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Building Detection from Satellite Images based on Curvature Scale Space Method

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Abstract

Remote sensing, which provides satellite and aerial images, has recently become the subject of intensive scientific research. It provides an important source of information for the geographical and topographical description of territories, and it allows the collection of information to be used to understand the changes in the environment. This paper deals with the segmentation of satellite images into various textures (building, road, grass, forest, etc.). The automatic extraction of buildings from satellite imagery in urban and suburban areas is the main objective of this paper; it presents a novel approach for building detection using corner detection after the reduction of shadow. The first step is the pre-processing of satellite images by using the Gaussian filter so as to reduce the effects and noises due to the atmospheric components on the electromagnetic radiation, then to increase the contrast between contours to detect shadows, which are the main obstacles in recognizing buildings, by using adaptive thresholding on HSV space color in order to get only the shadow regions; in the second step, points of interest of buildings are detected by using a modified Curvature Scale Space (CSS) for corner detection with a contours-based method. The proposed method is tested with images captured from Google Earth and from some published test images. Some other corner detection methods are used in comparison with the results of the proposed method, and the results indicate that the proposed method works robustly and efficiently.

Keywords: Corner detectors, buildings detection, satellite images, segmentation, object detection

Introduction

The image occupies a special place in many fields of daily life (remote sensing, satellites, medicine, publicity, industry, etc.); this encourages researchers in the imaging field to develop new techniques to extract information from images by different methods. The issue that interests us in this paper is the problem of the detection of buildings, from satellite and aerial images, which is becoming an important problem in computer vision and remote sensing.

To understand changes in the environment, remote sensing provides satellite and aerial images, and gives an important source of information on the geographical and topographical description of territory; it allows the collection of information, which can be used in many fields. Large collections of images are becoming available to the public, from satellite images to aerial photos. More than 10 different active Earth observing satellite systems are in orbit, such as Quick Bird, Ikonos, AISA, etc. Satellites and aerial images are very complex, and are composed of a large number of spatially heterogeneous objects, so the systems need algorithms to detect objects of interest. There are many difficulties when detecting objects using satellite or aerial images: engendering different colors, different points of view, and problems concerning contrast and, especially, shadow conditions, which make detection difficult. The issue that interests us in this paper is the development of a building detection method using satellite images but, firstly, we must reduce and eliminate the shadows that are the main obstacles in building recognition.

A limited number of automated systems have been reported in the literature; some of these works presented instances of, limited, good results and, mostly, they focused on spectral information and textural characteristics [1,2]. The process to detect buildings in aerial images can be divided into 2 main tasks: first, the detection of the object, second, the reconstruction. Regarding these topics, many reviews of building detection methods can be found. In this section we introduce some building detection methods. In [3] the authors proposed a survey focusing on buildings for automatic object extraction from aerial images. A building detection approach was introduced by Sırmaçek [4], using local feature vectors and a probabilistic framework using 4 different local feature vector extraction methods, such as Harris-Corner-Based Local Feature Vectors [5], Gradient-Magnitude-Based support regions [6], Gabor-Filtering-Based Local Feature Vectors [7] and FAST-Based Local Feature Vectors [8]. Extracting local feature vectors serve as observations of the probability density function to be estimated, and a variable-kernel density estimation method can be used to estimate the corresponding probability density function. Sırmaçek *et al*. proposed a building detection method using scale invariant feature transform [9,10] and graph theoretical tools; they represent each SIFT keypoints as a vertex of the graph. The unary and binary relationships between these vertices lead to the edges of the graph. Then, they extract separate buildings in the urban area using a novel graph cut method.

Ok *et al*. [1] proposed an approach that uses single ortho-rectified multi-spectral images; firstly, they extracted the vegetation and shadow areas based on multi-spectral information, widely accessible in most VHR satellite images. Then, a post-processing step prepared the shadow areas for the detection of buildings by applying prior knowledge of the solar illumination angles during image acquisition. Kim and Muller [11] extracted buildings in aerial images based on line extraction in 4 stages: in the first one, they extracted linear and features characteristics; in the second stage, geometric relationship of these lines was examined and a line-relation-graph was created. In the third stage, this graph was used to generate and made a combination of lines, any closed loop in the generated graph corresponds to a hypothesis building. Finally, verification was achieved by removing false hypothesized buildings using merging process, detecting vertical shadow lines, and detecting vertical lines. For more detail see [11].

The remainder of this paper is organized as follows. The next section presents the process of the proposed method; experimental results are reported and discussed in Section 4. Finally, the paper is ended by a conclusion.

Materials and methods

Materials and satellite data

Our input data consist of images differing in term of resolution; the resolution of the images has a strong influence on the representation of both buildings and other objects. The proposed method was tested using 2 types of images; the first one are images captured from Google Earth, covering the area of Beni Mellal city, Morocco, and the second one are some Ikonos satellite images.

Corner detectors methods

Corner detectors are methods that can detect pixels as final results with specific features. They represent a lot of useful information, and they play an important role in describing object features for recognition and identification. There are a lot of corner detector algorithms: the Harris detector, proposed in 1988, has been used in corner detection [12]. It is a gradient based method. The Speeded Up Robust Features (SURF) [13] algorithm is based on interest points in a 2-D grayscale input image, and selects a distinctive location in the image to find blob features, such as corners. It is a scale and rotation-invariant interest point detector and descriptor.

In the present case, the segmentation of buildings (roofs) from satellite images rich in detail can be presented as shadow information, so the proposed method is divided into 2 stages, as described in the below flowchart, **Figure 1**.

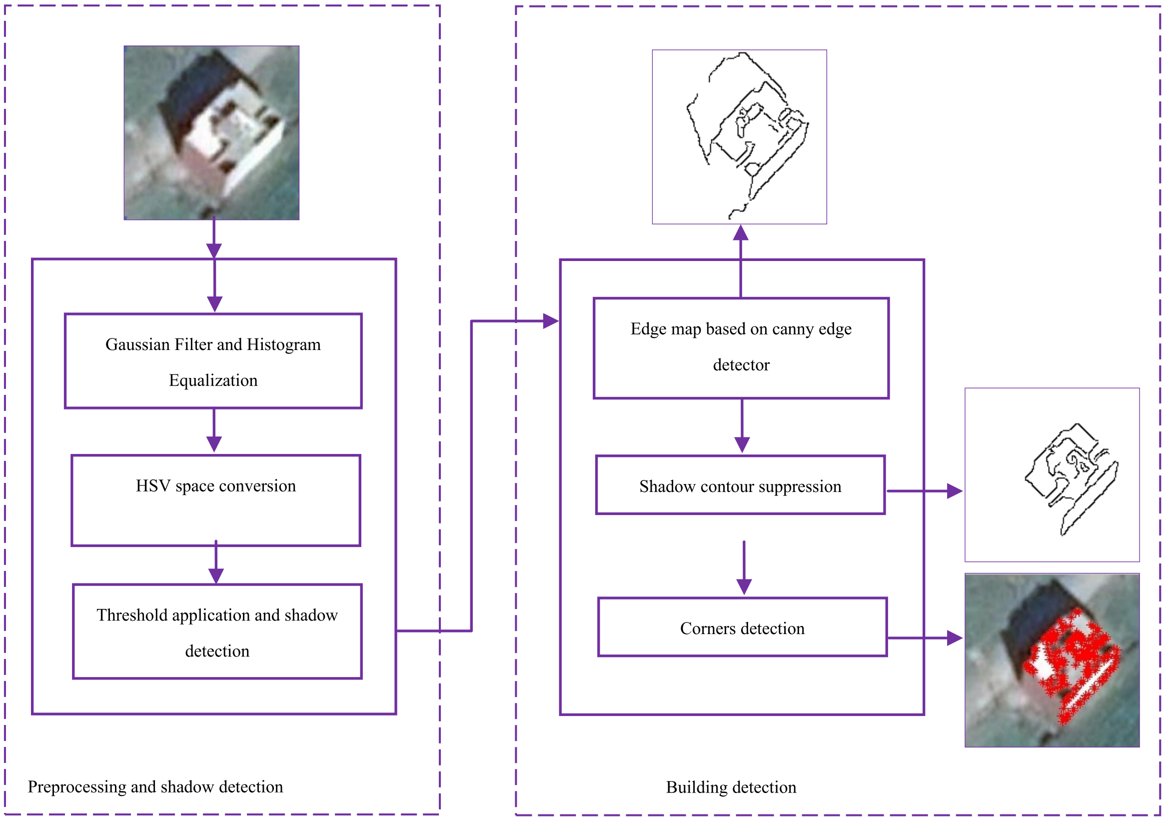

Figure 1 General flowchart of the approach.

In the first stage, we are interested in shadow detection, which is the main obstacle in detecting buildings, as described below:

Shadow detection

- Filter the original image with a Gaussian Filter;
- Adjust image intensity values to enhance the contrast of each RGB component by application of Histogram Equalization;
- Convert RGB image into HSV color space, which returns a matrix M×N with 3 components: the Hue, Saturation and Value components of the image; Value is the brightness of the color, and varies with color saturation. It ranges from 0 to 100 %; when the value is ‘0’ the color space will be totally black. With increase in the value, the color space brightness increases and shows various colors. Thereafter, we use adaptive thresholding on V channel to get the shadow regions only. The result of this first stage is to detect any shadow using a threshold. **Figure 2** illustrates the results obtained.

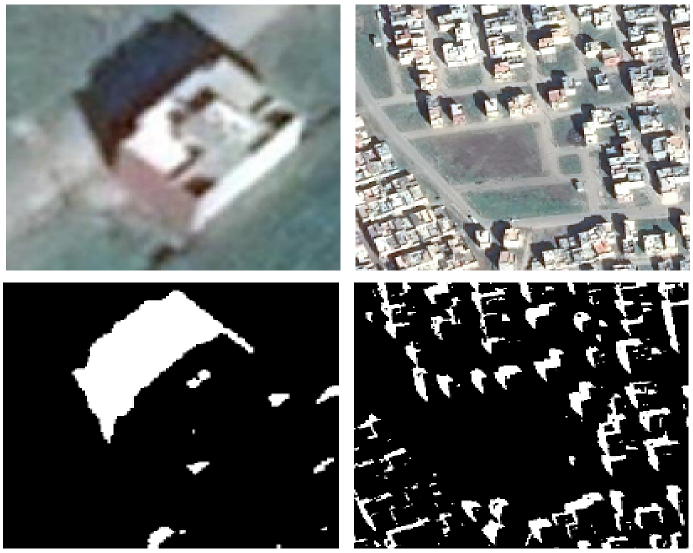

Figure 2 (First row) original images, (second row) shadow detection -white color- based on proposed method.

Building detection

As has been described in the previous section, the first step of the proposed method is the detection of shadows; in order to remove them thereafter, the image is converted into HSV space, while in this second step, to locate buildings based on the proposed method, the image is converted to grayscale.

Since shadow can be detected, building detection becomes much more accessible. In addition to color and texture features, generally, buildings have predefined forms, as square shapes, rectangular shapes, polygonal shapes, and those shapes that have angles that automatically engender the corners. To detect those corners, we use the Curvature Scale Space (CSS) Corner [14], which allows us to locate buildings in images.

CSS corner detector

In this section, we discuss the original and enhanced CSS corner detector. CSS is a good technique which has been recently used in corner detection in many fields: Image Corner [15], medical images allowing detection of disc optics [16], etc. It extracts corners by using the canny edge detector, then extracts the edge contours from the edge-map.

The process of original CSS [17] image corner detection is as follows:

1. Use the Canny edge detector [18] to extract edges from the original image.
2. Extract the edge contours from the edge image:
   - Fill the gaps in the edge contours.
   - Find the T-junctions and mark them as T-corners.
3. Compute the curvature at highest scale and determine the corner candidates by comparing the maxima of curvature to the threshold t and the neighboring minima.
4. Track the corners to the lowest scale to improve localization.
5. Compare the T-corners to the corners found using the curvature procedure and remove those which are very close.

- Firstly this paper changes step 2 of the general CSS method; the edge contour C is extracted.

$$C = \{P_1, P_1, P_1 \dots . P_N\} \tag{1}$$

where $P_i = (x_i, y_i)$ are pixels on the given contour, and N is number of pixels in the contour, we obtain 2 types of contours: the open contour and the closed one, as shown in Eq. (2); we define the contour as closed if the distance between its end points is small enough, and otherwise open.

$$C\begin{cases} \text{open} & \text{if } \overline{|P_1P_N|} > T \\ \text{closed} & \text{if } \overline{|P_1P_N|} < T \end{cases} \tag{2}$$

where T is the threshold used to determine whether the 2 end points are close enough. For an open contour, a certain number of points should be kept at both ends of the contour when it is smoothed. For this, the contour convolved with a less Gaussian smoothing kernel g is denoted by;

$$C_{smoth} = C \otimes g \tag{3}$$

$$g = \frac{e^{\frac{-t*t}{2\times\sigma}}}{2\times\pi\times\sigma} \tag{4}$$

where C is an initial contour and g is a Gaussian function with width (t) controlled by σ.
By detecting curves from the images and finding the T-junctions, each extracted curve is smoothed with the appropriate Gaussian kernel ($\sigma = 1$) to blur and remove detail and noise from it. Thereafter, the curvature value of each pixel of the contour is computed using Eq. (5).

$$K(u,\sigma) = \frac{\dot{X}(u,\sigma)\ddot{Y}(u,\sigma) - \dot{X}(u,\sigma)\dot{Y}(u,\sigma)}{(\dot{X}(u,\sigma)^2 - (\dot{Y}(u,\sigma)^2)^{1.5}}; \tag{5}$$

where $\dot{X}(u,\sigma) = x(u) \otimes \dot{g}(u,\sigma)$; (6)

$$\ddot{X}(u,\sigma) = x(u) \otimes \ddot{g}(u,\sigma); \tag{7}$$

$$\dot{Y}(u,\sigma) = y(u) \otimes \dot{g}(u,\sigma); \tag{8}$$

$$\ddot{Y}(u,\sigma) = y(u) \otimes \ddot{g}(u,\sigma) \tag{9}$$

where $\otimes$ is the convolution operator, $g(u,\sigma)$denotes a Gaussian function with derivation σ, $\dot{g}(u,\sigma)$and $\ddot{g}(u,\sigma)$ are the first and second derivatives of $g(u,\sigma)$, respectively.

- Secondly, in step 5, especially in the maximum obtuse angle, in the original CSS, the parameter θ_{obtuse} designates the maximum obtuse angle that a corner can have and still be considered as a true corner using the following condition;

$$if ang > \theta_{obtuse} \& ang < 360 - \theta_{obtuse} \tag{10}$$

where ang is the angle of the detected corner and θ_{obtuse} = 162 deg. In our case, in order to determine clearly the edges of buildings we kept all interest points based between both ends of the contour, so all interest points are included in the list of corner candidates, with θ_{obtuse} = 180 deg.

Results and discussion

This section presents the experimental results in order to evaluate the performance of the proposed method. Building detection is performed on images captured from Google Earth and high resolution grayscale Ikonos satellite images [7]; the proposed building detection method is compared with other interest point detection methods: SIFT Keypoints [7], Gradient-Magnitude-Based support regions [6] and the SURF method [13]. **Figures 3** and **4** illustrate building detection based on the proposed method.

From the results, in **Figures 3** and **4**, we can see that the proposed method has the best detection performance visually, and almost all of the interest points that locate buildings are reliably successfully detected, with some false detection.

Figure 3 shows the extracted boundaries of building classes with the original image as a background: the red color indicates the corners point of a building. It can be seen that, overall, most of the interest points of a building were correctly identified, with a good visual quality.

Building detection performance

One important step is the evolution of performance of the proposed system; here, performance is evaluated by measures suggested by Lin and Nevatia [19]. The accuracy of a shape is determined by counting correct building and non-building images; in order to determinate the detection percentage and branch factor, by visual inspection, the accuracy of detection is defined as the ratio between the number of buildings classified correctly, and the total number of buildings. However, the analysis of the results shows that the source of errors lies with confusion between buildings and roads or streets. These confusions are mainly due to the fact that some types of roads have angles called T-junctions and have similar shapes as buildings.

The measures of the quality of the results are presented below;

Detection Percentage: $\mathrm{DP} = \frac{\mathrm{TP}}{\mathrm{TP+TN}} \times 100$ (11)

Branch Factor: $\mathrm{BF} = \frac{\mathrm{FP}}{\mathrm{TP+FP}} \times 100$ (12)

where TP (True Positive) is number of the buildings detected manually and automatically, TN (True Negative) is number of buildings detected manually only, and FP (False Positive) is the number of buildings detected automatically only. The BF gives an index on how many false alarms are in the scene that contains the building; in this case, building detection means detection of the true interest points that locate building boundaries. **Table 1** shows the evaluation of the results of the proposed method on images shown in **Figures 3** and **4** and other test images. Our aim is to increase the detection percentage, and decrease the branch factor, **Table 1** shows that, for a number of images that are equal to 7, the proposed system gives rather consistent results for most images.

Table 1 Evaluation of the detection results in the test image set.

Test image	No. of building	Detection percentage	Branch factor
Image 1	34	88.23 %	11.70 %
Image 2	21	95.20 %	8.00 %
Image 3	23	100.00 %	4.16 %
Image 4	65	98.46 %	11.11 %
Image 5	19	100.00 %	5.26 %
Image 6	32	84.37 %	8.82 %
Image 7	30	86.66 %	7.14 %

From the experimental results shown in **Figures 3** and **4**, the total detection percentage is 93.27 %, with 6.42 % false detection; the numerical results in **Table 2** summarizes these effects in comparison with some other interest point detection methods.

Table 2 Results obtained by detector methods.

Methods	Building detection	False detection
SIFT Keypoints	88.40 %	14.40 %
SURF method	91.00 %	18.00 %
Gradient-Magnitude	88.17 %	14.33 %
Proposed method	93.27 %	6.42 %

In terms of computation time, for a 590×530 pixel image that contains 65 buildings, the total computing time is about 7.162 s, running in a software framework (Matlab© R2012b). The entire process is performed on a 2.4 GHz Intel Core i3 with 4 GB of RAM memory.

(a) (b) (c) (d)

Figure 3 Experimental results of proposed methodology in Google Earth images. Test images (a, b) and their interest points are detected and plotted on original images (c, d).

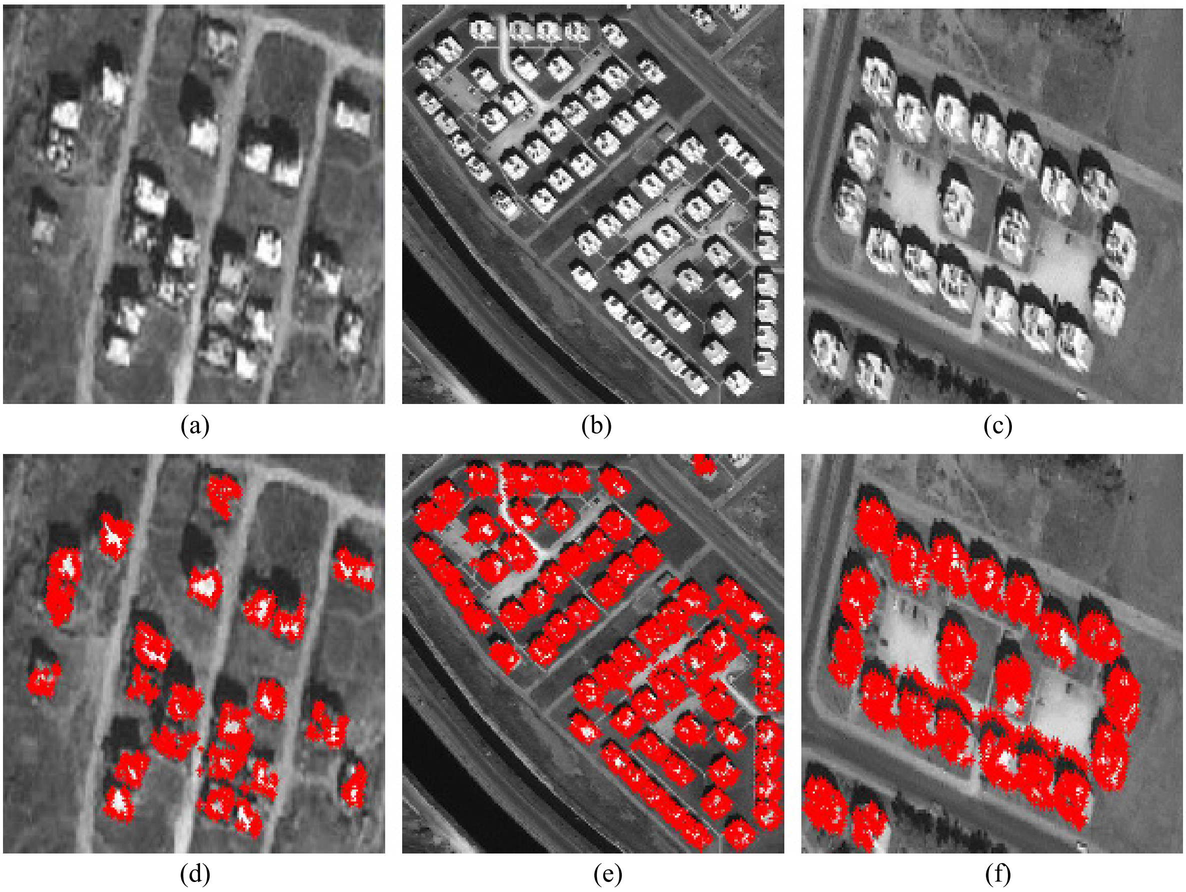

Figure 4 Experimental results of proposed methodology in Ikonos images. Test images (a, b) and their interest points are detected and plotted on original images (c, d).

Conclusions

There have been many proposed building detection methods in the literature; mostly, these methods have focused on spectral information and textural characteristics. In this study, a novel approach is proposed for the detection of buildings and shadows in satellite images. First, the shadow areas are extracted. Secondly, buildings are detected using the curvature scale-space technique by application of canny edge, and the curvature extracted to obtain corners. We test our algorithm on several Ikonos satellite images and images captured from Google Earth images.

Experiment results show that the proposed method can be applied to object detection in satellite images, and is robust with the variation of images and performs better compared to other building detection methods based on points of interest. However, there exist false results for buildings, so we need to focus on preprocessing and apply more information, such as object shape.

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