due to the Gaussian smoothing is an isotropic diffusion; the edge information may be also restricted in the process of noise reduction with the improper scale. The directional filter then becomes one solution. Yi et al. (2009) proposed an anisotropic diffusion, the Shearlet transformation, to simultaneously preserve edge gradients and reduce noises. On the other hand, the gradient selection is another way to identify edges. In conventional methods, hysteresis thresholds depend on interactive modification to estimate proper values. For automation point of view, Medina-Carnicer et al. (2011) proposed an unsupervised concept to estimate initial hysteresis thresholds by the collected candidates. Furthermore, these methods indicate that prior experience is necessary for test images. The refinement of selected thresholds is still an important step in the detection process.

Based on archival studies, their detected results indicate that different images and targets may need to refine the used thresholds. Because these developed mathematical models have their specific explicabilities, the complexity of localization criterion means that these detectors are difficult to be optimal for all edge constants (McIlhagga, 2011).

To improve boundary detection ability, this paper utilizes the topological criteria to analyze the permutation of local extrema instead of threshold selection. The proposed scheme can thus increase the automation degree and adapt to diverse image sources. Different kinds of images were collected for detecting building boundaries.

2. METHODOLOGY

This paper implements the topological gradient analysis to identify the local extrema and detect edges without any threshold selection. The basic concept contains three components: (a) every edge can be separated into the fundamental elements with a 3-by-3 area; (b) the gradient along the edge direction should be smaller than the gradient cross the edge direction; (c) local extrema of part of one edge have specific permutations. According to the considered permutations, the detection process can thus detect edges under the topological constraints. In the proposed scheme, we have three steps to detect edges (shown as Figure 1): (1) grayscale refinement, (2) gradient computation, and (3) topological analysis.

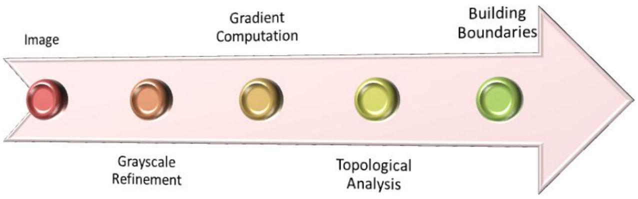


Figure 1. The workflow

2.1 Grayscale Refinement

The first step is to modify the distribution of grayscales. Because the filter is difficult to be optimal, the improper filter or scale may cause false edges, information losses, or over computation. Therefore, this study only uses the Gaussian smoothing to modify the distribution of grayscales and maintain the smoothness in the edge areas. The used equation is

$$I'(x,y) = I(x,y) * G(x,y,\sigma) \tag{1}$$

where $I(x,y)$ is the original grayscale distribution, $G(x,y,\sigma)$ is the Gaussian kernel, "$*$" denotes the convolution operation, and $I'(x,y)$ is the smoothed grayscale distribution. σ is the standard deviation to control the Gaussian kernel. The value is fixed in the processes.

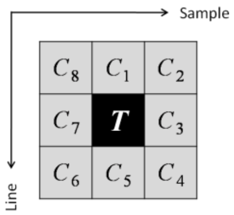
2.2 Gradient Computation

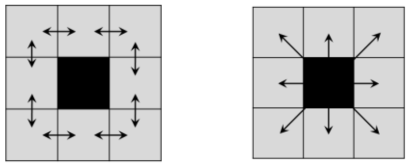
The second step analyzes the relative gradients in dual directions which are cross direction and along direction. The basic kernel is illustrated in Figure 2. Due to gradients along one image edge should be smaller than gradients cross one edge, we thus compute two orthogonal directions to identify edge pixels. Figure 3 shows these two directions: radiant direction and circular direction. The used formulas are listed in equation (2) and (3).

$$RC_i = \left|C_i - T\right|_{i=1\sim 8}, T, C_i \in I' \tag{2}$$

$$CC_i = \left|C_{i-1} - C_{i+1}\right|_{i=1\sim 8}, C_{i-1}, C_{i+1} \in I' \tag{3}$$

where RC_i is the gradient of the radiant direction, and CC_i is the gradient of the circular direction.





(a) (b)

Figure 2. Basic kernel

Figure 3. Gradient directions
(a) Circular direction; (b) Radiant direction

After the gradient computation, we then execute two series of relative gradients in dual directions (shown as equation (4) and (5)).

$$RC' \in \{RC_1, RC_2, \cdots, RC_n\}_{n=1\sim8} \tag{4}$$

$$CC' \in \{CC_1, CC_2, \cdots, CC_n\}_{n=1\sim8} \tag{5}$$

where RC' is the set of relative gradients of radiant direction in the core layer, and CC' is the set of relative gradients of circular direction in the core layer. Following the proposed concepts, edges exist in the intersection of two directional gradients. Edge candidates then are identified by the minimum radiant gradients and the maximum circular gradients.

2.3 Topological Analysis

The third step is to analyze the topological criterion of edge candidates to identify whether the nucleus is an edge pixel or not. Since adjacent edge pixels belong to some specific patterns, we then induce the topological criterion to be twelve patterns. This step compares edge candidates with the designed templates for edge identification. The designed patterns are illustrated in Figure 4. The gray pixels, which are edge candidates, indicate the topological condition surrounding the nucleus. If these edge candidates are sufficient for one pattern, the detection process then identifies this candidate as a part of one edge. On the other hand, non-matched candidates are regarded as noises and removed directly.

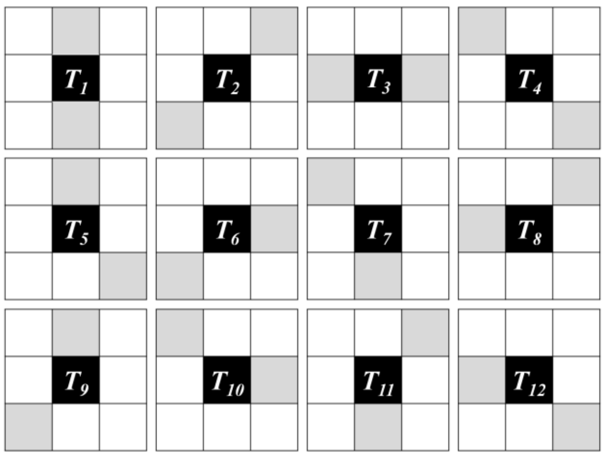


Figure 4. Designed templates

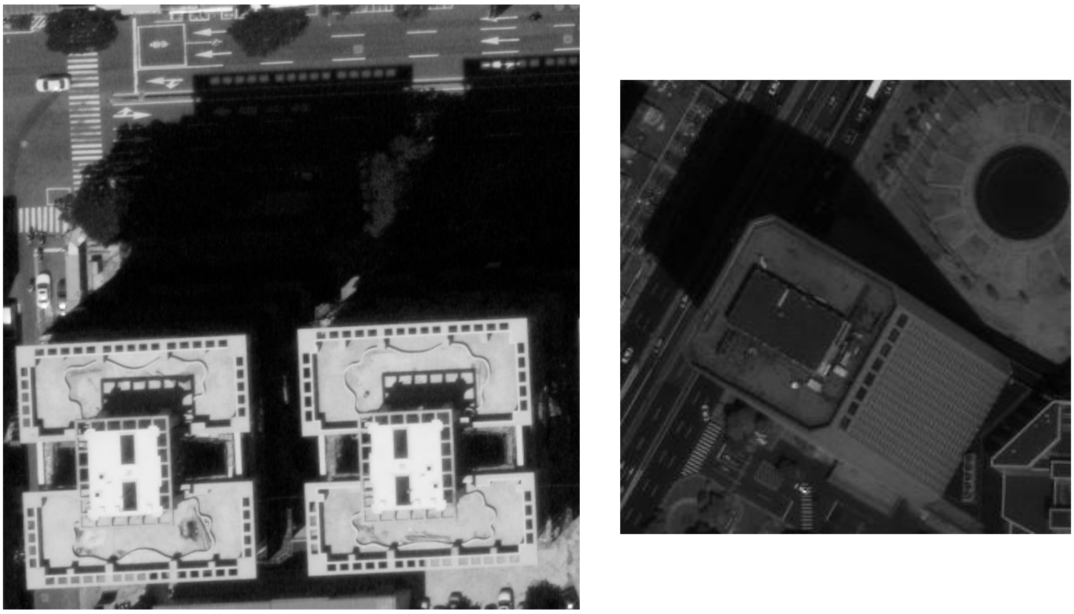
3. EXPERIMENTAL RESULTS

This paper employed the topological gradient analysis for building boundary detection derived from aerial images and satellite images. The aerial image was scanned in 2010 by DMC II; the satellite image was provided by GeoEye in 2009. The spatial resolutions of two datasets are 7 cm and 50 cm, respectively. Within the detection processes, the proposed scheme fixed the scale of the Gaussian smoothing to “1.0” for all testing sets. We compared the detected results with Canny’s edges for validation. The used scale of Canny operator was fixed to “1.0” as well, and then we modified the hysteresis thresholds of Canny operator to derive reference edges manually. The used thresholds of Canny operator are listed in Table 1. The comparison index is the root mean squares error (RMSE) to calculate the delocalization error between our edges and Canny’s edges. In addition, we use Pratt’s figure of merit

(FOM)(1978) to estimate the completeness of strong edges. The formula of FOM is shown as equation (6). The value of FOM is from 0 to 1. The detected results are perfect matched when FOM reaches 1. Figure 5 illustrates the experimental images, and Figure 6 represents the detected results and Canny's edges. The quality of detected edges with strong gradients is listed in Table 2. According to the comparison, these automatic detected edges of proposed scheme are close and similar to Canny's edges. More importantly, other edges with small gradients also can be detected. These categorized edges lead the possibility for further applications with different priorities such as image matching and 3D modeling.

$$FOM = \frac{1}{\max(N_d, N_r)} \sum_{i=1}^{N_d} \frac{1}{1+\alpha e(i)^2} \tag{6}$$

where N_d is the number of detected pixels, N_r is the number of reference pixels, α is a constant with an empirical value as 1/9, $e(i)$ is the function of delocalization error.



(a) (b)

Figure 5. The experimental images
(a) case I; (b) case II

Table 1. The used thresholds of Canny operator

Case	Scale	High Threshold	Low Threshold
I	1.0	0.152	0.07
II	1.0	0.100	0.05

Figure 6. The experimental results
(a) detected edges of case I; (b) detected edges of case II;
(c) reference edges of case I; (d) reference edges of case II

Table 2. The comparison results

Case	RMSE (pixel)	FOM
I	1.486	0.858
II	2.353	0.758

4. CONCLUSIONS

This study presented the topological gradient analysis to detect building boundaries without threshold selection. The aerial image and the satellite image are employed to estimate the applicability of the proposed scheme. According to the comparison, these detected edges with strong gradients are close to Canny's edges. Other edges, which locate in shadows, with weak gradients can be also detected without tuning the thresholds. The future direction will focus on image matching using aerial imagery with these categorized edges for 3D modeling. For satellite imagery, these experimental results may provide an opportunity for building detection in urban residential areas.

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