L-shaped Corner Detector for Rooftop Extraction from Satellite/Aerial Imagery

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ABSTRACT

Rooftop extraction from satellite/aerial imagery is an important geospatial problem with many practical applications. However, rooftop extraction remains a challenging problem due to the diverse characteristics and appearances of the buildings, as well as the quality of the satellite/aerial images. Many existing rooftop extraction methods use rooftop corners as a basic component. Nonetheless, existing rooftop corner detectors either suffer from high missed detection or introduce high false alarm. Based on the observation that rooftop corners are typically of L-shape, we propose an L-shaped corner detector for automatic rooftop extraction from high resolution satellite/aerial imagery. The proposed detector considers information in a spatial circle around each pixel to construct a feature map which captures the probability of L-shaped corner at every pixel. Our exper-imental results on a rooftop database of over 200 buildings demonstrate its effectiveness for detecting rooftop corners. Furthermore, our proposed detector is complementary to many existing rooftop extraction approaches which require reliable rooftop corners as their inputs. For instance, it can be used in the quadrilateral footprint extraction methods or in driving level-set-based segmentation techniques.

Keywords: Rooftop extraction, corner, remote sensing, satellite, aerial.

1. INTRODUCTION

Rooftop extraction from satellite/aerial imagery is an important geospatial problem with many practical applications such as urban planning, military simulation, and geo-mapping. However, rooftop extraction remains a challenging problem due to the diverse characteristics (size, shape) and appearances (illumination, viewing angle) of the buildings, as well as the quality (resolution, contrast, and visibility) of the satellite/aerial images.

Many rooftop extraction methods have been reported in the literature and many of these methods use rooftop corners as a basic component. One typical approach to detect rooftop corners is by finding the intersections of edges. Nonetheless, this approach can lead to many missed detections, as the detected edges are often fragmented due to the line extraction process and occlusion. Another typical approach to detect rooftop corners is by using generic corner detectors. Nonetheless, as generic corner detectors are designed to identify corners of arbitrary shape and scale, they can introduce many false alarms.

Figure 1 illustrates some common rooftop corners. Based on the observation that rooftop corners are typically of L-shape, we propose an L-shaped corner detector for rooftop extraction. The proposed detector considers information in a spatial circle around each pixel to construct a feature map which captures the probability of L-shaped corner at every pixel.

This paper is organized as follows. First, a literature review on rooftop extraction is discussed in Section 2. Then, our proposed method is presented in Section 3. Subsequently, the experimental results are shown in Section 4. Finally, we conclude in Section 5.

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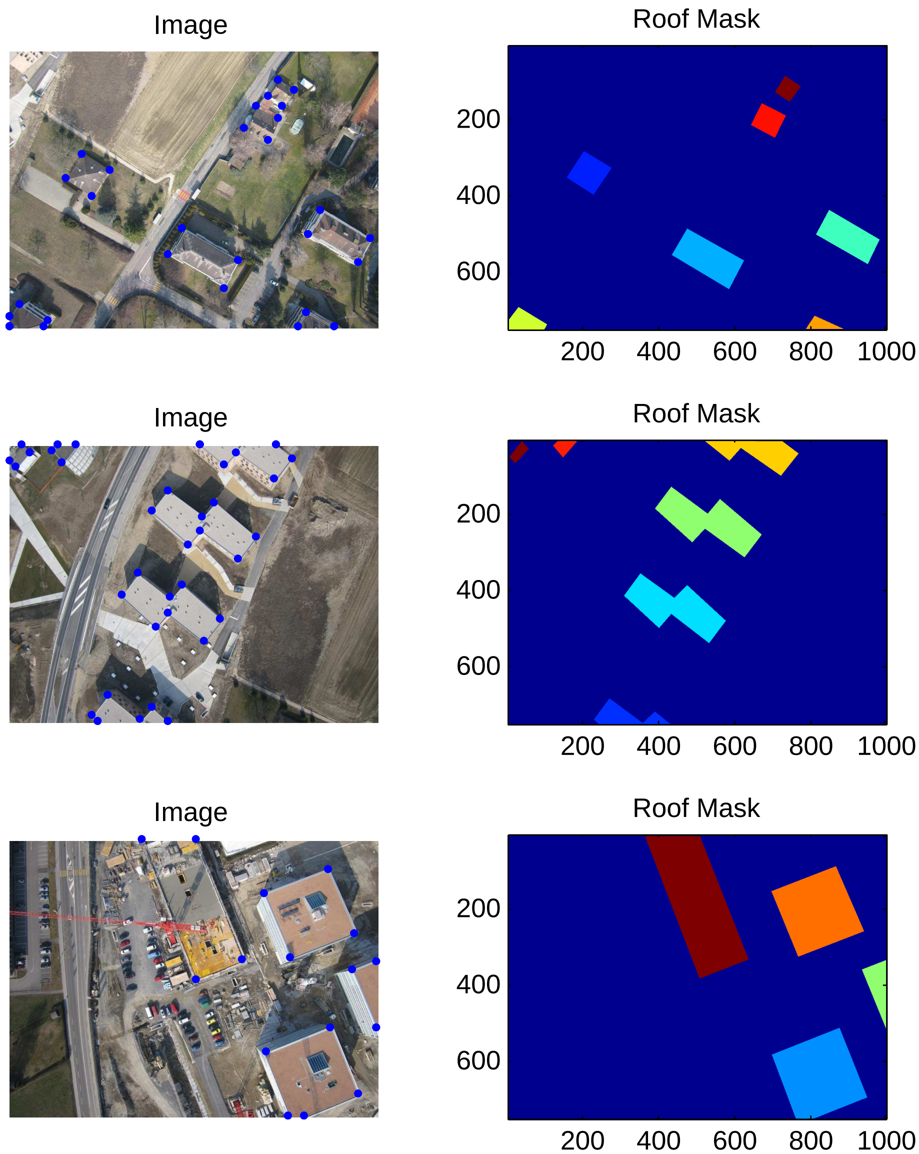


Figure 1. Illustration of rooftop corners.

2. LITERATURE REVIEW

Various rooftop extraction methods have been discussed in the literature, and are reviewed by Mayer et al. [1], Shufelt et al. [2], Baltsavias et al. [3], Unsalan et al. [4], and Brenner et al. [5] etc. Based on the generalization that rooftops are polygons with variable number of vertices, one common approach for rooftop extraction is by polygon extraction [6]-[7]. Huertas et al. first extracted edges, corners, and shadows, and then used the relationships among the edges, corners and shadows to construct rooftop outlines [6]. Similarly, Lin et al. first extracted edges then used the edges to construct parallelograms [8]. Their proposed method is limited to flat rectilinear rooftops of "L", "T", or "I" shapes. To handle arbitrary angles of the corners, Nosrati et al. extracted corners with their associated angles. They then constructed rooftop outlines by using a dynamic programming approach that searches for loops in the corners graph [9]. The Hough transform is also commonly used for constructing polygonal rooftop outlines [10][11[12]. Furthermore, as the geometrical primitives are often susceptible to outliers and the incomplete edges do not form explicit segments, Krishnamachari et al. constructed rooftop outlines by grouping lines using Markov random fields (MRFs) [13]. Similarly, Izadi et al. used graph-based search to infer rooftop hypothesis from lines and line intersections [7].

Another common approach for rooftop extraction is by using active contours segmentation. Parametric active contours segmentation or snake is attempted by Peng et al. [14], Ruther et al. [15] and Zhu et al. [16], while geometric active contours segmentation or level-set is used by Yang et al. [17] and Cote et al. [18].

Among these discussed methods, many use rooftop corners as a basic component. For instance, Nosrati et al. uses the intersections of edges to detect corners for quadrilateral footprint extraction [9]. Nonetheless, detecting corners from the intersections of edges can lead to many missed detections, as the detected edges are often fragmented due to the line extraction process and occlusion. In addition, Cote et al. uses corners for level-set segmentation [18], whereby their corners are extracted using generic corner detectors. Nonetheless, as generic corner detectors are designed to identify corners of arbitrary shape and scale, they can introduce many false alarms. In this paper, we focus on extracting reliable rooftop corners with reduced false alarm and low missed detection.

3. PROPOSED METHOD

Based on the observation that rooftop corners are typically of L-shape, we propose an L-shaped corner detector for rooftop extraction. The proposed detector considers information in a spatial circle around each pixel to construct a feature map which captures the probability of L-shaped corner at every pixel. By employing equal-distance and equal-length rays that radiate from each pixel, the proposed detector computes the L-shape structural strength of the pixel. The L-shape structural strength of a pixel is computed based on how well any pair of rays fits to the rooftop edges and how well the pair of rays fits to a 90-degree structure.

For each pixel $c = (c_x, c_y)$ in the input image, let $p_c = (p_{c_x}, p_{c_y})$ be the points on the circumference of a circle which is of radius R and centred about c, i.e., $(p_{c_x} - c_x)^2 + (p_{c_y} - c_y)^2 = R^2$. For each $p_c(i)$, $i \in \{1, \ldots, N\}$,

$$e(p_c(i)) = \sum_{(x,y)\in L_{p_C(i)}} E(x, y), \tag{1}$$

and

$$v(p_c(i)) = \sum_{(x,y)\in L_{p_C(i)}} V(x, y), \tag{2}$$

where $L_{p_c(i)}$ is a set of all coordinates along the line connecting $p_c(i)$ to c. E and V are edge map and local standard deviation map of the input image respectively. Next, a subset of points, $p_c(s)$, are selected such that

$$e(p_c(s)) = \max_{i=s-n}^{i=s+n} e(p_c(i)), \tag{3}$$

and

$$e(p_c(s)) \geq \frac{k}{N} \sum_{\forall i} e(p_c(i)). \tag{4}$$

$N = 144$, $n = 5$ and $k = 3$ in our implemented system.

For all combination of points in the subset, the combination which is closest to 90-degree is identified and used for computing the feature map. That is to find t and t' such that

$$f(t, t') = \min_{\forall(s,s')} f(s, s') = \min_{\forall(s,s')} |\angle(p_c(s), p_c(s')) - 90|. \tag{5}$$

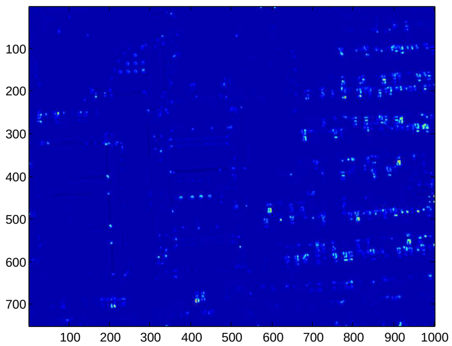
The feature map F is subsequently computed as

$$F(c) = \frac{e(p_c(t)).e(p_c(t')).v(p_c(t)).v(p_c(t'))}{\exp^{f(t,t')}}. \tag{6}$$

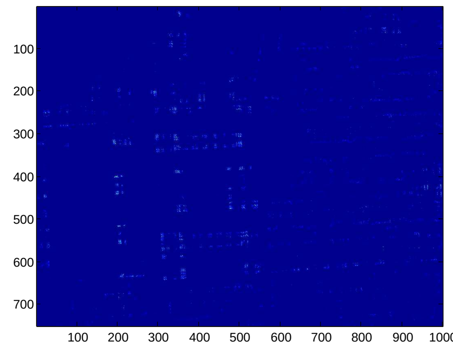
$F(c)$ is high when $f(t, t')$ is low, that is, a feature map value is high when there is good match between rooftop edges with 90-degree structure. The corners can finally be easily extracted by thresholding and non-maximum suppressing the feature map.

4. EXPERIMENTAL RESULTS

Our proposed detector is first evaluated on a rooftop database [19] comprising 32 aerial images of 209 buildings. R is experimentally set to 30. The Otsu's automatic threshold [20] followed by non-maximum suppression in a 11×11 window are then applied to the feature maps. As an example, Figures 2(a) and 2(b) illustrate the feature maps produced by the widely used Harris detector [21] and our proposed detector respectively, while Figures 2(c) and 2(d) illustrate the detection results of the Harris detector and our proposed detector respectively. It can be clearly seen that the proposed detector produces much fewer false alarms when compared to the Harris detector. Particularly, false alarms due to the detection of vehicles are greatly reduced.



(a) Feature Map - Harris Detector.



(b) Feature Map - Proposed Detector.

(c) Detected Corners - Harris Detector.

(d) Detected Corners - Proposed Detector.

Figure 2. (a) and (b) illustrate the feature maps produced by the widely used Harris detector and proposed detector respectively, while (c) and (d) illustrate the detection results of the Harris detector and proposed detector respectively.

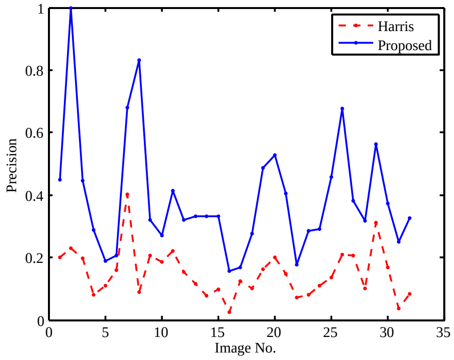
Furthermore, the performance of the proposed detector across the whole database is quantitatively evaluated in terms of precision P, recall R, and F-measure F, where

$$P = \frac{TP}{TP + FP}, \tag{7}$$

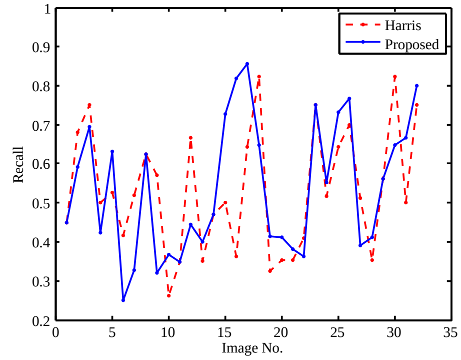
$$R = \frac{TP}{TP + FN}, \tag{8}$$

$$F = \frac{2TP}{2TP + FP + FN}. \tag{9}$$

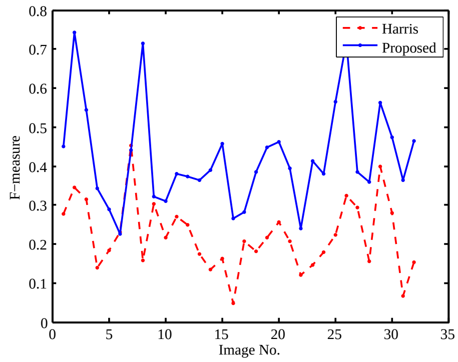
TP, FP, and FN denote the number of true positives, false positives, and false negatives respectively. Figures 3(a), 3(b), and 3(c) show the plot of precision, recall, and F-measure respectively across the whole database. It can be seen that, across the whole database, the proposed detector greatly increases precision with little decrease in recall. That is, the proposed detector greatly reduces false alarms with little increase in missed detections. Consequentially, since F-measure is the harmonic mean of precision and recall, the proposed detector gives a higher average F-measure over the database. The good results can be attributed to the effective use of spatial instead of very local information around each pixel.



(a) Precision scores across database.



(b) Recall scores across database.



(c) F-measure scores across database.

Figure 3. (a), (b), and (c) show the plot of precision, recall, and F-measure respectively over the whole database. Values for Harris detector and proposed detector are in red and blue respectively.

Next, the proposed detector is also evaluated on satellite imagery. 0.5m pansharpened GeoEye-1 and Worldview-2 images are used. Figure 4 illustrates the detection results of the Harris detector and proposed detector. As can be observed, the Harris detector often wrongly detects vehicles and small structures on rooftops. On the other hand, the proposed detector implicitly considers scale and hence can more effectively detect rooftop corners. Furthermore, corners of building sides are also effectively reduced.

Since rooftop corner detection is a basic component of many rooftop extraction methods, reliable rooftop corners can help ease subsequent processing in the rooftop extraction methods. For instance, in the quadrilateral footprint methods, quadrilaterals may be more easily formed by connecting the detected rooftop corners which are linked by strong edges. Also, in the level-set segmentation methods, better adherence of the contours to the rooftops may be obtained by letting the contours snap to the detected rooftop corners.

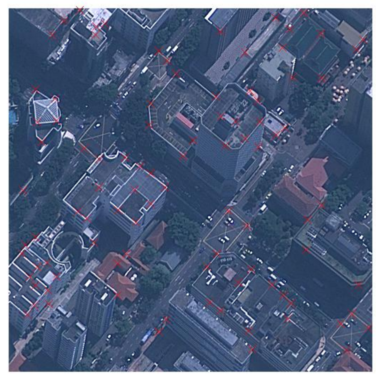
5. CONCLUSION

In this paper, based on the observation that rooftop corners are typically of L-shape, we propose an L-shaped corner detector for rooftop extraction. The proposed detector considers information in a spatial circle around each pixel to construct a feature map which captures the probability of L-shaped corner at every pixel. Our experimental results demonstrate its effectiveness for detecting rooftop corners. Furthermore, the proposed detector is complementary to many existing rooftop extraction approaches which require reliable corners as their inputs. In the future, we will use the rooftop corners in the quadrilateral footprint extraction methods [9] or in driving level-set-based segmentation techniques [18].

(a) Detected Corners - Harris Detector.

(b) Detected Corners - Proposed Detector.

(c) Detected Corners - Harris Detector.



(d) Detected Corners - Proposed Detector.

Figure 4. Detection results of the Harris detector and proposed detector respectively for 0.5m pansharpened GeoEye-1 and Worldview-2 images.

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