An Adaptive Thresholding Approach Based on Improved Harris Corner Detection for Estimation of Built up Region from Remote Sensing Images

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Abstract. This paper proposes an approach to estimate the possible built-up areas from high-resolution remote sensing images covering different scenes for monitoring the built-up areas within limited time and minimal cost. The motivation behind this work is that the frequently recurring patterns or repeated textures corresponding to common objects of interest (e.g., built-up areas) in the input image data can help in discriminating the built-up areas from others. The proposed method consists of two steps. First step involves extracting a large set of corners from the input image by employing an improved Harris Corner detector. The improved Harris Corner selects the local maxima from the extracted corners by performing the gray scale morphological dilation operation. It then finds those points in the corner strength image that matches the dilated image and is greater than the threshold value. In the second step, an adaptive global thresholding is applied to the corner response image and binary morphological operations are performed to obtain the candidate regions. Experimental results show that the proposed approach outperforms the existing algorithms in the literature in terms of detection accuracy.

Keywords: Harris corner · Spectrum clustering · Global thresholding

1 Introduction

Remote sensing technologies play a vital role in sourcing the information in fields like geography, surveillance, city planning etc., It is instrumental in gauging the distribution, evolution and characteristics of built up area and it can be of great help in updating the land maps and draw city Plans. One of the most important steps in Remote sensing Technologies is extraction of the built up Regions/Urbanized regions from the satellite images. Most current techniques that are used to find urbanized areas are based on

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texture analysis [5]. The built up area represents both manmade and Natural objects since the texture of the scene is often not clear from that of the natural objects.

While accessing the urban information, it is often seen that there are repeated patterns or textures, which makes it difficult in discriminating the built-up area and the natural objects, hence an unsubstantiated approach was proposed to detect built up regions using high-resolution satellite images. It is often observed that urban areas exhibit a multitude of straight line features. The numerical measurement of these straight lines help in analyzing the measurement of length, orientation and locality [1].

A new segmentation method used on the connected section in images based on syntactic characteristics was proposed which make use of the semantic leveling and range for defining the characteristics. This may result in producing an elaborate effect, a border effect and vagueness in discriminating the object from the background [2].

The mathematical semantic methods are used for the high phantom of data to classify the shadowy data with high altitudinal resolution to investigate the urban areas. This approach helps in bringing the transformations in isolation of the bright and dark structures in the images which means that the images are brighter or darker than the adjacent features in the images. The two high semantic urban datasets are further classified and used for visual network and are compared with other methods of numerical components and feature extractions [3]. The high resolution satellite images provide vital information to the remote sensing devices in monitoring the urban regions. Hence these high resolution aerial satellite images helps in optimum results and was tested on various three dimensional aerials and Satellite image data set [6].

The challenges of detecting the built-up area images is hence proposed through high resolution satellite images under the perception that the built up areas often detected through these images can be measured by the geometrical structures [7, 8]. This method proposes a systematic beginning through this approach for gauging the built up area estimation.

This work proposes a use of adaptive global thresholding approach for built-up area estimation. The remainder of this article is segmented into different sections: Sect. 2 discusses about the proposed method and its step by step implementation process, Sect. 3 provides the discussion about the results obtained and Sect. 4 provides the conclusion about the present work and the scope for future enhancements.

2 Proposed Method

This work proposes a framework towards discovering built-up regions from high-resolution satellite images. The process flow of the proposed method is depicted in Fig. 1. The proposed method have two components:

1. A likelihood function based method to extract candidate built-up regions in which an upgraded Harris corner detection operation is proposed.
2. Adaptive global Thresholding based algorithm for the Built-up area detection.

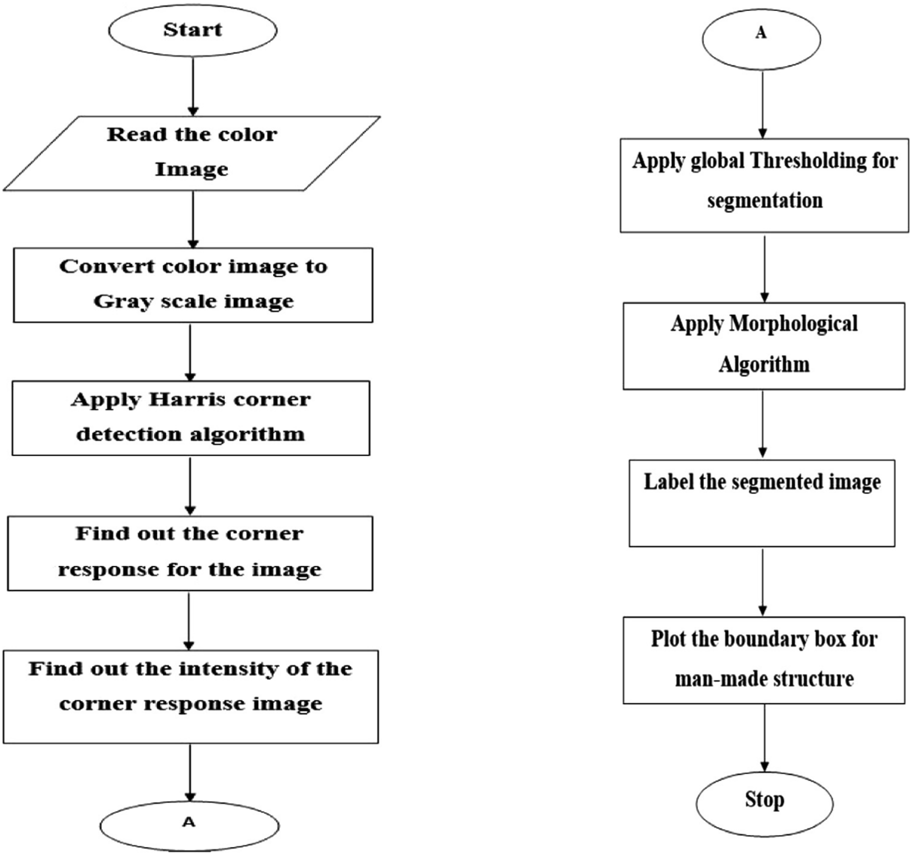

Fig. 1. Flowchart

Step-1. In the first step, the high resolution satellite color image as shown in Fig. 2 is converted to gray scale image as depicted in Fig. 3. The conversion of color image to gray scale image is done using the expression (1):

$$0.2989 * \mathrm{R} + 0.5870 * \mathrm{G} + 0.1140 * \mathrm{B} \tag{1}$$

Fig. 2. Original image

Fig. 3. Gray scale image

Step-2. Figure 4 is an example of Corner detector on the gray scale converted image and the symbol '+' defines the corners detected. Harris Corner Detector is based on the autocorrelation of image gradient values or image intensity values. The gradient covariance matrix is given by:

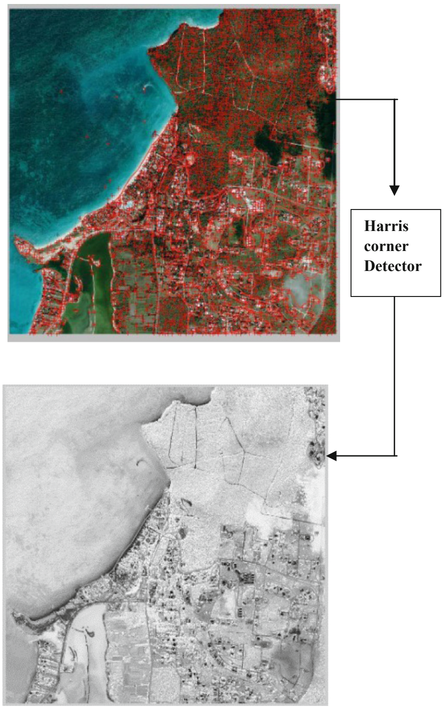

Fig. 4. Corner detection by Harris Corner detection

$$G_{x,y} = \begin{bmatrix} (\frac{\partial I}{\partial x})2 & \frac{\partial I}{\partial x}\frac{\partial I}{\partial y} \\ \frac{\partial I}{\partial y}\frac{\partial I}{\partial x} & (\frac{\partial I}{\partial y})2 \end{bmatrix} = \begin{bmatrix} Ix2 & IxIy \\ IxIy & Iy2 \end{bmatrix}$$

Where I_a and I_b denote the image gradients in the a and b directions. Harris Corner Detector considers the minimum and maximum Eigen values, α and β, of the image gradient covariance matrix $G_{a,b}$ in developing corner detector. A ‘corner’ is said to occur when the two Eigen values are large and similar in magnitude. Harris devises a measure using the determinant and trace of the gradient covariance matrix.

The steps involved in the Harris corner detection algorithm are described below:

1. Compute a and b derivative of image $I_a = G\sigma^a * I \quad Ib = G\sigma^b * I$
2. Compute products of derivatives at every pixel

$$I_{a2} = I_a.I_a \, Ib_2 = I_b.I_b \quad I_{ab} = I_a.I_b$$

3. Compute the sums of the products of derivatives at each pixel

$$S_{x2} = G\sigma * Ix_2 \quad S_{y2} = G\sigma * I_{y2} \quad S_{xy} = G\sigma * I_{xy}$$

4. Define at each pixel (x,y) the matrix $H(a,b) = Sa2(a,b) \quad Sab(a,b), Sab(a,b)$ $Sa2(a,b)$
5. Compute the response of the detector at each pixel

$$\text{a. } R = \ \text{Det}(H) - k(\text{Trace}(H))^2$$

Fig. 5. Corner response

Fig. 6. Adaptive global thresholding binary image

Harris corner detector is a mathematical approach for defining which case holds. First consider the measure of corner response R as shown in Fig. 5, which is required to be a function of A and P alone, on grounds of rotational invariance [4]. It is attractive to use Tr(M) and Det(M) in the formulation, as this avoids the over eigen value decomposition.

Grouping the Built up regions using spectral cluster is used to solve the grouping problem. Spectral clustering algorithm can be used [10].

Typically adaptive thresholding takes a gray scale or color image as input operation and produces an output in a binary image. It represents the segmentation. Each pixel in the image, a threshold has to be calculated [9]. Binarization Processing is the simplest method of image segmentation converting gray scale image to binary image.

The Global Thresholding algorithms have following steps.

1. Selecting an initial estimate for the global threshold, *T*.
2. Segmenting the image using which will produce two group of pixels G_1 consisting of all pixels with intensity values >T, and G_2 consisting of all pixels with values >T.
3. Calculating the mean intensity values m_1 and m_2 for pixels in G_1 and G_2
4. Compute a new threshold value: $T = 1/2(m_1 + m_2)$.
5. Repeat steps 2–4 until the mean values and in successive iterations do not change.

The field of scientific morphology contributes a wide-range of operators to image processing, all concepts are taken from set theory. The operators can be useful for edge detection, noise removal, image enhancement and image segmentation and analysis of binary images. Morphological techniques image itself is a structuring element. Hence the structuring element is positioned at all possible locations (Fig. 5).

Morphological opening is carried out on the threshold binary image to remove false positive urban areas, and owing to the fact that urbanized areas have high concentration of corners; the opening enhances the clustering and groups the built-up areas together. Figure 6 shows the morphological opening applied on the threshold binary image. Figure 7 shows the grouping based on the opened binary image.

Fig. 7. Adaptive global thresholding method output

3 Results and Discussion

The proposed method has been evaluated on the dataset consisting of five high resolution remote sensing images with varied spatial resolution. The performance parameter considered is the number of segments and the area of segments. The performance comparison of the proposed method is done with the Otsu thresholding and Graph cut method. In order to compare the system performance, built-up regions in the original image are marked manually and are compared against the system output. The results of the proposed method, Otsu thresholding and Graph cut method are indicated for few randomly selected images from the dataset. Figure 8, shows the randomly selected original image from the dataset, Fig. 9 shows the manually marked built-up areas, Figs. 10, 11 and 12 depicts the output of proposed, Graph cut and Otsu method respectively. Further Figs. 13, 14 and 15 indicate that the difference between the manually marked images and the output obtained from the adaptive threshold method on the corresponding panchromatic satellite image is negligible. Table 1 compares the segmentation of proposed method with competing methods, such as graph cut and OTSU.

First row against each method in the Table 1 indicates the number of segments and the second row indicate pixel count corresponding to built-up region. It is observed from the result and images of Table 1 that the proposed method is considerably accurate, and is able to segment built-up areas well. In doing the comparison, a

Fig. 8. Original image: random sample 1

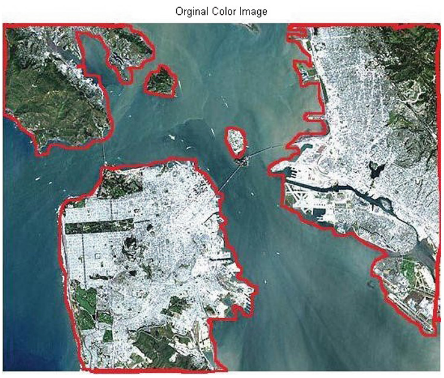

Fig. 9. Manually marked built-up regions of Fig. 8

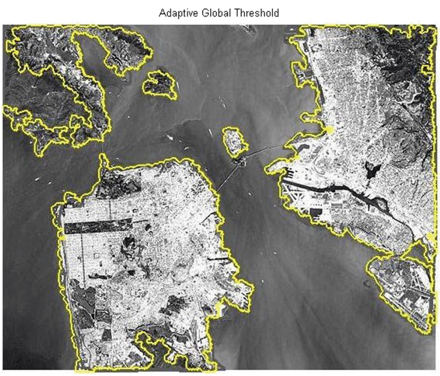

Fig. 10. Segmented image of the proposed method

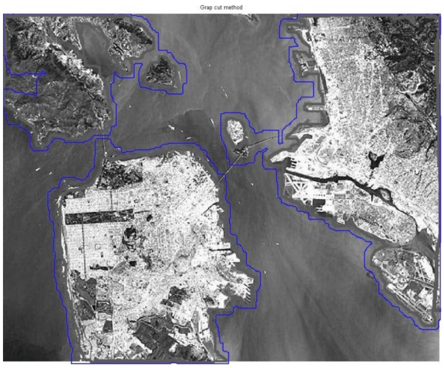

Fig. 11. Segmented image of the graph-cut method

Fig. 12. Segmented image of the Otsu method

Fig. 13. Manually marked built-up regions: random sample 2

quantitative measure of the number of segments deciphered by the newly proposed method and manual method has been used. It is observed that the proposed method results are visually more accurate. While the proposed method is robust in most scenarios, it produces false positives, in cases where there are prominent corner features in natural habitat, such as the "forest road" areas as depicted in Fig. 7.

Fig. 14. Manually marked areas vs. Areas marked using proposed method for random sample 2

Fig. 15. Manually marked areas vs. Areas marked using proposed method for random sample 3

Table 1. Performance comparison

Algorithm/Data	1	2	3	4	5
Manual marked image	5	3	7	2	1
	122647	17544	81244	84657	887036
Graph cut	3	5	2	2	1
	144699	36738	111558	109597	887253
Otsu method	3	2	1	1	1
	141892	120637	145787	122773	816632
Proposed	5	5	6	2	1
	120930	21472	82895	90661	823307

4 Conclusion

This work presents a framework for estimating the built-up regions from satellite images. The proposed method includes two major components, first being a likelihood-function to extract candidate built-up regions, in which an improved Harris operation is proposed, and the second being adaptive Global-Thresholding based algorithm for the final built-up area detection. Based on the results obtained, the proposed approach demonstrates increased accuracy when compared to the existing works in the literature. Future work in this direction is to improve the detection using machine-learning classification models, which would not only allow segmenting the urban areas in a much cleaner way, but also allow reading the city texture in a much detailed way.

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