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A novel algorithm in buildings/shadow detection based on Harris detector

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ABSTRACT

A novel method based on corner detectors is proposed in detecting shadow and buildings in this paper. Its most outstanding point is employing Harris corner detector in region-based detection, despite that Harris detector traditionally used to select pixels as final results. Different densities of buildings are generally influenced by different features for recognition. First time, images are self-grouped into two groups according to the distribution of buildings, and two specifical algorithms are ready for detection specifically. A region-based method is used in comparison with our algorithm, and the results indicate that the new idea works not only more robustly, but also more effectively. It is a fast and simple method, which needs average 3.28×10^{-5} s to run per square image.

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1. Introduction

Buildings detection has been one of the most significant aspects in assessing the progress of investment programs and urban planning. Numerous algorithms have been proposed, and mostly, they are focused on spectral information and textural characteristics. Shadow is companying buildings everywhere and it is the main obstacle in recognizing buildings, especially in urban environment. Good shadow detection contributes to accurate recognition of buildings. Corner detectors are the methods that can detect points with specific features. Harris detector [1] has been widely used in corner detection [2,3] and image segmentation [4]. It is one of the most well-known algorithms in detecting feature points of interest, because of its robust in the variation of illumination, rotation and noise. Among the multiple corner detectors proposed now, Schmid, Mohr and Bauckhage have conducted several researches on evaluating the methods and concluded that Harris detector performed best [5].

To date, corner detectors are not commonly used in region based buildings or shadow detection, because it is designed for extracting pixels, which are intended to be final results. However, in this paper, corner detection is partly adopted and synthesized with the idea proposed in [6] to detect region-based shadow. The new algorithm is a simple, but efficient one. It is not only with high accuracy in detecting buildings, but also sensitive to shadow. The principle idea is discussed in Section 2 and the validation experiments are introduced in Section 3. Final part is the conclusion.

2. Proposed method

Commonly, researchers are trying to detect buildings regardless of their distribution density. Nevertheless, buildings with different densities are with different features. Densely distributed buildings tend to share little open space, and shadow is the main obstacle in identification. On the contrary, sparsely distributed buildings would have more open spaces, especially soil, which mainly suppresses recognition. Therefore, our proposed method is divided into two subparts after detecting shadow based on Harris corner detector and the idea proposed in [6].

Harris detector is a auto-correlated function, which measures the local variation by shifting in various orientations [7]. The general idea is convoluting the original image with a kernel, which is often intended to be Gaussian function. Because it has been proved to be the only possible scale-space kernel [8] by Koenderink [9] and Lindeberg [10]. Thereafter, the scale-space of the original image $I(x,y)$ can be generated as below:

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

where $G(x,y)$ is the Gaussian function and * marks convolution operation.

Smoothed Gaussian filters are used in [6] and they are used in two directions, horizontal and vertical ones.

$$G_x(x, y) = \frac{-x}{2\pi} \exp\left(-\frac{x^2 + y^2}{2}\right) \tag{2}$$

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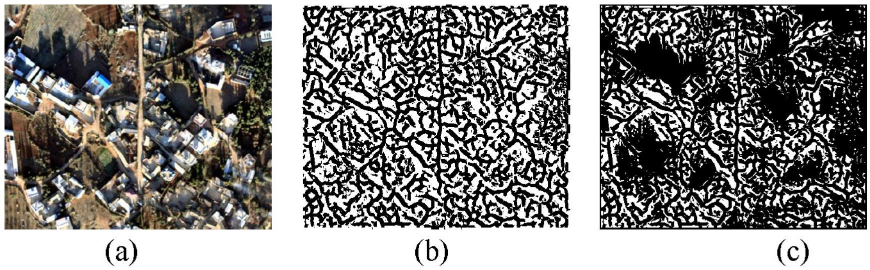

Fig. 1. Sample images for algorithm description: (a) original image, (b) feature points detected based on Harris corner detector and (c) binary magnitude image.

$$G_y(x, y) = \frac{-y}{2\pi} \exp\left(-\frac{x^2 + y^2}{2}\right) \quad (3)$$

In our paper, we have a smoothing window of 7×7. x, y in Eqs. (2) and (3) represent the positions of every pixel in the window. Therefore, two kernels G_x and G_y focusing on two orientations are formed. Then, we can have $I_x(x,y)$ and $I_y(x,y)$ after convolution with the two kernels.

After every convolution, we have a T calculated as follows:

$$T(A) = Det(A) - \varepsilon Tr^2(A) \quad (4)$$

where A is a matrix composed of four elements

$$A = \begin{pmatrix} a_{xx} & a_{xy} \\ a_{xy} & a_{yy} \end{pmatrix} \quad (5)$$

and a_{xx} is the summary of all the $I_x{}^2(x_i,y_j)$, belonging to the smoothing window. a_{xy} is the total value of all the $I_x(x_i,y_j)I_y(x_i,y_j)$, and accordingly, a_{yy} is the sum of $I_y{}^2(x_i,y_j)$.

Harris and Stephens [1] believed that the corner points are selected by examining the maximum T of every 7×7 window after generating all the T in the image. And a sample image based on Harris corner detector is shown in Fig. 1(b).

To show the gradients among feature points, magnitude $M(x,y)$ is adopted from [6] and defined as:

$$M(x, y) = \sqrt{I_x^2(x, y) + I_y^2(x, y)} \quad (6)$$

In order to present the magnitudes more obvious, Otsu's method is applied [6] because of its automation and intelligence. No further subjective factors and manual work is required. Fig. 1(c) shows the result.

Obviously, shadow in Fig. 1(c) is entirely detected and maintained the original shape. Moreover, other feature points describing buildings or open spaces are kept quite well. Therefore, image $shadow(x,y)$ can be generated by conducting a minus operation between inversed Harris corner image and inversed binary $M(x,y)$.

Since shadow can be generally extracted, building detection becomes much more accessible. HSV color space has been widely used in image segmentation, and H channel can be used to extract built-up areas for its robustness toward illumination and shadow. Then, we have initiatory built-up image $Built\_up(x,y)$ by

$$Built\_up(x, y) = H\_bi(x, y) - shadow(x, y) \quad (7)$$

where H_bi is the binary image obtained by Otsu method on H channel.

Further detection is based on $Built\_up$ image (Fig. 2(a)), and more features are considered according to the distribution of buildings.

Sparsely distributed buildings are heavily influenced by open spaces and soil. V channel in HSV is short for "value", which means brightness of a pixel. It is determined by the maximum normalized value by 255 in three channels. Since soil and open spaces mostly have low reflectivity compared with concrete in buildings, they tend to have low brightness values. Therefore, it is more likely for soil and open spaces to be distinguished from buildings. Binary V is displayed in Fig. 2(b).

From Fig. 2, we can see that binary V can well delineate open spaces, soil and roads, which are barriers for sparsely buildings detection. However, most obstacles can be extracted by subtracting binary V from built-up image.

The proposed method for sparsely distributed buildings is not a method for all. It does not suit densely distributed buildings. Because Otsu's method is adopted in the process of binarization, and it is performed according to its background. In the environment of multiple buildings, most pixels share high brightness value, and binaryzing would mistake some buildings with dark roofs as backgrounds. Therefore, quite many buildings would be missed. Since built-up image has rejected the most disturbing shadow from buildings, and it can well indicate the buildings exactly, there is no need for further procession.

Post procession for both densely and sparsely distributed buildings is necessary, because some small spots would ruin the neatness of the result and they should be omitted. It is done by thresholding the connected components, and labeling them as backgrounds.

Generally, the new method can be summarized in the following steps:

Step 1. Filter noise of original image with Gaussian filter.
Step 2. Sharpen image by histogram stretching.
Step 3. Reject plants by thresholding an image P and

$$P = \frac{2G}{R + B} \quad (8)$$

Step 4. Detect feature points from the image obtained in Step 3 by Harris corner detector.
Step 5. Obtain $M(x,y)$ according to Eq. (6).
Step 6. Transform original image into HSV and achieve built-up image in (7).
Step 7. Determine whether the image belongs to sparsely distributed buildings or densely one by calculating the average number of connective components of shadow image. Since

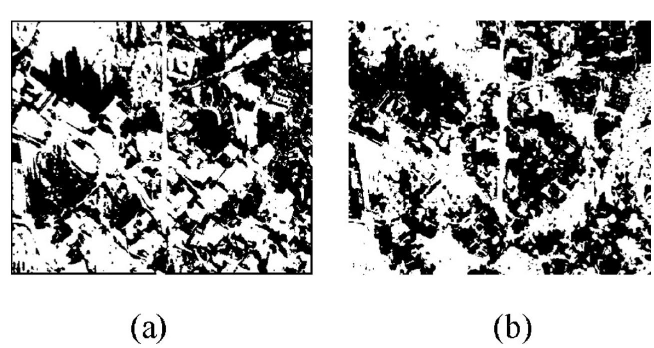

Fig. 2. Sample images indicating sparsely distributed buildings detection. (a) Built-up image and (b) binary V image.

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