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ROBUST UNSUPERVISED CLASSIFICATION OF BUILT-UP AREAS IN APPLICATION TO REMOTE SENSING IMAGE

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Abstract - *Modeling the effective localization of built-up area using static clustering technique for simultaneously detecting possible built-up areas from given set of high-resolution remote sensing images covering different scenes is presented in this paper. A novel approach of segregating the finest of built-up area of region of interest is developed using the proposed algorithm. This proposed algorithm can be categorized into two stages. The first stage is to extract large set of corners from each input image by Harris corner detector and at the second stage corners are extracted using likelihood function which localizes the candidate regions in each input image. In order to discover the frequently recurring texture patterns corresponding to built-up areas as an unsupervised grouping problem, the candidate regions with histogram representation of texture feature is modeled and the grouping problem is solved by spectrum clustering.*

Key Words: **Built-up area, Harris corner detector, Spectrum clustering, High resolution image**

1. INTRODUCTION

High-resolution remote sensing images have become critical sources of information in various fields such as geography, cartography, surveillance, city planning, and so on. Among them, monitoring the distribution, growth and characteristics of built-up area gains a significant attention for the aid of local agency to update land maps and draw city plans [1]-[3]. In such applications, the basic step is to extract built-up regions from the high-resolution remote sensing images. In general built-up area represents a dynamic environment which is mostly consists of both manmade and natural objects which are based on texture analysis. Unsalan and Boyer [4] combine line-support regions with spectral features to measure built-up areas. To extract texture information from the image Pesaresi and Benediktsson [5] introduce a novel mathematical morphological transformation, called differential morphological profile. Its application for built-up region detection can be found in [6]. In recent year, built-up area detection based on local invariant features has revealed promising results. Main objective of this paper is to optimize the detection of built up areas from high resolution satellite image using unsupervised classification. In [7], Sirmacek and Unsalan develop a method to detect built-up areas and buildings in very high resolution Ikonos satellite images based on scale-invariant feature transform features and graph theory. However, it needs some template building images for training and therefore suffers from a high computing complexity and memory requirement. In later [8], a more direct method is used. However, since it solely depended on local features for recognition, it can often be too weak of a signal to reliably detect the built-up regions in complex satellite image. Existing methods [9] have their own limitations. The spectral features of some areas of known land cover types are extracted from the image which is known as the "**training areas**". Each pixel in the whole image is then classified as belonging to one of the classes depending on how close its spectral features are to the spectral features of the training areas. On detecting build regions from an image have to label a large volume of training samples to provide sufficient prior information for high detection rate and it's a tedious process. This can be overcome by means of automatic Grouping of pixels in the image into separate clusters, depending on their spectral features.

2. AUTOMATED EXTRACTION OF CORNER POINTS FROM HARRIS CORNER DETECTOR

In general, urban environment is replete with corners from building roofs, road marks, and other man-made objects. If we could detect all such corner points from images, the built-up regions would be naturally implied from the density of corners. Thus, the corner feature which is used to infer the locations of potential built-up regions in the given images. To extract certain kinds of features and infer the contents of image, corner detection is an approach used within computer vision systems. Corner detection is most widely used in various applications like image registration, image mosaicing, motion detection, video tracking, 3D modeling and object recoganization. The Corner detection overlaps with the topic of detection.

A well-defined position and can be robustly detected point in an image is an interest point. It has some typical local property. For example, if square objects are present in the image, then corners are very good interest points. Corners in image can be located using local detectors and it serve better

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than lines when the correspondence problem is to be solved. Edge detectors themselves are not stable at corners. This is natural as the gradient at the tip of the corner is ambiguous.However, near the corner there is a discontinuity in the gradient direction. This observation is used in corner detectors.

The simplest corner detector is the Moravec detector, which is maximal in pixel with high contrast. These points are on corners and sharp edges. This produces a good result and computationally more expensive. An alternative method is proposed by Harris and Stephens [18], which in turn is an improvement of a method by Morave's by considering the difference of the corner score(sum of square difference).

2.1 A. Harris Corner Detection

The Harris Corner Detector is a mathematical operator that finds "High similarity features" in an image f and this method is popular because it is rotation, scale and illumination variation independent. The basic Principle behind this is corner; the image intensity will change largely in multiple directions. Harris corner detector is based on the local autocorrelation function of an image and this function measures the local changes of the signal with patches shifted by a small amount in different directions. Given a shift (x, y) and a point the autocorrelation function is defined as

$$S[u,v] = \sum_{x,y} w(x,y)[I(x+u,y+v) - I(x,y)]^2 \quad (1)$$

Where S is the difference between the original and the moved window, u is the window's displacement in the x direction, v is the window's displacement in the y direction and w(x, y) is the window at position (x, y).

This acts like a mask which ensuring that only the desired window is used. I represent the intensity of the image at a position (x, y) where I(x+ u, y+ v) is the intensity of the moved window and I(x, y) is the intensity of the original image. Maximize the intensity of an image term:

$$\sum_{x,y} [I(x+u,y+v) - I(x,y)]^2 \quad (2)$$

Then, we expand this term using the Taylor series. It's just a way of rewriting this term in using its derivatives

$$S[u,v] \approx \sum_{x,y} [I(x,y) + uI_x + vI_y - I(x,y)]^2 \quad (3)$$

I(x+ u, y+ v) changed into a totally different form (I(x, y) + uI_x + vI_y).That's the Taylor series in action. And because the Taylor series is infinite, we've ignored all terms after the first three. It gives a pretty good approximation. But it isn't the actual value. Next, we expand the square. I(x, y) cancels out, so it's just two terms we need to square.

$$S[u,v] \approx \sum_{x,y} u^2(I_x^2) + 2uvI_xI_y + v^2(Iy^2) \quad (4)$$

Now this messy equation can be tucked up into a neat little matrix form like this:

$$S[u,v] \approx [u,v] \left(\sum \begin{bmatrix} I_x^2 & I_xI_y \\ I_xI_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix} \quad (5)$$

Rewriting the summed-matrix, and it is denoted as M. Harris matrix is symmetric and positive semi-definite.

$$M = \sum w(x,y) \begin{bmatrix} I_x^2 & I_xI_y \\ I_xI_y & I_y^2 \end{bmatrix} \quad (6)$$

The equation (1) is modified as:

$$S[u,v] \approx [u,v]\, M \begin{bmatrix} u \\ v \end{bmatrix} \quad (7)$$

It was figured out the Eigen value (λ) of the matrix can to help to determine the suitability of the window. A score R, is calculated for each window

$$R = \det M - k(\text{trace } M)^2 \quad (8)$$

Where det M = $\lambda_1 \lambda_2$, trace M= $\lambda_1 + \lambda_2$ and k=0.04

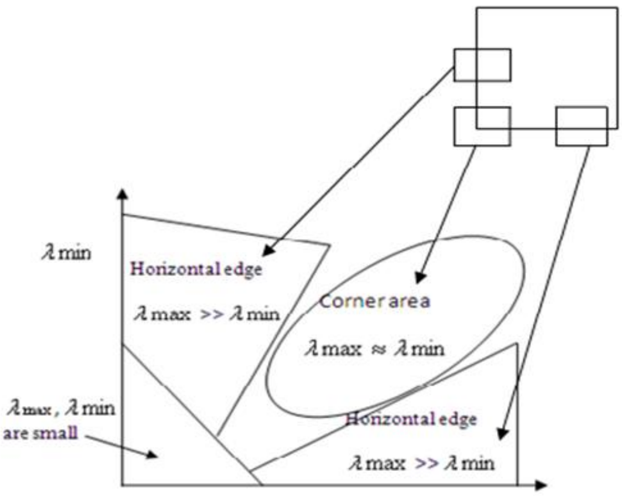

Fig -1: Corners and edge detection using Eigen value

- Both Eigen values are small, and then the pixel is "flat". There are no edges and corners in this location.
- One eigenvalues is large, and the other is small, then the pixel is an edge
- Both Eigen values are large, then the pixel is a corner

Based on the Eigen values of an image Harris corner output is shown in Fig.2

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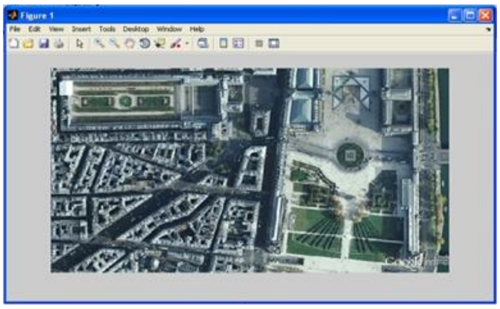
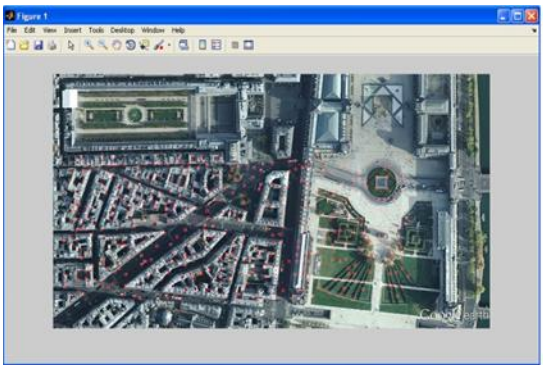
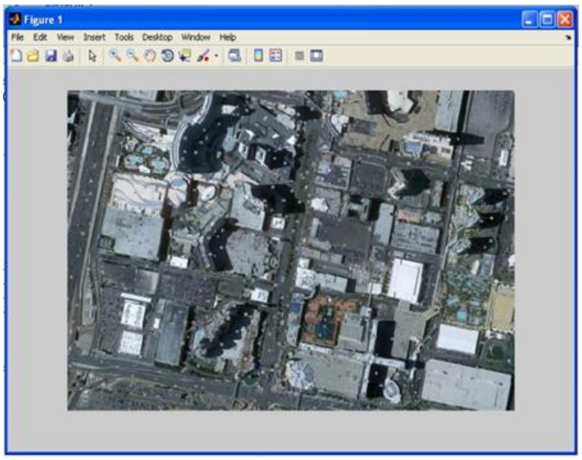


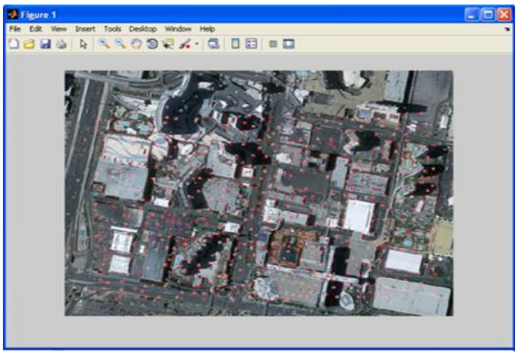
(a)



(b)



(c)



(d)

Fig -2: Test input image 1(a) and (b) Harris corner output

3. EXPERIMENTS

3.1 Data Set Description

To test the performance of built-up area detection method using clustering technique, we consider m*n array of input image presented in conventional form, which composed of 30 satellite image(Ikonos and Quickbird images) downloaded from Google Earth. This data set is used to test the detection ability of the proposed method for images acquired by different sensors and different spatial resolutions

3.2 Results and Discussion

In this experiment, the basic Idea of developing such a model is to extract the particular built-up area for a specified region of interest. The proposed technique has been tested on several satellites. To quantify the detection result, we use the evaluation measures widely accepted for built-up region extraction, which are true positive rates (TPRs) and false positive rates (FPRs).

Harris Corner detection founds itself prominent in highlighting the edges and corners that comes to the base for the building block of built-up area detection which is based on sigma and threshold value has been proposed in [26]-[27]. As indicated in Table I the maximum number of Harris Corner points are detected for the values between threshold 0.1 to 1 with sigma value equal to one and when the sigma value increases, the detection of points are decreased. This method provides 85% correction rate and decreases FPR.

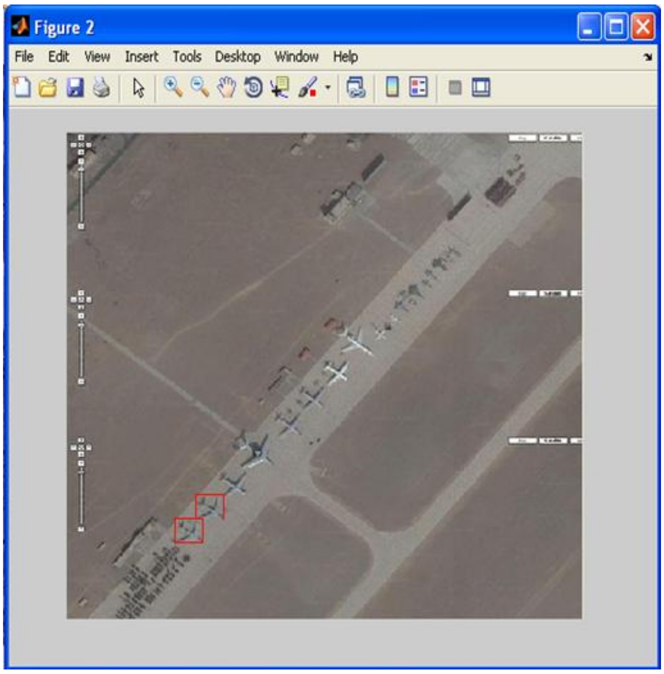


Fig -3: Detection of required airplane of fig.11

4. CONCLUSIONS

In this paper, an unsupervised framework of simultaneously detecting the built-up areas from multiple high-resolution satellite images is discussed. The proposed method includes a likelihood-function based approach to extract candidate built-up regions, in which Harris corner detector is proposed, and spectrum clustering for the final built-up area detection. Based on these tests, the proposed approach demonstrates the following advantages over the previous works. First, it can simultaneously detect built-up regions from multiple images; second, the entire process is highly automatic and requires no human interaction

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